

SENSING STRATEGIES FOR OPPORTUNISTIC SPECTRUM ACCESS
IN COGNITIVE RADIO NETWORKS

by

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A Thesis

Submitted to the

Graduate Faculty

of

George Mason University

In Partial fulfillment of

The Requirements for the Degree

of

Master of Science

Electrical Engineering

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Summer Semester 2015
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Dedication

To maman Nahid, baba Saeid, and Alireza.

Acknowledgments

I would like to sincerely thank my advisor, Dr. Bijan Jabbari, for his kind support and guidance throughout my graduate studies. I would also like to express my gratitude to my professors and members of my committee, Dr. Shih-Chun Chang and Dr. Brian Mark for their honest and valuable advice.

I am thankful to my dear husband, Alireza, as well as my family for their love and trust in me.

Finally, thanks to all my precious friends, who have always been there for me no matter the distances.

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Abstract

SENSING STRATEGIES FOR OPPORTUNISTIC SPECTRUM ACCESS IN COGNITIVE RADIO NETWORKS

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George Mason University, 2015

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In this thesis, we address an important issue in opportunistic spectrum sensing, dealing with medium access strategies in decentralized cognitive radio networks. Specifically, our focus is on MAC layer channel selection schemes for efficient discovery and allocation of spectrum opportunities. Opportunistic Spectrum Access (OSA) is developed as a dynamic resource allocation model to efficiently utilize the scarce resource of wireless spectrum. Particularly, low-priority Secondary Users (SUs) are allowed to share the spectrum with licensed Primary Users (PUs) in an opportunistic non-intrusive manner, such that no interference will be introduced to the PUs. This involves spectrum sensing, where SUs monitor the activity of PUs to identify and further utilize the idle bands, whenever no primary activity is detected.

Recognizing hardware restrictions and the overhead caused by central infrastructure, we assume SUs have no prior knowledge about primary activity and channel state information. In this uncertain environment, secondary nodes that are cognitive devices have to distributively learn the primary activity parameters at the same time as sensing the spectrum for accessing idle bands. The goal is to maximize secondary network spectral utilization while minimizing interference introduced to the primary. This is where exploration versus

exploitation dilemma arises in search for a balance between choosing empirically best channel while investigating other channels for potential opportunities. Moreover, competition should also be dealt with in order to prevent collision when multiple secondary users in the network intend to access the same channel.

In this thesis, after introducing the concept of OSA for dynamic resource allocation, and discussing relevant existing work in the literature, we consider the problem of spectrum sensing and arising issues in a fading environment. Collaborative spectrum sensing is then addressed as a method to combat undesired fading effects. Afterwards, MAC layer sensing and channel selection problem is considered. First, by modeling the problem as a multi-armed bandit, a sub-optimal channel selection algorithm referred to as modified-myopic strategy is proposed for the single-user scenario. Providing analysis and simulation results, we will show efficient as well as timely performance of our method compared to other strategies in the literature. Next, taking advantage of generalized Carrier Sense Multiple Access-Collision Avoidance (CSMA-CA) technique, we extend our algorithm to design a fair and low-complexity asymptotically optimal access strategy in the multi-user scenario. Analyses and simulation results are provided to evaluate the performance in dense as well as sparse networks. As a result, maximal network utilization, fairly distributed among users, is achievable in high-density decentralized network.

Chapter 1: Introduction

1.1 Motivation

In the past decade, there has been a dramatic growing demand for wireless spectrum due to the advances in wireless technology and increasing number of spectrum-hungry services and applications such as video steaming. Studies assert that the amount of IP addresses allocated to wireless networks will roughly be increased by a factor of 100 by 2020 [1]. However, the wireless spectrum is a limited natural resource, which according to the Fixed Spectrum Allocation (FSA) policy that Federal Communication Commission (FCC) has enforced, is statically allocated to the license owners. That being said, scarcity of wireless bands is an ineluctable fact.

On the other hand, studies reveal that licensed spectrum resources are being under-utilized [2]. In fact, even more restricting than the spectrum scarcity, is the fact that there are so many vacant bands spread in the spectrum, , also known as spectrum holes. This fact reveals the inefficiency of the FSA policy as well as the inevitable need to overcome the spectrum under-utilization.

To this end, Dynamic Spectrum Access (DSA) has been introduced and approved by FCC as a promising spectrum management policy towards reforming the wireless spectrum. Several dynamic spectrum access strategies have been introduced, among which we can name *spectrum commons*. In spectrum commons, the wireless spectrum is open for peer users to share in a centralized or distributed fashion. IEEE 802.11 technology (WiFi) is a very well known spectrum sharing method, where the unlicensed industrial, scientific, and medical (ISM) radio band is open for wireless services to operate in.

Another important access model derived from DSA is *Spectrum Overlay*, or namely *Opportunistic Spectrum Access* (OSA)[3]. In OSA, the licensed spectrum is open for a group

of unlicensed secondary users to share with license owners, also known as primary users, in a hierarchical non-intrusive manner. More specifically, secondary users in a given location and a given time, identify and further exploit the local and instantaneous transmission opportunities (spectrum holes, aka white spaces) by monitoring the activity of the primary users. The importance of OSA appears in not constraining the transmission power of secondary users. However, they are still confined to avoid interfering the primary users' activity.

Opportunistic Spectrum Access, consists of three basic tasks:

1. Spectrum opportunity identification; to explore and detect idle frequency bands that are dynamic in time and space.
2. Spectrum opportunity exploitation; to utilize the identified idle bands discovered in previous phase. This task might take place using a scalable waveform unit, which makes the communication possible over a given frequency and a given bandwidth.
3. Regulatory policy; to make sure secondary user is compatible with legacy system.

Cognitive Radio, inclusive of software-defined radio, is the key technology for realization of opportunistic spectrum access. Promoted by Dr. Joseph Mitola in 1998, Cognitive Radio is defined by FCC as *a radio capable of changing its transmitter parameters based on interaction with its environment. This interaction may involve active negotiation or communications with other spectrum users and/or passive sensing and decision making within the radio* [4]. Further, Haykin defines Cognitive Radio in 2005 in this way [5]:

Cognitive radio is an intelligent wireless communication system that is aware of its surrounding environment (i.e., outside world), and uses the methodology of understanding-by-building to learn from the environment and adapt its internal states to statistical variations in the incoming RF stimuli by making corresponding changes in certain operating parameters (e.g., transmit-power, carrier-frequency, and modulation strategy) in real-time, with two primary objectives in mind:

- *highly reliable communications whenever and wherever needed;*
- *efficient utilization of the radio spectrum.*

A cognitive radio network consists of two groups: the *primary (licensees) network* operating in a certain band, and the *secondary network* consisting of a group of cognitive radio users. Both networks may be equipped with integrated infrastructure to control their activities through a base station or not. Also, the secondary users can access both the licensed and unlicensed spectrum bands. Thus, there are three types of spectrum access available for secondary users: *cognitive radio network access*—secondary users can access their own base station, *cognitive radio ad hoc access*—ad hoc communication between cognitive users, and *primary network access*—accessing the primary base station through licensed spectrum [6]. Figure 1.1 shows the structure of a cognitive radio network.

In addition, cognitive radio also has to deal with challenges such as interference avoidance, QoS awareness, and seamless communication. The main functionalities required for the cognitive users to address these challenges in OSA technology may be expressed as follows [6]:

- *Spectrum sensing*: monitoring activity of the primary users in the surrounding RF bands to identify spectrum availability, i.e., to detect spectrum holes.
- *Spectrum decision*: allocating channels based on the availability results.
- *Spectrum sharing*: coordinating spectrum access among multiple cognitive users in the network to avoid collision.
- *Spectrum mobility*: vacate and seamlessly switch the channel once the primary user appears.

Cognitive radio tasks are not fully separated. Mainly, efficient opportunistic access requires intensive interaction across physical (PHY) layer and medium access control (MAC) layer.

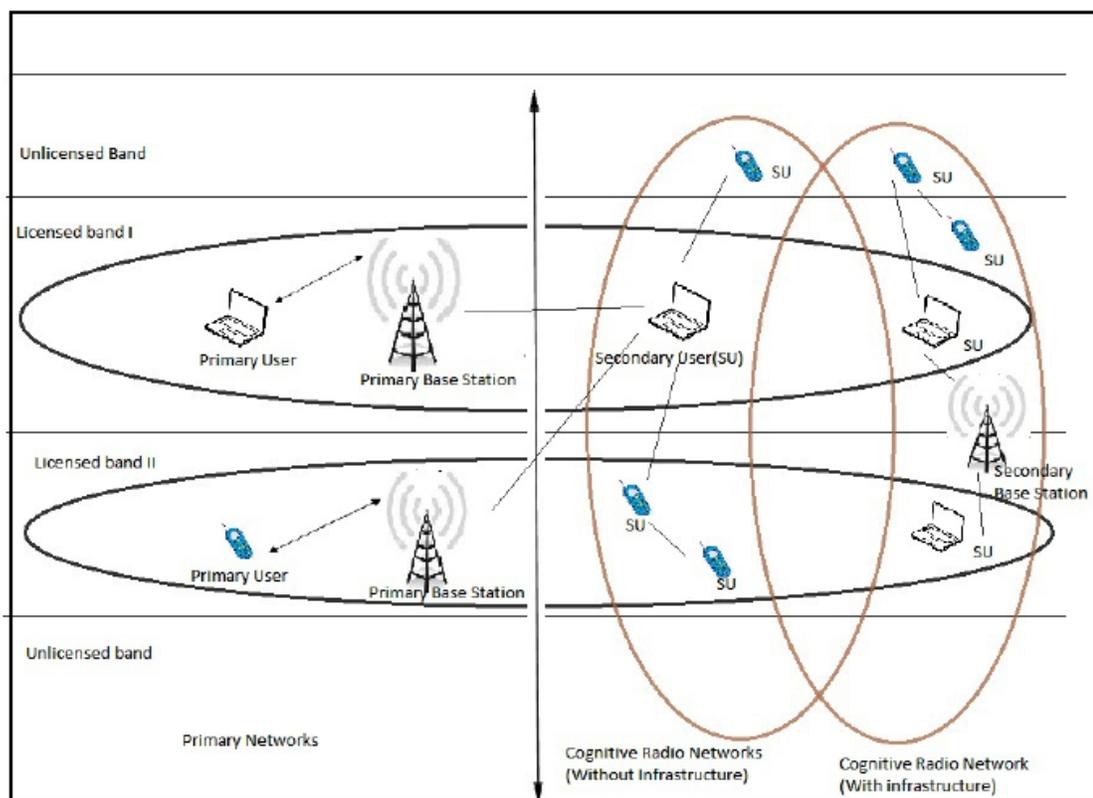


Figure 1.1: Cognitive radio network architecture [7].

1.2 Problem Statement

Throughout this thesis we consider a secondary user, and further generalize to a secondary network consists of K cognitive radios, who opportunistically access to the licensed spectrum of a primary network with N orthogonal channels. The channels may be frequency bands with certain bandwidth, or code division multiple access (CDMA) spreading codes, or a set of orthogonal frequency division multiplexing (OFDM) sub-carriers. Nevertheless, we assume there is no cross-talking between channels, so that primary signal in one channel will not affect sensing results in another channel. Also, secondary transmission in one channel will not disturb transmissions in other channels.

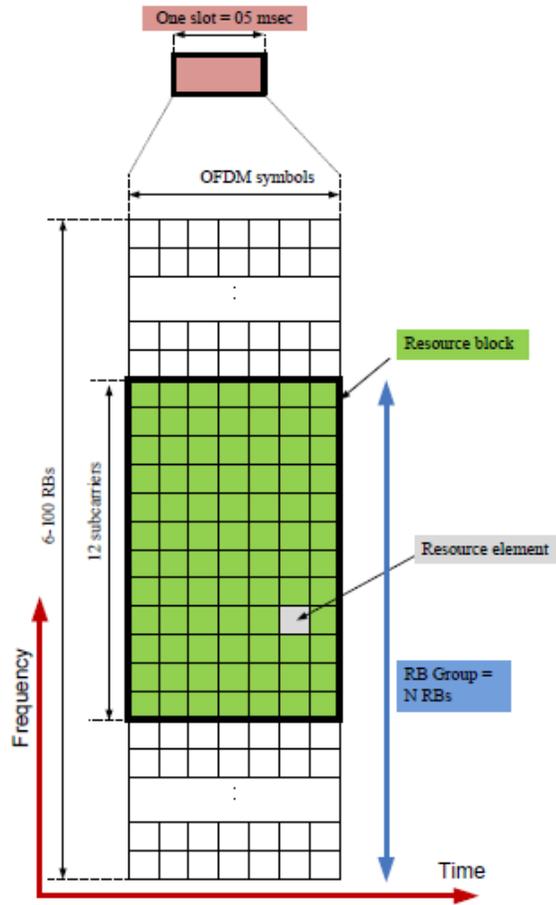


Figure 1.2: LTE resource block [8].

We consider a synchronous time-slotted system for both primary and secondary networks. Under these terms and conditions, Long Term Evolution (LTE) system offers an appropriate framework due to its properties resulting from resource blocks structure, i.e. being well partitioned in time and frequency as shown in figure 1.2. Also, employing OFDM in LTE is another advantage, due to the carrier aggregation feature which makes transmission over non-contiguous frequency bands possible [2].

There have been numerous studies about physical layer aspects of spectrum sensing, from detection methods (energy detection, matched filtering, feature estimation, etc. [9])

to imperfect sensing [10]. However, MAC sensing which is the subject of this thesis, and responsible for scheduling the timings and orders, and is crucial for spectrum sensing/access, has been less discussed in the literature [11]. Essentially, prior to the actual sensing procedure, channel selection problem comes into the picture. Cognitive radios cannot sense all the channels in the spectrum and must decide which channel to attempt sensing in advance. It is of importance to note that the channel selection strategy is independent of the detection method. However, as the definition of cognitive radio implies, the observations and sensing results from physical layer, like primary user activity ratio and sensing accuracy, are passed to the MAC layer to be used in the scheduling process for access and next sensing round.

As mentioned before, cognitive users cannot sense/access all the channels at the same time. We assume that the secondary users are able to sense/access only one channel at a time slot. This assumption might be further extended to the case where the secondary users are capable of sensing/accessing multiple channels simultaneously, however, it would require multiple antennas and introduces complexity on the secondary user's part, as well as causing severe interference among the antennas [11].

Since cognitive users can only sense one channel in a time slot, they need to decide which one to attempt sensing so as to find more spectrum holes and thus maximize their spectral utilization. The fact that secondary users do not have full knowledge of the primary activities, makes this process even more challenging. Thus, cognitive users have to perform two tasks simultaneously:

- Sense the channels to exploit transmission opportunities,
- Explore channels to estimate their availability statistics using the sensing results.

Here stems a trade-off between exploring the availability statistics of different channels, and exploiting the most likely transmission opportunity based on previous observations. Moreover, in a decentralized cognitive radio network where there is a possibility that multiple secondary users select the same channel to sense/access, problem of competition also arises. Therefore, a securing MAC protocol for scheduling access and fair allocation of

resources is essential to maximize the network utilization.

In this thesis, after reviewing the radio channel characteristics in chapter two, we will first discuss the physical layer aspects of spectrum sensing and analyze the effect of multi-path fading and shadowing, as well as collaboration in spectrum sensing in chapter three. Next, in chapter four, we will consider the MAC layer sensing and scheduling module, along with proposing our modified-myopic scheme for single-user case, which will further be extended to multi-user case. Analyses as well as simulation results will be provided to demonstrate the efficiency of our strategy compared to other schemes in the literature. finally, in chapter five, we will conclude our work and provide future research topics.

1.3 Background and Related Work

The problem of spectrum sensing for cognitive radio has been widely studied in the literature from different perspectives [9], [12],[13]. According to [9], spectrum sensing is one of the most essential components of cognitive radio, based on which the quality of service of the primary system is secured by minimizing the interference introduced to primary signal. Different methods of detection are discussed, such as energy detection, feature detection, and blind detection [9], [14]. Although in the presence of white Gaussian noise, the appropriate process of signal detection is matched filtering, yet, with little knowledge about signal structure and statistics, it seems appropriate to use a basic energy detector for determining the presence of a signal [15]. However, due to fading channels, imperfect sensing may result in missed detection and false alarm errors when using energy detection. Collaborative spectrum sensing is proposed in [10] to combat the effect of shadowing and fading. Extensive studies exist on cooperative spectrum sensing, whether distributed or centralized, discussing different signal models, fusion rules, or performance issues such as sensing-throughput trade-off [16–18].

MAC sensing and channel selection problem have also been studied frequently in the literature. A very recent and complete classification for MAC protocols in cognitive radio networks is provided in [19]. General discussion as well as broad references are given to

answer questions such as: *how to model and learn PU channels activity*, or *how to coordinate sensing to target most appropriate channel sets*, *how to do multiple access*, etc. In this thesis, however, we will address this question: ***how to simultaneously learn and use channel availability information to strike a maximum and fair network utilization?***

Several studies have been attracted to the above problem in different frameworks. For instance, a decentralized cognitive MAC protocol has been proposed for ad hoc networks based on the theory of partially observable Markov decision process, which integrates physical layer spectrum sensing with MAC layer access design to optimize the performance of secondary users [20]. Channel allocation to multiple users in cognitive radio network has been formulated as a combinatorial multi-armed bandit to present a matching-learning algorithm that maximizes the expected sum throughput, taking into account that each secondary user sees different primary behavior on a channel due to geographical dispersion [21]. In [22], a general framework for decentralized policies with unknown reward statistics is established using multi-armed bandit. Problem of cognitive medium access has also been addressed in [23], where optimal as well as low-complexity protocols are proposed based on the result of UCB algorithm for multi-armed bandit problem [24], to strike a balance between exploration and exploitation in competitive environments. Considering the exploration/exploitation dilemma, and the simplicity of myopic sensing strategy [25], we designed a sub-optimal access strategy for single-user scenario without prior information about primary activity in [26]. Extension of [26] to an ad hoc network with multiple secondary users is given in [27].

Chapter 2: Radio Channel Overview

2.1 Introduction

Reliable high-speed communication is a challenging task in wireless radio environment. In addition to noise, interference, and large power losses, randomness is also an impediment in the wireless channel. In fact, as a result of user mobility and environment dynamics, wireless channel is unpredictably varying over time. In general, the effects of a typical wireless channel are categorized into two types based on the received power variation over distance: large-scale effects and small-scale effects [28]. Large-scale effects include pathloss and shadowing, whereas small-scale effect is known as multipath fading. The large as well as small-scale effects of wireless channel on the signal power are shown in figure 2.1. In the following sections we review and model these wireless channel characteristics.

2.2 Large-scale Effects

Pathloss is caused by power dissipation in the radiated signal over the transmit-receive distance, which happens over long distances (100-1000 m). Shadowing, on the other hand, is caused by the obstacles in the propagation path that attenuate signal power through absorption, reflection, scattering, and diffraction, which result in power variation on the order of the obstacle size [28]. This is why pathloss and shadowing are referred to as large-scale propagation effects.

2.2.1 Pathloss

Consider signal s_t to be transmitted with power P_t in the wireless channel. The major dissipation that the received signal s_r faces is caused by pathloss over long distances. Pathloss

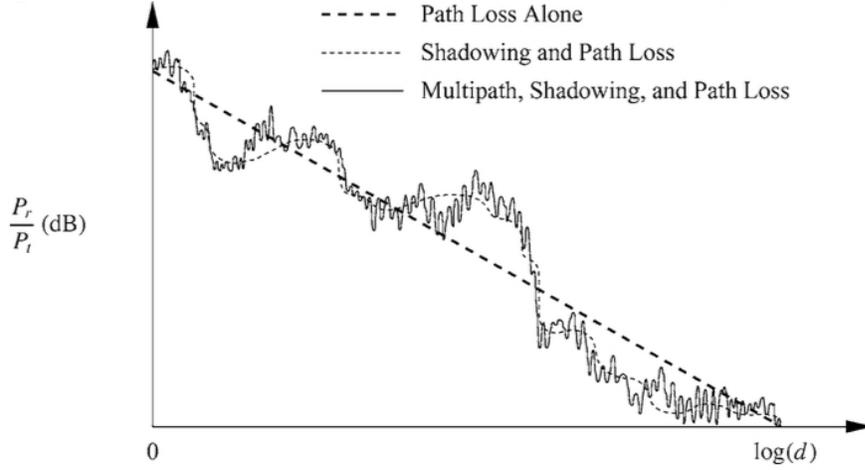


Figure 2.1: Effects of radio channel on the signal power: pathloss, shadowing, and multipath fading versus distance [28].

L_P relates the received signal power P_r to the transmit signal power P_t in the following way:

$$P_r = P_t \frac{G_r G_t}{L_P} \quad (2.1)$$

where G_t and G_r are transmit and receive antenna gains, respectively. The received signal to noise ratio (SNR) then equals to:

$$SNR = \frac{P_r}{P_N} = \frac{P_t \cdot G_t \cdot G_r}{N_0 \cdot B \cdot L_P} \quad (2.2)$$

where N_0 is the noise power spectral density, and B is the bandwidth. Assuming unity antenna gains, the SNR can be found as follows:

$$SNR = \frac{P_t}{\sigma_N^2 L_P} \quad (2.3)$$

where $\sigma_N^2 = N_0 B$ is the AWGN noise variance.

Pathloss L_P is the deterministic component of power loss that signal faces, and may be modeled in different ways. The most common and simplest pathloss model is the *free-space model*. Assuming the signal is transmitted through free space to a receiver at distance d , without any obstacles in the space, it will propagate along a straight line, known as line-of-sight (LOS). In the free-space model, pathloss is given by Friis's formula:

$$\begin{aligned} L_P &= \left(\frac{4\pi d}{\lambda_c} \right)^2 \\ &= \left(\frac{4\pi f_c d}{c} \right)^2 \end{aligned} \tag{2.4}$$

where λ_c is the signal wavelength, f_c is the carrier frequency, and c is the speed of light in free space. As equation (2.4) implies, pathloss increases proportional to the squared of distance d and frequency f_c , which means we have even more power loss in high frequencies.

The *two-ray channel model* is a more realistic model, where in addition to the LOS path, a reflected path is also considered in free space propagation. In this model, the two received signals along the two paths will add constructively or destructively, and the pathloss will be found as follows:

$$\begin{aligned} L_P &= \frac{1}{4} \left(\frac{4\pi f_c d}{c} \right)^2 \left(\frac{1}{\sin \left(\frac{2\pi f_c h_b h_m}{cd} \right)} \right)^2 \\ &\approx \left(\frac{d^2}{h_b h_m} \right)^2, \end{aligned} \tag{2.5}$$

approximation valid for $d \gg h_b, h_m$, where h_b and h_m are transmit and receive antenna heights, respectively. As implied in equation (2.5), pathloss is proportional to d^4 in typical urban areas. Note that the received power falls dramatically for values of d at which the

sine function equals zero, i.e.

$$\begin{aligned}\frac{2\pi f_c h_b h_m}{cd} &= n\pi \\ \Rightarrow d &= \frac{2h_b h_m}{n\lambda_c}.\end{aligned}\tag{2.6}$$

for integer values of n .

The path-gain (inverse of pathloss) in dB is depicted in figure 2.2 for a two-ray as well as four-ray model, where in addition to the ground, a wall (vertical reflector) is also considered in the propagation environment. For this simulation, the transmitter and receiver antenna heights are respectively considered 30m and 2m, the carrier frequency f_c is assumed 900MHz, and thus, the signal wavelength is $\lambda_c \simeq 0.33\text{cm}$. The distances at which nulls happen are visible in this figure, implying the large-scale effect of pathloss.

There are also several empirical models for pathloss, one of which is *Okumura-Hata model* given as follows:

$$L_{P(dB)} = A + B \log_{10}(d)\tag{2.7}$$

where for urban environments, we have

$$\begin{aligned}A &= 69.55 + 26.16 \log_{10}(f_c) - 13.82 \log_{10}(h_b) - a(h_m) \\ B &= 44.9 - 6.55 \log_{10}(h_b)\end{aligned}\tag{2.8}$$

$$a(h_b) = (1.1 \log_{10}(f_c) - 0.7)h_m - (1.56 \log_{10}(f_c) - 0.8).$$

However, often a simpler pathloss model that emphasizes the dependence on distance suffices:

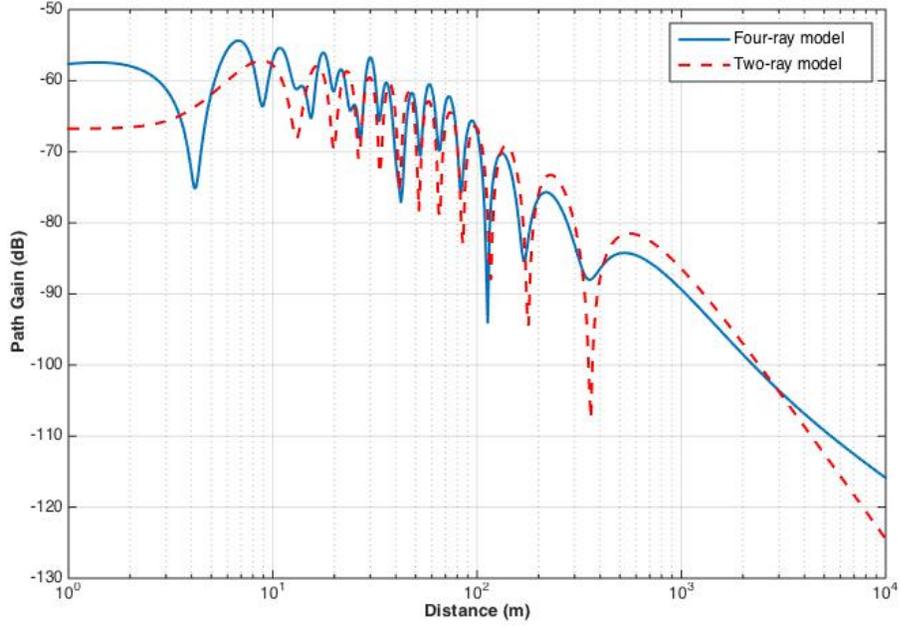


Figure 2.2: Path-gain vs. distance for two-ray as well as four-ray model (with a vertical reflector in addition to the ground) at frequency $f_c = 900\text{MHz}$.

$$L_P = K \left(\frac{d}{d_0} \right)^\gamma \quad (2.9)$$

or equivalently in dB:

$$L_{P(dB)} = 10 \log_{10}(K) + 10\gamma \log_{10}\left(\frac{d}{d_0}\right). \quad (2.10)$$

where frequency dependence, antenna gains, and geometry are absorbed in K , d_0 is a reference distance and the model is valid for $d > d_0$, and γ is the pathloss exponent, usually between 3 and 5.

2.2.2 Shadowing

The pathloss models described in the previous section, are deterministic models depending on the distance, frequency, and environment. However, shadowing or shadow fading is the random component of pathloss which describes random fluctuations due to obstructions. Therefore, pathloss becomes a random variable Ψ_{dB} , with mean equal to $L_{P(dB)}$. The commonly used model is log-normal shadowing, according to which Ψ_{dB} in logarithmic scale is modeled as a Gaussian random variable with mean $L_{P(dB)}$ and standard deviation $\sigma_{\Psi,dB}$, which describes variation around deterministic part of pathloss, $L_{P(dB)}$, with common values 4dB-10dB.

2.3 Small-scale Effects

In spite of pathloss and shadowing effects which cause signal power variations over relatively long distances, wireless channel also introduces variations over very short distances, on the order of the signal wavelength, referred to as small-scale propagation effects, visible in figure 2.1. Small-scale effects are caused by constructive and destructive addition of signals received from multiple paths in the propagation environment, known as multipath fading, as well as time-varying nature of channel.

2.3.1 Multipath Fading

Multiple replicas of the signal, with different delays, phase shifts, and attenuations are received from different paths. Thus, the baseband equivalent of multipath channel impulse response may be found as follows:

$$h(t) = \sum_{k=1}^K a_k e^{j\phi_k} e^{-j2\pi f_c \tau_k} \delta(t - \tau_k) \quad (2.11)$$

where a_k is the path attenuation, τ_k is the path delay, and ϕ_k is the phase shift along path k caused by delay τ_k . From equation (2.11), channel frequency response may be given

as follows:

$$\begin{aligned}
 H(f) &= \sum_{k=1}^K a_k e^{j\phi_k} e^{-j2\pi f_c \tau_k} e^{-j2\pi f \tau_k} \\
 &= \sum_{k=1}^K a_k e^{j\phi_k} e^{-j2\pi(f_c - f)\tau_k}
 \end{aligned} \tag{2.12}$$

Therefore, for any frequency f , the frequency response is a sum of complex numbers. When these terms add destructively, the frequency response is very small or even zero at that frequency. These nulls in the channel's frequency response are typical for wireless communications and are referred to as *frequency-selective fading*.

In general, multipath leads to signal distortion, and is equivalent to undesired filtering. It is especially bad for wideband signals, where signal bandwidth, B_W , is relatively larger than the channel *coherence bandwidth*, B_c . Coherence bandwidth of a multipath channel is the statistical measurement of the range of frequencies over which the channel frequency response can be considered approximately constant, or in other words, two frequencies of a signal are likely to experience comparable amplitude fading. The inverse of coherence bandwidth is known as *time delay spread*, $T_d \simeq \frac{1}{B_c}$, which is defined as the time delay between the arrival of the first received signal component (LOS) and the last received signal component associated with a single transmitted pulse, and is typically about a few μsec in urban environments. A wideband signal in time domain, has duration $T_s \simeq \frac{1}{B_W}$ relatively short.

However, for narrowband signals where $B_W \ll B_c$ or equivalently $T_s \gg T_d$, different frequency components do not experience much variations in the frequency response of the channel. In fact, frequency components of a narrowband signal are likely to be filtered the same way, so the received signal looks like the transmitted signal, and is not distorted. This is known as *flat fading* which is simpler to deal with in communications systems.

2.3.2 Time-variability

Beyond multipath fading, a second characteristic of wireless communication channels is their time-variability, which is mainly due to users mobility. In particular, as a mobile user changes its position by $\vec{\Delta d}$, the length of k -th path increases by $\vec{\Delta d} \cos(\psi_k)$, where ψ_k denotes the angle between the direction of the mobile user and the k -th incoming ray. Consequently, characteristics of each propagation path changes correspondingly.

The change in path gain a_k which decays inversely proportional to the square of distance, $a_k \sim d_k^{-2}$, is generally small enough to be negligible. However, the change in delay τ_k which is equal to $|\vec{\Delta d}|/c$, is not negligible, since it gets multiplied by the carrier frequency, f_c , to produce phase shifts. Consequently, the phase change arising from the movement is equal to:

$$\begin{aligned} \Delta\phi_k &= -2\pi f_c/c |\vec{\Delta d}| \cos(\psi_k) \\ &= -2\pi |\vec{\Delta d}|/\lambda_c \cos(\psi_k). \end{aligned} \tag{2.13}$$

These phase changes are significant and lead to changes in the channel properties over short time scales, known as *fast fading*. If mobile is moving with constant velocity v , then we have $|\vec{\Delta d}| = vt$. Consequently, the phase change for the k -th path according to equation (2.13) becomes

$$\begin{aligned} \Delta\phi_k(t) &= -2\pi v/\lambda_c \cos(\psi_k)t \\ &= -2\pi v/c \cdot f_c \cos(\psi_k)t. \end{aligned} \tag{2.14}$$

We can see that due to mobility, the phase becomes a linear function of time t . Hence,

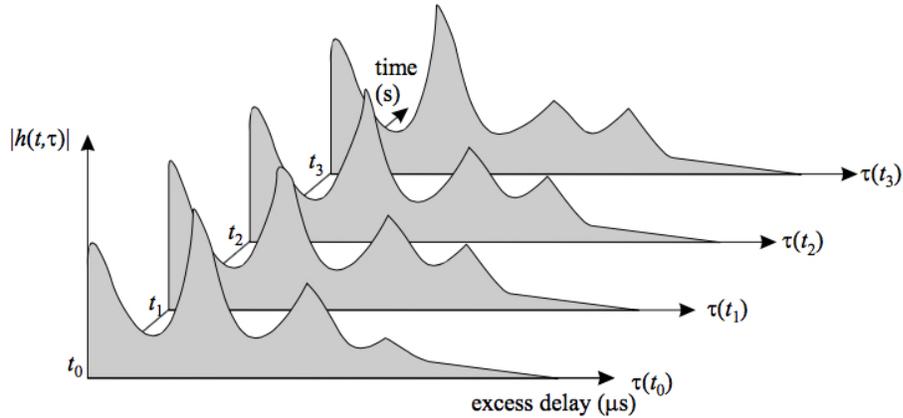


Figure 2.3: An example of time-varying impulse response of wireless channel [29]

along this path, the signal experiences a frequency shift $f_{d,k} = v/c \cdot f_c \cos(\psi_k)$. This frequency shift is called *Doppler shift*. Each path experiences a different Doppler shift, all of which together create a *Doppler Spectrum*. Maximum Doppler shift is denoted by f_d .

The time over which the channel remains approximately constant is called the *coherence time* of the channel T_c , which is approximately equal to the inverse of maximum Doppler shift, $T_c \simeq \frac{1}{f_d}$. If the signal duration T_s is relatively smaller than the coherence time, i.e. $T_s \ll T_c$, or equivalently, $B_W \gg f_d$, the channel may be considered constant and is said to be *slow-fading*, which is of more interest in communications systems.

2.4 Statistical Characterization of Channel

A statistical model that captures the important features of the wireless channel, i.e. multipath and time-varying nature of the channel, is desirable. The time-varying descriptions of channel are functions of two decoupled parameters: time t that indicates when the channel was observed, and frequency f or delay τ that reflects the time since the input was applied.

The time-varying impulse response of a wireless channel is denoted by $h(t, \tau)$ which is a complex value, as shown in figure 2.3 received signal is found by $r(t) = \int h(t, \tau)s(t - \tau)d\tau$.

The *power-delay profile* is defined as the average power in the impulse response over delay τ , which can be found as follows:

$$\Psi_h(\tau) = \frac{1}{K+1} \sum_{k=0}^K |h(t_k, \tau)|^2. \quad (2.15)$$

The power-delay profile given in equation (2.15) captures both time varying and statistics of multipath effects of the channel. The underlying physical model assumes a large number of propagation paths associated with delay τ . Therefore, according to the central limit theorem, $h(t, \tau)$ at a given delay τ is modeled as a complex Gaussian random variable. If the LOS ray is present, then the mean is zero, otherwise the mean is non-zero. Hence, the phase of the channel gain is uniformly distributed, and the magnitude of the channel gain, $|h(t, \tau)|$, has a Rayleigh distribution for zero-mean case, and Ricean distribution for non-zero-mean case. In the former case, the power-delay profile, which is proportional to the square of channel magnitude $|h|^2$, is exponentially distributed. A channel with this specifications is called *Rayleigh fading channel*

The *RMS delay spread* of the channel, as defined previously by $T_d \simeq \frac{1}{B_c}$, may also be found exactly using the power-delay profile as follows:

$$T_d^2 = \int_0^\infty \Psi_h^{(n)}(\tau) \tau^2 d\tau - \left(\int_0^\infty \Psi_h^{(n)}(\tau) \tau d\tau \right)^2 \quad (2.16)$$

where

$$\Psi_h^{(n)}(\tau) = \Psi_h(\tau) / \int_0^\infty \Psi_h(\tau) d\tau. \quad (2.17)$$

In general, for simpler implementation purposes, narrowband signals are used so as to avoid frequency-selective fading and intersymbol interference. For wideband communications systems, different methods of diversity are employed to overcome fading, which

introduce overheads such as channel estimation and equalization to the devices. Also, in mobile communications systems, fast-fading models are not of interest, since the channel impulse response varies over the transmission time. As a matter of fact, for flat-fading and slow-fading communications, a signal with duration T_s and bandwidth B_W is desirable such that $T_d \ll T_s \ll T_c$, or equivalently in the frequency domain, $f_d \ll B_W \ll B_c$, as in OFDM systems.

2.5 Conclusion

In this chapter, an extensive overview of the wireless propagation environment was provided. Channel characteristics were studied, and statistical models were addressed as well. The concepts of pathloss, shadowing, and Rayleigh fading were thoroughly investigated, and required conditions were given for flat and slow fading communications. These assumptions hold throughout what follows in this thesis.

Chapter 3: Spectrum Sensing

3.1 Introduction

Due to the growing demand for spectrum and high data rate communications in wireless services and applications, spectrum scarcity is becoming an inevitable issue. Although it truly prevents the interference among users, but studies reveals the inefficiency of the current static spectrum access policy. Cognitive radio technology, as a potential platform to implement the Dynamic Spectrum Access (DSA), has captured the interest of researchers in recent years. In this technology, intelligent radios are capable of sensing the spectrum, that is monitoring the activity of primary users to identify and further utilize idle bands- also known as white spaces- when no primary signal is detected.

Two major concerns in cognitive radio are first identification of white spaces, and next, efficiently using these resources. Identification can be done whether by negotiated or by opportunistic approach [30]. In the former, an inter medium channel provides the signaling between primary and secondary users, which requires direct interaction among them, and thus results in extensive overhead for terminals. Here we focus on opportunistic spectrum access, where secondary nodes directly sense the spectrum. Spectrum sensing can also be carried out using a dedicated sensor network, however it would require extra effort for handling and maintenance, which is out of the interest of this thesis.

It is very important in direct spectrum sensing, which is the subject of opportunistic spectrum access, that the secondary activities do not disturb the high-priority primary traffic. In other words, no serious interference may occur while secondaries are coexisting with the primary users.

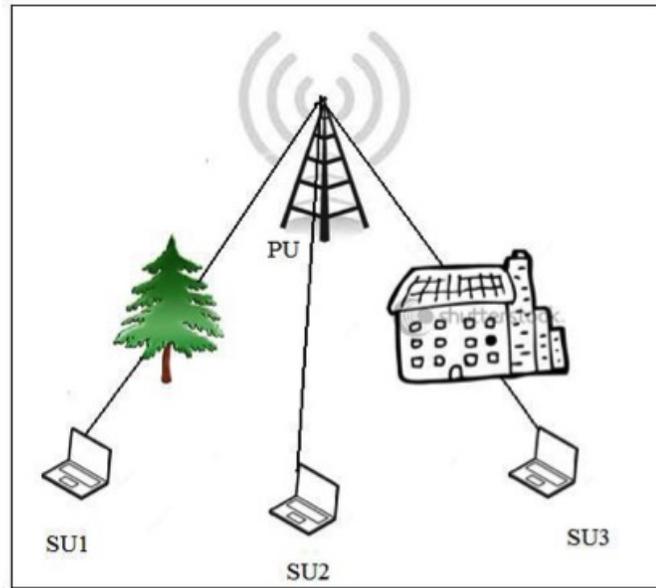


Figure 3.1: Hidden terminal problem [7].

Evidently, spectrum sensing is the first and most essential step for the realization of cognitive radio technology. For implementing sensing module, energy detector appears to be the common and feasible choice. In fact, matched filter followed by a threshold comparator is the optimal detector when the structure of primary signal is known and in the presence of Gaussian noise [10]. However, this type of coherent detector requires synchronization, which results in extra complexity in secondary terminals. Moreover, known structure of primary signal might not always be the case. Therefore, a general-purpose energy detector is more desirable.

Nevertheless, the performance of energy detector is deeply affected for hidden terminal nodes, as depicted in figure 3.1. In particular, when secondary users experience signal attenuation due to path loss, it will no longer be easy for them to distinguish between a white space and a deep fade. In addition, multipath fading and shadowing also introduce randomness to the signal which makes detection problem even harder. This may result in harmful interference to the primary user on one extreme, or low utilization on the other extreme.

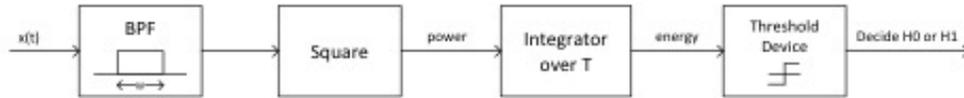


Figure 3.2: Block diagram of an energy detector.

Indeed, while some secondary nodes may be suffering from deep fade, some others may be receiving strong primary signal, and thus have a better detection. Here arises the idea of collaboration among secondary users towards detecting the primary signal. In fact, a group of secondary users cooperate with each other by sharing their sensing information, so as to combat the effect of channel loss and randomness in the decision process. Collaborative spectrum sensing helps reducing the uncertainty of secondary users in detecting the primary signal. This is similar to the approach applied in Wireless Regional Area Network (WRAN) IEEE 802.22 where all Customer Premises Equipments (CPEs) perform a fast sensing algorithm using energy detector and then all the results are gathered at the 802.22 Base Station (BS) which makes the final decision [30].

In this chapter we will discuss physical-layer aspects of spectrum sensing and collaboration towards detection and identification of idle bands. We will analyze the performance of spectrum sensing using energy detector in fading environments and will further investigate the result of collaboration. Comparison will be provided between local and collaborative sensing. Effect of the number of collaborating users as well will be discussed.

3.2 System Model

Consider an ad hoc cognitive radio network consisted of n secondary users, looking for opportunistic access to the spectrum bands of a primary system. We assume all SUs are using energy detector with common parameters as shown in figure 3.2. The input signal $x(t)$ is first shaped using a bandpass filter to specify the bandwidth W , next, the output is squared to measure the signal power, followed by an integrator to determine the energy of the received signal during the observation interval T . Finally, the output of the integrator

Y , is passed through a threshold device to be compared with the threshold λ , in order to decide whether the signal is present or not.

Basically, the received signal at the input of energy detector can be written as follows:

$$x(t) = \begin{cases} n(t) & H_0 \\ hs(t) + n(t) & H_1 \end{cases} \quad (3.1)$$

where $s(t)$ is the primary signal, $n(t)$ is additive white Gaussian noise (AWGN), and h is the channel amplitude gain. Essentially, our mission is to decide between the two hypotheses H_0 and H_1 . H_0 denotes the absence of PU signal in the target channel, and thus an idle band and transmission opportunity for SU, whereas H_1 indicates the presence of primary signal in the band.

Our decision statistic, Y , is the output of the integrator, representing the signal energy within bandwidth W and during the time interval T . Let $m = TW$ and suppose it is an integer value for simplicity. It can be shown that Y has a chi-square distribution as follows [10]:

$$Y \sim \begin{cases} \chi_{2m}^2 & H_0 \\ \chi_{2m}^2(2\gamma) & H_1 \end{cases} \quad (3.2)$$

where γ is the signal to noise ratio (SNR) of the received signal, and χ_{2m}^2 and $\chi_{2m}^2(2\gamma)$ are central and non-central chi-square distribution, respectively, each with $2m$ degrees of freedom, and the latter with a non-centrality parameter of 2γ .

In order to make the final decision, Y is compared to threshold λ , and the detection result is given as follows:

$$\hat{H} = \begin{cases} H_0 & Y < \lambda \\ H_1 & Y \geq \lambda \end{cases} \quad (3.3)$$

Assuming a static channel without any multipath or shadowing effect, the value h and thus, SNR γ will be deterministic. We define two probabilities to evaluate the performance of a detector; *probability of detection* and *probability of false alarm*. The higher the probability of detection, the better the primary users are protected. However, from secondary users perspective, the lower the probability of false alarm, the more chances the channel can be reused when it is idle, and therefore, the higher the achievable throughput for the secondary network [18]. In the subsequent sections we will analyze and evaluate the performance of secondary users both in local and collaborative environments.

3.3 Local Spectrum Sensing

Consider a single SU trying to identify an idle band using the energy detector discussed above. The probability that secondary user detects the primary signal given that PU is present, is called probability of detection, which in a non-fading environment, is given as follows [10]:

$$P_d = Pr\{Y > \lambda | H_1\} = Q_m(\sqrt{2\gamma}, \sqrt{\lambda}) \quad (3.4)$$

where $Q_m(\cdot, \cdot)$ is the generalized Marcum Q-function given as follows:

$$Q_m(a, b) = \int_b^\infty \frac{x^m}{a^{m-1}} e^{-\frac{x^2 + a^2}{2}} I_{m-1}(ax) dx. \quad (3.5)$$

In equation (3.5) a and b are non-negative real numbers, and m is a positive integer. Also, $I_{m-1}(\cdot)$ is the modified Bessel function of the first kind and of order $m - 1$.

Probability of missed detection is then defined as the probability that the PU is present, but SU fails to detect it, as given by

$$P_m = 1 - P_d = Pr\{Y < \lambda | H_1\} \quad (3.6)$$

False alarm is defined as the probability that SU detects primary signal while there is no PU present in the band. This happens when the threshold is low enough for noise to be mistaken as primary signal. In a non-fading environment, probability of false alarm is given as follows [10]:

$$P_f = Pr\{Y > \lambda|H_0\} = \Gamma(\lambda/2, m) \quad (3.7)$$

where $\Gamma(\cdot, \cdot)$ is the upper incomplete Gamma function given by

$$\Gamma(x, m) = \frac{\int_x^\infty e^{-t} t^{m-1} dt}{\Gamma(m)} \quad (3.8)$$

and $\Gamma(m)$ is the complete Gamma function as follows:

$$\Gamma(m) = \int_0^\infty e^{-t} t^{m-1} dt. \quad (3.9)$$

Our performance measures are the probabilities of false alarm and missed detection which have fundamental trade-off, which is controllable through threshold λ and sensing duration. If we are interested in reducing the probability of missed detection so as to minimize the interference introduced to the primary signal present in the band, we need to increase the sensitivity of the detector by lowering the threshold λ . On the other hand, in order to decrease probability of false alarm, which results in higher utilization, the threshold needs to be high enough for noise not to be mistaken by primary signal.

This problem is known as the sensing-throughput trade-off, which has been widely addressed in the literature. In [18] the problem of designing sensing duration is studied to maximize the achievable secondary network throughput, under the constraint that the primary user is sufficiently protected.

Now consider channel randomness and fading characteristics. In this case, h and consequently γ are randomly varying. Under this circumstances, since P_d is a function of SNR γ ,

it needs to be integrated over all possible values, as follows. However, P_f will not change.

$$P_d = \int Q_m(\sqrt{2x}, \sqrt{\lambda}) f_\gamma(x) dx \quad (3.10)$$

where $f_\gamma(x)$ is the probability density function of SNR under fading.

In the following we will study the performance of the system under multipath fading and shadowing channels.

3.3.1 Rayleigh Fading Channel

Consider a flat Rayleigh slow fading model, where the signal duration is relatively shorter than the coherence time. As discussed in the previous chapter, due to multipath effect in a wireless environment, channel gain h is normally distributed. Evidently, $|h|$ and $|h|^2$ can be shown to have Rayleigh and exponential distributions, respectively. A channel with these characteristics is known as Rayleigh fading channel. In this case, the received SNR, $\gamma = \frac{P|h|^2}{\sigma^2}$, is also exponentially distributed with mean $\bar{\gamma}$, where P is the primary transmit power, and σ^2 is the AWGN noise variance, and the probability density function of SNR is given as follows:

$$f_\gamma(x) = \frac{1}{\bar{\gamma}} e^{-x/\bar{\gamma}}. \quad (3.11)$$

Hence, we can derive the following relationship by substituting in equation (3.10) [10]:

$$P_d = e^{-\lambda/2} \sum_{k=0}^{m-2} \frac{1}{k!} \left(\frac{\lambda}{2}\right)^k + \left(\frac{1+\bar{\gamma}}{\bar{\gamma}}\right)^{m-1} \times \left(e^{-\lambda/2(1+\bar{\gamma})} - e^{-\lambda/2} \sum_{k=0}^{m-2} \frac{1}{k!} \left(\frac{\lambda\bar{\gamma}}{2(1+\bar{\gamma})}\right)^k \right). \quad (3.12)$$

Simulation result of local opportunistic spectrum access using energy detector with

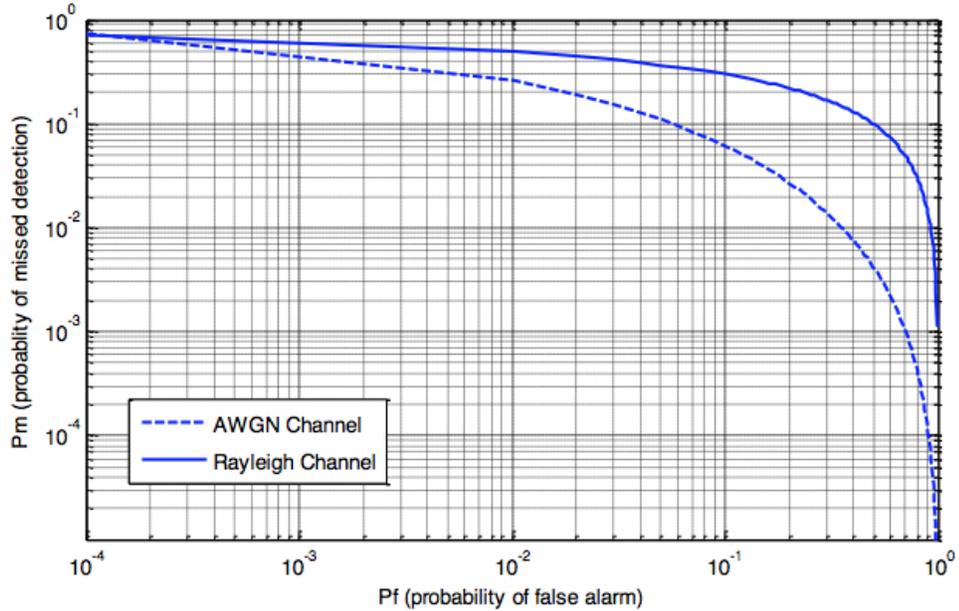


Figure 3.3: Complementary receiver operating characteristic (ROC) in Rayleigh fading ($\bar{\gamma} = 10dB$) and AWGN channels using energy detector with $m = TW = 5$ in local detection.

$m = TW = 5$ is depicted in figure 3.3, in AWGN as well as Rayleigh fading channels with average received SNR $\bar{\gamma} = 10dB$.

Clearly, Rayleigh fading degrades the performance of energy detector by introducing randomness, and gives rise to the probabilities of missed detection and false alarm. It can be observed in figure 3.3 that for a given P_m , i.e. a certain level of PU protection, P_f is increased, which means less spectral utilization compared to the AWGN channel. For instance, with $P_m = 0.01$, it requires P_f to go from 0.35 in AWGN to 0.9 in Rayleigh fading, which is a significant utility loss.

3.3.2 Log-Normal Shadowing Channel

The signal in wireless environment may also experience large scale shadowing, which in fact consists of distance dependent path-loss with random variations due to obstacles. Typically, log-normal shadowing model is used, where the received power and thus SNR in dB scale follow a normal distribution with average $\bar{\gamma}$ and variance σ_{dB}^2 . Therefore in linear scale, the

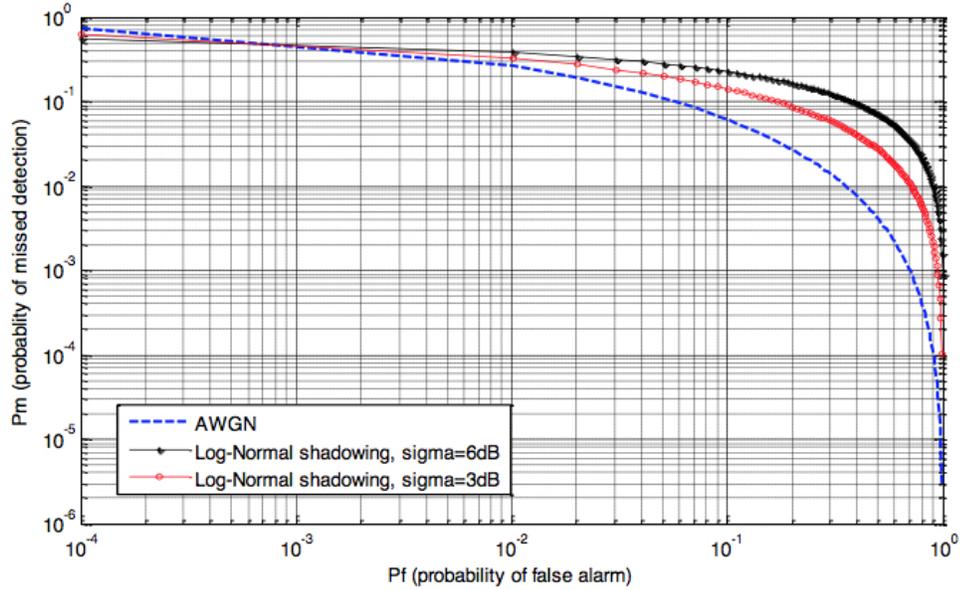


Figure 3.4: ROC in log-normal shadowing ($\bar{\gamma} = 10dB$) and AWGN channels using energy detector with $m = TW = 5$ in local detection.

distribution is called log-normal, with probability density function given as:

$$f_{\gamma}(x) = \frac{10/\ln 10}{x\sigma_{dB}\sqrt{2\pi}} e^{-\frac{(10 \log_{10} x - \bar{\gamma})^2}{2\sigma_{dB}^2}} \quad (3.13)$$

In this case, we cannot find a closed form solution for P_d and it may be evaluated numerically. Simulation result of local sensing using the same energy detector as discussed in previous section, is depicted in figure 3.4 in AWGN as well as log-normal shadowing channels with $\bar{\gamma} = 10dB$ and different values of dB-spread, σ_{dB} .

Figure 3.4 shows how shadowing degrades the performance of energy detector and gives rise to the probabilities of missed detection and false alarm compared to the AWGN channel. It may also be observed that in denser shadowing environments with higher dB-spread, it is even more difficult to sense the spectrum and the error increase.

3.4 Collaborative Spectrum Sensing

In order to combat the effect of multipath fading and shadowing, collaborative spectrum sensing is proposed where a group of secondary users share their sensing information to make a collaborative decision about the presence of primary signal. Suppose there are n secondary nodes cooperating in the cognitive network for detection, and further assume all nodes use energy detectors and experience independent identically distributed fading. According to likelihood ratio test (LRT), it is optimum for each node to individually sense the spectrum using a specific energy detector with corresponding threshold λ_k for $k = 1, 2, \dots, n$, which are not necessarily equal [10]. However, for simplicity we assume common detector structure with threshold λ .

There exist several studies in the literature to optimize collaborative spectrum sensing in different criteria. Distributive collaboration is carried out using a fusion rule known as OR-rule, or 1-out-of- n rule, such that each user receives $n - 1$ hard decisions from all other users, i.e. one bit indicating either H_0 or H_1 . Each user then updates its decision in this way that it decides H_1 if at least one out of the total n nodes reports H_1 [10]. Here, in the symmetric case, probabilities of detection and false alarm for the collaborative network denoted by Q_d and Q_f respectively, are defined as follows:

$$Q_d = 1 - (1 - P_d)^n \quad (3.14)$$

$$Q_f = 1 - (1 - P_f)^n \quad (3.15)$$

where P_d and P_f are the local probabilities of detection and false alarm for each of the secondary nodes. Equations (3.14) and (3.15) show that collaboration increases probabilities of detection and false alarm with number of cooperating users n . However, we will show that the overall performance will be improved.

Figures 3.5 and 3.6 illustrate the effect of collaboration on spectrum sensing under Rayleigh fading and log-normal shadowing respectively. The ROC curves for different numbers of collaborative users, n , is depicted as well as AWGN local case for comparison.

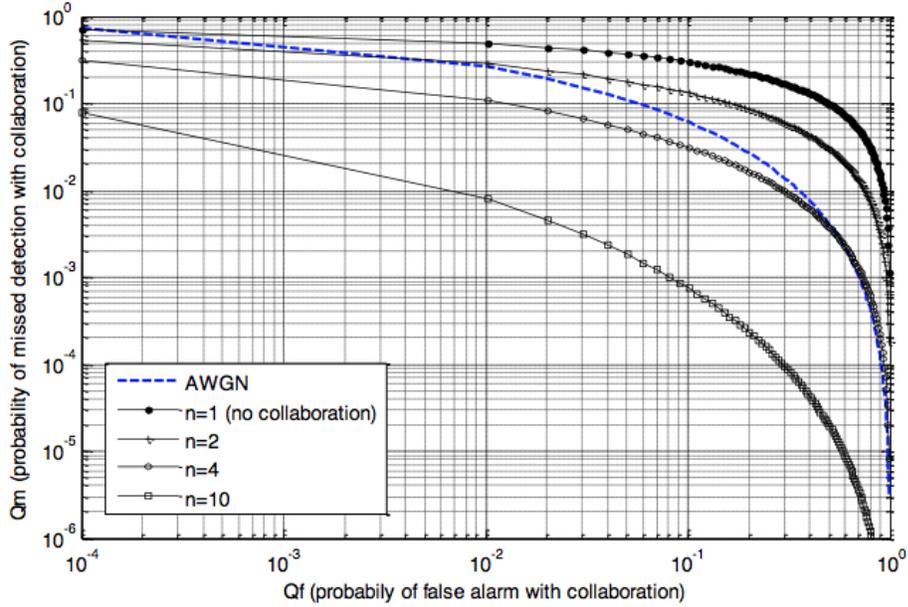


Figure 3.5: ROC in Rayleigh fading ($\bar{\gamma} = 10dB$) and AWGN channels using energy detector with $m = TW = 5$ in collaborative detection with different number of users n .

Assume average SNR of $\bar{\gamma} = 10dB$ and $m = 5$, and dB-spread of $\sigma_{dB} = 6dB$ for the log-normal case.

Case $n = 1$ is equivalent to local sensing without collaboration, which is illustrated to perform the worst. However, as expected, increasing n results in improved sensing. For large enough n , we can even outperform the AWGN channel. This is due to the fact that for n large enough, there would be higher chance to have at least one user with a good channel better than average non-fading AWGN. This way, we have been able to cancel the undesired effect of fading and shadowing on spectrum sensing by collaboration, and the cost is the signaling overhead as well as delay introduced for collaboration.

3.5 Conclusion

In fading environments, a secondary user may not be able to distinguish between an idle band and a deep fade. However, since other users in the network may have better channels,

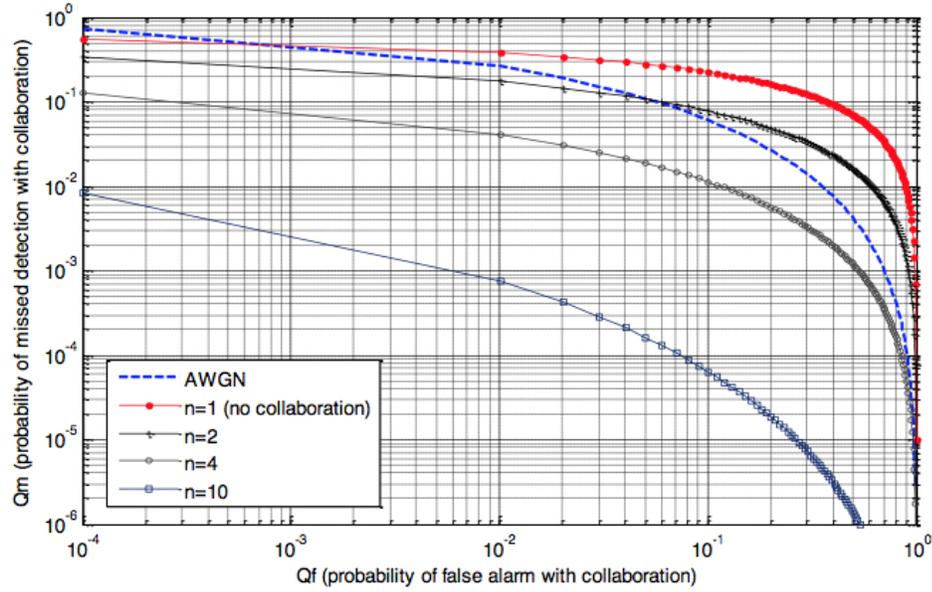


Figure 3.6: ROC in log-normal shadowing ($\bar{\gamma} = 10dB$, $\sigma_{dB} = 6dB$) and AWGN channels using energy detector with $m = TW = 5$ in collaborative detection with different number of users n .

collaboration is proposed to improve the overall sensing performance of the network.

In this chapter, we studied the effect of Rayleigh fading and log-normal shadowing on spectrum sensing using energy detectors, and showed how collaboration can improve the performance. Our simulation results demonstrate that sensing results enhance significantly as the number of collaborative users increases, such that with large enough number of collaborative users, it is even possible to outperform the AWGN channel.

Chapter 4: Spectrum Access Strategies

4.1 Introduction

In spectrum overlay systems, or namely, opportunistic spectrum access (OSA) model, secondary users (SUs) are allowed to dynamically share the spectrum in a hierarchical way with primary users (PUs, or licensees), who are recognized for under-utilizing the scarce resource of wireless spectrum [3]. For this purpose, cognitive radios (CRs) that are *context-aware* intelligent devices capable of learning and adapting to their wireless environment, are employed as low-priority secondary users. Specifically, SUs monitor the activity of PUs by sensing the spectrum bands to identify and further utilize transmission opportunities, also known as white spaces, whenever the PUs are idle.

Definite functionalities are defined for CRs for the realization of spectrum overlay: *spectrum sensing*, *spectrum decision*, *spectrum sharing*, and *spectrum mobility* [6]. In this chapter, we mainly focus on spectrum decision as well as sharing tasks in an ad hoc cognitive radio network. Due to the overhead introduced by centralized coordination, distributed channel allocation and sharing is typically preferred [12]. We consider single-hop communication within secondary nodes or with their base station without any central coordinator or dedicated control channel.

Cognitive radio tasks are not fully detached, and efficient opportunistic access requires intensive interaction across physical and medium access control (MAC) layers. Essentially, based on the results of detection module (typically energy detector) from physical layer, SUs should decide which channels to attempt sensing in future to maximize their spectral utilization. This is a medium access problem for scheduling sensing order, also known as channel selection or access strategy. Especially in our case of study, where secondary nodes

distributively require opportunistic access to the spectrum, a securing MAC policy that avoids collision among secondary and primary transmissions is vital.

It is of essence for the SUs not to interfere with the high-priority time-variant primary traffic. Moreover, it is practically impossible for SUs to keep track of all available bands contiguously, because of the hardware constraints. The fact that SUs are not aware of primary activities in all channels, makes the medium access problem more challenging. In this uncertain environment, the only solution for the cognitive users, as the definition implies, is to learn the traffic information online. Particularly, SUs need to take into account the activity statistics of PUs at the same time as sensing the spectrum, to improve their decisions towards efficient channel selection which will result in higher utilization.

In this chapter, we will first discuss our system model. Next, we will study the access strategies and propose our algorithm for single and multiple user scenarios. And finally, we will conclude this chapter by examining our simulation results. The results of this chapter are presented in [27] as well.

4.2 System Model

Consider a decentralized ad hoc network with K cognitive secondary users, exploring the licensed spectrum for transmission opportunities for single-hop communication, whenever no primary activity is detected. We assume the available spectrum consists of N orthogonal frequency channels with equal bandwidth B , such that cross-channel interference is negligible. We also consider a time-slotted system to make synchronization among all nodes feasible. The system model is depicted in figure 4.1. LTE resource blocks as shown in figure 1.2 offer a fit model for this purpose both in frequency and time domains criteria. In addition, OFDM modulation employed in LTE is an appropriate candidate for OSA, because of carrier aggregation feature which provides SUs with possibility to transmit over non-contiguous bands [2].

Further, we consider an observation block of T time slots, over which primary activity statistics in all channels are invariant. Depending on the application, short or long block

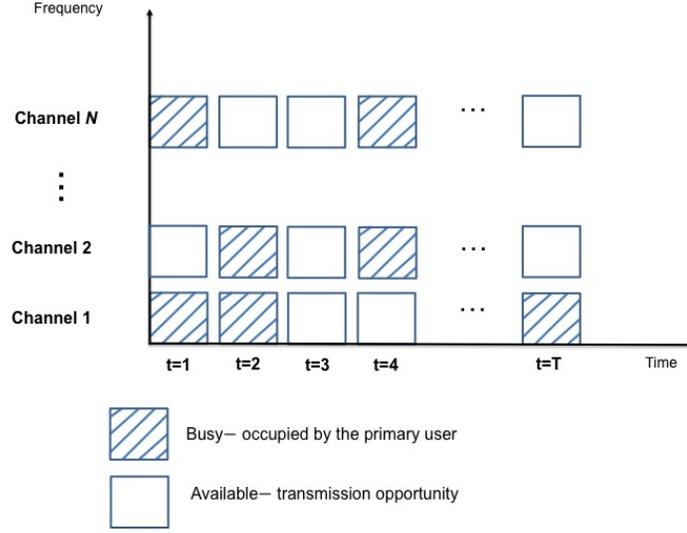


Figure 4.1: Channel availability model.

varying traffic assumption is sufficiently suitable. Information about the value of T is easily available to SUs by observing the PU activity.

Let $i \in \{1, 2, \dots, N\}$ and $j \in \{1, 2, \dots, T\}$ represent channel and time indices respectively. We define $\psi_i(j)$ to indicate state of channel i at time slot j as follows:

$$\psi_i(j) = \begin{cases} 1 & \text{idle channel} \\ 0 & \text{busy channel} \end{cases} \quad (4.1)$$

In fact, channel i at each time slot is either idle, with probability θ_i , which is constant over observation block of T time slots, or busy with probability $1 - \theta_i$. This information is the sensing results, provided by the detection module from physical layer. Note that different criteria such as channel gain and capacity, sensing errors, etc. might also be considered when making this hard decision to report to the scheduling module. For now we assume the sensing results to be error-free. Effect of false alarm and missed detection errors will be discussed later.

Assuming independent state transitions, $\psi_i(1), \psi_i(2), \dots, \psi_i(T)$ will become independent identically distributed Bernoulli random variables with parameter θ_i . The problem may also be generalized to Markovian process [20],[11]. Since $\boldsymbol{\theta} = \{\theta_1, \dots, \theta_N\}$ are consistent during T , availability percentage of channel i given θ_i during the block of observation, ϕ_i , would be distributed as follows:

$$\phi_i \sim \text{Binomial}(T, \theta_i). \quad (4.2)$$

As for the cognitive users, they tend to explore the channels to identify and further exploit idle bands, so as to maximize their utilization. Trivially, SUs would rather reach out for channels with higher probability of being free, because they are more likely idle, which would lead to further transmission opportunities and spectral usage. However, the problem arises when SUs are unaware of the PU's traffic statistics, specifically, availability probabilities, and need to estimate those values $\hat{\boldsymbol{\theta}} = \{\hat{\theta}_1, \dots, \hat{\theta}_N\}$ at the same time as sensing.

On the other hand, we consider SUs being capable of sensing/accessing a single channel at a time slot. Sensing/accessing multiple channels simultaneously requires multiple antennas which will introduce severe interference and complexity on SU part. In this situation, it is essential for SUs to select the best possible channel for sensing and further accessing to boost their throughput. However, they also have to consider learning purpose in the scheduling process, in order to recognize potential opportunities in any of the frequency bands. A trade-off arises here between exploration and exploitation in channel selection process [23]. Should SU choose the channel that believes, according to current information, is more likely available, or should it go for the one with few observations, to improve its estimations? Moreover, how should collision be avoided when multiple SUs select the same channel? These are the questions we will be addressing in next section.

4.3 Access Strategies

A low-complexity solution is desired for the above distributed access problem with unknown parameters to guarantee maximum possible network throughput. Optimal solution can be derived for the cognitive medium access problem using a Bayesian framework [23], however it suffers from computational complexity that grows exponentially with T . Here, we will develop low-complexity sub-optimum strategies for distributed access. First, we consider a single cognitive user case and establish a solution to strike a balance between exploration and exploitation, then, recognizing a cognitive ad hoc network of multiple users, we will take into account the multiple access and competition problem as well.

4.3.1 Single-User Scenario

Consider a single secondary user looking for opportunistic access among N frequency channels, each with bandwidth B and unknown availability probability of θ_i , $i = 1, 2, \dots, N$. The goal for SU is to maximize its average throughput, which is defined as the expected number of transmitted packets over an observation block of T . Given that SU selects channel $\sigma_j \in \{1, 2, \dots, N\}$ at time slot j , and that channel σ_j is free, maximum of B packets can be transmitted in that time slot. Let $\delta_i(j)$ be the probability that SU selects channel i at time slot j . Using equation (4.1), we can express the throughput for SU as follows:

$$\begin{aligned}
W &= \mathbb{E} \left\{ \sum_{j=1}^T B \sum_{\sigma_j=1}^N \psi_{\sigma_j}(j) \right\} \\
&= \sum_{j=1}^T B \sum_{\sigma_j=1}^N \mathbb{E} \{ \psi_{\sigma_j}(j) \} \\
&= B \sum_{j=1}^T \sum_{\sigma_j=1}^N Pr \{ \psi_{\sigma_j} = 1 \} \\
&= B \sum_{j=1}^T \sum_{\sigma_j=1}^N \theta_{\sigma_j} \\
&= B \sum_{j=1}^T \sum_{i=1}^N \theta_i \delta_i(j).
\end{aligned} \tag{4.3}$$

From equation (4.3) it is perceived that maximum throughput is achievable if SU selects the channel with highest availability probability θ_{\max} at each time slot. This is also intuitively valid that SU selects the most likely available channel (best channel) which is more probably idle. This method is known as *myopic strategy*. In case of known θ that SU recognizes the best channel, maximum possible throughput is achieved, which is equal to:

$$\begin{aligned}
W_{\max} &= \sum_{j=1}^T B \theta_{\max} \\
&= TB \theta_{\max}.
\end{aligned} \tag{4.4}$$

However, in case of unknown θ , there is no guarantee for the myopic strategy to converge to the optimal solution. In this case, SU has no means but to make decision based on its estimations, i.e. $\hat{\theta}$. As discussed previously, here SU faces a challenge known as

Table 4.1: The proposed Modified-Myopic channel selection strategy

1. Initializing to meet the consistency requirement:
Spend the first $N\lceil \ln T \rceil$ time slots on sensing all channels uniformly, i.e. $\lceil \ln T \rceil$ times on each channel, where $\lceil \cdot \rceil$ denotes the ceiling integer. Form vectors \mathbf{X}_i , \mathbf{Y}_i , and $\hat{\boldsymbol{\theta}}_i$ for $i = 1, 2, \dots, N$ where
$\hat{\theta}_i(j) = X_i(j)/Y_i(j). \quad (4.6)$
2. Channel selection:
At time slot j for $j = N\lceil \ln T \rceil + 1, \dots, T$ select channel i to sense, where
$i = \operatorname{argmax}_i \hat{\theta}_i(j). \quad (4.7)$
3. Updating:
After sensing channel i , update the values of $X_i(j)$, $Y_i(j)$, as well as $\hat{\theta}_i(j)$ according to (4.6).

exploration/exploration trade-off; whether to choose the channel which believes is best by far, or the ones with few observations and potential opportunities? Modeling this problem as a multi-armed bandit, the answer is found as follows: a strategy is consistent— meaning that it can strike a balance in the exploration/exploitation problem; if its throughput loss compared to the optimal situation grows at least logarithmically in the number of trials [24]. For strategy Γ , throughput loss using equations (4.3) and (4.4) is given as follows:

$$\begin{aligned}
 L(\boldsymbol{\theta}, \Gamma) &= W_{\max} - W \\
 &= TB\theta_{\max} - B \sum_{j=1}^T \sum_{i=1}^N \theta_i \delta_i(j).
 \end{aligned} \tag{4.5}$$

In order for strategy Γ to be consistent, it is required that $L(\boldsymbol{\theta}, \Gamma) \sim O(\ln T)$. This condition may be interpreted that SU needs to take at least $O(\ln T)$ samples from each channel to guarantee the probability estimates will converge to the actual availability probabilities,

Table 4.2: The order optimal strategy proposed in Rule 1 [23]

<p>1. Initializing: At the beginning of each block, sense each channel once.</p>
<p>2. After the initialization period, the cognitive user obtains an estimate $\hat{\boldsymbol{\theta}}$ at the beginning of time slot j, given by $\hat{\theta}_i(j) = X_i(j)/Y_i(j)$, and assign an index</p> $\Lambda_i(j) = \hat{\theta}_i(j) + \sqrt{2\ln j/Y_i(j)} \quad (4.8)$ <p>to the ith channel. The cognitive user chooses the channel with the largest value of $\Lambda_i(j)$ to sense at time slot j. After each sensing, the cognitive user updates \mathbf{X} and \mathbf{Y}.</p>

and thus, best decisions in channel selection can be made. Therefore, the myopic strategy is not consistent.

Based on this conclusion, we propose modified-myopic channel selection scheme. Let $\mathbf{Y}_i = \{Y_i(1), \dots, Y_i(T)\}$ and $\mathbf{X}_i = \{X_i(1), \dots, X_i(T)\}$ be two vectors representing the number of times that SU has sampled channel i and the number of times channel i is sensed to be free up to time slot j , respectively. The strategy works as given in Table 4.1. Order-optimal single-index strategy given as Rule 1 in [23] is also given in Table 4.2.

4.3.2 Multi-User Scenario

In this section, we assume the presence of K cognitive users in the secondary network, distributively searching the spectrum consisted of N frequency channels for transmission opportunities, when there is no coordination or prior information about channel availabilities. In addition to exploration/exploitation challenge, the medium access problem in this scenario faces another challenge: competition. Specifically, all SUs in the network should explore the channels and estimate their availabilities to make optimal decision in channel selection, and also deal with the multiple user competition. As a matter of fact, in order for the secondary user to access the spectrum, not only no primary activity should be detected,

but also it needs to be free of secondary activity from competing cognitive users as well, otherwise collision occurs.

In this scenario, it is not optimal anymore, neither from a network point of view, nor from each SU's perspective, to access the most likely available (best) channel. The reason is access would become too competitive that probability of collision increases, while potential opportunities in other spectrum bands are being wasted.

A decentralized strategy is required for scheduling spectrum sensing/access for all secondary users in the network, such as to maximize total network utilization while splitting the opportunities fairly among all secondary users. In fact, the strategy should guaranty an equilibrium state with maximal reward for users, such that deviation from the strategy would result in throughput loss, and thus all individual users would follow the rule.

In case multiple SUs select the same channel, we employ a generalized Carrier Sense Multiple Access-Collision Avoidance (CSMA-CA) protocol similar to what is used in IEEE 802.11 standard, as follows.

Consider $K_i(j) \in \{1, 2, \dots, K\}$ SUs deciding to access channel i at time slot j . They sense this channel individually, and if it is sensed to be busy with primary activity, they lean back and wait until next time slot to start channel selection and sensing over again. Otherwise, if no primary activity is detected, each of $k \in K_i(j)$ users waits a random time according to exponential back-off mechanism, and senses the channel again. As a result, the secondary user whose back-off time happens to be the minimum will win the competition and gains access to the channel to transmit in the remainder of the time slot.

Priorities and other factors may be considered in generating back-off time as well, however, for a symmetric fair decentralized access, exponential distribution with common parameter is of interest. Let $T_{k_i(j)}$ be the random waiting time generated for user k who decides to sense/access channel i at time slot j . Assume the distribution is exponential with parameter λ_k

$$T_{k_i(j)} \sim Exponential(\lambda_k) \tag{4.9}$$

truncated to the time slot duration, for all $k \in K_i(j)$. Here we consider symmetric case $\lambda_1 = \dots = \lambda_K = \lambda$ for fairness. We may want to optimize the value of λ , however, that topic is out of the focus of this paper.

We can show that user k with back-off time $T_{k_i(j)}$ wins the competition over channel i , given it is idle, at time slot j with probability

$$\lambda_k / \sum_{l=1}^{K_i(j)} \lambda_l = 1/K_i(j), \quad (4.10)$$

which implies equal chance to access an idle band.

Assume user k selects channel i at each time slot with probability $p_{k,i}$. An optimal symmetric solution as well as asymptotically optimal low-complexity medium access strategy is given in [23]. At this moment, consider the case with known θ for simplicity. The problem can be modeled as a non-cooperative game where SUs are the players who want to maximize their reward (expected throughput). The asymptotic solution is then achieved for the Nash equilibrium for $K \rightarrow \infty$ if

$$\begin{aligned} p_{k,i} &= \theta_i / \sum_{l=1}^N \theta_l \\ &= p_i \end{aligned} \quad (4.11)$$

for $k = 1, 2, \dots, K$, that is the normalized availability of channel i . This implies that on average, $p_i K$ users select channel i at each time slot. In this situation, each user has probability τ_k to transmit at each time slot, where

$$\begin{aligned}
\tau_k &= \sum_{i=1}^N p_i \theta_i \frac{1}{p_i K} \\
&= \sum_{i=1}^N \theta_i / K
\end{aligned} \tag{4.12}$$

which indicates fair division of opportunities among all SUs. We can show that if any SU deviates from this rule, it will have a less chance for transmission [23]. Assume user k deviates from the strategy and chooses a channel differently, e.g. channel i' . Therefore, the number of users sensing channel i' will be equal to $p_{i'}K + 1$, and the probability that user k gains the access to the channel is reduced as follows:

$$\tau'_k = \frac{\theta_{i'}}{p_{i'}K + 1} < \frac{\theta_{i'}}{p_{i'}K} = \tau_k. \tag{4.13}$$

Therefore, following this strategy, secondary users have no motivation to diverge from the rule, and thus, fair and systematic performance is guaranteed.

Under this circumstances, total network throughput can be found using equations (4.3) and (4.12) as follows:

$$\begin{aligned}
W_{\text{Net}} &= \sum_{k=1}^K \sum_{j=1}^T B \sum_{i=1}^N \tau_{k,i}(j) \\
&= TB \sum_{k=1}^K \frac{\sum_{i=1}^N \theta_i}{K} \\
&= TB \sum_{i=1}^N \theta_i.
\end{aligned} \tag{4.14}$$

Now consider the case of unknown θ . Adopting the above results to govern the competition, and the modified-myopic scheme to take care of the exploration/exploitation problem

Table 4.3: The proposed medium access strategy

<p>1. Initializing to meet the consistency requirement:</p> <p>All users spend the first $N\lceil \ln T \rceil$ time slots on sensing all channels uniformly, i.e. $\lceil \ln T \rceil$ times on each channel. User k then forms vectors $\mathbf{X}_{k,i}$, $\mathbf{Y}_{k,i}$, and $\hat{\boldsymbol{\theta}}_{k,i}$ for $k = 1, 2, \dots, K$ and $i = 1, 2, \dots, N$ where</p> $\hat{\theta}_{k,i}(j) = X_{k,i}(j)/Y_{k,i}(j). \quad (4.15)$
<p>2. Channel selection:</p> <p>At time slot j for $j = N\lceil \ln T \rceil + 1, \dots, T$, user k selects channel i to sense with probability</p> $p_{k,i}(j) = \hat{\theta}_{k,i}(j) / \sum_{i=1}^N \hat{\theta}_{k,i}(j). \quad (4.16)$
<p>3. Updating:</p> <p>After sensing, user k updates the values of $X_{k,i}(j)$, $Y_{k,i}(j)$, as well as $\hat{\theta}_{k,i}(j)$ according to (4.15).</p>

simultaneously, we propose our low-complexity, consistent, and fair access strategy, which maximizes the total network throughput as given in Table 4.3. Table 4.4 also summarizes the algorithm of Rule 3 given in [23].

4.4 Effect of Sensing Error

Even though sensing errors, happening due to fading environments as discussed in chapter two, affect the performance of cognitive radio significantly, however, they do not change the medium access policy. We only need to briefly modify the availability estimations considering the sensing errors.

Let η denote the tolerable missed detection error for the primary, i.e. the probability that PU is present in the band but SU fails to detect it. Also, let μ be the probability that channel is sensed to be occupied, while it is actually idle, or namely, false alarm probability. Considering these two sensing errors, the probability that channel i is sensed to be free

Table 4.4: The low-complexity asymptotically optimal strategy given in Rule 3 [23]

<p>1. Initializing: Each user k maintains the following two vectors: \mathbf{X}_k, which records the number of time slots in which user k has sensed each channel to be free; and \mathbf{Y}_k, which records the number of time slots in which user k has sensed each channel. At the beginning of each block, user k senses each channel once, and transmits through this channel if the channel is free and it wins the competition. Also, set $X_{k,i} = 1$, regardless of the sensing result of this stage.</p>
<p>2. at the beginning of time slot j, user k estimates $\hat{\theta}_i$ as</p> $\hat{\theta}_i(j) = X_{k,i}(j)/Y_{k,i}(j) \quad (4.17)$ <p>and chooses each channel $i = \{1, \dots, N\}$ with probability</p> $\hat{\theta}_i(j) / \sum_{i=1}^N \hat{\theta}_i(j). \quad (4.18)$ <p>After each sensing, \mathbf{X}_k and \mathbf{Y}_k are updated.</p>

is equal to $(1 - \mu)\theta_i + \eta(1 - \theta_i)$. Thus, the availability of channel i can be modeled as a binomial random variable with parameter $(1 - \mu)\theta_i + \eta(1 - \theta_i)$, which actually is the value that the ratio X_i/Y_i converges to. Therefore, equations (4.6) and (4.15) in Table 4.1 and Table 4.3 should be replaced with equation (4.19) as follows, but the rest of the algorithms holds the same [23].

$$\hat{\theta}_i(j) = \frac{X_i(j)/Y_i(j) - \eta}{1 - \eta - \mu} \quad (4.19)$$

4.5 Performance Analysis and Simulation Results

For simulation purposes, we assume $N = 20$ frequency channels with normalized bandwidth, such that $B = 1$ packet can be transmitted per time slot, over an observation block of $T = 10000$ time slots. We further consider a moderately congested primary network, with average

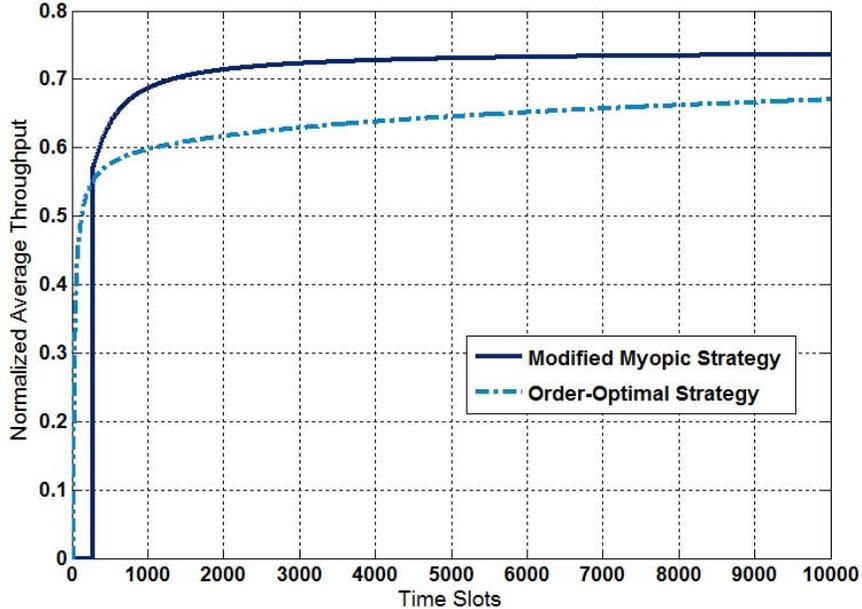


Figure 4.2: Performance comparison of the proposed modified-myopic scheme vs. order-optimal strategy.

of 60% availability, to generate random θ for all channels, i.e. $\bar{\theta} = 0.6$. In our simulations, the highest availability probability turns out to be $\theta_{\max} = 0.76$, and $\sum_{i=1}^N \theta_i = 11.42$. Note that the performance is evaluated assuming sensing results reported from detection module to be error-free, however effect of sensing errors is also depicted for the single user scenario in figure 4.3

4.5.1 Single-User Analysis

In the single-user scenario where SU identifies the best channel shortly after the initialization period, considering the Binomial distribution of channel availability percentage given in equation (4.2), and the fact that T is large enough, we can approximate the highest expected throughput by $T\theta_{\max}$ based on central limit theorem (which is compatible with equation (4.4) as well). Consequently, the highest achievable time-normalized expected throughput would converge to $\theta_{\max} = 0.76$.

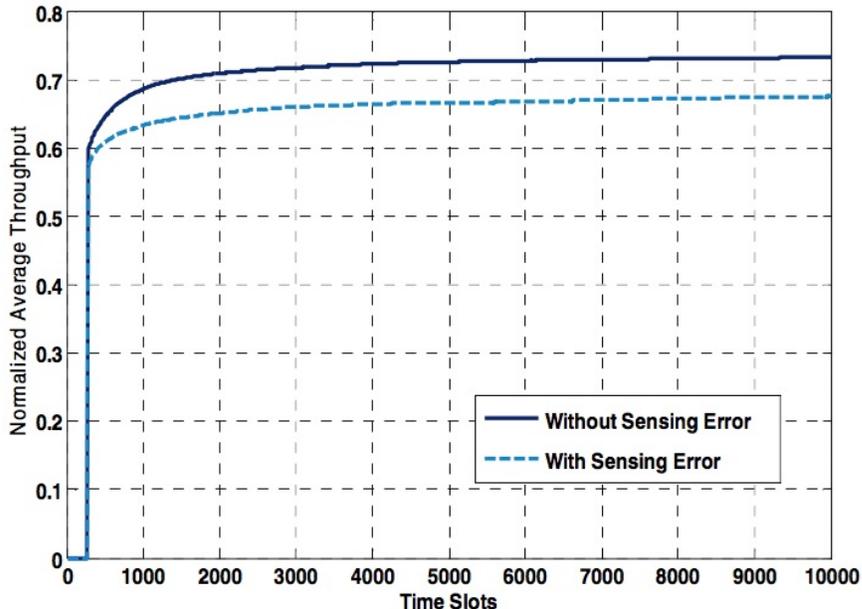


Figure 4.3: Performance comparison of proposed modified-myopic scheme under perfect and imperfect sensing, with probabilities of missed detection and false alarm equal to 0.01 and 0.05, respectively.

Figure 4.2 shows the performance of modified-myopic strategy compared to the order-optimal strategy of Rule 1 proposed in [23]. We can observe that our proposed modified-myopic strategy outperforms the order-optimal strategy and saturates at the maximum possible gain shortly after initialization period, whereas the order-optimal strategy does not even reach 90% of the maximum gain. This is a significant achievement especially in applications with fast variations of primary activity that T cannot be considered as large. The reason is mainly that we do not waste time slots on exploring channels which we may not be interested in, and that by taking appropriately sufficient samples, we obtain fairly accurate estimates of channel availabilities shortly after the initialization period.

Figure 4.3 demonstrates how sensing errors introduced by fading environment degrade the performance of secondary as compared to perfect sensing results. In the given situation, with missed detection probability of $\eta = 0.01$ and false alarm probability of $\mu = 0.05$, the

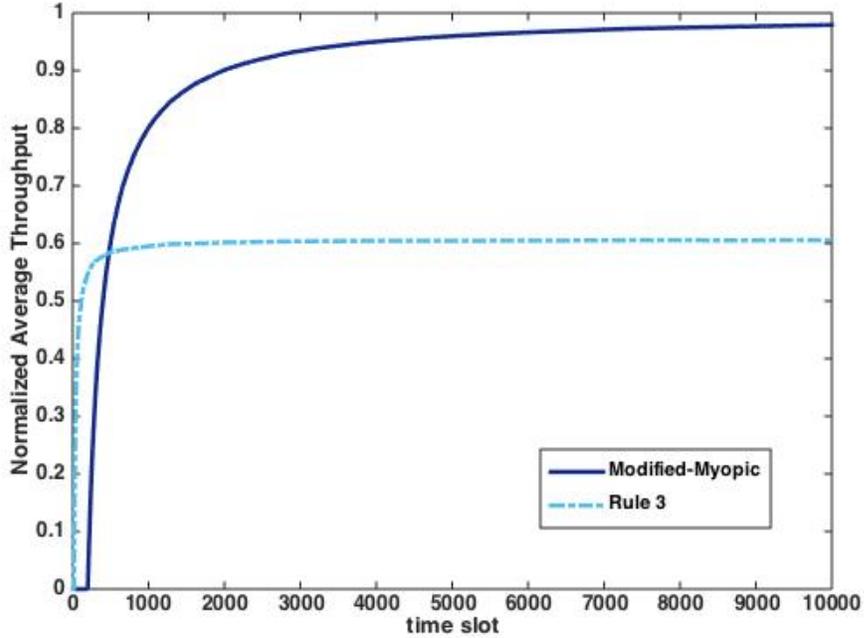


Figure 4.4: Performance comparison of the proposed multiple access strategy vs. Rule 3 from network perspective for $K = 200$ SUs.

degradation is not significantly destructive though, only 6.8%.

4.5.2 Multi-User Analysis

For the multi-user scenario, we first consider a dense network with $K \gg N$, next, we simulate a sparse network where $K \leq N$.

Dense Network

In a dense cognitive radio network, since K is large enough, based on asymptotic result of equation (4.14), we expect the highest time-normalized expected throughput of the network to converge to $W_{\text{Net,max}} = \sum_{i=1}^N \theta_i = 11.42$.

Performance of a dense network with $K = 200$ secondary users and $N = 20$ channels with the same θ as generated before, is depicted in figure 4.4 to compare our proposed access

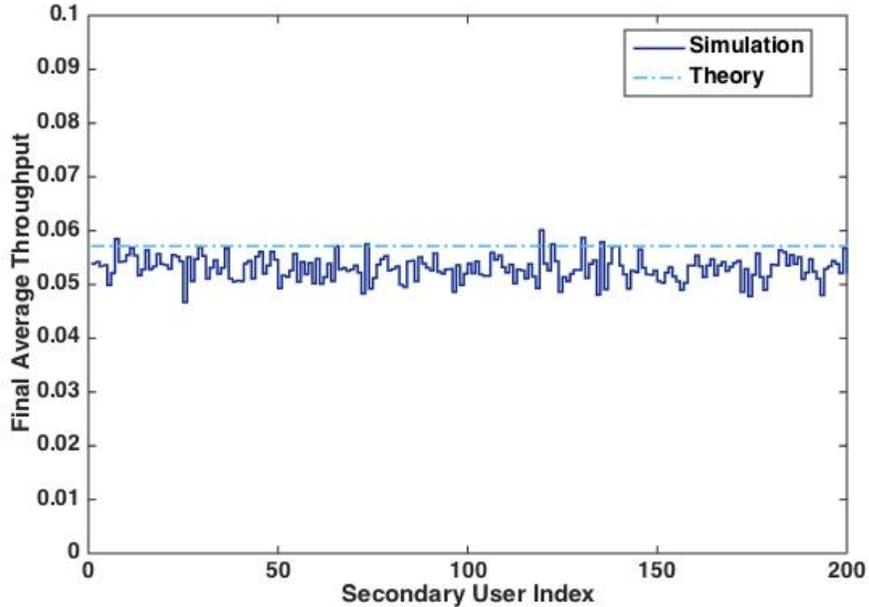


Figure 4.5: Secondary users' utilization for $K = 200$.

strategy to the Rule 3 algorithm given in [23]. Time-normalized expected throughput of the network is normalized with respect to the maximum value $W_{\text{Net,max}} = 11.42$ for better demonstration. The efficiency of our proposed approach is inevitable, which converges to the maximum possible gain.

Figure 4.5 shows the final expected throughput of each of $K = 200$ secondary users in the network. Since K is large and the algorithm is symmetric, the theoretical expected throughput of each user is $W_{\text{Net,max}}/K = 0.057$. We can see that there is almost no noticeable variations in the gain distribution among users. Additionally, our algorithm performance is significantly close to theory, with mean 0.053 and standard deviation 0.0022.

It is important to note that in dense networks, the utilization from a network point of view is maximal, cost for which is the overhead of CSMA-CA method. However, from secondary user's point of view, small throughput is achievable due to intense competition.

Sparse Network

In sparse situation, since K is not large enough, we cannot expect the asymptotic algorithm to work effectively. In fact, since there are few cognitive users in the network compared to the number of channels, and since each user is capable of accessing a single channel at a time, not all the opportunities in the entire spectrum are discovered and utilized. In other words, there are more supplies than demands, as opposed to the dense network situation. This is why network utilization is not as high in sparse networks. Yet, system overhead is lower, also each secondary user gains higher throughput compared to dense situation.

Noting that an opportunity in channel i is exploited if at least one user selects that channel; the total expected throughput of the sparse network may be formulated as follows:

$$\begin{aligned}
 W_{\text{Net,s}} &= \sum_{j=1}^T B \sum_{i=1}^N \theta_i \Pr\{K_i(j) > 0\} \\
 &= \sum_{j=1}^T B \sum_{i=1}^N \theta_i (1 - (1 - p_i)^K) \\
 &= TB \sum_{i=1}^N \theta_i \left(1 - \left(1 - \frac{\theta_i}{\sum_{l=1}^N \theta_l} \right)^K \right).
 \end{aligned} \tag{4.20}$$

For simulation purpose, we consider $K = 8$ users and $N = 20$ frequency channels with the same θ as before. From equation (4.20), theoretical expected throughput of the network will be equal to $W_{\text{Net,s}} = 3.93$. Figure 4.6 demonstrates expected throughput of the network normalized to the maximum ($W_{\text{Net,max}} = 11.42$) for our proposed algorithm compared to the Rule 3 in a sparse network. In figure 4.7, final expected throughput of each user is depicted for both strategies. Each user's throughput theoretically is equal to $W_{\text{Net,s}}/K = 0.49$. Using proposed modified-myopic scheme, average user's throughput is equal to 0.39 with standard deviation 0.0015. As we expected, each SU gains considerably higher throughput compared to the dense network situation.

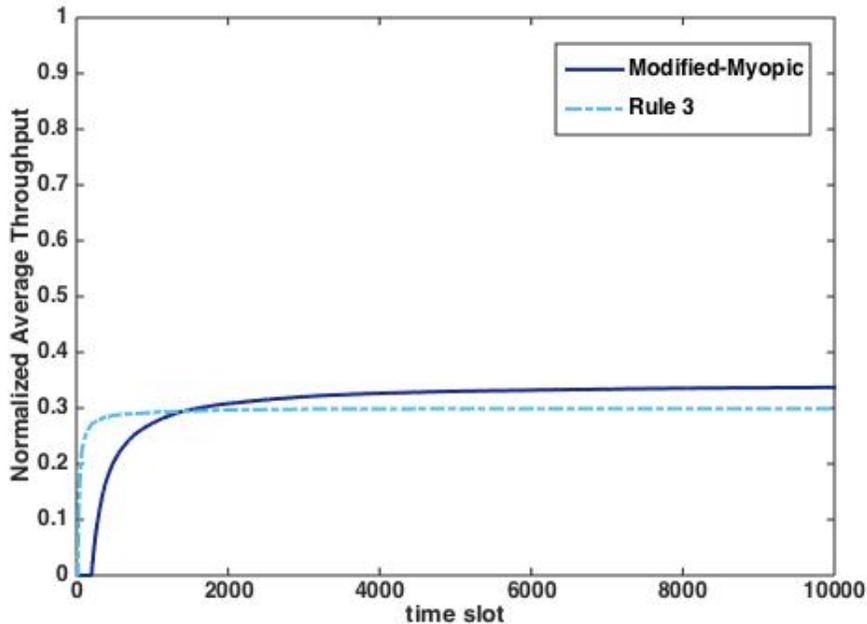


Figure 4.6: Performance comparison of the proposed multiple access strategy vs. Rule 3 from network perspective for $K = 8$ SUs.

4.6 Conclusion

Channel selection problem for opportunistic spectrum access in decentralized cognitive radio networks was studied in this chapter. First, we considered a single-user scenario. Recognizing the exploration/exploitation challenge in scheduling spectrum sensing without prior information about primary activity and channel availabilities, we designed a low-complexity sub-optimal access algorithm, referred to as modified-myopic strategy to maximize spectral utilization while confining interference introduced to the primary network. Next, for a multi-user scenario, we took into account the competition that arises in the multiple access problem as well. Combining our modified-myopic strategy with generalized CSMA-CA protocol, we proposed a fair distributed access algorithm to maximize network utilization. Analysis as well as simulation results were provided to prove the efficiency of our work, compared to the existing solutions in the literature.

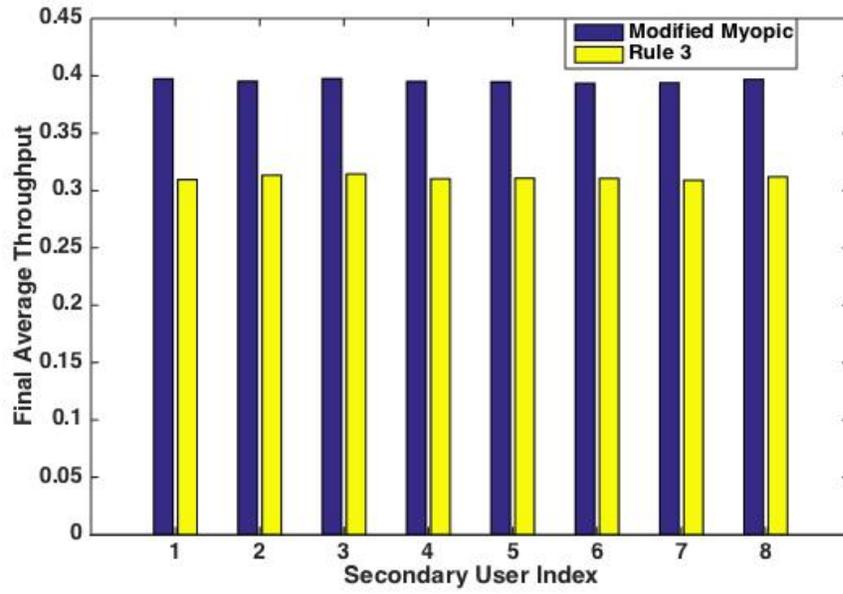


Figure 4.7: Secondary users' utilization for $K = 8$.

Chapter 5: Summary, Contributions, and Future Work

5.1 Summary and Contributions

This thesis addressed the problem of spectrum sensing and medium access in cognitive radio networks. First, we introduced the concept of opportunistic spectrum access and cognitive radio networks, and gave an extensive overview on the wireless propagation environment. With the background given in chapters one and two, the physical-layer spectrum sensing and issues with energy detection were studied in chapter three, where sensing-throughput trade-off was discussed. Collaborative spectrum sensing was also studied as the solution to overcome undesired fading effect. Next, MAC-layer sensing was discussed in chapter four. A sub-optimal channel selection referred to as modified-myopic scheme was first proposed based on the multi-armed bandit problem for a single-user scenario without prior information about PU activity. Next, we modeled the multiple access problem as a non-cooperative game where secondary users were players who intended to maximize their expected reward (throughput). Based on the resulting Nash equilibrium, and the modified-myopic strategy given above, a low-complexity asymptotically optimal distributed access strategy was proposed for a decentralized cognitive radio network using Carrier Sense Multiple Access-Collision Avoidance (CSMA-CA) technique.

Analyses and simulation results using MATLAB were provided to demonstrate the efficiency of our proposed algorithms. The modified-myopic scheme was shown to perform optimally and conclude in a timely manner, which is a significant privilege in applications such as LTE mobile, where the time-invariant period of the primary cannot be considered lengthy. In fact, the modified-myopic scheme was able to achieve the maximum highest expected throughput approximately in 10% of the observation block, whereas the order-optimal strategy could not even reach 90% of the maximum throughput in the whole block

of observation. Thereafter, our proposed multiple access strategy in the multi-user case was shown to perform asymptotically optimal, especially in a dense network situation that we were able to achieve maximum possible expected throughput, which was fairly distributed among all users. Although, due to the CSMA-CA protocol overhead and back-off time delay, it took longer for the algorithm to converge compared to the single-user scenario and Rule 3– reached 90% of the utilization in almost 20% of the observation block.

5.2 Future Work

We can briefly summarize our future work as follows:

- In chapter 3 for the multi-user scenario, we used a generalized CSMA-CA protocol with exponential back-off mechanism. However, the practical way to implement this is to employ binary exponential back-off mechanism as used in IEEE 802.11 standard, where the waiting times are quantized in range $[0, CW - 1]$, where CW is the contention window size. This will cause probability of SUs colliding to arise, which we have to contemplate in our analysis and simulation.
- In order to avoid hardware complexity on SU's part, we assumed SUs are capable of sensing/accessing a single channel at a time. However, with the advanced antenna technologies that nowadays secondary users might be equipped with, we have to take into account simultaneous sensing/accessing as well.
- The main contribution of our work will be in designing a joint cross-layer medium access and routing algorithm for multi-hop ad hoc networks, where we have cognitive users scattered in a geographical area with multiple primary networks operating in a cellular fashion as depicted in figure 5.1.

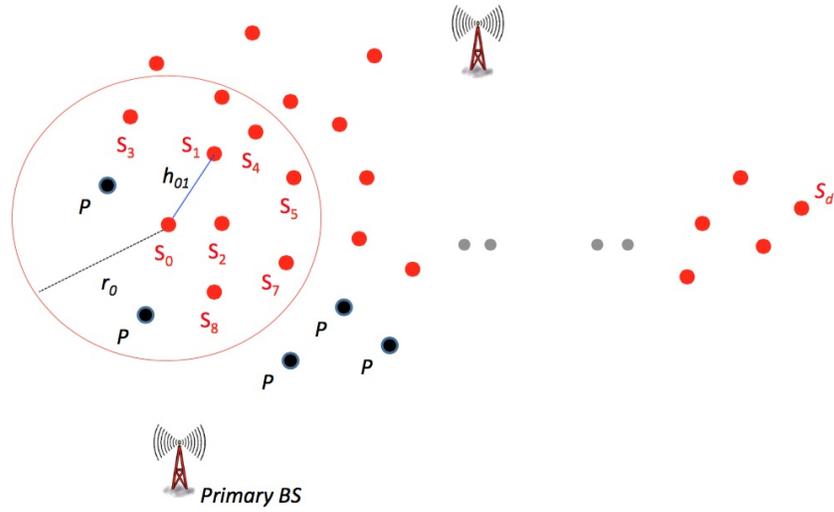


Figure 5.1: Multi-hop ad hoc cognitive radio network [31].

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Curriculum Vitae

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