

# **Spectrum Decision Making in Distributed Cognitive Radio Networks using an Optimal Foraging Approach**

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**by**

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**A Thesis submitted in fulfilment of the requirements for  
the degree of ‘Doctor of Philosophy’**

**in the**

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Faculty of Science and Agriculture  
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**2018**

## DECLARATION

I, O.A. Oki hereby declare that this thesis is my own original work, conducted under the supervision of Prof. M.O. Adigun and Prof. T. O. Olwal. It is submitted for the degree of Doctor of Philosophy in Computer Science in the Faculty of Science and Agriculture at the University of Zululand, South Africa. No part of this research has been submitted in the past or is being submitted for a degree or examination at any other University. I declare that this thesis is based on some of the author's work published in scientific journals and book chapters listed under the publications outline. These published papers serve as the foundation of this thesis. I declare that some of these papers are contained verbatim in this thesis and all other sources used in this thesis have been duly acknowledged.

Signature: \_\_\_\_\_  
OKI O.A.

\_\_\_\_\_  
Date

## **DEDICATION**

I dedicate this work to my family and to God Almighty for giving me the privilege to be able to complete this work.

## ACKNOWLEDGEMENTS

I would like to thank God for the opportunity he gave me, for providing an intellectually and socially stimulating and well-organised environment for me and for giving me the strength to pull through the difficult times.

My special thanks go to my supervisors Professor M.O. Adigun and Professor T.O. Olwal for guidance, support, advice and for making this research work realisable. They also stood by me from the beginning until the end, *Ngiyabonga kakhulu*. I would like to also thank Dr P. Mudali and Mr B. Mutanga, whose support, advice and guidance got me through the tough times. Their work as my mentors contributed immensely to the successful completion of this work. Your down-to-earth spirits and passion for helping others are remarkable.

Special thanks go to Telkom, whose sponsorship of my work through their Centre of Excellence program enabled me to meet my financial obligations, thus allowing me to focus on the completion of this research work. I would like to thank the Wireless Mesh Network cluster situated at the Department of Computer Science and my other research colleagues in the centre with whom I had the pleasure to discuss, argue and work, etc. This work would have been impossible without their contributions.

I am grateful to my family, particularly to my loving wife and beautiful daughter, for their patience, love and words of encouragement. My sincere gratitude also goes to my mother, my late father, my Brothers (Olayinka Oki & Olalekan Oki) who really acted as a father to me. Also, thanks to my other family members and all my fellow Nigerians at the University of Zululand for their understanding, advice, support and encouragement.

Finally, I have been favoured by God to have the support of many true friends and sisters within and outside the University who have been Divine helpers and a great source of inspiration. A few of them are Segun Oke (Unizulu Nigerian Embassy), Dr Wale Adeleke, Foluke Taiwo, Madam Ijeoma and Nombuso, Chinaza Uleanya, Joshua, Paul, Thabile, Tosin, Pst. Dr Folusho Osunsanmi, Dr Ogunyinka's family, Madam Edwina, Dr Toyin Shobiye (area mother) and RCCG Christ Assembly. I am grateful to you all.

## ABSTRACT

In the recent past, Cognitive Radio (CR) technology has been regarded in the literature as the most promising technology for performing dynamic spectrum management. One of the major aspects of the spectrum management is referred to as the decision-making ability of CR users. Spectrum decision-making process involves the dynamic spectrum characterisation, selection as well as reconfiguration. The study of dynamic selection and reconfiguration of the frequency and channel bandwidth in spectrum decision-making is important specifically for the realisation of optimal spectrum utilisation in a distributed CR network (CRN).

Dynamic spectrum reconfiguration has previously been reported to improve the spectrum utilisation in CRNs. In exploiting spectrum reconfiguration of frequency and channel bandwidth to improve spectrum utilisation, various approaches have been adopted to develop models. However, the existing approaches have not been able to achieve optimal spectrum utilisation due to slow convergence, computational complexity, and repeatability challenges. Hence, the study of the efficacy of dynamic selection and reconfiguration approaches as a mechanism for improving the spectrum utilisation in a distributed CRN remains an open issue.

This study addresses this knowledge gap by studying the existing approaches that other researchers have used to develop models for spectrum reconfiguration. This provides unique insight into how those approaches converge slowly, consume computational resources, are non-generic and negatively affect the performance of the models that have been developed from those approaches. The biological approach has generic, simple analytic and high applicability properties. Motivated by the well-established properties of the biological foraging approach, a novel Foraging Inspired Spectrum Selection and Reconfiguration (FISSER) model is proposed.

In the proposed FISSER model, foraging animals are considered as Secondary Users (SU), whilst the prey are the available Primary Users' frequencies. Similar to the biological foraging methodology, whereby the foraging animals search for prey the same way each SU with a message searches for possible available PUs' frequency to be used for communication. The FISSER model is aimed at achieving both efficient spectrum utilisation and SUs' node communication in a distributed CRN. The efficacy of the proposed FISSER model has been extensively validated both analytically and through computer simulations.

The simulation and analytical results obtained in this study have shown that the FISSER model yields improved communication performance, guarantees the energy efficiency, and maximises the spectrum utilisation compared to the most recently studied approaches.

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## LIST OF COMMONLY USED ABBREVIATIONS

ACST	Average Channel Switching Time
AHP	Analytic Hierarchy Process
ANT	Average Network Throughput
BEACH	Bio-Inspired Energy and Channel
CCC	Common Control Channel
CRNs	Cognitive Radio Networks
DoE	Design of Experiment
EE	Energy Efficiency
EGSD	Energy-efficient Game theory based Spectrum Decision
FCC	Federal Communications Commission
FISSER	Foraging Inspired Spectrum Selection and Reconfiguration
GUT	Giving-Up Time
ICASA	Independent Communications Commission of South Africa
LASD	Location Aware Spectrum Database
PU <sub>s</sub>	Primary Users
RF	Radio Frequency
STP	Successful Transmission Probability
SU <sub>s</sub>	SecondaryUsers

# CHAPTER ONE

## INTRODUCTION

In recent years, the massive growth of wireless communication technologies and smart devices that enable multimedia-based services and other social networking applications has led to the limitation of radio frequency (RF) spectrum which is fast becoming scarce. The spectrum usage measurements from previous studies [49-51, 95] have shown that, with the current RF spectrum access approach, the frequency bands assigned to licensed users are largely underutilised, while the demand for access to the unlicensed RF spectrum is growing significantly [See Figure 1]. Hence, the limited available unlicensed frequency bands and the inefficient usage of the licensed RF bands have necessitated the need for a new and better way of assigning the RF spectrum. This concept is been referred to as sub-optimal spectrum utilisation, which is discussed in detail in Section 1.3.

### 1.1 Overview of Spectrum Management

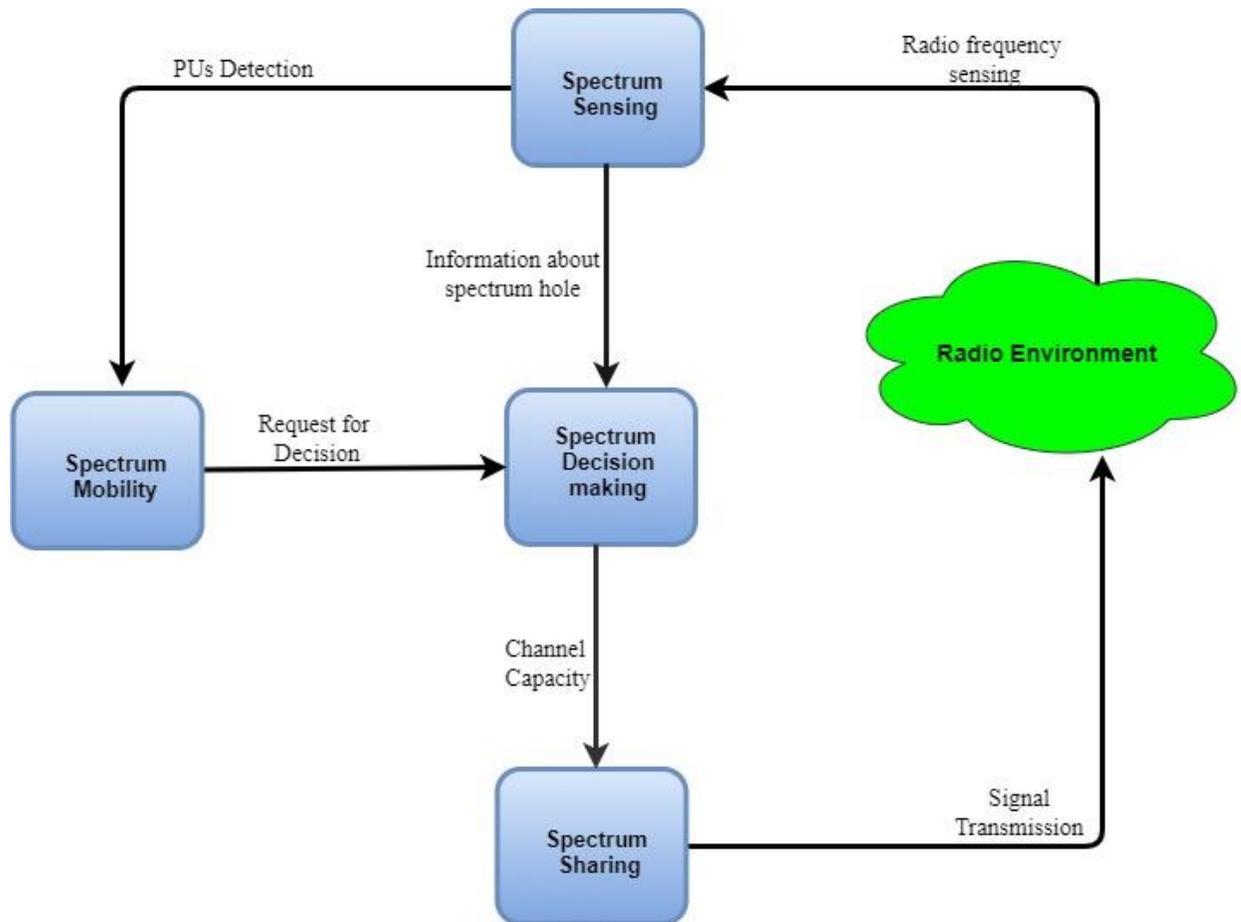
The dynamic spectrum access and management techniques have been introduced to address the current RF bands' inefficiency challenges [4, 10, 18]. The recent advancement in wireless networking technologies, such as cognitive radio (CR) technology promises to address the issues (such as interference, network performance degradation etc.) and challenges of the depletion and inefficient utilisation of the RF spectrum by opportunistically accessing the usable spectrum in a dynamic and optimal manner. Hence, CR technology is being regarded as the most promising technology in the dynamic spectrum access and management [13, 19].

A Cognitive Radio Network (CRN) is an intelligent wireless transmission system that possesses the ability to change its transceiver parameters such as frequency and channel bandwidth based on the interaction (e.g. spectrum sensing) with the environment wherein it operates [1, 10, 13]. The basic idea of a CRN is that it should be capable of



Hence, as soon as PU activities are detected on a given channel, the SU must immediately vacate the channel and continue its transmission on another available channel.

The process of realising efficient spectrum utilisation using CR technology requires a dynamic spectrum management framework. This dynamic spectrum management framework comprises spectrum sensing, decision making, sharing and spectrum mobility as depicted in Figure 2.



**Figure 2: Dynamic Spectrum Management Framework**

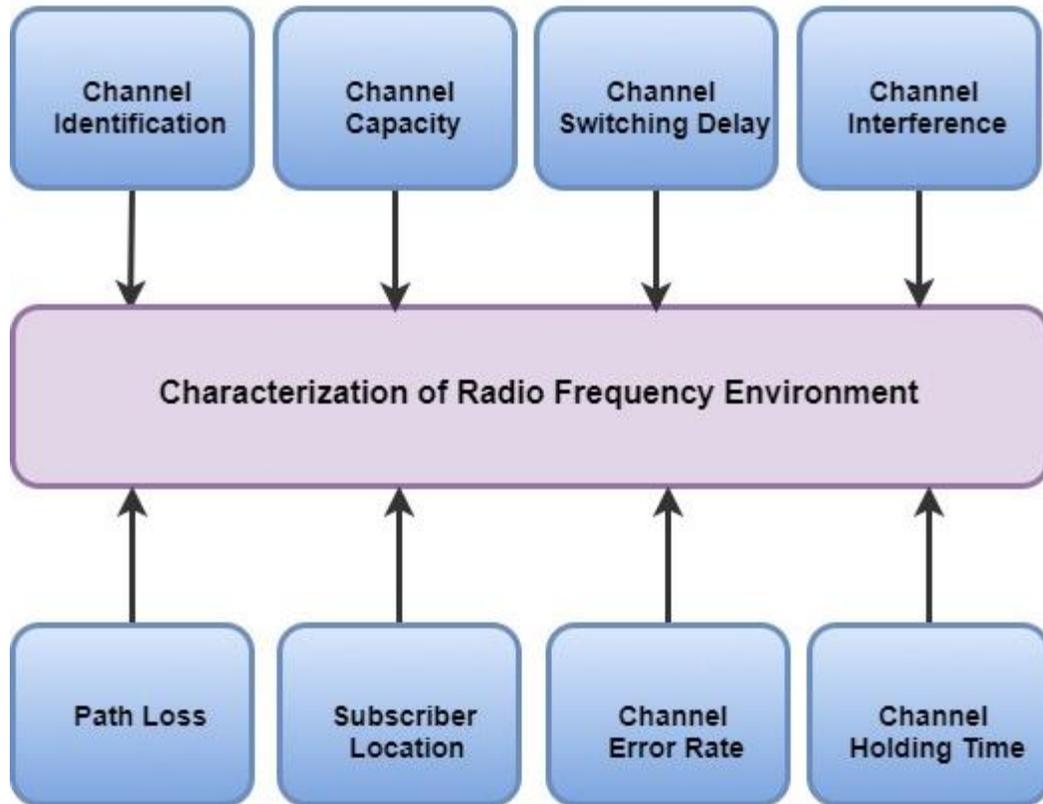
Spectrum sensing involves identification of spectrum holes and the ability to quickly detect the arrival of PU transmissions in the spectrum hole occupied by the SUs. Spectrum sharing refers to the coordinated access to the selected channel by the SUs,

while spectrum mobility is the ability of a cognitive radio to vacate the channel when it detects a PU. Spectrum decision is the ability of the SUs to select the best available spectrum band to satisfy the SU's communication and Quality of Service (QoS) requirements without causing any harmful interference to the primary users [10, 64]. One of the major processes in achieving an efficient spectrum utilisation in CRNs is the spectrum decision making; as it enables the SUs to make an efficient decision on the best channel bandwidth to use for communication. However, a critical challenge in CRNs is how to make an efficient spectrum decision for the SUs, while meeting the QoS and minimising the interference with the PUs [28].

Spectrum decision comprises three main stages: spectrum characterisation, spectrum selection and dynamic reconfiguration of transceiver parameters for CRNs [9, 94].

Many spectrum bands with different channel characteristics exist in CRNs, where there is a wide frequency range. However, in order to select the most appropriate spectrum band, it is very important to identify the characteristics of each spectrum band that are available. Hence, spectrum characterisation allows the SUs to characterise the spectrum bands by considering the strength of the signals received, level of interference, and the number of users currently residing in the spectrum, based on the observation of radio frequency [2]. Due to the dynamic nature of CRNs where the available spectrum bands usually have different characteristics, the SUs are expected to continuously characterise the radio frequency usage, time and space. The process of spectrum characterisation in CRNs is based on the estimation of eight parameters [63] as shown in Figure 3.

After the identification and characterisation of spectrum holes, the next step in CRN decision-making is the selection of the best available spectrum that is suitable for the SU's communication and specific QoS requirements. In mobile CRNs, the set of available frequencies and channel bandwidths for each user is not static. This phenomenon makes both the network topologies and radio frequency propagation keep changing as the mobile CR station changes its position. For this reason, the spectrum selection approaches for both centralised and distributed CRNs should be closely coupled with routing protocols (commonly called joint spectrum selection) [93, 103].



**Figure 3: Radio Frequency Characterisation Elements**

A detailed analysis of spectrum characterisation can be found in “A Survey on Spectrum Management in Cognitive Radio Networks,” IEEE Communications Magazine, vol. 2, no. 3, pg. 40-48, 2008 [2].

The dynamic reconfiguration of transceiver parameters occurs after the spectrum has been characterised and selected. Cognitive radio reconfiguration techniques enable the secondary users to dynamically reconfigure its transmission parameters (such as operating frequency, channel bandwidth and transmission power) for optimal operation in a certain spectrum band so as to satisfy the user’s QoS requirements. The SU’s QoS requirements include application requirements, such as throughput and latency, operational policies and radio frequency environmental conditions requirements. Potentially, a number of approaches can be used to determine how the operating frequency and channel bandwidth parameters settings affect the network performance. Operating frequency and channel bandwidth are the two major reconfigurable

parameters in CRNs [48, 52]. Operating frequency is the ability of a SUs to dynamically reconfigure the centre frequency of the cognitive radio based on the radio frequency environment, while the channel bandwidth is the spectrum width over which a cognitive radio transceiver signals are spread. It is of high importance to the SUs of CRN to be able to adapt to a varying operating frequency and channel bandwidth so as to be able to operate on different wireless technologies.

Similar to the traditional wireless networks, CRN spectrum selection and reconfiguration operates either in a centralised (infrastructure-based) or a distributed (infrastructure-less or ad hoc based) network topology. In the centralised topology, a central node such as a base station or access point is deployed with several SUs associated with it, while the SUs communicate directly with each other without any central or controlling node, in the distributed topology.

However, most of the existing research in the area of dynamic reconfiguration of transmission parameters (operating frequency and channel bandwidth) has focused on centralised-based CR [9-12, 28]. This can be attributed to the fact that it is easier to set-up and to manage a centralised-based CRN since almost all the computational work is done on a central control system or base station. Also, the centralised CRN operational cost is minimal compared to that of distributed CRNs. However, some of the issues with a centralised system include failure or link disconnection on the part of the central system, which will automatically mean that the entire network cannot function effectively. Another related issue is the applicability of a centralised control system in a mobile network environment where nodes can leave and join the network at any time.

Due to the recent rapid increase in the number of potential mobile network applications such as is experienced in military battle-field communication and natural disaster relief, the need for the reliable communication of nodes is inevitable. Such applications have compelled the current research attention to be directed toward investigating the dynamic reconfiguration of transceiver parameters on spectrum-efficiency performance in a distributed CRNs.

Centralised and traditional wireless ad hoc networks are usually characterised by a fixed and low number of supported channels (mostly less than ten or at most in order of tens). However, spectrum selection and reconfiguration of transceiver parameters in a distributed CRN, where the number of supported channels ranges in the order of thousands is a serious challenge that needs to be addressed [2, 4, 10, 9].

In a distributed CRN environment such as in a mobile ad hoc network, when there are several frequencies and channel bandwidths available, dynamically selecting the optimal frequency and channel bandwidths is an important challenge, which still remains an open issue. The complexity of this challenge is increased when spectrum quality and the QoS requirements of different kinds of applications are considered. A low-frequency signal (e.g., 700MHz) can travel farther and penetrate walls and other obstacles, but its information capacity is lower and the accuracy in determining the direction of arrival is poorer [19]. However, a higher frequency signal (e.g., 5.0GHz) can only travel a shorter distance, but will be able to carry more information and will exhibit better directionality. This diversity in spectrum bands and the guiding principles issued by the communications regulatory agencies on how to access the spectrum implies that the CR nodes for mobile ad hoc networks should dynamically reconfigure their operating frequency and channel bandwidths, as network conditions dictate.

In a cognitive radio network, the SUs nodes may find the frequency and channel bandwidth availability to be high at a particular place at some point in time and become very low at another time in the same place due to the PU's activity. This contradicts the traditional ad hoc networks, where the network operates on a pre-decided set of frequency and channels, which remain unchanged over time. The CR nodes within the network must then be able to decide on which optimal frequency and channel bandwidth to use for effective communication. They must also dynamically reconfigure their transceiver parameters so that the desired efficient spectrum utilisation goal is achieved.

The dynamic selection and reconfiguration of both the operating frequency and channel bandwidth in a distributed CR network have not received sufficient scholarly attention despite its importance in spectrum decision making [4, 19, 34, 67]. In distributed cognitive radio networks, the set of available frequencies for each SU is not static,

hence; it makes both the network topologies and radio frequency propagation keep changing. These continuous changes require the SUs to dynamically select and reconfigure their transceiver parameters in order to maintain communication among the nodes. Due to this reason, the SUs need an approach that will help them to dynamically select and reconfigure their operating frequency and channel bandwidth, so as to achieve an optimal spectrum utilisation.

Various research works have attempted to solve the dynamic spectrum selection and reconfiguration problem using various approaches such as Design of Experiment (DOE) & Statistical [11, 44-46, 65], Bayesian [87-92], game theory [66-69], machine learning [82-86], Predictive [96, 106, 112], Markov theory [54-60], Reinforcement [70-75] and Common Control Channel (CCC) [12, 19, 47]. However, these approaches suffer from challenges such as high computational complexity, repeatability, slow convergence, applicability and ambiguity. Thus, the study of dynamic selection and reconfiguration of both frequency and channel bandwidth as a mechanism to improve the spectrum utilisation in CRN remains an open issue [52].

The biologically-inspired foraging approach has been described and is being adopted by many researchers in the field of wireless communication networks due to its analytical simplicity and its generic applications. The results from previous studies [7, 8, 14-16] in other wireless networking situations, shows that the biologically-inspired foraging approach has generic, simple and high applicability properties. In studies [14, 15], biologically-inspired foraging approach was utilised to develop BEACH and FIREMAN protocols for green multi-radio networks respectively. Both studies evaluated the developed protocols' performances by measuring both the throughput and energy-efficiency in distributed heterogeneous networks. Based on the results of their studies, it was observed that the proposed biologically-inspired foraging approach protocols performed better than other conventional approaches in the field of heterogeneous networks. Motivated by the biologically-inspired foraging approach performance in other wireless networks, this study proposes a novel Foraging Inspired Spectrum Selection and Reconfiguration (FISSER) model in addressing the challenges of dynamic selection and reconfiguration of frequency and channel bandwidth in distributed cognitive radio networks.

## 1.2 Delimitations of the Study

The scope of this research will cover the following:

1. Spectrum selection and reconfiguration of transceiver parameters: spectrum management in CRN comprises of spectrum sensing, decision making, sharing and mobility. Many research works are focusing on spectrum sensing, despite the importance of spectrum decision making to the realisation of efficient spectrum access. Hence, this thesis focuses on decision making for CRN. Decision making comprises of spectrum characterisation, selection and parameters reconfiguration. The spectrum characterisation has been dealt with extensively in the literature, hence this thesis focuses on both spectrum selection and reconfiguration of transceiver parameters.
2. Operating frequency and channel bandwidth: the transceiver parameters that the SUs needs to reconfigure in CRN includes: operating frequency, channel bandwidth, transmission power, modulation and coding schemes. The reconfiguration of transceiver parameters in CRNs has not received sufficient attention despite its importance to decision making. Hence, this thesis focuses on operating frequency and channel bandwidth because they serve as the bedrock upon which other aspects of transceiver parameters operate.
3. Distributed topology: the centralised topology control in decision making for a CRN has been dealt with recently [9-12]. However, due to challenges such as base station/central system link disconnection and applicability of a centralised control system in a mobile ad hoc environment, where nodes can leave and join the network at any time. Hence, this thesis' focus is on distributed topology for decision making in a CRN.
4. Analytical and Computer simulations: due to the time constraints and non-availability of hardware equipment, this study will be limited to literature survey, analytical and simulation methodology and will not include field testing. The objectives of this research can be adequately assessed by both analytical and computer simulations.

### **1.3 Sub-optimal Spectrum Utilisation**

The term radio frequency (RF) spectrum refers to the full frequency range, from 3kHz - 300GHz, that is available for wireless communication. The radio frequency spectrum is one of the most valuable network resources in wireless communications due to its limited availability. Wireless communication technologies capable of offering multimedia services and applications have grown rapidly over the past few decades which has fuelled an increased demand for the radio frequency spectrum and resulted in the use of previously unused frequency bands.

It is widely understood that the radio frequency spectrum can serve as a platform for economic and social development [110], as such governments worldwide have established regulatory agencies (such as the Independent Communications Commission of South Africa (ICASA) and the Federal Communications Commission (FCC) of the United States of America) to promote the efficient, effective and equitable use of the radio frequency spectrum. Regulators of the RF spectrum have traditionally allocated a fixed portion of the radio spectrum to each new radio-based service. In recent times, it has become increasingly difficult to find usable radio spectrum frequencies to accommodate the rapidly expanding demand. However, studies have shown that the spectrum scarcity can be seen as temporal situation, because the actual spectrum utilisation on a block of licensed radio frequency spectrum band was found to vary between 15% and 85% at different geographic locations over time [30, 44, 57]. This temporal spectrum scarcity is, to a large degree, the result of inefficiencies in traditional static spectrum management regulations.

Faced with a scarcity of spectrum for new applications, the underutilisation of the licensed spectrum is driving the shift of the spectrum allocation paradigm from static to dynamic. A promising implementation of this paradigm is called cognitive radio (CR). The basic idea of CR networks is to allow a group of unlicensed secondary users (SUs) to opportunistically access frequency bands originally allocated to some licensed primary users (PUs). Opportunistic spectrum usage requires SUs to dynamically determine the portions of the spectrum currently available (spectrum sensing) and to

select the best available frequency and channel (spectrum decision) for SUs' communication.

With CR technology, spectrum utilisation can be increased significantly by making sure that the SUs make optimal decisions in terms of selecting an appropriate frequency among the available options, without causing any harmful interference to the licensed PUs. Spectrum decision techniques are used by SUs to decide on the best frequency to select among the available PUs' frequencies at a given time. The parts of the spectrum not being used by PUs are available to SUs and are called white/spectrum holes (or available channels).

## **1.4 Research Focus**

The focus of this study is to develop an optimal model for dynamic selection and reconfiguration of spectrum in a distributed cognitive radio network for the purpose of balancing communication performance while minimising energy consumption and achieving optimal spectrum utilisation.

*In this study, we argue that the performance of a distributed CRN that is experiencing sub-optimal spectrum utilisation can be improved by exploiting dynamic selection and reconfiguration of frequency and channel bandwidth such as FISSER model.*

In approaching the focus of this study, an analysis of the problem led to two major interdependent themes. The first theme argues that in order to develop an optimal dynamic spectrum selection and reconfiguration model for distributed CRNs, one must first have a clear understanding of why the existing reconfiguration approaches which researchers are using to develop models are not achieving optimal results. After the understanding of why the existing approaches are not achieving optimal results, comes the second part of the argument: the formulation and the development of the optimal model to dynamically select and reconfigure frequency and channel bandwidths for the SUs in a distributed CRN. The next section summarises the aim and objectives of this study.

## 1.5 Research Aim and Objectives

Subsection 1.5.1 presents the aim of this research work. The aim is further divided into four research objectives in subsection 1.5.2

### 1.5.1 Research Aim

The aim of this study is to develop an optimal model for dynamic selection and reconfiguration of both frequency and channel bandwidths in a distributed CRN.

### 1.5.2 Research Objectives

The aim of this work can be decomposed into four research objectives that are listed as follows:

- i. To investigate why the current spectrum selection and reconfiguration approaches do not select the optimal operating frequency and channel bandwidths for SUs' communication.
- ii. To formulate a FISSER model that will dynamically reconfigure the selected operating frequency and channel bandwidths in order to meet the QoS requirements.
- iii. To carry out validation and performance analysis of the proposed FISSER model on a distributed cognitive radio simulator.
- iv. To test the efficacy of the proposed FISSER model by evaluating the performance against most recently proposed approaches in a distributed CRN.

Achieving the four objectives stated above helps to address the challenges with the existing spectrum selection and reconfiguration approaches and ultimately to achieve:

- i. **Optimal communication performance:** this is defined as the ability of SUs to achieve both the optimal network performance and efficient spectrum utilisation simultaneously. One of the major aims of FISSER model in CRN is to ensure optimal network performance and to achieve an efficient spectrum utilisation. The nodes' communication performance can be measured by both

the number of bits that were successfully processed by the SUs over a reasonable amount of time (network throughput) and the time it takes an SU to switch and reconfigure itself from one frequency to the other when a PU appears.

- ii. **Reduce the communication overhead:** communication overhead is characterised by the probability that the SUs' nodes' communication is successful (successful transmission probability). This aim is important as it can help to reduce the network energy consumption and other overhead costs.
- iii. **Significant efficient use of energy:** This study aims to maximise the data delivery while minimising the power consumed by the SUs' nodes during the communication. This aim reflects the energy utilisation of the SUs' node.

## 1.6 Contributions and Publications Outline

The sub-sections under this section provide the key contributions of this thesis to the body of knowledge and a brief description of the publications that have been converted into thesis chapters or part of a chapter.

### 1.6.1 Contributions of the Study

In this study, the FISSER model was developed to address the dynamic spectrum selection and reconfiguration of transceiver parameters by the SUs in a distributed CRN. The main contributions of this thesis are:

- i. A number of research efforts have gone into spectrum selection and dynamic reconfiguration of transceiver parameters for SUs in CRNs. Researchers have been proposing different models using various approaches such as game-based, machine learning, artificial intelligence, statistical and predictive for spectrum selection and reconfiguration in CRNs. However, why these existing models are not achieving the optimal result for spectrum selection and reconfiguration remains an open issue. In addressing this open issue, first, this thesis documented extensively the relevant literature, thus classifying the existing models by their solution approaches. Second, the review outlined the challenges with each of the

solution approaches and the reasons why they are not achieving optimal results. To the best of our knowledge, the survey is the first in the spectrum selection and reconfiguration literature to identify challenges and explain why the existing solution approaches are not achieving optimal results. This contribution will also help other researchers when selecting an approach against which to compare and/or develop a new model.

- ii. It is well-documented in the literature that the biologically-inspired optimal foraging approach has generic, simple and high applicability properties. Even though the biologically-inspired optimal foraging approach has been previously employed in other wireless networks, as found in [14-16, 35-36], this study represents the first time that it has been employed to develop a model (FISSER) for dynamic selection and reconfiguration of the transceiver parameters for SUs in a distributed CRN.
- iii. The establishment (via analytical and simulations evaluations) that the biological FISSER method is a viable approach in resolving challenges with existing approaches and achieving optimal spectrum selection and reconfiguration results for SUs in a distributed CRN. Previous studies [14-16, 35-38] in other wireless networks have established the good performance of the biological optimal foraging approach. This study establishes, via simulation evaluations against another three existing models, that the biological FISSER model can be employed to resolve the challenges with the existing spectrum selection and reconfiguration approaches and achieve optimal spectrum utilisation simultaneously. One of the novel features of FISSER model, which help to achieve better performance is its two modes (intensive and extensive) switching ability for searching and selection process. The existing models use single mode for their searching and selection process, which makes them consume more energy and high delay.

## 1.6.2 Outline of Publications from this Study

This thesis builds on a number of research studies which have previously been reported in a book chapter, journals and conference papers.

- i. Chapter 2 is based on a paper entitled “Dynamic Spectrum Reconfiguration for Distributed Cognitive Radio Networks” [28]. The paper is published in *Journal of Intelligent & Fuzzy Systems*, 32(4): 3103-3110, 2017. The paper reviews and examines existing spectrum selection and reconfiguration approaches, in order to identify the reasons why the existing approaches are not achieving optimal results.
- ii. Chapter 3 is based on a paper entitled “Biologically-Inspired Foraging Decision making in Distributed Cognitive Radio Networks” [29]. The paper is published as a book chapter in *Advances in Intelligent Systems and Computing*, vol. 683, 2018, Springer, Cham. This paper presents and describes the FISSER model formulation using biological optimal foraging theory and analytical results. The achieved analytical results were used as baseline results, and these baseline results were also presented in this paper. The baseline results help to establish a certain range of values, used in the simulation experiment. The combination of both FISSER model formulation and baseline results forms Chapter Three of this thesis.
- iii. Part of Chapter Four is based on a paper entitled “Using Biologically-Inspired Foraging Approach for Spectrum Reconfiguration in Distributed Cognitive Radio Networks” [53]. The manuscript appeared in the 2018 IEEE 5G World Forum Conference (5GWF’18), California, USA. This paper presents part of the performance validation results of the proposed FISSER model in a distributed CRN environment using computer simulations. Some of the baseline results from (ii) above were used to assign the simulation parameters.
- iv. Finally, Chapter 5 is based on a paper entitled “Performance Evaluation of Optimal Foraging Approach for Dynamic Spectrum Reconfiguration in Cognitive Radio Networks” [52]. The paper is accepted for publication<sup>1</sup> in *Special Issue Journal on Advances in Mechanical system and ICT-convergence*,

2018. ISSN: 0973-5763. This paper compared the simulation results obtained from the proposed FISSER model in (iii) above with other three spectrum selection and reconfiguration models obtained from (i) above.

## 1.7 Organisation of the Thesis

The remainder of this thesis consists of five chapters and these chapters' structure is depicted in Figure 4.

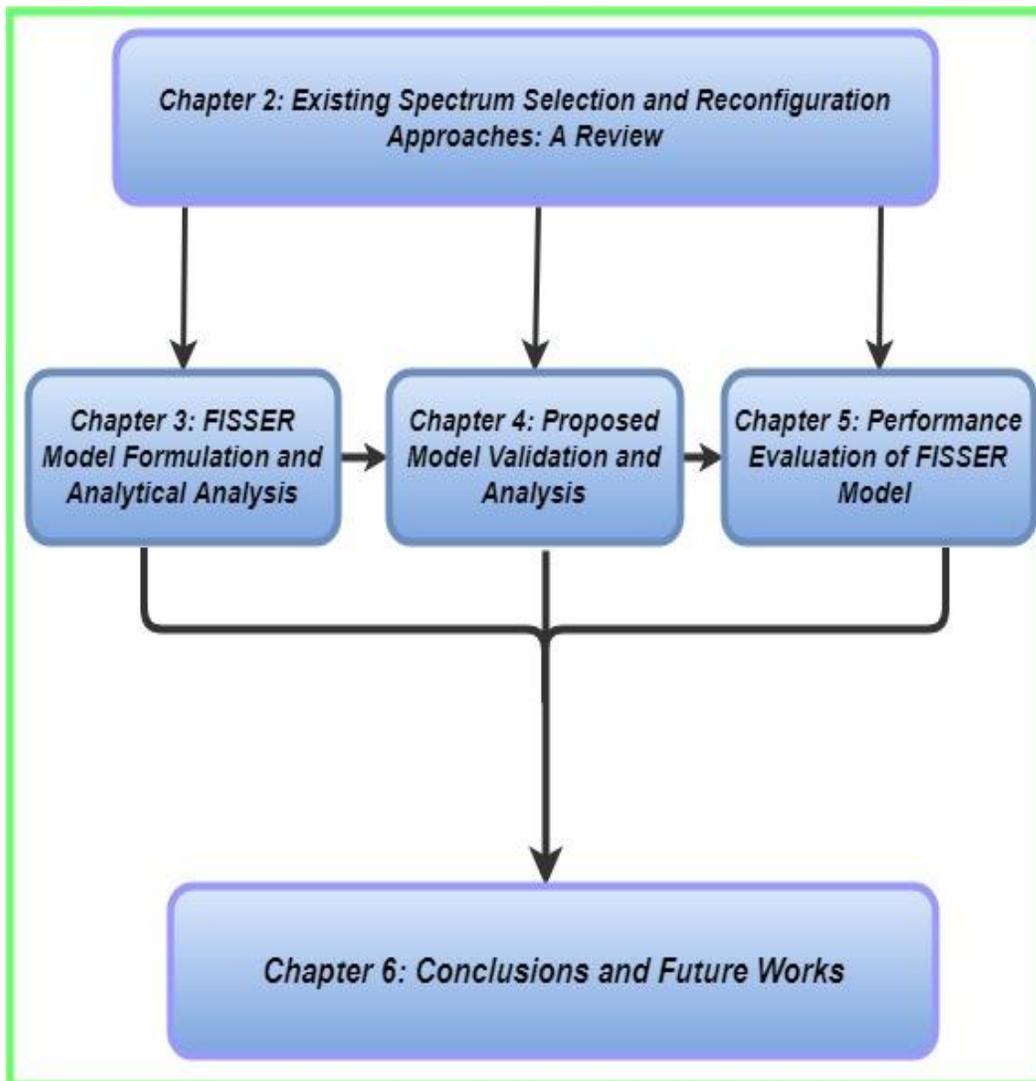


Figure 4: Thesis Structure

- In Chapter 2, the existing spectrum selection and reconfiguration approaches in cognitive radio networks are explored. The taxonomy of the existing solution approaches was classified in terms of game theory, machine learning and artificial intelligence, case-based, statistical, and predictive approaches. The strengths and limitations of these approaches were also presented and finally, the chapter proposed a biologically-inspired FISSER method to address the challenges with existing approaches with the aim to achieve optimal results for communication.
- Chapter 3 introduces biological optimal foraging theory and presents the formulation of FISSER model using motivation from biological foraging behaviour of organisms. The performance of this model was tested using analytical analysis.
- In Chapter 4, the detailed simulation setup and measurement methodology employed for various metrics considered are presented. The chapter also presents the validation and simulation analysis of FISSER model in dynamic spectrum selection and reconfiguration for a distributed CRN.
- Chapter 5 presents the performance evaluation of FISSER model in a distributed CRNs environment. The evaluation was done by comparing the proposed model with the other three existing models in order to validate the efficacy of the proposed model.
- Chapter 6 concludes this thesis by summarising the work, highlights the researcher's contributions to knowledge and provides direction for future works.

## **1.8 Chapter Summary**

This chapter has laid the background for this research study by introducing the concept of sub-optimal spectrum utilisation and how the dynamic selection and reconfiguration of both frequency and channel bandwidths can improve the spectrum utilisation in a distributed CRN. The chapter also introduced the three main stages that are involved in spectrum decision for both centralised and distributed CRNs topology. Delimitations of

the study, contributions to the body of knowledge, and the publications outline are also overviewed. The chapter closes with the outline of the thesis organisation.

The next chapter classifies the existing spectrum selection and reconfiguration models using their solution approaches. The existing solution approaches were explored for both centralised and distributed CRNs. The chapter also explores why those approaches are not achieving optimal spectrum selection and reconfiguration results.

## CHAPTER TWO

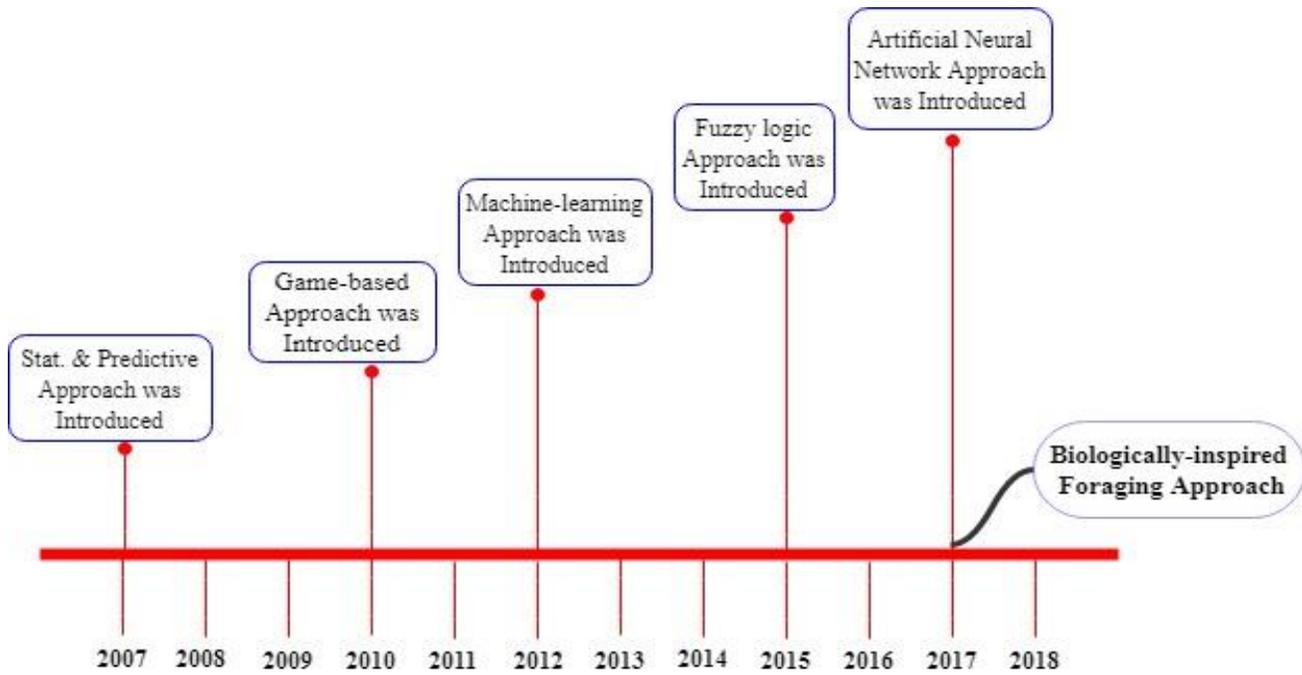
### SPECTRUM SELECTION AND RECONFIGURATION APPROACHES IN CRNS

#### 2.1 Introduction

The traditional wireless networks' radio terminals are usually configured statically to operate over a pre-defined frequency and channel [40]. However, due to the dynamic nature of spectrum access, it requires radio terminals that are very flexible (able to operate over different frequencies and channel bandwidths). CRNs' spectrum selection and reconfiguration offer such flexibility and are also able to rapidly adapt their transceiver parameters. The dynamic selection and reconfiguration of transceiver parameters in spectrum decision making for CRNs has not received sufficient research attention, despite its importance in achieving optimal spectrum utilisation [1-2, 4, 10]. The first publication on spectrum selection and reconfiguration in CRNs was published in 2007, where the authors used a statistical approach to develop a model, which predicted when SUs should select a frequency. However, there has been progress in research, where different models have been proposed to address the challenges of spectrum selection and reconfiguration. In this chapter, the existing models were classified based on their solution approaches. Figure 5 depicts the timeline of major spectrum selection and reconfiguration approaches that have been adopted over the period 2007-2017. Figure 5 also indicates the progression in researchers' interest in addressing the challenges of spectrum selection and reconfiguration. The dynamic selection and reconfiguration of CRNs can be seen as an optimisation problem, where the SUs need to select an available frequency and channel bandwidth that maximises its performance, without causing interference to the PUs. Finding an optimal available frequency and channel bandwidth is still an open issue in spectrum selection and reconfiguration for SUs in CRNs.

In the light of extensive related works in the literature, the aim is not to provide complete coverage of the area in this thesis, but rather to outline the major contributions towards

achieving optimal spectrum utilisation performance. The taxonomy of the existing approaches regarding the spectrum selection and reconfiguration in CRNs is depicted in Figure 6. The broad classifications of these approaches include machine learning and artificial intelligence based, case-based, game-theory and statistical/predictive approaches. This chapter presents the trending facts in spectrum selection and reconfiguration approaches that have been used by the researchers in attempting to achieve an optimal spectrum utilisation performance. Section 2.2 explores the models that adopted the statistical and predictive approach, while models that are based on the game-theory approach were explored in Section 2.3. In Section 2.4, the publications based on machine learning algorithms were explored and Section 2.5 explored the research works based on the artificial intelligence approach. Section 2.6 reviews the research works that are case-based, while the chapter is concluded with a summary in Section 2.7.



**Figure 5: Timeline of Major Spectrum Selection and Reconfiguration Approaches**

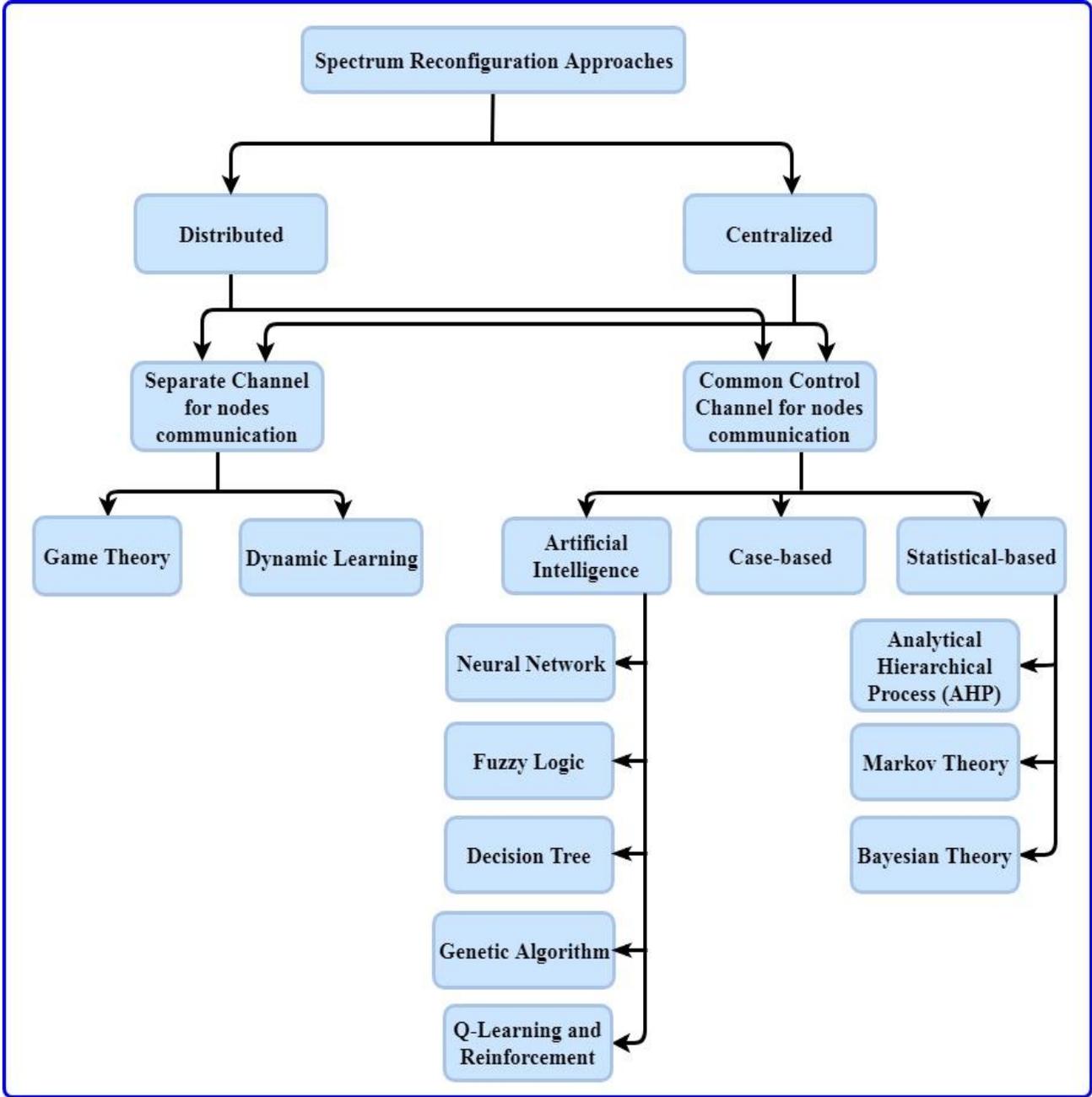


Figure 6: Taxonomy of Spectrum Reconfiguration Approaches

## 2.2 Statistical and Predictive Based Spectrum Reconfiguration Approaches

The statistical approach is the collection and analysis of large numerical data for the purpose of extracting certain hidden information which helps in the prediction of the system's future behaviour [44]. Different statistical methods such as the Analytic Hierarchy Process, Bayesian, Markov and Design of Experiments (DOE) have been adopted in spectrum selection and reconfiguration for SUs in both centralised and distributed CRNs.

The authors [17, 23] proposed a dynamic spectrum management framework for a distributed CRNs and this framework focused on spectrum selection and reconfiguration of operating frequency. The Analytic Hierarchy Process (AHP) statistical tool was used to develop the proposed framework [17, 23]. The authors used their proposed framework to select an optimal available frequency band for SUs. The framework was evaluated using simulation and three performance metrics were measured; spectrum reconfiguration, throughput and spectrum handoff rate for SUs. Based on their results, it was shown that the proposed AHP-based framework performs better than multiple attributes decision making (MADM) model in the achieved throughput and reconfiguration time. AHP is a popular method, useful for making complex decisions. However, its high computational complexity and the uncertainty related to the findings in the pairwise comparison-matrix which are not considered, limits the application of AHP results in a dynamic environment such as CRNs.

Weingart *et al.* [21] presented the concept of a decision making prediction model, using both the Design of Experiment (DOE) and analysis of variance statistical approach. DOE is an asset of tools and methods for determining cause and effect relationships within a system. Their prediction model was used to develop a reconfiguration method for the SUs based on the nodes' communication requirements. Some of the challenges that the authors tried to address include making decisions about how and when to change the physical, data link, network and application layers' parameters configuration and how the configuration changes will be propagated throughout the entire network. Also, the

amount of time spent in computing the new configuration. The model was tested using OPNET simulator and four performance metrics were considered: latency, jitter, throughput, and bit loss. The DOE method applied in their study, uses periodic data gathered from the central system, hence; the performance at every point in time is only based on the last data collected. One of the challenges with this kind of approach is that it is not dynamic and since the decision as to which frequency to select and reconfigure is only based on the last periodic data, it makes most of the reported result unreliable. In a mobile ad hoc environment, where nodes join and leave at any time, making a decision based on last collected periodic data makes such results unreliable, especially during situations like war or natural disaster [98, 99, 116]. However, it would be interesting if the authors could make the proposed prediction model to be based on real-time data collection, so as to ensure a real-time prediction.

The Markov model is a statistical model usually used for random processes modelling. The random process does not use any memory and the future actions usually depend on the current state [60]. The Markov model was used [56] to model and analyse the spectrum selection and reconfiguration for SUs in a CRN. The author formed a CRN by multiple channels and dissimilar SUs. Also, the complex Markov model was decomposed into separate Markov chains for each of the SUs. The proposed model performance was evaluated by measuring the SUs' average throughput. Based on their achieved results, it was claimed that the proposed Markov model improved the SUs' average throughput significantly, but with some computational complexity.

Two channel bandwidth reconfiguration frameworks which include minimum variance-based (MVSD) and maximum capacity-based (MCSD) were presented [4]. The proposed framework was used to determine the spectrum bands usage, based on different QoS requirements. Both MVSD and MCSD channel bandwidth frameworks were designed for a centralised CRN. Based on the result of their study, it was observed, that the proposed MCSD introduced some additional frequency-channel switching delay, which led to some degradation in the application QoS requirements. One of the reasons for the switching delay experienced by both MVSD and MCSD can be attributed to the time it

takes the nodes to send their results to the base station and also to wait for a decision from the base station.

In summary, this section has reviewed some research works on spectrum selection and reconfiguration of operating frequencies and channel bandwidths using both predictive and statistical approaches. However, challenges such as high computational complexity, reliability and switching delays make the approach inadequate to achieve optimal results in selecting the frequency and channel bandwidth for SUs communication. In the literature [6, 67-69], some methods such as game theory and machine learning algorithms have been introduced to address some of the challenges with the statistical and predictive approaches. However, due to some challenges such as slow convergence speed and computational complexity introduced by game and machine learning approaches respectively, achieving an optimal spectrum reconfiguration in CRNs remains an open issue [52].

### **2.3 Game Theory-Based Spectrum Selection and Reconfiguration Approaches**

Game theory is a theoretical approach to describing strategic interactions and their possible outcomes [76]. Game theory technique is usually used to make a decision when several players need to make choices, which will subsequently affect the interest of other players. In game theory, each player decides on his actions individually based on the past history of actions used by other players in such a situation [31]. In CRNs, the SUs are the players, while the actions are the selection and reconfiguration of transceiver parameters such as channel bandwidth and frequency. Hence, each SU will learn from its past history, observe the actions of the other SUs and adjust its actions appropriately [68-69].

I. Malanchini, M. Cesana, and N. Gatti [119] introduced a game-based model to evaluate the SUs spectrum selection decision in a CRN. In their proposed model, the process of selecting a frequency and channel bandwidth was modelled as a non-cooperative game among the SUs. Their proposed model was used to select the “best” frequency and

channel bandwidth opportunistically, without causing any harm/interference with the PUs.

However, due to the transient nature of information exchange between each network node, the players need to continuously change their strategies in order for them to reach equilibrium. The numerical evaluation of the proposed game-based model was conducted by measuring the channel bandwidth and opportunity holding time. The reported numerical results help to assess the quality of the proposed model's equilibria. The continuous changing of strategies by each player lead to a slow convergence speed. However, in order to address the slow convergence challenge in the game approach, some researchers [6, 89, 112] have introduced the machine learning approach.

Ma and Zhang [117] proposed a multi-channel bandit game model to select an idle/available frequency for each SU. The model was used to evaluate the convergence rate to Nash equilibrium solutions in selecting a channel under incomplete information. "Nash equilibrium is a set of strategies such that no player has an incentive to unilaterally change its action [117, 102]". The authors used Maximal Average Regret (MAR) learning algorithm to evaluate the performance of online algorithms' convergence rates. In order to obtain the Nash equilibrium for each SU, two online learning algorithms were implemented. The proposed game model was validated using computer simulation, and based on their achieved results, it was concluded that the proposed game model could improve the SUs frequency selection convergence rate.

Salim and Moh [102] presented a distributed energy-efficient game theory based spectrum decision (EGSD) model for CRNs. In their study, the proposed EGSD model selects the "best" operating channel for the SUs among the available channels. The main goal of the proposed EGSD was to improve/prolong the network lifetime. The EGSD model comprises two spectrum selection algorithms (random- and game theory based selection) and a clustering algorithm. The proposed model was validated using MATLAB™ simulation. Based on their evaluation results, it was concluded that the proposed EGSD performed better than the minimum variance-based spectrum decision (MVSD) model in the achieved network lifetime and communication overhead.

In summary, this section has explored some research works on spectrum selection and reconfiguration of both the operating frequency and channel bandwidth using game theory approach. Based on the studies explored, game theory approach provides solutions for SUs' spectrum selection and reconfiguration in distributed CRNs. However, this approach is limited by the number of players in the game, hence, the gaming approach analysis turns out to be progressively complicated [93]. The prior knowledge of both the environment and labelled training data are required by the game theory. In the context of CRNs, the players are the SUs, which require prior knowledge of different transceiver parameters either from base stations or from individual SUs. In CRNs, the frequency and channel bandwidth ranges in thousands, having prior knowledge of different frequencies and channel bandwidths before making a decision on which spectrum to select and reconfigure would be impractical in many situations and it would also lead to slow convergence speed for the game theory approach [28]. Hence, the need for an improved approach that will address the challenge of slow convergence speed in game theory and achieve an optimal spectrum selection and reconfiguration for CRNs.

## **2.4 Machine Learning Based Spectrum Selection and Reconfiguration Approaches**

In recent times, the machine learning and artificial intelligence approaches have been gaining a lot of research interest in CRNs, with most works' focuses on spectrum sensing. Machine learning in CRNs may be represented but not limited to the following techniques: reinforcement, dynamic strategy and distributed learning algorithms.

Reinforcement learning is an online technique that uses the feedback signal from the environment to determine the optimal decision [70]. Reinforcement learning approach includes two major parts; environment and agent [70-71]. Arunthavanathan, S. Kandeepan and R.J. Evans [75] proposed a joint reinforcement learning model for channel selection and routing in a CRN. Their proposed model combined a system of errors and rewards based on the decision made by each SU's node, hence, every agent

needs to maximize its own rewards. After some trial and error, the SU will reach an optimal level in their decision making and in turn help to maximize the spectrum utilisation. The proposed reinforcement learning approach allows the SU to select the optimal available route through continuous determination of the next hop. The reinforcement learning technique needs to undergo a learning phase, in order to obtain the optimal and suboptimal policy. In a dynamic environment such as CRNs, it would be challenging to provide the agents with precise actions associated with the present situation.

Barve and Kulkarni in [73] presented a dynamic channel selection learning model, which dynamically adapts the channel selection strategy in order to maximise the utility function of the SU nodes. The proposed model assumes that the SU's node has different priorities. The model focused both on multimedia applications, which are delay sensitive, and priority queuing analysis. In order to evaluate the performance of the proposed model, multiple video users sharing CRNs were simulated and based on the obtained results, it was concluded that the dynamic strategy learning model performs better than the conventional single-channel dynamic resource allocation in the achieved packet loss rate.

H. Jian, P. Jun, J. Fu, Q. Gaorong, and L. Weirong [6] considered the decision on channel bandwidth selection for the cognitive radio sensor network. The study developed a spectrum selection framework called distributed Q-learning algorithm. The algorithm was used to develop a learning strategy selection model, which was used to analyse the network channel selection and energy efficiency of the nodes. In their model, a joint channel selection framework, where the nodes make their decision centrally was developed. The effectiveness of the proposed Q-learning model was validated by using computer simulation and four performance metrics were measured: energy efficiency, average channel switching times, successful transmission probability, and average throughput. In order to evaluate the proposed model, an optimal Q-value was introduced to solve the problem using an optimisation solution. The efficacy of their proposed model was also evaluated against the other two models: game, and dynamic strategy model, using four metrics. Based on the obtained result, it was concluded that Q-learning

model performs better than game and dynamic strategy model in the achieved energy efficiency, channel switching time, successful transmission probability, and average throughput. The metrics measured in their study helped to balance the communication performance, reduced overhead cost and addressed the energy efficiency challenge. Hence, this thesis takes the work of H. Jian, *et al.* [6] further by measuring the four aforementioned performance metrics and also includes mean efficiency and optimal giving-up time.

In summary, this section has reviewed some research works on spectrum selection and reconfiguration for SUs in a CRN using machine learning techniques. One of the common challenges with machine learning technique is computational complexity and the possibility of slow convergence speed in a large mobile network environment. In CRNs, SUs are opportunistic users, hence, delaying in utilising the PU spectrum by SUs will defeat the aim of achieving optimal spectrum utilisation.

## **2.5 Artificial Intelligence Based Spectrum Selection and Reconfiguration Approaches**

The cognitive engine can be defined as an intelligent agent controlling the cognition tasks' management in a CRN [48]. The term "intelligent" is referred to as a consistent behaviour with a specified aim [93]. Hence, a cognitive radio can be viewed as an application of artificial intelligence with the specific focus on SUs' decision making. Artificial intelligence in CRNs can be represented but not limited to the following approaches: fuzzy logic, neural network, decision tree and Bayesian theory.

The fuzzy logic technique is an efficient approach, which can be used to represent real-world problems in an intelligent manner [32]. Hong-Sam and Hung [120] present a rule-based fuzzy logic model to coordinate the spectrum reconfiguration for the SUs in a CRN. The work selected SUs based on three descriptors: spectrum utilisation efficiency, the degree of mobility, and the distance travelled by the SUs before finding the available frequency for communication. The proposed model used twenty-seven fuzzy rules, which are derived from linguistic knowledge. The model was validated using computer

simulation and spectrum utilisation efficiency was measured. Based on the result of their study, it was concluded that the higher the SUs' distance from PUs, the lower the spectrum utilisation and the higher the degree of mobility that the proposed fuzzy logic model can help the SUs to make an optimal selection and reconfiguration decision when accessing the spectrum band.

Kaur *et al.* [62] used the fuzzy logic technique-based model to analyse the selection and reconfiguration in a CRN, where the SUs can maximise the spectrum utilisation. The proposed model uses three descriptive factors to select the SUs: SU's velocity, spectrum band and SUs' distance from the PUs. Twenty-seven linguistic knowledge-based rules were used to set up the model. The proposed model was validated using MATLAB<sup>TM</sup> simulation and SU decision possibility was the only metric measured. Based on the results of their study, it was concluded that the SUs' and PUs' distance has a direct impact on the spectrum selection possibility for the SUs. The lower the distance between SUs and PUs, the higher the SUs' frequency selection chances.

M.E. Bayrakdar and A. Calhan [40], introduced a fuzzy logic approach to address the problem of decision making by the SUs in a CRN. Three input parameters were considered: channel usage, data rate, and priority, using both audio and video data traffic. Two scenarios were considered (audio and video data traffic) in evaluating the proposed model performance using MATLAB<sup>TM</sup> simulation. The two scenarios considered were assigned 3 different priorities: urgent data, real-time, and non-real time data. Based on the achieved results, the authors concluded that repetitive decision making for SUs decreases significantly when subjected to different data rates.

In summary, the fuzzy logic approach makes a decision about spectrum selection and reconfiguration based on the derived rules and this reduces the computational complexity and also makes the approach suitable for real-time applications such as decision making in CRNs. However, one of the main challenges with the fuzzy logic approach is the derivation of rules that are relevant and have relevant features. The accuracy of the spectrum selection and reconfiguration by fuzzy logic approach depends on the accuracy and completeness of the derived rules. Inaccurate or incomplete rules

would make the approach return inappropriate decisions and also the optimality of such systems are not guaranteed.

Artificial neural networks are computer models that are being used to formulate the structure of the brain mathematically. According to Lopez *et al.* [115], “Artificial neural networks is a mathematical model of the theories of mental and brain activities, based on the exploitation of the parallel local processing and properties of distributed representation”. The neural network model makes a decision by extracting knowledge from the past experience. Lopez *et al.* [115] introduced a multi-layer perceptron neural networks approach for the reconfiguration of operating frequency and channel bandwidth by the SUs in CRNs. The goal of their work was to improve the average time it will take the SUs to switch among the available PUs’ network and to predict the future of PUs’ channels state. The proposed model was validated using computer simulation and only one metric was considered; the SUs’ average channel switching time. Based on their results, the authors concluded that the proposed multi-layer neural network performs better than other traditional approaches. However, as part of their conclusions, the authors stated that in order to achieve an optimal reconfiguration decision in a distributed CRN, there is still need to find additional methods that can address the poor generalisation challenge in neural networks.

The fuzzy neural network is an artificial intelligence technique that combines the features of fuzzy logic and neural networks. In "An Optimum Decision Making in Cognitive Radio via Fuzzy Neural Network" [100], C. Choudhari and V. Jain presented a rule-based fuzzy neural network model for reconfiguration of operating frequency by the SUs in a CRNs. The authors validated their proposed model using MATLAB<sup>TM</sup> simulation. The performance of the proposed fuzzy neural network model was evaluated against a fuzzy logic system model. Based on the evaluation results, it was concluded that fuzzy neural network outperforms fuzzy logic system in the time it takes the SUs to select and reconfigure their parameters (average channel switching time). Hence, their proposed fuzzy neural network model improves the spectrum utilisation.

Sarmiento *et al.* [101] proposed a centralised artificial intelligence based support vector machine (SVM) and ANFIS models that can decide on an appropriate frequency band

for SUs among the available network, which can be used in an opportunistic manner to satisfy the QoS requirements. Best effort and real-time assignment were used as the two QoS criteria for assigning an available frequency. The main goal of their study was to optimise the spectrum band selection and reconfiguration process, in order to reduce the collisions between SUs and PUs. The models were validated using MATLAB™ simulation. The proposed SVM and ANFIS were evaluated by comparing their performance against LSTM proactive and reactive strategy. Three performance metrics were considered: successful transmission probability, delay error, and throughput. Based on the evaluation results, the authors concluded that proactive strategy performs better than reactive strategy in the achieved channel selection and average switching time at the base station. However, Viveros *et al.* [110] take the work further by introducing an adaptive neuro-fuzzy inference system technique for decision making by SUs in CRNs. The proposed technique was divided into two phases; ANFIS-GRID (this phase uses a grid partition concept) and ANFIS-FCM (it uses fuzzy c-means clustering concept). The goal of their study was to be able to predict spectrum usage of PUs and from there, make the decision for SUs on when to select a new frequency and how to reconfigure the spectrum opportunistically. The proposed ANFIS was validated by using MATLAB™ simulation, and the performance was evaluated against the neural network long short-term memory (LSTM) technique. Three performance metrics were considered: correlation coefficient, prediction accuracy, and the successful transmission probability. Based on the results of their study, it was concluded that the proposed ANFIS technique performs better than LSTM in the achieved prediction accuracy and high correlation coefficient. The integration of grid and c-mean clustering into the proposed ANFIS technique introduced some additional computational complexity both in the application execution time and learning time. Although such complexity may be tolerated in the centralised CRN topology, in a distributed CRN environment, its implementation would be practically impossible. Hence, there is still a need to investigate other approaches that will reduce the computational complexity as well as achieving an optimal spectrum selection and reconfiguration for the SUs in CRNs.

The Bayesian technique is one of the artificial intelligence techniques that are commonly used to address the problems of uncertainty and which can also be used for decision-

making processes [87]. Y. Huang, J. Wang and H. Jiang [89], introduced a Bayesian-based model for spectrum reconfiguration and cognitive radio learning interference. The “junction tree algorithm” was used to develop the probabilistic model used in their study for interference. The goal of their work was to develop a model that can assist the SUs to adapt their transceiver parameters to the QoS requirement of the users. The proposed model was validated using computer simulation. Based on the result of their study, it was concluded that the Bayesian approach could be used in developing a spectrum reconfiguration engine for SUs in a CRN.

Homayounvala [41] takes the work of Huang *et al.* [89] further by using the Bayesian approach to select the best channel and frequency over a specific period of time. The goal of their work was to maximise the SUs’ average throughput and minimise the switching delay experienced by SUs. The proposed model was validated using computer simulation and the performance was evaluated by measuring both throughput and delay. The author concluded that the proposed Bayesian-based model performed better than the “blind opportunistic” SUs’ selection model in the achieved throughput and delay.

Rivas *et al.* [114] introduced a dynamic Bayesian approach to select and predict the PUs’ activity over a period of time. The author used the prediction gathered from the base station to make the decision for the SUs. The proposed model used both Bayes theorem and classical probability to generate PUs’ activity predictions. The authors concluded that their proposed model performed better in terms of activity prediction as compared to that of statistical and probabilistic prediction models. However, the author indicated that, due to the complexity involved, the proposed model implementation is mostly feasible in a centralised CRN topology.

In summary, the Bayesian approach is a good probabilistic prediction approach with simple interpretations. However, from the reviewed studies [33, 41, 87-90, 97, 114], the Bayesian approach is mostly applicable when all the prior knowledge is reliable and all the transceiver parameters are known. Another challenge with the Bayesian approach, especially in a distributed environment, is the computational complexity, due to its high-dimensional integrals. Hence, the need for the researchers to still investigate another

approach that can address these challenges and also achieve an optimal spectrum selection and reconfiguration in a distributed CRNs.

## **2.6 Case-Based Spectrum Selection and Reconfiguration Approaches**

The case-based approach was introduced by Li D. Xu [76] for decision-making based on the past experience gathered from a particular location or from past solutions. This approach builds a database by gathering information over a period of time or about past situations and then uses the gathered information to make a decision for the current situation. A decision-making model based on Location-Aware Spectrum Database (LASD) was proposed by L. Mfupe, L. Montsi, M. Mzyece, and F. Mekuria [11]. The main goal of the authors was to develop efficient spectrum selection in TV white space and Limpopo province was used as a case study. In their proposed model, the usability characteristics of a TV channel for the purpose of opportunistic transmission was measured based on Limpopo TV spectrum geo-location statistics. In their model, data collection, spectrum selection and reconfiguration of frequency and channel bandwidth are done by the central system/base station. The model uses a threshold mechanism to filter channels with frequent primary users' appearance. The TVWS Reconfiguration time was evaluated, using the data gathered. Based on the results achieved, it was concluded that, if local conditions are satisfied, then the solution can be adopted in other parts of the African continent. The model proposed in their study is location-based and the SUs make selection and reconfiguration decisions based on the last data gathered by the central system. However, in distributed mobile networks, where the nodes' movements are dynamic and transient in nature, the data used to develop the model can change at any time and the network behaviour in different locations varies. Hence, these make the proposed LASD model difficult to implement in a different location and also for such results to be reliable, there will be a need for the real-time update of the database information.

Z-J Zhao and H-C Lai [81] proposed a quantum genetic algorithm using a case-based reasoning (CBR-QGA). The proposed CBR-QGA algorithm was used to adjust and optimise cognitive radio transceiver parameters. While the environmental variation

factor was used to measure the similarity between the current problem and the cases in the database. The initial quantum bits generated by CBR-QGA algorithm helps to avoid the blindness of initial population search and speed up the optimisation of quantum genetic algorithm. The quantum algorithm was evaluated by measuring both the convergence rate and the optimisation capability, using computer simulation. Based on their achieved results, it was concluded that their proposed CBR-QGA performed better than other three genetic algorithms in the achieved convergence rate and transceiver parameters reconfiguration optimisation capability.

D. Ali, J.M.J. Park and A. Amanna [80], presented a case-based approach called “bucketed”. The approach was used for efficient spectrum management, balancing of network traffic and system efficiency. The proposed bucketed approach uses a tree-based classification to group the information gathered. Each group contains the problem, solution, and its corresponding result to provide the SUs’ nodes with better spectrum utilisation information such as; the input, previous decisions, and the consequences of previous decisions taken. The authors aimed to reduce switching time by finding similarities between cases and bucketing. Computer simulation was used to validate the performance of the proposed approach, and based on their achieved results, it was concluded that the bucketed approach performed better than traditional case-based decision theory methods.

Reddy [79] introduced a case-based reasoning approach to identify an appropriate channel bandwidth for SUs and also introduced an automatic collaborative filtering approach to assigning a channel to the highest prioritised SUs. These two approaches were combined with the cooperative game concept to select the preferred channel for SUs at a given period. The performance of the two proposed approaches was validated using MATLAB<sup>TM</sup> simulation. Based on their achieved results, the authors identified issues such as high delay in the time it takes to switch between available spectrum holes. In a CRN, the switching time is an important metric, as it determines how long it would take the SUs to vacate a channel when a PU arrives or to switch to another channel for communication. Hence, the lower the value of the channel switching time, the better the spectrum utilisation.

In summary, this section has reviewed some research works on spectrum selection and reconfiguration using a case-based approach [76-81]. Generally, the case-based approach recommends the best solution based on the existing solutions found in the previous solutions database. However, when there is a large database, searching for an appropriate solution becomes complex and that will introduce delays. Also, the case-based approach requires a set of predefined and relevant cases, from which the SUs make a decision. This makes the case-based approach not generally applicable without first gathering relevant cases. Hence, the challenges of complex searching, mistakes propagation and predefined cases make the case-based approach inadequate to achieve optimal results in selecting the frequency and channel bandwidth for SUs' communication.

## **2.7 Potential Solution to the Existing Spectrum Selection and Reconfiguration Approaches**

The studies on selection and reconfiguration of spectrum in CRNs reviewed thus far used machine learning [6, 70-72], statistical and predictive [11, 20, 30], game theory [65-69, 117], artificial neural networks [93, 111-115] and case-based [76-80, 104] approaches and they are mostly focused on centralised topology. The reviews provide unique insight into the challenges with the existing approaches. The identified challenges include high computational complexity, repeatability, reliability and slow convergence speed. These challenges limit the practical implementation and usability of those existing approaches in a highly dynamic distributed environment like CRNs. Hence, there is still the need for an approach, which can address the challenges with the existing approaches and still achieve an optimal spectrum selection and reconfiguration for the SUs in a distributed CRN. In order for an approach to address the challenges with existing approaches and achieve an optimal result in a distributed CRNs environment, such an approach should be analytically simple and applicable in generic situations.

The biologically inspired approach has been described and been adopted by many researchers in the field of communication networks, due to its analytical simplicity and its generic applications [28]. Different biologically-inspired approaches such as swarm optimisation [3, 8], ant-colony optimisation [34], collective robotic systems [16], and

optimal foraging theory [14-16], have been proposed in other areas of wireless networking.

The results from previous studies [14-16, 35-36] in other wireless communication networks show that the biologically-inspired foraging approach has generic, simple and high applicability properties. T.O. Olwal, M.T. Masonta, and F. Mekuira [14] proposed a Bio-inspired Energy and Channel (BEACH) management for wireless multi-radio ad hoc networks. The aim of their study was to address energy efficiency and channel utilisation problems. Biological foraging theory of nutrient optimisation was used in developing the BEACH model and the model's efficacy was evaluated using MATLAB<sup>TM</sup> simulation. Based on the result of their study, it was shown that the proposed BEACH model improved the performance of energy efficiency and average network throughput. In [15], a biological Foraging-Inspired Radio-communication Energy Management (FIREMAN) model for energy management in green multi-radio networks was proposed. The FIREMAN model was developed based on behavioural ecology. The FIREMAN model was validated using MATLAB<sup>TM</sup> simulation. Based on their achieved average throughput and energy-efficiency, it was shown that the FIREMAN performs better than other conventional energy management models.

A biologically inspired consensus-based model for spectrum sensing in cognitive mobile ad hoc networks was presented [22]. Their proposed model was inspired by the self-organising behaviour of animal groups, in which the individual animals (fish and birds) sense their predator. This concept helps in spectrum sensing for decentralised nodes in a distributed cognitive radio network. The effectiveness of the consensus-based model was validated using computer simulations. Based on the achieved results, it was shown that their biologically inspired model performs better than other conventional models. Lorenzo and Barbarossa [8], presented a bio-inspired swarming model for decentralised access into a spectrum by cognitive radio nodes. The model was developed using biological foraging behaviour of a swarm and the aim of their study was to develop a distributed resource allocation model for the SUs in cognitive radio networks. Their proposed model was validated using MATLAB<sup>TM</sup> simulation. Some other biologically inspired methods have been proposed in the literature, which includes robotic system [16] and chaosology system [7].

However, based on the results achieved by the biologically inspired optimal foraging theory from previous studies [14-16] in other wireless communication networks, this thesis adopts the use of a biologically-inspired optimal foraging approach to develop a novel Foraging Inspired Spectrum Selection and Reconfiguration (FISSER) model. The FISSER model is used to address the sub-optimal spectrum selection and reconfiguration problem in a distributed CRN. One of the main advantages of biologically-inspired optimal foraging approach is its analytical simplicity and optimum solution. This advantage will help the FISSER model to address the shortcomings of the existing approaches and also help to achieve optimal spectrum selection and reconfiguration in a distributed CRN.

## **2.8 Chapter Summary**

This chapter reviewed the existing spectrum selection and reconfiguration approaches in CRNs. The review was done using the taxonomy depicted in Figure 6. The taxonomy includes statistical and predictive, game theory, machine learning, artificial intelligence, and case-based approaches. The review provides unique insight into some of the challenges with the existing approaches such as computational complexity both in machine learning and in artificial intelligence, repeatability, reliability, and switching delays in statistical and predictive methods and slow convergence speed in game theory approach. Table 1 summarises the existing spectrum selection and reconfiguration approaches and their respective strengths and challenges, which were identified in this chapter. However, due to the challenges with the existing approaches, those approaches are unable to achieve optimal results in distributed CRNs. Hence, the study of the efficacy of dynamic spectrum selection and reconfiguration approaches as a mechanism for improving the spectrum utilisation in distributed CRNs remains an open issue that needs to be addressed.

This study adopts the biologically-inspired foraging approach to develop a model, which addresses the challenges with the existing spectrum selection and reconfiguration approaches, which in turn helps to achieve optimal spectrum utilisation in a distributed CRN. The biologically-inspired foraging approach was adopted in this study due to its

well-established analytical simplicity and generic applications properties, also due to its achieved results from previous researchers in other fields of network communication.

The next chapter details the biological optimal foraging theory and the role it played in this study to develop the FISSER model is described. The formulation of FISSER model and analytical analysis for the proposed FISSER model are also presented in Chapter Three.

**Table 1: Summary of Existing Spectrum Selection & Reconfiguration Approaches**

Existing approaches	Strengths	Limitations and challenges
Dynamic Learning approach [30]	Dynamic reconfiguration of SUs based on environmental changes. Optimisation of the multi-objective system.	Computational complexity. Prior knowledge of the system is required. Slow convergence with a large network.
Q-learning approach [6]	Good probabilistic decision making model. Energy efficient.	Computational complexity.
Game theory approach [65-69]	Simplify multi-agent system decision making. It minimises the adaptation complexity.	Prior knowledge of the labelled training data and system is required. Slow convergence speed.
AHP approach[20]	Useful for making complex decisions.	Computational complexity. Pairwise comparison-matrix uncertainty.
Fuzzy logic approach [61-64]	Simplify solution. Decisions are directly inferred from rules, hence, reduces complexity.	Rules derivation is needed. Optimisation problem due to changes in the rules. The system accuracy is only based on the derived rules.

Bayesian approach [87-92]	Good probabilistic decision making models.	Computational complexity. Prior knowledge of the system is required. High delay.
Markov model approach [54-60]	High scalability. Good statistical model.	Computational complexity. Prior knowledge of the system is required.
Predictive approach [82-86]	High statistical accuracy.	Require prior collection of data Applicability problem The system accuracy is only based on last data collected.
Case-based approach [76-81]	An acceptable solution is achieved based on predefined cases in the database	Propagation of mistakes Complex search if the database is large
Artificial Neural networks approach [100-101, 109-110]	Ability to adapt to small changes Construction using few examples, hence, lowering the complexity	Require training data labels. Overfitting

## CHAPTER THREE

### BIOLOGICAL OPTIMAL FORAGING THEORY IN DYNAMIC SPECTRUM SELECTION AND RECONFIGURATION

#### 3.1 Introduction

One of the main challenges in achieving an optimal spectrum utilisation in distributed CRNs is overcoming the inability of SUs to dynamically select and reconfigure the spectrum parameters. In Chapter Two, five different categories of approaches previously explored by other researchers in addressing the dynamic selection and reconfiguration of spectrum parameters were reviewed. The strengths and challenges of existing approaches and why they are unable to achieve optimal results were also highlighted in Chapter Two. The chapter was concluded by adopting a biologically-inspired optimal foraging approach both as a solution to the challenges with the existing selection and reconfiguration approaches and to achieve an optimal spectrum selection and reconfiguration result.

This chapter describes the concept of biological foraging theory and its relevance to developing our FISSER model for the selection and reconfiguration of frequency and channel bandwidth for the SUs in a distributed CRN. Section 3.2 presents the biological optimal foraging theory, while the foraging based spectrum management model for distributed CRN is presented in Section 3.3. The formulation of the FISSER model is presented in Section 3.4. Section 3.5 presents the mathematical analysis of the FISSER model and the chapter is concluded in Section 3.6.

#### 3.2 The Biological Optimal Foraging: Theoretical Overview

The study of how naturally foraging animals in a random environment make optimal decisions when searching for food/prey is referred to as biological optimal foraging theory [26, 29]. The foraging theory was first introduced by MacArthur Zadeh in 1965

[61], where he states that “*Natural selection favours animals whose behavioural strategies maximize their net energy intake per unit time spent foraging.*” MacArthur introduced the concept of optimal foraging theory after investigating why animals often confine themselves to a few types of prey out of the wide range of available prey. In his conclusion, MacArthur stated that “*an animal usually makes a decision between two contrasting strategies: spending a long time (using more energy) searching for highly profitable food items, or devoting minimal time (using less energy) to more common but less profitable food items.*” Different conditions such as the predation risk can cause the animals to make either of the decisions stated in the aforementioned MacArthur’s conclusion. Although catching prey provides the foraging animals with energy, the process of searching and capturing the prey requires time and energy. Hence, the goal of foraging animals is to achieve maximum energy using the lowest possible cost (time), so as to maximise their fitness. The optimal decisions made by foragers help them to maximise their efficiency, have a long lifetime and reduce possible threats.

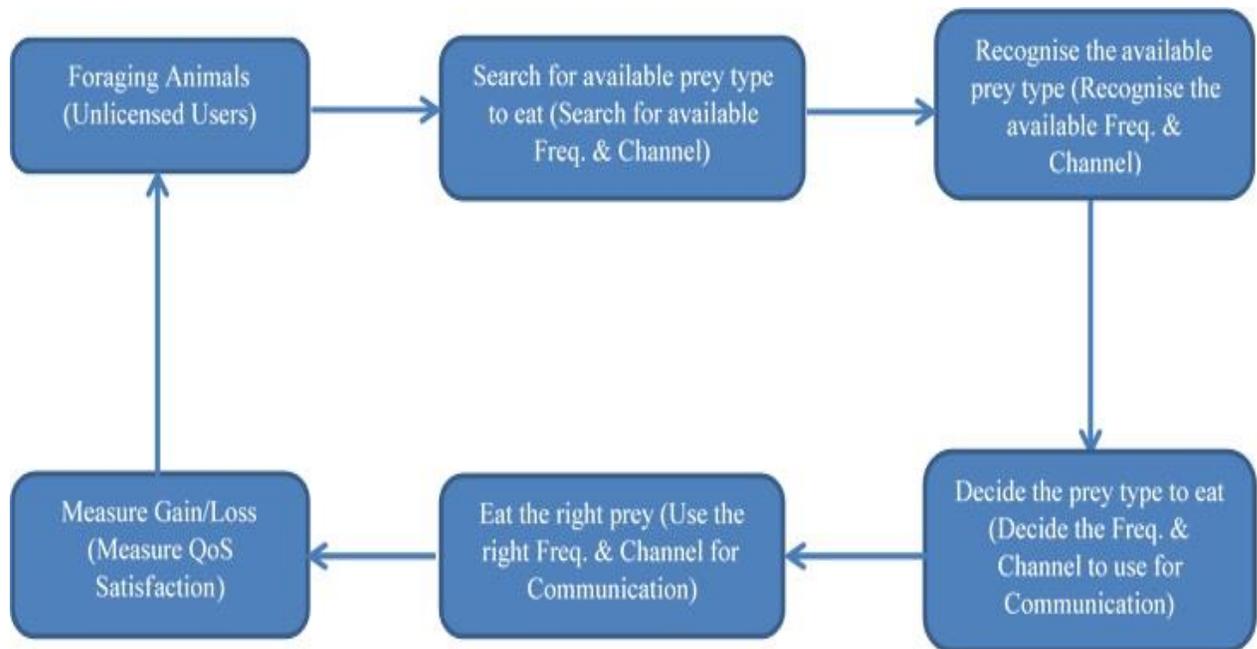
Optimal foraging theory uses diverse models to describe how solitary foraging animals search for prey, sort, and make decisions on which prey to feed on so as to maximize their efficiency [24-25]. The classifications of nutrient consumption by foraging animals were adopted and modelled as an optimisation process which is now commonly known as optimal foraging theory [27, 35-38]. The ability of a forager to make an optimal decision on the most suitable prey type to consume so as to maximise their efficiency within the shortest possible time is one of the core advantages of the optimal foraging theory. Some of the other advantages of the optimal foraging theory include flexibility, scalability, self-organisation, high adaptation and propagation speed. However, in spite of all these advantages, one of the major factors that influence the foraging efficiency is the selection criteria used by the forager in selecting a prey type to consume. Hence, foragers should aim at matching their search efforts to the relative profitability of various parts of their surroundings.

One of the fundamental features of the biological foraging approach is the ability of the foragers to dynamically evolve in response to external influences within a short time. However, the existing approaches are unable to evolve their functional structure to

accommodate new external influences within a short time, hence this is one of the key reasons why the existing approaches are not achieving optimal results.

### **3.3 Foraging Based Spectrum Management Model for Distributed Cognitive Radio Network**

This section presents a novel Foraging Inspired Spectrum Selection and Reconfiguration (FISSER) model, which can dynamically evolve in response to its interaction with the external surrounding environment. The dynamic evolution of the FISSER model to accommodate new external influences within a short time helps to achieve an optimal spectrum selection and reconfiguration of both frequency and channel bandwidth in a distributed CRN. The main concept in developing the FISSER model comes from the biological foraging theory, where the foraging animals make optimal decisions on which prey to feed on, so as to maximise their energy gain whilst minimising the associated risks. Figure 7 depicts the analogy between the biological foraging cycle and the proposed FISSER model cycle for a distributed CRN. Using the biologically-inspired foraging methodology depicted in figure 7, the foraging animals mimic the Secondary Users, whilst the prey are considered as the available Primary Users' frequencies to be searched for by the SUs. Similar to what happens in the biological foraging cycle whereby the foraging animals search for prey, in the same way, each SU with a message searches for possible available PUs' frequency to be used for communication. The next phase in the proposed FISSER cycle is for each of the SUs (foraging animals) to decide which of the available frequencies and channel bandwidths (prey) can be selected for communication in order to maximise their efficiency and reduce possible threats, such as interference to the PUs' network. This phase can be referred to as the spectrum selection and reconfiguration in CRNs. In biological foraging, the colony does not have any central control, hence, members of the colony make decisions on an individual basis. This is similar to a distributed environment in CRNs, where each SU node is expected to make its decision without any central control or base station.



**Figure 7: Proposed FISSE Cycle Model for Distributed CRN**

Often times, the foraging animals do not know the exact location where the prey are located, hence, they rely on search strategies to find the prey. There are many existing methods which biological foraging animals usually use to search for prey [38]. These searching methods include: composite search (the foragers move through spaces until resources within its perceptual radius are found [24, 36]), intermittent search [27], area concentrated search [26, 29] or area restricted search [25], random search [38] and patch-use search [37]. The composite search method describe the search/movement pattern that the foragers should execute to find the resources without having prior knowledge of the location of the resources. However, in other search methods, the emphasis is usually on how the foragers determine when to leave the prey and the foragers have prior knowledge of the location of resources. In a wireless networks environment, where the nodes movements are dynamic, waiting for all the location of resources before making a decision will lead to high computational complexity and delay in nodes communication. Hence, the reason why composite search method is more preferable than other methods in the wireless networking environment.

In a dynamic distributed CRN environment, where the nodes can join or leave the network at any time, the nodes should be able to dynamically search for the available resources within their perceptual radius without having prior knowledge of the resources' location. Hence, the proposed FISSER model adopts the composite search method because of its effectiveness and applicability to the decision making for a distributed CRN. The mathematical formulation of the FISSER model for dynamic selection and reconfiguration of SUs' communication in a distributed CRN is presented in the next section.

### **3.4 The Foraging Inspired Spectrum Selection and Reconfiguration (FISSER) Model**

The mathematical formulation of the FISSER model for SUs' node communication in a distributed CRN is presented in this section. The aim of this model is to address the sub-optimal spectrum utilisation problem, by optimising the selection and reconfiguration of both frequency and channel bandwidth for SUs' node. The proposed FISSER model presented in this thesis utilises the biological foraging composite search method. In the proposed FISSER model, available PUs are denoted as points, while each of the SUs has a fixed perceptual radius, within which it can detect available PUs. The SUs do not have prior knowledge of the location of available PUs, hence, each of the SUs must move across space until they find an available PU within its perceptual radius. The SUs' perceptual radius is the visibility/coverage zone within which the SU searches for any available PU frequency. The perceptual radius is defined as a random parameter, within which SUs look to find available PUs. The type of movement pattern used by the SUs for searching is called a stochastic process. The combination of SUs' movement and checking for available PUs within the defined coverage zone is defined as the spectrum selection phase. The proposed FISSER model comprises of both the selection and reconfiguration phases. Sub-section 3.3.1 presents the FISSER spectrum selection phase, while the spectrum reconfiguration phase is presented in subsection 3.3.2.

### 3.4.1 FISSER - Spectrum Selection Phase

This subsection presents the spectrum selection phase for the proposed FISSER model. The spectrum selection phase is the phase where the SUs decide on which PUs' frequency should be used for communication. Assume that there are  $N$  PUs' frequency with different bandwidth values and  $B_f$  denotes the bandwidth of frequency  $f$ . Similar to the biological foraging, where the foragers need to consider the predators while searching for the prey to feed on, the SUs' nodes also need to consider different interference levels while searching for the available PU's frequency to use for communication. The interference could occur as a result of PUs' arrival, which will make the frequency not available for SUs' nodes. Let  $n_{if}$  denote the interference level incurred by SU node  $i$  if it uses the frequency  $f$ . While  $A_i$  is the set of PUs' frequency IDs that are periodically selected by SUs' node. Hence, the total rate of gain of node  $i$  in selecting a PU's frequency,  $f_i$ , is given as:

$$f_i = \sum_{f \in A_i} \frac{a_{if} B_f}{a_{if} n_{if}}$$

Where  $a_{if}$  is the probability that node  $i$  uses frequency  $f$ . The maximisation of  $f_i$  will allow the SUs' node  $i$  to select a frequency with high bandwidth while minimising the level of interference between PUs and the SUs. Hence, the goal of SUs' node  $i$  is to maximise  $f_i$  by solving:

$$f_i = \frac{a_{if} B_f + \zeta_i}{a_{if} n_{if} + \lambda_i}$$

Where  $\zeta_i$  and  $\lambda_i$  are given as:

$$\zeta_i = \sum_{\substack{z \in A_i \\ z \neq f}} a_{iz} B_f \quad \text{and} \quad \lambda_i = \sum_{\substack{z \in A_i \\ z \neq f}} a_{iz} n_{iz}$$

Using the zero-one rule, the selection of  $a_{if}$  for maximizing  $f_i$  is given as:

$$\text{Set } a_{if} = 0 \text{ if } \frac{B_f}{n_{if}} < \frac{\zeta_i}{\lambda_i}$$

$$\text{Set } a_{if} = 1 \text{ if } \frac{B_f}{n_{if}} > \frac{\zeta_i}{\lambda_i}$$

Where  $(B_f/n_{if})$  is the frequency selection maximisation and it characterises the amount of gain for SUs' node  $i$  if it uses frequency  $f$ .

Below is the algorithm for SUs' spectrum selection process:

---

```

1 foreach Frequency  $f$  in  $A_i$  do
  2 determine  $B_f$  and  $n_{if}$ 
  3 end
  4 foreach Frequency  $f$  in  $A_i$  do
    5 if  $\{f \mid \forall k \in A_i : (B_k/n_{ik}) < (B_f/n_{if})\}$  then
      6 select frequency  $f$  for communication
    7 end
  8 end

```

---

### 3.4.2 FISSER - Spectrum Reconfiguration Phase

The proposed FISSER model assumes that there are “n” different types of prey, which the foragers can consume for energy.  $P_i$  is the relative frequency or the probability of a forager encountering a prey type  $i$ . The average rate of encountering a prey type  $i$  is  $\lambda_i$  and  $V_i$  is the expected amount of energy intake from captured prey  $i$ . While  $T_i$  is the expected time to seek and capture prey  $i$ . Hence, the efficiency  $E$  of a forager can be

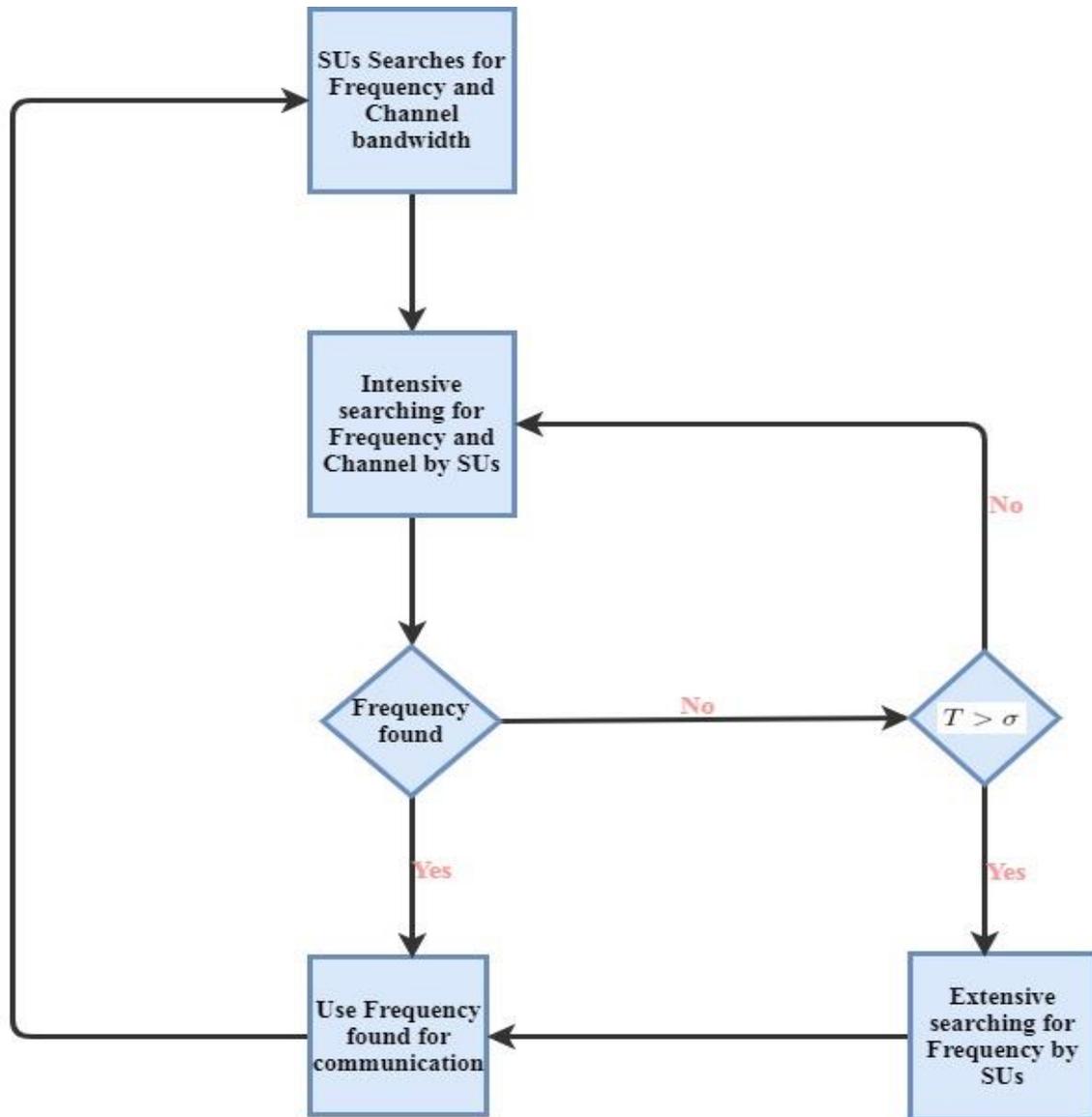
defined as the ratio of the expected intake energy to the time spent by the forager. This is represented mathematically as:

$$E = \frac{\sum_{i=1}^n P_i \lambda_i V_i}{\sum_{i=1}^n P_i \lambda_i T_i} \quad (1)$$

The maximisation of the forager's efficiency,  $E$ , involves finding the optimal values of  $P_i$  for all prey  $i$ . Based on the zero-one rule used by foragers to determine optimal values of  $P_i$ , it can be noticed that this theory establishes a solid basis for the decision making approach and optimisation problems.

In the biological foraging environment, the foragers usually start searching for prey within their immediate environment and only go far, if no prey is found [24, 29]. Similar to the biological foraging behaviour, the proposed FISSER model uses two stages (Intensive and/or Extensive) to search across the search space [28, 29]. The first stage of the search involves an intensive search, which is characterised by frequent changes of direction effected by making short steps in the search area. This search mode is usually area-intensive and can be employed in resource-rich areas, such as rural areas, where there are many available frequencies, which the SUs can use opportunistically. The kind of motion adopted in the intensive search mode is based on the Brownian (non-heavy-tailed) motion.

However, if the intensive search mode has not been successful, that is, if no frequency has been encountered by SUs after a particular time ( $\sigma$ ), defined as the Giving-Up Time (GUT), the SU switches to the extensive search mode. In extensive search mode, the SUs take relatively longer steps, using Ballistic motion with a lesser change of direction until it finds an available frequency. This search mode can be employed in resource-poor areas, such as urban or suburb areas, where there are fewer available frequencies which can be opportunistically used by the SUs. The proposed FISSER model flow process for both intensive and extensive search mode is depicted in Figure 8.



**Figure 8: FISSER Model Flow Process**

The overall objective in any foraging-based modelling is the optimal foraging strategy. This optimal foraging strategy is the condition/parameter that maximises the overall energy gain by the foraging animals. In my proposed FISSER model, the optimal foraging strategy is to find an optimal value of GUT ( $\sigma$ ) that minimises the expected distance travelled by an SU before finding an available frequency. In order to achieve this, the following simplifying assumptions were made:

1. The SUs search for an available frequency in a one-dimensional line.
2. The SU starts at a position  $X_0$  (where it last found a food item).
3. The SUs use a Brownian movement pattern in the intensive mode and a ballistic movement in the extensive mode.
4. The distance the SUs must travel before finding a food item after switching to the extensive mode is exponentially distributed with mean  $D = \frac{d}{2}$ . This distance is independent of the position of the SUs, i.e.  $X(\sigma)$ , after completing the intensive search.

In a biological foraging environment, the foragers usually start to search for prey within their immediate environment, and only search long distance, if no prey was found. Hence, this study starts with the Brownian type random search movement in which the forager moves in the intensive mode, described by the stochastic differential equation:

$$dX(t) = \alpha dW(t) \quad (2)$$

Where  $X_{(t)}$  is the position of the SUs at any time  $t$ ,  $W_{(t)}$  is a Wiener process with parameter  $\tau^2$  (variance). Now, the mean instantaneous speed of the intensive search process described by equation (2) is:

$$v_I = \sqrt{\frac{2}{\pi\tau}} \quad (3)$$

Thus, the total distance travelled during the intensive phase is:

$$d = \nu_I T \quad (4)$$

At  $\mathbf{T} > \sigma$  (Expected time to seek for available frequency > GUT), the SUs switch to the extensive search mode. The distance travelled by the SUs between successive available frequencies,  $L$ , is given for the two search phases as:

$$L = \begin{cases} \nu_I T & \text{if } T \leq \sigma \text{ (Intensive);} \\ \nu_I T + R & \text{if } T > \sigma \text{ (Extensive).} \end{cases} \quad (5)$$

Here, random variable  $\mathbf{R}$  is the distance taken from an exponential distribution, i.e.  $R \sim e^{-\frac{2}{d}}$ .

The probability density function of the total distance travelled by SUs (from equation (5)) before finding an available frequency is given as:

$$f(l) = \begin{cases} \frac{1}{\nu_I} f_T\left(\frac{1}{\nu_I}\right) & \text{for } l \leq \nu_I \sigma; \\ (1 - F_T(\sigma)) f_R(l - \nu_I T) & \text{for } l > \nu_I \sigma. \end{cases} \quad (6)$$

It is assumed in this study that the energy cost during a search by the SUs is directly proportional to distance travelled and that the energy obtained from each available frequency found is the same. The reason for this assumption is that frequencies found by the SUs are used for communication, so the final goal of SUs' energy acquisition is for communication. Hence, by minimising the average distance travelled between available frequencies, the SUs are able to maximise their net energy gain.

From equation (6), the expected distance travelled  $E(L)$  by the SUs before finding an available frequency for communication is:

$$E(L) = \int_0^\infty l f_L(l) dl = \nu_I \int_0^\infty t f_T(t) dt + (1 - F_T(\sigma)) \times \left( \nu_I \sigma + \int_0^\infty s f_R(s) ds \right) \quad (7)$$

The equation (7) can be written in a closed form as:

$$\frac{E(L)}{d} = \sqrt{\frac{4x_0\sigma}{\pi d^2}} e^{\left(-\frac{x_0}{\pi\nu_I\sigma}\right)} + \left(\frac{2x_0^2}{\pi\nu_I d} + \frac{\nu_I\sigma}{d} + \frac{1}{2}\right) \operatorname{erf}\left(\sqrt{\frac{x_0^2}{\pi\nu_I^2\sigma}}\right) - \frac{2x_0^2}{\pi\nu_I d} \quad (8)$$

If  $\varphi = \frac{\nu_I \sigma}{d}$  and  $\epsilon = \frac{2x_0^2}{\pi \nu_I d}$ , then,

$$\frac{E(L)}{d} = \sqrt{\frac{2\epsilon\varphi}{d}} e^{\frac{\epsilon}{2\varphi}} + \left(\epsilon + \varphi + \frac{1}{2}\right) \operatorname{erf}\left(\sqrt{\frac{\epsilon}{2\varphi}}\right) - \epsilon. \quad (9)$$

where “erf” is the error function and “d” is the total distance travelled. Suppose there is a local minimum in  $E(L)$  for a positive value of  $\varphi$ , then this will occur where the derivative of  $E(L)$  with respect to  $\varphi$  is 0. That is:

$$\frac{dE(L)}{d\varphi} = 0$$

This corresponds to:

$$\frac{\epsilon^{\frac{1}{2}}}{2^{\frac{3}{2}} \pi^{\frac{1}{2}} \varphi^{\frac{3}{2}}} e^{-\left(\frac{\epsilon}{2\varphi}\right)} - \operatorname{erf}\left(\sqrt{\frac{\epsilon}{2\varphi}}\right) = 0 \quad (10)$$

From equation (10), there is no closed form solution to obtain the optimal value of  $\varphi^*$ , since (10) is a transcendental equation for  $\varphi$ . Hence, the only way forward is to consider the two terms in equation (10) separately. That is, let

$$A(\varphi) = \frac{\epsilon^{\frac{1}{2}}}{2^{\frac{3}{2}} \pi^{\frac{1}{2}} \varphi^{\frac{3}{2}}} e^{-\left(\frac{\epsilon}{2\varphi}\right)} \quad \text{and} \quad B(\varphi) = \operatorname{erf}\left(\sqrt{\frac{\epsilon}{2\varphi}}\right) = 0$$

So that equation (10) becomes:

$$A(\varphi) - B(\varphi) = 0. \quad (11)$$

Therefore, two cases arise:

**CASE 1:** If  $A(\varphi) < B(\varphi)$  for all  $\varphi \geq 0$ , then,  $E(L)$  is a monotone increasing function of  $\varphi$ . While the optimal value of  $\varphi$ , i.e.  $\varphi^*$ , occurs at  $\varphi^* = 0$ .

**CASE 2:** If  $A(\varphi) > B(\varphi)$ ,  $E(L)$  becomes a decreasing function of  $\varphi$ . In this case, a local maximum and minimum exist in  $E(L)$ . The local minimum turns out to be a global minimum if it is smaller than the value of  $E(L)$  at  $\varphi = 0$ .

Suppose the local maximum occurs at  $\varphi = \varphi_a$ . Therefore, by solving  $A(\varphi_a) = 0$ , one obtains  $\varphi_a = \frac{\epsilon}{3}$ . The implication of this is that  $A(\varphi) > B(\varphi)$  if and only if

$$\frac{3^{\frac{3}{2}}}{2^{\frac{3}{2}} \pi^{\frac{1}{2}} e^{\frac{3}{2}} \epsilon} > \operatorname{erf} \left( \frac{3^{\frac{1}{2}}}{2^{\frac{1}{2}}} \right) \quad (12)$$

This means,

$$\epsilon_a < \epsilon \simeq \frac{1}{4}$$

To obtain an approximation to equation (10), we assume that  $K = \frac{1}{\varphi}$  and then find the power series representations of  $A$  and  $B$  in  $K$ . Hence, we have:

$$\frac{2^{\frac{1}{2}}}{\pi^{\frac{1}{2}}} \left( (\epsilon k)^{\frac{1}{2}} - \frac{(\epsilon k)^{\frac{3}{2}}}{6} + \frac{(\epsilon k)^{\frac{5}{2}}}{40} + o((\epsilon k)^{\frac{7}{2}}) \right) - \frac{\epsilon^{\frac{1}{2}}}{2^{\frac{3}{2}} \pi^{\frac{1}{2}}} k^{\frac{3}{2}} \left( 1 - \frac{\epsilon k}{2} + \frac{(\epsilon k)^2}{8} + o((\epsilon k)^3) \right) = 0$$

Collecting the powers of  $K$  gives:

$$1 - \left( \frac{\epsilon}{6} + \frac{1}{4} \right) k + \epsilon \left( \frac{\epsilon}{40} + \frac{1}{8} \right) k^2 - \frac{\epsilon^2}{24} k^3 + o((\epsilon k)^3) = 0 \quad (13)$$

Recall that in Case II, we have a solution to equation (10) that is  $\epsilon \ll 1$  by equation (12). Thus, we may seek a solution as a power series in  $\epsilon$  as follows:

$$k = \sum_{n=0}^{\infty} k_n \epsilon^n \quad (14)$$

Substituting (14) into (13) and equating coefficients of  $\epsilon^n$  ( $n = 0, 1, 2$ ) give the coefficients in the series for  $K$  as follows:

$$k_0 = 4, \quad k_1 = \frac{16}{3}, \quad k_2 = \frac{392}{45}$$

Suppose (12) is satisfied, then there exists a local minimum  $E(L)$  with respect to  $\sigma$  and this occurs at:

$$\begin{aligned} \sigma^* &= \frac{d}{v_I} \left( 4 + \frac{16}{3} \epsilon + \frac{392}{45} \epsilon^2 + O(\epsilon^3) \right)^{-1} \\ &= \frac{d}{4v_I} \left( 1 - \frac{4}{3} \epsilon - \frac{2}{5} \epsilon^2 + O(\epsilon^3) \right) \end{aligned} \quad (15)$$

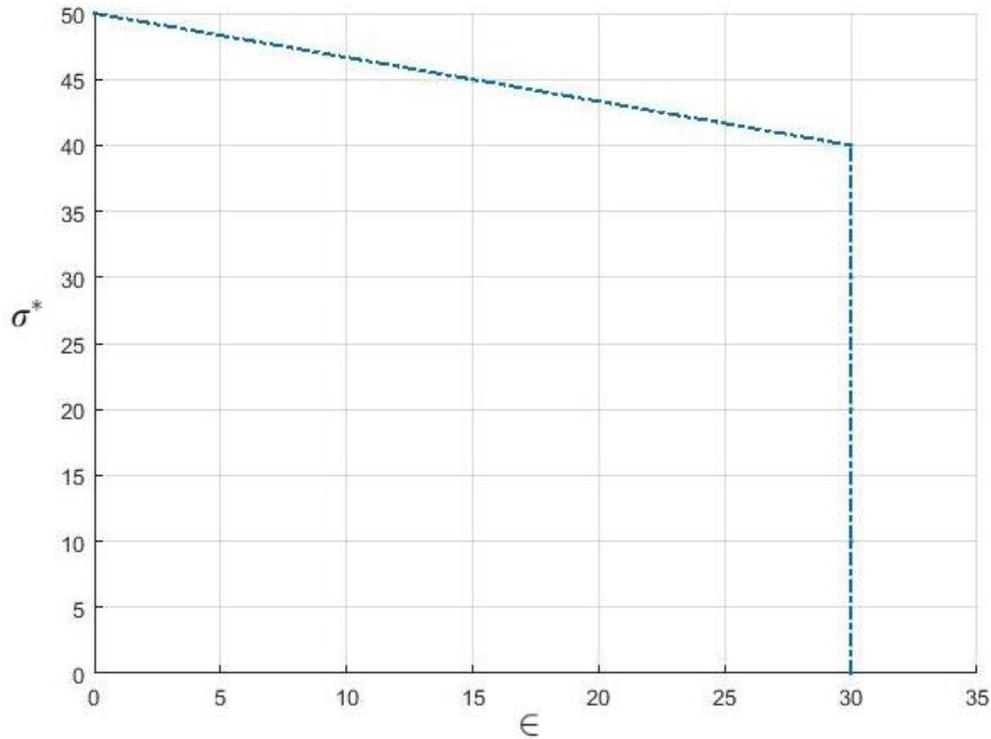
Disregarding the terms of order  $\epsilon^3$  in the equation (15) above gives:

$$= \frac{d}{4v_I} \left( 1 - \frac{4}{3} \epsilon - \frac{2}{5} \epsilon^2 \right) \quad (16)$$

Recall that from equation (8),  $\epsilon = \frac{2x_0^2}{\pi\nu_I d}$  where  $\epsilon$  is the perceptual radius of the SUs' node. The optimal value of  $\sigma^*$  against  $\epsilon$  is depicted in Figure 9, and it was calculated by minimising equation (8) and using the analytical approximation of equation (16). From figure 9, it can be deduced that if frequencies are densely distributed relative to the number of SUs within an environment,  $\epsilon > 30$ , then the optimal strategy is always to search using straight line (extensive), until a frequency is found. Moreover, the mean distance travelled is  $d/2$ . However, if  $\epsilon \leq 30$ , then the mean efficiency is improved by using Brownian motion (Intensive) to search. The optimal duration of intensive searching increases as  $\epsilon$  decreases.

The analytical result presented in figure 9 also shows that if  $\epsilon > 30$ , then the minimum value of  $E(L)$  occurs at  $\sigma = 0$ . However, while  $\epsilon \leq 30$  both  $\sigma^*$  and  $\epsilon$  show good

agreement. It can also be observed that as the SUs' perceptual radius ( $\epsilon$ ) increases, the optimal switching time increases. However, the expected distance travelled by the SUs before finding an available frequency,  $E(L)$  decreases.



**Figure 9: The effect of Perceptual radius ( $\epsilon$ ) against Optimal switching time ( $\sigma^*$ )**

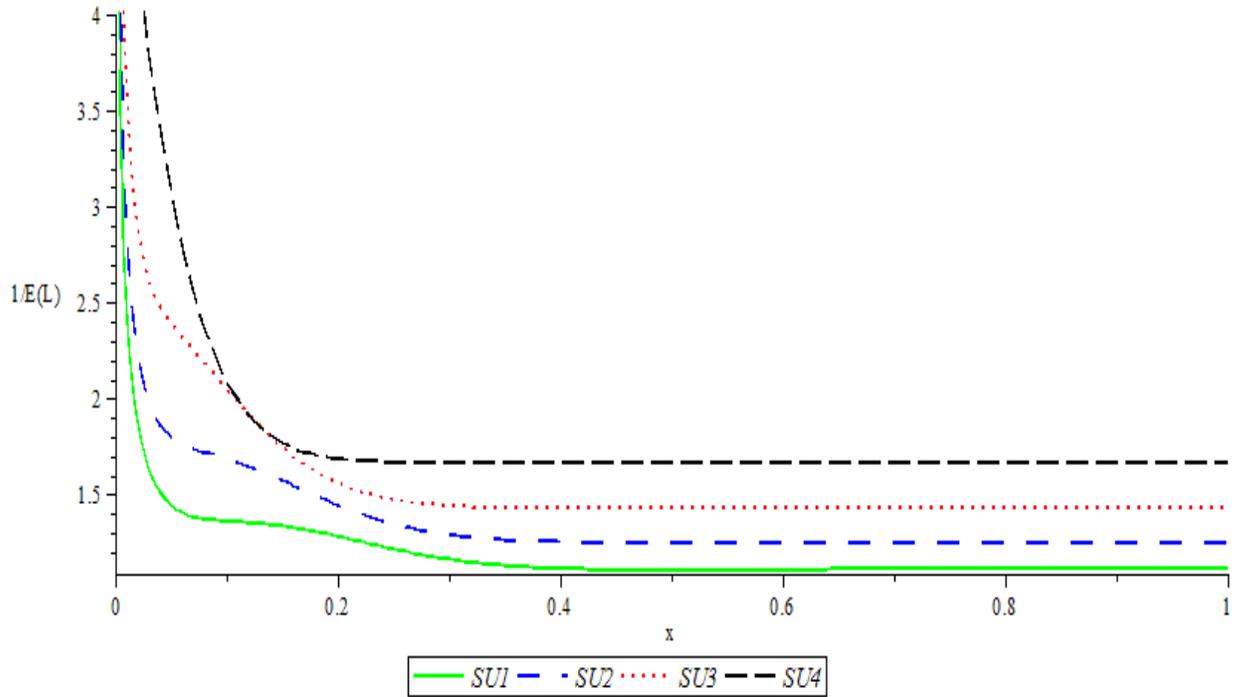
### 3.5 Analytical Presentation of the FISSER Model

This section covers the analytical presentation of the FISSER model derived from the mathematical model in the previous section. The mean efficiency and distance travelled by SUs before getting a frequency for communication when subjected to different SUs' node positions ( $X_0$ ) and GUT ( $\sigma$ ) were analytically formulated. The aim of this formulation is to be able to know the appropriate time that should be used as GUT in the simulation and to be able to determine the efficiency of the proposed FISSER model at different times.

The distances travelled by 16 SUs when subjected to different time and positions were analysed, so as to know the distance that can maximise the net energy gain, since the

shorter the distance travelled, the better the net energy gain. All the 16 SUs considered perform almost the same way, hence, the results were categorise into 4 groups, using time and positions. The best performing from each group were presented as SU1, SU2, SU3 and SU4.

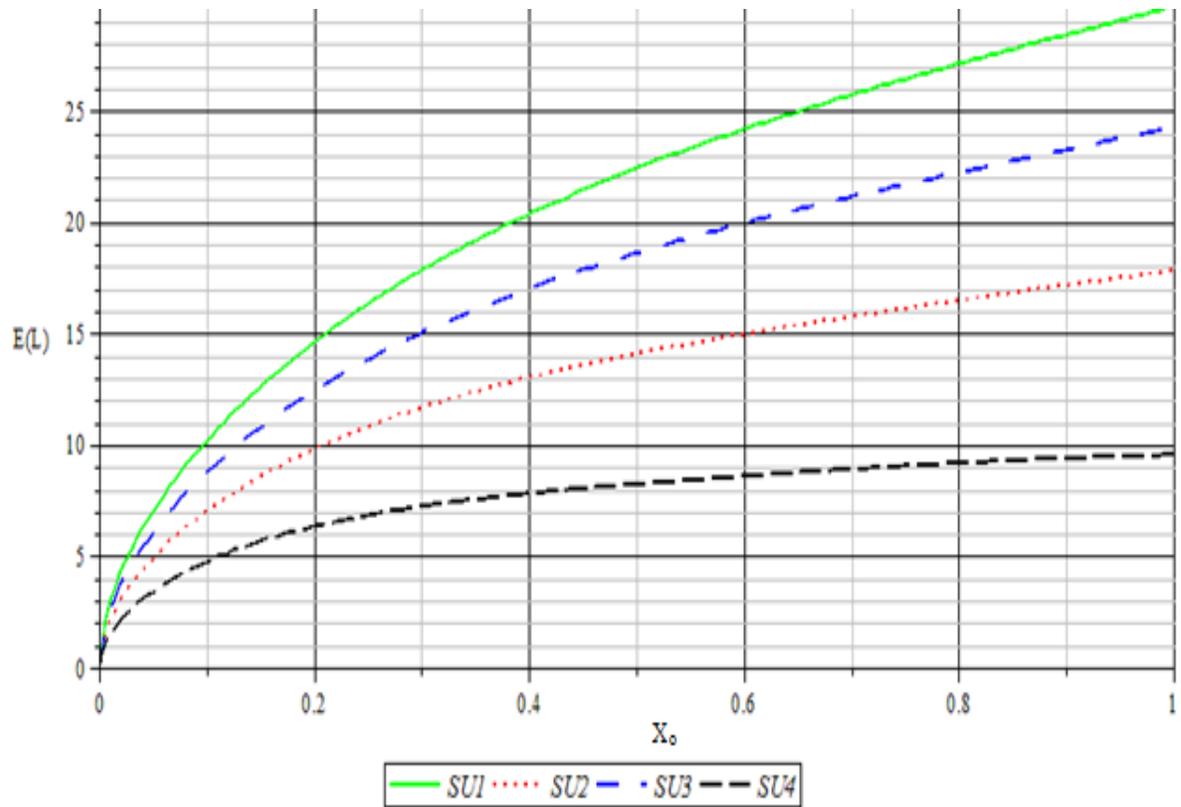
The mean efficiency is the reciprocal of distance travelled by the SUs before finding an available frequency for communication [29]. Figure 10 shows the mean efficiency over a range of starting positions for different SUs. The mean efficiency at the optimal switching time was calculated using equations (8) and (16). It was observed that each of the SUs considered, have various efficiency value. The differences in the SUs efficiency value can be attributed to the different distance travelled by each group of SUs before finding an available frequency for communication. The longer the distance travel, the higher the energy consume and the lower the mean efficiency. In a dynamic environment, such as distributed CRN, the PUs nodes movement are dynamic. Hence, the reason why the SUs travel different distances before finding an available frequency. However, it can be observed that from  $X_o = 0.2$ , the mean efficiency of each of the SUs remains constant. This behaviour is in line with the mean exponential distribution  $\frac{d}{2}$ , which is the efficiency of a ballistic strategy in a random environment. It can also be observed that while  $0 < X_o \leq 0.2$ , the smaller the  $X_o$ , the higher the mean efficiency.



**Figure 10: The Effect of SUs' Positions on Mean Efficiency**

The effects of different SUs' positions on the distance travelled before finding an available frequency for communication were presented in Figure 11. The distances travelled by SUs were calculated using equation (8). It was observed that as  $X_0$  increases, the distance travelled by SUs ( $E(L)$ ) tends towards  $R \sim e^{\frac{2}{a}}$ , exponential distribution. When the SUs travel long distances before getting an available frequency, it results in poor net energy gain. This result is in agreement with what was achieved in the mean efficiency [see figure 10], where the higher the distance travelled, the lower the efficiency achieved.

Based on the results depicted in Figures 10 and 11, it was observed that the proposed FISSER model performs very well at a lower distance. In a distributed CRN environment, where the SUs are opportunistic users, travelling a short distance by each of the SUs' nodes to get an available frequency, will help to optimise the spectrum selection and reconfiguration of both frequency and channel bandwidth.

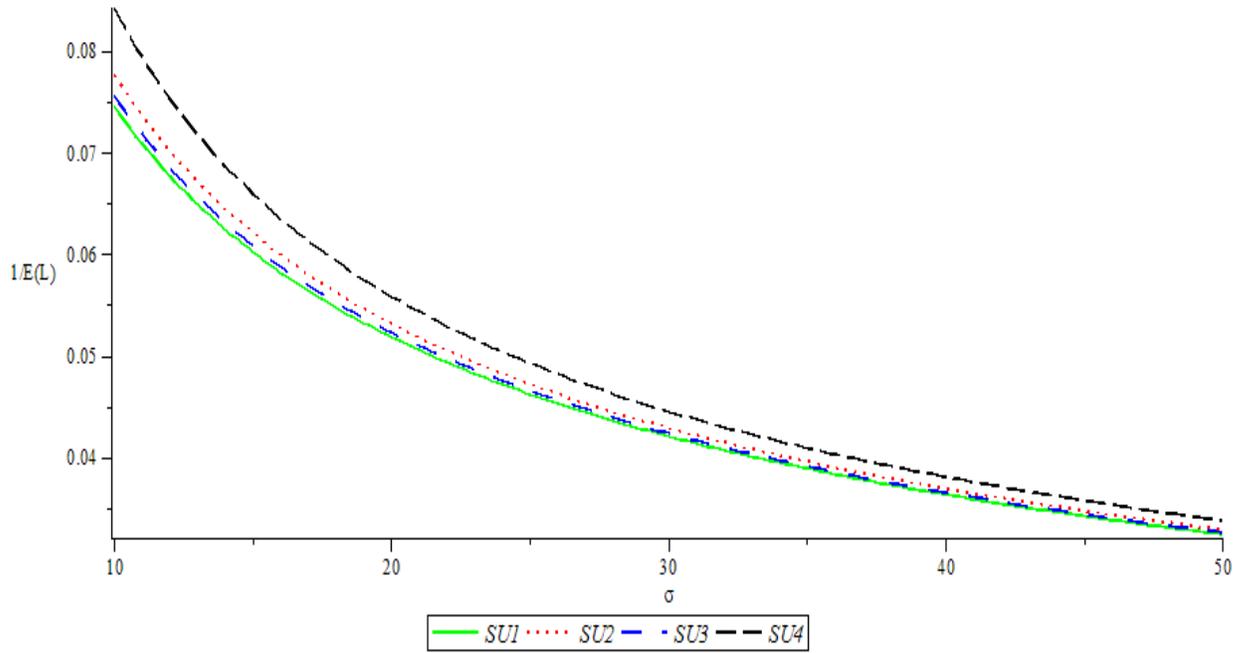


**Figure 11: The effects of SUs’ positions on distance travelled before getting the available frequency**

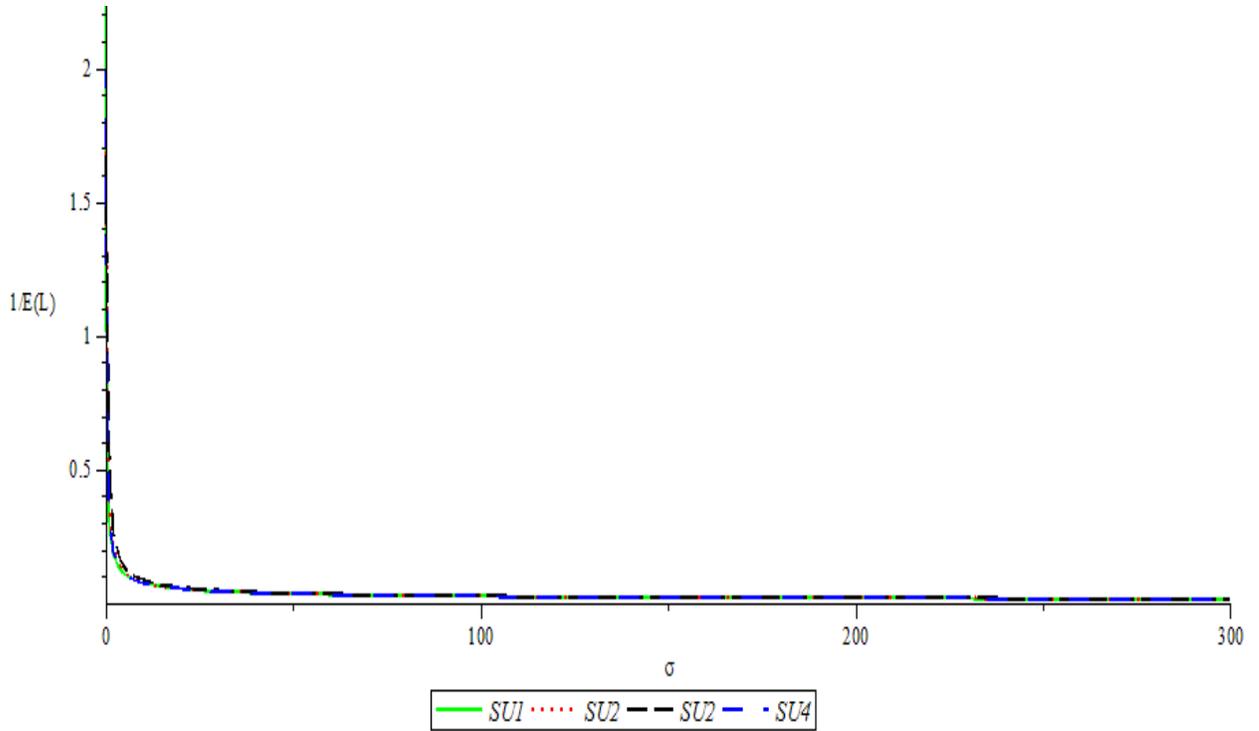
Figures 12 and 13 present the SUs’ mean efficiency when subjected to different GUT ( $\sigma$ ). Two sets of GUT were considered: early and late GUT. Where early GUT is defined as “ $10 \leq \sigma \leq 50$ ” and the late GUT is defined as “ $60 \leq \sigma \leq 300$ ”. The early and late GUT values were calculated by numerical minimisation of equation (7) and using the approximation of equation (16), which is in agreement with the analytical result presented in figure 9. The reciprocal of equation (8) was used to calculate the mean efficiency, which is plotted against various GUT. The optimal value of GUT ( $\sigma$ ) is the one that minimises the distance travelled ( $E(L)$ ) by the SUs before finding an available frequency for communication and can be approximated by equation (16). It can be observed from Figure 12 that the mean efficiency drops significantly as  $\sigma$  increases. However, when  $\sigma > 50$ , it was observed that the mean efficiency drops drastically to almost zero, as depicted in Figure 13. The very low mean efficiency achieved could be attributed to the delay incurred when  $\sigma > 50$ . The delay could lead to the arrival of PUs,

thereby making the frequency unavailable for SUs communication which in turn leads to low mean efficiency.

However, in order to properly understand the effect of GUT on the proposed FISSER model, the effect of both early and late GUT on distance travelled by the SUs was also analysed and the results are depicted in Figures 14 and 15.



**Figure 12: The effect of early GUT on Mean Efficiency**

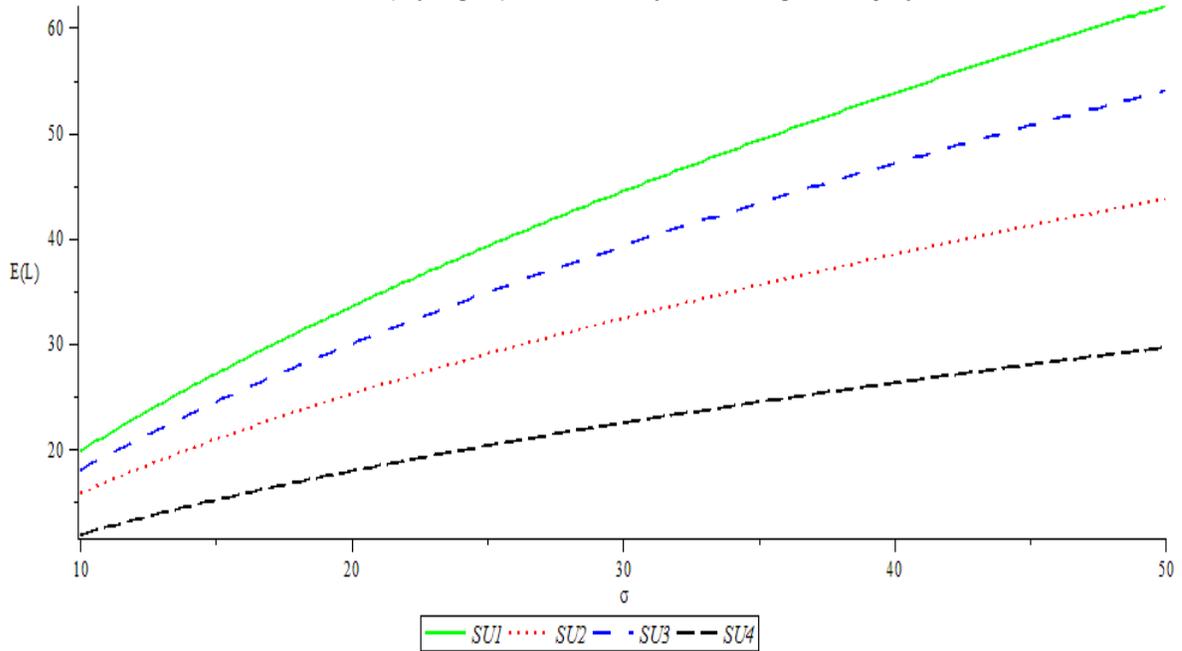


**Figure 13: The effects of Late GUT on Mean Efficiency**

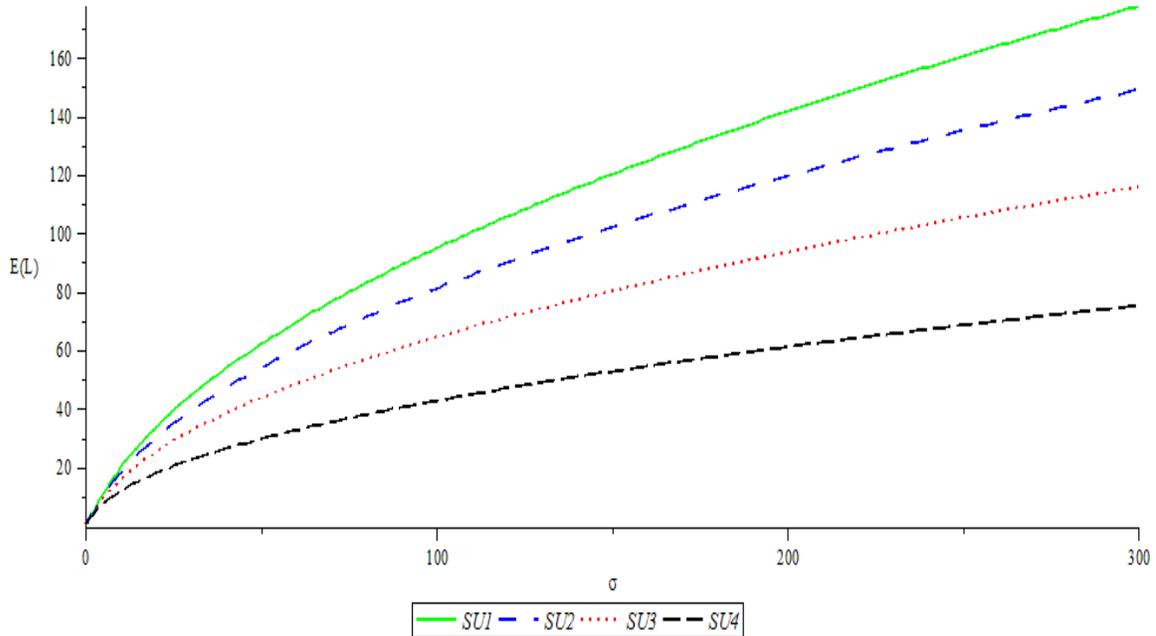
Figures 14 and 15 show the effect of GUT on  $E(L)$ . Both Figures 14 and 15 depict the Distance travelled by the SUs before finding an available frequency for communication ( $E(L)$ ) against early and late GUT ( $\sigma$ ) respectively. The  $E(L)$  was calculated using equation (8) in both cases; the lower the  $E(L)$  the better the system performance. It can be observed in Figures 14 and 15 that as  $\sigma$  increases, the  $E(L)$  also increases exponentially. Based on our observation, the model performs better while  $\sigma \leq 50$ . It is generally assumed that the higher the distance travelled, the higher the energy expenditure and that in biological foraging, the energy obtained from each food item found is the same [15, 42]. Hence, by minimising the distance travelled before finding the available frequency, the SUs will be able to maximise their overall energy gain and achieve high mean efficiency.

The high mean efficiency achieved by the proposed FISSER model at low GUT and distance helps the SUs in selecting an available frequency within a short distance and time. This performance, in turn, helps to minimise the communication overhead and improve the efficient use of energy. The major feature of FISSER model that led to its

high mean efficiency performance is the high adaptation and propagation speed, which help the model to dynamically evolve in responding to the external influences within a short time.



**Figure 14: The effect of early GUT on distance travelled by SUs before finding an available frequency**



**Figure 15: The effect of late GUT on Distance travelled by SUs before finding an available frequency**

### 3.6 Chapter Summary and Remarks

In this chapter, the analogy between the biological optimal foraging concept and distributed CRNs was presented and this concept relevance fostered to develop a FISSER model. The developed FISSER model uses both intensive and extensive search mode for the SUs to search for available frequencies and channel bandwidths. The SU starts the search using intensive search mode and if after a certain period of time called “Giving-up time (GUT)”, the SU has not been able to get any available frequency, then it switches to the extensive mode. The two search modes (intensive and extensive) use Brownian and ballistic movement respectively.

The main objective of this chapter was to develop a model that can address the sub-optimal spectrum utilisation problem in a distributed CRN by improving the dynamic selection and reconfiguration of frequency and channel bandwidth. In Chapter Two, the author discussed why the existing approaches that other researchers have used to develop models for spectrum selection and reconfiguration are not achieving optimal spectrum utilisation. To the author’s knowledge, none of the existing models considered different levels of spectrum usage aggregation in their model development. For example, the spectrum usage behaviour in an area with more aggregated frequencies will be different from the area with less/scanty aggregated frequencies. The existing models use single mode for their reconfiguration process, hence, they consume more energy and display a high switching time. However, our proposed FISSER model with two modes (intensive and extensive) for spectrum reconfiguration process is novel in the field of spectrum selection and reconfiguration for distributed CRNs. The intensive and extensive search modes help the FISSER model to adapt to different spectrum usage aggregations, which in turn will reduce the energy consumption, average switching time and optimise the spectrum utilisation.

The analytical results presented in this chapter revealed that as the SUs’ optimal switching time increases, the efficiency decreases and as the SUs’ node perceptual radius increases, the distance travelled by the SUs before finding an available frequency decreases. The SUs achieved optimal value when  $0 < X_0 \leq 0.2$ ,  $\sigma \leq 50$  and  $\epsilon \leq 30$ , and

this indicates a good agreement between the perceptual radius and optimal switching time. Chapter Four, therefore, validates the performance of the FISSER model both in the nucleated and dispersed settlement patterns, where there are different levels of spectrum usage. The validation was conducted using computer simulations.

## **CHAPTER FOUR**

### **THE EXPERIMENTAL SETUP AND PERFORMANCE ANALYSIS OF FISSER MODEL**

#### **4.1 Introduction**

The biological foraging approach has been proposed for spectrum selection and reconfiguration in a distributed CRN due to its analytical simplicity and generic applications. Chapter Three of this thesis discussed the biological optimal foraging theory and its role in the mathematical and analytical formulation of our FISSER model for SUs' frequency and channel bandwidth selection in a distributed CRN. Based on the analytical results presented in Chapter Three, an optimal GUT value was achieved and this value was assigned as the simulation "giving-up time" for SUs before switching to the extensive search.

The crux of this chapter is the performance analysis of the FISSER model for the SUs' nodes in a distributed CRN using both nucleated and dispersed settlement patterns. In a CRN environment, the frequency availability is not static like that of traditional networks. There are resource-rich regions, where many frequencies are available for the SUs and resource-poor regions, where there are only a few frequencies available for SUs. An example of a resource-rich region is the rural areas, where many frequencies are not being fully utilised and an example of a resource-poor region is the urban areas, where the number of available frequencies is low. Hence, this motivates the need to evaluate the performance of the FISSER model in both rural and urban settlement patterns. Section 4.2 presents the details of the simulation setup and the settlement patterns, which were used to validate the performance of the FISSER model. Section 4.3 presents the performance analysis results obtained from the simulation experiments and the chapter is concluded with a summary and remarks in Section 4.4.

## 4.2 Simulations Setup

This section presents the experimental setup of the FISSER model developed in Chapter Three, using MATLAB™ version 9.2 simulation tool. As opposed to the conventional network simulators, MATLAB™ simulator was used in this study in order to have more accurate and realistic network conditions which can be tractably tested. Also, MATLAB™ was chosen because of its ability to handle intensive computational information [107]. To assess the impact of the FISSER model on the distributed CRN topology, several computer simulations of randomly placed 10 PUs' nodes and 30 SUs' nodes were uniformly placed in a 600m x 600m area, using a time span of 500 steps. Following the FISSER algorithm presented in Chapter Three, the SUs started with the intensive search mode using Brownian motion and switched to the extensive search mode, if no frequency was found to be available after the specified GUT. The GUT was set to 50ms; this GUT value was based on the result of our analytical solution presented in Chapter Three. The SUs used available TV Ultra High Frequency (UHF) spectrum between 470MHz – 890MHz and the channel numbers 14 – 83 of channel-widths 20MHz each in the IEEE 802.22 [108].

In Chapter Three, the effects of the perceptual radius on optimal switching time and distance travelled by the SUs were presented, and it was observed that while the perceptual radius was less than or equal to 30m, the model performed well. However, in order to analyse the effect of perceptual radius on the FISSER model performance, two settlement patterns were considered: nucleated and dispersed settlement patterns. Dispersed settlement pattern refers to a kind of settlement pattern where houses are scattered over a large area and that represents a rural area type of settlement. Whereas a nucleated settlement pattern represents a type of settlement where many houses are cramped together around a centre and this represents the type of settlement typical of an urban area. Figure 16 illustrates a typical dispersed (rural) and nucleated (urban) settlement pattern. The two settlement patterns were implemented using the Atarraya simulator. These analyses help to know how the FISSER model will perform in both the rural and urban areas when the SU nodes are subjected to a different perceptual radius.



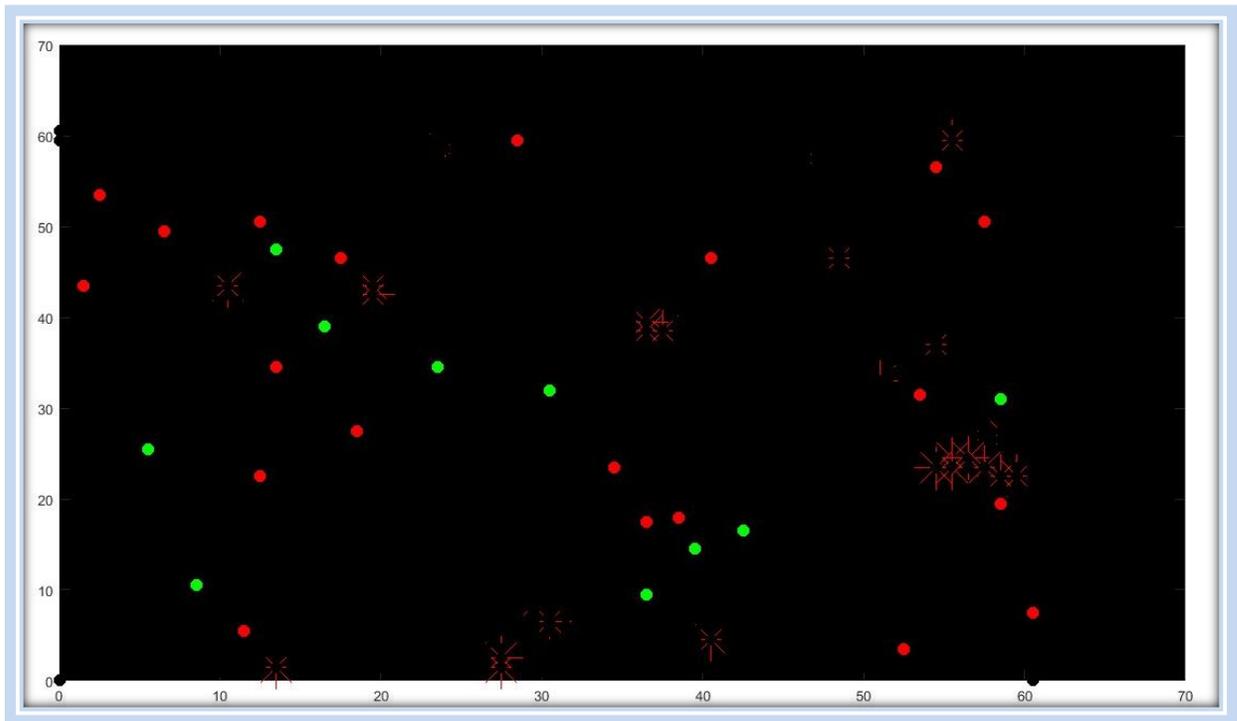
a. Dispersed Settlement



b. Nucleated Settlement

**Figure 16: Illustration of Dispersed and Nucleated Settlement Patterns [122]**

Figure 17 shows the schematic diagram of the FISSER model; the red dots denote the SUs which are searching for an available frequency (denoted by green dots), while the red stars indicate the SUs that are currently communicating with one another. The axes denote the specified simulation area where the nodes communicate. For further implementation details see appendix



**Figure 17: Schematic diagram of a Simulation layout**

### 4.3 Simulation Results and Discussions

This section presents the performance validation of the FISSER model proposed in Chapter Three for the SUs' communication in a distributed CRN. Based on the analytical results presented in Chapter Three, it was observed that one of the factors that determine the performance of the FISSER model is the SUs' node perceptual radius. It was observed that while the perceptual radius is less than 30m, the model performs very well, however, when the radius is above 30m, the performance drops significantly [see Figure 9]. Hence, two different sets of perceptual radius (low and high radius) were considered in this section. The low perceptual radius was defined as 30m, while the high perceptual radius was defined as 50m. The effects of both low and high perceptual radii on the FISSER model were considered using both dispersed (rural) and nucleated (urban) settlement patterns. The performance analyses results will help researchers to know how the FISSER model will perform in rural and urban areas. The analysis was carried out using four performance metrics: *average channel switching time*, *average network throughput*, *successful transmission probability*, and *energy efficiency*. The performance validation concerning the aforementioned four metrics after executing the FISSER model was performed for a period sufficient for the stability of result statistics. Each of the reported results in the next subsections were the average of twenty data points from twenty simulation runs, for each scenario that was considered.

#### 4.3.1 Scenario I: The effect of perceptual radius on the FISSER model in a dispersed settlement pattern

This subsection presents the results of the simulations that were carried out in order to investigate the FISSER model performance for SUs' nodes in a dispersed (rural area) settlement pattern where the SUs' nodes were subjected to low and high perceptual radii. Table 2 contains summarised details of the simulation setup parameters that were used for all the experiments reported in this subsection.

**Table 2: Summarised Simulation Setup Details for Scenario I**

<b>Parameters</b>	<b>Value(s)</b>
Settlement Pattern	Dispersed
Number of PUs	10
Number of SUs	30
Simulation Area	600m x 600m
Simulation time	500 seconds
SUs' node Perceptual radius	30m, 50m
MAC Protocol	IEEE 802.22
Frequency range	470MHz – 890MHz
Channel Bandwidth	14 - 83
Channel Size	20MHz
Giving-Up Time (GUT)	50 milliseconds
Performance Metrics	Average channel switching time, Successful transmission probability, Average network throughput, and Energy efficiency

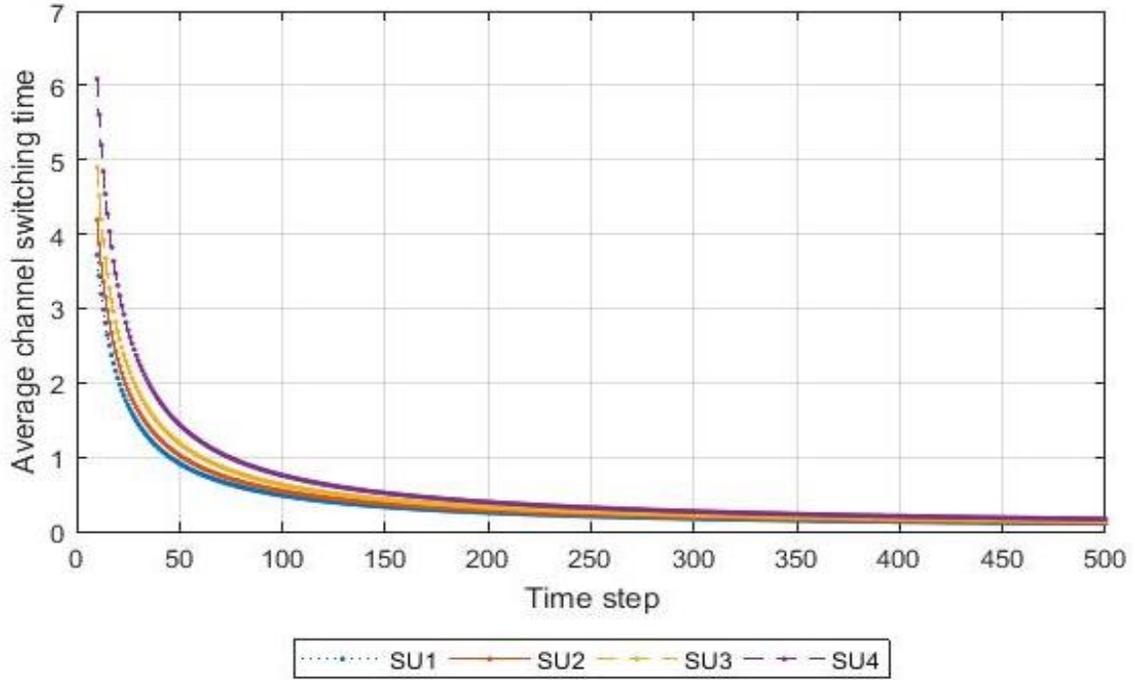
#### **4.3.1.1 Experiment I: Average Channel Switching Time**

The average channel switching time is the total time it takes the SUs both to switch to another frequency when a PU appears and also to reconfigure its transceiver parameters after switching. The main objective of this metric is to reduce the number of unnecessary disconnections and reconnection delays, which can lead to the CRN's performance degradation. The process of switching and reconfiguration by SUs incurs a certain level of delay which should be kept minimal, so as to avoid overheads. Based on the results of some existing studies [2-3, 11-13], the acceptable range of values for channel switching delay should be 10 – 40 milliseconds (ms), so as to meet the application's QoS requirements. Hence, in this thesis, I assume the average time for switching and reconfiguration operation delay to be 10ms. The lower the channel switching time value the better the model performance as the lower values will increase the packet delivery rate and mitigate the delay [12, 52]. The channel switching time is an important metric in

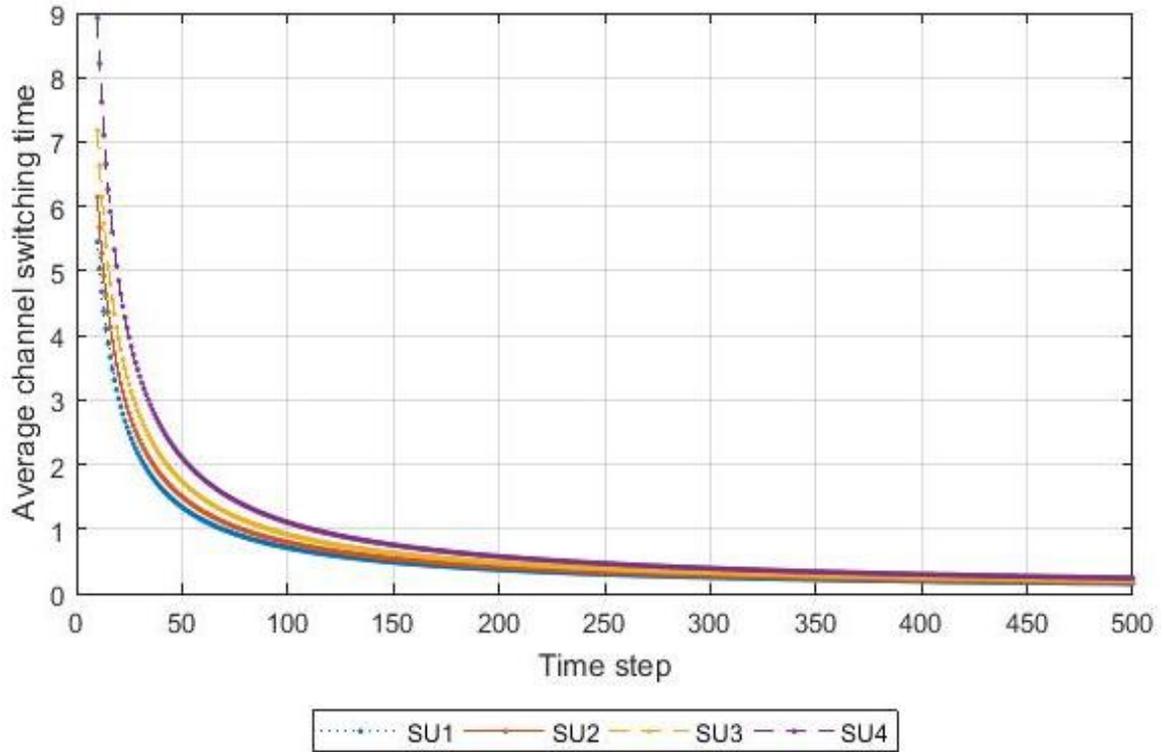
dynamic spectrum management because it helps to know the extent of disruptions that a PU can encounter if the SUs do not leave the spectrum in time.

Figures 18 and 19 show the average channel switching time over a range of time steps for different SUs' nodes in a dispersed settlement pattern at low and high perceptual radii respectively. It can be observed from figure 18 that the average channel switching time for all the SUs considered using low perceptual radius is less than 6.5ms. However, it can be observed from figure 19 that when a high perceptual radius was used for all the SUs considered, the average channel switching time increased to 8.91ms. Based on figures 18 and 19, it can be observed that the FISSER model performs better when the SUs' node uses a low perceptual radius. The achieved high channel switching time by the SUs when subjected to a high perceptual radius can be attributed to the increase in the interference level due to co-channel contentions among the SUs' nodes which in turn lead to some delay in channel switching time. It was observed that as the perceptual radius increases, the SUs can easily sense available frequencies from a distance, however, when the perceptual radius exceeds 30m, the transmission noise among the SUs' nodes increases, and in turn increases the interference level among the SUs' nodes.

The results presented in figures 18 and 19 conform to the analytical results presented in figure 9. Also, the results presented in both figures 18 and 19 perform better than the existing results [3, 11-13, 42], where the set baseline for channel switching delay is 10–40ms so as to meet the SUs' applications' QoS requirements. The achieved low channel switching time by the FISSER model helps the SUs to choose the best channel, switch and reconfigure their transceiver parameters within a short period and this will in-turn help the SUs to achieve optimal communication performance and improve the spectrum utilisation.



**Figure 18: The average channel switching time of SUs' nodes at low perceptual radius**

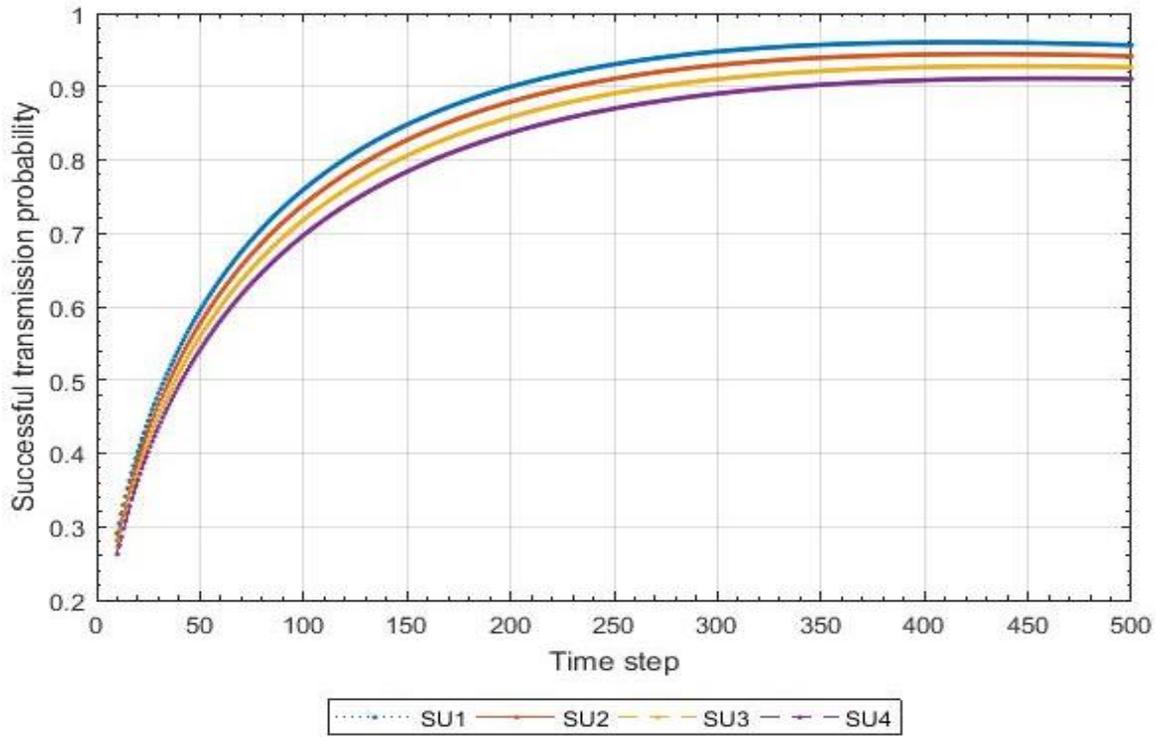


**Figure 19: The average channel switching time of SUs' nodes at high perceptual radius**

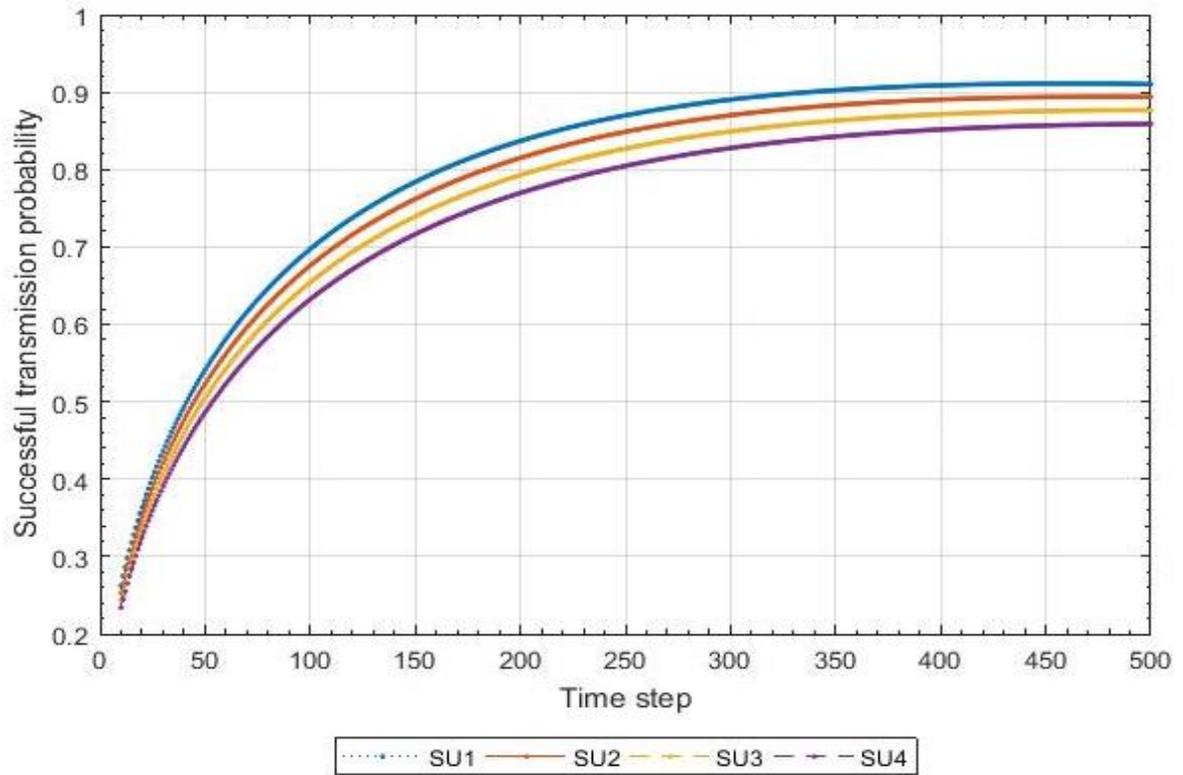
### 4.3.1.2 Experiment II: The Successful Transmission Probability

This subsection presents the successful transmission probability among the SUs' nodes. The successful transmission probability is the probability that the SUs' nodes communication is successful [52]. The higher the value, the better the transmission probability performance. The better performance of this metric would help to reduce the communication overhead, and in turn, reduce the energy consumption.

The successful transmission probability of SUs at different time steps for SU nodes in a dispersed settlement pattern at low and high perceptual radii was presented in Figures 20 and 21 respectively. It can be observed in Figures 20 and 21 that all the SUs considered has more than 90% successful transmission probability. The achieved high successful transmission probability can be attributed to the search technique utilised by the FISSER model, where an individual SU makes their decision. Thus, it reduces collision among the SUs' node. However, the SUs with low perceptual radius (see Figure 20) perform better than the SUs with high perceptual radius (see Figure 21). The disparity in the performance of SUs with high perceptual radius and that of the low perceptual radius can be attributed to the delay introduced by the frequency signal contention among the SUs' nodes, which in turn led to link instability and thereby caused the performance degradation for the SUs with high perceptual radius. Also, the achieved successful transmission probability presented in Figures 20 and 21 are in line with the average channel switching time presented in Figures 18 and 19. The efficient channel switching time helps the SUs to achieve high successful transmission probability by switching as early as possible before the arrival of PUs. The achieved low channel switching time and high successful transmission probability at low perceptual radius for SUs' nodes helps the FISSER model in the optimal selection and reconfiguration of frequency and channel bandwidth for communication.



**Figure 20: Successful transmission probability of SUs' nodes at low perceptual radius**



**Figure 21: Successful transmission probability of SUs' nodes at high perceptual radius**

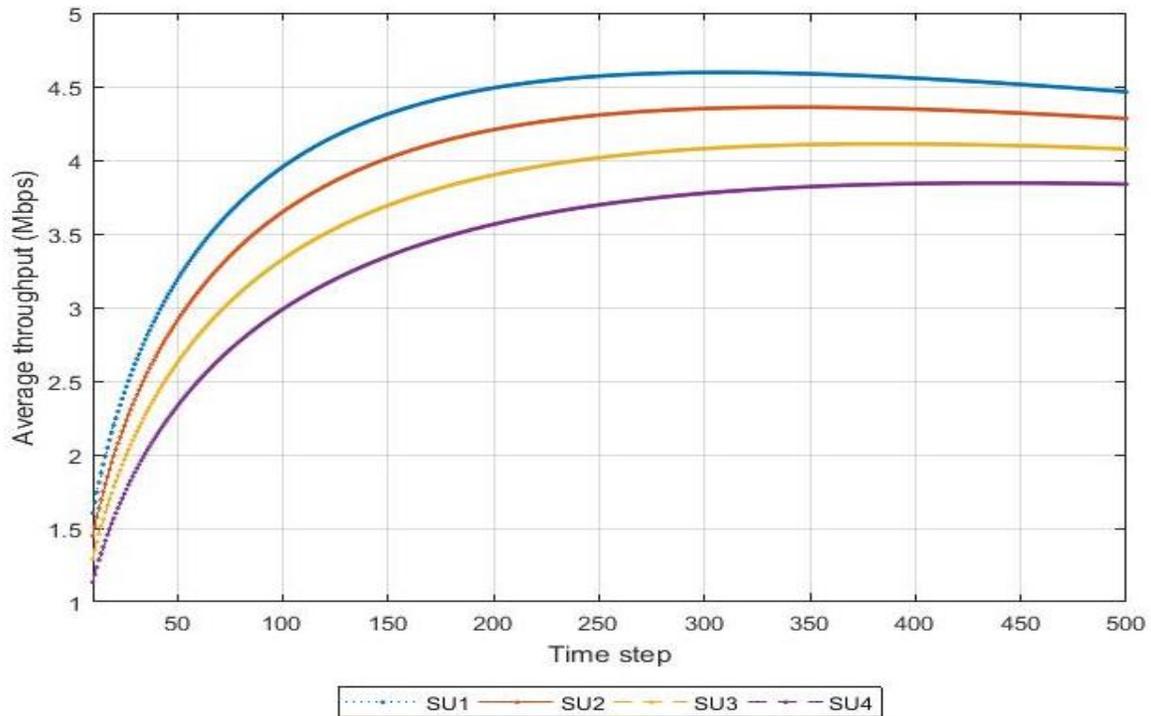
### 4.3.1.3 Experiment III: Average Network Throughput

The average network throughput is the number of bits that were processed over a period of time in 1Hz bandwidth. In a distributed CRN where the data traffic is high, the probability that the PU channels will be occupied is high. The time to select and to reconfigure the transceiver parameters tool would be high, which in turn, will affect the throughput performance. Hence, there is a need to have an approach that can help to reduce both the selection and the reconfiguration time, so as to improve the throughput performance. Based on the existing results from the literature [24-27, 38], it has been observed that the random based approach achieved high results. The network throughput index shows the network communication performance; the higher the throughput value, the better the network communication performance. The network scenarios considered were based on known source-destination pairs so as to address the shortest path exploitation.

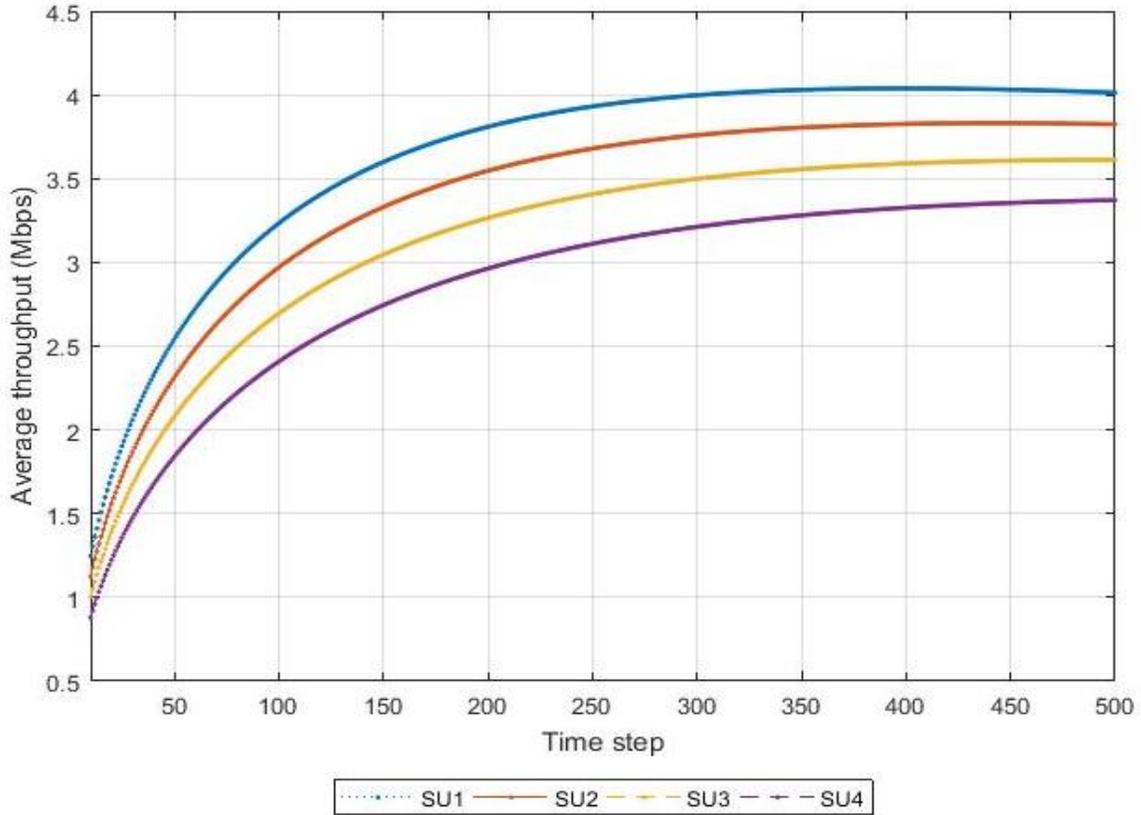
The network average throughput for different SUs at low and high perceptual radii are depicted in Figures 22 and 23 respectively. It can be observed from figure 22 that the average throughput for the SUs with low perceptual radius is more than 90%. While the highest average throughput for the SUs that use high perceptual radius is 81%. Based on figures 22 and 23, it can be observed that the FISSER model performs very well in terms of the achieved throughput, however, the model performs better when the SUs' node uses a low perceptual radius.

Increasing the nodes' perceptual radius will help the SUs to travel a short distance before getting an available frequency to use for communication. However, one of the main challenges with high perceptual radius in a CRN environment is that high perceptual radius usually introduces frequency contention among the nodes, thereby increasing the level of interference among the nodes. The increase in the interference level will, in turn, lead to network performance degradation. This concept causes the disparity between the achieved network throughput depicted in figures 22 and 23 when the SUs' nodes are subjected to low and high perceptual radii respectively.

Based on figures 18-19 and 22-23, we observe that there is a trade-off between the achieved throughput and the channel switching time. As the channel switching time decreases, the network throughput increases. An efficient channel switching approach will yield a high network throughput performance, that is, the lower the channel switching time the higher the throughput performance. This observation conforms to P. Li, N. Scalabrino, and Y. Fang [12], where the authors concluded that high channel switching time can cause a throughput loss of up to 3%, exclusively. The study [12] focused on wireless mesh networks and the author concluded that the throughput loss due to high channel switching time would be worse in CRNs, where both the PUs and SUs exhibit random characteristics. Hence, based on the achieved results from channel switching time and average throughput, when the SUs' nodes use low perceptual radius, the FISSER model developed in this thesis can select an optimal channel and frequency quickly, which in turn will improve the rate of data communication and provide better quality of service for CR spectrum utilisation.



**Figure 22: The average throughput of SUs' nodes at low perceptual radius**



**Figure 23: The average throughput of SUs' nodes at high perceptual radius**

#### 4.3.1.4 Experiment IV: Energy Efficiency

One of the major concerns in a wireless network environment such as CRNs where the energy can be entirely non-renewable is the efficient use of energy. This is due to the fact that the cost of energy is relatively high, especially in the developing nations and the need for green communications [113] is paramount. The energy efficiency metric is considered to include some other metrics (such as throughput and channel switching time), which makes it an important metric in determining the overall network performance [12, 37, 113]. Hence, the optimisation of energy efficiency in CRNs is very important, so as to ensure high QoS in the network.

There have been different definitions for energy efficiency in the literature [14-15, 37, 113], however, this thesis adopts the definition by the European Technical Standards Institute (ETSI) [121], because of its wide acceptance and usage. Hence, the energy

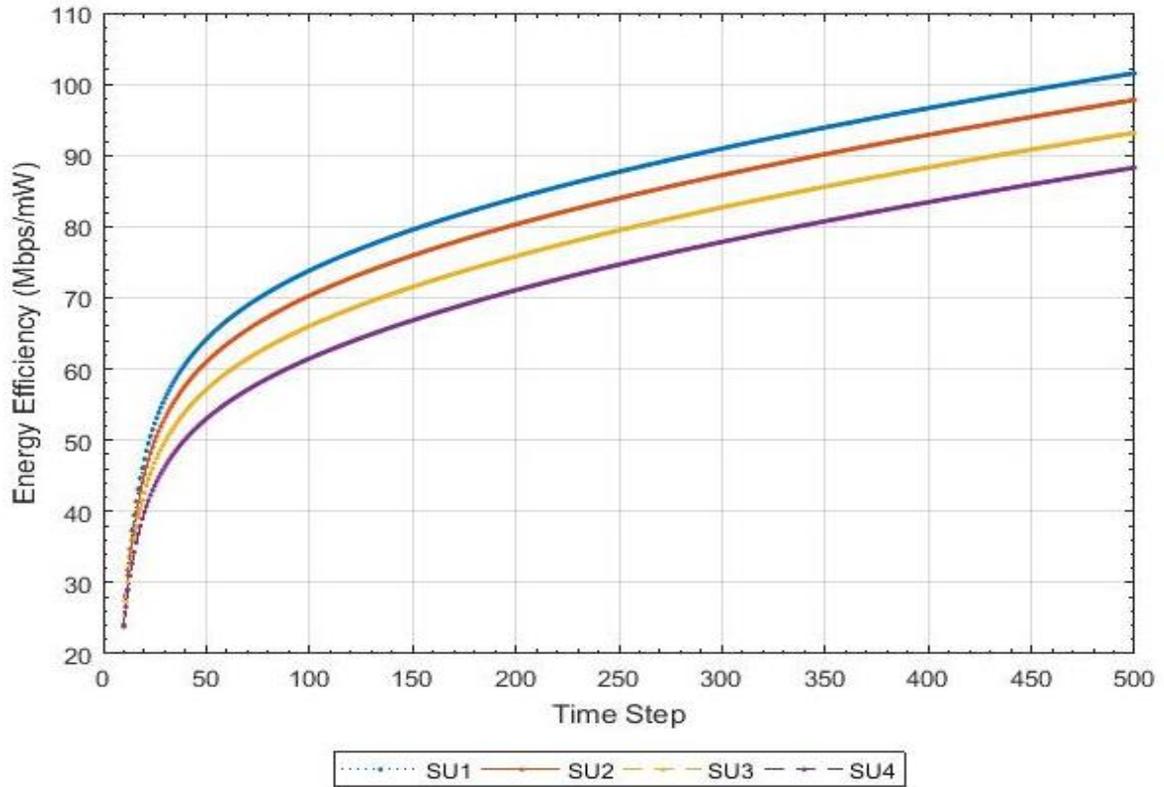
efficiency metric is defined as the ratio of the total bits that were successfully delivered to the destination nodes across the network and the power consumed by the network nodes to deliver the sent bits. It can also be defined as the ratio of the total network throughput to the energy consumed. Mathematically denoted as per E. F. Orumwense T. J. Afullo, and V. M. Srivastava [113]:

$$\text{EnergyEfficiency} = \frac{\text{total amount of data delivered (Mbps)}}{\text{total amount of energy consumed (mW)}} \quad (5.1)$$

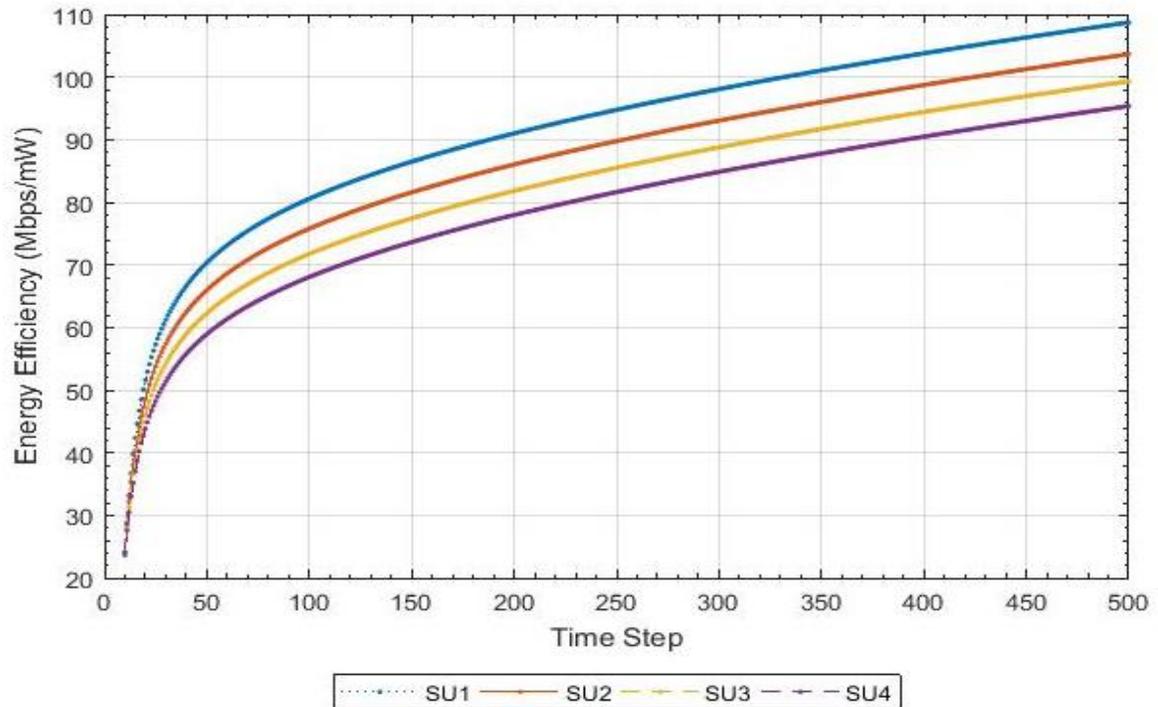
The goal of this metric is to maximise the data delivery whilst minimising the power consumption. Hence, the higher the energy efficiency value, the better the model performance.

Figures 24 and 25 show the energy efficiency for different SUs' nodes in a dispersed settlement pattern at low and high perceptual radii respectively. It can be observed from figure 24 that the highest energy efficiency achieved by the SUs with low perceptual radius is 101.8Mbps/mW whilst the highest energy efficiency for the SUs that use high perceptual radius is 109.2Mbps/mW [see Figure 25]. Based on figures 24 and 25, it can be observed that the FISSER model performs well in terms of the achieved energy efficiency, however, the model performs better when the SUs' node uses a high perceptual radius. The achieved better performance by the SUs' nodes at high perceptual radius can be attributed to the decrease in the distance that the SUs' nodes need to travel before finding an available frequency. This result also conforms to the analytical result presented in figure 9, where it was observed that as the perceptual radius ( $\epsilon$ ) increases, the distance travelled by the SUs ( $E(L)$ ) before finding an available frequency decreases. Hence, the decrease in distance travelled by the SUs before finding an available frequency helps the SUs to maximise their net energy gain (The higher the distance travelled, the higher the energy consumed).

The combination of low channel switching time, high network throughput and good energy efficiency metrics, makes the FISSER model a good approach to address the spectrum selection and reconfiguration challenges for SUs' nodes in a distributed CRN for a dispersed settlement pattern. Table 3 summarises the simulation results achieved from the metrics that were considered.



**Figure 24: The energy efficiency of SUs' nodes at low perceptual radius**



**Figure 25: The energy efficiency of SUs' nodes at high perceptual radius**

**Table 3: Summarised Analysis Results for Dispersed Settlement Pattern**

	ACST (ms)	STP (%)	ANT (%)	EE (Mbps/mW)
<b>Low perceptual radius</b>	6.5	96.2	91.4	101.8
<b>High perceptual radius</b>	8.91	91.5	82.1	109.2

*ACST – Average Channel Switching Time; STP – Successful Transmission Probability; ANT – Average Network Throughput; and EE – Energy Efficiency*

### **4.3.2 Scenario II: The effect of perceptual radius on the FISSER model in a nucleated settlement pattern**

This subsection presents the results of the simulations that were carried out, in order to investigate the FISSER model performance for SUs' nodes in a nucleated (urban area) settlement pattern, when the SUs' nodes are subjected to low and high perceptual radii. One of the major challenges usually faced by the wireless networks in an urban area is the interference problem. The interference problem can occur due to high data traffic, cross-frequency signals or co-channel contention, WiFi transmissions noise, connection obstruction due to high-rise buildings etc. However, the interference level can be reduced if properly accounted for during the model development so as to achieve acceptable network performance that will meet the users' applications' QoS requirement. Table 4 contain summarised details of the simulation setup parameters that were used for all the experiments reported in this subsection.

**Table 4: Summarised Simulation Setup Details for Scenario II**

<b>Parameters</b>	<b>Value(s)</b>
Settlement Pattern	Nucleated
Number of PUs	10
Number of SUs	30
Simulation Area	600m x 600m
Simulation time	500 seconds
SUs' node Perceptual radius	30m, 50m
MAC Protocol	IEEE 802.22
Frequency range	470MHz – 890MHz
Channel Bandwidth	14 – 83
Channel Size	20MHz
Giving-Up Time (GUT)	50 milliseconds
Performance Metrics	Average channel switching time, Successful transmission probability, Average network throughput, and Energy efficiency

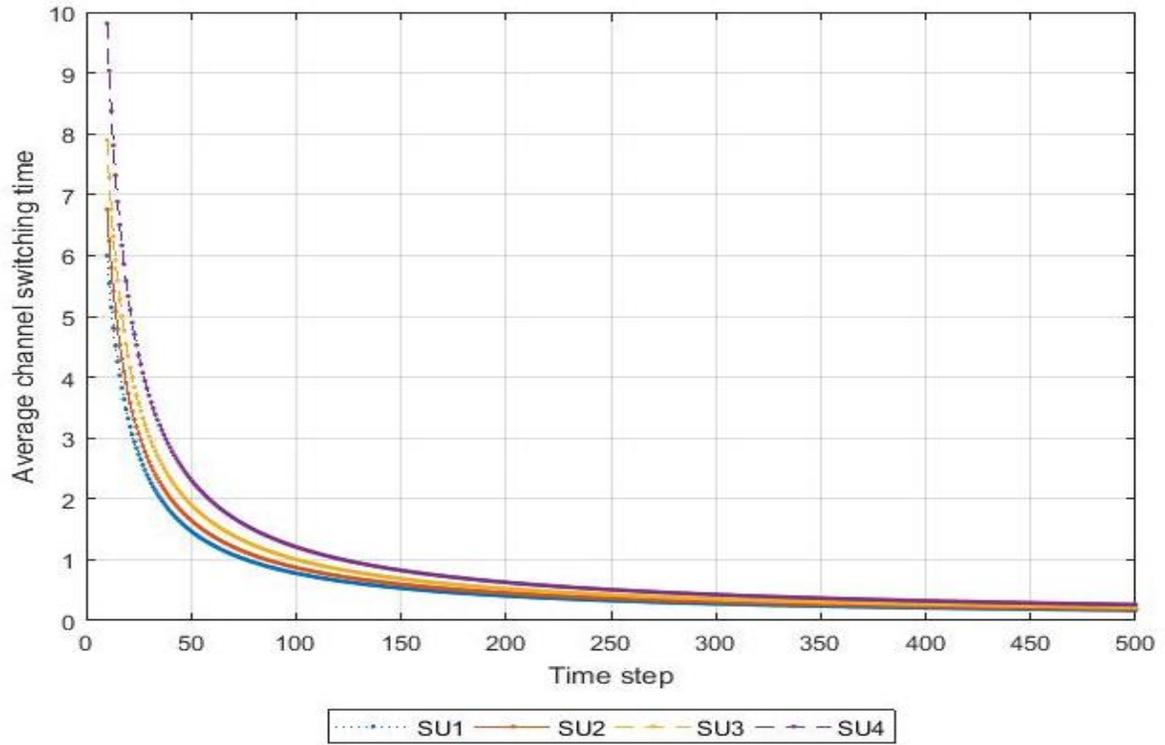
#### **4.3.2.1 Experiment I: Average Channel Switching time**

The average channel switching time is the total time it takes the SUs both to switch to another frequency when a PU appears and also to reconfigure its transceiver parameters after switching. The lower the channel switching time value the better the model performance, as the lower values will increase the packet delivery rate and mitigate the delay [12, 52].

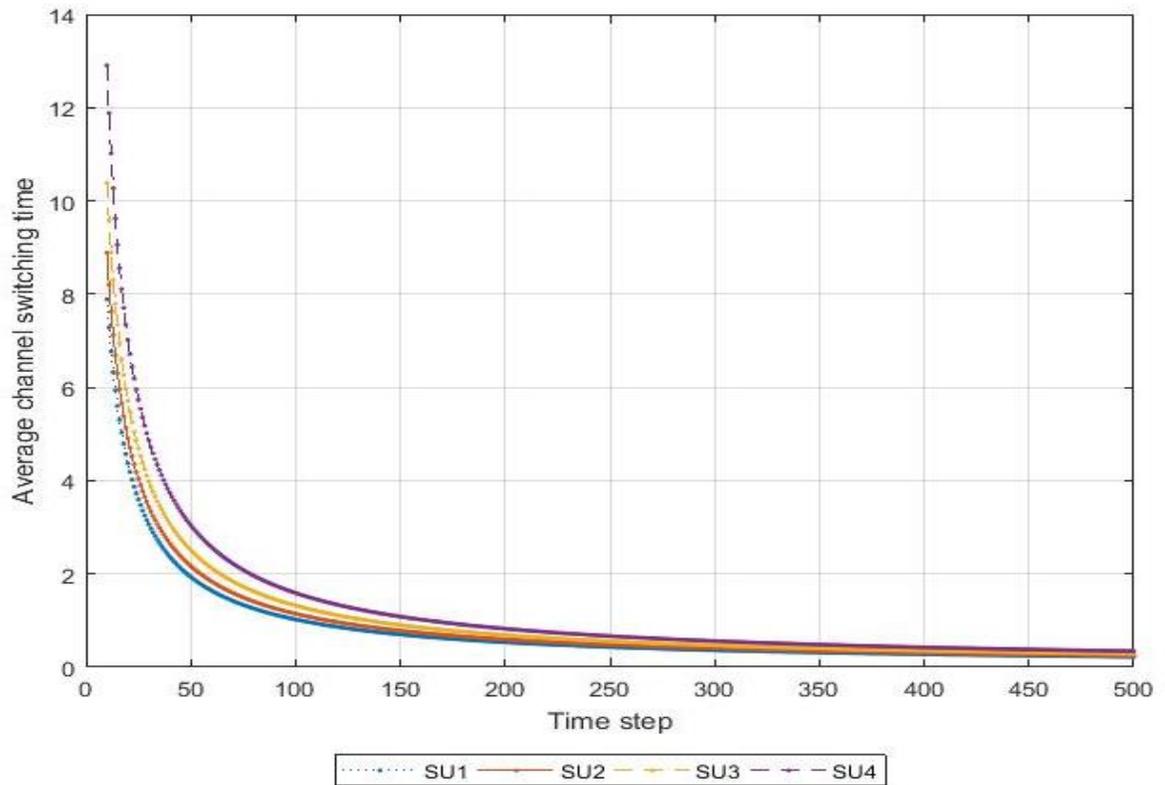
Figures 26 and 27 show the average channel switching time over a range of time steps for different SUs' nodes in a nucleated settlement pattern at low and high perceptual radii respectively. It can be observed from figure 26 that the highest average channel switching time for all the SUs considered, using low perceptual radius is 9.92ms, while in figure 27 the highest channel switching time for SUs at high perceptual radius is 13.13ms. Based on figures 26 and 27, it can be observed that the FISSER model performs better when the SUs' node uses a low perceptual radius. However, the model

performs better in a dispersed settlement pattern for both low and high perceptual radii. The decline in the model performance can be attributed to the high level of interference in the nucleated area caused by co-channel contention and Wi-Fi transmission noise as compared to that of the dispersed area where there are few network users, hence, the contention and transmission noise level is reduced.

The results presented in figures 26 and 27 conform to the analytical result presented in figure 9, where the high perceptual radius led to high optimal switching time. The results presented in both figures 18 and 19 for dispersed settlement patterns perform better than that of nucleated settlement patterns in figures 26 and 27. However, the FISSER model results in nucleated settlement patterns perform better than the existing results [3, 11-13, 42] where the set baseline for channel switching delay was 10–40ms so as to meet the SUs' QoS requirements. The good performance of the FISSER model in the achieved channel switching time helps the SUs to select the best channel and reconfigure their transceiver parameters within a short period and this in-turn helps the SUs to achieve optimal performance and improve the spectrum utilisation.



**Figure 26: The average channel switching time of SUs' nodes at low perceptual radius**



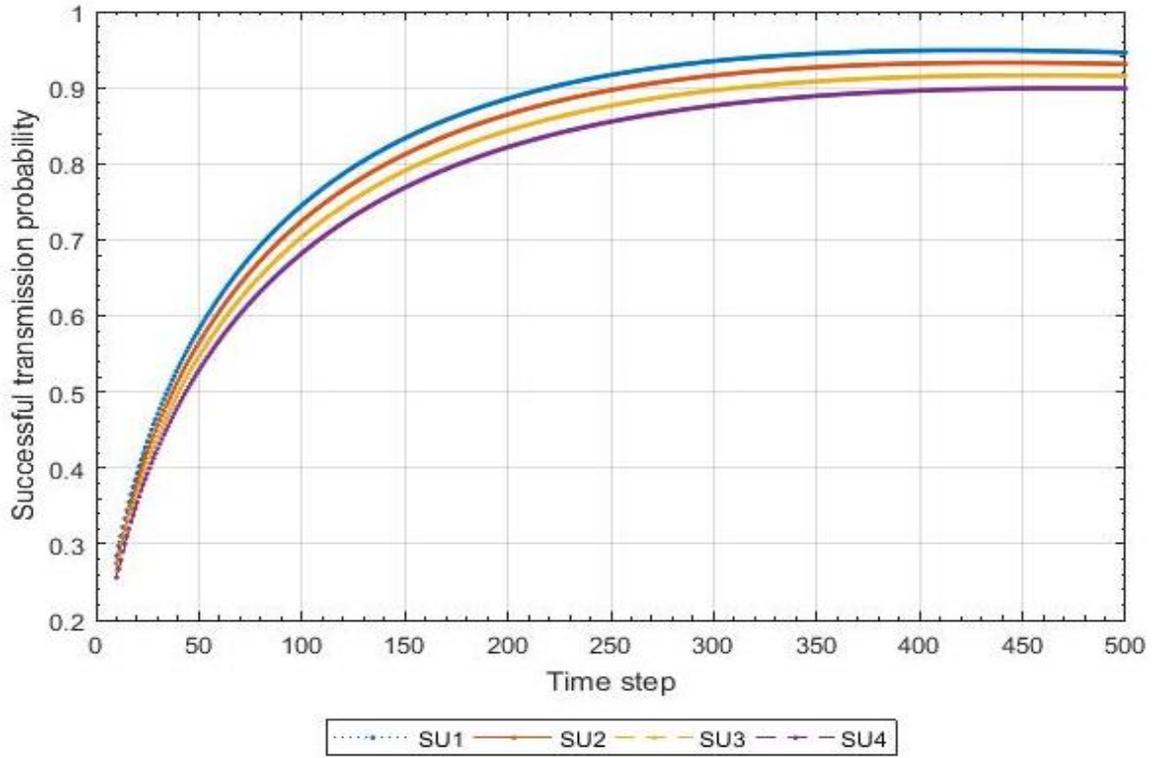
**Figure 27: The average channel switching time of SUs' nodes at high perceptual radius**

### **4.3.2.2 Experiment II: The Successful Transmission Probability**

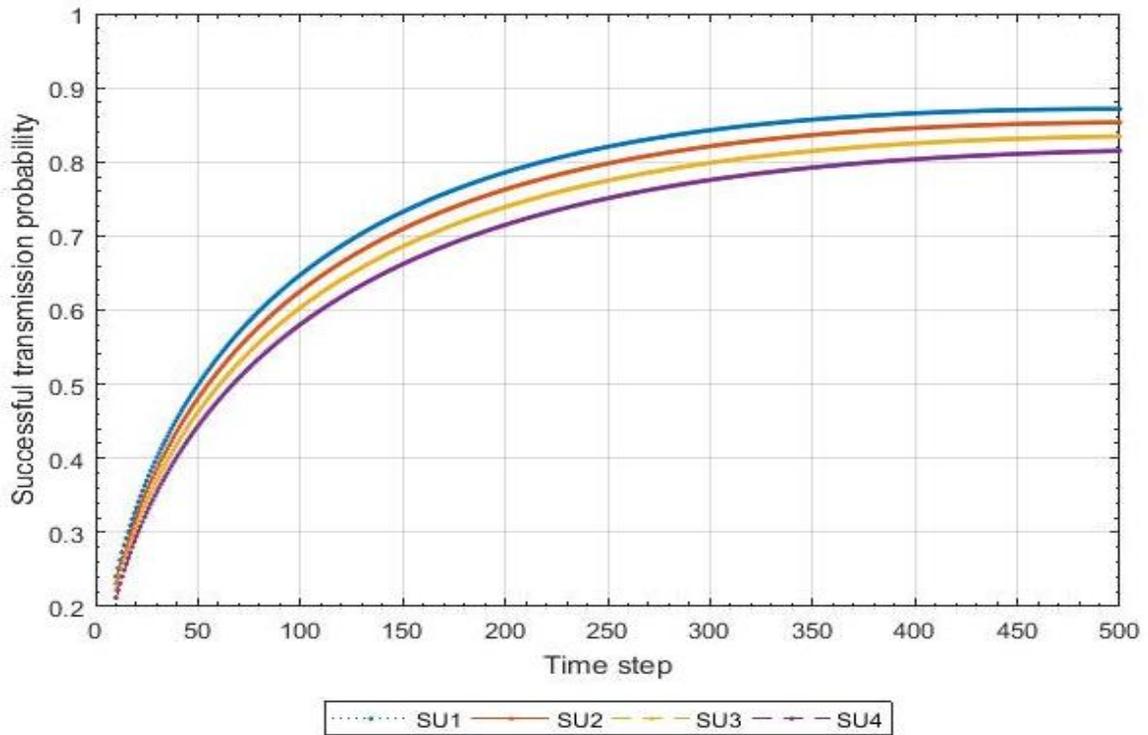
This subsection presents the successful transmission probability of SUs' nodes at different time steps in a nucleated settlement pattern. The SUs' nodes were subjected to both low and high perceptual radii. The successful transmission probability is the probability that the SUs' nodes communication is successful [52, 105]. The higher the transmission probability value, the better the transmission probability performance.

Figures 28 and 29 depict the SUs' successful transmission probability at both low and high perceptual radii respectively. It can be observed from figure 28 that the highest successful transmission probability for all the SUs considered, using low perceptual radius is 94.2%, while in figure 29 the highest successful transmission probability for SUs at high perceptual radius is 87.7%. Based on figures 28 and 29, it can be observed that the FISSER model performs better when the SUs' node uses a low perceptual radius. The performance of SUs' nodes when using high perceptual radius can be attributed to the co-channel contention among the SUs' nodes which led to an increase in the interference level and thereby caused link instability and performance degradation.

However, based on the successful transmission probability results presented in dispersed and nucleated settlement patterns [see figure 20-21 and 28-29 respectively], the FISSER model performs very well in the achieved successful transmission probability. Hence, the achieved high successful transmission probability for SUs' nodes will help the FISSER model in the optimal reconfiguration of channel and frequency for SUs' communication.



**Figure 28: Successful transmission probability of SUs' nodes at low perceptual radius**



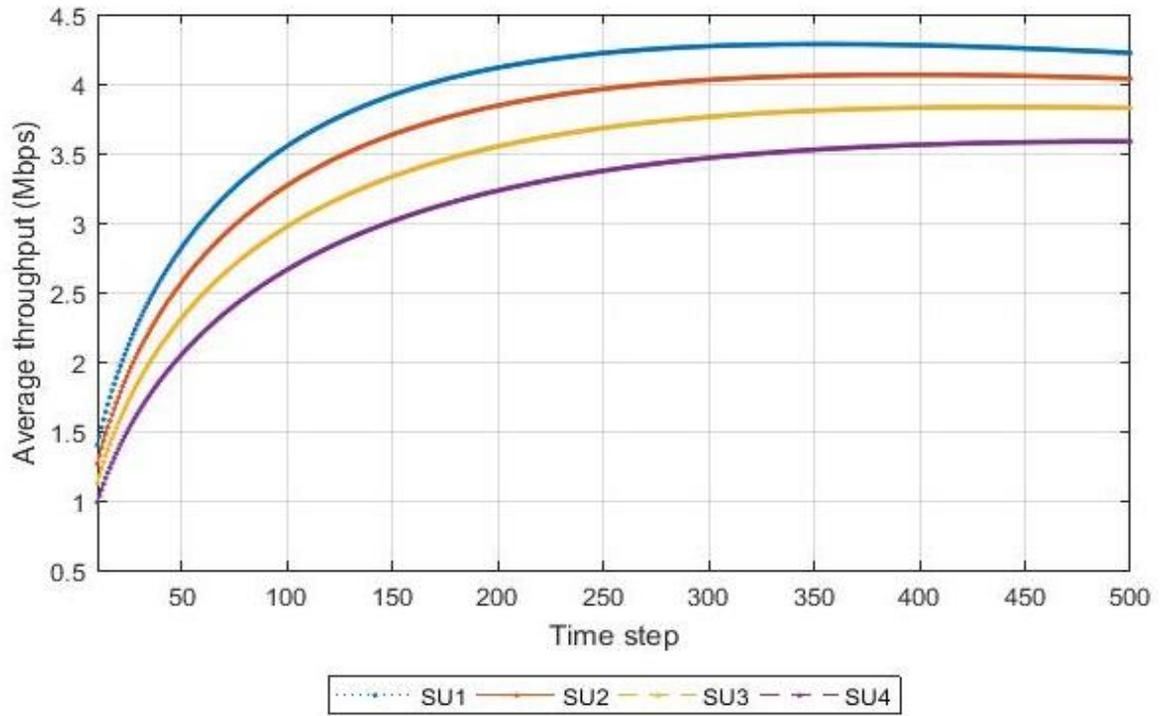
**Figure 29: Successful transmission probability of SUs' nodes at high perceptual radius**

### 4.3.2.3 Experiment III: Average Network Throughput

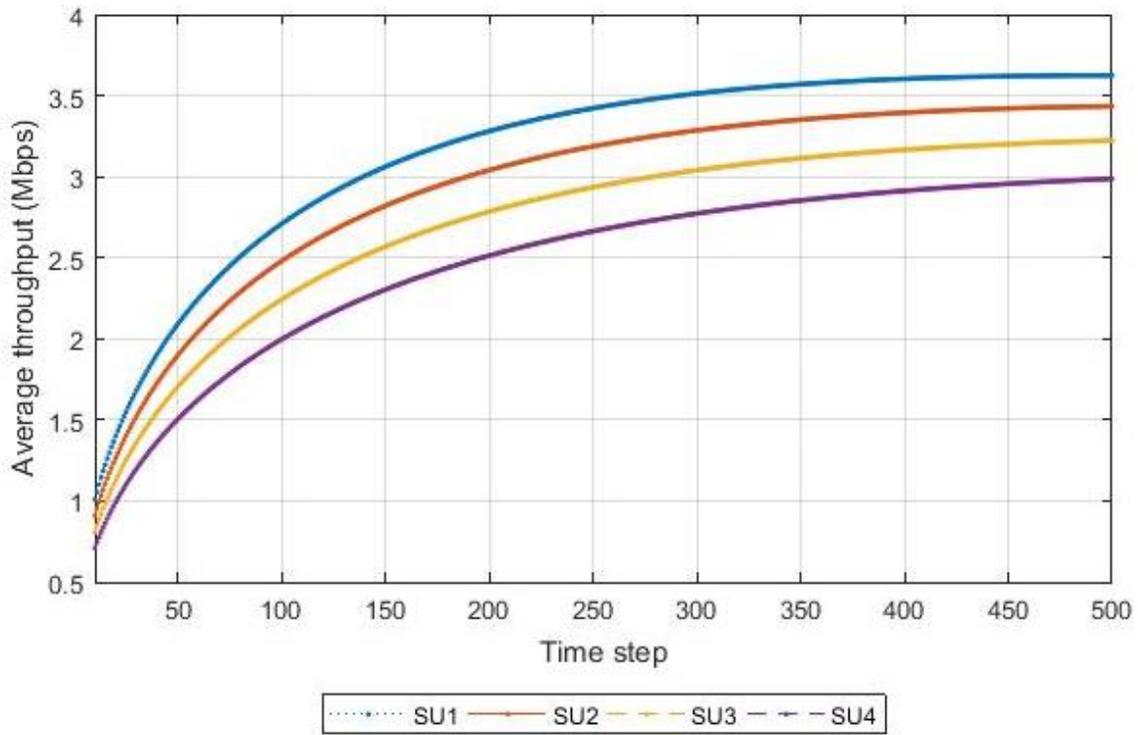
This subsection presents the average throughput for SUs' nodes at different time steps in a nucleated settlement pattern. The SUs' nodes were subjected to both low and high perceptual radii. The average network throughput is the number of bits that were processed over a period of time in 1Hz bandwidth. The throughput index shows the network communication performance. The higher the achieved value, the better the network communication performance.

The network average throughput for different SUs at low and high perceptual radii are depicted in Figures 30 and 31 respectively. It can be observed from figure 30 that the highest average throughput achieved by the SUs with low perceptual radius is 86.4% whilst the highest average throughput achieved by the SUs with high perceptual radius is 72.2% [see Figure 31]. Hence, the SUs with low perceptual radii perform better than the SUs with high perceptual radii. The disparity in the performance of SUs with high perceptual radii and that of the low perceptual radii can be attributed to the SUs' link instability introduced by the frequency signal contention among the SUs' nodes, which in turn led to the performance degradation for the SUs with high perceptual radii.

Based on Figures 26-27 and 30-31, we observe that there is a trade-off between the achieved throughput and the channel switching time. It can be observed that both the channel switching time and average throughput at both low and high perceptual radii converge to 150 and 200 time steps respectively. Hence, as the channel switching time decreases the network throughput increases or the lower the channel switching time, the higher the throughput performance.



**Figure 30: The average throughput of SUs' nodes at low perceptual radius**



**Figure 31: The average throughput of SUs' nodes at high perceptual radius**

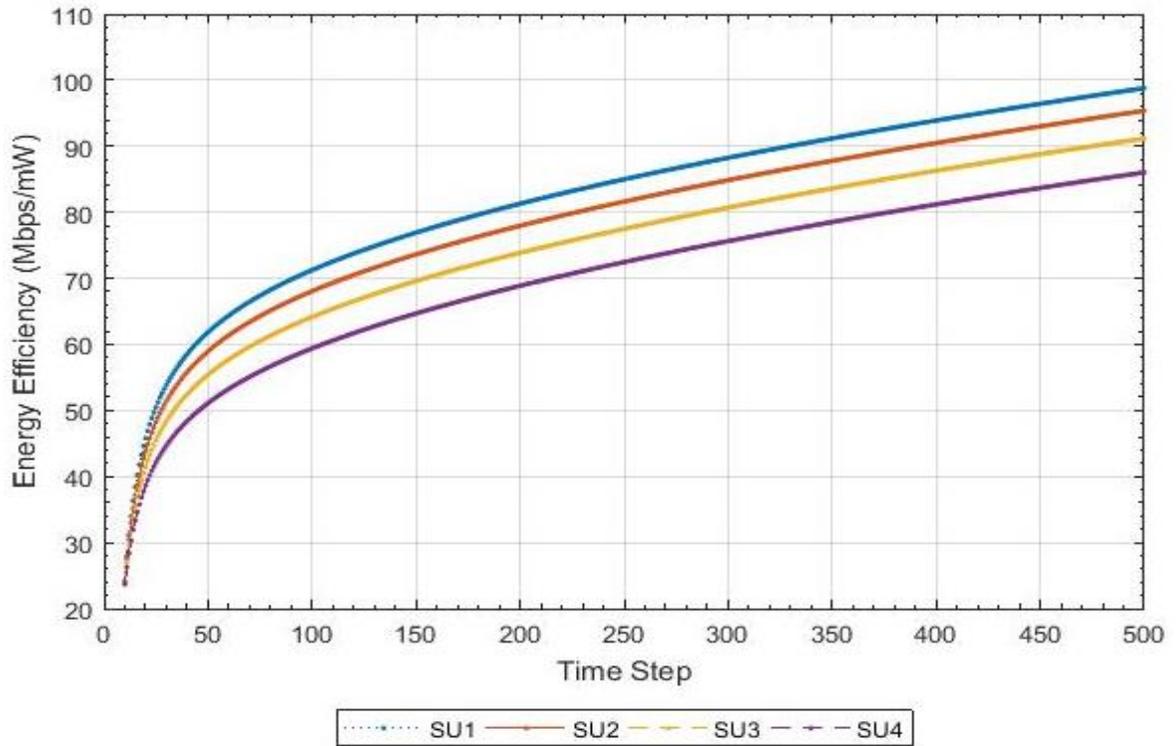
#### 4.3.2.4 Experiment IV: Energy Efficiency

This subsection presents the energy efficiency for SUs' nodes at different time steps in a nucleated settlement pattern. The SUs' nodes were subjected to both low and high perceptual radii. The energy efficiency metric is defined as the ratio of the total bits that were successfully delivered to the destination nodes across the network and the power consumed by the network nodes to deliver the sent bits. The goal of this metric is to maximise the data delivery whilst minimising the power consumption. Hence, the higher the energy efficiency value, the better the model performance.

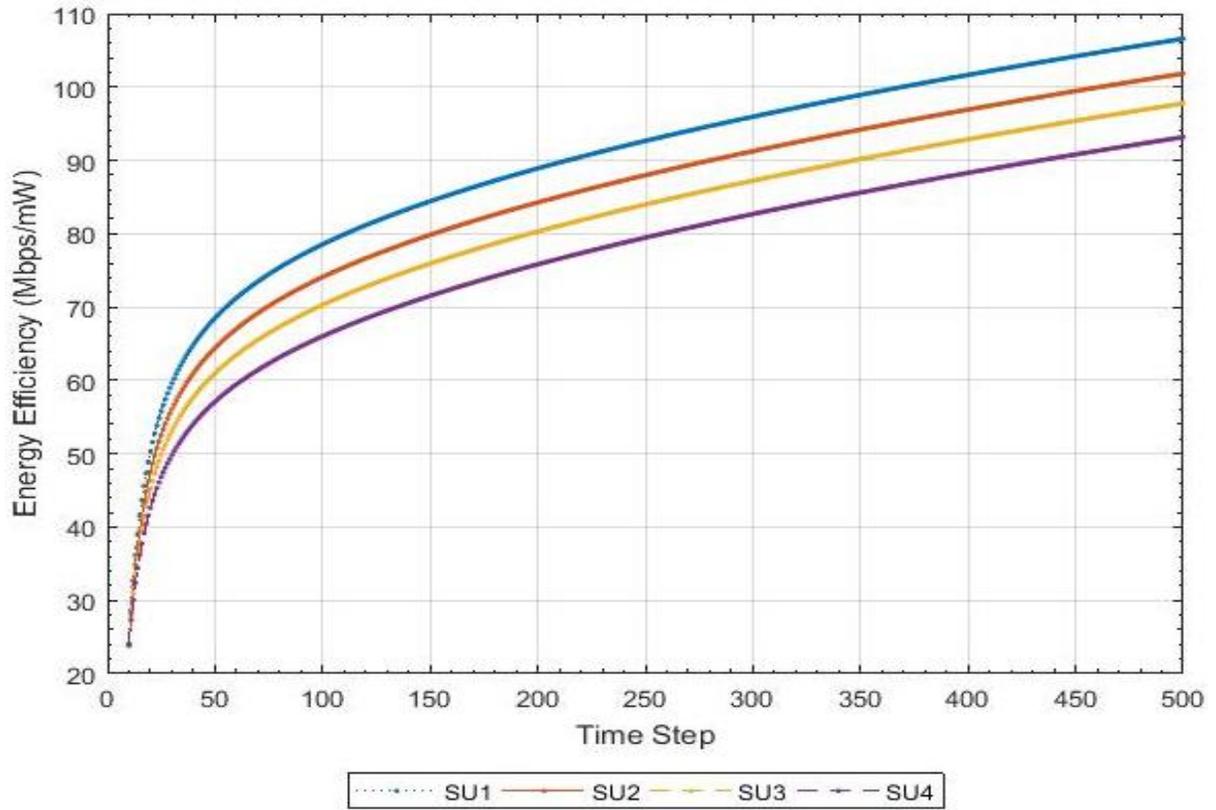
Figures 32 and 33 show the energy efficiency for different SUs' nodes in a nucleated settlement pattern at low and high perceptual radii respectively. It can be observed from figure 32 that the highest energy efficiency achieved by the SUs with a low perceptual radius is 99.8Mbps/mW whilst the highest energy efficiency for the SUs that use a high perceptual radius is 106.4Mbps/mW [see Figure 33]. Based on figures 32 and 33, it can be observed that the proposed model performs better when the SUs' node uses a high perceptual radius. The achieved better performance by the SUs' nodes at high perceptual radii can be attributed to the decrease in the distance that the SUs' nodes need to travel before finding an available frequency. As the perceptual radius increases, the SUs' ability to sense available frequencies also increases and this, in turn, reduces the distance that the SUs need to travel to find an available frequency. Hence, the decrease in distance travelled by the SUs before finding an available frequency helps the SUs to maximise their net energy gain.

It can generally be observed from Figures 18-33 that there are few differences in the results among the SUs. This difference can be attributed to distance travelled by the individual SU before finding an available frequency for communication. In a distributed environment, the nodes movement are dynamic, hence, both the SUs and PUs nodes are randomly placed within the simulation. The random placement of nodes lead to the SUs nodes travelling different distance before finding available PUs frequency. This in turn lead to the differences among the SUs nodes result presented for all the scenarios considered.

Based on the results achieved by the SUs in both dispersed and nucleated settlement patterns, the FISSER model is recommended to address the spectrum selection and reconfiguration challenges for SUs' nodes in a distributed CRN. Table 5 summarises the simulation results achieved from the metrics that were considered in the nucleated settlement pattern.



**Figure 32: The energy efficiency of SUs' nodes at low perceptual radius**



**Figure 33: The energy efficiency of SUs' nodes at high perceptual radius**

**Table 5: Summarised Analysis Results for Nucleated Settlement Pattern**

	ACST (ms)	STP (%)	ANT (%)	EE (Mbps/mW)
<b>Low perceptual radius</b>	10.02	94.2	86.4	99.8
<b>High perceptual radius</b>	13.13	87.7	72.2	106.4

## 4.4 Chapter Summary and Remarks

This chapter presents both the simulation setup and the performance analysis of the FISSER model developed in Chapter Three. The MATLAB<sup>TM</sup> version 9.2 was used as the simulation tool for this study due to its ability to provide accurate and realistic network conditions which can be tractably tested. In validating the performance of the proposed foraging model, two settlement patterns: dispersed and nucleated, were considered. The dispersed represents the rural areas, whilst the nucleated settlement pattern represents the urban areas. Several computer simulations were carried out using four performance metrics: average channel switching time, successful transmission probability, average network throughput, and the energy efficiency. These metrics were measured when subjected to high and low perceptual radii at different time steps.

The existing models in the literature use a single validation process for their developed models. One of the important considerations in developing and validating a model in a dynamic environment, such as distributed CRN, is the robustness of the applicability. For example, it is possible to develop a model that performs very well in rural areas, but not in the urban areas due to different data traffic levels. Hence, while developing a model for a dynamic environment such as distributed CRN, it is important to consider the applicability in any settlement patterns. In achieving an optimal spectrum utilisation, the applicability of the approach in both rural and urban areas is an important factor that needs to be considered. To the author's knowledge, none of the existing models in the field of spectrum selection and reconfiguration for distributed CRNs has considered the model performance in the context of settlement patterns (rural and urban). The robust analysis of the FISSER model in the context of rural and urban settlement patterns, using different perceptual radii is novel in the field of spectrum selection and reconfiguration for distributed CRNs.

The argument of this study is that the spectrum utilisation of a distributed CRN can be improved by exploiting the dynamic selection and reconfiguration of frequency and channel bandwidth. The simulation results presented in this chapter show that the FISSER model for SUs' nodes in a distributed CRN can achieve optimal communication

performance, mitigate the communication overhead, and improve the energy efficiency both in the dispersed and nucleated settlement patterns. Hence, the achieved results show that using the FISSER model for SUs' nodes communication in a distributed CRN improves the spectrum selection and reconfiguration and in turn improves the spectrum utilisation.

CRNs can be deployed to support the various usage scenarios such as military operation, disaster management and community security surveillance networking. These disparate usage scenarios require guaranteed node communication performance and energy efficiency. Thus, these usage scenarios are supported by the FISSER model. The use of both the high and low perceptual radii by the SUs' nodes, in combination with other parameters, has been shown to influence the performance and the energy efficiency of the SUs' nodes in a distributed CRN. A high perceptual radius has been shown in the literature to improve the energy efficiency and data communication performance in wireless mesh and ad hoc networks. However, the simulation results reported in this chapter show that even though the high perceptual radius improves the nodes' energy efficiency it does not achieve optimal data communication performance compared to when the nodes use a low perceptual radius for their communication.

In the next chapter, the simulation results obtained from this chapter are compared with the other three models so as to determine the efficacy of the FISSER model in a distributed CRN environment.

## CHAPTER FIVE

### PERFORMANCE EVALUATION OF FISSER MODEL IN A DISTRIBUTED COGNITIVE RADIO NETWORK

#### 5.1 Introduction

In Chapter Four, the performance of FISSER model for spectrum selection and reconfiguration in a distributed CRN was analysed using MATLAB™ simulation tool. The achieved analyses results showed that the FISSER model can help the SUs in a distributed CRN to achieve efficient spectrum selection and reconfiguration and in turn achieve optimal spectrum utilisation. However, there is still a need to evaluate the proposed FISSER model's performance against other existing spectrum selection and reconfiguration models in order to validate the efficacy of the FISSER model.

Hence, this chapter is focused on the performance evaluation of the FISSER model for SUs in a distributed CRN. The FISSER model was compared to Dynamic, Q-learning and Game-based models, using four performance metrics. Section 5.2 describes the criteria used in selecting the three models compared with the FISSER model. Section 5.3 presents the performance evaluation results obtained from the simulations and the chapter is concluded with a summary and remarks in Section 5.4.

#### 5.2 Comparative Models Selection

This subsection describes the criteria that were used in selecting the three models used for comparison to the FISSER model. The review conducted in Chapter Three of this thesis helped to establish the criteria for selecting the three models used for evaluation in this chapter. The three selected models include game-based theory [119], dynamic strategy [30] and Q-learning strategy [6].

The taxonomy presented in figure 6 shows both the distributed and the centralised topology approaches. However, we focused more on the distributed approaches that use

a separate channel for nodes' communication, because this is in-line with the problem that this thesis is addressing. Hence, the reason for selecting the dynamic strategy model as one of the models to compare with the FISSER model. Apart from the reason stated above, the game-based model was selected as it was indicated in Chapter Three of this thesis that it has been used to address the problem with the models that were developed using statistical and predictive approaches. In addition, the game-based model is one of the popular models that many researchers have adopted in addressing the spectrum selection and reconfiguration challenges both in the centralised and distributed topology. Hence, it will be interesting to see how the proposed FISSER model perform in relation to the game-based model.

In order to balance the evaluation, we selected a Q-learning based model which represents the centralised topology with the common control channel for nodes' communication. Also, the learning approach is part of artificial intelligence, which combines both machine and neural network approaches. Two of the main features of artificial intelligence are its ability to generalise multiple functions and conceptually scalable. These features are important in a distributed CRN environment, where the SUs nodes needs to make decision on which frequency to select for communication within a short time, which is one of the core problem that this thesis is addressing. Hence, this makes the artificial intelligence approach an important model to compare with the FISSER model. Artificial intelligence is also one of the most popular approaches that many researchers have been using to develop models in the field of CR spectrum management [93, 111].

### **5.3 Performance Evaluation Results**

This section presents the performance evaluation of the FISSER model, by comparing the best performing results from Chapter Four with Q-learning [6], dynamic strategy [30] and game-based [119] models. A consistent comparison and evaluation of the four aforementioned models in the context of distributed CRNs is achieved by keeping the simulation environment and parameters the same for all of our simulation experiments. The MATLAB<sup>TM</sup> version 9.2 simulator was used for the simulation environment.

Although the authors of Q-learning, dynamic strategy and game-based models did not give their respective experimental setup details, however, this study used their mathematical model formulation to replicate their experiments in MATLAB simulator. In order to check the correctness of our implementation of their models, we compare our generated results with the results they presented and they are all correct. Thereafter, we proceed to the performance evaluation phase.

Table 6 contains the summarised details of the simulation setup parameters that were used for all the experiments reported in this section. All the simulations were carried out during a period sufficient for the stability of result statistics. Each of the reported results was the average of twenty data points from twenty simulation runs. The models were evaluated using the following performance indicators: *average channel switching time, average network throughput, successful transmission probability, and energy efficiency* metrics.

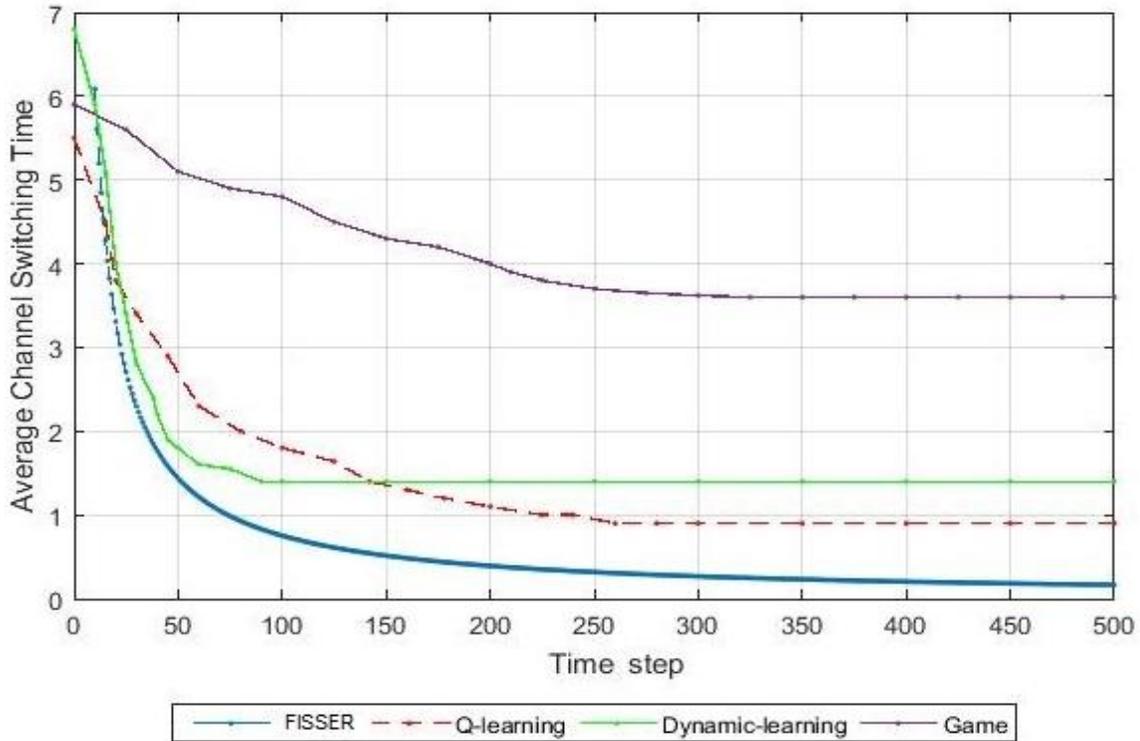
**Table 6: Summarised Simulation Setup Details for Performance Evaluation**

<b>Parameters</b>	<b>Value(s)</b>
Number of PUs	10
Number of SUs	30
Simulation Area	600m x 600m
Simulation time	500 seconds
Models compared	FISSER, Q-learning, Dynamic strategy and Game-based
MAC Protocol	IEEE 802.22
Frequency range	470MHz – 890MHz
Channel Bandwidth	14 – 83
Channel Size	20MHz
Performance Metrics	Average channel switching time, Successful transmission probability, Average network throughput, and Energy efficiency

### 5.3.1 Experiment I: Average Channel Switching time

The average channel switching time is the time it takes the SUs' nodes to switch between available frequencies and to reconfigure their transceiver parameters when a PU appears. The lower the value the better the model performance. The channel switching time is an important metric that helps to know the extent of disruptions that a PU can experience if the SUs do not leave the spectrum on time.

Figure 34 shows the average channel switching times over a range of time steps. It can be observed that the FISSER model switching times are convergent to 0.5ms, while Q-learning, dynamic strategy and game models are convergent to 0.9ms, 1.5ms and 3.7ms respectively. The game-based model requires the communication among each of the SUs' nodes to follow the changes of nodes' information which introduced a slow convergence in the game model which in-turn lead to some delays in selection and reconfiguration of frequency and channel bandwidth. Hence, the reason for the poor performance of the game-based model in the average channel switching time result presented.



**Figure 34: The average channel switching time of SUs' nodes**

The performance of both Q-learning and dynamic strategy are close to one another. This can be attributed to the fact that both models use adaptive learning strategy scheme to make decisions about the SUs' switching. However, the difference in their achieved results can be attributed to the fact that the dynamic strategy did not consider the other nodes strategy, which lead to the adjusting of channel from time to time and in-turn lead to some switching time delay. The Q-learning on the other hand, considered the other nodes estimation strategy for channel selection, hence, it has lesser channel switching time than dynamic strategy. Both Q-learning and dynamic strategy have been introduced in the literature [6, 93, 109] to address the slow convergence challenge in the game-based model. However, due to many selection strategies that the SUs need to learn before making the switching and reconfiguration decision, it introduced some computational complexity which in-turn affected the performance of both the Q-learning and dynamic strategy models compared with that of FISSER model.

The FISSER model was able to achieve the optimal result because of its analytical simplicity and generic application which helped to address both slow convergence and

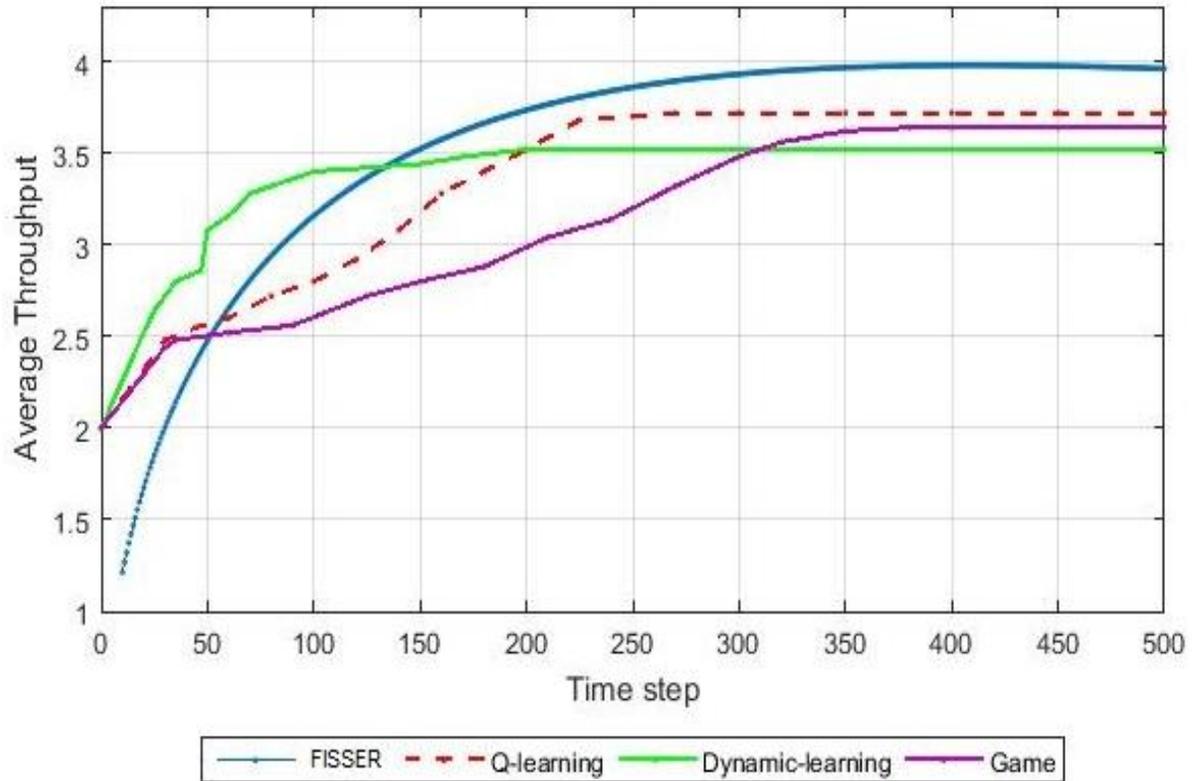
computational complexity that affect other models' performance. The achieved optimal result by the FISSER model helped the SUs in selecting the best channel, switching and reconfiguring their transceiver parameters within a short period and this, in turn, helped the SUs to achieve optimal communication performance and improve the spectrum utilisation.

### **5.3.2 Experiment II: Average Network Throughput**

The average network throughput is the number of bits that were processed over a period of time in 1Hz bandwidth. The throughput index shows the network communication performance and the higher the achieved value, the better the model performance.

The network average throughput for different models is shown in Figure 35. It can be observed that the FISSER model outperformed other models in the achieved throughput performance. The achieved high throughput result by the FISSER model can be attributed to the model search technique (intensive/extensive), where the SUs start their searching for available frequencies by taking short steps and only switch to long steps when there is no available frequency within the short steps' radius. However, with the other models the same number of decision steps are taken every time when they need to search for available frequencies, hence the reason for the better performance of the FISSER model.

It can also be observed in Figures 34 and 35 that there is a correlation between the achieved channel switching time and the average network throughput. The better the switching and reconfiguration time, the better the network throughput. Based on the results achieved by P. Li *et al.* [12], the author concluded that high channel switching time could lead to an average throughput loss of at least 3%. Hence, the optimal network throughput result achieved by the FISSER model shows that our proposed model can achieve an optimal data communication rate and provide better QoS for CR spectrum utilisation.



**Figure 35: The average network throughput of SUs' nodes**

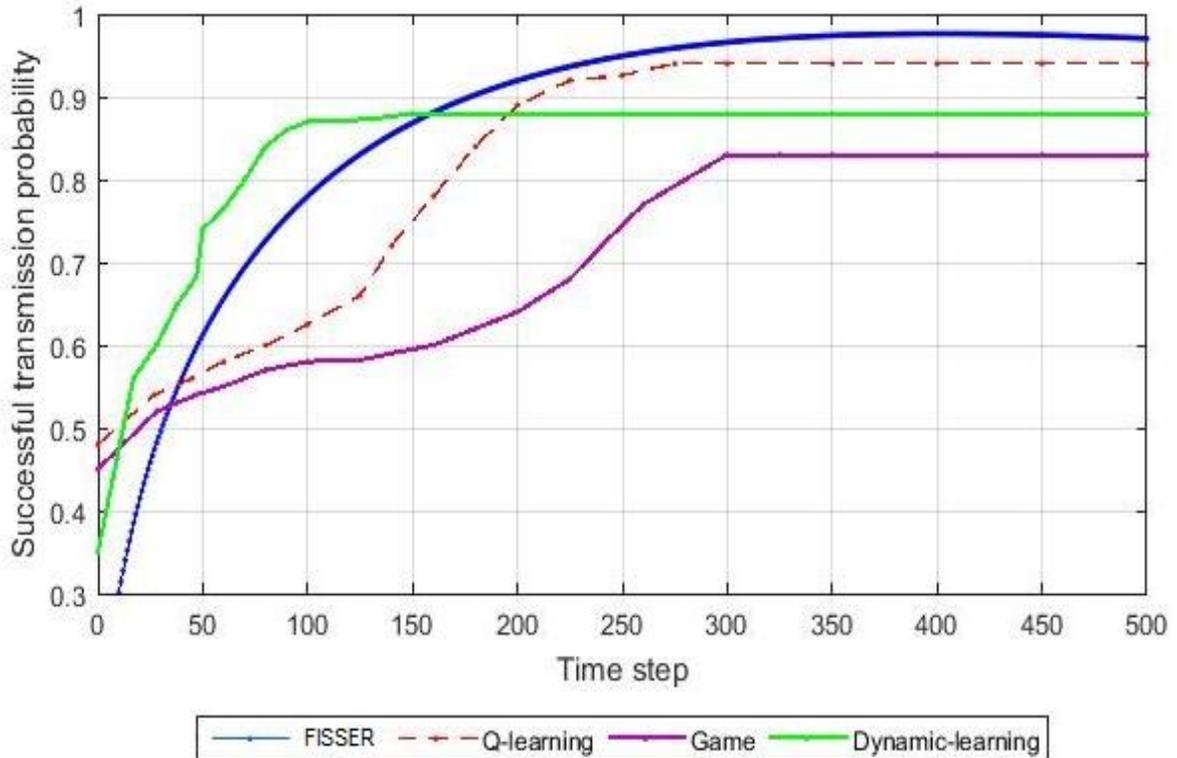
### 5.3.3 Experiment III: Successful Transmission Probability

The successful transmission probability is the probability that the SUs' nodes' communication is successful [52, 105]. The higher the transmission probability value, the better the model performance and this metric would help to reduce the communication overhead, which in turn will reduce the energy consumption.

In figure 36, the successful transmission probability for different models was presented. It was observed that the game model reached 83% and the dynamic strategy reached 88%, while Q-learning reached 94.1% and our FISSER model achieved 97.4%. The game-based and dynamic strategy models performance can be attributed to the fact that each node does not consider other nodes while making decisions hence, it reduces the successful global optimum rate and leads to their inferior performance compared to the

Q-learning and FISSER models. The Q-learning model's performance can be attributed to the estimation strategy that exists between the SUs' nodes, which help them in selecting a channel and frequency. However, the optimal result achieved by the FISSER model can be attributed to the search technique adopted while developing this model, where individual SUs make their decisions, hence it reduced collision among the SUs' nodes and in turn resulted in better transmission probability.

The achieved optimal channel switching time, successful transmission probability, and network throughput will help the FISSER model in the optimal reconfiguration of frequency and channel bandwidth for SUs' data communication and in turn lead to a more efficient spectrum utilisation.



**Figure 36: The successful transmission probability of SUs' nodes**

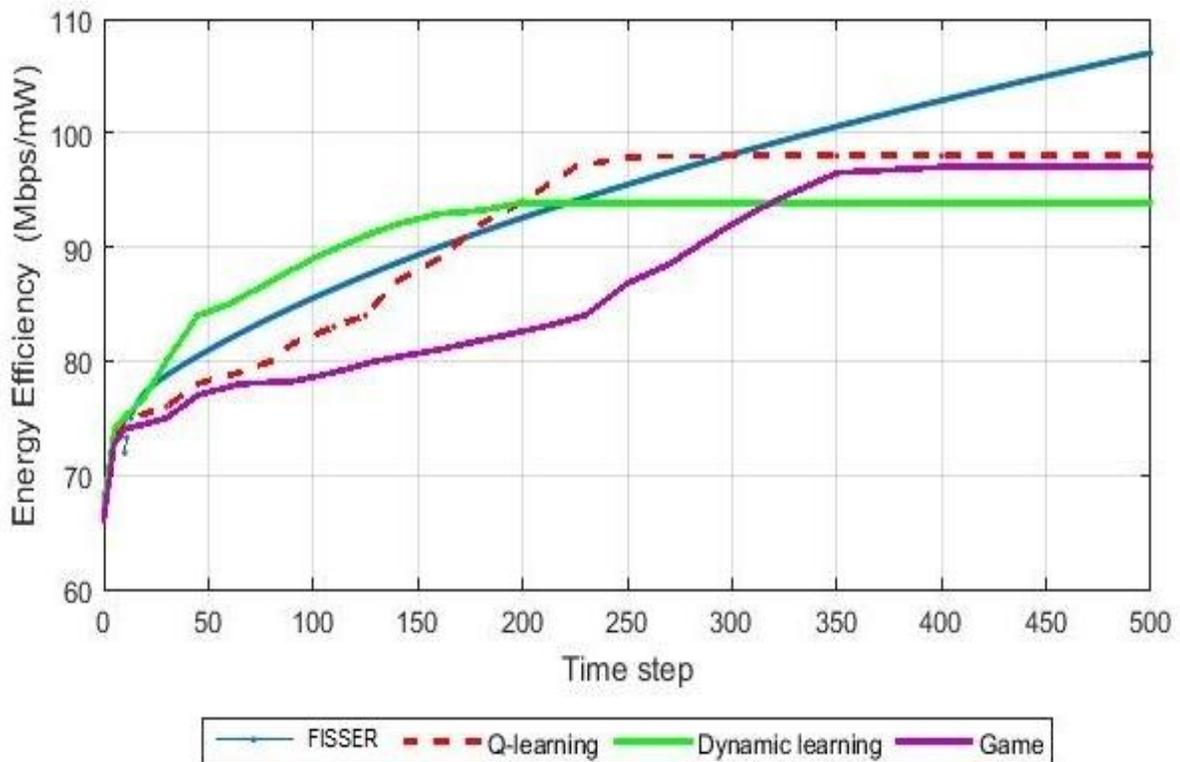
### 5.3.4 Experiment IV: Energy Efficiency

The energy efficiency is the ratio of the total bits that were successfully delivered to the destination nodes across the network and the power consumed by the network nodes to deliver the sent bits [113, 121]. The goal of this metric is to maximise the data delivery whilst minimising the power consumption. Hence, the higher the energy efficiency value the better the model performance. The energy efficiency metric can be mathematically represented as [113]:

$$\text{EnergyEfficiency} = \frac{\text{total amount of data delivered (Mbps)}}{\text{total amount of energy consumed (mW)}} \quad (5.1)$$

The energy efficiency of the different models considered is presented in Figure 37. It can be observed from Figure 37 that the FISSER model outperforms other models in the achieved energy efficiency. The game-based model's performance can be attributed to the slow convergence that resulted from continuous changing of strategies by each player/SU. This slow convergence introduces some delays, which in turn leads to more energy consumption. The lower performance of both Q-learning and dynamic strategy models can be attributed to the computational complexity which resulted from the SUs' learning of all the rules before making a decision. The computational complexity makes the two models consume more resources in learning the rules. This, in turn, leads to more energy consumption. However, the FISSER model is able to outperform other models because of its simple searching criteria, which helps to minimise the distance travelled by SUs before finding the available frequency for communication.

Based on the achieved average channel switching time, network throughput, successful transmission probability, and energy efficiency results, it can be concluded that by using our proposed FISSER model in a distributed CRN environment the SUs can get the optimal communication channel and reduced communication overhead which guarantees the SUs' spectrum reconfiguration, energy efficiency, and improved efficient spectrum utilisation simultaneously.



**Figure 37: The energy efficiency of the SUs' nodes**

## 5.4 Chapter Summary and Remarks

In this chapter, the performance of the FISSER model in a distributed CRN was evaluated using MATLAB™ simulation. The FISSER model's performance was compared against the dynamic strategy, game-based and Q-learning models. The crux of this chapter was to determine the efficacy of the FISSER model in terms of improving the spectrum utilisation in a distributed CRN by exploiting optimisation of selection and reconfiguration of frequency and channel bandwidth for the SUs' nodes.

This objective was achieved by evaluating the performance of the FISSER model against the three aforementioned models in a distributed CRN environment using four performance indicators: average channel switching time, network throughput, successful transmission probability, and energy efficiency. Table 7 summarises the simulation results achieved from the metrics that were considered.

**Table 7: Summarised Performance Evaluation Results**

	<b>Q-Learning</b>	<b>Dynamic Strategy</b>	<b>Game-based</b>	<b>FISSER</b>
<b>ACST (%)</b>	12.86	21.43	52.86	7.14
<b>STP (%)</b>	94.1	88	83	97.4
<b>ANT (%)</b>	82.67	78	82.22	91.11
<b>EE (%)</b>	89.09	84.55	88.18	97.27

*ACST – Average Channel Switching Time; STP – Successful Transmission Probability; ANT – Average Network Throughput; and EE – Energy Efficiency*

The efficacy of the developed FISSER model has been extensively validated via computer simulations and the obtained results show that the SUs' nodes in a distributed CRN achieved optimal communication performance, reduced the communication overhead and guaranteed the efficient use of energy. Hence, the FISSER model yields improved spectrum utilisation and communication performance simultaneously.

In a distributed CRN environment, there exists a wide range of frequencies and channel bandwidths, which the SUs' nodes can use for communication in an opportunistic manner. However, in order for the SUs' nodes to select the most appropriate frequency and channel bandwidth, the nodes should be able to dynamically search for the available frequency without having prior knowledge of the frequency location. Hence, the ability of the SUs' nodes to respond to external environmental changes within a short time span is very important. The simulation results reported in this chapter revealed that for the SUs' nodes in a distributed CRN to achieve an optimal spectrum utilisation, the nodes must be able to dynamically evolve their functional structure to respond to their external environmental changes within a short time span.

Chapter Six summarises the key findings, contributions and future research directions related to this study.

## CHAPTER SIX

### CONCLUSIONS AND FUTURE WORK

*“The performance of a distributed CRN that is experiencing suboptimal spectrum utilisation can be improved by exploiting dynamic selection and reconfiguration of frequency and channel bandwidth such as the FISSER model.”*

The statement above is the argument of this study, which has been proven by adopting the natural principle of biological foraging in developing a novel Foraging Inspired Spectrum Selection and Reconfiguration (FISSER) model. The model was validated through mathematical analysis and computer simulations. The efficacy of the developed FISSER model was extensively validated through computer simulations and the FISSER model shown to yield optimal spectrum utilisation by improving the selection and reconfiguration of frequencies and channel bandwidths. This chapter concludes the study, details the key contributions and outlines the future work related to this research.

#### 6.1 Summary of the Findings

The study of dynamic spectrum selection and reconfiguration of the frequency and channel bandwidth in spectrum decision making has been motivated because of its importance to the realisation of optimal spectrum utilisation in distributed cognitive radio networks.

Dynamic spectrum reconfiguration has been previously reported to improve the spectrum utilisation in CRNs. In exploiting spectrum reconfiguration of frequency and channel bandwidth to improve spectrum utilisation, various approaches have been adopted to develop models. However, these existing approaches have not been able to achieve optimal spectrum utilisation due to slow convergence, computational complexity, applicability, and repeatability challenges. Hence, the study of the efficacy of dynamic selection and reconfiguration approaches as a mechanism for improving the spectrum utilisation in a distributed CRN remains an open issue.

The work presented in this thesis has focused on addressing the dynamic selection and reconfiguration of frequencies and channel bandwidths in a distributed cognitive radio network so as to balance the communication performance, improve the energy efficiency, and achieve optimal spectrum utilisation simultaneously. The investigations into the existing spectrum selection and reconfiguration approaches and why those existing approaches are not achieving optimal results were presented in Chapter Two. Chapter Two provides unique insight into “why” and “how” those existing approaches converge slowly, consume computational resources, and are non-generic which negatively affect their models’ performance.

The successful investigation resulted in the introduction of biologically-inspired optimal foraging theory to develop a FISSER model, which was used to address the identified problems with the existing approaches and to achieve an optimal spectrum utilisation result. The formulation, development and analytical analysis of the FISSER model are detailed in Chapter Three. The developed FISSER model was subjected to robust simulation-based performance validations using MATLAB™ simulation tool and the details of the simulation setup and measurement methodology were provided in Chapter Four. Lastly, Chapter Five provided the efficacy of the FISSER model by comparing its performance against three appropriate recently studied models (game-based, dynamic strategy and Q-learning models), using four performance metrics.

The simulation-based experimental results achieved in this study show that the FISSER model achieved 97.4% successful transmission probability, while Q-learning, dynamic strategy and game-based models achieved 94.1%, 88% and 83% respectively. Also, for average network throughput, the FISSER model achieved 91.11% while the best performing among other models achieved 82.67%. For energy efficiency, the FISSER model achieved 97.27% and the best among other models achieved 89.09%. These results indicate that for the SUs’ nodes in a distributed CRN to achieve optimal spectrum utilisation, the nodes must be able to dynamically search for and select an available frequency, without having prior knowledge of the frequency’s location. Also, the nodes should dynamically evolve in response to their external surrounding environment within a short time.

Finally, both the analytical and simulation results presented in this thesis confirm that the FISSER model yields optimal spectrum selection and reconfiguration of both frequency and channel bandwidth and in turn improves the spectrum utilisation of a distributed CRN.

## 6.2 Summary of Contributions

In order to achieve the goal of this thesis, the suboptimal spectrum utilisation problem was addressed by exploiting the dynamic selection and reconfiguration of frequency and channel bandwidth for SUs in a distributed CRN using a FISSER method. The case for this approach was motivated in Chapter Two. It was shown that there are some challenges with the existing spectrum selection and reconfiguration approaches and hence, the need for another approach that can achieve an optimal spectrum utilisation result. The main contributions of this thesis may be outlined as follows:

- **Survey:** in this thesis, an overview of the existing spectrum selection and reconfiguration approaches and why those approaches are not achieving the optimal result for network communication is presented. The existing models are classified according to their solution approaches. The review provided in this thesis presents a starting point for choosing a biologically inspired approach to develop a FISSER model used in different scenarios of distributed CRNs. The presented survey is a logical extension of the existing literature in the field of spectrum selection and reconfiguration, thereby adding value to other research efforts when selecting an approach against which to compare and/or develop a new model.
- **Modelling:** in this thesis, using the concept of the ecological behaviour of animals' nutrients optimisation to formulate the FISSER model to address the problem of spectrum selection and reconfiguration in a distributed CRN is an innovation. Although biologically inspired foraging approach has been used to develop models in some other aspects of wireless networking, no research work

has been reported on the use of biological optimal foraging approach to develop a model for spectrum selection and reconfiguration in a distributed CRN.

- ***Two-in-one approach (resolve-optimize)***: until now, not much has been done about resolving challenges with the existing approaches and achieving an optimal spectrum selection and reconfiguration result using one approach. In the literature, researchers have only been addressing the challenge/s on an individual approach basis by proposing another approach to address the problem with the identified individual approach. For example, the game-based approach was introduced to address the problem of reliability and computational complexity in statistical and predictive approaches. However, due to the slow convergence challenge introduced by the game-based approach, artificial neural networks and machine learning algorithms were proposed to address the slow convergence speed but they also have some computational complexity problems as explained in Chapter Two of this thesis. However, to the best of the author's knowledge, no single approach has attempted to resolve all the aforementioned challenges at once. The FISSER model developed in this thesis demonstrates how the existing approaches can be innovatively combined and the performance results compared against three other existing models as detailed in Chapter Five. Coupled with addressing the existing approaches' challenges, the FISSER model also achieved optimal spectrum selection and reconfiguration.

### **6.3 Future Work**

This section presents how this thesis opens up avenues for future research directions. Some of those possible further research directions could be summarised as follows:

The next logical step after the analytical and simulation investigations presented in this thesis is to extend this work to actual prototype implementations and field-testing. This will enable further validation of the results obtained in this thesis.

Another promising avenue for further research is to apply the FISSER model to the decision making in the smart home application, which is one of the application areas of the Internet of Things (IoT). The recent rapid evolution of the IoT requires diverse

wireless technology support which has led to the challenges of how to manage and utilise the spectrum resources (such as frequency and channel bandwidth) effectively. However, it would be worthwhile research to see how biological optimal foraging theory can be applied in the smart home application of the IoT.

In this thesis, it was made clear that the biological optimal foraging approach is generic with respect to any distributed wireless networking, however, the major focus was on IEEE802.22 based cognitive radio networks. Performance evaluations of the FISSER model with respect to other wireless communication such as broadband wireless metropolitan area networks and wireless sensor networks would be an interesting area for future studies.

Due to the current effect of global warming all over the world, the energy efficiency metric has become a very important metric to consider in any network deployment. Although this thesis has analysed the energy efficiency of the FISSER model in the distributed CRN, it would be of interest to investigate the energy efficiency of the FISSER model in a distributed green communication network.

Finally, one of the major challenges in the Tactical mobile ad hoc networks is the user required configuration and reconfiguration time [99,116]. Applying the FISSER model to dynamically reconfigure the Tactical nodes within the shortest possible period would similarly be a challenging but interesting research area for future studies.

## **6.4 The Benefit of Collaboration**

Exploring ways of combining behavioural ecology, mathematical and wireless network communication fields has been enlightening and encouraging. The researchers in these fields deal with similar problems but from distinctly different directions. The collaboration among these fields would lead to unforeseen insights of genuine value. Supposing the results achieved in this thesis do not directly apply to the field of mathematics, it is likely that starting a collaborative discussion among the researchers of these diverse fields will ultimately yield mutual benefits.

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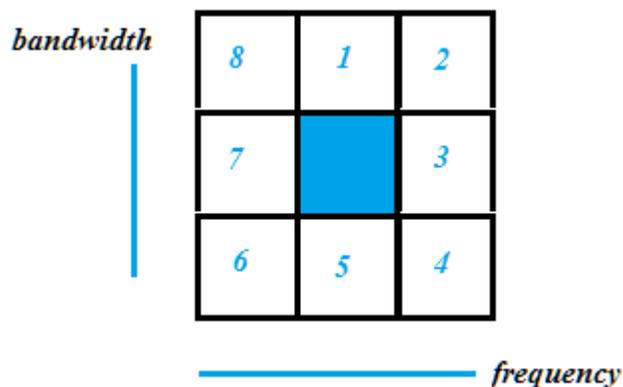
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## APPENDIX A: FURTHER FISSER MODEL IMPLEMENTATION DETAIL

All users of the network are divided into two types: primary users (PUs) i.e. the current licensees; secondary users (SUs) trying to share the existing resources. Each SU is a biological forager searching for a “prey” (PU) in the existing environment. The environment can be described as a set of parameters important for a SU to make a decision.

A good visualization can be obtained for a 2D-model, where 2 parameters are used. In our case, they are 1) frequency (radio wave length); 2) distance to a node (PU). Thus, we obtain surface with two dimensions: X – operating frequency, Y – channel bandwidth. Given the steps for X and Y,  $\Delta X$  and  $\Delta Y$ , we draw a grid on the surface. Now, each PU or SU can be allocated in the corresponding cell of this grid. A SU searches for the “nearest” prey that provides an optimal solution.

The initial positions: for PUs – at the arena right edge, for SUs – in the arena centre. During the simulation, PUs and SUs can occupy the same cells. Nodes (PUs) can leave and join the network at any time at any distance offering any frequency. Thus, we can model their “movement” within the 2D surface as random, in 8 possible directions



Possible moves of a PU within “Distance/Frequency” surface

A SU has two strategies to join a PU: intensive and extensive search. In the intensive search mode, a SU moves randomly, as shown on fig.1. This search mode does not use any additional computational sources and can be successful within the arena rich with PUs. In the extensive search mode, a SU “observes” the arena within its visibility zone of the given radius R. After spotting a PU, the SU stops observing and starts a bullet-like movement towards the PU. After a leap of 5 steps, the SU has to check the current position of the PU, taking into account its continuous random moves. This search mode is 100% successful but demands significant additional computations. Thus, it should be limited. The ratio of extensive moves to the total number of moves is

$$k = \frac{E}{I + E}$$

where E – number of extensive moves, (I+E) – total number of moves. For example, if  $k = 0.05$ , every 20 steps should include 19 intensive and 1 extensive moves of a SU (their consequence should be random).

After the PU is “caught”, the SU ceases to exist; meanwhile the PU keeps on its random movement. In other words, the prey eats its hunter. The simulation stops after all the SUs have found their PU nodes.

### **Input Parameters**

N – number of intervals for the “frequency/bandwidth” grid

NP – number of PUs

NS – number of SUs

R – radius of visibility zone

k – ratio of extensive moves

### **Output Parameters**

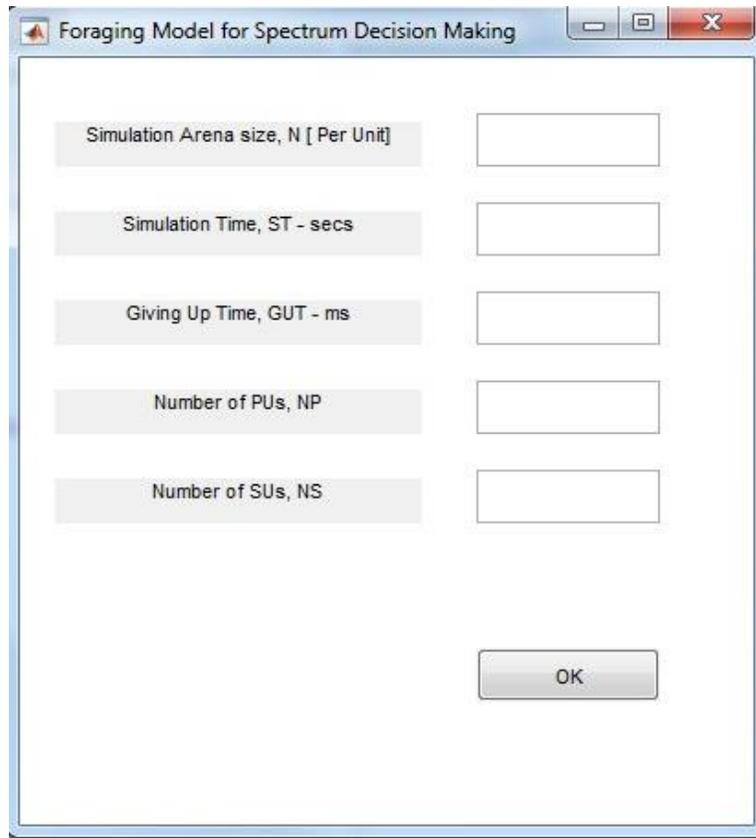
TT – total time of simulation

t – average time of finding a PU

dP – density of PUs  $dP = NP / N^2$

dS – density of SUs  $dS = NS / N^2$

The simulation visual environment, where the user need to input some of the aforementioned parameters.



The image shows a dialog box titled "Foraging Model for Spectrum Decision Making". It contains five input fields for parameters: "Simulation Arena size, N [ Per Unit]", "Simulation Time, ST - secs", "Giving Up Time, GUT - ms", "Number of PUs, NP", and "Number of SUs, NS". Each field is represented by a grey label box and an empty white text box. An "OK" button is located at the bottom right of the dialog.

Simulation Arena size, N [ Per Unit]	<input type="text"/>
Simulation Time, ST - secs	<input type="text"/>
Giving Up Time, GUT - ms	<input type="text"/>
Number of PUs, NP	<input type="text"/>
Number of SUs, NS	<input type="text"/>

OK

**The Simulation parameter settings**

## APPENDIX B: PUs & SUs SEARCHING MOVEMENT

```

function RealVis(N, ST, GUT, NP, NS)
J=N+1;
delay = 0.001;      %pause in sec
SU = ones(NS, 4) * ((J - 1)/randi(12));
SU(:, 4) = 0;      %intensive move
PU = ones(NP, 3) * (J - 1/randi(2));
R=2;
CP=NP;

g_x = 1:J;
g_y = 1:J;

k=0.1;
%Create simulation environment
figure('MenuBar', 'None',...
      'Name', 'Visualization',...
      'units', 'normalized', 'outerposition', [0 0 1 1],...
      'Color', [1 1 1]);
%-----initial layouts
%grid

axis square;
axis off;
set(gca, 'xtick', [], 'ytick', [])

% Initiate the PUS and SUS
%SUs - intitial position in the center
%SUs - intitial position in the center

%SU = ones(NS, 4) * ((J - 1)/2);
RDPS = abs(J - 9);
RDPPS = abs(J - 2);
for i = 1:NS

    SU(i, 1) = randi(RDPS);
    SU(i, 2) = randi(RDPPS);
    plot (SU(i,1), SU(i,2), 'r.', 'markersize',30);
    set(gca, 'Color', 'black');
    hold on;
    rng(i);
end;

%PUs - initial positions at the right edge
% M = double(idivide(int32(N),int32(NP)));
RDP = abs(J - 6);
RDPP = abs(J-3);
for i = 1:NP
    % PU(i, 2) = i*M - 1/randi(2);

    PU(i, 2) = randi(RDP);
    PU(i, 1) = randi(RDPP);
    plot (PU(i, 1), PU(i, 2), 'g.', 'markersize',30);

```

```

        set(gca, 'Color', 'black');
        hold on;

        rng(i);
    end;
    pause(delay);

% do the process while the Simulation Time last

GUTLim    = GUT;
iniTime = clock;
limit     = ST; % Seconds

NSUI = size(SU, 1);
NSU  = size(SU, 1);
while etime(clock, iniTime) < limit
    % while the simluation time last, placed the PU's randomy

    if etime(clock, iniTime) < GUTLim
        % while the simluation time last, placed the PU's randomy
        for i = 1:NP
            PU(i, 3) = randi(8);
            plot (PU(i, 1), PU(i, 2), 'black.', 'markersize',30);
            [PU(i,1) PU(i,2)] = Move(PU(i,1), PU(i,2), J, PU(i, 3));
            plot (PU(i, 1), PU(i, 2), 'g.', 'markersize',30);
        end;

    for i = 1:NSUI
        SU(i, 3) = randi(8);
        plot (SU(i, 1), SU(i, 2), 'black.', 'markersize',30);
        [SU(i,1) SU(i,2)] = Move(SU(i,1), SU(i,2), J, SU(i, 3));
        plot (SU(i, 1), SU(i, 2), 'r.', 'markersize',30);
    end;

    %check if PUs found
    lucky = zeros(1, NSUI);
    for i = 1:NSUI
        for j = 1:NP
            if (SU(i, 1) == PU(j,1) && SU(i, 2) == PU(j,2))

                % save the coordinate of the SU and PU's
                % that uses each other

                plot (SU(i, 1), SU(i, 2), 'r*', 'markersize',30);

                % plot (SU(i, 1), SU(i, 2), 'r*', 'markersize',20);
                lucky(i) = 1;

                break;
            end;
        end;
    end;
end;

```

```

end;
%reset SUs array
s = sum(lucky);

if (s == NSUI)
    % break;      %end of simulation, all SUs found their PUs
end;

if (s > 0 && s < NSUI)
    X = zeros(NSUI - s, 4);
    j = 1;
    for i = 1:NSUI
        if (lucky(i) == 0)
            X(j, :) = SU(i, :);
            j = j + 1;
        end;
    end;

    SU = X;
    NSUI = NSUI - s;
end;
% pause(delay);
% hold for awhile and let the PU and SU reappears

%SU reappears

if NSUI < NS
    Pd=NSUI+s;
    NSUI=Pd;

end;
%PUs appearance
% Make PUs unavailable
switch NP
case 2
    if (( GUTLim - (etime(clock, iniTime)) == 20) && (NP <= CP))
        NP = CP - 1;
    else
        % NP=CP;
    end;

case 3
    if (( GUTLim - (etime(clock, iniTime)) == 15) && (NP <= CP))
        NP = CP - 1;
    else
        % NP=CP;
    end;

otherwise
    NP = CP;

end;

```

```

pause(delay)

else
    % NSU = size(SU, 1);
    % Switch to extensive move for the SU's

    % aimulating the SU's in extensive mode
    NSU = size(SU, 1);
    tick = 0;
    ex_move = k * NSU;
    ex_lim = 0;
    if (ex_move < 1 && ex_move > 0)
        ex_lim = 1 / ex_move;
    end;
    ex_count = 0;

    while (etime(clock, iniTime) <= limit)

        for i = 1:NP
            PU(i, 3) = randi(8);
            plot (PU(i, 1), PU(i, 2), 'black.', 'markersize',30);
            [PU(i,1) PU(i,2)] = Move(PU(i,1), PU(i,2), J, PU(i, 3));
            plot (PU(i, 1), PU(i, 2), 'g.', 'markersize',30);
        end;
        %find SUs for extensive moves
        if (ex_move >= 1) %one and more ex moves per epoch
            for i = 1:ex_move
                choice = randi(NSU);
                SU(choice,4) = R; %extensive
                SU(choice,3) = ReasonableDirection(J, PU, R,
SU(choice,1), SU(choice,2), SU(choice,3));
            end;
        else %1 ex move per several epoches
            if (ex_move < 1 && ex_move > 0)
                ex_count = ex_count + 1;
                if (ex_count >= ex_lim) %time to choose
SU for ex move
                    choice = randi(NSU);
                    SU(choice, 4) = R; %extensive
                    SU(choice,3) = ReasonableDirection(J, PU, R,
SU(choice,1), SU(choice,2), SU(choice,3));
                    ex_count = 0; %reset counter
                end;
            end;
        end;

        %next SUs moves

        for i = 1:NSU
            plot (SU(i, 1), SU(i, 2), 'black.', 'markersize',30);
            if (SU(i,4) > 0) %extensive move
                SU(i,4) = SU(i,4) - 1;
            else

```

```

        % SU(i,4) = SU(i,4) - 1;
        SU(i, 3) = randi(8);
    end;

    [SU(i,1) SU(i,2)] = Move(SU(i,1), SU(i,2), J, SU(i, 3));
    plot (SU(i, 1), SU(i, 2), 'r.', 'markersize',30);
end;

tick = tick + 1;

%check if PUs found
lucky = zeros(1, NSU);
for i = 1:NSU
    for j = 1:NP
        if (SU(i, 1) == PU(j,1) && SU(i, 2) == PU(j,2))
            plot (SU(i, 1), SU(i, 2), 'r*', 'markersize',30);
            %indicate with a label on the figure
            lucky(i) = 1;
            break;
        end;
    end;
end;

%reset SUs array removing "lucky" users
s = sum(lucky);

% if ((etime(clock, iniTime) >= limit))
%     break;      %end of simulation, Simulation time lapse
%end;

if (s > 0 && s < NSU)
    X = zeros(NSU - s, 4);
    j = 1;
    for i = 1:NSU
        if (lucky(i) == 0)
            X(j, :) = SU(i, :);
            j = j + 1;
        end;
    end;

    %SU = NS;
    NSU = NSU - s;
    % SU = ones(NS, 4) * ((J - 1)/2);
    % SU(:, 4) = 0;
end;
%pause(delay);
if NSU < NS
    Pd=NSU+s;
    NSU=Pd;
end;

%PUs appearance
% Make PUs unavailable
switch NP

```

```
case 2
    if ((etime(clock, iniTime)) <= 50) && (NP <= CP)
        NP = CP - 1;
    else
        NP=CP;
    end;

case 3
    if ((etime(clock, iniTime)) <= 100) && (NP <= CP)
        NP = CP - 1;
    else
        NP=CP;
    end;

otherwise
    NP = CP;

end;

    pause(delay);

    end

end

end

h = msgbox(['Simulation Ends']);

end
```

## APPENDIX C: THE MODEL USER INTERFACE CODE

```
function realforaging
%interface for visualization and experiments
%using foraging model for spectrum sharing

%-----Main Form
sz = [430 400]; % figure size
screensize = get(0, 'ScreenSize');
xpos = ceil((screensize(3)-sz(2))/2); % center the figure on
thescreen horizontally
ypos = ceil((screensize(4)-sz(1))/2); % center the figure on
thescreen vertically

figure ('MenuBar', 'None', ...
        'Name', 'Foraging Model for Spectrum Decision Making', ...
        'NumberTitle', 'Off', ...
        'Position', [xpos, ypos, sz(2), sz(1)], ...
        'Color', [1 1 1]);

lb1 = uicontrol('Style', 'Text', ...
               'Position', [20,370,200,25], ...
               'String', 'Simulation Arena size, N [ Per Unit]');
lbst = uicontrol('Style', 'Text', ...
                'Position', [20,320,200,25], ...
                'String', 'Simulation Time, ST - secs');

lbgut = uicontrol('Style', 'Text', ...
                 'Position', [20,270,200,25], ...
                 'String', 'Giving Up Time, GUT - secs');

lb2 = uicontrol('Style', 'Text', ...
               'Position', [20,220,200,25], ...
               'String', 'Number of PUs, NP');

lb3 = uicontrol('Style', 'Text', ...
               'Position', [20,170,200,25], ...
               'String', 'Number of SUs, NS');

%lb4 = uicontrol('Style', 'Text', ...
% 'Position', [20,120,200,25], ...
% 'String', 'Frequency Range, FQ');

txt1 = uicontrol ('Style', 'Edit', 'String', ' ', ...
                 'Position', [250,370,100,30], ...
                 'HorizontalAlignment', 'Left');

txt2 = uicontrol ('Style', 'Edit', 'String', ' ', ...
                 'Position', [250,320,100,30], ...
                 'HorizontalAlignment', 'Left');

txt3 = uicontrol ('Style', 'Edit', 'String', ' ', ...
```

```

        'Position', [250,270,100,30], ...
        'HorizontalAlignment', 'Left');

txt4 = uicontrol ('Style', 'Edit', 'String', ' ',...
    'Position', [250,220,100,30], ...
    'HorizontalAlignment', 'Left');

txt5 = uicontrol ('Style', 'Edit', 'String', ' ',...
    'Position', [250,170,100,30], ...
    'HorizontalAlignment', 'Left');

% txt6 = uicontrol ('Style', 'Edit', 'String', ' ',...
%     'Position', [250,120,100,30], ...
%     'HorizontalAlignment', 'Left');

uicontrol ('Style', 'PushButton', 'String', 'OK',...
    'Position', [250, 70 ,100,30],...
    'CallBack', @get_parameters);

function get_parameters(h, eventdata)
    N = str2double(get(txt1, 'String'));
    ST = str2double(get(txt2, 'String'));
    GUT = str2double(get(txt3, 'String'));
    NP = str2double(get(txt4, 'String'));
    NS = str2double(get(txt5, 'String'));

    RealVis(N, ST,GUT, NP, NS);

end

end

```

## APPENDIX D: MODEL ANALYSER

```
function [ r1 ] = ReasonableDirection( N, PU, R, x0, y0, r0 )
%direction according to the PUs layout within area (1+2R) x (1+2R)

map = zeros(N);
NP = size(PU,1);
for i = 1:NP
    k = int32(PU(i, 1) + 1/2);
    m = int32(PU(i,2) + 1/2);
    map(k,m) = 1;
end;

%visinity zone
zone = zeros(1 + 2*R);
up = int32(y0 + 1/2 - R);
if (up < 1)
    up = 1;
end;
down = int32(y0 + 1/2 + R);
if (down > N)
    down = N;
end;
left = int32(x0 + 1/2 - R);
if (left < 1)
    left = 1;
end;
right = int32(x0 + 1/2 + R);
if (right > N)
    right = N;
end;

for i = up : down
    for j = left : right
        if (map (i,j) == 1)
            zone(i-up+1, j-left+1) = map(i, j);
        end;
    end;
end;

r1 = r0;
s = sum(zone);
if (s>0)
    found = false;
    for i = 1:(1+2*R)
        for j = 1:(1+2*R)
            if (zone(i,j) == 1)
                dx = j - (1+R);
                dy = i - (1+R);

                %find best direction
                %vertical
                if (abs(dx) < 2)
                    if (dy > 0)

```

```

        r1 = 1;
    else
        r1 = 5;
    end;
    found = true;
    break;
end;

%horizontal
if (abs(dy) < 2)
    if (dx > 0)
        r1 = 3;
    else
        r1 = 7;
    end;
    found = true;
    break;
end;

%diagonal
if (dx > 0)
    if (dy > 0)
        r1 = 2;
    else
        r1 = 4;
    end;
else
    if (dy > 0)
        r1 = 8;
    else
        r1 = 6;
    end;
end;
found = true;
break;
end;
end;
if (found)
    break;
end;
end;
end

```

```
% x = [0 pi];
```

```
% y = sin(x.^2);
```

```
% plot(x,y);
```

```
x = 0 : 1;
```

```
pi = 0.2;
```

```

d = 1;

v = 0.5;

%b = rand(0.1,10);

b = 0.2;

%b2 = 0.1 : 1: 10;

%b3 = 0.1 : 1: 100;

%b = [b1 b2 b3];

%b = [1,2,3,4,5,6,7,8,9,10];

%b = [0:2:10];

f = (sqrt((4*x*b)/(pi*d^2)).*exp(-x./(pi*v*b)) + ((2*x^2)/(pi*v*d) + (v*b)./d +
1/2).*erf(sqrt((x^2)/(pi*v^2*b))) - ((2.*x^2)/(pi*v*d))).*d;

%f = (sqrt((4*x*b)/(pi*d^2)).*exp(-x./(pi*v*b)) + ((2*x^2)/(pi*v*d) + (v*b)./d +
1/2).*erf(x^2/(pi*v^2*b)) - (2.*x^2)/(pi*v^2*b)).*d;

plot(x,1./f, 'i');

%legend('v=2');

hold on;

x = 0 : 1;

pi = 0.2;

d = 1;

v = 0.5;

b = 0.4;

f = (sqrt((4*x*b)/(pi*d^2)).*exp(-x./(pi*v*b)) + ((2*x^2)/(pi*v*d) + (v*b)./d +
1/2).*erf(sqrt((x^2)/(pi*v^2*b))) - ((2.*x^2)/(pi*v*d))).*d;

%f = (sqrt((4*x*b)/(pi*d^2)).*exp(-x./(pi*v*b)) + ((2*x^2)/(pi*v*d) + (v*b)./d +
1/2).*erf(x^2/(pi*v^2*b)) - (2.*x^2)/(pi*v^2*b)).*d;

plot(x,1./f, '-');

%legend('v=1');

```

```

hold on;

x = 0 : 1;

pi = 0.2;

d = 1;

v = 0.5;

b = 0.6;

f = (sqrt((4*x*b)/(pi*d^2)).*exp(-x./(pi*v*b)) + ((2*x^2)/(pi*v*d) + (v*b)./d +
1/2).*erf(sqrt((x^2)/(pi*v^2*b))) - ((2.*x^2)/(pi*v*d))).*d;

%f = (sqrt((4*x*b)/(pi*d^2)).*exp(-x./(pi*v*b)) + ((2*x^2)/(pi*v*d) + (v*b)./d +
1/2).*erf(x^2./(pi*v^2*b)) - (2.*x^2)/(pi*v^2*b)).*d;

plot(x,1./f, '--');

%legend('v=0.5');

hold on;

x = 0 : 1;

pi = 0.2;

d = 1;

v = 0.5;

b = 0.8;

f = (sqrt((4*x*b)/(pi*d^2)).*exp(-x./(pi*v*b)) + ((2*x^2)/(pi*v*d) + (v*b)./d +
1/2).*erf(sqrt((x^2)/(pi*v^2*b))) - ((2.*x^2)/(pi*v*d))).*d;

%f = (sqrt((4*x*b)/(pi*d^2)).*exp(-x./(pi*v*b)) + ((2*x^2)/(pi*v*d) + (v*b)./d +
1/2).*erf(x^2./(pi*v^2*b)) - (2.*x^2)/(pi*v^2*b)).*d;

plot(x,1./f, '*');

%legend('v=0.25');

% x = 0.5;

% pi = 3.2;

```

```

% d = 10;

% v = 1;

% % hold on;

% b = 0.1 : 1: 10;

% f = (sqrt((4*x*b)./(pi*d^2)).*exp(-x./(pi*v*b)) + ((2*x^2)./(pi*v*d) + (v*b)./d +
1/2).*erf(x^2./(pi*v^2*b)) - (2.*x^2)./(pi*v^2*b)).*d;

% plot(b,f);

%axis([ 0 1 0 1 ]);

% legend('HFP','FR','PRP','LS');

ylabel('Mean Efficiency (1/E(L))');

xlabel('Giving Up Time (\sigma)');

```