ALTERNATIVE TECHNIQUES FOR THE IMPROVEMENT OF ENERGY EFFICIENCY IN COGNITIVE RADIO NETWORKS

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DETAILS OF CONTRIBUTION TO PUBLICATIONS that form part and/or include research presented in this thesis (include publications that have been submitted, *in press* and published and give details of the contributions of each author to the experimental work and writing of each publication)

BOOK CHAPTER

1. **Efe F. Orumwense, Thomas J. Afullo, and Viranjay M. Srivastava,** "Cognitive radio networks: A social network perspective," Chapter 13, Advances in Intelligent Systems and Computing , Springer International Publishing Switzerland, May, 2016. (DOI: 10.1007/978-3-319-27400-3_39).

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2. **Efe F. Orumwense, Thomas J. Afullo and Viranjay M. Srivastava**, "Using Massive MIMO and Small Cells to Deliver a Better Energy Efficiency in Cognitive Radio Networks" Accepted for publication in the *International Journal on Communications, Antenna and Propagation (IRECAP),* October, 2016.

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CONFERENCE PUBLICATIONS

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7. **Efe F. Orumwense, Thomas J. Afullo, and Viranjay M. Srivastava**, "Main trade-offs for energy efficiency in cognitive radio networks," *In Proceedings of the IEEE Conference on IST Africa (IST-Africa 2016),* Durban. South Africa, 11-13 May 2016, pp. 1-8.

8. **Efe F. Orumwense, Thomas J. Afullo, and Viranjay M. Srivastava,** "Secondary user energy consumption in cognitive radio networks," *IEEE International Conference on AFRICON (IEEE AFRICON-2015),* Addis Ababa, Ethiopia, pp. 14-17, September, 2015, pp. 87-91.

9. **Efe F. Orumwense, Thomas J. Afullo, and Viranjay M. Srivastava**, "Effects of malicious users on the energy efficiency of cognitive radio networks," *Southern Africa Telecommunication Networks and Applications Conference (SATNAC-2015),* Western Cape, South Africa, 6-9 September, 2015, pp. 431-435.

Dedication

To God Almighty – The Great Architect of the Universe

“Now to the King eternal, immortal, and invisible, the only God, be honor and glory forever and ever. Amen.” – 1 Timothy 1:17

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ABSTRACT

As a result of the tremendous pace of development in the world of wireless communication technology over the last decade, the need for wireless radio spectrum access has drastically been on the high demand. Due to this, several wireless systems and applications communicating in unlicensed radio spectral bands have steadily led to the overcrowding of these bands thereby making them scarce and unavailable. Also on the contrary, research has shown that a fairly huge amount of the licensed radio spectral bands are also underutilized by licensed users. It however becomes a necessity to find a lasting solution to this problem of spectrum scarcity, unavailability and underutilization hence cognitive radio was proposed. Cognitive radio technology is seen as a potential and enterprising paradigm geared at improving the utilization of unlimited spectrum resource by opportunistically allowing unlicensed users to gain access to licensed spectral bands as long as no interference is caused to the licensed users. Cognitive radio is involved in a lot of functionalities to deliver a better quality of service (QoS) to its users; hence a lot of energy is being consumed in order to perform the required task. Extra energy consumption also emanates from cognitive radio network components especially the radio base stations which require large amount of energy to transmit and receive signals from cognitive radio users. These energy efficiency issues pose a major drawback to cognitive radio network's implementation and design. This thesis is aimed at introducing alternative techniques which can bring about an improvement in the energy efficiency of cognitive radio networks. As a starting point, an analysis of energy efficiency metrics for cognitive radio networks is provided relating to its design and operational characteristics. The sensing performance metrics and the metrics developed at different levels of the network are also evaluated. In a view to facilitating higher energy efficiency in the architectural organization of the network, the combinatory use of small cells and massive MIMO is employed to optimize the energy efficiency of the network. The main goal is to achieve a significant boost in the network's energy efficiency by dynamically assigning a cognitive radio user to an optimal base station for transmission. A major challenge that still stands out for cognitive radios is the amount of energy that is consumed in the spectrum sensing operation of the network. Energy is consumed by secondary users in utilizing licensed spectrum band before giving up access to the licensed user. One important step to improving the network's energy efficiency is to firstly investigate the total amount of energy that is consumed by these secondary users to deliver secondary data via the opportunistic use of the spectral bands. The energy consumed in each state of the secondary user's activities is evaluated and results reveal that the network size also have an implication on the network's energy efficiency. In a cognitive radio network, some secondary users might become malicious thereby providing false spectrum occupancy information to the fusion center in order to utilize the vacant spectrum band for their own selfish gains. The effects these unlicensed malicious users has on the network's energy efficiency are studied and a secured energy detection cooperative spectrum sensing technique is developed and analysed to reduce these effects and boost the network's energy efficiency. Spectrum sensing is usually undertaken cooperatively by secondary users to improve reliability of the sensed results. However, cooperative spectrum sensing consumes a significant amount of energy which is also a challenge to cognitive radio users. An energy-efficient cooperating spectrum sensing technique required to address the problem of energy efficiency in the spectrum sensing stage of the network is developed and analysed. The simulated results revealed an improved performance in the network's energy efficiency while simultaneously maintaining the sensing accuracy of the spectrum sensing process when compared to the normal cooperative spectrum sensing process.

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List of Abbreviations

AC	Alternating Current
ACMA	Australian Communications and Media Authority
BBU	Base Band Unit
BPF	Band Pass Filter
BS	Base Station
CR	Cognitive Radio
CRN	Cognitive Radio Networks
DVB	Digital Video Broadcasting
DSA	Dynamic Spectrum Access
DSP	Digital Signal Processor
ECR	Energy Consumption Rating
EE	Energy Efficiency
EPM	Energy Performance Metrics
ETSI	European Technical Standards Institute
FBS	Femtocell Base Stations
FC	Fusion Center
FCC	Federal Communications Commission
FSU	Femtocell Secondary Users

ICT	Information Communication Technology
MIMO	Multiple-Input and Multiple-Output
MSU	Mobile Secondary Users
PA	Power Amplifier
PU	Primary User
QoS	Quality of Service
RBS	Radio Base Station
RF	Radio Frequency
SC-BS	Small Cell Base Station
SDR	Software Defined Radio
SU	Secondary User
WLANs	Wireless Local Area Networks

CHAPTER ONE

GENERAL INTRODUCTION

1.0 Introduction

Over the last decade, wireless communications has indeed become one of the most vibrant aspects in the field of communications both in engineering and in academia. The fact that wireless applications and devices has progressively evolved and been on the increase over the years has made it the fastest developing and growing sector in the communications industry. Wireless communications plays an increasingly significant role in our daily lives, for example, wireless devices like our Global Positioning System (GPS), radio, cell phones and Televisions (TVs) use the invisible radio waves for data transmission through the air medium called spectrum which serves as an essential resource that is required for radio communications. The name spectrum is coined from the fact that wireless signals can be transmitted on a range seen as *spectrum of frequencies* otherwise known as electromagnetic spectrum.

As wireless devices continue to increase and as more devices tend to go wireless with limited available bandwidth, the demand for wireless spectral bands however becomes higher making them limited and scarce. Spectrum regulatory bodies all over the world such as the Federal Communications Commission (FCC) in the US, European Telecommunications Standard Institute (ETSI) in Europe and Australian Communications and Media Authority (ACMA) in Australia have allocated various spectrum frequency blocks for specific uses and also assign licences for these spectrum users. A greater percentage of the available spectral bands have already been assigned to quite a number of communications systems like Wireless Local Area Networks (WLANs), Digital Video Broadcasting (DVB), mobile cellular communications amongst others. This however may seem as a brilliant idea, but in the long run, there is little or no spectrum available for developing and emerging wireless products and services. Studies and reports however reveal that a greater part of the licensed spectrum bands are either predominantly unoccupied or partially occupied in vast ranges of temporal and geographical domain [1] [2]. This issue triggered the main drive behind the suggestion for the ability of wireless devices to use advance radio and signal processing technology to exploit the underutilized spectral frequency bands. Cognitive radio (CR) which was first envisioned by Joseph Mitola [3] emerged as an ingenious technology to indeed accomplish this opportunistic and efficient use of these spectral bands and solve the issue of spectrum scarcity.

In a typical CR scenario, an unlicensed user or secondary user (SU) can opportunistically gain access to unoccupied licensed spectrum while simultaneously guarantying the rights of incumbent licensed users also known as primary users (PU) who possesses a "*first class*" access or legacy rights across the spectral band [4]. Cognitive radio has the ability to learn from its environment and automatically and intelligently adjust its parameters based on what has been learned. In other words, a CR can be able to learn about the spectrum usage status of a spectrum band and automatically decides if the spectrum is available for use by the SU. The process in which a CR can learn about the spectrum usage status of spectral bands in called spectrum sensing [5] [6]. In a spectrum sensing process, if a PU decides to transmit across a particular spectrum occupied by an SU, the SU is ideally required to give up the spectrum immediately and automatically scan for a vacant spectrum for usage.

Cognitive radio is involved in a lot of functionalities so as to be able to deliver a better quality of service (QoS) to its users and in doing this; a lot of energy is being consumed to perform these required tasks. These functionalities CR possesses make a cognitive radio network more energy-demanding thereby seriously impacting on the energy consumed in the network and also reduce its energy efficiency. The energy consumption in a CR network affect all layers, components and functions of the cognitive radio network. Hence, ensuring an energy efficient communications in CR networks however becomes a difficult task as it is faced with enormous difficulties in fulfilling the competitive demands of primary users and secondary users in the network. This work is however geared towards seeking alternative techniques that can be useful in the improvement of energy efficiency in cognitive radio networks.

1.1 Research Motivation

Since wireless communications is responsible for more than fifty percent of the total energy consumption in Information and Communications Technology (ICT) [7], energy efficiency is unquestionably becoming a huge source of concern for all wireless networks including cognitive radio networks as it is now being researched in the area of green communications. The ever rising and escalating energy rates and consumption coupled with the unfriendly and stiff environmental standards have gradually led to an evolving trend of addressing the energy efficiency issues relating to wireless communications. Energy efficiency is also motivated by problems relating to battery lifetime of wireless devices, especially considering the increasing data rates. Therefore, there is a consensus in the academia, industry, policy makers and standardization bodies on the need of efficient wireless communications [8].

Since cognitive radio is involved with a lot of functionalities [9], extra energy consumption however arises in cognitive radio networks when related to other conventional wireless networks due to its inherent properties which potentially counteract its advantages and impede its large-scale deployment. There exist several challenges faced by cognitive radio in order to deliver energy efficient communications. For instance, while cognitive radio operators are expected to deliver high QoS to its cognitive radio users, PUs has placed austere requirements on the utilization of the spectrum and on the other hand, CR operators also desire low management and operating cost. Also, in a way of avoiding interference with PUs, a cognitive radio will have to make a decision about which spectral bands to sense, when it should be sensed and for how long it should be sensed. The already sensed spectrum occupancy information should at least be satisfactory enough for the CR to accurately conclude on the spectrum availability. Correspondingly, the spectrum sensing technique must also be swift enough in order to have a brilliant knowledge of the radio environment. These various spectrum sensing issues does not only put rigorous requirements on the design and implementation of cognitive radio but it is also seen as a main energy consumption process of a typical cognitive radio network.

With energy efficiency affecting all layers and components of a CR system, the energy consumed by radio base stations (RBS) in cognitive radio networks is also another major source of concern [10] [11]. As the number of these base stations increases in order to meet the demands of its users in the network, the energy consumption of the network will also increase. Therefore, a more resourceful and efficient way of reducing energy consumption along the radio frequency interface between the network and cognitive radio user will lead to better energy efficient cognitive radio networks.

In CRN, improving energy efficiency must be considered as a vital key point in ensuring the successful transmission of secondary data and a good workability of the network communication and protocol architectures. Enhancing the energy efficiency of CRN will not only reduce environmental impacts but will also cut network cost so as to enable an economical green cognitive radio. Therefore, this work aims at investigating the energy consumption in cognitive radio networks and also proffer effective techniques that can facilitate higher energy efficiency in the network.

1.2 Aims and Objectives

The main aims and objectives of this work are to:

- ❖ Investigate the various metrics used in measuring energy efficiency in cognitive radio networks with respect to its operational characteristics and design.

- ❖ Study the cognitive capabilities of cognitive radio networks and investigate the major trade-offs necessary in facilitating higher energy efficiency in the networks.

- ❖ Determine an effective technique to achieve possible energy efficiency improvements in cognitive radio networks.

- ❖ Determine the energy consumed by secondary users in a cognitive radio network when opportunistically using a licensed spectrum.

- ❖ Analyse the possible effects of malicious cognitive radio users on the network's energy efficiency especially in the spectrum sensing operation.

1.3 Thesis Overview

The structure of this thesis is organised and developed in seven chapters. The first chapter gives a general introduction of the work, the motivation and the aims and objectives guiding the research. An overview of the thesis, its contribution to knowledge, and the resulting peer reviewed publications, are also detailed in this chapter. A summary of the remaining chapter of this thesis is documented as follows:

Chapter two gives a brief introduction and review into cognitive radio and cognitive radio networks as well as the concept of energy efficiency in cognitive radio networks. Important energy efficiency trade-offs that should be taken into consideration in the design and implementation of cognitive radio networks are also detailed in this chapter. Related work associated with energy efficient approaches in cognitive radio networks are also presented.

Chapter three gives an in-depth analysis of the energy efficiency metrics for cognitive radio networks. Metrics at the component level, equipment level and the network level are all discussed.

Cognitive radio performance metrics are also studied and the accompanying discussions and results are presented in this chapter.

Energy efficiency relating to cognitive radio base stations is examined in Chapter four, and a scheme is proposed to put idle base stations to sleep in the network. In addition, in this chapter, an effective way to deliver better energy efficiency in the network is developed in which a combination of massive Multi-Input-Multi-Output (MIMO) and small cells is used to bring about potential progress in the energy efficiency of the network. The performance of the proposed technique is also evaluated and results are presented at the end of the chapter.

Chapter five investigates the amount of energy that is consumed in delivering secondary data via available spectral bands in a CRN. The energy consumption of secondary users in each state of the network is analysed. In addition, the chapter explores other secondary users that have the tendency of being malicious and investigate how much they affect the network's energy efficiency as well as how these effects can be minimised.

Chapter six presents a cooperative spectrum sensing technique that is energy efficient that ensures a better detection of spectral bands in the network. This is to ensure an improved performance in the network's energy efficiency while simultaneous maintaining a high sensing accuracy of the spectrum sensing process. Results and discussions are also given at the end of this chapter.

Chapter seven concludes the work undertaken in this research. A summarized overview of the research presented in this thesis is also documented and possible future research areas are also highlighted.

1.4 Contributions to Knowledge

This research work is primarily focused on providing alternative and effective methods to improve energy efficiency of cognitive radio networks. The contribution this research makes to the field of cognitive radio networks is four-fold.

Firstly, the metrics used for calculating energy efficiency in cognitive radio networks is developed and analysed in terms of its operational characteristics and design. Cognitive radio network performance metrics is also formulated in this work and its sensing performance measured at different fusion rules. Energy efficiency metrics is seen as a key and essential indicator of a good and quality cognitive radio transmission hence it is used in different ways for various purposes, especially comparing the energy efficiency performance at different levels. It is important to emphasize that identifying and understanding these metrics provides measured and quantized metrics on how to calculate energy efficiency at any level in a CRN.

Secondly, the amount of energy consumed by secondary unlicensed users in CRNs has been analysed in this work so as to improve the energy efficiency under a desired QoS requirement for both the licensed primary and the unlicensed secondary users. Energy consumption analysis is demonstrated in this work and the overall energy consumed in the network investigated as a crucial step in improving energy efficiency of cognitive radio networks. Also, misbehaving and malicious secondary users that disrupt the spectrum sensing process and the overall sensing performance of the network are examined. The thesis contributes in analysing how much effect malicious secondary users has on the network's energy efficiency and also proposes an improved secured energy detection and sensing mechanism that aids to reduce these effects.

Thirdly, in CRNs, secondary users perform spectrum sensing to make decisions about the availability of spectral bands. The spectrum sensing process undertaken by secondary users often leads to additional energy consumption in the network. Hence, the development of an energy efficient spectrum sensing technique that ensures quicker sensing time and better detection of spectrum bands has been established in this work. A two-step cooperative spectrum sensing technique is thus developed to optimize the energy efficiency in the sensing process of the network with the aid of a simulated annealing algorithm so as to achieve a better energy-efficient cognitive radio network.

Finally, an effective way in reducing the energy consumed by cognitive radio base stations is also demonstrated in this work. A base station sleep mechanism is developed to put unnecessary and idle base stations to sleep when traffic is low. Also, massive MIMO techniques combined with small cells is employed in cognitive radio base stations to bring about possible improvements in the energy efficiency of the network.

The findings from this research will assist cognitive radio operators in determining sources of unnecessary energy consumption in cognitive radio networks which will aid in the implementation and design of energy efficient and secured cognitive radio networks. It will also help in saving a lot of finance and resources which has being channelled into reducing the energy consumption of cognitive radio networks especially in the radio base station component of the network which is seen to consume a substantial amount of energy due to the provision of radio frequency interface between the network and cognitive radio users.

1.5 Resulting Peer Reviewed Publications

The peer reviewed publications below have been derived from the work undertaken during this research. These publications makes up the topic of the chapters in this dissertation and they are as follows:

1. **Efe F. Orumwense,** Thomas J. Afullo, and Viranjay M. Srivastava**,** "Cognitive radio networks: A social network perspective," Chapter 13, Advances in Intelligent Systems and Computing , Springer International Publishing Switzerland, May, 2016. (DOI: 10.1007/978-3-319-27400-3_39).

2. **Efe F. Orumwense,** Thomas J. Afullo and Viranjay M. Srivastava, "Using Massive MIMO and Small Cells to Deliver a Better Energy Efficiency in Cognitive Radio Networks" Accepted for publication in the *International Journal on Communications, Antenna and Propagation (IRECAP),* October, 2016.

3. **Efe F. Orumwense,** Thomas J. Afullo, and Viranjay M. Srivastava**,** "Achieving a better energy-efficient cognitive radio network," *International Journal of Computer Information Systems and Industrial Management Applications (IJCISIM)*, vol. 8, pp. 205-213, March, 2016.

4. **Efe F. Orumwense,** Thomas J. Afullo, and Viranjay M. Srivastava**,** "Energy efficiency in cognitive radio networks: A holistic overview," *International Journal of Communication Networks and Information Security*, vol. 8, no. 2, pp. 75-85, April 2016.

5. **Efe F. Orumwense,** Thomas J. Afullo and Viranjay M. Srivastava, "Improving Energy Efficiency in Cognitive Radio Networks using a 2-Step Cooperative Spectrum Sensing Approach" *In the proceedings of the Southern Africa Telecommunications Networks and Applications (SATNAC 2016).* George, South Africa, pp. 3-7 September 2016, pp. 344-348.

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7. **Efe F. Orumwense,** Thomas J. Afullo, and Viranjay M. Srivastava, "Main trade-offs for energy efficiency in cognitive radio networks," *IEEE Conference on IST Africa (IST-Africa 2016),* Durban. South Africa, 11-13 May 2016, pp. 1-8.

8. **Efe F. Orumwense,** Thomas J. Afullo, and Viranjay M. Srivastava**,** "Secondary user energy consumption in cognitive radio networks," *IEEE International Conference on AFRICON* ***(****IEEE AFRICON-2015),* Addis Ababa, Ethiopia, 14-17 September, 2015, pp. 87-91.

9. **Efe F. Orumwense,** Thomas J. Afullo, and Viranjay M. Srivastava, "Effects of malicious users on the energy efficiency of cognitive radio networks," *Southern Africa Telecommunication Networks and Applications Conference (SATNAC-2015),* Western Cape, South Africa, 6-9 September, 2015, pp. 431-435.

CHAPTER TWO

LITERATURE REVIEW

2.0 Objective

The main objective of this chapter is to provide a theoretical background of cognitive radio and cognitive radio networks with strong emphasis on the significance of energy efficiency in the network. The main trade-offs for energy efficiency in the network is studied. This chapter also aim at examining the different key areas that are related to this work.

2.1 Introduction to Cognitive Radio and Cognitive Radio Networks

Wireless communication technology has received a lot of research interest over the last decade. With the recent developments in technology and in the world of wireless communications, cognitive radio technology has gradually paved its way as a potential paradigm to improve the effective utilization of limited spectrum resource.

2.1.1. What is Cognitive Radio?

In the early 1990s, software defined radio (SDR) became popular and gained recognition as a radio consisting of a radio frequency end with a software controlled tuner [12]. Mitola and Maquire in 1999 took this concept of SDR further and developed it into a fully reconfigurable wireless transceiver that is able to automatically adapt its communication parameters to network demands and termed it cognitive radio [3]. Since this concept was proposed, it has undergone much developmental efforts and research. Cognitive Radio is a generic term which is used to describe a radio system that is observant of its environment and can potentially tune and adapt its transmissions according to its user needs. In other words, cognitive radio is defined as a radio or system that obtains knowledge of its operational environment, and dynamically adjusts its operating parameters to suit the already obtained knowledge so as to accomplish its predefined aims and objectives and also learn from the results obtained [13].

Cognitive radio gives opportunity to secondary users to transmit in several licensed spectral bands when primary users are absent in those spectral bands in as much as interference is not caused to the primary users. Hence cognitive radio is employed by secondary users to sense which spectrum band or bands are not being utilized by a PU, select the best available channel, opportunistically use the channel and immediately vacate the channel when the PU becomes active. This new approach is referred to as Dynamic spectrum access (DSA) [14]. The major key functions of a cognitive radio are the capabilities of observing, learning and adapting. It also possesses the ability to combine multiple sources of information, decide on its current operational settings and cooperate with other cognitive radios in a wireless network. When cognitive radios are interconnected, they form cognitive radio networks.

2.2 Cognitive Radio Networks

Cognitive radio networks are not only a network of interconnected CRs, but they also composed of several kinds of communication systems and networks that can also be regarded as a sort of heterogeneous network. Cognitive radios possess the ability to sense available communications systems and networks in its operating environment. A typical CRN is made up of a primary user or a number of primary radio networks that coexist in the same geographical location with the cognitive radio network. A primary user or a primary network is an existing network that is licensed to operate in a certain licensed spectrum band. The basic components of a CRN are the cognitive radio users or secondary users, the primary users, base stations and core networks. CRNs can be deployed either in a centralized manner, distributed manner or in an ad-hoc or mesh manner so as to serve the needs of both licensed and unlicensed user applications. The three kinds of network architecture in CRNs are the infrastructural, ad-hoc and mesh architectures [15]. The design of these CRN architectures is aimed at utilizing the entire network resources rather than only maximizing the spectral efficiency.

2.2.1 Infrastructural Network Architecture

In the infrastructural based network architecture, as shown in figure 2-1, the transmission activities of the CR users or SUs are controlled and coordinated by the cognitive radio base stations. The base station or fusion center collects all the spectrum related information from the SUs over both licensed and unlicensed spectral bands. The fusion center then makes a final decision on the spectral availability based on the collected information from the secondary users. SUs under the transmission of the same base station communicate with each other through that same base station. The channel between the PU and the SUs is called the sensing channel while that of the SUs and the base station is the reporting channel.

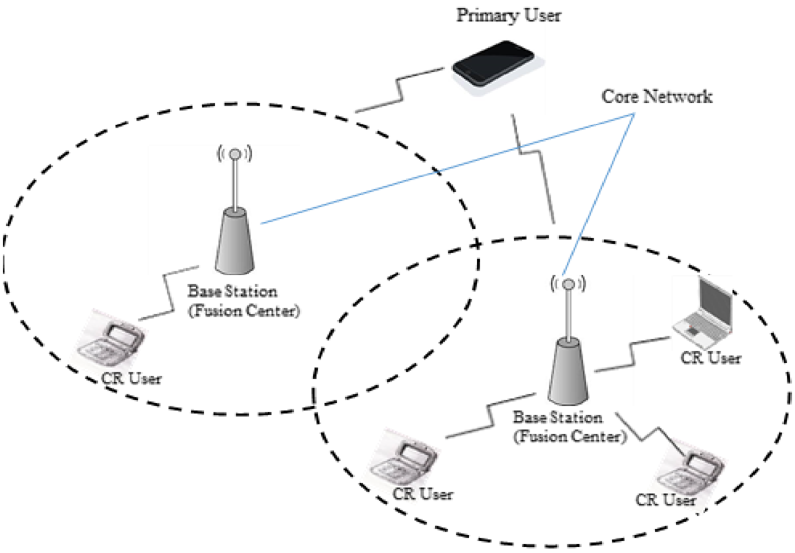

Figure 2-1: Infrastructural based network architecture [20]

2.2.2 Ad-hoc based network Architecture

In the ad-hoc based network architecture as shown in figure 2-2, there is no infrastructural support. The SUs communicate with each other directly in an ad-hoc manner and information is shared amongst the SUs that fall within this communication range. The SUs in this network architecture can either communicate with each other using existing communication protocols or by dynamically using the spectrum. The SUs however do not have any communication channel with the PU and only rely on their local observation during their operation.

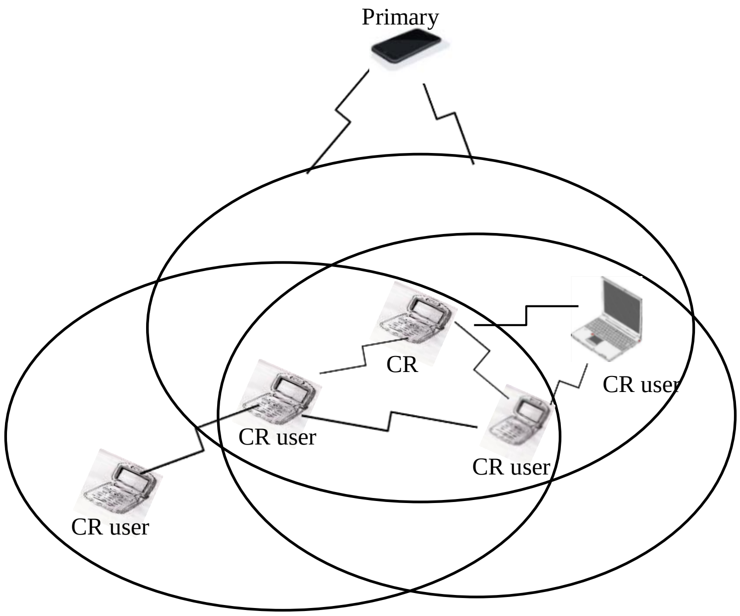

Figure 2-2: Ad-hoc based network architecture [20]

2.2.3 Mesh Based Network Architecture

The mesh based network architecture is a combination of both the infrastructure and ad-hoc architecture. In this architectural arrangement, SUs can either communicate with the base station directly or using other SUs as multi-hop relay nodes.

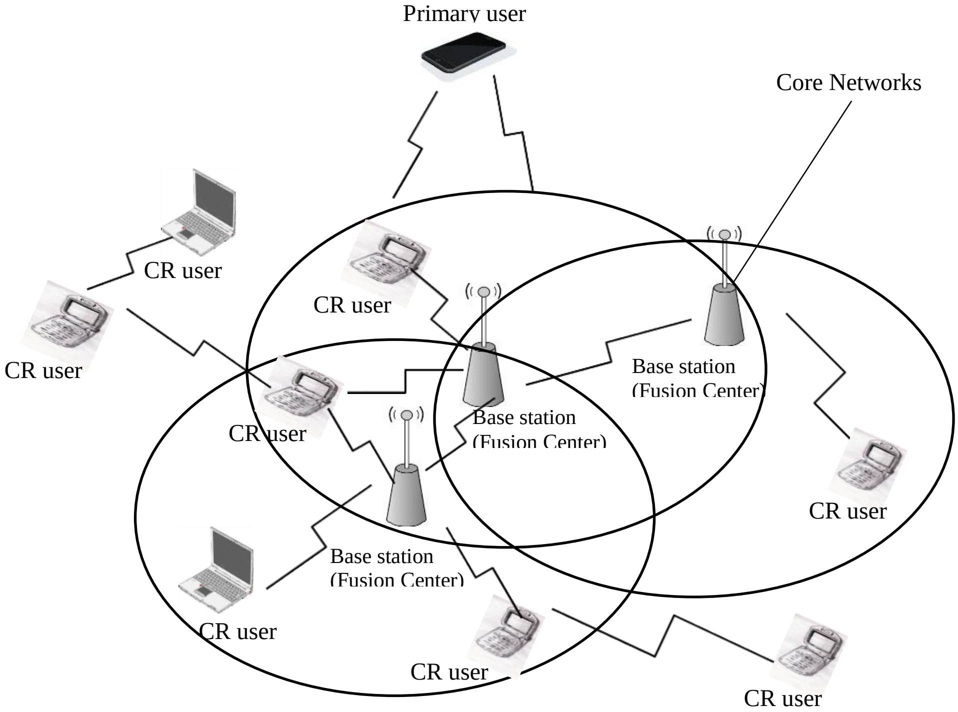

Figure 2-3: Mesh based network architecture [20]

2.3 Capabilities of Cognitive Radio Networks

The capabilities of CRs in a CRN are purely dependent on their functionalities [16]. Hence we will be examining these capabilities in the network as it relates to its terminals or nodes and categorize them according to their functionalities. The three main cognitive radio network capabilities as briefly explained as follows:

2.3.1 Cognitive Capabilities

A major capability CR possesses is the ability to sense for the availability of spectral bands for transmission. It can be able to detect spectral bands that are not being utilized by PUs and transmit in these bands as long as there is little or no harmful interference to the PU. Spectrum sharing is another capability of CRs whereby spectrum resources can be shared amongst SUs in the network with or without a prior agreement between users.

CRs also possesses a location identification characteristic which has the capability to determine its location and other user's location in the network and then selects the suitable operating parameters for transmission.

Another capability of CRs in CRNs is the ability of discovering available networks around its location for quality transmission. An example can be seen where a CR user places a phone call, it automatically determines if there is a base station/WiFi access point close by. If there is no direct communication between the CR user and the base station/WiFi access point but through CR users some access networks are reachable, the call can still be made in this circumstance.

2.3.2 Self-Organized Capabilities

Self-organisation is another major strength of CRNs. It can be able to effectively organize and manage spectrum sensing information among CR users and employ suitable spectrum management techniques when necessary. It also possesses the capability of an accurate mobility and connection management that aids in neighbourhood detection, detection of available connection access and support which enables CRs to select route and networks. CRNs also have a defined trust or security management, but due to its homogenous nature, security has been compromised lately by malicious CR users who take advantage of the network for their exclusive use [17].

2.3.3 Reconfigurable Capabilities

The key strength of a CR is the ability to modify its operating frequency to suit user's needs. It can dynamically select the suitable frequency for transmission based on the sensed signals from other transmitters by employing any of the spectrum sensing methods. Cognitive radio also possesses an adaptive modulation technique which enables it to modify its transmission characteristics and waveform so as to provide a more efficient use of the spectrum. It can also select a more suitable modulation type for usage with specific transmission systems to enable interoperability between systems.

Finally, CRs also possess power control technique which enables them to automatically switch between different transmission power levels during transmission. They can reduce their transmission power level to allow greater sharing of spectrum when the high power transmission is not needed. It also possesses the ability to access multiple communication systems/networks running in different protocols by configuring itself to be compatible with these systems/networks.

2.4 Spectrum Sensing in Cognitive Radio Networks

One of the basic and major functionality of a CR is realised in the form of spectrum sensing. This basic function aids the CR to learn about the availability of spectral bands in its environment. In CRNs, SUs perform spectrum sensing to enable them determine which spectrum band is available for transmission without creating any type of interference to the PUs. In literature, there exist several types of spectrum sensing techniques [18-19][141] and they can be classified or categorised into the interference temperature detection sensing technique, local or non-cooperative spectrum sensing technique and cooperative spectrum sensing technique as shown in figure 2-4.

The interference temperature detection sensing technique is commonly used in the ultra-wide band technology where SUs coexist with PUs and are permitted to transmit with low power and are restricted if the interference level becomes high so that harmful interference does not occur to the PUs. The local spectrum sensing technique exploits the physical layer characteristics of the PU transmissions such as its energy, cyclostationary properties or spectral density modulation [21]. The cooperative spectrum sensing technique tends to collectively improve on the local spectrum sensing by allowing SUs to exchange spectrum sensing information amongst each other. The major local spectrum sensing techniques are the energy detection spectrum sensing, cyclostationary feature detection spectrum sensing and the matched filter detection spectrum sensing as outlined in this chapter.

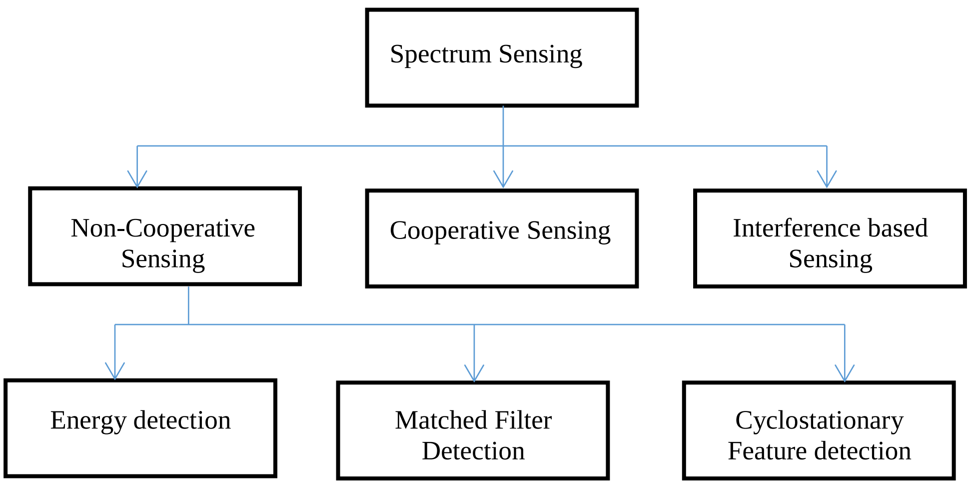

Figure 2-4: Classification of Spectrum Sensing Techniques

2.4.1 Energy Detection Spectrum Sensing

Energy detection spectrum sensing technique is of the simplest and commonly used technique for detecting vacant spectral bands in CRNs. This spectrum sensing technique does not need the *priori* knowledge of a primary signal energy [22] and has a low computational complexity. In this type of sensing as represented in the block diagram in figure 2-5, signal is passed through a band pass filter (BPF) that selects the centre frequency and the bandwidth of interest W and then through a squaring device before it is integrated over time interval by the integrating device. The output from the integrator block is compared with a predefined threshold value which is set based on channel conditions so as to decide about the presence and absence of a signal.

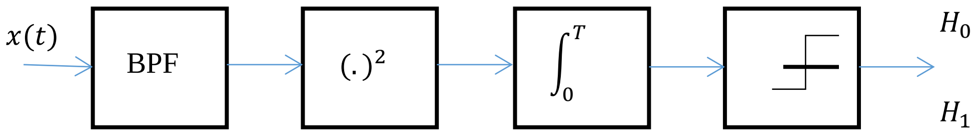

Figure 2-5: Block Diagram of Energy Detector [28]

The signal detection can be broken down into a non-complex identification problem and written as a hypothesis test

$$y(n) = \begin{cases} n(k) & H_0 \\ x(k) + n(k) & H_1 \end{cases}, \tag{2.1}$$

where $y(n)$ represents the sample to be analysed at each instant k, $n(k)$ represents the noise with zero mean and variance σ_n^2. H_0 represents the hypothesis that the primary signal is absent and H_1 represents the hypothesis that the primary signal is present. Let $y(n)$ be the sequence of received samples $k \in (1,2 \ldots N)$ at the signal detector then the decision rule can be stated as

$$\begin{matrix} H_0 \ldots \ if \ \Upsilon < v \\ H_1 \ldots \ if \ \Upsilon > v \end{matrix} , \tag{2.2}$$

where $\Upsilon = E|y(k)|^{\,2}$ is the estimated energy of the received signal and v is chosen to be the noise variance σ_n^2 .

2.4.2 Matched Filter Detection Spectrum sensing

The matched filter detection spectrum sensing technique one of the best technique due to its ability to maximize the signal to noise ratio (SNR) of the signal received in the presence of additive Gaussian noise [23]. When SUs has a *priori* knowledge of the PU signal, matched filter detection technique is often employed. Figure 2-6 shows a simple block diagram of the matched filter detection technique where an unknown signal is convolved with the impulse response of the matched filter and the matched filter output is then compared with the threshold of the reference signal. The matched filter operation can be written as

$$Y[k] = \sum_{K=-\infty}^{\infty} h[k-n]x[n], \tag{2.3}$$

where x is denoted as the unknown signal, and it is convolved with h, the impulse response of the match filter that is matched to the reference signal to maximize SNR. It is important to state that the usage of matched filter detection in cognitive radio is very limited due to the fact that it requires the *priori* knowledge about the primary user signal.

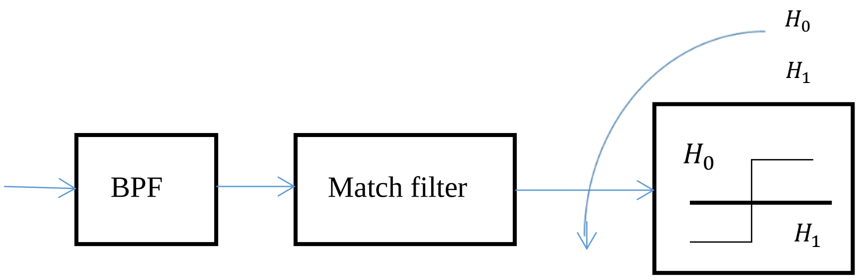

Figure 2-6: A Simple Block Diagram of a Matched Filter Detector

2.4.3 Cyclostationary Feature Detection Spectrum Sensing

This type of technique exploits the periodicity which is usually embedded in cyclic prefixes, spreading code or sinusoidal carriers in the received primary signal in order to identify the presence of PUs. Due to the periodicity, these cyclostationary signals display the characteristics of spectral correlation and periodic statistics which is absent in the stationary noise and interference [24]. Figure 2-7 illustrates the block diagram of the cyclostationary detection technique where the spectral correlation function is obtained by calculating the discrete Fourier transformation of the cyclic auto correlation function. Detection is finally completed with a search for the unique cyclic frequency which correspond to the peak in the spectral correlation function plane. One major short coming of this technique is the high computational complexity involved and longer sensing time. Due to these, the technique is not popular in cognitive radio networks.

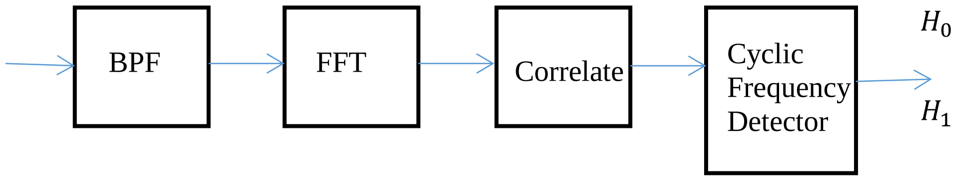

Figure 2-7: Block Diagram of Cyclostationary Feature Detector

2.4.4 Cooperative Spectrum Sensing

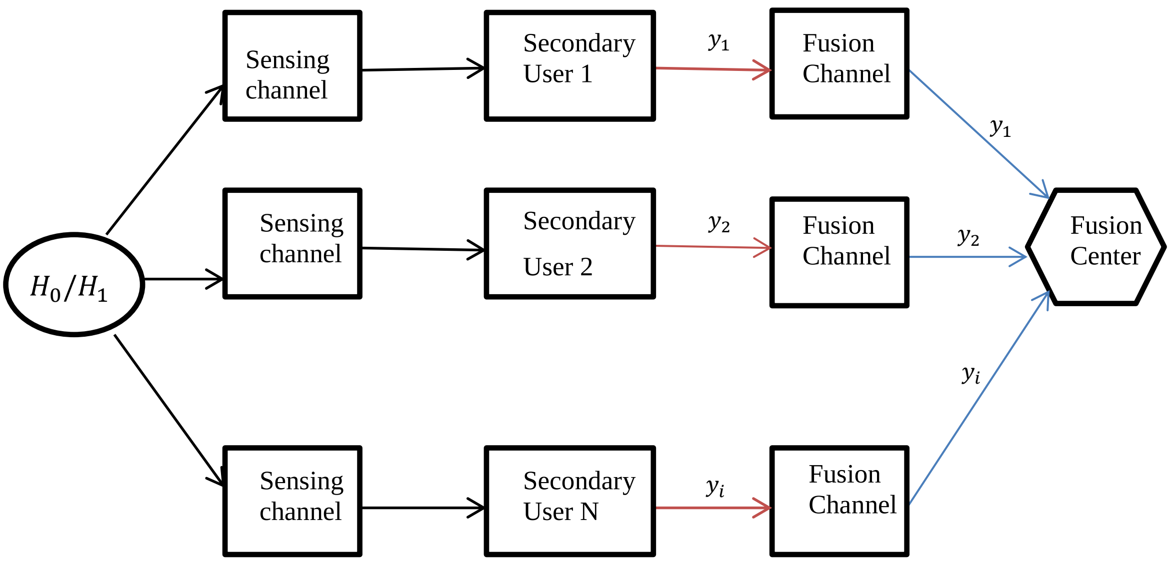

Figure 2-8: Cooperative Spectrum Sensing (CSS) in CRNs.

One issue that relates to SUs single handily performing local spectrum sensing techniques is reliability due to the fact that the SU might be shadowed or in deep fade [25]. In order to solve this hidden node problem and to achieve progress on the performance of the spectrum sensing, several or multiple SUs can be coordinated to undergo cooperative spectrum sensing to increase the probability of detecting PU signals [26-27][137].

In cooperative spectrum sensing process, each SU can perform local spectrum sensing process independently and forward its decisions about the availability of the spectrum to a base station or fusion center (FC). The FC fuses all the binary decision from the SUs in the network and makes a final decision about the availability of the spectrum using fusion rules. There are a lot of fusion rules that can be applied at the FC, but the most efficient and popular rules are the *k*-out-of-*N* rule, the logic OR fusion rule and the logic AND fusion rule. In the *k*-out-of-*N* rule, the FC takes a decision in favour of the hypothesis H_1 (the presence of a PU) when *k* out of *N* secondary users reports the presence of a PU. In the OR fusion rule, the FC takes a decision in favour of the hypothesis H_1 even if one SU reports the presence of a PU. While in the AND fusion rule, the FC takes a decision in favour of the hypothesis H_1 only when all SUs in the network reports the presence of a primary user.

Cooperative spectrum sensing process has been proven to yield better and accurate spectrum sensing results [28] [29] and can be employed either in a distributed or centralized manner. In the centralized manner, the FC is designated to collect local spectrum sensing information from all the SUs in the network and takes a decision on the available spectrum and broadcast this information to the SUs. While in the case of the distributed spectrum sensing, the SUs in the network exchange spectrum sensing information amongst each other and collectively take their own decisions on which particular spectrum is available for use. Figure 2-8 illustrates the cooperating spectrum sensing process of SUs in cognitive radio networks where y_1, y_2 and y_i are the reporting channels.

2.5 Energy Efficiency in Cognitive Radio Networks

The term "*Energy efficiency*" is interpreted differently according to its intended usage. But basically energy efficiency can be defined as a way of managing and restraining growth in energy consumption in order to increase productivity [30]. Energy efficiency in CRNs has gradually become a main concern to various wireless networking stakeholders in the communications industry. Since CRNs consist of energy demanding features and components such as the SU nodes, base stations and backbone networks, the network lifetime is completely dependent on the energy expended by these features and components in the various stages of communication. Hence energy efficiency must be taken into serious consideration in every aspect of CRN operation and design.

There exist numerous ways in which energy can be saved in CRNs. One major approach is to save energy in the different levels of CR user activities while another approach is to increase the effectiveness and speed of SU's spectrum sensing so that time and energy can be save under active modes. Also, another approach is to possibly reduce the interference to the PU to the barest minimum and attain a high SNR with the same transmission power.

2.5.1 Importance of Energy Efficiency in Cognitive Radio Networks

As the number of wireless connecting devices and equipment continue to increase, there will always be a corresponding increase in the demand for more energy supply and a constant need in crafting out more energy efficient devices. The need to improve the energy efficiency of CRNs does not only rest on the network service providers and operators alone but also on device manufacturers who will be able to manufacture and design more compelling solutions for the operators to implement and also for consumers to purchase. Global warming have also become an essential factor not to be ignored in recent times as most network device manufacturers, network service providers, government agencies and most users are now disturbed about the energy efficiency issues of wireless devices as they used to. The importance of improving energy efficiency in CRNs is numerous but most of them points to the issue of design, green communications policy, savings as regards monetary cost and end user's gratification and fulfilment [16].

The more the energy being expended in a wireless communication device, the more the heat due to the fact that energy used up in wireless devices give rise to heat. When a cognitive radio user is in communication, heat is given off and if the device becomes over heated, it will start malfunctioning or might totally or partially become destroyed. In the vein to reducing the temperature, a fairly large cooling system might be needed but unfortunately, this cannot be applicable to wireless mobile devices. The installed cooling system will also require extra energy to run which will also give rise to more heat. As a result of these design issues, there is a serious need for wireless communication devices including devices employing CR to be more energy efficient.

Environmental issues like green-house gas problem have also been a major source of concern to numerous government agencies around the world. The more the energy being used, the more green-house gas is being produced. As a result of this, a lot of compulsory and non-compulsory standards necessitates wireless devices to become more energy efficient. With these standards in place according to country regulations, manufacturers now use them to market their products since consumers prefer to buy products that has lesser negative effects [31]. Therefore, impacting energy efficiency protocols in CRNs will not only reduce its energy consumption but will also make it easily certifiable by these energy efficiency standards.

Currently, more than 80% of the power in mobile telecommunications is consumed by radio base stations [32]. Base stations often require large amounts of energy to transmit and receive wireless signals. With an efficient energy utility protocol put in place, lesser amount of heat will emanate from wireless components of base stations. If lesser amount of heat is generated, that means lesser amount of energy will be required to maintain the environmental temperature of the base stations. In ensuring this, service providers will also be able to save cost on electricity used in running these base stations. Cognitive radio users in CRNs normally have high expectations of mobility for their networking terminals. These users will always prefer a lighter weight and longer battery life wireless convenient devices. Conversely, recent researches on battery technologies can expand the battery capacity. Hence, a good energy efficiency protocol could save extra power and increase battery life. Better energy efficiency measures are also needed by various agencies and societies, network service providers, device manufacturers as well as CR users. To provide these, energy efficiency protocols will require various measures to be put in place to make a CR device run more efficiently.

2.6 Trade-Offs for Energy Efficiency in Cognitive Radio Networks

Since Energy Efficiency (EE) and energy consumption affects all layers and components of a cognitive radio system, there are five important energy efficiency trade-offs that should be put into consideration in the design of CR networks as these trade-offs are instrumental to its implementation. The trade-offs are Quality of Service (QOS), Primary User interference, Fairness, Network architecture and Security. These trade-offs are related and inseparably interwoven with each other. For instance, in the vain of looking for a lasting solution for the problem of PU interference with regards to energy efficiency, the trade-off for network architecture and energy efficiency will eventually be affected because of CR's complexity and deployment cost. However, there is a need to investigate these trade-offs and the possible implications for facilitating higher energy efficiency in the network and also what needs to be sacrificed so as to boost the overall energy efficiency of the network.

2.6.1 Quality of Service – Energy Efficiency

The proliferation in the use of wireless devices and the recent increase in multimedia traffic have made it difficult to guarantee QoS in cognitive radio networks especially under energy efficiency requirements. Inherent factors like power budget of the cognitive radio system, imperfect channel sensing and interference limitations has inhibited the improvement of QoS and also contradicts the requirements for high energy efficiency in the network as reflected in [33]. In a Dynamic Spectrum Access (DSA) point of view, the fundamental protocols in DSA can also hinder the deployment of QoS mechanisms. Therefore QoS can be examined in three approaches. Firstly, is the Primary User Centric (PUC) approach where the main emphasis is to shield the QoS under DSA protocols. In doing so, the spectrum sensing technique and medium access mechanism have to be secondary user insensitive and very energy conservative. Hence, the major control is not to disrupt the primary users while ensuring quality of service and energy efficiency in the system. Secondly, is the Secondary User Centric (SUC) approach where priority is given to the secondary users without harmful effects to the primary user to achieve QoS. In doing so, the interference limitations are made flexible and the solution bank of the problem becomes larger. This aims to reduce the false alarm probability as little as possible.

In the first two approaches, the desired probability criterion can be realized by a longer sensing duration, sampling frequency and signal-to-noise ratio (SNR). Owning to the fact that the primary user's SNR is totally out of the control of the cognitive radio network and the sampling frequency is not reliant on the device, only the sensing time can be increased. Increasing the sensing time however increases the energy consumption in the network which results to low energy efficiency. So the best alternative is that if QoS of secondary users cannot be met, prioritization schemes can be used to increase user satisfaction [34]. The last approach is the Hybrid approach where a hybrid setting is created so that the QoS of the secondary and primary users are not distinguished but rather assessed in a better and flexible way.

In infrastructural based cognitive radio networks, the cognitive base station (CBS) can assign already determined spectrum opportunities using any of the three approaches. The CBS can take advantage of several diversities to achieve an optimal trade-off between QoS and energy efficiency. Different diversity techniques [35] that can be employed can be classified into link diversity, where amongst all secondary receivers, the one with the best link condition is selected. Also is channel diversity, where the best channel is employed for communication, Spatial diversity for better frequency reuse and multi-radio diversity in which multiple channels are used at the same time.

Since CR consumes power in channel reconfiguration, hence much energy is expended. To aid this problem, switching of channels have to be executed only when the newly found channel is capable of providing net gains in terms of energy efficiency of the cognitive radio [36]. Achieving QoS in multihop CRNs is becoming more challenging as the routing paths amongst the network nodes are extremely dependent on the availability of a channel [37]. The most viable solution for a routing QoS mechanism is to create routes that are bandwidth guaranteed while putting energy efficiency into consideration.

2.6.2 Primary User Interference – Energy Efficiency

The spectrum sensing process of cognitive radios allows cognitive radio users to observe the spectral bands and detect the vacant channels for utilization without initiating any harmful primary user interference. Interference in CRNs arises under two scenarios: Primary user misdetection and Primary user reappearance. To mitigate interference under primary user misdetection, the CRs must conduct spectrum sensing with high probability of detection (P_d) so that the probability of colliding with a primary user is kept minimal. In achieving high probability detection, various techniques like cooperative spectrum sensing, high sampling frequency and longer sensing duration are employed. However, in doing this, more energy is consumed compared to a technique that requires little reliability that is low power of detection (P_d). For the primary user reappearance scenario, regardless how high the achieved (P_d) is, there would be a primary user interference owning to the periodic sensing employed. In periodic sensing, a cognitive radio is oblivious of a possible reappearance of the primary user until another sensing period. This is so because CRN works in a frame-to-frame concept whereby a particular section of the frame is devoted to sensing and the other for transmission. So therefore, the time interval existing between two successive spectrum sensing periods actually decides the performance of spectrum detection and also its resulting primary user interference. Frequent spectrum sensing leads to an increase in the energy consumption and higher overhead in the vein of improving the sensing performance. Hence the decision on the sensing and transmission duration is a major concern for primary user interference with respect to energy efficiency [38]. To decrease interference, a CR must behave conservatively both at the sensing and transmission stages of the cognitive cycle. Period adaptation and increased sensing accuracy can be employed at the sensing stage while regulation of transmission power can be employed at the transmission stage [39]. Another solution which be taken to increase energy efficiency in PU interference-EE trade-off can be by channel aggregation [35] and relaying [39].

To also reduce the energy consumption in a CRN, we should be aware that providing energy efficiency whilst guaranteeing the PU interference restriction necessitates us to juggle with the cognitive radio network architecture-EE trade-offs. That means each cognitive radio may have to function as a relay for the others in order to reduce energy consumption.

2.6.3 Network Architecture – Energy Efficiency

There exist different types of CRN architectures that tend to contribute to its energy efficiency, but adding an infrastructural layer (cognitive small cells and relays) [40] between the cognitive radio and the core network will help in reducing the energy cognitive radios require for transmission by reducing its transmitting distance. The cognitive small cells can be in the form of femtocells, macrocells or microcells whose aim is to take off user traffic from the cognitive base station (CBS) as seen in figure 2-9. A heterogeneous CR is considered where the mobile secondary users (MSUs) are directly connected to the macrocell and the femtocell secondary users (FSUs) are directly connected to the femtocells base stations (FBS). The primary networks *(l)* also offer to lease their spectrum resource *(w)* for opportunistic usage. Cognitive small cells can also deal with interference issues originating from impromptu scheduling of cognitive small cells to an extent by using the unutilized primary user spectral bands.

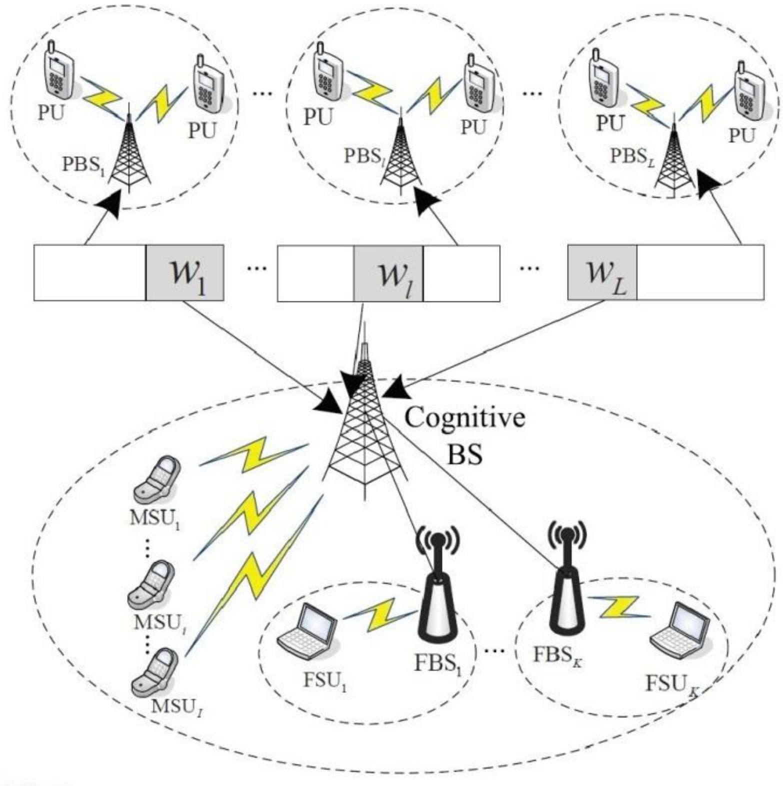

Figure 2-9: A femtocell based cognitive radio network

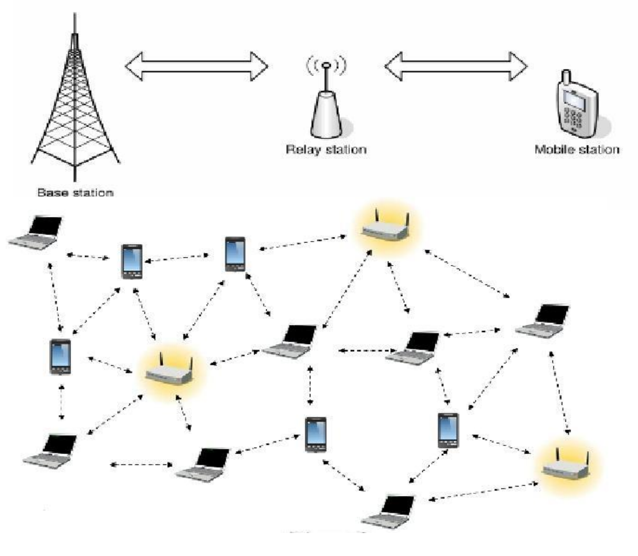

Figure 2-10: Relaying between cognitive radio users

The other alternative is using relays coupled with an "a*mplify-and-forward"* or "*decode-and-forward"* cooperative communications to recover transmission energy by reducing the retransmissions trials and the distance as shown in figure 2-10. However, the use of relay might not be energy-efficient when traffic is low, but will be very energy efficient in good channel conditions since the transmitter is in close proximity to the receiver [41] [16]. So the best strategy to employ when using the relay is to decide on using it on a case by case basis so as to improve energy efficiency.

2.6.4 Fairness – Energy Efficiency

Fairness in communications systems is described as the degree at which the users utilizes a fair amount of a system's resources [42]. Fairness can be measured using Jain's fairness index as

$$\frac{\left(\sum_{i=1}^{n} x_i\right)^2}{n \sum_{i=1}^{n} x_i^2}, \tag{2.4}$$

where x_i is the normalized throughput and n is the number of connections.

However, in a dynamic spectrum sensing cognitive radio environment, cognitive radio users are opportunistically permitted to share spectrum resources when the primary user is not in use. Therefore, ensuring fairness amongst these secondary users in usually not guaranteed. The energy trade-off in a typical energy efficiency setting is that the system being unfair in some scenario can somehow be advantageous to the energy efficiency of the system. The major fundamental condition is to assign spectrum resource as fairly as possible in a way that spectrum resource usage can be maximized while maintaining a high level of energy efficiency [43].

Fairness in cognitive radio networks can be seen as a multi-objective optimization problem due to the fact that it is usually not regarded as the sole aim for cognitive radio network's operability, design and implementation. Thus, the energy efficiency fairness trade-off is usually embedded in resource optimization and QoS problems. An example can be seen in [36] where a satisfaction ratio is introduced for each cognitive radio users so as to enable the spectrum scheduler fairness –aware and integrates this as a multiplication term in the resource allocation problem. There is no much work on fairness as it relates to energy efficiency but in general, fairness can be balanced with energy efficiency if the CRs with minimum required transmission energy for a specified throughput are given transmission priority.

2.6.5 Security – Energy Efficiency

Security in CRNs has been an integral part of its development over the years but equipping cognitive radios with security protocols will give rise to additional processing both at the receiving and transmitting ends. In an already secured cognitive environment, these protocols may tend to decrease the energy efficiency of the network due to additional processing power and time and also time spent for data authentication.

Conversely, in cognitive environments with malicious nodes, further security protocols may maintain high energy efficiency by avoiding interactions with these malicious users. An example is when a cognitive radio user with security protocols detects primary user emulation attacks (PUEA) [17] and automatically being able to use the vacant spectrum band that would otherwise would have been left fallow. Therefore, the effects of security protocols on energy efficiency are intricate and extremely dependent on the nature of the operating environment.

Attacks involving CRNs mainly cripple the sensing capabilities of the network allowing the network to fail at the sensing stage of the cognitive cycle due to shortage of transmission opportunities. These attacks arises either by an insider as in spectrum sensing data falsification (SSDF) attacks or by an outsider as in PUEA. In PUEA, the attacker impersonates the primary user and selfishly uses the spectrum band and prevents all other CR transmission. In [44], the ideal number of security bits in a message required in attaining the optimum trade-off between the obtainable security level and energy efficiency as regards to SDDF attacks is determined. However, the ideal number is directly dependent on the logic fusion rule employed at the fusion center (FC), the number of both the attackers and legitimate users available in the network. Authorization, authentication and trust-based approaches with punishment and reward schemes can also be seen to prevent attacks as long as they require low processing power. The best possible way to achieving high energy efficiency while coping with security threats is for CRNs to employ security procedures that encourages cooperation amongst trusted cognitive radio users and continue to put the trustworthiness of all CRs in the network into consideration [45].

Fig. 2-11, shows the interaction and relationship between the trade-offs for energy efficiency in a CRN. It can be seen that the security factor can be characterized into various approaches such as detection and mitigation, attack models and trust level. If the trust level between the cognitive nodes of the network is high, there will be an increase in energy efficiency. This will be so because the availability of malicious users that tend to transmit wrong spectrum sensing information to other users will be very low. Also in figure 2-11, the deployment and network architecture factor can be viewed as offloading, heterogeneous network architecture and relaying. Cooperation level is a dominant effect as an increase in the cooperation level will bring about an increase in energy efficiency but the trust level amongst the cognitive nodes will be the sacrificing factor.

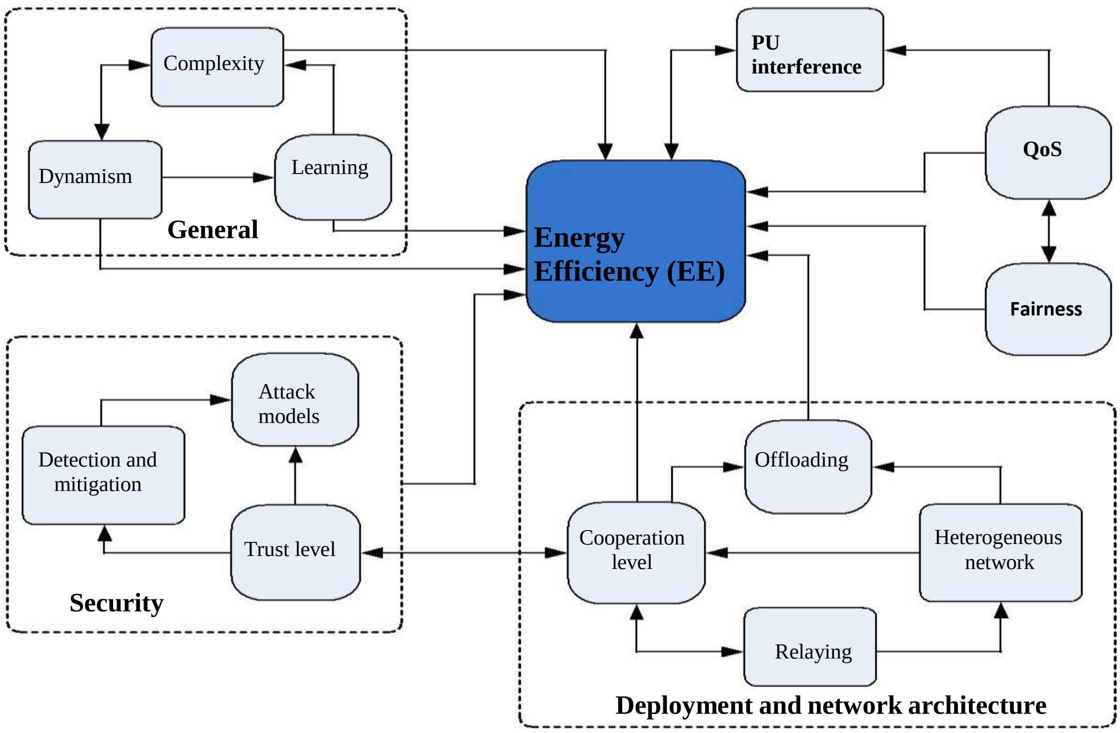

Figure 2-11: Relationship between energy efficiency trade-offs in a CRN viewpoint

2. 7 Energy Efficient Approaches

Energy efficiency in wireless communication networks and systems including cognitive radio networks are improved mainly for both economic and environmental reasons. Since CRNs comprises of several components, different protocol, mechanism and operational characteristic, it is imperative to take a general review of the different approaches in literature that aim to ensure better energy efficiency in cognitive radio networks. Most of these approaches are generally concerned about the reduction of power and energy consumed in the network. Most of the approaches are concerned about increasing transmission rate while other works are concerned about improving the spectrum sensing process of the network. In this section, we will be reviewing and discussing the different approaches available in literature that ensures energy efficiency in cognitive radio networks.

2.7.1 Energy efficient approaches in Radio Base Stations

Energy efficiency in radio base stations has drawn a significant amount of research in wireless communication networks in recent times due to the alarming energy consumption rate. Radio base stations which are responsible for providing the radio frequency interface between the network and its users consume up to 2.0 KW of energy depending on its usage [46]. This may continue to rise in future if no substantial measure is employed to reduce the high energy consumption in radio base stations. A lot of work have been proposed recently to tackle energy efficiency in radio base stations. These approaches are geared towards enabling a green base station through improving hardware design of base stations, using energy aware techniques or including other additional system features for network planning in order to arrive at a balance between energy consumption and performance.

Some researchers have focused on hardware improvements in order to boost energy efficiency performance of cognitive radio base stations. For instance, Wu et al in [47] proposed a novel switchable quad-band antenna that can be applicable to cognitive radio base stations. A switchable and multi-band radiator element is introduced and optimized to offer a radiation pattern in frequency bands. This two element array demonstrates beam width narrowing and beam tilting along the E-plane as desired by base stations. The design and measurement results are also presented in the work. A multi scalable reconfigurable antenna for CR base stations is also presented in [48] where the antenna is designed based on a symmetric repeatable topology making it scalable to incorporate in different frequency bands. This however increases the gain and the energy efficiency of the base station.

Energy consumption in radio base stations can also be minimised by developing energy efficient radio resource management protocols without affecting the Quality of Service (QoS) of its users. Sleep mode mechanisms is one of the approaches used in increasing the energy efficiency of the network. Saker et al in [49] proposed a sleep mechanism for base stations to shut down a number of system resources in a dynamic manner. These resources are activated or deactivated based on the load of the network. The authors also showed that the dynamic shut down brought about larger energy deductions when compared to the semi static mechanism but distance between its users was not considered. Charaviglio et al in [50] proposed a base station switching-off mechanism that randomly switches off base stations to guarantee QoS constraints. In their work however, the energy efficiency of the base station is not fully optimized as the base station switches off in a random manner. An algorithm that minimizes energy consumption by turning off base stations based on the traffic demand was also presented by Gong et al in [51]. The authors proposed an energy saving algorithm by dynamically adjusting the sleep and active mode of the BS based on the traffic variation and the blocking probability requirement. Also, Lorincz et al in [52] also initiated an energy saving method which is based on the traffic load and location estimations between the base station and its users so as to select the exact number of access points to be turned on in the network.

2.7.2 Energy Efficient Approaches in Network Organisation

Network organising techniques is also one major approach in achieving improvement in the energy efficiency in cognitive radio networks. Yongjun et al in [53] proposed a distributed power control algorithm with QoS requirement in the view of minimizing the total power consumption of SUs under time varying scenarios. In [54], Hua et al employed a joint base station assignment with weights and power allocation approach to minimize the signal-to-inteference-plus-noise ratio of a small cell network. A MIMO cooperative cognitive radio architecture was also developed to maximize the utilities of PU and SUs using a Stackelberg optimization model. In [55], Bjornson et al accomplished a significant reduction in transmission power using a soft-cell coordination in a hybrid network. Also, Fu et al in [56] proposed an energy efficient optimal transmission algorithm for a MIMO cognitive radio network where high energy savings was achieved but dependent on the traffic load of the secondary system.

In enhancing the energy efficiency of cognitive radio networks, relays are sometimes used as an alternative to multi antenna systems whose key purpose is to assist in forwarding information from a user in a poor signal coverage area to a radio base station. In [57], the authors discussed modern developments in the physical layer using cooperative relaying technology. Decode-and-forward relaying method was used to improve the wireless data rate by exploiting the spatial diversity in the physical layer. The capacity improvement gained from the cooperative relaying is due to the exploitation of the received signals that were initially taken as noise and interference.

2.7.3 Energy efficient approaches in the Spectrum Sensing Process

There has been a substantial amount of research aimed at reducing the energy consumption of the spectrum sensing process of cognitive radio networks. In a typical spectrum sensing process, cooperative spectrum sensing has been proven to yield better spectrum sensing results. However, there exist two possible ways in which the energy efficiency of the cooperative spectrum sensing process can be maximized. The overall energy consumed at the local spectrum sensing process can either be reduced or the energy used in reporting these local spectrum sensing results to the FC.

In the vain of reducing the total energy consumed in the local spectrum sensing process, Althinubat et al in [58] proposed a simple cooperative spectrum sensing where the number of SUs participating in the spectrum sensing process is reduced in order to maximize the network's energy efficiency. The results in the work showed a huge amount of energy savings in the network. In [59], Maleki et al formulated an energy efficiency optimization problem by minimizing the number of SUs involved in the spectrum sensing process while satisfying the predefined constraints on the probability of detection and the probability of false alarm. If a limited frame length for sensing is to be put into consideration, minimizing the number of SUs might not necessarily bring about an increase in the energy efficiency of the network. Also in [60], Ergul et al proposed a technique used to select SUs in the network that will participate in sensing. This was accomplished by proposing an algorithm that excludes SUs that possesses high correlated sensing results from the sensing process. In this work, it was assumed that every SU possess the capability to overhear the spectrum sensing results of the other SUs in the network which is not possible at all times. An algorithm that can split the participating SUs into subsets of energy efficiency maximization is studied by in [61]. The selection of subset is based on the most guaranteed high detection accuracy and lowest cost function. The decision accuracy is also based on two thresholds on both the false alarm probability and detection probability and the cost function is denoted as the energy consumption. While the achievable throughput was not discussed, the authors also assumed that the SUs local spectrum sensing performance is always designated at the FC. This may however require extra energy and time in the spectrum sensing process.

In a view to also reducing the energy consumed in reporting spectrum sensing results, authors in [62-64] developed a clustered type of cooperative spectrum sensing technique. In each cluster, SUs are meant to forward their spectrum sensing results to a cluster controller. The cluster controller then merges these results together and forwards it to the FC so that energy efficiency in reporting the spectrum sensing information can be maximized. Xu et al in [65] optimized the sampling rate of the sequential sensing so as to reduce the energy consumption. This work only considered a single SU in the network and the energy expended in the cooperative spectrum sensing process was not taken into consideration in the formulated optimization problem. A confidence voting technique is presented by Lee and Wolf in [66]. In this scheme, if the spectrum sensing of a specific SU is in consonance with global decision from the FC, it automatically gains its confidence and if not, its confidence is lost. An SU is considered as unreliable and stop sending sensing results when the level of confidence falls below a certain threshold. Once the level of confidence goes beyond the threshold, the confidence is regained and re-joins voting. In this work, the level of confidence is wholly dependent on the global decision which in most times, might not be totally reliable and might be a weak link for malicious SUs to exploit. Also, the detection accuracy might not be very accurate since the number of SUs reporting varies at each sensing rounds.

2.7.4 Other Energy Efficient Approaches

There are other key works in literature that relates to improving the energy efficiency in CRNs which is gradually gaining much research attention. For instance is energy harvesting in cognitive radio networks where energy is internally harvested in the network and then used to run the network. This energy efficient approach can be very useful in locations where power lines are not able to supply energy and also where battery life is very critical. Energy sources such as radio frequency energy, solar, thermal, wind energy are all potential energy sources that can be harvested in a cognitive radio network and are also regarded as environmental friendly.

There exist several protocols that can be applied in order to efficiently harvest energy. In [67], Park et al developed a cognitive radio network with an energy harvesting transmitter with the aim of improving the energy efficiency of the network. The authors derived an optimal detection threshold that maximizes the expected total throughput with the total consumed energy being less than the total harvested energy. The results showed that the energy arrival rate is lower than the expected energy consumption for a single spectrum sensing process. Lee et al in [68] also proposed an energy harvesting technique where energy is harvested from PU transmitters by the SU transmitters while opportunistically accessing the licensed spectrum band. Based on a stochastic-geometry model, each PU is equipped with a guard zone to protect its intended receiver from secondary transmitter interference and simultaneously delivers Radio Frequency (RF) energy to the secondary transmitter located in an energy harvesting zone.

2.7 Chapter Summary

An important and theoretical background of this research work has been presented in this chapter. Cognitive radio and cognitive radio network has been introduced while the network architecture has been analysed. Spectrum sensing technique which is a key operation in cognitive radio networks was also discussed and the various spectrum sensing techniques were presented. Energy efficiency and its importance in cognitive radio networks have been explained. Key approaches available in literature that can positively boost the energy efficiency of cognitive radio networks applied at different stacks and protocols have been reviewed. Various key areas that are of importance to this work as described in the following chapters have also been introduced.

CHAPTER THREE

ENERGY EFFICIENCY METRICS

3.0 Objective

The main objective of this chapter is to understand the concept of energy efficiency in cognitive radio networks and also to investigate the metrics used in measuring energy efficiency. This will be achieved by showing the energy efficiency metrics developed in cognitive radio networks with respect to its design and operational characteristics. Establishing a comprehensive metric for evaluating, measuring and reporting the energy efficiency of cognitive radio networks is a crucial step to achieving an energy-efficient cognitive radio network. It is also imperative to accentuate the importance of energy efficiency metrics in cognitive radio networks as it provides measured and quantized information to calculate efficiency.

3.1 Introduction

Energy efficiency (EE) is perceived to be a very important constraint in the design, operation and implementation of most wireless communication networks especially those composing of devices that are battery operated. Energy efficiency in cognitive radio networks (CRN) is gradually gaining prominence amongst researchers and has received a lot of research attention lately as the network becomes more and more energy-demanding. This demand has obviously been triggered by high energy cost and the need for green communications. Energy efficiency is considered to encompass all other sub-system metrics so as to represent the overall performance of CRN system while taking into consideration the entire energy consumption, achievable throughput and the detection accuracy. The fusion of these various indicators into a single metric has branded the EE metric as a significant and important indicator of a good quality transmission [69]. Since energy is considered as a major constraining resource for CRNs, the lifetime of the network is seen as a significant performance metric due to its relation to the energy used in processing and transmitting of data and also the energy dissipated at different levels and components of the network. Putting this into consideration, energy efficiency must be taken as an important factor in every aspect of CR operation and design, not only for specific parts of the network but also for the whole network communication [70].

Maintaining energy efficient communications in CRNs appears to be a very daunting task as it is faced with great difficulties in satisfying competitive demands from SUs in the network. Hence it requires improved technologies and solutions to better the energy efficiency of the network.

In order to ensure an energy efficient CRN, it is necessary to firstly investigate the various metrics used in quantizing and calculating energy efficiency. In this chapter, the energy efficiency metrics developed in CRNs in terms of its system design and operation are shown. The taxonomy of EE metrics developed at different levels of a CRN and its performance metrics is also analysed.

3.2 Energy Efficiency Metrics

As EE metrics continue to gain popularity amongst researchers, several standard organizations like the Alliance for Telecommunications Industry Solutions (ATIS) and the European Technical Standards Institute (ETSI) have been making frantic efforts to present a generally acceptable definition for EE metrics for wireless networks [71-72]. However, Energy efficiency metrics has been formally defined by Gao et al in [73] as the total number of bits which can be transmitted successfully with unit energy consumption. It can also be regarded as the ratio of the overall throughput to the energy consumed for a given transmission. Energy efficiency metrics plays a key role in the comprehensive assessment of energy savings and performance of cognitive radio systems. This metrics help in providing detailed information in making direct comparison of various components of the network and also assessing and measuring the energy consumption of the entire network. It also assists in setting various benchmarks in the realization of energy consumption reduction.

With numerous research activities been carried out relating to energy efficiency and due to the intrinsic differences of various communication components imbedded in a communication network, it is difficult for a single metric to suffice. However, an accurate EE metric should encompass all parameters relevant to the energy consumption necessary for communication, while considering the amount of data to be delivered under specified QoS requirements. Authors in [74-76] defined an accepted and widely used measure for energy efficiency as

$$EE = \frac{Total\ amount\ of\ energy\ consumed}{Total\ amount\ of\ delivered\ data}\ {}^{Joule}\!/_{bit.} \tag{3.1}$$

The inverse of equation 3.1, EE^i which is $\frac{1}{EE}\ {}^{bit}\!/_{joule}$ has been adopted in [77-80]. Therefore, we can now deduce that in optimizing the energy efficiency, the measure of EE from equation 3.1 should be minimized while its inverse EE^i should be maximized.

Also, another commonly used metric which is mostly used in accessing the energy efficiency of a wireless link is given in [81]. Its usage has also been employed in the assessment of the entire wireless network as seen in [82-85]. Let η denote the bit/joule efficiency of the network which can be written as

$$\eta = \frac{C_{net}}{P_{net}}, \tag{3.2}$$

where C_{net} is expressed as the total network capacity measured in bit/s, P_{net} is expressed as the overall power consumed in the network measured in watts.

A different but generally recognised energy efficiency metric that relates power consumption and area is seen in [86-89]. It practically relates the overall power consumed by the network (P_{net}) to the size of the area covered (ξ). The energy efficiency metric is denoted as Ψ and given as

$$\Psi = \frac{P_{net}}{\xi}. \tag{3.3}$$

The optimal energy efficiency can be attained when the metric is minimized in terms of $Watt/km^2$ or maximized in terms of bit/joule.

For a modified metric which accounts for a data rate and communication distance, $bit\ meter \big/ _{joule}$ can be employed. This metric refers to the efficiency of effectively conveying the bits over a measured distance towards the required destination per unit energy consumed.

Another metric for energy efficiency in systems when it is not continous is seen in [90] as the average goodput over per unit average power transmitted and it is given by the formula

$$\eta = \frac{g_d}{P_{total}}, \tag{3.4}$$

where P_{total} is denoted as the average power transmitted by SUs and g_d is denoted as the "average goodput" also originating from the SUs. The goodput can also be termed as the number of bits transmitted successfully by an SU with the unit *bit/s* which can be expressed as [141]:

$$goodput\ (g_d) = \frac{(t_1 + t_2 + \ldots\ldots t_n)\,(1 - P_e)\,r}{T} \tag{3.5}$$

where r is denoted as the data rate measured in bit/s, P_e is expressed as the packet error rate (PER), T denotes the packet duration and t_i denotes the time interval or duration in which an i^{th} SU is transmitting during the interval T.

A different metric known as the joint energy performance metrics (EPM) for ad-hoc networks that permits routing protocols to be evaluated for energy consumption and network performance was discussed by Bhatnagar et al in [91]. This metric captures the good behaviour of a communication system. The EPM for communication networks was defined as

$$EPM(\alpha) = (Average\ Energy\ )(Average\ Performance)^{-\alpha}, \tag{3.6}$$

where α is defined as the parameter that defines the trade-off between energy and its performance. The overall energy of the entire nodes in the network is taken as the average energy of the network. Evaluating the average network performance of a CRN is a very difficult task. The average performance of a CRN is solely grounded on its ability to deliver large amounts of packets successfully, which is regarded in literature as transmission efficiency, that is, network packets received over the network packets transmitted. The lower the EPM values of the network, the higher the energy efficiency and the improved joint energy-performance. So by putting these definitions into equation 3.6 will give

$$EPM(\alpha) = (Network\ Energy/number\ of\ nodes)(Transmission\ Efficiency)^{-\alpha}$$

$$EPM(\alpha) = \left(\frac{Network\ Energy}{Number\ of\ nodes}\right) \times \left(\frac{Amount\ of\ Network\ Packets\ Transmitted}{Amount\ of\ Network\ Packets\ Received}\right)^{\alpha} \tag{3.7}$$

It is important to note that this form of energy performance metric has energy as its unit due to the fact that the performance component has no units. The unit of EPMs are usually considered as relative metrics, but this very type of EPM is considered as a performance-scaled value of energy. The only difficulty of this EPM is choosing a desirable value for α. For a value of EPM (0), the metric turns into a pure energy metric, while for a value of EPM (α), the metric turns into a pure performance metric.

3.3 Taxonomy of Energy Efficiency Metrics

It is certain that the assessment of a metric is derived from measurements, therefore, a metric is accompanied by accuracy and also additional information to access the energy consumption of the different components and also the entire network. This section focuses on describing energy efficiency metrics in CRNs while classifying them into separate categories. These metrics are categorized into three major classes which are the facility or component level metrics, the equipment level metrics and the network level metrics. The component level is regarded as a high level system in which equipment are deployed. The equipment level metric is mainly used in evaluating performance of each equipment in a component while the network level metric is used in accessing the performance of equipment that relates to the coverage and capacity of the network.

3.3.1 Component Level Metrics

A typical CRN architecture can either be organized in an ad-hoc based setup or in an infrastructural set-up. In the ad-hoc set-up, no infrastructural support is required while in the infrastructural based CRN architecture, CR nodes mostly communicate with each other through radio base stations (RBS). In this kind of network set-up, both the RBS and the CR nodes are integrated parts of the network.

Since CRNs are basically wireless, a general model of a simple wireless equipment consisting of basic wireless constituents as shown in figure 3-1 is employed for our analysis. The basic constituents of the wireless equipment model used for this analysis are antennas(s), antenna support system, radio frequency (RF) front end unit, baseband processor, power supply and a detachable component which can be an air conditioning system or climate control system. The RF front end unit is involved in the transmitting and receiving business of the equipment. The component that critically impacts on the energy efficiency of the equipment is the power amplifier (PA), which can be found in the transmission chain. The support system is involved in linking the different protocol layers. It also performs various control functions and furnishes other network elements in the system with an interface. The power source consists of a power supply which can either be a battery power source or an alternating current (AC) power supply. Lastly, the climate control component which might be an air conditioner can be optional depending on the environment usage.

In analysing the energy efficiency metrics of the different constituents of the equipment, the energy efficiency of the antenna is a function of the antenna's input power and also the radiated power of the antenna. A large amount of the input power is usually radiated away in an antenna with a very high efficiency while most power are absorbed as losses in an antenna with low efficiency. Therefore, the energy efficiency of an antenna can be expressed as the ratio of the power radiated to its input power as

$$\eta_{Ant} = \frac{P_{radiated}}{P_{input}}. \tag{3.8}$$

The energy efficiency of an antenna can also be quantified through its antenna gain. The gain of the antenna assists in ascertaining the amount of power required to transmit in the direction of peak radiation to that of an isotropic source which radiates in all directions [74]. Therefore, the gain of the antenna can be expressed as:

$$Gain = 4\pi \frac{Radiation\ indensity}{Input\ power\ of\ antenna}. \tag{3.9}$$

In the radio frequency front end unit, the power amplifier is responsible for most of the component's power consumption. The authors in [92] discussed that in a typical cellular radio base station, the power amplifiers consumes about 35% of the total available power. The energy efficiency of the power amplifier is described as the ratio of both the output and input power and this can be expressed as

$$\eta_{PA} = \frac{P_{output}}{P_{input}}. \tag{3.10}$$

In order to tackle the energy efficiency issues relating to the power amplifier, special design techniques can be employed and the power amplifier can be automatically shut down if the transmitter is not transmitting or is in idle mode.

Also, in the wireless equipment, exist a baseband processor which in CRNs, it is regarded as digital baseband processor and uses its digital signal processor (DSP) for processing. The energy efficiency of a DSP is often measured by the performance per unit of energy consumed. The performance metrics is normally given in FLOPS (Floating-point Operations per Second) and the energy efficiency metrics of a DSP of the baseband processor is measured in FLOP/watt or Million FLOPS/watt. Also in the equipment, the support system which is classified as a computer system uses Million Instructions per Second (MIPS) as it performance metrics. Since a cognitive radio network can automatically sense its environment, learn from sensed information and adapt to the environment, the memory access and the Input/Output can significantly influence the performance of the computer support system and the DSP. The processing capacity of the baseband and the computer system may cause congestion in the whole equipment which will in turn have an effect on the energy efficiency of the equipment. The energy efficiency of the power supply can be quantified by the output power to the input power since its basic function is to provide power to the equipment. The energy efficiency of the climate control system is not normally evaluated in communication systems but however, its consumed energy is reduced as much as possible. Research efforts are also in place to design the use of applied passive cooling techniques in the equipment which will phase out climate control.

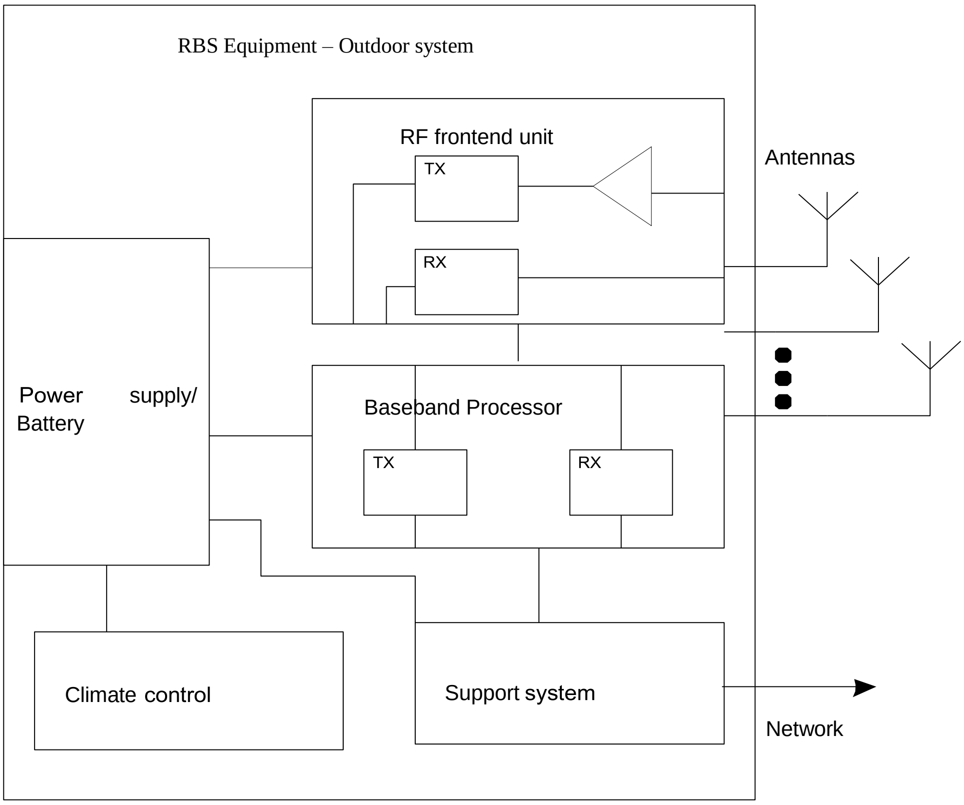

Figure 3-1: Key constituents of a basic wireless equipent

3.3.2 Equipment Level Metrics

When measuring the energy efficiency at equipment level of a CRN, the main equipment that is associated to this level are the radio base station (RBS) as a whole and the wireless terminals which are taken into consideration for analysis. The RBS in this case can also be regarded as wireless access points while the wireless node terminals refers to the CR user nodes equipped with a wireless interface. Metrics relating to power per user ratio or the ratio of the total equipment power to the number of CR user calculated in [Watt/User], and also the energy consumption rating (ECR) which is the ratio of energy consumption to effective full duplex system throughput measure in [Watt/Gbps] are mostly used [93]. The effective full duplex system throughput is responsible for counting the frame overhead of the physical layer.

European Telecommunications Standard Institute (ETSI), a standard body responsible for producing globally acceptable standards for the Telecommunications as well as the Information Communications Technology (ICT) industries defined energy efficiency metrics and methods to determine energy efficiency of RBS in [94]. The RBS can be seen either as a concentrated or a distributed RBS depending on the design. The concentrated RBS has its entire antenna element in one location while the distributed RBS employs a remote radio head (RRH) in proximity to the antenna element so as to minimize feeder loss. At different load conditions, the power consumption is taken into consideration. For a concentrated RBS, the average power consumed in watts is defined as

$$P_{equipment} = \frac{P_{bhl}t_{bhl}+P_{mtl}t_{mtl}+ P_{ll}t_{ll}}{t_{bhl}+ t_{mtl}+t_{ll}} \quad (3.11)$$

where P_{bhl}, P_{mtl} and P_{ll} are the power consumptions for busy hour load, medium term load and low load respectively and also t_{bhl} , t_{mtl} and t_{ll} are duration for busy hour load, medium term load and low load respectively. For distributed RBS, its power consumption for the equipment is given as

$$P_{equipment} = P_{RRH} + P_C, \quad (3.12)$$

where P_{RRH} is the RRH power consumption and P_C is the consumed power for the central elements.

Linear and constant energy profiles for evaluating the overall power consumption of a radio base station is given by Dufkova et al in [95]. In the constant energy profile, the consumed power of the base station is assumed to be independent of its traffic load measured in *Erlangs* and it is represented as

$$P_{equipment} = P_C = constant \quad (3.13)$$

From the real-world data of power consumption collected at different base station sites [95], a constant average value of 800 W was selected. In the linear energy profile, the constant power in a base station is assumed to be proportional to its traffic load measured in *Erlangs*. In the case of no data traffic present, an initiate power σ is added and represented as

$$P_{equipment} = \sigma A + P_C \quad (3.14)$$

The linear energy profile is likely to be a lot more desirable and appropriate for CRNs and other future technologies with large data traffic and a more energy consuming digital power amplifiers.

In a view to investigating the energy efficiency of a wireless terminal of a CR, the whole function of the terminal should be taken into consideration. A mobile phone, mobile computer and other user equipment that employ CR for its operation can be seen to have a typical CR mobile terminal. Since these equipment are usually energy constrained, energy efficiency is one of the important factor taken into consideration during the design. It can be agreed that the stand-by time and talk time of a fully charged mobile phone is a good measure of its energy efficiency and if the data are controlled by the capacity of the battery, its energy efficiency metrics can be obtained.

3.3.3 Network Level Metrics

Network level metrics is employed in accessing the overall performance of network equipment while its properties and features relating coverage and capacity of the network is considered. It is a very challenging task to define network level metrics because a lot of factors like load conditions, coverage area, density of base station, throughput and also the users are to be taken into consideration. Network level energy efficiency metrics takes into consideration not only the energy consumption of the base station equipment but also considers the characteristics and features relating to traffic volume, coverage and capacity of the network. The energy efficiency metric of the coverage area of the network reflects the level of energy that is required to achieve a desired coverage. For example, in the rural areas or a less dense area, the network is hardly loaded. In [96], Bouras et al expressed the energy efficiency for the coverage area of a rural area as

$$PI_{rural} = {A_{coverage}}/{P_{site}}, \tag{3.15}$$

where $A_{coverage}$ is denoted as the coverage area of the base station in km^2 and P_{site} is the average site power consumption. While on the contrary, in the urban or dense areas, the traffic demand is always greater than the capacity of the base station. Hence, its capacity rather than its coverage is usually demonstrated in an appropriate energy efficiency metric which can be written as

$$PI_{urban} = {N}/{P_{total}}, \tag{3.16}$$

where N is denoted as the number of CR users and the total power consumed by the base station is represented as P_{total}.

An energy efficiency metric was also presented in [97] that can be used to access the energy saving performance in a network and it is given as:

$$\vartheta = \frac{total\ amount\ of\ \ data\ delivered}{total\ amount\ of\ energy\ consumed} \tag{3.17}$$

At the network layer of a CRN, the energy efficiency is also concerned with the reporting of sensed signals. In an ad-hoc infrastructural set-up of CRs, this might have a major impact. It does not only impact on the energy savings of the network but can create network partitioning whereby the same node is frequently chosen for reporting sensing signals. Their batteries get depleted rapidly and the network connectivity is affected. To solve the network partitioning issue, CR nodes in the network should be aware of the residual energy of each node before sensed signal is reported. So in evaluating the energy savings performance of the network and the energy aware reporting metrics, two important factors should be taken into considerations which are the residual battery level of each node and the energy cost of the reporting node. The reporting energy cost is a direct function of the distance between two neighbouring nodes and their residual battery levels drawn into cost function, where the cost is inversely proportional to the battery level.

Table 3.1 Energy Efficiency Metrics Classification

Level	Units	Description
Component Level	Power Amplifier efficiency is a ratio	This is the ratio of the power output to the input power
	Power Usage Efficiency is a ratio ≥ 1.	The ratio of the total power consumed by component to the total power consumed by equipment
	Data Centre Efficiency is a percentage (%)	The ratio of the output power to the ratio of the input power
	MIPS/Watt	Millions of Instructions per Second Watt
	MFLOPS/Watt	Millions of floating-point operations per Second per Watt
Equipment Level	Watt/User	The ratio of total equipment power to the number of CR users
	Watt/Gbps	The ratio of energy consumed to the effective system capacity
	Gbps/Watt	The ratio of useful work done to the power consumed
	A(Erlangs)	Power consumption of base station relating to its traffic load
Network Level	Km^2/Watt	The ratio of the area covered to the site power comsumption
	Watt/Km^2	The power consumed per unit area
	User/Watt	The ratio of CR users communicating during peak traffic hours to the site power consumed
	Watt/bps/m^2	The energy consumed with respect to the number of transferred bits and the coverage area
	J/bit/m^2	The energy consumption relating to the number of transferred bits and the coverage area

3.4 Cognitive Radio Network Performance Metrics

It is imperative to ascertain and establish metrics used in quantifying the performance of a cognitive radio network in order to identify the gains achieved through the introduction of energy-efficient strategies in the network. It will also assist in determining its overall operational potential, network design and deployment startegies.

In a typical CRN, unlicensed secondary users usually employ CR to identify vacant spectral bands for communication and effective usage. This is achieved by a spectrum sensing process where CRs are able to monitor available spectral bands, capture their information and identify vacant spectrum holes for communication. For efficient spectrum sensing, cooperative spectrum sensing is normally employed. The authenticity of this spectral availability information for communication can be accessed using some sensing quality specification. These features compose of the performance metrics of CRN. The overall performance can be evaluated by the detection accuracy of the global decision taken by the secondary base station or fusion center. However, the local independent spectrum sensing process of each CR user gives rise to a binary hypothesis-testing problem of having

Primary user is absent : H_0

Primary user is present : H_1

The main metrics used in accessing the performance of the spectrum sensing process of the CR are the probabilities of correct decision which is denoted as $Probability\{Decisn = H_1|H_1\}$ and $Probability\{Decisn = H_0|H_0\}$. Also, is the probability of false alarm which is given by $Probability\{Decisn = H_1|H_0\}$ and the probability of miss detection which is also dentoed as $Probability\{Decisn = H_0|H_1\}$. Considering a CRN composing of N number of unlicensed secondary CR users and a base station or a fusion center as shown in figure 3-2, the fusion center manages all the local spectrum sensing information delivered by the CR users or SUs in the network. It is assumed that each CR in the network performs spectrum sensing independently.

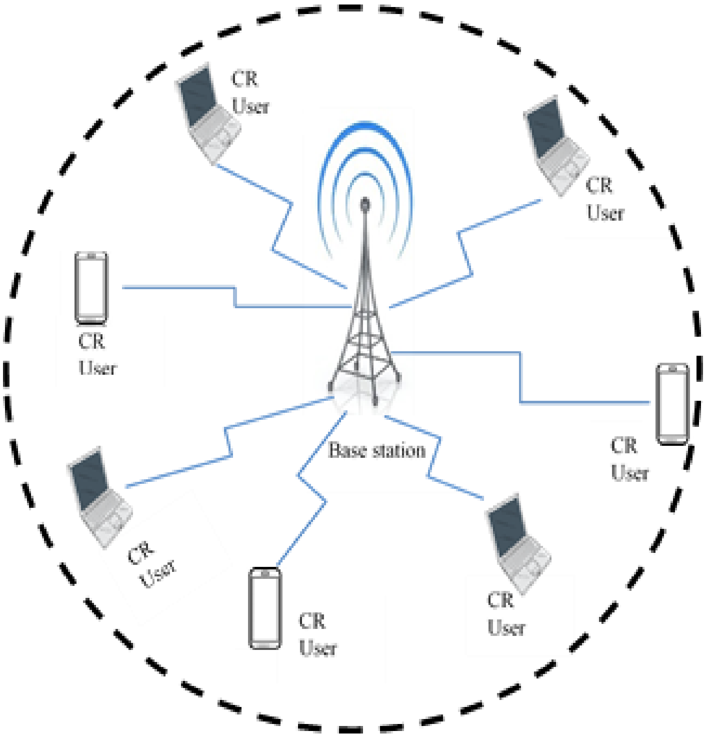

Figure 3-2: A cognitive radio network with N number of CR users and a Base station/FC

In order to study the performance metrics, we consider an i^{th} SU employing energy detection spectrum sensing at the local spectrum sensing stage. The local spectrum sensing problem is to decide between the resulting hypotheses:

$$x_i(t) = \begin{cases} h_i s(t) + w(t), & H_1 \\ w(t), & H_0 \end{cases}, \tag{3.18}$$

where $x_i(t)$ is the signal received at the i^{th}SU, h_i is the channel gain between the i^{th}SU and the PU, $s(t)$ is the transmitted signal from the primary transmitter and $w(t)$ is denoted as the white additive Gaussian noise. We assume that the channel used is time-invariant when sensing is in progress. The energy detection sensing is carried out by measuring the energy of the signal received over an observation time window denoted as T. The energy collected in the frequency domain is given as Y_i, which serves as a statistical distribution below

$$Y_i \sim \begin{cases} \chi^2_{2v}(2\gamma_i) & H_1 \\ \chi^2_{2v} & H_0 \end{cases}, \tag{3.19}$$

where $\chi^2_{2v}(2\gamma_i)$ is a noncentral chi-square distribution with v degrees of freedom and a non-centrality parameter $2\gamma_i$. χ^2_{2v} denotes the chi-square distribution with $2v$ degrees of freedom. The instantaneous SNR of the signal received at the i^{th} SU is τ_i and $v = TW$ which is the product of the time and bandwidth (W). In comparing the energy Y_i with a defined threshold ξ_i, the PU signal detection is carried out. Therefore, the probability of detection is given as $p_d^i = Prob\{Y_i > \xi_i | H_1\}$ and probability of false alarm is denoted as $p_f^i = Prob\{Y_i > \xi_i | H_0\}$. The average probability of detection, false alarm and missed detection over Rayleigh fading channels are given below as

$$p_d = e^{-\frac{\xi_i}{2}} \sum_{p=0}^{v-2} \frac{1}{p!}\left(\frac{\xi_i}{2}\right)^p + \left(\frac{1+\bar{\gamma}_i}{\bar{\gamma}_i}\right)^{v-1} \text{x} \left[e^{-\frac{\xi_i}{2(1+\gamma_i)}} - e^{-\frac{\xi_i}{2}} \sum_{p=0}^{v-2} \frac{1}{p!}\left(\frac{\xi_i \bar{\gamma}_i}{2(1+\bar{\gamma}_i)}\right)^p\right], \quad (3.20)$$

$$p_f^{(i)} = \frac{\Gamma\left(v, \frac{\xi_i}{2}\right)}{\Gamma(v)}, \quad (3.21)$$

where $\Gamma(.)$ and $\Gamma(.,.)$ are regarded as the Gamma function and upper incomplete Gamma function [98] respectively. Both derivations can be found in appendix A.

$$p_m^{(i)} = 1 - p_d^{(i)}. \quad (3.22)$$

In a cooperating spectrum sensing environment, each CR users forward their 1-bit decisions to the FC for a final decision regarding the availability of the sense spectrum band. Let $D_i \in \{0,1\}$ which denotes the local spectrum sensing results of a i_{th} CR user where $\{0\}$ indicates the absence of PU in the spectrum band and $\{1\}$ indicates the presence of PU in the spectrum band. The FC will however fuse all 1-bit decisions together using a logic fusion rule.

$$Z = \sum_{i=1}^{N} D_i \begin{cases} \geq k, & H_1 \\ < k, & H_0 \end{cases}, \quad (3.23)$$

where H_1 and H_0 denotes that the PU is transmitting or not transmitting respectively. For the OR fusion rule, the FC will declares that the spectrum is occupied when at least one of the CR users detect a PU signal, otherwise the spectrum is regarded as vacant. For the AND fusion rule, the spectrum band is declared vacant by the FC only when all the CR users detects the PU signal otherwise, the band is regarded to be vacant. While for the MAJORITY fusion rule, the FC declares that the spectrum is vacant if half or more CR users detect the PU signal. In equation 3.22, it can be seen that there exist at least *k out of N* CR users where the OR logic rule corresponds to the case of $k = 1$ and the AND rule corresponds to case of $k = n$. In these fusion rules, the OR rule appears to be very traditional for CR users in accessing the licensed spectrum band, hence, the chance of causing interference to the PU is minimized. The probability of false alarm for cooperative spectrum sensing based on the OR rule is written as

$$Q_f = 1 - \prod_{i=1}^{N}(1 - p_f^{(i)}) , \tag{3.24}$$

while the missed detection probability of the cooperative spectrum sensing process is written as

$$Q_m = \prod_{i=1}^{N} p_m^{(i)} . \tag{3.25}$$

Assuming every CR user achieves identical probability of false alarm and probability of miss detection in the local spectrum sensing (i.e, $p_f = p_f^{(i)}$ and $p_m = p_m^{(i)}$, $\forall i = 1,2,\dots,N$), the probability of false alarm and missed detection of the cooperative spectrum sensing process will then be denoted as

$$Q_f = (1 - p_f)^N, \tag{3.26}$$

$$Q_m = (p_m)^N. \tag{3.27}$$

It is also worthy to mention that the detection probability of the cooperative spectrum sensing process can be written as $Q_d = 1 - Q_m$.

Error probability or "*false decision*" probability is also a widely used performance metric. It defines the probability of making a wrong spectrum sensing decision which is the combination of both the probability of false alarm and probability of missed detection metrics and it is expressed as

$$P_e = p(H_0)p_f^{(i)} + p(H_1)\left(1 - p_d^{(i)}\right) = p(H_0)p_f^{(i)} + p(H_1)p_m^{(i)} , \tag{3.38}$$

where $p(H_0)$ means that the spectrum band is vacant, $p(H_1)$ means that the spectrum is in use, low values of p_e indicates the high accuracy of the spectrum decision by the CR user which will positively influence the other aspects of the network performance.

3.4.1 Performance Measurement

Receiver's performance is usually quantified by portraying the receiver's operating characteristics (ROC) curves. This curves serves as an important tool in selecting and studying the metric performance of a sensing scheme. ROC graphs are mostly preferred as a performance measure since simple classification accuracy do not contain much detail, hence it is a poor metric for measuring performance [99]. ROC curves are also employed to show trade-offs between the probability of detection and the false alarm rates thereby permitting the determination of an optimal threshold. ROC curves also depicts curves of probability of missed detection and also the probability of false alarm. These curves also aids in exploring the relationship between sensitivity (probability of detection) and specificity (false alarm rate) and other scenarios of interest [5].

Through simulations, the main metrics in accessing the spectrum sensing performance of cognitive radio networks is evaluated using MATLAB[1] version R2012a. MATLAB is an application with tools for numerical computation and a Fourth-generation programming language. MATLAB contains tools for data visualization serving as a convenient "laboratory" for computation and analysis.

Figure 3-3 depicts the complementary receiver operating characteristics (ROC) curves plotted to investigate the performance of the probability of detection over the probability of false alarm metrics at an SNR of -10dB and 1000 number of Monte Carlo sample points. For lesser errors made by a CR user in sensing, there is an increase in the detection accuracy which is measured by the probability of detection metric. Both the simulated and the theoretical probability of detection are plotted in the same figure. The reason for a slight mismatch for both curves is that the theoretical derivation is for an ideal set-up while the simulation may tend to have random effects as per simulation settings and intrinsic limitations.

Figure 3-4 also shows the ROC plot of the performance for the probability of miss detection with a corresponding probability of false alarm metrics for both simulation and theory computation. When a CR user misses detection, the probability of false alarm is seen to be very small. Figure 3-5 also investigates the performance of the detection accuracy of the CR user quantified by the probability of detection at different SNRs. It is seen that there is a better performance in the probability of detection with an increasing SNR value. Also, at a probability of detection decreases with decreasing values of SNR. That means SNR plays an important role in the performance of the probability of detection metric.

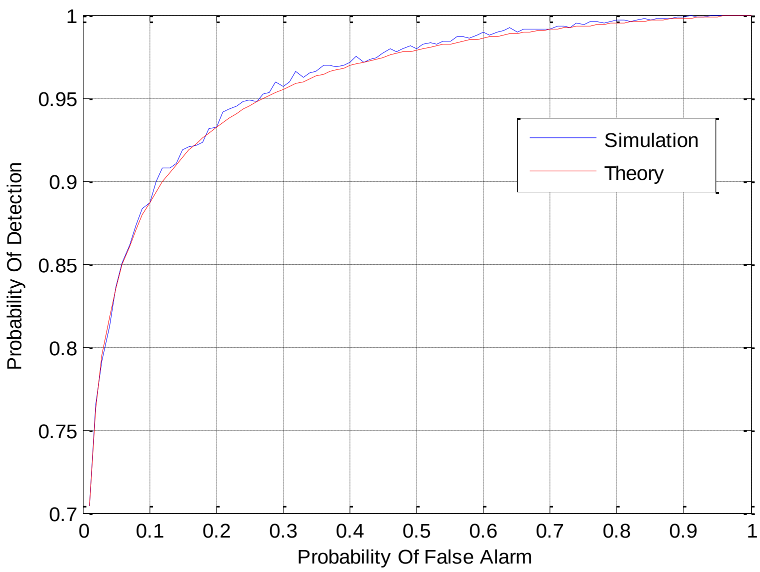

Figure 3-3: ROC plot for the probability of detection vs the probability of false alarm

[1] MATLAB is a product of The Mathworks Inc.

Figure 3-6 shows the performance of the probability of missed detection and probability of false alarm metrics for cooperating spectrum sensing for different fusion rules using the energy detection sensing technique. From the figure, the OR rule gives a much better performance than the AND and MAJORITY rules. This can be credited to the fact that the OR rule includes result of a minimum of a single user out of K energy detection nodes to declare the presence of a PU.

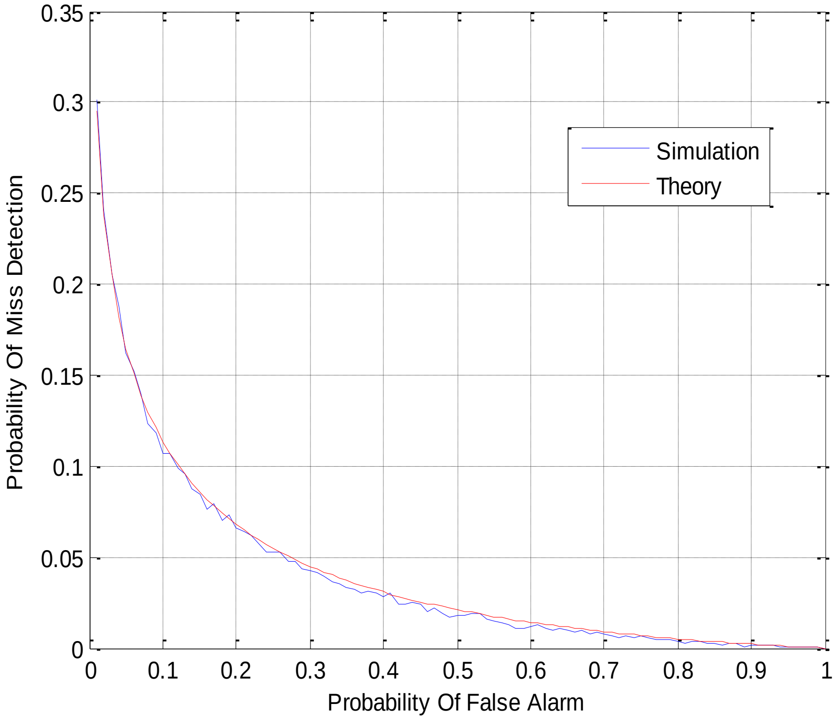

Figure 3-4: ROC plot for the probability of miss detection vs the probability of false alarm

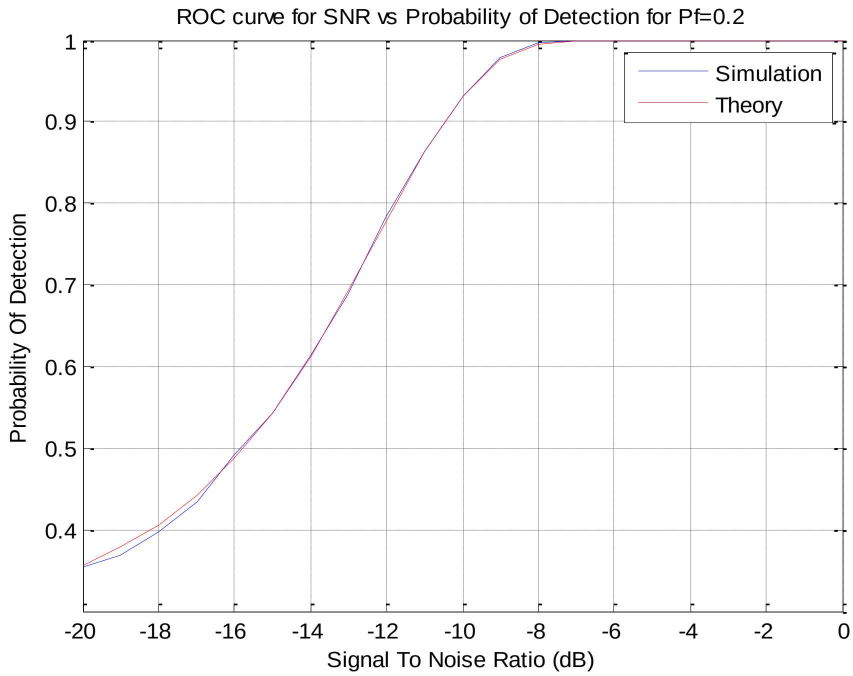

Figure 3-5: ROC plot for probability of detection vs SNR

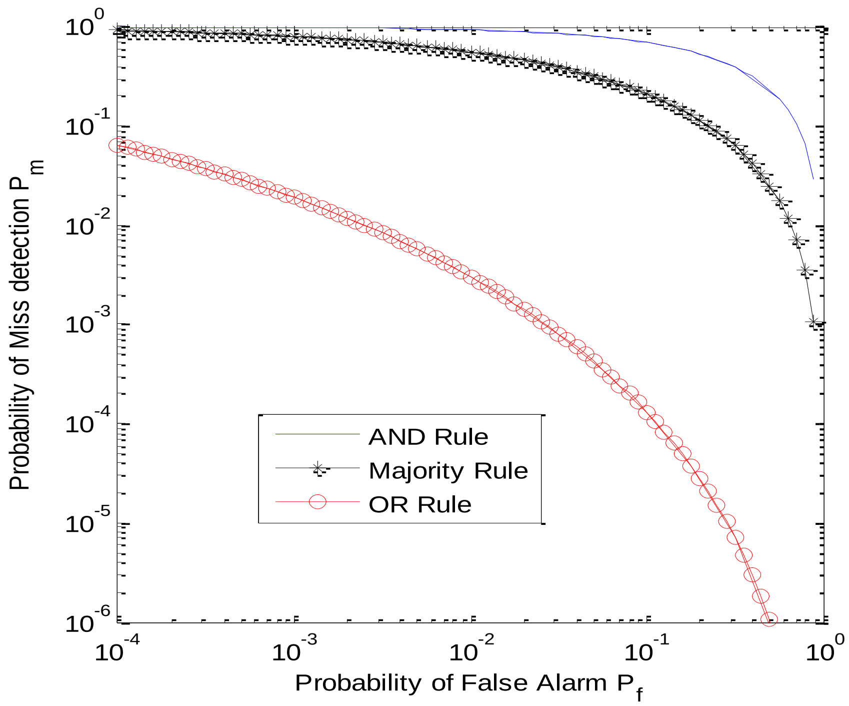

Figure 3-6: Cooperative spectrum sensing performance metrics for various fusion rules

The total energy consumption and the achievable throughput of a CRN can also serve as a vital evaluation metrics of a CRN performance. The average achievable throughput *(A)* is seen as the average successfully transmitted data of transmitting CR users, while the energy consumption (E_c) can be seen as the average energy consumption at each state of the CR user's activity. The achievable throughput is measured in *bits* while the energy consumption is measured in *joules*. It can be noticed that these metrics are directly affected by the detection accuracy of the CR users in the network as a high achievable throughput will result to a higher energy consumption and vice versa. Hence a standard metric that combines both achievable throughput and energy consumption is generally used to measure the overall energy efficiency and it is called energy efficiency metric as seen in equation 3.1 which can be equally written as

$$\mu = \frac{A}{E_c}\,, \qquad 3.39$$

It is imperative to note that energy efficiency (μ) is a comprehensive metric that encompasses all other network performance metrics including detection accuracy, achievable throughput and energy consumption in all the states of a CR user's activity. So it can be regarded as a fair indicator of the whole CRN performance. Also, since there lies a connection between throughput and energy, energy efficiency (μ) has been generally accepted as an important metric capable of achieving the balance between the various parts of CRN performance.

3.5 Chapter Summary

Energy efficiency in CRNs has been a growing concern in recent times as the network strive to ensure high *Quality of service* (QoS) to its users. Before energy efficiency issues relating to the network are tackled, a standard and accurate indicator for measuring and evaluating energy efficiency needs to be realized. In this chapter, we provided an overview of energy efficiency metrics in CRNs relating to its design and operation. Metrics are categorized into the component, equipment and network levels for easy analysis. The performance metrics of the network was also analysed where the probability of false alarm, probability of detection and probability of missed detection metrics were evaluated. The error of probability metrics was studied and acknowledged as a good performance metric for CRNs. It is believed that determining an accurate energy efficient metric for CRNs will pave a solid foundation for more research in the field of greener communications. It will also be a crucial step in enabling a sustainable growth in the wireless communications industry.

CHAPTER FOUR

DELIVERING A BETTER ENERGY EFFICIENT COGNITIVE RADIO NETWORKS

4.0 Objective

The objective of this chapter is to examine possible means by which energy efficiency can be improved in a cognitive radio network architectural arrangement. This chapter is split into two parts. The first part is to investigate an effective way to reduce the energy consumed by cognitive radio base stations in the network. In doing so, a base station sleep mechanism is developed to put unnecessary and idle base stations to sleep when traffic is low. While the second part is to exploit possible improvements in the energy efficiency of a cognitive radio network by employing massive MIMO technique at the base station together with small cells scattered around the network.

4.1 Introduction

In cognitive radio networks, energy consumption must be considered as a vital key point in ensuring successful transmission of secondary data and good workability of the network communication and protocol architectures. A cognitive radio network mainly consist of the primary users (PUs), the cognitive radio users or the secondary users (SUs), the backbone or core networks and the radio base stations (RBS) or access points. The base station is responsible for the radio frequency interface between the network and the cognitive radio users. As the number of base station increases to be able to guarantee a certain Quality of Service (QoS) to cognitive radio users in a CRN, the energy consumed in the network also increases. The energy consumption of a typical single base station can amount up to 2.0 kW depending on the usage [46]. For instance, in a cellular communication network, the base station is responsible for more than 60% of the total energy consumption of the network [101-103] and the energy consumption is expected to drastically increase in the future if no measure is employed to alleviate this trend. Apart from environmental impacts that emanates from high energy consumption, energy cost can also trigger the total network expenses. Base station alone account for about 15% of the total network operating expenses and can rise to as much 50% in areas where basic electricity supply from the national grid is extremely unreliable [104].

The energy consumed by the major components of a typical radio base station is shown in figure 4-1, where a significant portion of the energy is consumed by the power amplifier including the feeder since sufficient power is required to reach users with high power losses [105]. So therefore, it is imperative that the energy efficiency of base stations should be improved. Developing more hardware and less-power consuming power amplifiers might seem to be a better way to minimize the energy efficiency of radio base stations but is it economically viable and does it guarantee better energy savings? Base stations of a CRN can be more energy efficient and a substantial amount of energy can be saved or reduced by putting to sleep idle base stations in the network taking into consideration the time varying traffic conditions.

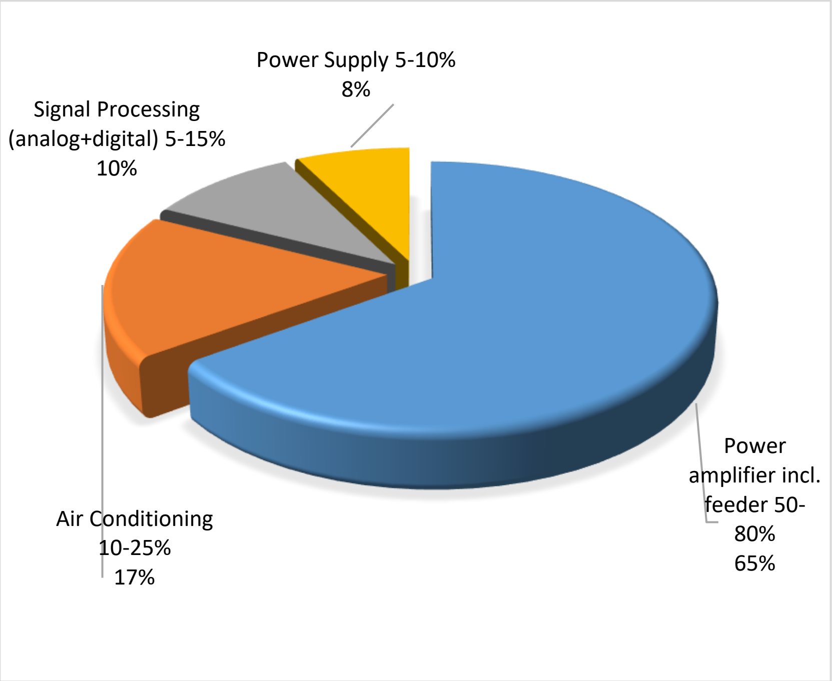

Figure 4-1: Energy consumption of the major components of a radio base station [92].

4.2 Increasing Energy Efficiency of Cognitive Radio Base Stations

In an attempt to increase the energy efficiency of cognitive radio base stations as discussed in the section above, a base station sleep scheme is developed employing an energy efficient algorithm that ensures base stations are put to sleep during low traffic in an energy efficient manner.

Although several base station sleep scheme have been proposed in literature [49-52, 131, 132]. In this developed scheme, the distance between the base stations and benefitting users are taken into consideration.

4.2.1 Base Station Sleeping Scheme

Idle BS in CRNs can be put to sleep when not in use in the network so as so save energy. Since a CR network is usually designed in a way to serve CR users at both off-peak and peak hour traffic, the resources of the network during peak hours are normally shared amongst the existing users in order to meet particular QoS constraints. So when traffic reduces, a larger part of the resources becomes redundant and the existing traffic in a non-distant area can then be served by the deployed base stations if any. This way, under-utilized base stations can be put to sleep in a resourceful way so as to save energy. The number of BSs going into sleep mode and the transmission power of the active BSs leads to a trade-off that must be designed to improve the effectiveness of the energy efficient algorithms.

4.2.2 Base Station Power Consumption Model

A base station is primarily composed of an active cooling system, a main supply and an AC-DC converter, a baseband unit (BBU) for digital signal processing, radio frequency module which includes the signal generator and the power amplifier (PA). We summarize the BS power consumption model as

$$P = \frac{P_{PA} + P_{BB} + P_{RF}}{(1-\sigma_{power}) - (1-\sigma_{cooling})} \tag{4.1}$$

where P denotes the total power consumption in the BS, P_{PA}, P_{BB} and P_{RF} represents the power consumption of the power amplifier, baseband unit and the radio frequency module. The loss factor of power is represented as σ_{power} while $\sigma_{cooling}$ represents the active cooling and both are taken as fixed parameters. The power consumption of a typical power amplifier can be divided into the dynamic part which is related to the traffic $P_{PA,dy}$ and the fixed part which is for fixed coverage $P_{PA,fc}$. Therefore, the power consumption of the power amplifier can be written as

$$P_{PA} = P_{PA,dy} + P_{PA,fc}. \tag{4.2}$$

And equation 4.2 can also be represented as

$$P_{PA} = \frac{P_{out}}{\eta_{PA}(1-\sigma_{feeder})} + \varphi . P_{PAmax} , \tag{4.3}$$

where P_{out} is the power measured at the input of the antenna element, η_{PA} is the power amplifier efficiency, σ_{feeder} denotes the loss factor of the feeder, P_{PAmax} is the maximum power attainable by the PA and φ is the proportion in percentage for the static part which provides the basic coverage even if there is no user.

The power consumption when the BS is on sleep mode P_{sleep} can be expressed as

$$P_{sleep} = \begin{cases} P_0 + \Delta_P . P_{out}, & 0 < P_{out} \leq P_{max} \\ P_{sleep}, & P_{out} = 0 \end{cases}, \quad (4.4)$$

where P_0 is the total power consumed at the minimum non-zero output power and Δ_P is the slope of the power consumption which is load-dependent.

4.2.3 System Model

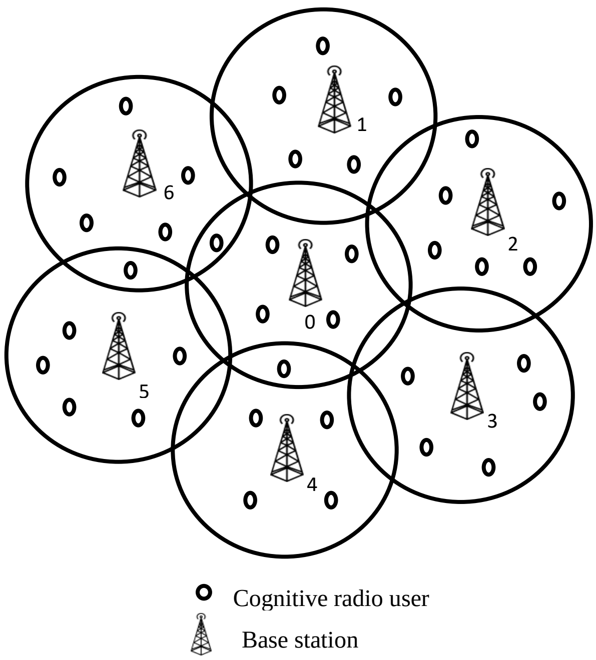

Figure 4-2. System model of a base station clustered network

In the system model, we consider a CRN with the assumption that all BSs goes into a cluster of 7 in a hexagonal formation as shown in figure 4-2. The BS cluster covers a certain area with each BS overlapping each other and having a number for identification, labelled as $i \in [0,6]$. Cognitive radio users are uniformly distributed within each BS. We use the real traffic information given in [106] also shown in figure 4-3 to observe the traffic load during peak periods and off-peak periods. The network traffic load analysis is formulated based on multi-server queueing Erlang-

C model. The Markov chain of the traffic model of a BS representing the traffic flow between the BS and the CR users are based on the assumption that:

i. The sessions in each hour of each BSs are produced using a Poisson process. The service time is exponentially distributed and the inter-arrival times are also exponential with both having mean values of ${}^{1}/_{\lambda}$ and ${}^{1}/_{\mu}$ *s/call* respectively.

ii. There are *c* servers, where *c* denotes the maximum number of sessions which can be served concurrently, given $c = {}^{C}/_{R}$ and C represents the total capacity of the BS and R represents the constant bit rate.

iii. The sessions are served in order of *first come, first serve basis.*

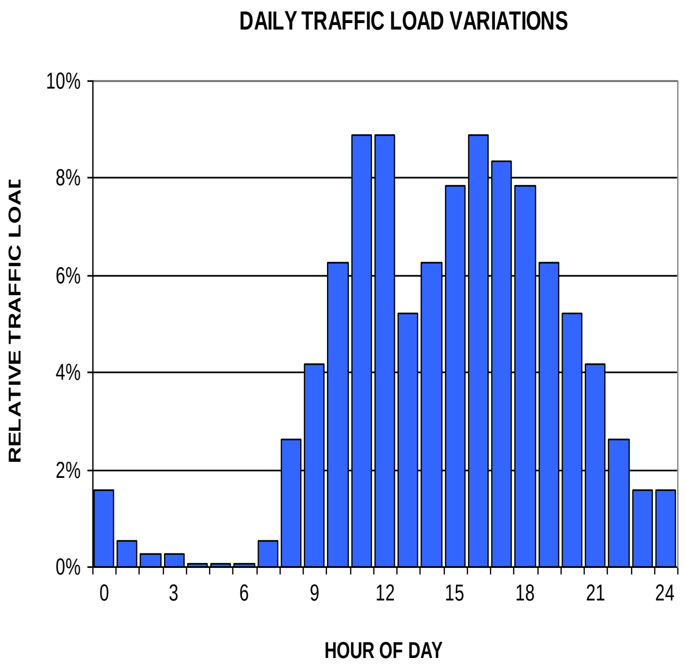

Figure 4-3. Voice traffic load variation for 24hours of a weekday [106].

Each state of the system is characterized by the number of active sessions where p_n represents the equilibrium probability of having n calls in the system. The traffic generation rate can be written as

$$\mu_n = \mu, \quad n = 0,1,2, \ldots, \tag{4.5}$$

while the service rate can be written as

$$\lambda_n = \begin{cases} n \,.\, \lambda, & n = 1,2, \ldots, c \\ c \,.\, \lambda, & n \geq c \end{cases} \tag{4.6}$$

The relative traffic load α as represented in traffic pattern in figure 4-3 can be written as

$$\alpha = \frac{\mu}{c.\lambda} \tag{4.7}$$

where the traffic rate μ can be extracted. The valid transitions can be represented with the steady-state probabilities p_0 and p_n by using the M/M/c queuing system in [107] to give

$$p_0 = \left(\sum_{n=0}^{c-1} \frac{\gamma^n}{n!} + \frac{\gamma^c}{c!} \cdot \frac{1}{1-\alpha}\right)^{-1}, \tag{4.8}$$

and

$$p_n = \begin{cases} \frac{\gamma^n}{n!} \cdot p_0, & n = 0,1,\dots,c-1 \\ \frac{\gamma^n}{c!c^{n-c}} \cdot p_0, & n \geq c \end{cases}, \tag{4.9}$$

where $\gamma = \frac{\mu}{\lambda}$.

The energy saving scheme will only serve its purpose when the QoS of the CR user is always above a certain required level. In this work, we consider the call blocking probability as the metric for QoS. The call blocking probability Q_B is seen as the number of calls that cannot be served due to system overload and can be denoted as

$$Q_B = \sum_{n=c}^{\infty}(n-c)\, p_n = p_0 \frac{\gamma^c}{c!(1-\alpha)^2}\alpha. \tag{4.10}$$

The average throughput $T_{P,BS}$ of a BS can be represented as

$$T_{P,BS} = N_{bits} . R , \tag{4.11}$$

where

$$N_{bits} = \sum_{n=1}^{c} \frac{\gamma^n}{n!} \cdot p_0 . n, \tag{4.12}$$

which represents the transmitted number of bits calculated as the probability of being in a system state multiplied by the number of session in the corresponding state.

The average energy consumption of an active BS E_{BS} which consists of the part of energy required for antenna and cooling can be analysed into the power consumed by a BS during the time, t_t corresponding to the total time that the BS remains active and can be expressed as

$$E_{BS} = t_t . (P + P_{idle} \cdot p_0 + \sum_{n=1}^{c} P_{tx} . p_n . n), \tag{4.14}$$

where P_{idle} is the power consumed in the state p_0 where the BS is idle and no ongoing session waiting to be served and P_{tx} is the transmission power.

The energy efficiency of a BS η_{BS} can be written as

$$\eta_{BS} = \frac{N_{bits}}{E_{BS}}, \tag{4.13}$$

4.2.4 Energy Efficient Sleep Algorithm

The basic idea of the BS sleeping scheme is to improve CRN energy efficiency by putting to sleep some BSs with low traffic. We present an algorithm that decides which BS or BSs goes into sleep mode and which remains active so as not to degrade the required QoS. Once the base stations goes into sleep mode, its responsible coverage area will be covered by the neighbouring active BSs. For coverage area to be increased, transmission power of the neighbouring active BS might also be increased.

A flow chart of our algorithm is graphically detailed in figure 4-4 and can be applied at hours of the day when traffic is low. The algorithm contains the steps that is repeated every hour to ensure maximum energy efficiency. It computes the possible number of BSs that is to remain active based on the traffic load variations.

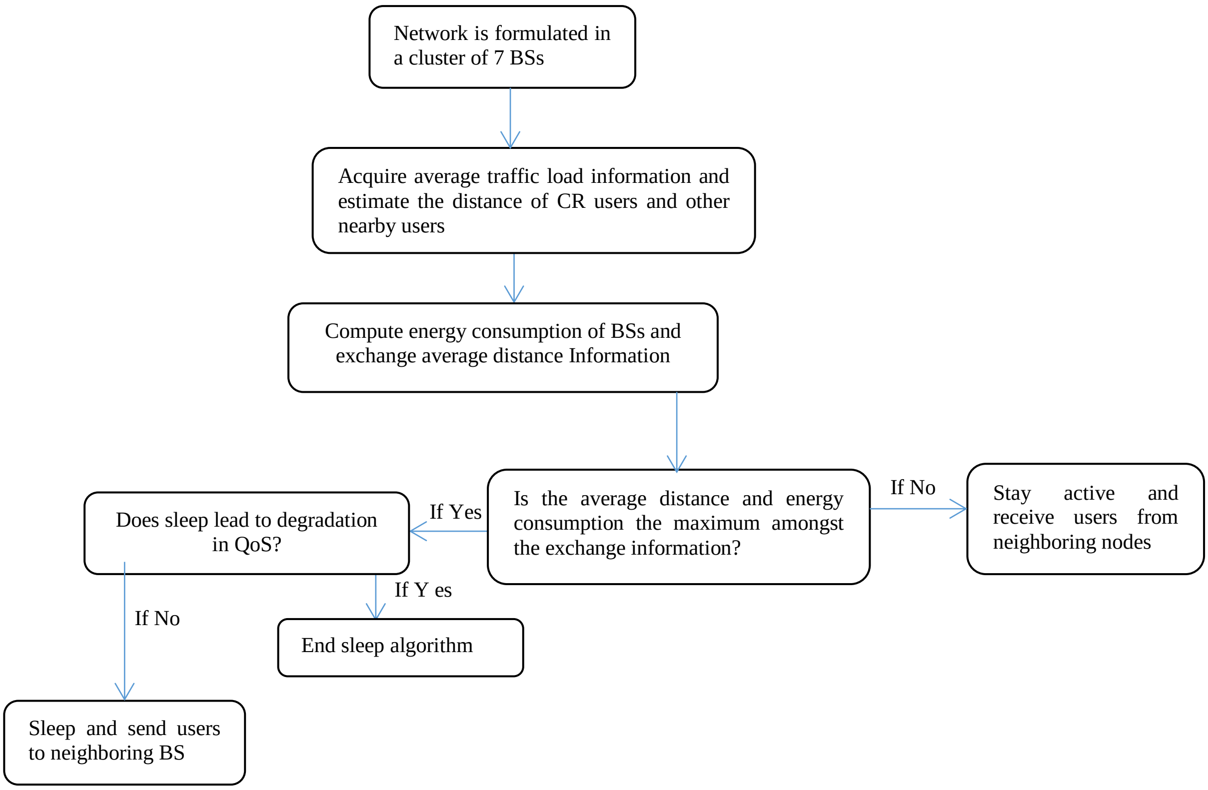

Figure 4-4**:** Flow chart of the propsoed base station sleeping scheme

From the flow chart of the proposed base station sleeping scheme, in the beginning, all BS in the network forms a cluster of 7 and estimates the distance information of its CR users and broadcast amongst other BS.

- Each BS i then shares information about its distance and traffic pattern (fig. 4-3) to other BS based on the first step and the traffic arrival rate is estimated.
- In the cluster of 7, the energy consumption is computed using the estimated traffic rate and exchanged amongst the BSs.
- The BS with the maximum energy consumption and average distance from its CR users goes into sleep first if it does not lead to degradation in QoS. It is assumed that the traffic of the sleeping BS is served by the neighbouring BS having the smallest identification number.
- The neighbouring BS remains active and increases transmission power. The algorithm is repeated from step 2 otherwise ends if degradation in QoS occurs.

It is imperative to note that a BS with a higher average distance will lead to a higher average transmission power which will also lead to higher energy consumption. Hence, the BS with the highest energy consumption and highest average distance becomes a candidate for sleep selection in the network.

4.2.5 Evaluation and Discussion

This section provides simulated results to study the performance of the developed BS sleep algorithm. MATLAB[2] version R2012a was employed for the purpose. MATLAB is an application with tools for numerical computation and a Fourth-generation programming language. MATLAB contains tools for data visualization serving as a convenient "laboratory" for computation and analysis.

We considered a typical urban setup and assumed a network with a total of 42 base stations in which the CR users are uniformly distributed around the BSs and traffic for each hour is generated according to a Poison process. We also assumed $1/_{\lambda}$ is exponentially distributed with mean of 180s and considered a cell radius of 0.8 Km, base station bandwidth C of 20 MHz, transmission rate R of 384 kbps, transmission power P of 10 W and an idle power of 0.1 W.

In evaluating the performance of the energy efficient sleeping algorithm, we compare our sleep algorithm with a scenario where all the BSs are always active and none of the BS goes into sleep

[2] MATLAB is a product of The Mathworks Inc.

mode and also with a scenario where the sleep algorithm does not consider position of users like in [51] which is referred to in this work as the dynamic sleep mode.

Figure 4-5 shows the energy efficiency of the developed sleep mode and the dynamic sleep mode and also a scenario where all base station remain active all through the day and none is put to sleep. We notice that the energy efficiency is a function of the traffic load variation. This observation proves the fact that the proposal of an energy efficient sleep algorithm with dynamic distance in consideration appears to be a smart strategy, because it completely adapts to traffic variations and switches off a different number of base stations by taking into account the number of users and their distances from their respective base stations.

As base stations are put to sleep during low traffic conditions, fewer bits are transmitted hence, lesser energy is consumed. Comparing the schemes, we observe that the none sleep mode is almost constant 24 hours of the day since all the base stations are always active and no sleep algorithm is applied. We also observe that a better performance is achieved by the proposed sleep mode than the dynamic sleep mode in terms of performance and blocking probability. Hence, energy is saved in the network while QoS is still maintained.

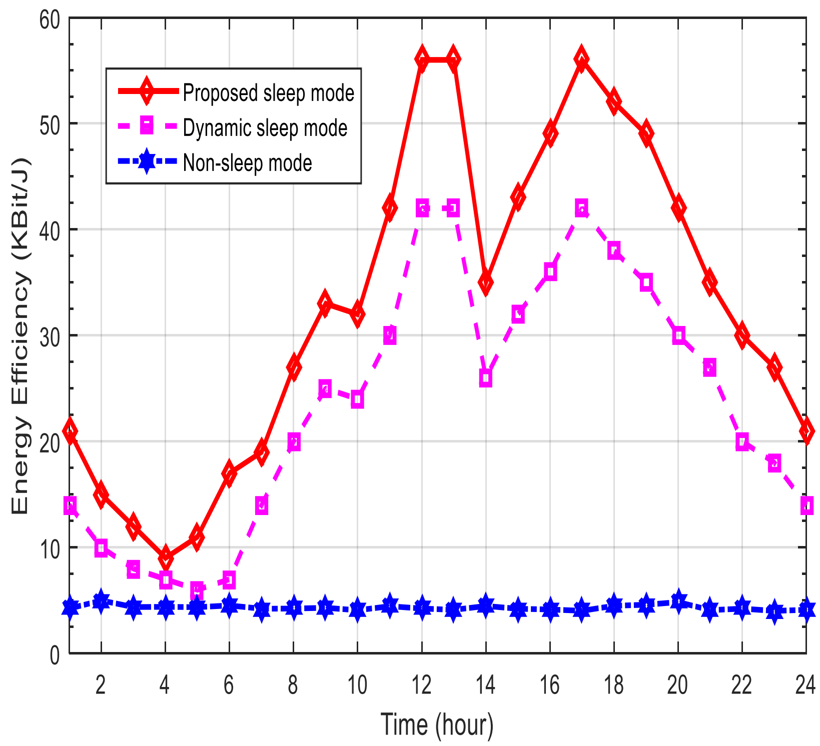

Figure 4-5. Energy efficiency of sleep mode schemes

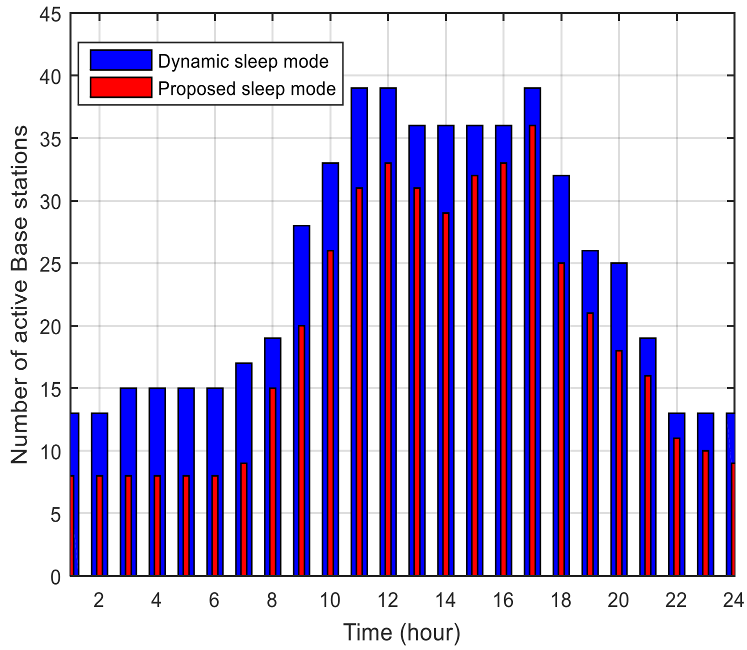

Figure 4-6: Number of active base stations during sleep mode schemes

The number of base stations that remain active during the 24 hour period of the day when the schemes are applied is displayed in figure 4-6. From the figure, we can observe that more base stations are kept active during the day when compared to night hours. The dynamic sleep mode algorithm keeps more active base stations in order to serve the ongoing calls of the CR users which are already covered by existing nearby base stations. As a result of this, fewer CR users are in outage when the algorithm is applied but more base stations are active leading to higher energy efficiency. The implementation of the energy efficient sleep algorithm enables only the base stations required by CR users to be active in the network thereby increasing the energy efficiency of the network.

4.3 Introduction to Massive MIMO and Small Cells

In a typical CRN consisting of a macro-cell base station, an increase in secondary users certainly have an impact the energy efficiency of the network and also, the QoS expectations might be compromised. Approaches that enable very high spatial reuse of spectral bands could be a possible technique in increasing the spectral and energy efficiency of the network. Amongst these approaches are the multiple antenna technique known as multiple-input-multiple-output (MIMO) [108] and also small cell networks [109].

Massive MIMO systems are considered as one of the most ubiquitous technique which provides a higher date rate over the MIMO system [110]. In a massive MIMO cognitive radio system, large scale antenna arrays are deployed at the macro base stations to serve the cognitive radio users [111]. This enables stronger signal paths along the channel with little or no user interference occurrence thereby providing more paths between the BS and the CR users. The antenna arrays can receive and transmit multitude of signals for CR users at different spatial locations. This brings about an increase in the energy efficiency of the system with less transmission power due to an array gain but however, the circuit power will increase when the base station antenna increases. However, Massive MIMO possesses more advantages which includes the use of inexpensive low-power components and reduced latency coupled with its robustness to interference and intentional jamming.

Small cells are also one of the most resourceful techniques to improve and better the efficient usage of radio spectrum thereby minimizing the energy consumption in a cognitive radio network [112]. In a CRN, small cells access points or base stations (SC-BS) are positioned in the network to offload data traffic from the macro BS. This technique tend to reduce the distance between CR users and BSs which results to low transmission power, reduction in propagation losses, better spectrum utilization and low operational cost. Due to the advantages of small cells, it has received recent research attention as a method to increase capacity and reduce power consumption in wireless radio networks.

The combination of macro BS and small cell BS will bring about a potential progress in achieving an increase in the energy efficiency of a network even at the expense of additional hardware due to the fact that the overall energy efficiency of the network have been improved. It is very essential that in achieving an improvement of the overall energy efficiency of the network, both the BSs should be suitably deployed and optimized.

The key objective of this section is to possibly achieve an increase in energy efficiency of a CRN and also dynamically assigning a CR user to an optimal base station for transmission. Massive

MIMO is employed at the macro BS together with small cells overlaid around the network. Large number of antennas in the form of antenna arrays are placed at the macro BS to help increase spectral capacity to the CR user which results in higher efficiency.

4.3.1 System Model

In a view to optimizing the energy efficiency of a CRN using massive MIMO and small cell approach, we consider a CRN as shown in figure 4-7 with N number of CR users with a single macro BS furnished with T_{BS} number of antennas and N_{SC} number of small-cells base station (SC-BS) with T_{SC} antennas. It is assumed that there is a perfect channel acquirement and there is also an existing backhaul network that supports interference coordination. The CR users receive information from the BS by linear non-coherent joint transmission, that is, multiple transmission as in [113] which enables CR users barely served by a SC-BS to receive signal from the macro BS or other small cells in the network.

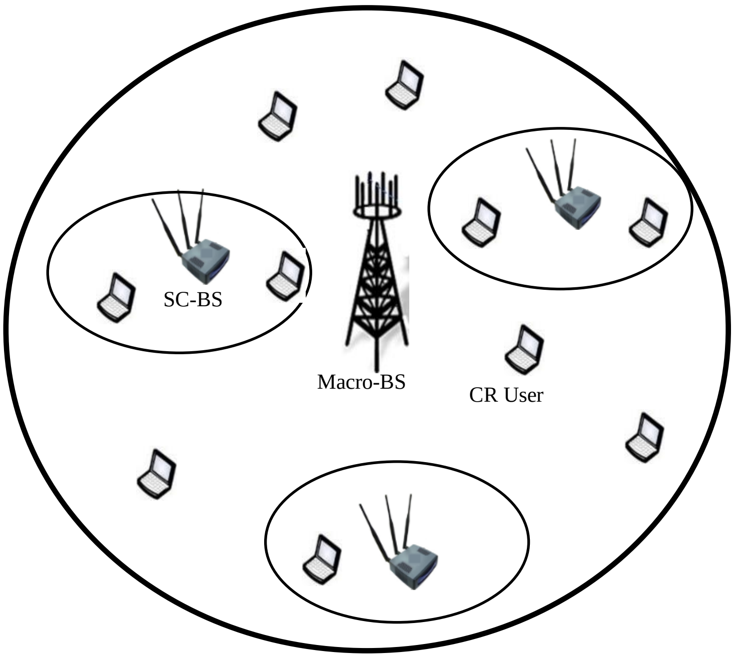

Figure 4-7: A system model of a network of cognitive radio user being served by a BS with T_{BS} antennas and/or a SC-BS with T_{SC} antennas.

The channels to CR users are modelled as block fading and the signal received at the CR user n is expressed as

$$y_n = \underbrace{\mathbf{h}_{n,0}^H \sum_{n=1}^{N} \mathbf{u}_{n,0} s_{n,0}}_{\text{Macro BS}} + \underbrace{\sum_{i=1}^{N_{SC}} \mathbf{h}_{n,i}^H \sum_{n=1}^{N} \mathbf{u}_{n,i} s_{n,i}}_{\text{Small-cell BS}} + \omega_n, \tag{4.14}$$

where $\mathbf{h}_{n,0} \in \mathbb{C}^{1\times T_{BS}}$ and $\mathbf{h}_{n,i} \in \mathbb{C}^{1\times T_{SC}}$ denotes the channel from the macro BS and SC-BS respectively while $s_{n,j}$ and $\mathbf{u}_{n,j}$ represents the information symbols and beamforming vectors from any of the BS to the user k respectively. The term ω_n also represents the circularly-symmetric complex receiver noise with zero mean and variance σ_n^2.

Based on the received signal, the signal to interference and noise ratio (SINR) observed by CR user n can be modelled as

$$SINR_n = \frac{\left|\mathbf{h}_{n,0}^H \mathbf{u}_{n,0}\right|^2 + \sum_{i=1}^{N_{SC}} \left|\mathbf{h}_{n,i}^H \mathbf{u}_{n,i}\right|^2}{\sum_{j=1, j\neq 1}^{N} \left(\left|\mathbf{h}_{n,0}^H u_{j,0}\right|^2 + \sum_{i=1}^{N_{SC}} \left|\mathbf{h}_{n,i}^H u_{j,i}\right|^2 + \sigma_n^2 \right)}. \tag{4.13}$$

In the same way, the total achievable rate by the system can be given as

$$R_T = \sum_{n=1}^{N} R_n \,, \tag{4.14}$$

where $R_n = \sum_{n=1}^{N} \log_2(1 + SINR_n)$.

The total power consumption (per sub carrier) can be written as $P_T = P_{TX} + P_{CT}$. Where P_{TX} is the transmit power and P_{CT} is the circuit power and both can be expressed respectively as

$$P_{TX} = \sum_{n=1}^{N} \left\|\mathbf{u}_{n,0}\right\|_2^2 + \sum_{i=1}^{N_{SC}} \sum_{n=1}^{N} \left\|\mathbf{u}_{n,i}\right\|_2^2, \tag{4.15}$$

and

$$P_{CT} = T_{BS} \frac{\gamma_0}{C} + \sum_{i=1}^{N_{SC}} T_{SC} \frac{\gamma_i}{C}, \tag{4.16}$$

The circuit power is proportional to the number of antennas and $\gamma_i \geq 0$ models the power dissipated in the circuit of each antenna which encompasses the powers dissipated in the filters, converters, base band and mixers. The circuit power is normalized with the total number of subcarriers $C \geq 1$.

4.3.2 Problem Formulation

In this section, we consider maximizing the energy efficiency while fulfilling the rate and power for optimal base station selection. Energy efficiency η in bit/Hz/Joule can be taken as the total achievable rate over the total power consumption of the system which is expressed as

$$\eta = \frac{R_T}{P_T} \tag{4.17}$$

$$= \frac{\sum_{n=1}^{N} \log_2(1+SINR)}{\sum_{n=1}^{N} \left\| \mathbf{u}_{n,0} \right\|_2^2 + \sum_{i=1}^{N_{SC}} \sum_{n=1}^{N} \left\| \mathbf{u}_{n,i} \right\|_2^2 + T_{BS} \frac{\gamma_0}{C} + \sum_{i=1}^{N_{SC}} T_{SC} \frac{\gamma_i}{C}} . \tag{4.18}$$

While the energy efficiency for a cognitive radio user link n is the number of bits successfully transmitted per Joule energy and can be expressed as

$$\tilde{\eta}_n = \frac{R_n}{P_n} . \tag{4.19}$$

The optimization problem that maximizes the energy efficiency by balancing the transmit power for a CR user link under the data rate requirement for the user and the maximum transmit power constraint of the BS and SC-BS can be formulated as

$$\text{maximize} \qquad \tilde{\eta}_n = \frac{R_n}{P_n} \tag{4.20a}$$

$$s.t \qquad C_1 : R_n \geq R_n^{req}, \ \ \forall_n \tag{4.20b}$$

$$C_2 : \sum_{n=1}^{N} \left\| \mathbf{u}_{n,j} \right\|^2 \leq P_j^{\max} \Delta_j , \forall_j = 0,1,..., N_{SC} \tag{4.20c}$$

where R_n^{req} is the required rate of CR user n, while $P^{\max}$ is the maximum available transmit power at a serving BS j. Any of the CR user may choose the beamforming vector that optimizes its own energy efficiency and disregarding the energy efficiency of the other links. It is assumed that there is perfect channel knowledge of the other links.

4.3.3 Optimization of Energy Efficiency

In this section of this chapter, we aim to optimize the energy efficiency problem developed in the previous section. In optimizing the problem in equation 4.20, we put forward an energy efficient algorithm for maximizing the energy efficiency optimization problem for a cognitive radio user in the network using the Dinkelbach's method. This method assists in converting the original fractional problem into a solvable sequence of auxiliary problems. The computational complexity of this method is dependent on the convergence rate of the sub-problem sequence. To simplify our analysis, the maximization problem in equation 4.20 is however converted into an equal minimization form as in

$$\text{minimize } \frac{\boldsymbol{P_n}}{\boldsymbol{R_n}} \tag{4.21}$$

$$s.t \text{ constraints (4.20b) and (4.20c).}$$

Since it is a non-convex fractional problem, determining the optimal solution would be a very challenging task hence, equation 4.21 is however transformed into a more solvable form through fractional programming.

Lemma 1: *Given* $P_n > 0$ *and* $R_n > 0$*, the transmission strategy* $\mathbf{u}_{n,j}$ *for a CR user n will attain its maximum energy efficiency* $\tilde{\eta}_n$ *if and only if,* $\min_{\mathbf{u}_{n,j}} P_n(\mathbf{u}_{n,j}) - \bar{\alpha}_n R_n(\mathbf{u}_{n,j}) = P_n(\bar{\mathbf{u}}_{n,j}) - \bar{\alpha}_n R_n(\bar{\mathbf{u}}_{n,j}) = 0$ *where* $\bar{\alpha}_n = \frac{1}{\bar{\eta}_n}$.

Proof: Let $\bar{\mathbf{u}}_{n,j}$ be a solution to the problem in equation 4.21 and Q be the set including all eligible $\bar{\mathbf{u}}_{n,j}$ under constraints $C_1$and C_2. Then we have $\bar{\alpha}_n = \frac{1}{\bar{\eta}_n} = \frac{P_n(\bar{\mathbf{u}}_{n,j})}{R_n(\bar{\mathbf{u}}_{n,j})} \leq \frac{P_n(\mathbf{u}_{n,j})}{R_n(\mathbf{u}_{n,j})}$ for all $\mathbf{u}_{n,j} \in Q$.

Hence,

$$P_n(\mathbf{u}_{n,j}) - \bar{\alpha}_n R_n(\mathbf{u}_{n,j}) \geq 0, \forall \mathbf{u}_{n,j} \in Q \tag{4.22}$$

$$P_n(\bar{\mathbf{u}}_{n,j}) - \bar{\alpha}_n R_n(\bar{\mathbf{u}}_{n,j}) = 0 \tag{4.23}$$

From equation 4.22, we have $\min_{\mathbf{u}_{n,j}} P_n(\mathbf{u}_{n,j}) - \bar{\alpha}_n R_n(\mathbf{u}_{n,j}) = 0$, and from equation 4.23, the minimum is also taken on $\bar{\mathbf{u}}_{n,j}$. Hence, that completes of the first part of the proof.

Let $\bar{\mathbf{u}}_{n,j}$ be a solution for $\min_{\mathbf{u}_{n,j}} P_n(\mathbf{u}_{n,j}) - \bar{\alpha}_n R_n(\mathbf{u}_{n,j}) = 0$ and $P_n(\bar{\mathbf{u}}_{n,j}) - \bar{\alpha}_n R_n(\bar{\mathbf{u}}_{n,j}) = 0$. It implies

$$P_n(\mathbf{u}_{n,j}) - \bar{\alpha}_n R_n(\mathbf{u}_{n,j}) \geq 0, \forall \mathbf{u}_{n,j} \in Q \tag{4.24}$$

$$P_n(\bar{\mathbf{u}}_{n,j}) - \bar{\alpha}_n R_n(\bar{\mathbf{u}}_{n,j}) = 0 \tag{4.25}$$

Also from equation 4.24, we have $\bar{\alpha}_n \leq \frac{P_n(\mathbf{u}_{n,j})}{R_n(\mathbf{u}_{n,j})}$ for all $\mathbf{u}_{n,j} \in Q$, so we see that $\bar{\alpha}_n$ is the minimum for problem in equation 4.21 and $\bar{\eta}_n = \frac{1}{\bar{\alpha}_n}$ is the maximum for problem in equation 4.20. From equation 4.25, we notice that $\bar{\alpha}_n = \frac{P_n(\mathbf{u}_{n,j})}{R_n(\mathbf{u}_{n,j})}$, which is same as $\bar{\eta}_n = \frac{1}{\bar{\alpha}_n} = \frac{R_n(\mathbf{u}_{n,j})}{P_n(\mathbf{u}_{n,j})}$ so the optimum for problem in equations 4.20 and 4.21 is taken on $\bar{\mathbf{u}}_{n,j}$.

The necessary and sufficient condition to describe the optimal transmission strategy for problem in equation 4.20 is detailed in Lemma 1. The problem in equation 4.20 can now be solved as a parametric sub-problem with an algorithm in updating the parameter. The sub-problem is defined as

$$\begin{aligned} &\text{maximize } R_n - \bar{\eta}_n P_n \\ &s.t. \;\; C_1 \text{ and } C_2. \end{aligned} \tag{4.26}$$

Applying Dinkelbach's method, an iterative algorithm as presented in algorithm 1 is employed to solve the problem in equation 4.20. The convergence of the Dinkelbach's method has been proved in [114].

Algorithm 1 Optimizing Energy Efficiency using Dinkelbach's Method

1: **Input** $\mathbf{u}_{j,}\forall_j \in BS, N_{SC}, j \neq n.$

2: For any i^{th} CR user link, select any feasible precoding matrix $\overline{\mathbf{u}}_{n,j}$ and calculate R_n and P_n, then set $\overline{\eta}_n = \dfrac{R_n}{P_n}$

3: For a given $\overline{\eta}_n$, solve the sub-problem in equation 4.26. Represent the solution as $\overline{R}_n$ and $\overline{P}_n$ respectively.

4: If $R_n - \overline{\eta}_n P_n = 0$, stop and return $\overline{\mathbf{u}}_{n,j}$ as the optimal precoding matrix for the n^{th} user link. Otherwise, update $\overline{\eta}_n = \dfrac{R_n}{P_n}$ and reverse to step 3.

5: Repeat step 1-4 for all CR user links $n = 1, 2, \ldots N$, until convergence.

From Algorithm 1, finding the solution to the problem in equation 4.20 would require us to find the solution to equation 4.26 with a given $\tilde{\eta}_n$, and then updating $\tilde{\eta}_n$ until the condition is established. To solve problem in equation 4.26, the Newton's method based Dinkelbach algorithm is employed [115]. Since R_n and P_n are functions of beamforming vectors $\mathbf{u}_{n,j}, \forall_{n,j}$, therefore, $F(\overline{\eta}_n)$ can be represented as $F(\overline{\eta}_n) = \max\{R_n - \overline{\eta}_n P_n\}$ which is convex, continuous and strictly decreasing in $\overline{\eta}_n$ [114]. From the maximization problem in equation 4.26, it is observed that the maximization problem would require maximizing R_n while minimizing P_n. This kind of scalarized bi-criterion optimization problem can be solved by finding the root of $F(\overline{\eta}_n)$ using the Newton's method based Dinkelbach algorithm which is able to determine the root of $F(\overline{\eta}_n)$ with super-linear convergence rate.

Algorithm 2 Newton's method based Dinkelbach algorithm to find the root of $F(\bar{\eta}_n)$.

Initialization: Initialize $\bar{\eta}_0$ satisfying $F(\bar{\eta}_0) \geq 0$, tolerance $\tau, v = 0$

While $|F(\bar{\eta}_v)| > \tau$

1: Solve equation (4.26) with $\bar{\eta}_n = \bar{\eta}_v$ to get $\mathbf{u}_{n,j}, \forall_{n,j}$.

2: $\bar{\eta}_{v+1} = R_n / P_n$ and set $v = v + 1$

End While

Regardless of the super linear convergence rate of the algorithm, the user's choice of beamformers makes it uneasy to independently solve equation 4.26. Hence, to efficiently tackle such problem, DC programming theory is employ and the objective function can be re-written as a difference between two convex (DC) functions [116] [117] as written below in equation 4.27.

$$R_n - \bar{\eta}_n P_n = f_1(\mathbf{D}) - f_2(\mathbf{D}) = g(\mathbf{D}), \tag{4.27}$$

where $f_1(\mathbf{D})$ and $f_2(\mathbf{D})$ are labelled as

$$f_1(\mathbf{D}) = \sum_{n=1}^{N} \log_2 \left[\left\{ \sum_{j=1}^{N} \sum_{i=0}^{N_{SC}} \left| \mathbf{h}_{n,i}^H \mathbf{u}_{j,i} \right|^2 \right\} + \sigma_n^2 \right] - \bar{\eta}_n P_n, \tag{4.28}$$

and

$$f_2(\mathbf{D}) = \sum_{n=1}^{N} \log_2 \left[\left\{ \sum_{j=1, j \neq n}^{N} \sum_{i=0}^{N_{SC}} \left| \mathbf{h}_{n,i}^H \mathbf{u}_{j,i} \right|^2 \right\} + \sigma_n^2 \right], \tag{4.29}$$

where $f_1(\mathbf{D})$ and $f_2(\mathbf{D})$ are both convex functions so therefore, the objective function in equation 4.27 is a standard difference of convex function problem which can be solved by replacing $f_2(\mathbf{D})$ by its affine convex majorant using the first order convex approximation. The problem is solved iteratively as in algorithm 3.

Algorithm 3 Iterative, suboptimal solution for DC problem

Initialization: Initialize $\mathbf{D}^{(0)}$, set $v = 0$ (iteration number)

Repeat

1: Define the auxiliary function $\hat{g}^{(v)}(\mathbf{D})$

$$\hat{g}^{(v)}(\mathbf{D}) \triangleq f_1(\mathbf{D}) - \left[f_2(\mathbf{D})^{(v)} + tr(\nabla f_2(\mathbf{D}^v)(\mathbf{D} - \mathbf{D}^v)) \right] \tag{4.30}$$

2: Solve the optimization problem in equation 4.31 below to get $\mathbf{D}^{(n+1)}$

$$\text{Maximize } \hat{g}^{(v)}(\mathbf{D}) \tag{4.31a}$$

$$s.t., C_1, \text{ and } C_2.$$

(4.31b)

3: $v = v + 1$

The gradient ∇ of $f_2(\mathbf{D})$ in equation 4.30 is defined as

$$\nabla f_2(\mathbf{D}) = \sum_{n=1}^{N} \frac{1}{\sum_{j=1, j\neq 1}^{N} tr\left(\mathbf{H}_k \mathbf{U}_j\right) + \sigma_n^2} \frac{E_n}{\ln 2}. \tag{4.32}$$

where $\mathbf{H}_{n,} \mathbf{D}_n \in \mathbb{C}^{M\times M} \left(M = T_{BS} + (N_{SC} \times T_{SC}) \right)$ is a block diagonal matrix where each block j contains the matrix $\mathbf{h}_{n,j}^H \mathbf{h}_{n,j}$ and $\mathbf{u}_{n,j}^H \mathbf{u}_{n,j}$ respectively $\forall_j = 0,1,...N_{SC}$, and zero elsewhere. Also, $\mathbf{E}_n = blkdiag(\mathbf{H}_n,....,\mathbf{H}_n)$ containing L blocks with l^{th} block as $0_{M\times M}$, and $\mathbf{D} = blkdiag(\mathbf{D}_n,....,\mathbf{D}_n)$.

Due to the convex approximation of the original objective function, problem in equation 4.31 can be solved efficiently via 'interior points' method if the rate constraint (C_1) is convexized. In order to show the convergence of sequence $g(\mathbf{D})$ in Algorithm 3, we would require $g(\mathbf{D}^{(v)}) \leq g(\mathbf{D}^{(v+1)})$ [103]. Let us start by the fact that $g(\mathbf{D}^{(v)})$ and $\hat{g}^{(v)}(\mathbf{D}^{(v)})$ are the same for given $(\mathbf{D}^{(v)})$. Since $\mathbf{D}^{(v+1)}$ is considered as the optimal value for the maximization problem in equation 4.31, we can write $\hat{g}^{(v)}(\mathbf{D}^{(v)}) \leq g^{(v)}(\mathbf{D}^{(v+1)})$. Also, due to the convex majorant assumption in equation 4.30, the inequality $\hat{g}^{(v)}(\mathbf{D}^{(v+1)}) \leq g(\mathbf{D}^{(v+1)})$ is also true. Therefore, $g(\mathbf{D})$ monotonically increases with v and converges.

The developed solution for energy efficiency maximization via macro BS and small cells BS selection can be achieved by running algorithm 1 while algorithm 2 and algorithm 3 runs within.

4.3.4 Results and Discussion

In order to evaluate the performance of the presented algorithm, computer simulations were carried out using MATLAB simulation software. The channel parameters for simulation are given in Table 4-2 as in [118]. We consider a system with a single macro-cell BS having $T_{BS} \geq N$ antennas and a total number of N_{SC} small cell BS. The small cell base stations are spaced 350 meters away from the macro-BS which is at an angle of 360° to the small cells. We also assume that the total available power $P_j^{\max}$ for SC-BS is fivefold lesser than the macro BS. The power consumption is taken based on the parameters in table I in [119] and other parameters are detailed in table 4-2.

Table 4-2: Channel Parameters used for evaluation

Parameters	**Value**
Macro cell radius	$500m$
Small cell radius	$50m$
Small scale fading distribution	$h_{k,j} \sim CN(0,1)$
Standard deviation of log normal shadowing	$7dB$
Path and penetration loss, distance d (km) (Macro cell)	$148.1 + 37.6\log_{10}(d)dB$
Path and penetration loss, distance d (km) (Small cell)	$127 + 30\log_{10}(d)dB$
Carrier frequency	$2GhZ$
Number of subcarriers	600
Noise variance σ_n^2	$-127dBm$
Noise figure	$5dB$
Iteration thresholds (τ and ε)	1×10^{-7}

Firstly, we investigate the effects of employing different number of antennas at both the macro BS and the SC-BS where $T_{BS} \in \{20, 30, ..., 100\}$ and $T_{SC} \in \{0, 1, 2, 3\}$. In figure 4-8, we show the plot of total power consumption against the number of antennas T_{BS} at the macro BS. From the figure, we can see that adding extra number of antennas T_{BS} at the macro BS still maintains a low level of power consumption in the network. This is due to the fact that there are fewer propagation losses which eventually outweighs the extra power incurred from adding more antennas to the macro base station. The effects of employing massive MIMO in the network can be seen to successively maintain the total power consumed by the system while improving the energy efficiency. Also as seen in figure 4-8, the effects of employing SC-BS close to active cognitive radio users can effectively boost the energy efficiency of the network. Adding more antennas T_{SC} to the SC-BS tend to maintain a low power consumption when compared to the case with no SC-BS in the network.

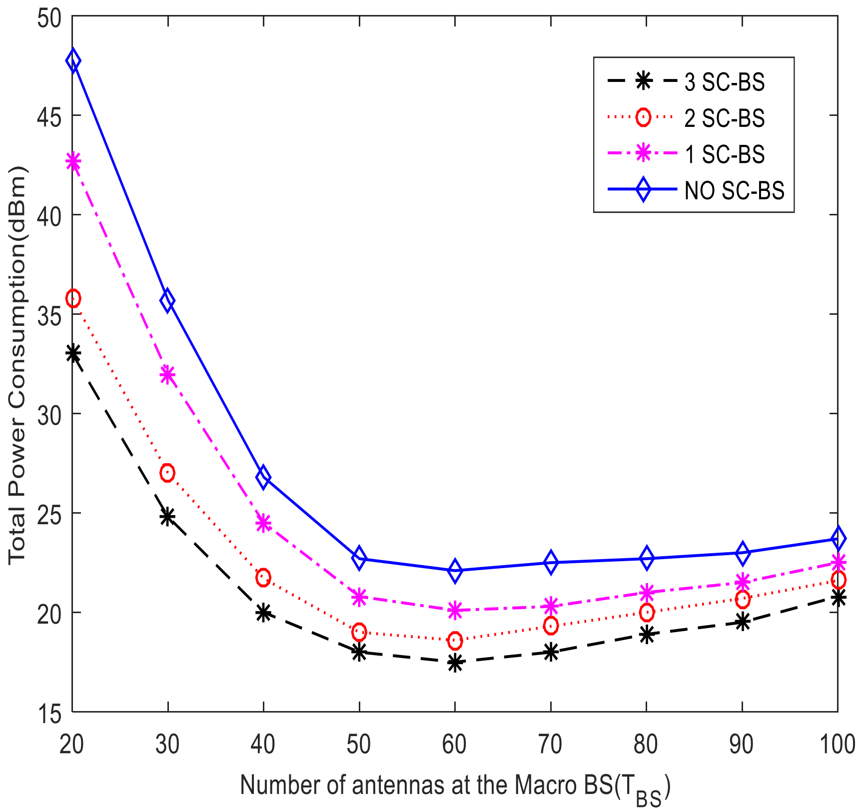

Figure 4-8: Total power consumption considered at different number of T_{BS} and T_{SC}

The same power consumption can be achieved with about half the number of antennas in the macro BS when a single antenna SC-BS is introduced in an area concentrated with CR users. That is to say that there is a point where increasing the number of antennas at the macro BS can no longer bring about a reduction in the power consumption, hence, the optimum number of antenna that can maintain a low power can be implemented. The combination of massive MIMO and SC-BS can bring about a reduction in the power consumption of the system when their antennas are effectively combined.

Figure 4-9 shows the total power consumed against the achievable rate per CR user at 50 T_{BS} in macro BS and 3 T_{SC} in SC-BS. As observed in the figure, the higher the rate achieved by a user, the more power is consumed. Also, more power is consumed when only the macro base station is selected to serve the CR user and a lot more power is also consumed when only the macro BS is selected compared to when the optimal base station is selected. The optimal BS selection technique achieves better results due to the fact that users in proximity to a SC-BS are being offloaded to that SC-BS for coverage.

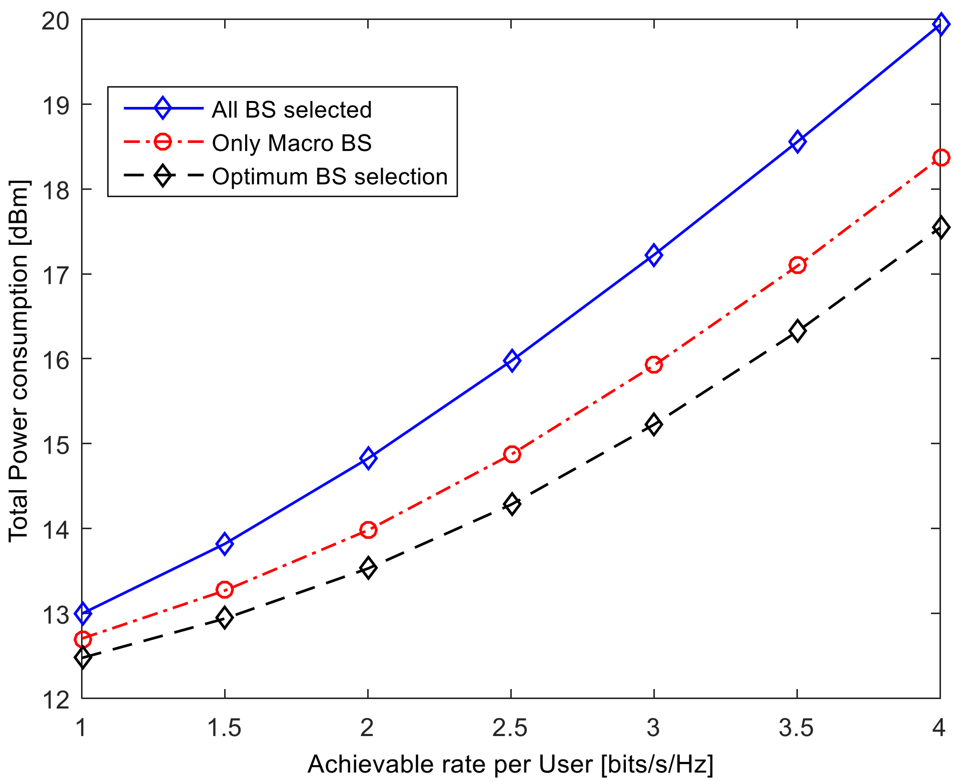

Figure 4-9: Total power consumed against the achievable rate for a CR user

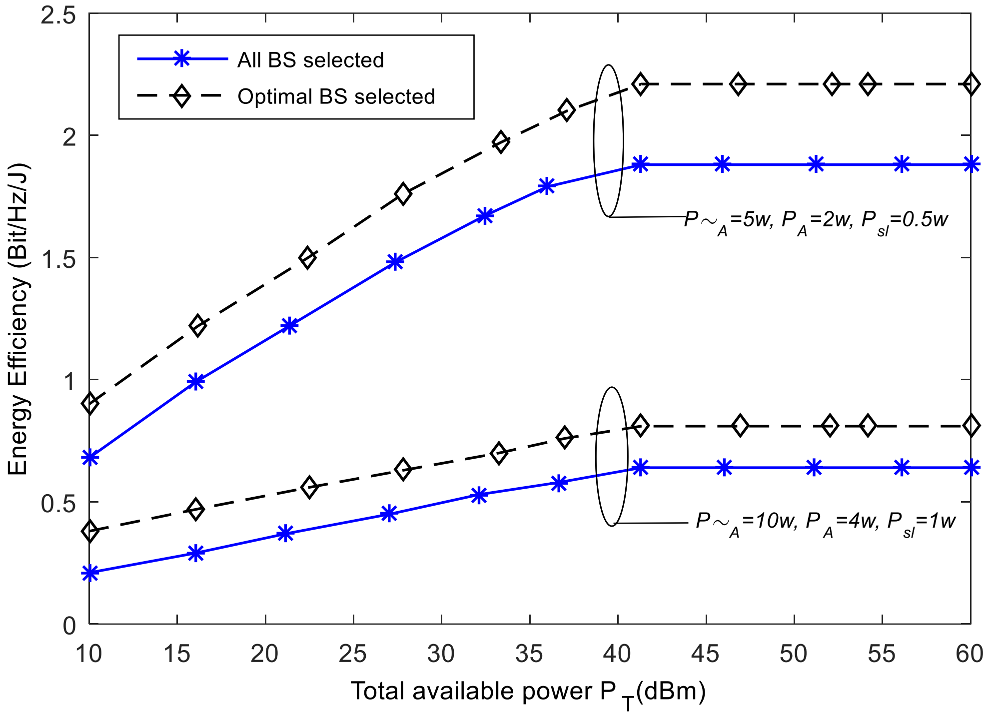

Figure 4-10: Energy efficiency comparison for different BS selection

The performance of selecting the optimal SC-BS in proximity to the CR user compared to when all base station is selected for communication is evaluated in figure 4-10. As seen in the figure, the optimal base station selection yields more energy efficiency and the smaller gap between the case of when all base station is selected and when the optimal base station is selected tends to increase as the number of small cell base stations increases in the system. The optimal BS selection achieves a higher energy efficiency since only a selected BS serves a particular user unlike when all BS are selected. Hence, idle power is accumulated and saved by unselected BS. Also, the energy efficiency of the system is also dependent on the circuit power P_{CT} . A lower P_{CT} yields better energy efficiency.

The effects of engaging more antennas T_{BS} at the macro BS on the energy efficiency of the system at a constant circuit power is displayed in figure 4-11. At a constant circuit power of 50 dBm for all T_{BS} , increasing the number of antennas increases the spectral efficiency of the system which in turn leads to an increase in the energy efficiency of the system. The optimal BS selection still yields a better energy efficiency due to the increase in the spectral efficiency and lesser P_{TX} when compared to the scenario of all BS are selected and that of only a macro BS is present or when the small cell base stations are left idle in the network.

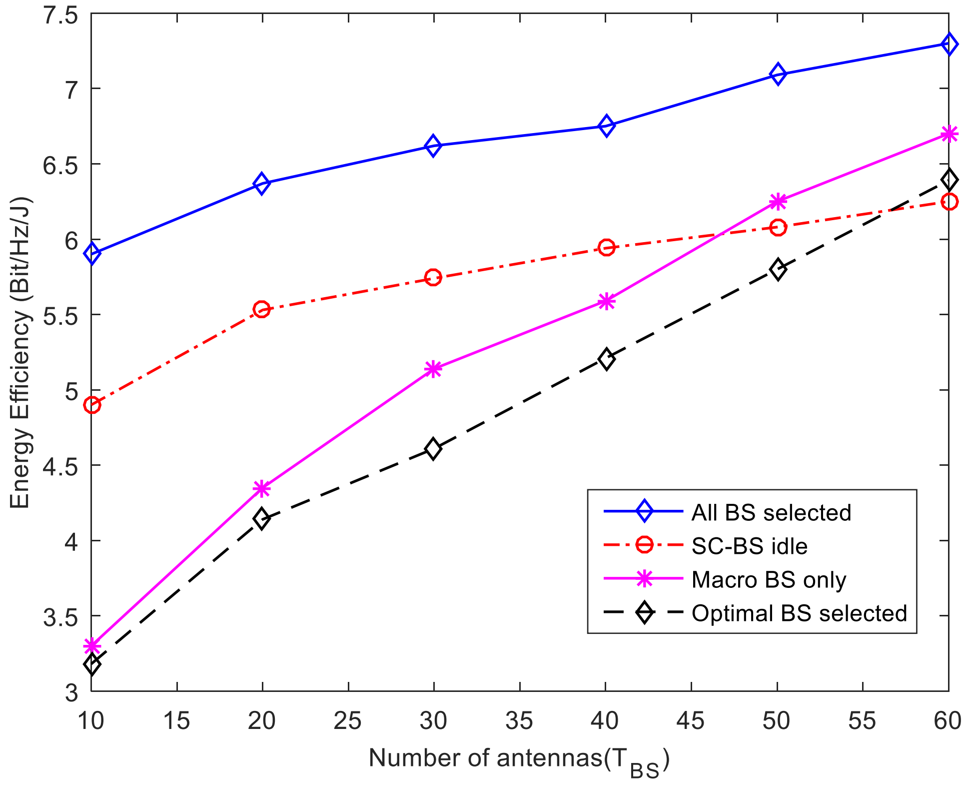

Figure 4-11: Energy efficiency on the number of T_{BS} at a constant P_{CT} of 50 dBm

4.4 Chapter Summary

Energy efficiency has been a major concern in cognitive radio networks as base stations have been responsible for a larger percentage of the total energy consumption. In this chapter, we focused on the problem of energy efficiency in cognitive radio networks. How base stations can be effectively put into sleep mode during off-peak time is studied. A sleep mode scheme was developed where an energy efficient algorithm that puts unnecessary base stations to sleep at different traffic load variation during a 24 hour weekday was introduced. Results showed that the developed base station scheme delivers a better energy savings when compared to the dynamic sleep scheme and that fewer base stations are active in the network during the developed sleep scheme.

In an attempt to improve the energy efficiency of cognitive radio networks, massive MIMO and small cells were deployed in the network. An energy efficiency optimization problem was formulated and Dinkelbach method was used to solve the problem iteratively. With the resulted optimal solution, a CR user can dynamically choose an optimal base station for transmission. Results shows that the total power consumption can be significantly improved by adding more antennas to the macro base station and also increasing the number of antenna small cell base stations. Also, energy efficiency of the network can be greatly enhanced when an optimal base station is selected for transmission.

CHAPTER FIVE

ENERGY EFFICIENCY OF SECONDARY USERS AND MALICIOUS USERS IN COGNITIVE RADIO NETWORKS

5.0 Objective

The contents of this chapter involves examining the total amount of energy consumed by secondary unlicensed users in cognitive radio networks. The energy consumption in each state of the secondary user's activities is analysed as this is a crucial step in improving the secondary user's energy efficiency in the network. Also in this chapter, we study the effects malicious secondary users has on the cognitive radio network's energy efficiency. We also present a secured detection mechanism that reduces these effects on the network in order to improve on the energy efficiency of the network.

5.1 Introduction

In cognitive radio systems, through the spectrum sensing process, secondary or unlicensed users (SUs) can opportunistically utilize the licensed spectrum only when the primary or licensed user is absent at that particular time slot and specific geographical location. However, when the licensed user decides to transmit across the spectrum band that is occupied by the secondary user, the secondary user should immediately vacate the spectrum band in order not to create interference with the primary user. These extra technologies and processes which a cognitive radio possesses has led to a rise in the energy consumed in the network. The amount of energy consumed to sense and deliver secondary data via spectrum holes need to be improved under a desired QoS requirement for both the primary and secondary users. However, boosting the energy efficiency in cognitive radio networks will also require investigating the amount of energy consumed by the secondary user's activities in the network.

When cooperative spectrum sensing process is carried out in cognitive radio networks, it might be vulnerable to some misbehaving secondary users which will disrupt the network's spectrum sensing etiquette and the obtainable overall performance. This misbehaviour of secondary users is caused by reporting false spectrum occupancy information in order to influence the final decision made by the fusion center (FC). A malicious SU usually sends information that the spectrum is used to the FC which helps to identify the spectrum as used in taking the final decision. The resultant effect of this is that other SUs will identify the malicious SU as a licensed user thereby vacating the occupied spectrum band for the malicious SU believing it is a primary user [17].

An attack in the cooperative spectrum sensing process of a cognitive radio network in which the malicious user pretends to be a licensed user by sensing false spectrum sensing occupancy information in order to gain unrivalled access to a vacant spectrum is called Primary User Emulation Attacks (PUEA) [17]. One of the possible approaches in preventing PUEA in the network is to build a secure link between the SUs and the FC in order to be sure that only authenticated spectrum sensing occupancy results obtained from a trusted SU is accepted by the FC in making its final decisions. In order to build a secure link, authentication, integrity and accurate spectrum sensing mechanism are taken into consideration [120]. An energy efficient detection mechanism must also be used to accurately detect vacant spectrum bands. This way, the effects of malicious SUs on the energy efficiency of the network is improved.

5.2 Secondary User Energy Consumption in Cognitive Radio Networks

From the discussion in section 5.1, analysing the energy consumption of secondary users at a successful transmission state, collision state, idle state, sleep state, channel scanning state and back off state is important to improving the energy efficiency of the network. The system model of the network for analysis is presented in the next section.

5.2.1 System Model

Considering a typical cognitive radio network consisting of several static wireless nodes communicating with each other using N licensed channels operating within a licensed coverage area. In the network, the secondary users are equipped with spectrum sensors which periodically scan the spectrum for a good channel to communicate in and are also allowed to select the channels they desire to use for communication, with no central node authority.

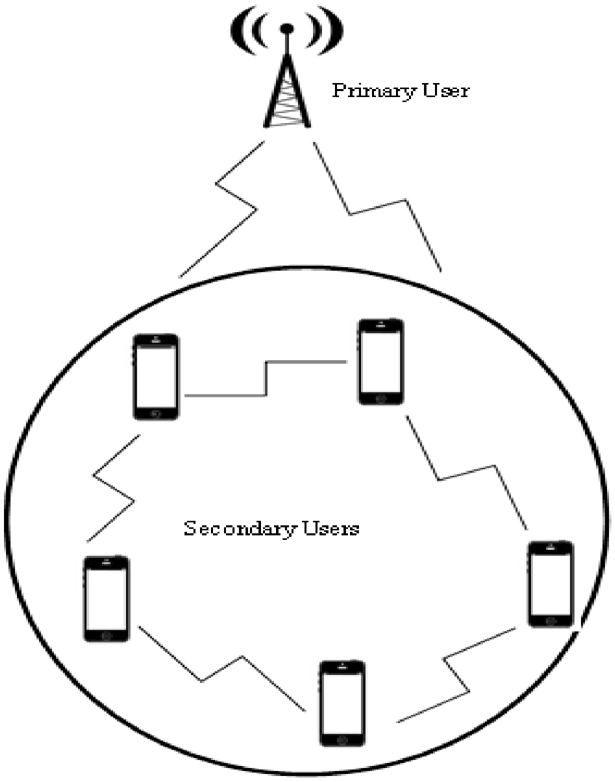

Figure 5-1: An ad-hoc cognitive radio network environment

If we assume that every secondary node has packets to send, then the energy consumed by the secondary user can be modelled as the energy required in scanning for a new channel for communication and also the sum of energy required to communicate packets to this recently found channel. We also assumed that a different radio is used to scan and select a channel simultaneously.

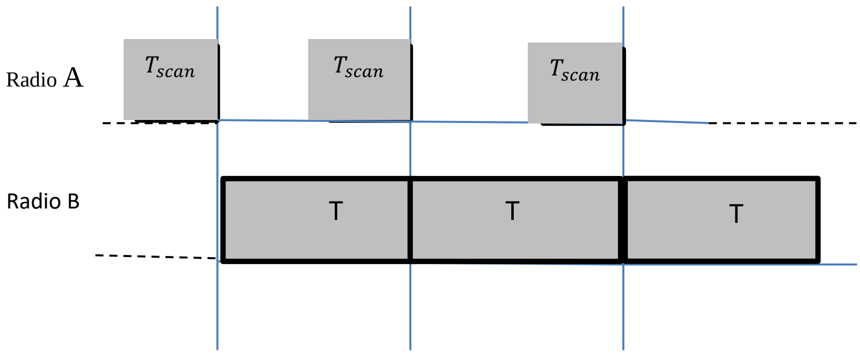

Figure 5-2: Secondary user periodic scanning and communication

As shown in figure 5-2, T_{scan} is the duration of time used in scanning for a new channel and T is the duration of time between each scan. We take E_{scan} to be the expected total energy consumption in the scanning process while E_{pkt}^{k} and T_{pkt}^{k} are the expected energy that is required to send packets and the corresponding time respectively. Then, the expected per packet energy consumed by a secondary user, E_S with k amount of nodes contending for that same channel can be modeled as

$$E_s = E_{pkt}^{k} + \frac{E_{scan}}{T/T_{pkt}^{k}} \qquad (5.1)$$

5.2.3 Energy Consumption Analysis

In this section, the energy consumed by SUs in different states is evaluated by analysing E_s. The power levels of the secondary users are adjusted according to the QoS requirements and user's states. In analysing E_s, we simplify our analysis by using a basic energy model in describing the different frames involved in the communication process.

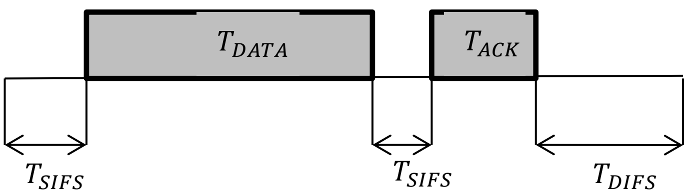

Figure 5-3: An example of the basic access mode Packet communication of the IEEE 802.11 standard

From figure 5-3, we can analyse the activities and timing of the secondary user node either in a transmitting, receiving or in an idle mode using the basic access mode without the request-to-send/clear-to-send mechanism as in [121]. T_{DATA} is the duration of time for data packets communication, T_{DIFS} is the distributed inter-frame space time, T_{ACK} is the duration of time for ACK transmission which is transmitted at the end of the packet after a period of time called short inter-frame space (SIFS) to signal a successful packet transmission. For simplicity of our analysis, T_{SIFS} is ignored and it is assumed to be used up in switching between modes of a radio.

Table 5-1: Parameter Description

Parameter	Description
P_{trans}	Power consumption at transmit mode
P_{recv}	Power consumption at receive mode
P_{idle}	Power consumed at idle mode
P_{sleep}	Power consumed in sleep mode
P_{switch}	Power to switch channels
T_{data}	Time for Data packet
T_{ack}	Time for ACK packet
T_{difs}	Time for DIFS
T_{scan}	Scan duration
T_{hdr}	Time for packet header
T_{slot}	Slot duration
T_{switch}	Time to switch channels
T_{bckoff}	Time taken for back-off
T_{coll}	Time taken during collision
T_c	Duration of collision
M	Number of channels to scan

5.2.3.1 Energy Consumption at Transmission State

The energy consumption of a secondary user in a successful transmission can be given as

$$E_{trans} = P_{trans}T_{data} + P_{recv}T_{ack} + P_{idle}T_{difs}. \tag{5.2}$$

When there is a collision in packet transmission, which is likely to be caused by false detection of a vacant channel, then the consumed energy by the secondary user can be written as

$$E_{coll} = P_{trans}P_{data} + P_{idle}(T_{ack} + T_{difs}). \tag{5.3}$$

5.2.3.2 Energy Consumption at Receiving State

The energy consumed when packets are received by a secondary user can be categorized into three scenarios.

- Scenario one: when the packet received is for the intended secondary user, the energy consumed will be expressed as

$$E_{recv} = P_{recv}T_{data} + P_{trans}T_{ack} + P_{idle}T_{difs}, \tag{5.4}$$

- Scenario two: when the received packets is not for the intended user and has to be discarded then, the energy consumed at that state is

$$E_{dis} = P_{recv}T_{hdr} + P_{idle}T_{difs} + P_{sleep}T_{nav}, \tag{5.5}$$

where $T_{nav} = T_{data} - T_{hdr} + T_{ack}$.

- Scenario three: when the received packet is jammed due to collision then the energy consumption can be modeled as

$$E_{recvc} = P_{recv}T_{hdr} + P_{idle}(T_c + T_{difs} - T_{hdr}). \tag{5.6}$$

5.2.3.3 Energy Consumed During Back-off

The energy spent between two successive decrement of a secondary node's backoff counter is also regarded as the energy consumed during tick period as seen in [121],[122]. The tick period is perceived by a node in backoff state and hence has $n - 1$ potential transmitting nodes where n is regarded as the number of secondary user nodes on the current channel. Backoffs countdowns are suspended if the channel is sensed busy, and only resumes again when the channel is available.

There are two scenarios that arises when a node is trying to transmit in a given tick time with $n - 1$ other potential transmitters. The first scenario is the probability that only this node transmits, ρ_i which can be written as

$$\rho_i = (n-1)\tau(1-\tau)^2, \tag{5.7}$$

where τ is the probability that a node transmit at a given tick time.

The second scenario is the probability that more than one secondary node attempts to transmit which can be written as

$$\rho_{nc} = 1 - (1-\tau)^{n-1} - (n-1)\tau(1-\tau)^2. \tag{5.8}$$

So the average energy consumption in the backoff state can now be expressed as

$$E_{bkoff} = P_{idle}T_{slot} + \rho_i(p_r E_{recv} + (1-p_r)E_{dis}) + \rho_{nc}E_{recvc} . \tag{5.9}$$

5.2.3.4 Energy Consumed when Communicating with a Channel

From the analysis given in [121], and from our energy model given in equation 5.1, the energy consumed by a secondary user in communicating a packet with a k amount of secondary user nodes contending for same channel can be expressed as

$$E_{pkt} = E_{trans} + \frac{p_k}{1-p_k} E_{coll} + \dot{R}(pk) E_{bkoff}, \tag{5.10}$$

where p_k is the probability that a collision occurs with k number of contending secondary nodes. k can assume any number hence, it is omitted for simplicity. $\dot{R}(p)$ is the expected number of slots that needs to be counted down before the packet can be sent and can be expressed as

$$\dot{R}(p) = \left[W_0 \frac{(1-p)-p(2p)^m}{1-2p} - 1\right], \tag{5.11}$$

where W_0 is the initial contention window size, m is regarded as the number of times the backoff window can be incremented before it reaches the maximum allowed size. It is of importance to mention that $\dot{R}(p)$ depends on the number of contending secondary user nodes and that determines the relevant values of p.

5.2.3.5 Energy Consumed to Scan Channels

The energy consumed in scanning for channels by a secondary user depends on the scanning algorithm used. For this work, we considered the optimal scanning algorithm which is described below. In optimal scanning algorithm, all the channels are scanned by the secondary user and the optimal channel among the scanned channels is chosen and this can be expressed as

$$E_{scan} = (M-1)[E_{scanch} + P_{switch} T_{switch}] + p_{switch} P_{switch} T_{switch}, \tag{5.12}$$

where P_{switch} is the probability that a channel better than the current one is found and its value is taken as 1 in this analysis. Equation 5.12 also accounts for the total energy used to switch between channels and also a final switch to the desired channel.

Also, using the analysis in [121] where E_{scanch} depends on what fraction of scanning period T_{scan} is spent receiving packets either collision free or collided and what fraction it remains in the idle mode can be written as

$$E_{scanch} = \frac{T_{scan}}{T_{bckoff}} [P_{idle} T_{slot} + \rho_i E_{dis} + \rho_{nc} E_{recvc}], \tag{5.13}$$

the term $P_{idle}T_{slot}$ is regarded as the energy consumed by a secondary user in an idle mode and $\frac{T_{scan}}{T_{bckoff}}$ accounts for the number of backoffs in a scanning period T_{scan} and T_{bckoff} is written as

$$T_{bckoff} = T_{slot} + \rho_i\big(T_{hdr} + T_{difs} + T_{nav}\big) + \rho_{nc}(T_{hdr} + T_{difs} - T_{coll} + T_{hdr}), \tag{5.14}$$

where T_{bckoff} can also be regarded as T_{tick}.

5.3.1 Evaluation

In this section, we evaluate the secondary user's total energy consumption in a cognitive radio network in the different stages of communication. The presented results are based on the numerical evaluations of the expressions developed in the previous sections. The values of the parameters used are given in table 5-2 (the values where obtained from the 802.11 standard) [123], [124].

Table 5-2: Analytical Parameters

Symbol	Description	Value
P_{trans}	Power consumption at transmit mode	1000mW
P_{recv}	Power consumption at receive mode	1500mW
P_{idle}	Power consumed at idle mode	850mW
P_{sleep}	Power consumed in sleep mode	10mW
P_{switch}	Power to switch channels	750mW
T_{data}	Time for Data packet	0.2ms
T_{ack}	Time for ACK packet	0.006ms
T_{difs}	Time for DIFS	0.07ms
T_{hdr}	Time for packet header	0.003ms
T_{switch}	Time to switch channels	0.07ms
T_{slot}	Slot duration	0.07ms

Figure 5-4 shows the total energy consumption of the secondary user in a successful transmission state. It can be observed that the total energy consumption decreases as the number secondary users in the network increases. This can be attributed to the fact that the total successful secondary packets delivered will decrease due to the secondary network size. As the network size increases, collision will occur and more secondary users will continue to participate in receiving packets, transmission of packets, and scanning of channels for utilization. Therefore, the total energy of these activities will continue to affect the total energy consumption of the entire network causing it to increase. Hence the amount of energy consumed during a successful transmission is wholly dependent on the secondary network size.

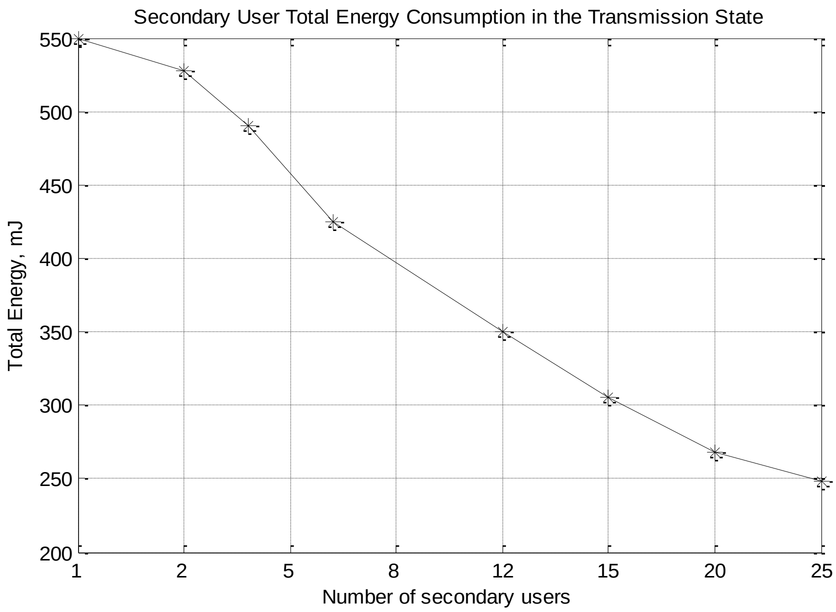

Figure 5-4: Secondary user total energy consumption at success transmission versus number of secondary users

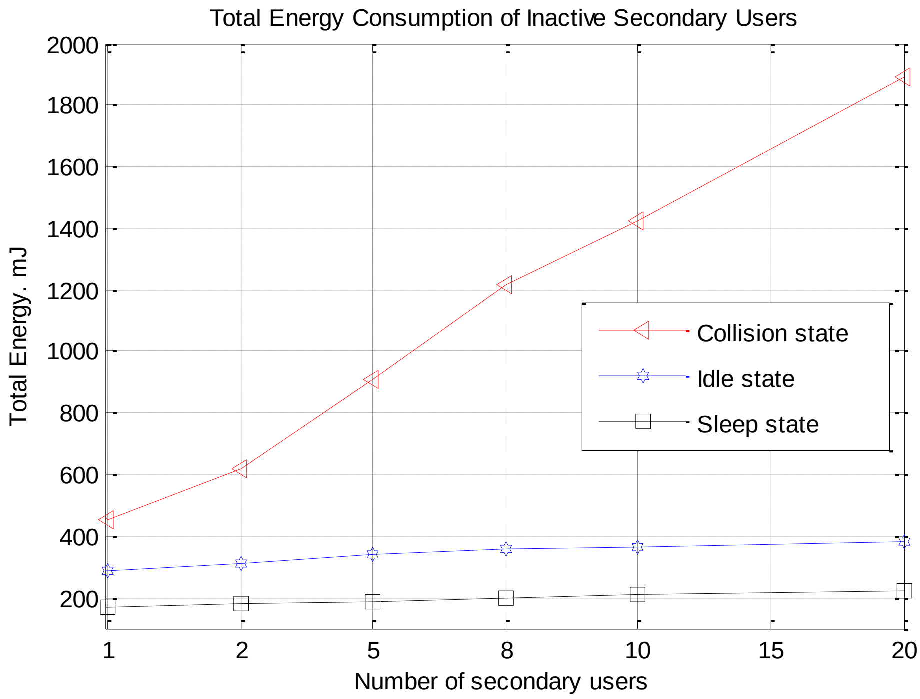

Figure 5-5: Total energy consumption (at collision, idle and sleep states) versus the secondary network size.

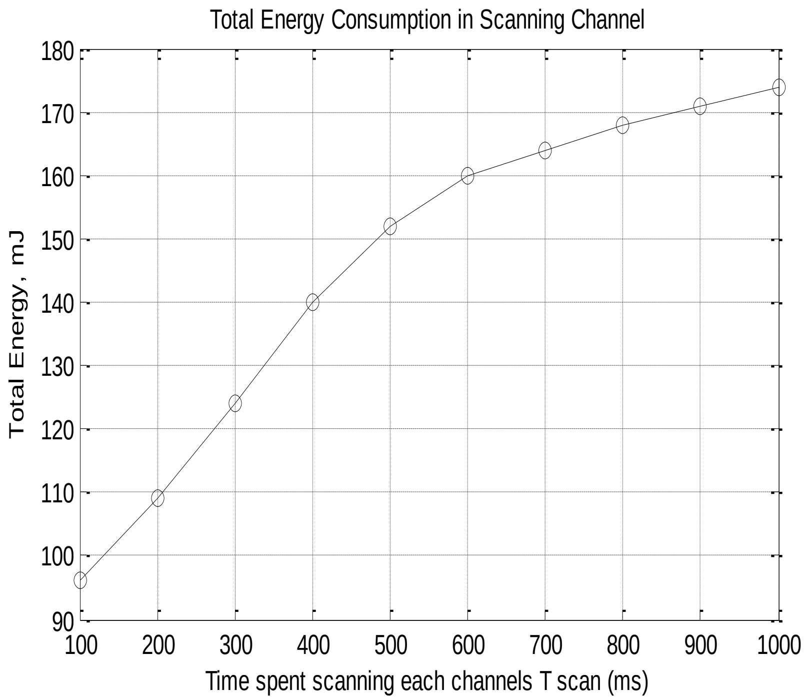

Figure 5-6. Total energy consumption by secondary users versus the time spent scanning each channels.

The total energy consumption of inactive secondary users in the network is shown in figure 5-5. The result verifies that less energy is consumed when secondary users are in the idle state and even lesser energy is consumed when secondary users are in sleep state. There is also high energy consumption by secondary users at the collision state as the number of secondary users increases in the network. This is expected to be so because as the number of secondary users increases, there is an increase in the probability of false alarm in the network causing secondary users to wrongly communicate in a busy spectral band.

Figure 5-6 also shows the total energy consumed by secondary users in scanning each channels using the optimal scanning scheme. The result shows that the energy consumption by secondary users increases as the time taken to scan each channels increases. Hence a small amount of time can be spent in scanning channels so as so conserve energy in the network. It is also worthy to note that when more time is spent scanning the channels for opportunistic utilization, the lower the throughput in the network.

5.4 Malicious Users on the Energy Efficiency of Cognitive Radio Networks

In a cognitive radio network, a secondary user might decide to go malicious so as to selfishly gain access to a vacant spectrum band. This however impacts on how energy efficient of the network can be. A secured energy detection cooperative spectrum sensing mechanism is developed to assist in maximizing the energy efficiency of the network and also reduce the effects of these attacks on the network. The system model used in performing our analysis is given in the section below.

5.4.1 System Model

A system with N number of secondary users or cognitive radio users (CRUs) trying to access a licensed spectrum band in a cognitive radio network is considered. The probability that the spectrum is not being used by a licensed user is denoted by P_0. To avoid interference, each CRU senses a specific spectrum at a specific time and takes a local binary decision $u_i = \{1,0\}$ about the availability of the spectrum. If the decision $u_i = 1$ is taken then the CRU decides that the spectrum is being used. If otherwise, then the CRU decides that the spectrum is vacant. After a binary decision have been taken by all the CRUs and sent to the FC, the FC receives these decisions and fuses them by using specific fusion rules that can be applied at the FC [125]. For this work, we are focusing on the OR rule and AND rule since in these rules, given a targeted probability of detection or a targeted probability of false alarm, each CRU threshold can be derived.

Secondary or CRUs users that do not normally follow the spectrum sensing etiquette which results in the downgrading of the overall performance of the considered cognitive radio network is referred to as malicious users. What the malicious user does for its own selfish gain is to always report a spectrum sensing decision of 1 so that the decision of the FC can be influenced. This however increases the probability of the FC in taking a final decision of 1 and therefore, none of the legitimate CRUs can use the spectrum and the malicious user then uses the spectrum for its transmission. We consider the numbers of malicious user to be M so that the number of CRUs in the network, both legitimate and malicious becomes $N + M$.

In a cooperative spectrum sensing environment (CSS), the probability of detection (P_d) and the probability of false alarm (P_f) are used as the metric for determining the spectrum sensing performance of the CRUs in the network. The probability of detection and the probability of false alarm employing the OR fusion rule in terms of M and N can be expressed as

$$P_D^{OR}\ (M,N) = \begin{cases} \sum_{i=k-M}^{N} \binom{N}{i} P_d^i (1-P_d)^{N-i} & , \ M<K \\ 1 & \ \ M \geq K \end{cases} \tag{5.15}$$

$$P_F^{OR}\ (M,N) = \begin{cases} \sum_{i=k-M}^{N} \binom{N}{i} P_f^i \left(1-P_f\right)^{N-i} & , \ M<K \\ 1 & \ \ M \geq K \end{cases} \tag{5.16}$$

While, the probability of detection and the probability of false alarm employing the AND fusion rule in terms of M and N can also be expressed as

$$P_D^{AND}\ (M,N) = \begin{cases} \sum_{i=k-M}^{N} \binom{N}{i} P_d^i (P_d)^{N-i} & , \ M<K \\ 1 & \ \ M \geq K \end{cases} \tag{5.17}$$

$$P_F^{AND}\ (M,N) = \begin{cases} \sum_{i=k-M}^{N} \binom{N}{i} P_f^i \left(P_f\right)^{N-i} & , \ M<K \\ 1 & \ \ M \geq K \end{cases} \tag{5.18}$$

where K is denoted as the predefined threshold on the number of CRUs that detects the spectrum.. In equation 5.15 and 5.16, when $M\ \geq K$, the FC's final decision will be 1 and this is due to the fact that the FC will always receive a number that is larger than or equal to K reported by the malicious users. But when $M < K$, the lower bound summation will be decreased by M.

P_d^i and P_f^i are the probability of detection and false alarm respectively in the local spectrum sensing process of an i^{th} CRU in the cognitive radio network. This can be expressed as

$$p_d^i = p(D_{on}^i\,|\,H_1)\ , \tag{5.19}$$

and

$$p_f^i = p(D_{on}^i|H_0)\ , \tag{5.20}$$

where D_{on}^i indicates that the i^{th} CRU has decided that a primary user signal is present, $H_1$and H_0 indicates the presence and absence of a primary user signal respectively.

The effect of malicious users on the overall performance of the network can be seen in P_D and P_F. An increase in P_D creates a more efficient network while a decrease in P_F degrades the efficient usage of the unused spectrum. In formulating the effects of malicious users on the network's resources, we define the energy efficiency metric (μ) as the ratio of the total successfully transmitted bits to the total number of energy consumed by the legitimate CRUs. Data can only be successfully transmitted if the spectrum is vacant and no false alarm is reported, which results to non-zero efficiency. The average energy efficiency (μ) can be expressed as

$$\mu = \frac{P_0\,(1-P_F)RT}{E_{css} + e_t}, \tag{5.21}$$

where the factor $P_0\,(1-p_F)$ denotes the probability of no false alarm case, R represents the data rate in *bps*, T is the transmitted time, E_{css} is the energy consumed by all the legitimate CRUs during sensing and e_t is the energy transmitted by the scheduled CRU. From equation 5.21, an increase in the false alarm probability will lead to a decrease in the amount of successfully transmitted data which on the other hand lowers the energy efficiency.

5.4.2 Secured Energy Detection Based Cooperative Spectrum Sensing Mechanism

In order to reduce the effects of malicious users on a CRN and to boost the energy efficiency of the network, it is imperative to build a secured CSS which will help in this regard. This section presents a proposed energy efficient cooperative spectrum sensing method which will aid in increasing the detection of licensed signals in the targeted spectrum band.

Since a malicious user is present in the system to always report the presence of a licensed signal where there is actually none, then fake signals will be sent by a PUEA and received by other legitimate CRUs under H_0 only. So in the event of an attacker, only the probability of false alarm p_f^i will be affected. So involving the presence or absence of an attacker A_1 and A_0 respectively in equation 5.20, we then have

$$p_f^i = p\left(D_{\text{on}}^i \middle| A_0, H_0\right) p(A_0|H_0) + p\left(D_{\text{on}}^i \middle| A_1, H_0\right) p(A_1|\, H_0), \tag{5.22}$$

where $p(A_0|H_0)$ and $p(A_1|\, H_0)$ are conditional probabilities regarding the absence and presence of fake PUEA attacker signals which are related to the attacker strategy. Considering $p(A_0|H_0)$ and $p(A_1|\, H_0)$ as constant values, for simplicity of notations, we can denote them as

$$p(A_1|H_0) = \beta \,, \tag{5.23}$$

and

$$p(A_0|H_0) = 1 - p(A_1|H_0) = 1 - \beta \,, \tag{5.24}$$

where β denotes the presence of an attacker. We can therefore rewrite equation 5.22 as

$$p_f^i = p\left(D_{\text{on}}^i \middle| A_0, H_0\right)(1 - \beta) + p\left(D_{\text{on}}^i \middle| A_1, H_0\right)\beta. \tag{5.25}$$

5.4.2.1 Energy Detection Based Spectrum Sensing Technique

A local spectrum sensing is performed by the all the CRUs, both legitimate and malicious ($N + M$). It is assumed that every CRUs adopts the energy detection technique in which G samples of the energy y_i^k are summed up during a detection interval,

$$Y_i = \sum_{k=1}^{G} |y_i^k|^2 \tag{5.26}$$

Y_i is compared to a threshold which every CRUs decides locally about the presence and absence of a licensed user signal. The probability of detection and the probability of false alarm for an i^{th} CRU in energy detection can be written as:

$$p_d^i = p(Y_i \geq T_i | H_1) , \tag{5.27}$$

$$p_f^i = p(Y_i \geq T_i | H_0) , \tag{5.28}$$

where T_i is the threshold used in energy detector of the i^{th} CRU. Based on equation 5.26, Y_i in energy detection is sum of y_i^k squared of the CRU received signal. y_i^k is Gaussian random variable with zero mean and variance $\sigma_{j,i}^2$ under z_j, $j \in \{1, 2, 3\}$. So Y_i will be compliant with the central Chi-square (χ^2) distribution with $2G$ degrees of freedom and parameter $\sigma_{j,i}^2$.

$$Y_i = \begin{cases} \chi_{2M}^2 \ (\sigma_{1,i}^2) \,, & \text{under } z_1 = \{A_0, H_1\} \\ \chi_{2M}^2 \ (\sigma_{2,i}^2) \,, & \text{under } z_2 = \{A_1, H_0\} \\ \chi_{2M}^2 \ (\sigma_{3,i}^2) \,, & \text{under } z_3 = \{A_0, H_0\} \end{cases} \tag{5.29}$$

where z_1 is the possible outcome of the presence of a licensed user signal, z_2 is the presence of a malicious user (PUEA) signal and z_3 is the presence of none of the signals. In determining the analyzed cooperative spectrum sensing method used, we employ Neyman-Pearson criterion [126] to determine the probability of detection using energy detection based cooperative spectrum sensing. Neyman-Pearson technique provides a threshold for detection subject to a constant probability of false alarm p_f^i. Based on equation 5.22, we need the values of $p\left(D_{\text{on}}^i \middle| A_1, H_0\right)$ and $p\left(D_{\text{on}}^i \middle| A_0, H_0\right)$, which can be written in energy detection as

$$p\left(D_{\text{on}}^i \middle| A_1, H_0\right) = p(Y_i \geq T_i | A_1, H_0) \tag{5.30}$$

$$p\left(D_{\text{on}}^i \middle| A_0, H_0\right) = p(Y_i \geq T_i | A_0, H_0) \tag{5.31}$$

So we can now rewrite p_d^i in equation 5.19 for the energy detection based cooperative spectrum sensing as p_d^*

$$p_d^* = \frac{\Gamma(M, \frac{T_i}{\sigma_{1,i}^2})}{\Gamma(M)} , \tag{5.32}$$

where $\Gamma(.)$ and $\Gamma(.,.)$ are Gamma function and upper incomplete Gamma function [85], respectively. Equation 5.22 can also be written as p_f^*

$$p_f^* = \frac{\Gamma(M,\frac{T_i}{\sigma_{3,i}^2})}{\Gamma(M)}(1-\beta) + \frac{\Gamma(M,\frac{T_i}{\sigma_{2,i}^2})}{\Gamma(M)}\beta \,. \tag{5.33}$$

In Neyman-Pearson criterion, it is shown that for a given probability of false alarm, the optimal threshold which maximizes the probability of detection can be obtained if the given probability of false alarm is the actual considered probability of false alarm.

The probability of detection P_D^{imp} and the probability of false alarm P_F^{imp} based on our improved mechanism for both the OR and AND fusion rules are reformulated respectively, as follows

$$P_D^{OR^{imp}} = \sum_{j=0}^{M}\binom{M}{j} p_d^{j^*}(1-p_d^*)^{M-j} \quad P_D^{OR}(j,N) \tag{5.34}$$

$$P_F^{OR^{imp}} = \sum_{j=0}^{M}\binom{M}{j} p_f^{j^*}\left(1-p_f^*\right)^{M-j} \quad P_F^{OR}(j,N) \tag{5.35}$$

$$P_D^{AND^{imp}} = \sum_{j=0}^{M}\binom{M}{j} p_d^{j^*}(p_d^*)^{M-j} \quad P_D^{AND}(j,N) \tag{5.36}$$

$$P_F^{AND^{imp}} = \sum_{j=0}^{M}\binom{M}{j} p_f^{j^*}(p_f^*)^{M-j} \quad P_F^{AND}(j,N) \tag{5.37}$$

where $P_D(j,N)$ and $P_F(j,N)$ can easily be deduced by substituting M with j in equations 5.15 – 5.18 respectively.

In the same manner, the achievable energy efficiency in our improved secure CSS (μ^{imp}) can be re-written as

$$\mu^{imp} = \frac{P_0\left(1-P_F^{imp}\right)RT}{E_{CSS}^{imp}+e_t}\,, \tag{5.39}$$

where $E_{CSS}^{imp} = N_{e_s} + N_{e_r}$, e_s is the energy consumption of a CRU during the local spectrum sensing and e_r is the energy that is required to report its spectrum occupancy information to the FC.

5.4.3 Simulation Results and Discussion

In this section, we aim at evaluating the energy efficiency performance of the developed secured energy detection based cooperative spectrum sensing technique. The proposed techniques are implemented in MATLAB for evaluation and comparison with the normal cooperative spectrum sensing technique. We implemented the simulations on a cognitive radio network consisting of

10 legitimate users(N). The simulation parameters used as regards the network specification are given in table 5-2 below

Table 5-3 Simulation Parameters

Parameters	**Value**
P_0	0.5
p_d	0.8
p_f	0.2
T	0.3
R	100Kbps
e_r	2×10^{-3} $Joule$
e_s	10^{-2} $Joule$
e_t	1 $Joule$

Figure 5-7 shows the effects of malicious users on the energy efficiency of a cognitive radio network. The attainable energy efficiency is plotted against the number of malicious users in the system. It is evident that as the malicious users continue to increase in the network, the energy efficiency decreases. It can be observed that there is higher energy efficiency with the proposed energy detection based cooperative spectrum sensing technique in both the AND and OR fusion rules than the normal cooperative spectrum sensing technique employing the OR rule [29]. That is to say that there is an improvement in the energy efficiency achieved by the proposed secure algorithm in both rules over the normal cooperative spectrum sensing protocol. This is so because the proposed secure algorithm takes into consideration the presence of an attacker in the cooperative spectrum sensing process hence the probability of detection and the probability of false alarm is improved both in the AND rule and OR rule leading to a higher energy efficiency in the network.

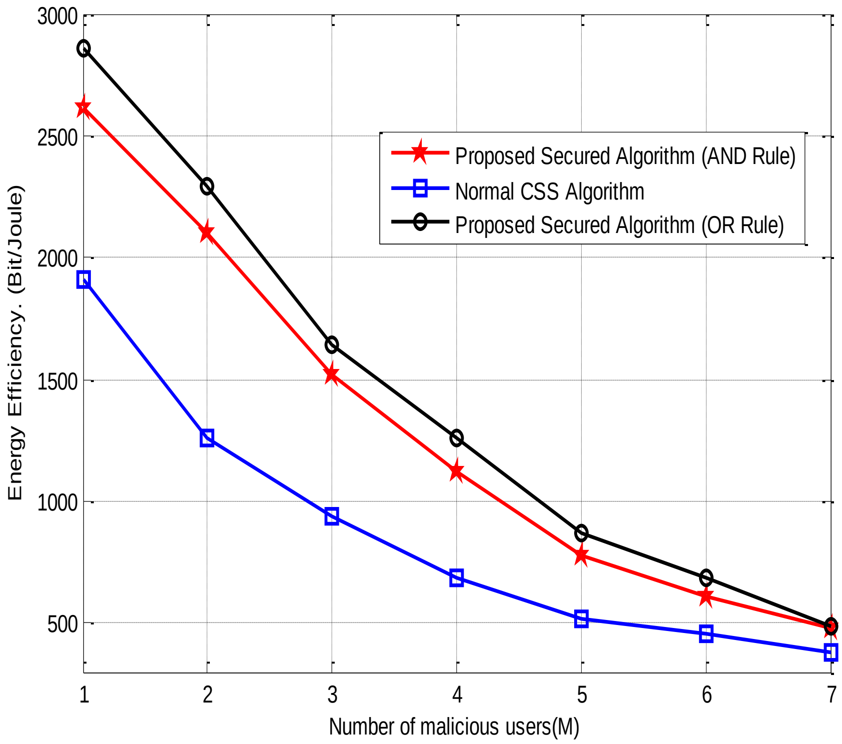

Figure 5-7: The achievable energy efficiency (μ) against the number of malicious users in a cognitive radio network for the normal and proposed secured CSS algorithm.

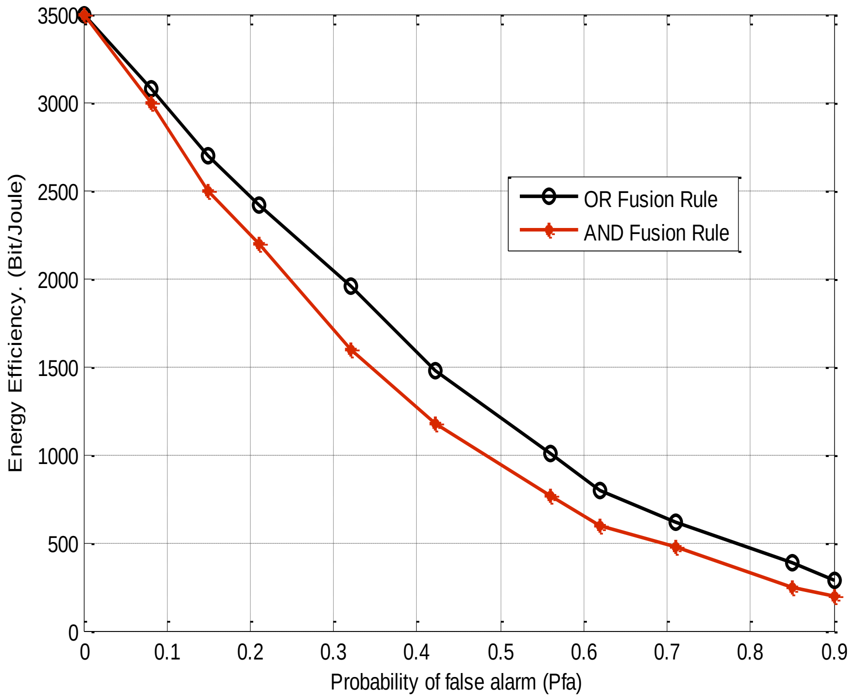

Fig. 5-8: The achievable energy efficiency (μ) against the probability of false alarm in a cognitive network for the proposed secured CSS algorithm in the OR and AND Fusion rules.

The results in Figure 5-8 shows the performance of the AND and OR fusion rules of the proposed secured energy detection based cooperative spectrum sensing technique. The energy efficiency achieved is plotted against the probability of false alarm. As the probability of false alarm increases, the energy efficiency of the network also decreases. It is certain that the increase in the probability of false alarm is caused by malicious CRUs taking wrong spectrum occupancy decisions thereby affecting the number of legitimate users in the network. The result shows that there is a better performance of the OR fusion rule over the AND fusion rule. This is due to the fact that in the AND rule, the presence of the primary user is declared by the FC only when all the secondary users detect the primary signal in the network which will eventually lead to poor energy efficiency in the network. Unlike the OR rule, primary user signal is detected when at least one of the secondary users detect the primary signal hence leading to a higher energy efficiency in the network.

5.5 Chapter Summary

In this chapter, an investigation into the total energy consumption of secondary users in a cognitive radio network is carried out by presenting an analysis of energy consumption in the different states or activities of secondary users in the network. Results of this analysis revealed that the number of secondary users in the network and the time taken to scan the channels has an effect on the energy consumption of the network. Also in this chapter, the effects of secondary users that have turned malicious on the cognitive radio network's energy efficiency is studied. A secured energy detection based cooperative spectrum sensing technique is developed to strengthen the security of the spectrum sensing process of cognitive radio users in the network where the final decision about the spectrum occupancy is taken by a fusion center employing fusion rules. In carrying out this, the energy efficiency of the network is also boosted. Simulation results show that malicious users has a great impact on the energy efficiency of the network and our developed secured technique has a significant improvement on the attainable energy efficiency when compared to the normal cooperative spectrum sensing technique.

CHAPTER SIX

IMPROVING ENERGY EFFICIENCY IN THE SPECTRUM SENSING PROCESS OF A COGNITIVE RADIO NETWORK

6.0 Objective

The main objective of this chapter is to improve the energy efficiency in the spectrum sensing process of a cognitive radio network. This is achieved by proposing a 2-step energy efficient cooperative spectrum sensing technique which will address the problem of energy efficiency in the local sensing stage of the network.

6.1 Introduction

Due to a steady increase in the scarcity of spectrum resources, most communication bodies like the Federal Communications Commission (FCC) and the office of communications (OFCOM), agencies responsible for regulating interstate and international communications have permitted unlicensed secondary users to utilize the licensed spectrum when not in use by the primary or licensed user. Cognitive radio technology, has been employed for this purpose and has proven to be a long lasting solution to the issue of spectrum shortage and scarcity. Cognitive radio (CR) carries out a spectrum sensing process for the main objective of identifying fallow or vacant spectral bands for communication. In this spectrum sensing process [5][18][127], secondary users also known as the unlicensed users observe the frequency spectral band and sense the available or vacant bands for communication while simultaneously maintaining the interference to the primary below an acceptable threshold.

However, major challenges limits the operation of spectrum sensing processes in cognitive radio. A key challenge is that the sensed signal received from the cognitive radio may tend to deteriorate due to attenuation caused by multipath fading or shadowing and any other impairment. Due to these challenges, secondary users may identify an occupied spectrum band as vacant and transmit in this band thereby causing unwanted interference in the system. To overcome this challenge, cooperative spectrum sensing can be performed in which multiple cognitive radio users can cooperatively perform successful spectrum sensing with each other so as to also increase detectability. Cooperative spectrum sensing enables each cognitive radio users to conduct local spectrum sensing process independently and forward its binary decisions about the availability of the spectrum to a fusion center (FC) for fusion of all the binary decisions from the unlicensed users in order to make a final decision.

In a typical cognitive radio networks (CRNs), the cooperative spectrum sensing process has proven to lead to a more accurate detection of primary signals and yield better spectrum sensing results [28][29]. However, from an energy efficiency view point, the energy consumption of cooperating spectrum sensing process is relatively higher than that of the normal spectrum sensing process. This is because more secondary users take part in the spectrum sensing process hence more energy is dissipated thereby constraining the application of the sensing process. Therefore, a cooperative spectrum sensing process that is energy efficient is however needed in cognitive radio networks so as to ensure a better detection of spectrum bands.

6.2 Related Works on Cooperative Spectrum sensing Energy Efficiency

In recent times, there has been some substantial amount of research aimed at reducing the energy consumption of cooperative spectrum sensing. Two possible ways in which energy efficiency can be maximized in the spectrum sensing process of a cognitive radio network is to reduce the overall energy that is being consumed by the local spectrum sensing process and also to minimize the energy used in reporting these local sensing results to the FC. In the vain of decreasing the total energy consumed in the local spectrum sensing process, Althinubat et al in [58] proposed a simple algorithm to reduce secondary users participating in the spectrum sensing in order to maximize energy efficiency in the network. Peh et al [128] evaluated an optimal fusion rule and an optimal energy detector threshold so as to decrease sensing time and maximize energy efficiency. Sun et al [129] presented a technique to accurately apportion secondary users to sense different frequency bands based on their channel conditions so that the energy consumption in the network can be minimized. Also, an optimal policy for choosing cognitive radio nodes in carrying out spectrum sensing in the different time slots was evaluated by Sodagri and Bilen [130] where an efficient solution was proposed to solve the issue of power optimization in cooperative spectrum sensing so as to increase network lifetime.

Zhang and Tsang [131], Feng et al [132] and Chatterjee et al [133] studied and presented optimal sensing time methods in a cooperative spectrum sensing process of a cognitive radio network so as to reduce the energy expended in the network. In a view to reducing the energy consumed in reporting spectrum sensing results, Bai et al [62], De Nardis et al [63] and Rasheed et al [64] developed a clustered type of cooperative spectrum sensing technique. In each cluster, secondary users are meant to forward their spectrum sensing results to a cluster controller. This cluster controller then merges these results together and forwards it to the fusion center so that energy efficiency in reporting spectrum sensing information can be maximized.

In most of these highlighted techniques, a selection of secondary users undergo spectrum sensing in each of the time slots and this often cause unnecessary and unwanted energy consumption. It is however imperative that there should be an improvement in the energy efficiency of the network while simultaneously retaining the sensing accuracy of the spectrum sensing process. An efficient 2-step cooperative spectrum sensing approach (2SCSS) is developed in this chapter to address the problem of energy efficiency in the local spectrum sensing operation of a cognitive radio network. The local spectrum sensing process is however shared into two-steps and the proposed 2SCSS technique will put the sensing to a halt in the first step only when the sensed channel is not vacant. The system model of the network is given below.

6.3 System Model

Considering a cognitive radio network (CRN) consisting of N number of secondary or cognitive radio users and a fusion center with the secondary users partitioned into two groups. We denoted M as the number of secondary users in the first group and denote $N - M$ as the number of secondary users in the second group. The secondary users in the network employs energy detection for their local spectrum sensing process. The detection probability for each of the secondary users is represented with p_d while that of the probability of false alarm is p_f. For the individual secondary user sensing results to be processed, a fusion center is introduced which uses the *K-out-of-N* logic fusion rule to make its final decisions in the cooperative spectrum sensing process. The detection probability and the probability of false alarm in the cooperative spectrum sensing process is given as P_F and P_D respectively.

In our proposed energy efficient 2SCSS technique, the second step of sensing which is carried out by the $N - M$ secondary users is mainly dependent on the outcome of the decision made by the FC at the first step of sensing so that energy can be conserved in the spectrum sensing process. Figure 6-1 shows the cognitive frame structure of the energy efficient 2SCSS technique where T is regarded as the total time length of the frame, T_s is denoted as the sensing time, T_r as the reporting time and T_x as the transmission/waiting time. During T_s, secondary users can carry out spectrum sensing and their sensing results reported to the FC for a decision during the T_r time frame. In T_x, when a vacant channel is sensed, a secondary user may utilize this channel for its transmission, otherwise the secondary users will have to wait until the beginning of the next frame.

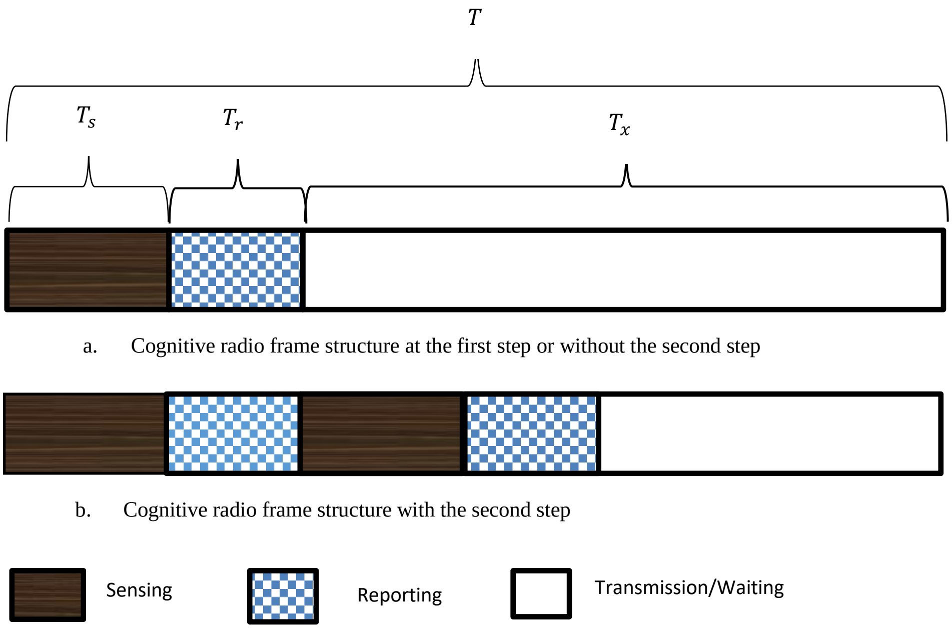

Figure 6-1: Cognitive frame structure of our proposed method

6.3.1 Problem Formation

In a cooperative spectrum sensing environment of a CRN, much energy is consumed in the sensing, reporting and transmission processes. The energy used in the sensing and reporting process is a function of the how many of secondary users are participating in the cooperative spectrum sensing process. So for every secondary user, the energy dissipated in sensing is represented as E_{sense} while the energy dissipated in reporting is represented as E_{rep}. When an idle channel is sensed, a secondary user may utilize it in transmitting its own data with a transmitting energy of E_{trans}. The transmitting energy is a product of the transmission time and the transmission power. The average energy consumption E for the cooperative spectrum sensing process is therefore represented as

$$E = mE_{sense} + mE_{rep} + (1 - P(H_0)P_f - P(H_1)P_d)E_{trans} , \quad (6.1)$$

where m denotes the number of secondary users participating in the sensing process. $P(H_0)$ is represented as the probability that the sensed channel is vacant and $P(H_1) = 1 - P(H_0)$ is represented as the probability that the channel sensed is not vacant.

When a licensed user is not transmitting in a channel or when a channel is sensed as vacant and it is truly vacant (i.e with no occurring false alarm), a secondary user can favourably transmit in that channel. The transmission gain can therefore be related to the type of the sensing result and the channel state. Hence, the average transmission gain *G* for the duration of a transmission frame can then be represented as

$$G = RT_T P(H_0)(1 - P_f), \tag{6.2}$$

where T_T is the transmission time and Q is denoted as the revenue in throughput per unit time and is given as

$$Q = log_2(1 + SNR_s), \tag{6.3}$$

where SNR_s is the signal to noise ratio when a secondary user is transmitting.

The utility function which considers the energy consumption and transmission gain can now be represented as

$$\mu = \frac{G}{E} = \frac{QT_T P(H_0)(1-P_f)}{mE_{sense}+mE_{rep}+(1-P(H_0)P_f-P(H_1)P_d)E_{trans}}\,. \tag{6.4}$$

In the cooperative spectrum sensing process of the network, the utility function is used as the metric for the energy efficiency of the network.

6.4 Analysis of the 2SCSS Technique

For the energy efficiency of the local spectrum sensing process of a CRN to be improved while the sensing performance and transmission gain is considered, a 2-step cooperative spectrum sensing (2SCSS) technique is developed. This technique is proposed to maximize the utility function given in equation 6.4 while guarantying an acceptable sensing performance. The energy efficiency scheme of our technique is however outlined below.

First of all, all secondary users in the network, *N* are divided into two groups, SU^1 and SU^2 representing the first and second group respectively. SU^1 contains *M* number of secondary users while SU^2 contains *N-M* number of secondary users and the sensing process is also split into two steps. It is assumed that the FC employs the *K-out-of-N* rule in making decisions at first and second steps. Also, *K1* and *K2* are set as the fusion threshold of both steps respectively.

6.4.1 First Sensing Step

For this first sensing step, only the secondary users in SU^1 perform energy detection and the sensing results are reported to the FC. A decision is then made by the FC based on the spectrum sensing results received. If the FC decides that the channel is not vacant, then the first sensing step of the 2SCSS technique halts and the channel is however taken as occupied. In this first stage, the detection probability $P_{d,1}$ and the probability of false alarm $P_{f,1}$ can both be represented as

$$P_{d,1} = \sum_{j=K_1}^{M} \binom{M}{j} p_d^j (1-p_d)^{M-j}, \tag{6.5}$$

$$P_{f,1} = \sum_{j=K_1}^{M} \binom{M}{j} p_f^j (1-p_f)^{M-j}. \tag{6.6}$$

The average energy consumed at this first stage E_{1a} is given as

$$E_{1a} = (MP_{sense}\lambda + MP_{trans}\rho)\big(P(H_1)P_{d,1} + P(H_0)P_{f,1}\big), \tag{6.7}$$

where λ and ρ are regarded as the sensing time and reporting time of the individual secondary users respectively while P_{sense} is denoted as the sensing power and P_{trans} is denoted as the transmission power.

6.4.2 Second Sensing Step

In this second sensing step, if the FC decides that the channel is idle or vacant in the first sensing step, then the second sensing step is carried out and the secondary users in SU^2 performs energy detection and the sensing results is reported afterwards. This time, the FC declares a final decision based on the spectrum sensing results of all the secondary users in SU^1 and SU^2. This result is seen as the sensing result for the 2SCSS process. The detection probability and the probability of false alarm of this stage can both be represented as

$$P_{d,2} = \sum_{j=0}^{K1-1} \binom{M}{j} p_d^j (1-p_d)^{M-j} \sum_{i=k2-j}^{N-M} \binom{N-M}{i} p_d^i (1-p_d)^{N-M-i}, \tag{6.8}$$

$$P_{f,2} = \sum_{j=0}^{K1-1} \binom{M}{j} p_f^j (1-p_f)^{M-j} \sum_{i=k2-j}^{N-M} \binom{N-M}{i} p_f^i (1-p_f)^{N-M-i}. \tag{6.9}$$

If the FC declares that the channel is occupied, then the average energy consumption is denoted as

$$E_{2a} = (NP_{sense}\lambda + NP_{trans}\rho)(P(H_1)(1-P_{d,1})P_{d,2} + P(H_0)(1-P_{f,1})P_{f,2}. \tag{6.10}$$

If the FC declares that the channel is idle, a secondary user may utilize the channel for transmission and the average energy consumption will be denoted as

$$E_{2b} = (NP_{sense}\lambda + NP_{trans}\rho + P_{trans}T_{trans})(P(H_1)(1 - P_{d,1})(1 - P_{d,2}) + P(H_0)(1 - P_{f,1})(1 - P_{f,2}). \tag{6.11}$$

Therefore, the overall energy consumption of the 2SCSS can be represented as

$$E_T = E_{1a} + E_{2a} + E_{2b}. \tag{6.12}$$

6.4.3 Optimizing Energy Efficiency

The energy utility function which was is expressed in equation 6.4 can now be re-written as

$$\mu = \frac{QT_T P(H_0)(1-P_f)}{E_{1a}+ E_{2a}+ E_{2b}}, \tag{6.13}$$

where the detection probability is now $P_d = P_{d,1} + P_{d,2}$ and the probability of false alarm is now $P_f = P_{f,1} + P_{f,2}$.

However, the energy utility function which can also be regarded as the energy efficiency performance index can be maximized in order to achieve a balance point between the energy consumption and the average throughput. The optimization problem that needs to be maximized can be expressed as

$$\begin{aligned} &\boldsymbol{max} && \mu \\ &s.t && P_f \le \overline{P_f} \\ & && P_d \ge \overline{P_d} \\ & && M \le N \end{aligned} \tag{6.14}$$

The optimization problem in equation 6.14 belongs to the class of non-linear integer programming problems which can be very cumbersome to solve. Hence an algorithm called Simulated Annealing (SA) algorithm is however employed to find a suboptimal solution to the maximization problem [134].

6.5 Simulated Annealing Algorithm

The Simulated Annealing (SA) algorithm is a very reliable method for solving hard combinatorial optimization and deterministic problems. It is an optimization technique that derived its name based on the analogy to a physical system that has to do with the annealing process of solids. When the solids are heated and then allowed to cool down, its molecules reaches a low energy state, the solid in this state will be free from defects. In the high energy state, the molecules are can move freely while their freedom is restricted as the temperature reduces. Similarly, the SA algorithm allows "*hill climbing*" when the temperature is high, in this way, those points that are in proximity to the search point but have a higher utility function value can still be selected with a certain probability. Hence the simulated annealing algorithm is a powerful technique in locating the global optimum solution. In this section, we will use the SA algorithm to solve equation 6.14 The algorithm starts by picking any random variable x_i from the solution space using the equation

$$x_i = x_{i,min} + (x_{i,max} - x_{i,min})\boldsymbol{v}_i, \tag{6.15}$$

where $x_{i,min}$ and $x_{i,max}$ denoting the bounds of the variable, $\boldsymbol{v}_i$ is a uniform random number between [0,1]. The energy state for the variable which is given by the value of its utility function is expressed as

$$E_{old} = c^1, \tag{6.16}$$

A candidate solution x_{i+1} is generated by perturbing x_i in its neighbourhood. The perturbation $\Delta\boldsymbol{x}_i$ can however be computed as

$$\Delta\boldsymbol{x}_i = \varphi\boldsymbol{x}_i\boldsymbol{v}_i, \tag{6.17}$$

where φ is a small number fixed at the start of the simulation. A unique characteristic of SA is that it accepts not only the best solutions but also solutions with a certain probability in order to escape local optimal points. The next search point is therefore expressed as

$$x_{i+1} = x_i + \Delta\boldsymbol{x}_i. \tag{6.18}$$

If the variables x_{i+1}exceed their bounds, they are artificially brought back into the feasible bound using the equation

$$x_{i+1} = x_{i,min} + (x_{i,max} - x_{i,min})\boldsymbol{v}_i, \tag{6.19}$$

The energy state of the new point is given as

$$E_{new} = c^2. \tag{6.20}$$

If the new energy state c^2 is greater than c^1, the utility function has improved and the values of c^1 is replaced with c^2. The transition probability a of accepting a best solution is expressed as

$$a = e^{\frac{-(c^1 - c^2)}{T_k}}, \tag{6.21}$$

where T_k is the temperature at time or iteration k and I is the number of iterations needed to find the global optimum solution. In each iteration, the transition probability is compared with the uniform random number *v* on the range [0, 1]. If the transition probability value is greater or equal to *v,* then "*hill climbing*" is allowed and the best solution is accepted, otherwise it is rejected. If rejected, another solution within the bounds will be generated and evaluated. The duration for each temperature level determines the number of iterations at a certain temperature where the temperature decreases during the search according to the cooling schedule. The iterations are repeated until there is no more improvement in the utility function value. The algorithm employs a cooling schedule with a constant decay parameter ϱ that is chosen to suit the specific problem where $0 < \varrho < 1.0$. The process for solving for the best solution in equation 6.14 is given in the algorithm.

Optimizing Energy Efficiency with SA Algorithm

Step 1: Initialize parameters and bounds. Determine initial temperature $T_{initial}$.

$T_k = T_{initial}$

Step 2: Do while $T_k > T_{pause}$, where T_{pause} is the stopping temperature.

Set $i = 1$;

Step 3: For $i < I$, where I is the length of inside loop in which the temperature remains constant.

Step 4: Compute $E_{old} = c^1$

Step 5: Compute equation 6.17 and 6.18

If x_{i+1} exceeds bounds then compute equation 6.19.

Step 6: Compute $E_{old} = c^2$

Step 7: Calculate $\Delta c = c^2 - c^1$

Step 8: If $\Delta c < 0$

Then goto Step 10

Else randomly generate $\boldsymbol{v} = Uniform[0,1]$

Step 9: If $\boldsymbol{v} < a$

Then goto Step 10

Else reject

Set $i = i + 1$

Back to Step 3

Step 10: accept c^2

Set $i = i + 1$ and **goto Step 3**

Step 11: Set $T_{k+1} = \varrho . T_k$ and **goto step 2** until function not improving.

6.6 Simulation Results and Discussion

This section of the chapter provides the simulation results of our developed energy efficient 2-step cooperative spectrum sensing (2SCSS) technique and then compared to that of a normal single step cooperative spectrum sensing (SSCSS) as it relates to the energy efficiency. We assume that the fusion center employs the *K-out-of-N* fusion rule for fusion and also that the same fusion threshold is used for both the SSCSS and the second sensing step of our 2SCSS technique. For the SA algorithm employed, we chose $T_{initial}$ and T_{pause} such that the probability of accepting a *"hill climb"* equal to one-tenth of the range of possible c values are equal to 0.9 and 0.001 respectively. The other main parameter values for the simulation are detailed in table 6-1 below.

Table 6-1: List of Parameters for Simulation

Parameter	**Value**
Number of secondary users	20
P_{sense}	0.2W
P_{trans}	4W
Sampling frequency f_s	7MHz
Fusion Threshold for 2nd stage (*K2)*	12
Maximum probability of false alarm	0.1
Minimum probability of detection	0.9

In figure 6-2, the achievable energy efficiency of the secondary users in a CRN is plotted against the sensing time for both the single step cooperative spectrum sensing technique and our developed 2-step cooperative spectrum sensing technique. The figure shows that the 2SCSS outperforms the SSCSS delivering a better energy efficiency. This is due to the fact the average energy consumed in the 2SCSS is lesser than that of the SSCSS. In the 2SCSS technique, only *M* SUs perform spectrum sensing and also halt when the channel is occupied while the other SUs do not need to perform spectrum sensing in that period hence the energy consumption of our proposed sensing method is reduced. In the SSCSS technique, all the SUs are required to perform spectrum sensing regardless whether the channel is occupied or not thereby leading to more energy consumption in the network. It is also seen that the quicker the secondary users in sensing the spectrum, the higher the energy efficiency of the network which has better energy efficiency at 20 dB. With a longer sensing time, the energy efficiency decreases due to loss of throughput gain.

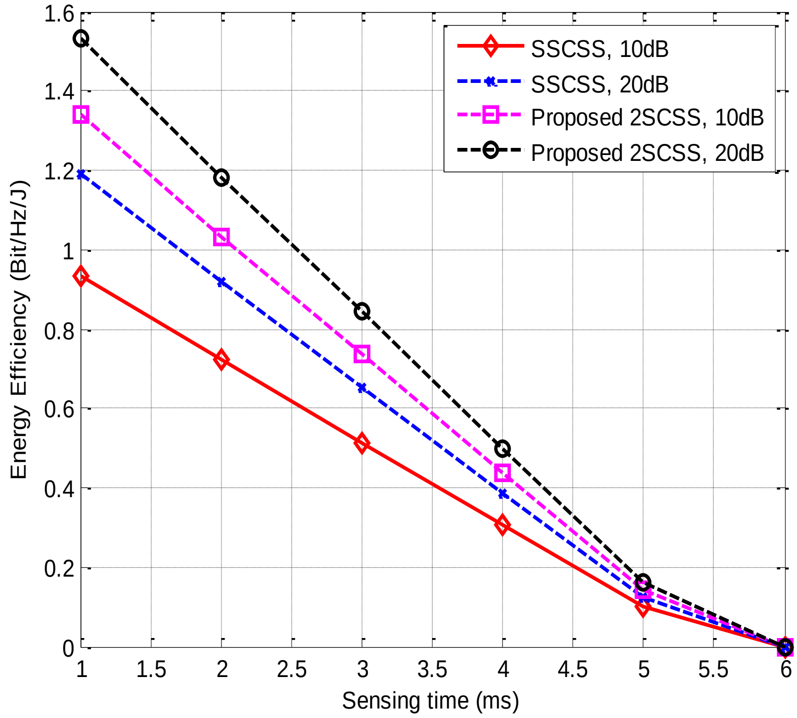

Figure 6-2: Achievable energy efficiency against the sensing time for the SSCSS and 2SCSS techniques

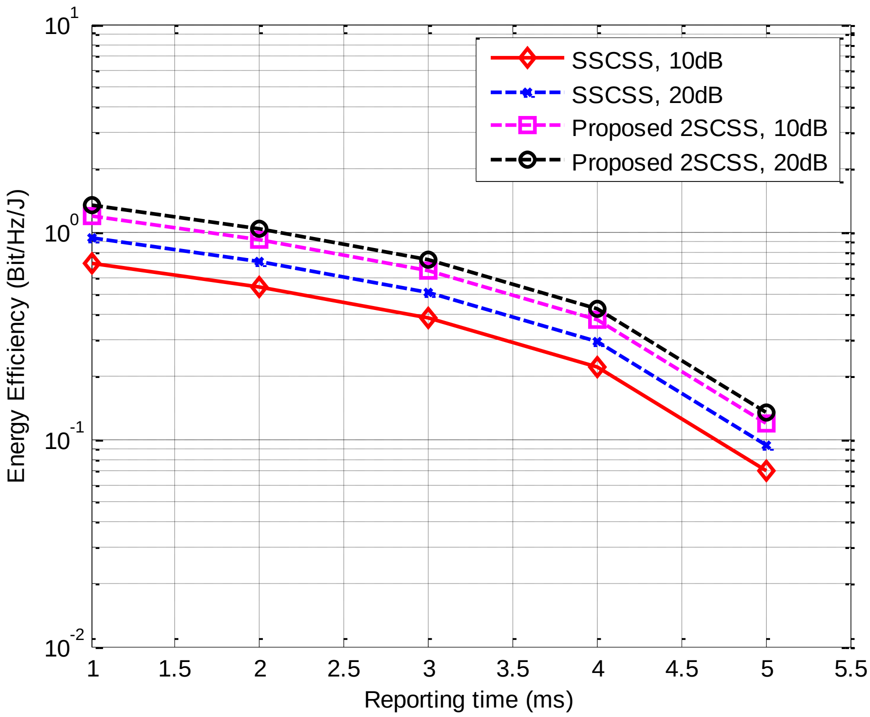

Figure 6-3: Achievable energy efficiency against the reporting time for the SSCSS and 2SCSS techniques

Also in figure 6-3, we illustrate the achievable energy efficiency of the secondary users in a CRN at different secondary users' reporting time. From the figure, we can notice that there is an improvement in the achievable energy efficiency in the network at different reporting times for the 2SCSS technique under different SNR values when compared to the single step cooperative spectrum sensing technique. This is due to the fact that the same number of SU involved in the spectrum sensing process will also participate in the reporting process. In the 2SCSS technique, lesser number of secondary users are involved in reporting the already sensed spectrum which gives rise to an increase the energy efficiency of the network with lesser time. Unlike the SSCSS technique, all the secondary users are involved in the reporting process thereby leading to a higher energy efficiency in the network as seen in figure 6-3. It is also obvious that as the reporting time increases or as the secondary users spend more time in reporting, the energy efficiency of the network decreases.

6.7 Chapter Summary

Secondary users in a cognitive radio network (CRN) can successfully carry out a spectrum sensing process to detect vacant or idle frequency bands for communication. In carrying out this process, the energy consumption in the network increases and the energy efficiency of the network is thereby compromised.

In this chapter, an energy efficient 2-step cooperative spectrum sensing (2SCSS) technique in CRNs is developed to successfully perform secondary user spectrum sensing in the vain of increasing the energy efficiency in the network. The spectrum sensing of the developed technique is split into two steps and the spectrum sensing is put to a halt at the first sensing step only if the FC decides that the channel is not vacant while the second sensing step is carried out if the channel is sensed as vacant so as to maintain a high sensing accuracy in the network. The energy consumed by our developed technique was analysed and results presented show that the employment of the 2SCSS technique can successfully yield better energy efficiency in the network.

CHAPTER SEVEN

CONCLUSION AND FUTURE WORKS

7.1 Conclusions

Recently, technologies and innovations in wireless radio networks are continuously gaining significant progress and improvements. Due to this, the demand and competition for access to the electromagnetic spectrum for communication has substantively increased thereby making the electromagnetic spectrum scarce and unavailable. With this problem at hand, wireless technologies needs to cooperate with each other and share the electromagnetic spectrum in a non-interfering manner for beneficial and useful communication. In an effort to extinguishing the problem, most regulatory bodies like the Federal Communications Commission (FCC), European Telecommunications Standard Institute (ETSI) in Europe and Australian Communications and Media Authority (ACMA) in Australia have decided to allow secondary unlicensed users to take advantage of the opportunity of using vacant spectral bands not in use by a primary licensed user at a specific time and location. This can however be achieved by the employment of cognitive radio.

The major functions a cognitive radio possesses are the abilities to monitor accessible spectral bands, capture their information and automatically identify which spectrum is vacant. This process of determining which spectral bands are vacant for possible communication can be achieved by a spectrum sensing process employed by cognitive radio users in a cognitive radio network. Since cognitive radio is involved in a lot of functionalities to ensure effective utilization of vacant spectrum bands, a lot of energy is being expended to perform its required tasks. When compared to a conventional wireless network, the cognitive radio possesses new and extra technologies which eventually give rise to additional energy consumption in the network. In the comprehensive research work that have been carried out, we investigated the amount of energy consumed by cognitive radio users in the network and develop alternative techniques to improve the already energy constrained network. This will help in eliminating unnecessary sources of energy consumption in the network and also providing a better energy efficient network which in turn will enhance the overall network throughput.

In chapter 2, the concept of cognitive radio network was presented and the architecture and basic function were studied. The major spectrum sensing techniques used by cognitive radio in sensing a spectrum was also examined. The importance of energy efficiency in cognitive radio networks and various sources of energy consumption in the network were also outlined. The major trade-offs for ensuring an energy efficient network was also examined. Energy efficient approaches that exist in cognitive radio base stations, in the network organisation, in the spectrum sensing process and other areas available in literature were also discussed. Other area of importance that is related to the theoretical foundation of this work was also discussed.

In other to accurately access the energy efficiency of a cognitive radio network, in chapter 3, standardized metrics for analysing energy efficiency in the network was studied. An analysis for energy efficiency metrics of the network in respect to its design and operation was discussed. Energy efficiency metrics was broken and analysed in three different levels which are the component metrics, equipment metrics and the network metrics. Cognitive radio performance metrics which encompasses the probability of false alarm, probability of detection and probability of misdetection where also studied as a good measure of sensing performance in cognitive radio networks. Establishing a comprehensive metric for evaluating and measure energy efficiency in cognitive radio networks is a crucial step to achieving an energy efficient cognitive radio network.

It has been perceived in literature that base stations are responsible for a greater percentage of the energy consumed in a network [88-90]. In an attempt to tackle this, a sleep mode scheme for base stations in a cognitive radio network was introduced which puts unnecessary base station to sleep at different traffic load variations. Based on the results, the sleep scheme delivers a better energy efficiency savings in the base stations of cognitive radio networks.

Also, in a way of ensuring an energy efficient cognitive radio network, massive MIMO technique and small cells technique were introduced into the network organisation of the network to boost its performance. A cognitive radio network with massive MIMO employed at the macro base station and small cells overlaid around the network was considered. An energy efficiency problem was formulated and Dinklebach method was used to optimize the problem. The resulting optimal solution is taken as the optimal link between the CR and the base station. Based on our results, the total power consumption can be significantly improved by adding more antennas to the base stations. Also, the energy efficiency of the network is greatly enhanced when an optimal base station is selected for transmission.

In chapter 5, the amount of energy consumption by secondary users in a cognitive radio network was examined. The energy consumed at each stage of the secondary user's activity in the network was analysed. The numerical results revealed that the number of secondary users in the network and also the time taken to scan for channels for communication in the network has an effect on the energy consumption of the network. Also in this chapter, the effects of malicious secondary users on the network's energy efficiency were also detailed. A secured energy detection based cooperative spectrum sensing technique was developed to boost the security of the spectrum sensing process of the network. In doing this, malicious users' impact on the network's energy efficiency was reduced. Based on results obtained, the developed technique was seen to have a significant improvement on the attainable energy efficiency of the network when compared to the regular cooperative spectrum sensing technique which has no secured mechanism. Also from the fusion rules employed by the fusion center for decision making, the OR fusion rule is seen to yield more energy efficiency than the AND rule.

The spectrum sensing process often carried out by cognitive radio users to detect vacant spectral bands often lead to a high energy consumption in a cognitive radio network. In chapter 6, an energy efficient cooperative spectrum sensing technique was proposed. The aim of this technique was for cognitive radio users to successfully perform spectrum sensing in an energy efficient manner. The spectrum sensing process of the proposed technique is split into two steps and spectrum sensing is put to a halt at the first step only if the FC decides that the channel is not vacant. The second step of the spectrum sensing process is performed if the channel is sensed as vacant. Simulated annealing algorithm was employed to optimize the energy efficiency of the technique. The energy consumed by the developed cooperative spectrum sensing technique was analysed and results presented indicated that there is an improvement in the energy efficiency of the network when the technique is employed.

7.2 Future Works

This research work focused on possible ways in improving energy efficiency in cognitive radio networks. However, the concept of energy efficiency in cognitive radio networks is relatively new and there is still much work to do in this regard. The other areas of possible research that maybe explored may include the following.

- In chapter 2, spectrum sensing techniques in cognitive radio networks was briefly discussed. Spectrum sensing is indeed a very complicated problem that demands coordinated efforts from both the regulatory and technical sides which makes it relatively uneasy for cognitive radio users' successfully implementation. While a lot of research have been undergone on the functionality of the process, less attention has been given to its implementation. Therefore, an important aspect for further research can possibly be looking at modalities and avenues in which spectrum sensing can be successfully implemented and thus still meeting the stringent regulatory requirements.

- In chapter 3, a cognitive radio performance metric was presented. It was assumed that the channel used in sensing is not dependent on time. This however might not be possible in practice. In examining cognitive radio performance metric, further work can be carried out without the assumption that sensing is time-invariant.

- In most of the model in this thesis, it was assumed that the secondary users have a perfect knowledge of the channel state information. In chapter 4, it was also assumed that there exists a backhaul network that supports interference coordination. More work can be carried out on the case where there are different channel estimation errors. Possible ways in which circuit power can be reduced to improve energy efficiency can also be a subject of interest. Energy efficiency can also be evaluated in the network without compromising the quality of service constraints and also putting into consideration fairness between cognitive radio users in the system.

- In chapter 5, channel conditions were not taken into consideration when selecting channels for communication. In future works, the channel conditions can be considered and also exploring other channel scanning schemes and also optimization of the total energy consumed by users in the network. This should create further avenues to investigate other energy related issues in the network and also other implications of the techniques used by secondary users in the network.

- In chapter 6, Simulated Annealing (SA) has been employed in optimizing the energy efficiency of the network. As part of future work, there is a need to compare this method with swarm intelligence based techniques such as Particle Swarm Optimization [140] and Evolutionary Computation based Techniques such as Differential Evolution [141].

- Further investigation can be carried out on finding other possible ways in which the energy consumption in a cognitive radio network can be reduced and also the energy efficiency of the network can be boosted.

- The incorporation of this work into a physical cognitive radio testbed or a cognitive radio simulator can also be undertaken in future works.

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APPENDICES

APPENDIX A: Derivation of p_d and p_f

The probability of detection and the probability of false alarm for a given threshold are represented in by

$$P_d = P(Y > \xi | H_1) \tag{A.1}$$

$$P_f = P(Y > \xi | H_0) \tag{A.2}$$

where ξ is the decision threshold, expressing P_d and P_f in terms of the probability density function from [97],

$$fY(y) = \begin{cases} \frac{1}{2^v \Gamma(\mathrm{v})} y^{v-1} e^{-\frac{y}{2}}, \\ \frac{1}{2}\left(\frac{y}{\varsigma}\right)^{\frac{v-1}{2}} e^{-\frac{\varsigma+y}{2}} I_{d-1}\left(\sqrt{\varsigma y}\right). \end{cases} \tag{A.3}$$

where non-centrality parameter ς is given as energy of signal over the power spectral density and will yield

$$p_f = \int_{\xi}^{\infty} fY\,(y) dy, \tag{A.4}$$

applying (A.3),

$$p_f = \frac{1}{2^v \Gamma(\mathrm{v})} \int_{\xi}^{\infty} (\tfrac{y}{2})^{v-1} e^{-\frac{y}{2}}\, dy, \tag{A.5}$$

substituting $\frac{y}{2} = t$, $\frac{dy}{2} = dt$ and changing the limits of (A.5), we have

$$p_f = \frac{1}{\Gamma(\mathrm{v})} \int_{\frac{\xi}{2}}^{\infty} (t)^{v-1} e^{-(t)}\, dt, \tag{A.6}$$

or

$$p_f = \frac{\Gamma(\mathrm{v}, \frac{\xi}{2})}{\Gamma(\mathrm{v})}. \tag{A.7}$$

From (A.3), the probability of detection is obtained by the cumulative distribution function (CDF) which is given by

$$p_d = 1 - F_Y(y), \tag{A.8}$$

$$F_Y(y) = 1 - Q_d(\sqrt{\varsigma}, \sqrt{y}), \tag{A.9}$$

$$p_d = Q_d(\sqrt{\varsigma}, \sqrt{\xi}), \tag{A.10}$$

equivalent to

$$p_d = Q_d(\sqrt{2\gamma}, \sqrt{\xi}), \tag{A.11}$$

where $Q_d(.,.)$ is the generalized Marcum-Q function.

SNR γ, follows and exponential PDF [100],

$$f(\gamma) = \frac{1}{\gamma}\exp(-\frac{\gamma}{\gamma}), \qquad \gamma \geq 0 \tag{A.12}$$

averaging (A.11) over (A.12) gives the probability of detection as

$$p_d = \int_0^\infty p_d f(\gamma) d\gamma, \tag{A.13}$$

from (A.11),

$$p_d = \frac{1}{\gamma}\int_0^\infty Q_d\,(\sqrt{\gamma}, \sqrt{\xi} \exp\left(-\frac{\gamma}{\gamma}\right) d\gamma, \tag{A.14}$$

substituting $\sqrt{\gamma} = x$; $d\gamma = 2xdx$, (A.14) gives

$$p_d = \frac{2}{\gamma}\int_0^\infty x. Q_d(\sqrt{2x}, \sqrt{\xi} \exp\left(\frac{-x^2}{\bar{\gamma}}\right) dx. \tag{A.15}$$

From the solution in [87] when evaluating for integer m, substitute $p^2 = \frac{2}{\bar{\gamma}}, a = \sqrt{2}, b = \sqrt{k}$ and $M = v$ will give the probability of detection as

$$p_d = e^{-\frac{\xi_i}{2}} \sum_{p=0}^{v-2} \frac{1}{p!}\left(\frac{\xi_i}{2}\right)^p + \left(\frac{1+\bar{\gamma}_i}{\bar{\gamma}_i}\right)^{v-1} \text{x} \left[e^{-\frac{\xi_i}{2(1+\gamma_i)}} - e^{-\frac{\xi_i}{2}} \sum_{p=0}^{v-2} \frac{1}{p!}\left(\frac{\xi_i\bar{\gamma}_i}{2(1+\bar{\gamma}_i)}\right)^p\right] \tag{A.16}$$