EFFICIENT SPECTRUM ALLOCATION FOR COGNITIVE RADIO NETWORKS

Fareduddin Ahmed J S

BlueRose ONE .com DIY
Stories Matter

Title: EFFICIENT SPECTRUM ALLOCATION FOR COGNITIVE RADIO NETWORKS
Language: English
Character set encoding: UTF-8

First published by

BlueRose ONE .com DIY
Stories Matter

An Imprint of BlueRose Publishers

Head Office: B-6, 2nd Floor,
ABL Workspaces, Block B, Sector 4,
Noida, Uttar Pradesh 201301
M: +91-8882 898 898

BlueRose ONE .com
Stories Matter
DIY

Dedicated to my wife Rizwana and
my
children Faizan, Furquan, and Farhan

ACKNOWLEDGEMENTS

First and foremost, praises and thanks to the God, the Almighty, for His showers of blessings throughout my research work to complete the book successfully. I would like to express my deep and sincere gratitude to my research supervisor, Dr. Rohitha U M, Professor and Head, Electronics and Communications Engineering Department, Proudhadevaraya Institute of Technology(PDIT), Hospete, for giving me the opportunity to do research and providing invaluable guidance throughout this research. His dynamism, vision, sincerity and motivation have deeply inspired me. He has taught me the methodology to carry out the research and to present the research works as clearly as possible. It was a great privilege and honor to work and study under his guidance. I am extremely grateful for what he has offered me. I would also like to thank him for his friendship, empathy, and great sense of humor. I am extremely grateful to my parents for their love, prayers, caring and sacrifices for educating and preparing me for my future. I am very much thankful to my wife and my children for their love, understanding, prayers and continuing support to complete this research work. I would like to express my sincere gratitude to Dr. Yashvanth Bhupal, director BITM Ballari, Prof. Prithviraj Bhupal, deputy director BITM Ballari, Dr. Yadavalli Basavaraj , principal BITM Ballari and Dr. V. C. Patil(Dean R&D), Dr. U. Eranna (Dean Students and Staff affairs) Dr. K M Sadyojatha HOD E&CE BITM Ballari and all the colleages in BITM for their moral support.

FAREDUDDIN AHMED J S

FOREWORD

In the realm of wireless communication, the ever-increasing demand for spectrum resources has given rise to a fundamental challenge - how to effectively and efficiently allocate the limited spectrum to a multitude of users and applications. It is my distinct pleasure to introduce this groundbreaking work, which delves into the captivating book on "Efficient Allocation for Cognitive Radio Networks."

As we embark on this intellectual journey, we find ourselves at the intersection of cutting-edge technology and the ingenious potential of cognitive radio networks. Cognitive radio, with its cognitive capabilities, promises to revolutionize the way we perceive and utilize the radio frequency spectrum. By sensing the environment, adapting to varying conditions, and making intelligent decisions, cognitive radio networks hold the key to unlocking previously untapped spectrum resources, thus ushering in an era of unprecedented spectral efficiency.

The author of this book has displayed a remarkable grasp of the subject matter, presenting a comprehensive exploration of the intricacies involved in spectrum allocation for cognitive radio networks. Their expertise and dedication shine through the pages, making this work an invaluable resource for researchers, engineers, and enthusiasts alike.

The efficient allocation of spectrum resources has far-reaching implications, extending beyond mere technological advancement. It impacts the realms of telecommunication, networking, and beyond, with the potential to enhance connectivity, spur innovation, and improve the quality of life for billions around the globe.

However, this pursuit is not without its challenges. Striking a delicate balance between ensuring fair access for all users, protecting incumbent systems, and maximizing spectral utilization requires a nuanced approach. The authors tackle these complexities head-on, offering insights and solutions that chart a path towards the sustainable coexistence of diverse wireless services.

As we immerse ourselves in the wealth of knowledge contained within these pages, let us not forget the human element that underpins these remarkable advancements. The collaborative efforts, tireless research, and the shared vision of a better-connected world have led to this moment. It is a testament to the remarkable synergy between human ingenuity and the transformative potential of technology.

I extend my heartfelt appreciation to the author for their remarkable contributions, to the institutions and organizations that supported their endeavors, and to all those who tirelessly pursue the frontiers of knowledge. May this work serve as a guiding light, igniting curiosity, fostering innovation, and propelling us ever closer to a future where cognitive radio networks unlock the full potential of the spectrum, benefitting humanity in ways beyond our imagination.

With great enthusiasm and anticipation,

Dr. K M Sadyojatha

HOD E&CE BITM Ballari

PREFACE

In today's ever-connected world, wireless communication has become the backbone of modern society, enabling seamless interactions and powering a myriad of applications and services. However, as the demand for wireless services continues to skyrocket, the finite radio spectrum resources are being stretched to their limits. The traditional approach of statically allocating spectrum to specific users and services is proving to be inefficient and unsustainable, leading to spectrum scarcity and underutilization.

Cognitive Radio (CR) emerges as a promising solution to tackle the spectrum scarcity challenge. This revolutionary technology enables intelligent, adaptive, and dynamic spectrum allocation, allowing unlicensed secondary users to opportunistically access the underutilized or unused portions of the spectrum while avoiding interference with primary users. The efficient spectrum allocation in Cognitive Radio Networks (CRNs) presents an innovative paradigm shift that promises to revolutionize the wireless communication landscape.

This book is an exploration of the cutting-edge techniques, principles, and methodologies that underpin efficient spectrum allocation in cognitive radio networks. My journey begins with an introduction to the fundamental concepts of cognitive radio and the key challenges faced in spectrum management. I delve into the spectrum sensing techniques that enable cognitive radios to detect and identify unused spectrum opportunities, ensuring that secondary users can make well-informed decisions.

As I progress, I delve into spectrum sharing mechanisms, cooperative spectrum sensing, and interference management techniques that allow CRNs to coexist harmoniously with traditional wireless networks. The book explore the various cognitive radio network architectures and protocols that facilitate dynamic spectrum access, promoting efficient utilization of the spectrum while ensuring fairness among competing users.

Furthermore, this book examines state-of-the-art machine learning and artificial intelligence techniques that empower cognitive radios to learn from past experiences, adapt to dynamic environments, and optimize spectrum allocation strategies in real-time. It discuss the importance of policy-based approaches in governing spectrum usage, along with regulatory considerations and standardization efforts to foster the widespread deployment of cognitive radio technologies.

Throughout this book, we provide practical examples, case studies, and simulations to illustrate the concepts and demonstrate their real-world applicability. The book also address the security and privacy challenges in cognitive radio networks, acknowledging the need for robust and secure spectrum allocation mechanisms.

The aim in writing this book is to present a comprehensive guide that will serve as a valuable resource for researchers, engineers, and practitioners working in the field of wireless communications and cognitive radio. It is our hope that the insights gained from this exploration will contribute to the development of sustainable, efficient, and intelligent spectrum allocation solutions, leading us towards a future where spectrum scarcity is a thing of the past.

Let me embark on this journey together, as we navigate the fascinating world of cognitive radio networks and shape the future of wireless communications.

Dr. Fareduddin Ahmed J S

PROLOGUE

In the vast expanse of the digital age, the incessant thirst for connectivity and communication permeates every aspect of human existence. From the early days of telegraphy to the advent of cellular networks, the world has witnessed a remarkable evolution of wireless communications. However, with the increasing demand for wireless services, a looming scarcity of the radio frequency spectrum threatens to hinder progress and stifle innovation.

Enter the realm of Cognitive Radio Networks (CRNs), an innovative solution born out of the pressing need for efficient spectrum utilization. CRNs represent a paradigm shift in wireless communication, where artificial intelligence and machine learning are harnessed to enable dynamic spectrum access and efficient spectrum sharing.

This tale delves into the heart of spectrum allocation in Cognitive Radio Networks, uncovering the intricacies and complexities that govern the unseen battles for wireless frequencies. Our journey traverses through the maze of regulations, technical challenges, and policy decisions that shape the landscape of CRNs.

Follow the trail of brilliant minds who dared to challenge the status quo, as they embark on a mission to unlock the hidden potential of the electromagnetic spectrum. Witness how these pioneers harness the power of cognitive radio technology to sense, learn, and adapt, transcending the limitations of traditional static spectrum allocation.

As we embark on this odyssey, we will encounter the clash of interests between government agencies, telecommunication providers, and industry stakeholders vying for their share of the spectrum pie. We will explore the delicate balance between maximizing spectrum utilization while ensuring equitable access for all.

Amidst the technical marvels and policy debates, we will encounter the ever-present specter of security and privacy concerns, threatening to cast a shadow over the utopian promise of CRNs. Our protagonists must navigate through these treacherous waters, for the stakes are nothing less than the future of wireless communication.

In the pages that follow, we shall explore the brilliant minds and visionary thinkers who stood at the crossroads of innovation, determined to revolutionize the way we communicate and connect. Through their trials and triumphs, we shall witness the birth of a new era in wireless communications - an era where spectrum allocation is not confined to rigid boundaries, but an ever-evolving symphony orchestrated by the minds of man and the brilliance of machines.

So, dear reader, fasten your seatbelts and embark on this riveting journey through the uncharted waters of spectrum allocation in Cognitive Radio Networks. Brace yourself for a whirlwind of technological marvels, policy intricacies, and the relentless pursuit of a connected world where spectrum scarcity shall be a distant memory and cognitive radios shall reign supreme.

CONTENTS

1. INTRODUCTION

Radio spectrum is one of the scarcest and precious assets, similar to real estate in current situation. Hence there is growing competition in the telecommunication field to acquire this scarce resource. The cognitive radio(CR) in a general sense, exploits on the Moore's law for computational power in the electronic field. The utilization of radio-frequency spectrum and the supervision of radio emissions are managed by the national regulatory body FCC (Federal Communications Commission), which in its report says that the radio spectrum is highly underutilized. The Federal Communications Commission allocates spectrum to registered users, otherwise called primary users (PUs), on long-lasting basis for a chunk of region. However, a large segment of the allocated spectrum remains underutilized as shown in Figure 1.1. To plug this unproductive usage of radio spectrum resulted in the development of dynamic spectrum access(DSA) schemes [1], where the secondary users(SUs) with no spectrum licenses, are allocated temporarily with the unused spectrum.

In recent years, the FCC has been considering more adaptable and widespread usages of the vacant RF spectrum through CR technology [2]. The restrictions in spectrum access because of the static spectrum licensing scheme lead to unused spectrum called the spectrum holes (Figure 1.2).

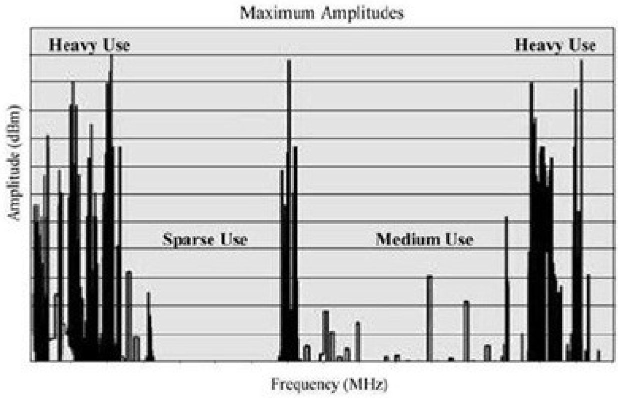


Figure 1.1: Spectrum is wasted in sparse use and medium use

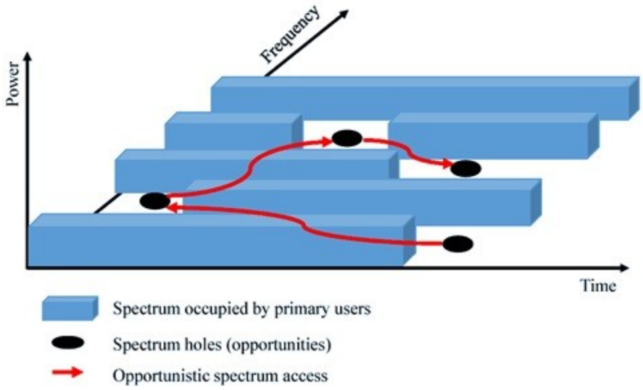


Figure 1.2: Spectrum holes

The term cognitive radio was first defined in [3] as "an intelligent wireless communication system that is responsive to its ambient environment. such cognitive radio will learn from the environment and adjust to the statistical variations of the prevailing RF environment by altering the transmission parameters (e.g. frequency band, modulation mode, and transmit power) in real-time. A CR network allows us to form communication links between CR nodes. The operating parameters can be altered according to the variations in the environment, topology, operating conditions, or user requirements".

The official definition of Cognitive Radio is expressed by Mitola in his Ph.D. thesis, as follows: "The term cognitive radio identifies the point at which wireless personal digital assistants (PDAs) and the related networks are sufficiently computationally intelligent about radio resources and related computer-to-computer communications to: (a) detect user communications needs as a function of use context, and (b) to provide radio resources and wireless services most appropriate to those needs".

There are two key characteristics of the CR that can be defined as follows:

- *Cognitive capability*: It denotes the capability of the system to locate the information from its radio environment. This capability can't just be acknowledged by checking the signal energy in the given frequency spectrum, yet increasingly complex systems. The main capabilities of cognitive radio include *Sensing the environment*, *explore the sensed data* and *Adapt to the working environment.*
- *Re-configurability*: The cognitive capability gives the spectrum information, whereas re-configurability empowers the radio to be dynamically programmed corresponding to the radio environment [4]. Further, the CR can be automated to send and receive signals at different frequencies and to use distinctive transmission methods in accordance to its system design.

A definitive goal of the CR is to get the best accessible spectrum over cognitive capability and re-configurability as discussed earlier. Since most of the radio spectrum is already allocated, the main challenge is to assign the unused spectrum with minimum allowable interference to the primary users as shown in Figure 1.2. The CR allows the usage of the unused spectrum, which is referred to as a spectrum hole or a white space [3].

The two types of cognitive behavior we consider are:

- Spectrum overlay (spectrum interweave):

The unlicensed users utilize the licensed spectrum without causing interference to the primary or licensed users. The signals from both these users operate orthogonally to one another. The primary and secondary users may operate on the same channel in such a manner that guarantees that both licensed and unlicensed users coexist on the same channel with least interference to one another. The secondary users must be aware of their radio environment to achieve the information of the spectrum holes in the primary system. The interference avoiding behavior with which the secondary users occupy the spectrum holes, is referred to as *spectrum overlay*.

- Spectrum underlay:

The primary and secondary users operate on the same channel, in such a way that the inflicted interference from the secondary users to the primary users is within the tolerable level defined by the Quality of Service constraints. Such an interference controlling behavior is termed as *spectrum underlay* in which the networks operate with such low transmission powers, that they appear as channel noise for the primary system. The requisite channel awareness is information regarding the tolerable levels of interference defined by primary QoS constraints along with the information of the impact of the secondary user at the primary receiver. Hence the secondary user system must be aware of all the channel state information in the network.

1.1 Background and Motivation

In the field of wireless communication radio spectrum is an essential asset. All over the globe, spectrum usage is regulated to maintain the vital services without harmful interference. Conventional radio spectrum regulation has leaned toward fixed long-term allocation of spectrum usage in relatively large regions, usually centered on the wireless technologies employed during decision making. Specifically, the FCC has always allocated spectrum blocks for explicit uses, and allotted licenses for these blocks to specific parties. Although the fixed spectrum assignment scheme has prompted numerous effective applications like, for instance, broadcasting and cellular phones, it has also led to nearly all of the available spectrum being allotted for various applications. This has resulted in situation that there is almost no spectrum left for the upcoming wireless applications and services. Contrary to this several studies indicate that the radio spectrum in highly underutilized. Further reports show that even during the extreme usage period of a convention held in 2004 in New York City, only about 13% of the spectrum bands were utilized [5]. Similar spectrum underutilization pattern is reported from several other events in the spectrum bands from 30 MHz to 3 GHz [6]. These outcomes indicate that advanced devices and services must exploit underutilized spectrum. A great part of the early inspiration for cognitive radio technology was in fact to achieve such opportunistic spectrum access. This futuristic technology could revolutionize the way spectrum is assigned worldwide. Further, this could yield added bandwidth to cater to the growing requirement for better quality and high bit rate wireless products and services in the future.

1.2 Purpose of the research work

The idea of cognitive networks is fairly new and there are numerous difficulties that need to overcome before spectrum allocated to licensed users. Of both hypothetical and reasonable significance is the issue: what are the principal boundaries of communication in a CR network? Information theory gives an ultimate context for exploring this question, as it incorporates a variety of tools required for such fundamental studies. The boundaries obtained defines yardsticks for the functioning of CR networks, where researchers may assess the and get insight as to which direction to carry out their design. The unproductive usage of the scare radio spectrum leads to the development of dynamic spectrum access(DSA) scheme. The basic underlying concept of DSA/CR is to allow the secondary users with no spectrum licenses to opportunistically utilize the unused licensed spectrum. This has provided a promising solution to re conciliate the conflicts between the growing spectrum demand and its under utilization.

The simple core concept of CR is to allow secondary users (SUs) to access in an opportunistic and non-interfering manner some licensed bands temporarily unoccupied by the primary users (PUs). Dynamic spectrum sharing is a fundamental building block in time and space sharing system. An intelligent radio communication system can assess the spectrum availability and channel capacity, and opportunistically re-program itself to optimum resource utilization while addressing interference mitigation. Cognitive radio is an attempt in this direction. It takes advantage of the waveform programmable hardware platform also known as software-defined radio(SDR). One of the main concern of radio communication is the energy efficiency specifically in remote battery operated nodes. In CR scheme, the main energy intense and essential operation is spectrum sensing. It is now proved that numerous challenging aspects still need to be further investigated, making CR an open research area, such as continuous spectrum handovers, interference avoidance, spectrum sensing and allocation, energy efficiency etc.

1.3 Problem definition

The spectrum underutilization problem is the main reason for the emergence of cognitive technology. Though much of the work has done in CR to bridge the gap between spectrum underutilization and spectrum demand still there are many fundamental engineering issues that need to be addressed further the existing work has failed to address the concerns related to the sharing of the resources on different channel fading. In this regard this study has proposed efficient Multi level spectrum sensing and optimized power control mechanism for hybrid overlay/underlay transmission over different fading channels. Further this book proposes novel algorithms and analytical expressions for spectrum sensing and allocation over different fading channels.

1.4 Objectives of the book

- To enable efficient utilization of the radio spectrum.
- Designing innovative spectrum allocating algorithms such that cognitive users can work without causing excessive interference to the primary users.
- To Develop joint sensing and allocation strategies in CR Networks.
- Devising efficient resource allocation strategies based on the spectrum occupancy of the primary users.
- To Develop mathematical models for spectrum sensing and allocation over fading channels.
- To provide highly reliable communication for all users of the network whenever and wherever needed.

1.5 Contributions of the book

Contributions made by this book in cognitive radio networks is summarized as follows:

1. Our proposed "FOX" scheme in chapter 4 is a dual-phase spectrum sensing scheme followed by optimized resource allocation for CR Networks.

The scheme implements dual phase sensing the "Fast", phase followed by "Optimal" phase and then "eXplore" for optimal power allocation. The crucial features of the scheme are (1) Efficient spectrum sensing with dual-phase signal detection which lowers the probability of false alarm (2) Adaptive to channel noise: Single phase at low noise (high SNR) and dual phase at higher noise (low SNR) which lowers the probability miss detection. (3) Flexible resource allocation: by operating in both overlay and underlay modes. The simulation results verify the above scheme which outperforms the other similar schemes in literature.

2. Although different studies have been carried out on various features and functioning of energy detector, not much has been done to analyze different signal conditions under one platform. This book analyzes three distinctive signaling conditions over Rayleigh-fading and quantifies SNR, Number of samples and P Using closed form expression of P_d and P_f.

3. The radio resource allocation problem in cognitive radio networks, has been considered and the optimal power allocation strategies to achieve the fundamental capacity limits of a secondary network over different fading channels were investigated. In particular, both the ergodic capacity and the outage capacity are considered. Closed-form expressions were derived for both scenarios. Further the study considers both the peak and normal transmitter power limitations set for the secondary users as well as the interference power limitations set by the primary user. The necessary theoretical expressions of optimal resource allocations were also derived for the above said conditions. Furthermore, the analysis considers two coexisting networks of primary and secondary users which is hardly found in literature.

4. The work carried out visibly follows a planned approach to deal with the optimization of resource such as bandwidth and transmit-power allocation for Nakagami-m, LogNormal and Ricianfading channels in cognitive radio networks. Initially, a basic framework for optimization of resource allocation was developed for a hypothetical case under AWGN channel, then the expressions obtained for this problem is then adapted to the more specific channel fading such asRician, Nakagami-m and LogNormal fading The necessary theoretical expressions of optimal resource allocations were also derived for the Nakagami-m, LogNormal and Ricianfading conditions. Simulation provided verifies the optimization performed in resource allocation such as bandwidth and transmit-power for Nakagami-m, LogNormal and Ricianfading channels.

5. Multistage detection with Direction of Arrival (DOA) scheme for spectrum exploitation and exploration which further decreases the miss-detection and completely isolates the PU signal from other signals. This approach isolates the PU signal from the interference due to another SU or from malicious user consequently reducing the probability of missdetection.

1.6 Summary of the publications and organization of the book

This dissertation emphasis on Efficient radio spectrum sensing and resource allocation in cognitive radio networks. With this goal a joint two level adaptive sensing and dynamic power assignment technique for hybrid overlay/underlay CR networks is proposed. Additionally an innovative optimal power and bandwidth allocation scheme is proposed for LogNormal, Nakagami-m, and Rician fading channels in CR networks. The book consists of eight chapters that are organized as follows:

Chapter2: This chapter outlines literature review of spectrum sensing and assignment techniques in CR networks. At First, the basic functioning of cognitive radio approach is described followed by radio spectrum sharing models. Next, various spectrum sensing methods are described briefly along with their complexity and accuracy comparison. The last part of this chapter describes the spectrum sharing methods along with the challenges involved.

Chapter3: In this chapter, an optimized modulation scheme is proposed for Energy Detector to be used in signal sensing [7]. The optimization is performed for cognitive radio network over Rayleigh fading channel. The study involves the performance evaluation of different modulation schemes over Rayleigh fading channel. It is verified from simulation results that the energy detector works fine over Rayleigh fading channel in detecting the signals under low noise. Further, the chapter analyzes the relative variation of Bit Error Rate (BER) of the energy detector over AWGN and Rayleigh channels.

Chapter4: In this chapter, a multi-stage signal sensing scheme with dynamic power sharing is proposed [8]. This scheme implements noise adaptive dual phase signal sensing, with one stage for lower noise channels and two stages for higher noise channels, followed by optimal power allocation. The key features of the scheme are (1) Efficient spectrum sensing with dual-phase signal detection which lowers the probability of false alarm (2) Adaptive to channel noise: Single phase at low noise (high SNR) and dual phase at higher noise (low SNR) which lowers the probability miss detection. The pipelining feature of this scheme overcomes the delay problem in sensing. (3) Flexible resource allocation: by operating in both overlay and underlay modes. The simulation results verify the above scheme which outperforms the other similar methods in literature.

Chapter5: In this chapter, the optimization of the spectrum exploration and exploitation processes in cognitive radio networks has been considered. Spectrum exploration is the process of obtaining local awareness of the spectrum state through spectrum sensing. The goal of spectrum exploration is to find idle spectrum that can then be exploited. Optimization of spectrum exploration includes optimization of the whole spectrum sensing process that determines which frequency bands are sensed, when they are sensed and for how long and by which users, and how are the sensing results from multiple users combined. Spectrum exploration is coupled with spectrum exploitation. Spectrum exploitation addresses the questions: what happens after idle spectrum has been found; and how is the idle spectrum subsequently exploited? The chapter investigates the direction of Arrival(DOA) technique appended to dual phase sensing scheme [9] discussed in chapter4.

Chapter6: This chapter addresses the dynamic resource sharing issues in cognitive radio networks, where in the secondary users utilize the radio spectrum allotted to primary users. The proposed method employs the sum ergodic capacity as the performance metric for the entire network of SUs. The proposed work [10-12] articulates the optimal power sharing schemes to reach the goal of essential capacity bounds of SU network with Nakagami-m, LogNormal and Ricianfading channels. Initially, a basic framework for optimization of resource allocation was developed for a hypothetical case under AWGN channel, then the expressions obtained for this problem is then adapted to the more specific channel fading such as Rician, Nakagami-m and LogNormal fading states. The necessary theoretical expressions of optimal resource allocations were also derived for the Nakagami-m, LogNormal and Rician fading conditions considering both ergodic capacity and outage capacity. Moreover, the analysis considers two parallel networks of primary and secondary users. Various peak/average transmit power constraints at the secondary users as well as the interference constraints defined by QoS of primary user are taken into consideration. Simulation provided verifies the optimization performed in resource allocation such as bandwidth and transmit-power for Nakagami-m, LogNormal and Rician fading channels.

Chapter7: In this chapter conclusions of the dissertation are drawn by summarizing the major research challenges and by highlighting the important results achieved.

Chapter8: Finally, this chapter outlines the future work to be carried out.

References:

1. M. Salem, S. A. El-kader, S. M. Ramadan, and M. Zaki, "Opportunisticspectrum access in cognitive radio ad hoc networks," *International Journal ofComputer Science Issues (IJCSI)*, vol. 11, no. 1, 2014.
2. F. Akyildiz, W.-Y. Lee, M. C. Vuran, and S. Mohanty, "NeXt generation/dynamic spectrum access/cognitive radio wireless networks: A survey,"*Elsevier Computer Networks*, vol. 50, no. 13, pp. 2127–2159, 2006.
3. Kolodzy, I. Avoidance, and S. Models, "Spectrum Policy Task Force," Federal Commun. Comm., Washington, DC, Rep. ET Docket no. 2 -135, Nov. 2002.
4. Joseph Mitola, "Software Radio Architecture: Object-Oriented Approaches to Wireless Systems Engineering," Wiley-Interscience, 2000.
5. Mitola, G. Q. Maguire, "Cognitive radio: Making software radios more personal," IEEE Pers. Commun., vol. 6, no. 4, pp. 13 – 18, Aug. 1999.
6. Haykin, "Cognitive radio: Brain-empowered wireless communications,"*IEEE Journal on Selected Areas in Communications,* vol. 23, no. 2,pp. 201–220, 2005.
7. K. Jondral, "Software-defined radio: Basic and evolution to cognitiveradio," *EURASIP Journal on*

Wireless Communication and Networking,vol. 2, no. 1, pp. 275–283, 2008.

8. McHenry, D. McCloskey, and G. Lane-Roberts, "New York City Spectrum Occupancy Measurements Sep. 2004," Tech. Rep., Dec. 2004.

9. Shared Spectrum Company, "General survey of radio frequency bands – 30 MHz to 3 GHz," Tech. Rep., Sep. 2010.

10. Rohitha Ujjinimatad and Siddarama R Patil, " Signal Detection in Cognitive Radio Networks Based on the Ratio of Largest Eigenvalue to the Trace of a Covariance Matrix, " in proceedings of IEEE International Conference on Communication, VLSI and Signal Processing (ICCVSP-2013), SIT Tumkur, India. Feb. 20th – 22nd , 2013, pp. 226–229

11. Rohitha Ujjinimatad and Siddarama R Patil, "Spectrum Sensing in Cognitive Radio Networks with the Known and Unknown Noise Levels," IET Communications, vol. 7, Issue 15, pp. 1708 - 1714. October 2013. ISSN:1751–8628

12. Rohitha Ujjinimatad and Siddarama R Patil, "Mathematical Analysis for the Detection of Unknown Signals in Cognitive Radio Networks Over Wireless Communication Channels, " IET Journal of Engineering, doi: 10.1049/joe.2014.0173

2. COGNITIVE RADIO TECHNOLOGY

2.1 Introduction

The upcoming wireless systems are evolving towards the ad hoc networks with ambiguous topologies and the main perception in upcoming wireless technology is to develop networks that are self-configuring, self-organizing, self-optimizing, and self-protecting. It is henceforth, such cognitive radio networks must learn and adapt instantly to their working environment subject to the operational radio-frequency, thus offering far required flexibility and operational scalability.

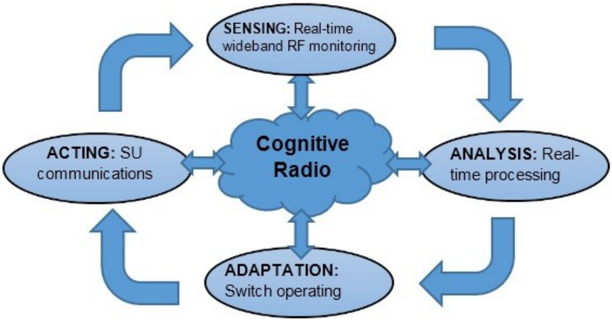


Figure 2.1 Cognitive cycle for CR network.

Furthermore, in order to adjust to their working parameters consequently and intelligently, signal processing is viewed to be the main phase in these sorts of systems. To locate for a free radio spectrum, an individual SU ought to experience through a subjective cycle beginning from detection, analysis, adaptation, and action [1,2] as illustrated in Figure 2.1. Among the four distinct phase of cognitive cycle, sensing phase is more significant as the remaining phases are depends on the sensed data.

2.2 Radio Spectrum access and Sensing:

In Cognitive Radio networks, the spectrum sensing assumes a key position to achieve its full possibility of radio spectrum usage in a real-time situation as the detected signal state governs the functioning of secondary user system. The SUs execute the sensing process for the possible free radio spectrum, and then the received data is analyzed to formulate the decision to use the channel.

The dynamic spectrum access(DSA) has become a new idea contrary to static frequency allocation and control. The DSA schemes can be roughly classified into three categories as follows:

2.2.1 Dynamic Exclusive Use Model

This model is similar to a conventional model where the service providers are given license for the exclusive use of radio spectrum. Moreover, to have the flexibility to enhance the spectrum efficiency, the model allows two approaches:

- The licensees have full property rights to choose technologies, and sell or lease their reserved spectrum.
- Dynamic spectrum allocation in which service providers exclusively allocated with the spectrum for a particular area and time.

2.2.2 Open Radio Spectrum Sharing Model

This model involves wireless services operating in ISM band similar to wireless local area network (WLAN), where all nodes are given equal probability to access the channel. However, the secondary users always choose the channels with lower traffic, over those with higher traffic.

2.2.3 Hierarchical Radio Spectrum Access Model

This model comprises of a progressive system between the authorized PUs and the secondary users. This model allows secondary users or unauthorized users to operate on primary spectrum opportunistically by ensuring that the interference induced by the secondary users to the primary users, is within the acceptable level defined by the QoS of PU. Basically the model has two approaches: spectrum overlay and spectrum underlay [3,4].

In the spectrum overlay model, the SUs will have to identify the idle spectrum bands, which are not used by the licensed system at a given time and location, and use those idle bands dynamically. In the spectrum underlay approach, the SUs are allowed to transmit with low transmit power.

Moreover, the dynamic spectrum sharing by the SUs in a given spectrum band can be categorized as follows:

- *Horizontal sharing,* where SUs and PUs have equal opportunities to access the spectrum such as in wireless LAN operating in the ISM band at 2.4 GHz, and in order to improve the overall system performance, SUs can choose the channels that have less traffic or less number of users. In this approach, SUs and PUs coexist in the system and use the bands simultaneously.
- *Vertical sharing,* where SUs have less preference over the PUs, and, thus, SUs must vacate the spectrum as fast as possible once the licensed PUs

are detected in the band. However, SUs can use the spectrum with potential whenever they detect the idle spectrum band. Moreover, in this approach, the CR system needs the operator's assistance.

2.3 Signal Detection Methods for Spectrum Sensing

This section gives the review of different methods for signal processing which are employed in spectrum sensing for SUs. The CR system under consideration has two parallel networks of primary and secondary users. The secondary network performs spectrum sensing using a relay with numerous sensors. Let there be K sensors, with distance between two consecutive sensors be$d=\lambda_m/2$, and λ_m is minimum detectable wavelength.

If the channel has no primary signal then it represents a spectrum hole (H_o), on the other hand the channel is said to be occupied (H_I) if the signal is detected. In either case the channel has a steady noise Additive White Gaussian Noise(AWGN). The received signal is given as

$$y_i(n) = \begin{cases} w_i(n), & H_0: channel\ free \\ g_i s_i(n) + w_i(n), & H_1: channel\ occupied \end{cases} \tag{2.1}$$

Two feasible hypotheses for PU identification that can be written for the received signal are: H_O whichrepresents that channel is free from PU activity and H_I specifies that the channel is preoccupied by PU. In both hypotheses the AWGN noise $w(n)$ is assumed to be present on the channel.

2.3.1 MF-Based Signal Detection

Matched Filter(MF) based detection is preferred when the signal state information is known at the transmitter side (SUs) [5]. This method is best suited under noisy channel (low SNR). A simple MF-based detection uses threshold to estimate the signal. Cabric et al. [6] used MF for pilot signal and MF-based detection where the method assumes that the PU sends a pilot signal along with the data. The MF achieves best results when the signaling details of the signal to be received are known well in advance at the receiver. Despite its best outcome, this method has more drawbacks than merits: First, MF depends on the complete knowledge of the PU information such as frequency of operation, modulation employed etc., which are required to be detected. As we know, CR will use wideband spectrum wherever it finds the spectrum opportunities. Therefore, it is almost impossible to have MF implemented in the CR for all types of signals in the wideband regime. Second, this method has high degree of complexity [18] as the CR system requires the receivers to be equipped with all signal types. Lastly, huge amount of power is lost these multi-detection processes as SU devices scan the channel for spectrum.

2.3.2 Covariance-Based Signal Detection

This is another method to detect the primary signal by SUs. Zeng and Liang [7] proposed the covariance-based signal detection technique whose core concept is to utilize the covariance between signal and noise as the covariance between signal and noise is generally distinct. These signal and noise covariance characteristics are used to distinguish signal from noise where the received signal's sample covariance matrix is calculated on the basis of the receiving filter. The signal received in vector form can be written as [19]

$$y = G_s + w \tag{2.2}$$

Where is the channel-matrix over which the signal travels. The covariance matrices for received signal and noise are

$$\left.\begin{array}{c} R_y = E\left[yy^T\right] \\ R_s = E\left[ss^T\right] \\ R_n = E\left[ww^T\right] \end{array}\right\} \quad (2.3)$$

Here E[.] represents estimated value of [.]. In no signal condition (s = 0), R_s = 0, and the off diagonal values of Ry are all zeros. If signal detected (s ≠ 0) and its values are correlated, then R_s is no longer a diagonal matrix. Hence, R_y must have a few non-zero off-diagonal elements. Hence This technique uses covariance matrix to detect the presence of signal. That is, if all the off-diagonal values of the matrix R_y are zeros, then the PU is not using the band at that time and location, and otherwise, the band is not idle.

2.3.3 Waveform-Based Detection

In this approach of signal detection, the parameters concerning to the signal to be detected, such as preambles, midambles, usual pilot patterns, and spreading sequences, are usually utilized in radio communication systems to assist detecting the signal presence. If the signal with known pattern is found, the detection process can be applied by correlating the received signal with a known copy of itself [8], this method is referred to as waveform-based detection (WBD). Tang [8] showed that with respect to convergence time and reliability WBD method is far better than energy-based detection. Further the efficiency of the algorithm improves as the duration of the known signal pattern increases. By considering the received signal the calculation of the detection metric for this method is as follows [8]:

$$D = Re\left[\sum_{n=1}^{N} y(n)\, s \times (n)\right] = \sum_{n=1}^{N} |s(n)|^2 + Re\left[\sum_{n=1}^{N} w(n)\, s \times (n)\right] \quad (2.4)$$

Where N is the length of the known pattern The detection metric D for waveform-based detection in this equation consists of two terms: the first term of the

Therefore, we can conclude that when the PU is idle D in Equation 2.4 will have only the second term that is only noise, and when signal from PU is detected, then D will have both terms in above equation. To detect the signal, the metric D value can be compared to a certain threshold value λ and the signal detection is expressed as

$$\left.\begin{array}{r} P_d = P_r(D > \lambda \mid H_1) \\ P_f = P_r(D > \lambda \mid H_0) \end{array}\right\} \tag{2.5}$$

where: , are the probability of signal detection and probability of false alarm respectively. We note that the threshold selection λ plays an important role in this detection strategy and can be estimated using noise variance. Furthermore, the simulations by Cabric et al. [9] show that WBD method have shorter signal detection delays, but it is prone to errors.

2.3.4 Energy-Based Detection

One of the most common PU detection method in spectrum sensing is Energy-based Detection (ED). This method is viewed as one of the most common method of signal sensing due to its ease of implementation and computational simplicity [6]. Unlike in MFs and other approaches, the receivers in this technique does not require any prior knowledge such as frequency of operation, modulation employed etc. of the PU signal to be detected. The signal detection in this method involves comparing the received signal with the predefined threshold value [10], which in turn is estimated using channel state information.

Figure 2.3 show the implementation of energy-based detection. In this method the signal is first converted from analog to digital and then fast Fourier transform (FFT) is applied. The output of the FFT process is squared, which is then averaged to get test statistics. Based on the test statistics, the absence or presence of the signal in the particular band is identified. For energy-based detection technique, Equation 2.1 shows the system model and the decision metric is given as

$$D = \sum_{n=1}^{N} |y(n)|^2 \quad (2.6)$$

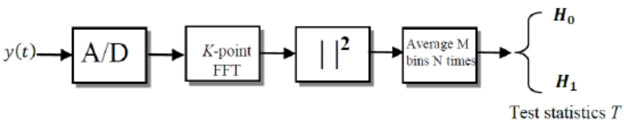


Figure 2.2: Digital implementation of energy-based detection with periodogram: FFT magnitude squared and averaged

Assuming the variance of AWGN σ_n and the variance of the signal σ_s, the decision threshold D follows chi-square distribution with 2N degrees of freedom [10] and can be modeled two hypotheses as follows:

$$D = \begin{cases} \left(\frac{\sigma_w^2}{2}\right) \chi_{2N}^2 H_0 \\ \left(\frac{\sigma_s^2+\sigma_w^2}{2}\right) \chi_{2N}^2 H_1 \end{cases} \quad (2.7)$$

In this approach, the false alarm probability P_f and the true detection probability P_d is computed by means of two hypotheses and comparing with the selected threshold value as in Equation 2.3. Again we note that the method has some disadvantages such as, if the choice of threshold value fails then this method results in poor detection probability and increased false alarm, which causes erroneous results at low SNR, and is incapable to distinguish between PU signal and noise. In addition, this approach does not work optimally for detecting spread spectrum such as code division multiple access (CDMA) signals [6].

2.3.5 Cyclostationarity-Based Detection

This approach has several merits over other signal sensing methods in cognitive radio networks. This method exploits the cyclo-stationarity features of the PU transmission signals [11,12] to be detected. The digital implementation of this approach is depicted in Figure 2.2. The method basically explores the periodicity features of the PU signals. Generally, the transmitted signals are stationary random process; moreover, the cyclo-stationarity features, which are the periodic features in the signal to be received such as mean, autocorrelation etc., are introduced due to the modulation of signals with sinusoid carriers, cyclic prefix in orthogonal frequency division multiplexing (OFDM). Thus, this technique can single out PUs' activity on channel from noise [11]. In a given frequency band, this method detects the signals by using cyclic spectral correlation function (SCF). The SCF for the detected signal can be obtained from Eq 2.1as [11,12]

$$S_{yy}^{\alpha} = \sum_{\tau=-\infty}^{\infty} R_{yy}^{\alpha}(\tau)\, e^{-j2\pi f} \tag{2.8}$$

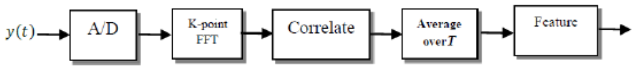


Figure 2.3: Digital implementation of cyclostationarity-based feature detection

Where Ryy(T) is the cyclic autocorrelation function achieved by evaluating conjugate autocorrelation function of s(n), with periodicity n and α denotes cyclic frequency. We note that if α = 0, the SCF becomes the power spectral density (PSD). This technique results in maxima in cyclic SCF whenever the signal is active in the specified frequency spectrum, which implies that the PU is active. If such a maxima does not exist, the technique suggests that the specified spectrum band is vacant or that at a specified moment and place there is no PU present. Based on this assessment, at a specified moment and place, SUs recognize the absence or presence status of PUs in the specific radio frequency band.

2.3.6 Random Hough Transform-Based Detection

This method is borrowed from image processing field. Random Hough transform is applied to a received signal to identify the presence of PU transmission. Detecting curves like straight lines, circles, and ellipses from an image is one of the major tasks of image processing. These curves frequently consist of sets of points in binary image data. The Hough Transform (HT) is a sophisticated method of extracting global features such as curve segments from binary edge images. The Hough Transform and its alternatives are normally used even though they are more complex, expensive and memory consuming. The main difference between the conventional Hough Transform and the Random Hough Transform (RHT) for line detection is that while a single pixel in the original image is mapped to a curve in the parameter space in the Hough Transform, a pair of pixels is mapped to a single cell in the parameter space in the Random Hough Transform. Hence, when the HT curves are mapped on the parameter space by means of a function which produces all parameter groupings compatible with both the detected pixel and the curve model, the Random Hough Transform only generates a small subset of all parameter combinations. Thus, The RHT uses many-to-one mapping or converging mapping.

2.3.7 Centralized Server-Based Detection

In this method, a central server unit of the network accumulates all the sensed data associated with channel occupancy from SU radios, centrally sums the existing information, and then disseminates this accumulated information related to the channel state to all other SUs [13,14]. When the SUs receive the aggregated information related to spectrum occupancy, they adapt their transmission parameters according to the received information. As the server collects the information from all other users, this spectrum server is assumed to be just a data accumulator lacking a built in spectrum sensing ability. Hence the central server functions as an information fusing node in cognitive radio network and plays no role in signal detection. Furthermore, different SUs may sense the data on the channel and send the same to their network server. They participate in information collaboration. They decide to utilize the spectrum dynamically depending on the combined information received from a network server instead of discretely sensed data.

2.3.8 External Detection

This technique is regarded as an alternative method to centralized detection. similar to centralized detection, this method, also requires that all SUs obtain the network information through some detection agent [15]. These external agents, performs signal detection as they are equipped with additional signal detection capability by means of signal detection sensors. Upon sensing the spectrum, these agents, broadcasts the information collected about the channel state to other SUs. Further, it is important to point out here that unlike in centralized detection the individual SUs are not equipped with signal sensing capabilities. SUs do not have their signal detection modules installed; even so, they can select which radio frequency band to utilize and what specifications and techniques to be employed for transmission. This strategy also helps to resolve the miss detected PU dilemma and the ambiguity due to fading owing to agent-based sensing [15]. Furthermore, this scheme is highly efficient in terms of time, spectrum and power usage from the perspective of CR systems as SUs have no signal detection capability [15] as the spectrum sensing functions are executed by the external agent. This strategy is often regarded as an ideal model for the cognitive radio network to overcome the technical problems; however, before suggesting it for application in the cognitive radio network, it is important to perform the price-benefit assessment.

2.3.9 Distributed Detection

Unlike centralized and external methods, in Distributed Detection SUs make their own decision based on the sensing information and the status update from other interacting SUs in the network. However, this method requires individual SUs to have their own sensing units to scan for the signal in their surrounding environment. Consequently, we do not need a complex centralized management infrastructure and it is more economical than other methods. Rather than deciding on the utilization of spectrum vacancies based on independently sensed information, this strategy takes into account sensed data from different participating SUs which are also seeking the spectrum availability for their transmissions. This scheme has high probability of true detection and low probability of false alarm related to actual spectrum occupancy. Basically, the distributed approach can be implemented in SU devices by using spectrum load smoothing algorithms [16].

2.3.10 Location awareness and geolocation

Location awareness and geolocation are at the core of situational awareness in cognitive radio systems. Or, more precisely, awareness of one's location relative to the other spectrum users is at the core of situational awareness since, depending on the application, it may not be necessary for a cognitive radio user to know its exact geographical location; rather a location relative to the other users of the spectrum may suffice. Nevertheless, location information plays an important role in spectrum access and interference management. The more accurately a secondary user knows the locations of the other users of the spectrum and the network topologies, the more accurately it can estimate the level of interference caused to them by its transmissions and subsequently adjust its transmission parameters accordingly. Location information is also beneficial in routing and scheduling problems. The capability to understand propagation phenomena and detection distances, primary user communication distances, and interference distances add to the location awareness and allow for modeling areas of harmful interference, achieving high data rates, as well as satisfying the interference constraints. The question then arises: how can a cognitive radio user obtain this location information? Outdoors, a mobile secondary user may employ satellite positioning techniques such as global positioning system (GPS) to obtain its own geolocation. In some cognitive radio applications this may already provide the secondary user a wealth of information for efficient and effective spectrum exploitation. For example, the reuse of digital TV frequency bands is such an application. The TV broadcast towers are located in fixed, static positions that are typically publicly available. Hence, a cognitive radio user knowing its own geolocation can easily determine the nearby TV broadcast towers and the channels employed. However, in general, the primary transmitter geolocations may not be available in advance. Moreover, if the user is indoors or no GPS or other satellite positioning system is available the user may have difficulty in determining its own geolocation. Finding out an unknown location of a wireless transmitter is a challenging problem requiring advanced signal processing algorithms. Moreover, reliable and accurate localization requires distributed cooperative techniques. Various proposed approaches include received signal strength- (RSS) [17], time-of-arrival- (TOA) [18-22], direction-of-arrival- (DOA) [33], and sensing result-based [23] techniques. The above techniques can also be applied to determine the locations of the other secondary users. However, such information may be obtained through other means as well, such as information exchange or mutual ranging [24], provided that the secondary users in the cognitive radio network cooperate with each other.

Finally, we would like to point out that the interference in a wireless communication system is experienced at the receiver and not at the transmitter, hence, knowing the location of the primary receivers is much more beneficial than knowing the location of the primary transmitters. However, this is notoriously difficult if the receivers are passive, as, for example, TV receivers are. In principle, even passive receivers may be detected by exploiting the local oscillator leakage power emitted by the RF front-end of a wireless receiver when a signal is received. However, the typical leakage power is very low, limiting the detection range to only a few meters at best. Thus, in applications involving passive receivers, one may have to be content with knowing only the locations of the primary transmitters.

2.3.11 Wavelet-Based Detection

This method is frequently used for edge or boundary detection in image processing. Tian and Giannakis [25] used wavelets for detecting the edges in the PSD of a wideband channel. This method is illustrated in Figure 5.10. In this approach, signal spectrum is decomposed into smaller non overlapping sub-bands to apply the wavelet-based approach for detecting the edges in the PSD. We note that the edges in the PSD are the divider of occupied bands and non-occupied bands (or spectrum holes) for a given time and location. Based on this information, SUs can identify spectrum holes or opportunities and exploit them optimally. Hur et al. [26] proposed another wavelet approach for spectrum sensing by combining coarse and fine sensing resulting in multiresolution spectrum sensing. The basic idea is correlating the received signal with the modulated wavelet to obtain the spectral contents of the received signal around the carrier frequency in the given band processed by the wavelet. By analyzing stretched forms of the wavelet and scaling functions, wavelet has the capability to tune time and frequency parameters [27] dynamically. In addition, time resolution can be negotiated and traded-off with high-frequency resolution for segments of slow varying signal [27].

2.3.12 Multitaper Spectrum Sensing/Estimation

Thomson [28] proposed the multitaper spectrum estimation (MTSE), in which the last N samples of the received signal are accumulated in a vector-form and denoted them as a set of Slepian base vectors. These vectors are used to detect the spectrum opportunities in the given spectrum band. The main idea of this approach is to utilize its fundamental property, that is, the Fourier transforms of Slepian vectors have the highest energy in the bandwidth (fc − W) to (fc + W) over a given sample size [28]. After MTSE, by analyzing this feature, SUs can identify whether there is spectrum opportunity. This method is also regarded as an efficient method for small sample spaces [29].

2.3.13 Filter Bank-Based Spectrum Sensing

This method is a simplified form of MTSE by introducing only one prototype filter for each band and was proposed for CR networks in [29]. The main idea of FBSE is to assume that the filters at the receiver and transmitter sides are a pair of matched root-Nyquist filters H(z) as shown in Figure 2.3. Specifically, the FBSE was proposed for multicarrier modulation-based CR systems by using a pair of matched root-Nyquist filters [29]. The approach for demodulation of the received signal with i^{th} subcarrier before it is processed through root-Nyquist filter is presented in Figure 2.4.

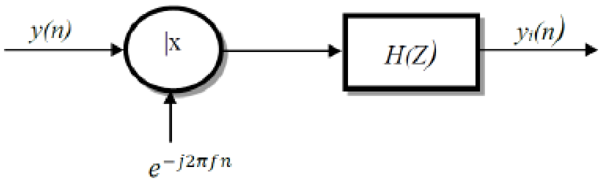


Figure 2.4: Demodulation of a received signal with i^{th} subcarrier

2.3.14 Compressive Radio Spectrum Sensing

Generally speaking, signals of interest are often sparse in a certain domain and the number of samples needed to estimate the signal may be much lower than the number required to recreate the unknown scattered signal itself. [30,31]. Thus, compressive spectrum sensing techniques can effectively reduce the acquisition costs of high-dimensional signals using compressive sensing for the sparse signals [30,31,32]. By estimating the sparsity order on the fly, compressed sensing can significantly lessen the sampling costs while attaining the preferred sensing accuracy [30], whereas in conventional spectrum sensing, each and every channel should be sensed in a sequential manner, which consumes both battery life and time.

2.4 Comparison of Radio Spectrum Sensing Methods

We presented several signal processing methods for spectrum sensing applicable to CR systems. Among them some methods are suitable for one system consideration and technologies and others are suitable for different system consideration and technologies. Note that there is no such ideal and complete method available yet, which is suitable for all kinds of technologies for CR systems in the wideband regime. In this section, we compare the main signal processing techniques for spectrum sensing in terms of sensing accuracies and complexities. The different methods of primary transmitter detection are presented in Figure 2.5. Among them, MF gives the highest accuracies with high complexity, which is due to implementation of many MFs in SU devices for spectrum sensing in the wideband regime.

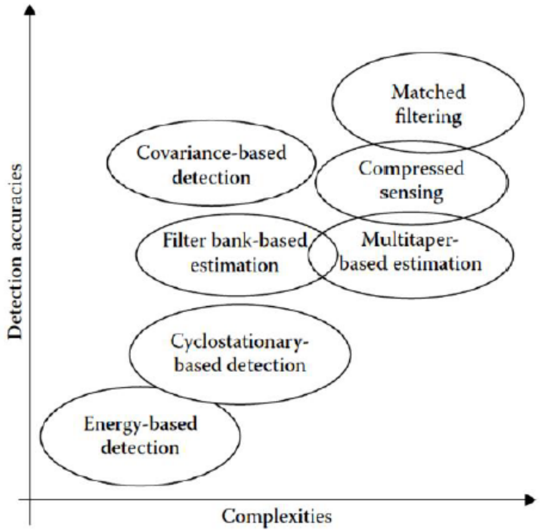


Figure 2.5 Comparison of different techniques for spectrum sensing methods for spectrum overlay in terms of sensing accuracies and implementation complexities.

However, energy-based detector is least accurate and least complex since we do not need any special kind of filters and the detector uses the energy of the signal during the detection process. In terms of implementation complexity, this approach is suitable for the CR system; however, it is more prone to noise level and interference from close proximity. Others are in the kind of middle in terms of accuracy and complexities.

2.5 Spectrum assignment techniques

This section, reviews some of most common methods employed for resolving the spectrum allocation problem in CRNs. The channel assignment techniques employed by the advanced channel allocation algorithms in CRNs are game theory, linear programming (LP), nonlinear programming (NLP), heuristics, network-based graph, genetic algorithms, evolutionary algorithms and soft computing.

2.5.1 Game theory

Game theory [33-37] is a mathematical framework which consists of models and techniques that can be used to analyse the iterative decisions behaviour of individual units concerned. The goal of the channel allocation algorithm based on game theory is to achieve the Pareto-optimal solution for the issue of channel allocation. Game theory has been commonly employed in cognitive spectrum allocation algorithms as it is a strong mechanism for decision-making which can be used for both cooperative and non-cooperative SU decisions. Cooperative game is a game in which all players are concerned about the general advantages instead of their own private advantages. In non-cooperative game each user is primarily worried about their individual advantages and therefore all their choices are made in a reactive and more selfish manner Usually a cognitive SA game has three sets of components: players, action space, and function(s) of the utility. Players select their behaviour in ordinary games in a manner that improves their private advantage or payoff. Most games achieve a state where no user can boost their utility function, which implies that all utility functions have reached a state of balance or stabilization. This state is called the Nash equilibrium (NE). A game-theoretic model is proposed in [38] that analyses the behaviour of SUs in distributed adaptive CA.

2.5.2 Linear programming

The LP [26,40] scheme optimizes the linear objective function subject to linear equality and linear inequality constraints. The problem formulation in LP is easy and simple. Some of the existing channel allocation algorithms in CRNs utilize binary linear programming (BLP) and mixed integer linear programming (MILP) to formulate the problem. BLP solves problems when the variables are limited to be either one or zero. In [41], the authors consider a resource allocation (RA) scheme based on interference minimisation (IM) in OFDMA-based CRNs and formulate an optimisation problem. In this problem they optimise sub-channel/power allocation, and rate control, with an intent to minimise the sum interference introduced to PUs, and assuring each user's QoS. Second, they simplify the RA problem as an integer linear programming problem (ILP) by three steps and solve it by ILP optimisation techniques easily. Tabassum et al. [42] develop conflict graphs of link-band pairs to describe the interference relationship among source-destination vehicle pairs on different channels and determine independent sets of vehicle pairs that can communicate simultaneously to maximise the spatial reuse of the licensed channels. Finally, they formulate a high throughput CA problem as a mixed-integer linear programming (MILP) problem.

2.5.3 Nonlinear programming

NLP [43] attempts to overcome the channel assignment optimisation problem, which is defined by limitations of equalities and inequalities. The objective function to be optimised or some of the constraints are nonlinear. Pareek and Lee [44] use particle swarm optimisation (PSO) to solve the mixed integer nonlinear programming (MINLP) in an OFDMA-based two-way cognitive relay network that comprises of multiple source-destination pairs and multiple relays. In [45], the authors propose a cross-layer routing framework for centralised multi-hop CRNs in TV white spaces. The problem is mathematically modelled a mixed integer nonlinear program that requires an appropriate solution methodology.

2.5.4 Heuristics

Heuristic methods [46-49] are frequently employed to expedite the process of spectrum assignment and to find out an optimum solution swiftly in situations where an comprehensive search is unrealistic. These does not involve preventive assumptions of the optimisation routines and they allow the use of models which are similar to real-world problems. Heuristic methods provide a near-optimal solution at reasonable computational cost for algorithmically complex and time-consuming problems. El Khatib and Salameh [50] propose a routing protocol, STARD that maximises the capacity of the network while minimising the number of channels allocated. The channel assignment problem is a BQP NP-hard problem and their method uses a heuristic to solve the problem in polynomial time.

2.5.5 Network graph-based

It is possible to model each network as a graph where the vertices relate to the mobile devices or nodes and edges refer to the links between mobile devices. To solve graph-based [51-53] spectrum assignment problems, several methods are used. The methods are generally based on building the network conflict graph that detects the interference between neighbouring SUs. Graph colouring is widely used in cognitive SA algorithms where the cognitive radio network is mapped to a graph, which is either unidirectional or bi-directional in accordance with the characteristics of algorithm. The vertices represents the SUs and the edges show the interference between the SUs. In [66], the authors use conflict graph and graph colouring concepts and propose a graph colouring-based dynamic channel allocation (GC-DCA) algorithm which minimises the network interference when the PUs and SUs share the channel simultaneously. In [55], the authors solve the SA problem as a graph colouring problem, while introducing the CR specificity. In [54], the authors propose a graph colouring algorithm for channel assignment. They also design and simulate a VANET scenario and provide numerical simulation results to delineate the possible challenges of dynamic spectrum access (DSA) in cognitive radio-enabled vehicular ad hoc networks (CR-VANETs). Xiaoganget al. [57] propose a topology control algorithm, ICGCA with the objective of bi-channel connected and conflict free transmission. They also present an improved MPH algorithm to make it re-connected, whose philosophy is to give priority to the link on these nodes that have the large path weights, and it has been shown that the improved MPH algorithm can achieve connecting the network while reducing the cost.

2.5.6 Soft computing

Another approach to solve SA optimisation problems in CRN is through soft computing-based optimisation. In this approach, for allocating resources to users within the network various software/computer-based programming have been used. The developed schemes use intelligent techniques such as artificial intelligence, neural networks and fuzzy systems.

2.6 Performance metrics

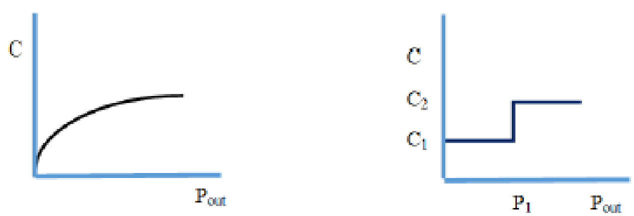
The fundamental performance limits of a cognitive radio network define its best possible performance relative to one or more specific metrics. Many different metrics can be used to measure performance, such as capacity, throughput, outage, energy consumption, as well as combinations of these and other metrics. Since cognitive radio networks exhibit significant dynamics (user movement, data traffic, channel variations, etc.), these dynamics must be taken into account in the definition of the network performance metrics. The most common fundamental performance limit for time-invariant communication systems is Shannon capacity [58] – the highest rate that can be achieved over a channel asymptotically with least possible error. For single-user channels the Shannon capacity is a number, the maximum data rate of the channel, as will be defined mathematically in terms of the channel's maximum mutual information in the next section. For a multiuser (broadcaster multiple access) channel Shannon capacity is a K-dimensional region defining the maximum rates possible for all K users simultaneously. Shannon capacity of wireless single-user and multiuser channels is known in many cases, including static and time-varying single-user, broadcast and multiple access channels with noise, fading, multipath, and/or multiple antennas. Time-varying channels are typically modeled based on the notion of a channel state. The channel state slices within a given set S of all possible channel states, which may be discrete or continuous. For stationary and ergodic time-varying channels, at any given time the channel is assumed to be in state s with probability $p(s)$, and we denote the channel capacity in state s as $C(s)$. This model is also referred to as a composite channel [59]. The Shannon capacity or capacity region of a time-varying stationary and ergodic channel with channel state known at the receiver(s) is therefore called the ergodic capacity, since it corresponds to the data rate or rate region in a particular channel state (e.g., a particular fading value) averaged over the probability distribution of the channel states (e.g., the fading distribution):

$$C_{erg} = \int C(s)\, p(s)\, ds. \tag{2.9}$$

When the channel state is known at the transmitter(s), the transmission strategy and system resources are typically adapted to the time-varying channel so that $C(s)$ denotes the capacity or capacity region of the channel in state s with transmit parameters such as power and rate optimally adapted over all channel states. An alternative performance metric for stationary and ergodic time-varying channels is outage capacity, whereby transmission to one or more users is suspended in some channel states, deemed outage states, and a fixed transmission rate is used in the non-outage states. The average data rate associated with outage capacity is then the maximum fixed rate that can be achieved in non-outage states with asymptotically small error probability, multiplied by the probability of non-outage (since the data rate is zero in outage states). The maximum fixed rate for non-outage states is typically determined based on the worst-case channel state that is not an outage state and the outage capacity is given by

$$C_{out} = (1 - P_{out}) \left[\min_{s \in S_{out}} C(s) \right] \tag{2.10}$$

The outage capacity metric is based on the underlying assumption that the transmitter knows the channel state and hence can suspend transmission during outage states. Thus, the transmission strategy is binary: no transmission in outage states and fixed rate transmission in non-outage states. Outage capacity cannot exceed Shannon capacity, since the latter adapts transmission parameters such as power and rate to each channel state. However, outage capacity is a useful metric for applications, such as voice and video, that require fixed-rate transmission. By allowing for suspension of transmission in some states, outage capacity achieves a higher average rate than if a single rate must be maintained in all channel states, including very poor ones.



(a)Continuous-state channel (b) Two-state channel

Figure 2.6 Capacity versus outage probability for a single-user channel.

When the channel state is unknown at the transmitter, the performance metric used is capacity versus outage probability. In this case the transmitter cannot adapt to channel conditions; it therefore selects a given fixed rate R (for single-user systems) or set of fixed rates $\mathbf{R}$ (for multiuser systems) to transmit to the user(s). If the channel supports these rates, i.e., the rates are within the capacity or capacity region of the channel under its realized channel state, then the data are received without error; if not, errors occur which are deemed a data outage. For single-user channels the capacity versus outage probability metric takes the form of a function characterizing the capacity C associated with each outage probability Pout. The capacity versus outage probability function, illustrated in Fig. 2.6a for a continuous-state single-user channel, thus corresponds to the transmitter's data rate versus the probability that this rate cannot be supported by a given channel. The plot of C versus Pout is non decreasing with Pout, since at high outage probability more of the *bad* channel states need not support rate C, and hence a higher capacity can be achieved in the non-outage states. Consider now a finite-state channel, where the set of channel states S is finite, and assume the states are ordered so that the capacity C_i in state i satisfies $C_i \leq C_j$ for $i \leq j$. Then C versus P_{out} has a staircase shape with discrete increases for each n such that , where p_i is the probability of the i^{th} channel state. For example, in a two-state channel with capacity C_i for state i and state probability P_i, i= 1, 2, if $C_1 < C_2$ then capacity versus outage is C2 for $P_{out} \geq P_1$, and C1 for Pout < p1, as shown in Fig. 2.6b. Note that when the channel is non ergodic, such that the channel state is chosen at random from the set S and remains constant for all time, the channel is referred to as a *compound channel*. In this case the capacity generally corresponds to achievable rates associated with the worst-case channel state [72]. Capacity results are much more limited for general cognitive radio networks with multiple sources and multiple destinations, even for simple static models. For a K-node network where each node is both a source and a destination, the capacity is a $K \times (K - 1)$-dimensional region defining the maximum rates achievable between all node pairs. Such regions are typically characterized by two-dimensional slices, which define the maximum rates between two source–destination pairs in the network. More general capacity regions whereby one source sends data to multiple destinations, also called *multicasting*, can include multi-hop routing via relaying, whereby intermediate nodes relay data toward their final destination. Such relaying can increase the achievable data rates for the network as well as other performance metrics, often significantly [61]. Other advanced capabilities in the system design, such as power control, multiple frequency bands to enable *frequency reuse* (the reuse of the same frequency at spatially separate locations), and interference cancellation can further increase network performance. This is illustrated in Fig. 2.7 (from [61]), where a two-dimensional capacity region slice for a five node network is illustrated for different design assumptions about the network. We see from this figure that spatial reuse of frequencies, multi-hop routing, and interference cancellation all significantly increase the achievable rates within this slice. The Shannon capacities for many of the most basic wireless networks, including the three-node relay channel and the four-node interference channel, illustrated in Fig. 2.7, have remained open problems for decades. This makes it unlikely that the capacity region can be obtained exactly for these and other similar networks, especially when the number of users is larger than in these canonical examples. Instead, capacity regions are often characterized by their upper and lower bounds rather than the exact region (where these bounds meet). Lower bounds are easier to obtain than upper bounds, as any communication scheme yields an achievable rate. Upper bounds are more difficult to obtain as they must contain all achievable rate regions. Fano's inequality is the most common tool used to obtain capacity upper bounds [74]. There has also been substantial improvement on deriving capacity scaling laws, which describe how the maximum sum of user rates scales in an asymptotically large network [63]. Moreover, these laws offer just one point, the sum-rate point, on the $K \times (K - 1)$-dimensional network capacity region.

Figure 2.7 Simple ad hoc networks for which capacity is unknown.

In particular, a network's scaling law defines how the ratio of the sum-rate divided by the number of users behaves in an asymptotically large network. The sum-rate point, i.e., the point on the capacity region corresponding to the maximum sum of user rates simultaneously achievable, can also be of interest for finite-size networks, especially symmetric networks where this point defines the maximum symmetric rate per user. Similarly, interference alignment can achieve the sum-rate point in interference networks, but fail to attain full capacity region [64, 65]. Cognitive radio networks are wireless networks where secondary users overhear the transmissions of primary users in the network and use that information in their encoding and decoding. From a Shannon capacity perspective, the two-user cognitive radio channel is a generalization of the two-user interference channel of Fig. 2.7 in that information about the primary user (source–destination pair 2) is assumed known by the secondary user (source–destination pair 1). In particular, for the underlay paradigm source 1 knows the amount of interference it causes to destination 2; for the interweave paradigm source1 knows the activity of source 2 across time, space, and frequency dimensions (possibly through coordination with destination 1) and refrains from transmitting in those dimensions when the primary user is active; for the overlay paradigm source 1 is assumed to know the data sequence and encoding scheme of source 2 along with network channel gains, and uses that information in its encoding. The cognitive radio network performance region where capacity is not the only performance metric of interest. Indeed, delay (average, maximum, tail probability, or the entire delay distribution) is an important metric for many applications. Furthermore, wireless channels may show improved rates if some outage or error is allowed (Shannon capacity regions assume zero outage). Further as the system constraints on average delay and outage are relaxed, capacity increases. Note that transmit power is not explicit in this performance region but rather is a parameter of the underlying model. Other model parameters might include available bandwidth, number of antennas at each node, and complexity limitations. The capacity metric generally increases as delay and/or outage increase, as indicated in the figure, since this entails a relaxation of system constraints. Shannon capacity generally assumes infinite delay and zero outage. Outage capacity and capacity versus outage have been well studied for point-to-point and multiuser channels, but there are few fundamental outage results for general wireless networks, where outage can be declared for any subset of node pairs within the network. For systems with multiple *degrees of freedom,* i.e., multiple dimensions over which to transmit data, the tradeoff between different performance metrics can be characterized more formally. In such systems some degrees of freedom can be used for diversity whereby the same information is sent over multiple dimensions for robustness to errors and outage. Other degrees of freedom can be used for multiplexing; whereby independent data are multiplexed over independent channels enabled by the multiple degrees of freedom. The multiple dimensions associated with degrees of freedom are typically obtained via space, time, and frequency. Time and frequency degrees of freedom are obtained by dividing the total signaling dimension into orthogonal time and frequency slots. The spatial dimension is obtained via multiple antennas at the transmitter and receiver (MIMO) systems. For single-user MIMO systems, Zheng and Tse[66] developed a fundamental diversity–multiplexing tradeoff (DMT) in the limit of asymptotically large signal-to-noise power ratio (SNR). The multiplexing gain r in this setting is defined as the number of degrees of freedom utilized for data transmission: more formally, the constant that precedes the log function in the bandwidth-normalized capacity expression (called the capacity *pre-log*). Diversity gain d is defined as the negative of the slope of the probability of error curve as a function of SNR at a fixed transmission rate.

1. The diversity–multiplexing tradeoff at asymptotically high SNR was shown to obey the simple expression $d(r) = (M_r - r)(M_t - r)$, where M_t and M_r are the number of transmit and receive antennas, respectively. The DMT region has also

been investigated for broadcast, multiple access, and relay channels. The single user region was also extended to include delay, creating a performance region called the diversity–multiplexing–delay tradeoff (DMDT) region [67]. In this work the delay tradeoff is introduced by automatic-repeat-request (ARQ), which provides robustness by identifying data received in error and requesting a retransmission of such data. This introduces diversity in the time domain at the expense of delay in the request for are transmission. The DMDT has also been extended to multi-hop networks with ARQ, where delay is caused by both queueing and ARQ retransmissions. The number of ARQ retransmissions invokes a diversity–delay tradeoff, and these retransmissions must be optimally allocated between all hops in the network as well as in the end-to-end link to achieve the optimal DMDT tradeoff. The DMDT of multi-hop networks under hierarchical cooperation, whereby the network is stratified into tiers and cooperation takes place within a tier, has also been characterized in [80]. While capacity, delay, and outage are key performance metrics for most wireless networks, they are not the most critical metrics for every system. For example, nodes powered by non-rechargeable batteries, as is typical in sensor networks, have energy consumption as a critical metric. Shannon-theoretic analysis was used in [69] to obtain fundamental results for capacity per unit energy (cost) of point-to-point, multiple access, and interference channels. Since this landmark paper there have been many follow on works examining capacity per unit cost under different channel conditions, different input alphabet constraints, and different single and multiuser channel models. The most relevant for wireless networks are [70, 71] (and the references therein). The first of these works develops the bits-per-joule capacity of wireless networks, a scaling law that defines the maximum total number of bits that the network can deliverer joule of transmit energy deployed into the network. This scaling law is found to be for γ the common path loss exponent of all channels and K the number of nodes in the network. The assumptions used to obtain this energy scaling law are similar to those used to develop capacity scaling laws. The second paper takes a unique approach relative to most work on minimum energy per bit; it considers total energy consumption – transmit energy plus circuit energy – as opposed to just transmit energy. In particular, [70] derives the tradeoff between total energy consumption and end-to-end data rate in wireless multi-hop networks, assuming interference treated as noise and orthogonal scheduling of user transmissions. The inclusion of circuit energy, which can include the energy associated with analog front-end electronics as well as signal processing hardware, can change the nature of the energy–rate tradeoff dramatically when transmit power does not dominate total energy consumption (e.g., at relatively short transmission distances). For example, sophisticated codes and multiple antenna techniques can save transmit power but increase circuit power. Similarly, in multi-hop routing, using intermediate nodes to forward data saves total transmit power but increases circuit power due to intermediate node processing. Thus, optimizing energy consumption in networks depends heavily on transmission distances (since transmit power dominates circuit power at large distances but not at small ones), as well as the precise models for circuit energy consumption associated with the different hardware blocks of a transceiver. Characterizing the tradeoffs between energy consumption and other network performance metrics has generally been hampered by a lack of fundamental energy consumption models for hardware. Hence, a fundamental characterization of such tradeoffs remains largely an open problem. Robustness is also important for many systems, yet it is not clear how to capture robustness in a mathematical metric. Information-theoretic tools are not always well-suited to characterizing fundamental performance limits in networks that have bounded delay, complexity, and power. In [72] a new theoretical framework is proposed to determine fundamental performance limits of wireless networks based on an interdisciplinary approach that incorporates Shannon theory along with network theory, combinatory, optimization, stochastic control, and game theory.

1. Rohitha Ujjinimatad and Siddarama R Patil, "Sensing Algorithm for Cognitive Radio Networks Based on Random Data Matrix, " International Journal of Computer Application (IJCA), Vol. 62 No. 3, January 2013, pp. 32-37. ISSN:0975-88872006.

2. W. Thomas, L. A. DaSilva, and A. B. MacKenzie, "Cognitive Networks,"*Proceedings of the 1st IEEE International Symposium on New Frontiers indynamic Spectrum Access Networks*, Baltimore, MD, November 2005,pp. 352–360.

3. Zhao and B. M. Sadler, "A Survey of Dynamic Spectrum Access,"*IEEE Signal Processing Magazine*, vol. 24, no. 3, pp. 79–89, May 2007.

4. B. Rawat and D. Popescu, "Precoder Adaptation and Power Control for Cognitive Radios in Dynamic Spectrum Access Environments," *IET Communications*, vol. 6, no. 8, pp. 836–844, 2012.

5. G. Proakis, *Digital Communications*, 4th edn. Boston, MA: McGraw-Hill,2000.

6. Cabric, S. Mishra, and R. Brodersen, "Implementation Issues in Spectrum Sensing for Cognitive Radios," *Asilomar Conference on Signals, Systems and Computers*, Pacific Grove, CA, June 2004, pp. 772–776.

7. Zeng and Y.-C. Liang, "Spectrum-Sensing Algorithms for Cognitive Radio Based on Statistical

Covariances," *IEEE Transactions on Vehicular Technology*, vol. 58, no. 4, pp. 1804–1815, 2009.

8. Tang, "Some Physical Layer Issues of Wide-band Cognitive Radio Systems," *IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Networks*, Baltimore, MD, June 2005, pp. 151–159.

9. Cabric, A. Tkachenko, and R. Brodersen, "Spectrum Sensing Measurements of Pilot, Energy, and Collaborative Detection," *Proceedings of the IEEE Military Communication Conference*, Washington, DC, October 2006, pp. 1–7.

10. Urkowitz, "Energy Detection of Unknown Deterministic Signals," *Proceedings of the IEEE,* vol. 55, pp. 523–531, April 1967.

11. Oner and F. Jondral, "Air Interface Identification for Software Radio Systems," *AEÜ International Journal of Electronics and Communications*, vol. 61, no. 2, pp. 104–117, February 2007.

12. Gardner, "Exploitation of Spectral Redundancy in Cyclostationary Signals," *IEEE Signal Processing Magazine*, vol. 8, no. 2, pp. 14–36, 1991.

13. Yates, C. Raman, and N. Mandayam, "Fair and Efficient Scheduling of Variable Rate Links via a Spectrum Server," *Proceedings of the IEEE International Conference on communications*, Istanbul, Turkey, June 2006, pp. 5246–5251.

14. A. Weiss and F. K. Jondral, "Spectrum Pooling: An Innovative Strategy for the Enhancement of Spectrum Efficiency," *IEEE Communications Magazine*, vol. 42, no. 3, pp. S8–S14, March 2004.

15. Han, R. Fan, and H. Jiang, "Replacement of Spectrum Sensing in Cognitive Radio," *IEEE Transactions on Wireless Communications*, vol. 8, no. 6, pp. 2819–2826, 2009.

16. Berlemann, S. Mangold, G. R. Hiertz, and B. H. Walke, "Spectrum Load Smoothing: Distributed

Quality-of-Service Support for Cognitive Radios in Open Spectrum," *European Transactions on Telecommunications*, vol. 17, pp. 395–406, 2006.

17. Kim, H. Jeon, and J. Ma, "Robust localization with unknown transmission power for cognitive radio," Proc. IEEE Military Communications Conf. (MILCOM 2007), Orlando, FL, Oct. 29–31, 2007.

18. Celebi and H. Arslan, "Adaptive positioning systems for cognitive radios," Proc. 2nd IEEE Int. Symp. New Frontiers in Dynamic Spectrum Access Networks (DySPAN 2007), Dublin, Ireland, Apr. 17–20, 2007, pp. 78–84.

19. Celebi and H. Arslan, "Cognitive positioning systems," IEEE Trans. Wireless Commun., 6, no. 12, 4475– 4483, Dec. 2007.

20. Gezici, H. Celebi, H. V. Poor, and H. Arslan, "Fundamental limits on time delay estimation in dispersed spectrum cognitive radio systems," IEEE Trans. Wireless Commun., 8, no. 1, 78–83, Jan. 2009.

21. Kandeepan, S. Reisenfeld, T. C. Aysal, D. Lowe, and R. Piesiewicz, "Bayesian tracking in cooperative localization for cognitive radio networks," Proc. 69th IEEE Vehicular Technology Conf. (VTC 2009-Spring), Barcelona, Spain, Apr. 26–29, 2009.

22. Kocak, H. Celebi, S. Gezici, K. A. Qarake, H. Arslan, and H. V. Poor, "Time delay estimation in dispersed spectrum cognitive radio systems," EURASIP J. Adv. Signal Process. Special Issue on Advanced Signal Processing for Cognitive Radio Networks, 2010, Article ID 675959, 10 pages,2010.

23. Ma, W. Chen, K. B. Letaief, and Z. Cao, "A semi range-based iterative localization algorithm for cognitive radio networks," IEEE Trans. Veh. Technol., 59, no. 2, 704–717, Feb. 2010.

24. Haghparast, T. Abrudan, and V. Koivunen, "OFDM ranging in multipath channels using time

reversal method," Proc. 10th IEEE Int. Workshop Signal Processing Advances for Wireless Communications (SPAWC 2009), Perugia, Italy, June 21–24, 2009, pp. 568–572.

25. Tian and G. B. Giannakis, "A Wavelet Approach to Wideband Spectrum Sensing for Cognitive Radios," *Proceedings of the IEEE International Conference on Cognitive Radio Oriented Wireless Networks and Communications*, Mykonos, Greece, June 2006, pp. 1054–1059.

26. Hur, J. Park, W. Woo, K. Lim, C. Lee, H. Kim, J. Laskar, S. Center, G. Tech, and G. Atlanta, "A Wideband Analog Multi-Resolution Spectrum Sensing (MRSS) Technique for Cognitive Radio (CR) Systems," *Proceedings of the IEEE International Symposium on Circuits and Systems*, Island of Kose, Greece, 2006, p. 4.

27. Lakshmanan and H. Nikookar, "A Review of Wavelets for Digital Wireless Communication," *Wireless Personal Communications*, vol. 37, no. 3, pp. 387–420, 2006.

28. J. Thomson, "Spectrum Estimation and Harmonic Analysis," *Proceedings of the IEEE*, vol. 20, pp. 1055–1096, 1982.

29. Farhang-Boroujeny and R. Kempter, "Multicarrier Communication Techniques for Spectrum Sensing and Communications in Cognitive Radios," *IEEE Communication Magazine*, vol. 48, no. 4, pp. 80–85, 2008.

30. Wang, Z. Tian, and C. Feng, "Sparsity Order Estimation and Its Application in Compressed Spectrum Sensing for Cognitive Radios," *IEEE Transactions on Wireless Communications*, vol. 11, no. 6, pp. 2116–2125, 2012.

31. Yin, Z. Wen, S. Li, J. Meng, and Z. Han, "Dynamic Compressive Spectrum Sensing for Cognitive Radio Networks," *Proceedings of the*

IEEE CISS, Baltimore, MD, March 23–25, 2011, pp. 1–6.

32. Wang, Z. Tian, and C. Feng, "A Two-Step Compressed Spectrum Sensing Scheme for Wideband Cognitive Radios," *Proceedings of the IEEE Globecom Conference,* Miami, FL, December 2010.

33. Byun, S., Balasingham, I. and Liang, X. "Dynamic spectrum allocation in wireless cognitive sensor networks: improving fairness and energy efficiency", *IEEE 68th Vehicular Technology Conference*, Calgary, BC, pp.1–5. 2008

34. Hongshun, Z. and Xiao, Y. "Advanced dynamic spectrum allocation algorithm based on potential game for cognitive radio", *2nd International Symposium on Information Engineering and Electronic Commerce (IEEC)*, pp.1–3, IEEE. 2010

35. Zhang, X-C. and He, S-B. (2010) 'A game algorithm of dynamic spectrum allocation based on spectrum difference', *The 19th Annual Wireless and Optical Communications Conference*, pp.1–4.

36. Wu, Z., Cheng, P., Wang, X., Gan, X., Yu, H. and Wang, H. (2011) 'Cooperative spectrum allocation for cognitive radio network: an evolutionary approach', *IEEE International Conference on Communications (ICC),* Kyoto, pp.1–5.

37. Li, Y-B., Rui, Y. and Fang, Y. (2010) 'Non-cooperative spectrum allocation based on game theory in cognitive radio networks', *IEEE Fifth International Conference on Bio-Inspired Computing: Theories and Applications (BIC-TA)*, Changsha, pp.1134–1137.

38. Nie, N. and Comaniciu, N. (2006) 'Adaptive channel allocation spectrum etiquette for cognitive radio networks', *Mobile Netw. Applicat.*, Vol. 11, No. 6, pp.779–797.

39. Irwin, R.E., MacKenzie, A.B. and DaSilva, L.A. (2013) 'Resource-minimized channel assignment for multi-transceiver cognitive radio networks', *IEEE J. Sel. Areas Commun.*, Vol. 31, No. 3, pp.442–450.

40. Yu, L., Liu, C. and Hu, W. (2010) 'Spectrum allocation algorithm in cognitive ad-hoc networks with high energy efficiency', *The International Conference on Green Circuits and Systems*, Shanghai, pp.349–354.

41. Liu, M., Song, T., Zhang, L. and Hu, J. (2016) 'Interference minimization approach for joint resource allocation in cognitive OFDMA networks', *IEEE 83rd Vehicular Technology Conference (VTC Spring)*, Nanjing, pp.1–5.

42. Tabassum, M., Razzaque, M., Hassan, M., Almogren, A. and Alamri, A. (2016) 'Interference-aware high-throughput channel allocation mechanism for CR-VANETs', *EURASIP Journal on Wireless Communications and Networking*, Vol. 2016, No. 1, p.2.

43. Chen-li, D., Guo-an, Z., Jin-yuan, G. and Zhi-hua, B. (2009) 'A route tree-based channel assignment algorithm in cognitive wireless mesh networks', *International Conference on Wireless Communications and Signal Processing*, Nanjing, pp.1–5.

44. Pareek, U. and Lee, D.C. (2011) 'Resource allocation in bidirectional cooperative cognitive radio networks using swarm intelligence', *IEEE Symposium on Swarm Intelligence*, Paris, pp.1–7.

45. Salah, A., El-Atty, H.A. and Rizk, R.Y. (2015) 'Cross-layer routing optimization for centralized multi-hop cognitive radio networks', *11th International Computer Engineering Conference (ICENCO)*, Cairo, pp.25–31.

46. Saleem, Y., Bashir A., Ahmed, E., Qadir, J. and Baig, A. (2012) 'Spectrum-aware dynamic channel assignment in cognitive radio networks',

International Conference on Emerging Technologies, Islamabad, pp.1–6.

47. Kim, W., Kassler, A.J., Di Felice, M. and Gerla, M. "Urban-X: Towards distributed channel assignment in cognitive multi-radio mesh networks", *IFIP Wireless Days*, Venice, pp.1–5. 2010

48. Alsarahn, A. and Agarwal, A. (2009a) 'Channel assignment in cognitive wireless mesh networks', *IEEE 3rd International Symposium on Advanced Networks and Telecommunication Systems (ANTS)*, pp.1–3, IEEE.

49. Alsarahn, A. and Agarwal, A. (2009b) 'Cluster-based spectrum management using cognitive radios in wireless mesh network', *18th International Conference on Computer Communications and Networks*, pp.1–6, IEEE.

50. El Khatib, R.F. and Salameh, H.B. (2017) 'A routing scheme for Cognitive Radio networks with Self-Interference Suppression capabilities', *Fourth International Conference on Software Defined Systems (SDS)*, Valencia, pp.20–25.

51. Zhao, C., Zou, M., Shen, B., Kim, B. and Kwak, K. (2008) 'Cooperative Spectrum allocation in centralized cognitive networks using bipartite matching', *Glob Telecommunications Conference, IEEE GLOBECOM*, pp.1–6.

52. Xin, C., Ma, L. and Shen, C-C. "A path-centric channel assignment framework for cognitive radio wireless networks", *Mobile Networks and Applications*, Vol. 13, No. 5, pp.463–476. 2008.

53. Zhao, J. and Cao, G. 'Robust topology control in multi-hop cognitive radio networks', *Proceedings IEEE INFOCOM*, Orlando, FL, pp.2032–2040. 2012

54. Tushir, B., Dhurandher, S.K., Woungang, I., Obaidat, M.S. and Teotia, V. (2016) 'Graph colouring technique for efficient channel allocation in cognitive radio networks', *IEEE International*

Conference on Communications (ICC), Kuala Lumpur, pp.1–5.

55. Tabakovic, Z. and Grgic, M. (2016) 'Cognitive radio frequency assignment with interference weighting and categorization', *EURASIP Journal on Wireless Communications and Networking*, Vol. 2016, No. 1, p.45.

56. Sohan, T.A., Haque, H.H., Hasan, A., Islam, J. and Islam, A.A. (2016) 'A graph coloring based dynamic channel assignment algorithm for cognitive radio vehicular ad hoc networks', *International Conference on Networking Systems and Security (NSysS)*, Dhaka, pp.1–8.

57. Xiaogang, Q., Limin, Z. and Lifang, L. (2017) 'Topology control based on steiner tree in cognitive radio networks', *International Conference on Smart Grid and Electrical Automation (ICSGEA)*, Changsha, pp.105–108.

58. E. Shannon, "A mathematical theory of communication," *Bell Sys. Tech. Journal*, 379–423, 623–656, 1948.

59. Effros, A. Goldsmith, and Y. Liang, "Generalizing capacity: new definitions and capacity theorems for composite channels," *IEEE Trans. Inf. Theory*, 56, no. 7, July 2010.

60. Verd´u and T. S. Han, "A general formula for channel capacity," *IEEE Trans. Inf. Theory*, 40, no. 4, 1147–1157, July 1994.

61. Toumpis and A. J. Goldsmith, "Capacity regions for wireless ad hoc networks," *IEEE Trans. Wireless Commun.*, 2, no. 4, 736–748, July 2003.

62. Goldsmith, M. Effros, R. Koetter, M. M´edard, A. Ozdaglar, and L. Zheng, "Beyond Shannon: the quest for fundamental performance limits of wireless ad hoc networks," *IEEE Commun. Mag.*, 49, no. 5, 195–205, May 2011.

63. Xue and P. R. Kumar, "Scaling laws for ad-hoc wireless networks: an information theoretic approach," *NOW J. Found. Trends Netw.*, 1, no. 2, 145–270, 2006.

64. R. Cadambe and S. A. Jafar, "Interference alignment and degrees of freedom of the K-user interference channel," *IEEE Trans. Inf. Theory*, 54, no. 8, 3425–3441, Aug. 2008.

65. A. Maddah Ali, S. A. Motahari, and A. K. Khandani, "Communication over MIMO X channels: interference alignment, decomposition, and performance analysis," *IEEE Trans. Inf. Theory*, 54, no. 8, 3457–3470, Aug. 2008.

66. Zheng and D. N. C. Tse, "Diversity and multiplexing: a fundamental trade-off in multiple antenna channels," *IEEE Trans. Inf. Theory*, 49, no. 5, 1073–1096, May 2003.

67. El Gamal, G. Caire, and M. O. Damen, "The MIMO ARQ channel: diversity-multiplexingdelay tradeoff," *IEEE Trans. Inf. Theory*, 52, no. 8, 3601–3621, Aug. 2006.

68. Ozgur and O. Leveque, "Throughput–delay tradeoff for hierarchical cooperation in ad hoc wireless networks," *IEEE Trans. Inf. Theory*, 56, no. 3, 1369–1377, March 2010.

69. Verd´u, "On channel capacity per unit cost," *IEEE Trans. Inf. Theory*, 36, no. 5, 1019–1030, Sep. 1990.

70. Bae and W. E. Stark, "End-to-end energy/bandwidth tradeoff in multihop wireless networks," *IEEE Trans. Inf. Theory*, 55, no. 9, 4051–4066, Sep. 2009.

71. Rodoplu and T. H. Meng, "Bits-per-joule capacity of energy-limited wireless networks," *IEEE Trans. Wireless Commun.*, 6, no. 3, 857–865, March 2007.

72. L. Stüber, Principles of Mobile Communications, second ed. Norwell, MA: Kluwer Academic Publishers, 2002.

3. ENERGY DETECTION WITH DIFFERENT DIGITAL MODULATION TECHNIQUES OVER RAYLEIGH FADING CHANNELS IN CRN

3.1 Introduction

In cognitive radio, the Secondary Users(SUs) performs the channel sensing for possible vacant PU spectrum, and if found, SUs may utilize this idle spectrum to perform the communication with other SUs in the network. However, while transmitting its own data, the SU continuously performs spectrum sensing to look for any PU activity on the channel, and if PU becomes active, SU must immediately vacate the band to keep a strategic distance to avoid any interference with PU. Energy detection has been widely used among the present spectrum sensing techniques since it does not require prior knowledge of the signal to be detected and is also the easiest to implement compared to other techniques [1]. In Energy Detection, the primary user signal is detected by comparing the received signal energy with a threshold (λ_{ED}) defined by the channel state information.

We analyze three digital modulation schemes the BPSK, QPSK, and 16-QAM for optimization. This chapter proposes the optimization for energy detector over Rayleigh fading channel. The analysis involves the performance evaluation of energy detector with discrete signals over BPSK, QPSK, and 16-QAMmodulation schemes using detection probability (P_d) versus SNR and ROC curves for various values of SNR, and the number of samples. Accordingly, we analyze and measure the improvement in detection capability of the energy detector under different signal conditions wherein the parameters such as Number of samples, SNR, threshold, false alarm probability (P_f) can be optimized.

Although different studies have been carried out on the performance of energy detector by means of inexplicit signal in various channel, no study is found that has analyzed different signals conditions under one platform. Our study was to analyze three distinct signal conditions simultaneously under Rayleigh fading and to quantify SNR, Number of samples and $P_{f.}$ Using closed form expression of P_d and P_f, P_d Vs SNR curve and ROC curves were plotted.

3.2 Basic Spectrum Sensing.

3.2.1 System model

The CR system under consideration has two parallel networks of primary and secondary users. The secondary network performs spectrum sensing using a relay with numerous sensors. Let there be K sensors, with distance between two consecutive sensors be $d=\lambda_m/2$, and λ_m is minimum detectable wavelength.

If the channel has no primary signal then it represents a spectrum hole (H_0), on the other hand the channel is said to be occupied (H_1) if the signal is detected.

$$y_i(n) = \begin{cases} v_i(n), & H_0 : channel\ free \\ a_i x_i(n) + v_i(n), & H_1 : channel\ used \end{cases} \quad (3.1)$$

Where denotes AWGN present on channel, and is PU signal.

The possible outcomes of signal detection are:

- *Pr(Ho/Ho)* – Claiming no signal when PU is inactive which is true.
- *Pr(H1/H1)* – Claiming the presence of signal when PU is active which is true.
- *Pr(Ho/H1)* – Claiming the absence of signal when PU is active which is false. (Miss detection).
- *Pr(H1/Ho)* – Claiming the presence of signal when PU is inactive which is false.(False alarm)

3.2.2 Energy detection

One of the most common PU detection method in spectrum sensing is Energy Detection (ED). This method is regarded as the most popular method of signal sensing due to its ease of implementation and computational simplicity. Unlike in MFs and other approaches, in this method, the receivers do not need any kind of knowledge of the PUs' signals. In this method, the signal detection is performed by comparing the output of energy detector with a given threshold value. Figure 3.1 show the implementation of energy detection using Band Pass Filter (BPF), Squarer, Integrator and decision device. In this method the signal is first converted from analog to digital and then filtered to remove unwanted frequency components. The output of the filter is squared, which is then averaged to get test statistics. Based on the test statistics, the absence or presence of the signal in the particular band is identified. For energy-based detection technique, Equation 2.1 shows the system model and the decision metric is given as

$$T_{ED} = \frac{1}{N} \int_{n=0}^{N} |y_i(n)|^2 \tag{3.2}$$

Where T_{ED} is the decision statistics and N denotes the sampling range in integers.

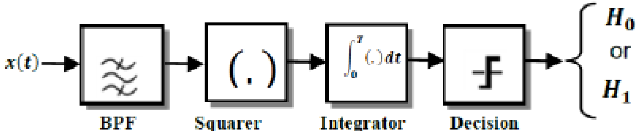


Fig.3.1 Energy Detector

3.3 Detection and False Alarm Probabilities Over AWGN and Rayleigh Fading Channels.

3.3.1 AWGN channel.

The probability with which the signal is truly detected *Pr(H1/H1)* is called probability of detection , and theprobability with which the signal is falsely detected *Pr(H1/Ho)* is called probability of false alarm . These probabilities are given as

$$p_d = Q\left[\frac{\lambda_{ED} - (\sigma_v^2 + \sigma_s^2)}{(\sigma_v^2 + \sigma_s^2)/\sqrt{N/2}}\right] \tag{3.3}$$

$$p_f = Q\left[\frac{\lambda_{ED} - \sigma_v^2}{\sigma_v^2/\sqrt{N/2}}\right] \tag{3.4}$$

Whereis energy detector decision threshold, Q(.) denotes the Gaussian aggregating distribution function, N represents sample size and

are channel noise and PU signal variances.

For a given false alarm, noise and sample size we have

$$\lambda_{ED} = \left(Q^{-1}(p_{f,ED})\sqrt{2/N} + 1\right)\sigma_v^2 \tag{3.5}$$

The SU network which has a central decision making relay node, receives the sensing data from all other nodes and decides in favor H_1 when there exists at least *k* out of L cognitive radios inferring H_1 concluding that the channel is preoccupied by the primary user. Otherwise, the central node decides in favor of H_0 indicating that the channel is vacant and can be dynamically utilized.

$$E = \sum_{i=1}^{L} Y_i \begin{cases} \geq k, & H_1 \\ < k, & H_0 \end{cases} \tag{3.6}$$

The cumulative probabilities in the network with L nodes are

$$P_d = 1 - (1 - p_d)^L \tag{3.7}$$

3.3.2 Rayleigh Fading channel.

When the received composite signal contains a big number of plane waves, for given scattering environments, the received signal has a Rayleigh distribution [2]. In Rayleigh fading, ω would have an exponential distribution given by

$$f(\omega) = \frac{1}{\omega}\exp\left(-\frac{\omega}{\overline{\omega}}\right), \qquad \geq 0 \tag{3.9}$$

And the detection probability in Rayleigh fading is given by,

$$P_{d,Ray} = \exp\left(-\frac{\lambda}{2}\right)\sum_{k=0}^{u-2}\frac{1}{k!}\left(\frac{\lambda}{2}\right)^k + \left(\frac{1+\overline{\omega}}{\overline{\omega}}\right)^{u-1} \tag{3.10}$$

$$\times\left(\exp(-\frac{\lambda}{2(1+\overline{\omega})}) - \exp(-\frac{\lambda}{2})\sum_{k=0}^{u-2}\frac{1}{k!}(\frac{\lambda\overline{\omega}}{2\,(1+\overline{\omega})})^k\right)$$

3.4 BER performance of different modulation schemes in AWGN, Rayleigh channels.

In this section, we evaluate the influence of fading on different digital modulation schemes. The bit-error-probability P_b also known as Bit Error Rate (BER) is a specific performance measure to gauge a modulation scheme.

the Bit Error Rate for a given discrete modulation scheme in an AWGN channel is given as

$$P_b = \int_0^{\infty} P_{bAWGN}(\omega) P_{df}(\omega)\, d\omega \tag{3.11}$$

Whereis the probability of error and denotes probability-density-function for the given AWGN channel.

3.4.1 BER of BPSK modulation in AWGN and Rayleigh fading channel

The Bit Error Rate for M-PSK over AWGN channel is [3]

$$BER_{M-PSK} = \frac{2}{max(log_2 M, 2)} \sum_{k=1}^{\max(M/4,1)} Q\left(\sqrt{\frac{2E_b \log_2 \mathrm{M}}{N_0}} sin \frac{(2k-1)\pi}{M}\right) \tag{3.12}$$

For Binary PSK(BPSK) M=2, hence from Eq. (3.12) we have

$$BER_{BPSK} = Q\left(\sqrt{\frac{2E_b}{N_0}}\right) \tag{3.13}$$

where

$$Q(A) = \frac{1}{\sqrt{2\pi}} \int_{A}^{\infty} exp\left(-\frac{B^2}{2}\right) dB \tag{3.14}$$

Alternatively,

$$BER_{BPSK:AWGN} = \frac{1}{2} erfc\left(\sqrt{\frac{E_b}{N_0}}\right) \tag{3.15}$$

where is the bit energy tonoiseratioand erfcrepresents the error-function associatedto the Q(.) function as

$$Q(A) = \frac{1}{2} erfc\left(\frac{A}{\sqrt{2}}\right) \tag{3.16}$$

Denoting h as Rayleigh distributed andas chi-square distributed we have

$$P_{df}(\omega) = \frac{1}{\overline{\omega}} \exp\left(-\frac{\omega}{\overline{\omega}}\right) \tag{3.17}$$

where is the average signal tonoise ratio. For , represents the average for the fading channel. By using Eqs. (3.11) and (3.13), the BER in a slowly Rayleigh-fading-channel modulated with BPSK can be expressed as [4], [5]

$$BER_{BPSK:RAY} = \frac{1}{2}\left(1 - \sqrt{\frac{\overline{\omega}}{1+\overline{\omega}}}\right) \tag{3.18}$$

3.4.2 BER of QPSK modulation in AWGN and Rayleigh fading channels

$$BER_{QPSK:AWGN} = \frac{1}{2} erfc\left(\sqrt{10^{\left(\frac{Eb}{N_0}\right)/10}}\right) \tag{3.19}$$

in Rayleigh Fading

$$BER_{QPSK:RAY} = \frac{1}{2}\left(1 - \sqrt{\left(10^{\left(\frac{Eb}{N_0}\right)/10}\right) / \left(10^{\left(\frac{Eb}{N_0}\right)/10} + 1\right)}\right) \tag{3.20}$$

3.4.3 BER of 16-QAM modulation in AWGN and Rayleigh fading channel

The BER of gray encoded M-QAM can be more precisely computed in AWGN by [3]

$$BER_{16QQAM:AWGN} =\approx \frac{4}{log_2 M}(1-\frac{1}{\sqrt{M}})\sum_{i=1}^{\frac{\sqrt{M}}{2}} Q\left(\sqrt{\frac{3\mathrm{log2MEb}}{(M-1)\,N_0}}\right) \quad (3.21)$$

the overall BER for M-QAM in Rayleigh distribution is given by [6]

$$BER_{16QAM;RAY} \approx \frac{2}{log_2 M}\left(1-\frac{1}{\sqrt{M}}\right) \times\sum_{i=1}^{\frac{\sqrt{M}}{2}}\left(1-\sqrt{\frac{1.5(2i-1)^2\overline{\omega}\log_2 \mathrm{M}}{M-1+1.5(2i-1)^2\overline{\omega}\log_2 \mathrm{M}}}\right) \quad (3.22)$$

3.5 Simulation results

This section presents the validation of analytical optimization proposed in sections 3.3 and section 3.4 through MATLAB simulations.

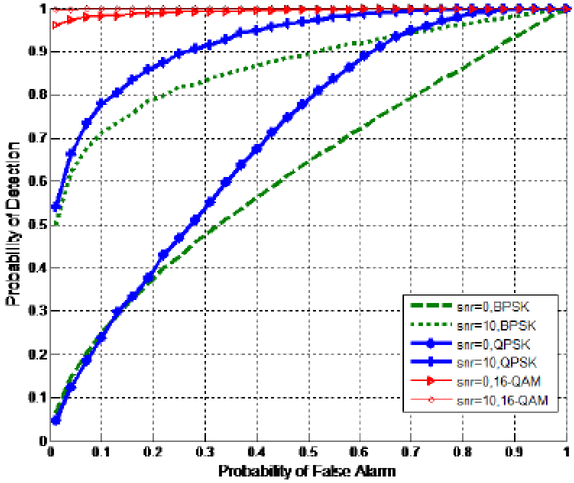


Figure 3.2: Pd vs Pf ED with 16-QAM, QPSK, and BPSK. *(SNR [0dB, 10dB], M=2, N=100000, L=1).*

Fig.3.2. illustrates the variation of probability of detection (P_d)with respect to probability of false alarm (Pf)over Rayleigh distribution for (SNR=0 dB and SNR=10 dB). It can be observed that, P_d shows much better performance for higher SNR levels. The analysis has clearly winner the 16-QAM scheme which has best performance over Rayleigh fading compared to other schemes discussed.

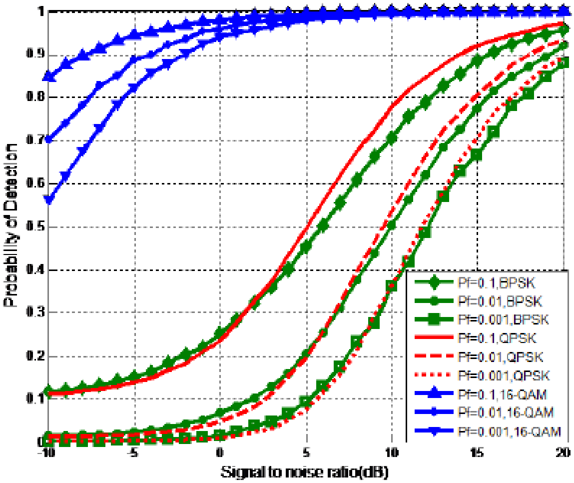


Fig.3.3. Pd vs Pf ED with BPSK, QPSK, and 16-QAM. (SNR=0dB and 10dB, L=1, N=100000, M=2)

Fig.3.3 depicts the variation of probability of detection (P_d) of the Energy Detector as function of SNR for given false alarm (P_f)values using BPSK, QPSK, and 16-QAM over Rayleigh fading. It can be seen that P_d is inversely proportional to P_f, conversely the performance of Energy Detector is best at low P_f values with high signal detection probabilities as shown in figure 4.

For example,for any value of SNR and L.

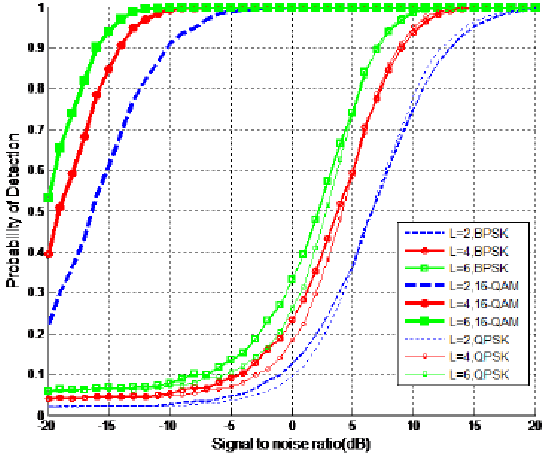


*Fig.3.4. Pd vs SNR of ED with BPSK, QPSK, and 16-QAM. (*Pf=0.1, Pf=0.01 and Pf=0.001*, L=1, N=100000, M=2)*

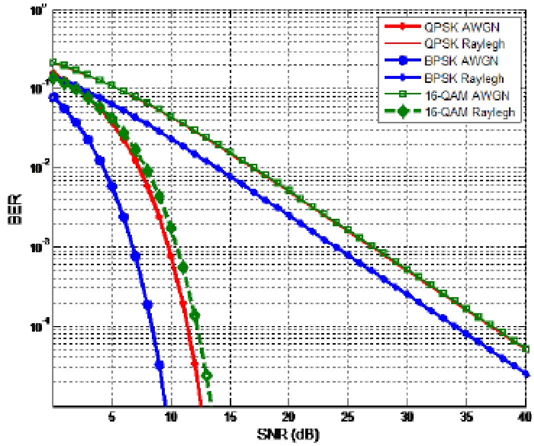


Fig.3.5 BER performances BPSK, QPSK, and 16-QAM in AWGN and Rayleigh fading.

Fig.3.4 shows the variation of probability of detection (P_d) of the Energy Detector as function of SNR for given values of L (Number of SUs in network) using BPSK, QPSK, and 16-QAM over Rayleigh fading. It is observed that P_d is directly proportional to L, conversely the performance of Energy Detector increases with more and more SUs in network.

Fig.3.5 shows the Bit Error Rate of the three modulation schemes over AWGN and Rayleigh distribution. The BER plots for the range of SNR [0dB - 40 dB] shows that for all the methods under consideration BER is inversely proportional to SNR for any fading channel. Further, at low noise, BER falls significantly in AWGN while it decreases steadily in Rayleigh fading.

3.6 Chapter summary

This chapter proposes the optimization for energy detector over Rayleigh fading channel. The analysis involves the performance evaluation of energy detector with discrete signals over BPSK, QPSK, and 16-QAM modulation schemes. It can be shown that, over Rayleigh fading channel, the energy detector performs the channel sensing efficiently at low channel noise but as the noise increases the performance degrades. Of the three digital modulation schemes analyzed, it is observed that the 16-QAM's detection probability is much better than QPSK and BPSK signals. Furthermore, the chapter analyzes AWGN and Rayleigh fading channels used in ED for their performance over Bit Error Rate. It is found that the BER performance of Rayleigh channel is much better compared to AWGN channel. However, in both channels the channel noise has negative impact on BER.

References:

1. Kolodzy, I. Avoidance, and S. Models, "Spectrum Policy Task Force," Federal Commun. Comm., Washington, DC, Rep. ET Docket no. 2 -135, Nov. 2002.

2. Lu, J., Lataief, K.B., Chuang, J.C.I., Liou, M.L.: M-PSK and M-QAM BER computation using single space concepts. IEEE Trans. Commun. 47, 181–184 (1999).

3. Rappaport, T.S.: Wireless Communications: Principles and Practice. IEEE Press, Piscataway (1996)

4. Simon,M.K.,Alouinii,M.S.:Digital Communication Over Fading Channels: A Unified Approach to Performance Analysis. Wiley, New York (2000).

5. C. Liang, G. Pan and Y. H. Zeng, "On the performance of spectrum sensing algorithms using multiple antennas," IEEE Global Telecommunications Conference, pp. 1-5, December 2010.

6. Bezdek, J., Hathaway, R.: 'Some notes on alternating optimization'. Proc. Int. Conf. on Fuzzy Systems (ICFC), 2002

4. MULTISTAGE SENSING OPTIMIZATION

4.1 Introduction

This chapter proposes a novel scheme for joint sensing and power assignment the "Fast-Optimal-eXplorative (FOX)" scheme which is a dual-phase spectrum sensing scheme followed by optimized resource allocation for CR Networks. The scheme implements dual phase sensing the "*Fast*" phase followed by "*Optimal*" phase and then "*eXplore*" phase for optimal power allocation.

The crucial features of the scheme are:

- Efficient spectrum sensing with dual-phase signal detection which lowers the probability of false alarm. In the first phase employs one of the most common PU detection method in spectrum sensing the Energy Detection (ED). This method is regarded as the most popular method of signal sensing due to its ease of implementation and computational simplicity. Unlike in other approaches, in this method, the receivers do not need any kind of prior knowledge of the PUs' signals.
- Adaptive to channel noise: Single phase at low noise (high SNR) and dual phase at higher noise (low SNR) which lowers the probability miss

detection. The proposed method adapts to the channel noise by switching between one stage with high speed sensing at low channel noise (high SNR) and two stage at high channel noise. In second stage high accuracy in signal detection is desired due to low SNR to reduce the probabilities of miss detections and false alarm. The pipelined structure employs Maximum Eigen Detection (MED) in second stage which has very high probability of detection at high channel noise.

- Flexible resource allocation: by operating in both overlay and underlay modes. The simulation results verify the above scheme which outperforms the other similar schemes in literature.

The two types of cognitive behavior we consider are:

- Spectrum overlay (spectrum interweave): The unlicensed users utilize the licensed spectrum without causing interference to the primary or licensed users. The signals from both these users operate orthogonally to one other: The primary and secondary users may operate on the same channel in a such a manner that guarantees that both licensed and unlicensed users coexist on the same channel with least interference to one another. The secondary users must be aware of their radio environment to achieve the information of the spectrum holes in the primary system. The interference avoiding behavior with which the secondary users occupy the spectrum holes, is referred to as *spectrum overlay*.
- Spectrum underlay: The primary and secondary users operate on the same channel, in such a way that the inflicted interference from the secondary users to the primary users is within the tolerable level defined by the Quality of Service constraints. Such an interference controlling behavior is termed as *spectrum underlay* in which the networks operate with such low transmission powers, that

they appear as channel noise for the primary system. The requisite channel awareness is information regarding the tolerable levels of interference defined by primary QoS constraints along with the information of the impact of the secondary user at the primary receiver. Hence the secondary user system must be aware of all the channel states information in the network.

4.2 Challenges of Joint sensing and allocation in CRNs

The research of CR technology utilizes spectrum resources efficiently. A compatible coexistence between heterogeneous networks and interactive applications shows great prospects. To make cognitive devices transmit information efficiently in the most optimal way in a limited signal space, cross-layer design of routing algorithms for DSA networks must be adopted, which allocates spectrum and selects the route through spectrum sensing information provided by the physical layer and spectrum scheduling information provided by the link layer synthesized by the network layer. The close collaboration between the physical, link, and network layers provides an optimal path while improving spectral efficiency for nodes. In order to meet the rapidly changing environment of wireless spectrum, piggybacked status information collecting the change of spectrum on the path in real time can estimate transmission quality and judge timely avoiding routing interrupts on system performance. Simultaneously mixing routing will be the focus of study. Maintaining partial routing information can create routing quickly and avoid routing affected by the stale route information, while reducing the network load caused by routing establishment and maintenance. Intelligent reasoning ability of CR itself is the most important characteristic of DSA networks so that its routing algorithms should also be intelligent. Routing algorithms can create reasoning models of network routing and provide evidence for various indicators of joint optimization such as latency, delay jitter, and package loss rate while providing support for the upper applications through the study of spectrum environment, information of path status, spectrum selection, and routing making. Joint routing and SA is a key design issue for CRNs and many past efforts have proposed lots of techniques from different perspectives. This gives overall view of the development of SA in CRNs, routing schemes for CRNs, and joint routing and SA design. Nevertheless, there are still challenges and open problems for realizing effective and efficient joint routing and SA for CR communications.

4.2.1 Spectrum Characterization

Most schemes use a single target [i.e., fairness, Signal to Interference plus Noise Ratio (SINR), or throughput] to define the traffic load of the inspected spectrum blocks and select an optimal channel based on either throughput requirements or interference threshold of the SUs. According to each SU's service demand, there can be different QoS factors, such as delay, jitter, throughput, and bit error rate. Since various applications are used into different performance/QoS requirements, which might operate concurrently on the SU's hardware, the joint routing and SA algorithms may be unable to be optimal methods because these schemes need to consider all the QoS parameters for the spectrum channels, so it is necessary to find optimal solutions to solve the problem.

- Robust Route for SA

The presentation of PUs plays more serious on e2e connectivity for multihop communications than that in the single-hop case. The source nodes and destination nodes can only consider the local channel availability when this situation is in single-hop communications. However, in the multihop communications, each pair of nodes should be taken into the channel availability of the entire route. Therefore, it is important to find a robust route in CRNs, which is ignored in the most work. In traditional networks, the robust routing without considering the impact of PUs, so they only pay attention to the problem of node mobility, even the strong interference from the neighboring nodes. The existing work on routing and SA in CRNs ignores both these issues and single-flow scenarios.

- Hidden User Effect

Detecting a primary transmitter signal is a major misconception in CR literature, which is equivalent to finding spectrum opportunities. However, joint routing and spectrum opportunistic access is affected by the following three main problems when the primary signals can be perfectly detected: (1) the hidden transmitter, (2) the exposed transmitter, and (3) the hidden receiver.

- Spectrum Mobility Challenge

Each time or space an SU changes its frequency, the operation parameters should be modified of the network protocols. When an SU captures the best spectrum band, the activity of PU on the selected spectrum can necessitate so that it can alter its operating spectrum band(s); this scheme is denoted as spectrum mobility. This is a big challenge that must be solved in the jointed routing and SA schemes. The open research issues that are solved in the joint routing and SA schemes, which can improve the efficient spectrum mobility in CRNs, are as follows:

- The spectrum mobility in the time domain: According to the information of available bands, CRNs adapt to the wireless spectrum accurately. As these existing idle channels also change over time, the QoS in this environment is challenging.
- The spectrum mobility in the space domain: As PUs or SUs move from one place to another, the available bands also change. Therefore, continuous allocation of spectrum is a major challenge.

4.3 System model and basic spectrum sensing.

4.3.1 System model

The CR system under consideration has two parallel networks of primary and secondary users. The secondary network performs spectrum sensing using a relay with numerous sensors. Let there be K sensors, with distance between two consecutive sensors be $d=\lambda_m/2$, and λ_m is minimum detectable wavelength. If the channel has no primary signal then it represents a spectrum hole (H_0), on the other hand the channel is said to be occupied (H_1) if the signal is detected.

The received signal is given as

$$y_i(n) = \begin{cases} v_i(n), & H_0 : channel\ free \\ a_i s_i(n) + v_i(n), & H_1 : channel\ occupied \end{cases} \qquad (4.1)$$

Where denotes AWGN present on channel, and is PU signal.

4.3.2 Energy detection

One of the most common PU detection method in spectrum sensing is Energy Detection (ED). This method measures the received signal energy and then compares it with the decision threshold. The comparison can result in two possible outcomes. (1) The channel is not free (H_1 PU is operating on channel) or (2) the channel is free (H_0 spectrum opportunity). Energy Detection is the simplest and fastest of all the signal detection methods. This method has least computational complexity. However, ED is unreliable, when the received signal has low SNR. This method has a few issues related to threshold selection for detection of PUs, further this method cannot differentiate between the interference from PUs or from channel noise. A secondary user in the CR system observes the neighboring wireless spectrum by deriving the received signal power using energy detector.

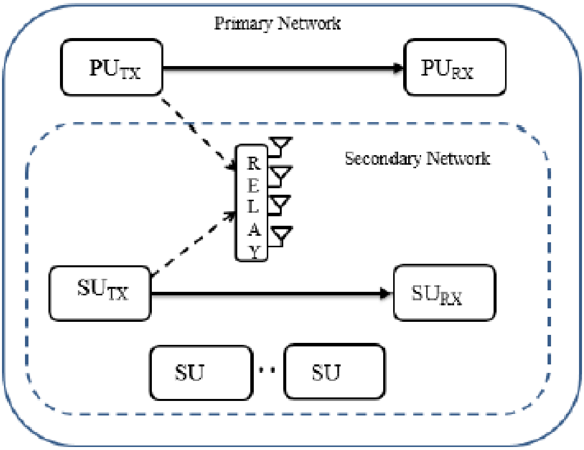


Figure 4.1: System model.

Then the observation results in two hypotheses given in (4.1). The decision statistics based on the average energy of the received signal is

$$T_{ED} = \frac{1}{N} \int_{n=0}^{N} |y_i(n)|^2 \tag{4.2}$$

Where ith sample of the received signal, TED denotes the decision statistics and *N* is sampling interval.

The probabilities of true detection *(P_D,ED)* and false-alarm *(P_F,ED)* for energy detector is given by:

$$p_{d,ED} = Q\left[\frac{\lambda_{ED} - (\sigma_v^2 + \sigma_s^2)}{(\sigma_v^2 + \sigma_s^2)/\sqrt{N/2}}\right] \quad (4.3)$$

$$p_{f,ED} = Q\left[\frac{\lambda_{ED} - \sigma_v^2}{\sigma_v^2/\sqrt{N/2}}\right] \quad (4.4)$$

Where is decision threshold, and refers to noise variance and signal variance respectively, and Q(.) denote Gaussian distribution function.

Equation (4.4), can be rewritten in terms of decision threshold as

$$\lambda_{ED} = \left(Q^{-1}(p_{f,ED})\sqrt{2/N} + 1\right)\sigma_v^2 \quad (4.5)$$

The ED performs exceptionally well for random signal with known noise level. Further this method is highly robust to random multipath fading with least complexity and computational cost. The drawback of ED is it highly sensitive to uncertain noise levels.

4.3.3 Maximum eigenvalue detection

This method is known for accurate signal sensing over a noisy environment. MED is highly immune to channel noise and works fine at low SNR values. This method works by evaluating maximum eigenvalue of the sample covariance matrix of the received signal and comparing with the decision threshold. The comparison leads to two possible outcomes. (1) maximum eigenvalue is higher than the decision threshold and hence channel is not free (H_1 PU is operating on channel) otherwise (2) the channel is free (H_0 spectrum opportunity).

From (1) for we have

$$Y_i(n) = a_i S_i(n) + V_i(n) \quad (4.6)$$

Where

$$Y_i(n) = [y_i(n)\, y_i(n-1)\ \ldots\ \ y_i(n-N+1)] \tag{4.7}$$

$$S_i(n) = [s_i(n)\, s_i(n-1)\ \ldots\ \ s_i(n-N+1)] \tag{4.8}$$

$$V_i(n) = [v_i(n)\, v_i(n-1)\ \ldots\ \ v_i(n-N+1)] \tag{4.9}$$

The statistical covariance for the given signal condition can be written as

$$R_y = E\left[Y_i(n)\, Y_i^T(n)\right] \tag{4.10}$$

$$R_s = E\left[S_i(n)\, S_i^T(n)\right] \tag{4.11}$$

$$R_w = E\left[V_i(n)\, V_i^T(n)\right] = \sigma_w^2 I_N \tag{4.12}$$

The above equations are related as

$$R_y = R_s + \sigma_w^2 I_N \tag{4.13}$$

In MED the probabilities of detection *(P_D,MED)* and false alarm *(P_F,MED)* for the known threshold are given as [2]

$$p_{d,MED} = 1 - W_M^m\left(\sqrt{N}\left(\beta\lambda_{MED} - 1\right)\right) \tag{4.14}$$

$$p_{f,MED} = 1 - F_M^m\left(\sqrt{N}\left(\lambda_{MED} - 1\right)\right) \tag{4.15}$$

WhereF(m) and W(n) denotes the allocation of the subsequent test indicators of and over Ho and H1 respectively.

4.4 A novel dual phase sensing and power allocation.

This section gives a novel scheme for joint sensing and power assignment the “Fast-Optimal-eXplorative (FOX)” scheme which is a dual-phase spectrum sensing scheme followed by optimized resource allocation for CR Networks. The scheme implements dual phase sensing the "Fast" phase followed by "Optimal" phase by adapting to the channel noise. The scheme switches between one stage with high speed sensing at low channel noise (high SNR) and two stage at high channel noise. In second stage high accuracy in signal detection is desired due to low SNR to reduce the probabilities of miss detections and false alarm. The pipelined structure employs Maximum Eigen Detection (MED) in second stage which has very high probability of detection at high channel noise. Finally, "eXplore" phase provides flexible resource allocation by operating in both overlay and underlay modes as illustrated in Fig.4.2.

4.4.1 With decision statistics ED:H_0, -Two stage ED-MED sensing.

The joint two stage probability of detection can be derived as

$$p_d = 1 - (1 - p_{d,ED})(1 - p_{d,MED}) \tag{4.16}$$

Substituting (4.3), (4.14) in (4.16)

Which can be written as

$$p_d = 1 - \left(1 - Q\left[\frac{\lambda_{ED} - (\sigma_v^2 + \sigma_s^2)}{(\sigma_v^2 + \sigma_s^2)/\sqrt{\frac{N}{2}}}\right]\right)\left(W_M^m\left(\sqrt{N}\left(\beta\lambda_{MED} - 1\right)\right)\right) \tag{4.17}$$

$$p_d = 1 - W_M^m\left(\sqrt{N}\left(\beta\lambda_{MED} - 1\right)\right) + Q\left[\frac{\lambda_{ED} - (\sigma_v^2 + \sigma_s^2)}{(\sigma_v^2 + \sigma_s^2)/\sqrt{N/2}}\right] W_M^m\left(\sqrt{N}\left(\beta\lambda_{MED} - 1\right)\right) \tag{4.18}$$

In the same way, the probability of false-alarm can be derived as

$$p_f = 1 - (1 - p_{f,ED})\,(1 - p_{f,MED}) \tag{4.19}$$

Substituting (4), (15) in (32)

$$p_f = 1 - \left(1 - Q\left[\frac{\lambda_{ED} - \sigma_v^2}{\sigma_v^2/\sqrt{N/2}}\right]\right)\left(F_M^m\left(\sqrt{N}(\lambda_{MED} - 1)\right)\right) \tag{4.20}$$

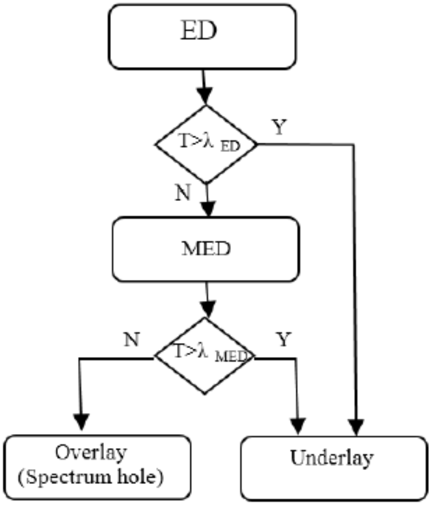


Figure 4.2: Block diagram of the proposed "FOX" scheme.

The following algorithm gives the implementation above scheme with adaptive power allocation.

Algorithm 4.1: two-state sensing/power allocation

Received signal at CR $y \Leftarrow hs + n$

Signal energy, $E = |y|^2$

If $E > \lambda_{ED}$ then

underlay transmission with power P_1

elseif $T > \lambda_{MED}$

underlay transmission with power P_1

else

overlay transmission with power P_0

endif

Fig.4.3 sensing and power allocation

4.4.2 Explorative Power Allocation

The Hybrid mechanism combines opportunistically both the underlay and overlay operations. If the sensing results in spectrum hole (H_0) the scheme allows the unlicensed users to communicate on the channel in overlay mode (P_0) otherwise, the scheme restricts to underlay mode (P_1).

The miss detection in sensing, results in an erroneous decision in favor of spectrum hole while the PU is still on the channel. This is prevented with an interference check, termed as 'interference temperature' [1], [5].

The transmission power in overlay mode (P_0) from [3], [4]

$$P_0 = \left[\frac{-(B_0/A_0) + \sqrt{(B_0/A_0)^2 - 4\,(C_0/A_0)}}{2} \right]^+ \tag{4.21}$$

where

$$\frac{B_0}{A_0} = \frac{2\sigma_0^2 + P_P g_{psr}}{g_{ss}} - \frac{\rho_0}{\lambda \varepsilon g_{sp} + \mu \rho_0} \tag{4.22}$$

$$\frac{C_0}{A_0} = \frac{1}{g_{ss}} \left[\frac{\sigma_0^4 + \sigma_0^2 P_P g_{psr}}{g_{ss}} - \frac{\sigma_0^2 \rho_0 + \alpha_0 P_P g_{psr}}{\lambda \varepsilon g_{sp} + \mu \rho_0} \right] \tag{4.23}$$

Similarly, the transmission power in underlay mode (P_1)

$$P_1 = \left[\frac{-\left(B_1/A_1\right) + \sqrt{\left(B_1/A_1\right)^2 - 4\left(C_1/A_1\right)}}{2} \right]^+ \tag{4.24}$$

where

$$\frac{B_1}{A_1} = \frac{2\sigma_0^2 + P_P g_{ps}}{g_{ss}} - \frac{\rho_1}{\lambda \left(1 - \varepsilon\right) g_{sp} + \mu \rho_1} \tag{4.25}$$

$$\frac{C_1}{A_1} = \frac{1}{g_{ss}} \left[\frac{\sigma_0^4 + \sigma_0^2 P_P g_{ps}}{g_{ss}} - \frac{\sigma_0^2 \beta_1 + \alpha_1 \left(P_P g_{ps} + \sigma_0^2\right)}{\lambda \left(1 - \varepsilon\right) g_{sp} + \mu \rho_1} \right] \tag{4.26}$$

Where {,,,} are the channel gain from PU_{TX} to SU_{RX}, PU_{TX} to SU_{TX}, SU_{TX} to PU_{RX}, and SU_{TX} to SU_{RX} respectively.

4.5 Simulations and Discussion

The operation of Energy detector involves the prior knowledge of noise power, which unfortunately is most uncertain [7, 3]. Because of this noise uncertainty, the expected noise level may be different from the actual noise level.

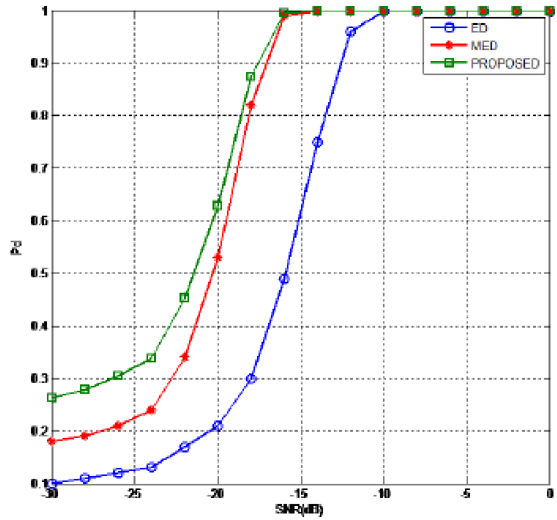


Fig. 4.4: Comparison of probability of detection for SNR between −30 dB and 0 dB and P_{fa} = 0.1.

Let the estimated noise power be . We define the noise uncertainty factor (in dB) as . It is assumed that (in dB) is evenly distributed in an interval [-B, B]. In practice, the noise uncertainty factor of receiving device is normally 1 to 2 dB [3a, 5a].the plot of equations (3), (14) and (30) for (false alarm) P_{fa} = 0.1, L = 10; N = 5,000; and SNR [−30 dB to 0 dB]. Further it compares the proposed scheme with single phase techniques employed. It can be clearly seen that the proposed strategy has better detection probability than the other methods.

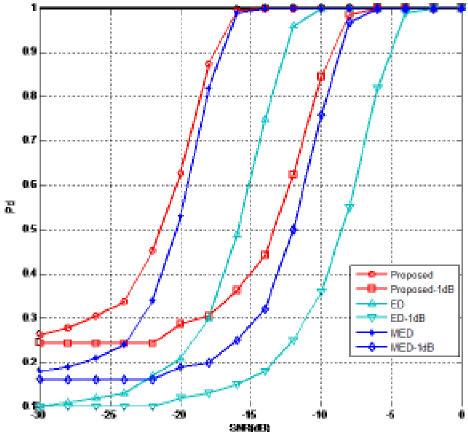


Fig. 4.5: *Comparison of probability of detection against SNR between −30 dB and 0 dB and* P_{fa} *= 0.1. with and without noise uncertainty.*

Fig.4.5 *shows the probability of detection vs SNR of the proposed scheme for (false alarm)* P_{fa} *= 0.1, L = 10; N = 5,000; and SNR [−30 dB to 0 dB]. Further it compares the proposed scheme with single phase techniques employed. The analysis is done by adding a component of channel noise [0dB and 1dB]. It can be clearly seen that the proposed strategy has better detection probability than the other methods.*

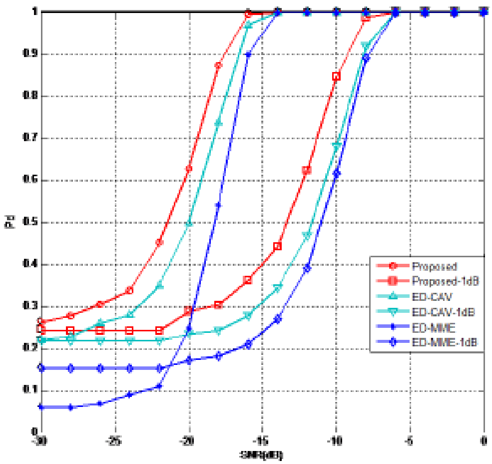


Fig. 4.6: Comparison of probabilities of detection with other two stage methods. SNR between −30 dB and 0dB and P_{fa} = 0.1. with and without noise uncertainty.

Fig.4.6. gives the comparison of proposed scheme with similar methods in literature. The evaluation is done by adding a component of channel noise [0dB and 1dB]. The analysis is done for independent and identically distributed (iid) signal for (false alarm) P_{fa} = 0.1, L = 10; N = 5,000; and SNR [−30 dB to 0 dB].

In this chapter, the optimization of the spectrum exploration and exploitation processes in cognitive radio networks has been considered. Spectrum exploration is the process of obtaining local awareness of the spectrum state through spectrum sensing. The goal of spectrum exploration is to find idle spectrum that can then be exploited. Optimization of spectrum exploration includes optimization of the whole spectrum sensing process that determines which frequency bands are sensed, when they are sensed and for how long and by which users, and how are the sensing results from multiple users combined. This involves trading off quantities such as diversity, detection speed, and performance. Spectrum exploration is coupled with spectrum exploitation.

Spectrum exploitation addresses the questions: what happens after idle spectrum has been found; and how is the idle spectrum subsequently exploited? Spectrum exploitation optimization involves optimizing the spectrum access process that determines which idle frequency bands to access, for how long, and by which users. It involves choosing the transmit powers and waveforms to be employed, as well. The goal of spectrum exploitation combined with spectrum exploration is to maximize the throughput of the secondary network and provide a desired quality of service for the secondary network while guaranteeing that the level of interference caused to the primary users is below the given interference constraints. In chapter 2, advanced spectrum sensing techniques, such as distributed detection and sequential and quickest detection, have been reviewed. Distributed detection among spatially dispersed secondary users allows improving the sensing reliability by increasing the probability of detection for a given probability of false alarm. Or alternatively the sensing time can be reduced without sacrificing the sensing performance. Sequential and quickest detection aim at making the decision as quickly as possible for the given error levels. Quickest detection techniques facilitate also the secondary users rapid evacuation from a frequency band when a primary user becomes active. Both distributed detection and sequential and quickest detection techniques are thus important for more efficient and effective spectrum exploration.

This chapter is focused on the design of optimum spectrum sensing and access policies for optimized spectrum exploration and exploitation. Various approaches for modelling, analysing, and learning the behaviour of other spectrum users have been considered. Introductions to dynamic programming, bandit problems, reinforcement learning, game theory, and their applications in cognitive radio systems have been provided. Dynamic programming is an optimization approach in which the original problem is broken into recursively solved simpler sub problems. Although this reduces the complexity of finding the optimal solution, the computational complexity of dynamic programming still limits its usefulness in practical cognitive radio systems. In high-dimensional problems the computational complexity of obtaining an optimal solution through dynamic programming may be prohibitive in particular for battery-operated terminals with limited computing power. Hence, computationally efficient techniques that may be used to obtain a close-to-optimal or asymptotically optimal solution are of interest.

A truly cognitive radio should possess the ability to learn from the environment and the outcomes of its previous actions. More complicated, full-blown reinforcement learning problems and algorithms may be needed, in particular, if the actions of the secondary users are allowed to be also something other than sensing or accessing a certain frequency band. Nevertheless, both bandit problems and more general reinforcement learning problems deal with the exploitation vs. exploration dilemma. That is, the agent or agents must in each state decide whether to exploit the currently best action or to explore other actions in the hope of a better future reward. The learning is performed through trial and error and by reinforcing actions leading to good rewards, not through a teacher telling whether the chosen action was correct or not. Hence, these techniques are particularly suitable for cognitive radio applications in which the radio environment is unknown, highly dynamic, and nonstationary. Game theory, on the other hand, provides a collection of mathematical methods and tools for modelling, analysing, and predicting the behaviour of multiple interacting entities.

In cognitive radio systems, game theory offers a framework for modelling and analysing the interaction of multiple competing and/or cooperating spectrum users. The majority of existing game theory deals with static single-shot or repeated games. This means that the players face the same game each time. Thus, the players' strategies do not depend on the current state of the environment. This does not provide a very good fit to cognitive radio applications in which the radio environment may be highly dynamic. However, a subfield of game theory called stochastic games provides an excellent fit to the dynamic environment encountered in cognitive radio applications. In stochastic games there are numerous states that change stochastically throughout the course of the game. This also means that the players' strategies will depend on the current state. In addition, stochastic games provide a connection between game theory and multivalent reinforcement learning since multivalent reinforcement learning problems can be modelled as stochastic games.

The main focus in this chapter has been on optimizing spectrum exploration and exploitation in interweave cognitive radio networks. For the vast majority of introduced techniques and algorithms the employed system framework assumes one or multiple primary systems and a single cognitive radio network consisting of identical (homogeneous) secondary users. However, in practice, there may be multiple heterogeneous secondary systems simultaneously trying to find and exploit the same underutilized spectrum. The coexistence of such heterogeneous secondary systems and networks has not been considered in this chapter.

What are the implications of heterogeneous secondary systems coexisting on the same frequency bands? In principle, two heterogeneous secondary systems may employ completely different waveforms, modulation, coding, and access schemes from one another, for example. How then can two or more completely different secondary systems coexist efficiently and effectively in a licensed primary frequency band while controlling the interference caused to the primary users? Can the other secondary systems be treated only as noise? On the other hand, how do the other asynchronous secondary systems affect the sensing process since quiet periods for sensing cannot be assumed anymore? Obviously the employed sensing algorithms should be able to distinguish among the secondary systems and the primary systems if underutilized spectrum is to be exploited as efficiently as possible. However, how much does the interference from the other secondary systems affect the reliability of sensing? How about spectrum access then? How do the interference and collisions with other secondary systems affect the efficiency of the spectrum access algorithms? These are all open questions that need to be answered before free coexistence of heterogeneous secondary systems can become reality.

4.6 Chapter summary

This chapter contributes a novel scheme for joint sensing and power assignment the "Fast-Optimal-eXplorative (FOX)" scheme which is a dual-phase signal sensing scheme followed by enhanced resource allocation for CR Networks. The scheme implements dual phase sensing the "Fast" phase followed by "Optimal" phase by adapting to the channel noise. The system switches between one stage with high speed sensing at low channel noise (high SNR) and two stage at high channel noise. In second stage high accuracy in signal detection is desired due to low SNR to reduce the probabilities of miss detections and false alarm. The pipelined structure employs Maximum Eigen Detection (MED) in second stage which has very high probability of detection at high channel noise. Finally, "eXplore" phase provides flexible resource allocation by operating in both overlay and underlay modes. The simulation results have clearly shown that the proposed scheme outperformed the other schemes in literature.

References:

1. Kolodzy, I. Avoidance, and S. Models, "Spectrum Policy Task Force," Federal Commun. Comm., Washington, DC, Rep. ET Docket no. 2 -135, Nov. 2002.

2. Rohitha Ujjinimatad and Siddarama R Patil, " Signal Detection in Cognitive Radio Networks Based on the Ratio of Largest Eigenvalue to the Trace of a Covariance Matrix, " in proceedings of IEEE International Conference on Communication, VLSI and Signal Processing (ICCVSP-2013), SIT Tumkur, India. Feb. 20th – 22nd , 2013, pp. 226–229

3. Rohitha Ujjinimatad and Siddarama R Patil, "Spectrum Sensing in Cognitive Radio Networks with the Known and Unknown Noise Levels," IET Communications, vol. 7, Issue 15, pp. 1708 - 1714. October 2013. ISSN:1751–8628

4. Rohitha Ujjinimatad and Siddarama R Patil, "Mathematical Analysis for the Detection of

Unknown Signals in Cognitive Radio Networks Over Wireless Communication Channels, " IET Journal of Engineering, doi: 10.1049/joe.2014.0173

5. Joseph Mitola, "Software Radio Architecture: Object-Oriented Approaches to Wireless Systems Engineering," Wiley-Interscience, 2000.

6. Mitola, G. Q. Maguire, "Cognitive radio: Making software radios more personal," IEEE Pers. Commun., vol. 6, no. 4, pp. 13 – 18, Aug. 1999.

7. Haykin, "Cognitive radio: Brain-empowered wireless communications,"*IEEE Journal on Selected Areas in Communications,* vol. 23, no. 2,pp. 201–220, 2005.

8. K. Jondral, "Software-defined radio: Basic and evolution to cognitiveradio," *EURASIP Journal on Wireless Communication and Networking,*vol. 2, no. 1, pp. 275–283, 2008.

9. McHenry, D. McCloskey, and G. Lane-Roberts, "New York City Spectrum Occupancy Measurements Sep. 2004," Tech. Rep., Dec. 2004.

10. Shared Spectrum Company, "General survey of radio frequency bands – 30 MHz to 3 GHz," Tech. Rep., Sep. 2010.

5. EXPLORATION BASED SPECTRUM SENSING AND ALLOCATION

5.1 Introduction

Sensing and access policies provide solution to the issues related to what the radios should sense and access, and when? Moreover, in centrally controlled multiuser systems spectrum sensing and resource allocation are distributed among different nodes in the network. That is, the spectrum of interest could be very wide and noncontiguous. Thus, from the perspective of a single secondary user, sensing the whole spectrum of interest in each sensing instant may not be practical due to the difficulties it presents to the sensing receiver's radio frequency (RF) front-end design as well as due to the high energy consumption of such an approach. Consequently, a more practical solution involves dividing the spectrum of interest into smaller frequency sub bands that can be sensed one at a time. Hence, the problem becomes deciding which frequency band or bands to sense and subsequently access and by which user or users in order to optimize the cognitive radio network's performance. Obviously the secondary users should sense and access frequency bands in which there exist persistent spectral opportunities and high average throughput. Moreover, in a cognitive radio network it becomes essential to distribute the frequency bands for sensing and access among the network members in the most efficient and effective manner that results in a high probability of finding available spectrum as well as in low interference to both primary and secondary users of the spectrum. In order to make such decisions most effectively, the cognitive radio network must obtain situational awareness. Thus, various approaches to modeling, learning, and predicting the time, frequency, and location-varying spectrum state and the behavior of other spectrum users are of special interest.

The nature and constraints of the optimization problem and the design of sensing and access policies depend on whether the cognitive radio network model is a single-user or multiuser network model, whether the spectrum model is a single-band or multiband model, whether the users sense and access the spectrum synchronously or asynchronously, and whether the secondary users in a multiuser model cooperate or compete with each other, among other things .In general, in an infrastructure-based network cooperation among the secondary users is more naturally enforced than in an ad-hoc network in which the users are more inclined to compete with each other. However, this by no means rules out the possibility of competition in an infrastructure based network or cooperation among the users in an ad-hoc network. On the contrary, such approaches may offer substantial benefits by simplifying the system design and/or by providing improved performance. In this section we will describe various different approaches and cognitive radio network models that are competitive, cooperative, or a combination of the two. We will mostly focus on the design of spectrum sensing and access policies in cognitive radio networks, and introduce various approaches such as bandit problems, reinforcement learning, and game theory that may be employed to address these issues. However, we will start this section by looking at some more direct optimization techniques for optimized spectrum exploration and exploitation in cognitive radio networks.

5.2 Interference channels

5.2.1 K-user interference channel

In cognitive radio networks, we would like to characterize capacity associated with communications between primary user pairs and between secondary user pairs. Although one could envision deployment of relays to improve the performance, these networks typically do not involve multi-hop routing of information, i.e., there is no forwarding of information through intermediate nodes. Without cognition, networks with K source–destination pairs can be modeled as a K-user interference channel, as shown in Fig. 2.10. Although the capacity region of this channel is in general unknown, there has been a lot of progress in understanding how to cope with interference in this model and, consequently, in developing spectrally-efficient transmission schemes for this channel.

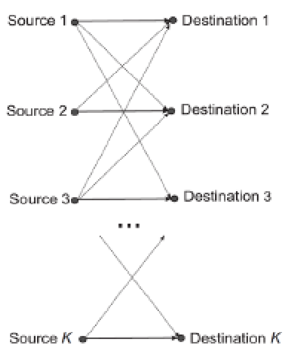


Figure 5.1 K-user interference channel. Sender k wishes to communicate to destination k.

In some scenarios, these techniques lead to capacity. A cognitive radio network forms a two-tier K-user interference channel, due to the different capabilities and restrictions of primary and secondary users. Schemes that efficiently cope with interference can improve performance of both primary and secondary users in these networks. For that reason, some of the techniques developed for interference channels have been adopted for overlay cognitive networks as well. We next review these techniques, their performance and their known capacity results. In addition, cognition enables additional encoding/decoding techniques to improve the performance. Hence, performance of interference channels can serve as a lower bound to the capacity of cognitive networks.

In the K-user interference channel model, each of the K sources wishes to communicate with its corresponding destination over a shared wireless channel, as illustrated in Fig. 2.10. Source skencodes and sends a data sequence Wkat rate Rkto destination dk. The K-user interference channel is a special case of a K-user wireless network.

5.2.2 Two-user interference channel capacity

A two-user discrete-time memoryless interference channel is shown in Fig. 2.11. The interference channel contains only two communicating pairs (K = 2). Therefore, there are two channel inputs, X1 and X2, and two channel outputs, Y1 and Y2. Recall that the multiple access channel consists of multiple transmitters simultaneously sending to one receiver. The channel MAC1 consists of two encoders and decoder 1 and, similarly, the channelMAC2 consists of two encoders and decoder 2. The capacity region of this network is in general a lower bound on the capacity of the interference channel because both receivers need to decode data sequences sent from both sources. In the interference channel, in contrast, each receiver decodes data sequences sent from only one source. In strong interference, however, each receiver can decode unwanted data sequences without reducing the capacity region of the interference channel, and the capacity region of the interference channel then coincides with (2.38). Note that, in strong interference, the capacity is achieved by joint decoding of both data sequences at the decoders. In the special case of very strong interference, decoders do not need to perform joint decoding of the data sequences. Instead, interference cancellation can be performed successively, allowing for interference-free decoding of the desired data sequence [10]. In this regime, the interfering data sequence cannot be decoded, but it is not strong enough to significantly degrade the rate of the impacted user. When the interference is weak, intuitively we expect that the optimal decoding strategy is to treat it as noise. However, it has been difficult to prove that this intuition is correct, and hence the capacity remains unknown. Conditions under which treating interference as noise leads to sum-rate capacity in two-user Gaussian channels were determined in [1, 63, 75].

Not surprisingly, in strong interference the highest-rate scheme is to decode the unwanted data sequences and subtract their corresponding signals, thus removing their interference from the received signal. In the other extreme of weak interference, the highest-rate strategy is to ignore the interference, that is, treat it as noise. In regimes that are in between the two extremes, the interference is not strong enough so that decoding of the unwanted data sequence is optimal, nor is it weak enough to be treated as noise without loss of optimality. In this scenario, decoding part of an interfering data sequence to partially remove interference from the received signal is beneficial. This idea is realized in the scheme developed by Carleial and subsequently improved by Han and Kobayashi, also referred to as rate-splitting [11, 40].

To perform rate-splitting, each encoder divides its data sequence into two data subsequences, each of lower rate than the original sequence, and encodes them via superposition coding, which was originally developed for the broadcast channel [16]. In superposition coding, the source encodes each of the two data sequences using separate but correlated codebooks. Specifically, it encodes the first data sequence based on the optimal input distribution, and the second data sequence based on the optimal conditional distribution between the two data sequences. Separate encoding enables each receiver to decode one of the data subsequences intended for the other user jointly with its own data sequence, while treating the signal carrying the other undesired data subsequence as noise. The communication rate for this user increases due to reduced interference, but the rate for the other communicating pair decreases due to an additional decoding constraint. Hence, there is a tradeoff between the amount of information sent only to the desired receiver and the amount of interference decoded at the other receiver.

In AWGN interference channels, this encoding tradeoff translates into optimizing the power allocated to each of the two parts of the encoder's data sequence. By choosing Gaussian codebooks, i.e., random codebooks generated according to a Gaussian distribution, and a specific power split, the Han–Kobayashi scheme achieves rates within one bit per dimension from the two-user interference channel capacity [26]. The power split is chosen so that the created interference at each receiver has the same power as the Gaussian noise at that receiver. Thus, the created interference is sufficiently weak so as not to significantly impair performance. At the same time, the undesired data sequence that is decoded at each destination allows for significant interference reduction. In a K-user interference channel, each receiver is exposed to interference arriving from multiple sources. A generalization of the Han–Kobayashi scheme would allow for partial decoding of each interfering signal. A receiver could then jointly decode its own data sequence along with some portion of the interfering data sequences dictated by the rate-splitting code design. While such a generalization is possible mathematically, it would result in very complex encoding and decoding schemes at each node.

Specifically, this approach requires a receiver to separately decode parts of interfering data sequences sent from many interferers in order to reduce interference. Instead, the interference at each receiver can be treated collectively in a more efficient manner via interference alignment [7, 57] or via structured codes [65]. These approaches exploit the fact that a receiver is not interested in information associated with interfering data sequences and hence does not need to decode them (or parts of them). Interference alignment achieves the optimal capacity scaling law in the interference channel [69]. Lattice codes outperform the Han–Kobayashi scheme in the K-user interference channel [83].

The AWGN channel considered so far in this section assumes constant channel coefficients and hence does not capture flat or frequency-selective fading. Incorporating these channel characteristics leads in general to channel models that are more difficult to analyze. However, these characteristics open up possibilities for encoding and transmission strategies that exploit fading. In particular, frequency-selective and time-varying channels can be modeled as parallel interference channels [8]. Results in [8] demonstrate that parallel interference channels are optimized by joint encoding across subchannels.

This is in contrast to point-to-point, multiple access, and broadcast parallel channels in which separate encoding over the subchannels is optimal. Further exploration of K-user interference channels has revealed that time-variations can be exploited to combat interference in the form of interference alignment. Interference alignment relies on channel time-variations to achieve half of the interference-free capacity for each user in the system [7, 66].

5.2.3 Interference channel techniques for cognitive radio

In interference networks with no cognition, a plausible transmission scheme to avoid interference is to split the bandwidth and assign orthogonal channels to each communicating pair, e.g., via a MAC protocol that divides channels orthogonally in time, frequency, or space. In cognitive radio networks, this corresponds to the interweave approach to avoid interference between cognitive and primary users. However, in general, dividing the bandwidth orthogonally reduces spectral efficiency in comparison with assigning the full bandwidth to all users and then coping with the introduced interference. One exception is in the low-SNR regime where the network is power-limited rather than interference-limited. In this regime, bandwidth is plentiful compared to power, and thus assigning orthogonal channels to users incurs no performance loss. In the interference-limited regime this is no longer true. Furthermore, as the number of network users increases, the rate per user of an orthogonal MAC scheme goes to zero. This reasoning emphasizes why the overlay approach may be a more spectrally efficient technique for cognitive radios than the interweave approach.

5.3 Optimization techniques

In this subsection various techniques and approaches for optimizing the performance of cognitive radio networks are studied. We begin by briefly introducing an optimization technique called *dynamic programming*. Dynamic programming is a collection of optimizationtechniquesthatsolvecomplicatedsequentialdecisionproblemsbyb them into smaller easily solved sub problems. Moreover, dynamic programming is paramount for understanding the nature of learning techniques such as reinforcement learning that will be studied later in this chapter. In addition, in this section we will look at a few interesting dynamic programming and other optimization approaches for maximizing the cognitive radio throughput by means of optimizing the frequency band sensing order or the sensing parameters, such as the detection thresholds, sensing and transmission times, and the allocation of sensing resources.

5.3.1 Dynamic programming

The Dynamic programming divides a given problem into simple and more manageable entities and attempts to provide an optimum solution for the same. Dynamic programming applies to many different types of problems. However, here we focus on solving finite Markov decision processes (MDPs) to illustrate the main idea of dynamic programming. The MDP consists of the following:

- a sequence of discrete time steps $n = 0, 1, 2, \ldots$;
- a finite set of possible states of the environment $s \in S$;
- a finite set of possible actions in each state $a \in A$;
- a state transition function $\phi : S \times A \times S \rightarrow [0, 1]$ which defines the transition probability $P\,[s_{n+1} \mid s_n, a_n]$;
- a reward function $r : S \times A \times S \rightarrow R$ which gives a reward for taking action a_n in state s_n resulting in new state s_{n+1}.

Dynamic programming offers a computationally more efficient method of finding the optimal solution compared to brute-force techniques. However, dynamic programming still suffers from *the curse of dimensionality*:

the computational and memory requirements grow exponentially as the number of states and actions increases. Hence, dynamic programming may not be the best overall solution in many cognitive radio applications, especially, those involving mobile, battery-powered user equipment with limited computational and memory resources.

Finally, we would like to point out that dynamic programming requires a model for the state transitions and rewards. In the following we will briefly review a few dynamic programming as well as other optimization approaches for optimizing the performance of cognitive radio systems.

5.3.2 Optimizing the sequential order of sensing multiple frequency bands

In [76] the optimization of the frequency band sensing order in a multiband cognitive radio system is considered. That is, in each time slot, given n_B frequency bands, the secondary user senses the frequency bands one at a time successively until a frequency slot that is available and also has adequate channel quality is found. Then the secondary user proceeds to transmit on that frequency band for the rest of that time slot. The goal is to optimize the frequency band sensing order so that the expected throughput of the secondary user is maximized. Dynamic programming is employed to obtain the optimal sensing order in both cases of known and unknown availability probabilities ω_i. The optimal solution in the case of unknown ω_i balances between short-term and long-term gains. Dynamic programming suffers from the curse of dimensionality, and thus obtaining the optimal solution via dynamic programming may become computationally prohibitive if the number of frequency bands is large. Hence, computationally more efficient, yet optimal sensing orders are obtained for certain special cases of availability probabilities and achievable rates. Moreover, it is shown in [76] that the intuitive sensing order selecting the frequency bands in the order of their availability probabilities ω_i is in general not optimal if adaptive modulation is employed, and thus the achievable rates are not equal on different frequency bands.

Other approaches to optimizing the sensing order in multiband cognitive radio systems have been proposed in [83,126] and in[52], where a collaborative spectrum search strategy is proposed for maximizing the expected number of frequency bands identified as being available.

5.3.3 Optimizing the secondary system throughput

In [163, 165] an optimal energy-detection-based joint multiband detection approach for cognitive radio systems is proposed. The throughput of the secondary system ismaximized by finding optimal detection thresholds for the joint energy detection problem over multiple frequency bands. Let i = 1, 2,..., n_B denote the different frequency bands. The single secondary user optimization problem is formulated as:

$$\max_{\psi} R(\psi) = r^T [1 - P_{FA}(\psi)] \quad (5.1)$$

where

$$sum_{i\epsilon S_j} c_i P_{MD}^{(i)}(\psi_i) \le \varepsilon_j, \ j = 1, 2, \ldots.., J, \qquad (5.2)$$

$$P_{MD\psi} \le \beta, \qquad (5.3)$$

$$P_{FA_\psi} \le \alpha, \qquad (5.4)$$

Where **r** is a column vector of the achievable rates on the different frequency bands, ψ is a vector of the energy detector thresholds for the different frequency bands, $\mathbf{P}_{FA}(\psi)$ is a vector of probabilities of false alarm at the different frequency bands given ψ, $\mathbf{P}_{MD}(\psi)$ is a vector of probabilities of missed detection at the different frequency primary user j, s_j is a constraint for the interference caused to the primary user j, $\boldsymbol{\beta}$ is a vector of probability of missed detection constraints for the different frequency bands, and $\boldsymbol{\alpha}$ is a vector of probability of false alarm constraints for the different frequency bands. The constraints in (5.3) and (5.4) are defined item-wise. The above generally non convex optimization problem is reformulated in [163, 165] in a convex form with convex constraints under certain conditions by exploiting the properties of the energy detector and its distributions under both hypotheses. That is, the fact that the Q-function is monotonically nonincreasing allows transforming the constraints (5.1) and (5.2) into linear constraints. Moreover, an alternative formulation in which the priority weighted probability of missed detection, i.e., $\mathbf{c}^T\mathbf{P}_{MD}(\boldsymbol{\psi})$, is minimized given constraints on the minimum secondary throughput as well as on the probabilities of missed detection and false alarm on the different frequency bands is proposed. In addition, a collaborative spectrum sensing optimization problem controlled by a fusion center is formulated. The secondary users transmit their local summary energy measurements to the fusion center that performs a linear combination to obtain the global test statistics for the different frequency bands.

$$\varepsilon_j = \sum_{k=1}^{N_{SU}} a_{k,i}\varepsilon_k, \;\; i = 1, 2, \ldots.., n_B, \tag{5.5}$$

Where N_{SU} is the number of collaborating secondary users, $a_{k,i}$ is a weighting factor for the frequency band i of the secondary user k, and $E_{k,i}$ is the summary energy detection test statistic for the frequency band i of the secondary user k. An optimization problem, similarly to (5.1)–(5.4), is formulated in which both the weights $a_{k,i}$ and the thresholds ψ_i are optimized to maximize the secondary system throughput. Two near-optimal solutions to this generally nonconvex problem are proposed. In [172] genetic algorithms, a global optimization approach, have been considered for solving this problem as well.

5.4 Machine learning

In spectrum sensing, machine learning methods are used to determine the accessibility of primary users. The benefit of machine learning compared to traditional collaborative sensing systems is that it is more flexible because there is no need for advance knowledge about the channel [41]. In addition, in spectrum optimization, machine learning methods are often used to assess the primary user's conduct based on its previous operations. The different categories are as follows [11]:

- *Supervised learning*

In this scheme the classifier learnsat first by means of a givensample datawith a predefined input and output. After the classifier learns, it can now resolvethe output of a fresh set of information. To determine the accessibility of PU channels, methods including support vector machines (SVMs) and weighted k-nearest neighbors (kNNs) are used [41].

- *Unsupervised learning*

Unsupervised learning utilizes clustering methods without the training phase to define the class of a specified input. Some of the techniques used includes“k-means” and “Gaussian mixture models (GMMs)” [41].

- *Reinforcement learning*

Reinforcement learning again does not involve a training phase. The agent in this scheme, moreover, investigates all feasible activities and benefits with a trial-and-error approach. This results in optimizedsystem performance [11]. Of the three classes, reinforcement learning methods are the most suitable for cognitive radio tasks, such as spectrum sensing and access. The correct action in each state is in general unknown or difficult to find out due to the dynamically changing environment. Hence, supervised algorithms are difficult to employ in practice. However, the natural rewards for reinforcement learning methods in these tasks are related to the throughput of the secondary users and collisions encountered with other users of the spectrum.

5.4.1 Hidden Markov models.

Hidden Markov algorithms are among the major predictive machine learning methods. Because of their strong rational basis and computational complexity, HMMs were used for forecast in different areas, including inventory markets and voice recognition [20]. In the regulation of cognitive radio, first the PU channel utilization pattern needs to be explored so as to obtain the request access to the spectrum, then projections about future PU trends can be decided on the basis of learned pattern. The use of HMMs is discussed in [1–3, 12, 37 42–45] for PU pattern prediction. In [12], the secondary user first uses a concealed Markov model to study the PU's pattern. The primary user is formulated as a "continuous-time Markov chain (CTMC)" whose constraints are acquired by means of gradient technique.

5.5 Game-theoretic approaches

Game theory is a collection of mathematical methods and tools for modeling, analyzing, and predicting the behavior of multiple interacting entities. In cognitive radio applications, game theory is important for modeling and analyzing the interaction of individual spectrum users, as well as designing algorithms for efficient and effective sharing of the scarce spectrum resources.

The simplest model of strategic game with numerous decision makers is given below:

Game theory is broadly categorized into cooperative and noncooperative types. Noncooperative games apply naturally to cognitive radio systems in which the secondary users act selfishly and compete with each other, while cooperative games apply to systems in which the users cooperate with each other and act jointly. In addition, we will take a brief look at auction games and finally an overview of stochastic games that provide an excellent fit to the dynamic environment encountered in cognitive radio applications will be given.

5.5.1 Non cooperative games

In a noncooperative game the players choose their strategies independently to achieve their own goals. Note, however, that this does not mean that the players are not allowed to cooperate in a noncooperative game. It only means that this cooperation cannot be enforced. That is, each player decides individually whether to cooperate with the other players or not. *Nash equilibrium* is a fundamental concept in noncooperative game theory. Nash equilibrium is a strategy profile $a^* \in A$ such that

- a set of players $N = \{1, \dots, N_{SU}\}$;
- a set of strategies (actions) for each player A_i, $i \in N$. A strategy $a_i \in A_i$ is a complete plan of action for each situation in the game. Moreover, let a_{-i} denote the strategies of all the other players except player i. The combined strategy space is the set of strategy profiles $A = A_1 \times \cdots \times A_{NSU}$;
- payoff (utility) functions $r_i : A \rightarrow R$, $i \in N$, which give the players a payoff (utility)
  for the joint strategies $a_1, \dots, a_N$.

That is, no player can unilaterally improve his/her payoff by changing his/her strategy if the other players employ the Nash equilibrium strategies. Accordingly each player's optimum reaction approach is defined given the other players' strategies. However, in general, a Nash equilibrium is not necessarily the optimal equilibrium providing the highest cumulative payoff due to the noncooperative nature of the game. Moreover, a game may have multiple Nash equilibria with different payoffs. Hence, different concepts such as Pareto optimality, evolutionary equilibrium, and correlated equilibrium as well as different techniques such as pricing have been proposed for choosing the optimal equilibrium and improving and refining in efficient equilibria. For more information on these concepts, see, e.g., [118,209].

In [174] the spectrum access in cognitive radio networks is formulated as a strategic noncooperative game with power and interference constraints. Each secondary user aims at maximizing its own transmit rate given local constraints on the transmit power and interference caused to the primary users. Both null and soft interference constraints are considered. That is, the projection of the transmitted signal power along the sub- spaces corresponding to the primary users (in the spatial, frequency, or time domain) is either zero (null constraint) or below a given threshold (soft constraint). Distributed asynchronous MIMO iterative water filling algorithms (IWFAs) are proposed for the cognitive radio network under different interference constraints. The Nash equilibrium is shown to exist for all of the different game formulations. Moreover, sufficient conditions for its uniqueness and the convergence of the proposed distributed algorithms to the Nash equilibrium are established.

Spectrum access in cognitive radio networks under global interference constraints has been considered in [154]. Each secondary user seeks to maximize its own transmit rate over multiple frequency bands given a local constraint on the transmit power and global constraints on maximum per-carrier and total aggregate interference caused to the primary users. A pricing mechanism introduces a penalty in the payoff function depending on the interference levels. The noncooperative game is formulated using the frame work of finite dimensional variational inequalities(VIs). Conditions for the uniqueness of the Nash equilibrium are established and distributed algorithms with minimum signaling from the primary users to the secondary users (i.e., to broadcast the updated prices) converging to the Nash equilibrium are proposed.

Similar pricing based interference management concept is employed in [70] and distributed ad hoc cognitive radio networks.

The algorithms in [70,154,174] assume perfect knowledge of the channel state information (CSI) between the secondary transmitters and primary receivers. In [213] a noncooperative strategic game formulation of spectrum access in cognitive radio networks with robust interference constraints is proposed. Each secondary user is assumed to know only the nominal channels to the primary receivers. A nominal channel is defined as a corrupted version of the actual channel corrupted with an error belonging to an elliptical uncertainty region. Thus, each secondary user should satisfy the worst-case interference constraints defined by the uncertainty region. The robust noncooperative strategic game in which the secondary users aim at maximizing their own transmit rates given the robust interference constraints is formulated as a VI problem and asynchronous distributed algorithms are proposed for achieving the Nash equilibrium.

In [230] a collaborative spectrum sensing framework is proposed in which the secondary users try to maximize individual revenue functions that depend on the achievable rate as well as on delay and energy consumption due to cooperative sensing. The problem is formulated as a noncooperative game in which the secondary users decide whether to participate in cooperative sensing or not. Distributed algorithms based on information exchange among the secondary users are proposed for obtaining a Nash equilibrium with both identical and non-identical detection and false alarm probabilities among the users.

5.5.2 Cooperative games

In general, cooperation among the players provides an opportunity to improve the over all collective result. In CR network cooperation can be realized in different forms: the nodes may share their sensing outcomes to find more free channel space, as well as helping the other users in interference management, routing etc.

An important class of cooperative games comprises *coalitional games* [171]. Coalition games are collaborative games where players form coalitions that can implement coalition collaboration. A coalition game can, therefore, be regarded as a game between coalitions rather than between players. A coalitional game consists of

- a set of players $N = \{1,..., N_{SU}\}$;
- a coalition value function v that quantifies the worth of a coalition S.

  The value of a coalition S is denoted by $v(S)$.

A widely used and important subclass of coalitional games is composed of coalitional games that are in *characteristic form*. In coalitional games that are in characteristic form the value of a coalition depends only on the members. Moreover, a coalitional game may have either transferable or nontransferable utility. The value of a coalition may not always be represented as a single real number or be divided in a meaningful manner among the members of the coalition. Such games are called coalitional games with non-transferable utility.

In [170] collaborative single-band spectrum sensing in cognitive radio networks is modeled as a coalitional game with nontransferable utility. Distributed algorithms are proposed for forming the coalitions. That is, the secondary users autonomously form coalitions using merge and split rules to maximize their payoff in terms of probability of detection and a cost for false alarms. Due to the cost for false alarm and coalition is rarely the optimal structure, hence, the class of games formed belong to the class of coalition formation games [171]. Moreover, a coalitional voting game for guaranteeing a desired probability of detection is proposed and used to complement the merge and split based algorithm. In the proposed coalitional games each coalition head acts as the fusion center in the collaborative detection. The user with the highest probability of detection is chosen as the coalition head in each coalition.

5.5.3 Auction games

An auction is a sales process in which the prospective buyers compete by bidding according to the rules of the auction to buy the goods or services under auction. Auctions are most often used in situations when the seller does not have a clear idea of how the prospective buyers are valuing the goods under auction. A particularly interesting form of auction, especially from the cognitive radio perspective, is the second-price sealed-bid auction in which the bidder placing the highest bid wins the sealed-bid auction but instead of paying the price equal to his/her own bid the bidder pays the price equal to the second highest bid. The appealing feature of a second-price sealed-bid auction is that it gives incentive to the bidders to bid truthfully since bidding truthfully is the optimal strategy [205].

In [68] spectrum access in cognitive radio networks is formulated as a repeated auction game with entry and monitoring fees. The auction is coordinated by a secondary coordinator. The entry fee accounts for the energy consumption due to the spectrum access and channel estimation needed for bidding and the monitoring fee accounts for the cost of spectrum sensing and the subscription to the common control channel to obtain past auction history information. The entry fee is paid only when the user participates in the auction while the monitoring fee is paid in each time period. The repeated auction of spectral opportunities follows the second-price sealed-bid auction format in each time period. A learning scheme based on Dirichlet processes is proposed to optimize the bidding of the distributed secondary users. The Dirichlet process is employed to model the distribution of the winning bid given the past auction history.

5.5.4 Stochastic games

The concept of stochastic games was already introduced in Section 5.3.3 when we defined the multi agent reinforcement learning problem as a stochastic game. Stochastic games are an extension of MDPs in which multiple players interact in noncooperative or cooperative manner. We repeat the formulation of a stochastic game from the reinforcement learning section for convenience using more game-theoretic terminology.

Stochastic games differ from the other games discussed earlier in the sense that there are several states that change throughout the game execution. Hence, stochastic games provide an excellent fit to the constantly changing dynamic conditions in CR Networks. The consequence is that in a stochastic game the players' tactics depend on the current state. The mapping of the states to actions is called a policy.

Multiagent reinforcement learning is one of the most prominent approaches for optimizing the behavior of the players in a stochastic game (i.e., learning a policy that maximizes a given objective function). See Section 5.3.3 for an introduction to multiagent reinforcement learning, solving stochastic games, and their applications to cognitive radios.

That is, a stochastic game consist of

- a sequence of discrete time steps $n = 0, 1, 2, \ldots$;
- a set of players $N = \{1, \ldots, N_{SU}\}$;
- a set of possible states $s \in S$;
- a set of possible actions for each player in each state $a_i \in A_i, i \in N$. The combined action space is $A = A_1 \times \cdots \times A_{N_{SU}}$;
- a state transition function $\phi : S \times A \times S \to [0, 1]$ which defines the transition probability $P\,[s_{n+1} \mid s_n, a_{1,n}, \ldots, a_{N_{SU},n}]$;
- payoff functions $r_i : S \times A \times S \to R$, $i \in N$, which give the players a payoff for the

joint action $a_{1,n}, \ldots, a_{N_{SU},n}$ of the players in state s_n

resulting in new state s_{n+1}.

5.6 Location awareness and geolocation

Location awareness and geolocation are at the core of situational awareness in cognitive radio systems. Or, more precisely, awareness of one's location relative to the other spec- trum users is at the core of situational awareness since, depending on the application, it may not be necessary for a cognitive radio user to know its exact geographical location; rather a location relative to the other users of the spectrum may suffice. Nevertheless, location information plays an important role in spectrum access and interference man- agement. The more accurately a secondary user knows the locations of the other users of the spectrum and the network topologies, the more accurately it can estimate the level of interference caused to them by its transmissions and subsequently adjust its transmission parameters accordingly. Location information is also beneficial in routing and scheduling problems. The capability to understand propagation phenomena and detec- tion distances, primary user communication distances, and interference distances add to the location awareness and allow for modeling areas of harmful interference, achiev- ing high data rates, as well as satisfying the interference constraints. The question then arises: how can a cognitive radio user obtain this location information?

Outdoors, a mobile secondary user may employ satellite positioning techniques such as global positioning system (GPS) to obtain its own geolocation. In some cognitive radio applications this may already provide the secondary user a wealth of information for efficient and effective spectrum exploitation. For example, the reuse of digital TV frequency bands is such an application. The TV broadcast towers are located in fixed, static positions that are typically publicly available. Hence, a cognitive radio user know- ing its own geolocation can easily determine the nearby TV broadcast towers and the channels employed. However, in general, the primary transmitter geolocations may not be available in advance. Moreover, if the user is indoors or no GPS or other satellite posi- tioning system is available the user may have difficulty in determining its own geoloca- tion. Finding out an unknown location of a wireless transmitter is a challenging prob- lem requiring advanced signal processing algorithms. Moreover, reliable and accurate localization requires distributed cooperative techniques. Various proposed approaches include received signal strength- (RSS) [85], time-of-arrival- (TOA) [33, 34, 58, 80, 87], direction-of-arrival- (DOA) [80], and sensing result-based [128] techniques.

The above techniques can also be applied to determine the locations of the other secondary users. However, such information may be obtained through other means as well, such as information exchange or mutual ranging [66], provided that the secondary users in the cognitive radio network cooperate with each other.

Finally, we would like to point out that the interference in a wireless communication system is experienced at the receiver and not at the transmitter, hence, knowing the location of the primary receivers is much more beneficial than knowing the location of the primary transmitters. However, this is notoriously difficult if the receivers are passive, as, for example, TV receivers are. In principle, even passive receivers may be detected by exploiting the local oscillator leakage power emitted by the RF front-end of a wireless receiver when a signal is received [29, 221]. However, the typical leakage power is very low, limiting the detection range to only a few meters at best. Thus, in applications involving passive receivers, one may have to be content with knowing only the locations of the primary transmitters.

5.6.1 Location based hybrid spectrum sensing and power allocation

In this stage, it is presumed that the SU transmits with overlay mode (P_O) at the same time it keeps scanning the channel to check for possible interference due to signals from PU or other users. In dual phase sensing discussed in chapter 4,the first phase scans the channel to locate for interference, if found, the second phase detection is carried out to locate the source of interference to verify that the signal is from PU. Upon verification, SU must vacate the channel and switch to underlay mode (P_I). If the verification fails, then it is concluded that the signal is from other SU or a possible miss detection in which case SU can continue to operate in overlay mode. Algorithm 5.1 gives this process of sensing and power assignment.

To ascertain the source of interference, the parameters such as distance, angle of arrival of the signal must be detected. The directional antennas are used to locate the incoming signal direction which is known as DOA (direction-of-arrival) estimation. The detection mechanism involves the use of antenna arrays with each element receiving the same signal. As these elements are separated by a finite distance, the received signal at each element will have a phase difference. The evaluation of the phase difference among the array elements in turn give direction (θ). The estimation is done by means of a function called pseudo spectrum PMU (θ).

There are different techniques that can be found in literature [20], [21]for the assessment of PMU(θ) such as maximum likelihood, beam-forming, eigen analysis, MUSIC, minimum variance, root-MUSIC, etc.

Algorithm 5.1: Dual phase Detection with DOA

1: Received signal at CR $y \Leftarrow hs + n$
2: Signal energy ,$E = |y|^2$
3: If E< λ then
4: Overlay transmission P_1
5: else //interference detected
6: Underlay transmission P_0
6: Identify source by DOA detection
7: From MUSIC Algorithm find (θ_x)
8: if ($\theta_x == \theta_p$) then //compare with PU
9: PU active Underlay transmission P_0
10: else
11: PU not active Interference is due
12: 1) miss detection from another user or
13: 2) malicious user active
14: channel dominance by usage continuation until channel is free//channel jamming
15: endif
16: endif
17: Repeat from step 1 to step 9

Fig.4. illustrations the model for estimation of PMU (θ) using MUSIC algorithm [11].

The antenna array elements (Fig.5) receives the same signal with phase difference form a distant source, *i.* is given as

$$x_m(t) = S_i(t)\sum_{i=1}^{d} e^{j(m-1)\mu_i} + n_m(t) \quad (5.6)$$

The antenna array elements are spaced uniformly by where is the signal wavelength. Let ??(?) be a plane wave radio signal emitted by the source i (PU) impinging on the receiver's antenna array at an incidence angle ??. After travelling from source (PU) to destination (SU) it first hits the leftmost (nearest) element. Considering there are d sources the signals generated by all the *d* sources, ??, *1≤i≤ d,* the overall signal and noise powers received by the mth array element at time *t* is given as [22]:

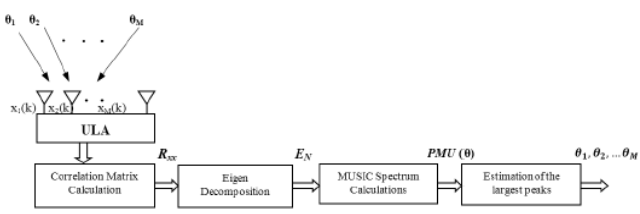


Fig.5.3. Model to estimate DOA(PMU(θ).

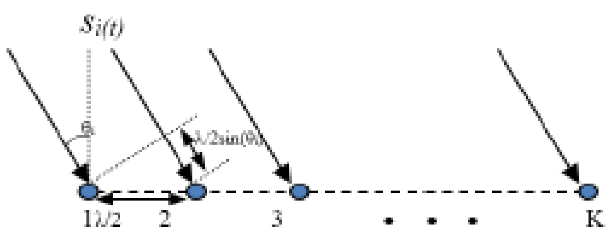


Fig.5.4. Uniform linear array antenna.

which can be written as

$$x(t) = [a(\theta_1), a(\theta_2) \ldots \ a(\theta_d)] \begin{bmatrix} S_1(t) \\ S_2(t) \\ \vdots \\ S_d(t) \end{bmatrix} + n(t) \tag{5.7}$$

$$x(t) = AS(t) + n(t) \tag{5.8}$$

where

$$x(t) = [x_1(t)\, x_2(t) \ldots x_k(t)]^T \tag{5.9}$$

$$S(t) = [S_1(t)\, S_2(t) \ldots S_K(t)]^T \tag{5.10}$$

$$n(t) = [n_1(t) \ \ n_2(t) \ldots n_K(t)]^T \tag{5.11}$$

is a zero mean spatially uncorrelated additive noises with covariance matrix.

A represents steering matrix [KXD]

$$A = [\vec{a}(\theta_1)\, \vec{a}(\theta_2) \ldots \vec{a}(\theta_D)] \tag{5.12}$$

where

$$\vec{a}(\theta_i) = \left[1 \ \ e^{j\varphi_i} e^{2j\varphi_i} \ldots \ \ e^{(K-1)j\varphi_i}\right]^T \tag{5.13}$$

is the steering vector.

$$\varphi_i = \frac{2\pi}{\lambda}\frac{\lambda}{2}\sin(\theta_i) \quad (5.14)$$

$\frac{2\pi}{\lambda}$ is wave number and $\frac{\lambda}{2}$ is element spacing.

$$\varphi_i = \pi\sin(\theta_i) \ (5.15)$$

is wave number and is element spacing.

Where is known as special frequency.

The idea is to move the antenna array along a given direction at a time measuring the received power. The DOA estimation involves locating the direction of the signal which corresponds to the maximum power received. This is accomplished by moving the antenna array mechanically or electronically.

$$Y(t) = w^H X(t) \quad (5.16)$$

The received power aggregated over N samplesis given as [23]

$$P(w) = \frac{1}{N}\sum_{n=1}^{N}|Y(t_n)|^2 = \frac{1}{N}\sum_{n=1}^{N} w^H X(t_n) X^H(t_n) \ (5.17)$$

A measure ??? of the covariance matrix is obtained and its eigenvectors are divided into signal and noise subspace ( ) and the DOA is calculated from one of these subspaces by MUSIC algorithm. The resulting spectrum is expressed as [11]

$$PMU(\theta) = \frac{\vec{a}(\theta)^H . \vec{a}(\theta)}{\vec{a}(\theta)^H \vec{E}_N \vec{E}_N^H \vec{a}(\theta)} \quad (5.18)$$

where

$$a(\theta)^H E_N E_N^H a(\theta)$$

represents Euclidean distance, EN is the noise subspace and is composed of K−D eigenvectors associated with the noise.

H= "Hermitian" means conjugate transpose

5.7 Simulation results

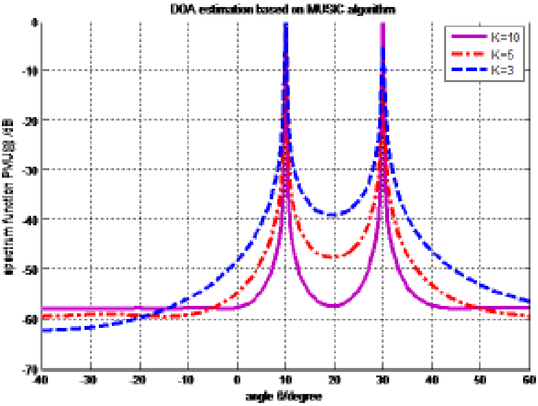


Fig.5.5. Music spectrum for d=λ/2, and N = 200 and varying 'K'

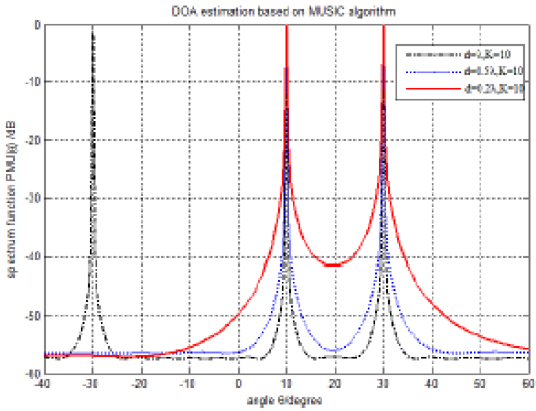


Fig.5.6. Music spectrum for K=10, and N = 200 and varying 'd'

Fig.5.5 showsthe relation of MUSIC spectrum with number of antenna elements(K) for given sample size N.As can be seen from the simulation results that with increase in the response of MUSIC spectrum turn out to be sharper which results in enhanced accuracy.

Fig.5.6 shows the plot of music spectrum versus the range(d). It can be clearly seen that as the distance between array elements decreases the coupling effect increases. Further as the distance increases the probability of estimation falls exponentially.

5.8 Chapter summary

In this chapter, the optimization of the spectrum exploration and exploitation processes in cognitive radio networks has been considered. Spectrum exploration is the process of obtaining local awareness of the spectrum state through spectrum sensing. The goal of spectrum exploration is to find idle spectrum that can then be exploited. Optimization of spectrum exploration includes optimization of the whole spectrum sensing process that determines which frequency bands are sensed, when they are sensed and for how long and by which users, and how are the sensing results from multiple users combined. This involves trading off quantities such as diversity, detection speed, and performance. Spectrum exploration is coupled with spectrum exploitation. Spectrum exploitation addresses the questions: what happens after idle spectrum has been found; and how is the idle spectrum subsequently exploited? Spectrum exploitation optimization involves optimizing the spectrum access process that determines which idle frequency bands to access, for how long, and by which users. It involves choosing the transmit powers and waveforms to be employed, as well. The goal of spectrum exploitation combined with spectrum exploration is to maximize the throughput of the secondary network and pro- vide a desired quality of service for the secondary network while guaranteeing that the level of interference caused to the primary users is below the given interference constraints.

References:

1. M. Salem, S. A. El-kader, S. M. Ramadan, and M. Zaki, "Opportunisticspectrum access in cognitive radio ad hoc networks," *International Journal ofComputer Science Issues (IJCSI)*, vol. 11, no. 1, 2014.
2. F. Akyildiz, W.-Y. Lee, M. C. Vuran, and S. Mohanty, "NeXt generation/dynamic spectrum access/cognitive radio wireless networks: A survey,"*Elsevier Computer Networks*, vol. 50, no. 13, pp. 2127–2159, 2006.
3. Kolodzy, I. Avoidance, and S. Models, "Spectrum Policy Task Force," Federal Commun. Comm., Washington, DC, Rep. ET Docket no. 2 -135, Nov. 2002.
4. Joseph Mitola, "Software Radio Architecture: Object-Oriented Approaches to Wireless Systems Engineering," Wiley-Interscience, 2000.
5. Mitola, G. Q. Maguire, "Cognitive radio: Making software radios more personal," IEEE Pers.

Commun., vol. 6, no. 4, pp. 13 – 18, Aug. 1999.

6. Haykin, "Cognitive radio: Brain-empowered wireless communications,"*IEEE Journal on Selected Areas in Communications,* vol. 23, no. 2,pp. 201–220, 2005.

7. K. Jondral, "Software-defined radio: Basic and evolution to cognitiveradio," *EURASIP Journal on Wireless Communication and Networking,*vol. 2, no. 1, pp. 275–283, 2008.

8. McHenry, D. McCloskey, and G. Lane-Roberts, "New York City Spectrum Occupancy Measurements Sep. 2004," Tech. Rep., Dec. 2004.

9. Shared Spectrum Company, "General survey of radio frequency bands – 30 MHz to 3 GHz," Tech. Rep., Sep. 2010.

10. Rohitha Ujjinimatad and Siddarama R Patil, " Signal Detection in Cognitive Radio Networks Based on the Ratio of Largest Eigenvalue to the Trace of a Covariance Matrix, " in proceedings of IEEE International Conference on Communication, VLSI and Signal Processing (ICCVSP-2013), SIT Tumkur, India. Feb. 20th – 22nd , 2013, pp. 226–229

11. Rohitha Ujjinimatad and Siddarama R Patil, "Spectrum Sensing in Cognitive Radio Networks with the Known and Unknown Noise Levels," IET Communications, vol. 7, Issue 15, pp. 1708 - 1714. October 2013. ISSN:1751–8628

12. Rohitha Ujjinimatad and Siddarama R Patil, "Mathematical Analysis for the Detection of Unknown Signals in Cognitive Radio Networks Over Wireless Communication Channels, " IET Journal of Engineering, doi: 10.1049/joe.2014.0173

13. Rohitha Ujjinimatad and Siddarama R Patil, "Sensing Algorithm for Cognitive Radio Networks Based on Random Data Matrix, " International Journal of Computer Application (IJCA), Vol. 62

No. 3, January 2013, pp. 32-37. ISSN:0975-88872006.

14. W. Thomas, L. A. DaSilva, and A. B. MacKenzie, "Cognitive Networks,"*Proceedings of the 1st IEEE International Symposium on New Frontiers indynamic Spectrum Access Networks*, Baltimore, MD, November 2005,pp. 352–360.

15. Zhao and B. M. Sadler, "A Survey of Dynamic Spectrum Access,"*IEEE Signal Processing Magazine*, vol. 24, no. 3, pp. 79–89, May 2007.

16. B. Rawat and D. Popescu, "Precoder Adaptation and Power Control for Cognitive Radios in Dynamic Spectrum Access Environments," *IET Communications*, vol. 6, no. 8, pp. 836–844, 2012.

17. G. Proakis, *Digital Communications*, 4th edn. Boston, MA: McGraw-Hill,2000.

18. Cabric, S. Mishra, and R. Brodersen, "Implementation Issues in Spectrum Sensing for Cognitive Radios," *Asilomar Conference on Signals, Systems and Computers*, Pacific Grove, CA, June 2004, pp. 772–776.

19. Zeng and Y.-C. Liang, "Spectrum-Sensing Algorithms for Cognitive Radio Based on Statistical Covariances," *IEEE Transactions on Vehicular Technology*, vol. 58, no. 4, pp. 1804–1815, 2009.

20. Tang, "Some Physical Layer Issues of Wide-band Cognitive Radio Systems," *IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Networks*, Baltimore, MD, June 2005, pp. 151–159.

21. Cabric, A. Tkachenko, and R. Brodersen, "Spectrum Sensing Measurements of Pilot, Energy, and Collaborative Detection," *Proceedings of the IEEE Military Communication Conference*, Washington, DC, October 2006, pp. 1–7.

22. Urkowitz, "Energy Detection of Unknown Deterministic Signals," *Proceedings of the IEEE*, vol.

55, pp. 523–531, April 1967.

23. Oner and F. Jondral, "Air Interface Identification for Software Radio Systems," *AEÜ International Journal of Electronics and Communications*, vol. 61, no. 2, pp. 104–117, February 2007.

24. Gardner, "Exploitation of Spectral Redundancy in Cyclostationary Signals," *IEEE Signal Processing Magazine*, vol. 8, no. 2, pp. 14–36, 1991.

25. Yates, C. Raman, and N. Mandayam, "Fair and Efficient Scheduling of Variable Rate Links via a Spectrum Server," *Proceedings of the IEEE International Conference on communications*, Istanbul, Turkey, June 2006, pp. 5246–5251.

26. A. Weiss and F. K. Jondral, "Spectrum Pooling: An Innovative Strategy for the Enhancement of Spectrum Efficiency," *IEEE Communications Magazine*, vol. 42, no. 3, pp. S8–S14, March 2004.

27. Han, R. Fan, and H. Jiang, "Replacement of Spectrum Sensing in Cognitive Radio," *IEEE Transactions on Wireless Communications*, vol. 8, no. 6, pp. 2819–2826, 2009.

28. Berlemann, S. Mangold, G. R. Hiertz, and B. H. Walke, "Spectrum Load Smoothing: Distributed Quality-of-Service Support for Cognitive Radios in Open Spectrum," *European Transactions on Telecommunications*, vol. 17, pp. 395–406, 2006.

29. Kim, H. Jeon, and J. Ma, "Robust localization with unknown transmission power for cognitive radio," Proc. IEEE Military Communications Conf. (MILCOM 2007), Orlando, FL, Oct. 29–31, 2007.

30. Celebi and H. Arslan, "Adaptive positioning systems for cognitive radios," Proc. 2nd IEEE Int. Symp. New Frontiers in Dynamic Spectrum Access Networks (DySPAN 2007), Dublin, Ireland, Apr. 17–20, 2007, pp. 78–84.

31. Celebi and H. Arslan, "Cognitive positioning systems," IEEE Trans. Wireless Commun., 6, no. 12,

4475– 4483, Dec. 2007.

32. Gezici, H. Celebi, H. V. Poor, and H. Arslan, "Fundamental limits on time delay estimation in dispersed spectrum cognitive radio systems," IEEE Trans. Wireless Commun., 8, no. 1, 78–83, Jan. 2009.

33. Kandeepan, S. Reisenfeld, T. C. Aysal, D. Lowe, and R. Piesiewicz, "Bayesian tracking in cooperative localization for cognitive radio networks," Proc. 69th IEEE Vehicular Technology Conf. (VTC 2009-Spring), Barcelona, Spain, Apr. 26–29, 2009.

34. Kocak, H. Celebi, S. Gezici, K. A. Qarake, H. Arslan, and H. V. Poor, "Time delay estimation in dispersed spectrum cognitive radio systems," EURASIP J. Adv. Signal Process. Special Issue on Advanced Signal Processing for Cognitive Radio Networks, 2010, Article ID 675959, 10 pages,2010.

35. Ma, W. Chen, K. B. Letaief, and Z. Cao, "A semi range-based iterative localization algorithm for cognitive radio networks," IEEE Trans. Veh. Technol., 59, no. 2, 704–717, Feb. 2010.

36. Haghparast, T. Abrudan, and V. Koivunen, "OFDM ranging in multipath channels using time reversal method," Proc. 10th IEEE Int. Workshop Signal Processing Advances for Wireless Communications (SPAWC 2009), Perugia, Italy, June 21–24, 2009, pp. 568–572.

37. Tian and G. B. Giannakis, "A Wavelet Approach to Wideband Spectrum Sensing for Cognitive Radios," *Proceedings of the IEEE International Conference on Cognitive Radio Oriented Wireless Networks and Communications*, Mykonos, Greece, June 2006, pp. 1054–1059.

38. Hur, J. Park, W. Woo, K. Lim, C. Lee, H. Kim, J. Laskar, S. Center, G. Tech, and G. Atlanta, "A Wideband Analog Multi-Resolution Spectrum Sensing (MRSS) Technique for Cognitive Radio

(CR) Systems," *Proceedings of the IEEE International Symposium on Circuits and Systems*, Island of Kose, Greece, 2006, p. 4.

39. Lakshmanan and H. Nikookar, "A Review of Wavelets for Digital Wireless Communication," *Wireless Personal Communications*, vol. 37, no. 3, pp. 387–420, 2006.

40. J. Thomson, "Spectrum Estimation and Harmonic Analysis," *Proceedings of the IEEE*, vol. 20, pp. 1055–1096, 1982.

41. Farhang-Boroujeny and R. Kempter, "Multicarrier Communication Techniques for Spectrum Sensing and Communications in Cognitive Radios," *IEEE Communication Magazine*, vol. 48, no. 4, pp. 80–85, 2008.

42. Wang, Z. Tian, and C. Feng, "Sparsity Order Estimation and Its Application in Compressed Spectrum Sensing for Cognitive Radios," *IEEE Transactions on Wireless Communications*, vol. 11, no. 6, pp. 2116–2125, 2012.

43. Yin, Z. Wen, S. Li, J. Meng, and Z. Han, "Dynamic Compressive Spectrum Sensing for Cognitive Radio Networks," *Proceedings of the IEEE CISS*, Baltimore, MD, March 23–25, 2011, pp. 1–6.

44. Wang, Z. Tian, and C. Feng, "A Two-Step Compressed Spectrum Sensing Scheme for Wideband Cognitive Radios," *Proceedings of the IEEE Globecom Conference,* Miami, FL, December 2010.

45. Byun, S., Balasingham, I. and Liang, X. "Dynamic spectrum allocation in wireless cognitive sensor networks: improving fairness and energy efficiency", *IEEE 68th Vehicular Technology Conference*, Calgary, BC, pp.1–5. 2008

46. Hongshun, Z. and Xiao, Y. "Advanced dynamic spectrum allocation algorithm based on potential game for cognitive radio", *2nd International*

Symposium on Information Engineering and Electronic Commerce (IEEC), pp.1–3, IEEE. 2010

47. Zhang, X-C. and He, S-B. (2010) 'A game algorithm of dynamic spectrum allocation based on spectrum difference', *The 19th Annual Wireless and Optical Communications Conference*, pp.1–4.

48. Wu, Z., Cheng, P., Wang, X., Gan, X., Yu, H. and Wang, H. (2011) 'Cooperative spectrum allocation for cognitive radio network: an evolutionary approach', *IEEE International Conference on Communications (ICC)*, Kyoto, pp.1–5.

49. Li, Y-B., Rui, Y. and Fang, Y. (2010) 'Non-cooperative spectrum allocation based on game theory in cognitive radio networks', *IEEE Fifth International Conference on Bio-Inspired Computing: Theories and Applications (BIC-TA)*, Changsha, pp.1134–1137.

50. Nie, N. and Comaniciu, N. (2006) 'Adaptive channel allocation spectrum etiquette for cognitive radio networks', *Mobile Netw. Applicat.*, Vol. 11, No. 6, pp.779–797.

51. Irwin, R.E., MacKenzie, A.B. and DaSilva, L.A. (2013) 'Resource-minimized channel assignment for multi-transceiver cognitive radio networks', *IEEE J. Sel. Areas Commun.*, Vol. 31, No. 3, pp.442–450.

52. Yu, L., Liu, C. and Hu, W. (2010) 'Spectrum allocation algorithm in cognitive ad-hoc networks with high energy efficiency', *The International Conference on Green Circuits and Systems*, Shanghai, pp.349–354.

53. Liu, M., Song, T., Zhang, L. and Hu, J. (2016) 'Interference minimization approach for joint resource allocation in cognitive OFDMA networks', *IEEE 83rd Vehicular Technology Conference (VTC Spring)*, Nanjing, pp.1–5.

54. Tabassum, M., Razzaque, M., Hassan, M., Almogren, A. and Alamri, A. (2016) 'Interference-

aware high-throughput channel allocation mechanism for CR-VANETs', *EURASIP Journal on Wireless Communications and Networking*, Vol. 2016, No. 1, p.2.

55. Chen-li, D., Guo-an, Z., Jin-yuan, G. and Zhi-hua, B. (2009) 'A route tree-based channel assignment algorithm in cognitive wireless mesh networks', *International Conference on Wireless Communications and Signal Processing*, Nanjing, pp.1–5.

56. Pareek, U. and Lee, D.C. (2011) 'Resource allocation in bidirectional cooperative cognitive radio networks using swarm intelligence', *IEEE Symposium on Swarm Intelligence*, Paris, pp.1–7.

57. Salah, A., El-Atty, H.A. and Rizk, R.Y. (2015) 'Cross-layer routing optimization for centralized multi-hop cognitive radio networks', *11th International Computer Engineering Conference (ICENCO)*, Cairo, pp.25–31.

58. Saleem, Y., Bashir A., Ahmed, E., Qadir, J. and Baig, A. (2012) 'Spectrum-aware dynamic channel assignment in cognitive radio networks', *International Conference on Emerging Technologies*, Islamabad, pp.1–6.

59. Kim, W., Kassler, A.J., Di Felice, M. and Gerla, M. "Urban-X: Towards distributed channel assignment in cognitive multi-radio mesh networks", *IFIP Wireless Days*, Venice, pp.1–5. 2010

60. Alsarahn, A. and Agarwal, A. (2009a) 'Channel assignment in cognitive wireless mesh networks', *IEEE 3rd International Symposium on Advanced Networks and Telecommunication Systems (ANTS)*, pp.1–3, IEEE.

61. Alsarahn, A. and Agarwal, A. (2009b) 'Cluster-based spectrum management using cognitive radios in wireless mesh network', *18th International Conference on Computer Communications and Networks*, pp.1–6, IEEE.

62. El Khatib, R.F. and Salameh, H.B. (2017) 'A routing scheme for Cognitive Radio networks with Self-Interference Suppression capabilities', *Fourth International Conference on Software Defined Systems (SDS)*, Valencia, pp.20–25.

63. Zhao, C., Zou, M., Shen, B., Kim, B. and Kwak, K. (2008) 'Cooperative Spectrum allocation in centralized cognitive networks using bipartite matching', *Glob Telecommunications Conference, IEEE GLOBECOM*, pp.1–6.

64. Xin, C., Ma, L. and Shen, C-C. "A path-centric channel assignment framework for cognitive radio wireless networks", *Mobile Networks and Applications*, Vol. 13, No. 5, pp.463–476. 2008.

65. Zhao, J. and Cao, G. 'Robust topology control in multi-hop cognitive radio networks', *Proceedings IEEE INFOCOM*, Orlando, FL, pp.2032–2040. 2012

66. Tushir, B., Dhurandher, S.K., Woungang, I., Obaidat, M.S. and Teotia, V. (2016) 'Graph colouring technique for efficient channel allocation in cognitive radio networks', *IEEE International Conference on Communications (ICC)*, Kuala Lumpur, pp.1–5.

67. Tabakovic, Z. and Grgic, M. (2016) 'Cognitive radio frequency assignment with interference weighting and categorization', *EURASIP Journal on Wireless Communications and Networking*, Vol. 2016, No. 1, p.45.

68. Sohan, T.A., Haque, H.H., Hasan, A., Islam, J. and Islam, A.A. (2016) 'A graph coloring based dynamic channel assignment algorithm for cognitive radio vehicular ad hoc networks', *International Conference on Networking Systems and Security (NSysS)*, Dhaka, pp.1–8.

69. Xiaogang, Q., Limin, Z. and Lifang, L. (2017) 'Topology control based on steiner tree in cognitive radio networks', *International Conference on Smart*

Grid and Electrical Automation (ICSGEA), Changsha, pp.105–108.

70. E. Shannon, "A mathematical theory of communication," *Bell Sys. Tech. Journal*, 379–423, 623–656, 1948.

71. Effros, A. Goldsmith, and Y. Liang, "Generalizing capacity: new definitions and capacity theorems for composite channels," *IEEE Trans. Inf. Theory*, 56, no. 7, July 2010.

72. Verd´u and T. S. Han, "A general formula for channel capacity," *IEEE Trans. Inf. Theory*, 40, no. 4, 1147–1157, July 1994.

73. Toumpis and A. J. Goldsmith, "Capacity regions for wireless ad hoc networks," *IEEE Trans. Wireless Commun.*, 2, no. 4, 736–748, July 2003.

74. Goldsmith, M. Effros, R. Koetter, M. M´edard, A. Ozdaglar, and L. Zheng, "Beyond Shannon: the quest for fundamental performance limits of wireless ad hoc networks," *IEEE Commun. Mag.*, 49, no. 5, 195–205, May 2011.

75. Xue and P. R. Kumar, "Scaling laws for ad-hoc wireless networks: an information theoretic approach," *NOW J. Found. Trends Netw.*, 1, no. 2, 145–270, 2006.

76. R. Cadambe and S. A. Jafar, "Interference alignment and degrees of freedom of the K-user interference channel," *IEEE Trans. Inf. Theory*, 54, no. 8, 3425–3441, Aug. 2008.

77. A. Maddah Ali, S. A. Motahari, and A. K. Khandani, "Communication over MIMO X channels: interference alignment, decomposition, and performance analysis," *IEEE Trans. Inf. Theory*, 54, no. 8, 3457–3470, Aug. 2008.

78. Zheng and D. N. C. Tse, "Diversity and multiplexing: a fundamental trade-off in multiple

antenna channels," *IEEE Trans. Inf. Theory*, 49, no. 5, 1073–1096, May 2003.

79. El Gamal, G. Caire, and M. O. Damen, "The MIMO ARQ channel: diversity-multiplexingdelay tradeoff," *IEEE Trans. Inf. Theory*, 52, no. 8, 3601–3621, Aug. 2006.

80. Ozgur and O. Leveque, "Throughput–delay tradeoff for hierarchical cooperation in ad hoc wireless networks," *IEEE Trans. Inf. Theory*, 56, no. 3, 1369–1377, March 2010.

81. Verd´u, "On channel capacity per unit cost," *IEEE Trans. Inf. Theory*, 36, no. 5, 1019–1030, Sep. 1990.

82. Bae and W. E. Stark, "End-to-end energy/bandwidth tradeoff in multihop wireless networks," *IEEE Trans. Inf. Theory*, 55, no. 9, 4051–4066, Sep. 2009.

83. Rodoplu and T. H. Meng, "Bits-per-joule capacity of energy-limited wireless networks," *IEEE Trans. Wireless Commun.*, 6, no. 3, 857–865, March 2007.

84. L. Stüber, Principles of Mobile Communications, second ed. Norwell, MA: Kluwer Academic Publishers, 2002.

85. Lu, J., Lataief, K.B., Chuang, J.C.I., Liou, M.L.: M-PSK and M-QAM BER computation using single space concepts. IEEE Trans. Commun. 47, 181–184 (1999).

86. Rappaport, T.S.: Wireless Communications: Principles and Practice. IEEE Press, Piscataway (1996)

87. Simon,M.K.,Alouinii,M.S.:Digital Communication Over Fading Channels: A Unified Approach to Performance Analysis. Wiley, New York (2000).

88. C. Liang, G. Pan and Y. H. Zeng, "On the performance of spectrum sensing algorithms using multiple antennas," IEEE Global Telecommunications Conference, pp. 1-5, December 2010.

89. Bezdek, J., Hathaway, R.: 'Some notes on alternating optimization'. Proc. Int. Conf. on Fuzzy Systems (ICFC), 2002

90. Yalin Zhang, Qinyu Zhang, Bin Cao: 'Joint sensing and power allocation for hybrid spectrum sharing in fading channels' IET Commun., 9, Iss. 1, pp. 17–27, 2015

91. Sahai and D. Cabric, "Spectrum sensing: fundamental limits and practical challenges," in Proc. IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Networks (DySPAN), (Baltimore, MD), Nov. 2005.

92. Shellhammer, G. Chouinard, M. Muterspaugh, and M. Ghosh, Spectrum sensing simulation model. http://grouper.ieee.org/groups/802/22 /Meeting documents/2006 July/22-06-0028-07-0000-Spectrum Sensing-Simulation-Model.doc, July 2006.

93. B. Carleial, "A case where interference does not reduce capacity," IEEE Trans. Inf. Theory, 21, no. 5, 569–570, Sep. 1975.

94. S. Annapureddy and V. Veeravalli, "Gaussian interference networks: sum capacity in the low interference regime and new outer bounds on the capacity region," IEEE Trans. Inf. Theory, 55, no. 7, 3032–3050, July 2009.

95. S. Motahari and A. K. Khandani, "Capacity bounds for the Gaussian interference channel," Proc. of the IEEE International Symposium on Information Theory, Toronto, Canada, July 6–11, 2008.

96. Shang, G. Kramer, and B. Chen, "A new outer bound and the noisy-interference sumrate capacity

for Gaussian interference channels," IEEE Trans. Inf. Theory, 55, no. 2, 689–699, February 2009.

97. B. Carleial, "Interference channels," IEEE Trans. Inf. Theory, 24, no. 1, 60–70, Jan. 1978. 5.3.2-5.3.3

98. Han and K. Kobayashi, "A new achievable rate region for the interference channel," IEEE Trans. Inf. Theory, 27, no. 1, 49–60, Jan. 1981.

99. Cover, "Broadcast channels," IEEE Trans. Inf. Theory, 18, no. 1, 2–14, Jan. 1972.

100. Etkin, D. N. C. Tse, and H. Wang, "Gaussian interference channel capacity to within one bit," IEEE Trans. Inf. Theory., 54, no. 12, 5534–5562, May 2008.

101. Nazer and M. Gastpar, "Computation over multiple-access channels," IEEE Trans. Inf. Theory, 53, no. 10, Oct. 2007.

102. Ozgur and D. N. C. Tse, "Achieving linear scaling with interference alignment," Proc. of the IEEE International Symposium on Information Theory, Seoul, Korea, June 28–July 3, 2009, pp. 1754–1758.

103. Sridharan, A. Jafarian, S. Vishwanath, S. A. Jafar, and S. Shamai (Shitz), "A layered lattice coding scheme for a class of three user Gaussan interference channels," Proc. Allerton Conference on Communication, Control and Computing, Monticello, IL, Sep. 24–26, 2008, pp. 531–538.

104. R. Cadambe and S. A. Jafar, "Parallel Gaussian interference channels are not always separable," IEEE Trans. Inf. Theory, 55, no. 9, 3983–3990, Sep. 2009.

105. Nazer, M. Gastpar, S. Jafar, and S. Vishwanath, "Ergodic interference alignment," Proc. IEEE International Symposium Information Theory,

Seoul, S. Korea, June 28–July 3, 2009, pp. 1769–1773.

106. Jiang, L. Lai, R. Fan, and H. V. Poor, "Optimal selection of channel sensing order in cognitive radio," *IEEE Trans. Wireless Commun.*, 8, no. 1, 297–307, Jan. 2009.

107. [H. Kim and K. G. Shin, "Efficient discovery of spectrum opportunities with MAC-layer sensing in cognitive radio networks," *IEEE Trans. Mobile Comput.*, 7, no. 5, 533–545, May 2008.

108. Fazeli-Dehkordy, K. N. Plataniotis, and S. Pasupathy, "Wide-band collaborative spectrum search strategy for cognitive radio networks," *IEEE Trans. Signal Process.*, 59, no. 8, 3903–3914, Aug. 2011.

109. Quan, S. Cui, H. V. Poor, and A. H. Sayed, "Collaborative wideband sensing for cognitive radios," *IEEE Signal Process. Mag. – Special Issue on Signal Processing for Cognitive Radio Networks*, 25, no. 6, 60–73, Nov. 2008.

110. Quan, S. Cui, A. H. Sayed, and H. V. Poor, "Optimal multiband joint detection for spectrum sensing in cognitive radio networks," *IEEE Trans. Signal Process.*, 57, no. 3, 1128–1140, Mar. 2009.

111. Sanna and M. Murroni, "Optimization of non-convex multiband cooperative sensing with genetic algorithms," *IEEE J. Sel. Topics Signal Process.*, 5, no. 1, 87–96, Feb. 2011.

112. Hossein, D. Niyato, and Z. Han, Dynamic Spectrum Access and Management in Cognitive Radio Networks. Cambridge, UK: Cambridge University Press, 2009.

113. Thilina et al., "Machine learning techniques for cooperative spectrum sensing in cognitive radio networks," IEEE Journal on Selected Areas in Communications, vol. 31, no. 11, pp. 2209–2221, Nov. 2013.

114. Rabiner, “A tutorial on hidden Markov models and selected applications in speech recognition,” Proceedings of the IEEE, vol. 77, no. 2, pp. 257–286, Feb. 1989.

115. Nguyeny, B. Mark, and Y. Ephraim, “Hidden Markov process based dynamic spectrum access for cognitive radio,” in 2011 45th Annual Conference on Information Sciences and Systems (CISS), Mar. 2011, pp. 1–6.

116. Nguyen, B. Mark, and Y. Ephraim, “Spectrum sensing using a hidden bivariate Markov model,” IEEE Transactions on Wireless Communications, vol. 12, no. 9, pp. 4582–4591, Sep. 2013.

117. W. Choi and E. Hossain, “Opportunistic access to spectrum holes between packet bursts: A learning-based approach,” IEEE Transactions on Wireless Communications, vol. 10, no. 8, pp. 2497–2509, Aug. 2011.

118. Zhang et al., “Channel exploration and exploitation with imperfect spectrum sensing in cognitive radio networks,” IEEE Journal on Selected Areas in Communications, vol. 31, no. 3, pp. 429–441, Mar. 2013.

119. W. Choi and E. Hossain, “Estimation of primary user parameters in cognitive radio systems via hidden Markov model,” IEEE Transactions on Signal Processing, vol. 61, no. 3, pp. 782–795, Feb. 2013.

120. Chen et al., “Channel state prediction in cognitive radio, part ii: Single-user prediction,” in 2011 Proceedings of IEEE Southeastcon, Mar. 2011, pp. 50–54.

121. J. R. Liu and B.Wang, *Cognitive Radio Networking and Security*, Cambridge University Press, 2011.

122. Wang, Y. Wu, and K. J. R. Liu, “Game theory for cognitive radio networks: an overview,”

Comput. Netw., 54, no. 14, 2537–2561, Oct. 2010.

123. Scutari and D. P. Palomar, "MIMO cognitive radio: a game theoretical approach," IEEE Trans. Signal Process., 58, no. 2, 761–780, Feb. 2010.

124. -S. Pang, G. Scutari, and D. P. Palomar, "Design of cognitive radio systems under temperatureinterference constraints: a variational inequality approach," IEEE Trans. Signal Process., 58, no. 6, 3251–3271, June 2010.

125. Hong and A. Garcia, "Equilibrium pricing of interference in cognitive radio networks," IEEE Trans. Signal Process., 59, no. 12, 6058–6072, Dec. 2011.

126. Wang, G. Scutari, and D. P. Palomar, "Robust MIMO cognitive radio via game theory," IEEE Trans. Signal Process., 59, no. 3, 1183–1201, Mar. 2011.

127. Yuan, H. Leung, S. Chen, and W. Cheng, "A distributed sensor selection mechanism for cooperative spectrum sensing," IEEE Trans. Signal Process., 59, no. 12, 6033–6044, Dec. 2011.

128. Saad, Z. Han, M. Debbah, A. Hjørungnes, and T. Bas¸ar, "Coalitional game theory for communication networks: a tutorial," IEEE Signal Process. Mag., 26, no. 5, 77–97, Sep. 2009.

129. Saad, Z. Han, T. Bas¸ar, M. Debbah, and A. Hjørungnes, "Coalition formation games for collaborative spectrum sensing," IEEE Trans. Veh. Technol., 60, no. 1, 276–297, Jan. 2011.

130. Vickrey, "Counterspeculation, auctions, and competitive sealed tenders," J. Financ., 16, no. 1, 8–37, Mar. 1961.

131. Han, R. Zheng, and H. V. Poor, "Repeated auctions with Bayesian nonparametric learning for spectrum access in cognitive radio networks," IEEE

Trans. Wireless Commun., 10, no. 2, 890–900, Mar. 2011.

132. X. Brown, "An analysis of unlicensed device operation in licensed broadcast service bands," *Proc. 1st IEEE Int. Symp. New rontiers in Dynamic Spectrum Access Networks (DySPAN 2005)*, Baltimore, MD, Nov. 8–11, 2005, pp. 11–29.

133. Wild and K. Ramchandran, "Detecting primary receivers for cognitive radio applications," *Proc. 1st IEEE Int. Symp. New rontiers in Dynamic Spectrum Access Networks (DySPAN 2005)*, Baltimore, MD, USA, Nov. 8–11, 2005, pp. 124–130.

134. Schmidt, R., 1986. Multiple emitter location and signal parameter estimation. IEEE Transactions on Antenna Propagation 34 (2), 276–280.

135. Masatada,H.,Nobuyoshi,K.,Kunio,S.'Target direction estimation by MIMO radar using root-MUSIC with minimum redundancy array' Proc. IEEE symp,International Symposium on Antennas and Propagation (ISAP) Year: 2016.

136. Chen, G. Gokeda, and Y. Yu, Introduction to Direction-of-Arrival Estimation, Artech House, vol. 34, no. 37, pp. 46-47, 2010.

137. Krim and M. Viberg, "Two decades of array signal processing research," IEEE Signal Processing Magazine, vol. 13, no. 4, pp. 67, July 1996

138. Musavian and S. Aissa, "Capacity and power allocation for spectrum sharing communications in fading channels," IEEE Trans. Wireless Commun., vol. 8, pp. 148–156, Jan. 2009.

139. Ghasemi and E. S. Sousa, "Fundamental limits of spectrum sharing in fading environments," IEEE Trans. Wireless Commun., vol. 6, pp.649– 658, Feb. 2007.

140. Kang, Y.-C. Liang, A. Nallanathan, H. K. Garg, and R. Zhang, "Optimal power allocation for fading channels in cognitive radio networks Ergodic

capacity and outage capacity," IEEE Trans.Wireless Commun., vol. 8, pp. 940–950, Feb. 2009.

141. Tian, X. Yuan, T. Hou, W. Lou, and Z. Yang, "Cost minimization for cooperative traffic relaying between primary and secondary networks", IEEE Trans. Mob. Comp., vol. 17, no. 9, pp. 2014–2027, Sept. 2018

142. Li, J. Liu, L. Yan, S. Han, and X. Guan, "Relay selection for underwater acoustic sensor networks: A multiuser multi-armed bandit formulation", IEEE Access, vol. 6, no. 2, pp. 7839–7853, Feb. 2018

143. Singh, A. Gupta, T. Ratnarajah, and M.-L. Ku, "A general approach toward green resource allocation in relay-assisted multiuser communication networks", IEEE Trans. Wireless Commun., vol. 17, no. 2, pp. 848–862, Feb. 2018.

144. Rohitha Ujjinimatad and Siddarama R Patil, " Semi-blind Detection Method for Cognitive Radio Networks in Multiple Antenna Systems, " 3rd IEEE International Conference on Microelectronics, Communications and Renewable Energy (AICERA-2013), Kerala, India. June 4th to 6th 2013. ISBN:978-1-4673-5149-2 (Available at http://ieeexplore.ieee.org)

145. Rohitha Ujjinimatad and Siddarama R Patil, "Signal Detection in CR Networks Over AWGN, Nakagami-m and Nakagami-q Channels," 11th IEEE International Conference on Wireless and Optical Communications Networks (WOCN2014), Vijayawada, Andhra Pradesh, India. September 11th to 13th 2014. ISBN:978- 1-4799-3155-2 (Available at http://ieeexplore.ieee.org)

146. Feng, V. C. M. Leung, and F. Ji, "Performance study for SWIPT cooperative communication systems in shadowed Nakagami fading channels", IEEE Trans. Wireless Commun., vol. 17, no. 2, pp. 1199–1211, Feb. 2018.

147. Jitvanichphaibool, R. Zhang, and Y.-C. Liang, "Optimal resource allocation for two-way relay-assisted ofdma," IEEE Trans. Veh. Technol., vol. 58, no. 7, pp. 3311–3321, 2009.

148. Guftaar, F. Gao, W. Chen, and A. Nallanathan, "A joint resource allocation scheme for multiuser two-way relay networks," IEEE Trans.Commun., vol. 59, no. 11, pp. 2970–2975, 2011.

149. Li, "A recommendation system in cognitive radio networks with random data traffic," IEEE Trans. Veh. Technol., vol. 60, no. 4, pp. 1352–1364, 2011.

150. W.Matolak, "Generation of a Lognormal Fading Process: Part I – System View®," Lockheed Martin Telecommunications report, August 25, 1998.

151. L. Stuber, Principles of Mobile Communication, Kluwer Academic Publishers, Boston, MA, 1996.

152. D.Parsons, The Mobile Radio Propagation Channel, Wiley, New York, NY, 1992

153. Michel Daoud Yacoub, Jose Edson Vargas Bautista, and Leonardo Guerra de Rezende Guedes, "On Higher Order Statistics of the Nakagami-m Distribution," IEEE Transactions on Vehicular Technology, vol. 48, No. 3, May 1999.

154. P. Bertsekas and D. P. Bertsekas, Nonlinear Programming, 2nd ed. Athena Scientific, 1999.

6. POWER ALLOCATION OPTIMIZATION FOR FADING CHANNELS IN COGNITIVE RADIO NETWORKS

6.1 Introduction

This chapter proposes optimal power and bandwidth allocation in a cognitive radio network under Rician, Nakagami-m and Log Normal fading channels. The performance metric for the network used is the ergodic-capacity of all the SUs. Further, this chapter investigates the optimal power allocation schemes to achieve the primary capacity bounds of a secondary network with Rician, Nakagami-m and Log Normal fading channels. Specifically, the ergodic-capacity is considered. Besides, the peak/average transmit-power constraints at the SUs and the peak/average interference power constraint imposed by the PU. The equations of optimal power allocations are also formulated under peak-power and peak-interference constraints. Further, the analysis is done for a network of SUs. Simulation results depicted with figures and tables show that the optimal power and bandwidth allocation for the above fading channels. The investigation and analysis on optimal power and bandwidth allocation can be used for future reference of resource allocation in the cognitive radio networks over Rician, Nakagami-m and Log Normal fading channels. Various works have as of late contemplated data theoretic limits for radio resource allocation in CR. The authors in [5], developed maximum ergodic-capacity for the secondary user to target the optimal power allocation subject to the average-interference-power (AIP) and peak-interference-power (PIP) constraint set by a primary user. The secondary user outage-capacity, ergodic-capacity, and minimum-rate-capacity were investigated earlier in [3-6].

The literature stated above studies the system having only one SU specifically for Rayleigh fading whereas, the proposed work considers radio resource allocation over a network of SUs with Rician, Nakagami-m and Log Normal fading channels. Even though fading channels have been extensively studied in the current literature [7–13] they fail to address the issues of resource allocation on these fading channels. This chapter, revisits some of the equations derived in the above stated works and apply the considered channel conditions.

In this chapter we shall first give a more detailed description of the popular single state fading models with a brief mathematical introduction to the fading phenomenon and then describe the proposed radio resource allocation over a network of SUs with Rician, Nakagami-m and Log Normal fading channels.

6.2 Fading channel impulse response

Multipath fading arises physically from the addition of a large number of multipath reflections at the receiver. These reflected signals (from buildings, hills, the ground, etc.) are often nearly equal amplitude, but random in phase. It can be shown [4] that the complex baseband channel impulse response corresponding to this type of fading is

$$h(t;\tau) = \sum_{k=0}^{N-1} \alpha_k(t) \exp\{j[\omega_{D,k}(t-\tau_k(t)) - \omega_c \tau_k(t)]\}\delta[t-\tau_k(t)] \qquad (6.1)$$

where represents the k^{th} received amplitude, the exponential term represents the k^{th} received phase, and the kth path is delayed by a time- varying delay. The function is a Dirac delta, and where is the carrier frequency. The term represents the Doppler shift associated with the k^{th} received multipath echo. The Doppler shift represents the shift in frequency of the received signal due to motion of the transmitter and/or receiver. The Doppler shift will be discussed in more detail in the next section when we describe the Rician model.

It is to be noted that in the work that we have done we are considering a nondispersive channel in which case the time delays are very closely spaced in time and much smaller than any signal symbol duration. In this case we approximated all as, and when all amplitudes are equal, the sum of the exponentials is our multipath-fading envelope. For the Rician case, one of the amplitudes is much larger than the others.

6.3 Popular Fading Models

6.3 Rayleigh Fading

This distribution is usually used to model a channel when there exists no significant LOS component and radio propagation is usually achieved by local scattering. When there are a large number of scatterers in the channel that contribute to the signal at the receiver (i.e., no prominent LOS path), then the composite received signal consists of a large number of equal amplitude plane waves. This kind of fading is commonly encountered in urban areas, for instance a mobile user among many high-rise buildings.

If the number of received waves N is sufficiently large, from (6.1) and by the Central Limit Theorem the complex received envelope can be modelled as a wide-sense stationary Gaussian random process. The real and imaginary parts of the complex received envelope are independent and identically distributed zero-mean Gaussian random variables, thus the envelope, the square root of the sum of the squared in-phase and quadrature (I & Q) zero-mean Gaussian processes, is said to be Rayleigh distributed. These I and Q processes are completely characterized by their mean value and autocorrelation function. When the time delays are on the order of $1/ f_c$ and larger, the random phase terms are essentially uniformly distributed over the interval [0,2π], and vary rapidly (the path delays themselves vary slowly, but the delays multiplied by the carrier frequency vary rapidly [1]). Since the means of the I & Q channel processes are zero, the variance of the quadrature components equals the mean-squared value (the mean power). The Rayleigh probability density function (pdf) is completely characterized by this mean square value. As noted, under these conditions the envelope of the channel response at any time instant has a Rayleigh probability distribution and the phase is uniformly distributed in the interval (0, 2π). This translates to the following: a Rayleigh process is the envelope of two zero-mean Gaussian processes, where by envelopes we mean the square root of the sum of the squares. That is the envelope *r(t)* of the complex received signal is given by

$$r(t) = \sqrt{I^2(t) + Q^2(t)} \tag{6.2}$$

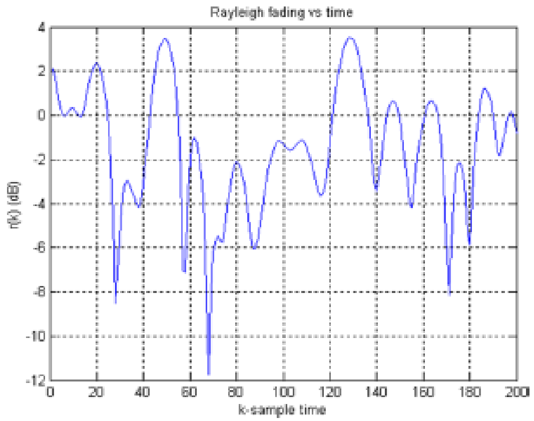


Figure 6.1: Time series of Rayleigh fading samples.

And the *pdf* is given by

$$P_R(r) == \begin{cases} \frac{2r}{\Omega} exp\left(-\frac{r^2}{\Omega}\right), & r \geq 0 \\ 0, & otherwise \end{cases} \tag{6.3}$$

Where

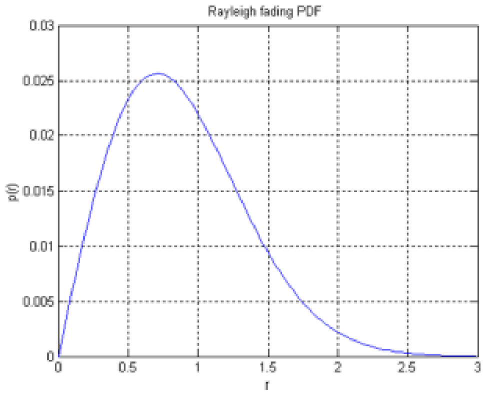


Figure 6.2: Rayleigh fading probability distribution function.

Fig. 6.1 is the output of a simulation that uses the above-mentioned Gaussian processes, and these processes are filtered with a filter of normalized bandwidth B=0.1, to yield the time correlation. Bandwidth is relative to the sampling frequency of the simulation.

The probability distribution of the phase () can be obtained by integrating the joint pdf equation over r, which results in a uniform distribution [3]. Shown in Fig 6.1 and Fig 6.2 is a time series plot of Rayleigh faded signal envelope as a function of time and the Rayleigh pdf, for $E(r^2)=1$.

6.3.2 Rician fading

There are many radio channels in which fading is encountered that are basically LOS communication links with multipath components arising from secondary reflections, or signal paths, from surrounding terrain or other obstacles. In such channels, the number of multipath components is usually small and hence the channel may be modelled in a manner somewhat similar to the Rayleigh model but with an important difference: the presence of the specular component and the presence of a Doppler shift in the frequency associated with this LOS component or specular component. Whenever relative motion exists between the transmitter and receiver, there is a shift in the frequency of the received signal due to the Doppler Effect. The Doppler shift represents the frequency shift of the received signal due to motion of the transmitter and/or receiver. The Doppler frequency parameter is the maximum Doppler shift that the signal undergoes. Waves arriving from ahead of the mobile have a positive Doppler shift, i.e., an increase in frequency, while the reverse is the case for waves arriving from behind the mobile. Waves arriving from directly ahead of, or directly behind the vehicle are subjected to the maximum rate of change of phase, giving [3]

Where -Maximum Doppler shift, Hz

- wavelength of the carrier, m

- velocity of the mobile unit, m/s

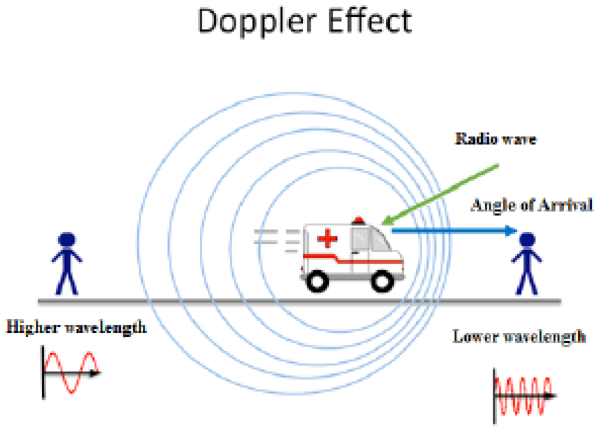


Figure 6.3: Illustration of Doppler shift.

Fig. 6.3 shows an illustration of the mechanism causing the Doppler shift in frequency. Let the nth reflected wave with amplitude *c* and phase arrive from an angle relative to the direction of the motion of the antenna.

The Doppler shift of this wave is then

$$\Delta f_n = \frac{v}{\lambda} cos\alpha_n endequation \tag{6.5}$$

where v is the speed of the antenna and is the angle of arrival.

Referring back to Eq (6.5), the Doppler frequency, for terrestrial velocities $f_{D,K}$ is most often much smaller than 1/T where T is the shortest baseband signal duration (symbol, bit, or chip time). Thus usually the maximum Doppler shift is much smaller than the signal bandwidth. The phase terms associated with the Doppler shift of the kth path generally vary much more slowly than the random phase terms, as $f_{D,K}$ (which can itself be a function of time) is in general much smaller than f_c .

The pdf of the Rician distribution is given by [2]

$$p_r(r) = \frac{r}{\sigma^2} exp\left\{-\frac{r^2+s^2}{2\sigma^2}\right\} I_0\left(\frac{rs}{\sigma^2}\right),\ r \geq 0 \tag{6.6}$$

where - power in the dominant component,

 - power in the scattered components

In the literature a Rician process is often characterized by 2 parameters: its maximum Doppler frequency and its Rice-factor or "K–factor". The Rice Factor is defined as follows:

$$K = \frac{Power\ in\ LOS\ component}{Power\ in\ scattered\ components}$$

Interpreting the Rice factor in mathematical form we have, in dB

$$K = 10 log \frac{s^2}{2\sigma^2}\ dB \tag{6.7}$$

The envelop distribution can be rewritten in terms of the Rice factor and average envelop power

$$E[r^2]=\Omega_p=s^2+2\sigma^2$$

by noting that

$$s^2 = \frac{K\Omega_p}{K+1}, 2\sigma^2 = \frac{\Omega_p}{K+1} \tag{6.8}$$

The Rician pdf in terms of the Rice factor is

$$p_r(r) = \frac{2r(k+1)}{\Omega_p} exp\left\{-k - \frac{(k+1)r^2}{\Omega_p}\right\} I_0\left\{2r\sqrt{\frac{k(k+1)}{\Omega_p}}\right\}, \ r \geq 0 \tag{6.9}$$

It can be observed that for $K = 0$ the channel exhibits Rayleigh fading, and when

K = ∞ the channel does not exhibit any fading at all. The pdf of the envelope is shown in Fig 6.4 for various values of K. From the plots it can be observed that for K = 0 the pdf is a Rayleigh distribution and for K>>1 the pdf becomes approximately Gaussian with a mean square value (power) s^2. In Fig. 6.4 the mean square values of the *pdf* have been normalized to one.

Similar to the Rayleigh distribution, when the time delays are on the order $1/f_c$ and larger, the random phase terms are essentially uniformly distributed over the interval [0,2π], resulting in a uniformly distributed random phase for the scattered components.An example time series of the Rician fading samples is shown in Fig. 6.5 for K= 5 dB. As expected, the presence of the specular or the LOS component reduces the number of deep fades when compared to the Rayleigh distribution time series in Fig. 6.1. For the simulations used to generate Fig. 6.4 we used N =100,000 samples with the mean square value for each case set equal to one. The filter bandwidth was set to 0.2 and the maximum Doppler frequency was set equal to 0.05. For Fig. 6.5 the parameters for the simulation were same as that of Fig. 6.4 except that we just 200 samples to generate the time series.

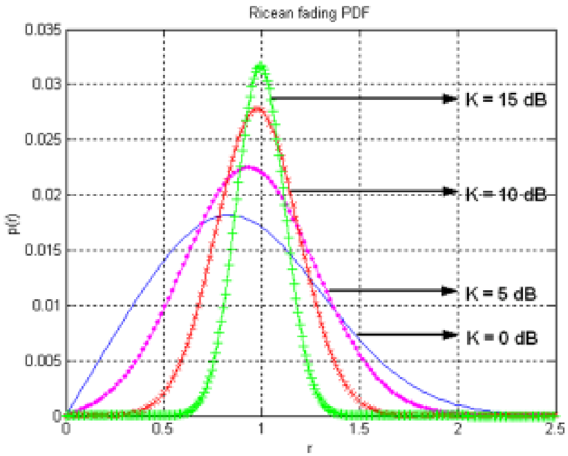


Figure 6.4: Rician PDF's for different K values.

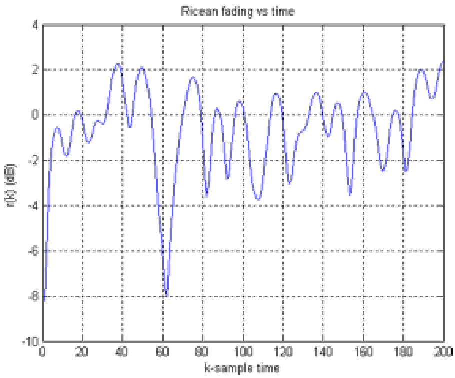


Figure 6.5: Time series of Rician fading samples, K = 5 dB.

6.3.3 Nakagami-m Fading

As explained in the previous chapter, the Nakagami distribution is very popular due to its versatility in providing greater flexibility and accuracy in matching some experimental data, and also due to the fact that the distribution has been found to provide a very good fit for the mobile radio channel. Beyond its empirical justification, the Nakagami distribution is often used because the distribution can model fading conditions that are either more or less severe than Rayleigh fading. When m = 1, the Nakagami distribution is the Rayleigh distribution, when m = 1/2 it is a one-sided Gaussian distribution, and when the distribution becomes an impulse (no fading) [2].

Two useful relations in our case are those relating the Nakagami-m shape factor mand the Rician k factor and σ^2 (the power of the scattered waves), given by [6]

$$m \sim \frac{(1+k)^2}{2k+1} \tag{6.10}$$

$$k \sim \frac{\sqrt{m^2-m}}{m-\sqrt{m^2-m}} \qquad m > 1 \tag{6.11}$$

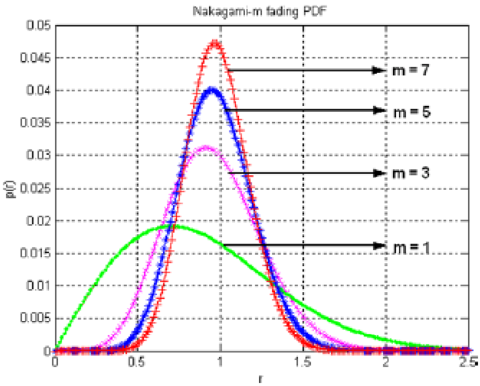


Figure 6.6: Nakagami – m fading probability distribution function.

Note that the above relations between m and k and not exact but approximations. Since the Rice distribution contains a Bessel function while the Nakagami distribution does not, the Nakagami distribution often leads to convenient closed-form analytical expressions that are otherwise unattainable.

The Nakagami-m probability density function p(r) of the envelope r is given by[6]

$$p(r) = \frac{2m^m r^{2m-1}}{\Gamma(m)\Omega^m} \exp\left(\frac{-mr^2}{\Omega}\right) \tag{6.12}$$

Where $m = E^2[r^2]/var(r^2)$, $\Omega = E[r^2]$

$$E[r^v] = \frac{\Gamma(m+\frac{v}{2})}{\Gamma(m)} \left(\frac{\Omega}{m}\right)^{v/2} \tag{6.13}$$

And

$$\Gamma(m) = \int_0^\infty x^{m-1} \exp(-x)\, dx \tag{6.14}$$

is the Gamma function. Fig. 6.6 shows the Nakagami distribution for several values of m. It can be observed that the Nakagami-m pdf for m = 1 resembles the Rayleigh pdf. For the simulations used to generate Fig 6.6 we have used N = 100,000 samples with a filter bandwidth of 0.1

6.3.4. Log-normal fading

Statistical path loss models provide us with an estimate of the mean path loss as a function of distance and other parameters such as frequency and antenna heights. Since these models treat the path loss as a random variable, it is useful to know not just the mean but also the distribution of this random variable. This would allow us to predict how much variability we can expect and compensate for this variability by providing additional margin so as to provide reliable coverage. Experimentally it has been found that the path loss in cluttered multipath environments is log-normally distributed. This means that the log of the path loss (for example, the path loss expressed in dB) has a normal distribution.

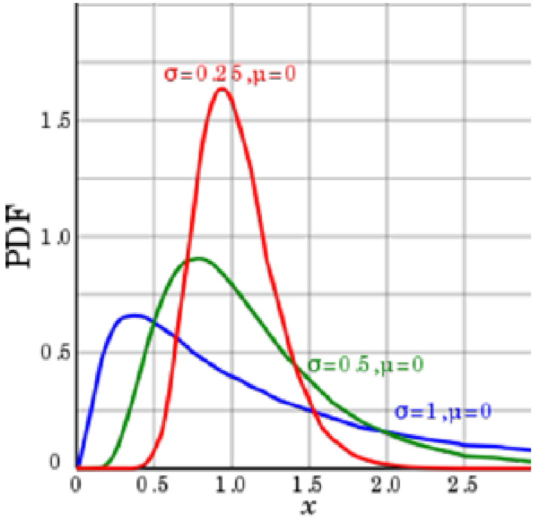


Figure 6.7: log-normal density functions with identical parameter but differing pa rameters .

A normal distribution is defined by two parameters: the mean, which is provided by the statistical path loss models and the variance which is typically estimated based on the type of propagation environment (WLAN, rural cellular, etc). An explanation for the log-normal shadowing distribution is that for any path there are many factors contributing to the overall path loss (combinations of free space loss, diffraction, reflection, transmission, etc). Each of these losses is a random variable. The total loss expressed in dB will be sum of all of these losses (each in dB). The central limit theorem states that the distribution of the overall loss (in dB) will trend to a normal distribution. Another name for this effect is "log-normal shadowing". This refers to a model where the signal "shadowed" by a variable number of objects and this results in the observed log-normal distribution.

A positive random variable X is log-normally distributed if the logarithm of X is normally distributed

Log-normal Distribution A random variable γ is log-normal iff ((γ)~N(μ,σ^2).

$$p(\gamma) = \frac{\xi}{\sigma\gamma\sqrt{2\pi}} e^{-\frac{(\ln\gamma - \mu)^2}{2\sigma^2}} \tag{6.15}$$

The Probability density function of lognormal random variable is given by

The variance is

$$\left[e^{(\sigma^2)} - 1\right] e^{(2\mu+\sigma^2)} \tag{6.16}$$

6.4 System model

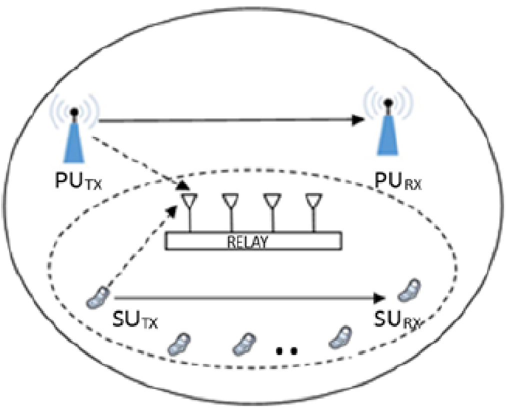


Figure 6.8: System model.

The cognitive radio system assumed (Fig.1) consists of one or more Primary users and N secondary users with a relay having multiple sensors. The primary users and the secondary users operate in the same spectrum with bandwidth W for their transmissions. Let h_i and g_i denotes the channel gain between secondary transmitter and secondary receiver(SU_{TX}-SU_{RX}) and between secondary transmitter and the primary receiver (SU_{TX}-PU_{RX}) respectively.

Further let H and G denote the probability-density-function (PDF) of the two channels discussed above, and let and represents instantaneous channel power gains, all the above parameters are assumed to be known for secondary users.

6.4.1 Optimal resource allocation

In this section, This chapter examines the resource sharing issues for one user. Let us assume that there are channels arranged in decreasing order in accordance with their channel-gain to the interference-noise ratio(CINR) quantified at the recipient. The channels sorted so that, assigned channels can be used to define the start of the channel assignment in place of the binary parameter B is the bandwidth of each channel, and the PU action indicator is where is the indicator(1 to). This results in the total the number of channels and the power turns out to be the user power allocation entities to be found so that the data rate constraint can be fulfilled. The optimization for the resource sharing problem can be articulated as below:

$$\min_{K,p}\{F_B F_P\} \ : F_B = \sum_{k=1}^{K} B\tilde{\omega}^{(k)}, F_P = \sum_{k=1}^{K} p^{(k)} \tag{6.17}$$

provided

$$\sum_{k=1}^{K} B \log \left(1 + \frac{g^{(k)} p^{(k)}}{\eta + \sum_{p\in P} \partial_p^{(k)}}\right) \geq \phi. \tag{6.18}$$

The above problem can be solved in two steps. The process begins by determining the power for the given channels , and then determines the peak value of that minimizes the bandwidth-power product on the application of power.

6.4.2 Channel Allocation:

After locating the optimum power values for a given number of assigned channels , it results in that minimizes the BP product:

$$\min_{K} \left\{ \left(\sum_{k=1}^{K} B\tilde{\omega}^{(k)}\right) \left(\sum_{k=1}^{K} \frac{2^{\frac{\phi}{K^* B}}}{\prod_{K*} (h^{(k)})^{1/K^*}} - \frac{1}{h^{(k)}}\right) \right\} \tag{6.19}$$

Gauss-Newton technique [18] can be applied iteratively to solve the above problem. If it is assumed that is the mean over all channels , and is the difference between the instant value of CINR and its mean ,

This gives . As a result, (6.19) becomes:

$$\min_{K} \left(\sum_{k=1}^{K} \widetilde{\omega}^{(k)} \right) \left(\frac{K 2^{\frac{\phi}{KB}}}{\prod_k (\overline{h} + \Delta^{(k)})^{\frac{1}{K}}} - \sum_{k=1}^{K} \frac{1}{(\overline{h} + \Delta^{(k)})} \right) \tag{6.20}$$

for multiple user

$$\min \sum_{j=1}^{|J|} \sum_{k=1}^{K} \left(\frac{B}{1 - \omega^{(k)}} x_j^{(k)} \right) \tag{6.21}$$

subject to

$$\sum_{k \in \overline{K}_j} x_j^{(k)} = 0, \forall x_j^{(k)} \in \{0, 1\} \tag{6.22}$$

$$\sum_{j=1}^{|J_i|} x_j^{(k)} \leq 1, \forall i \in C \tag{6.23}$$

$$\sum_{k=1}^{K} B x_j^{(k)} \log \left(1 + \frac{g_j^{(k)} p_j^{*(k)}}{\eta + \sum_{p \in P} \partial_{pj}^{(k)}} \right) \geq \phi_j. \tag{6.24}$$

6.5 Optimal Power Allocation

For fading channels, ergodic capacity is defined as the maximum attainable rate averaged on all the fading slabs The solution to the following optimization problem gives peak power assignment.

$$PI : \max_{p1, p2} E[\sum_{i=1}^{2} r_i] \tag{6.25}$$

That gives,

$$p_1 \geq 0, p_2 \geq 0, \tag{6.26}$$

$$g_1 p_1 + g_2 p_2 \leq I, \tag{6.27}$$

where represents the statistical probability above all the concerned fading channel gains. This makes it easy to prove that P_I is a convex-optimization problem. Thus, the duality gap is zero and solving its dual problem is the same as solving the main problem. The Lagrangian of this problem can be given as

$$L(p,\ \lambda,\ \gamma) = E\left[\ ln\ (1+h_1 p_1) +\ ln\ (1+h_2 p_2)\right] + \lambda_1 p_1 + \lambda_2 p_2 - \gamma\left(g_1 p_1 + g_2 p_2 - I\right) \tag{6.28}$$

here and are the positive dual variables

$$q(\lambda,\ \gamma) = \max_p L(p,\ \lambda,\ \gamma)$$

related to the constrictions. The dual function is

$$\min_{\lambda \geq 0, \gamma \geq 0} q(\lambda,\ \gamma)$$

The Lagrange dual problem is then given by

Hence, the optimal solution requires to satisfy the KKT constraints below:

$$p_i \geq 0,\ \lambda_i \geq 0,\ \gamma \geq 0, \tag{6.29}$$

$$g_1p_1 + g_2p_2 \leq I, \tag{6.30}$$

$$\lambda_i p_i = 0, \tag{6.31}$$

$$\gamma(g_1p_1 + g_2p_2 - I) = 0, \tag{6.32}$$

Solving the above constraints using methods as [19], the optimal solution is then deduced as

$$\frac{\partial L(p,\lambda,\beta,\gamma)}{\partial p_i} = \frac{h_i}{1 + h_i p_i} + \lambda_i + \gamma g_i = 0. \tag{6.33}$$

where is determined by solving

Next it is examined that how Interference-Transmission-Ratio(ITR) (the ratio of transmission to interference power) influences the transmission strategy of each transceiver. The analysis with three regions is summarized as follows:

$$p_i^* = \begin{cases} \frac{1}{\gamma g_i}\frac{1}{h_i}, & if \frac{1}{\gamma} > \frac{g_i}{h_i}, \\ 0, & if \frac{1}{\gamma} < \frac{g_i}{h_i}, \end{cases} \forall i \in \{1,2\} \tag{6.34}$$

$$g_1p_1^* + g_2p_2^* = I.$$

Combining the results obtained under all the cases, the optimal solution strategy for Pl can be summarized above.

$$p_1^* = \begin{cases} 0 & , R_1 > R_2 + I \\ \frac{1}{2}\left(\frac{I}{g_1} - \frac{1}{h_1} + \frac{R_2}{g_1}\right) & , R_2 + I > R_1 > R_2 - I \\ \frac{I}{g_1} & , R_1 < R_2 - I \end{cases} \tag{6.35}$$

$$p_2^* = \begin{cases} \frac{I}{g_2} & , R_1 > R_2 + I \\ \frac{1}{2}\left(\frac{I}{g_2} - \frac{1}{h_2} + \frac{R_1}{g_2}\right) & , R_2 + I > R_1 > R_2 - I \\ 0 & , R_1 < R_2 - I \end{cases} \tag{6.36}$$

It is observed that for a transceiver the interference power constraint (IPC) and Interference-Transmission-Ratio(ITRs) define the optimal transmission strategies. Usually, the transceiver with smaller ITR has the opportunity to transmit.

6.5.1 Rician fading

A Rician fading channel can be defined by two parameters: The first one, K, is the ratio between the power in the direct path and the power in the other, scattered, paths:

$$K = \frac{\nu^2}{2\sigma^2}$$

The second one, Ω, is the total power from both paths, and acts as a scaling factor to the distribution:

$$\Omega = \nu^2 + 2\sigma^2$$

The received signal amplitude (*not* the received signal power) is then Rice distributed with the following parameters:

$$\nu^2 = \frac{K}{1+K}\Omega$$

$$\sigma^2 = \frac{\Omega}{2(1+K)}$$

The resulting Probability density function is:

$$f(x) = \frac{2(K+1)x}{\Omega}\exp\left(-K - \frac{(K+1)x^2}{\Omega}\right) I_0\left(2\sqrt{\frac{K(K+1)}{\Omega}}x\right),$$

The CDF

$$F(n) = 1 - Q_1\left(\frac{v}{\sigma_n}, \frac{n}{\sigma_n}\right) \tag{6.38}$$

where $Q_I(.,.)$ is the Marcum-Q function. With H and G are joint probability-density-function (PDF) of the rician channel gains.

From classical water-filling power assignment problem and its optimal solution [18]

$$\max_{\{p_i(h,\ g),\forall h,g\}\in\mathcal{F}} \mathrm{E}_{\mathbf{H},\mathbf{G}}\{H(\{p_i(H,\ G)\})\} \tag{6.39}$$

1. *Optimal Power Allocation over Peak-transmit-power(PTP) and PIP Conditions:*

In this case, F {PTP, PIP} and the optimal value of (29) is denoted as the maximum of with for specific realizations and given by

$$f_1(h,\ g) \triangleq \max_{p_i(h,\ g)} H(\{p_i(h,\ g)\}) \tag{6.40}$$

$$p_i(h,\ g) \leq P_i^{pk}, \forall i \tag{6.41}$$

$$\sum_{i=1}^{N} g_i p_i(h,\ g) \leq Q^{pk}. \tag{6.42}$$

if the optimal solution of the problem is *then thereexists,*

we have

$$p^*_{s_i} = P^{pk}_{s_i}, \forall i, 1 \leq i \leq k-1, 0 < p^*_{s_k} \leq P^{pk}_{s_k}, \tag{6.43}$$

and

$$p^*_{s_i} = 0, \forall i, k+1 \leq i \leq N. \tag{6.44}$$

This gives the structure of the optimal solution for power allocation over the PTP and PIP conditions.

1. *Optimal Power Allocation over Average-Transmit-Power(ATP) and PIP Constraints:*

Here,

$$\mathcal{F}' = \{\text{ATP, PIP}\}$$

$$f_4(\{\lambda_i\}) \triangleq E_{H,G}\{f'_4(H,\ G)\} + \sum_{i=1}^{N} \lambda_i P_i^{av})(6.45)$$

and the dual function is given as

$$f'_4(h,\ g) \triangleq \max\ H(\{p_i(h,\ g)\}) - \sum_{i=1}^{N} \lambda_i p_i(h,\ g)(6.46)$$

with

$$sum_{i=1}^{N} g_i p_i(h,\ g) \leq Q^{pk} \tag{6.47}$$

where are the positive dual variables associated with the ATP conditions. Here is written as

Denoting the optimal solution of the problem as , Thus, for the optimal power allocation under the ATP and PIP constraints, there exists at most only two users that transmit at nonzero power.

6.5.2 Nakagami-m Fading

probability density function (pdf) and Its cumulative distribution function is

$$f\left(x;m,\Omega\right)=\frac{2m^{m}}{\Gamma\left(m\right)\Omega^{m}}x^{2m-1}\exp\left(-\frac{m}{\Omega}x^{2}\right),\forall x\geq 0. \tag{6.48}$$

$$m\geq 1/2,\ \text{and}\ \Omega>0)$$

$$F(x;m,\Omega)=P(m,\frac{m}{\Omega}x^{2})$$

The parameters m and Ω are

$$m=\frac{E^{2}[X^{2}]}{\mathrm{Var}[X^{2}]},\Omega=E[X^{2}]$$

1. *Optimal Power Allocation under PTP and PIP Constraints:*

   Similar analysis as in A.1 can be performed to find the optimal solution as *then there exists,*

suchthat

$$p_{s_{i}}^{*}=P_{s_{i}}^{pk},\forall i,1\leq i\leq k-1,0<p_{s_{k}}^{*}\leq P_{s_{k}}^{pk}, \tag{6.49}$$

And

$$p_{s_{i}}^{*}=0,\forall i,k+1\leq i\leq N. \tag{6.50}$$

This gives the structure of the optimal solution for power allocation under the PTP and PIP constraints.

2. Optimal Power Allocation under and PIP Constraints:

similar analysis as in A.2 can be performed to find the optimal solution as .

$$f_4(\{\lambda_i\}) \triangleq E_{H,G}\{f_4'^{(H,\ G)}\}+\sum_{i=1}^{N}\lambda_i P_i^{av})\quad(6.51)$$

where $\{\lambda_i|1\ \leq\ i\ \leq\ N\}$ are the positive dual variables related to ATP conditions. Here $f_4'^{(h,\ g)}$ is written as

$$f_4'^{(h,\ g)}\triangleq\ \max\ H(\{p_i(h,\ g)\})-\sum_{i=1}^{N}\lambda_i p_i(h,\ g)\quad(6.52)$$

$$sum_{i=1}^{N} g_i p_i(h,\ g) \leq Q^{pk} \qquad (6.53)$$

6.5.3 Log-Normal fading

Log-normal Distribution A random variable is log-normal iff. The Probability density function of lognormal random variable is given by

$$p\left(\gamma\right) = \frac{\xi}{\sigma\gamma\sqrt{2\pi}}e^{-\frac{(\ln\gamma-\mu)^2}{2\sigma^2}} \qquad (6.54)$$

The variance is

$$[\exp(\sigma^2) - 1]\exp(2\mu + \sigma^2) \qquad (6.55)$$

$$\max_{\{p_i(h,\ g),\forall h,g\}\in\mathcal{F}'} \mathrm{E}_{\mathrm{H,G}}\{H(\{p_i(H,\ G)\})\} \qquad (6.56)$$

From classical water-filling power assignment problem and its optimal solution [18]

6.6 Simulation and discussion.

This chapter considers a cognitive radio network with one PU and a network of SUs. Two separate fading channels the Rician and Nakagami-m are considered. About 1000 randomly generated sets of channel power gains h and g are used. Other parameters assumed are W=1,=1.

Fig. 6.9 shows the simulation of the sum ergodic capacity in PTP+PIP, and PTP+AIP constriction against. The simulation is carried out for N=2 and N=4 for Rician fading channel. It can be seen from the figure that the maximum sum ergodic capacity attained in PTP+AIP is higher than that obtained over PTP+PIP for any given number of secondary users. This is for the reason that the power assignment is handier for SUs over the ATP constriction than over the PTP constriction. Further achieved maximum ergodic-capacity improves with more number of SUs.

Fig.6.10 shows the simulation of sum ergodic capacity in PTP+PIP, and PTP+AIP constriction against with Nakagami-m fading channel for N=2 and N=4. The results are more or less similar as in Fig 6.9. However, nakagami-m channel has better maximum sum ergodic capacity than the Rician channel. Further, it can be observed that the performance of ergodic capacity increases with the number of SUs.

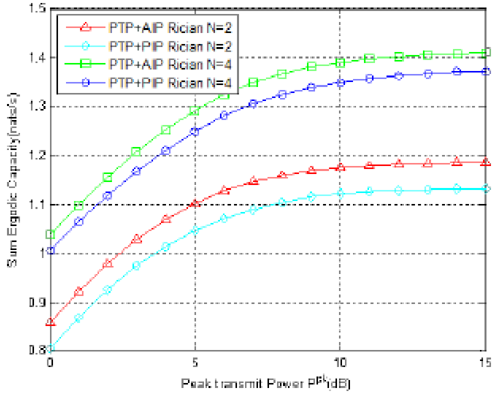


Fig. 6.9. Sum ergodic capacity with Rician fading

channel versus .

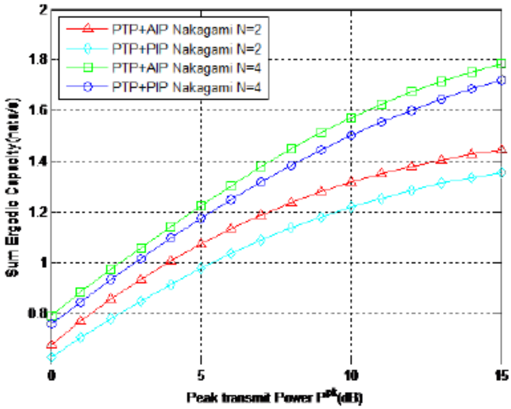


Fig. 6.10. Sum ergodic capacity with Nakagami-m fading channel versus .

Fig.6.11. shows the plot of sum ergodic capacity in PTP+PIP and ATP+PIP constriction against . The simulation is carried out for N=2 and N=4 for the Rician fading channel. It can be seen from the figure that the maximum sum ergodic capacity attained in ATP+PIP is higher than that obtained under PTP+PIP for any given number of secondary users. This is for the reason that the power assignment is handier for SUs over the ATP constriction than over the PTP constriction. Further achieved maximum ergodic-capacity is better with higher number of SUs.

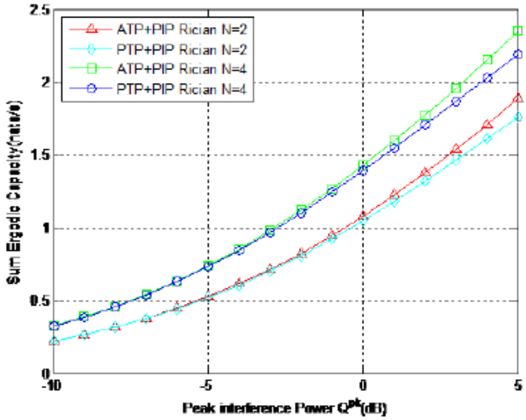


Fig. 6.11. Sum ergodic capacity with Rician fading channel versus .

Fig. 6.12. shows the plot of sum ergodic capacity in PTP+PIP and ATP+PIP constrictions against . The simulation is carried out for N=2 and N=4 for Nakagami-m fading channel. It can be seen from the figure that the maximum sum ergodic capacity attained in ATP+PIP is higher than that obtained under PTP+PIP for any given number of secondary users. This is for the reason that the power assignment is handier for SUs over the ATP constriction than over the PTP constriction. Further achieved maximum ergodic-capacity is better more number of SUs. It can also be observed that the nakagami-m channel has better maximum sum ergodic capacity than Rician channel.

Fig.6.13 shows the plot of maximum sum ergodic capacity in PTP+AIP, ATP+PIP, ATP+AIP versus W for N=2 and N=4 with Rician fading channel. It can be seen that the increase in the number of secondary users results in better maximum sum ergodic capacity. Here it can be observed that with the increase in W does not cause saturation in the sum ergodic capacities.

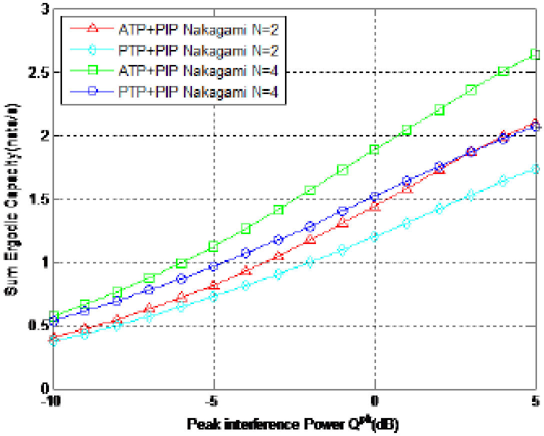


Fig. 6.12. Sum ergodic capacity with Nakagami-m fading channel versus .

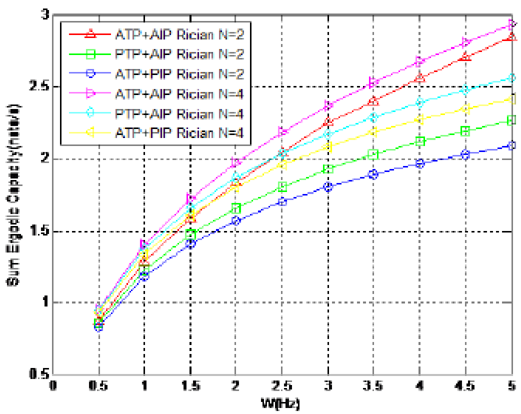


Fig.6.13. Sum ergodic capacity with Rician fading channel versus W.

Fig. 6.14 shows the plot of maximum sum ergodic capacity in PTP+AIP, ATP+PIP, ATP+AIP versus spectrum(W) for N=2 and N=4 with Nakagami-m fading channel. It can be observed that the performance remains similar to the earlier plots of Nakagami-m fading channel. Again nakagami-m channel has better maximum sum ergodic capacity than the Rician channel.

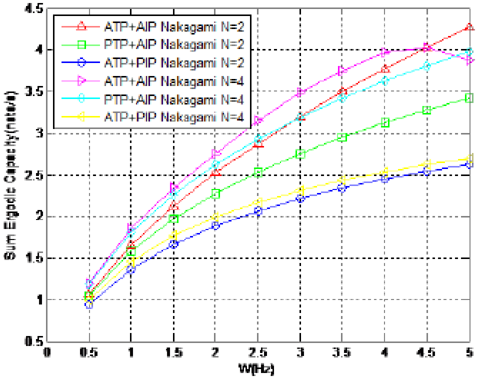


Fig. 6.14. Sum ergodic capacity with Nakagami-m fading channel versus W.

Here we consider a cognitive radio network with one PU and several SUs. We consider two separate fading channels the LogNormal. We use 1000 randomly generated sets of channel power gains h and g. Other parameters assumed are W=1,=1.

Fig. 6.15 shows the simulation of sum ergodic capacity in PTP+PIP, and PTP+AIP constriction against. The simulation is carried out for N=2 and N=4 for LogNormal fading channel. It can be seen from the figure that the maximum sum ergodic capacity attained in PTP+AIP is higher than that obtained over PTP+PIP for any given number of secondary users. This is for the reason that the power assignment is handier for SUs over the ATP constriction than over the PTP constriction. Further achieved maximum ergodic-capacity is better more number of SUs.

Fig. 6.16 shows the plot of sum ergodic capacity in PTP+PIP and ATP+PIP constriction against . The simulation is carried out for N=2 and N=4 for the LogNormal fading channel. It can be seen from the figure that the maximum sum ergodic capacity attained in ATP+PIP is higher than that obtained under PTP+PIP for any given number of secondary users. This is for the reason that the power assignment is handier for SUs over the ATP constriction than over the PTP constriction.

Further achieved maximum ergodic-capacity is better with higher number of SUs.

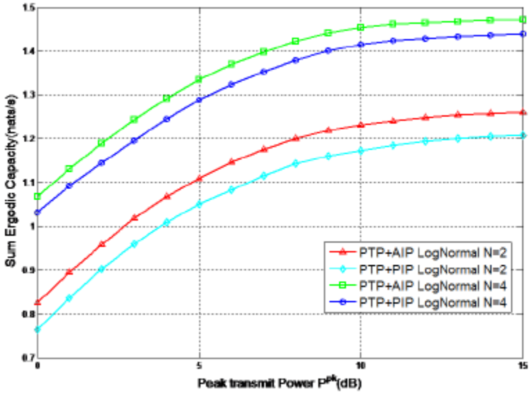


Fig. 6.15. Sum ergodic capacity with LogNormal fading channel versus .

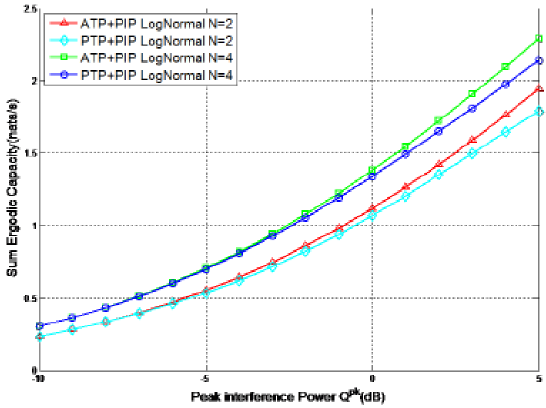


Fig. 6.16. Sum ergodic capacity with LogNormal fading channel versus .

Fig.6.17. shows the plot of maximum sum ergodic capacity in PTP+AIP, ATP+PIP, ATP+AIP versus W for N=2 and N=4 with LogNormal fading channel. It can be seen that the increase in the number of secondary users results in better maximum sum ergodic capacity. Here we

observe that with the increase in W we found no saturation in the sum ergodic capacities.

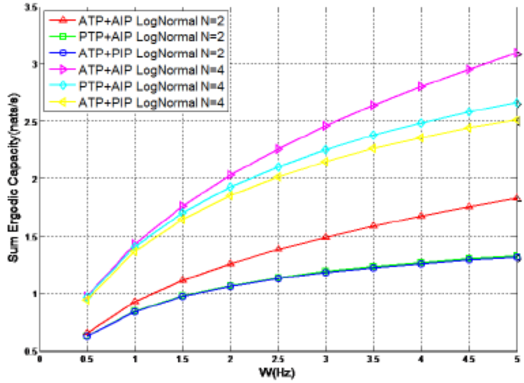


Fig. 6.17. Sum ergodic capacity with Log-Normal fading channel versus W.

6.7 Chapter summary

In this chapter, radio resource allocation problem in cognitive radio networks, where secondary users (SUs) use the spectrum allocated to primary users (PUs) has been considered. The sum ergodic capacity of all the SUs is taken as the performance metric of the network. While the literature discussed above focusses only on Rayleigh fading channel, the work carried out formulates the optimal power allocation strategies to achieve the fundamental capacity limits of a secondary network with Rician, Nakagami-m and Log Normal fading channels which is the main objective of this chapter. In particular, the ergodic capacity is considered. Closed-form solutions are obtained for all the three scenarios. Further the system model considers a network of SUs which is hardly addressed in previous literature. Different peak/average transmitter power constrictions at the secondary users and the peak/average interference power constrictions set by the primary user are considered. The equations of optimal power allocations are also derived under peak power and peak interference constraints. Simulation results depicted by both figures and tables show that the optimal power and bandwidth allocation for Rician, Nakagami-m and Log Normal fading channels.

References:

1. M. Salem, S. A. El-kader, S. M. Ramadan, and M. Zaki, "Opportunisticspectrum access in cognitive radio ad hoc networks," *International Journal ofComputer Science Issues (IJCSI)*, vol. 11, no. 1, 2014.

2. F. Akyildiz, W.-Y. Lee, M. C. Vuran, and S. Mohanty, "NeXt generation/dynamic spectrum access/cognitive radio wireless networks: A survey,"*Elsevier Computer Networks*, vol. 50, no. 13, pp. 2127–2159, 2006.

3. Kolodzy, I. Avoidance, and S. Models, "Spectrum Policy Task Force," Federal Commun. Comm., Washington, DC, Rep. ET Docket no. 2 -135, Nov. 2002.

4. Joseph Mitola, "Software Radio Architecture: Object-Oriented Approaches to Wireless Systems Engineering," Wiley-Interscience, 2000.

5. Mitola, G. Q. Maguire, "Cognitive radio: Making software radios more personal," IEEE Pers. Commun., vol. 6, no. 4, pp. 13 – 18, Aug. 1999.

6. Haykin, "Cognitive radio: Brain-empowered wireless communications,"*IEEE Journal on Selected Areas in Communications,* vol. 23, no. 2,pp. 201–220, 2005.

7. K. Jondral, "Software-defined radio: Basic and evolution to cognitiveradio," *EURASIP Journal on Wireless Communication and Networking*,vol. 2, no. 1, pp. 275–283, 2008.

8. McHenry, D. McCloskey, and G. Lane-Roberts, "New York City Spectrum Occupancy Measurements Sep. 2004," Tech. Rep., Dec. 2004.

9. Shared Spectrum Company, "General survey of radio frequency bands – 30 MHz to 3 GHz," Tech. Rep., Sep. 2010.

10. Rohitha Ujjinimatad and Siddarama R Patil, " Signal Detection in Cognitive Radio Networks Based on the Ratio of Largest Eigenvalue to the Trace of a Covariance Matrix, " in proceedings of IEEE International Conference on Communication, VLSI and Signal Processing (ICCVSP-2013), SIT Tumkur, India. Feb. 20th – 22nd , 2013, pp. 226–229

11. Rohitha Ujjinimatad and Siddarama R Patil, "Spectrum Sensing in Cognitive Radio Networks with the Known and Unknown Noise Levels," IET Communications, vol. 7, Issue 15, pp. 1708 - 1714. October 2013. ISSN:1751–8628

12. Rohitha Ujjinimatad and Siddarama R Patil, "Mathematical Analysis for the Detection of Unknown Signals in Cognitive Radio Networks Over Wireless Communication Channels, " IET Journal of Engineering, doi: 10.1049/joe.2014.0173

13. Rohitha Ujjinimatad and Siddarama R Patil, "Sensing Algorithm for Cognitive Radio Networks Based on Random Data Matrix, " International Journal of Computer Application (IJCA), Vol. 62 No. 3, January 2013, pp. 32-37. ISSN:0975-88872006.

14. W. Thomas, L. A. DaSilva, and A. B. MacKenzie, "Cognitive Networks,"*Proceedings of the 1st IEEE International Symposium on New Frontiers indynamic Spectrum Access Networks*, Baltimore, MD, November 2005,pp. 352–360.

15. Zhao and B. M. Sadler, "A Survey of Dynamic Spectrum Access,"*IEEE Signal Processing Magazine*, vol. 24, no. 3, pp. 79–89, May 2007.

16. B. Rawat and D. Popescu, "Precoder Adaptation and Power Control for Cognitive Radios in Dynamic

Spectrum Access Environments," *IET Communications*, vol. 6, no. 8, pp. 836–844, 2012.

17. G. Proakis, *Digital Communications*, 4th edn. Boston, MA: McGraw-Hill,2000.

18. Cabric, S. Mishra, and R. Brodersen, "Implementation Issues in Spectrum Sensing for Cognitive Radios," *Asilomar Conference on Signals, Systems and Computers*, Pacific Grove, CA, June 2004, pp. 772–776.

19. Zeng and Y.-C. Liang, "Spectrum-Sensing Algorithms for Cognitive Radio Based on Statistical Covariances," *IEEE Transactions on Vehicular Technology*, vol. 58, no. 4, pp. 1804–1815, 2009.

20. Tang, "Some Physical Layer Issues of Wide-band Cognitive Radio Systems," *IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Networks*, Baltimore, MD, June 2005, pp. 151–159.