MATLAB SIMULATION OF THE THROUGHPUT RATE OF A COGNITIVE RADIO COMMUNICATIONS SYSTEM

Nerses Baliozian

Bachelor of Engineering

Telecommunications Engineering

MACQUARIE University

Department of Engineering

Macquarie University

2016

ACKNOWLEDGMENTS

I would like to acknowledge few people who helped me throughout my undergraduate degree and this thesis.

First of all my family who did everything they can, even more, to make my dreams become reality. Thank you to my parent for bringing me up the way you did. Thank you to my sister from whom I have learned the true meaning of sacrifice. Thank you to my uncles and aunts from each one of them I have learned how to overcome any difficulties in my life.

My deepest gratitude goes towards the University of Aleppo where I studied for five years. Five years that has been essential for me to complete this degree.

I would also like to thank my friends for their consistent encouragement.

Lastly, I would like to thank my dedicated supervisor from whom I have learned and am still learning a lot not only about this project or telecommunication industry but also about life in general. Thank you Professor Sam for all your time and attention.

STATEMENT OF CANDIDATE

I, Nerses Baliozian, declare that this report, submitted as part of the requirement for the award of Bachelor of Engineering in the Department of Electronic Engineering, Macquarie University, is entirely my own work unless otherwise referenced or acknowledged. This document has not been submitted for qualification or assessment at any other academic institution.

Student's Name: Nerses Baliozian

Student's Signature: NB

Date: November 07 2016

ABSTRACT

Based on the latest researches it has been shown that around the two third of the available spectrum has not been efficiently utilised. This inefficiency led to shortage in frequency which increased the price of occupying the bandwidth.

Wireless applications have become more popular and the available spectrum of radio frequencies has become a precious asset. Research also shows that that the frequency spectrum is not used completely at a given time. Some frequency bands are not used; some bands are overutlised whereas other bands are underutilised.

Taking all the above into consideration cognitive radio has been considered the best solution to overcome the problem of underutilisation of frequency bands. In cognitive radio systems the idea of secondary user; who is not the main user of the spectrum has been introduced. The secondary user can only use the spectrum when the primary user; the main user of the spectrum is not using the spectrum. This requires sensing the spectrum to check for the available spectrum bands and use them accordingly.

In this project the different spectrum sensing techniques will be discussed furthermore a MATLAB simulation for the throughput will be illustrated.

Table of Contents

Table of Figures

Chapter 1

1. Introduction

In the last couple decades the use of wireless applications has significantly increased which increased the need of the radio spectrum. The strategy of assigning fixed spectrum band to some applications led to some problems given the fact that those applications are not efficiently using the spectrum assigned to them which led to having overutlised and underutilised bands in the spectrum.

Cognitive radio concept that was introduced by Joseph Mitola has been accepted as an innovative technology which will help to overcome the problem of efficiency using the spectrum. In cognitive radio systems users have the ability to adapt and use the radio spectrum based on their surrounding environment's conditions. [1]

The efficient use of spectrum has been an important aspect in radio communications. One of the best ways of improving the utilisation of the spectrum at a given time is giving the secondary users (SU) who are not serviced users the ability to use the unoccupied bands of the spectrum which are not being used by the primary users (PU). This is the main concept behind cognitive radio systems. [2]

1.1 Background

In the early decades of the 20th century when the radio communication became popular, people were afraid that the new users will interfere with the existing users hence each user obtained his own licence to avoid the interference. However, it became difficult afterwards for other wireless applications to operate properly in the radio spectrum given the fact that most of the spectrum has been used. William Kennard former chairperson of the United States Federal Communication Commission (FCC) referred to this problem as ''Spectrum Drought'' [3].

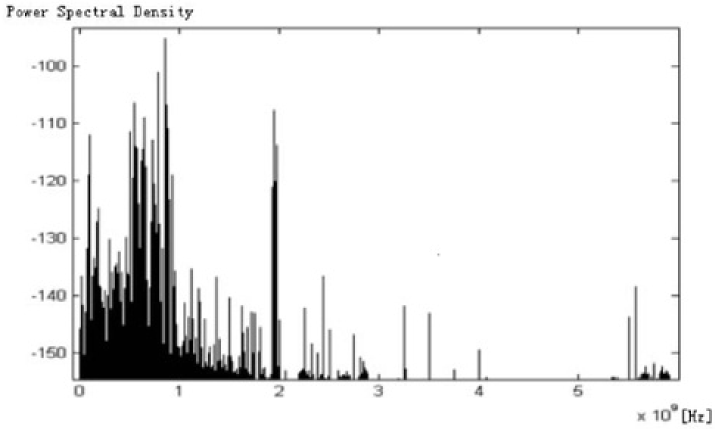


Figure 1: Spectrum Utilisation Measurement at Berkeley Wireless Research Centre

From figure 1 above we can see that the lower frequencies are used more than the higher frequencies. It is very difficult to reconfigure the use of spectrum hence cognitive radio will give us the ability to establish an understanding and share the spectrum between the licensed users who are the main users of the spectrum and the unlicensed users who can only use the spectrum when the licensed users are not using it.

1.2 History

In 1999 Joseph Mitola introduced the concept of cognitive radio in his paper ''Cognitive Radio: Making Software Radios More Personal'' [4]. Mitola continued his research and produced other papers where he described cognitive radio systems. Mitola's research made regulatory bodies in countries such as the United Stated and United Kingdom realise that the radio frequency spectrum is used in an inefficient way. Hence, the regulatory bodies have started considering the use of cognitive radio technique.

Moreover, the new emerging technology of cognitive radio systems have been included in wireless standards such as IEEE802.11k in which sensing information have been used in order to detect to which network a wireless device needs to be connected. The wireless local area network can be a good example to explain the use of cognitive radio; wireless devices in the network tend to connect to the access point that provides the strongest signal which might lead to having access points serving users over their capacity and other access points serving none. With IEEE802.11k the user will check if the access point has reached its maximum capacity it will choose another access point which hasn't. Hence, the efficiency of the network will increase.

1.3 Cognitive Radio Definition

To get an in-depth understanding about the cognitive radio we need to understand the concept of cognitively. The encyclopaedia of Computer Science defines cognitively as *mental states and processes intervene between input stimuli and output responses.* Moreover, in his paper Simon Haykin defines cognitive radio as *''Cognitive radio is an intelligent wireless communication system that is aware of its surroundings environment, and uses the methodology of understanding-by-building to learn from the environment and adapt its internal states to statistical variations in the incoming RF stimuli by making corresponding changes in certain operating parameters in real-time with two primary objectives in mind: highly reliable communications whenever and wherever needed and efficient utilisation of radio spectrum''.* The rapid change in technology made the implementation of cognitive radio systems more feasible. [2]

From the definition above we can say that cognitive radio is an intelligent system that can make decisions about the efficient use of the radio spectrum based on the information gathered from the surrounding environment. As we mentioned above the most important aspect of cognitive radio is the coexistence of both the primary users and secondary users in the system to make sure of the efficient use of the radio spectrum in which the secondary user can only use the spectrum when the primary user is not using it. This requires the primary user not to change its infrastructure in order to give the ability to the system which in turn will give access to the spectrum to the secondary user. [3]

Hence we can state that the main purpose of cognitive radio system is to increase the efficiency of spectrum utilisation and to avoid the interference between the primary and secondary users of the network.

1.4 Literature Review

During the preliminary work for this project a research has been conducted and some papers have been checked and the following are examples of what were found:

In [4] the term cognitive radio has been used for the first time by Joseph Mitola. In his paper Mitola also suggested using Radio Knowledge Representation Language (RKRL) which provides a standard language to dynamically adopt for unanticipated data exchange.

Simulation and analysis of cognitive radio systems have been discussed in Goutam Ghosh's article [5]. The reuse of unoccupied frequency bands in order to increase the efficiency of the bandwidth allocated was already discussed in this paper.

Simon Hayken discussed the tasks that are meant to be accomplished by cognitive radio systems and the emergent behaviour of the systems in his 2005 article [6]. His paper discusses in details Mitola's visionary ideas and gives detailed explanations by presenting detailed expositions of signal processing which is one of the most important aspects of cognitive radio systems.

Cognitive Radio technique Detect and Avoid (DAA) has been discussed by Prof. Sam Reisenfeld in his 2009 paper [7]. The paper talks about the importance of DAA in providing high reliable decision when a primary user is not using a particular frequency band.

The fundamentals, architecture and applications of cognitive radio networks were presented in the 2011 paper [1] by Beibei Wang and K. J. Ray Liu. Important issues of dynamic spectrum sharing have also been discussed in the paper.

The resource allocation for ad hoc cognitive radio networks has been discussed in the 2011 journal article [8] by Seung-Jun Kim. Few solutions have been suggested and numerical results and simulation has also been presented in the document.

The physical, MAC and network layer of cognitive radio networks has been discussed in [9]. The paper can provide us with cross-layer overview when designing cognitive radio networks.

The spectrum sensing techniques, challenges of cognitive radio networks and the methods used to analyse resource allocation have been discussed in the 2016 article [10].

An in depth illustration of cognitive radio networks have been presented in the Ahmed Khattab's book [11].

Various spectrum sensing techniques have been discussed by the literature review paper prepared by Scott Parson [12] .Energy detector based sensing, Coherent based sensing, Matched filter sensing, cyclostationary based sensing and hybrid based sensing techniques were explained thoroughly in the paper.

Spectrum sensing, spectrum sharing and spectrum access have been discussed in [13].

1.5 This Project

After discussing the various techniques used in sensing the spectrum in cognitive radio networks and through simulating the throughput rate of cognitive radio systems we will be able to simulate the throughput of the channel for three different sensing techniques which will lead us to make the right decision and make an efficient use of the frequency spectrum.

As chapter one serves as an introduction for this paper and discusses the history, background and literature review related to cognitive radio networks the second chapter discusses the fundamentals of cognitive radio. Different spectrum sensing techniques have been discussed in the third chapter. A system model for each of the spectrum sensing techniques have been presented in chapter four whereas the Matlab code has been presented in chapter five. The results have been discussed in the last chapter.

Chapter 2

2. Fundamentals of Cognitive Radio

2.1 Characteristics of Cognitive Radio

Energy and bandwidth are considered to be the most important resources of communications. Hence, to improve the quality and the capacity of the communication network the mentioned resources need to be taken into consideration. Recently researches are trying to find new resources that can efficiently improve the quality and the capacity of the service. [1]

Cognitive radio has been considered the technology that can efficiently utilise the available resource in an intelligence and flexible way. The main difference between the cognitive radio networks and other networks is that the devices in the cognitive radio networks can adapt and change the parameters, by which they are participating in the network, based on their environment. [1]

The two main characteristics of cognitive radio networks are cognitive capability and reconfigurability. [1]

2.1.1 Cognitive Capability

Before adjusting their function based on the surrounding environment cognitive radios have to collect information about the surrounding environment. This function where the cognitive radio devices get information about the surrounding network parameters such as transmitted waveform, geographical information and radio frequency is referred to as cognitive capability. [1]

Cognitive capability characteristic can be divided into three sub-functions which are also presented in figure 2. Those sub-functions will be described in more details in the next sections. [1] [14]

Spectrum sensing – where the device gets the necessary information about the surrounding network and detect of spectrum holes. [14]

Spectrum analysis – where characteristic estimation for the detected spectrum hole is done. [14]

Spectrum decision – where the most convenient spectrum is selected after checking important parameters. [14]

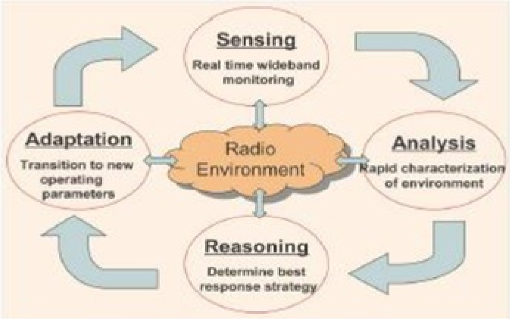


Figure 2: Cognitive Capability Sub-Functions

2.1.2 Reconfigurability

Once the Cognitive radio devices gathered the necessary information about the surrounding environment they will change their parameters based on the information gathered in order to achieve the best performance. This characteristic is referred to as reconfigurability. [1]

2.2 Functions of Cognitive Radio

The duty cycle of a cognitive radio includes detecting the white space (spectrum hole) in the spectrum, detecting the best frequency bands, managing spectrum access with the other users of the network and leaving the network when primary users wants to use it. We can summarise the steps mentioned above in the following three categories. [1]

2.2.1 Spectrum Sensing and Analysis

In this stage cognitive radio will detect pats of the frequency spectrum that is not being used by primary user which is referred to as white space or spectrum hole. After detecting those holes cognitive radio will try to make the best use of them. However, when the primary user starts using the network again i.e. the white spectrum is not available anymore, cognitive radio can detect that and it will make sure that no interference between the primary and secondary users will occur. [1]

2.2.2 Spectrum Management and Handoff

After sensing the spectrum and finding the spectrum holes, the secondary users of the cognitive radio network will choose the best frequency bands and use them based on their communication's Quality of Service. This function is called spectrum management and handoff. When the primary user wants to use a band that is occupied by a secondary user, the secondary user will hop in to the next preferred spectrum hole which can be chosen based on the parameters of the secondary user. [1]

2.2.3 Spectrum Allocation and Sharing

To achieve optimal spectrum efficiency a good spectrum allocation and sharing technique is required given the fact that some of the spectrum could be shared amongst secondary users or between primary and secondary users. When the secondary users are sharing the spectrum with primary users there is a certain level of interference that is allowed to occur, anything above that threshold requires the secondary user to leave the spectrum. When the spectrum is shared amongst secondary users then cognitive radio will make sure to avoid collision and interference between the secondary users. [1]

2.3 Network Architecture and Application

Figure 3 below shows the network architecture of a cognitive radio network that includes a primary network and secondary network.

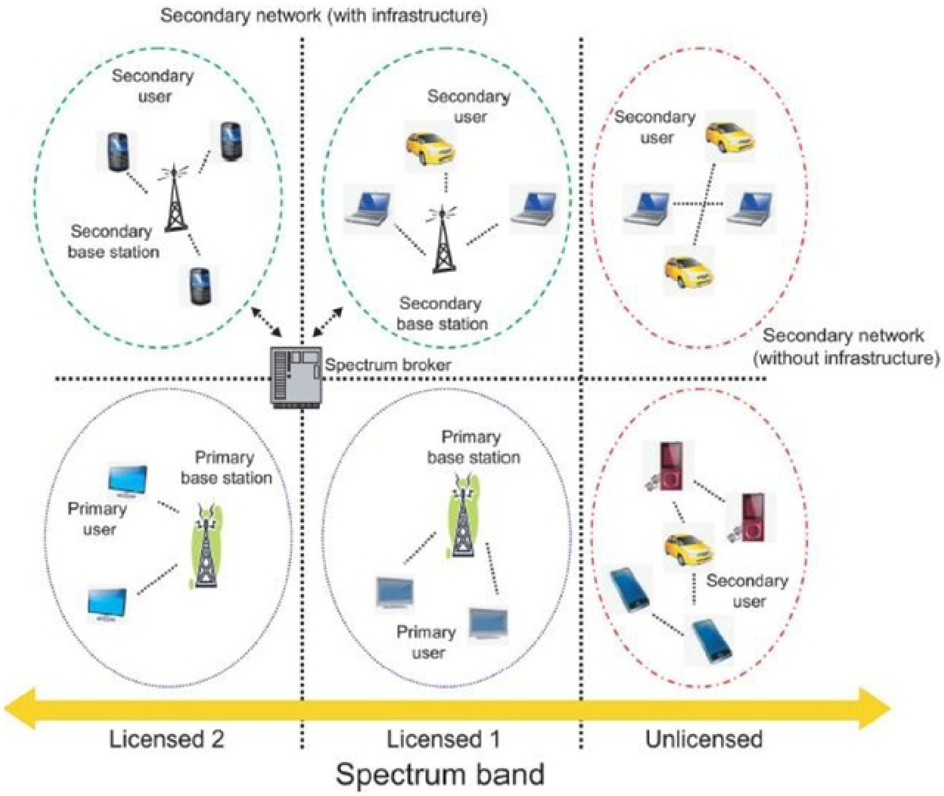


Figure 3: Cognitive Radio Architecture

The secondary network is defined as a network that consists of secondary users either with or without a base station. The users in this network can access the licensed spectrum only if there is no primary user using the spectrum. The access of the secondary users to the network is usually managed by a secondary base station. All the components of the secondary network are equipped with the functions of cognitive radio. In a network when more than one secondary network is sharing a common spectrum band an entity called spectrum broker might be used to manage and coordinate the usage of the spectrum. The spectrum broker gets the information from each secondary network and distributes the network resources to make sure an optimal efficiency is achieved. [1]

The primary network is defined as the network that consists of primary users and a primary base station. The users in this network are the authorised users of the spectrum in the network and the spectrum access is managed by the base station in the network. The transmission of primary users should not be effected by the transmission of the secondary users. The users of this network are not equipped with the functions of cognitive radio. Hence, when the secondary network is using the bandwidth alongside the network it should not only sense the spectrum, find the white space (spectrum hole) and utilise the best spectrum band but it should also sense the presence of the primary network and leave the spectrum to the next available spectrum band in order to avoid interference. [1]

Cognitive radio can be used in different applications. Cognitive radio systems can sense the environment, detect any change in the radio frequency and reconfigure the characteristics to adapt with the changes. All the above made the optimal use of the spectrum a reality. Moreover, the decentralised decision making for spectrum sharing resulted in decreasing the limitation of centralised spectrum management techniques. [1]

Cognitive radio systems can provide military with a secure and adaptive communications. The military communication has a low capacity because of the shortage in the radio spectrum given the fact that static assignments of bandwidth will result in some bands remaining unused. With the dynamic spectrum assignment and access technique used in cognitive radio systems the problem has been eliminated where cognitive radio can provide spectrum access to make sure that the available bandwidth is used efficiently. [1]

Cognitive radio is also used in public safety and state emergency services. Communicating the necessary information is an essential in case of a natural disaster or a terrorist attack which sometimes might lead to destroying the available communication channels. Cognitive radio can detect the available spectrum and direct the communication there in order to achieve an efficient and reliable communication. More than one service type is also supported by cognitive radio networks (video, voice, date) which make it have an essential role during emergency situations. [1]

Rapidly growing wireless application needs to have an access to the spectrum. Cognitive radio can provide the necessary spectrum access to those applications given the fact that it can sense the spectrum and direct the communication to the available spectrum slots in the network. Another advantage of using cognitive radio in wireless applications is that it is very easy to maintain the network specially when there is no need to update the hardware of the network. The entire network can be maintained by upgrading the software of radio management. [1]

Chapter 3

3. Cognitive Radio Spectrum Sensing

The previous chapter described the main functions of cognitive radio networks from which we have noticed that spectrum sensing is the most important step towards perfectly completing the functions of cognitive radio. As spectrum sensing allow the user to know the available spectrum in any given time. [12]

Spectrum sensing is defined as detecting the presence of signals. The unused frequency slots in the spectrum will be used to accommodate for a new communication. The secondary users of the network who are occupying the spectrum that are leased by the primary users should detect the incoming primary user and move to another vacant slot in the spectrum [15].

Various methods are used to detect the use of the spectrum and make sure to make the most usage of the spectrum. Spectrum sensing devices are used to achieve the maximum throughput of the cognitive radio network. Some of the above mentioned devices are capable of sensing the spectrum and others can make decision based on the information they gather from the surrounding spectrum sensing units [15].

The spectrum sensing techniques are dependent on the application that the cognitive radio network is being used for. Some applications might not need to have information about the signal on air. Other applications need to know information about the specification of the signal. Whereas other applications are more interested about the identification of a given signal [15].

In this chapter three spectrum sensing techniques will be discussed. The advantages and disadvantages of each technique will be briefly discussed in this chapter as well [15].

3.1 Energy Detection

Energy detection technique is considered to be the most common technique used in spectrum sensing of cognitive radio networks. The main reason for being the most common used technique is the less amount of computation required and the low amount of information needed about the possible signal. A threshold is established and the energy level that will be detected will be compared to it [15].

Energy detection can be implemented in time or frequency domain. The square of the signal is being averaged while using the time domain. An FFT is required to implement energy detection in the frequency domain and after that the signals will be averaged over the observation time. The final stage of both implementation methods in comparing the results with the threshold [15].

In energy detection it is very hard to distinguish between the original signal, noise and interference which was one of the reasons that this method is not used in many cognitive radio applications [15].

Despite being cheap, a very useful technique in some complex cognitive radio strategies and a simple method its performance at lower SNR levels which might lead to false detection made the use of this method very limited [15].

3.2 Matched Filter Detection

This spectrum sensing method provides us with the best signal to noise ratio and the reason for that is because it matches a specific signal. In this method a demodulation of the signal is required which will provide us with more information about the signal of the primary user [15].

This method is considered to be a costly method of sensing the spectrum because detailed information (modulation technique, bandwidth, frequency synchronisation, frame format) about the signal needs to be stored in the spectrum sensing device hence implementing it has been considered impractical [15].

Waveform detection can be considered as a simplified type of matched filter detection. In waveform detection the implementation complexity and the security of the primary user has been improved. The waveform detection also assumes that the secondary user will definitely know and detect a pattern that exists in the primary user's signal [16].

Although waveform detection requires less detection time and has a good detection performance, it also can have synchronisation errors which can significantly decrease the performance of the network [16].

3.3 Cyclostationary Detection

By definition any modulated signal will most probably have periodicity. Which means that autocorrelation of the signal will produce a grade of periodicity as well [15].

Given the fact that the noise is not correlated it is relatively easy to distinguish noise from signals. Cyclic correlation function is used instead of power spectral density in the cylclostationary spectrum sensing method [15].

At the presence of cyclic frequency the peak of that frequency is usually presented in the Cyclic Spectral Density [15]. This is shown in the last chapter of this report.

Cyclostationary spectrum sensing technique is considered to be a very complicated method given the fact that it needs more than one FFT calculation and correlation.

The above mentioned method are discussed and simulated in the next chapters of this report.

3.4 Cooperative Spectrum Sensing

In some radio systems such as hidden source, fading channels and local interference it is very hard for the system to collect information about the surrounding environment which might make data recovering an impossible task to achieve. However, the probability of detection increases if multiple spectrum sensing devices share their information amongst each other in the same network [15].

Cooperative spectrum sensing can be achieved by using a central unit which can manage the frequency spectrum based on the information it gets from the surrounding environment [15].

Despite the fact that using cooperative spectrum sensing technique will be a good communication strategy between the central device and the radio link, it will also consume a lot of bandwidth [15].

3.5 Other Methods

Wavelet transform, radio identification and multitaper spectral estimation are considered to be other methods of spectral sensing. It is also common to find a combination of more than one technique used in spectrum sensing in order to improve the performance of the communication link. However, it is better to find out the requirements of the application and the sensing environment and choose the spectrum sensing technique and strategy based on those two aspects [15].

Chapter 4

4. System Model

The objective of cognitive radio systems is the detection of the presence of signal in a heavily noisy channel. Ideally, the radio must be able to detect the presence of primary user in case the signal is present and report an available for use channel if the signal is not present. However, since both signal and noise are of random nature, error is inevitable. Therefore, the performance of the detection algorithm is measured based on the probability of missed detection in the case of occupied channel and the probability of false detection when no signal is present. High performance algorithms must ensure small probabilities for both missed detection and false detection scenarios.

The performance of different detection schemes, including energy sending, waveform sensing and cyclostationary detection algorithms under the presence of noise is analyzed in the following sections. Furthermore, the criteria for achieving maximum likelihood (i.e., probability of missed detection equal to probability of false detection) are discussed.

4.1 Energy Sensing

4.1.1 Formulation of energy sensing algorithm

Let's denote the primary user signal, channel noise, and received signal with x, z and y, respectively. Also, let's characterize the detection of primary user signal by the binary hypothesis test H, where H0 is the hypothesis of the channel being free and H1 is the hypothesis the primary user signal is present. So,

$$H_0: \qquad y(n) = z(n)$$

$$H_1: \qquad y(n) = x(n) + z(n)$$

In order to detect the availability of the channel, the receiver processes the channel to acquire a series of samples of the complex envelope. The samples are put together to form a block with length N_B. The energy of the received signal is then calculated by adding up the squared magnitude of the complex samples, as follows:

$$S = \sum_{n=1}^{NB} |y(n)|^2$$

In which y(n) are the complex samples of the received signal. The radio then compares the energy with a threshold S_T to decide if the channel is free or occupied by the primary user.

The statistical characteristics of energy metric S are defined as

$$\mu_{s0} = E(S|H_0)$$

$$\mu_{s1} = E(S|H_1)$$

$$\sigma_{s0}{}^2 = Var(S|H_0)$$

$$\sigma_{s1}{}^2 = Var(S|H_1)$$

The SNR of the signal is defined as

$$SNR = \frac{E(|x(n)|^2)}{\sigma_z^2}$$

The mean values are calculated as follows:

$$\mu_{s0} = E(S|H_0) = E\left\{\sum_{n=1}^{NB} |z(n)|^2\right\} = \left\{\sum_{n=1}^{NB} E(|z(n)|^2)\right\} = N_B E\{|z(n)|^2\} = N_B \sigma_z^2$$

$$\mu_{s1} = E(S|H_1) = E\left\{\sum_{n=1}^{NB} |x(n) + z(n)|^2\right\} = N_B E\left\{|x(n)|^2 + |z(n)|^2 + \overbrace{2|x(n)||z(n)|}^{independent:0}\right\}$$

$$= N_B\{\sigma_x^2 + \sigma_z^2\}$$

$$\mu_{s1} = N_B\{SNR\sigma_z^2 + \sigma_z^2\} = N_B\sigma_z^2(SNR + 1)$$

The variance of S subject to H0 is:

$$\sigma_{s0}{}^2 = Var(S|H_0) = VAR\left\{\sum_{n=1}^{NB} |z(n)|^2\right\} = \sum_{n=1}^{NB} VAR(|z(n)|^2) = \sum_{n=1}^{NB} \sigma_z^4 = N_B\sigma_z^4$$

$$\sigma_{s0} = \sqrt{N_B}\sigma_z^2$$

For the variance of S subject to H1, we have:

$$\sigma_{s1}{}^2 = Var(S|H_1) = VAR\left\{\sum_{n=1}^{NB} |x(n) + z(n)|^2\right\}$$

$$= \sum_{n=1}^{NB} VAR(|x(n)|^2 + |z(n)|^2 + 2|x(n)||z(n)|)$$

$$\sigma_{s1}{}^2 = N_B\{VAR(|x(n)|^2) + VAR(|z(n)|^2) + 2VAR(|x(n)||z(n)|)\}$$

$$\sigma_{s1}{}^2 = N_B\{E(|x(n)|^4) - E^2(|x(n)|^2) + \sigma_z^4 + 2E(|x(n)|^2)E(|z(n)|^2)\}$$

$$\sigma_{s1}{}^2 = N_B\left\{\left(\frac{E(|x(n)|^4)}{E^2(|x(n)|^2)} - 1\right)E^2(|x(n)|^2) + \sigma_z^4 + 2E(|x(n)|^2)\sigma_z^2\right\}$$

$$\sigma_{s1}{}^2 = N_B\left\{\left(\frac{E(|x(n)|^4)}{E^2(|x(n)|^2)} - 1\right)(\sigma_z^2 SNR)^2 + \sigma_z^4 + 2(\sigma_z^2 SNR)\sigma_z^2\right\}$$

$$\sigma_{s1}{}^2 = N_B\sigma_z^4\left\{\left(\frac{E(|x(n)|^4)}{E^2(|x(n)|^2)} - 1\right)SNR^2 + 1 + 2SNR\right\}$$

Defining $\alpha = \frac{E(|x(n)|^4)}{E^2(|x(n)|^2)}$, so we have:

$$\sigma_{s1}{}^2 = N_B\sigma_z^4\{(\alpha - 1)SNR^2 + 1 + 2SNR\}$$

$$\sigma_{s1} = \sqrt{N_B}\sigma_z^2\sqrt{(\alpha - 1)SNR^2 + 1 + 2SNR}$$

The parameter α can change between 1 and 2 depending on the type of modulation technique used. In case of OFDM modulation, the transmitted signal can be modelled as a Gaussian random process:

$$x(n) = a(n) + jb(n)$$

Where $a(n)$ and $b(n)$ are random variables with normal distribution. In this case, the value of α is equal to 2.

On the other hand, in case of constant envelope modulation, the transmitted signal is modelled as:

$$x(n) = \frac{a(n) + jb(n)}{r(n)}$$

Where $r(n) = \sqrt{a(n)^2 + b(n)^2}$ is included to keep the absolute value of $x(n)$ constant. In this case, the the value of α is equal to 1.

4.1.2 Maximum likelihood analysis

In order to correctly detect both occupied and free channel conditions, the parameter ST should be selected wisely. Too large values of ST will result in false detection of an occupied channel and too small values will cause missing of a free channel.

False detection means that hypothesis H_0 is correct but $S>S_T$ so we wrongly detect the presence of primary user. Missed detection means that hypothesis H_1 is correct but $S<S_T$ so we think that the channel is free while the primary user has occupied the channel. The maximum likelihood detection occurs when the probability of false detection is equal to the probability of missed detection:

$$P_{FD} = P_{MD} = SEF = Q\left(\frac{\mu_{s1} - \mu_{s0}}{\sigma_{s0} + \sigma_{s1}}\right)$$

in which SEF refers to sensing error floor. From above we can say that SEF can be represented with the following equation:

$$SEF = Q\left(\sqrt{N_B}\ \frac{SNR}{1 + \sqrt{[(\alpha-1)SNR^2 + 2SNR + 1]}}\right)$$

The ST corresponding with the maximum likelihood detection is calculated according to [7]:

$$S_T = \frac{\mu_{s0}\sigma_{s1} + \mu_{s1}\sigma_{s0}}{\sigma_{s0} + \sigma_{s1}}$$

Substituting the mean and standard deviations into the above equation, we have

$$S_T = \frac{N_B\sigma_z^2\left[\sqrt{N_B}\sigma_z^2\sqrt{(\alpha-1)SNR^2 + 1 + 2SNR}\right] + [N_B\sigma_z^2(SNR+1)]\sqrt{N_B}\sigma_z^2}{\sqrt{N_B}\sigma_z^2 + \sqrt{N_B}\sigma_z^2\sqrt{(\alpha-1)SNR^2 + 1 + 2SNR}}$$

$$S_T = N_B\sigma_z^2\frac{\left(\sqrt{(\alpha-1)SNR^2 + 1 + 2SNR} + 1\right) + SNR}{1 + \sqrt{(\alpha-1)SNR^2 + 1 + 2SNR}}$$

$$S_T = N_B\sigma_z^2\left(1 + \frac{SNR}{1 + \sqrt{(\alpha-1)SNR^2 + 1 + 2SNR}}\right)$$

4.2 Waveform sensing

4.2.1 Formulation of waveform sensing algorithm

The waveform sensing algorithm assumes the availability of the transmitted data at the receiver. In this case, the detection algorithm uses the transmitted and received data to obtain the detection statistic, S, according to:

$$S = Re\left[\sum_{n=1}^{NB} y(n)x^*(n)\right]$$

According to the analysis detailed in [7], the probability of false detection is related to the detection threshold (S_T) as

$$P_{FD} = Q\left(\frac{S_T}{\sqrt{\frac{N_B}{2}\sigma_z^2\sqrt{SNR}}}\right)$$

Furthermore, the probability of missed detection is measured as

$$P_{FD} = Q\left(\frac{\sqrt{N_B}SNR - \frac{S_T}{\sqrt{N_B\sigma_z^2}}}{\sqrt{(\alpha-1)SNR^2 + 0.5SNR}}\right)$$

4.2.2 Maximum likelihood analysis

Under the maximum likelihood condition, the SEF is calculated according to:

$$SEF = Q\left(\sqrt{N_B}\frac{\sqrt{SNR}}{\sqrt{(\alpha-1)SNR + 0.5} + \sqrt{0.5}}\right)$$

Equating P_{FD} and SEF, the maximum likelihood threshold is obtained as

$$\frac{S_T}{\sqrt{\frac{N_B}{2}\sigma_z^2\sqrt{SNR}}} = \sqrt{N_B}\frac{\sqrt{SNR}}{\sqrt{(\alpha-1)SNR + 0.5} + \sqrt{0.5}}$$

$$S_T = \sqrt{\frac{N_B}{2}\sigma_z^2\sqrt{SNR}}\sqrt{N_B}\frac{\sqrt{SNR}}{\sqrt{(\alpha-1)SNR + 0.5} + \sqrt{0.5}}$$

$$S_T = \frac{N_B \sigma_z^2 SNR}{\sqrt{2(\alpha - 1)SNR + 1} + 1}$$

4.3 Cyclostationary detection

4.3.1 Cyclostationary feature

The received signal can be expressed in the form [17]

$$y(t) = x(t) + z(t) = a(t)e^{j(2\pi f_0 t + \theta(t))} + z(t)$$

In which a and θ are random variables and f_0 is the carrier frequency. Since the mean value and the autocorrelation function of $y(t)$ are periodic, the received signal is regarded as a cyclostationary signal. The signal $y(t)$ has some non-random information, which can be used to discriminate the signal from noise. This information includes symbol period, modulation type and carrier frequency.

The periodicity of the mean of the received signal can be shown by considering the mean of y at $t + T_0$:

$$E(y(t + T_0)) = E\left(a(t + T_0)e^{j(2\pi f_0 (t+T_0) + \theta(t+T_0))} + z(t + T_0)\right)$$

$$= E\left(a(t + T_0)e^{j(2\pi f_0 t + \theta(t+T_0))}\right) + E(z(t + T_0))$$

$$= E\left(a(t + T_0)e^{j(2\pi f_0 t + \theta(t+T_0))}\right)$$

$$= E\left(a(t)e^{j(2\pi f_0 t + \theta(t))}\right)$$

$$= E(y(t))$$

Furthermore, the periodicity of the correlation function is expressed as

$$R_y(t, \tau) = E(y(t + \tau/2)y^*(t - \tau/2)) = R_y(t + T_0, \tau + T_0)$$

Since the autocorrelation is periodic, it can be expressed as the following Fourier series:

$$R_y(t, \tau) = \sum_{\alpha} R_y^{\alpha}(\tau)e^{j2\pi\alpha t}$$

In which $\alpha = mf_0$ is the cycle frequency.

4.3.2 Cyclic power spectrum

Since the received signal has cyclic behavior, it can be detected from noise by computing its cyclic power spectrum. The cyclic power spectrum is computed according to the following algorithm [15]:

1- Compute signals *u* and *v* by according to

$$u = y * e^{-j\pi\alpha t}$$

$$v = y * e^{j\pi\alpha t}$$

2- A time window is selected. The length of the time window should be a fraction of the length of the received signal.

3- A section of signals *u* and *w* is selected by using the time window.

$$u_w = u * Window$$

$$v_w = v * Window$$

4- The Fourier transform of the selected signals is calculated.

$$U_w(f) = FFT\{u_w\}$$

$$V_w(f) = FFT\{u_w\}$$

5- Cyclic power spectrum for the selected window is calculated as

$$CPS_w(f) = U_w V_w^*$$

6- The time window is shifted forward and the steps 3-5 are repeated until the window reaches the end of the received signal.

7- The cyclic power spectrum of the whole signal is calculated as

$$CPS(f) = \frac{1}{N_w} \sum_w CPS_w(f)$$

In which N_w is the total number of windows.

The above algorithm computes the cyclic power spectrum as a function of spectral frequency (f) for a specific value of α. By repeating the above procedure for various different values of α, the cyclic power spectrum is obtained as a 2 variable function of f and α.

Chapter 5

5. Simulation

5.1 Why simulation

Computer simulation is a useful technique for the study of engineering problems. They enable emulating practical systems to study their performance without having to actually build the real system. The main advantage of computer simulations is that they allow practicing several different scenarios without spending large amounts of money and time for building a real benchmark system. Furthermore, they enable changing the system configuration and studying critical scenarios which cannot be done in actual experiments.

In particular, computer simulations have proven to be a useful tool for analysis, evaluation and designing of the communication systems. In this project, computer simulations are conducted to attest the performance of cognitive radio in terms of signal detection. In this context, the objective of simulations is to analyze the performance of different detection algorithms in terms of probability of missed/false detection under various different noise powers and present appropriate plots to showcase the effect of additive noise on the accuracy of detection algorithms. Simulations are repeated for different types of modulations as well as different lengths of detection window.

The simulation results provide insightful information about the performance of the detection algorithms under different scenarios. Furthermore, they can show that the actual performance of the system is in accordance with the analytical formulations obtained from theory. Additionally, they help the communication engineers design the detection parameters so as to satisfy the design goals. For instance, if the desirable percentage of error should be smaller than a specific value, simulations can be used to estimate the required length of data which should be used for detection.

5.2 Simulation techniques

Since the primary user signal and noise are random processes, Monte Carlo simulation techniques must be employed to study the performance of the detection method. In this technique, the detection algorithm is tested several times and the success or failure of the algorithm is determined for each test. The number of failures are then counted to determine the performance of the algorithm.

Each test involves the following stages:

1- In the first stage, the primary user signal and noise are generated as a series of random numbers such that the ratio of the signal power over the noise power is in accordance with the specified SNR.

2- Then, the detection algorithm is used to detect the presence or absence of the primary user in the channel.

3- By comparing the outcome of the detection algorithm with the actual situation (signal present or channel unoccupied), the success or failure of the algorithm is decided.

For each specific SNR, the tests are repeated numerous times, each time with a new series of random primary user signal and random noise. The total number of failures are then counted and divided by the total number of tests to detect the probability of missed/false detection. Then, the probability of missed/false detection is plotted as a function of SNR.

The details of MATLAB programs for different detection algorithms are described in the following subsections.

5.3 Energy sensing

The energy sensing algorithm and the MATLAB program used to simulate this technique are detailed in the following.

1- Define the SNR as a vector of numbers. To test the algorithm for different values of SNR, the SNR vector is defined as a vector starting from the minimum SNR and increasing with steps of 2.5dB up to the maximum SNR:

```
SNR=-30:2.5:0;
```

2- Use a “for” loop to span over different values of SNR:

```
for j=1:length(SNR)
```

3- Reset the error counters. Two variables are used to count the number of missed and false detection. It is important to reset those variables for each SNR since the number of errors should be counted from zero.

```
i_fd=0;
```

```
i_md=0;
```

4- The variance of noise (Az) and the magnitude of SNR are computed as:

```
Az=10^(-SNR(j)/20);
snr=10^(SNR(j)/10);
```

5- Calculate the statistical features of the channel. According to the mathematical analysis provided in Section 4.1.1, the variance (sig) and mean (mu) corresponding with scenarios S0 and S1 are computed as:

```
    sig0=sqrt(Nb)*Az^2;
    mu0=Nb*Az^2;
    sig1=Nb*Az^4*((alpha-1)*snr^2+2*snr+1);
    sig1=sqrt(sig1);
    mu1=Nb*(snr+1)*Az^2;
```

6- Compute the maximum likelihood threshold and the theoretical SEF. According to the mathematical analysis presented in Section 4.1.2, the maximum likelihood threshold and the theoretical SEF are obtained as:

```
ST=(mu0*sig1+mu1*sig0)/(sig0+sig1);
num=sqrt(Nb)*snr;
denom=1+sqrt((alpha-1)*snr^2+2*snr+1);
SEF_theory(j)=qfunc(num/denom);
```

7- Use a while loop to conduct Monte Carlo simulations for the specified SNR:

```
while i_md<Maxerr
```

8- Generate the signal and noise vectors. The noise is defined as a complex random process with normal distribution and variance Az:

```
        z=Az*sqrt(0.5)*(randn(1,blocklen)+
1i.*randn(1,blocklen));
```

The primary user signal is defined as a Gaussian ($\alpha = 2$) or constant envelope ($\alpha = 1$) random process:

```
        x=sqrt(0.5)*(randn(1,blocklen)+
1i.*randn(1,blocklen));
        if alpha==1
            x=x./abs(x);
        end
```

9- Simulate scenario H0. In this scenario, the channel is unoccupied and hence the received signal contains only noise. False detection occurs if the energy of the received signal is larger than the detection threshold:

```
        y=z;
        S=sum(abs(y).^2);
        Sz(i,j)=S;
        %False detection
        if S>ST
            i_fd=i_fd+1;
        end
```

10- Simulate scenario H1. In this scenario, the primary user signal is present. Missed detection occurs if the energy of the received signal is smaller than the detection threshold:

```
        y=x+z;
        S=sum(abs(y).^2);
        Sy(i,j)=S;
        %Missed detection
        if S<ST
            i_md=i_md+1;
        end
```

11- After the number of missed detections reaches its maximum the "while" loop stops. At this stage, the Monte Carlo experiment for the j^{th} SNR is finished. The probability of false (missed) detection is calculated as the ratio of total number of false (missed) detections to the total number of tests:

```
Pfd(j)=i_fd/i;
Pmd(j)=i_md/i;
```

12- The results are plotted.

5.4 Waveform sensing

The steps 1-4 for the waveform sensing algorithm are the same as the energy sensing algorithm. The other steps are detailed below.

5- Compute the maximum likelihood threshold and the theoretical SEF. The maximum likelihood threshold and theoretical SEF are obtained according to the mathematical analysis presented in Section 4.2.2:

```
num=Nb*snr*Az^2;
denom=sqrt(2*(alpha-1)*snr+1)+1;
ST=num/denom;
num=sqrt(Nb)*sqrt(snr);
denom=sqrt((alpha-1)*snr+0.5)+sqrt(0.5);
SEF_theory(j)=qfunc(num/denom);
```

6- Use a while loop to conduct Monte Carlo simulations for the specified SNR.

7- Generate the signal and noise vectors (similar with energy sensing method).

8- Simulate scenario H1. In this scenario, the primary user signal is present. Missed detection occurs if S is smaller than the detection threshold:

```
y=x+z;
S=sum(real(y.*conj(x)));
%Missed detection
if S<ST
    i_md=i_md+1;
end
```

11- After the number of missed detections reaches its maximum the "while" loop stops. At this stage, the Monte Carlo experiment for the j^{th} SNR is finished. The probability of missed detection is calculated as the ratio of total number of missed detections to the total number of tests:

```
Pmd(j)=i_md/i;
```

12- The results are plotted.

5.5 Cyclostationary sensing

A MATLAB function namely "CalcCycl" is used to compute the cyclic power spectrum for a specific value of α. The main program uses a "for" loop to span over the range of α and calls "CalcCycl" to compute the cyclic prefix for each value of α. In the following, the MATLAB program is described.

5.5.1 Cyclic power calculation for a specific value of α

The cyclic power is calculated by function "CalcCycl", which accepts two signals (x and y) as well as the value of α as input, and returns the cyclic power spectrum for the specified α as output. The calculations are performed in the following steps:

1-Define the window. While using a rectangular window is convenient, the detection performance is not optimal in that case. To improve the detection performance, Hanning window is used here. The window is defined as:

```
Window = hanning(Nwindow);
```

in which Nwindow is the length of the window.

2-As detailed in Section 4.3.1, the signals x and y are multiplied by $e^{-j\pi\alpha t}$ and $e^{j\pi\alpha t}$, respectively:

```
y = y.*exp(-1i*pi*alpha*t);
x = x.*exp(1i*pi*alpha*t);
```

3- The indies which lie inside the window are defined as vector index. Initially, the window lies at the beginning of data. So:

```
index = 1:Nwindow;
```

4- a "for" loop is used to slide the window over the signal. The four loop is repeated K times, where K is equal to $K = (\text{length of signal} - \text{Overlap length})/(\text{Nwindow} - \text{Overlaplength})$

```
for i=1:K
```

5- The Cyclic power spectrum is calculated according to the procedure defined in Section 4.3.1:

```
    xw = Window.*x(index);
    yw = Window.*y(index);
    Yw1 = fft(yw,nfft);      % Yw(f+a/2) or Yw(f)
    Xw2 = fft(xw,nfft);      % Xw(f-a/2) or Xw(f-a)
    CPS = Yw1.*conj(Xw2) + CPS;
```

6- To slide the window along time domain, the index vector is updated according to

```
index = index + (Nwindow - Noverlap);
```

7- After the window reaches the end of the data, the loop stops. Then, the cyclic power spectrum is normalized:

```
CPS = CPS/(K*norm(Window)^2);
```

5.5.2 Main program

The main program generates random signal, calculates cyclic power spectrum of the signal and plots the results. These tasks are done through the following steps:

1- Define the primary user signal parameters as well as noise:

```
fs=1e6;
datalen=512;
symlen=32;
m=symlen*datalen;
SNR=-5;
tt=(0:1:m-1)';
```

```
f0=2/symlen;
Az=10^(-SNR/20);
z=Az*randn(1,m);
z=z';
```

2- Generate the primary user signal. In this stage, the digital data is generated as a Gaussian signal:

```
data=sqrt(0.5)*(randn(datalen,1)+ 1i.*randn(datalen,1));
```

During modulation process, each symbol is transmitted over two cycles of carrier. Therefore, the amplitude and phase of the carrier (specified by a) remains fixed during the symbol period:

```
a=[];
 for i=1:datalen
     a=[a;ones(symlen,1)*data(i)];
 end
```

Then, the data is mixed with a sinusoidal carrier with frequency f_0:

```
y=real(abs(a).*exp(2*pi*f0*1i*tt+1i*angle(a)));
```

3- Define the cyclostationary analysis paramters:

```
L = length(x);       % signal length
Nwindow = 128;           % window length
nfft = 2*Nwindow;        % FFT length
f = (0:nfft/2-1)/nfft; %Normalized frequency
n=length(x);
t = (0:n-1)';
Noverlap=floor(2/3*Nwindow);     % block overlap
K = fix((n-Noverlap)/(Nwindow-Noverlap));    % Number of
windows
```

```
dela = 1/L;          % cyclic frequency resolution
amin = 2;            % first cyclic freq. bin to scan (i.e.
cyclic freq. a1*da)
amax = 50;           % last cyclic freq. bin to scan (i.e.
cyclic freq. a2*da)
```

4- Use a “for” loop to calculate the cyclic power spectrum over the full range of α.

```
for i=amin:amax
    alpha=i/L;
    j=i-amin+1;
CPS(:,j)=CalcCycl(x,x,alpha);
end
```

5- Plot the results.

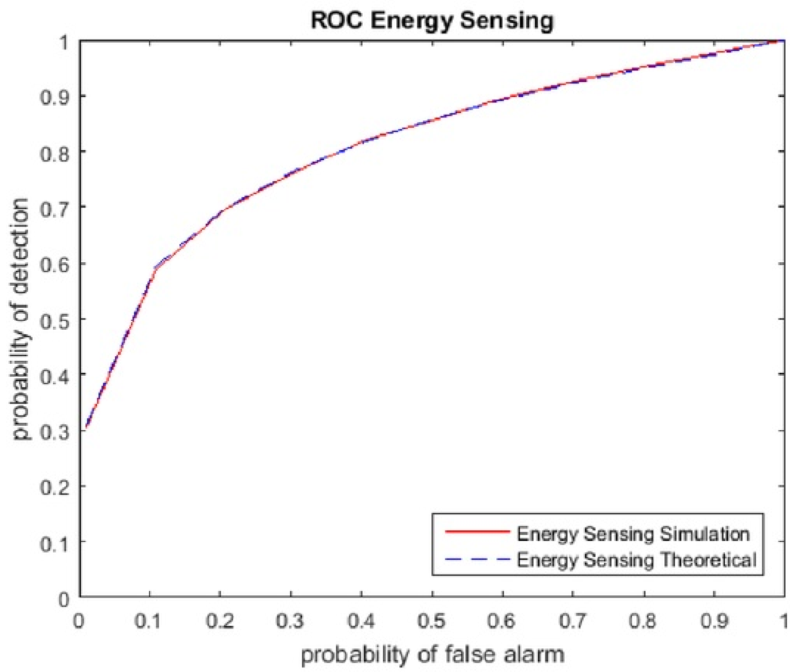
Chapter 6

6. Results, Discussions and Conclusion

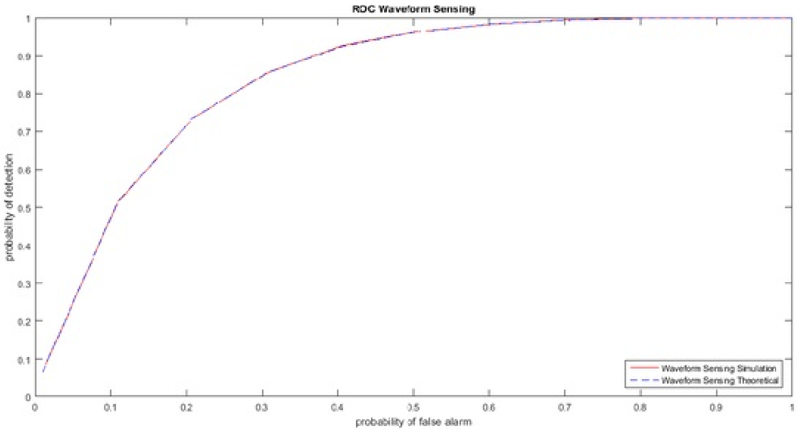
6.1 Receiver operating characteristics for energy/waveform sensing algorithms

6.1.1 Simulation results

The receiver operating characteristic for energy/waveform sensing algorithms with probability of false alarm changing from 0.01 to 1is shown in Figure 4. In Figure 4 (a), the SNR is -13dB and the spectrum sensing technique used is energy sensing. In Figure 4(b), SNR is -20dB and the spectrum sensing technique used is waveform sensing.



(a)



(b)

Figure 4 : The receiver operating characteristics for energy/waveform detection algorithm

6.1.2 Discussion

The probability of false alarm depends on the SNR value and the detection threshold. For a specific SNR value, the probability of detection can be improved by increasing sensitivity of the detector (reducing ST). However, the increased sensitivity worsens the performance of the detector in terms of false detection, as shown in figure 4. The ROC curve for waveform sensing algorithm rises faster than the energy sensing algorithm. Therefore, the waveform sensing algorithm is more effective in the sense that it can maintain a higher probability of detection for a specific probability of false alarm.

6.2 Energy / waveform sensing algorithms for Gaussian signal

6.2.1 Simulation results

The sensing error floor (SEF) performance for energy and waveform sensing algorithms are with Gaussian signal ($\alpha = 2$) as a function of SNR is shown in Figures 4-6.

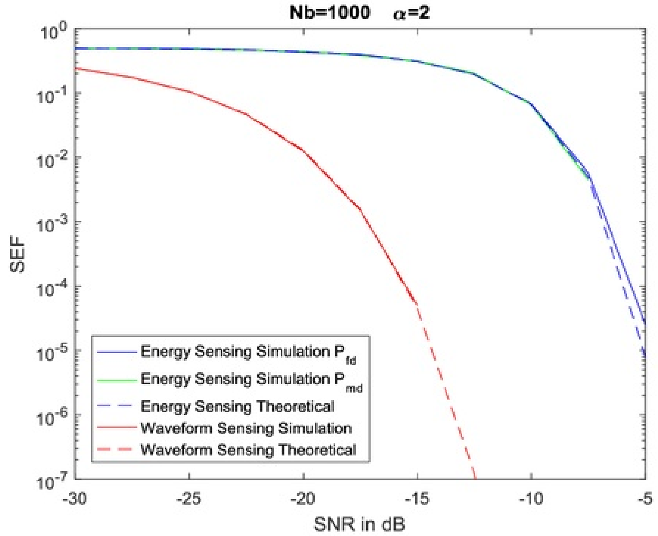


Figure 5 : The SEF performance for energy/waveform sensing algorithms for Nb=1000

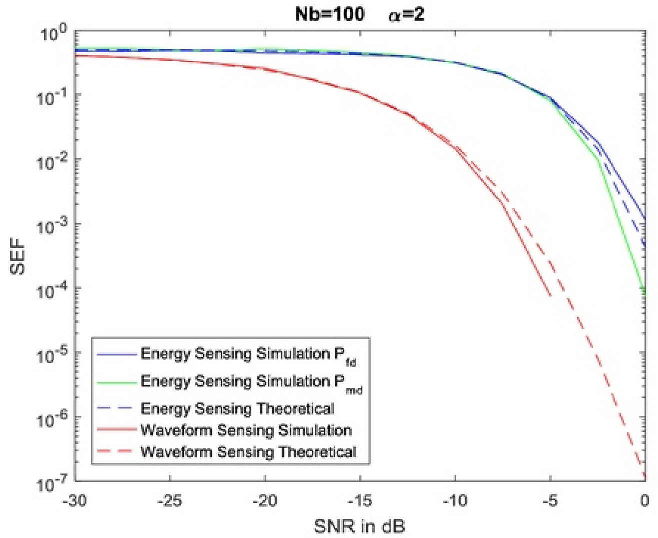


Figure 6 : The SEF performance for energy/waveform sensing algorithms for Nb=100

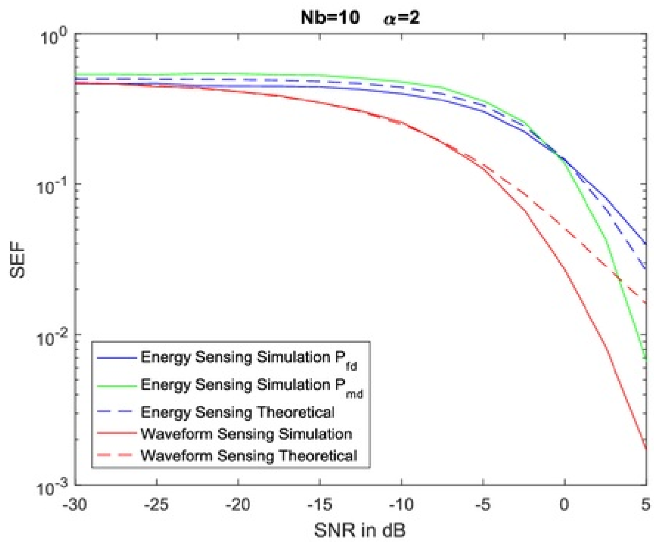


Figure 7 : The SEF performance for energy/waveform sensing algorithms for Nb=10

6.2.2 Discussion

The energy sensing method is the simplest form of detection used in cognitive radio application. On the other hand, the most complex form is waveform sensing which uses complete details of the primary signal for detection. Therefore, these algorithms represent two extreme cases, which exhibit the worst and best detection accuracy.

Figure 3 show the Simulated and theoretical SEF for sensing length Nb=1000. In case of energy sending algorithm, both probability of false detection (Pfd) and probability of missed detection (Pmd) are shown. It is seen that Pfd and Pmd closely match with each other. This result proves that the ST is indeed adjusted according to maximum likelihood criteria. The waveform sensing algorithm provides a much smaller SEF compared to the energy sensing method. The difference between the two methods is smaller for low values of SNR but drastically increases as SNR is increased towards 0dB.

Figures 4 and 5 show the SEF for sensing lengths Nb=100 and Nb=10, respectively. For both energy sensing and waveform sensing algorithms, the decrease in sensing length causes the SEF to rise. For example, if SNR=-10dB, the SEF of energy sensing method increases from 0.065 (Nb=1000) to 0.44 (Nb=10).

For low SNR values, there is good agreement between simulation and theory but the difference between the curves is escalated at higher SNR values due to the fact that the detection statistics eventually deviate from Gaussian distribution.

6.3 Energy / waveform sensing algorithms for constant envelop signal

6.3.1 Simulation results

The SEF performance for energy and waveform sensing algorithms are for constant envelope ($\alpha = 1$) is shown in Figures 7-9.

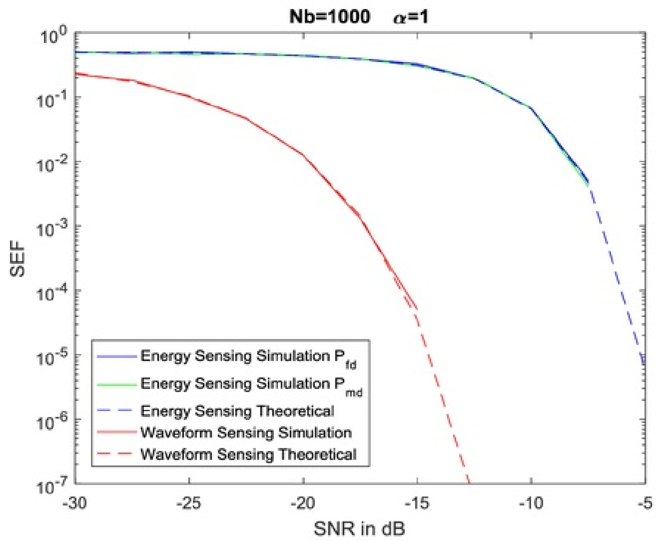


Figure 8 : The SEF performance for energy/waveform sensing algorithms for Nb=1000

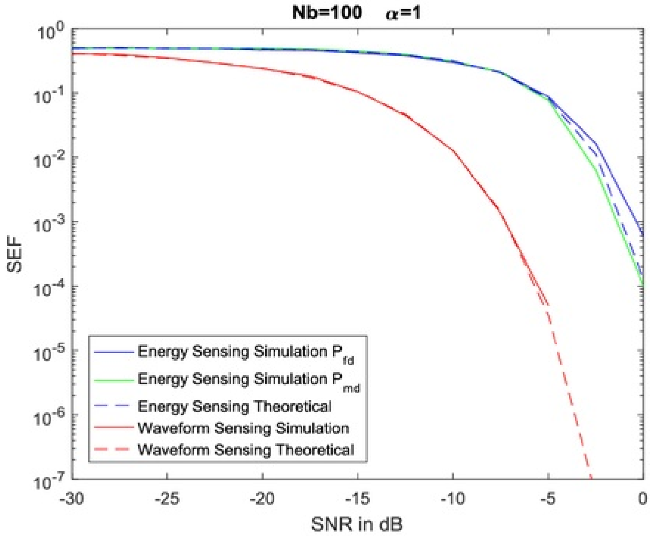


Figure 9 : The SEF performance for energy/waveform sensing algorithms for Nb=100

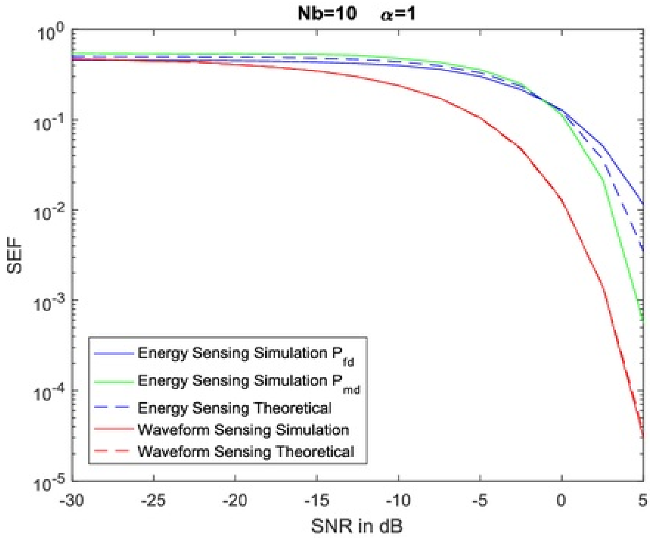


Figure 10 : The SEF performance for energy/waveform sensing algorithms for Nb=10

6.3.2 Discussion

The SEF performance for constant envelope modulation is similar with Gaussian modulation except that the former has a smaller SEF. From Figures 7 and 4, it is seen that the SEF performances are very similar for Nb=1000. The difference becomes larger at Nb=100 and

Nb=10, where the SEF performance of Gaussian signal drops quickly but the SEF performance of constant envelope signal remains at acceptable levels. The reason for this improvement is that the amplitude of constant envelope signal is not random, hence the degree of randomness is reduced, which facilitates the discrimination of signal from noise.

6.4 Probability of Detection equals Probability of False Alarm

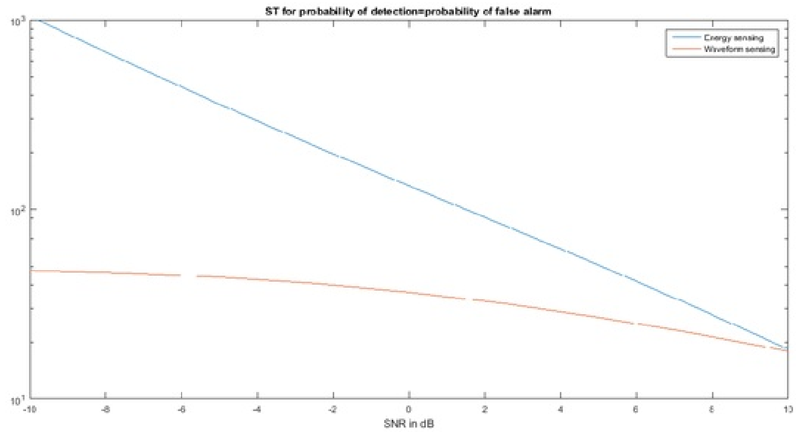


Figure 11 : ST for Probability of detection = Probability of False Alarm

The figure above shows the maximum likelihood threshold for energy sensing and waveforms sensing algorithms with Nb=100 and α=2. The threshold for energy sensing method is at 10^3 (ST/Nb=10) for SNR=-10dB and drops to around 18 (ST/Nb=0.18) at SNR=10dB. These values are larger than energy of noise (10 at SNR=-10dB and 0.1 at SNR=10dB) but less than the total energy of the noise and primary signal. The threshold for waveform sensing method starts at around 47.72 at SNR=-10dB and drops to around 17.91 at SNR=10dB. The smaller threshold for waveform sensing means more sensitive detection. Therefore, waveform sensing method has a higher probability of detection and lower SEF compared to the energy sensing algorithm.

6.5 Cyclostationary sensing algorithm

6.5.1 Simulation results

Figure 10 shows the zoomed in waveforms of primary user signal and the received signals for SNR=0dB. The figure shows three symbols. The length of each symbol is 32 samples, the period of carrier is 16 samples and the sample rate is 1MHz. So the carrier frequency is 1MHz/16=62.5kHz and the symbol rate is 1MHz/32=31.25kHz. It is seen that during each symbol, the phase and amplitude of the carrier remains unchanged.

Figure 11 shows the cyclic power spectrum for SNR=0dB. The cyclic power has peaks at spectral frequency of 62.5kHz, which is equal to the carrier frequency. The Cyclic frequency is related with the frequency components of data, which covers the frequency range 0Hz up the symbol rate frequency (31.25kHz).

Figure 12 shows the average cyclic power spectrum as a function of spectral frequency.

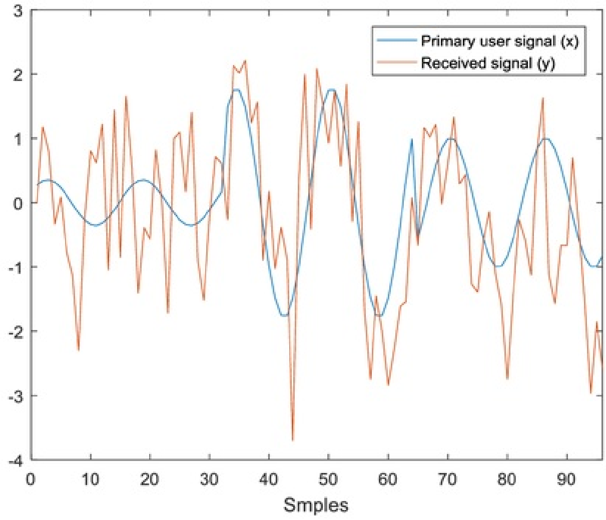


Figure 12 : The waveforms of primary user signal and received signal for SNR=0dB

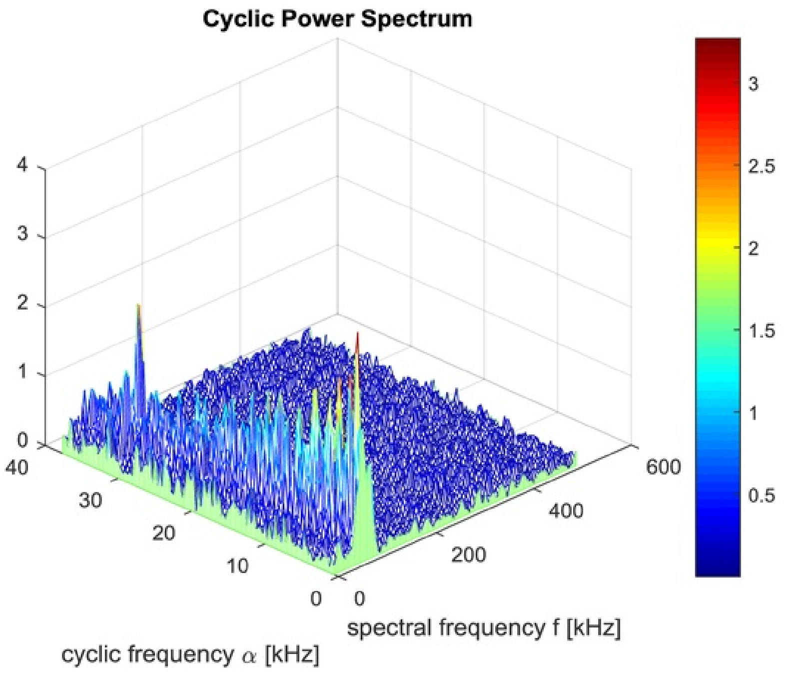


Figure 13 : The cyclic power spectrum of the received signal for SNR=0dB

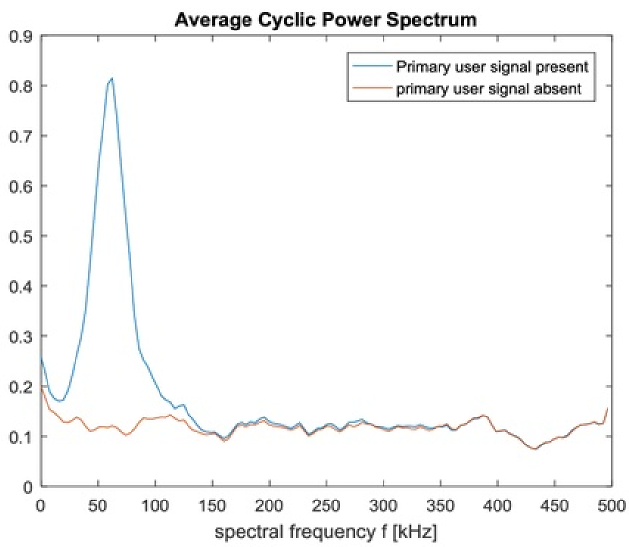


Figure 14 : The average cyclic power spectrum of the received signal as a function of spectral frequency for SNR=0dB

6.5.2 Discussion

Figures 12 and 13 show that the cyclostationary algorithm can discriminate the primary user signal from noise. Additionally, this algorithm is capable of the detection of the carrier frequency and cyclic frequency of the primary user signal. This information is helpful for finding which channel is occupied by the primary user and which channel is free for use by the secondary controller.

The advantages of cyclostationary algorithm are more evident when the primary user signal includes pilots (for OFDM modulation). In reference [15] it is shown that the pilots will appear as large peaks in the cyclic power spectrum, which let the secondary user detect the presence of primary user signal more efficiently.

6.6 Comparison of the three algorithms

The energy sensing algorithm is the simplest form of detect and avoid, which processes the energy of the received signal and compares it with a threshold to determine the presence or absence of primary user signal. The waveform sensing method is highly reliable but since the primary user signal is usually not available in practice, this method is only applicable in theory and not in practice. The energy sensing method has a good performance when the SNR is larger than 0dB. However, for lower SNR values, this method is no longer reliable.

The cyclostationary algorithm uses advanced processing techniques to improve the SEF performance for lower SNR values. As shown in Figure 14, for -12.5dB<SNR<-5dB the SEF performance of the cyclostationary method is much better compared with the energy sensing method. However, the performance of cyclostationary method is poor for very low values of SNR (SNR<-10dB).

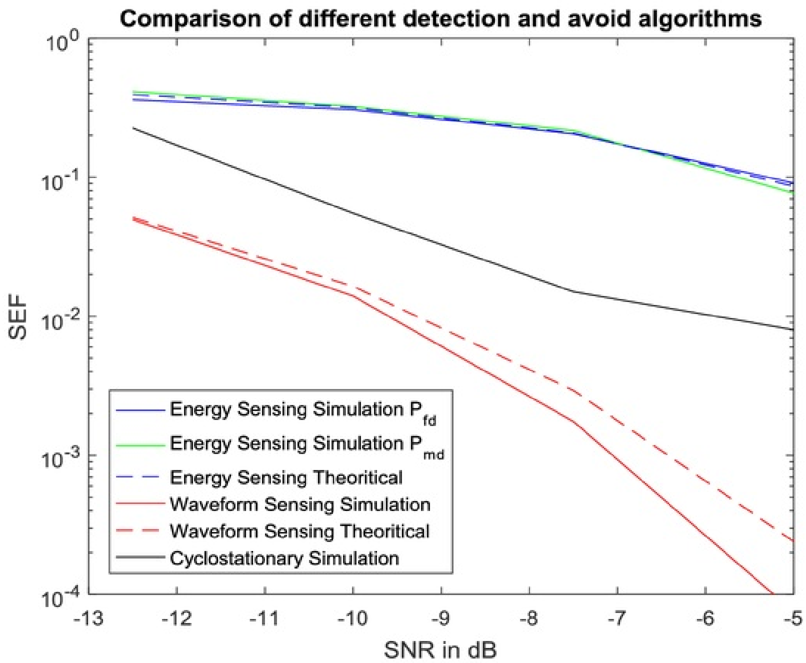


Figure 15 : Comparison of different detection and avoid algorithms

6.7 Conclusion

The need for an efficient use of the radio spectrum has been considered to be one of the most important topics that interests the communication industry. Cognitive Radio Networks are considered to be the suitable solution to achieve the efficiency required. To increase the throughput of cognitive radio network a suitable spectrum sensing technique should be chosen depending on the requirements of the network.

In this project cognitive radio has been presented and three spectrum sensing techniques, including energy sensing, waveform sending and cyclostationary sensing algorithms were discussed and simulated. All methods detect the presence or absence of primary user signal in a radio channel by examining a set of data samples. The energy sensing technique is the simplest detection algorithm which detects the presence of primary user signal by comparing the energy of the received signal with a threshold. Despite the simple implementation, energy sensing algorithm is shown to be unreliable when the SNR is small. The waveform sensing method uses the primary user signal and the received signal to obtain the parameter S. The inclusion of the primary user signal reduces the vulnerability of the algorithm to noise and improves the SEF performance. The cyclostationary method uses the periodic feature of the communication signals to discriminate the radio signals from the noise. This technique improves the SEF performance at low SNR values. The main advantage of cyclostationary method is that it is more practical compared to the waveform sensing algorithm because it does not require the primary user signal for detection. However, the cyclostationary algorithm is computationally complex and slower compared to the waveform sensing and energy sensing techniques.

Monte Carlo simulations have been performed to test the SEF performance of the three detection algorithms. The simulation results are in close agreement with the theoretical values obtained from the literature.

Cognitive radio is a new topic and there are several areas to be explored in the future. One area is to validate the performance of detection algorithms when the actual SNR is different from the estimated value. All of the algorithms discussed in this thesis use the value of SNR to obtain a suitable value for the detection threshold. The condition of maximum likelihood is only achievable when the threshold is selected according to the estimated SNR. If the SNR of the received signal is different from the estimated SNR, the SEF performance will degrade. Another area is to incorporate the features of the primary user signal in the detection algorithm.

Bibliography

[1] B. W. a. K. J. R. Liu, “Advances in Cognitive Radio Networks: A Survey,” *IEEE JOURNAL OF SELECTED TOPICS IN SIGNAL PROCESSING,* vol. 5, no. 1, pp. 5-23, 2011.

[2] S. Haykin, “Cognitive Radio: Brain-Empowered Wirless Communications,” *IEEE JOURNAL ON SELECTED AREAS IN COMMUNICATIONS,* vol. 23, no. 2, pp. 201-220, 2005.

[3] X. Wu, “The Survey of Detection Methods and Testbeds For Cognitive Radio Application,” University of Gavle, Sweden, 2009.

[4] G. Q. M. J. Joseph Mitola, “Cognitive Radio: Making Software Radios More Personal,” *IEEE Personal Communications,* pp. 13-18, August 1999.

[5] P. D. a. S. C. Goutam Ghosh, “Simulation and Analysis of Cognitive Radio System Using MATLAB,” *International Journal of Next-Generation Networks (IJNGN),* vol. 6, no. 2, pp. 31-45, 2014.

[6] L. F. I. Simon Haykin, “Cognitive Radio: Brain-Empowered Wirless Communications,” *IEEE JOURNAL ON SELECTED AREAS IN COMMUNICATIONS,* vol. 23, no. 2, pp. 201-220, 2005.

[7] S. Reisenfeld, “Performance Bounds for Detect and Avoid Signal Sensing,” in *Second International Workshop on Cognitive Radio and Advanced Spectrum Management*, Aalborg, 2009.

[8] G. B. G. Seung-Jun Kim, “Optimal Resource Allocation for MIMO Ad Hoc Cognitive Radio Networks,” *IEEE TRANSACTIONS ON INFORMATION THEORY,* vol. 57, no. 5, pp. 3117-3131, 2011.

[9] K.-C. C. Y. L. M. Ying-Chang Liang, “Cognitive Radio Networking and Communications: An Overview,” *IEEE TRANSACTIONS ON VEHICULAR*

TECHNOLOGY, vol. 60, no. 7, pp. 3386-3407, 2011.

[10] S. B. M. Zaid Abdul Samad Bardan, "Literature Review of Resource Allocation Methods in Cognitive Radio Networks," *International Journal of Science and Research (IJSR),* vol. 5, no. 3, pp. 1056-1060, 2016.

[11] D. P. B. Ahmed Khattab, Cognitive Radio Networks From Theory to Practice, New York: Springer, 2013.

[12] S. Parsons, "Literature Review of Cognitive Radio Spectrum Sensing," Stanford University, California, 2014.

[13] P. K. W. Z. Konstantinos Pelechrinis, "Cognitive Radio Networks: Realistic or Not?," *ACM SIGCOMM Computer Communication Review,* vol. 43, no. 2, pp. 44-51, 2013.

[14] W. Ejaz, "SPECTRUM SENSING IN COGNITIVE RADIO NETWORKS," National University of Sciences and Technology, Pakistan, 2006.

[15] M. E. Castro, "Cyclostationary Detection for OFDM," University of Nebraska, Nebraska, 2011.

[16] K. Chang, "Spectrum Sensing, Detection and Optimisation in Cognitive Radio for Non-Stationary Primary User Signals," Queensland University of Technology, Queensland, 2012.

[17] A. G. Z. Jian Chen, "Cylcostationary Spectrum Detection in Cognitive Radios," in *IET Seminar on Cognitive Radio and Software Defined Radios: Technologies and Techniques*, 2008.

[18] W. Wang, "Spectrum Sensing for Cognitive Radio," in *Third International Symposium on Intelligent Information Technology Application Workshops*, Lanzhou, China, 2009.

[19] F. A. A. K. M. U. S. Ahmad Ali Tabassam, "Building Software-Defined Radios in MATLAB Simulink - A Step Towards Cognitive Radio," in *UKSim 13th International Conference on Modelling and Simulation*, 2011.

[20] S. R. K. G. M. M. Quang Thai, "Energy-Efficient Spectrum Sensing Using

Cyclostationary," Sydney, 2011.

[21] M. C. P. Angela Sara Cacciapuoti, "On the Route Priority for Cognitive Radio Networks," *IEEE TRANSACTIONS ON COMMUNICATIONS,* vol. 36, no. 9, pp. 3103-3117, 2015.

[22] A. Ç. Muhammed Enes Bayrakdar, "Simulation Model of Spectrum Handoff Process for Medium Access Control Protocols in Cognitive Radio Networks," Duzec University, Duzec, 2015.

[23] J. H.-S. a. M. S. O. Le´on, "Securing cognitive radio networks," *INTERNATIONAL JOURNAL OF COMMUNICATION SYSTEMS,* vol. 23, no. 1, pp. 633-652, 2010.

Appendix A

MATLAB Program

ROC Energy Sensing

```
clc;clear;close all;
Nb = 1000;
Maxfd=11;
snr = 10.^(-13/10);
Pfa = linspace(0.01,1,Maxfd);
Nmonte=50000;
% energy sensing
for m = 1:Maxfd
    i_det = 0;
    for n=1:Nmonte
        z = randn(1,Nb);
        x = sqrt(snr).*randn(1,Nb);
        y = x + z;
        S = abs(y).^2;
        S =(1/Nb).*sum(S);
        ST(m) = (qfuncinv(Pfa(m))./sqrt(Nb))+ 1;
        if(S >= ST(m))
            i_det = i_det+1;
        end
    end
    Pdet(m) = i_det/Nmonte;
end

figure;
plot( Pfa,Pdet,'r');
hold on
ST = (qfuncinv(Pfa)./sqrt(Nb))+ 1;
Pdet_the = ((ST - (snr + 1)).*sqrt(Nb))./(sqrt(2).*(snr + 1));
Pdet_the=qfunc(Pdet_the);
```

```
plot(Pfa, Pdet_the, 'b--')
axis ([0 1 0 1])
title ('ROC Energy Sensing')
xlabel('probability of false alarm')
ylabel('probability of detection')
legend ('Energy Sensing Simulation','Energy Sensing
Theoretical','location','southeast')
```

ROC Waveform Sensing

```
clc;clear;close all;
Nb = 1000;
Maxfd=11;
snr = 10.^(-25/10);
Pfa = linspace(0.01,1,Maxfd);
Nmonte=50000;
%waveform sensing
for m = 1:Maxfd
    i_det = 0;
    for n=1:Nmonte
        z = randn(1,Nb);
        x = sqrt(snr).*randn(1,Nb);
        y = x + z;
        S = real(y.*conj(x));
        S =(1/Nb).*sum(S);
        ST(m) = qfuncinv(Pfa(m))./sqrt(Nb/2).*(sqrt(snr));
        if(S >= ST(m))
            i_det = i_det+1;
        end
    end
    Pdet(m) = i_det/Nmonte;
end
```

```
plot( Pfa,Pdet,'r');
hold on
ST = qfuncinv(Pfa)./sqrt(Nb/2).*(sqrt(snr));
Pdet_the = ((ST -
(snr)).*sqrt(Nb))./(sqrt(snr.^2+0.5*snr))/sqrt(2);
Pdet_the=qfunc(Pdet_the);
plot(Pfa, Pdet_the, 'b--')
title ('ROC Waveform Sensing')
axis ([0 1 0 1])
xlabel('probability of false alarm')
ylabel('probability of detection')
legend ('Waveform Sensing Simulation','Waveform Sensing
Theoretical','location','southeast')
% legend('Energy Sensing Simulation ',...
%      'Energy Sensing Theoretical','Waveform Sensing
Simulation','Waveform Sensing
Theoretical','location','southeast')
```

Energy Sensing and waveform sensing program

```
clc;clear;close all;
% modulation type
alpha=2;
blocklen=100;
Nb=blocklen; %Number of bits in each block
SNR=-10:2.5:10;
iMax=1000;
Maxblock=20e3;
% Energy Sensing algorithm

for j=1:length(SNR)
    SNR(j)
    i_fd=0;
    i_md=0;
    %calculate the statistical features of the channel
```

```
    Az=10^(-SNR(j)/20);
    sig0=sqrt(Nb)*Az^2;
    mu0=Nb*Az^2;
    snr=10^(SNR(j)/10);
    sig1=Nb*Az^4*((alpha-1)*snr^2+2*snr+1);
    sig1=sqrt(sig1);
    mu1=Nb*(snr+1)*Az^2;
    %obtain ST
    ST=(mu0*sig1+mu1*sig0)/(sig0+sig1);
    STvecenergy(j)=ST;
    %Obtain theoritical SEF
    num=sqrt(Nb)*snr;
    denom=1+sqrt((alpha-1)*snr^2+2*snr+1);
    SEF_theory(j)=qfunc(num/denom);
    i_md=0;
    i=0;
    while i_md<iMax
        i=i+1;
        % Generate the signal and noise vectors
        z=Az*sqrt(0.5)*(randn(1,blocklen)+
1i.*randn(1,blocklen));
        x=sqrt(0.5)*(randn(1,blocklen)+
1i.*randn(1,blocklen));
        if alpha==1
            x=x./abs(x);
        end

        %Energy detection if H0
        y=z;
        S=sum(abs(y).^2);
        Sz(i,j)=S;
        %False detection
        if S>ST
            i_fd=i_fd+1;
```

```
        end

        %Energy detection if H1
        y=x+z;
        S=sum(abs(y).^2);
        Sy(i,j)=S;
        %Missed detection
        if S<ST
            i_md=i_md+1;
        end
        if i>Maxblock
            break
        end
    end
    Pfd(j)=i_fd/i;
    Pmd(j)=i_md/i;

end

semilogy(SNR,Sy(3,:))
hold on
semilogy(SNR,Sz(3,:))
hold on
semilogy(SNR,STvecenergy)
legend('Primary user is active','Primary user
inactive','Threshold')
xlabel('SNR in dB');
ylabel('Energy of the received signal');
title(['Energy Detection Method   Nb=',num2str(Nb),'
\alpha=',num2str(alpha)])

figure
semilogy(SNR,Pfd,'b')
hold on
```

```
semilogy(SNR,Pmd,'g')
hold on
semilogy(SNR,SEF_theory,'b--')

% Waveform Sensing algorithm
for j=1:length(SNR)
    i_fd=0;
    i_md=0;
    %calculate the statistical features of the channel
    Az=10^(-SNR(j)/20);
    snr=10^(SNR(j)/10);
    %obtain ST
    num=Nb*snr*Az^2;
    denom=sqrt(2*(alpha-1)*snr+1)+1;
    ST=num/denom;
    STvecwaveform(j)=ST;
    %Obtain theoretical SEF
    num=sqrt(Nb)*sqrt(snr);
    denom=sqrt((alpha-1)*snr+0.5)+sqrt(0.5);
    SEF_theory(j)=qfunc(num/denom);
    i_md=0;
    i=0;
    while i_md<iMax
        i=i+1;
        % Generate the signal and noise vectors
        z=Az*sqrt(0.5)*(randn(1,blocklen)+
1i.*randn(1,blocklen));
        x=sqrt(0.5)*(randn(1,blocklen)+
1i.*randn(1,blocklen));

        if alpha==1
            x=x./abs(x);
        end
```

```
        %Waveform detection
        y=x+z;
        S=sum(real(y.*conj(x)));
        %Missed detection
        if S<ST
            i_md=i_md+1;
        end
         if i>Maxblock
            break
        end
    end
    SEF(j)=i_md/i;
end
semilogy(SNR,SEF,'r')
hold on
semilogy(SNR,SEF_theory,'r--')
xlabel('SNR in dB');
ylabel('SEF');
% ylim([1e-7,1]);
legend('Energy Sensing Simulation P_f_d','Energy Sensing
Simulation P_m_d',...
    'Energy Sensing Theoretical','Waveform Sensing
Simulation','Waveform Sensing
Theoretical','location','southwest')
title(['Nb=',num2str(Nb),'    \alpha=',num2str(alpha)])

figure
semilogy(SNR,STvecenergy)
hold on
semilogy(SNR,STvecwaveform)
ylim([1e1,1e3]);
legend('Energy sensing','Waveform sensing')
xlabel('SNR in dB');
```

```
title('ST for probability of detection=probability of false
alarm');
```

Cyclostationary Program

```
clear;clc;close all
global L Nwindow nfft t Noverlap K
fs=1e6;
datalen=100;
symlen=32;
m=symlen*datalen;
SNR=0;
tt=(0:1:m-1)';
f0=2/symlen;
 Az=10^(-SNR/20);
z=Az*randn(1,m);
z=z';
%generate digital data:OFDM
data=sqrt(0.5)*(randn(datalen,1)+ 1i.*randn(datalen,1));

a=[];
 for i=1:datalen
     a=[a;ones(symlen,1)*data(i)];
 end
y=real(abs(a).*exp(2*pi*f0*1i*tt+1i*angle(a)));
x=z+y;
plot(y)
hold on
plot(x)
xlim([0,3*symlen]);
xlabel('Smples')
legend('Primary user signal (x)','Received signal (y)');

%Define parameters
L = length(x);       % signal length
```

```
Nwindow = 128;           % window length
nfft = 2*Nwindow;        % FFT length
f = (0:nfft/2-1)/nfft; %Normalized frequency
n=length(x);
t = (0:n-1)';
Noverlap=floor(2/3*Nwindow);    % block overlap
K = fix((n-Noverlap)/(Nwindow-Noverlap));   % Number of
windows

dela = 1/L;            % cyclic frequency resolution
amin = 2;             % first cyclic freq. bin to scan (i.e.
cyclic freq. a1*da)
amax = 120;            % last cyclic freq. bin to scan (i.e.
cyclic freq. a2*da)
for i=amin:amax
    alpha=i/L;
    j=i-amin+1;
CPS(:,j)=CalcCycl(x,x,alpha);
CPSz(:,j)=CalcCycl(z,z,alpha);
end
%Plot the CPS as a 3D figure
CPS_1sided=CPS(1:nfft/2,:);
CPS_1sidedz=CPSz(1:nfft/2,:);
aplot=[amin:amax]/L;
figure
%Multiply by fs to convert normalized frequency to actual
frequency divide by 1e3 to express in kHz
meshz(f*fs/1e3,aplot*fs/1e3,abs(CPS_1sided'))
% imagesc(aplot,f,abs(CPS_1sided)),
colormap(jet),colorbar,axis xy,title('Cyclic Power Spectrum'),
ylabel('cyclic frequency \alpha [kHz]'),xlabel('spectral
frequency f [kHz]')
figure
```

```
CPSavg=sum(abs(CPS_1sided'))/amax;
CPSavgz=sum(abs(CPS_1sidedz'))/amax;
CT=ones(length(CPSavg),1)*Az;
plot(f*fs/1e3,abs(CPSavg))
hold on
plot(f*fs/1e3,abs(CPSavgz))
% hold on
% plot(f*fs/1e3,CT)
xlabel('spectral frequency f [kHz]')
title('Average Cyclic Power Spectrum');
legend('Primary user signal present','primary user signal
absent');
figure
plot(abs(CPS_1sided(16,:)))
hold on
plot(abs(CPS_1sidedz(16,:)))


function CPS= CalcCycl(x,y,alpha)
global nfft t Noverlap K Nwindow
%Define window
% Window = kaiser(Nwindow);
Window = hanning(Nwindow);
% Introduce the frequency shift to x and y
y = y.*exp(-1i*pi*alpha*t);
x = x.*exp(1i*pi*alpha*t);
% compute CPS
CPS = 0;
index = 1:Nwindow;
for i=1:K
    xw = Window.*x(index);
    yw = Window.*y(index);
    Yw1 = fft(yw,nfft);     % Yw(f+a/2) or Yw(f)
    Xw2 = fft(xw,nfft);     % Xw(f-a/2) or Xw(f-a)
```

```
    CPS = Yw1.*conj(Xw2) + CPS;
    index = index + (Nwindow - Noverlap);
end

% normalize the CPS with respect to window
CPS = CPS/(K*norm(Window)^2);
```

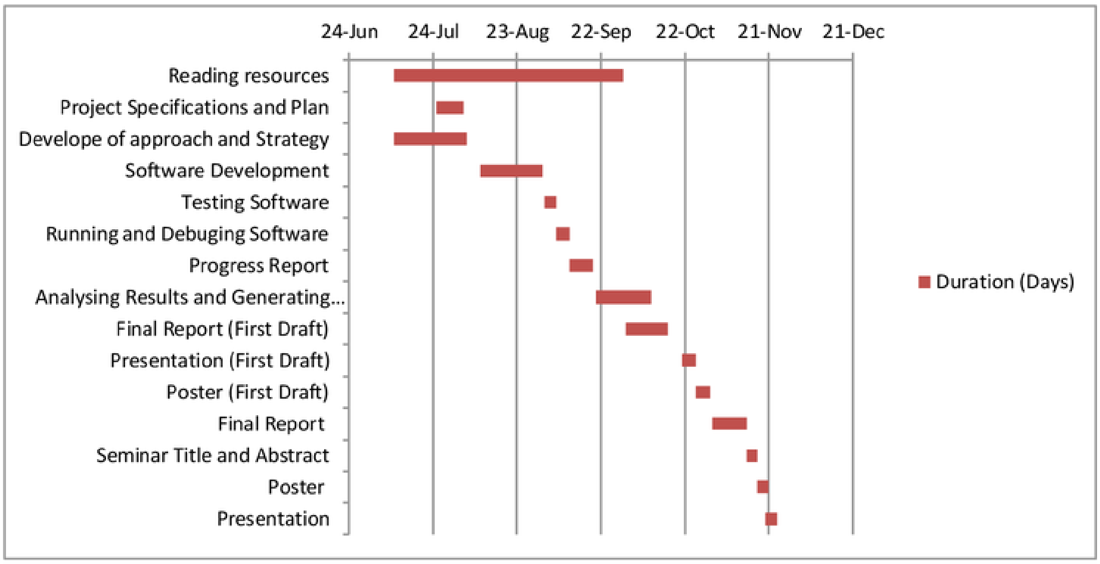
Appendix B

Project Plan

In semester one 2016 a project plan has been prepared based on the ENGG411 requirements of the previous semester. The project plan and activities breakdown are shown in the table below.

Start Date	End Date	Description
10-Jul	30-Sep	Reading resources
25-Jul	05-Aug	Project Specifications and Plan
10-Jul	15-Aug	Develope of approach and Strategy
10-Aug	01-Sep	Software Development
02-Sep	05-Sep	Testing Software
06-Sep	10-Sep	Running and Debuging Software
11-Sep	18-Sep	Progress Report
20-Sep	30-Sep	Analysing Results and Generating Conculsions
01-Oct	20-Oct	Final Report (First Draft)
21-Oct	25-Oct	Presentation (First Draft)
26-Oct	30-Oct	Poster (First Draft)
01-Nov	12-Nov	Final Report (First Draft)
13-Nov	16-Nov	Seminar Title and Abstract
17-Nov	20-Nov	Poster
20-Nov	23-Nov	Presentation
01-Jul	15-Nov	Log Book

The following Gantt chart was also prepared based on the activity breakdown mentioned in the table above:



However, based on the timetable presented in the second semester the activity breakdown and Gantt chart have been modified to accommodate the changes mentioned in the new guidelines of the unit.

It is worth to mention that most of the activities have stayed as they are and carried out according to the original plan. Dates, deliverables and assessment task have been modified in the new plan.

Appendix C

Consultation Meetings Attendance Form

Throughout the semester few meetings with my project supervisor have been scheduled and the consultation meeting attendance form below shows the meetings date and topics discussed in the meeting.

More in depth information about the meetings have been recorded in the logbook.

Consultation Meetings Attendance Form

Week	Date	Comments (if applicable)	Student's Signature	Supervisor's Signature
0	29/07/2016	Cognitive Radio Project Planning		
1	05/08/2016	Project Planning		
3	19/08/2016	Project Planning		
4	26/08/2016	Project Planning		
5	02/09/2016	Project Details		
7	16/09/2016	Result Review		
7+	23/09/2016	Result Review		
7++	28/09/2016	Simulation		
8	7/10/2016	Simulation & Report Planning		
9	14/10/2016	Progress Review		
11	28/10/2016	Progress Review		
12	4/11/2016	Report Review		