MULTI-CHANNEL COOPERATIVE SPECTRUM SENSING IN COGNITIVE RADIO NETWORKS

A DISSERTATION

Submitted in partial fulfillment of the requirements for the award of the degree of

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By

GAURAV BAFNA

DEPARTMENT OF ELECTRONICS AND COMPUTER ENGINEERING

INDIAN INSTITUTE OF TECHNOLOGY ROORKEE

ROORKEE - 247 667 (INDIA)

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CANDIDATE'S DECLARATION

I hereby declare that the work presented in this dissertation report entitled, **"Multi-Channel Cooperative Spectrum Sensing in Cognitive Radio Networks"**, towards the partial fulfilment of the requirements for the award of the degree of **Integrated Dual Degree** (Bachelor of Technology and Master of Technology) in Electronics and Communication Engineering with specialisation in **Wireless Communication**, submitted in the Department of Electronics and Computer Engineering, Indian Institute of Technology, Roorkee (INDIA), is an authentic record of my own work carried out during the period from May 2011 to June 2012, under the guidance of **Dr. D.K. MEHRA, Professor, Department of Electronics and Computer Engineering, Indian Institute of Technology Roorkee.**

I have not submitted the matter embodied in this dissertation for the award of any other Degree or Diploma.

Date: 11th June, 2012

Place: Roorkee

GAURAV BAFNA

CERTIFICATE

This is to certify that the above statement made by the candidate is correct to the best of my knowledge.

Date: 11.06.2012

Place: Roorkee

Dr. D.K.MEHRA

Professor,

E & C Department,

IIT Roorkee,

Roorkee, 247667 (INDIA)

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ABSTRACT

A cognitive radio by virtue of its ability to sense and adapt to the dynamic spectrum scenario, can increase the spectral efficiency. In order to be non-invasive, a cognitive radio must adhere to strict benchmarks in the quality of spectrum sensing for primary users of a band. Thus, spectrum sensing has a major role to play in cognitive radio. IEEE 802.22, the first standard for cognitive radio devices, imposes strict requirements for the detection and false alarm probability on all spectrum sensing devices at SNR up to -20 dB.

Energy detection is the simplest and near optimum technique that is widely used for spectrum sensing. However, its performance is drastically affected by uncertainty in noise variance due to SNR wall [1]. Energy detection works well in Gaussian noise scenarios, which, however, is not appropriate to be directly utilized in wireless fading environments. To that end, cooperative sensing strategies have been studied to combat the wireless fading in [2], where multiple secondary users (SU) independently detect the licensed primary channel using an energy detector and report their initial detection results to a fusion center (FC). In the past, most of research in cooperative spectrum sensing has focused on single channel systems where all SUs sense the same channel together. However, with the popularity of multi-channel systems, such as the orthogonal frequency division multiplexing (OFDM) systems, improving sensing performance of one channel is not sufficient. It is important to find more channels satisfying the required sensing performance by cooperative spectrum sensing. Thus, the study of multi-channel cooperative spectrum sensing is necessary for cognitive radio (CR) networks.

Multi-band joint detection using a set of narrowband energy detectors using cooperative spectrum sensing is evaluated. This thesis also presents a comparative analysis of multi-channel cooperative spectrum sensing in Rayleigh fading and Gaussian noise environment. Both hard combining and soft combining of data at the fusion centre is considered. Algorithms to determine the optimal sensing time durations have been developed and analysed. The throughput deterioration while going from soft combining to hard combining and from AWGN to Rayleigh Fading environment has been studied.

LIST OF FIGURES AND TABLES

CONTENTS

Chapter 1

Introduction

The usable electromagnetic radio spectrum - a precious natural resource is of limited physical extent. However, wireless devices and applications are increasing daily. It is therefore not surprising that we are facing a difficult situation in wireless communications. Moreover, given the reality that, currently, the licensed part of the radio spectrum is poorly utilized, this situation will only get worse unless we find new practical means for improved utilization of the spectrum. Cognitive radio (CR), a new and novel way of thinking about wireless communications, has the potential to become the solution to the spectrum underutilization problem [3]. Cognitive radio is a paradigm for wireless communication in which either a network or a wireless node changes its transmission or reception parameters to communicate efficiently avoiding interference with licensed or unlicensed users. This alteration of parameters is based on the active monitoring of several factors in the external and internal radio environment, such as radio frequency spectrum, user behaviour and network state.

1.1 Cognitive Radio

Joseph Mitola coined the term 'Software Defined Radio', while pursuing his doctoral dissertation work at KTH Sweden in 1992 [4]. He called these radios up to 80% programmable beyond the antenna output terminals and thus capable of doing RF, IF, baseband and bitstream operations using high speed Analog to Digital to Analog (A/D/A) converters and microprocessors. Subsequently he extended the concept of a Software Radio to 'Cognitive Radio' [3], [5] as follows,

" (A cognitive radio is) a radio frequency transceiver designed to intelligently detect whether a particular segment of the radio spectrum is in use, and to jump into (and out of) the temporarily unused spectrum very rapidly, without interfering with the transmission of other authorized users".

Such an intelligent radio would be able to learn about the network condition and structure. It could detect unused frequency bands and allow unlicensed users to opportunistically access licensed bands without causing any interference to the primary user. This would intuitively improve the spectrum utilization. In the terminology of cognitive radio, users who have not obtained prior permission for accessing a band are referred to as secondary users while the authorized users of a band are called primary users. Studies have suggested that while most frequency bands are licensed to primary users, many of these like military, marine communication, amateur radio etc. remain highly underutilized giving rise to a virtual scarcity in spectrum [6]. Fuelled by such revelations along with exponentially increasing number of wireless devices in the market like cordless telephones, remote surveillance cameras, the interest in cognitive radios has been growing at an amazing pace. Cognitive radios require unlicensed users who want to use the licensed bands opportunistically, to be highly adaptive in their parameters like frequency of operation, modulation technique, power allocation etc.

Haykin [7] states that a Cognitive Radio has to perform three basic tasks as listed below.

(1) Radio-scene analysis: This consists of two main tasks, namely,

- Estimation of interference temperature of the radio environment;
- Detection of spectrum holes.

The interference temperature in a band is a measure of the total RF interference present at the receiver with no primary signal present. This helps define a limit on the maximum interference power a band can accommodate without adversely affecting the primary transmission. Following the measurement of interference temperature, the RF spectrum is categorized as either *white* or *black* depending on whether it is occupied by high power signals or contains only ambient noise signals. This categorization may be performed through many methods such as the MTM-SVD (Multi Taper Method Singular Value Decomposition) [8], energy detection [9], and cyclostationary detection [10]. A *white* spectrum signifies a spectrum opportunity. This task of detecting *spectrum holes* or vacant spaces in the spectrum is called *Spectrum Sensing.*

(2) Channel identification: This consists of the following two tasks, namely,

- Estimation of channel-state information(CSI)

- Prediction of channel capacity for use by the transmitter.

Channel state information can be estimated at the receiver by using pilot transmission or semi-blind approaches. Subsequently the channel coefficients must be tracked at the receiver through a mathematical model such as Kalman or particle filter [11]. The estimate of CSI must be fed back to the transmitter to enable adaptive modulation.

(3) Transmit power control and dynamic spectrum management: Once the spectrum holes have been identified and their CSI estimates are available, a cognitive radio transmitter must choose its transmission bands accordingly and dynamically adjust them as and when the RF scenario changes. It also needs to optimise the transmit power in each band, in sync with the interference temperature limit for that band.

While the first two tasks are performed by the cognitive receiver, the third is performed at the transmitter. Figure 1.1 shows the different stages of cognitive cycle emphasizing the role of a feedback channel from the receiver to transmitter for conveying various channel parameters.

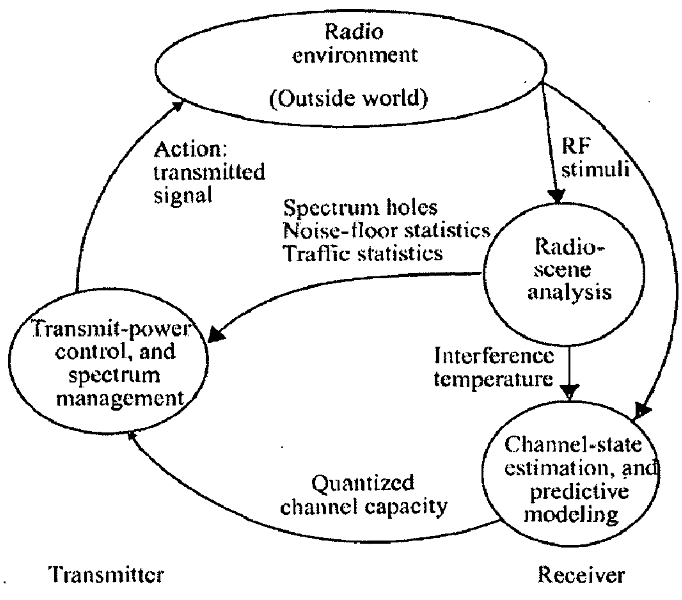

Figure 1.0.1: The cognition cycle [7]

A cognitive radio must be adaptive, reconfigurable, intelligent and flexible enough to detect different kinds of primary transmissions like BPSK, QPSK, and QAM and also switch between them as the channel conditions demand. Because the location of *spectral holes* in frequency and time is continuously changing a cognitive radio must have the ability to selectively transmit on any given set of frequency bands from a wideband range as the primary transmission requires. In this context, OFDM (Orthogonal Frequency Division Multiplexing) is a multi-carrier modulation technique that lends itself naturally to such adaptive modulation. OFDM offers the ability to selectively modulate those subcarriers with data where a spectral hole is currently available while leaving other subcarriers untouched. It is also possible to use *bit-loading* in OFDM by which the bit-rate for a specific subcarrier can be optimised according to its SNR [7]. OFDM has already been adopted as the PHY layer for many kinds of standards eg.DVB, DAB, IEEE 802.11a/g/n WLAN standards and the 802.16 Wi-MAX standard.

Efficient detection of spectrum holes, or spectrum sensing, is currently a major challenge for cognitive radios because of its overarching need in implementing a secondary system without interfering with primary system. Spectrum sensing by far is the most important component for the establishment of cognitive radio.

Spectrum Sensing

Spectrum sensing is thus the task of obtaining awareness about the spectrum usage and existence of primary users in a geographical area. Also parameters related to the radio channel characteristics, availability of spectrum and power, interference and noise temperature, radio's operating environment, user requirements, and applications are important [12]. In CR, the PUs are referred to as those users who have higher priority or legacy rights on the usage of a part of the spectrum. Spectrum sensing is a key element in CR communications, as it enables the CR to adapt to its environment by detecting spectrum holes. The most effective way to detect the availability of some portions of the spectrum is to detect the PUs that are receiving data within the range of a CR. However, it is difficult for the CR to have a direct measurement of a channel between a primary transmitter and receiver. Therefore, most existing spectrum sensing algorithms focus on the detection of the primary transmitted signal based on the local observations of the CR.

Transmissions in licensed bands are normally subjected to interference from adjacent bands, other secondary devices and ultra wideband devices etc. [13]. Additionally, the primary signal may be subjected to fading or shadowing [1] causing its SNR to drop below 0dB. Hence, reliable spectrum sensing at low SNR regimes becomes a necessity. In terms of hardware, this means that a substantial dynamic power detection range of the sensing device should be present to detect both low and high power primary users. There must be a continuous monitoring of the spectrum and fast adaptive capability. This requires wideband and high sampling rate (few Gsps) ADC/DAC's [14] and computationally fast DSP/FPGA's. Some of the commercially available hardware and software platforms for the cognitive radio are the GNU Radio [15], Universal Software Radio Peripheral (USRP) [16] and Shared Spectrum's XG Radio [17].

1.2 SPECTRUM SENSING TECHNIQUES

Energy detection and cyclostationary detection are mainly used for narrowband sensing ,while for wideband sensing compressed sensing [18] is used. Other techniques include Matched-filtering [19] when the transmitted signal is known and Radio Identification Based Sensing in which spectrum characteristics can be obtained by identifying the transmission technologies used by primary users. Such identification enables cognitive radio with a higher dimensional knowledge as well as providing higher accuracy [13]. Waveform-Based Sensing is used when preambles, midambles, regularly transmitted pilot patterns, spreading sequences etc, which are the known patterns to assist synchronization are utilized for sensing.

Energy Detection

Energy detection based approach, also known as radiometry or periodogram, is the most common way of spectrum sensing because of its low computational and implementation complexity. It calculates the energy of the signal in the band of interest and compares it with a threshold to determine the presence or absence of the PU. In addition, it is more widely applicable as receivers do not need any knowledge on the primary users' signal. It is discussed in detail in later Chapter.

Cyclostationary Detection

Most man-made signals show periodic patterns related to symbol rate, chip rate, channel code or cyclic prefix, that can be appropriately modelled as a cyclostationary random process. A discrete-time zero-mean stochastic process $x(t)$ is said to be second-order cyclostationary if with a period T (T being a positive integer) if it's mean is periodic,

$$E\{x(t+lT)\} = E\{x(t)\}, \qquad \forall t, l \in I \tag{1.1}$$

where I denotes the set of integers and its autocorrelation $R_{xx}(t,\tau)=\mathrm{E}\{x(t+\tau/2)x^*(t-\tau/2)\}$ is periodic such that t.

$$R_{xx}(t+lT,\tau)=R_{xx}(t,\tau) \qquad \forall t,\tau,l\in I \tag{1.2}$$

Since the autocorrelation function $R_{xx}(t,\tau)$ is periodic in the variable t, its discrete Fourier series coefficient can be expressed as

$$R_{xx}^{\alpha}(\tau)=\langle x(t+\tau/2)x^*(t-\tau/2)\mathrm{e}^{-j2\pi\alpha t}\rangle \tag{1.3}$$

where the $\langle\cdot\rangle$ operation denotes time averaging as $\langle y\rangle=\lim_{Z\to\infty}\frac{1}{2}\sum_{l=-Z}^{Z}y(l)$. The Fourier series coefficient $R_{xx}^{\alpha}(\tau)$ is called the *Cyclic Autocorrelation Function (CAF)* and α is the cycle frequency. In case of a discrete signal, the $R_{xx}^{\alpha}(\tau)$ can be written as

$$R_{xx}^{\alpha}(\tau)=\frac{1}{N}\sum_{l=\tau}^{N+\tau-1}x(l)x^*(l-\tau)e^{-i2\pi\alpha lT_s} \tag{1.4}$$

Where T_s is the sampling time and N is the total number of samples of $x(n)$. The process $x(t)$ is said to be cyclostationary if there exists an α such that $R_{xx}^{\alpha}(T)>0$.

The *cyclic spectrum* of the signal $x(t)$ is the Fourier coefficient

$$S_x(\alpha,\omega)=\sum_{T}R_{xx}^{\alpha}(T)e^{-j\omega t} \tag{1.5}$$

The cyclic spectrum is the density of correlation for cyclic frequency α . Knowing these cyclic characteristics of a signal, Gardner in [20] proposed detectors that exploit the cyclostationarity of the signal.

Cyclostationary feature detection is robust to noise uncertainties and performs better than energy detection in low SNR regions. Although it requires a priori knowledge of the signal characteristics, cyclostationary feature detection is capable of distinguishing the CR transmissions from various types of PU signals [9]. This eliminates the synchronization requirement of energy detection in cooperative sensing. Moreover, CR users may not be required to keep silent during cooperative sensing and thus improving the overall CR throughput. This method has its own shortcomings owing to its high computational complexity and long sensing time. Due to these issues, this detection method is less common than energy detection in cooperative sensing.

1.3 Cooperative Spectrum Sensing:

The critical challenging issue in spectrum sensing is the hidden terminal problem, which occurs when the CR is shadowed or in severe multipath fading or is faced with receiver uncertainty problem. Fig. 1.2 shows that CR 3 is shadowed by a high building over the sensing channel. In this case, the CR cannot sense the presence of the primary user, and thus it is allowed to access the channel while the PU is still in operation. To address this issue, multiple CRs can be designed to collaborate in spectrum sensing [12]. In a heavily shadowed/fading environment collaborative spectrum sensing can be used to greatly enhance the performance [1].

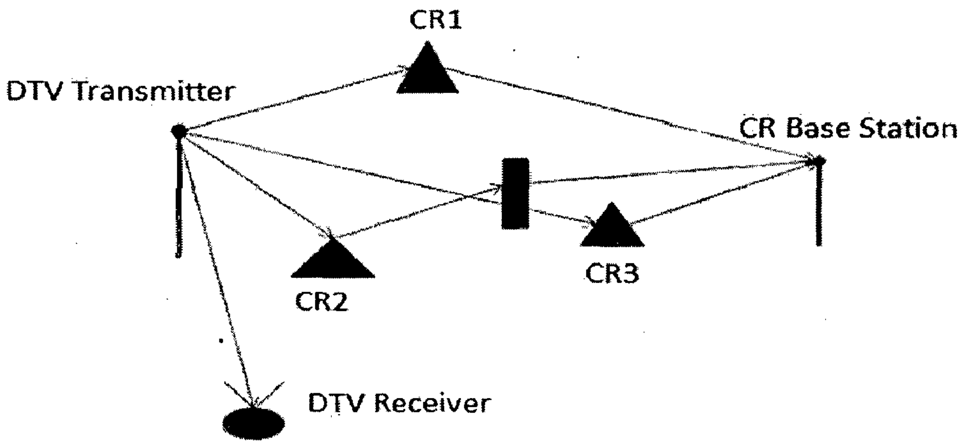

Figure 1.2 : Cooperative spectrum sensing CR 3 is shadowed over the reporting channel and CR 2 is shadowed over the sensing channel.

The main idea of cooperative sensing is to enhance the sensing performance by exploiting the spatial diversity in the observations of spatially located CR users. By cooperation, CR users can share their sensing information for making a combined decision more accurate than the individual decisions .The performance improvement due to spatial diversity is called cooperative gain. The cooperative gain can be also viewed from the perspective of sensing hardware. Owing to multipath fading and shadowing, the signal-to-noise ratio (SNR) of the received primary signal can be extremely small and the detection of which becomes a difficult task. To have capability of detecting weak signals, strict sensitivity requirement will be imposed on the receiver thus greatly increasing the implementation complexity and the associated hardware cost. Fortunately, the sensitivity requirement and the hardware limitation issues can be considerably relieved by cooperative sensing.

Cooperative spectrum sensing is of three types based on how cooperating CR users share the sensing data in the network: centralized, distributed and relay based external sensing [21]. These three types of cooperative sensing are illustrated in Figure.1.3

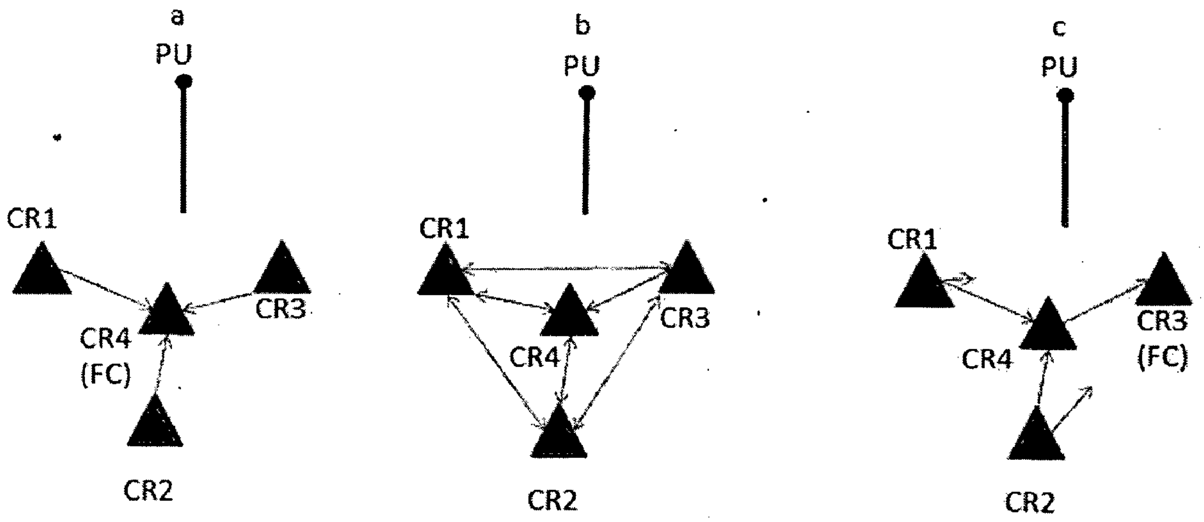

Figure 1.3 Classification of cooperative sensing: (a) centralized, (b) distributed, and (c) relay-assisted.

In centralized cooperative sensing, a central identity called fusion centre (FC) selects a channel or a frequency band of interest for sensing and instructs all cooperating CR users to individually perform local sensing. Second, all cooperating CR users report their sensing results via the control channel. Then the FC combines the received local sensing information, determines the presence of PUs, and diffuses the decision back to cooperating CR users. Distributed cooperative sensing does not rely on a FC for making the cooperative decision. In this case, CR users communicate among themselves and converge to a unified decision on the presence or absence of PUs by iterations. With Relay-assisted cooperative sensing when both sensing channel and report channel are not perfect, a CR user observing a weak sensing channel and a strong report channel and a CR user with a strong sensing channel and a weak report channel, for example, can complement and cooperate with each other to improve the performance of cooperative sensing.

Elements of cooperative spectrum sensing

Conventional cooperative sensing is generally considered as a three-step process: local sensing, reporting, and data fusion. We call these fundamental and yet essential components as the elements of cooperative sensing. The process of cooperative sensing is presented and analysed by four key elements: (i) cooperation models, (ii) sensing techniques, (ii) hypothesis testing (iii) control channel and reporting, (iv) data fusion. Cooperation models concerns how CR users cooperate to perform spectrum sensing and achieve the optimal detection performance. The most popular approach originated from the parallel fusion (PF) model in distributed detection and data fusion [22]. Statistical hypothesis testing is typically performed to test the sensing results for the binary decision on the presence of Primary users (PU). A common control channel (CCC) is commonly used by CR users to report local sensing data to the FC or share the sensing results with neighboring nodes. Finally data fusion is a process of combining local sensing data for hypothesis testing.

1.4 Multi-Channel Cooperative Spectrum Sensing

Most of the works in Cooperative Spectrum Sensing use either one or multiple SUs to perform sensing on a single channel in one sensing period. During each sensing period, only one channel could be detected, and the detection of other channels is not allowed. The cooperation among several SUs is expected to improve the sensing accuracy of the sensed single channel. However, the strategy on sensing a single channel by one SU or several SUs simultaneously may largely limit the sensing efficiency. Xie in [23] proposed parallel cooperative spectrum sensing in which every SU scans a different channel. To improve the sensing performance, multi-channel spectrum sensing done with Cooperation was proposed by [24].

Fan and Jiang in [24] considers an optimization problem which maximizes the throughput of secondary users while keeping detection probability for each channel above a pre-defined threshold. He determined the total sensing time and how to distribute the total sensing time to different channels in cooperative soft-decision spectrum sensing. Two sensing modes were analyzed: slotted time sensing mode and continuous time sensing method. In each time slot, the first portion is used for spectrum sensing, and the second portion is used for packet transmission (if the channel is detected idle).

Fan and Jiang in their other work [25] formulated and addressed jointly the sensing duration timing and resource allocation problem. Unlike in previous work [24] here the secondary user has a variable transmission power and rate for every PU. After determination of spectral holes, each secondary user is allocated portion of the channel with the power level assigned for the SU-PU pair. Maintaining the average transmission power, maximal instantaneous power of the secondary transmitter and the interference on every channel under constraint, the throughput is maximized solving the non-convex problem using bi-level optimization and monotonic programming method. For energy constrained CRN, optimal multi-channel strategy was suggested by Yu [26]. The sensing time was determined to maximize the throughput keeping the energy consumption within constraints.

Wang et al. in [27] proposed the channel assignment in Cooperative Spectrum Sensing (CSS) by heuristic centralized scheme to increase the number of available channels satisfying the sensing performance requirement. In one scheme signal to noise ratio (SNRs) over all channels from each SU are reported to the Fusion Centre (FC). The FC then applies the heuristic scheme to form coalitions for every SU. FC will broadcast the assignment results to all SUs. Also, to reduce the communication overhead (information from each secondary user, e.g. primary signal-to-noise ratios), a greedy centralized scheme was proposed by allowing each SU report SNRs of a few system channels. The idea is to assign the channel to the SU having the higher SNR.

In [28], each secondary user chooses an Ideal-Soliton-Distributed number of channels to sense, and then do energy detection and partial detection results are then passed to a fusion centre. FC generates a tanner graph with the sensing information received and judges whether the number of sensing results is not smaller than the number of channels. The fusion center compute the log-likelihood ratio of the activity of each channel according to the belief propagation algorithm and compares them with the defined threshold .A heuristic method to release the detected channels from the whole spectrum bands was also proposed to reduce the sensing complexity.

In [29], secondary users sense one channel at a time and send data to the FC. SU keeps the history of previous channel sensing in a vector form. Every channel sensing that finds an empty channel increases the corresponding probability for that channel and every channel sensing that finds a busy channel decreases that probability. After FC receives vectors, it determines the best channel that each SU should sense. He used bipartite matching from the graph theory for this optimal channel allocation.

In [30], the secondary users sense different channels, and some of these may also sense the same channel cooperatively. The Iterative Hungarian Algorithm based strategy aiming at the optimization of the sensing performance by minimizing the overall probability of misdetection for fixed probability of false alarm is used.

For non-infrastructure based cognitive radio networks coalitional game theory was proposed by [31], for cooperative multi-channel spectrum sensing for the. Each SU can only sense some primary channels (PCs), due to the hardware and energy consumption constraints. In the scheme, a multi-channel coalition game is played among SUs so that multiple coalitions are formed for each channel. Then, the coalition with the highest coalition value is selected to sense the corresponding channel.

For multiband joint detection, Quan et al. [32] proposes a framework for wideband sensing in a single CR using a bank of narrowband detectors. Given constrained interference to the primary communication system, Paysarvi et al. [33], formulated the sensing problem as a joint optimization of the sensing slot duration and individual narrowband detectors. The optimization problem has been proved to be convex in certain practical constraints.

1.5 Problem Statement

Robust spectrum sensing at low SNR is a necessity that the signal energy detector cannot achieve due to fading and noise uncertainty. Cooperative detection must be done to overcome the limitations of energy detection over multiple channels. This dissertation work aims to consider the following.

- Channel assignment for secondary users and determination of sensing time in Multi-channel cooperative spectrum sensing in Rayleigh fading channels. Both Hard combining as well as Soft combining of data sent to the Fusion Centre are considered.

- Comparison of throughput of Multi-channel cooperative spectrum sensing in Rayleigh and additive white Gaussian noise channels.
- Joint optimal detection of multi-band using cooperating narrowband energy detectors

1.6 Organisation of the report

In Chapter 2, joint optimal detection of multi-band by cooperating narrowband energy detectors is investigated. Given the total interference on a wideband channel, throughput is maximized by using many narrowband energy detectors.

Chapter 3 provides the problem formulation of multi-channel cooperative spectrum sensing in Rayleigh fading channels. It presents the iterative algorithm to achieve sub optimal throughput for the given interference constraint. The results are compared in Rayleigh fading channels and additive white Gaussian noise environment.

Chapter 4 discusses the case in which hard combining of the statistics are done at the fusion centre. Channel assignment and sensing time are determined for the same. The throughput obtained with this algorithm is compared with the results obtained by soft combining and using algorithm proposed in Chapter 3. A Channel selection strategy is also proposed which selects the channels based on their throughput.

Chapter 5 presents the conclusion of the thesis.

Chapter 2

Multiband Joint Detection

Joint optimal detection framework for multiband sensing using cooperating narrowband energy detectors is considered in this Chapter. The spectrum sensing problem is formulated as a class of optimization problem, which maximize the aggregated opportunistic throughput of a cognitive radio system under some constraints on the interference to the wideband channel of a primary communication system. We propose to do cooperative spectrum sensing in a parallel way on multi-band such that sensing is done with sufficient accuracy on every channel .Enough secondary user scan a channel cooperatively to give probability of detection high and of false alarm low . Since we have many SU available out of which only some of the SUs scan one channel, many channels can now be scanned simultaneously which is termed as parallel spectrum sensing [23]. Section 2.1 discusses the system model followed by energy detection technique. The multiband joint detection framework is then formulated and simulation results are presented to show the performance of the proposed scheme.

Multiband joint detection (MJD) framework for wideband sensing was proposed in [32] where the decisions are jointly made over multiple frequency bands. In the MJD framework, a set of individual secondary detectors are optimized so as to enhance the cognitive radio performance while protecting the primary network from harmful interference. The sensing is done over all detectors simultaneously in a single CR. The situation in which individual cognitive radios might not be able to reliably detect weak primary signals due to channel fading/shadowing is also considered. Exploiting the spatial diversity, a cooperative wideband spectrum sensing scheme spatial-spectral joint detection was proposed, which did linear combination of the local statistics from multiple spatially distributed cognitive radios [32].

Paysarvi in his thesis [34] extended the above work by adding periodic sensing to the system model. In a case in which the amount of time used for sensing is a design parameter, unlike in [32], the sensing problem was formulated as a joint optimization of the sensing slot duration and individual narrowband detectors, in which he optimized the secondary network sensing performance in an interference limited primary network. For the cases in which cost/priority coefficient of different bands are difficult to determine, a decoupled sequential multi-channel joint detection framework has been proposed. In this the probability of interference on each channel is limited independently for this case, making the individual channels partially decoupled. A low-complexity algorithm which quickly and efficiently solves the formulated optimization problem has been designed. The complexity of the algorithm will be of particular interest when implementing a practical wideband spectrum sensing system.

2.1 System Model

A group of secondary users is assumed to form a single-hop wireless sensor network (WSN) within the transmission range of which there are no other secondary network (SN) interfering or cooperating with that SN. These WSN consist of SUs which are typically constrained in size and cost which, in turn, leads to a severe limitation of the available energy resources and computational power. The tasks of the SU include periodic or event triggered transmission of sampled and pre-processed sensor data to a central node where the data is collected and further processed. In WSNs longer distances between a sensor node and the receiving central processing node are normally spanned by using multi hop routing. In our case, the distances are shorter; hence it is a single hop WSN. Every secondary user in the secondary network is assumed to be equipped with a single antenna. Each secondary user works as a transceiver, as well as a sensor in its secondary network. The secondary user uses energy detection for spectrum sensing.

Consider a primary communication system (e.g., multicarrier modulation based) operating over a wideband channel that is divided into N non overlapping narrowband subbands. This can be done using the Orthogonal Frequency Division Multiplexing (OFDM) technique with adaptive and selective allocation of OFDM subcarriers to utilize any subset of N licensed channels at the same time. In a particular geographical region and within a particular time interval, some of the subbands might not be used by the primary users and are available for opportunistic spectrum access. OFDM modems employ a set of subcarriers in order to transmit information symbols in parallel in so-called sub channels over the channel. Since the system's data throughput is the sum of all the parallel channels' throughputs, the data rate per sub channel is only a fraction of the data rate of a conventional single-carrier system having the same throughput. This allows us to design a system supporting high data rates while maintaining symbol durations much longer than the channel's memory, thus circumventing the need for channel equalization.

We model the detection problem on sub band as one of choosing between a hypothesis ("0"), which represents the absence of primary signals, and an alternate hypothesis ("1"), which represents the presence of primary signals. An example where primary users have occupied only some of the bands is depicted in Figure 2.1. The underlying hypothesis vector is a binary representation of the subbands that are allowed for or prohibited from opportunistic spectrum access.

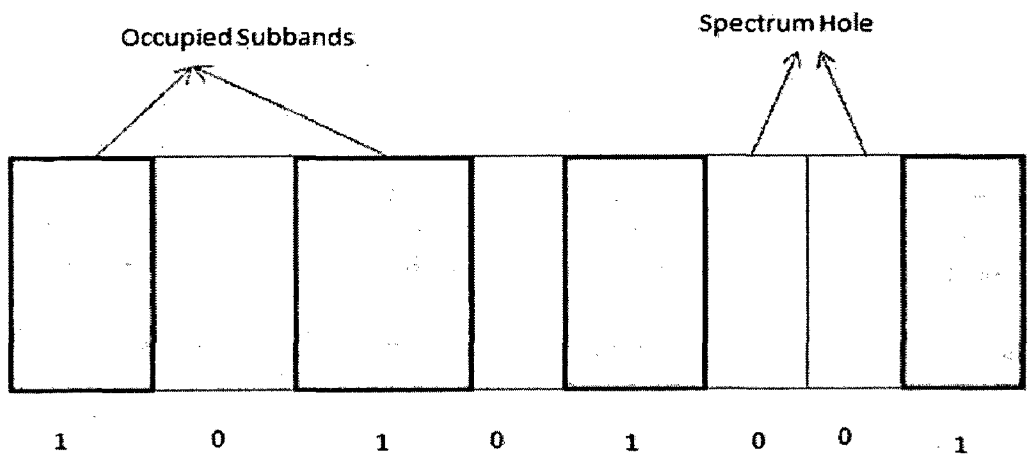

Figure 2.1: Schematic illustration of the occupancy of a multiband channel

The crucial task of spectrum sensing is to sense the subbands and identify spectral holes for opportunistic use. For simplicity, we assume that the upper-layer protocols, e.g., the medium access control (MAC) layer, can guarantee that all cognitive radios do not transmit during the detection interval such that the only spectral power remaining in the air is radiated out by the primary users. In this chapter, we propose to use a multiband joint detection technique, which jointly takes into account the detection of primary users across multiple frequency bands. Multiple band joint detection starts at energy detection at individual SU. Following section discusses in detail this sensing method.

2.2 Energy Detection

Energy detection is the simplest technique in terms of implementation complexity. It detects the presence of a signal by measuring the total incumbent energy in the band of interest and comparing it to a predefined threshold. This threshold must be decided in a manner, so as to limit the false alarm rate, and it can be set independent of the transmitted signal energy. Once the noise and signal variance are known, the problem of spectrum sensing can be formulated as a binary hypothesis testing problem. Using the complex baseband model of bandpass signal transmission, the received and transmitted signals are represented by their complex low-pass equivalents. The two hypotheses may be formulated as follows:

$$\begin{aligned} H_0 &: y[i] = w[i] \\ H_1 &: y[i] = s[i] + w[i] \end{aligned} \tag{2.1}$$

where $y[i]$ is the received sample, $w[i]$ is an AWGN sample with variance σ_w^2 and $s[i]$ is the transmitted signal value. At the receiver the test statistic used is defined as the energy of P received samples.

$$\begin{aligned} E &= \sum_{i=1}^{P} |y[i]|^2 \\ &= \sum_{i=1}^{P} |y_R[i]|^2 + |y_I[i]|^2 \end{aligned} \tag{2.2}$$

where P is the number of complex observation samples and $y_R[i]$ & $y_I[i]$ denote the real and imaginary parts of $y[i]$ each having a variance of $\sigma_w^2/2$. Under both the hypotheses, the test statistic E is a sum of squares of 2P real Gaussian random variables with the equal variance. Hence the distribution of the random variable E is the chi-square distribution with a non-centrality parameter=0 under H_0 and 2γ under H_1.

$$\mathrm{E} = \begin{cases} \chi_{2N}^2 & ,\mathrm{H}_0 \\ \chi_{2N}^2(2\gamma) & ,\mathrm{H}_1 \end{cases} \tag{2.3}$$

where γ is the average SNR given by $\gamma = S/\sigma_w{}^2$ & $S = 1/P \sum_{i=1}^{P} |s[i]|^2$. The probability of detection and false alarm are defined as,

$$\begin{aligned} P_f &= \Pr\{E > \varepsilon \mid H_0\} \\ P_d &= \Pr\{E > \varepsilon \mid H_1\} \end{aligned} \tag{2.4}$$

There are two ways of obtaining closed form expressions for these probabilities. The first, which is through direct integration of the chi-square distribution over the tail of the distribution function giving us the following results [35],

$$P_f = \frac{\Gamma(P, \lambda/2)}{\Gamma(P, 0)}$$

$$P_d = Q_P(\sqrt{2\gamma}, \sqrt{\lambda}) \tag{2.5}$$

Q(.) is defined as

$$Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^{\infty} \exp(-\frac{z^2}{2}) dz \tag{2.6}$$

Another way of computing the probabilities in (2.4) is through application of the Central Limit theorem assuming that the number of samples in question (P) is high, in which case the resultant distribution becomes normal and hence expressions for P_d and P_f can be obtained by finding the area under the Gaussian tail for which standard expression are available in terms of Q-function [36].

$$P_f = Q\left(\frac{\lambda - P\sigma_w^2}{\sqrt{\sigma_w^4 P}}\right)$$

$$P_d = Q\left(\frac{\lambda - 2P(\frac{\sigma_w^2}{2} + S)}{(\frac{\sigma_w^2}{2} + S)\sqrt{4P}}\right) \tag{2.7}$$

Energy detector can be implemented by first passing the signal through band-pass filter and calculating the energy as shown in Figure 2.2. The input band-pass filter selects the centre frequency, *fs*, and bandwidth of interest. This filter is followed by a squaring device to measure the received energy and an integrator which determines the observation interval, *T*. Finally, output of the integrator, *Y*,is compared with a threshold, λ, to decide whether signal is present or absent as shown by Figure 2.2.

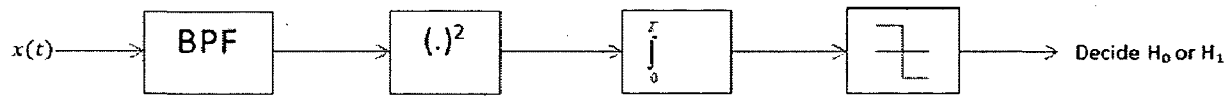

Figure 2.2: Block Diagram of an Energy Detector

Some of the challenges with energy detector based sensing include selection of this threshold which varies highly with noise, inability to differentiate interference from primary users and noise and poor performance under low signal-to-noise ratio (SNR) values and in shadowing/fading environments [2].

The threshold used in energy detector based sensing algorithms depends on the noise variance. Consequently, a small noise power estimation error causes significant performance loss. A nominal value of noise power uncertainty is ± 1dB [1]. This uncertainty leads to drastic drop in detection performance of the radiometer and renders it incapable of reliably detecting the signal below a SNR threshold called the SNR wall. Below the SNR wall, no matter how large the sensing time, the detection probability does not improve. This nature of energy detector can be characterized theoretically, as under noise uncertainty of x dB where $x = 10\log_{10}\rho$ the detection and false alarm probabilities of equation (2.7) can be modified as follows [1]

$$P_f = \max_{\sigma_w^2 \in \frac{\sigma_w^2}{\rho}, \sigma_w^2 \rho} Q\left(\frac{\varepsilon - P\sigma_w^2}{\sqrt{P\sigma_w^4}}\right)$$

$$= Q\left(\frac{\varepsilon - P\rho\sigma_w^2}{\sqrt{\rho^2 P\sigma_w^4}}\right)$$

$$P_d = \max_{\sigma_w^2 \in \frac{\sigma_w^2}{\rho}, \sigma_w^2 \rho} Q\left(\frac{\varepsilon - 2P(\sigma_w^2/2 + S)}{(\sigma_w^2/2 + S)\sqrt{4P}}\right)$$

$$= Q\left(\frac{\varepsilon - 2P\left(\frac{\sigma_w^2}{2\rho} + S\right)}{\left(\frac{\sigma_w^2}{2\rho} + S\right)\sqrt{4P}}\right) \quad (2.8)$$

2.3 Signal Detection on Individual Sensor

To decide whether the n^{th} subband is occupied or not, we test the following binary hypotheses at every individual sensor.

$$
\begin{aligned}
&H_n^0 : y_n(i) = w_n(i) \\
&H_n^1 : y_n(i) = s_n(i) + w_n(i)
\end{aligned}
\tag{2.9}
$$

where y_n is the secondary received signal , s_n is the primary transmitted signal and w_n is the noise . For a subband n, we compute the summary statistic as the sum of received signal energy over an interval of P samples,

$$
Y_n = \sum_{i=1}^{P} \left| y_n(i) \right|^2 \tag{2.10}
$$

The overall test statistic is compared with a threshold ε_n .The primary user in band n is estimated to be idle if all $Y_n \le \varepsilon_n$, or busy otherwise. Here ε_n is the decision threshold of subband.

Using the central limit theorem for large P, the statistics are approximately normally distributed [36] with statistics

$$
\begin{aligned}
&H_n^0 : E[Y_n] = P\sigma^2 \\
&H_n^1 : E[Y_n] = P(\sigma^2 + |s_n|^2)
\end{aligned}
\tag{2.11}
$$

$$
\begin{aligned}
&H_n^0 : Var(Y_n) = 2P\sigma^4 \\
&H_n^1 : Var(Y_n) = 2P(\sigma^2 + 2|s_n|^2)\sigma^2
\end{aligned}
\tag{2.12}
$$

Thus, we can write these approximate statistics compactly as $Y_n \sim \mathrm{N}(E(Y_n), Var(Y_n))$. Using the decision rule, the probabilities of false alarm and detection in the n$^{\text{th}}$subband can be approximately expressed as

$$
P_n^f(\varepsilon_n) = \Pr(Y_n > \varepsilon_n \mid H_n^0) = Q(\frac{\varepsilon_n - P\sigma^2}{\sigma^2\sqrt{2P}}) \tag{2.13}
$$

$$P_n^d(\varepsilon_n) = \Pr(Y_n > \varepsilon_n \mid H_n^1) = Q\left(\frac{\varepsilon_n - P(\sigma^2 + |s_n|^2)}{\sigma^2\sqrt{2P(\sigma^2 + 2|s_n|^2)}}\right) \tag{2.14}$$

The signal to noise ratio of such an energy detector is defined as $\mathrm{SNR} = |s_n(i)|^2 / \sigma^2$, which plays an important role in determining the detection performance. The choice of the threshold ε_n leads to a tradeoff between the probability of false alarm and the probability of missed detection, $P_n^m(\varepsilon_n) = 1 - P_n^d(\varepsilon_n)$. Specifically, a higher threshold will result in a smaller probability of false alarm, but a larger probability of miss detection, and vice versa.

For simplicity, we assume that the transmitted signal in each subband has unit power, i.e. $\mathrm{E}[|s_n(i)|^2] = 1$. However, multiband joint detection algorithm does not rely on this assumption while only the knowledge of the received signal power and noise power is required.

The probabilities of false alarm and miss detection have unique significance for CR networks. Low probabilities of false alarm are necessary to maintain high spectral usage in CR systems, since a false alarm would prevent the unused spectral parts from being accessed by secondary users. On the other hand, the probability of missed detection measures the interference of secondary users to the primary users, which should be limited in opportunistic spectrum access. These implications are based on an assumption that if primary signals are detected, the secondary users will not use the corresponding channel, and if no primary signals are detected, then the corresponding frequency band will be used by secondary users.

2.4 Parallel Multiband detection

In the proposed centralized parallel cooperative sensing, a central identity called the fusion centre controls the three-step process of parallel cooperative sensing. First, the FC selects a wideband channel which is divided into set of narrow non overlapping frequency bands of interest for sensing. It then determines the number of SUs and the decision threshold for every band and instructs all cooperating CR users (SU) to individually perform local sensing on a channel selected for that SU and also the probability of false alarm or decision threshold used for that channel. Second, all the SU performs local sensing and take local decisions according to the signal statistic and the decision threshold. Third, all cooperating CR users report their sensing decisions via the control channel. Then the FC combines the received local sensing decision, applies the majority voting rule to determine the presence of PUs, and diffuses the decision back to cooperating CR users.

The design objective is to find the optimal number of SUs on all the subbands represented as vector $k=[k_1,k_2......k_N]^T$ and optimal threshold vector $\varepsilon=[\varepsilon_1,\varepsilon_2......\varepsilon_N]^T$, so that the cognitive radio system can make efficient use of the unused spectral segments without causing harmful interference to the primary users. Here N is the total number of subbands and k_n and ϵ_n number of SUs and the threshold for n^{th} subband respectively. For a given threshold vector and number of sensors vector, the probabilities of false alarm and detection can be compactly represented as

$$P^f(\varepsilon,k)=[P_1^f(\varepsilon_1,k_1),P_2^f(\varepsilon_2,k_2)......P_N^f(\varepsilon_N,k_N)]^T$$

$$P^d(\varepsilon,k)=[P_1^d(\varepsilon_1,k_1),P_2^d(\varepsilon_2,k_2)......P_N^d(\varepsilon_N,k_N)]^T \tag{2.15}$$

Similarly, the probabilities of missed detection can be written in a vector form as

$$P^m(\varepsilon,k)=[P_1^m(\varepsilon_1,k_1),P_2^m(\varepsilon_2,k_2)......P_N^m(\varepsilon_N,k_N)]^T \tag{2.16}$$

It is assumed that the primary user is sufficiently far away from both the secondary users and the FC [37]. Under this condition, the signal power received by every SU is approximately equal for a given band. Therefore, the received signal-to-noise ratio (SNR) is the same for each narrow subband for all SU. Also the noise is assumed to be independent additive white Gaussian noise (AWGN). The noise power is constant for every SU.

For every band, the majority voting rule is used at the FC to decide the presence of primary user. Both false alarm and detection would occur on n^{th} subband having k_n SUs scanning it if number of SUs sending '1' as their decision is greater than or equal to $\lceil k_n/2 \rceil$. Accordingly we can write the probability of false alarm and detection for every band as

$$P_n^f(\varepsilon_n,k_n)=\sum_{i=\lceil k_n/2\rceil}^{k_n} C_i^n(P_n^f(\varepsilon_n))^i(1-P_n^f(\varepsilon_n))^{k_n-i} \tag{2.17}$$

$$P_n^d(\varepsilon_n,k_n)=\sum_{i=\lceil k_n/2\rceil}^{k_n} C_i^n (P_n^d(\varepsilon_n))^i (1-P_n^d(\varepsilon_n))^{k_n-i} \tag{2.18}$$

Consider a CR device sensing the narrowband subbands to make use of the unused spectrum for opportunistic transmission. Let r_n denote the throughput achievable over the n^{th} subband if used by secondary users, and $r=[r_1,r_2.....r_N]^T$. If the received power at the secondary users are known, r can be estimated using the Shannon capacity formula. Since $(1-P_n^d(\varepsilon_n,k_n))$ measures the opportunistic spectral utilization of subband, the aggregate opportunistic throughput of the CR system can be defined as in [32] as

$$R(\varepsilon,k)=r^T[1-P_f(\varepsilon,k)] \tag{2.19}$$

which is a function of the threshold vector ε and number of sensors vector k. Due to the inherent trade-off between $P_n^f(\varepsilon_n,k_n)$ and $P_n^d(\varepsilon_n,k_n)$, maximizing the sum rate $R(\varepsilon,k)$ will result in large $P_n^m(\varepsilon_n,k_n)$, hence causing harmful interference to primary users.

However, the interference to primary users should be confined in a CR network. For a wideband primary communication system, the effect of interference induced by CR devices can be characterized by a relative priority factor for each primary user transmitting over the corresponding subbands, i.e., $c=[c_1,c_2.....c_N]^T$, where c_n indicates the cost incurred if the primary user in subband n is interfered with. Alternatively c_n can be defined as a function of the bandwidth of n^{th} subband since in some applications each particular subband does not have to occupy an equal amount of bandwidth as in Figure 2.1.

The aggregate interference to primary user can be written as

$$\sum_{n=1}^{N} c_n P_n^m(\varepsilon_n,k_n) \tag{2.20}$$

Our objective is to find the optimal thresholds $\{\varepsilon_n\}_{n=1}^N$ and optimal number of ED's $\{k_n\}_{n=1}^N$ for N subbands in order to collectively maximize the aggregate opportunistic throughput subject to total interference constraints for all narrow bands. Also there should be constraint which limits the interference in each subband with $\alpha = [\alpha_1, \alpha_2 ... \alpha_N]^T$, and the constraint which dictates that each subband should be able to achieve a minimum opportunistic spectral utilization given by $[1-\beta_1, 1-\beta_2 ... 1-\beta_N]^T$.

The opportunistic rate optimization problem can be formulated as [32]

$$\begin{aligned}
&\max_{\varepsilon,k} \; R(\varepsilon,k) \\
&\text{s.t} \sum_{n=1}^{N} c_i P_n^m(\varepsilon_n, k_n) \le \varepsilon \\
&P^m(\varepsilon,k) \le \alpha \\
&P^f(\varepsilon,k) \le \beta
\end{aligned} \tag{2.21}$$

The optimization problem (2.21) assumes the form of minimizing a convex function subject to a convex constraint, and thus the local optimum is also the global optimum.

A function is said to be convex if for any two points $x, y \in \Re$, if

$$f(\theta x + (1-\theta)y) \le \theta f(x) + (1-\theta) f(y), \qquad \forall \theta \in [0,1] \tag{2.22}$$

Geometrically, this means that, when restricted over the line segment joining and, the linear function joining x and y, the linear function joining $(x, f(x))$ and $(y, f(y))$ always dominates the function f.

It can be easily shown that the function $P_n^f(\varepsilon_n, k_n)$ in (2.15) is convex in ε_n if $P_n^f(\varepsilon_n, k_n) \le 1/2$

Differentiating $P_n^f(\varepsilon_n, k_n)$ twice we get,

$$\frac{d^2 P_n^f(\varepsilon_n,k_n)}{d\varepsilon_n^2} = \frac{d^2 P_n^f(\varepsilon_n,k_n)}{dP_n^{f^2}(\varepsilon_n)} \times \left(\frac{dP_n^f(\varepsilon_n)}{d\varepsilon_n}\right)^2 + \frac{dP_n^f(\varepsilon_n,k_n)}{dP_n^f(\varepsilon_n)} \times \frac{d^2 P_n^f(\varepsilon_n)}{d\varepsilon_n^2} \tag{2.23}$$

Differentiating (2.13) twice we get,

$$\frac{d^2 P_n^f(\varepsilon_n)}{d\varepsilon_n^2} = \frac{-1}{2\sigma^2\sqrt{\pi P}} \times \{\frac{d}{d\varepsilon_n}\exp[-(\frac{(\varepsilon_n - P\sigma^2)^2}{4P\sigma^4})]\}$$

$$= \frac{\varepsilon_n - P\sigma^2}{8P\sigma^6\sqrt{\pi P}}\exp[-(\frac{(\varepsilon_n - P\sigma^2)^2}{4P\sigma^4})] \tag{2.24}$$

If $P_n^f(\varepsilon_n, k_n) \le \frac{1}{2}$, it can be proved from (2.17) that $P_n^f(\varepsilon_n) \le 1/2$.

Suppose $P_n^f(\varepsilon_n) \ge 1/2$.

$\sum_{i=1}^{k_n} C_i^n (P_n^f(\varepsilon_n))^i (1 - P_n^f(\varepsilon_n))^{k_n - i} = 1$ which can be written as

$$\sum_{i=1}^{\lfloor k_n \rfloor} C_i^n (P_n^f(\varepsilon_n))^i (1 - P_n^f(\varepsilon_n))^{k_n - i} + \sum_{i=\lceil k_n/2 \rceil}^{k_n} C_i^n (P_n^f(\varepsilon_n))^i (1 - P_n^f(\varepsilon_n))^{k_n - i} = 1 \tag{2.25}$$

$$C_i^n (P_n^f(\varepsilon_n))^i (1 - P_n^f(\varepsilon_n))^{k_n - i} \le C_{n-i}^n (P_n^f(\varepsilon_n))^{k_n - i} (1 - P_n^f(\varepsilon_n))^i$$

Since $C_i^n = C_{n-i}^n$ and $P_n^f(\varepsilon_n) \ge 1/2$, second term in the above equation will be greater than equal to the first term for $i = \lceil k_n/2 \rceil$ to k_n.

From this, we can imply that the second summation will be greater than or equal to first summation in (2.25) which can be stated as

$$\sum_{i=\lceil k_n/2 \rceil}^{k_n} C_i^n (P_n^f(\varepsilon_n))^i (1 - P_n^f(\varepsilon_n))^{k_n - i} \ge 1/2.$$

From (2.17) and above relation, $P_n^f(\varepsilon_n, k_n) \ge 1/2$ which is not true. Hence $P_n^f(\varepsilon_n, k_n) \le \frac{1}{2}$ implies that $P_n^f(\varepsilon_n) \le 1/2$.

This implies that $\varepsilon_n \ge P\sigma^2$. Therefore $\frac{d^2 P_n^f(\varepsilon_n)}{d\varepsilon_n^2}$, the second derivative of $P_n^f(\varepsilon_n)$s greater than or equal to zero.

Differentiating (2.17) with respect to $P_n^f(\varepsilon_n)$,

$$\frac{dP_n^f(\varepsilon_n,k_n)}{dP_n^f(\varepsilon_n)} = \sum_{i=\lceil k_n/2 \rceil}^{k_n} C_i^n (P_n^f(\varepsilon_n))^{i-1}(1-P_n^f(\varepsilon_n))^{k_n-i-1}(i-k_nP_n^f(\varepsilon_n)) \tag{2.26}$$

$i-k_nP_n^f(\varepsilon_n)>0$ since $i\in[k_n,\lceil k_n/2\rceil]$ and $P_n^f(\varepsilon_n,k_n)\le 1/2$.

All the terms on the right hand side will be positive then.

Using (2.23), (2.24) and (2.26), we conclude that second derivative of $P_n^f(\varepsilon_n,k_n)$ is non-negative which implies that $P_n^f(\varepsilon_n,k_n)$ is convex in ε_n.

Similarly it can be shown that the function $P_n^m(\varepsilon_n,k_n)$ in (2.16) is convex in ε_n if $P_n^m(\varepsilon_n,k_n)\le \frac{1}{2}$.

By taking the second derivative of $P_n^d(\varepsilon_n)$, we can show that it is concave, and hence $P_n^m(\varepsilon_n,k_n)=1-P_n^d(\varepsilon_n,k_n)$ is a convex function.

The nonnegative weighted sum of a set of convex functions is also convex [38]. The problem (2.21) then becomes a convex program if we introduce the following conditions:

$$0<\alpha_n\le 1/2 \text{ and } 0<\beta_n\le 1/2\ ,\ n=1,2.....N$$

These probability values of false alarm and missed detection are of practical interest for achieving reasonable opportunistic throughput and interference levels in CR networks.

Alternatively, we can formulate the multiband joint detection problem into another optimization problem that minimizes the interference from CRs to the primary communication system subject to some constraints on the aggregate opportunistic throughput, i.e.

$$\min_{\gamma}\ c^TP^m(\varepsilon,k)$$

$$\text{s.t} \sum_{n=1}^{N} c_i P_n^m(\varepsilon_n, k_n) \le \varepsilon$$

$$P^m(\varepsilon, k) \le \alpha$$

$$P^f(\varepsilon, k) \le \beta$$

(2.26)

where δ is the minimum required aggregate opportunistic throughput.

Interior-point methods solve the problem of convex optimization which includes inequality constraints. Interior-point method is used to solve the problem (2.21) by applying Newton's method to a sequence of inequality constrained problems. The barrier method a particular interior-point algorithm for which proof of convergence and a complexity analysis can be found in [38], is used because of its reliability and low complexity.

2.5 Simulation Results

Consider a 24-MHz primary system where the wideband channel is equally divided into four subbands. For each subband n $(1 \le n \le 4)$, we assume an achievable throughput rate r_n if used by CRs and a cost coefficient c_n indicating the penalty if the primary signal is interfered with by secondary users. It is expected that the opportunistic spectrum utilization is at least 50%, i.e., $\beta_n = 0.5$ and the probability that the primary user is interfered with is at most $\alpha_n = 0.2$. For simplicity it is assumed that the noise power level is $\sigma^2 = 1$, and the length of each detection interval is $P = 100$. These parameters have also been taken in [32].

Table 2.1: Rate and Cost coefficients

r(kbps)	612	524	623	139
c	1.91	8.17	4.23	3.86

Figure 2.3 plots the maximum aggregate opportunistic rate against the aggregate interference to the primary communication system for 4 secondary users. Each subband is assigned 1 secondary user. In first case the threshold matrix, ε is determined optimally according to (2.21) while in other case uniform threshold is kept for each band which is determined from given aggregate interference.

Figure 2.4 compares the throughput for different number of SUs, 8, 6 and 4 to the case with 2 SUs and uniform threshold allocated to each band. The optimization for threshold matrix ε is done with all the possible values of k matrix. The ε, k pair which gives maximum throughput is selected. We can clearly state that the same throughput can be achieved with less number of cooperating SUs.

In figure 2.5, comparison is done between the case in which 2 SUs scan each band i.e. $k_n = 2, n = 1..N$ and the threshold matrix ε is optimally determined and the case in which both the number of SUs, k as well the threshold matrix, ε is determined optimally.

Figure 2.6 shows the case in which the alternate optimization problem is solved. The interference is minimized given the aggregate throughput for 4 secondary users. Each subband is assigned 1 secondary user. In optimal threshold case the threshold matrix, ε is determined optimally according to (2.26) while in other uniform threshold is kept for each band so as to have the desired aggregate throughput.

2.6 Conclusion

In this chapter, we have considered joint multi-band detection using a set of narrowband energy detectors. The framework for same was proposed and the optimization problem was shown to be convex for practical constraints over false alarm and detection probability. It can be seen that the multiband joint detection algorithm with optimized thresholds and optimizing number of secondary users scanning each band can achieve a much higher opportunistic rate than that achieved by the uniform threshold method. It can be also concluded that the same aggregate throughput can be attained for a given aggregate interference with lower number of cooperating energy detectors using the proposed framework. Use of less number of cooperating sensors will lower the cooperation overhead. Also the proposed multiband joint detection makes better use of the wide frequency band by balancing the conflict between improving spectral utilization and reducing the interference.

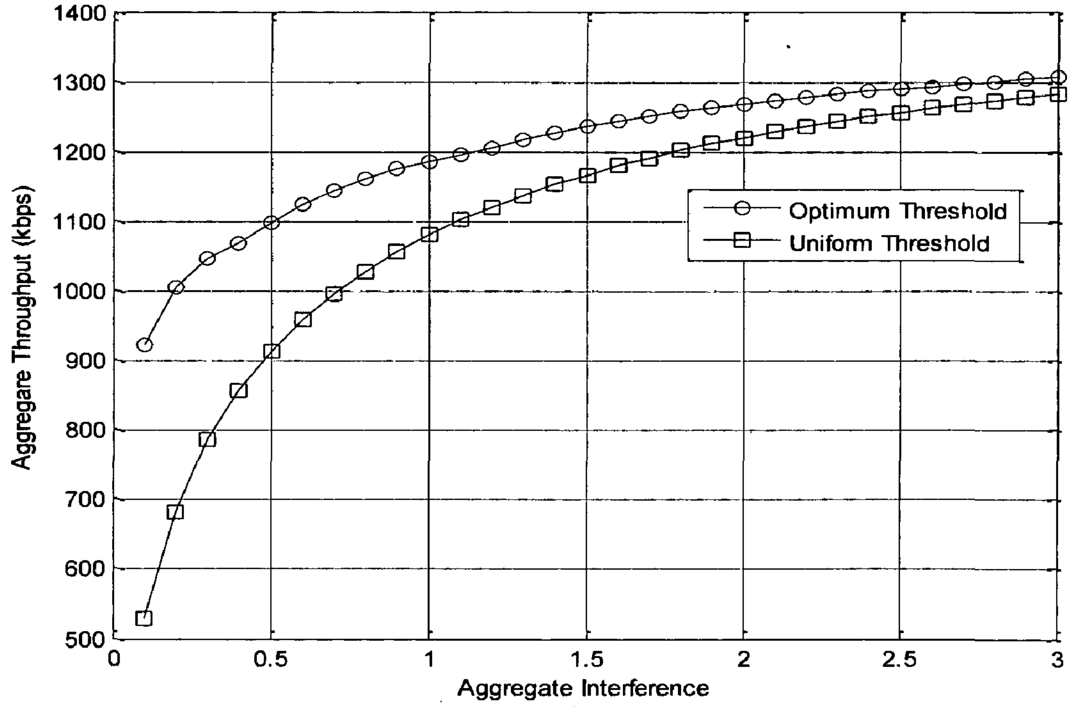

Figure 2.3: Comparison of throughput for uniform threshold and optimized threshold with uniform energy detectors allocated for each sub band

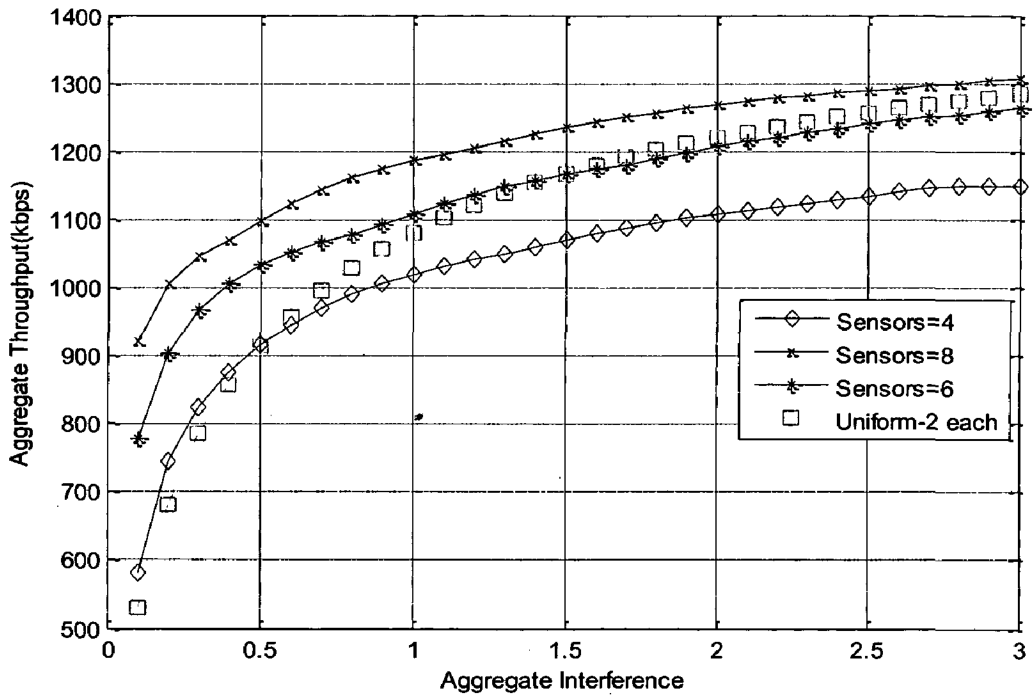

Figure 2.4 : Throughput with different number of energy detectors compared with uniform 2 energy detectors allocated for each sub band and uniform threshold.

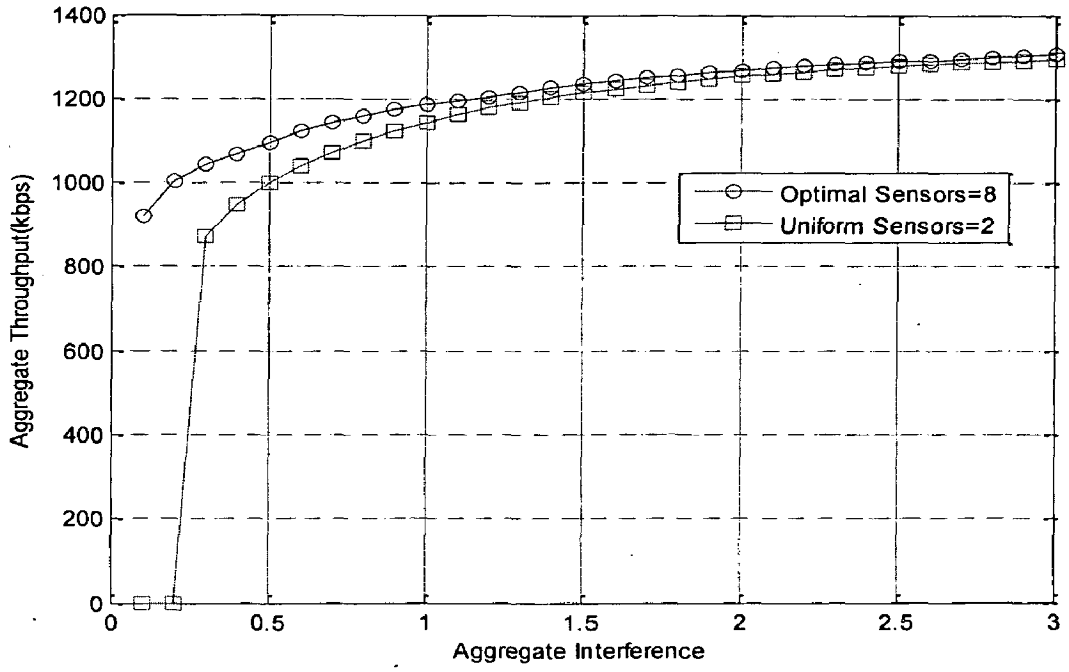

Figure 2.5 : Comparison of throughput versus interference for optimized threshold, uniform number of SUs with optimized threshold, optimized number of SUs.

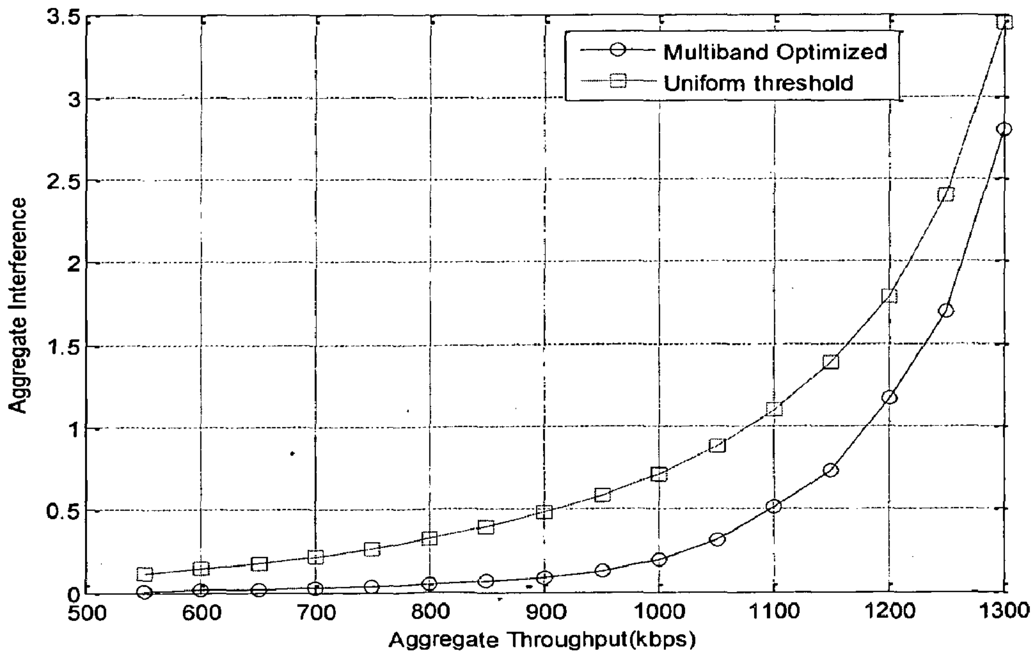

Figure 2.6 : The aggregate opportunistic throughput versus constrained aggregate interference to the primary communication system.

Chapter 3

Multi-Channel Cooperative Spectrum Sensing in Rayleigh Fading Channel

Spectrum sensing is regarded as a mandatory feature in cognitive radio networks, for which two typical signal detection approaches are available: energy detection and cyclostationary detection. These detectors work well in Gaussian noise scenarios, which, however, are not appropriate to be directly utilized in wireless fading environments. Towards this, cooperative sensing strategies have been studied to combat the wireless fading in [2], where multiple cognitive users termed as secondary users independently detect the licensed primary channel using energy detector and report their initial detection results to a fusion center. In the past, most of research in cooperative spectrum sensing focused on single channel systems where all SUs sense the same channel together. However, with the popularity of multi-channel systems, such as orthogonal frequency division multiplexing (OFDM) systems, improving sensing performance of one channel is not sufficient. It is more important to determine a number of channels satisfying the required sensing performance using Cooperative Spectrum Sensing. Thus, the study of multi-channel spectrum sensing is important for CR networks. In this chapter we consider cooperative sensing over multiple channels simultaneously in fading environment. Optimal strategies for the same are investigated.

A cognitive radio network with multiple potential channels is considered. Secondary users cooperatively sense the channels and send the sensing results to a coordinator, in which energy detection with a soft decision rule is employed to estimate whether there are primary activities in the channels. An optimization problem is formulated, which maximizes the throughput of secondary users while keeping detection probability for each channel above a pre-defined threshold.

We present the system model in Section 3.1. The problem of optimal sensing time setting is formulated and mathematically solved in Section 3.2 when the sensing time for each channel is a number of mini-slots. Simulation results are presented in Section 3.3

3.1 System Model

We consider a cognitive radio network with N frequency bands (or channels) and M secondary users (SU). In each channel, a primary user operates (which may not be active all the time). There is a fusion centre in the cognitive radio network, which collects sensing results from the secondary users, and takes the final decision about the presence of PU on each channel. The FC also assigns a secondary user to each channel for information transmission. If the coordinator estimates a channel, say channel n, to be idle, it apprises the secondary user assigned in the channel to transmit. The transmission power is P_n^s and the transmission rate is given as $\log(1+SNR_n^{ss})$ which depends on the signal-to-noise ratio (SNR) from the secondary user to its receiver for channel n.

A synchronous system is assumed, and time is divided into fixed-length slots. A slotted time frame structure has also been used for spectrum sensing in [39]. It is assumed that in each slot, the primary user in a channel is either active for the whole slot, or idle for the whole slot. Each slot is further partitioned into two phases: sensing phase and transmission phase. The duration of the sensing phase is a design parameter which has to be determined.

There is a trade-off of the cognitive radio throughput which will be addressed by jointly considering the spectrum sensing and secondary transmissions. As discussed in [40], the two individual phases cannot be optimized separately, since they affect each other. A reliable cognitive radio system with high data rates is achievable by using cooperative communications for both the spectrum sensing and secondary transmissions. However, the two individual designs of spectrum sensing and secondary transmissions cannot be optimized separately, since they affect each other. For example, when an available spectrum hole is not detected by spectrum sensing during a certain observation window, the spectrum hole utilization would decrease. To alleviate this issue, we may increase the observation time for the spectrum sensing phase, which, however, comes at the cost of degradation in secondary transmission performance since less time is now available for the secondary transmission phase.

In the sensing phase, all secondary users can sense a number of channels sequentially by energy detection where the sampling rate of the received signal in a channel is μ. The transmission phase is used by the secondary user assigned to the channel to transmit, if the channel is estimated to be idle. It is assumed that the channel gain for each channel (from the primary user to secondary users or between secondary users) is constant within the duration of a time slot.

Let t_n^m denote the time duration that secondary user m spends in sampling channel n. Given the sampling rate μ, the secondary user m has μt_n^m samples of channel n. For a secondary user m, the hypothesis mentioned in Chapter 2 can be restated as

$$\begin{aligned} H_n^0 &: y_n^m(i) = w_n(i) \\ H_n^1 &: y_n^m(i) = h_n^m s_n(i) + w_n(i) \end{aligned} \tag{3.1}$$

where H_n^0 and H_n^1 mean that the primary user in channel n is idle and busy respectively, i is the sample index, $y_n^m(.)$ is the received signal of channel n at secondary user(SU) m. $w_n(i)$ is background noise in channel n, which is assumed to be circular symmetric complex Gaussian (CSCG) with mean being zero and variance being σ^2. It is assumed to be equal for all the SU and $s_n(i)$ is the primary transmitted signal of channel n. h_n^m is the channel gain between the primary transmitter and the secondary receiver. Rayleigh fading channel is assumed.

For a particular channel n, mean SNR is assumed to be constant for every SU given by γ_n. This assumption is valid for a small-sized cognitive network (i.e., distance between the secondary users is much less than the distance from the primary user to the secondary users).

Then, the test statistic of secondary user's received signal energy in channel is calculated as

$$S_n^m = \sum_{i=1}^{\mu t_n^m} |y_n^m(i)|^2 \tag{3.2}$$

The test statistic of secondary user m for channel n is sent to the FC, which collects all values of S_n^m's from all the secondary users. Then the overall test statistic for channel is

$$S_n^{all} = \sum_{m=1}^{M} S_n^m \tag{3.3}$$

The overall test statistic is compared with a threshold, ε_n. The primary user in channel n is estimated to be idle if $S_n^{all} \leq \varepsilon_n$, or busy otherwise. This process is referred to as soft decision cooperative spectrum sensing, and the detection probability and false alarm probability in the process are given [24] as

$$P_n^f(\sum_{m=1}^{M} t_n^m, \varepsilon_n) = \Pr(S_n^{all} > \varepsilon_n \mid H_n^0) = Q((\frac{\varepsilon_n}{\sigma^2 \mu \sum_{m=1}^{M} t_n^m} - 1)\sqrt{\mu \sum_{m=1}^{M} t_n^m}) \tag{3.4}$$

$$P_n^d(\sum_{m=1}^{M} t_n^m, \varepsilon_n) = \Pr(S_n^{all} > \varepsilon_n \mid H_n^1) \tag{3.5}$$

For (3.5), simulation results are used to calculate ε_n for a given P_n^d and vice-versa.

In a real system, the detection probability P_n^d should not be less than 0.5 and the false alarm probability P_n^f should be no larger than 0.5.

For sensing the channel n, we have the following four scenarios:

1) If channel n is not used and is reckoned by the fusion centre to be unused, then the secondary user assigned to channel n will transmit in the associated transmission phase of the slot, with the average transmission rate given by $R_n^0 = E(\log(1 + \frac{|h_n^{ss}|^2 P_n^s}{\sigma^2}))$ where h_n^{ss} is the channel coefficient from the secondary user assigned to channel n to its receiver, and E(.) means expectation.
2) If channel n is not used and is reckoned by the fusion centre to be busy (i.e., a false alarm happens), the secondary user assigned to channel n will not transmit in the associated transmission phase of the slot.
3) If channel n is busy and is reckoned by the fusion centre to be busy, the secondary user assigned to channel n will not transmit in the associated transmission phase of the slot.
4) If channel n is busy and is reckoned by the fusion centre to be idle (i.e., a missed detection happens), then the secondary user assigned to channel n will transmit in the associated transmission phase of the slot. As the primary user's signal will serve as

interference to the secondary transmission, the average transmission rate of the secondary user is given by $R_n^1 = E(\log(1+\frac{|h_n^{ss}|^2 P_n^s}{\sigma^2 + |h_n^{ps}|^2 P_n^p}))$ where P_n^p is the transmission power of the primary user in channel n, and h_n^{ps} is the channel coefficient from the primary user to the secondary receiver in channel n. It can be inferred that $R_n^0 > R_n^1$.

3.2. Optimal Sensing Time

In the system, the sensing phase in a slot has K mini-slots each of duration δ. The value of K is a parameter to be optimized. Each mini-slot can be used by a secondary user to sense a channel. So there are totally KM mini-slots among the M secondary users to sense the N channels.

The total cases of allotting slots in each SU to the channels are of the order of $(KM)^N$ which increases very fast with increase in total number of slots, primary users and secondary users. Hence a sub optimal strategy has to be used.

For a particular channel, the sensing performance would be optimum if all the slots are equally divided in all the SU, as this would maximize spatial diversity. This would be very near to the optimal solution in the Cognitive Radio Network having low number of SUs which is a very practical assumption. The assumption of equal slots for a channel in every SU hence is very close to the optimal solution in a practical CRN.

Let $k_n > 0$ denote the number of mini-slots (among the K mini-slots) in every secondary user that are used for sensing channel n ∈ {1,2,...,N}. Then we have $\sum_{n=1}^{N} k_n = K$.

Let T denote the length of a time slot. Then the average throughput of channel n can be expressed [24] as

$$C_n(K,k_n,\varepsilon_n) = \frac{T-K\delta}{T}(\Pr(H_n^0)(1-P_n^f(k_n,\varepsilon_n))R_n^0 + \Pr(H_n^1)(1-P_n^d(k_n,\varepsilon_n))R_n^1) \quad (3.6)$$

$$P_n^f(k_n,\varepsilon_n)=\Pr(S_n^{all}>\varepsilon_n\mid H_n^0)=Q\left(\left(\frac{\varepsilon_n}{\sigma^2\mu k_n\delta}-1\right)\sqrt{\mu k_n\delta}\right) \tag{3.7}$$

$$P_n^d(k_n,\varepsilon_n)=\Pr(S_n^{all}>\varepsilon_n\mid H_n^1) \tag{3.8}$$

where $\Pr(H_n^0)\geq 0$ is the available probability of channel, and $\Pr(H_n^1)=1-\Pr(H_n^0)\geq 0$ is the busy probability of channel n.

Our aim is to maximize sum of the throughput of secondary users in all the channels which is $\sum_{n=1}^{N}C_n(K,\{k_n\},\{\varepsilon_n\})$ while keeping the detection probability of any channel, $P_n^d(k_n,\varepsilon_n)$, above a pre-specified threshold P_{th} ($P_{th}>0.5$) and the false alarm probability of any channel, P_n^f, no larger than 0.5. So the problem can be stated as follows.

Problem P1:

$$\max_{K,\{k_n\},\{\varepsilon_n\}} C(K,\{k_n\},\{\varepsilon_n\})=\sum_{n=1}^{N}\frac{T-K\delta}{T}(\Pr(H_n^0)P_n^f(k_n,\varepsilon_n)R_n^0+\Pr(H_n^1)P_n^d(k_n,\varepsilon_n)R_n^1)$$

$$\text{s.t } P_n^d>P_{th}>.5 \text{ and } P_n^f<.5$$

$$P_n^f(k_n,\varepsilon_n)=\Pr(S_n^{all}>\varepsilon_n\mid H_n^1)=Q\left(\left(\frac{\varepsilon_n}{\sigma^2\mu Mk_n}-1\right)\sqrt{\mu Mk_n}\right)$$

$$P_n^d(k_n,\varepsilon_n)=\Pr(S_n^{all}>\varepsilon_n\mid H_n^1)$$

$$\sum_{n=1}^{N}k_n=K,\quad k_n>0, k_n\in I, n=1,2..N$$

Here I is the set of all positive integers.

Problem P1 is a mixed-integer problem, which is usually NP-hard to be solved directly. In order to solve problem P1, we transform the problem into sub problems with low complexity, as follows.

$$\max_K C(K)=\frac{T-K\delta}{T}D(K)$$

$$\text{s.t. } 0 < K \leq \left\lfloor \frac{T}{\delta} \right\rfloor \tag{3.9}$$

where $D(K)$ is the optimal objective value of the following problem with a specific K value.

Now the problem can be written as

Problem P2:

$$\max_{\{k_n\},\{\varepsilon_n\}} D(\{k_n\},\{\varepsilon_n\}) = \sum_{n=1}^{N} (\Pr(H_n^0)(1 - P_n^f(k_n, \varepsilon_n))R_n^0 + \Pr(H_n^1)(1 - P_n^d(k_n, \varepsilon_n))R_n^1)$$

$$\text{s.t. } P_n^d > P_{th} > .5 \text{ and } P_n^f < .5$$

$$P_n^f(k_n, \varepsilon_n) = \Pr(S_n^{all} > \varepsilon_n \mid H_n^1) = Q((\frac{\varepsilon_n}{\sigma^2 \mu M k_n} - 1)\sqrt{\mu M k_n})$$

$$P_n^d(k_n, \varepsilon_n) = \Pr(S_n^{all} > \varepsilon_n \mid H_n^1$$

$$\sum_{n=1}^{N} k_n = K, \quad k_n > 0, k_n \in I, n = 1,2..N$$

The objective function $D(\{k_n\},\{\varepsilon_n\})$ in problem P2 achieves the maximal value when $P_n^d(k_n, \varepsilon_n) = P_{th},\ n = 1,2....N$.

Denote $D_n(k_n, \varepsilon_n) = \Pr(H_n^0)(1 - P_n^f(k_n, \varepsilon_n))R_n^0 + \Pr(H_n^1)(1 - P_n^d(k_n, \varepsilon_n))R_n^1$

Then $D(\{k_n\},\{\varepsilon_n\}) = \sum_{n=1}^{N} D_n$ .It may be seen that both $(1 - P_n^d(k_n, \varepsilon_n))$ and $(1 - P_n^f(k_n, \varepsilon_n))$ grow with increase in ε_n. On the other hand, the term $(1 - P_n^d(k_n, \varepsilon_n))$ should be bounded by $1 - P_{th}$. Therefore, $D_n(k_n, \varepsilon_n)$ achieves its maximal value when $(1 - P_n^d(k_n, \varepsilon_n))$ reaches its upper bound $(1 - P_{th})$, which happens when $P_n^d(k_n, \varepsilon_n) = P_{th}$.

We define,

$$S(\{k_n\}) = \sum_{n=1}^{N} \Pr(H_n^0)(1 - P_n^f(k_n, P_n^d = P_{th}))R_n^0 \tag{3.10}$$

where ε_n is calculated from the simulations such that $P_n^d = P_{th}$.

Substituting $P_n^d(k_n, \varepsilon_n)$ with P_{th} in the objective function in problem P2, we have

$$D(\{k_n\},\{\varepsilon_n\})|_{P_n^d(k_n,\varepsilon_n)=P_{th}} = S(\{k_n\}) + \sum_{n=1}^{N} \Pr(H_n^1)(1-P_{th})R_n^1 \ .$$

We define the following parameters:

1. $\mathbf{k}^{\min} = \{k_1^{\min}, k_2^{\min} \ldots k_N^{\min}\}$ is a $N \times 1$ vector where $k_n^{\min}$ is the minimum number of slots required for channel n for which $P_n^d = P_{th}$ and $P_n^f < .5$.

2. $s(k_n) = \Pr(H_n^0) \times (1 - P_n^f(k_n, P_n^d = P_{th}))R_n^0$

An incremental algorithm has been used to solve the above problem. The procedure for the incremental algorithm referred to as Algorithm 1 is on the lines of [24] and is given as follows.

3.3 Algorithm 1 for soft combining in Rayleigh Fading Channels

1. Find $\mathbf{k}^{\min}$ which gives the minimum number of mini-slots for satisfactory sensing performance that is $P_n^d = P_{th}$ and $P_n^f < .5$.
2. For a given K, if $\sum_{i=1}^{N} k_i^{\min} < K$, set $k = \{k_i^{\min}\}$ and proceed to 2 else problem is infeasible for the given K. Increase K and proceed from 2.
3. If $\sum_{n=1}^{N} k_n = K$, proceed to 4 else for n=1, 2...N, find $F(n) = s(k_n + 1) - s(k_n)$. Find $n^* = \arg\max_{1 \le n \le N} F(n)$.
4. $k_{n^*} = k_{n^*} + 1$, proceed to step 3.
5. Output $\{k_n\}$.

It can be shown that $D(K)$ is an increasing function of K.

Since increasing K in $D(K)$ decreases P_n^f of a particular channel for the same probability of detection $P_n^d = P_{th}$.

$D(K) - D(K-1) \geq D(K+1) - D(K)$

While going from K-1 to K & K to K+1, the increased slot might be on same channel (n^*) or a different channel (n^*).

If it is on different channel i.e. the value n^* is different in the two cases, $C(n)_{k-1 \to k} > C(n)_{k \to k+1}$ because $n^* = \arg\max_{1 \leq n \leq N} F(n)$

If it is on same n, rate of decrement in $P_n^f(k_n, P_n^d = P_{th})$ decreases with increasing value of k_n. This will be verified from the simulation result in the next section.

In both the cases, the above property will hold. This completes the proof.

Optimal Solution to Problem P1

Algorithm 1 solves problem P2, which is a sub problem of problem P1. Now, we next proceed to solve problem P1.With the solution of problemP2, denoted $D(K)$ for a specific K, problem P1 is equivalent to

$$\max_{K} C(K) = \frac{T - K\delta}{T} D(K)$$

$$\text{s.t. } 0 < K \leq \left\lfloor \frac{T}{\delta} \right\rfloor$$

For the objective function of this problem, we have the following

$C(K) - C(K-1) > C(K+1) - C(K)$

$$[C(K) - C(K-1)] - [C(K+1) - C(K)]$$
$$= \left[\left(1 - \frac{(K+1)\delta}{T}\right) D(K+1) - \left(1 - \frac{K\delta}{T}\right) D(K)\right] - \left[\left(1 - \frac{K\delta}{T}\right) D(K) - \left(1 - \frac{(K-1)\delta}{T}\right) D(K-1)\right]$$
$$= \left(1 - \frac{K\delta}{T}\right) \left[\left(D(K+1) - D(K)\right) - \left(D(K) - D(K-1)\right)\right] + \frac{\delta}{T}\left(D(K-1) - D(K+1)\right)$$

From earlier result $D(K) - D(K-1) \geq D(K+1) - D(K)$. We can imply that both the terms are negative. Thus we have $(K) - C(K-1) > C(K+1) - C(K)$.

From this property, we see that as K grows the increment of $C(K)$, denoted by $E(K) = C(K) - C(K-1)$, become smaller. Then, the optimal value of K, denoted by K^*, satisfies $E(K) \geq 0 \geq E(K+1)$.

To find K^*, for a given K value, the results obtained from previous iterations may be useful, in order to reduce the computation complexity in the current iteration.

These properties were proposed and proved in [24] for framework proposed for AWGN channels. We have shown that these properties hold good for our framework for Rayleigh Channels.

3.4. Simulation Results

The system setup is as follows. The sampling rate is μ=6 MHz, the slot duration is $T = 100$ ms, the threshold of detection probability is $P_{th} = 0.9$ and all secondary users are assumed to have a mean S.N.R. of 20 dB. SNR_n^{ps} (SNR from the primary user to a secondary use on channel n) follows exponential distribution because of the Rayleigh channel while SNR_n^{ss} (SNR from the secondary user to its receiver at channel n) is assumed to be constant. The mini-slot duration is $\delta = 0.1$ ms. The simulations are done in Matlab and are averaged over 1000 simulations for various number of mini-slots in Rayleigh fading channel.

For Figure 3.1 and 3.3, there are N = 5 channels and for Figure 3.4, N= 10 channels respectively. Channel n $(1 \leq n \leq N)$ has a free probability $\Pr(H_n^0)$= $1-0.05*n$, and the average channel gain from the primary user to a secondary user is $\gamma_n = -20 + n - 1$ dB.

For Figure 3.2 N=2 channels, with the available probability as $\Pr(H_1^0)$=0.8 and $\Pr(H_2^0)$=0.6, and mean SNR from primary user to both secondary users as $\gamma_1 = -15$ dB in channel 1 and $\gamma_2 = -20$ dB in channel 2, there are M =2 secondary users.

The values of SNR taken are very low because cooperative spectrum sensing is done only in the case where primary users are far from the cognitive radio network. The free probability of channels are taken are realistic in practical scenarios and same have also been taken in [24].

Figure 3.1 plots the variation of false alarm probability for all channels $n = 1,2,...5$ with increasing number of sensing mini-slots for that channel. From this plot, it can be implied that rate of decrease of $P_n^f(k_n, P_n^d = P_{th})$ for a constant probability of detection $P_n^d = P_{th}$ decreases with increasing value of k_n.

The simulations are done for Rayleigh and AWGN channels. The optimal time setting is derived for Rayleigh channels as described in algorithm 1. From the graphs we may calculate the optimal sensing time as the one maximising the throughput. While for AWGN channels, the algorithm proposed in [24] is used.

The optimal sensing number of sensing slots in Rayleigh fading is 120 compared to 80 in AWGN while the throughput obtained in Rayleigh is 7.25 bits/sec/Hz while in AWGN it is 8.7 bits/sec/Hz. We can see that the degradation in throughput at higher values of K is slower as compared to AWGN. This is because the sensing efficiency continues to improve at higher values of K for Rayleigh environment.

In Figure 3.3, the optimal number of sensing slots in Rayleigh fading is 100 compared to 50 in AWGN while the throughput obtained in Rayleigh is 21.0 bits/sec/Hz while in AWGN it is 27.2 bits/sec/Hz. From Figure 3.3 and Figure 3.4 it may be seen that increasing the number of users is more dominating than increasing the number of channels in determining the optimal sensing time due to spatial diversity obtained. Increasing number of channels from 5 to 10 for maximum throughput the number of sensing slots to 200 slots as compared to 100 as may be seen from Figure 3.3 and 3.4. The rate of decrease of the throughput from the optimal sensing time has also decreased. The throughput deterioration from AWGN to Rayleigh is 18% in M=10, N=5 as compared to 22% in M=5, N=5.

From the above results, it can be implied that the throughput rises with increase in K value initially. This is due to the decrease in false alarm probability on all the channels. Then it becomes steady because of the decrease in throughput due to increase in sensing time matches the increment caused by decrease in false alarm probability. After this the throughput begins to decrease as the increase in sensing time decreases the transmission time, which plays the dominant role than the increase in sensing efficiency.

In this chapter, we have considered the sub-optimal multi-channel cooperative spectrum sensing strategies in cognitive radio networks in Rayleigh fading channels. We have proposed strategies to determine the total sensing time and distribution of the total sensing time to different channels in cooperative soft-decision spectrum sensing. Considering the slotted-time sensing mode, we converted the initial non-convex mixed-integer problem into convex mixed-integer sub problems, and provided a low-complexity algorithm to achieve the sub optimal solution of the initial problem. We have evaluated the degradation of throughput and increase in optimal sensing time when the channels are assumed to be Rayleigh fading which is more realistic than the AWGN environment assumption for wireless channel.

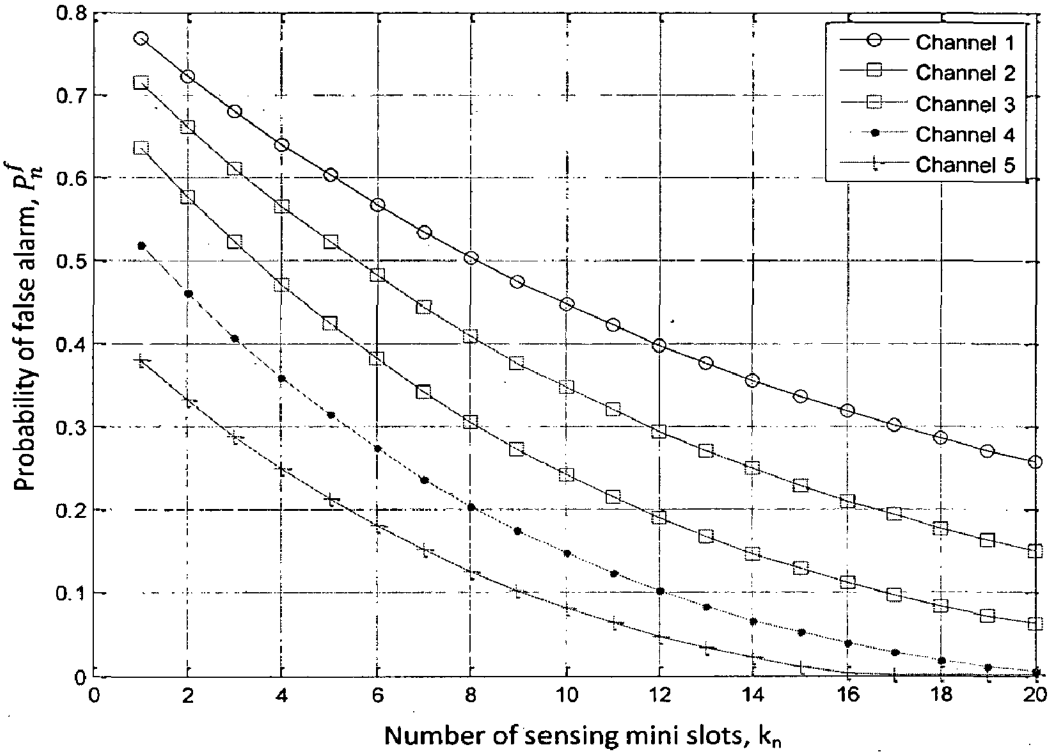

Figure 3.1 : Probability of false alarm variation with varying number of mini-slots

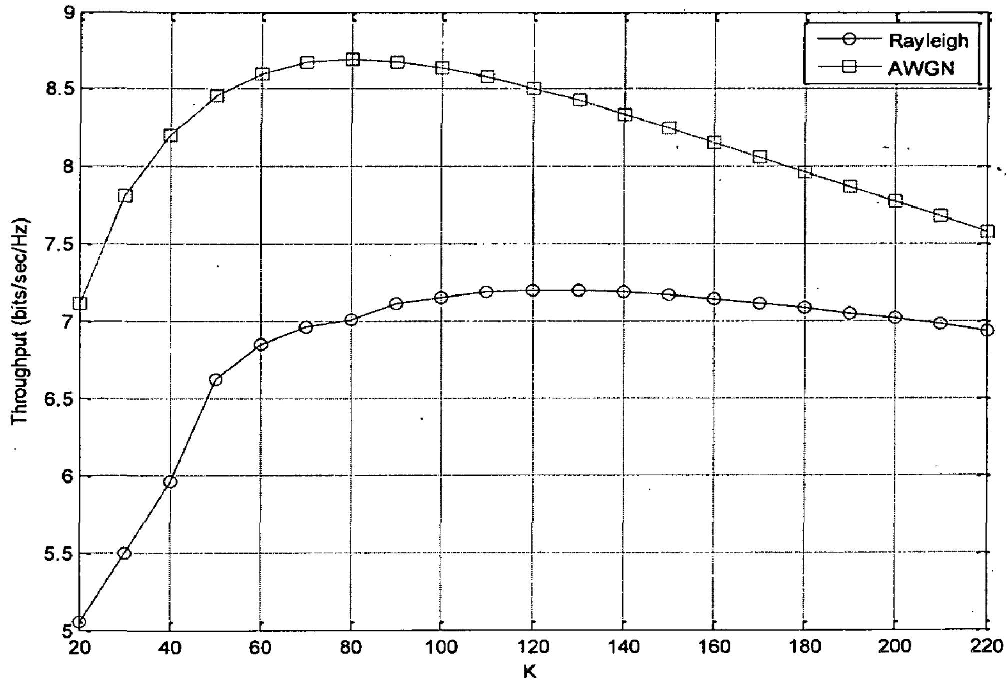

Figure 3.2 : Throughput Comparison for Multi-Channel Spectrum Sensing in AWGN and Rayleigh Channel for N=2, M=2.

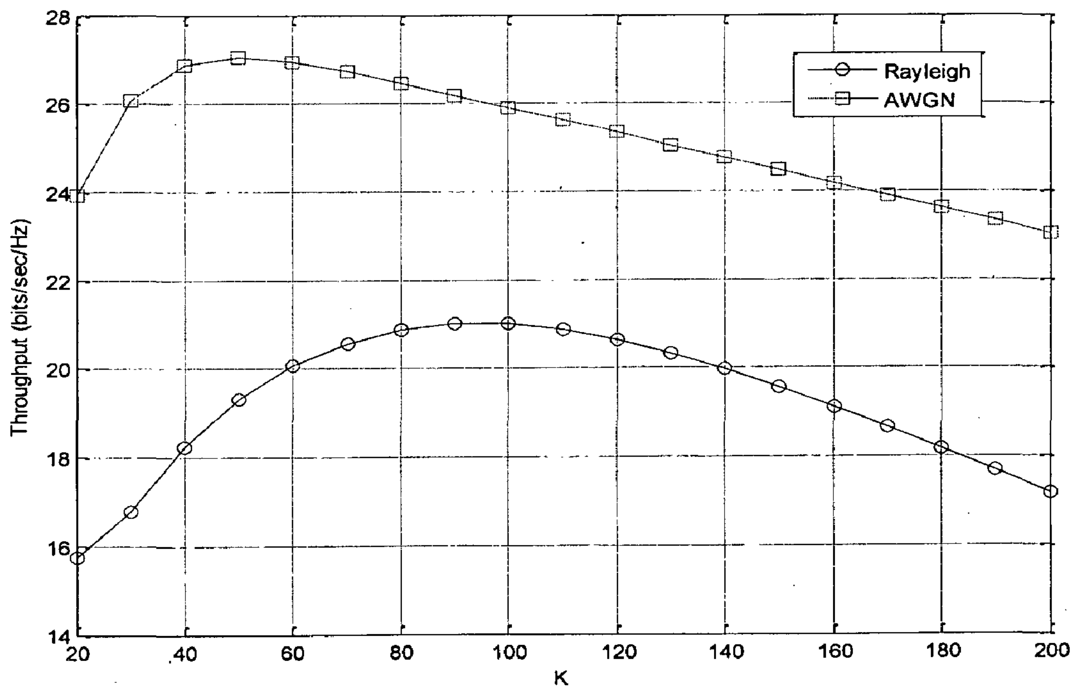

Figure 3.3 : Throughput Comparison for Multi-Channel Spectrum Sensing in AWGN and Rayleigh Channel for N=5, M=5.

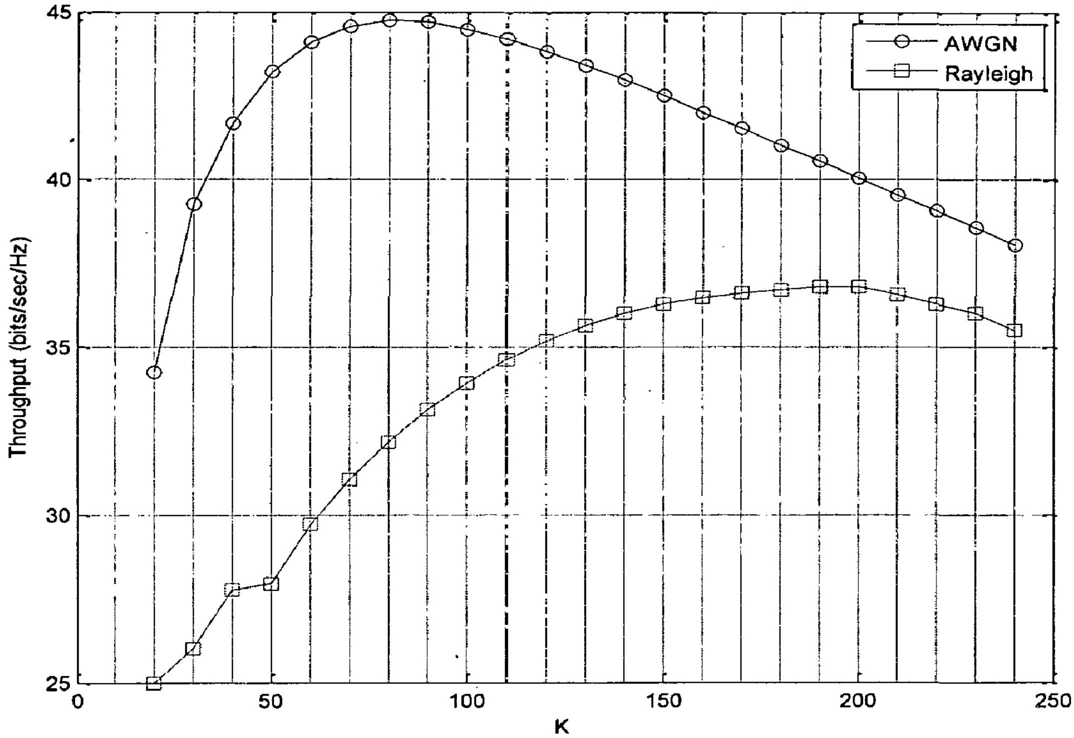

Figure 3.4 : Throughput Comparison for Multi-Channel Spectrum Sensing in AWGN and Rayleigh Channel for N=10, M=5.

Chapter 4

Multi-Channel Cooperative Spectrum Sensing with Hard Combining

In previous chapters multi-channel cooperative spectrum sensing was considered using soft combining at the fusion center. However in cognitive radio networks, the control channel bandwidth is often limited. For this reason, local decisions are usually sent from each secondary user. The fusion center then collects all the individual decisions and arrives at a unified decision about the presence of primary user. In this chapter, we consider cooperative sensing over multiple channels simultaneously in Rayleigh fading environment with hard decision transmitted by every participating secondary user. Sub optimal strategies for the same are investigated.

In cooperative sensing, a common control channel [41] is commonly used by CR users to report local sensing data to the FC or share the sensing results with neighbouring nodes. As a result, a control channel is the major element of cooperative sensing. The control channel can be implemented as a dedicated channel in licensed or unlicensed bands, or an underlay ultra-wideband (UWB) channel [12]. The problem of cooperative sensing under control channel bandwidth constraints is addressed by transmitting only the local decisions.

In addition to the bandwidth requirement, the reliability of the control channel has the great impact on cooperative sensing performance. Like data channels, the control channel is susceptible to multipath fading and shadowing. Hence, the channel impairments in turn increase the bandwidth requirement of the control channel in order to transmit data reliably.

Hard combining requires much less control channel bandwidth with possibly degraded performance due to the loss of information from quantization.

Multi-channel cooperative sensing with hard combining has been considered in [27] in which where authors propose the channel assignment in cooperative spectrum sensing (CSS) using heuristic centralized scheme to increase the number of available channels satisfying the sensing performance requirement. Signal to noise ratio (SNR) over the channel from each SU is reported to the Fusion Centre (FC). It then applies the heuristic scheme to form coalitions for every SU and broadcast the assignment results to all SUs. In our work, we have maximized the throughput from the channels available, keeping spectrum sensing time variable.

System model is described in Section 4.1 followed by signal detection on individual sensor in Section 4.2. Sensing time and allocation matrix determination is described in Section 4.3. Then selective channel sensing strategy for the same framework is proposed in Section 4.4. Section 4.5 shows simulation results of the performance of above algorithms and its comparison with the method used in chapter 2.

4.1. System Model

We consider a cognitive radio network with N frequency bands (or channels or primary users) and M secondary users (SU). In each channel, a primary user operates (which may not be active all the time). There is a fusion centre in the cognitive radio network, which collects sensing results from the secondary users, and takes the final decision about the presence of PU on each channel. The FC also assigns a secondary user to each channel for information transmission and also informs the secondary user about the probability of false alarm on the same. If the coordinator estimates a channel, say channel n, to be idle, it notifies the secondary user assigned for the channel to transmit. The transmission power is P_n^s and the transmission rate is given as $\log(1+SNR_n^{ss})$ which depends on the signal-to-noise ratio (SNR) from the secondary user to its receiver at channel n.

A synchronous system is assumed, and time is divided into fixed-length slots. In each slot, it is assumed that the primary user in a channel is either active for the whole slot, or idle for the whole slot. Each slot is further partitioned into two phases: sensing phase and transmission phase. The duration of the sensing phase is a design parameter. In the sensing phase, a secondary user can sense a number of channels sequentially by energy detection, and the sampling rate of the received signal in a channel is μ. The transmission phase is used for the secondary users assigned to the channels to transmit, if the channels are estimated to be idle. It is assumed that the channel gains in each channel (from the primary user to secondary users or between secondary users) are fixed within the duration of a time slot.

4.2 Signal Detection on Individual Sensor

To decide whether the n^{th} channel is occupied or not, we test the following binary hypothesis at every individual m^{th} sensor as mentioned in Equation (3.1).

$$
\begin{aligned}
H_n^0 &: y_n^m(i) = w_n(i) \\
H_n^1 &: y_n^m(i) = h_n^m s_n(i) + w_n(i)
\end{aligned}
\tag{4.1}
$$

Rayleigh fading channel is considered. Assuming the total number of samples is P, the test statistic of secondary user's received signal energy in channel n is calculated as

$$
Y_n^m = \sum_{i=1}^{P} \left| y_n^m(i) \right|^2 \tag{4.2}
$$

Then, the *test statistic* of secondary user's received signal energy in channel is compared with the threshold for that channel, ε_n. The primary user in band n is estimated to be idle if $Y_n^m \leq \varepsilon_n$, or busy otherwise. Here ε_n is the decision threshold of channel n.

The average SNR of the received signal from channel n is γ_n. It is assumed that the distance between PU-SU is much greater than SU-SU. This implies that the average SNR of a channel is a same for every SU.

The probabilities of false alarm and detection in the nth channel can be approximately, in the Rayleigh fading channel environment, expressed as the following [2]

$$
P_n^f(\varepsilon_n) = \Pr(Y_n^m > \varepsilon_n \mid H_n^0) = Q\left(\left(\frac{\varepsilon_n}{\sigma^2 P} - 1\right)\sqrt{P}\right) \tag{4.3}
$$

$$
\begin{aligned}
P_n^d(\varepsilon_n) = \Pr(Y_n^m > \varepsilon_n \mid H_n^1) &= \exp(-\varepsilon_n) \sum_{p=0}^{P-2} \frac{1}{p!} \left(\frac{1}{\varepsilon_n}\right)^p + \left(\frac{1+\gamma_n}{\gamma_n}\right)^{P-1} \\
&\times \exp\left(-\frac{\varepsilon_n}{2(1+\gamma_n)}\right) - \exp\left(-\frac{\varepsilon_n}{2}\right) \sum_{p=0}^{P-2} \frac{1}{p!} \left(\frac{\varepsilon_n \gamma_n}{2(1+\gamma_n)}\right)^p
\end{aligned}
\tag{4.4}
$$

4.3 Optimal Sensing Time

In the system, the sensing phase in a slot has K mini-slots. The value of K is a parameter to be optimized. Each mini-slot can be used by a secondary user to sense a channel. Every channel is scanned by a SU for t mini slots which is also design parameter. t is always a factor of K which implies that all the mini slots are utilized for sensing. All the design parameters are calculated at the fusion centre.

The primary user is assumed to be far from the cognitive radio network. The distance between the secondary users is very less compared to the distance between primary user and secondary user. In other words cognitive radio network lies in a very small distance. Hence the mean SNR for every primary user/channel is constant which is determined by the distance between them, path loss exponent and noise power. The fusion centre has the knowledge of mean SNR for every channel.

Every secondary user scans $L = \frac{K}{t}$ channels in a slot referred as L channel slots. The fusion centre will determine the total number of sensing mini-slots K and number of sensing mini-slots for every channel t. This information will be transmitted to the fusion centre. The secondary users will do the spectrum sensing as described above. It will send the localized decisions of all the channels scanned to the fusion centre. Fusion centre applies majority voting rule to determine the global decisions for all the channels.

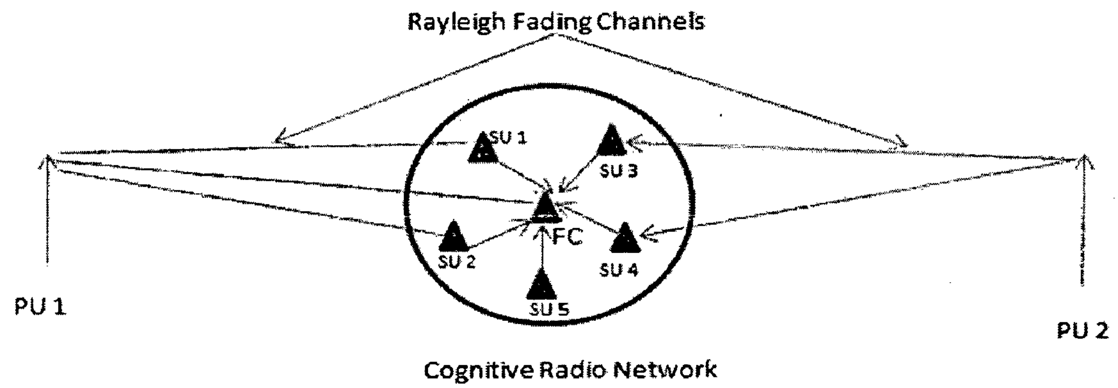

Figure 4.1 : System Model for Cooperative Spectrum Sensing

A is a $M \times L$ matrix in which $A_{i,j}$ signifies the channel scanned by the i^{th} secondary users in the j^{th} channel slot. It is referred to as allocation matrix.

Let T denote the length of a time slot. Then the average throughput of channel n can be expressed as in Chapter 2 as

$$C(A,K,t) = \frac{T-K\delta}{T}\sum_{n=1}^{N}(\Pr(H_n^0)(1-P_n^f(A,\varepsilon_n))R_n^0 + \Pr(H_n^1)(1-P_n^d(A,\varepsilon_n))R_n^1) \tag{4.5}$$

For a given A matrix, let the total number of SU sensing channel n is a_n. Then $\sum_{n=1}^{N} a_n = M \times L$. Overall probability of false alarm on a channel depends only on the total number of SUs sensing that channel and threshold represented as $P_n^f(a_n,\varepsilon_n)$. Since majority voting rule is used at the fusion centre, $P_n^f(a_n,\varepsilon_n)$ and $P_n^d(a_n,\varepsilon_n)$ is calculated as

$$P_n^f(a_n,\varepsilon_n) = \sum_{i=\lceil a_n/2\rceil}^{a_n} C_i^n (P_n^f(\varepsilon_n))^i (1-P_n^f(\varepsilon_n))^{k_n-i} \tag{4.6}$$

$$P_n^d(a_n,\varepsilon_n) = \sum_{i=\lceil a_n/2\rceil}^{a_n} C_i^n (P_n^d(\varepsilon_n))^i (1-P_n^d(\varepsilon_n))^{k_n-i} \tag{4.7}$$

$\Pr(H_n^0) \geq 0$ is the available probability of channel, and $\Pr(H_n^1) = 1-\Pr(H_n^0) \geq 0$ is the busy probability of channel n.

Our aim is to maximize sum of the throughput of secondary users in all the channels which is $\sum_{n=1}^{N} C_n(A,K,\{\varepsilon_n\})$ while keeping the detection probability of any channel, $P_n^d(a_n,\varepsilon_n)$, above a pre-specified threshold P_{th} ($P_{th} > 0.5$) and the false alarm probability of any channel, $P_n^f(a_n,\varepsilon_n)$ is no larger than 0.5. So the problem can be stated as follows.

Problem P1:

$$\max_{A,K,t} C(A,K,t) = \frac{T-K\delta}{T}\sum_{n=1}^{N}(\Pr(H_n^0)(1-P_n^f(a_n,\varepsilon_n))R_n^0 + \Pr(H_n^1)(1-P_n^d(a_n,\varepsilon_n))R_n^1)$$

$$\text{s.t } P_n^d > P_{th} > 0.5 \text{ and } P_n^f < 0.5$$

$$P_n^f(a_n,\varepsilon_n)=\sum_{i=\lceil a_n/2\rceil}^{a_n} C_i^n (P_n^f(\varepsilon_n))^i (1-P_n^f(\varepsilon_n))^{k_n-i}$$

$$P_n^d(a_n,\varepsilon_n)=\sum_{i=\lceil a_n/2\rceil}^{a_n} C_i^n (P_n^d(\varepsilon_n))^i (1-P_n^d(\varepsilon_n))^{k_n-i}$$

$$P_n^f(\varepsilon_n)=\Pr(Y_n^m>\varepsilon_n \mid H_n^0)=Q\left(\left(\frac{\varepsilon_n}{\sigma^2 t\delta\mu}-1\right)\sqrt{t\delta\mu}\right)$$

$$P_n^d(\varepsilon_n)=\Pr(Y_n^m>\varepsilon_n \mid H_n^1)$$

$$L=\left\lfloor\frac{K}{t}\right\rfloor,\ \sum_{n=1}^{N} a_n = M\times L,\ M\ge a_n>0, a_n\in I, n=1,2....N$$

We transform the problem into sub problems with low complexity, as was done in previous chapter and also in [24].

$$\max_{K} C(K)=\frac{T-K\delta}{T}D(K)$$

$$\text{s.t. } 0<K\le\left\lfloor\frac{T}{\delta}\right\rfloor \tag{4.7}$$

where $D(K)$ is the optimal objective value of the following problem with a specific K value. Now the problem with a specific K value becomes

Problem P2:

$$\max_{A,t} D(A,t)=\sum_{n=1}^{N}(\Pr(H_n^0)(1-P_n^f(a_n,\varepsilon_n))R_n^0+\Pr(H_n^1)(1-P_n^d(a_n,\varepsilon_n))R_n^1).$$

As mentioned earlier to utilize all the sensing slots, t should be a factor of K, i.e. $K \bmod t = 0$. We can again transform this function into sub problem with a specific value of t for a specific K value.

$$\max_{A} E(A,t)=\sum_{n=1}^{N}(\Pr(H_n^0)(1-P_n^f(a_n,\varepsilon_n))R_n^0+\Pr(H_n^1)(1-P_n^d(a_n,\varepsilon_n))R_n^1) \tag{4.8}$$

The objective function $E(A,t)$ in problem P2 achieves the maximal value when $P_n^d(a_n,\varepsilon_n)=P_{th}$, $n=1,2....N$

Denote $E_n(a_n,\varepsilon_n)=\Pr(H_n^0)(1-P_n^f(A,\varepsilon_n))R_n^0+\Pr(H_n^1)(1-P_n^d(A,\varepsilon_n))R_n^1$

Then $E(\{a_n\},\{\varepsilon_n\})=\sum_{n=1}^{N}E_n$ .It can be seen that both $(1-P_n^d(a_n,\varepsilon_n))$ and $(1-P_n^f(a_n,\varepsilon_n))$ grow with increase in ε_n. On the other hand, the term $(1-P_n^d(a_n,\varepsilon_n))$ should be bounded by $1-P_{th}$. Therefore, $E_n(a_n,\varepsilon_n)$ achieves its maximal value when $(1-P_n^d(a_n,\varepsilon_n))$ reaches its upper bound $(1-P_{th})$, which happens when $P_n^d(A,\varepsilon_n)=P_{th}$.

The number of possible assignments of A matrix, which is given by $(K\times M)^N$ grows exponentially with the number of secondary users and channels. Hence we need to devise a heuristic algorithm to solve this problem.

Define

$$S(A)=\sum_{n=1}^{N}\Pr(H_n^0)(1-P_n^f(a_n,P_n^d=P_{th}))R_n^0 \tag{4.9}$$

where ε_n is calculated from the simulations such that $P_n^d=P_{th}$.

Substitute $P_n^d(a_n,\varepsilon_n)$ with P_{th} in the objective function in problem P2, and we have

$$E(A,\{\varepsilon_n\})\,|_{P_n^d(a_n,\varepsilon_n)=P_{th}}=S(A)+\sum_{n=1}^{N}\Pr(H_n^1)(1-P_{th})R_n^1$$

Problem P3: With a given K and t

$$\max_A S(A)=\sum_{n=1}^{N}\Pr(H_n^0)(1-P_n^f(a_n,P_n^d=P_{th}))R_n^0$$

$$\text{s.t. } P_n^d=P_{th}>.5 \text{ and } P_n^f<.5$$

$$L=\frac{K}{t},\ \textstyle\sum_{n=1}^{N}a_n=M\times L, M\ge a_n>0, a_n\in I, n=1,2....N$$

We define the following and also give initial values for the variables.

1. A is initialized to a zero matrix of dimension $M \times L$. Zero at a particular place for $A(m,i)$ signifies that channel slot i of secondary user m is not assigned for any channel.
2. Occupancy vector $U(m)$ is a $M \times 1$ vector which contains number of channels assigned to each secondary user. $U(m) = \sum_{i=1}^{L} V(m,i)$ where $V(m,i) = 1\ if\ A_{m,i} = 0$ else $V(m,i) = 0$. $m = 1,2...M$
3. Channel utility, $s(a_n) = \Pr(H_n^0)(1 - P_n^f(a_n, P_n^d = P_{th}))R_n^0$ for $M \geq a_n > 0$

   $s(a_n) = s(M)$ for $a_n > M$

An incremental algorithm has been used to determine heuristic solution of problem P3 as in Chapter 3 and [24].

4.4 Algorithm 2 for hard combining in Rayleigh Fading Channels

1. For every channel $n = 1,2...N$, find minimum number of secondary users required for satisfactory sensing performance denoted by $a_n^{\min}$ that is $P_n^d = P_{th}$ and $P_n^f < 0.5$.
2. For a given K and t, if $\sum_{n=1}^{N} a_n^{\min} < L * M$, then proceed to 3 else problem is infeasible for the given pair of K and t. Increase t if possible. Else increase K.
3. The order of preference of channels for the allocation of sensing users should be in the decreasing order of sensing requirements for the said channel i.e. the channel requiring the maximum number of secondary users must be allocated first, followed by the channel requiring second highest number of users and so on. For this allocation, $a_n^{\min}$ least allocated secondary users should be chosen. This should be chosen by sorting the occupancy vector $U(m)$ and selecting the first $a_n^{\min}$ secondary users.
4. For the least allocated SU i.e. $m^* = \arg\min_{1 \leq m \leq M} U(m)$, find $J(n) = s_n(a_n + 1) - s_n(a_n)$. Find $n^* = \arg\max_{1 \leq n \leq N} J(n)$ such that $A_{m,l} \neq n$ for $= 1,2,..L$. Allocate this channel n^* in the allocation matrix A to secondary user m^*.
5. If all the mini-slots in A are filled, output A else go back to 4.

4.5 Channel Selection for SU

When the number of primary users is very large, it is impossible to scan all the channels due to hardware and energy constraints. In this scenario, we should select some channels such that the throughput attained is maximum with the given number of secondary users. In this unlike Algorithm 2, we choose channels selectively on the basis of its signal-to-noise ratio (SNR) from the secondary user to its receiver and the average transmission rate obtained on the channel. Previous work of channel selection was done by Wang et al. [27] in which they formed coalition of secondary users to scan the primary channels such that number of channels sensed could be maximized.

Since the number of SUs in the network and the number of channels sensed by each SU are limited, it will be better to assign channels requiring less SUs so that after each assignment, there are sufficient number of SUs left to sense other channels. Thus, intuitively, the channel assignment should be performed starting from the channels which require small number of SUs.

Channel utility is defined as

$$s_n(a_n) = \Pr(H_n^0)(1 - P_n^f(a_n, P_n^d = P_{th}))R_n^0 \text{ for } M \geq a_n > 0 \text{ .}$$

$$J_n = s(a_n + 1) - s(a_n) \text{, for } M > a_n > 0 \text{ and } a_n^{min} < M$$

$$J_n = 0 \text{ for } a_n = M \text{ or } a_n^{min} > M.$$

$$J_n = s(a_n^{min}) / a_n^{min} \text{ for } a_n = 0 \text{ and } a_n^{min} < M \text{ .} \tag{4.10}$$

The second definition means that channel cannot be scanned by given SU to required sensing accuracy and hence is of no utility for a given values of K and t. Here a_n^{min} is minimum number of secondary users required for satisfactory sensing performance. In the following section we state the algorithm 3 based on [24] and [27].

4.6 Algorithm 3 with Channel Selection

1. For every channel $n = 1,2...N$ find minimum number of secondary users, a_n^{min} required for satisfactory sensing performance that is $P_n^d = P_{th}$ and $P_n^f < 0.5$.

2. For the least allocated SU i.e. $m^* = \arg\min_{1\le m\le M} U(m)$ find $J = \{J_n\}_{n=1,2..N}$. Find $n^* = \arg\max_{1\le n\le N} J_n$ such that $A_{m,l} \neq n$ for $l = 1,2,..L$.
3. If $M > a_{n^*} > 0$, proceed to 4 else this channel should be allocated the required minimum $a_{n^*}^{\min}$ secondary users. For this allocation, $a_n^{\min}$ number of least allocated secondary users should be allocated this channel. This should be chosen by sorting the occupancy vector $U(m)$ and selecting the first $a_n^{\min}$ secondary users. Proceed to 5.
4. Allocate n^* channel in the allocation matrix A to secondary user m^*.
5. If all the slots in A are filled, output , else go back to 2.

Repeat both of these algorithms for all possible values of t. $t^* = \arg\max_{1\le t\le M, M \bmod t=0} S(A,t)$. This is also the solution for Problem P2. We have provided an optimal solution to problem P2, which is a sub problem of problem P1. Now, we can proceed to solve problem P1. With the solution of problem P2, denoted $D(K)$ for a specific K, problem P1 is equivalent to

$$\max_{K,t} C(K,t) = \frac{T-K\delta}{T} D(K,t)$$

$$\text{s.t. } 0 < K \le \left\lfloor \frac{T}{\delta} \right\rfloor.$$

To solve Problem P1, we have done simulations for various values of K and obtained the value for which the throughput is maximized.

4.7 Simulation Results

The system setup is same as in Chapter 2. The sampling rate is μ = 6 MHz, the slot duration is T = 100 ms, the threshold of detection probability is P_{th} =0.9 and secondary users are assumed to have a mean SNR of 20 dB between them. SNR_n^{ps} (SNR from the primary user to secondary user on channel n) follows exponential distribution because of the Rayleigh channel SNR_n^{ss} while (SNR from the secondary user to its receiver at channel n) is assumed to be constant. The mini-slot duration is $\delta = .1\, ms$. The simulations are done in Rayleigh fading channel and the optimal time settings are derived for Rayleigh channels as shown in the algorithm 2 unless stated otherwise.

For Figure 4.2, it is assumed that N=2, the available probability as $\Pr(H_1^0)$= 0.8 and $\Pr(H_2^0)$ = 0.6, and mean SNR from primary user to both secondary users as $\gamma_1 = -15$ dB in channel 1 and $\gamma_2 = -20$ dB in channel 2. There are M = 2 secondary users. For Figure 4.3, it is assumed that N = 5. For all the other cases, channel *n* $(1 \le n \le N)$ has a free probability $\Pr(H_n^0)$= $1-0.05*n$ and the average channel gain from the primary user to a secondary user is $\gamma_n = -20+n-1$ dB as in Chapter 3. The results are compared to soft combining of data using Algorithm 1 proposed in Chapter 3.

When N = 2 and M = 2, from Figure 4.2 we may note that the throughput at the optimal sensing time in soft combining is 7.2 bits/sec/Hz as compared to 7 bits/sec/Hz in hard combining. The optimal sensing time is 100 in soft combining as compared to 120 in hard combining.

For N = 5 and M = 5, from Figure 4.3 the optimal throughput deteriorates from 24 bits/sec/Hz in soft combining to 20.5 bits/sec/Hz in hard combining. In this case, the optimal sensing time has also increased from 120 slots in soft combining to 140 slots in hard combining. The throughput deterioration has increased in N = 5, M =5 case compared to N=2, M=2 case. It may be seen that the throughput is steady at the optimal value. The decrease is very slow at higher values of K. This is due to the fact that increasing K greatly increases the accuracy of individual decisions thus increasing overall accuracy and counteracting the effect of decrease in transmission time.

The throughput deterioration comes at the gain of only a decision which is binary value being transmitted to the fusion centre by the secondary user. It can also be seen that the throughput rises with increase in *K* value initially. This is due to the decrease in false alarm probability. Later on, it becomes steady because of the decrease in throughput due to increase in sensing time matches the increment caused by decrease in false alarm probability. After this the throughput begins to decrease as the increase in sensing time plays the dominant role. This behaviour is same as in case of soft combining of data at the fusion center. The optimal sensing time is greater by approximately 16% in both figures when hard combining is used instead of soft combining. This is due to the fact that there is a loss of data and hence sensing performance in hard combining. To compensate for this, sensing time has to be increased.

Figure 4.4 plots the variation of throughput for different values of sensing time t for a given value of K = 140. From this plot, the optimal value of t can be selected as 35. The throughput is lower at low values of t because lower sensing time has decreased the sensing efficiency of individual sensor . While for higher values of t, for a given K, spatial diversity decreases which is responsible for lower throughput.

Figure 4.5 and Figure 4.6 compares the throughput obtained by using Algorithm 2 and Algorithm 3 for N = 5, M=5 and N = 10, M=5 respectively. It can be inferred that Algorithm 2 gives zero throughput for values of K < 50 and K < 80 respectively for two cases, while Algorithm 3 gives non-zero throughput for the same. Almost equal throughput of 20 bits/sec/Hz is obtained for both the algorithms for higher values of K. The optimal sensing slots in both the cases are 140 .

Figure 4.7 plots the number of channels scanned for various value of total sensing duration, K. It can be seen that as we increase the value of K , higher number of channels can be scanned. At lower values of K, channels having higher SNR and greater throughput are selected, while at higher values channels having lower SNR and comparatively lower throughput will also be selected and scanned by the cognitive radio network. The network scans 4 channels at K = 20 which increases to maximum value i.e. the total number of primary users which is 10 at K=110.

In Figure 4.8, impact of number of secondary users on the throughput is shown for N=5 for hard combining as well as soft combining. It may be seen that when the number of secondary users increases, the optimal network throughput also increases. Interestingly, with a fixed value of N, when the value of M further increases beyond a certain value, the optimal network throughput seems to be constant. When M increases, the total sensing time for the channels also increases, which means that a smaller false alarm probability for each channel is expected. When M is large enough, the false alarm probability for each channel is almost zero. Using the objective function in P1 with constant probability of detection and near zero false alarm probability, it may be noted that throughput reaches to a saturation.

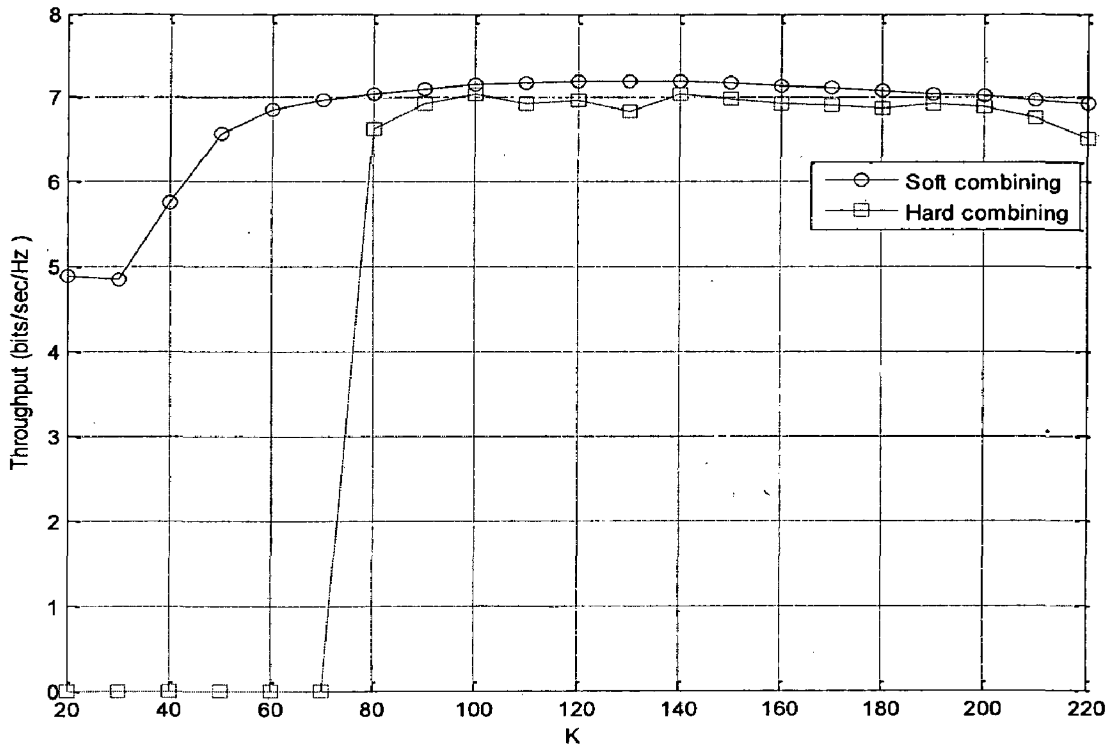

Figure 4.2: Throughput Comparison for soft combining and hard combining for Rayleigh fading channels, N=2, M=2

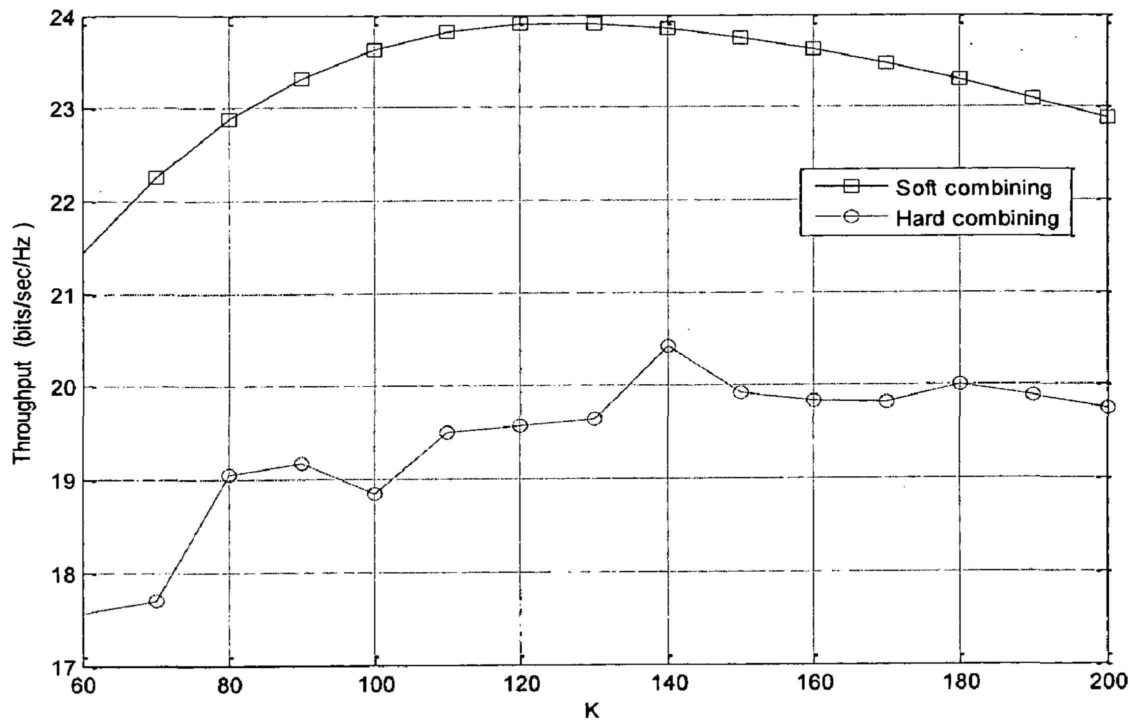

Figure 4.3 : Throughput Comparison for soft combining and hard combining for Rayleigh fading channels, N=5, M=5

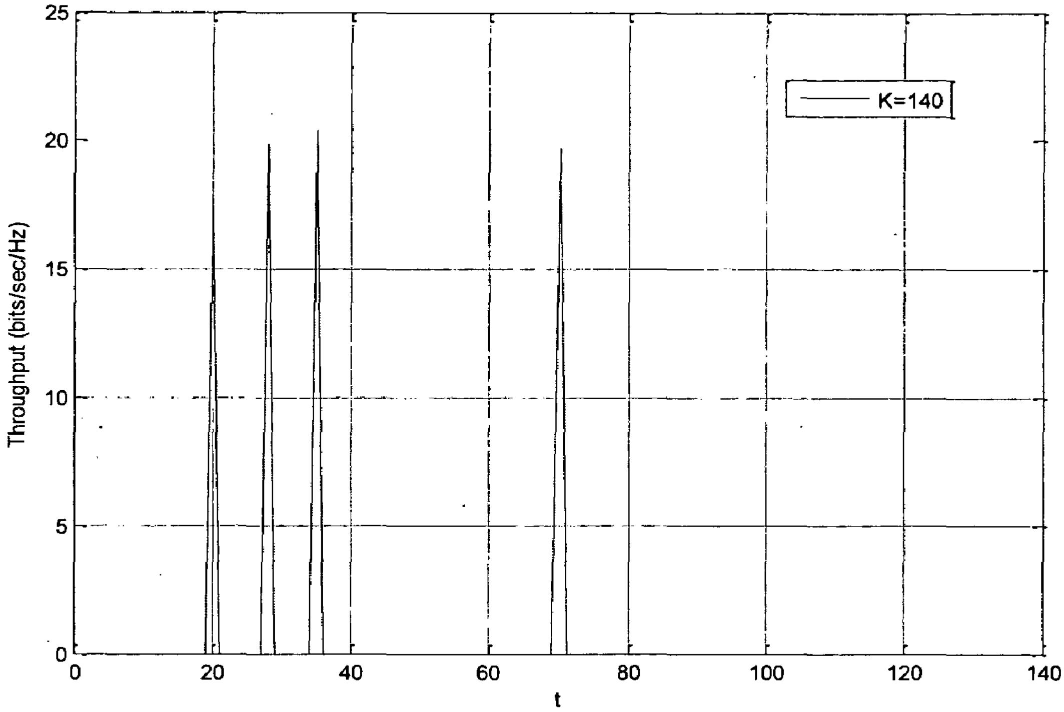

Figure 4.4 : Throughput for various values of sensing time t for K=140 for N=5, M=5 for selection of optimal sensing time

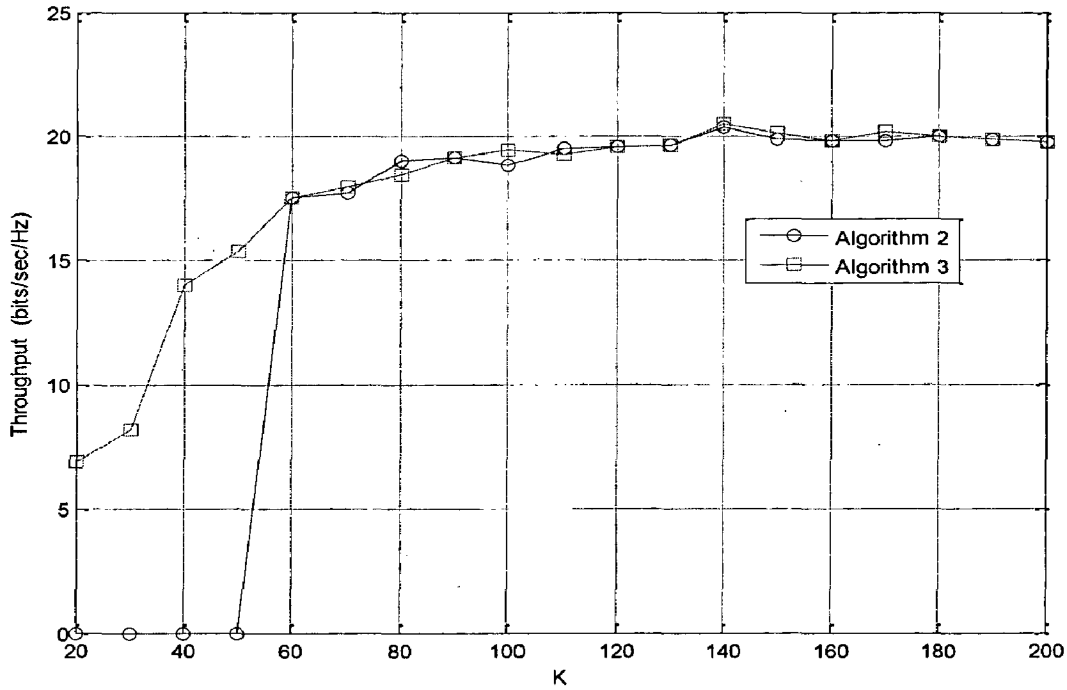

Figure 4.5 : Comparison of the throughput obtained by using Algorithm 2 and Algorithm 3 for N=5, M=5

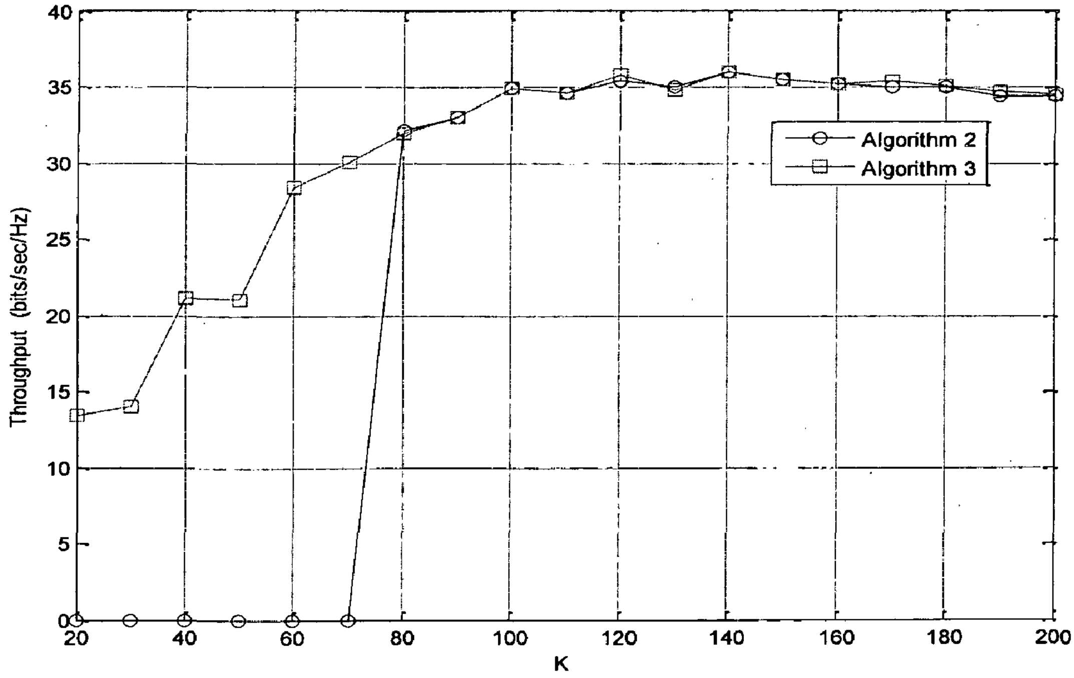

Figure 4.6 : Comparison of the throughput obtained by using Algorithm 2 and Algorithm 3 for N=10, M=5

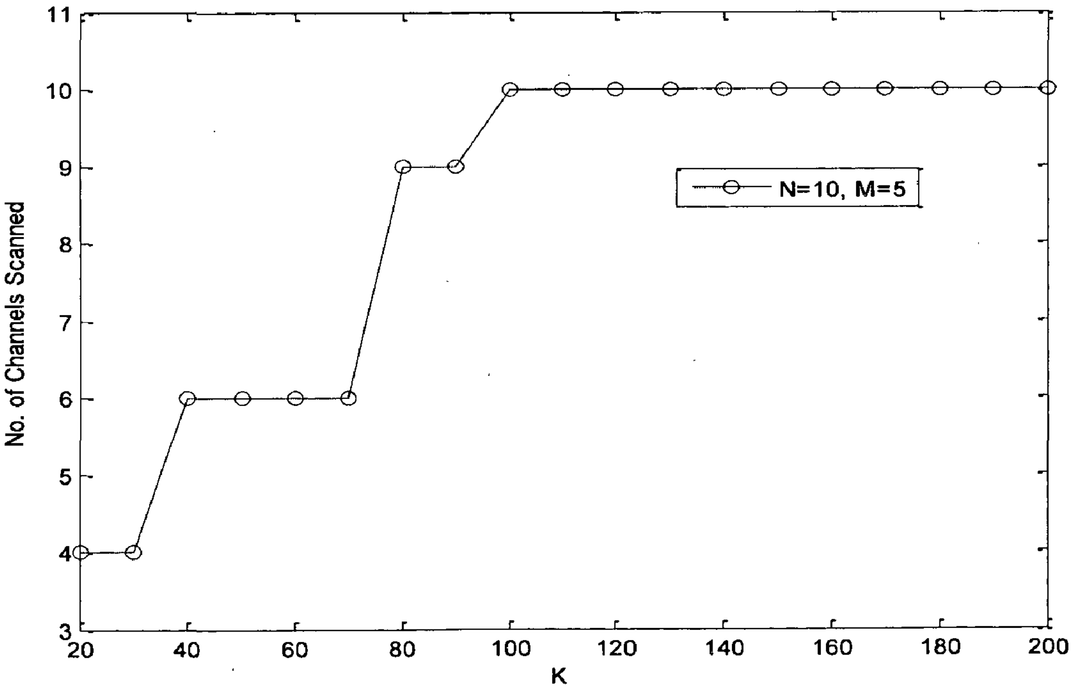

Figure 4.7 : Number of channels scanned for varying K for N=10 and M=5 using Algorithm 3

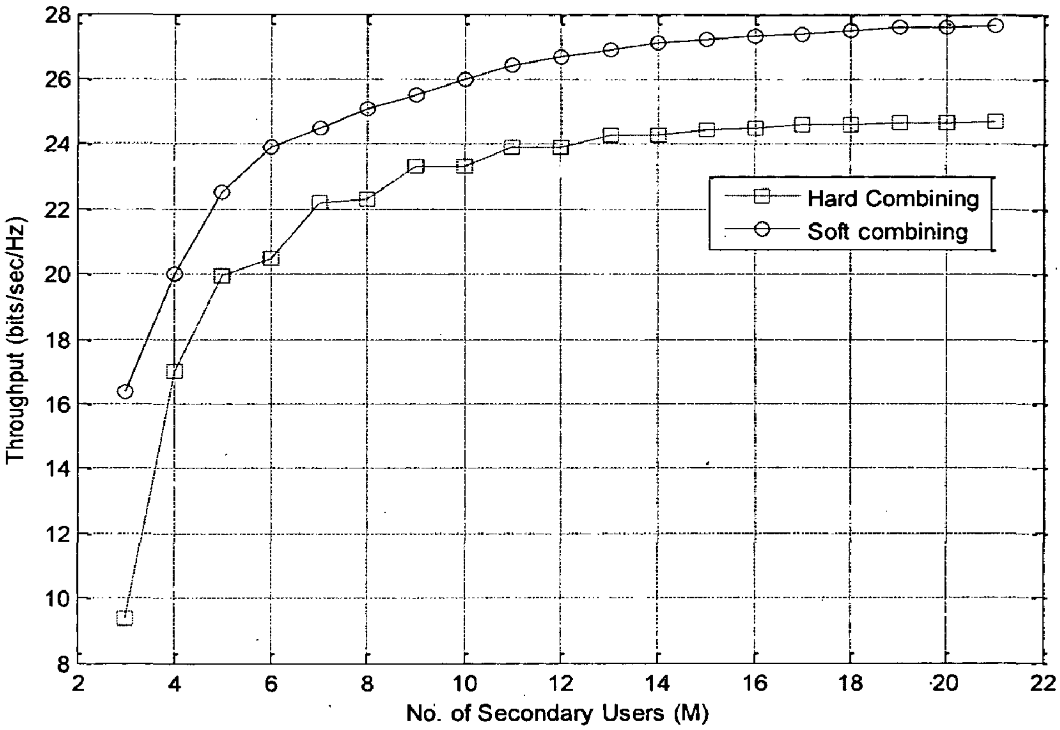

Figure 4.8: Variation of throughput with secondary users

Chapter 5

Conclusion and Future Work

This thesis attempts to study the emerging topic of cooperative spectrum sensing in cognitive radio networks. Multi-band joint detection by a set of narrowband energy detectors is studied. It presents a comparative analysis of cooperative spectrum sensing techniques using energy detection in AWGN and Rayleigh fading environment. Both hard combining and soft combining of data at the fusion centre is considered. Algorithms to determine the optimal sensing time durations have been developed and analysed. The throughput deterioration while going from soft combining to hard combining and from AWGN to Rayleigh Fading environment has been studied.

Chapter 1 presents an overview of the properties of cognitive radio such as adaptability and agility and various tasks a cognitive radio must perform. It explains the importance of spectrum sensing in a primary user-secondary user context and introduces various techniques used for spectrum sensing such as energy detection and cyclostationary detection and highlights their advantages and deficiencies. The need and elements of cooperative spectrum sensing is also explained.

In Chapter 2, we have considered joint multi-band detection by a set of narrowband energy detectors. The framework for the same was proposed and the optimization problem was proved to be convex in practical constraints over false alarm and detection probability. It has been concluded that the multiband joint detection algorithm with optimized thresholds and optimizing number of secondary users scanning each band can achieve a much higher opportunistic rate than that achieved by keeping uniform threshold and uniform number of secondary users for each band. With the proposed framework, the same aggregate throughput can be attained for a given aggregate interference with lower number of cooperating energy detectors. This in turn will lower the cooperation overhead. The proposed multiband joint detection makes better use of the wide frequency band by balancing the conflict between improving spectral utilization and reducing the interference.

In Chapter 3, the sub-optimal multi-channel cooperative spectrum sensing strategies in cognitive radio networks in Rayleigh fading environment is studied. We have given strategies to determine the total sensing time and distribution of the total sensing time to different channels in cooperative soft-decision spectrum sensing. Considering the slotted-time sensing mode, we converted the initial non-convex mixed-integer problem into convex mixed-integer sub problems, and provided a low-complexity algorithm to achieve the sub optimal solution of the initial problem. We have also seen the degradation of throughput and increases in optimal sensing time when the channels are assumed to be Rayleigh Fading which is more realistic than the AWGN assumption.

Chapter 4 discusses the multi-channel cooperative spectrum sensing strategies with hard combining used at the fusion center in Rayleigh fading channels. Heuristic algorithm has been designed to determine the allocation matrix which determines for each secondary user the list of all the channels to be scanned and the optimal sensing time for a channel and duration of sensing slot time. An algorithm which does channel selection out of the large number of available channels for limited number of secondary users based on signal to noise ratio and the throughput is also proposed. The throughput of the algorithm is compared to the case of cooperative soft-decision spectrum sensing considered in Chapter 3. We conclude that optimal sensing time increases and the throughput decreases while going from soft combining to hard combining as well as from AWGN to Rayleigh fading environment.

Optimal multi-channel strategy for energy constrained cognitive radio network [26] can be designed. The sensing time determination to maximize the throughput keeping the energy consumption and the interference constrained jointly should be addressed. .The problem can also be studied from a game theoretical point of view, in which each secondary user is assumed to be selfish but rational. This work is done for infrastructure based network in which each secondary user reports to the fusion centre which determines the presence or absence of primary user. This could be extended to cognitive radio networks not having a fusion centre too as done in [31]. In the case of hard combining, the data sent form secondary users transmitted to the fusion centre are binary unlike the complete data statistic sent in soft combining. The case in which quantized soft combining where the decision statistic is quantized in more than two levels as done in hard combining should be considered [42].

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