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Cooperative Spectrum Sensing in Multi-channel RF Energy Harvesting Cognitive Radio Networks

Akinbode Alex Olawole

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Cooperative Spectrum Sensing in Multi-channel RF Energy Harvesting Cognitive Radio Networks

Akinbode Alex OLAWOLE

Supervised by **Professor Fambirai TAKAWIRA**

Co-supervised by **Dr. Olutayo O. OYERINDE**

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Authorization

As the candidates supervisor, I have approved this thesis for submission.

Name: Professor Fambirai TAKAWIRA

Signed: ______________________________________

Date: ______________________________________

As the candidates co-supervisor, I have approved this thesis for submission.

Name: Dr. Olutayo O. OYERINDE

Signed: ______________________________________

Date: ______________________________________

Declaration

I, AKINBODE ALEX OLAWOLE declare that

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Dedication

To my family and friends

Acknowledgements

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Abstract

The need to improve the utilization efficiency of the limited radio resources in the face of the increasing number of radio network services, coupled with the growing interest in making wireless and mobile technologies energy smart has prompted research interest in energy harvesting based cognitive radio networks (EH-CRNs). EH-CRNs promises to jointly facilitate dynamic spectrum access (DSA) and a cheaper and more convenient energy alternative source to the replaceable batteries in wireless radio networks. However, investigations have shown that the performance of the technology is limited in terms of achievable throughput due to energy shortage occasioned by the random energy arrival at the SU terminal.

The main focus of this thesis is therefore to develop a cooperative spectrum sensing scheme, which maximizes the achievable throughput of energy harvesting based secondary users, while ensuring adequate protection of the primary user (PU) against interference. The objectives are four-fold. Firstly, to appropriately allocate the secondary users (SU) to the PU channels in a many-to-many combinatorial assignment, taking into consideration the effect of PU independence and the time-varying channel conditions. Secondly, to develop a robust and generalized cluster head selection scheme that follows the network dynamics for efficient cooperative spectrum sensing. Thirdly, to develop a decision fusion rule that minimizes the total error rate in cooperative spectrum sensing; and finally, to determine the cooperative sensing parameters that maximize the capacity of the SU, subject to the harvested energy and PU protection in the multichannel EH-CRNs.

Performance analysis and evaluation of the developed scheme is presented as simulations results and analytical models. The presented results demonstrate improved channel allocation, cooperative spectrum sensing performance, energy arrival rate and the SUs energy efficiency, when the characteristics of the PU channels, and the SU networks are taken into consideration.

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Abbreviations

AC	**A**lternating **C**urrent
AWGN	**A**dditive **W**hite **G**aussian **N**oise
BnB	**B**ranch and **B**ound
CH	**C**luster **H**ead
CR	**C**ognitive **R**adio
CRN	**C**ognitive **R**adio **N**network
CSI	**C**hannel **S**tate **I**nformation
CSS	**C**ooperative **S**pectrum **S**ensing
DC	**D**irect **C**urrent
DSA	**D**ynamic **S**pectrum **A**ccess
EH-CRN	**E**nergy **H**arvesting **C**ognitive **R**adio **N**etwork
FCC	**F**sderal **C**ommunications **C**ommission
GAP	**G**eneralized **A**ssignment **P**roblem
IEEE	**I**nstitute of **E**lectrical and **E**lectronic **E**ngineering
IET	The **I**nstitution of **E**ngineering and **T**echnology
i.i.d	**i**ndependent and **i**dentically **d**istribution
KKT	**K**arush-**K**uhn-**T**ucker
MATLAB	**MAT**rix **LAB**oratory
MINLP	**M**ixed **I**nteger**N**on **L**inear **P**roblem
MDP	**M**arkov **D**ecision **P**rocess
NP	**N**ondeterministic **P**olynomial
PDF	**P**robability **D**ensity **F**unction
PN	**P**rimary **N**etwork
POMDP	**P**artially **O**bservable **M**arkov **D**ecision **P**rocess
PSD	**P**ower **S**pectral **D**ensity
PSU	**P**ower **S**upply **U**nit
PU	**P**rimary **U**ser
QoS	**Q**uality **o**f **S**ervice

QPSK	**Q**uadrature **P**hase **S**hift **K**eying
RF	**R**adio **F**requency
SNR	**S**ignal to **N**oise **R**atio
SN	**S**econdary **N**etwork
SU	**S**econdary **U**ser
w.r.t.	**W**ith **r**espect *t*o
WSN	**W**ireless **S**ensor **N**etwork

List of Symbols

$\mathbf{N}$	Number of SUs in the network
$\mathbf{M}$	Number of PU channels
$\mathbf{y}_{i,j}$	Received signal at SUi from PUj
$\boldsymbol{d^{sp}_{i,j}}$	Distance between PUj and SUi
$\boldsymbol{d^{ss}_{i,k}}$	Distance between two SUs (i and k), where $i \neq k$
$\hat{\boldsymbol{h}}_{i,j}$	Estimated Channel response
$\boldsymbol{h}_{i,j}$	Outdated Channel response
$\boldsymbol{F^{max}_{d_{i,j}}}$	Maximum Doppler shift on channel$j$ at SU i
$\boldsymbol{t}_{i,j}$	The time at which sample of instantaneous SNR of PU j is taken by SU i
$\boldsymbol{\gamma}_{i,j}$	Outdated instantaneous signal-to-noise ratio
$\hat{\boldsymbol{\gamma}}_{i,j}$	Estimated instantaneous signal-to-noise ratio
$\bar{\boldsymbol{\gamma}}_{i,j}$	Average signal-to-noise ratio
$\boldsymbol{\tau}_{i,j}$	Time interval between taken measurement and evaluation for cluster formation
$\boldsymbol{T^o}$	Predefined observation period during cluster formation
$\boldsymbol{\rho}_{i,j}$	Correlation coefficient
$\boldsymbol{P}_{d,i,j}$	Probability of detection of SU i on channel j
$\boldsymbol{P}_{m,i,j}$	Probability of miss-detection of SU i on channel j
$\boldsymbol{P}_{e,i,c}$	Probability of reporting error from SU i to cluster head c
$\boldsymbol{Q}_{m,j}$	Cooperative probability of miss-detection for channel j
$\boldsymbol{Q}_{f,j}$	Cooperative probability of false alarm for channel j
$\boldsymbol{\alpha}$	Constraint on the cooperative probability of false alarm
$\boldsymbol{x}_{i,j}$	Channel assignment variable
$\boldsymbol{\chi}$	Channel assignment Matrix
$\boldsymbol{y}_j$	Variable for cooperative probability of miss-detection
$\boldsymbol{K}$	Constraint on the maximum number of channel for each SU
$\boldsymbol{K}_{ave}$	Average number of assigned channel per SU
$\boldsymbol{K}_{max}$	Maximum number of assigned channel per SU
$\boldsymbol{\xi}_{i,j}$	instantaneous signal-to-noise ratio (generalized)

$\boldsymbol{Cl}_i$	Channel list for SUi
$\boldsymbol{Cl}_{max}$	Maximum number of channel that can be assigned to each SU
$\boldsymbol{Cl}_{opt}$	Optimum number of channels for each SU
$\boldsymbol{\zeta}$	Ratio of the number of SUs to the number of channels
$\boldsymbol{n}_j$	Cluster size on channel$j$

Chapter 1

Introduction

1.1 General Background

The increasing demand for communication spectrum due to worldwide increase in the use of mobile telephones, Internet and multimedia services among others, coupled with the limited radio resources has brought about the recent effort at exploiting the usage of spectrum holes in the existing communication spectrum. Survey on the traditional use of the spectrum space has shown that high percentage of the spectrum allocated to primary (licensed) users (PU) is often idle [1]. Therefore it is possible for another user, which may be referred to as secondary user (SU) to share the spectrum opportunistically with the primary user. Cognitive radio (CR) technology [2], which allows dynamic spectrum access (DSA)[3] and the co-existence of primary users and secondary or unlicensed users in the same spectral resource, has been identified as a prominent solution to the demand for spectrum. When sharing the spectrum however, the secondary user which carries the cognitive functionalities must ensure that it does not interfere with the licensed use of the spectrum. As a result of this requirement, two main components are significant for successful operation of cognitive radio networks (CRNs). These are spectrum sensing [4–6], which detects spectrum holes in a primary network (PN); and spectrum assignment [7, 8], which deals with how to assign spectrum holes to secondary users.

The increase in the use of wireless / mobile sensors coupled with the need to make wireless radio application energy smart has equally generated the recent research interest in exploiting energy harvesting technology in cognitive radio (CR). This intend to jointly reduce energy cost and deal with the problem of having to replace batteries, which can be critical when quality of service is of utmost concern. However, investigations into the scheme shows that the performance of the energy (constrained) harvesting cognitive radios in terms of the average achievable throughput is still less than that of the battery (unconstrained energy) powered counterpart, due to energy supply shortage, occasioned by the random energy arrival at the SU terminal. This work therefore proposes an energy efficient network for improved secondary user's achievable throughput in multi-user, multi-channel energy harvesting based cognitive radio networks (EH-CRNs).

1.2 Problem Statement

The fundamental issue in the conventional CRNs with unconstrained energy is the sensing-throughput tradeoff which prescribes that an optimal sensing time exists where throughput is maximized. In the context of the EH-CRNs however, the sensing output, i.e., sensing time and sensing accuracy are both energy constrained, such that the achievable capacity is limited by energy. While existing works have attempted to improve performance through sensing parameter optimization, the achievable capacity is bounded by the random energy arrival and the meagre power density from the ambient energy sources. Moreover, research effort in this area has mainly been focused on a one-to-one and many-to-one network model, such that an energy harvesting node or group of nodes can only harvest from a single RF source on an opportunistic time-switching manner.

Therefore, to address the challenges and the limiting factors in the EH-CRNs, this thesis presents a many-to-many overlapping clustered channel assignment scheme, which guarantees PU protection and ensures QoS requirements for SU services. This takes into consideration the PU independent activities, the time-varying channel conditions, and network dynamics. The assignment scheme in turn, provides the framework to exploit the benefits and characteristics of the multi-user, multi-channel CRNs towards improving the energy arrival rate for improved SU capacity.

1.3 Research Question

Having carried out extensive literature survey on EH-CRNs vis-a-vis the existing trade-offs and limiting factors, the one pertinent question that needs an answer is: How can the energy efficiency of secondary users be improved in cooperative spectrum sensing based RF energy harvesting multi-channel cognitive radio networks? In order to address this main question, the following sub-questions are highlighted:

- In multi-channel cooperative CRNs, how can SUs be optimally clustered for effective spectrum sensing and transmission?

- What is the effect of outdated channel state information (CSI) on spectrum sensing and how can this be mitigated against?
- How can energy efficiency be optimized in a cooperative spectrum sensing based multi-channel cognitive radio network with RF energy harvesting?

1.4 Primary Objectives

The aim of this research is to jointly develop, formulate, and solve the problem of spectrum and energy efficiency in energy harvesting based cognitive radio networks. The objectives include the following:

1. To study and identify the challenges associated with the efficient channel assignment problem in cognitive radio networks, and investigate the influence of outdated channel state information on cooperative spectrum sensing.
2. To develop an efficient and dynamic cluster-based channel assignment scheme in multi-channel cognitive radio networks that minimizes interference to the primary user under time varying channel conditions and subject to the constraint on spectrum utilization of secondary users.
3. To develop a cluster head selection scheme that responds to the distribution dynamics of primary users and secondary users in cooperative spectrum sensing.
4. To develop a hard decision fusion rule that exploits the reliability of the cluster head's independent sensing decision for reduced error rate performance in cooperative spectrum sensing.
5. To develop a cooperative spectrum sensing scheme which, maximizes the achievable throughput of secondary networks in multi-channel energy constrained cognitive radio networks, taking into consideration the varying energy harvesting sources and subject to the constraint on primary user protection and energy causality.

1.5 Original Contributions

The main contributions in this thesis are derived from the aforementioned primary aims and objectives as follows:

1. The channel assignment problem in a multi-channel CRN is statistically modeled with outdated channel state information into a generalized assignment problem (GAP) with overlapping clusters. The assignment problem jointly takes into consideration the heterogeneities of PU channels in terms of primary user activities, as well as that of secondary users in terms of the effect of time-varying channel condition during the assignment.

2. The channel assignment is formulated into a nonlinear integer optimization problem that is generally known to be NP-hard. The original problem is transformed into a mixed integer linear problem, based on which, an optimal solution and two heuristic algorithms for sub-optimal solutions are obtained.

3. Development of a generalized and robust cluster head selection scheme that responds to detection threshold and cluster's heterogeneity in terms of the relative distribution of primary user and secondary users in the network.

4. A hard decision fusion rule that exploits the sensing reliability of cluster heads in making cooperative decision. This scheme makes the cluster heads non-cooperative sensing decision a necessary criteria for cooperative sensing decision in cognitive radio networks.

5. A cooperative spectrum sensing scheme for throughput maximization in multi-channel energy constrained cognitive radio networks. This takes into consideration varying number of energy harvesting sources and is subject to the constraint on primary users' protection and energy causality. The problem belongs to a general class of Markov decision processes (MDP) and is formulated as a stochastic optimal control with an infinite and continuous state and action spaces. Optimal solution to this is known to be computationally prohibitive and becomes even more complicated in a two dimensional problem such as considered. To reduce computational complexity, a myopic optimization approach is taken, and the problem reduces to a mixed integer nonlinear problem (MINLP) to determine the optimal channel assignment, and the sensing parameters which maximize the immediate reward.

1.6 Author Publications

The following are peer-reviewed journals publications from this thesis

- **A. A. Olawole**, F. Takawira and O. O. Oyerinde, "Channel Assignment Scheme in Multi-Channel Cognitive Radio Networks with Outdated CSI over Rayleigh Fading Channels," *WILEY - International Journal of Communication Systems*, vol. 31, no. 14, July 2018.

- **A. A. Olawole**, F. Takawira and O. O. Oyerinde, "Fusion Rule and Cluster Head Selection Scheme in Cooperative Spectrum Sensing," *IET Communications Journals*, vol. 13, no. 6, pp. 758 - 765, March 2019.

- **A. A. Olawole**, F. Takawira and O. O. Oyerinde, "Cooperative Spectrum Sensing in Multichannel Cognitive Radio Networks with Energy Harvesting," under revision for publication in *IEEE Access*.

1.7 Organization of Thesis

The rest of the thesis is organized as follows.

Chapter 2 presents the preliminary overview of some basic components of energy harvesting based cognitive radio networks. The chapter also investigates the related works in literature, focusing mainly on the channel assignments schemes for CRNs, cluster head selection schemes, decision fusion rules and performance improvement techniques in energy unconstrained and energy constrained cognitive radio networks.

Chapter 3 presents channel assignment schemes in multi-channel cognitive radio networks with outdated channel state information. The chapter provides detail on how to carry out many-to-many overlapping cluster based assignment, taking into consideration the heterogeneity of the PU in terms of their activities and the SUs in terms of their signal-to-noise ratio as influenced by the time-vary channel conditions. Moreover, with the objective to minimize interference to the PU, the assignment problem is formulated into a nonlinear integer programming, which is subsequently transformed to a mixed integer linear programming. Both optimal and suboptimal solutions to the optimization problem are enumerated and simulation-based performance evaluation is presented and analyzed to validate the scheme.

Chapter 4 presents a generalized cluster head selection scheme for clustered networks. The existing schemes in literature are analyzed through simulation and then a new robust scheme is presented. The scheme takes into account the heterogeneity of cluster's structure in terms of the relative distribution of the PU and SU to propose a selection method that minimizes the total error rate. Moreover, a hard decision fusion rule which takes into consideration the sensing reliability of the cluster head non-cooperative sensing result in making cooperative sensing decision is also presented. Simulation-based performance evaluation is presented to validate the proposed schemes.

Chapter 5: In this chapter, cooperative spectrum sensing in multichannel EH-CRNs is presented. In particular, two different scenarios are considered: a multiuser case with a single RF harvesting source, and then a multiple RF harvesting sources where each SU can opportunistically harvest from any of the assigned sources. For these scenarios, the problem is formulated as a stochastic optimal control with infinite and continuous state and action spaces. This is subsequently approximated into a myopic optimization policy. problem. The characteristic of the objective function is analyzed, and a near-optimal solution is obtained based on alternating convex optimization technique. Finally, the simulation-based performance evaluation for the considered problem is presented.

Chapter 6: This chapter summarizes the main points presented in this thesis, and also highlights the possible directions on how the accomplished work can be extended for future research.

Chapter 2

Literature Review

2.1 Introduction

This chapter presents some basic components of energy harvesting and cognitive radio networks, followed by a comprehensive review of the related works on recent advances on EH-CRNs in the literature. The previous research trends and accomplishments are summarized with more emphasis on cooperative spectrum sensing. Moreover, since the emergence of energy harvesting technology in cognitive radio, achieving the expected capacity has been a challenge due to energy arrival dynamics at the secondary user as dictated by the activities of PU transmissions. Thus, the presented review provides the foundation which serves as a preamble to the research ideas and contributions that are discussed in subsequent chapters.

The rest of the chapter is organized as follows: Section 2.2 is a preliminary overview detailing some of the basic components EH-CRNs. Section 2.3 presents the related works on channel assignment in CRNs, where in particular, the distributed assignment and centralized channel assignment are discussed. Section 2.4 looks into research works that revolve around cluster head selection schemes for cooperative spectrum sensing, underlining the critical issues in the context of clustered CRNs. Then Section 2.5 presents the related works on decision fusion rules in cooperative spectrum sensing, as well as highlighting the challenges. Section 2.6 details the research effort in energy efficiency in the conventional energy unconstrained CRNs. Section 2.7 is a review of the accomplishment in energy harvesting based cognitive radio networks towards improved performance, followed by Section 2.8, which summarizes the main points to conclude the overview presented in this chapter.

2.2 Preliminary Overview

2.2.1 Channel Models

A channel is a medium of communication between the transmitting antenna and the receiving antenna. This media can basically be grouped into two, namely, the guided medium and unguided medium. The guided medium includes twisted pairs, coaxial cables, wave guides, optical fibers etc. The unguided medium is essentially the free space, otherwise referred to as wireless medium. The characteristic of the signal passing through wireless channel often change as it transverse the distance between the transmitting antenna and the receiving antenna. These changes depend on the distance between the antennas, the path(s) taken by the signal, and the objects around the path. These lead to the phenomena of signal absorption, reflection, refraction, diffraction, and scattering of the signal. These factors give rise to a varying channel response, which result in fading[1]. Fading can be categorized into two main components, namely, large scale fading, and small scale fading.

Small scale fading can be described as the rapid fluctuation of the amplitude of a radio signal due to the phenomena of atmospheric ducting, reflections, refractions, diffraction and scattering either from the ionosphere or due to objects around the path of communication such as water bodies, mountains trees and buildings. As a result, multiple copies of the transmitted signal are received at slightly different times with different amplitudes, as multipath signal. Depending on the phase of each of the copies of the signal received, fading may occur depending on whether or not these multiple copies result in a destructive or constructive interference. Hence, the effect of multipath signal may include: (*i*) rapid changes in signal strength, (*ii*) random frequency modulation due to varying Doppler shift on different multipath signals, and (*iii*) time dispersion caused by multipath propagation delay.

On the other hand, large scale fading describes the signal loss in the free space where a line of sight exists between the transmitting antenna and the receiving antenna, with no object of reflection around the communication path. In such a case, the transmitted signal only attenuates based on inverse square law.

2.2.2 Cognitive Radio Networks

Cognitive radio system (CRS) is described as an intelligent wireless communication system that is aware of its environment and adapts its operational parameters to achieve a reliable communication and efficient spectrum utilization in the wireless channel [2]. It facilitates opportunistic

[1] Phenomenon that describes signal loss, in amplitude or/and phase

and dynamic channel access. The technology allows the co-existence of two groups of users, namely: the primary user, which is the licensed user of the channel, and another user which does not own the license, and can be referred to as the secondary users (SU), on the same channel. The SU carries the cognitive radio functionalities and can otherwise be referred to as cognitive radio (CR) user. However, the SU can only use the licensed channel in a way that will not degrade the quality of service (QoS) of the PU. There are three basic sharing techniques in cognitive radio networks namely: *overlay*, *underlay* and *hybrid* system[9, 10]. The underlay scheme allows the secondary user to transmit simultaneously with the primary user on the same channel in as much as the interference generated by the SU is below some acceptable threshold. The restriction, however, sometimes put a limit on the secondary user transmit power. On the other hand, in the overlay scheme, the spectrum opportunities are temporal, and the SU can only transmit during the idle period of the primary transmitter as illustrated in Fig. 2.1. Hybrid mode merges the merits of overlay and underlay modes by adopting both for SU transmissions.

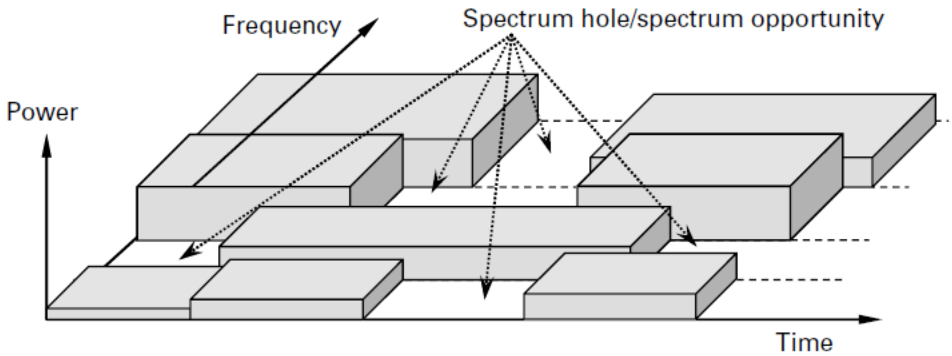


FIGURE 2.1: Spectrum opportunities
[8]

2.2.3 Radio Spectrum Management

Radio spectrum management helps to maximize the use of radio resource in wireless networks, while ensuring the QoS requirements for different users. The traditional method of spectrum allocation is usually done by agencies of government through administrative licensing. Spectrum bands are partitioned into slots and each exclusively assigned to a user for the duration of the license. In the context of cognitive radio system, information from both PU and SU is required for efficient spectrum assignment. This is a prerequisite to enhance the SU's spectrum utilization, while adequately protecting the PU from interference. The commonly employed methods for spectrum management are based on (*i*) heuristic methods [11, 12], (*ii*) game theory [13], (*iii*) graph theory, (*iv*) convex optimization [14, 15] and (*v*) stochastic modeling [8].

2.2.4 Spectrum Sensing

Spectrum sensing is the basic functionality of cognitive radio system, which monitors the spectrum bands at any given time, and detects the available spectrum holes on the licensed channels. It is usually done by measuring any of the signal's basic properties. Spectrum sensing techniques can be classified based on the size of the band of interest [16, 17]. In narrowband spectrum sensing, the task is to decide whether a particular portion of the spectrum is occupied or free [18]. In this case, the term "narrowband" implies that the frequency range is sufficiently narrow such that the channel response can be considered flat and might be occupied by a single PU. On the other hand, wideband spectrum sensing entails observing a wideband spectrum and identifying the portions or sub-band that are either free or occupied with PU signals [19, 20]. One of the approaches to achieve wideband spectrum sensing is for the SU to either scan through the spectrum or use multiple RF front-end for multi bands. These methods unfortunately result in long sensing delay inherent in sampling at Nyquist rate. Power becomes a limiting factor or computational complexity increases with hardware cost [21–23]. While recent development in compressive sensing seems to provide a solution by sampling the wideband at sub-Nyquist rate to relax the analog-to-digital (ADC) requirement, the main challenge remains that due to the insufficient sampling rate, a weak PU signal with a nearby strong signal may not be properly detected.

On a given frequency, spectrum sensing can be characterized as spatial, temporal and hybrid [24, 25]. Spatial spectrum sensing is characterized in terms of determining the region within the geographic space of the PU where interference from the SU will be within a tolerable value. Spatial spectrum hole describes a region where interference to PU transmission from the SU is negligible. Therefore, spatial sensing prescribes that a maximum transmission power that a secondary user can employ without causing harmful interference to primary users on the channel exists. Temporal spectrum sensing on the other hand is characterized in terms of the ON (busy) and OFF (idle) periods of the primary user on the channel. Temporal spectrum hole is a period of time for which the primary transmitter is idle. During such idle periods, a secondary user may opportunistically transmit on the given channel without causing interference. Hybrid spectrum sensing combines the advantages of both temporal and spatial sensing for SU transmission. The common methods by which spectrum sensing can be carried out in cognitive radio system include: energy detection method, matched filter, cyclostationary detection, and eigenvalue based detection. Summarized below is a brief description of the common spectrum sensing methods. Detailed review on this topic can be found in [4, 26].

2.2.4.1 Energy Detection

In this method of spectrum sensing, the average sample of the received signal energy is compared with a predetermined threshold, which depends on the noise floor, to make a decision on the status of the spectrum. Energy detection has received more attention for being the optimal sensing method for its simplicity of implementation and low computational complexity in sensing an unknown signal. Moreover, the detection scheme does not require prior knowledge of the signal being sensed. However, it is not without some challenges, which include the requirement for accurate threshold selection, the inability to differentiate interference from primary users, and poor performance under low signal-to-noise ratio value.

2.2.4.2 Matched Filter

A matched filter detection method is obtained by correlating a known signal with the unknown in order to detect the presence of the unknown signal. In this process, the signal-to-noise ratio is maximized if the two signals are correlated. Hence, the method is optimal when detecting a known PU signal. The main advantage of this detector is the short time to achieve the probability of detection and the probability of false alarm. However, the method is characterized with high implementation complexity. Moreover, since the method requires the secondary user to demodulate the received signal, accurate synchronization and perfect knowledge of the primary user signal is needed, which are most times not available to the cognitive radio user.

2.2.4.3 Cyclostationary Detection

This method of detection exploits the cyclostationary features of the received signals. A signal is said to be cyclostationary in wide sense if its mean and autocorrelation are periodic. Hence, instead of power spectral density (PSD) that is exploited in energy based detection, cyclic correlation function is used for detecting the presence of the signal in the spectrum. The cyclostationary based detection can differentiate noise from primary user signals. The method can also distinguish among different types of transmission and primary users. It is however computationally complex, leading to significantly long detection time to provide sufficiently low error probability.

2.2.4.4 Eigenvalue Based Detector

This method is based on the eigenvalues of the covariance matrix of the received signal. The ratio of the maximum or average eigenvalue to the minimum eigenvalue is used to detect the presence of the signal. The method can be used for signal detection without the prior knowledge of the signal, the channel, and noise power. It can perform better than the ideal energy detection method when the signals to be detected are highly correlated. Furthermore, different from matched filtering, the method does not require accurate synchronization.

2.2.4.5 Performance Evaluation of Spectrum Sensing

Considering a continuous time signal $s(t)$ transmitted from a distant PU transmitter, the received signal by the SU denoted by $x(t)$ can be expressed as

$$x(t) = h(t)s(t) + w(t), \tag{2.1}$$

where $h(t)$ and $w(t)$ represent the time varying channel coefficient, and the additive white Gaussian noise (AWGN) with zero mean μ, and variance σ^2 (i.e., $w \sim \mathcal{N}(0, \sigma^2)$) respectively. The goal of the spectrum sensing is for the SU to decide between two hypotheses, that is:

$$x(t) = \begin{cases} w(t) & : H_0 \ (PU \ signal \ absent) \\ h(t) \otimes s(t) + w(t) & : H_1 \ (PU \ signal \ present) \end{cases}, \tag{2.2}$$

where H_0 and H_1 hypotheses denote the absence and the presence of the PU signal on the channel respectively. In the energy detection based method, the detector evaluates the average sample energy of the PU signal, denoted as E and compares it with a threshold ε to determine the status of the channel. Hence, the decision that the PU signal is present is made if $E \geq \varepsilon$, otherwise the PU signal is absent. The performance of the detector can be measured in terms of the probabilities of detection and that of false alarm. The probability of detection is the probability that the SU decides that the PU signal is present when it is actually present, denoted as P_d. The probability of false alarm is the probability that the SU detects the presence of the PU signal when in reality, the signal is absent, denoted as P_f. That is, $P_d = Pr\left\{decision = H_1 | H_1\right\}$, and $P_f = Pr\left\{decision = H_1 | H_0\right\}$. The probability of miss-detection is the probability that the SU fails to detect the presence of the PU i.e., $P_m = 1 - P_d$, and can equally be expressed as $P_m = Pr\left\{decision = H_0 | H_1\right\}$.

Cooperative spectrum sensing (CSS) [27–37] describes a scenario where multiple SUs cooperate to sense the activities of a primary user. This provides better sensing performance compared to the local sensing as it overcomes the hidden terminal problem and channel fading by exploiting the spatial diversity of the randomly located SUs. In the scheme, individual SUs independently sense the PU channel, and the result from each SU are combined or shared in order to obtain a cooperative sensing result. This scheme can basically be grouped into two based on how the SUs cooperate to make a decision, which includes: centralized [30], and distributed [32], [33], [38], [37] spectrum sensing. In centralized based technique, a central system which can otherwise be refereed to as fusion center (FC)[2] aggregates the sensing results of the individual SUs based on either soft or hard decision fusion to decide the presence or otherwise of the PU on the channel. On the other hand, distributed cooperative sensing scheme does not depend on a central system. Cooperative partners communicate among themselves by sharing their local sensing results with their neighbours based on distributed algorithm. Each SU combines the received data with its own sensing data to arrive at a decision. If the decision does not satisfy the local criterion, the process continues iteratively until the algorithm converges, and decision reached.

Common issues with cooperative spectrum sensing include: (*i*) the effect of imperfect reporting channel due to Gaussian noise, multipath fading, shadowing, etc., (*ii*) limited control channel bandwidth, (*iii*) increased sensing overhead in terms of sensing time, reporting delay, synchronization problems, asynchronous reporting etc., and (*iv*) Energy efficiency.

2.2.5 Energy Harvesting

Energy harvesting is the process of gathering non-electrical energy from the environment and converting it to electrical energy. In wireless communication, this allow terminals to recharge their batteries from the external sources in the surrounding environment. Common sources of such energy include the conventional ones like light/solar, wind, vibration, motion, etc., and electromagnetic (EM) waves from transmitting radios. While the conventional technologies have been around for a while with lots of visible benefits, their applications could be limited in certain environment, time and weather. The limitation could be critical in areas where quality of service is of utmost priority. On the other hand, though electromagnetic wave provides the least power density, about $0.2nW/cm^2 \sim 1\mu W/cm^2$ from ambient RF compared to a solar source that could provide about $100mW/cm^2$ [39], its obvious benefit is in the increasing number of radio transmitters, and the fact that its application is not bounded by environmental factors. The same EM wave that carries information can equally be used to provide energy either through a time-switching or power-splitting protocol [40, 41]. Fig. 2.2 shows the basic components of the radio frequency (RF) energy harvesting system.

The incident RF from electromagnetic waves are collected by the antenna and transfered to the energy conversion circuit. The matching network is needed to ensure that maximum power is delivery from the antenna to the remaining circuit. The energy conversion module converts the RF power into DC voltage by using cascaded voltage multiplier circuits.

[2] can sometimes be referred to as common receiver, common control center or base station [1]

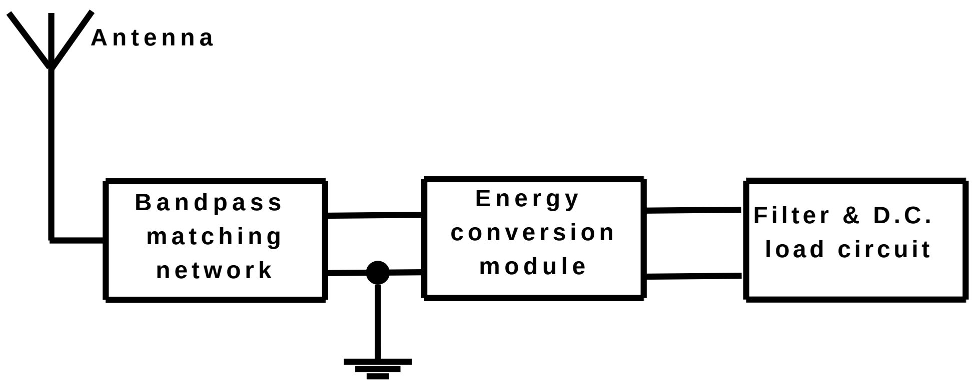


Figure 2.2: Radio frequency energy harvesting system.

2.3 Channel Assignment in Multichannel CRNs

Channel assignment is one of the basic components that influences the performance of wireless communication systems. It aims at dynamically assigns channel to cognitive radio users in order to achieve efficient spectrum utilization and minimize interference among (primary and secondary) users operating on the same channel. Cluster-based CSS [27, 37, 42] prescribes the arrangement of the SUs into smaller groups known as clusters, based on centralized [27] or distributed [37] algorithms. The cluster-based scheme thus tries to mitigate the problems militating against CSS in a large network, since each cluster are now made of smaller number of neighbour SUs. Studies in [27, 37, 42] considered a scenario where groups of SUs cooperate to sense and opportunistically utilize the licensed channel. The scenario in [27, 37, 42] is basically a one-to-one mapping, where the SU is assigned one PU channel to sense for opportunistic access, and then awaits another sensing period in the next frame to sense the channel again if it discovers that the PU channel sensed is busy. This limits the opportunities of the SU to utilize other probable idle primary user channels. Nevertheless, harnessing the needed gains in a practical multi-channel CRN can also result in a more complex system due to the requirement for optimal channel assignment. In [43], the authors studied and reported the theoretical improvement that could be made in practical cognitive radio networks if there is proper multi-channel coordination. Channel assignment in multichannel cognitive radio networks can be accomplished in any of two basic ways, namely: (*i*) distributed method of assignment and (*ii*) centralized assignment scheme. The third scheme combines the advantages in the two basic schemes to achieve an hybrid method of channel assignment scheme.

In a distributed assignment [33, 37, 44–47], the scheme is often modeled as a coalitional game with non-transferable utility (NTU) [48]. The coalitional game is said to be with NTU if the value or utility of the coalition[3] cannot arbitrarily be shared between the users which made up

[3]could also be referred to as cluster. It is a group of SUs assigned to a channel or set of channels

the coalition. The value $v(S)$ of a coalition S is described as a function that captures the trade-off between the probability of detection and the probability of false alarm within the coalition. Hence, $v(S)$ must be an increasing function of the probability of detection and a decreasing function of the false alarm probability as

$$v(S) = Q_d - C(Q_f, \alpha) \tag{2.3}$$

The payoff $\phi(S)$ on the other hand, describes the trade-off between the probability of detection and the probability of false alarm that a single SU achieves when acting as part of coalition S. Therefore, the utility of any coalition S can be mapped to a set V of payoff vectors. From the expression in (2.3), Q_d and Q_f represent the detection probability and false alarm probability respectively within the coalition, while $C(Q_f, \alpha)$ is the cost function that depends on the false alarm probability and the constraint on the false alarm α, which can be expressed as

$$C(Q_f, \alpha) = \begin{cases} -\alpha^2 \cdot \ln\left(1 - \left(\frac{Q_f}{\alpha}\right)^2\right) & Q_f < \alpha \\ +\infty & Q_f \geq \alpha. \end{cases} \tag{2.4}$$

In [33, 44], the distributed assignment problem is modeled into a non-overlapping cluster, while the studies in [37, 45–47], formulated the assignment into an overlapping clustered network. It is however reported in [37] that there is a non-negligible relative improvement of overlapping coalition over the non-overlapping in terms of network sensing performance, the needed overhead and the convergence rate.

In a centralized channel assignment [43, 47, 49–59], the assignment process is mainly carried out by a central system based on the existence of network infrastructure. Individual secondary users send their sensing decision and other local parameters to the central controller, which then compute the assignment based on any of the schemes identified in Section 2.2.3. In [49], the authors studied the channel assignment problem under the framework of partially observable Markov decision process (POMDP) to determine the number of SUs that should be assigned to a channel in order to maximize the SUs' energy efficiency. The authors in [55] investigated the assignment problem under three different scenarios as sequential, parallel and hybrid. In the sequential scenario, all SUs cooperate to sense the channels one-by-one, while in the parallel scenario, the central controller decides the number of users, which should sense each channel simultaneously. The proposed hybrid model prescribes a disjointed cluster-based assignment, where the target is to determine the subset of SUs to be assigned to certain subset of PU channel.

In [47], the channel assignment is formulated into a nonlinear integer programming (NLIP) problem to minimize the interference to the primary users to a predetermined level. The problem is formulated under the constraint of the probability of false alarm, taking into consideration the heterogeneity of the SU in terms of the received signal-to-noise ratio. The authors in [53] formulated the assignment problem to improve the energy efficiency of the secondary users while considering the heterogeneity of the SU in terms of their received signal-to-noise ratio to determine the optimal sensing duration. In [52], the authors formulated the assignment problem for the cooperative spectrum sensing into a nonlinear integer programming with the objective to find the optimal and efficient secondary users' assignment. In [52], the heterogeneity of PUs is considered in terms of channel protection criteria, idling probabilities and channel capacities. Extending the work in [52], Zhang *et al* in [56, 58], considered the heterogeneity of the PU channels as in [52], and that of the SUs in terms of energy detection threshold, received SNR, and geographical location and then formulated the problem into a Maximum Weight Matching problem. While the target in [52] is to merely find a group of SUs that can achieve good sensing performance on each channel, [56] proposes a cluster-based cooperative sensing to obtain a proper assignment policy that accurately indicates which SU should sense a particular channel.

Considering the afore-mentioned references, the common assumption is that all primary users transmit synchronously on the channels with the same traffic and activity pattern such that during channel assignment all the PUs are ON. However, results obtained with such assumptions are misleading if applied to a network with heterogeneity defined in terms of PU activities on the channels. Furthermore, the effect of small scale fading in wireless channels has been generally overlooked. The secondary users are assumed stationary, and the channel response time-invariant. Hence, the effect of varying channel condition on the received instantaneous signal-to-noise ratio during channel assignment has not been taken into consideration.

2.4 Cluster Head Selection in Cooperative Spectrum sensing

Cooperative spectrum sensing requires huge communication resources in terms of sensing time, control channel overhead and energy consumption for reporting sensing data to the fusion center, especially with increasing network size [34]. In order to mitigate against these limitations in cooperative sensing, and also to enhance sensing performance against the possible effect of fading [60] in the reporting channel, cluster-based cooperative spectrum sensing is proposed [27, 37, 42, 60, 61].

Cluster-based cooperative sensing prescribes the arrangement of the SUs into smaller groups called clusters, based on centralized [27], or distributed [37] algorithms. Thus the cluster-based scheme tries to mitigate the problems militating against cooperative sensing in a large network, since each cluster is now made of smaller number of neighbour SUs. In the cluster based networks, one of the users designated as cluster head (CH), which serves the role of common receiver aggregates the sensing decision of the other users to determine the status of the channel. The cluster head also organizes the cooperative nodes[4] for medium access through information broadcast. Therefore, proper selection of the CH is critical to obtaining the full benefit of cooperative spectrum sensing.

In [62], the user with the minimum sum of distance to the other users is adopted as cluster head. The work in [62] can achieve the same goal as the studies in [33, 63, 64], where the cluster head is selected as the secondary user closest to the cluster center or the user with the highest number of single-hop neighbors. Selection scheme based on the user with the lowest probability of miss-detection is considered in [33, 65]. In [47], authors adopted cluster head that minimizes the interference to the primary user coexisting with the secondary users in the cluster. In [60], the authors propose a cluster head selection algorithm in which cluster head are selected based on the second-order statistics of the reporting channel gain. In doing this, the author's motivation is mainly to avoid possible error inherent in estimating the instantaneous signal-to-noise value, due to its random nature. In [66, 67], the authors propose cluster head selection based on stochastic algorithm, subject to the residual energy availability. The authors in [68, 69] jointly considered the user's location within each cluster, its location with respect to the fusion center, its signal-to-noise ratio and residual energy as criteria for the selection. The study in [70], considered a procedure that select the user with the minimum total multi-hop error rate, and optimal routing path to other users using *Dijkstra's algorithm.*

Nevertheless, none of the afore-mentioned literature considered the heterogeneity of the clusters in terms of the relative distribution of the primary user and the secondary users. The general assumption is that secondary users are evenly distributed around the primary user such that selecting the CH as the SU closest to the center [33, 62–64, 70] or to the PU [33], [65] would achieve the same goal. However, results obtained with such assumption are prone to error if applied to heterogeneous clusters. Intuitively, as the PU moves away from the center of the cluster, cooperative sensing becomes less energy efficient or less accurate depending on whether the cluster head follows the primary user or remains closest to cluster center respectively.

[4] i.e. SUs in the network

$$
\begin{array}{lll}
OR\ Rule: & \begin{array}{ll} H_1 & : \sum_{k=1}^{n} \psi_k = 1 \\ H_0 & : otherwise. \end{array} & \\
AND\ Rule: & \begin{array}{ll} H_1 & : \sum_{k=1}^{n} \psi_k = n \\ H_0 & : otherwise \end{array} & [76] \\
Majority\ Rule: & \begin{array}{ll} H_1 & : \sum_{k=1}^{n} \geq \frac{n}{2} \\ H_0 & : otherwise. \end{array} &
\end{array}
\tag{2.5}
$$

2.5 Decision Fusion in Cooperative Spectrum Sensing

The performance of cooperative spectrum sensing largely depends on appropriately aggregating the sensing results from individual cognitive radio users. The fusion schemes in cooperative spectrum sensing can be categorized into two major types namely: soft data fusion [71–75] and hard decision fusion [76–82].

In soft data fusion, individual cognitive radio user forwards their energy values (considering an energy detection method) to a common receiver without making any prior independent decision on the status of the channel being sensed. The decision is made cooperatively at the common receiver by combining the individual results from the respective users. The basic combining rules in this category include (*i*) the square law combining (SLC), (*ii*) maximal ratio combining (MRC), and (*iii*) selection combining (SL). Soft data fusion is known to provide more accurate sensing result than the hard decision fusion, but at the expense of larger bandwidth for channel control [83–85] and overhead.

On the other hand, in the hard decision fusion, each cognitive radio user makes a decision on the presence or absence of the primary user, and then send a one bit decision (0,1) to the common receiver. Final decision is cooperatively made by fusing together the individual decisions from the respective users based on a predefined logic rule. The hard decision fusion comprises of three logic rules namely, the 'OR', AND and voting rule. The OR rule decides that a signal is present if at least one of the cooperating n users detects a signal. The AND rule on the other hand decides that a signal is present if all the n users have detected a signal. The voting rule decides that the signal is present if at least k of the n users have detected a signal with $1 \leq k \leq n$. Therefore, the OR, AND and majority rule are special cases of the voting rule with $k = 1$, $k = n$ or $k > \frac{n}{2}$ [76] respectively. Assuming the individual statistics ψ_k are quantized to one bit, with $\psi_k = \{0, 1\}$ denoting the hard decision from the k^{th} cognitive radio user, where 1 represents that the PU signal is present and 0 denotes that the PU signal is absence, then the rules can respectively be expressed as (2.5).

In terms of the cooperative probability of detection Q_d and cooperative probability of false alarm Q_f, the expression in (2.5) can be written respectively as (2.6) and (2.7)

$$Q_d = \sum_{i=k}^{n} \begin{pmatrix} n \\ k \end{pmatrix} (1 - P_{d,k})^{n-k} (P_{d,k})^k \tag{2.6}$$

$$Q_f = \sum_{i=k}^{n} \begin{pmatrix} n \\ k \end{pmatrix} (1 - P_{f,k})^{n-k} (P_{f,k})^k \tag{2.7}$$

The OR rule favors low probability of collision, at the expense of low spectrum usage, because a busy report from only one SU is all that is needed to cooperatively decide that the channel is occupied. Therefore, when an SU incorrectly reports a busy channel, even while every other SU reports contrary, the cooperative decision would result in false alarm. On the other hand, the AND rule results in high spectrum usage at the expense of high interference to the PU, leading to high energy consumption [76, 86, 87]. The half-voting rule is reported to be the optimal rule in minimizing the total error rate in additive white Gaussian noise channel based on energy detection method [88]. Under a Rayleigh fading channel, the OR rule is known to better exploit the benefit of cooperative sensing than the AND rule [86]. In [87], the authors studied the performance of 'k-ratio' logic as a hard decision fusion rule, where n in this case is a natural number between one and the total number of the cooperating secondary users. The decision fusion rule for multiple hypotheses in heterogeneous wireless sensor networks is investigated in [89], while an energy-efficient sequential decision fusion (SDF) scheme based on voting rule is proposed in [90].

The performance of cooperative sensing with regards to hard decision fusion is subject jointly to the received signal-to-noise ratio of the individual users, the control channel and the logic rule employed. As a result, a report received in error from just one of the users even while all the other users report a contrary but correct statistic can result in a global false alarm (in OR rule), or a miss-detection (in AND rule). This often leads to loss of opportunity to access the channel or interference with the primary user signal. Therefore, cooperative sensing decision obtained with the conventional rules are prone to error in a practical network, where the effect of both large scale and small scale fading are prominent.

2.6 Energy Efficient Cooperative Spectrum Sensing

A more robust metric to quantify the performance of cognitive radio network is the energy efficiency, which is defined as the ratio of the average achievable throughput to the average energy consumption in cognitive radio system. Energy efficiency can be considered in terms of (i) throughput maximization for a given energy budget, or (ii) energy consumption minimization for a target throughput. The review of the energy saving approaches in cognitive radio system can be found in [91]. The obvious avenue to maximize throughput is the proper management of the frame length. Since for a fixed frame length, the longer the time spectrum sensing, the shorter the time left for data transmission, and vice versa. Hence, an optimal sensing duration exist (at a target probability of detection) for which the throughput is maximum [5].

In [92] the throughput maximization problem is investigated by designing an optimal sensing time and power allocation scheme under the constraint of probability of detection. The authors in [93] proposed a multi-channel model where a group of SUs is assigned a set of PU channels. With the objective to find the optimal total sensing time in each frame, the optimal distribution of the total sensing time among the multiple channels sensed, and the detection threshold, the problem is formulated into a non-convex optimization. However, [93] considered only a simple model with two SUs and two PUs, and the SUs are assigned the same group of PUs. Moreover, neither the impact of the reporting time nor the reporting error is considered on the system performance.

However, in [94], with the objective to maximize the aggregate opportunistic throughput of the secondary network, the authors formulated the problem to optimize the overall sensing-plus-reporting time, the sensing time, reporting time and the decision threshold, under the constraint of total interference. The works in [95, 96] considered joint optimization of transmission power and sensing time to maximize the achievable throughput. The authors in [97] considered the problem in terms of optimizing the sensing time, the detection threshold, and the length of the SU modulated symbol sequence under the constraint of detection quality. In order to address the non-convexity and non-separable nature of the formulated problem in [97], the authors first find the expression for the optimal detection threshold and then propose an iterative solution algorithm to obtain an efficient pairs of sensing time and the length of modulated symbol sequence.

The authors in [98] formulated the problem into an unconstrained optimization to evaluate the optimal sensing time, detection threshold, and the fusion rule that maximize the average achievable throughput. In [99] the problem is considered by jointly optimizing the sensing time, the detection threshold and the number of cooperative secondary users under the constraints of the probabilities of detection and false alarm. In [38] the problem is formulated into a mixed integer non-linear programming (MINLP) to determine the optimal fusion rule, sensing time, energy detection, and transmit power, subject to the constraints on the probabilities of detection and that of false alarm. In [38], by first assuming an initial values for the fusion rule and sensing duration, the authors obtained a sub-optimal transmission power and then jointly optimize the other parameters.

However, in the afore-mentioned literature, only [93] investigated sensing time optimization for a practical multi-channel cognitive radio network. Nevertheless, the problem addressed in [93] is simplistic in that it only considered a case where all the available SUs are assigned the same group and number of available PU channels.

2.7 RF Energy Harvesting Based Cognitive Radio Networks

The fundamental issue in the conventional (unconstrained energy) cognitive radio is the sensing-throughput trade-off [5, 92, 94–99], which hinges on the sensing time and sensing accuracy. However, in the context of energy harvesting based cognitive radio networks (EH-CRN) [39], both sensing time and sensing accuracy are energy constrained. The system is a stochastic process in terms of the secondary user energy states over time. The energy level at the beginning of a frame depends on the residual energy and the action taken (sensing/transmission/harvesting) in the previous frame.

Park *et al* in [100] proposes an optimal spectrum sensing policy that maximizes the expected total throughput under energy causality, and collision constraint. The authors then categorized the system into a *spectrum-limited regime* and *energy-limited regime* based on the energy arrival rate, energy consumption, statistical spectrum occupancy and the spectrum sensing policy. In [101], the authors formulated the problem as a constrained partially observable Markov decision process (POMDP) to jointly determine the spectrum sensing policy and the detection threshold that maximize the expected total throughput under the energy causality and collision constraints. For a more efficient solution, the original problem in [101] is converted to a computationally tractable unconstrained POMDP. The authors in [101] later derived the optimal detection threshold which maximizes the upper bound on the achievable throughput under an energy causality constraint and a collision constraint in [102].

In [103], the authors identify the optimal pairing of the sensing duration and the detection threshold that maximize the average achievable throughput of the secondary network, and show that the optimal sensing duration that can be obtained depends on which of the constraints is giving more priority for the required performance. The authors in [104] considered a generalized multi-slot spectrum sensing paradigm with two types of fusion rules (i.e. hard fusion and soft fusion) to focus on the harvesting-sensing-throughput trade-off. The proposed model follows three consecutive steps namely; the energy harvesting period, the spectrum sensing and, the data transmission/energy harvesting period. During the sensing period, if the SU detects the absence of the PU, the subsequent period is used for data transmission, otherwise the SU transmitter continues with energy harvesting. The problem is formulated into a mixed integer non-linear programming (MINLP) with the objective to jointly optimize the time-splitter ratio (i.e. the fraction of time spent on energy harvesting), the sensing duration, sensing threshold as well as fusion rule that maximize the secondary user's achievable throughput.

In [105], the problem is formulated as a decentralized partially observable Markov decision process to determine the gradient parameter that maximizes the achievable throughput. Optimal solution is obtained by Lagrange multiplier and policy gradient method-based decentralized learning algorithm. The study in [106] formulated the problem into a mixed integer non-linear program (MINLP) with the objective to determine the access decision variables, the transmit power, the optimal sensing time and the number of slot that maximize the average throughput. In [107], the authors employ the finite-horizon POMDP model to derive the optimal policy that can maximize the expected throughput while satisfying the PU detection and the energy causality constraints. The study in [108] optimizes the optimal sensing time that maximizes average throughput and the harvested energy. In [109], for an overlay EH CRN, the authors aim to find an optimal sensing time to maximize throughput of SU and the harvested RF energy. Residual energy maximization is explored for spectrum sensing and SU transmission in [110].

The critical issue in EH-CRN from the afore-mentioned literature is that the RF energy arrival (from the assigned PU channel) is random, while the magnitude of the electrical energy that could be derived from the harvested RF may not always be sufficient to maximize throughput. The works in [111, 112] considered a hybrid energy harvesting network model where the secondary user is capable of harvesting energy from both renewable sources (e.g. solar) and ambient radio frequency signals. However, the concern with this is that the application of such conventional renewable energy could be limited in certain environment, time and weather and, this could be critical in applications where quality of service is of utmost concern. In [113], the authors formulated the problem to determine the optimal sub-channel set, sensing time, and transmission power that maximize the aggregate throughput, harvested energy and the energy efficiency of the SU over all the sub-channels. In [114], radio frequency (RF) energy could be harvested from the PU and the reporting SUs, and the problem is formulated into a multi-objective optimization (MOP) to optimize the spectrum sensing performance, under the constraints of the harvested energy at SU and the interference from SU on PU receiver. The afore-mentioned works only investigate a single channel case, which is quite simplistic and do not fully explore the challenges and benefits in a practical multi-user, multi-channel wireless communication environment.

Authors in [115, 116], propose a multi-band harvesting schemes where SU can sense the spectrum to determine the harvesting and communication geographical regions, such that it can take a decision to harvest or transmit data based on the belonging region. The number of sensing samples and sensing threshold are jointly optimized in order to minimize the sensing time and maximize the harvested energy. One obvious disadvantages in this framework is that some SUs may not be able to transmit due to their inability to harvest in the region they belong.

2.8 Chapter Summary

In this chapter, detailed review and information on channel assignment, cluster head selection schemes, decision fusion rules, and energy efficient CRNs in both energy unconstrained and energy constrained systems have been presented. This is with a view to highlight some significant research accomplishments in EH-CRNs with more emphasis on multiuser multichannel cognitive radio networks. The presented investigation provides the foundation for the research ideas and contributions that are enumerated in subsequent chapters. Given the challenges inherent in spectrum sharing, the emerging applications underline the need for improved network technologies, which are capable of meeting the needs and the QoS of the growing wireless radio networks. The main focus of this thesis is therefore to the develop an efficient spectrum management in wireless communication networks, taking into consideration, the varying channel conditions, networks dynamic and resource constraints.

The main investigation on channel assignment focused on users' scheduling to opportunistically coexist with the legacy user (PU) in a way that would not cause harmful interference with the primary user. Cognitive radio networks performance can be greatly improved with cooperative spectrum sensing that takes into consideration the peculiarity of network structure, decision making and resource constraints. The issue of channel fading and energy arrival rate have been identified as fundamental tp the performance of the EH-CRNs. Consequently, a spectrum management that takes into consideration the heterogeneity of both PU channels and SUs, while relaxing on the commonly used assumptions that are not practical, and exploiting the benefits of practical network are presented in subsequent chapters.

Chapter 3

Channel Scheduling in Multichannel CRNs with Outdated CSI

3.1 Introduction

This chapter presents channel scheduling schemes in multichannel CRNs. The main objective is to minimize interference to the PU while enhancing spectrum utilization of the secondary user. The problem takes into consideration the heterogeneity of primary user activities and the effect of time-varying channel condition on the received signal-to-noise ratio at the SUs' terminal during cluster formation. The assignment is modeled as an overlapping cluster-based network and formulated into a nonlinear integer problem (NLIP), which is generally known to be non-deterministic in polynomial time (NP). Hence, the nonlinear integer problem is subsequently transformed into a mixed integer linear problem. Thereafter, an optimal and suboptimal solutions are provided based on matrix method and heuristic algorithms respectively. Simulation results presented in this chapter show that good sensing performance and increased opportunistic spectrum utilization in multi-channel cognitive radio networks are two sides of a coin that depend on the ratio of the SUs to the number of PU channels. Part of the work presented in this chapter has been published in the *International Journal of Communication Systems*, vol. 31, no. 14, July 2018.

The remainder of the chapter is organized as follows: Section 3.2 highlights the related works for channel assignment schemes in literature, Section 3.3 describes the system, and the signal models. The details of the proposed centralized channel assignment: the problem formulation, solutions, and complexity analysis of the proposed solutions are described in Section 3.4. In Section 3.5, the numerical and simulation results are discussed, while the conclusion is drawn in Section 3.6.

3.2 Related Works

In [43], the authors studied the theoretical improvement that could be made in practical CRN if there is proper multi-channel coordination. In [47], the assignment is formulated into a nonlinear integer programming problem with the target to maximize the number of sensed channels in a wide-band spectrum sensing (where the number of PU channels are much greater than the SUs). However, the authors only derive the upper bound of the optimal solution and then provide heuristic algorithms for suboptimal solution. In [52], CSS is also formulated into a nonlinear integer programming problem with the dual objectives to find an optimal assignment of SUs, and an appropriate number of SUs needed to sense the PU channel, with the target to maximize the channel achievable rate. Heterogeneity of the PU in terms of channel protection criteria, idling probability and channel capacity are considered, and the dual objectives are optimized separately in a two-step heuristic algorithms. The authors in [53] however considered the heterogeneity of the SUs in terms of their different received SNR, and then formulated the problem as a mixed-integer nonlinear optimization problem with the objective to minimize energy consumption and spectrum sensing duration. In [56] and [58], by jointly taking into consideration the heterogeneities of both PU channels (in terms of channel idle probability and channel capacity) and the SUs (in terms of energy detection thresholds, and the received SNR), the problem is formulated into a maximum weight one-sided Biclique (MWB) problem with the objective to maximize the achievable throughput for the SUs.

However, the general assumption in the above-mentioned literature is that cluster formation is instantaneous, and all PU channels are active during the process. However, this is not possible in practice. This is partly due to the independence of the PU activities, and even if all the PUs are assumed to be active simultaneously, time is still needed by each SU to take samples of the PU signals, communicate with fusion nodes and make decisions. It is also important to note that the heterogeneity of SUs in terms of the effect of small scale fading (a time-varying quantity due to channel varying condition between PU and the SU) on the instantaneous SNR, during cluster formation has not been considered in any of the afore-mentioned literature, since the SUs are commonly assumed to be stationary. In [119], the authors studied the performance of energy detection scheme based on outdated channel state information (CSI) in a network, where a single SU terminal co-exits with a PU on the channel. However, the authors in [119] neither consider the multi-user, multi-channel network, nor the effect of the outdated channel state information on channel assignment scheme.

The critical issue investigated in this chapter is the channel assignment in a practical multi-user, multi-channel cognitive radio network based on outdated CSI in Rayleigh channel, where the heterogeneities of both PUs and SUs are taken into consideration. This involves (i) investigating the effect of outdated channel state information on a cooperative spectrum sensing, (*ii*) how to appropriately assign SUs to multiple PU channels in a many-to-many overlapping clustered network, where the independence of PUs in terms of PU activities, and the SUs in terms of the different and varying received SNR are considered, and (*iii*) studying the impact of the relative proportion of the number of secondary users to the number of available channels on the sensing performance and channel assignment. The main contributions of this chapter are as follows:

1. A more practical channel assignment in multi-channel CRN is considered. Different from [37], [47], [52], [53], [56] and [58], heterogeneities of PU channels in terms of PU activities, as well as that of SUs in terms of the effect of varying channel condition during channel assignment are jointly considered. Hence, the assignment is statistically modeled with outdated CSI into a generalized assignment problem with overlapping clusters.

2. With the objective to minimize interference to the PU while enhancing multiple spectrum utilization opportunity, the channel assignment is formulated into a nonlinear integer optimization problem, which is generally known to be NP-hard. In order to obtain an efficient solution, the nonlinear integer problem is transformed into a mixed integer linear problem to obtain an optimal solution based on matrix method in addition to two new heuristic algorithms for sub-optimal solutions. This differs from [47] in that, similar problem has also been addressed in the paper, but the authors only derive the upper bound of the optimal solution and then adopt heuristic algorithm for suboptimal solution.

3. Overlapping clusters have been reported to have better performance than the non-overlapping in CRNs in terms of sensing performance and rate of convergence. However, obtained simulation results in this chapter show that the degree of clusters overlapping is dependent on the ratio of the number of SUs to the available PU channels in the network.

3.3 Models and Assumptions

In this section, the models and assumptions adopted for the multi-channel assignment scheme are described. Channel assignment is performed before SUs commence spectrum sensing for opportunistic access. The PUs are characterized with different active periods on the channel, whereas the SUs are characterized with different and varying received SNR due to varying channel condition during the assignment policy.

3.3.1 System Model

This segment of the work considers a centralized channel assignment for distributed spectrum sensing in cognitive radio networks with M primary user channels (PCs), and N SUs. The number of SUs however varies in order to obtain different ratios of SUs to PU channels in the network. The PU activity on each channel is modeled as an ON/OFF source, alternating between state ON (busy) and state OFF (idle). The SUs and PUs are randomly deployed within a specific square area. The network as well includes a central controller (CC) located within the transmission range of the SUs. The CC gathers the individual SUs parameters such as the evaluated non-cooperative probability of miss-detection, the channel list, and the co-ordinates of the SUs locations. The CC is responsible for the frequency assignment based on the received information from the SUs. However, the CC does not have information about channel availability, although it is assumed that the CC knows the average SNRs of the PUs. Hence the work models a centralized channel assignment scheme for a distributed cooperative spectrum sensing (since cluster heads would be coordinating the users in each cluster for the purpose of sensing for spectrum access). Fig 3.1 shows the combined frame with the cluster formation preceding the sensing-transmission frame.

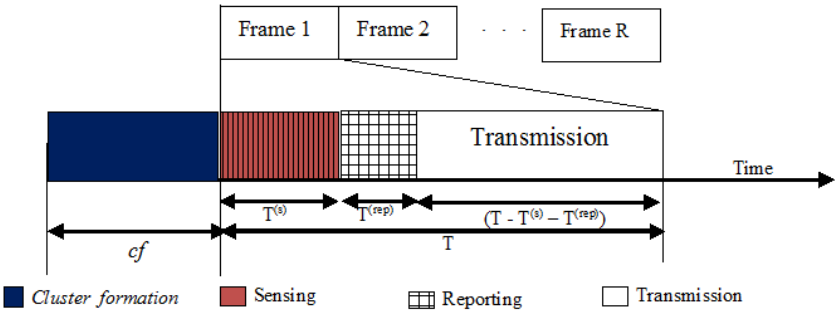


FIGURE 3.1: Cluster formation and sensing-transmission frame structure, with sensing phase, reporting phase, and transmission phase; T is the total frame length.

The distance between PU j and SU i is denoted as $d^{sp}_{i,j}$ whereas the distance between the SU i and SU k ($i \neq k$) as $d^{ss}_{i,k}$. Both $d^{sp}_{i,j}$ and $d^{ss}_{i,k}$ are random values, hence $d^{sp}_{i,j}$ could be equal, greater or less than $d^{ss}_{i,k}$ since the deployment of both PUs and SUs are assumed random. The use of different notations is thus necessary for mathematical computation and analysis. The instantaneous SNR of PU j as measured by SU i at time $t_{i,j}$ on channel link with coefficient $h_{i,j}$, is denoted as $\gamma_{i,j}$, which could be different from the actual SNR $\hat{\gamma}_{i,j}$ used for frequency assignment and cluster formation. Fig 3.2 shows the illustration of the SUi taking a sample measurement of the PU j, $j \in \{1, ..., M\}$ instantaneous SNR during the ON period of the former. It is assumed that the PUs have different and varying active periods, as a results, the sample measurements are taken at different times. T^o denotes the predefined observation period when all the SUs

$(1, ..., N)$ are expected to have taken a sample measurement of the SNR of the active PUs. The time lag between the time the measurement is taken and the end of the observation period when clusters are formed is denoted by $\tau_{i,j}$.

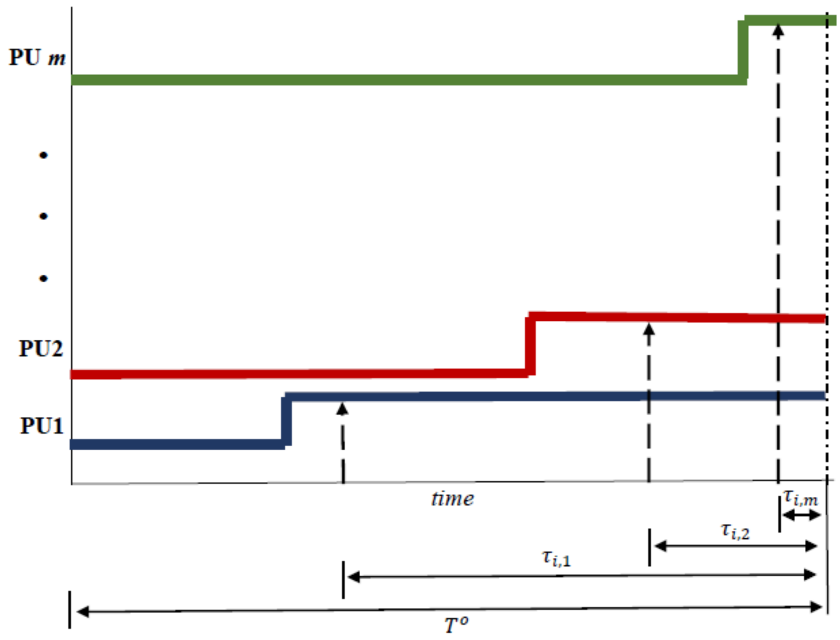


FIGURE 3.2: SU i measuring the instantaneous SNR of m PUs at different times, due to difference in PUs active periods

By definition, $\gamma_{i,j} = |h_{i,j}|^2 \bar{\gamma}_{i,j}$ and $\hat{\gamma}_{i,j} = \left|\hat{h}_{i,j}\right|^2 \bar{\gamma_{i,j}}$, where $\bar{\gamma}_{i,j}$ is the average SNR of PUj at SUi. Therefore, according to [119], if $\hat{h}_{i,j}$ and $h_{i,j}$ are jointly Gaussian then, $\hat{h}_{i,j}$ conditioned on $h_{i,j}$ follows a Gaussian distribution given by $(\hat{h}_{i,j}|h_{i,j}) \sim CN\left(h_{i,j}\rho_{i,j}, \sqrt{(1-\rho_{i,j}^2)}\right)$, where $\rho_{i,j} = J_0\left(2\pi F_{d,i,j}^{max}\tau_{i,j}\right)$ is the correlation coefficient between $\hat{h}_{i,j}$ and $h_{i,j}$ (based on Jakes' correlation model), $J_0(.)$ is the Bessel function of the first kind and zeroth order, and $F_{d,i,j}^{max}$ denotes the maximum Doppler shift. The fading amplitude in each link follows a Rayleigh distribution expressed as $f(r) = \frac{2r}{\alpha}\exp\left(\frac{-r^2}{\alpha}\right)$ and the instantaneous SNR $(\xi_{i,j})$ per symbol in each channel is distributed as

$$f\left(\xi_{i,j}\right) = \frac{1}{\bar{\xi}_{i,j}} exp\left(-\frac{\xi_{i,j}}{\bar{\xi}_{i,j}}\right) \tag{3.1}$$

The use of $\xi_{i,j}$ in (3.1) is to generalize the instantaneous SNR and distinguish it from both $\gamma_{i,j}$ and $\hat{\gamma}_{i,j}$. Assuming *i.i.d.* fading in each link, and given that both the estimated channel $\hat{h}_{i,j}$ with SNR $\hat{\gamma}_{i,j}$ and the outdated channel $h_{i,j}$ with SNR $\gamma_{i,j}$ are correlated, that is $\rho_{i,j} \neq 0$, the normalized joint *pdf* in ([120], Eqn. 3) can be evaluated for the case of $m = 1$, $n = 2$ for bivariate Rayleigh fading as:

$$f(\hat{\gamma}_{i,j},\gamma_{i,j}) = \frac{1}{\bar{\gamma}_{i,j}^2(1-\rho_{i,j}^2)} exp\left(\frac{\hat{\gamma}_{i,j}+\gamma_{i,j}}{\bar{\gamma}_{i,j}(1-\rho_{i,j}^2)}\right) \times I_0\left[\frac{2\sqrt{\rho_{i,j}^2\hat{\gamma}_{i,j}\gamma_{i,j}}}{\bar{\gamma}_{i,j}(1-\rho_{i,j}^2)}\right]. \tag{3.2}$$

The fading amplitude $f(r)$ in ([120], Eqn. 1) is being replaced by the instantaneous SNR per symbol of the channel $f(\xi)$ in (3.2), ([121], Eqns. 3.8 and 3.10).

3.3.2 Signal Model

Considering a continuous time signal $s_j(t)$ transmitted from a distant PU transmitter on channel j, the received signal by the SU i can be expressed as

$$y_{i,j}(t) = h_{i,j}(t)s_j(t) + n(t), \tag{3.3}$$

where $h_{i,j}(t)$ represents the time varying channel coefficient. The additive white Gaussian noise (AWGN) with zero mean μ, and variance σ^2 is denoted by $n(t)$. The goal of the spectrum sensing is for the SU to decide between two hypotheses, that is

$$y_{i,j}(t) = \begin{cases} n(t) & : H_0 \ (white\ space); \\ h_{i,j}(t) \otimes s_j(t) + n(t) & : H_1 \ (channel\ busy). \end{cases} \tag{3.4}$$

The H_0 and H_1 hypotheses denote the absence and the presence of the PU signal in the channel under consideration respectively. In order to quantify the sensing performance, the probabilities of detection $P_{d,i,j}$ as well as that of false alarm $P_{f,i,j}$ are defined as

$$\begin{aligned} P_{d,i,j} &= Pr\left\{decision = H_1|H_1\right\} \\ P_{f,i,j} &= Pr\left\{decision = H_1|H_0\right\}. \end{aligned} \tag{3.5}$$

That is, the probability of detection is the probability that the SU decides that the channel is busy when it is actually busy, whereas the probability of false alarm is the probability that the SU detects the channel to be busy when it is actually idle. The probability that the SU does not detect the PU in the channel when it is actually present is referred to as the probability of miss-detection, expressed as

$$P_{m,i,j} = Pr\left\{decision = H_0|H_1\right\} = 1 - P_{d,i,j}. \tag{3.6}$$

Each of the SUs adopt the energy detection scheme for sensing the PU signal. For the received signal represented in (3.3), the decision metric for the presence or absence of the PU signal is the energy value per sample at the SU, expressed as

$$E_{i,j} = \sum_{r=1}^{R} |y_{i,j}(r)|^2, \tag{3.7}$$

where $R = 2TW$ represents the number of samples or the size of observation vector and TW is the time-bandwidth product. The decision on the presence or absence of the PU signal can then be obtained by comparing the decision metric E against a threshold λ, which is equivalent to

$$E_{i,j} = \begin{cases} H_1 & : E_{i,j} \geq \varepsilon \\ H_0 & : E_{i,j} < \varepsilon. \end{cases} \tag{3.8}$$

Under AWGN channel, the performance of the detector can be measured by the probability of detection and that of false alarm as

$$P_{d,i,j}(\varepsilon) = Pr\left\{E_{i,j} \geq \varepsilon | H_1\right\} = Q_u\left(\sqrt{2\xi_{i,j}}, \sqrt{\varepsilon}\right), \tag{3.9}$$

$$P_{f,i,j}(\varepsilon) = Pr\left\{E_{i,j} \geq \varepsilon | H_0\right\} = \frac{\Gamma(\frac{R}{2}, \frac{\varepsilon}{2})}{\Gamma(\frac{R}{2})} \quad [122] \tag{3.10}$$

where $\Gamma(a,x) = \int\limits_{x}^{\infty} t^{a-1}e^{-t}dt$, is the incomplete gamma function and $\Gamma(a)$ the complete gamma function. The generalized Marcum Q-function $Q_u(a,b)$ having degree of freedom $u = TW$ can be expressed as ([123], Eqn. 17)

$$Q_u(a,b) = \frac{1}{a^{u-1}} \int\limits_{b}^{\infty} t^u exp\left(-\frac{t^2+a^2}{2}\right) I_{u-1}(at)dt. \tag{3.11}$$

In a Rayleigh channels, $P_{f,i,j}$ is independent of the signal-to-noise ratio, but the amplitude gain of the channel varies due to fading. The *pdf* of the SNR under fading hence, follows an exponential function, such that the estimated average probability of miss-detection conditioned on the outdated measured sample can be evaluated as:

$$\bar{P}^{Ray}_{m,i,j|\gamma_{i,j}} = 1 - \int\limits_{0}^{\infty} P_{d,i,j} \quad f(\hat{\gamma}_{i,j}|\gamma_{i,j})d\gamma_{i,j} \tag{3.12}$$

where $f_{\hat{h}_{i,j}|h_{i,j}}(\hat{\gamma}_{i,j}|\gamma_{i,j}) = \frac{f_{\hat{h}_{i,j},h_{i,j}}(\hat{\gamma}_{i,j},\gamma_{i,j})}{f_{h_{i,j}}(\gamma_{i,j})}$ is the conditional *pdf* of $\gamma_{i,j}$. After substituting (3.1) and (3.2), the conditional *pdf* can be expressed as

$$f(\hat{\gamma}_{i,j}|\gamma_{i,j}) = \frac{1}{\bar{\gamma}_{i,j}(1-\rho^2_{i,j})} exp\left(\frac{\hat{\gamma}_{i,j} + \gamma_{i,j}\rho^2_{i,j}}{\bar{\gamma}(1-\rho^2_{i,j}}\right) \times I_0\left[\frac{2\sqrt{\rho^2_{i,j}\hat{\gamma}_{i,j}\gamma_{i,j}}}{\bar{\gamma}_{i,j}(1-\rho^2_{i,j})}\right]. \tag{3.13}$$

Following ([119], Eqn. 8), Equation (3.12) can be evaluated as:

$$\bar{P}_{m,i,j|\gamma_{i,j}} \approx 1 - exp\left(-\frac{\varepsilon}{2} - \frac{\gamma_{i,j}\rho_{i,j}^2}{\bar{\gamma}(1-\rho_{i,j}^2)}\right) \sum_{k=0}^{L} \frac{\left\{\bar{\gamma}_{i,j}(1-\rho_{i,j}^2)\right\}^k}{\left\{\bar{\gamma}_{i,j}(1-\rho_{i,j}^2)+1\right\}^{k+1}} \sum_{j=0}^{u+k-1} \frac{1}{j!}\left(\frac{\varepsilon}{2}\right)^j$$

$$\times\ {}_1F_1\left(-k, 1; -\frac{\gamma_{i,j}\rho_{i,j}^2}{\bar{\gamma}_{i,j}(1-\rho_{i,j}^2)\left\{\bar{\gamma}_{i,j}(1-\rho_{i,j}^2)+1\right\}}\right). \tag{3.14}$$

Equation (3.14) is a generalized expression for the probability of miss-detection in a practical channel, since by setting $\rho_{i,j}^2 = 1$ or $\rho_{i,j}^2 = 0$ in (3.13), the expression in (3.14) evaluates to

$$P_{m,i,j|\gamma_{i,j}} = 1 - Q_u\left(\sqrt{2\gamma_{i,j}}, \sqrt{\varepsilon}\right) \tag{3.15}$$

or

$$\bar{P}_{m,i,j|\gamma_{i,j}}^{Ray} \approx 1 - \sum_{k=0}^{L} \frac{\{\bar{\gamma}_{i,j}\}^k}{\{\bar{\gamma}_{i,j}+1\}^{k+1}} exp\left(\frac{\varepsilon}{2}\right) \sum_{j=0}^{u+k-1} \frac{1}{j!}\left(\frac{\varepsilon}{2}\right)^j \tag{3.16}$$

respectively. Equation (3.16) can also be obtained by setting $\rho_{i,j}^2 = 0$ in (3.14). The expression in (3.16) is numerically equal to the average probability of miss-detection obtainable from ([122], Eqn. 9) for sufficiently large L.

In cooperative spectrum sensing, optimal fusion rule depends on network composition and channel condition. Under Rayleigh fading, investigations in [124, 125] show that OR fusion rule is better in protecting the PU signal, and [88] equally reported that it is the optimal rule in minimizing the total error for a fixed large detection threshold. Consequently, based on the OR rule, the cooperative probability of false alarm and miss-detection conditioned on the outdated measured sample are expressed as:

$$Q_{m,j|\gamma_{i,j}} = \prod_{i=1}^{n_j} [\bar{P}_{m,i,j|\gamma_{i,j}}(1-P_{e,i,c}) + P_{e,i,c}(1-\bar{P}_{m,i,j|\gamma_{i,j}})] \tag{3.17}$$

$$Q_{f,j} = \prod_{i=1}^{n_j} [(1-P_{f,i,j})(1-P_{e,i,c}) + P_{f,i,j}P_{e,i,c}] \tag{3.18}$$

Since the non-cooperative probability of false alarm is independent of SNR, we assume equal probability of false alarm for every SU i sensing PU j such that $P_{f,i,j} = P_f$. Based on the constraint on the cooperative probability of false alarm (as specified by IEEE 802.22 standards

[128]), the maximum integer number n_{max} of SUs that can be allowed in a cluster is obtained from (3.18) as

$$\frac{\ln(1-\bar{Q}_f)}{\ln(1-P_f)(1-P_{e,i,c})+P_f P_{e,i,c}}+1 \leq n_{max} \tag{3.19}$$

where $P_{e,i,c}$ is the probability of communication error between SU i and the cluster head c, which is assumed constant for the frequency assignment, hence $P_{e,i,c} = P_e$.

3.4 Overlapping Cluster Based Frequency Assignment for Cooperative Spectrum Sensing

This section describes the proposed centralized assignment scheme, the problem formulation and solution. With the objective to minimize interference to the PU while enhancing multiple spectrum utilization opportunity of the SUs, the channel assignment is formulated into a non-linear integer optimization problem, which is generally known to be NP-hard. In order to obtain an efficient solution, the original problem is transformed into a mixed integer linear problem, based on which both the exact solution and heuristic solutions are presented.

3.4.1 Proposed Assignment Scheme

The frequency assignment and cluster formation are implemented by the central controller. Each SU takes a sample measurement of the PU signal within its detection range at time t. It is assumed that the PUs are independent of one another and not synchronized, and hence may have different active periods on the channel. A window period of $T^o(0 \leq t \leq T^o)$ is allowed for all the SUs to take the sample measurement. At the end of the observation period, each of the SUs computes $P_{m,i,j|\gamma_{i,j}}$ based on (3.14).

The computed probability of miss-detections, the corresponding channel list Cl_i, and location coordinate of each secondary users $SU_i(x, y)$, (where (x, y) denotes the x-coordinate, and y-coordinate respectively), are then sent to the CC. Using the received information from the SUs, the CC assigned frequencies based on either the heuristic solutions (Algorithm 1) and (Algorithm 2) or the exact solution based on (3.51)-(3.53). The group of SUs that are assigned to a particular PU channel forms a cluster. A SU can belong to multiple clusters by being assigned multiple frequencies. The network can thus be described as a set of non-empty subsets of N SUs. That is $\Lambda = n_1, n_2, ..., n_M$, where n_j is a proposed cluster identified with channel j,

$\bigcup_{j=1}^{M} n_j \subseteq N$ and $\bigcap_{j=1}^{M} n_j \neq \emptyset$. The number of clusters is assumed to be the same as the number of the PU channels in the network.

3.4.2 Problem Formulation and Solutions

The channel assignment problem is formulated as a minimization of the cooperative probability of miss-detection as:

$$Z_\ell = \min_{\chi} \left\{ Q_{m,j|\gamma_{i,j}} \right\} \tag{3.20}$$

subject to :

$$Q_{f,j} \leq \alpha \tag{3.21}$$

$$\sum_{j=1}^{M} x_{i,j} \leq K, \ i \in \{1, 2, ..., N\} \tag{3.22}$$

$$x_{i,j} \in \{0, 1\} \tag{3.23}$$

The assignment matrix is represented by $\chi = \{x_{i,j}\}_{M \times N}$, that is $x_{i,j} = 0$ or 1 depending on whether SU i is assigned PU j or not. The problem in (3.20) is a nonlinear integer programming problem. However, by substituting (3.17) in (3.20), and then using the identities $min(.) \equiv min\ \ln(.)$ and that $\ln \prod(.) = \sum \ln(.)$, the objective function in (3.20) can be linearized, such that the original problem in (3.20) - (3.23) can be expressed as

$$Z_\ell = \min_{\chi_{i,j}} \sum_{j=1}^{M} \sum_{i=1}^{N} x_{i,j} \ln\{P_{m,i,j|\gamma_{i,j}}(1 - P_e) + (1 - P_{m,i,j|\gamma_{i,j}})P_e\} \tag{3.24}$$

subject to :

$$\sum_{i=1}^{N} x_{i,j} \leq n_{max}, \ j \in \{1, 2, ..., M\} \tag{3.25}$$

$$\sum_{j=1}^{M} x_{i,j} \leq K, \ i \in \{1, 2, ..., N\} \tag{3.26}$$

$$x_{i,j} \in \{0, 1\} \tag{3.27}$$

where the effect of channel varying condition is integrated in the objective function.

Equation (3.21) is equivalent to (3.25) from (3.19). When the assignment variable $x_{i,j} = 0$, SU i neither contribute to (3.24) nor to (3.25), while $x_{i,j} = 1$ means otherwise. Equation (3.24) is the objective function, while (3.25), (3.26) and (3.27) are constraints. Constraint in (3.25) puts a limit on the number of SUs that can be assigned to one PU channel based on the constraint on Q_f, which decides the spectrum utilization of each cluster. Constraint in (3.26) indicates that each SU cannot be assigned more than K channels, while constraint in (3.27) indicates the variable type. Problem in (3.24)-(3.27) is thus a linear integer programming problem, a case of many-to-many combinatorial optimization with overlapping clusters (since $K \geq 1$).

Exact Solution

By defining another variable y_j as the value of the cooperative probability of miss-detection in each cluster, the linear integer problem in (3.24)-(3.27) can then be written as:

$$Z_{Opt} = \min_{\chi, y_j} \sum_{j=1}^{M} y_j \tag{3.28}$$

subject to :

$$\sum_{i=1}^{N} x_{i,j} \leq n_{max}, \; j \in \{1, 2, ..., M\} \tag{3.29}$$

$$\sum_{j=1}^{M} x_{i,j} \leq K, \; i \in \{1, 2, ..., N\} \tag{3.30}$$

$$\sum_{i=1}^{N} x_{i,j} \psi_{i,j} = y_j, \; j \in \{1, 2, ..., M\} \tag{3.31}$$

$$x_{i,j} \in \{0, 1\} \tag{3.32}$$

where,

$\psi_{i,j} = \ln\{P_{m,i,j|\gamma_{i,j}}(1 - P_e) + (1 - P_{m,i,j|\gamma_{i,j}})P_e\}$

If the equality constraint in (3.31) is relaxed and replaced by an inequality, the problem in (3.28)-(3.32) can be reduced to the form of (3.33)-(3.37) as

$$Z_{Opt} = \min_{\chi, y_j} \sum_{j=1}^{M} y_j \tag{3.33}$$

subject to :

$$\sum_{i=1}^{N} x_{i,j} \leq n_{max}, \; j \in \{1, 2, ..., M\} \tag{3.34}$$

$$\sum_{j=1}^{M} x_{i,j} \leq K,\ i \in \{1, 2, ..., N\} \tag{3.35}$$

$$\sum_{i=1}^{N} x_{i,j}\psi_{i,j} \leq y_j,\ j \in \{1, 2, ..., M\} \tag{3.36}$$

$$x_{i,j} \in \{0, 1\} \tag{3.37}$$

The problem in (3.33)-(3.37) is a mixed integer linear programming problem (MILP). Constraint in (3.36) enforces the cooperative probability of miss-detection in each cluster to a minimum.

By defining the following matrix variable χ and the vectors x,y as:

$$\chi = \begin{pmatrix} x_{11} & \dots & x_{1M} \\ \vdots & \ddots & \vdots \\ x_{N1} & \dots & x_{NM} \end{pmatrix} \tag{3.38}$$

$$\begin{aligned} \boldsymbol{x} &= vec(\chi) \\ &= (x_{11}, ..., x_{N1}, x_{12}, ..., x_{N2}, ..., x_{1M}, ..., x_{NM})^T \end{aligned} \tag{3.39}$$

$$\boldsymbol{y} = (y_1, ..., y_M)^T \tag{3.40}$$

The problem in (3.33)-(3.37) can be expressed in terms of the augmented vectors as

$$\min_{\chi, \boldsymbol{y}} 0\boldsymbol{x} + C^T\boldsymbol{y} \tag{3.41}$$

subject to :

$$A_j\boldsymbol{x} + 0\boldsymbol{y} \leq n_{max},\ j \in 1, ..., M \tag{3.42}$$

$$Q_i\boldsymbol{x} + 0\boldsymbol{y} \leq K,\ i \in 1, ..., N \tag{3.43}$$

$$\psi_j\boldsymbol{x} + C_j\boldsymbol{y} \leq 0,\ j \in 1, ..., M \tag{3.44}$$

$$x_{i,j} \in \{0, 1\}, \qquad y_j \in \Re \tag{3.45}$$

Taking $\boldsymbol{z} = \begin{pmatrix} \boldsymbol{x} \\ \boldsymbol{y} \end{pmatrix}$ then, the problem becomes

$$\min_{\boldsymbol{z}} (0 \quad C^T)\boldsymbol{z} \tag{3.46}$$

subject to :

$$(A_j \quad 0)\boldsymbol{z} \leq n_{max},\ j \in 1, ..., M \tag{3.47}$$

$$(Q_i \quad 0)\boldsymbol{z} \leq K, \; i \in 1, ..., N \tag{3.48}$$

$$(\psi_j \quad C_j)\boldsymbol{z} \leq 0, \; j \in 1, ..., M \tag{3.49}$$

$$x_{i,j} \in \{0, 1\}, \qquad y_j \in \Re \tag{3.50}$$

By concatenating the constraints in (3.47), (3.48) and (3.49) in the following form:

$$P = \begin{pmatrix} A_1 & 0 \\ \vdots & \vdots \\ A_M & 0 \\ Q_1 & 0 \\ \vdots & \vdots \\ Q_N & 0 \\ \psi_1 & C_1 \\ \vdots & \vdots \\ \psi_M & C_M \end{pmatrix}, \qquad R = \begin{pmatrix} n_{max} \\ \vdots \\ n_{max} \\ K \\ \vdots \\ K \\ 0 \\ \vdots \\ 0 \end{pmatrix},$$

the problem in (3.46)-(3.50) can simply be written as

$$\min_{\boldsymbol{z}} \bar{c}^T \boldsymbol{y} \tag{3.51}$$

subject to :

$$P\boldsymbol{z} \leq R \tag{3.52}$$

$$x_{i,j} \in \{0, 1\}, \quad y_j \in \Re \tag{3.53}$$

where $\bar{c}^T = (0 \quad C^T)$.

The problem in (3.51)-(3.53) is solved using the solver from the optimization toolbox provided by MATLAB to solve a MILP formulated as [129].

$$\min_{x} f^T \boldsymbol{x} : \quad A \cdot \boldsymbol{x} \leq b, \quad lb \leq x \leq ub,$$

where vectors lb, ub, matrices A and corresponding vector b and a set of indices integer constraint (*intcon*) were initialized. Following initialization, the MILP solver is run to solve the problem for vector x, where $f(x)$ is the coefficient matrix of the objective function, lb and ub are lower and upper bounds respectively. Since this is an assignment problem, x can only be binary, such that $lb = 0$, and $ub = 1$. This solver involves the following main steps [129]:

1. Preprocessing the data to check the possibility of reducing its size.

2. Solve an initial relaxed (non-integer) problem using linear programming (dual-simplex method). The objective functions and constraints remain the same, but any integer constraints are removed.

3. Apply heuristics to find feasible points. Intermediate settings are used in order to optimize the runtime of the algorithm.

4. Apply Branch and Bound (BnB) algorithm to search systematically for the optimal solution. This solves linear programming relaxations with restricted ranges of possible values of the integer variables. It attempts to generate a sequence of updated bounds on the optimal objective function value.

5. The bud nodes continue to generate further nodes as we analyze and discard the ones that do not improve the value of the objective function until we reach incumbent solution such that the absolute gap tolerance is 10^{-5}.

Heuristic Algorithm 1

By re-writing the problem in (3.24)-(3.27) in the form of (3.54), that is:

$$Z_{SupOpt} = \sum_{j=1}^{M}\{\min_{\chi_{i,j}} \sum_{i=1}^{N} x_{i,j}\psi_{i,j}\} \tag{3.54}$$

subject to :

$$\sum_{i=1}^{N} x_{i,j} \leq n_{max},\ j \in \{1, 2, ..., M\} \tag{3.55}$$

$$\sum_{j=1}^{M} x_{i,j} \leq K,\ i \in \{1, 2, ..., N\} \tag{3.56}$$

$$x_{i,j} \in \{0, 1\}\,, \tag{3.57}$$

the problem is thus approximated to solving the minimization problem based on constraint in (3.55), and then applies constraint in (3.56) on the solution based on heuristic approach. The minimization problem inside the bracket in (3.54) is thus a 1-0 knapsack problem. In Algorithm 1, this is implemented by first solving the 1-0 knapsack problem formed by ignoring constraint (3.56), to obtain the initial solution $\chi^1_{i,j}$. This assigns n SUs that minimizes the cooperative probability of miss-detection on each PU channel. Thereafter, it checks through $\chi^1_{i,j}$ for any violation of constraint in (3.56). The channels with highest $P_{m,i,j|\gamma_{i,j}}$ are then excluded sequentially until constraint in (3.56) is satisfied for each SU, in order to obtain the final solution $\chi^0_{i,j}$. The pseudo-code for this approach is given in Algorithm 1

Algorithm 1 Heuristic Solution 1

procedure CENTRALIZED CHANNEL ASSIGNMENT SCHEME FOR COOPERATIVE SPECTRUM SENSING IN MULTI-CHANNEL CRN.
Input: n_{max}, $C\ell_{max}$
SU i communicates $P_{m,i,j|\gamma_{i,j}}$, $C\ell_i$ to CC
    for $j = 1 : M$ **do**
        for $i = 1 : N$ **do**
            $\chi^1_{i,j}$: Solve (3.54) without constraint (3.56)
        end for
        if $C\ell_i \leq C\ell_{max}, \forall i \in N$ **then**
            $C\ell_{op} \leftarrow C\ell_i$
        else
            $\beta_{i,j} = ArgmaxP_{m,i,j|\gamma_{i,j}}, \forall i \in N$
            $C\ell_i \leftarrow C\ell_i \setminus \beta_{i,j}$
        end if
    end for
Output:$\chi^o_{i,j}$
end procedure

where Cl_{max}, Cl_{op} and Cl_i denote the predefined maximum number of assigned channels (K) for each SU, the number of channels for each SU that satisfies the constraint in (3.56), and the initial number of channels for SU i on $\chi^1_{i,j}$ respectively.

Heuristic Algorithm 2

In Algorithm 1, the CC first solves the 0-1 knapsack problem by ignoring (3.56). Hence, the solution is not fully heuristic. The channel assignment in Algorithm 2 assigns channels by first forming a matrix of the probability of miss-detection based on the received information from the SUs. Following this, SUs with the highest probability of miss-detection are sequentially excluded from the rows, and then from the columns of the formed matrix until constraints in (3.25) and (3.26) are satisfied for n_{max} and K respectively. The pseudo-code for this assignment is as shown in Algorithm 2.

Algorithm 2 Heuristic Solution 2

1: **procedure** CENTRALIZED CHANNEL ASSIGNMENT SCHEME FOR COOPERATIVE SPECTRUM SENSING IN MULTI-CHANNEL CRN.
2: **Input**: n_{max}, K
3: **Initialization**: Generate matrix $\chi^*_{i,j} = \{P_{m,i,j|\gamma_{i,j}}\}_{M\times N}$, based on the evaluated probabilities of miss-detection received from each SU, where each row of $\chi^*_{i,j}$ represents channel $j \in 1, ..., M$ and each column the SU $i \in 1, , N$
4:     **for** $j = 1 : M$ **do**
5:         **for** $i = 1 : N$ **do**

- Exclude SU with maximum probability of miss-detection sequentially from each row of $\chi^*_{i,j}$ until the constraint on $\bar{Q}_f$ is satisfied and obtain matrix $\chi^1_{i,j}$.
- Based on matrix $\chi^1_{i,j}$, exclude channel with maximum probability of miss-detection sequentially from each column of $\chi^1_{i,j}$ until the constraint on the maximum number of assigned channels for each SU (K) is satisfied.

6:         **end for**
7:     **end for**
8: **Output**:$\chi^o_{i,j}$
9: **end procedure**

3.4.3 Complexity Analysis of Proposed Algorithms

Here, the computational complexity of the algorithms are compared using time and memory requirements, and as a function of size of the input data [130]. The mixed-integer linear optimization problem in (3.28) -(3.32) is an NP-complete problem, and has a computational complexity order of $\mathcal{O}(2^{NM+M})$. However, in the heuristic solution of Algorithm 1, in order to compute the channel assignment, three steps are required. First at initialization in line 3, an $N \times M$ matrix is generated based on the reported probabilities of miss-detection in all the channels ($j \in \{1, ..., M\}$), from each SUi ($i \in \{1, ..., N\}$), with time complexity $\mathcal{O}(MN)$. The **for** loop in lines 5 - 7 is an 0-1 Knapsack problem of size N for each of the M rows, requiring 2^N computational time. Furthermore, the **for** loop in lines 4-14 requires matrix sorting which takes up to $N(M \log M)$ comparison. Hence, the time complexity of the two-dimensional array $M \times N$ matrix sorting is $\mathcal{O}\left(NM^2\right)$, since $(M \log M) \leq M^2$ for an array of size M. Therefore, the worst case complexity of Algorithm 1 is $\mathcal{O}\left(2^N\right)$. Likewise, in the heuristic solution of Algorithm 2, initialization in line 3 requires a running time of $\mathcal{O}(MN)$. The **for** loop in lines 5 - 6 requires sorting, which takes up to $(N \log N)$ comparison in each row. Likewise, the **for** loop in lines 4 - 7 requires $(M \log M)$ comparison in each column. The worst case complexity of Algorithm 2 is $\mathcal{O}\left(MN(N + M)\right)$. Table 3.1 summarizes the computational complexity per iteration of the proposed algorithms and in comparison to the algorithm used in literature [47]. Heuristic solution 1 has a time complexity that is exponential, increasing with the number of SU, but independent of the number of PU channels. On the other hand, the complexity of Heuristic solution 2 is polynomial, increasing with the network size. The rate of convergence of the two heuristic solutions depends on the network size.

Table 3.1: Complexity Analysis of the channel assignment scheme

Solution Scheme	Time complexity	Space Complexity
Exact solution	$\mathcal{O}(2^{MN+M})$	$\mathcal{O}(MN+M)$
Proposed Heuristic 1	$\mathcal{O}(2^{N})$	$\mathcal{O}(MN)$
Proposed Heuristic 2	$\mathcal{O}(M^2+N^2)$	$\mathcal{O}(MN)$
Existing Heuristic [47]	$\mathcal{O}(N^{n_{max}})$	$\mathcal{O}(N^{n_{max}})$

3.5 Simulation Results

This section presents the simulation results of the generalized channel assignments in the multi-channel cognitive radio networks with outdated CSI over Rayleigh fading, based on centralized algorithm. The network consists of 20 PU channels and varying number of SUs between 10 and 100 (to evaluate the assignment under different number of SU to PU ratio) randomly deployed in a $5km \times 5km$ square area. The ratio of the number of SUs to the PU channels is denoted as ζ. Each PU is licensed to one channel. For the simulations, the following parameter values are used: $L = 100$, $u = 5$,$\mu = 3$, $\kappa = 1.0$, $P_f = 0.015$, $P_e = 0.01$ [33, 47], and the false alarm constraint ($\bar{Q}_f$) denoted as α is made to vary from 0 to 0.2, although analysis is essentially based on $\alpha = 0.1$ in agreement with the IEEE 802.22 standard recommendation. The parameters $\tau_{i,j}$ and $f^{max}_{i,j}$ are chosen randomly as $0.001sec \leq \tau_{i,j} \leq 10sec$, and $1 \leq F^{max}_{d,i,j} \leq 7$ respectively in order to obtain different correlation factor $\rho_{i,j}$. The P_{PU}, P_{SU} and N_0 are chosen as $50mW$, $20mW$ and $-90dBm$ respectively ([47] and [33]), in agreement with standard value, while the average SNR of the PU j at the SU i ($\bar{\gamma}_{i,j}$) is evaluated based on the inverse square law. The average number of assigned channels for each SU corresponds to the average degree of cluster overlapping.

Fig. 3.3 illustrates the performance of the many-to-many cluster-based cooperative spectrum sensing, whereas Figs. 3.4 and 3.5 show the performance under different channel considerations. In Fig. 3.6, the interference reduction capability with varying maximum assignment per SU is shown for different constraints on the probability of false alarm. These results show that performance generally improves with the degree of cluster overlapping (Fig. 3.3), and different under different channel considerations (Figs. 3.4 and 3.5). For given constraints of the probability of false alarm, and the maximum number of channels that can be assigned for each user, Figs. 3.4 and 3.5 show that the predicted channel state information results in lower probability of miss-detection. In Fig. 3.4, the performance of the cooperative spectrum sensing under the

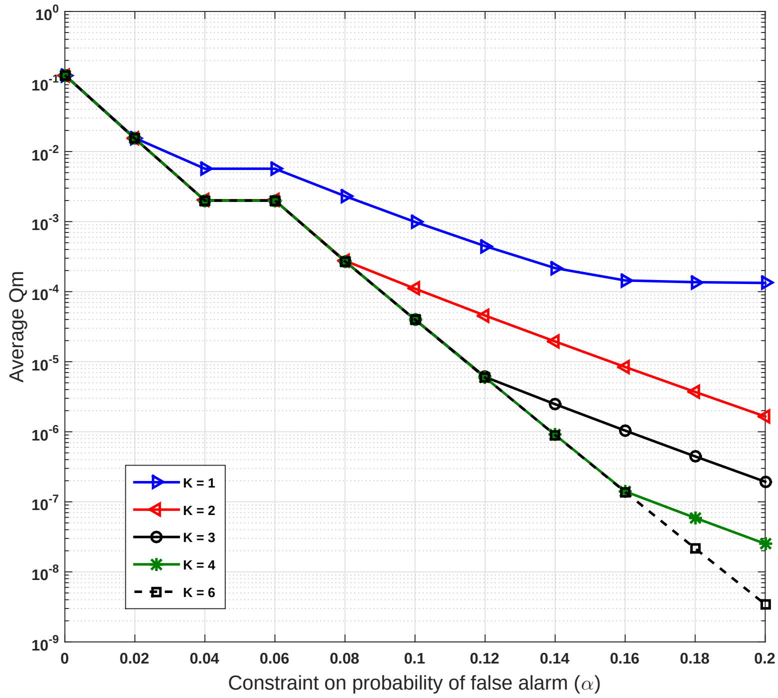


FIGURE 3.3: Performance gain of the overlapping cluster-based channel assignments based on exact solution: $M = 20$, $N = 60$, (i.e., $\zeta = 3$), and K is as previously defined.

traditional Rayleigh fading channel indicates an error floor at $Q_f > 0.1$. The error floor otherwise refers to as bit error probability (BEP) wall [131], illustrates the performance limitation for the cooperative spectrum sensing caused by the reporting channel error. Hence at these values, the result shows that it is impossible to improve the probability of miss-detection at the fusion center irrespective of the increasing probability of false alarm (or increase in the cluster size). Nevertheless, for the given constraints, the average cluster size and the average number of channels that could be assigned per user for both the traditional Rayleigh channel and the predicted channel information is the same, and the difference in the probability of miss-detection is due to the resulting composition of the clusters. Hence, estimating the CSI based on the outdated CSI presents a more reliable channel assignment for better spectrum sensing and access in the cognitive radio network.

The result in Fig. 3.6 shows that interference to the PU channels reduces to the extent that is permitted by the constraint on the probability of false alarm, since the probability of miss-detection is a decreasing function of the number of SUs cooperating in sensing, while the false alarm probability is an increasing function.

Fig. 3.7 shows the average cluster size against the maximum number of assigned channels K for each SU, while Fig. 3.8 demonstrates the average number of assigned channels K_{ave} per

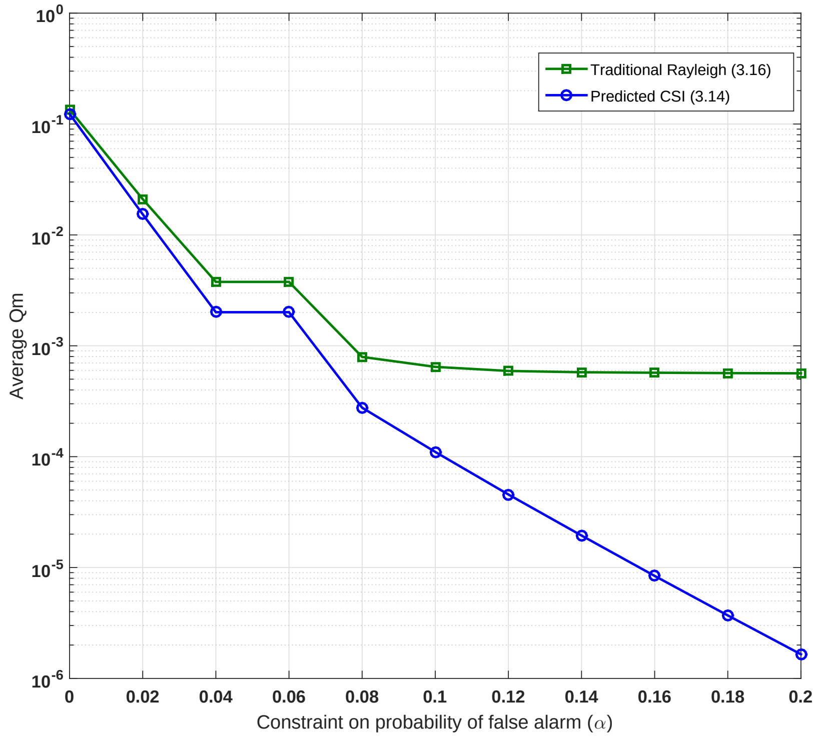


FIGURE 3.4: ROC under different fading considerations, $K = 2$.

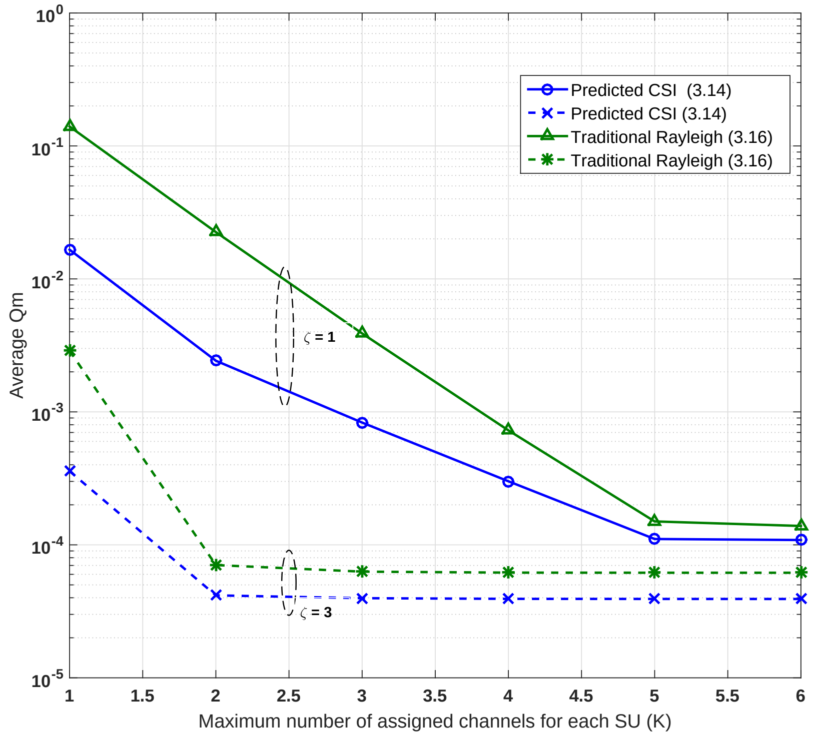


FIGURE 3.5: Average cooperative probability of miss-detection against the maximum number of assigned channels for each user (K) under different fading considerations, $\alpha = 0.10$, $K = 2$.

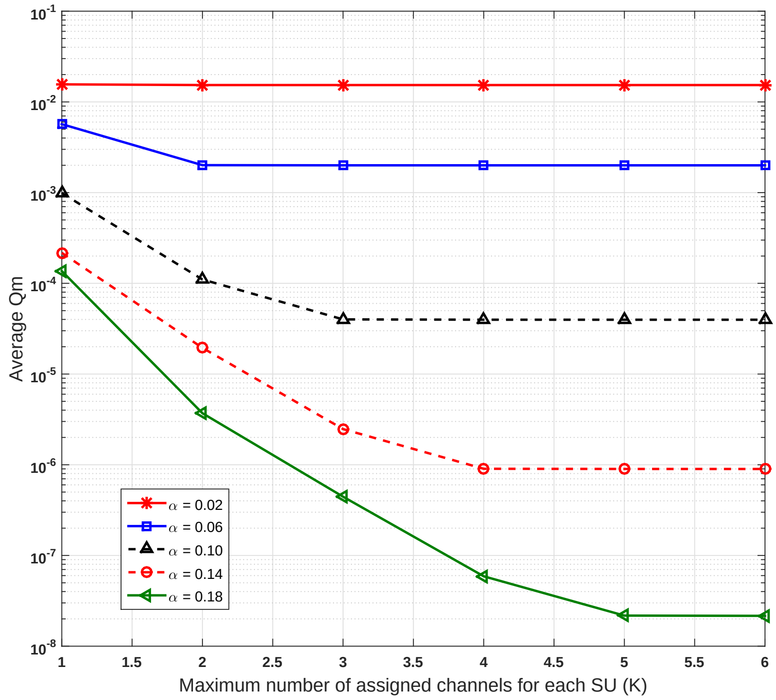


FIGURE 3.6: Average probability of miss-detection (Q_m) versus the maximum number of channels assigned for each SU (K) at varying α, based on exact solution: $\zeta = 3$.

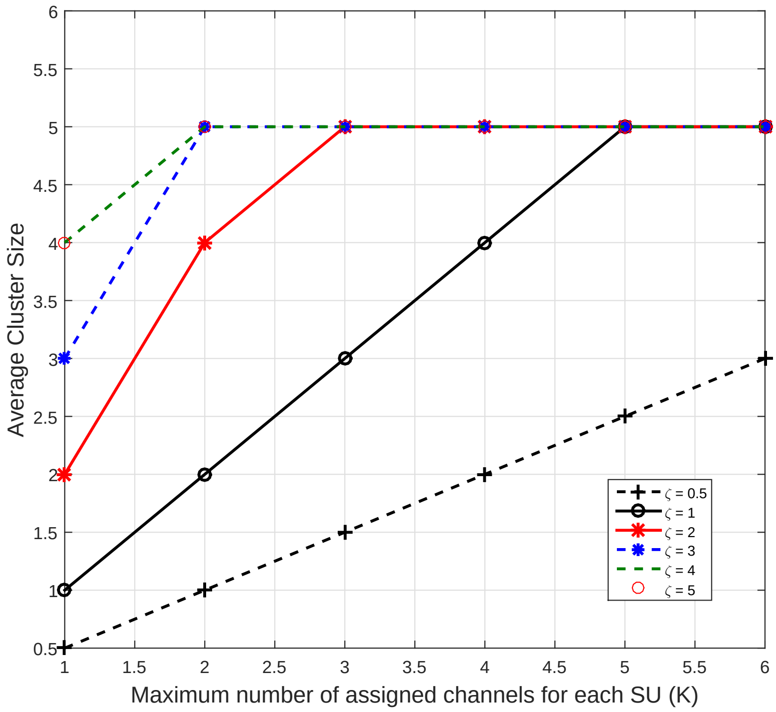


FIGURE 3.7: Average cluster size against K for different ratios of the number of SUs to PU channels (ζ) based on exact solution, $\alpha = 0.1$.

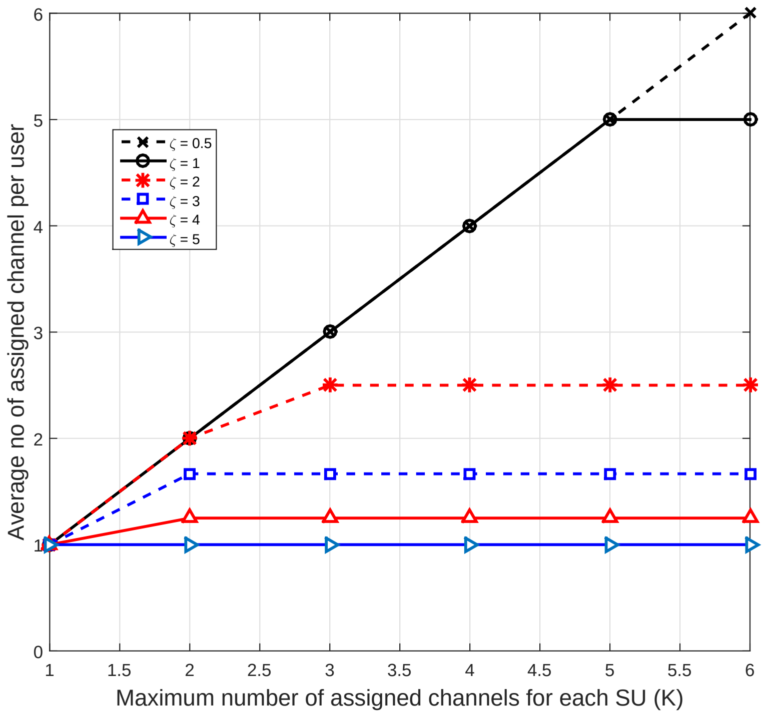


FIGURE 3.8: Average number of PU channel assigned per $SU(K_{ave})$ against the maximum number of channels assigned to each SU (K) for varying ζ, based on exact solution, $\alpha = 0.1$.

SU against K, both for varying ζ. The common observation from these plots are that average cluster size increases with ζ, whereas (K_{ave}) reduces with increasing ζ. The product of K_{ave} and ζ is upper bound by the constraint on the cooperative probability of false alarm α, such that the average cluster size $n_{ave} = K_{ave}\zeta$, ($n_{ave} \leq n_{max}$), and the average number of assigned channel for each SU $K_{ave} = n_{ave} \times \zeta^{-1}$, ($K_{ave} \leq K$). Therefore, as ζ increases for a set cooperative probability of false alarm, the degree of cluster overlapping reduces, approaching one (disjointed clusters). Complete disjointed clusters can be observed at $\zeta = 6$. Therefore, the quality of spectrum sensing improves with increasing ζ, since more SUs are available to participate in cooperative sensing. However, this is at the expense of spectrum utilization opportunities. Increasing ζ reduces the average number of assigned channels to each SU. On the other hand, the smaller the ζ, the more opportunity for spectrum utilization, but with a reduction in sensing performance since few SUs are available for sensing. Hence, a trade off is observed, and there exist an optimal ζ that satisfies a particular level of sensing performance and spectrum utilization.

Figs. 3.9 and 3.10 compare the performance of the proposed assignment schemes with respect to cluster size and average number of assigned channels per SU against ζ. These results show that the performance of the proposed algorithms in terms of average cluster size, and the average number of assigned channel are the same and approximate the exact solution with increasing ratio of the number of SUs to PU channels. The plot in Fig. 3.11 shows the comparative performance of the solution schemes in minimizing interference in the network at varying degree of cluster overlapping with different ratios of SUs to the PU channels in the network. It also shows the marginal improvement of the proposed heuristic algorithms over the existing algorithm in literature. The wide disparity in performance between the heuristic algorithms and the exact solution is as a result of the locality of the minimals in the heuristic algorithms as against the global minimal. In terms of time complexity, Algorithm 2 is better than both Algorithm 1 and the existing heuristic algorithm in literature. It is very interesting to also observe that the space complexity of the heuristic algorithm in the literature is higher than that of the exact solution. The summary of the complexity analysis is as shown in Table 3.1.

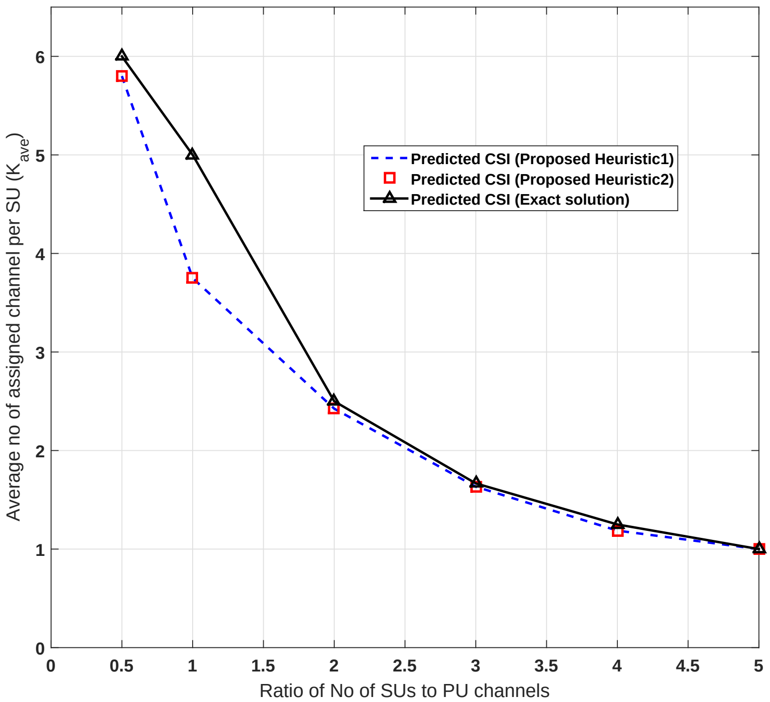


FIGURE 3.9: Heuristic versus optimal solution in terms the average number of channels assigned per SU for varying ζ, with : $\alpha = 0.1$ and $K = 6$.

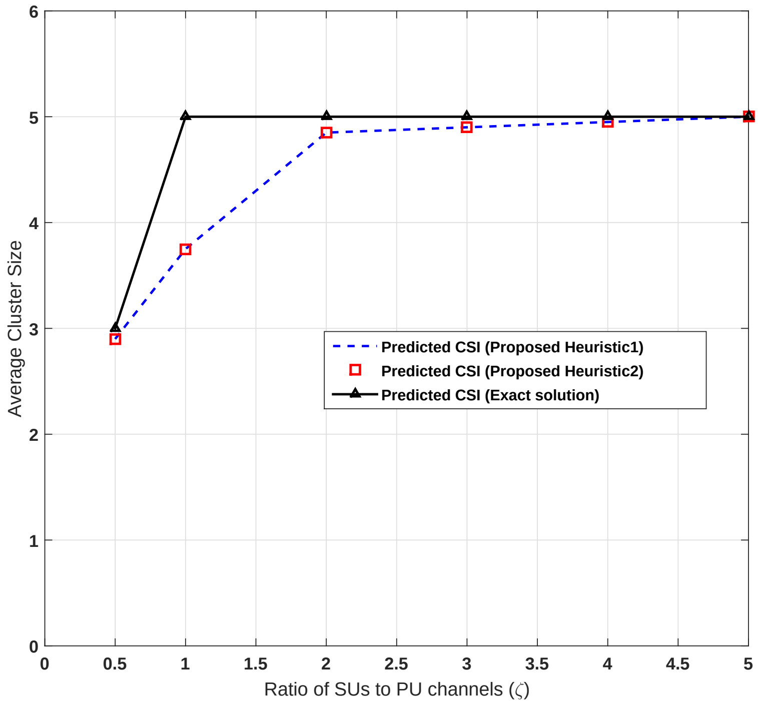


FIGURE 3.10: Heuristic versus optimal solution in terms of the average cluster size for varying ζ, with $\alpha = 0.1$ and $K = 6$.

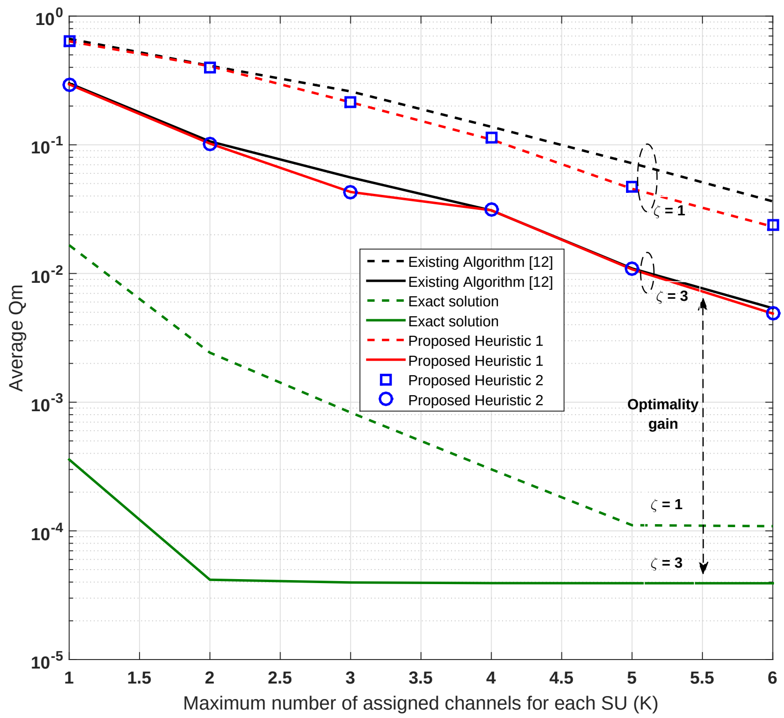


FIGURE 3.11: Heuristic versus exact solution-based channel assignment scheme in terms of interference minimization ability of the solution methods at varying K, and different ζ.

3.6 Chapter Conclusion

This chapter has detailed the studies of channel assignment and cluster formation in heterogeneous multi-channel cognitive radio networks. Firstly, the heterogeneities of both PU activities and SUs in terms of the varying channel condition on cluster formation for spectrum sensing and access, which have not been addressed in literature are taken into consideration. Based on these, cluster formation conditioned on the outdated CSI is statistically modeled. Secondly, with the target to minimize interference to the PUs and create multiple spectrum access opportunities for the SUs, the overlapping cluster-based assignment problem is formulated into a non-linear integer programming. In order to obtain an efficient solution, the problem is transformed into a mixed integer linear problem, based on which, an exact solution and two new heuristic algorithms with near-optimal solutions in the aspect of average cluster size and the average number of assigned channels per SU are proposed.

Chapter 4

Fusion Rule and Cluster Head Selection Schemes

4.1 Introduction

Cluster based cooperative spectrum sensing in cognitive radio networks provides for reduced sensing error, reporting delays and improved energy efficiency, in a practical network. However, achieving these advantages depends on suitably selecting a cluster head and adopting an appropriate fusion rule. This chapter investigates a new decision fusion rule, which makes the cluster heads non-cooperative sensing decision a necessary condition for cooperative decision making. The chapter also presents a comparative numerical study of three existing cluster head selection schemes with respect to their performance in CSS, under varying detection thresholds and cluster's heterogeneity. A robust and generalized cluster head selection scheme that overcomes the limitations of the existing schemes is thereafter proposed. The performance of the existing cluster head selection schemes depends on the distribution of secondary users (SUs) relative to the primary user's (PU) position, and the detection threshold. Simulation results show that the proposed cluster head selection scheme can overcome the limitations of existing schemes. Furthermore, the hard decision fusion rule being proposed indicates improved performance compared with the OR rule in minimizing the total error rate over Rayleigh fading channels. Part of the work presented in this chapter has been published in the *IET Communications*, vol. 13, no. 6, pp. 758 - 765, March 2019.

The rest of the chapter is organized as follows: Section 4.2 highlights the related works in hard decision fusion rule and cluster head selection schemes in the literature and then the main contributions presented in this chapter, Section 4.3 presents the system model. The cooperative spectrum sensing performance evaluation for the k-out-of-n fusion rule in homogeneous CRN is presented in Section 4.4, while the proposed decision fusion rule in an heterogeneous network is derived in Section 4.5. In Section 4.6, the comparative study of the existing cluster head selection schemes and the proposed scheme are presented. The simulation results are presented and analyzed in Section 4.7, with conclusion drawn in Section 4.8.

4.2 Related Works

Cooperative spectrum sensing is known to reduce the negative effect of the imperfection in wireless channel on the performance of spectrum sensing in cognitive radio networks. This results from the fact that it exploits the benefit of spatial distribution SUs [34, 132]. However, as network grows numerically and geographic size, the gains from cooperative sensing tends to decline due to the effect of fading and increase in reporting sensing decision. Grouping SUs into clusters help to circumvent the problem of large networks. In cluster based network [133, 134], SUs in the network are arranged into smaller groups known as clusters either through a self-organized distributed algorithm based on game theoretic approach [132], [33, 37, 47] or by centralized arrangement [43, 47, 52, 53, 56, 58] based on the existence of secondary user base station (SBS).

The commonly used hard decision fusion scheme to determine the status of PU is based on a k-out-of-n fusion rule [76]. This is equivalent to OR, AND, and majority rule with $k = 1$, $k = n$, or $k \geq \frac{n}{2}$ respectively. The OR rule favours low probability of collision, at the expense of low spectrum usage, because only one SU sensing result is needed to decide the status of a channel. When this SU result is in error, opportunity to access the channel is lost, resulting in low throughput. On the other hand, the AND rule results in high spectrum usage at the expense of high interference to the PU [76, 86, 87], leading to possible high energy consumption. Investigation by Zhang *et al* in [88] indicates that majority rule is optimal in minimizing the total error probability in an additive white Gaussian noise (AWGN) channel. The performance of the k-out-of-n rule is however different in a fading channel as the study in [84] shows that the OR rule is optimal in Rayleigh fading channel.

In [87], the authors studied the performance of 'k-ratio' logic as a hard decision fusion rule, where m in this case is a natural number between one and the total number of the cooperating SUs. The decision fusion rules for multiple hypotheses in heterogeneous wireless sensor networks are studied in [89], while an energy-efficient sequential decision fusion (SDF) scheme based on k-out-of-n rule is proposed in [90]. However, it is very interesting to note that it is a common convention in a clustered cognitive radio network that cluster heads are selected as nodes with optimum integrity in terms of residual energy and the accuracy of their non-cooperative sensing decisions. The afore-mentioned literature and others have not exploited this sensing decision integrity in cooperative decision making.

The cluster head implements the fusion activity and also organizes the cluster members for medium access through information broadcast. Proper selection of a cluster head is therefore critical to obtaining the full benefit of cooperative spectrum sensing. In [66], the residual energy of sensors is considered a selection criteria in the wireless sensor network. The motivation for this choice is that since cluster head is required to perform more functions than an ordinary node in the cluster, it must consume more energy. Another important consideration is also the location of the selected cluster head within the cluster space. This has a direct relationship with energy consumption of both the cluster head and the cooperating members during decision reporting and broadcasting. In [68], the cluster head is selected based on the ratio of the residual energy to the combination of the sum of squared distance from a proposed cluster head to every other user and a squared distance from the proposed cluster head to the base station (BS).

In [62], the user with the minimum sum of distance to the other users is adopted as cluster head. This is equivalent to selecting the cluster head as the SU closest to the cluster center [33, 63, 64], or the SU having the highest number of single-hop neighbors. This choice not only results in minimal reporting and broadcasting energy to the other cluster members, but also in reducing probability of reporting error, since both transmit energy and probability of error increases with distance. The authors in [33, 65] determine the cluster head as the SU with the lowest probability of miss-detection. The selection criteria in [33, 65] is based on the fact that since the cluster head needs not report its sensing decision as does other SUs, (in a distributed network arrangement), then a 'channel busy' decision from the cluster head would be sufficient to declare the channel in question as busy, based on OR fusion rule. In [47], authors adopted the cluster head that minimizes the cooperative probability of miss-detection in the cluster. However, none of the existing cluster head selection schemes has considered the heterogeneity of the clusters in terms of SUs distribution relative to the PU. The general assumption has been that secondary users are always uniformly distributed relative to the PU, which is not always the case in practice.

Therefore, in this chapter, a new decision fusion rule, which prioritize the non-cooperative sensing decision of the cluster head in making a cooperative decision in cognitive radio network is derived. A comparative study of three existing cluster heads selection schemes is also made and a new selection scheme which takes into consideration the heterogeneity of clusters is proposed. The main contributions of this chapter are therefore summarized as

1. A new fusion rule termed CH+k-out-of-n rule, which takes into consideration the sensing reliability of cluster head in making cooperative decision is presented. This is different from the existing k-out-of-n fusion rule in literature in that the proposed scheme prescribes that the non-cooperative sensing result of cluster head is a necessary criteria for cooperative sensing decision.

2. A derived expression for the presented CH+k-out-of-n fusion rule, which takes into consideration the heterogeneity of a practical cognitive radio networks in terms of differences in the received signal-to-noise ratio at the terminals of the SUs.

3. A comparative study of the three existing cluster head selection schemes in cognitive radio networks is presented. Results show that the performance of each scheme in cooperative sensing is subject to the detection threshold and SUs' distribution relative to position of the PU.

4. A generalized and robust cluster heads selection scheme that responds to the detection threshold and cluster's heterogeneity in terms of SUs distribution relative to the position of the PU is also presented.

4.3 System Model

An infrastructure based cognitive radio network with one PU and n SUs randomly located within a geographic area covered by the network is considered. The existence of SUs central controller (CC) is assumed and the coordinates of the SUs and the SNR value of the PU at the SUs are assumed to be known. The received signal from the PU at the secondary user has the form

$$x_i(t) = h_i(t)s(t) + w_i(t), \qquad i \in \{1, 2, ...n\}, \tag{4.1}$$

where $h_i(t)$ and $w_i(t)$ represent the time varying channel coefficient and the additive white Gaussian noise (AWGN) with zero mean μ, and variance σ^2 (i.e., $w \sim \mathcal{N}(0, \sigma^2)$). The goal of the spectrum sensing is for the SU to decide between two hypotheses, that is

$$x_i(t) = \begin{cases} w(t) & : H_0 \\ h_i(t) \otimes s(t) + w_i(t) & : H_1 \end{cases}, \tag{4.2}$$

where H_0 and H_1 hypotheses denote the absence and the presence of the PU signal on channel respectively. The energy detector of each evaluates the average sample energy of the PU signal, denoted as E_i and compares it with a threshold ε to determine the status of the channel. Hence, the decision that the PU signal is present is made if $E_i \geq \varepsilon$, otherwise the PU signal is absent.

The performance of the detector can be measured in terms of the probabilities of detection and that of false alarm. The probability of detection is the probability that the SU detector decides that the PU signal is present when it is actually present, denoted as $P_{d,i}$, while the probability of false alarm is the probability that the SU detects the presence of the PU signal when in reality, the signal is absent and it is denoted as $P_{f,i}$. That is $P_{d,i} = Pr\left\{decision = H_1|H_1\right\}$, and $P_{f,i} = Pr\left\{decision = H_1|H_0\right\}$.

In a Rayleigh channel, $P_{f,i}$ is independent of the signal-to-noise ratio, but the amplitude gain of the channel varies due to fading. The pdf of the SNR under fading follows an exponential function, and the average probability of detection under Rayleigh fading is derived as in (4.4)

$$P_{f,i} = Pr\left\{E_i \geq \varepsilon|H_0\right\} = \frac{\Gamma(u, \frac{\varepsilon}{2})}{\Gamma(u)}, \tag{4.3}$$

$$P_{d,i} = e^{\frac{\varepsilon}{2}} \sum_{k=0}^{u-2} \frac{1}{k!}\left(\frac{\varepsilon}{2}\right)^k + \left(\frac{1+\gamma_{i,j}}{\gamma_i}\right)^{u-1} \times \left\{e^{-\frac{\lambda}{2(1+\gamma_i)}} - e^{-\frac{\varepsilon}{2}} \sum_{k=0}^{u-2} \frac{1}{k!}\left(\frac{\varepsilon\gamma_i}{2(1+\gamma_i)}\right)^k\right\} [122], \tag{4.4}$$

where $\Gamma(a, x) = \int\limits_x^\infty t^{a-1}e^{-t}dt$, is the incomplete gamma function and $\Gamma(a)$ the complete gamma function. The parameter γ_i denotes the average signal-to-noise ratio of the PU signal at SU i. The probability that the SU does not detect the PU signal when it is actually present is referred to as the probability of miss-detection, expressed as

$$P_{m,i} = Pr\left\{decision = H_0|H_1\right\} = 1 - P_{d,i}. \tag{4.5}$$

4.4 Cooperative Spectrum Sensing Performance Evaluation

In the cluster based cooperative spectrum sensing, each SU sends its sensing result in terms of the probability of false alarm, and the probability of miss-detection as evaluated in (4.3), (4.4) and (4.5) to the cluster head, which evaluates these results based on any of the fusion rules. Using the k-out-of-n rule for the decision fusion, the cooperative probability of detection and false alarm can be expressed as in [5]. That is, decision in favor of the presence of PU on the channel is made by the fusion center if at least k SUs out of n cluster members report the presence of the PU on the channel, and absence otherwise. Hence, the cooperative probabilities of detection and that of false alarm as computed by the fusion center are expressed as [5, 88, 104],

$$Q_d = \sum_{i=k}^{n} \begin{pmatrix} n \\ k \end{pmatrix} (1 - P_d)^{n-i} P_d^i, \tag{4.6}$$

$$Q_f = \sum_{i=k}^{n} \begin{pmatrix} n \\ k \end{pmatrix} (1 - P_f)^{n-i} P_f^i, \tag{4.7}$$

where P_d and P_f are the average over the statistics of n SUs. That is, $P_d = \frac{1}{n}\sum_{i=1}^{n} P_{d,i}$ and $P_f = \frac{1}{n}\sum_{i=1}^{n} P_{f,i}$ ([91]). When the reporting error between the SUs and the fusion center is taking into consideration, the received local decision can be obtained by substituting P_d and P_f with $P_{d,i}^I$ and $P_{f,i}^I$ in (4.6) and (4.7) respectively to obtain

$$P_\chi^I = (1 - P_\chi)P_e + P_\chi(1 - P_e) \tag{4.8}$$

where $P_\chi^I = \frac{1}{N}\sum_{i=1}^{N} P_{\chi,i}^I$, and the parameter $P_{\chi,i}^I$ represents the probability of detection or false alarm of SU i. The subscript χ denotes d or f for "detection" or "false alarm" respectively. The expressions in (4.6) and (4.7) reduce to OR, majority rule, and AND rule for $K = 1$, $K > [\frac{N}{2}]$ or $K = N$ respectively. The probability of error in reporting the local decision at the fusion center $P_{e,i,c}$ is expressed as

$$P_{e,i,c} = \frac{1}{2}\left\{1 - \sqrt{\frac{\bar{\gamma}_{i,c}}{1 + \bar{\gamma}_{i,c}}}\right\}, \tag{4.9}$$

where $\bar{\gamma}_{i,c}$ is the average signal-to-noise ratio of SU i at the cluster head c.

4.5 Decision Fusion Rule in Heterogeneous Network

The studies in e.g. [5, 88, 104] assume an homogeneous secondary user network, where $P_{d,i}^I = P_d^I$ and $P_{f,i}^I = P_f^I$. Under this assumption, the global decision follows a *Binomial distribution* as expressed in (4.6), (4.7). However, this assumption can only yield an optimal result if SUs have identical signal-to-noise ratio and same reporting errors, which are not always the case in practice. In an heterogeneous network, SUs are characterized with non-identical SNRs on the sensing and reporting channels. As a result, the global decision follows a *Poisson-binomial* distribution as [126]

$$Pr(K) = \sum_{A \in F_k} \prod_{i \in A} p_i \prod_{j \in A^c} (1 - p_j) \tag{4.10}$$

The parameter F_k in (4.10) is the set of all combinations of k integers that can be obtained from $A \subset \{1, 2, 3, ..., N\}$. If $p_i = \bar{p}$ for all i, the expression in (4.10) reduces to the usual binomial distribution in (4.6) and (4.7). In the proposed hard decision fusion rule, the fusion activity at the common receiver can be evaluated as

$$\begin{cases} \sum_{i=1}^{n}(CH+\psi_i) \geq CH+K & : H_1 \\ otherwise & : H_0 \\ \quad 1 \leq k \leq n-1 \end{cases} \tag{4.11}$$

where ψ_i is the individual SU statistic defined as

$$\psi_i = \begin{cases} E_i \geq \varepsilon & 1 \\ otherwise & 0 \end{cases} \tag{4.12}$$

The expression in (4.11) is generalized to the conventional AND rule with $k = (n-1)$. Therefore, the global probability of detection and false alarm can be derived as

$$Q_d = Pr\{H_1|H_1\} = P_{d,c} \sum_{i=k}^{n \backslash c} \sum_{B \in F_k} \prod_{i \in B} P_{d,i}^{I} \prod_{r \in B^c} (1 - P_{d,r}^{I}) \tag{4.13}$$

and

$$Q_f = Pr\{H_1|H_0\} = P_{f,c} \sum_{i=k}^{n \backslash c} \sum_{B \in F_k} \prod_{i \in B} P_{f,i}^{I} \prod_{r \in B^c} (1 - P_{f,r}^{I}) \tag{4.14}$$

where $B \subset \{1, \cdots n\} \setminus c$ and B^c is a complement of B (i.e., $B \bigcup B^c \subseteq \{1, \cdots, n\} \setminus c$). The parameter n is the number of SUs in the cluster, c denotes SU index selected as the cluster head and F_k is the set of all combinations of k integers that can be obtained from $\{\{1, \cdots n\} \setminus c\}$ i.e., $|F_k| = \begin{pmatrix} n-1 \\ k \end{pmatrix}$ elements.

The fusion center therefore computes the global probability of false alarm, Q_f, and the global detection probability, Q_d, by using the local reported $P_{f,i}$ values from (4.3) and $P_{d,i}$ values in (4.4). The parameters $P_{d,c}$ and $P_{f,c}$ are the probability of detection and the probability of false alarm of the SU selected from $\{1, 2, ..., n\}$ as the cluster head, $P_{d,i}$ and $P_{f,i}$ are the set of k integers that can be selected from $\{\{1, 2, ..., n\} \setminus c\}$, while $P_{d,r}$ and $P_{f,r}$ are the complements of $P_{d,i}$ and $P_{f,i}$ that can be selected from $\{1, 2, ..., n\} \setminus c$. Therefore, $\{c \bigcup B \bigcup B^c\} \subseteq \{1, \cdots, n\}$, and $\{c \cap B \cap B^c\} = \emptyset$. The expressions in (4.13) and (4.14) generalized to the conventional AND rule for $k = n-1$ in an heterogeneous network. The case of $k = 1$ can be referred to as the modified OR rule.

The effect of possible error in the cluster heads non-cooperative decision on the global result and network performance is embedded in Equations (4.13) and (4.14). This is expressed in terms of the probability of detection and probability of false alarm of the non-cooperative sensing decision of the cluster head.

4.6 Cluster Head Selection Algorithm

In this section, three different existing cluster head selection schemes are explored with a view to propose a scheme that maximizes the network performance in the cooperative spectrum sensing. The heterogeneity of the cluster is considered in terms of the distribution of the SUs relative to PU.

4.6.1 Comparative study of existing schemes

The cluster head selection schemes in the clustered cognitive radio networks could be formulated as one of the following

- Scheme I: $Arg\min_{c} P_{m,i}$ [33, 65],
- Scheme II: $Arg\min_{c} Q_m$ [47],
- Scheme III: $Arg\min_{c} \sum_{\substack{v'=1 \\ v',v\ \in n \\ v\neq v'}}^{n} \{dist(v',v)\}$ [33, 62–64],

where $P_{m,i}$ is as previously expressed in (4.5). The cooperative probabilities of miss-detection (Q_m) and that of false alarm (Q_f) based on the modified OR rule (i.e. at $k = 1$) are obtained from (4.15) and (4.16) as

$$Q_m = 1 - P_{d,c} \sum_{i=1}^{n\backslash c} \sum_{B\in F_k} \prod_{i\in B} P^I_{d,i} \prod_{r\in B^c} (1 - P^I_{d,r}), \tag{4.15}$$

and

$$Q_f = P_{f,c} \sum_{i=1}^{n\backslash c} \sum_{B\in F_k} \prod_{i\in B} P^I_{f,i} \prod_{r\in B^c} (1 - P^I_{f,r}). \tag{4.16}$$

Scheme III selects the SU that minimizes the sum of distances to all the cluster members, and this is equivalent to selecting the cluster head as the SU closest to the cluster center, or the SU having the highest number of single-hop neighbors. The distance $d(v, v')$ from the cluster head to each of the cluster members can be found using Euclidean distance formula as

$$dist(v, v') = \sqrt{(x_v - x_{v'})^2 + (y_v - y_{v'})^2} \tag{4.17}$$

4.6.2 Proposed Cluster Head Selection Algorithm

In heterogeneous cognitive radio network where each cluster is peculiar in terms of the SUs' distribution, adopting any of the existing head selection schemes arbitrarily across all clusters may not yield an optimal result. In order to address this issue, a robust and generalized cluster head selection algorithm, which takes into consideration the heterogeneity of each cluster to maximize performance is proposed. In order to achieve this, each of the SUs initially assumes to be a cluster head, and obtain both $P_{m,z}$ (from the central controller) and $\bar{\gamma}_{i,z}$ (by measuring the average SNR of the other SUs within the cluster). With these information, each of the SUs computes Q_m, Q_f and d_{sum}, and then exchanges the computed results among themselves in order to identify the SU with the lowest value in these variables. The candidate SUs that minimize Q_m and d_{sum} computes the normalized penalty of each scheme on the cooperative probability of false alarm and the cooperative probability of miss-detection as expressed in (4.18), (4.19) and (4.20). The cluster head is selected as the SU that minimizes this normalized penalty. Algorithm 3 describes the proposed cluster head selection scheme.

Algorithm 3 Cluster Head Selection Scheme

1: **procedure** CLUSTER HEAD SELECTION.
2: **Input**: P_f, u
3: $CH^{initial} \leftarrow SUi, \quad i \in \{1, ..., n\}$
4: Each SU i measures $\bar{\gamma}_{i,z}$ of SUz and obtain both the probability of miss-detection ($P_{m,z}$) and the co-ordinates of SU z from central controller ($z \neq i$, $z \in \{1, ..., n\}$)
5: SU i computes Q^i_m, Q^i_f and d^i_{sum} ($= \sum_{i=1}^{n} \{dist(i, z)\}$) from (4.15), (4.16) and (4.17)
6: SU i broadcast Q^i_m Q^i_f and d^i_{sum} to SU z
7: SU i receives Q^z_m, Q^z_f and d^z_{sum} from SU z
8: SU i evaluates $\hat{Q}_m = arg\min Q_m$, $\hat{Q}_f = arg\min Q_f$ and $\hat{d}_{sum} = arg\min\{d_{sum}\}$ $CH \leftarrow min\{s, t, u\}$
9: **Output**: CH
10: **end procedure**

The parameters s, t and u from Algorithm 3 are the normalized penalties which can be expressed as

$$s = \frac{\left|\hat{Q}_m - Q_m(arg\min\{d_{sum}\})\right|}{\hat{Q}_m} \tag{4.18}$$

$$t = \frac{\left|\hat{Q}_f - Q_f(arg\min Q_m)\right|}{\hat{Q}_f} \tag{4.19}$$

$$u = \frac{\left|\hat{Q}_f - Q_f(arg\min\{d_{sum}\})\right|}{\hat{Q}_f} \tag{4.20}$$

One advantage of this scheme is in its ability to respond to the network dynamics. As the network structure changes in terms of the users' distribution and the detection threshold, the cluster head also follows the changes in order to maintain high sensing quality. The computational complexity of the algorithm is polynomial, and its rate of convergence depends on the number of SUs and the number of functions evaluation. The solutions for Q_m and Q_f require $(n-1)n^2$ computation each. It equally takes $3n^2$ computation to obtain the solution in 4.16 as showing in Table 4.1. The parameter n is the number of SUs. In all, the algorithm requires $2(n-1)n^2 + 3n^2$ computation with polynomial complexity order of $\mathcal{O}(n^3)$.

TABLE 4.1: Complexity Analysis for generalized cluster head selection scheme

Function Evaluation	Time complexity	Space Complexity
Q_m	$\mathcal{O}((n-1)n^2)$	$\mathcal{O}(n)$
Q_f	$\mathcal{O}((n-1)n^2)$	$\mathcal{O}(n)$
d_{sum}	$\mathcal{O}(3n^2)$	$\mathcal{O}(n^2)$

It is important to note that Q_m is a monotonically increasing function of the detection threshold ε, while Q_f monotonically decreases with ε. Hence the values of Q_m and Q_f that can be obtained based on the selected cluster head vary on the ε scale, and can instinctively decides the choice of cluster head selection scheme. The curve of the total error i.e. $(Q_m + Q_f)$ against the detection threshold has a global minimum at $\varepsilon^* = arg\min\limits_{\varepsilon}(Q_m + Q_f)$, which corresponds to the solution $\frac{\partial Q_m}{\partial \varepsilon} + \frac{\partial Q_f}{\partial \varepsilon} = 0$, where $Q_m = 1 - Q_d$. The expressions for $\frac{\partial Q_m}{\partial \varepsilon}$ and $\frac{\partial Q_f}{\partial \varepsilon}$ from (4.15) and (4.16) can be respectively obtained as

$$\frac{\partial Q_m}{\partial \varepsilon} = -\sum_{i=k}^{n\backslash c} \sum_{B \in F_K} \Bigg[\prod_{i \in B} P^I_{d,i} \prod_{r \in B^c} (1 - P^I_{d,r}) \frac{\partial P^I_{d,c}}{\partial \varepsilon} + P^I_{d,c} \prod_{r \in B^c} \left(1 - P^I_{d,r}\right) \sum_{i=1}^{k} \prod_{i' \in B \backslash i} P^I_{d,i'} \frac{\partial P^I_{d,i}}{\partial \varepsilon}$$
$$- P^I_{d,c} \prod_{i \in B} P^I_{d,i} \sum_{r=1}^{n-k} \prod_{r' \in B^c \backslash r} P^I_{d,r'} \frac{\partial P^I_{d,r}}{\partial \varepsilon} \Bigg] \quad (4.21)$$

where from (4.8),

$$\frac{\partial P^I_d}{\partial \varepsilon} = (1 - 2P_{e,i,c}) \frac{\partial P_d}{\partial \varepsilon}, \quad (4.22)$$

and,

$$\frac{\partial P^I_f}{\partial \varepsilon} = (1 - 2P_{e,i,c}) \frac{\partial P_f}{\partial \varepsilon} \quad (4.23)$$

.

Using the identity $\Gamma\left(a+1,x\right)=a!e^{-1}\sum_{m=0}^{a}\frac{x^m}{m!}$ ([127], 8.352), the expression in (4.4) can be written as

$$P_{d,i}=\frac{\left(u-1,\frac{\varepsilon}{2}\right)}{(u-2)!}+\left(\frac{1+\gamma_i}{\gamma_i}\right)^{u-1}\times e^{-\frac{\varepsilon}{2(1+\gamma_i)}}\left[1-\frac{\Gamma\left(u-1,\frac{\varepsilon\gamma_i}{2(1+\gamma_i)}\right)}{(u-2)!}\right] \tag{4.24}$$

where,

$$\frac{\partial P_d}{\partial\varepsilon}=\frac{1}{(u-2)!}\frac{\partial}{\partial\varepsilon}\Gamma\left(u-1,\frac{\varepsilon}{2}\right)+\left(\frac{1+\gamma_i}{\gamma_i}\right)^{u-1}\left[e^{-\frac{\varepsilon}{2(1+\gamma_i)}}\frac{\partial}{\partial\varepsilon}\left(1-\frac{\Gamma\left(u-1,\frac{\varepsilon\gamma_i}{2(1+\gamma_i)}\right)}{(u-2)}\right)\right.$$
$$\left.+\left(1-\frac{\Gamma\left(u-1,\frac{\varepsilon\gamma_i}{2(1+\gamma_i)}\right)}{(u-2)}\right)\frac{\partial}{\partial\varepsilon}e^{-\frac{\varepsilon}{2(1+\gamma_i)}}\right] \tag{4.25}$$

with $\Gamma(a,x)=\int_0^\infty e^{-t}t^{a-1}$([127], 8.350), the derivative of the incomplete gamma function can be evaluated as $\Gamma(a,x)'=-x^{a-1}e^{-x}$. Therefore, the first term of (4.25) can be expressed

$$\frac{1}{(u-2)!}\frac{\partial}{\partial\varepsilon}\Gamma\left(u-1,\frac{\varepsilon}{2}\right)=-\frac{1}{(u-2!)}\cdot\frac{\varepsilon^{u-2}}{2^{u-1}}e^{-\frac{\varepsilon}{2}} \tag{4.26}$$

while,

$$\frac{1}{(u-2)!}\frac{\partial}{\partial\varepsilon}\Gamma\left(u-1,\frac{\varepsilon\gamma_i}{2(1+\gamma_i)}\right)=-\frac{1}{(u-2)!}\frac{\gamma_i e^{-\frac{\varepsilon\gamma_i}{2(1+\gamma_i)}}}{2(1+\gamma_i)}\left(\frac{\varepsilon\gamma_i}{2(1+\gamma_i)}\right)^{u-2} \tag{4.27}$$

Therefore, the expressions in (4.25) can be expressed as

$$\frac{\partial P^I_{d,\xi}}{\partial\varepsilon}=(1-2P_{e,i,c})\left(\frac{1-\gamma_\xi}{\gamma_\xi}\right)^{u-1}\frac{e^{-\frac{\varepsilon}{2(1+\gamma_\xi)}}}{2(1+\gamma_\xi)}\times\left[\frac{\Gamma\left(u-1,\frac{\varepsilon\gamma_\xi}{2(1-\gamma_x i)}\right)}{(u-2)!}-1\right] \tag{4.28}$$

where $P^I_{d,\xi}$, $\xi\in\{c,i,r\}$ represents the non-cooperative probabilities of detection of the three categories of the SUs in (4.21). Similarly, γ_ξ, $\xi\in\{c,i,r\}$ also denotes the SNR of the three categories of the SUs as γ_c, γ_i, and γ_r.

$$\frac{\partial Q_f}{\partial\varepsilon}=\sum_{i=k}^{n\backslash c}\sum_{B\in F_K}\left[\prod_{i\in B}P^I_{f,i}\prod_{r\in B^c}(1-P^I_{f,r})\frac{\partial P^I_{f,c}}{\partial\varepsilon}+P^I_{f,c}\prod_{r\in B^c}\left(1-P^I_{f,r}\right)\sum_{i=1}^{k}\prod_{i'\in B\backslash i}P^I_{f,i'}\frac{\partial P^I_{f,i}}{\partial\varepsilon}\right.$$
$$\left.-P^I_{f,c}\prod_{i\in B}P^I_{f,i}\sum_{r=1}^{n-k}\prod_{r'\in B^c\backslash r}P^I_{f,r'}\frac{\partial P^I_{f,r}}{\partial\varepsilon}\right] \tag{4.29}$$

The expression for P_f^I can be obtained from (4.3) and (4.8) while, $\frac{\partial P_{f,\xi}^I}{\partial \lambda}$ can be expressed as

$$\frac{\partial P_{f,\xi}^I}{\partial \varepsilon} = -\frac{(1-2P_{e,i,c})}{(u-1)!}\frac{\lambda^{u-1}}{2^u}exp\Big(-\frac{\varepsilon}{2}\Big) \tag{4.30}$$

The parameter $P_{f,\xi}^I, \xi \in \{c, i, r\}$ represents the non-cooperative probabilities of false alarm of the three categories of SUs in (4.29). From (4.21) and (4.29), the solution to $\frac{\partial Q_m}{\partial \varepsilon} + \frac{\partial Q_f}{\partial \varepsilon} = 0.$ can be evaluated numerically.

4.7 Simulation Results

This section presents simulation results in a bid to verify the performance of the proposed schemes in comparison with the existing schemes. The cluster is assumed to be within a $2km \times 2km$ square area. The PU transmit power is set to $P_{PU} = 50mW$, and the SU transmit power to report sensing bits $P_{SU_i} = 20mW\ \forall i \in N$. The noise power $\sigma^2 = -90dBm$ [33], while for path loss, $\mu = 3$, $\kappa = 1.0$. Unless otherwise stated, the probability of false alarm $P_f = 0.015$ and the time-bandwidth product $u = 5$ [135–139]. The probability that the considered channel is idle is set as $P(H_0) = 0.8$ while the probability that the channel is busy $P(H_1) = 0.2$. Statistical results are averaged over 2000 random locations of SUs.

4.7.1 Decision Fusion Rule

Fig. 4.1 illustrates the total error rate against detection threshold in different network scenarios (i) when the probability of detection for each SU is the averaged over the statistic of n nodes, that is $P_d^I = \bar{P}_{d,i}^I, \forall i \in n$ [5, 88, 104] , and (ii) with different probability of detection for each SU. The result shows that the performance of the cooperative spectrum sensing under the assumption of homogeneity can be misleading if applied to an heterogeneous network especially at large detection threshold. The obtained result reveals that total error rate could be higher under the assumption of homogeneity. This is because in general, the product of n positive numbers is less or equal to the average over the statistic of n to the power of n (i.e $\prod_{i=1}^n b_i \leq \big(\frac{1}{n}\sum_{i=1}^n b_i\big)^n$) with equality holding only when all n numbers are equal. Consequently, $Q_m(\bar{P}_d) \geq Q_m(P_{d,i})$. Fig. 4.2, compares the receiver operating curve (ROC) of the existing fusion rule with the proposed rule. Basically, the proposed rule generalized to 'AND' for $k = n-1$. The result shows that for $k = 1$, the proposed rule can operate at a lower probability of false alarm than the OR fusion rule, but at the expense of a high probability of miss-detection.

Figs. 4.3 and 4.4 illustrate that OR (AND) rule can greatly minimize the cooperative probability of miss-detection (false alarm), but at the expense of increased probability of false alarm (miss-detection) in agreement with the literature. However, the result in Fig. 4.4, indicates that cooperative probability of false alarm decreases with increasing threshold in the proposed rule, while it remains constant after a particular threshold value in the k-out-of-n rule. In general, it can be seen that the proposed rule can achieve lower probability of false alarm than the k-out-of-n fusion rule for improved spectrum utilization.

The result in Fig. 4.5 indicates that the optimal value of k for which the proposed rule minimizes the total error rate depends on the detection threshold. At very small threshold, the optimal rule is at $k = 6$. As the detection threshold increases, the optimal k value that minimizes the total error approaches unity, with CH+($k = 1$)-out-of-n rule being the optimal at large value of detection threshold. Comparing the proposed rule with the k-out-of-n rule, the result indicates that the proposed rule at $k = 1$ is better than the OR rule and the AND rule for all regions of detection threshold, and also outperforms the majority rule at large value of detection threshold. However, as the number of SUs that are required to make sensing decision increases, the performance of the two rules is seen to be comparable. For instance, the performance of CH+k-out-of-n at $k = 5$, and that of k-out-of-n at $k = 6$ are very close.

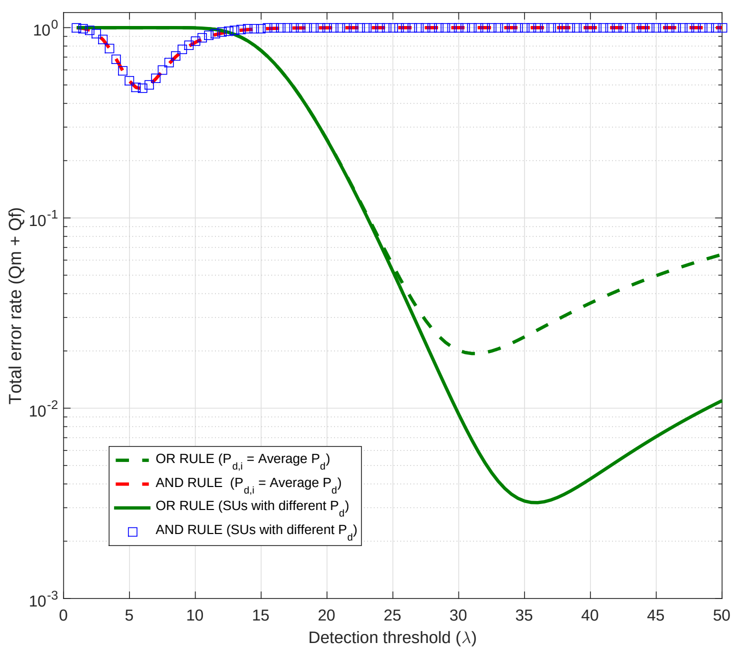


FIGURE 4.1: Comparing total error rate against detection thrshold for homogeneous and heterogeneous networks in Rayleigh fading channels.

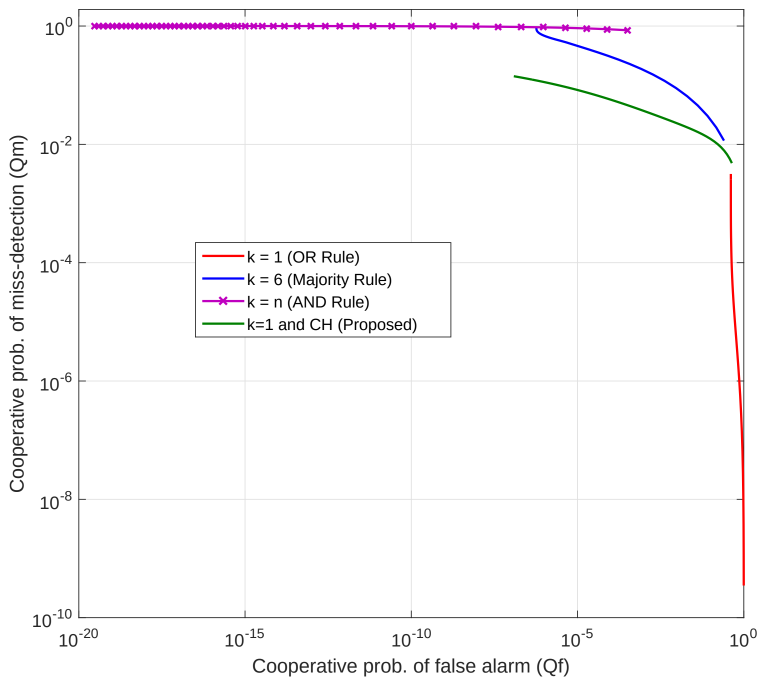


FIGURE 4.2: ROC performance comparison of the proposed rule and the conventional k-out-of-n rule in Rayleigh fading channels: $0 \leq \varepsilon \leq 50$.

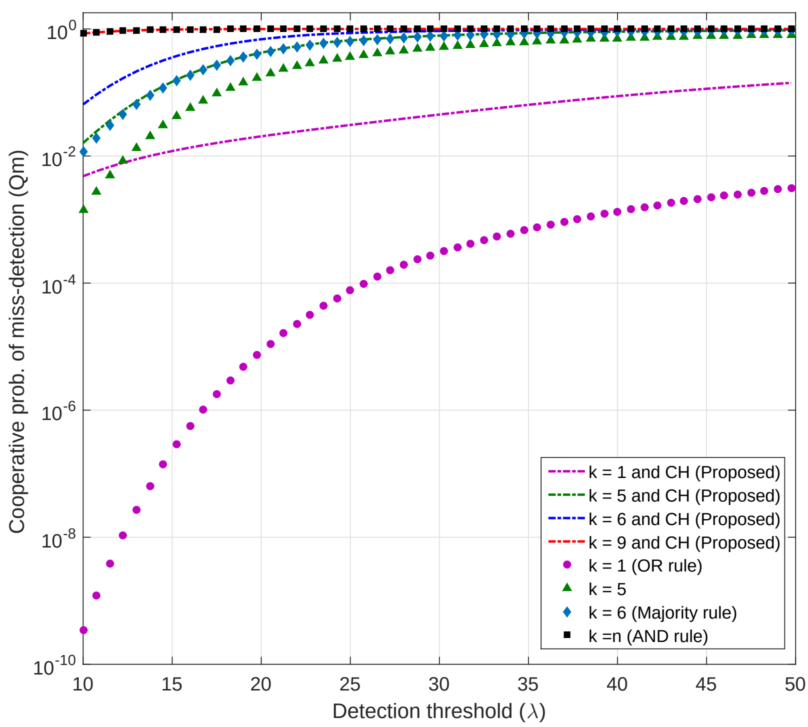


FIGURE 4.3: Cooperative probability of false alarm against detection threshold in the proposed and the conventional fusion rule in Rayleigh fading channels.

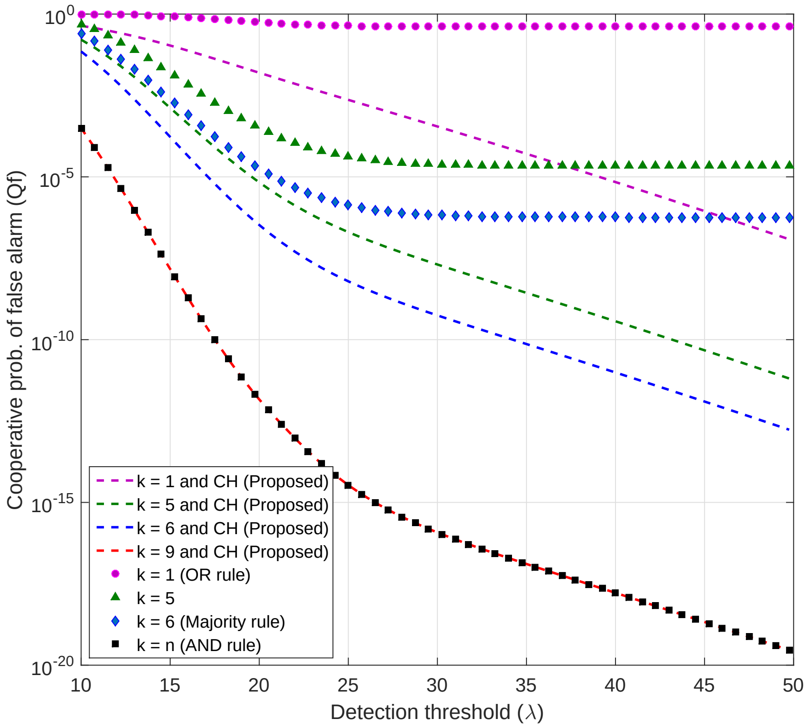


FIGURE 4.4: Cooperative probability of miss-detection against detection threshold in the proposed and the conventional fusion rule in Rayleigh fading channels.

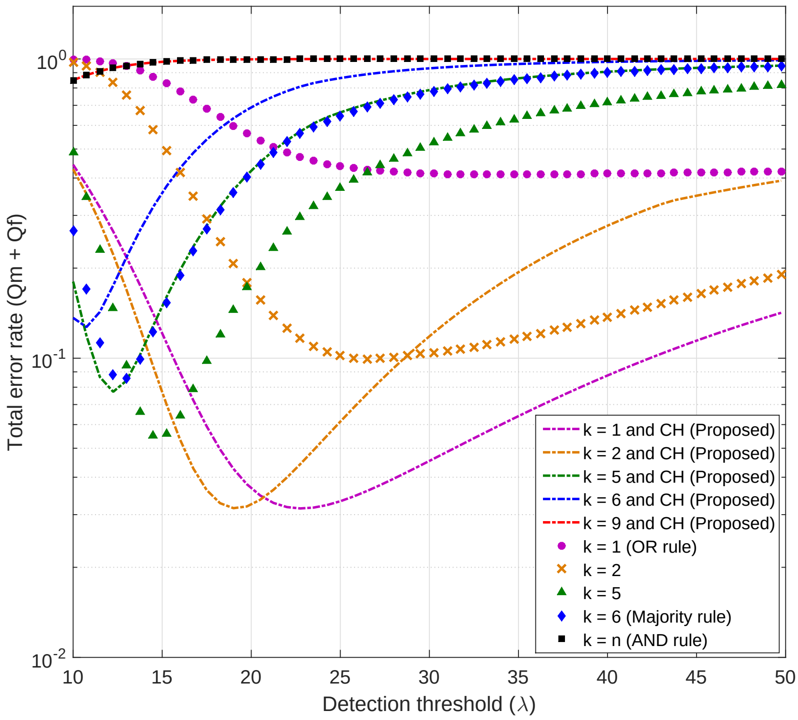


FIGURE 4.5: Total error rate against detection threshold in the proposed and the conventional fusion rule in Rayleigh fading channels.

4.7.2 Cluster Head Selection Scheme

The PU is first placed at the center of the cluster with SUs randomly deployed in the area around it. Subsequently, the PU is moved towards the boundary and then beyond (shown in Fig. 4.6) in order to investigate the impact of the position of the PU relative to the distribution of SUs. Fig. 4.7 shows the corresponding distance between the cluster head and the PU as the PU moves away from the cluster's center. With scheme I, the cluster head follows the PU closely until the PU reaches the boundary. The only criteria is to maximize its SNR for a reliable spectrum sensing. On the other hand, in schemes II and III, the distance between the PU and the cluster head increases as the PU distance from the center increases. The goal of scheme III is to ensure fairness among the SUs, hence its criteria does not depend on the property of PU signal. Scheme II on the other hand need to achieve trade-off between maximizing the SNR and fairness among the SUs. It is however worth noting that when SUs are uniformly distributed around a PU that is located at the center of a cluster, all the existing schemes seem to elect the same SU as the cluster head.

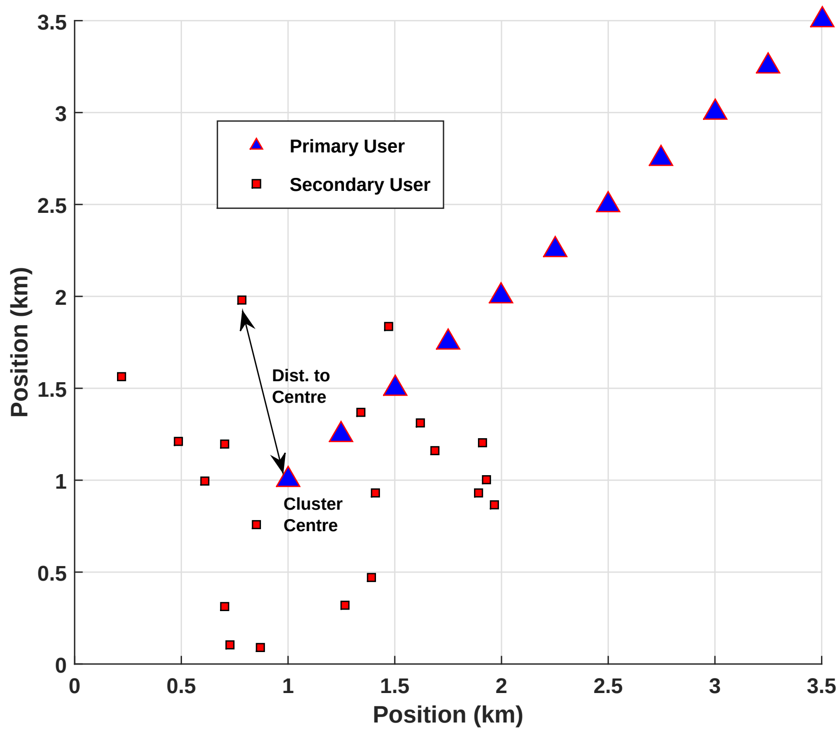


FIGURE 4.6: Secondary users distribution relative to varying PU location.

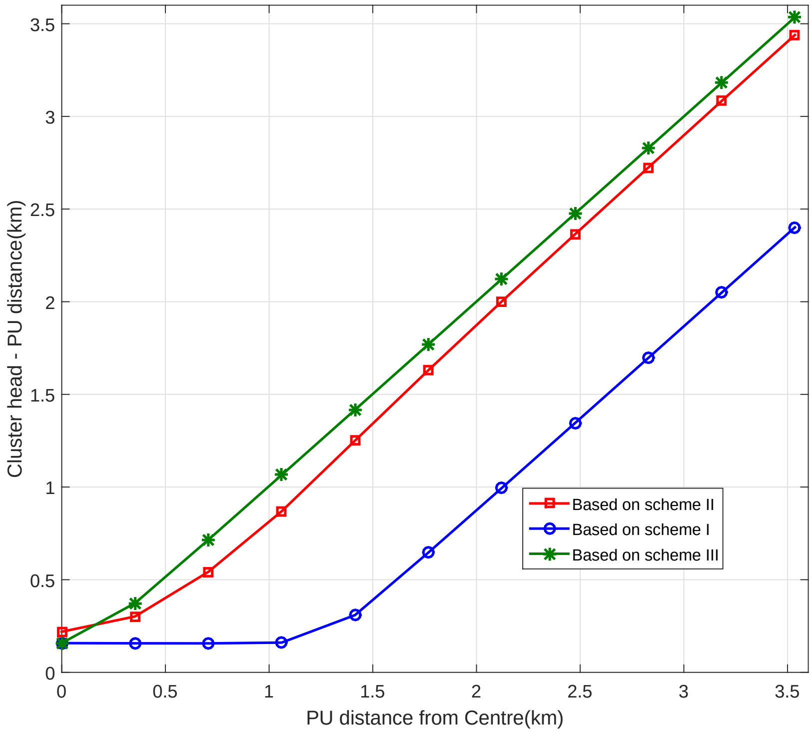


FIGURE 4.7: Cluster head to PU distance with varying PU location.

From the results in Figs. 4.8, 4.9, 4.10 and 4.11, it can be seen that as the PU moves away from the center (where the density of SUs is higher), the penalty of adopting any of the exiting schemes on the sensing performance changes. In each case, the penalty increases, reaches a maximum when the PU is at the cluster's boundary, and then decrease or remains constant as the PU moves further away from the center. Figs 4.8 and 4.9 show that the performance of each of the schemes is subject to the network dynamics in terms of the relative location of the PU to the SUs and the detection threshold (based on constant false alarm rate (CFAR)). In Fig. 4.8 with $P_f = 0.015$, scheme II is the optimal selection method since it does not only minimizes the cooperative probability of miss-detection, it also presents the lowest penalty on the cooperative probability on false alarm. However, at $P_f = 0.001$ in Fig. 4.9, scheme III becomes optimal as the PU moves further away the SUs' cluster area. Scheme I presents high penalty to both cooperative probability of false alarm and cooperative probability of miss-detection. In this scheme, since the cluster head follows the PU, the probability of reporting error from other SUs increases with increasing distance of the PU from the center, and this consequently increases both Q_f and Q_m.

Although a small u is common in cognitive radio networks spectrum sensing, a large time bandwidth product may be used in some instances when detection at low SNR is required. By increasing the observation time or the bandwidth used for sensing, the SUs can improve their non-cooperative probability of miss-detection. Figs. 4.10 and 4.11 show that at large value of $u = 100$, scheme II is optimal only when the PU is not too far from the center. As the distance increases, scheme III becomes optimal, since the penalty of adopting II on Q_f is very high. The results in Figs. 4.10 and 4.11 also show the performance of the proposed selection scheme in overcoming the limitations of the existing schemes. These results show that the proposed scheme can provide a robust and generalized selection method that jointly takes into consideration the varying detection threshold and general network dynamics in terms of varying SUs distribution relative to PU.

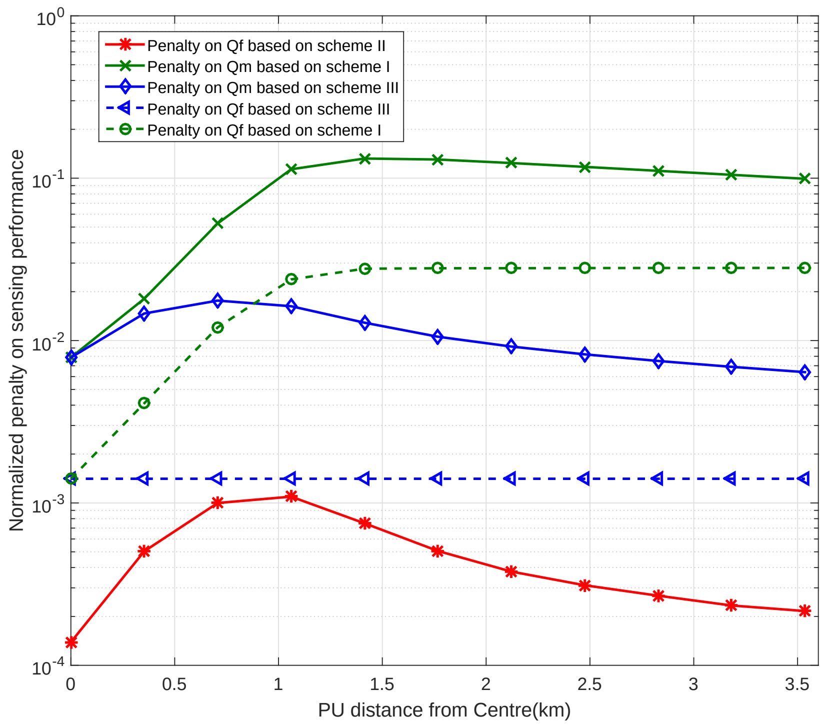


FIGURE 4.8: Performance comparison of different cluster head selection schemes in heterogenous clusters for cooperative spectrum sensing, $P_f = 0.015, u = 5$.

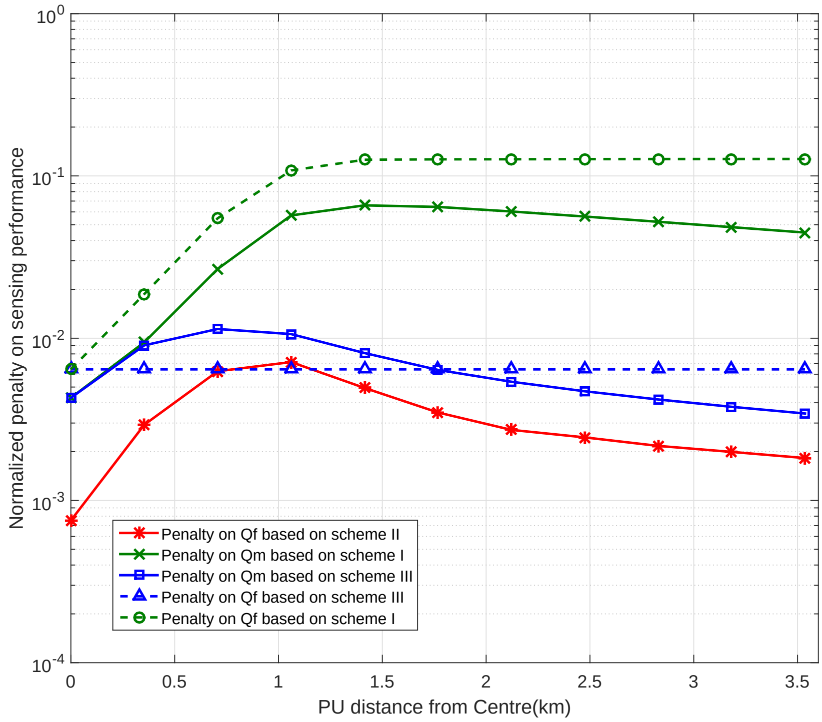


FIGURE 4.9: Performance comparison of different cluster head selection schemes in heterogenous clusters for cooperative spectrum sensing, $P_f = 0.001, u = 5$.

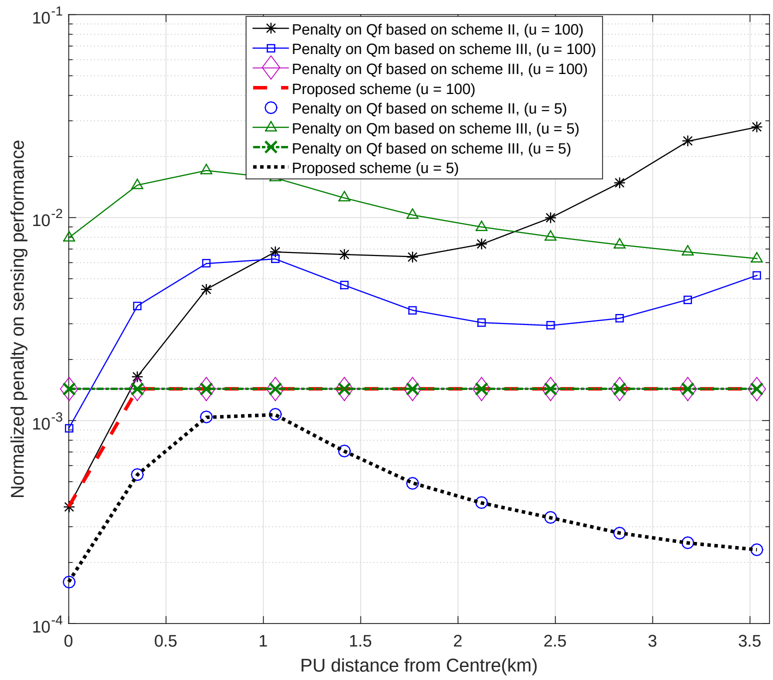


FIGURE 4.10: Performance comparison of different cluster head selection schemes in heterogenous clusters for cooperative spectrum sensing, $P_f = 0.015$.

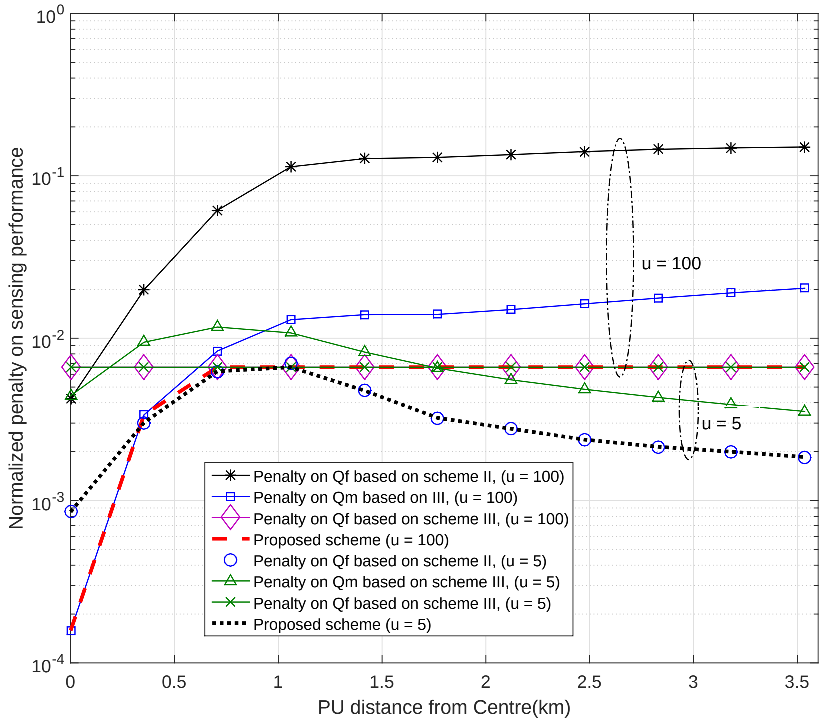


FIGURE 4.11: Performance of the proposed scheme in reducing the probability of sensing error, $P_f = 0.001$.

4.8 Chapter Conclusion

Achieving a target quality sensing performance in a clustered cognitive radio network depends on appropriate decision fusion rule and suitably selecting the cluster head. In this chapter a new hard decision fusion rule termed CH+k-out-of-n has been proposed. In this fusion rule, the non-cooperative sensing decision of the cluster head is prioritized and becomes a necessary criteria to decide the status of the channel being sensed. Results show that the proposed fusion rule can achieve a lower total error rate than the conventional k-out-of-n rule in a Rayleigh fading channel. In particular, the results presented indicate that the proposed modified OR rule can outperform the conventional OR rule in minimizing the total error rate in cooperative spectrum sensing. The OR rule however, remains the optimal decision fusion rule to minimize interference to the primary user signal in a Rayleigh fading channel.

In addition, a comparative study of the three existing cluster head selection schemes has been made. At small value of detection threshold, the selection method based on scheme II is optimal, because the scheme not only minimizes the cooperative probability of miss-detection, the penalty on the probability of false alarm is also very small. On the other hand, at high detection threshold (which is required when sensing low SNR signal), scheme III becomes the optimal method. It is also worth noting that the performances of the existing schemes highlighted are subject to network dynamics, and using any of the schemes arbitrarily can be critical in a network where clusters are heterogeneous in terms of the SUs' distribution relative to the PU, and the target sensing quality. This work therefore proposes a generalized and robust selection scheme that takes into consideration the varying detection threshold and cluster's heterogeneity to follow the network dynamics for improved cooperative spectrum sensing.

Chapter 5

Cooperative Spectrum Sensing in Multichannel EH-CRNs

5.1 Introduction

This chapter investigates cooperative spectrum sensing in a multi-channel cognitive radio networks (CRNs) with energy harvesting. In the conventional cognitive radio networks (which can otherwise be referred to as unconstrained energy CRN), a sensing-throughput trade-off [5] exists, which hinges on the sensing time and sensing accuracy. However, in the context of EH-CRNs, these outcomes of the sensing process (i.e. the sensing time and sensing accuracy) are energy constrained, making the EH-CRNs a more complicated scenario. The goal in this chapter therefore are two-folds. Firstly, to determine the optimal sensing parameters for effective management of the limited energy budget in order to maximize the achievable throughput. Secondly, to exploit the benefits of a practical CRN towards improving the performance of the EH-CRNs. Two different scenarios are considered. In the first, each secondary user (SU) is assigned a single RF harvesting source, while in the second, each SU is assigned multiple RF harvesting sources and can opportunistically harvest from any of the sources. For these scenarios, the problem is formulated as a stochastic optimal control with an infinite and continuous state and action spaces. This is known to be computationally intractable and becomes even more complicated in a two dimensional problem such as considered. In other to reduce the computational complexity, a myopic optimization approach is taken, and the problem reduces to a mixed integer nonlinear problem (MINLP) to determine the channel assignment, the sensing duration, the distribution of the sensing duration to the assigned channels and the detection threshold under the constraint of energy causality and PU protection. A near-optimal solution is obtained to the MINLP based on the alternating convex optimization technique. Simulation results obtained show that the considered work can improve the amount of energy harvested. Hence, the active probability of the SUs can be improved by exploiting the multi-channel benefit of a practical CRN for an enhanced throughput. Part of the work presented in this chapter has been submitted for publication, and it is currently under revision in the *IEEE Access Journal*.

The remainder of the paper is organized as follows. Section 5.2 is the summary of related work in literature and the main contribution presented in this Chapter. Section 5.3 describes the system model. Section 5.4 details the formulation of the problem as an optimal stochastic optimization, which is then converted to a myopic problem and solved in Section 5.5. Numerical results are provided in Section 5.8 while conclusions are presented in Section 5.9.

5.2 Related Works

The effect of energy arrival rate on spectrum sensing and access policy in EH-CRN is investigated in [100] and [101], where the authors formulated the problem as a constrained partially observable markov decision process (POMDP). In particular, the studies in [100] identify the optimal sensing policy, while [101] is an extension of [100] to determine the optimal sensing policy and detection threshold that maximize the expected total throughput under energy causality and collision constraints. Chung *et al* in [103] investigated the relationship between the optimal sensing duration and the corresponding sensing threshold with the purpose of conserving energy while the average throughput is maximized. In [102], the authors analyzed the theoretical upper bound on the maximum achievable throughput of the energy harvesting based secondary user as a function of the energy arrival rate and the temporal correlation of the primary traffic under an energy causality and collision constraints. The fundamental trade-off between spectrum sensing and the SU expected throughput for a conventional energy unconstrained CRN is studied in [5]. Inspired by [5], the authors in [104] focused on the harvesting-sensing-throughput trade-off and the joint optimization for save-ratio (i.e. the proportion of the frame length expended on harvesting energy, denoted as $\rho : 0 \leq \rho < 1$), sensing duration, sensing threshold and fusion rule to maximize the expected throughput in the EH-CRN. Nevertheless, [100–104] merely address a non-cooperative spectrum sensing where a single SU co-exits with only one PU on the channel.

The authors in [106] however, investigated a sensing-throughput optimization problem in EH-CRN based on cooperative spectrum sensing among the participating SUs. In particular, the authors focused on the trade-off between sensing time and sum capacity of the SUs with respect to transmission power and sensing time. In [111], the authors considered the design of a heterogeneous energy efficient and energy harvesting cooperative spectrum sensing (EEH-CSS) scheme subject to the fundamental EEH-CSS constraints. The authors considered the heterogeneity of the SUs in terms of the non-identical harvesting, sensing, and reporting characteristics. The problem in [111] is formulated to determine the optimal asymptotic active probability, sensing duration, and detection threshold that maximize the achievable total throughput.

The study in [106] formulated the problem into a mixed integer non-linear program (MINLP) with the objective to determine the access decision variables, the transmit power, the optimal sensing time and the number of slot that maximize the average throughput. In [107], the authors employ the finite-horizon POMDP model to derive the optimal policy that can maximize the expected throughput while satisfying the PU detection and the energy causality constraints. The study in [108] optimizes the optimal sensing time that maximizes average throughput and the harvested energy. In [109], for an overlay EH CRN, the authors aim to find an optimal sensing time to maximize throughput of SU and the harvested RF energy. Residual energy maximization is explored with spectrum sensing and SU transmission in [110].

The critical issue in EH-CRN from the afore-mentioned literature is that the RF energy arrival from the ambient RF is random, while the magnitude of the electrical energy derived from the harvested RF may not always be sufficient to maximize throughput. The work in [111, 112] considered a hybrid energy harvesting network model where the secondary user is capable of harvesting energy from both renewable sources (e.g. solar) and ambient radio frequency signals. However, the concern with this is that the application of such conventional renewable energy could be limited in certain environment, time and weather and, this could be critical in applications where quality of service is of utmost concern. In [113], the SU splits the channel into two sub-channel sets. One for sensing the PU and the other for collecting the RF of the PU signal. In the transmission slot, the harvested energy is supplied to compensate the sensing energy loss in order to guarantee the throughput. The problem is formulated to determine the optimal sub-channel set, sensing time, and transmission power that maximize the aggregate throughput, harvested energy and the energy efficiency of the SU over all the sub-channels. However, the details of the energy source for data transmission is missing. In [114], RF energy could be harvested from the PU and the reporting SUs, and the problem is formulated into a multi-objective optimization (MOP) to optimize the spectrum sensing performance, under the constraints of the harvested energy at SU and the interference from SU on PU receiver. The afore-mentioned works only investigate a single channel case, which is quite simplistic for communication systems. Practical wireless communication networks are inherently multi-user and multichannel with peculiar challenges and benefits.

The authors in [115, 116] propose a multi-band harvesting schemes where SU can sense the spectrum to determine the harvesting and communication geographical zones, such that it can take a decision to harvest or transmit data based on the zone it belongs. An SU requiring to transmit data would need to stay in at least one of harvesting zones of active PUs, otherwise the SU will have no energy for transmitting data. In [115] the problem is formulated to jointly optimize the sensing samples and sensing threshold in order to minimize the sensing time and hence maximize the harvested energy. The authors in [116] investigated the problem to determine the optimal channel selection probability that maximizes the average throughput of SUs. Nevertheless, cooperative spectrum sensing is not considered in [115, 116].

Optimal multi-channel cooperative spectrum sensing in energy unconstrained CRN has been studied in [93], where the authors formulated the problem to determine the optimal sensing time in a slot and how the total sensing time can be distributed to all channels. However, for energy harvesting system, the sensing-throughput trade-off that naturally exits in a conventional CRN is further complicated by energy constraint. Nevertheless, inspired by [93], the work presented in this chapter focuses on finding the optimal cooperative spectrum sensing parameters in multi-channel cognitive radio networks with energy harvesting. In addition, the work presents here also investigates a different network scenario from the study in [93], in terms of the channel assignment to each user. Hence, the main contributions of the work presented in this chapter are as follow.

1. Different from the studies on EH-CRNs, which focuses on single channel network model [106], [111], the work presented in this chapter considers the performance of energy harvesting secondary users in a practical multichannel environment. In order to enhance the spectrum sensing performance, the secondary networks (SN) is modeled as an overlapping clusters, where the number and the candidate channels assigned to each user are not necessarily equal. In addition, the heterogeneity of the network is also considered in terms of sensing quality of the cooperating secondary users.

2. The performance of the EH-CRNs has been reported to be limited in terms of the achievable throughput due to low energy arrival rate. However, by exploiting the benefit of the multi-channel scenario in this work, the amount of energy harvested can increase with increasing number of the assigned channels to each SU, which intuitively improves the active probability of the SUs towards enhancing the achievable throughput. However, this is not without a cost, since energy consumption also increases with the number of channels sensed, revealing that there is an optimum number of PU channels to SU exists which maximize the energy efficiency of the EH-CRN.

3. With a goal to maximize the average throughput of the energy harvesting based SUs, the problem is formulated into a mixed integer non-linear optimization problem (MINLP) to jointly determine the optimal channel assignment, sensing duration in each frame, distribution of the sensing duration among the assigned channels for every SUs, and the

detection threshold of each SU sensing each channel. This differs from [106], [111] and [93], in that while [106] and [111] only considered the problem in a single channel EH-CRN, the authors in [93] investigated the problem in a conventional (energy unconstrained) CRN, where a set of SUs are made to sense the same group of PU channels.

5.3 System Model

5.3.1 Cognitive Radio Network Model

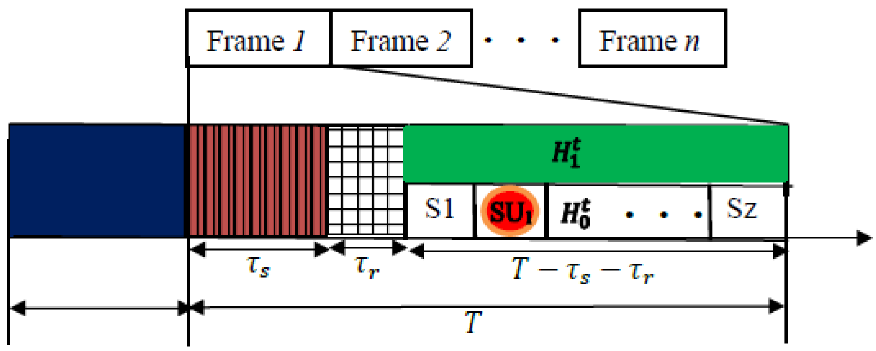
This work presented in this chapter considers cooperative spectrum sensing in multichannel cognitive radio networks with energy harvesting secondary users. The network comprises N SUs and M PUs, both randomly deployed within a $5km$ by $5km$ square area. The distance between PUj and SUi is denoted as $d_{i,j}^{sp}$ whereas the distance between SUi and SUk ($i \neq k$) is $d_{i,k}^{ss}$. Both $d_{i,j}^{sp}$ and $d_{i,k}^{ss}$ are random values, since the deployment of both PUs and SUs are assumed random. The secondary users' network includes a central controller (CC) located within the transmission range of the SUs. The CC gathers the individual SU parameters such as the evaluated non-cooperative probability of miss-detection, the channel list, and the co-ordinates of the SUs locations. The CC is responsible for the frequency assignment based on the received information from the SUs. Therefore, the frequency assignment is done centrally, while cooperative spectrum sensing for channel access is distributed since SUs in each cluster cooperatively decide the status of each channel.

The considered time slotted operation of active energy harvesting based secondary users (EH-SUs) with heterogeneous SNR is illustrated in Figures 5.1a and 5.1b, in which cluster formation (or channel assignment) precedes the sensing-transmission/ harvesting frame. The frame length T is divided into a sensing period with duration τ_s, the reporting/data fusion/broadcasting time of τ_r and the transmission/harvesting period of $t_T = T - \tau_s - \tau_r$. During the sensing phase, each SU executes local spectrum sensing of the assigned K channels within period τ_s based on energy detection method. The SUs then report the sensing results to the corresponding cluster heads in each of the K clusters for cooperative decision. Each SU is updated with the channel status by the cluster heads through broadcast. It is assumed that the secondary user network is scheduled to transmit on time division multiple access (TDMA) protocol. Therefore, the transmission period in each frame is further divided into (data transmission) slots, and each SU i is allocated a slot $t_{i,j}$ on its transmit channel j, which is equivalent to

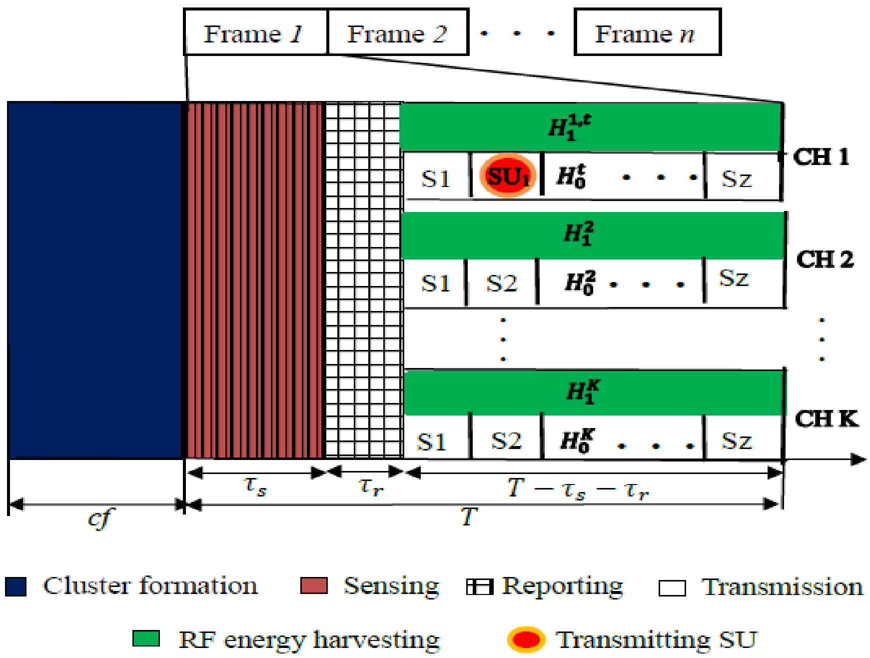
$$t_{i,j} = \frac{(T - \tau_r - \tau_s)}{z^j}, \quad \forall i \in \{1, 2, \cdots z^j\}, \tag{5.1}$$

where the parameter z^j denotes the number of SUs assigned to transmit on channel j.

Fig. 5.1a shows a scenario where each SU can opportunistically transmit or harvest RF energy from the transmit channel only. For instance, $SU1$ in the figure first cooperate with other SUs in all the K clusters to sense the PU channels in those K clusters. If the transmit channel is determined idle H_0^t, the SU would transmit its data in the transmission slot $S2$ and then sleep in the remaining period. However, if the transmit channel is busy H_1^t, the SU harvest energy throughout the period. It is assumed that channel status does not change within a frame. Fig. 5.1b on the other hand illustrates the scenario where SU can opportunistically harvest from multiple RF sources.



(a)



(b)

FIGURE 5.1: System model illustrating the frame structure of the cooperative spectrum sensing activities in EH-CRNs with (a) single RF harvesting source, (b) multiple RF harvesting sources.

In Fig. 5.1b, after cooperative spectrum sensing to determine the channel status, $SU1$ harvest RF energy from the transmit channel ($CH1$) if the channel is busy $H_1^{1,t}$. If the channel is idle $H_0^{1,t}$, the SU transmits on slot 2 of $CH1$ and then harvest opportunistically from any of the $K-1$ (i.e. $2, \cdots, K$) channels for the remaining period.

Fig. 5.2 illustrates the considered (overlapping) clusters, in which multiple channels are assigned to each SU, while each PU can cooperatively be sensed by multiple SUs. This is a case of many-to-many combinatorial assignment. Therefore, a cluster is made up of a group of SUs that cooperate to sense a particular PU channel. In this case, an SU can belong to multiple clusters. Hence, all the SUs in a cluster may not necessarily share one channel for transmission in every frame. Following the channel assignment at the beginning of each frame, each SU selects one of the K assigned channels randomly as a transmit channel. It is assumed that the energy requirement for cluster formation is negligible compared to the energy demand for spectrum sensing and data transmission, since the bulk of the cluster formation/channel assignment work is done by the central controller.

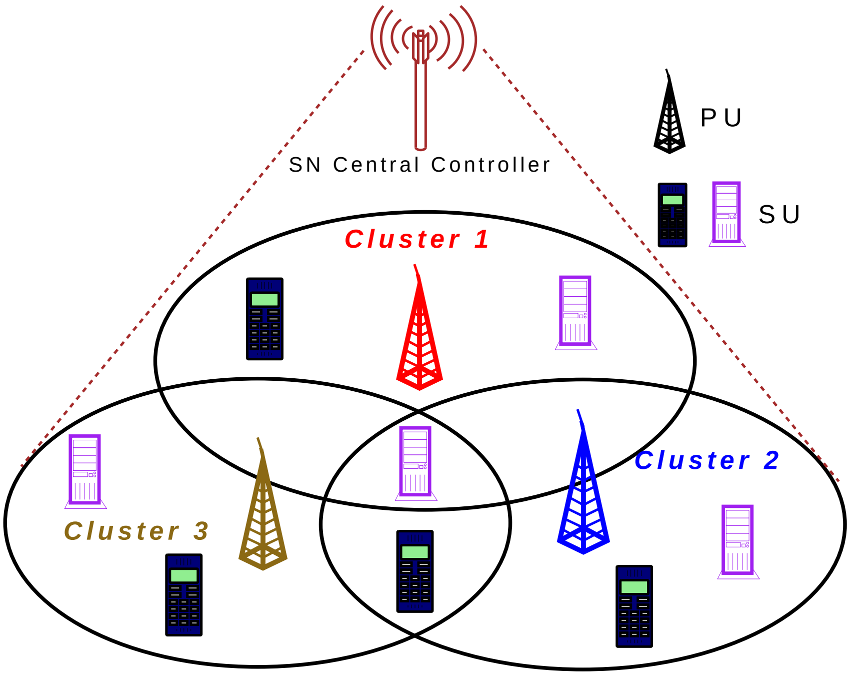


FIGURE 5.2: Network model illustrating overlap clustering assignment.

5.3.2 Primary Network Model

A primary network (PN) with M narrow band spectrum (channels) is considered. The network equally comprise of M PUs that share these spectrum, such that each PU is licensed to one channel. The primary user traffic on each channel is modeled as a time homogeneous discrete Markov process as assumed for example in [111]. Therefore, the spectrum randomly alternates its states between the channel being vacant and occupied. If $S_{j,t}$ denotes the spectrum occupancy state of channel j on slot t, then the binary hypothesis of the channel status can be represented as $S_{j,t} \in \{0(vacant), 1(busy)\}$. The steady state probabilities of the channel being idle and busy are denoted as $P(H_0)$ and $P(H_1)$.

5.3.3 Cooperative Spectrum Spectrum

Spectrum sensing is executed during the sensing phase. The number of channels assigned to each SU (otherwise referred to as channel list) is denoted as K, where K_i $(1 \leq K_i \leq M)$ is the number of channels assigned to user i. The channel list may be different for different users. Each SU independently senses the assigned channels sequentially within the sensing period denoted by $\tau_s = \sum_{j=1}^{M} x_{i,j}\tau_{i,j}$, $\forall i = \{1, ..., N\}$, where $x_{i,j}$ is the assignment variable and $\tau_{i,j}$ denotes the sensing time of SU i on channel j. The sensing results are then reported to the corresponding head in each cluster through a dedicated common control channel (CCC) based on time-slotted scheme. Each cluster head makes a cooperative decision about the channel status and updates the SUs through broadcasts. Hence, each SU is updated with the cooperative sensing decisions of the K assigned channels from the respective cluster heads.

Assuming a complex valued PSK modulated signal and circularly symmetric complex Gaussian (CSCG) noise for primary signal and additive noise in the wireless channel, the probabilities of detection and false alarm as evaluated by SU i on channel j can be expressed as

$$P_{d,i,j} = Q\left(\left(\frac{\varepsilon_{i,j}}{\sigma_w^2} - \bar{\gamma}_{i,j} - 1\right)\sqrt{\frac{\tau_{i,j} f_s}{2\bar{\gamma}_{i,j} + 1}}\right) \tag{5.2}$$

$$P_{f,i,j} = Q\left(\left(\frac{\varepsilon_{i,j}}{\sigma_w^2} - 1\right)\sqrt{\tau_{i,j} f_s}\right) \tag{5.3}$$

where, $\varepsilon_{i,j}$, $\bar{\gamma}_{i,j}$, f_s and σ_w denote the detection threshold of SU i on channel j, the average SNR of channel j on SU i, the sampling frequency and the noise variance respectively. The probability of a miss-detection can be obtained from (5.2) as

$$P_{m,i,j} = 1 - P_{d,i,j} \tag{5.4}$$

The cooperative probability of detection and the cooperative probability of false alarm as computed by each cluster head for each channel based on OR decision fusion are evaluated as

$$Q_{D,j} = 1 - \prod_{i=1}^{N} (1 - P_{d,i,j})^{x_{i,j}}, \quad \forall j = \{1, \cdots, M\} \tag{5.5}$$

$$Q_{F,j} = 1 - \prod_{i=1}^{N} (1 - P_{f,i,j})^{x_{i,j}}, \quad \forall j = \{1, \cdots, M\} \tag{5.6}$$

The OR rule is adopted as a decision fusion rule being the optimal rule to minimize interference to the primary user.

5.3.4 Energy Model

It is assumed that the SU can only perform either spectrum sensing followed by data transmission, or energy harvesting at a time. Therefore, the charging process must stop while the SU draws energy from the storage device to either sense the spectrum or transmit the data in its queue. The power consumption by each SU for spectrum sensing, cooperative spectrum sensing overhead and data transmission activities are denoted as p_s, p_r, and p_t respectively. The energy state of the SU storage facility (e.g. a super-capacitor) at the beginning of the n^{th} frame is denoted as $e_{i,n}$. Hence, SU cannot participate in the cooperative spectrum sensing when $e_{i,n} < (p_s\tau_s + p_r\tau_r)$.

It is assumed that the SU can harvest only RF energy from the transmitting PU, and the maximum amount of energy that can be harvested in the n^{th} frame is expressed as:

$$e_{h,i,n} = P_{avail}\ t_T\ Pr(\varrho), \tag{5.7}$$

where $t_T = (T - \tau_s - \tau_r)$ is the maximum period available for energy harvesting in each frame. The parameter $P(\varrho)$ denotes the probability that there is an harvestable RF energy, and $P_{avail} = P_R\ \eta_{H/C}$ represents the output of the secondary user harvesting circuit, which is defined as the product of the amount of received RF power P_R at the SU and the harvesting circuit efficiency $\eta_{H/C}$. The amount of harvested RF energy by secondary users therefore, depends on the magnitude of the received RF power, the harvesting circuit efficiency, the harvesting duration and the probability that an RF harvesting source is available.

The total energy consumption by SU i in the n^{th} frame denoted as $e_{c,i,n}$ can explicitly be expressed as

$$e_{c,i,n} = p_s\tau_s + p_r\tau_r + \Big[P(H_0)(1 - Q_{F,j}) + P(H_1)(1 - Q_{D,j})\Big] \times p_t\ t_T, \tag{5.8}$$

where the first, second and third expression on the RHS of (5.8) are the sensing energy, the reporting energy and transmission energy respectively. Parameters $P(H_0)$ and $P(H_1)$ are the probabilities that the transmit channel is vacant and occupied with PU signal respectively. When the harvested and consumed energy are both put into perspective, the residual energy (state) at the beginning of the next $(n+1)^{th}$ frame for an infinite energy storage capacity device can be updated as

$$e_{i,n+1} = max\{0, e_{i,n} + e_{h,i,n} - e_{c,i,n}\} \tag{5.9}$$

5.4 Problem Formulation

In this section, two different scenarios are considered namely: (i) single harvesting source where the SU can harvest only from the PU occupying the transmit channel, and (ii) multiple RF harvesting source in which the SU can opportunistically harvest from any of the PU in the assigned channels.

5.4.1 Single RF Energy Harvesting Source

Under this scenario, the SU can only harvest from the elected transmit channel when occupied with a primary user signal. This model can also be used for EH-CRN with a single dedicated RF energy harvesting source. The possible energy states during the n^{th} frame are as follows

1. The channel correctly detected to be busy with probability $P(H_1)Q_{D,j}$. In this case, secondary user does not transmit, but can harvest energy from the transmitting primary user in the rest of the n^{th} frame. Therefore, the throughput is zero.

2. Channel correctly detected to be idle with probability $P(H_0)(1-Q_{F,j})$. The SU transmits in the n^{th} frame for a period of $\frac{T-\tau_r-\tau_s}{z^j}$ and sleep for the rest of the frame. Energy harvested is zero.

3. Channel incorrectly detected to be busy (false alarm) with probability $P(H_0)Q_{F,j}$. The SU's opportunity to access the channel is lost. No energy is harvested and the achievable throughput is also zero.

4. Channel incorrectly detected to be vacant (miss-detection) with probability $P(H_1)(1-Q_{D,j})$. The SU transmits in the n^{th} frame, but the data interferes with the primary user's signal, and nothing is gained.

Therefore, under this scenario, the SU can harvest energy on the transmit channel with probability $P(H_1)Q_{D,j}$, transmit data with probability $P(H_0)(1-Q_{F,j})+P(H_1)(1-Q_{D,j})$, or remain idle (neither harvesting RF nor transmitting) with probability $P(H_0)Q_{F,j}$. The amount of energy consumed and energy harvested $e^{s,\mu}_{h,i,n}$ (where, $\mu \in \{0,1\}$ denotes the channel's idle and busy status respectively) in each state can be expressed as in (5.10). While an action is taken, the SU energy state in the next frame is evaluated as (5.11).

$$\begin{array}{lll}
e^{s,1}_{h,i,n} = P_{avail} t_T P(H_1), & e_{c,i,n} = p_s\tau_s + p_r\tau_r & : P(H_1)Q_{d,j} \\
e^{s,0}_{h,i,n} = 0, & e_{c,i,n} = p_s\tau_s + p_r\tau_r + p_t\left(\frac{t_T}{z^j}\right) & : P(H_0)(1-Q_{f,j}) \\
e^{s,0}_{h,i,n} = 0, & e_{c,i,n} = p_s\tau_s + p_r\tau_r & : P(H_0)Q_{f,j} \\
e^{s,1}_{h,i,n} = 0, & e_{c,i,n} = p_s\tau_s + p_r\tau_r + p_t\left(\frac{t_T}{z^j}\right) & : P(H_1)(1-Q_{d,j})
\end{array} \tag{5.10}$$

$$e^{s}_{i,n+1} = \begin{cases} e_{i,n} + e^{s,1}_{h,i,n} - p_s\tau_s - p_r\tau_r & : P(H_1)Q_{d,j} \\ e_{i,n} - p_s\tau_s - p_r\tau_r, & : P(H_0)Q_{f,j} \\ e_{i,n} - p_s\tau_s - p_r\tau_r - p_t\left(\frac{t_T}{z^j}\right) & : P(H_0)(1-)Q_{f,j}) + P(H_1)(1-Q_{d,j}) \end{cases} \tag{5.11}$$

Therefore, from (5.10) the amount of harvested energy in a single source scenario can be expressed as

$$e^{s}_{h,i,n} = P_{avail} \cdot t_T \cdot P(\varrho^s), \tag{5.12}$$

where $P(\varrho^s) = P(H_1)$ is the probability that the single channel assigned is occupied with PU signal.

5.4.2 Multiple RF Energy Harvesting Sources

This is particularly useful in a network where primary user services may be inactive for a long period of time (e.g., digital TV broadcasting), and the stored energy in the SUs would more likely get depleted resulting in outages. The possible states during the n^{th} frame are:

1. The transmit channel correctly detected to be busy with probability $P(H_1)Q_{D,j}$. In this case, secondary user does not transmit, but can harvest energy in the rest of the n^{th} frame. Therefore, the throughput is zero.

2. Transmit channel correctly detected to be idle with probability $P(H_0)(1-Q_{F,j})$. The SU transmits in the n^{th} frame for a period $t_{i,j}$ (as defined in (5.1)) and can then harvest from any of the $K_i - 1$ channels that is found busy for the rest of the frame.

$$
\begin{array}{lll}
e_{h,i,n}^{m,1} = P_{avail} \cdot t_T P(H_1), & e_{c,i,n} = p_s\tau_s + p_r\tau_r & : P(H_1)Q_{d,j} \\
e_{h,i,n}^{m,0} = P_{avail}\frac{(z^j-1)(t_T)}{z^j}P(\Omega_1), & e_{c,i,n} = p_s\tau_s + p_r\tau_r + p_t\left(\frac{t_T}{z^j}\right) & : P(H_0)(1-Q_{f,j}) \\
e_{h,i,n}^{m,0} = 0, & e_{c,i,n} = p_s\tau_s + p_r\tau_r & : P(H_0)Q_{f,j} \\
e_{h,i,n}^{m,1} = P_{avail}\frac{(z^j-1)(t_T)}{z^j}P(\Omega_1), & e_{c,i,n} = p_s\tau_s + p_r\tau_r + p_t\left(\frac{t_T}{z^j}\right) & : P(H_1)(1-Q_{d,j})
\end{array}
\tag{5.13}
$$

$$
e_{i,n+1}^{m} = \begin{cases}
e_{i,n} + P_{avail}t_T \cdot P(H_1) - p_s\tau_s - p_r\tau_r & : P(H_1)Q_{d,j} \\
e_{i,n} - p_s\tau_s - p_r\tau_r, & : P(H_0)Q_{f,j} \\
e_{i,n} + P_{avail}\frac{(z^j-1)(t_T)}{z^j}P(\Omega_1) & \\
\quad - p_s\tau_s - p_r\tau_r - p_t\left(\frac{t_T}{z^j}\right) & : P(H_0)(1-Q_{f,j}) + P(H_1)(1-Q_{d,j})
\end{cases}
\tag{5.14}
$$

---

3. Transmit channel incorrectly detected to be busy (false alarm) with probability $P(H_0)Q_{F,j}$. The SU's opportunity to access the channel is lost. The achievable throughput is therefore zero, and no energy is harvested.

4. Transmit channel incorrectly detected to be vacant (miss-detection) with probability $P(H_1)(1-Q_{D,j})$. The SU transmits in the n^{th} frame, but the data interferes with the primary user's signal, and nothing is gained. However, energy can be harvested from any of the $K_i - 1$ channels for the rest of the frame.

Therefore, different from the single harvesting source scenario, the SU can opportunistically harvest energy in every frame except when there is a false alarm on the transmit channel. The amount of energy consumed and harvested in each state can be expressed as in (5.13). When an action is taken, the SU energy state in the next frame can similarly be expressed as (5.14). The parameter $P(\Omega_1)$ is the steady state probability that at least one of the remaining $K_i - 1$ assigned channels would be occupied by PU and thus be available for energy harvesting by the SU. This probability follows a *binomial* distribution given as

$$
Pr(\Omega_1) = \sum_{j=1}^{K_i-1} \binom{K_i - 1}{j} Pr(H_1)^j (1 - Pr(H_1))^{K_i-1-j}, \tag{5.15}
$$

where

$$
\binom{K_i - 1}{j} = \frac{(K_i - 1)!}{(K_i - 1 - j)!j!}. \tag{5.16}
$$

From (5.13), the amount of harvested energy in the multiple harvesting sources scenario can be expressed as

$$e^{m}_{h,i,n} = P_{avail} t_T \cdot P(\varrho^m), \tag{5.17}$$

where $P(\varrho^m) = \min\left(1, \left(P(H_1) + P(\Omega_1)\left(\frac{z^j - 1}{z^j}\right)\right)\right)$ is the probability of energy harvesting in a multiple source scenario. At $K_i = 1$, the expression in (5.17) becomes $e^m_{h,i,n} = e^s_{h,i,n}$ since there is no event to choose from, making $Pr(\Omega_1) = 0$. Therefore, the multichannel gain on the harvested energy (i.e. the ratio of the harvested energy in a multiple harvesting source to the harvested energy in a single harvesting source) can be evaluated as

$$G^m_{h,i,n} = \frac{e^m_{h,i,n}}{e^s_{h,i,n}} = \frac{P(\varrho^m)}{P(\varrho^s)}, \tag{5.18}$$

where the expression in (5.18) is upper bounded as $P(H_1)^{-1}$.

In both cases considered in Sections 5.4.1 and 5.4.2, the EH-CRN results in a dynamic secondary user energy state over time, and the energy level in the $(n+1)^{th}$ frame depends on the residual energy and the action taken during the n^{th} frame. The design strategy for the EH-CRN can thus be formulated as an stochastic optimal control problem given by $\pi^* = arg \max_{\pi} V^{\pi}(S_0)$, and the expected reward is defined as [140]

$$V^{\pi}(s_0) = arg \max_{\pi} \mathbb{E}\left[\sum_{r=1}^{G} \delta^{r-1} R(s_r, a_r)\right], \tag{5.19}$$

where $0 < \delta < 1$ is a discount factor that trades off the importance of the immediate and future reward, the policy π maps the SU energy state at each frame to the possible action taken, while G represents the planning horizon. Therefore, (5.19) models a general class of Markov decision processes (MDP), in which states $\{s_1, \cdots s_G\} \in S$ refer to the SU energy states, and the actions $\{a_1 \cdots a_G\} \in A$ include, spectrum sensing, energy harvesting and data transmission. The optimal value function V^{π^*} of policy π represents the maximum cumulative function of rewards (i.e. $V^{\pi^*} \geq V^{\pi}$) which can be obtained as a solution of the Bellman recursion, given by

$$\begin{aligned}
V_n(S) &= \max_{\pi} \mathbb{E}\left[R(s) + \delta \sum_{s' \in S} T(s, a, s') V_{n-1}(s')\right] \\
&= \max_{\pi} \mathbb{E}\Bigg[\frac{t_T}{T}\Bigg\{(1 - Q_{F,j})P(H_0)C_{0,j} + (1 - Q_{D,j})P(H_1)C_{1,j} \\
&\quad + \delta \textstyle\sum_{s' \in S} \left(P(H_0)(1 - Q_{F,j}) + P(H_1)(1 - Q_{D,j})\right) \\
&\quad \times \left(e_{i,n} - p_s\tau_s - p_r\tau_r - p_t\left(\frac{t_T}{z^j}\right) + \beta_{h,i,n}\right) \\
&\quad + P(H_1)Q_{D,j}\left(e_{i,n} + \phi_{h,i,n} - p_s\tau_s - p_r\tau_r\right) + P(H_0)Q_{F,j}\left(e_{i,n} - p_s\tau_s - p_r\tau_r\right)\Bigg\}\Bigg],
\end{aligned} \tag{5.20}$$

where $\pi \in \{\tau_s, \tau_{i,j}, \varepsilon\}$, the parameter $\phi_{h,i,n}$ represents the energy harvested when the transmit channel is correctly detected to be busy (as expressed in both (5.10) and (5.13)). The parameter $\beta_{h,i,n}$ represents the energy harvested from any of the $K_i - 1$ channels, which is zero for $K_i = 1$, whereas $T(s, a, s') = Pr(s'|s, a)$ is the transition function, which expresses the probability that the SU energy state changes from s' to s when action a is taken.

However, the state and action space in (5.19) for EH-CRN are continuous and infinite, making the solution computationally intractable, more especially for the multiuser, multi-channel case under consideration. Hence, in the subsequent section, the impact of the current action on the future reward will be ignored, and focus only on maximizing the expected immediate reward in an optimal myopic strategy. This approximation method is also adopted in the works presented in [104] and [111] among others.

5.5 Approximate Formulation and Solution

Optimizing the original problem in (5.20) is a sequential decision making one which attempts to determine the immediate and future rewards based on the possible actions taken. However, this becomes very difficult due to the tight coupling between the current action and the future reward. In this section, the original stochastic optimal control problem is approximated to a myopic policy such that the optimal policy in (5.20) can be approximated as

$$\begin{aligned} V_n(S) &\approx R(x_{i,j}, \tau_s, \tau_{i,j}, \varepsilon_j) \\ &= \tfrac{(T-\tau_s-\tau_r)}{T}\Big\{(1-Q_{F,j})P(H_0)C_{0,j} + (1-Q_{D,j})P(H_1)C_{1,j}\Big\}, \end{aligned} \tag{5.21}$$

where (5.21) is the immediate reward on channel j based on the current action, the parameter $C_{0,j} = \log_2(1+\gamma_{i,j})$ represents the average capacity of the SU i on the idle channel j, and $C_{1,j} = \log_2(1+\frac{\gamma_{i,j}}{1+\gamma_j})$, denotes the capacity of the SU i when there is collision with the primary user signal (with SNR γ_j) due to miss-detection. Different from the direction solution to the problem in (5.20), this policy is essentially a static approach. Existing studies have however shown that myopic policy is close in performance to the optimal policy [141–143].

The objective is to jointly determine the optimal channel assignment ($x_{i,j}$), the detection threshold ($\varepsilon_{i,j}$), the sensing duration (τ_s), and the distribution of the sensing duration among the assigned channels ($\tau_{i,j}$). This is with a goal to maximize the average throughput of the secondary users. The time taken by user i to sense channel j, $j \in \{1, 2, .., M\}$ is denoted by $\tau_{i,j}$, $i \in \{1, 2, ..., N\}$, and both τ_s and $\tau_{i,j}$ are continuous variables. The average normalized throughput maximization per channel can thus be formulated as

Problem P1

$$\begin{aligned}
&\max_{\tau_s,\{\tau_{i,j}\},\{\varepsilon_{i,j}\},\{x_{i,j}\}} R(\tau_s,\tau_{i,j},\varepsilon_{i,j},x_{i,j}) \\
&= \max_{\tau_s,\{\tau_{i,j}\},\{\varepsilon_{i,j}\},\{x_{i,j}\}} \left[\frac{T-\tau_s-\tau_r}{TM} \times \sum_{j=1}^{M}\Big((1-Q_{F,j}(\tau_{i,j},\varepsilon_{i,j},x_{i,j}))P(H_0)C_{0,j}\right. \\
&\left. + (1-Q_{D,j}(\tau_{i,j},\varepsilon_{i,j},x_{i,j}))P(H_1)C_{1,j}\Big)\right],
\end{aligned} \tag{5.22}$$

subject to:

$$Q_{D,j}(\tau_{i,j},\varepsilon_{i,j},x_{i,j}) \geq \beta, \tag{C1}$$

$$e_{c,i,n} \leq \bar{e}_{h,n}, \quad i \in \{1,...,N\}, \tag{C2}$$

$$0 \leq \tau_s \leq (T-\tau_r), \tag{C3}$$

$$\sum_{j=1}^{M} x_{i,j}\tau_{i,j} = \tau_s, \quad \tau_{i,j} > 0, \qquad \forall i \in \{1,...,N\}, \tag{C4}$$

$$\sum_{j=1}^{M} x_{i,j} \leq K_{max}, \qquad \forall i \in \{1,...,N\}, \tag{C5}$$

$$\sum_{j=1}^{N} x_{i,j} \leq n_{max}, \qquad \forall j \in \{1,...,M\}, \tag{C6}$$

$$x_{i,j} \in \{0,1\}, \tag{C7}$$

where

$$\bar{e}_{c,i,n} = p_s\tau_s + p_r\tau_r + \frac{T-\tau_r-\tau_s}{M}p_t\sum_{j=1}^{M}\Big(P(H_0)(1-Q_{F,j}) + P(H_1)(1-Q_{D,j})\Big).$$

In problem P1, the expression in (5.22) defines the objective function. Constraint (C1) guarantees the protection of PU against interference from SUs, while (C2) and (C3) ensure that the energy causality and time causality are satisfied. The constraints in (C2) and (C3) guarantee that the average energy budget of the SU does not exceed its total available energy and that the time budget does not exceed the frame period respectively. Constraint (C4) ensures that the total time spent by any SU to sensing the assigned channels $K_i, (1 \leq K_i \leq M)$ does not exceed the sensing duration τ_s in a frame. In constraints (C5) and (C6), the number of PU channels that can be assigned to any SU, and the number of SUs that can be assigned to a single PU channel are limited to a specified values. Constraint (C7) defines the assignment variable type. From constraints (C5) and (C6), the assignment problem defines an overlapping cluster scheme, where an SU can belong to multiple clusters. Each cluster is however, identified with a particular channel or frequency.

The problem in P1 is a mixed integer non-linear optimization (MINLP) and non-convex jointly in $x_{i,j}$, τ_s, $\tau_{i,j}$, and $\varepsilon_{i,j}$. The problem defines a more complicated scenario due to the consideration for a practical overlapping clustered network in the multi-channel scenario. High degree of coupling also exists among the optimization variables, which makes direct decomposition difficult. In order to solve it, the approach of alternating convex optimization is adopted [144]. That is, given a non-convex problem $f(x)$ with variables $(x_1, ...x_n) \in \mathbb{R}^n$, while $t_1, ..., t_k \subset \{1, ...n\}$ are index subsets with $t_j \in \{1, ..., n\}$, and supposing the problem is convex in subset of variables x_i, $i \in t_j$, then alternating convex optimization method involves cycling through j, in each step optimizing over variable x_i while, $i \notin t_j$ are fixed [145]. Hence, the procedure alternates between determining the optimal assignment $x_{i,j}$ with fixed τ_s, $\varepsilon_{i,j}$, and $\tau_{i,j}$, and then given $x_{i,j}$, with fixed $\varepsilon_{i,j}$ and $\tau_{i,j}$, optimize over τ_s. Finally, with given $x_{i,j}$ and τ_s optimize over $\tau_{i,j}$, and $\varepsilon_{i,j}$, and vice-versa iteratively until the algorithm converges.

5.5.1 Optimal Channel Assignment

With fixed values of τ_s, $\varepsilon_{i,j}$, and $\tau_{i,j}$, problem P1 reduces to a channel assignment problem. For a fixed sensing budget in terms of the time-bandwidth product in the energy detection based sensing scheme, the sensing performance is an increasing function of the received signal-to-noise-ratio. Therefore, by taking SNR as an active parameter for determining the optimal channel assignment, the first expression in the RHS of the objective function in (5.22) reduces to a constant term since the probability of false alarm (5.2) is independent of SNR. Moreover, in the overlay CRN under consideration, the secondary users cannot have a successful transmission when the channel is occupied with the PU signal. Therefore, it is only reasonable to minimize the second expression on RHS of the objective function in problem P1, (i.e. $(1 - Q_{D,j})P(H_1)C_{1,j})$ in order to reduce both the interference to PU signal and energy consumption for unsuccessful transmission. This is equivalent to

Problem P2

$$\max_{\chi_{i,j}} Z(x_{i,j}, \tau_s, \tau_{i,j}, \varepsilon_{i,j}) = \min_{\chi_{i,j}} \sum_{j=1}^{M} \{1 - Q_{D,j}(x_{i,j})\}, \tag{5.23}$$

subject to :

$$\sum_{i=1}^{N} x_{i,j} \leq n_{max}, \; j \in \{1, 2, ..., M\}, \tag{C1}$$

$$\sum_{j=1}^{M} x_{i,j} \leq K_{max},\ i \in \{1, 2, ..., N\}, \tag{C2}$$

$$x_{i,j} \in \{0, 1\}. \tag{C3}$$

The assignment matrix is represented by $\chi = \{x_{i,j}\}_{M\times N}$, that is $x_{i,j} = 0$ or 1 depending on whether SU i is assigned channel j or not. The problem in (5.23) is a nonlinear integer programming problem. However, by substituting (5.5) into (5.23), and then using the identities $min(.) \equiv min\ log_e(.)$ and $log_e \prod(.) = \sum log_e(.)$, the objective function in (5.23) can be linearized, such that problem P2 can otherwise be expressed as a linear problem as follows

Problem P3

$$\max_{\chi_{i,j}} Z(\chi_{i,j}, \tau_s, \tau_{i,j}, \varepsilon_{i,j}) = \min_{\chi_{i,j}} \sum_{j=1}^{M}\sum_{i=1}^{N} x_{i,j} log_e \{P_{m,i,j}\}, \tag{5.24}$$

subject to :

$$\sum_{i=1}^{N} x_{i,j} \leq n_{max},\ j \in \{1, 2, ..., M\}, \tag{C1}$$

$$\sum_{j=1}^{M} x_{i,j} \leq K_{max},\ i \in \{1, 2, ..., N\}, \tag{C2}$$

$$x_{i,j} \in \{0, 1\}, \tag{C3}$$

where $P_{m,i,j}$ is the non-cooperative probability of miss-detection based on outdated channel state information [119], evaluated in Chapter 3 as

$$\bar{P}_{m,i,j} \approx 1 - exp\left(-\frac{\varepsilon_{i,j}}{2} - \frac{\gamma_{i,j}\rho_{i,j}^2}{\bar{\gamma}(1-\rho_{i,j}^2)}\right) \sum_{k=0}^{L} \frac{\left\{\bar{\gamma}_{i,j}(1-\rho_{i,j}^2)\right\}^k}{\left\{\bar{\gamma}_{i,j}(1-\rho_{i,j}^2)+1\right\}^{k+1}} \sum_{j=0}^{u+k-1} \frac{1}{j!}\left(\frac{\varepsilon_{i,j}}{2}\right)^j$$
$$\times\ {}_1F_1\left(-k, 1; -\frac{\gamma_{i,j}\rho_{i,j}^2}{\bar{\gamma}_{i,j}(1-\rho_{i,j}^2)\left\{\bar{\gamma}_{i,j}(1-\rho_{i,j}^2)+1\right\}}\right). \tag{5.25}$$

The motivation for (5.25) is to compensate for the independence of the PU activities and the effect of small scale fading during the channel assignment. The parameter $\gamma_{i,j}$ represents the instantaneous SNR of PU j at the terminal of SU i at time t, and $\bar{\gamma}_{i,j}$ denotes the average SNR of PU j at SU i. The parameter $\rho_{i,j} = J_0(2\pi F_{d,i,j}^{max}\epsilon_{i,j})$ is the correlation coefficient between the predicted channel response $\hat{h}_{i,j}$ and the outdated channel response $h_{i,j}$ (based on Jakes' correlation model), $J_0(.)$ is the Bessel function of the first kind and zeroth order, and $F_{d,i,j}^{max}$ denotes the maximum Doppler shift. Therefore, $\hat{h}_{i,j}$ and $h_{i,j}$ represent the channel responses at time $t + \epsilon_{i,j}$, and the outdated channel response at t respectively.

Equation (5.25) is a generalized expression for the probability of miss-detection in a practical channel. By setting $\rho_{i,j}^2 = 1$, which happens for $\epsilon_{i,j} = 0$ or in a properly correlated channel, the expression in (5.25) evaluates to

$$P_{m,i,j} \simeq 1 - \sum_{k=0}^{L} \sum_{j=0}^{u+k-1} \left(\frac{\varepsilon_{i,j}}{2}\right)^j \frac{\exp(-\frac{\varepsilon_{i,j}}{2})}{k!j!} \bar{\gamma}_{i,j} \exp\left(-\bar{\gamma}_{i,j}\right) \tag{5.26}$$

where the second expression on the RHS of (5.26) is the truncated series representation of a generalized Q-function ([146], Eqn. 4), which is equivalent to the non-cooperative probability of detection in an additive white Gaussian noise (AWGN) [88], that is

$$P_{d,i,j} = Q_u \left(\sqrt{2\bar{\gamma}_{i,j}}, \sqrt{\varepsilon_{i,j}}\right) \tag{5.27}$$

Problem P3 is thus a linear integer programming problem, that describes a generalized assignment problem (GAP) with overlapping clusters (since $1 \leq K_i \leq K_{max}$). The optimal solution to P3 can be easily obtained by following the same approach as presented in Chapter 3.

5.5.2 Optimal Sensing Duration in a Frame

In the objective function of problem P1, τ_s only appears in $(T - \tau_s - \tau_r)/TM$, but it is intertwined with $\tau_{i,j}$ by the constraint in (C4), hence, direct decomposition cannot be achieved. In the expression of the probability of detection and the probability of false alarm in (5.2) and (5.3), both $P_{d,i,j}$ and $P_{f,i,j}$ increase monotonically with decreasing ε, but it is practically desirable to have a high probability of detection but low probability of false alarm. Hence, the objective function in problem P1 can only achieve its maximum when constraint (C1) is at equality, which can be satisfied when the probability of detection for each user on channel j $P_{d,i,j} = P_{d,j}^{th}$. The proof to verify this is similar to that provided in [5]. The value of $P_{d,j}^{th}$ that satisfies this constraint (based on the OR - fusion rule) can be determined from (5.5) as

$$P_{d,j}^{th} = 1 - \exp\left(\frac{\log_e(1-\beta)}{\sum_{i=1}^{N} x_{i,j}}\right), \qquad \forall j \in \{1, ..., M\}, \tag{5.28}$$

where β is the constraint on the cooperative probability of detection $Q_{D,j}$. Therefore, (5.2) is equivalent to

$$\varepsilon_{i,j} = \sqrt{\frac{2\gamma_{i,j}+1}{\tau_{i,j} f_s}} Q^{-1}(P_d^{th}) + \gamma_{i,j} + 1, \tag{5.29}$$

and (5.3) can then be expressed in terms of P_d^{th} as

$$P_{f,i,j} = Q\left(\sqrt{(2\gamma_{i,j}+1)} Q^{-1}\left(P_{d,j}^{th}\right) + \gamma_{i,j}\sqrt{\tau_{i,j} f_s}\right). \tag{5.30}$$

Hence, the first constraint can be eliminated. Moreover, since $C_{0,j} \gg C_{1,j}$, and $(1 - Q_{F,j}) \gg (1 - Q_{D,j})$ in general, the value of the first expression in bracket on the R.H.S in (5.22) dominates the average throughput. Furthermore, due to the consideration for a network where the number of assigned channels to each SU are not necessarily equal, there is a dependence of K_i on the value of $\tau_{i,j}$ for each SU. Therefore, by substituting $\tau_{i,j} = \bar{\tau}_{i,j} := \frac{\tau_s}{K_i}, \ \ \forall i = \{1, \cdots, N\}$, and $P_{d,i,j} = P_{d,j}^{th}$, problem P1 can be approximated as

Problem P4: *with fixed $\tau_{i,j}$ and $\varepsilon_{i,j}$, given $\chi_{i,j}$*

$$\max_{\tau_s} \sum_{j=1}^{M} \bar{R}|_{(\tau_{i,j}=\bar{\tau}_{i,j})} = \max_{\tau_s} \frac{T_t}{TM} \times \sum_{j=1}^{M} \prod_{i=1}^{N} (1 - P_{f,i,j}(\tau_s/K_i, P_{d,j}^{th}))^{x_{i,j}} P(H_0) C_{0,j}, \tag{5.31}$$

subject to:

$$e_s + \frac{T_t}{M} p_t \sum_{j=1}^{M} \left\{ \prod_{i=1}^{N} (1 - x_{i,j} P_{f,i,j}) P(H_0) \right\} \leq \bar{e}_h, \tag{C1}$$

$$0 \leq \tau_s \leq (T - \tau_r), \tag{C2}$$

where $e_s = (p_s\tau_s + p_r\tau_r)$ and $T_t = (T - \tau_r - \tau_s)$. The Gaussian Q-function expression in (5.30) can also be written in terms of the complementary error function for ease of mathematical analysis as

$$P_{f,i,j} = \frac{1}{\sqrt{2}} \, erfc \left(\frac{\sqrt{2\gamma_{i,j} + 1} \; Q^{-1}(P_{d,j}^{th}) + \gamma_{i,j} \sqrt{\frac{f_s \tau_s}{K_i}}}{2} \right) \tag{5.32}$$

Using the same approach as in Section 5.5.1, problem P4 can be re-written in terms of logarithmic function as

$$\begin{aligned} \max_{\tau_s} \log_e \bar{R}|_{(\tau_{i,j}=\bar{\tau}_{i,j})} = \max_{\tau_s} \Bigg\{ & \log_e \frac{T_t}{TM} P(H_0) C_0 \\ & + \textstyle\sum_{j=1}^{M} \sum_{i=1}^{N} x_{i,j} \log_e \Big(1 - P_{f,i,j}(\tau_s/K_i, P_{d,j}^{th}) \Big) \Bigg\}, \end{aligned} \tag{5.33}$$

subject to:

$$E_s + \frac{T_t}{M} p_t \sum_{j=1}^{M} \left\{ \prod_{i=1}^{N} (1 - x_{i,j} P_{f,i,j}) P(H_0) \right\} \leq \bar{e}_h, \tag{C1}$$

$$0 \leq \tau_s \leq (T - \tau_r). \tag{C2}$$

Properties of Problem P4 In order to verify the convexity or otherwise of problem P4, there is the need to show that the objective function in (5.31) or (5.33) is concave in the range $0 \leq \tau_s \leq (T - \tau_r)$. To satisfy this, the function should be monotonically increasing for $0 \leq \tau_s \leq \tau_s^{opt}$, and monotonically decreasing for $\tau_s^{opt} \leq \tau_s \leq (T - \tau_r)$, such that $R(\tau_s^{opt})$ is the only maximal in the entire range. Therefore, the objective function must satisfy three conditions as follows

1. The first derivative must be positive at $\tau_s = 0$, i.e., $R'(\tau_s)|_{(\tau_s=0)} > 0$
2. It must be negative at $\tau_s = T - \tau_r$, i.e., $R'(\tau_s)|_{(\tau_s=T-\tau_r)} < 0$
3. The second derivative must be negative, i.e., $R''(\tau_s) < 0$

Proof: The first two conditions together imply that there must be a point in $0 \leq \tau_s \leq T - \tau_r$ that maximizes $R(\tau_s)$. The first and the third conditions together infer that $R(\tau_s)$ is strictly increasing in the range $0 < \tau_s < \tau_s^{opt}$, while the second and the third conditions together indicate that $R(\tau_s)$ is strictly decreasing in the range $\tau_s^{opt} < \tau_s < T - \tau_r$. Therefore, the three conditions together imply that $R(\tau_s)$ attains a global maximum within the range $0 \leq \tau_s \leq T - \tau_r$. The first and second derivatives of the objective function can be expressed as in (5.34) and (5.36) respectively.

$$\frac{\partial}{\partial \tau_s} R(\tau_s) = \frac{1}{\tau_r - T + \tau_s} - \frac{1}{M} \sum_{j=1}^{M} \sum_{i=1}^{N} x_{i,j} \frac{f_s \gamma_{i,j} \exp\left(-\left(\vartheta + \frac{\gamma_{i,j}\sqrt{\frac{f_s \tau_s}{K_i}}}{2}\right)^2\right)}{\left(erfc\left(\vartheta + \frac{\gamma_{i,j}\sqrt{\frac{f_s \tau_s}{K_i}}}{2}\right) - 2\right)\sqrt{\frac{2\pi f_s \tau_s}{K_i}}} \tag{5.34}$$

For the expression in (5.34) to be positive, the second expression on the RHS must be less than the first expression. In which case, it is necessary to show that (5.35) is satisfied.

$$\frac{\tau_r - T + \tau_s}{M} \sum_{j=1}^{M} \sum_{i=1}^{N} x_{i,j} \frac{f_s \gamma_{i,j} \exp\left(-\left(\vartheta + \frac{\gamma_{i,j}\sqrt{\frac{f_s \tau_s}{K_i}}}{2}\right)^2\right)}{\left(erfc\left(\vartheta + \frac{\gamma_{i,j}\sqrt{\frac{f_s \tau_s}{K_i}}}{2}\right) - 2\right)\sqrt{\frac{2\pi f_s \tau_s}{K_i}}} > 1 \tag{5.35}$$

As τ_s approaches a value very close to zero, in (5.35), the denominator is negative since, $erfc(\cdot) \leq 1$ in general, and $\sqrt{\frac{2\pi f_s \tau_s}{K_i}}$ is a small positive value. Similarly, the numerator is equally negative since $(\tau_r - T + \tau_s) < 0$ and $f_s \gamma_{i,j} \exp\left(-\left(\vartheta + \frac{\gamma_{i,j}\sqrt{\frac{f_s \tau_s}{K_i}}}{2}\right)^2\right)$ approximates to $f_s \gamma_{i,j}$, which is a large positive value. Moreover, it can easily be seen that $(\tau_r - T - \tau_s) f_s \gamma_{i,j} \gg \sqrt{\frac{2\pi f_s \tau_s}{K_i}}$, making the RHS of (5.35) greater than one. Therefore, $R(\tau_s)|_{(\tau_s=0)} > 0$ in (5.34) and the first condition is satisfied.

On the other hand, at the limiting value of $\tau_s = T - \tau_r$, the expression in (5.34) becomes negative. This is because, the denominator of the first expression in (5.34) becomes zero, such that $-\frac{1}{T-\tau_r-\tau_s} = -\infty$. Consequently, the first expression in (5.34) becomes relatively larger than the second expression, satisfying the second condition that is, $R(\tau_s)|_{(\tau_s = T-\tau_r)} < 0$.

$$\frac{\partial^2}{\partial\tau_s^2}R(\tau_s) = -\underbrace{\frac{1}{(\tau_r - T + \tau_s)^2}}_{\mathbf{A}} + \frac{1}{M}\sum_{j=1}^{M}\sum_{i=1}^{N} x_{i,j}\left\{\underbrace{\frac{\sqrt{2}{f_s}^2\gamma_{i,j}\exp\left(-\left(\vartheta + \frac{\gamma_{i,j}\sqrt{\frac{f_s\tau_s}{K_i}}}{2}\right)^2\right)}{8K_i^2\sqrt{\pi}\left(\frac{erfc\left(\vartheta + \frac{\gamma_{i,j}\sqrt{\frac{f_s\tau_s}{K_i}}}{2}\right)}{\sqrt{2}} - 1\right)\frac{(f_s\tau_s)}{K_i}^{3/2}}}_{\mathbf{B}} \right.$$
$$\left. - \underbrace{\frac{f_s\gamma_{i,j}^2\exp\left(-2\left(\vartheta + \frac{\gamma_{i,j}\sqrt{\frac{f_s\tau_s}{K_i}}}{2}\right)^2\right)}{8K_i\pi\tau_s\left(\frac{erfc\left(\vartheta + \frac{\gamma_{i,j}\sqrt{\frac{f_s\tau_s}{K_i}}}{2}\right)}{\sqrt{2}} - 1\right)^2}}_{\mathbf{C}} + \underbrace{\frac{\sqrt{2}f_s\gamma_{i,j}^2\exp\left(-\left(\vartheta + \frac{\gamma_{i,j}\sqrt{\frac{f_s\tau_s}{K_i}}}{2}\right)^2\right)\left(\vartheta + \frac{\gamma_{i,j}\sqrt{\frac{f_s\tau_s}{K_i}}}{2}\right)}{8K_i\sqrt{\pi}\tau_s\left(\frac{erfc\left(\vartheta + \frac{\gamma_{i,j}\sqrt{\frac{f_s\tau_s}{K_i}}}{2}\right)}{\sqrt{2}} - 1\right)}}_{\mathbf{D}}\right\} \tag{5.36}$$

where

$$\vartheta = \sqrt{2\gamma_{i,j} + 1}Q^{-1}(P_{d,j}^{th}).$$

Following the same logic, it can easily be seen that the first expression on the RHS of the second derivative (5.36), denoted as A is a positive value for all values of τ_s. The denominator (numerator) of the second expression denoted as B is negative (positive) for all values of τ_s (for the same reason as stated earlier), making the second expression negative. Both the numerator and denominator of the third expression designated as C are positive. The fourth expression denoted as D is negative since its denominator (numerator) is negative (positive). Therefore, putting A, B, C and D together, the second derivative in (5.36) is a negative value for all values of τ_s, that is, $\frac{\partial^2 R(\tau_s)}{\partial\tau_s^2} < 0$, satisfying the third condition. Figures 5.3a 5.3b and 5.3c are the plots of the expressions in (5.33), (5.34) and (5.36, illustrating the behavior of the objective function, the first derivative, the second derivative respectively. The characteristic of the plots shown also validates the analysis that the objective function is concave, making P4 strictly convex in the range $0 < \tau_s < \tau_s^{opt}$. Therefore, $R(\tau_s)$ satisfied the three conditions that the objective function

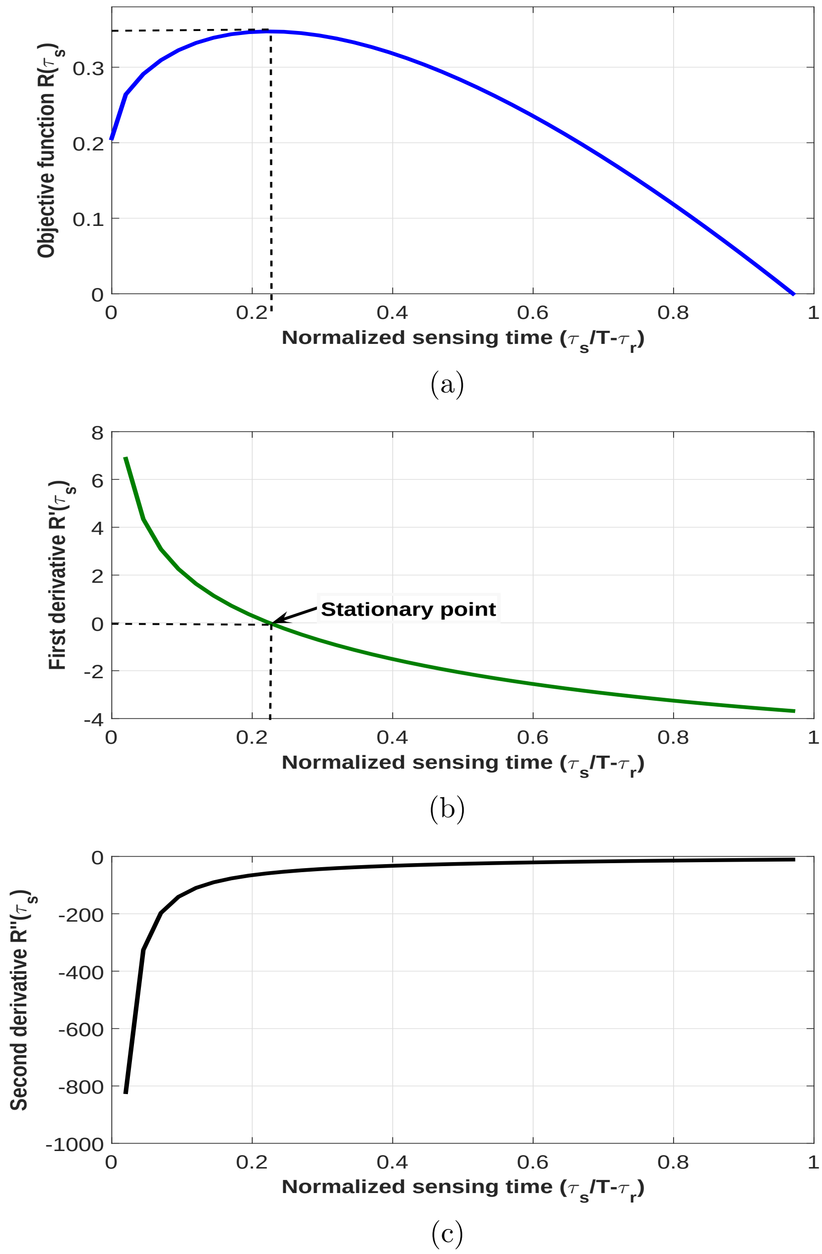


FIGURE 5.3: Plots of the objective function and the derivatives w.r.t. the normalized sensing time in problem P4 illustrating its concavity: (a) objective function, (b) the first derivative, (c) second derivative.

is strictly (unimodal) concave with respect to τ_s in the range $0 \leq \tau_s \leq (T - \tau_r)$.

Having proved that the objective function in P4 is a unimodal function, which by extension can also show that the first part of the constraint in (C1) of P4 is equally concave, the optimization problem in P4 can easily be solved as a convex problem. In order to to do this, the problem is analyzed under two scenarios as follows.

Case 1: *Optimal solution with unconstrained energy*
Under this scenario, the operation of the energy harvested SU is not limited by energy, and the SU can achieve maximum average throughput. Figure 5.4a shows the characteristic of the problem under energy unconstrained situation. In this case, the solution to the problem can be obtained merely through the sensing-throughput trade-off based on the objective function in (5.33) and the accompanied constraint in (C2). The problem is strictly unimodal and there exists an optimal solution $\tau_{s,o}^*$, which can be determined using Golden section search method for a fixed $\tau_{i,j}$, $j \in \{1, \cdots, K_i\}$, $\forall i$.

Case 2: *Optimal solution with energy constrained*
In this case, the operation of the energy harvested SU is subject to the energy causality constraint. Fig. 5.4b illustrates the characteristic of the problem under energy constrained scenarios with the feasibility regions shown shaded. From the figure, the parameter $e_{c,n}|(\tau_s = 0) = \prod_{i=1}^{N}(1-0.5)^{x_{i,j}} p_t T$, while $e_{c,n}|(\tau_s = T - \tau_t) = p_s(T - \tau_r) + p_r \tau_r$.

The intersection of the energy consumption curve and the energy harvested (i.e. when constraint (C1) is at equality) shows the possible sensing time ($\tau_{s,e}$) that could maximize the objective function in problem P4 while satisfying the energy causality. However, sensing time should be a small percentage of the total frame length (for sufficient data transmission time). Therefore, the optimal sensing duration can be obtained using Newton Raphson's method for a fixed $\tau_{i,j}$, $j \in \{1, \cdots, K_i\}$, $\forall i$ as

$$\tau_{s,e}^* : \min\left(f(\tau_{s,e}) = 0\right), \tag{5.37}$$

subject to:

$$0 \leq \tau_{s,e} \leq (T - \tau_r),$$

where $f(\tau_{s,e})$ is (C1) in problem P4 when the constraint is at equality. Based on Newton-Raphson approach, the solution to (5.33) can be determined as

$$\tau_{s,e}^{k+1} = \tau_{s,e}^{k} \pm \frac{f(\tau_{s,e}^{k})}{f'(\tau_{s,e}^{k})}, \tag{5.38}$$

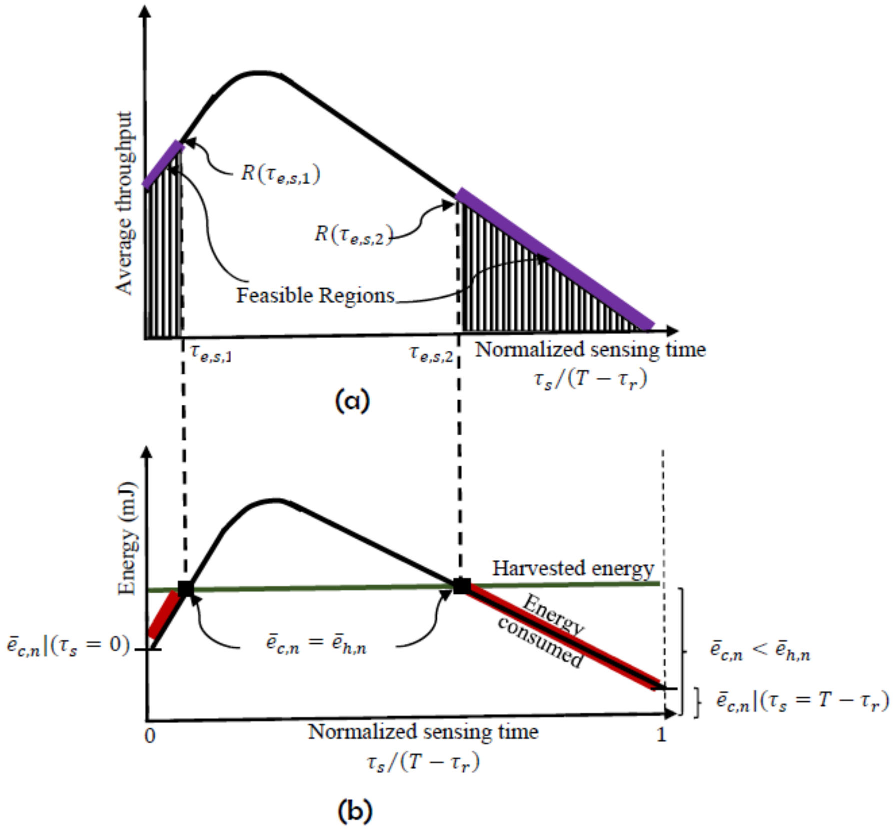


FIGURE 5.4: Characteristic curve of the problem P4 illustrating the feasibility regions for the energy constrained cognitive radio networks: (a) the objective function, (b) the energy constraint.

where the parameter k denotes an iteration index and $f'(\tau_{s,e}^k)$ is the derivative of $f(\tau_{s,e}^k)$, which is also formulated as constraint (C1) in problem P4. The general solution to problem P4 can therefore be expressed as $\tau_s^{opt} = \min(\tau_{s,o}^*, \tau_{s,e}^*)$. Both $\tau_{s,o}^*$ and $\tau_{s,e}^*$ are as earlier defined under case 1 (the unconstrained energy region) and case 2 (constrained energy region) respectively.

5.5.3 Optimal sensing parameter per channel

Given χ and τ_s, the optimal $\tau_{i,j}$ and $\varepsilon_{i,j}$ that maximize the objective function in problem P4 (with $\tau_{i,j}$ replacing τ_s/K_i) becomes

Problem P5

$$\begin{aligned}\max_{\{\tau_{i,j}\},\{\varepsilon_{i,j}\}} \sum_{j=1}^{M} R(\tau_{i,j}, \varepsilon_{i,j})|_{(\tau_s=\tau_s^*, \chi_{i,j}=\chi_{i,j}^*)} \\ = \max_{\{\tau_{i,j}\},\{\varepsilon_{i,j}\}} \sum_{j=1}^{M} x_{i,j} \log_e(1 - P_{f,i,j}(\tau_{i,j}, P_{d,j}^{th}))P(H_0)C_{0,j} \\ \forall i \in \{1, ..., N\},\end{aligned} \tag{5.39}$$

subject to:

$$\sum_{j=1}^{M} x_{i,j}\tau_{i,j} = \tau_s, \qquad i \in \{1, ..., N\}, \tag{C1}$$

$$0 < \tau_{i,j} \leq \tau_s, \qquad i \in \{1, ..., N\}. \tag{C2}$$

However, since the problem in P5 is maximized with $P_{d,i,j} = P_{d,j}^{th}$, then the optimal detection threshold can be simply obtained, given $\tau_{i,j}^{opt}$, as

$$\varepsilon_{i,j}^{opt} = \sqrt{\frac{2\gamma_{i,j}+1}{\tau_{i,j}^{opt} f_s}} \left(P_{d,j}^{th}\right) + \gamma_{i,j} + 1. \tag{5.40}$$

The problem then reduces to a single variable optimization as

Problem P6

$$\begin{aligned} &\max_{\{\tau_{i,j}\}} \sum_{j=1}^{M} R(\tau_{i,j})|_{\tau_s=\tau_s^*} \\ &\quad = \max_{\{\tau_{i,j}\}} \sum_{j=1}^{M} x_{i,j} \log_e(1 - P_{f,i,j}(\tau_{i,j}, P_d^{th}))P(H_0) \cdot C_{0,j} \\ &\qquad\qquad\qquad\qquad \forall i \in \{1, ..., N\}, \end{aligned} \tag{5.41}$$

subject to:

$$\sum_{j=1}^{M} x_{i,j}\tau_{i,j} \leq \tau_s, \qquad i \in \{1, ..., N\}, \tag{C1}$$

$$0 < \tau_{i,j} \leq \tau_s, \qquad i \in \{1, ..., N\}. \tag{C2}$$

Following the approach used in Section 5.5.2, it can be easily verified that the objective function in problem P6 is a monotonically increasing concave function in the range $0 \leq \tau_{i,j} \leq \tau_s$ since only the first condition among the three conditions listed is satisfied in this case.

Using the Lagrangian multiplier approach, the Lagrangian $\mathcal{L}(\boldsymbol{\tau}, \boldsymbol{\lambda})$ of (5.41) is given by

$$\begin{aligned} \mathcal{L}(\boldsymbol{\tau}, \boldsymbol{\lambda}) = \textstyle\sum_{j=1}^{M} x_{i,j} \log_e &\left\{ \left[1 - P_{f,i,j}(\tau_{i,j}, P_d^{th})\right] P(H_0)C_{0,j} \right\} \\ &- \lambda_j \left\{ \textstyle\sum_{j=1}^{M} x_{i,j}\tau_{i,j} - \tau_s \right\}, \\ &\qquad\qquad \forall i \in \{1, ..., N\} \end{aligned} \tag{5.42}$$

subject to:

$$0 < \tau_{i,j} \leq \tau_s,$$

where $\boldsymbol{\tau} = \{\tau_{i,j}\}_{M \times N}$ is the channel sensing-time matrix, and $\boldsymbol{\lambda} = \{\lambda_j, \forall i = \{1, \cdots, N\}\}$ is the non-negative Lagrangian multiplier associated with the channel sensing-time distribution for each secondary user. The Lagrangian dual function is defined as $g(\boldsymbol{\lambda}) = \max_{\{\tau_{i,j}\}} \mathcal{L}(\boldsymbol{\tau}, \boldsymbol{\lambda})$, and the dual problem as $\min_{\boldsymbol{\lambda} \geq 0} g(\boldsymbol{\lambda})$. The Lagrange dual variable $\boldsymbol{\lambda}$ can be obtained by solving the corresponding optimization problem in P6 using the following Karush-Kuhn-Tucker (KKT) conditions in (5.43) and (5.44), whereby the derivative of the Lagrangian with respect to the optimal and the dual variables are each set to zero, and then obtain the optimal variable as a function of the dual.

$$\sum_{j=1}^{M} x_{i,j} \frac{f_s \gamma_{i,j} \exp\left(-\left(\sqrt{(2\gamma_{i,j}+1)}\, Q^{-1}\left(P_{d,j}^{th}\right) + \frac{\gamma_{i,j}\sqrt{f_s \tau_{i,j}}}{2}\right)^2\right)}{\left(erfc\left(\sqrt{(2\gamma_{i,j}+1)}\, Q^{-1}\left(P_{d,j}^{th}\right) + \frac{\gamma_{i,j}\sqrt{f_s \tau_{i,j}}}{2}\right) - 2\right)\sqrt{2\pi f_s \tau_{i,j}}} - \lambda_j = 0 \qquad (5.43)$$

$$\sum_{j=1}^{M} x_{i,j}\tau_{i,j} - \tau_s = 0, \qquad \forall i \in \{1, ..., N\} \qquad (5.44)$$

It is however, obvious that a closed form expression cannot be obtained for the dual variable, hence, the need to determine both the dual and primal variable iteratively using a sub-gradient approach. Both the primal and Lagrangian dual variables are iteratively updated as

$$\tau_{i,j}^{t+1} = \tau_{i,j}^{t} + \delta_{\boldsymbol{\tau}}, \qquad i = 1, \cdots, N, \quad j = 1, \cdots, M \qquad (5.45)$$

$$\lambda_j^{t+1} = \lambda_j^{t} + \delta_{\boldsymbol{\lambda}}, \qquad \forall i \in \{1, \cdots, N\} \qquad (5.46)$$

until convergence towards a feasible optimal solution $\{\boldsymbol{\tau}^*, \boldsymbol{\lambda}^*\}$. The parameters $\delta_{\boldsymbol{\tau}}$ and $\delta_{\boldsymbol{\lambda}}$ denote step-sizes for the primal and the dual variables respectively. Algorithm 4 gives the summary of the solution method in Section 5.5

5.6 Computational Complexity Analysis

Following Table 3.1 in Chapter 3, the worst case scenario for obtaining the optimal channel assignment results in $\mathcal{O}(2^{MN+M})$ computational complexity cost. The parameters N and M represent the number of SUs and the PU channels respectively. The Golden Section search to determine the sensing time that maximizes the throughput for the unconstrained energy case has a computational complexity of $\mathcal{O}(MN)$, with linear convergence [147, 148]. The implementation of the Newton-Raphson method employed to determine the sensing time that maximizes the harvested energy requires a polynomial computational complexity in the order of $\mathcal{O}((MN)^2)$, with a quadratic convergence [147–149]. The computational complexity cost for the Lagrangian dual optimization to determine the optimal distribution of the sensing time among the assigned channels requires the initial root-finding search with corresponding computational complexity

Algorithm 4 Joint Channel Assignment and Cooperative Spectrum Sensing in Multichannel EH-CRN

procedure CHANNEL ASSIGNMENT AND SENSING PARAMETER OPTIMIZATION.
Input β, K_{max}, n_{max}
  for $j = 1 : M$ **do**
    for $i = 1 : N$ **do**
Obtain the channel assignment $\chi = (x_{i,j})_{N\times M}$; giving τ_s and $\tau_{i,j}$ by solving problem P3 in section 5.5.1

- Generate the matrix $\Lambda = (p_{m,i,j})_{N\times M}$ at the CC based on the reported non-cooperative probability of miss-detection on all PUs from each SU. Here, $p_{m,i,j}$ (5.25) is the non-cooperative probability of miss-detection of PU j evaluated by SU i
- Determine the channel assignment scheme / cluster formation following the method in Chapter 3.

$\chi^* \Leftarrow \chi$
Initialization $\delta \Leftarrow 0$
Repeat
Solve for optimal sensing duration $\boldsymbol{\tau}_s^*$ with fixed $\bar{\tau}_{i,j} := {}^{\tau_s^*}/_{K_i}$, giving χ^* in problem P4, section 5.5.2

- Obtain $\tau_{s,o}$ from the objective function in P4 based on a Golden Section search method (for unconstrained energy case)
- Determine $\tau_{s,e}$ from constraint C1 of problem P4 using Newton Raphson method (for constrained energy case)
- $\tau_s^* \Leftarrow \min\{\tau_{s,o}, \tau_{s,e}\}$
- $\tau_s^{(\delta+1)} \Leftarrow \tau_s^*$

Solve for the optimal sensing time $\boldsymbol{\tau}_{i,j}^*$ for every SU i on channel j in problem P5 or P6, section 5.5.3: giving $\chi_{i,j}^*$ and τ_s^{δ}:

- Determine $\tau_{i,j}^*$ from problem P6 using Lagrangian multiplier method and then $\varepsilon_{i,j}^*$ from (5.40),
- $\tau_{i,j}^{(\delta+1)} \Leftarrow \tau_{i,j}^*$

$\delta \Leftarrow (\delta + 1)$
until $\tau_s^{\delta} == \tau_s^{\delta-1}$, $\tau_{i,j}^{\delta} == \tau_{i,j}^{\delta-1}$
Determine the detection threshold $\boldsymbol{\varepsilon}_{i,j}^*$ from (5.40)
    end for
  end for
Output:$\chi^*, \tau_s^*, \{\tau_{i,j}^*\}, \{\varepsilon_{i,j}^*\}$,
end procedure

cost of order $(\Delta_f \Delta_k N)$ for solving the dual problem for N SU nodes. The parameters Δ_k and Δ_f denote the number of iterations and the number of function evaluations per iteration respectively. Then the computational complexity to solve the primal problem is equally in the order of the number of SU nodes, $\mathcal{O}(\Delta_f \Delta_k N)$. Hence, in all, Algorithm 4 requires total computational complexity cost of order $\mathcal{O}(2^{MN+M})$ in a worst case scenario. The rate of convergence depends highly on the choice of initial conditions, step-sizes and the number of iterations [150]. Table 5.1 summarizes the computational complexity cost per iteration of the proposed algorithm for the joint channel scheduling and cooperative spectrum sensing in CH-CRNs.

TABLE 5.1: Complexity Analysis of the joint channel scheduling and cooperative spectrum sensing in EH-CRNs

Solution Scheme	Time complexity	Space Complexity
Channel assignment	$\mathcal{O}(2^{MN+M})$	$\mathcal{O}(MN+M)$
Golden Section search	$\mathcal{O}(MN)$	$\mathcal{O}(MN)$
Newton-Raphson	$\mathcal{O}((MN)^2)$	$\mathcal{O}(MN)$
Lagrangian dual optimization	$\mathcal{O}(2\Delta_f \Delta_k N)$	$\mathcal{O}(NM)$

5.7 Convergence of the Alternating Convex Optimization

The analysis of the convergence and optimality of the procedure in Algorithm 4 is similar to that provided in [106, 151]. However, a brief explanation is given in this section. In the context of the alternating convex optimization, the following terms first need to be defined as follows [145]

Definition 5-1 *(Marginally Optimum Coordinate). Let f be a function of two variables constrained to be in the sets X, Y respectively. For any point $y \in Y$, it can be said that $\hat{x}$ is a marginally optimal coordinate with respect to y, i.e., $\hat{x} \in mOPT_f(y)$, if $f(\hat{x}, y) \geq f(x, y)$ for all $x \in X$. Similarly for any $x \in X$, it can be said that $\hat{y} \in mOPT_f(x)$ if $\hat{y}$ is a marginally optimal coordinate with respect to x.*

Definition 5-2 *(Bistable Point). Given a function f over two variables constrained within the sets X, Y respectively, a point $(x, y) \in X \times Y$ is considered a bistable point if $y \in mOPT_f(x)$ and $x \in mOPT_f(y)$ i.e., both coordinates are marginally optimal with respect to each other.*

Therefore, the optimum of the optimization problem must be a bistable point, and the procedure must converge after it has reached a bistable point. Although, the presented iterative algorithm may converge to a possible local maximum point, since the characteristic curve shown in Fig.

5.4, illustrates that the EH-CRN problem could have more than one bistable points, (one at τ_s close to zero, and the other at τ_s close to $(T - \tau_r)$). The bistable point to which the procedure converges depends on where the procedure is initialized between 0 and $(T - \tau_r)$.

However, taking into consideration that the sensing time must be a smaller fraction of the total frame length, the region of attraction for this problem is a bistable point selected as in (5.37). The objective function of the optimization problem in P1 is monotonically nondecreasing at every iteration, since it can be concluded from Algorithm 4 that

$$R(\chi^*, \tau_s^\delta, \tau_{i,j}^\delta, \varepsilon_{i,j}^\delta) \leq R\left(\chi^*, \tau_s^{(\delta+1)}, \tau_{i,j}^\delta, \varepsilon_{i,j}^\delta\right) \leq R\left(\chi^*, \tau_s^{(\delta+1)}, \tau_{i,j}^{(\delta+1)}, \varepsilon_{i,j}^{(\delta+1)}\right), \qquad \forall\delta. \tag{5.47}$$

Notwithstanding, the expression is upper bounded in the extreme scenario with $\tau_s^* = 0$, and $Q_{f,j} = 0$ as $\mathbb{E}\left\{\frac{T-\tau_r}{TM}\sum_{j=1}^{M}\left(P(H_0)C_{0,j} + (1-\beta)P(H_1)C_{1,j}\right)\right\}$, which indicates that it converges [113, 151]. In this particular case, the value of the objective function remains unchanged after a single iteration. Nevertheless, since the original problem is jointly non-convex in the optimization variables and the problem structure could have more than one bistable point, the convergence could only be guarantee to reach a local optimum, which in this scenario corresponds to the global optimum.

5.8 Simulation Results

This section presents the simulation results of the energy harvesting cognitive radio networks. The channel assignment is centrally implemented at the secondary user Base Station (SBS) based on outdated CSI, while the spectrum sensing and opportunistic energy harvesting are distributed. The network consists of varying number of PU channels and SUs randomly deployed in a $5km \times 5km$ square area. This becomes necessary in order to evaluate the performance of the multichannel CRN under varying number of assigned PU channels to each SU. The average number of assigned channels to each SU is dependent on the ratio of SUs to PU channels in the network (Chapter 3). For the simulations, the system parameters are summarized in Table 5.2, which draws mainly from [100]. In addition, the following parameter values are used: $S = 50$, $u = 5$, $\mu = 3$, $\kappa = 1.0$, [47] and [33]. The parameters $\epsilon_{i,j}$ and $F_{i,j}^{max}$ are chosen randomly as $0.001sec \leq \epsilon_{i,j} \leq 10sec$, and $1 \leq F_{d,i,j}^{max} \leq 7$ respectively in order to obtain different correlation factor $\rho_{i,j}$. The primary user's transmit power P_{PU} and the noise power N_0 are chosen as $50mW$ and $-90dBm$ respectively ([47] and [33]), in agreement with standard values, while the average SNR of PU j at SU i terminal ($\bar{\gamma}_{i,j}$) is evaluated based on the inverse square law.

Table 5.2: System Parameters

Symbol	**Description**	**Value**
u	Time-bandwidth product	5
f_s	Sampling frequency	1 MHz
p_s	Sensing power	110 mW
p_t	Transmission power	410 mW
p_r	Reporting power	410 mW
T	Frame duration	200 ms
τ_r	Reporting time	50 ms
P_{PU}	Primary user transmit power	1 W
γ_p	Signal-to-noise ratio of PU on channel	-15 dB
$P(H_0)$	Probability that a channel is not occupied by PU	0.8 dB
$P(H_1)$	Probability that a channel is occupied by PU	0.2 dB
N_0	Noise power	-90 dBm
β	Target probability of detection	0.9

5.8.1 Performance of CRN with Single RF Harvesting Source

Under this scenario, the value of N and M are set to 20 and 15 respectively. Therefore, based on this ratio, different number of PU channels are assigned to each SU across the network. Each SU is required to sense the assigned channels within the same sensing period τ_s^{opt}. However, the SU can only harvest RF energy from one source, which might be a dedicated RF source or its elect transmit channel. Result shows that optimal sensing period in a frame increases with the amount of harvested energy in the energy constrained region as shown in Fig. 5.5. The behavior of the plot in Fig.5.5 is similar to that obtained by Chung *et al* in [103] for a single SU, single channel case. In Figs. 5.6 and 5.7 results show that the optimal sensing time that maximizes average throughput and the average throughput to consumption ratio with increasing sensing duration (harvested energy). Interestingly, these results illustrate that there exists different optimal sensing duration that maximizes these two metrics. Average throughput to consumption ratio is seen to be maximized at a smaller sensing time.

Fig. 5.8 shows the sensing time distribution among the channels assigned to each SU in an overlapping cluster scheme. The sensing time on each channel is directly related to the magnitude of the received SNR of the PUs at the terminals of the SU. Hence, the sensing time are distributed such that its optimal pairing with the detection threshold and SNR of each PU signal at the SUs' terminal can achieve the target probability of detection on each channel (or cluster). As a

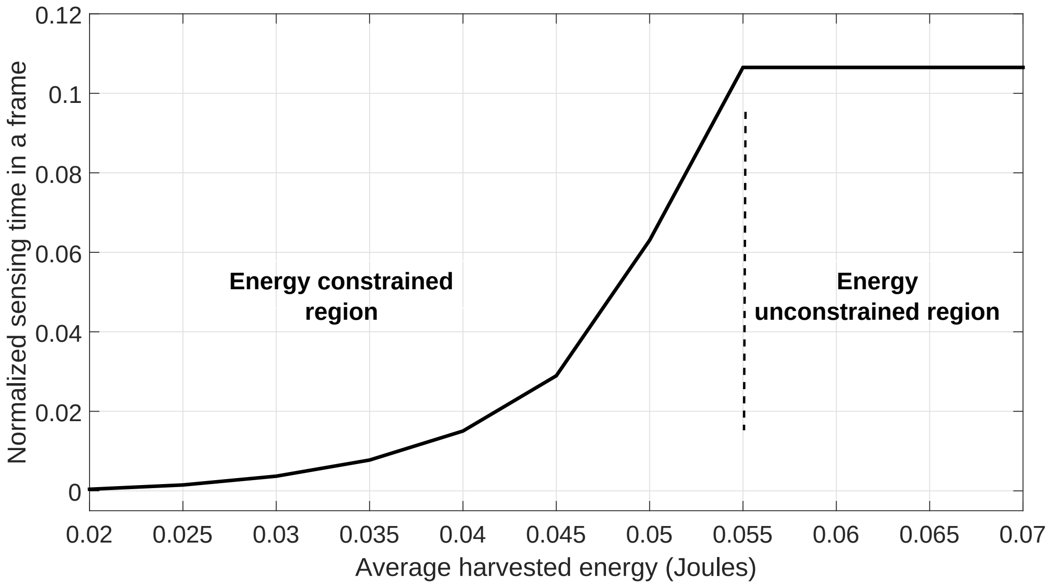


FIGURE 5.5: Plot showing the variation of sensing duration in a frame τ_s^{opt} with the harvested energy in the secondary user: $N = 25$, $M = 15$.

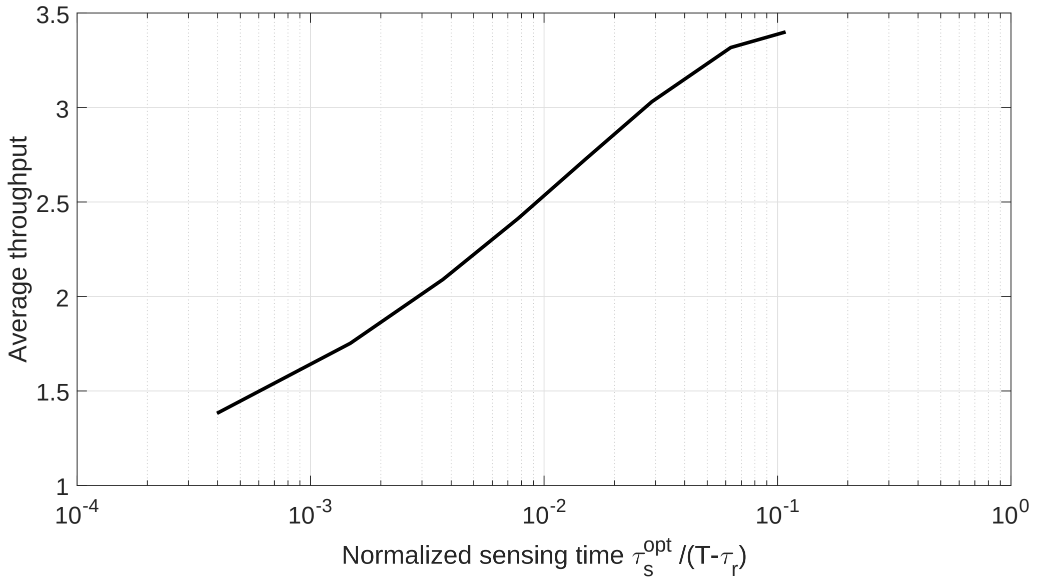


FIGURE 5.6: Optimal sensing duration $\tau_s^{opt}/(T - \tau_r)$ against average throughput.

result, channel with low SNR requires a larger sensing time than the one with smaller SNR in order to achieve the same sensing accuracy.

5.8.2 Performance of CRN with Multiple RF Harvesting Sources

The performance of the CRNs with multiple PU harvesting sources is hereby analyzed. Each SU is required to sense the assigned channels and opportunistically harvest RF energy from any of the assigned channels. Simulation result shows that the amount of energy harvested

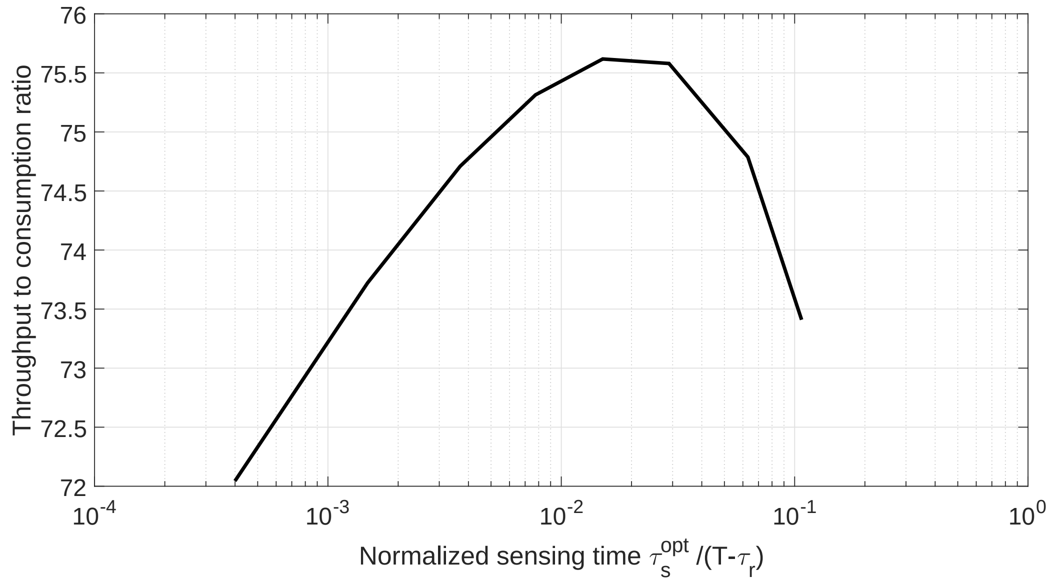


FIGURE 5.7: Optimal sensing duration $\tau_s^{opt}/(T-\tau_r)$ against average throughput to consumption ratio.

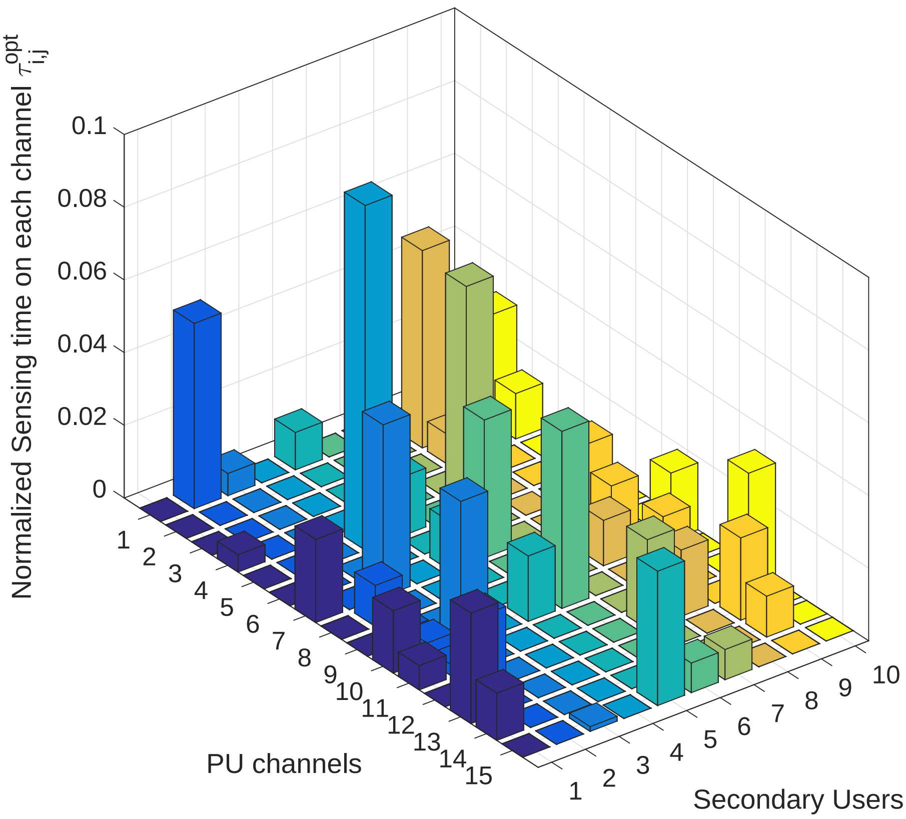


FIGURE 5.8: Optimal sensing time of each secondary user on each of the assigned PU channels $\tau_{i,j}^{opt}$. The figure only shows the first ten secondary users in the network for clarity $N = 25$, $M = 15$.

increases with the RF harvesting sources, and sensing time in a frame is equally enhanced with increasing number of channel (or PU harvesting sources) assigned per SU as shown in

Fig. 5.9. Very importantly, Fig. 5.10 shows that average harvesting to consumption energy ratio (otherwise refers to as active probability) can increase with increasing number of assigned PU harvesting sources. The result in Fig. 5.11 presents the relationship between the average achievable throughput and the number of RF harvesting sources. It shows that there is initial increase in the achievable throughput with increasing number of harvesting sources, which is reversed after a particular threshold. The logical explanation for this is that, increasing the number of RF harvesting sources enhances the energy budget and allows for adequate sensing period for better sensing accuracy. As sensing accuracy improves in terms of reduced false alarm rate, average throughput increases.

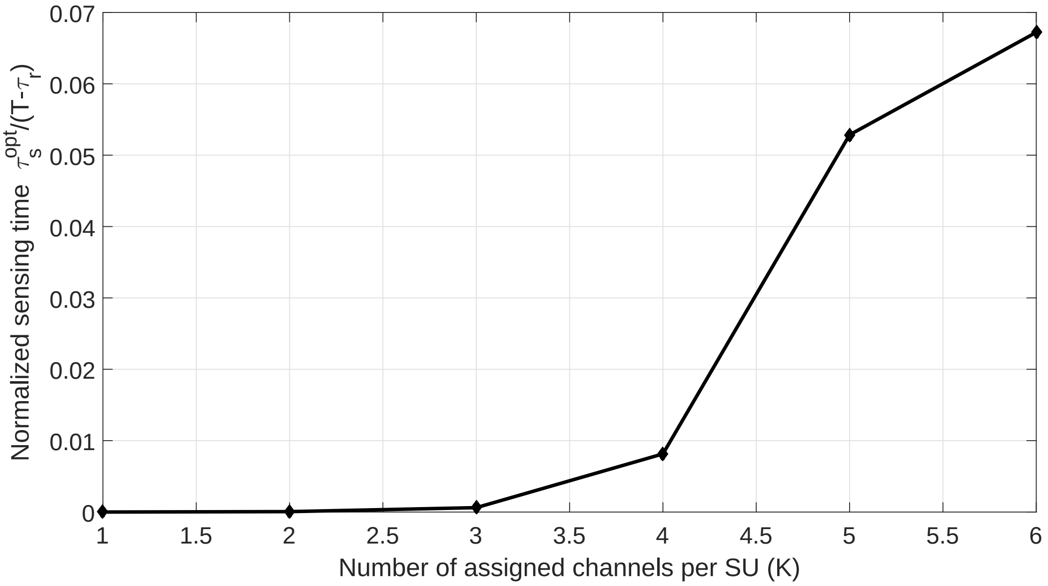


FIGURE 5.9: Optimal sensing duration corresponding to the number of RF harvesting sources K_i. SU can harvest RF from only one busy channel in a frame: $N = 30$, $M = 25$, $P_{avail} = 0.5 Watts$.

On the other hand, as the number of assigned RF harvesting sources increase, more channels are sensed, leading to increase in sensing time. As a result, the data transmission time reduces resulting in reduced average throughput. Therefore, a trade off exists between the number of RF sources (available for spectrum sensing and opportunistic energy harvesting), and the average throughput, and an optimal number of RF sources therefore exist, which maximizes the average throughput. In the same vein, in Fig. 5.12, the amount of energy consumption increases with the number of RF harvesting sources, since this brings about an increase in both sensing energy due to increased sensing time and data transmission energy (courtesy of improved sensing accuracy). The result in the figure shows that energy consumption is largest when throughput is at its peak. On the other hand, as more channels are sensed, increasing the sensing time, there is a continuous increase in sensing energy but a decline in data transmission energy due to the reduced data transmission time. The overall effect is a reduction of energy

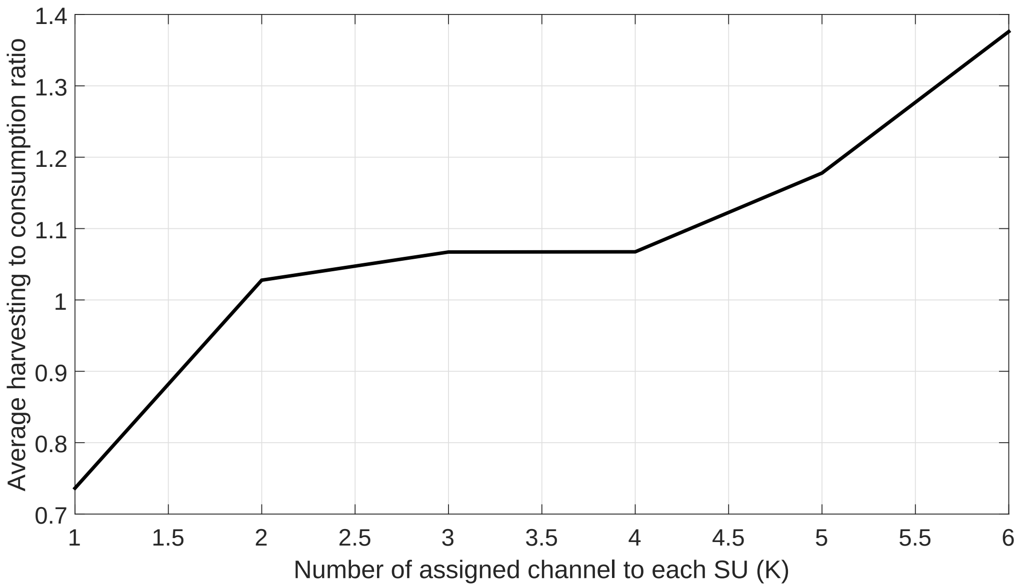


FIGURE 5.10: Active probability corresponding to the number of RF harvesting sources K_i: $N = 30$, $M = 25$, $P_{avail} = 0.5Watts$.

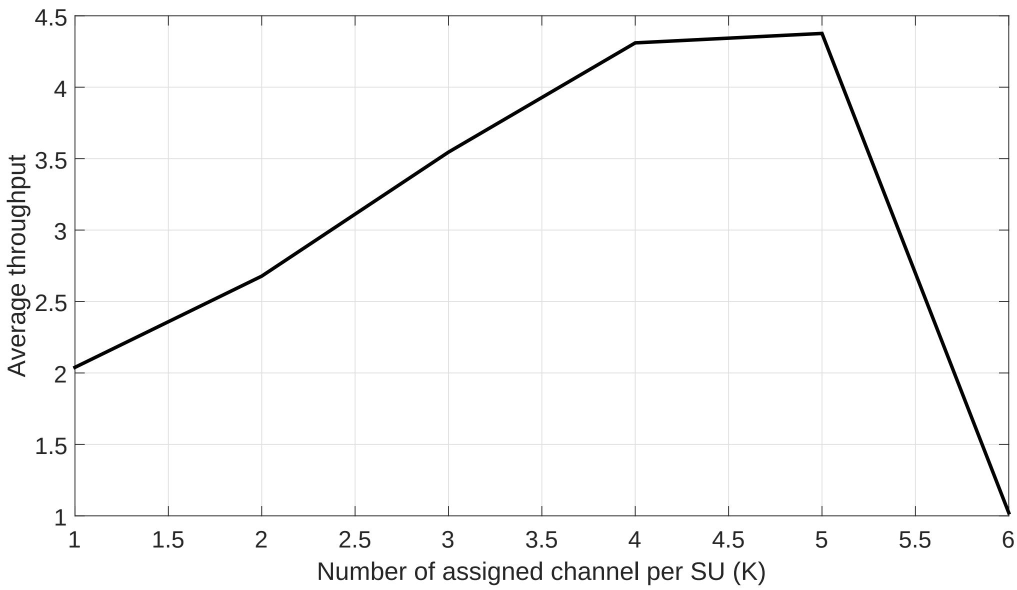


FIGURE 5.11: Average throughput against increasing number of harvesting sources, K_i: $N = 30$, $M = 25$, $P_{avail} = 0.5Watts$.

consumption since the effect of the loss of transmission energy is greater that the effect of the gain in sensing energy. This accounts for the gradual decline in energy consumption as shown in Fig. 5.12.

Fig. 5.13 illustrates the relationship between average throughput to consumption ratio, (which can otherwise be referred to as energy efficiency) and the number of assigned PU channels. This result shows that maximum numbers of RF harvesting sources exist over which the energy efficiency can be maximized. Within this region, both throughput and consumption increase

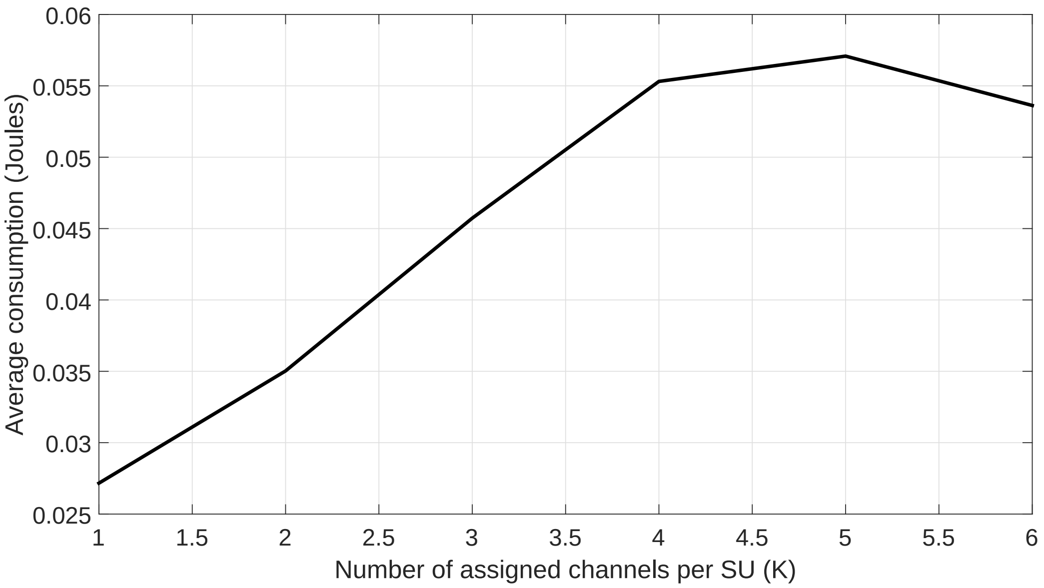


FIGURE 5.12: Average energy consumption against increasing number of harvesting sources, K_i: $N = 30$, $M = 25$, $P_{avail} = 0.5Watts$.

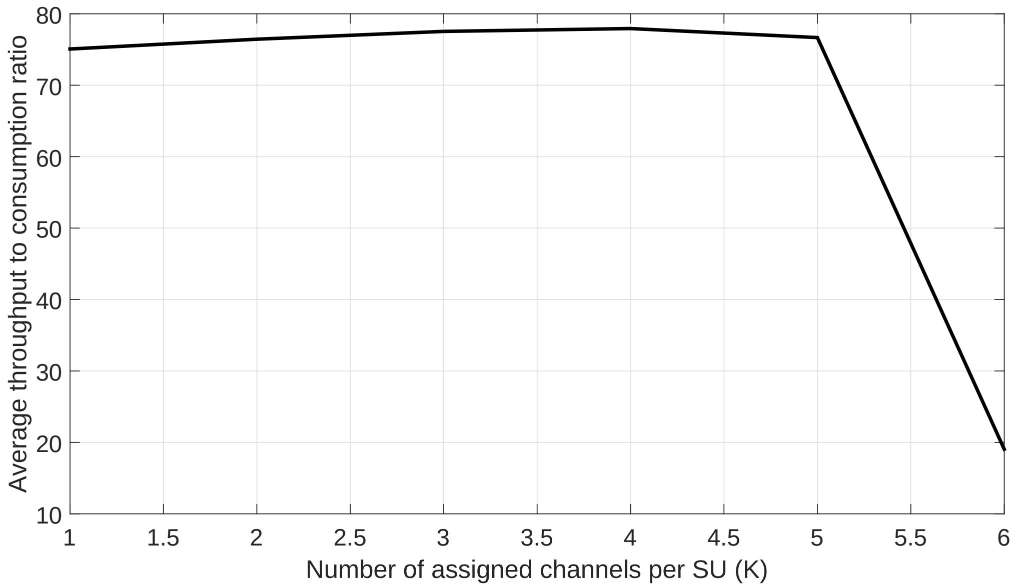


FIGURE 5.13: Average throughput consumption to consumption ratio against increasing number of harvesting sources, K_i: $N = 30$, $M = 25$, $P_{avail} = 0.5Watts$.

at almost equal proportion with increasing number of RF harvesting sources. However, it can be observed that throughput to consumption ratio is maximized at a lower number of RF sources than the average throughput and consumption. While both average throughput and consumption peak at $K = 5$, the ratio of average throughput to consumption is maximum at $K = 4$. Nevertheless, there is a rapid decline in the average throughput and throughput to consumption ratio at $K = 5$.

5.9 Chapter Conclusion

The work presented in this chapter has investigated an optimal multichannel cooperative spectrum sensing in an energy harvesting based cognitive radio networks. This involves determining the total sensing time needed by any secondary user in a frame and how to distribute the total sensing time among the number of the assigned channels in cooperative hard decision spectrum sensing. The initial non-convex, mixed integer nonlinear problem is transformed into a multiple convex optimization problem, which is then solved using alternating convex optimization technique. Simulation results obtained show that the considered work can improve the active probability of the SUs by exploiting the multi-channel benefit of practical CRN. Nevertheless, an optimum number of PU energy harvesting sources exits which maximize the average achievable throughput and average throughput to consumption ratio in the energy harvesting based multi-channel cognitive radio networks.

Chapter 6

Conclusion and Future Work

6.1 Introduction

This chapter summarizes the main points on which the works presented in this thesis are concluded, together with the possible investigations and directions for future work. The main introduction and background for the work presented in this thesis has been provided in Chapter 1. In Chapter 2, the preliminary overview of some basic components in EH-CRNs, and the review of the related studies in literature are detailed. These are followed by Chapter 3 to Chapter 5 where the main contributions in this thesis are presented.

6.2 Concluding Remarks

The study presented reveals and demonstrates the characteristics, benefits, shortcomings, trade-offs and network dynamics in a practical CRNs toward the development of an improved energy efficient EH-CRNs.

In particular, Chapter 3 presents channel assignment scheme in a multiuser multichannel CRNs, with objectives to minimize interference to the PU and enhance the opportunity of the SUs at accessing the licensed channels. The assignment problem is statistically formulated, taking into consideration the independence of the PUs activities and the time-varying channel conditions. The originally formulated nonlinear integer programming is transformed into a linear problem to obtain an optimal solution based on matrix approach and then two heuristic solutions. Simulation-based performance evaluation is presented for various network sizes and composition. It is shown that channel assignment under the common assumption of synchronous PU network and time-invariant channel condition are prone to error. The ratio of the available PU channels to the number of SUs is also a vital factor that could dictate clusters' characteristics and the performance of cooperative spectrum sensing and access in CRN.

In Chapter 4, a numerical comparative study of the commonly employed cluster head selection schemes is carried out, and then a generalized selection scheme that minimizes the total error rate is presented. The scheme takes into consideration the geographical location of the SUs and the relative distribution of the SUs to the PU in the cluster. Secondly, a new decision fusion rule that takes into consideration the cluster head's non-cooperative sensing result in making a cooperative sensing decision is also presented. A closed form expression is derived such that the cluster head's non-cooperative decision becomes a necessary condition for deciding the status of the channel in cooperative spectrum sensing. Simulation-based evaluation is presented, and it is illustrated that the performance of the existing cluster head selection schemes in the literature depends on the detection threshold and the network dynamics, and could be inefficient in a network with heterogeneous clusters. It is shown that the proposed CH selection scheme can overcome the limitations of the existing ones. The performance of the proposed hard decision fusion rule is also shown to be better than the existing common fusion rule in reducing the total error probability in Rayleigh fading channel.

In Chapter 5, the cooperative spectrum sensing scheme in the multichannel EH-CRNs is presented, with the objectives to determine the optimal assignment and sensing parameters that maximize the energy efficiency in the energy constrained cognitive radio networks. The study is investigated separately with single and multiple RF harvesting sources, and the problem formulated as a stochastic optimization, which is very difficult to solve directly and computationally intractable. Consequently, a myopic policy approach is taking, and the original problem is approximated into a mixed integer nonlinear programming, which is non-convex jointly in the optimization variables. An alternating convex optimization technique is adopted for a near-optimal solution.

Simulation-based performance evaluation and analysis are presented, and it is shown that while the achievable throughput is limited by the meagre and random energy arrival at the SU, as has been reported in the literature, the throughput can be enhanced in a multichannel CRNs environment if the SUs are appropriately assigned to exploit the benefit of multiple harvesting sources. However, an optimum number of RF harvesting sources for each SU exists, which maximizes the achievable throughput. As the number of RF sources increases, the energy efficiency of the SU reduces due to increased energy consumption.

6.3 Limitations and Future Direction

Cooperative spectrum sensing has been developed for optimal channel assignment, cooperative decision rule, cluster head selection, and cooperative spectrum sensing in the multichannel EH-CRNs. This section highlights the open issues to extend the work presented in this thesis for future research.

Channel assignment based on outdated CSI is presented in Chapter 3. Improvement to the assignment schemes in the literature is achieved by taking into consideration the heterogeneity of the primary users' activities and the effect of the time-varying channel conditions on the measured energy values. This is done by first allowing each secondary user takes a sample measurement of the energy value in each channel within a specified window period. Consequently, the channel response could be predicted at a later time and the channel assignment carry out based on the outdated CSI. The accuracy of this process could however, be limited by the number of sample measurements taking. Predicting the CSI, and consequently the channel assignment could be more accurate with the number of samples and the period allowed for this training process. This could be improved upon to constitute possible future extension. Scheduling with prediction technique in spectrum allocation would facilitate improved assignment and the frequency by which this operation is being carried out could be reduced for improved capacity.

A new hard decision fusion rule and a generalized cluster head selection scheme have been presented in Chapter 4. The reported performance gain of the new hard decision fusion rule in terms of minimizing the total error rate is however, at the expense of increased interference to the PU. Its use can therefore be limited when the protection of the PU is of major concern. The presented new cluster head selection scheme could select a cluster head that can respond to the dynamics of the users' distribution to achieve a better sensing performance at the expense of increased complexity. The issue of complexity mitigation technique therefore constitutes possible extension for future research.

Furthermore, the solution to the stochastic optimal control problem in Chapter 5 to determine the expected total reward (i.e. the throughput at the current time slot and the expected throughput at future time slots) over an infinite horizon is approximated to a myopic policy. While the myopic policy approach could provide a near-optimum solution with a reduced complexity, solving the stochastic optimal control problem directly constitutes a possible area for future work. Although, the proposed techniques may be complex in terms of implementation and computer time, the in-depth analyses presented in the thesis provide an exposition for significant theoretical insights into the performance gains that can be obtained in a multichannel EH-CRNs, as well as the future wireless networks.

Moreover, the solution presented assumes a uniform and constant harvested energy from the PUs. The spatial distribution and the energy evolution of the SUs are not taken into consideration. Therefore, investigating the effect of the stochastic behaviour of the harvested energy on the medium access control (MAC), and the general performance of the EH-CRNs constitutes an important area of future work.

In addition, the joint channel scheduling and cooperative spectrum sensing presented in Chapter 5 only considered an overlay cognitive radio network scheme based on temporal spectrum sensing. Exploiting a joint temporal-spatial cooperative spectrum sensing in the multichannel network, such that secondary users can take the advantage of joint overlay and underlay spectrum sharing technique for improved capacity constitutes another area for future work.

Multiple-input, Multiple-output (MIMO) systems in cognitive radio network prescribes a scenario where the cognitive radio user employs multiple receive antennas to mitigate the channel fading. In the system, preliminary decisions are first made by employing the conventional energy detector at each antenna based on which a final decision on the status of the PU channel is reached. The scheme has been reported to provide improved sensing performance as it employs the spatial diversity of the antennas to combat fading. Investigations on the performance of the EH-CRN under MIMO systems therefore, constitute possible area of future work.

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