Multi-Channel Sequential Sensing In Cognitive Radio Networks

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Abstract

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Finding white spaces and using them are major goals of cognitive radio networks. In this research work, we investigate multi-channel spectrum sensing for secondary users (SUs), and make improvements by forming sequential sensing as long as the secondary user does not get a channel to transmit on, and also as long as the user still has time left for transmission since waiting for the next cycle might not be the best scenario for the use of spectrum radio. We first formulate an optimization problem that maximizes the throughput of the system. Then, we introduce a power consumption model for our system since SUs are battery powered devices and the effectiveness of the system is jointly coupled with the energy consumption. Finally, we introduce an energy utility function, and we optimize it by considering both the throughput of the system and the amount of power consumed to achieve the optimal throughput. Numerical and simulation results are introduced at the end of this research, and they show better performance by the use of our suggested model compared to the work i the literature. The results also showed how to find the optimal number of channels to be sensed considering an efficient use of the SU's battery.

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Contents

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Abbreviations

ADC	Approxiated Analog to Digital Converter
ALRT	Likelihood Ratio Test
BS	Base Station
CFO	Carrier Frequency Offset
CR	Cognitive Radio
CRN	Cognitive Radio Network
CCC	Common Control Channel
CS	Compressed Sensing
CSS	Cooperative Spectrum Sensing
dB	decibel
DSA	Dynamic Spectrum Access
DSP	Digital Signal Processing
FC	Fusion Center
FCC	Federal Communication Commission
HDSM	Hybrid Distributed Sensing Matrix
IEEE	Institute of Electrical and Electronics Engineers
ISM	Industrial, Scientific and Medical Vector
MIMO	Multi Input Multi output

NBSS	Narrow Band Spectrum Sensing
PU	Primary User
PSD	Power Spectral Density
SDCSS	Semi-Distributed Cooperative Spectrum Sensing
SG	Smart Grid
SNR	Signal To Noise Ratio
SU	Secondary User
SS	Spectrum Sensing
WBSS	Wide Band Spectrum Sensing

Chapter 1

Introduction

1.1 The Need for Cognitive Radio

The fast growth in wireless communication and services has led to a dramatic shortage in the availability of spectrum radio. This shortage was, in many cases, an obstacle in developing specific applications like the Smart Grid (SG) and Public Safety or in increasing transmission rates as in the Broadband Mobile Networks [20]. For the free ISM (Industrial, Scientific and Medical) Band, the congestion of radio spectrum was due to its being shared by many communication devices freely and without license. For licensed bands, for decades, the assignment of the radio spectrum was done in many countries in a static way by giving exclusive licenses to some users in certain bands. However, for licensed bands the radio spectrum is not heavily congested, as in the ISM band. In fact, white spaces or spectrum holes are underutilized due to the sporadic use of the spectrum by the licensed user as shown in figure 1.1. Therefore, a dynamic spectrum access (DSA) assignment policy has been established to overcome the drawbacks of the old assignment policy. As the

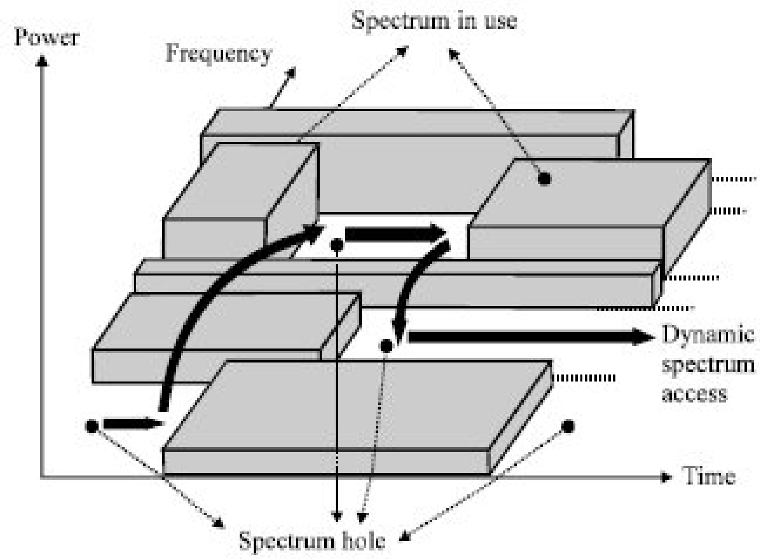


Figure 1.1: An illustration for the spectrum holes[1].

measurements of the radio spectrum by the FCC (Federal Communication Commission) have shown under-utilization of this radio that vary from 15% to 85% spatially, and along with a large temporal variation [1]. The FCC has suggested Cognitive Radio Networks (CRNs) as an enabling technology for the dynamic spectrum access.

1.2 Overview

The concept of Cognitive Radio was first raised by Joseph Mitola in 1999. Cognitive Radio is a radio that interacts with the surrounding environment by changing its characteristics. It is approved by the FCC for the Dynamic Spectrum Access for the radio spectrum. The basic idea of CRNs is to utilize the radio spectrum by secondary users (SUs) in a way that does not affect primary users (PUs). The SUs have a cognitive ability to discover and analyze the activities of the PUs. Since CR is an enabling technology for DSA, the CR

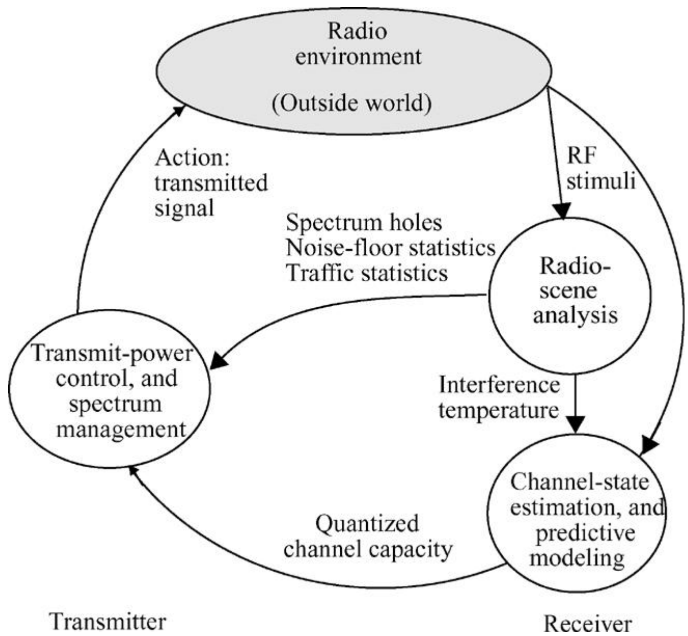


Figure 1.2: The Cognitive Cycle[9].

system should have the ability to know the surrounding environment (cognitive capability), and should also have the ability to dynamically change its parameters according to the environment (Reconfigurability) to enable CRN to utilize the radio spectrum efficiently [9]. The cognitive capability is referred to as the capability of measuring the surrounding environment and using the results of these measurements to discover white spaces in the licensed spectrum. The Reconfigurability refers to how CRN can dynamically readjust its parameters to make better use of spectrum radio. Figure 1.2 illustrates a cognitive cycle and the basic tasks that CRN has achieved.

From Figure 1.2 we can see that the cognitive cycle has three main tasks. Two of them, the radio analysis and the channel state estimation, are carried out at the cognitive receiver side, and the third task, spectrum management, is carried out at the cognitive transmitter side. The interaction between these tasks is achieved through the radio environment.

The cognitive cycle starts with sensing and analyzing the radio environment by the receiver. For instance, one of the very basic functions in Cognitive Radio is to run a spectrum sensing mechanism to discover the spectrum holes (idle primary user). Spectrum sensing is generally classified into Narrow Band Spectrum Sensing (NBSS)and Wide Band Spectrum Sensing (WBSS). In Narrow Band Spectrum Sensing, the secondary user senses a narrow frequency range which does not exceed the coherent range of a channel. The NBSS basically uses one of three different techniques. Two of these techniques necessitate prior knowledge of some of the characteristics of the primary user such as matched filter based sensing and cyclostationary based sensing, and the third does not require a prior knowledge of the primary user's characteristics such as energy detection based sensing[23]. In wide band spectrum sensing, the SUs have to sense a wide range of frequencies to achieve higher throughput[18].

After sensing and analyzing the spectrum, the receiver estimates the availability and the characteristics of idle channels. For example, it measures the size of the channel and whether the channel is idle or busy. This task is achieved using digital signal processing techniques (DSP).

Finally, the Cognitive Radio Transmitter decides to manage the use of idle channels by selecting suitable parameters to use the idle channel. For example, it decides the transmission power, the data rate,and the transmission mode.

This work will make the following contributions:

i) The model proposed in [12] will be extended, and a general model will be proposed to sense K Channels where the SUs sense the next channel only when all previous channels are inaccessible.

ii) A power consumption model will be proposed and will be included in the system to analyze the performance as the more channels are sensed the more power will be consumed by SUs,thus degrading the system efficiency.

iii) A utility function will be proposed to make a trade-off between sequentially sensing more channels and the resulting power consumption.

iv) Numerical and simulation results will be presented at the end of this research.

1.3 Motivation

The area of cognitive radio has experienced considerable research over the past few years since its appearance. Some of the investigated research areas focused on spectrum sensing and discovering the activities of PUs, and how to organize access to the channels by SUs. Single channel sensing and two channel sequential sensing are some of the models that have been suggested to find the spectrum holes. There are two main reasons that motivated us to conduct this research. The first reason was that investigating multi-channel sequential sensing could have a considerable effect on system throughput. In spectrum sensing, we could still make some improvements by sensing more channels as long as there is enough time for transmission even though the probability of sequentially sensing the next channel is getting lower as more channels are sensed. In addition, SUs are battery powered devices and the life time of the battery is important factor to measure the overall performance of the system. Therefore, it is important to find a trade-off between sensing many channels to increase the throughput and the amount of power consumption resulting from both sequentially sensing multi-channels and transmitting over the discovered vacant channel.

1.4 Problem Statement

Cognitive radio networks are introduced as a solution to overcome the restriction in the use of radio spectrum due to its static assignment policy. Spectrum sensing is one of the key functions for enabling the use of cognitive radio technology. The throughput of the CR system is a function of sensing time and transmission time. The less sensing time means the more time is left for transmission. However, if the sensing outcome detects the presence of PU, then the SU has either to stop sensing and wait for the next cycle to repeat the sensing process, or to continue sensing other suggested channels until it gets a channel or the sensing-transmission cycle finishes. This work includes two parts. In the first part a mathematical model will be built for sensing multi-channels within one sensing transmission cycle, and the results of sensing a different number of channels will be compared. Second, multi-channel sequential sensing keeps the SUs busy during the sensing transmission cycle and that affects the battery life of SUs. Thus, introducing and modeling a power consumption scheme will be very important to optimize the trade-off between sequentially sensing multi-channels to achieve higher throughput and the amount of power consumption resulting from sensing and transmission over the sensed channel.

1.5 Thesis Structure

The rest of this dissertation is organized as follows:

Chapter 2 presents a literature review about spectrum sensing in cognitive radio networks and some of the work that has been done so far in detecting the activities of primary users for both cooperative sensing and non-cooperative sensing. Also, some of the work regarding optimizing sensing time to increase the throughput and some power consumption research issues was reviewed.

In chapter 3, first a system model for sequentially sensing multi-channels is presented. Second, we formulate both the problem of finding the multi-channel sensing throughput and the power consumption resulting from sequentially sensing multi-channels. Finally, we propose and formulate a utility function problem for the system which optimizes the trade-off between the system throughput and the amount of power consumption in the secondary user.

In chapter 4, first, a simulation and numerical results are presented to demonstrate and justify the effectiveness of the suggested model. Second, a conclusion of this research work is presented at the end of the chapter.

Chapter 2

Background and Literature Review

Extensive work has been done so far in the area of Cognitive Radio which aims in general to enable this promising technology and to increase its performance and quality. The conducted research has investigated many topics like spectrum sensing techniques, optimizing sensing time, improving performance in a fading environment, coordinating sensing and access between users, reducing power consumption, etc. In this part we will try to shed light on some of the research work that has been done in the area of cognitive radio.

2.1 Spectrum Sensing

In cognitive radio networks, spectrum sensing is a key function to discover spectrum holes so that they can be used by SUs to transmit information. The mis-discovery of these holes could lead to interference with the activities of PUs or collisions with licensed information. Spectrum sensing is achieved by setting the SUs either at the transmitter side or at the receiver side of the PU. However, setting up the SU at the receiver side of the PU can be affected due to the difficulty of obtaining direct measurements, as in TV where all the receivers are passive. Thus, most of the research focused on detecting the activities at the transmitter side of the PU. Spectrum sensing revolves around the successful detection of the activities of licensed users and running a mechanism to discover the spectrum holes in the licensed spectrum. Spectrum sensing techniques are divided into two main categories depending on the size of the licensed band to be sensed.

2.1.1 Narrow Band Spectrum Sensing

narrow band spectrum sensing (NBSS) means that the sensed band of the radio spectrum does not exceed the coherent bandwidth of the channel. As was mentioned before, for narrow band sensing there are three main methods to discover the activities of PUs. These methods are Energy Detection, Matched Filter,and Cyclostationary Detection.

In the energy detection method the SUs compare the their sensing results to a threshold that represents noise power added to PUs' signal to decide whether the channel is idle or not. The Energy Detection is characterized by a short sensing time and simplicity of implementation. However, the changes in noise levels, especially a low Signal to Noise Ratio (SNR), affect the performance of this method [24].

In [26] a calibrated detection of threshold was proposed to mitigate the errors of detection caused by the noise uncertainty effect. The sparsity of energy and its changes in the channel were used to achieve proportional energy detection estimation for a channel state even in low SNR.

In [7] a soft decision cooperative spectrum sensing was used to mitigate the fading channel problem. The authors suggested a dynamic threshold based detection algorithm where the detection threshold switches between two levels of power to reduce the effect of noise uncertainty. The two dynamic threshold levels were estimated using a noise uncertainty factor.

In matched filter detection, prior knowledge of a licensed user's information signal is required at the unlicensed user side to coherently detect the activities of licensed users.

In [3, 16] a matched filter dynamic threshold detection was conducted to improve system performance over the use of static threshold detection as it is vulnerable to the random change in noise power.

Cyclostationary detection refers to underlying periodicity in communication signals to be detected. Cyclostationary feature detection has better performance in low SNR, however, it has more computational complexity [2].

In[14], a multi-input multi-output antenna (MIMO) detection was used to detect the autocorrelation signals, showing better performance in low SNR.

In[22], a cyclostationary feature detection was used to identify OFDM (orthogonal frequency division multiplexing) signal, where the periodicity property that exists in OFDM pilot signals was used to calculate the autocorrelation and to make an approximated likelihood ratio test (ALRT) based on the autocorrelation signal. The authors proposed an algorithm to approximate the CFO (carrier frequency offsets), needed to estimate the likelihood test.

2.1.2 Wide Band Spectrum Sensing

In wide band spectrum sensing (WBSS), the sensed band exceeds the coherent bandwidth of the channel. The conventional way of achieving this sensing is by using analog to digital Converters (ADC). However, it results in some problems such as high overhead and high computational complexity due to the very high sampling rate of the ADCs which are technically hard to achieve and costly. Thus compressed sensing is proposed for the WBSS, based on sampling the PUs signal below the Nyquist rate.

The authors in [11] proposed an improved wavelet detection of edges of the consecutive sub-bands for wide band spectrum sensing. Nonlinear scaling was done to the wavelet transform to maximize the detection of the irregularities and discontinuities at the consecutive edges of sub-bands. The nonlinear scaling was done after normalizing the power spectral density (PSD) of the wide band signal.

In [27] sequential cooperative compressed wide band sensing was suggested to discover the spectrum holes over the wide band. Compressed sensing is used with cooperative sensing to mitigate the noise uncertainty problem, and to reduce the detection time and the amount of sensing overhead needed to recover the compressed sensing signal.

Similarly, in the area of compressed sensing, the authors in [8] proposed a cooperative compressed sensing framework to improve the accuracy of detection and to reduce the wide band sensing overhead. A hybrid distributed sensing matrix (HDSM) algorithm was used by distributing the sensing process among a number of groups of secondary users and arranging these groups based on the quality of reporting channels between the groups and the FC (fusion center).

2.2 Optimization of Sensing and Transmission Time

As mentioned before, sensing time is an important factor to conduct spectrum sensing because it brings about sensing-throughput tradeoff. Sensing time is aslo important to determine the activities of PUs as the higher sensing time leads to a higher detection probability, which means more protection for the PU activities, and it also lower false alarm probability which means higher system throughput. However, the higher sensing time leads to a shorter time being left for transmission. Therefore it is crucial to optimize sensing time for better utilization of the unlicensed spectrum.

In [13], a sensing time optimization problem was proposed to determine the best sensing time in which the highest throughput can be achieved. The problem was optimized for both cooperative and non-cooperative sensing with the constraint of providing sufficient protection for the activities of the PU by choosing a specific value for the probability of detection.

In[12], the authors suggested two channel sensing schemes instead of one channel sensing within a single time slot, and similarly the optimal sensing time was investigated to find the best performance for the system.

In[17], optimizing sensing time using Neural Networks was proposed to have prior knowledge of the activities of PUs and then use this collected information to optimize system throughput.

In the low signal SNR environment the PUs might end up with a short transmission window to send their data because most of the time during the sensing period is used to discover vacant channels. in[25], the authors suggested an algorithm to find the best tradeoff between detection probability and sensing time length in low SNR.

2.3 Cooperative Sensing

Sensing a channel by single SU is usually affected by many factors as multipath fading, receiver uncertainty and shadowing. These factors make sensing results inaccurate and affect the performance. Cooperative sensing has been suggested as an efficient way to overcome the aforementioned problems where it exploits the spatial diversity of the SU, to improve the performance of detecting the SUs' activities. Cooperative sensing is divided into two types either centralized where an FC (fusion center) or BS (base station) is used to collect the detection information from all users and detect the spectrum holes, or decentralized where the users share the information to make the decision. Even though cooperative sensing is viable in finding vacant channels and tackling the aforementioned problems, it suffers from the rising of sensing overhead, which results in a longer sensing time and from computational complexity due to cooperation between secondary users[5]. The works that were done in cooperative sensing include:

In [6] multi-channel cooperative sensing between multi-users was investigated. The authors optimized sensing time to find idle channels and increase the throughput, and investigated the effect of cooperative sensing on coping with fading channel problems due to the use of several SUs diverted in locations to discover a vacant channel. The optimization was for both continuous time sensing mode and slotted time sensing mode.

In[19], a joint cooperative sensing with channel access protocol was suggested to find idle channels and coordinate access between users to increase the system throughput. A semi-distributed cooperative spectrum sensing (SDCSS) framework was proposed to find the spectrum holes. Then, an algorithm was devised by integrating this framework with the applied spectrum access mechanism to increase overall system efficiency.

Cluster based sensing is one of the cooperative sensing schemes that is used to reduce the computational complexity and sensing overhead. In [10], the authors suggested a novel clustering scheme consisting of three phases: pruning, selecting and clustering. In the first phase any SU that does not have sensing results will be excluded. In the second phase, the SU with the most reliable data will be selected as cluster overhead. In the clustering phase, the clusters change according to sensing results regarding the targeted channel.

2.4 Energy Consumption

Reducing power consumption has generally been receiving a great deal of attention in wireless communications. For instance, since the SUs are battery powered devices where different operations as sensing of channels, reporting of channels, and cooperative sensing between SUs, lead to a fast consumption of the battery power and degrade the performance of the whole system. Therefore, it is important to consider power consumption while designing any cognitive radio system.

In [21], an energy efficient design was investigated by proposing a utility function taking into account both system throughput and energy consumption. The system utility was tested by jointly integrating sensing time, detection threshold, and number of cooperative sensing devices.

In [15], a more careful design for energy efficiency was conducted. The authors investigated the optimizing of power consumption in three different steps. First, they designed a sensing strategy and defined when the system has to stop sensing the channel. Second, they defined an access strategy and the power levels at which a SU has to start transmission when it discovers a vacant channel. Finally, a joint design of channels sensing order and sensing-access strategies was investigated to evaluate the effectiveness of the proposed design.

The authors in [4] proposed a novel energy-efficient scheme for resource allocation in cognitive radio networks. The number of cooperative SUs and sensing time were optimized under a couple of constraints, including system transmission power to determine the optimum number of SUs for energy-efficient use of the cognitive system, and also to determine the optimum sensing time that maintains the target detection probability.

Further, compared to other research works, this work investigated system throughput, energy consumption in performing sequential sensing, and optimizing the number of channels to be sequentially sensed based on energy consumption.

Based on work that was done in[12], and since the transmission window is relatively larger than the sensing window, stopping sequential sensing at the second choice channel might not be the best scenario. For SUs, achieving some gain is worthwhile as long as there is time left for transmission in the time slot. Otherwise, SUs have to wait for the next time slot to run sensing again. However, the SUs are battery powered devices and the more time spent on sensing the more power is consumed, thus degrading the performance of the system especially with the conditional probability decreasing each time the SUs proceed to sense the next channel.

Chapter 3

Multichannel Sequential Sensing and System Throughput

In this chapter, we investigate the effect of sensing k channels on system throughput in a Cognitive Radio Network as opposed to sensing only one or two channels within one sensing-transmission cycle of the cognitive radio system. Since the utilization of scarce radio resources is vital to the future of cognitive radio, investigating all possible ways to increase throughput is necessary. As the discovery of spectrum holes is based on sensing and analyzing the availability of these holes, it may be worthwhile to sense k channels as long as there is still time left for transmission. Otherwise, the system either has to wait for the next sensing-transmission cycle or to stop sensing. However, the SUs are battery powered devices and the more sensing conducted by SU the more power is consumed. Therefore, we will introduce a power consumption model and formulate an optimization between system throughput and power consumption by introducing the utility function to find the best number of channels to be sensed with the optimal system throughput and power consumption. Table 3.1 introduce the symbols that are used the proposed model and the rest of this thesis.

Symbol	**Meaning**
λ	detection threshold
σ	signal power to noise power
P_{i0}	probability that channel (i) is idle
P_{i1}	probability that channel (i) is active
T	total time (sensing + transmission)
t_s	sensing time
C	The channel capacity
ρ_s	power consumption during sensing
ρ_t	power consumption during transmission
λ	detection threshold
γ	signal power to noise power
f_s	sampling frequency
P_d	probability of detection
P_f	probability of false alarm
R	the throughput
W	power consumption
T_{on}	PU being sensed as active by SU
T_{off}	PU being sensed as idle by SU
H_{on}	the PU is active
H_{off}	the PU is idle
S_i	probability of sequentially sensing channel (i)
σ^2	noise variance

Table 3.1: List of symbols

3.1 System Model

The proposed system is a Centralized Cognitive Radio Network (CRN) where the management of the system and the assignment of channels to SUs are done by a Central Unit like BS (Base Station)or FC (Fusion Center). Centralized networks have some advantages over non centralized ones as they reduce the complexity of the system and offer more management for the network[12]. The CRN is supposed to have N number of channels. We assume that the number of channels is high compared to the number of secondary users (M). If the number of channels is less, the requests for accessing channels will be discarded or delayed to the next time slot. Also, sequentially sensing and then accessing the channels will be useless since there is an insufficient number of channels to be sensed. In the model all the channels are supposed to have a rate capacity of C Mbps, and they are proposed to be identical in noise characteristics and fading. The channels are also independent from each other as on a wide-band the spectrum could belong to different Primary Networks. The secondary network and the primary network run in a synchronous way. Thus, the Primary Network does not return to its active mode while the Secondary Network is in active mode (sending data). We consider the CRN with M number of users sensing then accessing certain channels whenever they are available. For the sake of easing complexity, we consider that the central unit assigns the channels over the CCC (the common control channel) to each secondary user. The SUs sequentially sense the next choice channel as long as the current channel is sensed to be busy since we have assumed the number of channels is high enough that assigning different choices of channels to be sequentially sensed can be achieved in advance by central unit for each SU. However, in multi-channel sensing the channels can be assigned and accessed randomly which may result in collisions between SUs, but we did not consider this case since assigning the channels is beyond the scope of

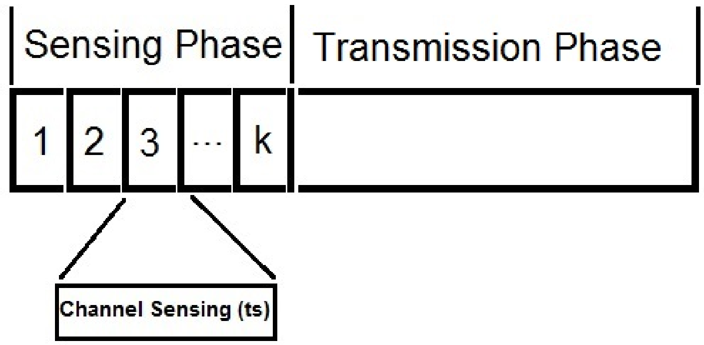


Figure 3.1: System Model: Timeslot Structure.

this work. The time slot structure that was adapted by the system is periodic as in Figure 3.1 where in each period of time the SUs start to sequentially sense the channels that were assigned by the central unit and keep sensing until a spectrum hole is discovered; then each secondary user performs a transmission over the discovered vacant channel.

3.2 Problem Formulation

Since spectrum sensing is a basic task for enabling cognitive radio networks to find spectrum holes, a detection technique should be adapted to run the spectrum sensing function. An energy detection technique is chosen in this work as it is simple and does not require any prior knowledge of PU information. The energy detection technique is represented as a binary hypothesis (0,1). Under the hypothesis H_{on} the primary user is supposed to be active (1), while under the hypothesis H_{off} the primary user is supposed to be idle(0).

The testing results of activities of the PUs are obtained by comparing the statistics of the signal received from the primary user at the SU receiver side to a certain threshold λ . The detection threshold is based on the power level of the noise signal that is added to the PU signal at the SU receiver side. Suppose that the sensing outcome is either T_{on} or T_{off}, denoting PUs being sensed as active or idle respectively. The probability of false detection is represented as from [13] as follows:

$$P_f(t_s, \lambda) = P(T_{on}|H_{off}) = Q((\frac{\lambda}{\sigma^2} - 1)\sqrt{t_s f_s}) \quad (1)$$

where Q(.) represents the cumulative density function of a normalized Gaussian distribution for a random variable (x) and is represented as:
$Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^\infty exp - (\frac{t^2}{2})\, dt$

The probability of detection is represented by:

$$P_d(t_s, \lambda) = P(T_{on}|H_{on}) = Q((\frac{\lambda}{\sigma^2} - \gamma - 1)\sqrt{\frac{t_s f_s}{2\gamma + 1}}) \quad (2)$$

σ^2 is the variance of circularly symmetric complex Gaussian noise. γ represents the average SNR at the SUs side. λ is the detection threshold, f_s is the sampling frequency. The (t_s) is the time required to sense one channel.
Usually in practice the probability of detection is set at a certain value. Therefore, for a target probability of detection p_{th}, the probability of a false alarm can be represented in terms of the targeted detection probability as follows:

$$P_f(t_s, \lambda) = Q(\sqrt{2\gamma + 1}Q^{-1}(p_{th}) + \sqrt{t_s f_s} \cdot \gamma)) \tag{3}$$

3.2.1 System Throughput

The throughput of the system over any channel (i) is subject to availability of that channel (P_{i0}) and the sensing result hypothesis of the channels. P_{i0} is the probability that channel (i) is idle (0), and is usually measured by observing the activities of primary users over a certain period of time so that a usage pattern database is formed and used to calculate the probability of availability.

In addition, the throughput of any SU over any channel is subject to sensing and transmission time where less sensing time results in more time left for transmission and thus higher throughput. Based on channel availability and the sensing result hypothesis, the throughput can be represented by one of the following scenarios:

i) The SU successfully detects the absence of the PU, so the SU will perform a transmission on the sensed channel with probability $P_{i0} \cdot (1 - P_f(t_s, \lambda))$ and will refrain from sensing other channels.

ii) The SU falsely senses the channel is idle with probability $P_{i0} \cdot P_f(t_s, \lambda)$, so the SU will run sensing again and will repeat sensing for k times until a vacant channel is discovered and perform transmission, or the cycle time for sensing transmission ends. The probability of sensing each current channel is conditional to the probability of the previous channel.

iii) The SU falsely senses that the channel is active with probability $P_{i1} \cdot (1 - P_d(t_s, \lambda))$, so the SU will start transmission and refrain from sensing.

iv) The SU successfully senses the channel is active with probability $P_{i1} \cdot P_d(t_s, \lambda)$, so the SU will run sensing again and will repeat sensing for k times as in step (ii), and will perform transmission as soon as it finds a free channel.

From step **(ii),(iv)** we can see that the SU has to perform sensing sequentially until an idle channel is discovered, and we can define S_i as a conditional probability for SUs to sequentially sense the next channel (i) given that the previous channel (i-1) was busy.
Thus, the probability of sequential sensing next channel (i)for any secondary user (m) is S_i^m, represented by:

$$S_i^m = \prod_{j=1}^{i-1} [P_{j0}^m \cdot P_f(t_s, \lambda) + P_{j1}^m \cdot P_d(t_s, \lambda)] \tag{4}$$

where :

P_{j0}^m: probability that that channel j which is assigned to Secondary User (m) is idle

P_{j1}^m: probability that channel j which is assigned to Secondary User (m)is active

the throughput of SU over channel i is given by:

$$R_i^m(t_s, \lambda) = P_{i0}^m(1 - P_f(t_s, \lambda)) \cdot C \cdot [T - i \cdot t_s] \tag{5}$$

where :

T: total time in one period m: total number of users, m=1,2,....,M

P_{i0}^m: the probability that channel i that is assigned to secondary user (m) is idle

The equation below shows the total throughput of the multi-user Multi-channel system.

$$R(t_s, \lambda, k) = \Sigma_{m=1}^{M}(R_1^m(t_s, \lambda) + \Sigma_{i=2}^{k}(S_i^m \cdot R_i^m(t_s, \lambda))) \tag{6}$$

where k is the number of sequential channels to be sensed before starting transmission, $R_1^m = R_i^m$ when $i = 1$

As we mentioned before, we consider full coordination of channel assignment by a central unit, and SUs do not contend to sense the same channel. Otherwise, the above formula for system throughput should also include the availability of a channel in case other users are sharing it, making the mathematical model of the problem very complicated to solve. Furthermore, from equation number (6) the system throughput is simply the summation of the throughput of all the secondary users in the network. Therefore, we could consider a simple case by taking into account only one secondary user (m=1) as represented by the following equation.

$$R(t_s, \lambda, k) = R_1 + \Sigma_{i=2}^{k} R_i(t_s, \lambda) \cdot S_i \tag{7}$$

where S_i = S_i^m when m=1, it becomes represented as the following:

$$S_i = \prod_{j=1}^{i-1} [P_{j0} \cdot P_f(t_s, \lambda) + P_{j1} \cdot P_d(t_s, \lambda)] \tag{8}$$

Numerical Solution:

The problem in (7) is an optimization problem. The maximization of system throughput is constrained to sensing time (t_s), probability of detection (P_d) ,and the number of channels (k) to be sensed.

$$max_{t_s,\lambda,k} R(t_s, \lambda, k) = R_1 + \Sigma_{i=2}^{k} R_i(t_s, \lambda) \cdot S_i \tag{9}$$

subject to constraints:

$0 < t_s < T/k$

$P_d(t_s, \lambda) = P_{th}$

$2 \leq k \leq N, k \in I = 1, 2, ...$

The problem in equation (9) has a couple of constraints. At the beginning, we transform it into a problem with less number of constraints, then we solve it. Since k represents an integer number of channels to be sensed within interval [0,k], we can solve the problem with a specific value of k. The problem in (9) can be transformed into:

$$max_k R(k) = R^*(k) \tag{10}$$

subject to constraint:

$2 \leq k \leq N, k \in I = 1, 2, ...$

where $R^*(k)$ represents the optimal objective function for the following problem (11) with specific value of k.

$$max_{t_s,\lambda} R(t_s, \lambda) = R_1 + \Sigma_{i=2}^{k} R_i(t_s, \lambda) \cdot S_i \tag{11}$$

subject to constraints:

$0 < t_s < T/k$

$P_d(t_s, \lambda) = P_{th}$

Since the probability of detection in practice is set to a certain threshold, and probability of false alarm becomes a function of probability of detection from equation(3); so the problem can be transferred into an optimization problem with one variable. Also, to keep the probability of false alarm detection below (0.5), sensing time can be setup to be greater than a minimum value as follows: From (3), we can find that $t_s > \frac{\sqrt{2\gamma}Q^{-1}(p_{th})}{\gamma\sqrt{f_s}} = t_{s\ min}$. Thus, the problem in (11) will be simplified to:

$$max_{t_s} R(t_s) = R_1 + \Sigma_{i=2}^{K} R_i(t_s) \cdot S_i(t_s) \tag{12}$$

subject to constraints:

$t_{s\ min} < t_s < T/K$

It is hard to know the convexity of this problem as it is very complicated to derive the objective function with sensing time, especially with the complexity becomes higher as more sequential channels are sensed. However, since (ts) lies within interval $(t_{s\ min}, T/k)$, the optimal value of the objective function can be obtained by applying exhaustive search within that interval.

3.2.2 Power Consumption and Utility Function

From the problem in last part the throughput does not contain any power factor. However, sensing more channels will lead to a higher power consumption which is not desirable. Therefore, we will calculate the amount of power consumed in the system and present a utility function to find the optimal tradeoff between the throughput of system and power consumption.

Let's suppose the ρ_s, ρ_t represent the power consumed in sensing phase and transmission phase respectively.

In the suggested model the power consumption is calculated over four different scenarios for the SU, as follows:

i) the SU senses the channel is idle successfully with probability $P_{i0}.(1 - P_f(t_s, \lambda))$, and the consumed power is estimated as:

$$M_1(t_s) = \rho_s \cdot t_s + \rho_t \cdot (T - i \cdot t_s)$$

ii) the SU senses the channel is idle falsely with probability $p_{i0}.P_f(t_s, \lambda)$, and the consumed power is estimated as:

$$M_2 = \rho_s \cdot t_s$$

iii) the SU senses the channel is active falsely with probability $p_{i1} \cdot (1 - P_d(t_s, \lambda))$, and the consumed power is estimated as:

$$M_3(t_s) = M_1(t_s)$$

iv) the SU senses the channel is active successfully with probability $p_{i1} \cdot P_d(t_s, \lambda)$, and the consumed power is estimated as:

$$M_4(t_s) = M_2(t_s)$$

From the above four steps, the average power consumption is represented as:

$$\mathcal{W}_i(t_s, \lambda, k) = (\rho_s \cdot t_s + \rho_t \cdot (T - i \cdot t_s))[P_{i0} \cdot (1 - P_f(t_s, \lambda)) + P_{i1} \cdot (1 - P_d(t_s, \lambda))]$$
$$+ (\rho_s \cdot t_s) \cdot [P_{i0} \cdot P_f(t_s, \lambda) + P_{i1} \cdot P_d(t_s, \lambda)] \tag{13}$$

The previous equation (13) can be expressed as :

$\mathcal{W}_i = (\rho_s \cdot t_s)[P_{i0} \cdot (1 - P_f(t_s, \lambda)) + P_{i1} \cdot (1 - P_d(t_s, \lambda))] + \rho_t \cdot (T - i \cdot t_s))[P_{i0} \cdot (1 - P_f(t_s, \lambda)) + P_{i1} \cdot (1 - P_d(t_s, \lambda))] + (\rho_s \cdot t_s)[P_{i0} \cdot P_f(t_s, \lambda) + P_{i1} \cdot P_d(t_s, \lambda)]$

By factoring $(\rho_s \cdot ts)$ from the two first parts of the previous equation, it can be expressed as:

$$\mathcal{W}_i = (\rho_s \cdot t_s)[P_{i0} \cdot (1 - P_f(t_s, \lambda)) + P_{i1} \cdot (1 - P_d(t_s, \lambda)) + P_{i0} \cdot P_f(t_s, \lambda) + P_{i1} \cdot P_d(t_s, \lambda)] + \rho_t \cdot (T - i \cdot t_s)[P_{i0} \cdot (1 - P_f(t_s, \lambda)) + P_{i1}.(1 - P_d(t_s, \lambda))] \tag{14}$$

By considering that$(P_{i0} + P_{i1} = 1)$ the equation (14) can be simplified by:

$$\mathcal{W}_i(t_s, \lambda, k) = \rho_s \cdot t_s + \rho_t \cdot (T - i \cdot t_s)[1 - P_{i0} \cdot P_f(t_s, \lambda) - P_{i1} \cdot P_d(t_s, \lambda)] \tag{15}$$

Since the power consumption in each channel is sequentially dependent on the availability of the previous channel, the total average power consumption can be represented by the following equation:

$$\mathcal{W}(t_s, \lambda, k) = \mathcal{W}_1(t_s, \lambda) + \Sigma_{i=1}^{k} \mathcal{W}_i(t_s, \lambda) \cdot S_i \tag{16}$$

The higher sensing time leads to higher detection probability and hence a better protection to licensed user's activities. However, it reduces the time left for transmission. In addition sensing more channels will lead to higher power consumption which affects the effectiveness of the system. We suggest a utility function which is presented as:

$$U = \frac{\textbf{throughput of the system}}{\textbf{average power consumption of the system}}$$

For our case the utility function can be represented by following equation:

$$U(t_s, \lambda, k) = \frac{R(t_s,\lambda,k)}{(\mathcal{W}(t_s,\lambda,k))^v}$$

Where(v) is a weighting factor for the power consumption, and it has range from [0-1]. For v=1, means the throughput of system is evaluated for unit power. The lower the weighting factor the less important the power consumed for sensing the channels.

Numerical Solution:

Our goal is to optimize the utility function with specific value of (v). From equations (7),(16), the objective utility function can be formulated as follows:

$$max_{t_s,\lambda,k} U(t_s, \lambda, k) = \frac{R_1(t_s, \lambda) + \Sigma_{i=2}^{k} R_i(t_s, \lambda).S_i}{(\mathcal{W}_1(t_s, \lambda) + \Sigma_{i=1}^{k} \mathcal{W}_i(t_s, \lambda) \cdot S_i)^v} \tag{17}$$

subject to constraints:

$0 < t_s < T/k$

$P_d(t_s, \lambda) = P_{th}$

$2 \leq k \leq N, k \in I = 1, 2, ...$

Similar to steps that was taken to formulate equation (10). The utility function can be simplified by a problem with one variable constraint as follows:

$$max_k U(k) = U^*(k) \tag{18}$$

subject to constraint:

$2 \leq k \leq N, k \in I = 1, 2, ...$

Where $U^*(k)$ is the optimal objective utility function with predetermined value of (k) for the following problem (19) .

$$max_{t_s,\lambda} U(t_s, \lambda) = \frac{R_1(t_s, \lambda) + \Sigma_{i=2}^{k} R_i(t_s, \lambda) \cdot S_i}{(\mathcal{W}_1(t_s, \lambda) + \Sigma_{i=1}^{k} \mathcal{W}_i(t_s, \lambda) \cdot S_i)^v} \tag{19}$$

subject to constraints:

$0 < t_s < T/k$

$P_d(t_s, \lambda) = P_{th}$

Similar to the analysis was done to find the solution for system throughput, the objective utility function can be transformed as below:

$$max_{t_s} U(t_s) = \frac{R_1(t_s) + \Sigma_{i=2}^{k} R_i(t_s) \cdot S_i}{(\mathcal{W}_1(t_s) + \Sigma_{i=1}^{k} \mathcal{W}_i(t_s) \cdot S_i)^v} \tag{20}$$

subject to constraints:

$t_{s\ min} < t_s < T/k, k \in I = 2, 3$

Similar to what was done for optimizing the objective function for system throughput in the last section, the exhaustive search can be applied within the constrained range of sensing time $(t_{s\ min}, T/k)$, to find the value that maximizes the objective utility function.

Chapter 4

Numerical and Simulation Results

In this section, we will present the general setting of the system. Then, numerical results will be reviewed and discussed to analyze the performance of the suggested model. Finally, we will conclude by briefly reviewing the contribution of this work.

4.1 System Settings

The suggested system has 30 channels and 5 users. However, our results will be restricted to sensing only six (6) channels for one SU (1) since the assignment of channels is done by the central unit. Thus, no collisions between SUs that can happen from trying to access the same channel. The average availability of these channels is arranged in descending order based of the observations on the primary user activities as follows. p_{i0}= [0.65 0.60 0.58 0.25 0.10 0.05]. The probability of detection is set to be (0.9) then (0.6) for comparison. The sampling frequency is set to be 6MHz. The time slot cycle is set to be 20msec. The value of Signal to Noise Ratio(SNR) that is received at SUs is set to be $\gamma = -15dB$ to assure enough protection for the PUs. The amount of power dissipated in sensing and transmission is 0.2 W, 0.5 W respectively. The weighting power's parameter (v) is set to be (0.6). The channel capacity is set to be C=2 Mbps. The table 4.1 shows the networks settings that are used to obtain the results.

Parameter	**Value**
C	2 Mbps
T	20 ms
P_{i0}	[0.65 0.60 0.58 0.25 0.10 0.05]
ρ_s	0.2 W
ρ_t	0.5 W
γ	-15 dB
f_s	6 MHz
P_d	0.9
K	6
v	0.6,0.5,0.4

Table 4.1: Network Settings

4.2 Results and Discussion

Numerical and simulation results of the system are presented and discussed. A 10000 times monte carlo simulation is run. In the simulation, the activities of PUs are simulated and compared to the P_f, P_d that are run in the simulation. For the H_{off} hypothesis, the activities are compered to the P_f, and for the H_{on} hypothesis, the activities are compered to the P_d. Both numerical and simulation results are obtained for $SNR =$-15 dB, $P_{th} =$ 0.9.

4.2.1 System Throughput

Compared to single channel[13]and two channel sensing [12], Figure 4.1 shows both mathematical and simulation results for multi-channel spectrum sensing up to six channels. The threshold of detection probability is set to be (0.9). From the figure it can be seen that sensing three channels can increase the throughput of the system about 36% compared to one channel and can increase the system throughput about 14% compared to two channels. In addition, we can notice that the optimal sensing time decreases as the number of sensed channels increases. This can be explained due to the dependency of throughput on the next channel on the availability of the previous channel. We can also notice that when sensing time is small, the throughput is low because of high false alarm probability; then the throughput increases significantly until its optimal point, after which the throughput slowly decline due to decreased time left for transmission. The more channels are sensed the less throughput gain can be achieved within the channel compared to the gain on the previous channel. This happens due to the decrease of the probability of sequentially sensing the next channel which depends on the availability of the previous channel.

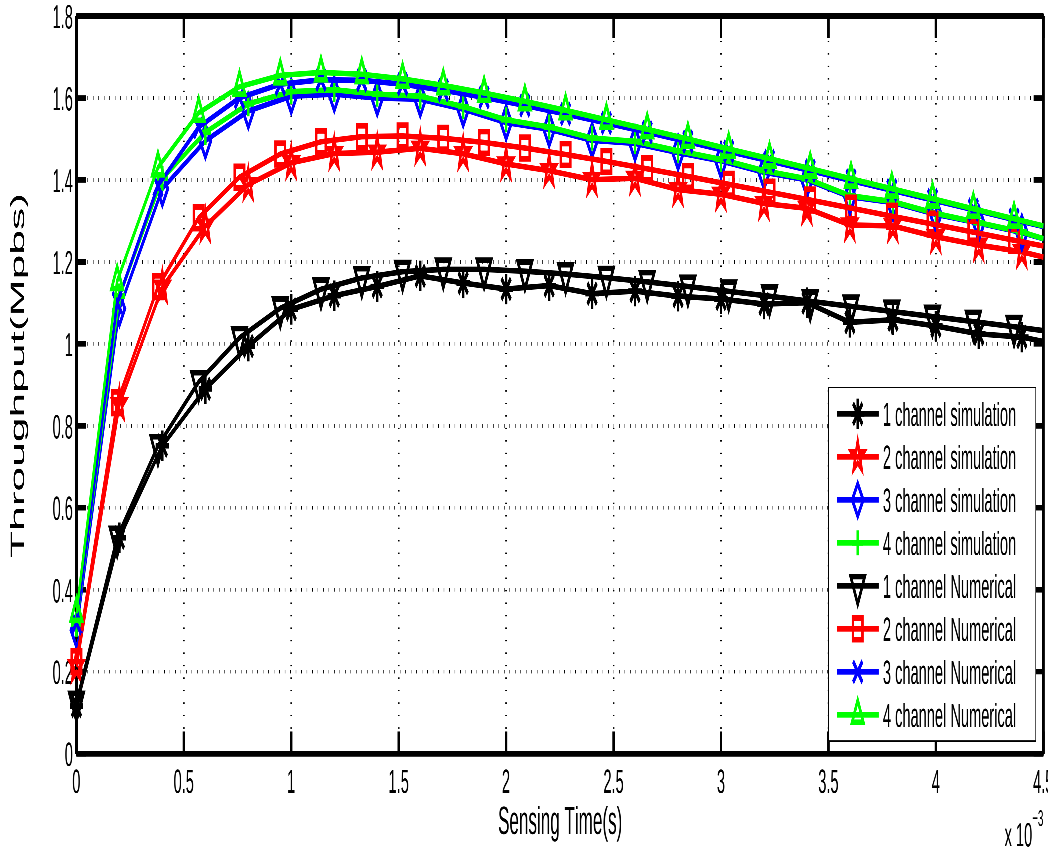


Figure 4.1: The throughput with $p_{th} = 0.9$

4.2.2 Energy Consumption

Figure 4.2 shows simulation results for the amount of power consumption for a SU resulting from sequentially sensing up to six (6) channels. From the graph it can be seen that the highest power consumption for a SU is when sensing the first three channels. This can be explained by the high availability of these channels and the high chance for the SU to transmit over them. However, continuing sensing more channels results in more power being consumed during sensing and less consumption in transmission power due to the continuous plummet in the availability of the next channels.

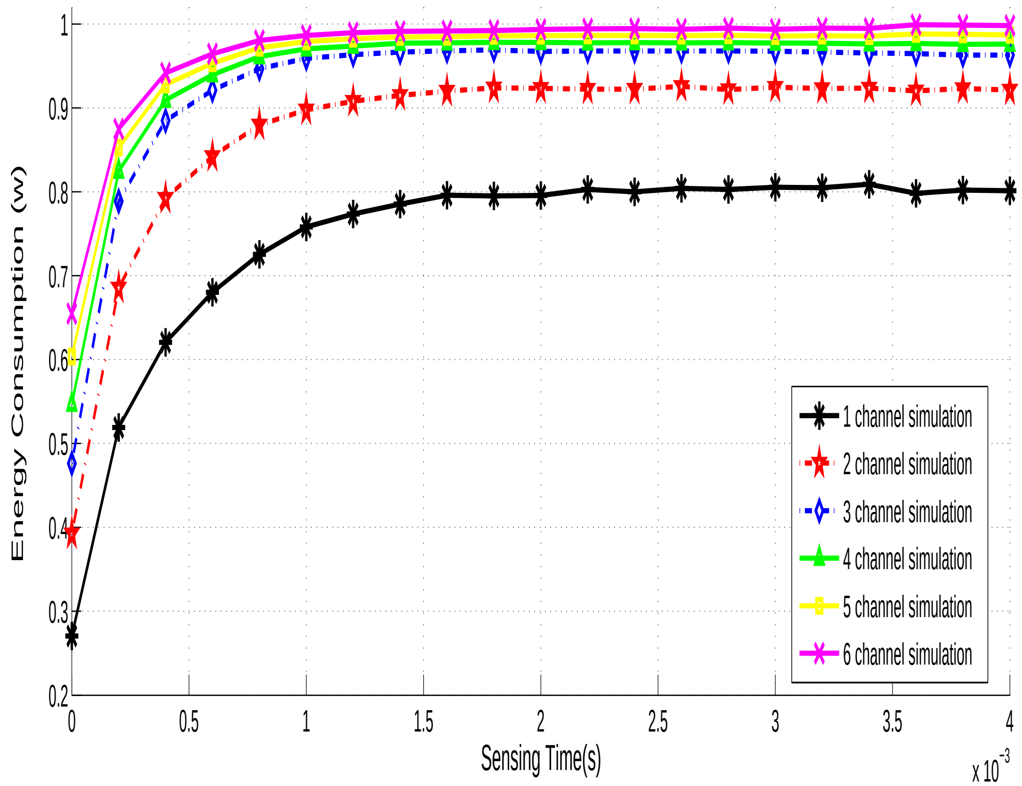


Figure 4.2: The energy Consumption

4.2.3 Throughput and Energy Consumption Tradeoff

Figure 4.3 illustrates the changes in energy utility function for sensing six (6) channels with sensing time. The weighting factor is set to be (0.6). It can be seen, from the graph, that the system achieves high utility function up to three channels where by comparing all six channels, we can notice that sensing three channels achieves a higher utility function compared to sensing one channel and two channels, but sensing more than three (3) channels will result in decreasing the utility function. This can be explained by the fact that by sensing more channels both the throughput and the power consumption decrease dramatically because of the low availability of the channels as mentioned before. However, the system spends more power for sensing the next channels as opposed to gaining less throughput.

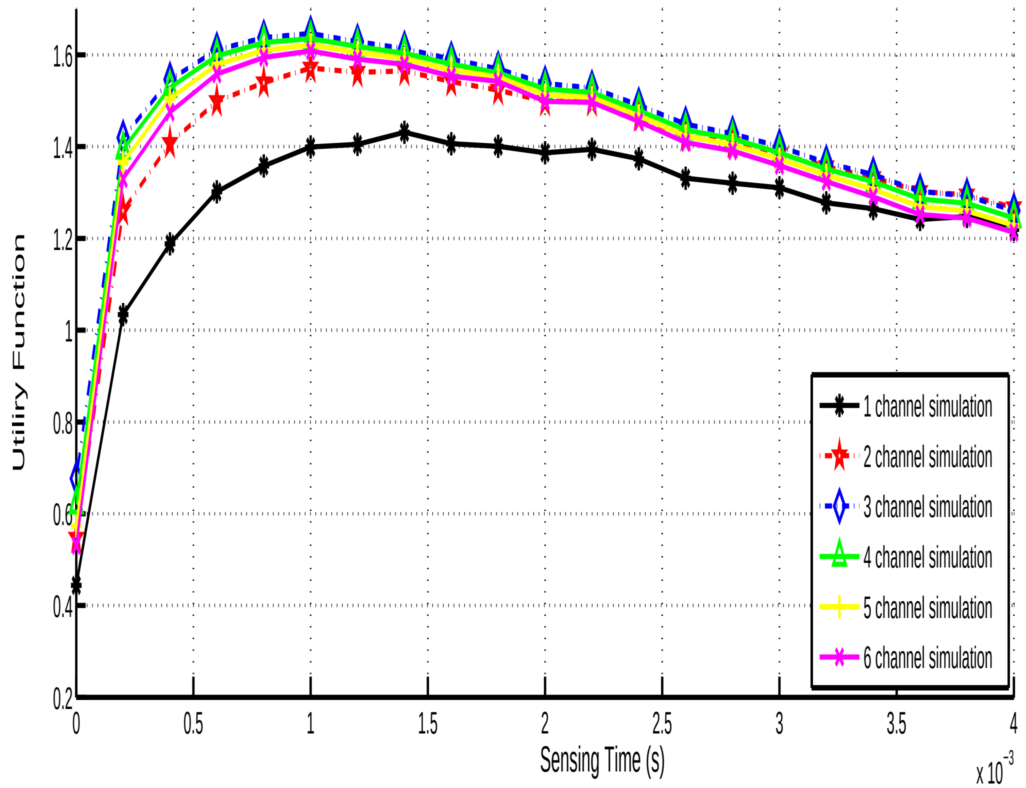
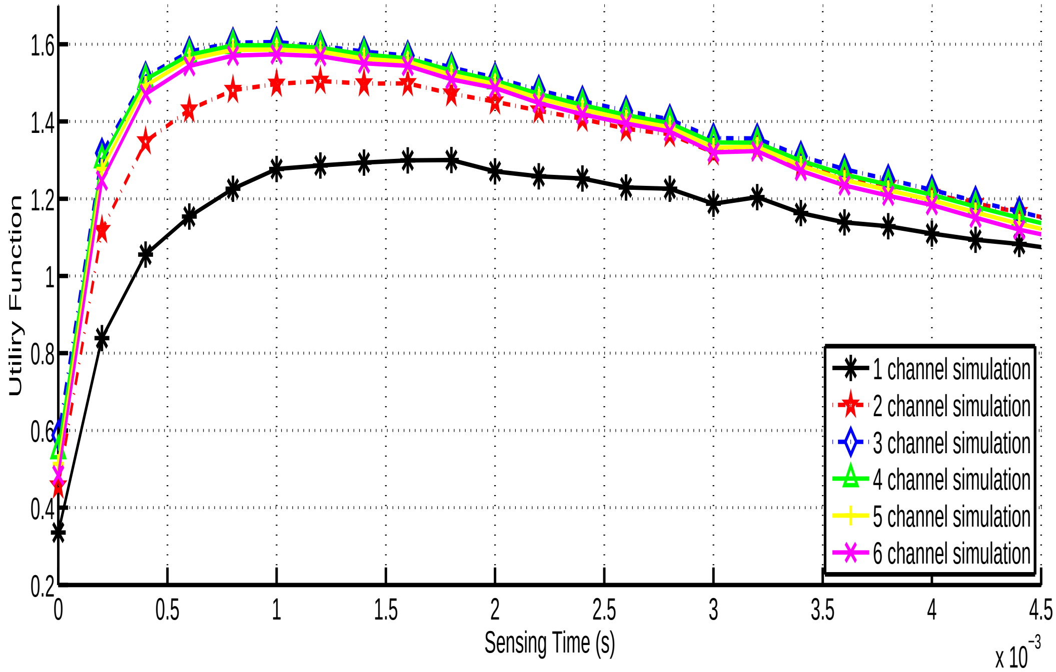
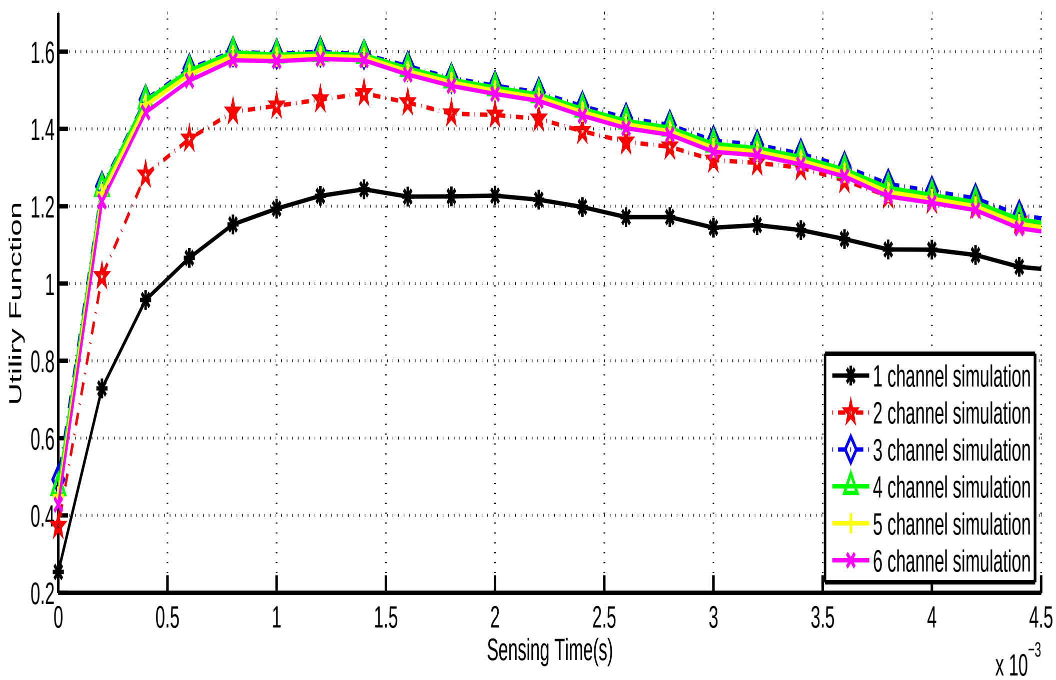


Figure 4.3: Utility function for v=0.6

Figure 4.4 show the utility function for two different values for weighting factor(0.5, 0.4). By comparing the two graphs in the figure with the results in previous graph for the v=0.6, it can be seen that sensing three channels still achieves the highest utility. However, as the weighting factor gets close to the unity, the utility for sensing one and two channels increases which means the power consumption is more important than increasing the throughput.



(a) v=0.5



(b) v=0.4

Figure 4.4: Utility function for different values of v

4.2.4 Comparison of System Throughput with Different Values of Detection Probability

Figure 4.5 shows a comparison between sensing three channels with two different detection probabilities 0.6 and 0.9. It can be seen that optimal sensing time is decreasing as the detection probability decreases. This is related to the fact that the throughput of the system increases proportionally with the low false alarm probability which is, on the other hand, proportional to the detection probability. The graph also shows that when one channel is sensed with detection probability 0.6, the throughput is higher than when detection probability is 0.9. However, when two or three channels are sensed with detection probability set to be 0.9, the throughput is higher compared to the throughput at 0.6 detection probability. This is because when sensing one channel, the SUs with lower detection probability have a lower false alarm probability, hence a higher throughput. In contrast, when sensing more channels sequentially, the probability of sequentially sensing the next channel rises when the value of detection probability is high. Thus, the user has a higher chance to achieve throughput with the (0.9) over the (0.6) detection probability when sensing more than one channel.

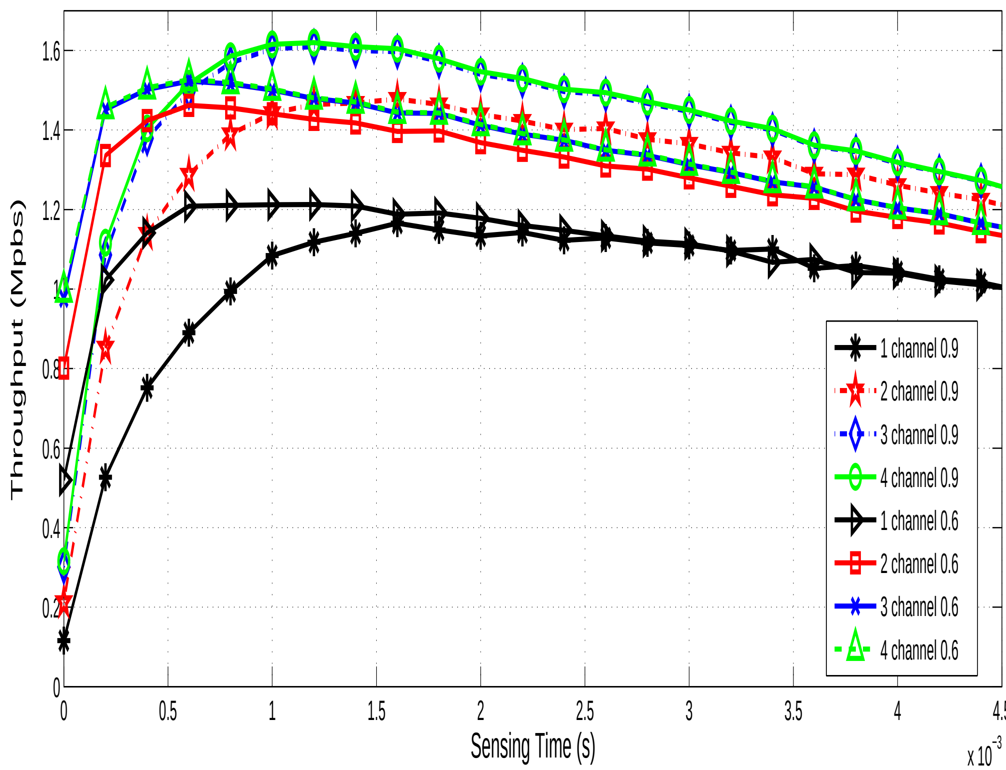


Figure 4.5: A comparison of throughput for two different values of detection probability

4.2.5 System Throughput for Two Cases for Channels Availability

In Figure 4.6, two cases of different channel availability were compared to each other. The availability of these two cases are as follows: case 1 is [0.5 0.4 0.35 0.1 0.05], and case 2 is [0.65 0.60 0.55 0.3 0.1]. It is clear from the graph and also from the availability vector for case 2 that the throughput in case two is higher due to the higher probability vector for these channels. It can be noticed, as well, that the optimal sensing time for each channel decreases as the availability of the channels increases. This is due to the dependency of optimal sensing throughput on the availability of previous and current channels, which is higher in case 2 compared to case 1.

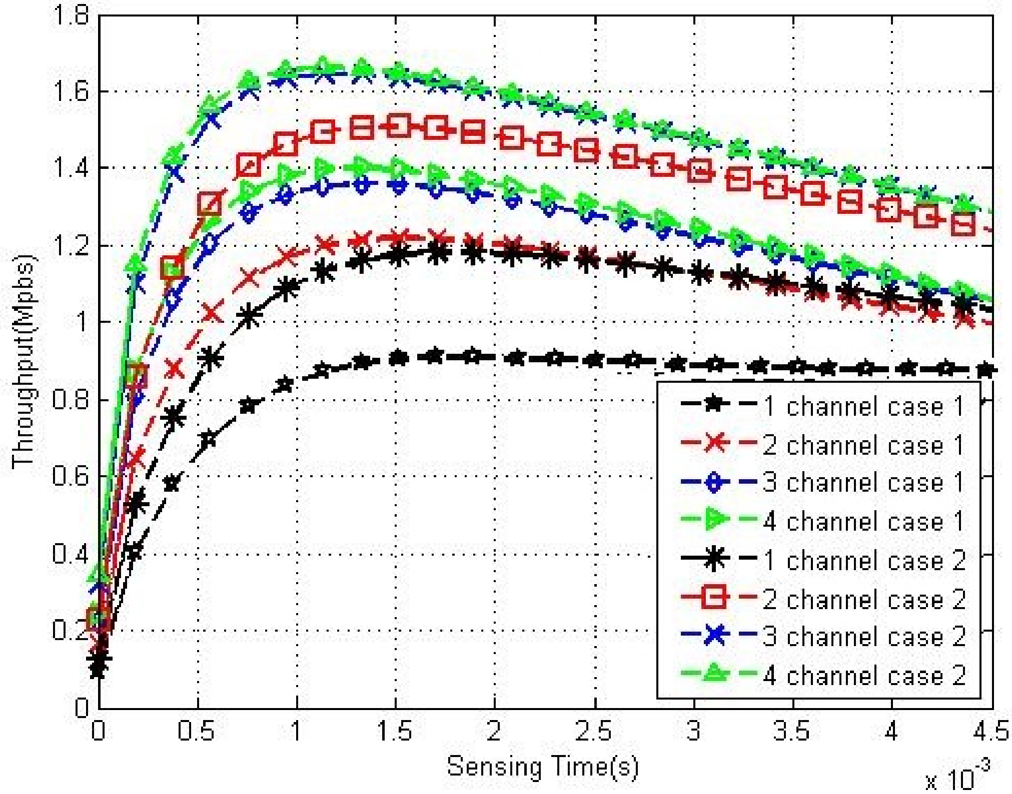


Figure 4.6: A comparison of throughput for two different availability cases of the channels.

Chapter 5

Conclusion

Spectrum sensing is a key enabling feature for Cognitive Radio Networks. Throughout this work, we have investigated the effect of sequential multi-channel sensing on system throughput. We have proposed a general model extending the work that was done in [12]. We have considered multi-channel sensing as opposed to two channels if the first choice channel is sensed as unavailable. Moreover, we have justified the optimal number of channels to be sensed by introducing a utility function which takes into account the tradeoff between the achieved throughput and the power consumption. The results show that sensing more channels can still make SUs increase their throughput effectively up to a certain number of channels. However, increasing the throughput is affected by the allowed amount of power consumption in the system. We have justified using a Utility Function that sensing three channels satisfies the highest Utility compared to one or two channels. To sum up, even though sensing multi-channel can increase throughput to some values, the power consumption is a measure issue that should be taken into consideration.

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