SPECTRUM SENSING SCHEDULING IN COGNITIVE RADIO NETWORKS

By

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SPECTRUM SENSING SCHEDULING IN COGNITIVE RADIO NETWORKS

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CHAPTER 1

Introduction

1.1 Cognitive Radio

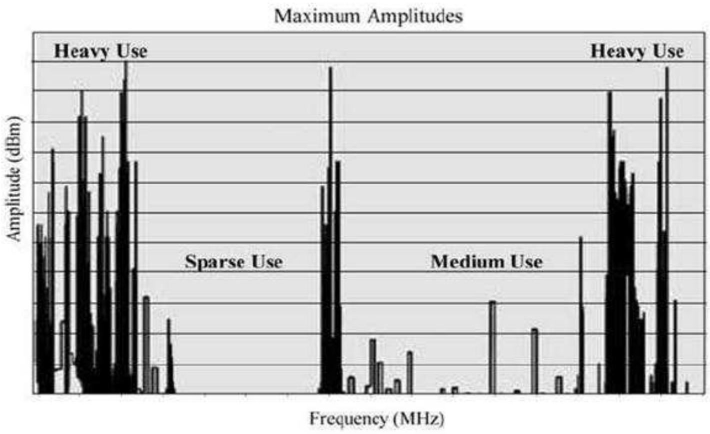


Figure 1.1: Spectrum Underutilization [1]

The need for higher data rate is increasing as a result of transition from voice only communication to multimedia type applications. Today, electromagnetic spectrum is considered a precious resource as it is the lifeline of communication. The use of this lifeline is regulated by governments and federal agencies all over the world. The current policy is to assign frequency bands to different applications on a long term lease basis. This includes wireless phones, TV channels, etc. In 2002, the Federal Communications Commission (FCC) came up with a report published by the Spectrum Policy Task Force, aimed at improving the way spectrum is managed in US [2]. The main reason for such a step is the underutilization of spectrum. It is seen in Fig. 1.1 that a large portion of the assigned spectrum is used scantily and utilization ranges from 15% to 85% [1]. Spectrum scarcity is thus an after-effect of the obsolete spectrum management protocol. This makes it clear that the spectrum bands are not utilized efficiently which is more of a significant problem than spectrum scarcity [3].

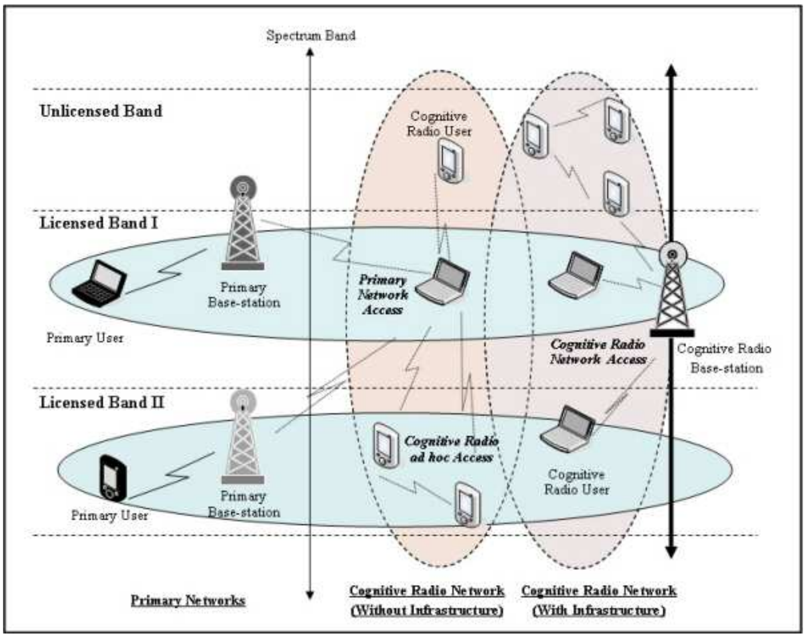


Figure 1.2: Concept of Primary user and Secondary User [4]

Innovative techniques are required that can handle spectrum underutilization and exploit the currently available spectrum. The dynamic spectrum access (DSA) policy involves assigning different frequency bands to different wireless networks only when a need arises. The concept of licensed or primary user (PU) and unlicensed or secondary user (SU) emerge in this process. PU has the priority or legal right on the usage of the designated spectrum. SU uses the licensed frequency bands without causing any interference to the licensed users. Such vacant bands are called spectrum holes or white spaces. A spectrum hole is a band of frequencies assigned to a primary user, but at a particular time and specific geographic location, the band is not utilized by the user [1]. Spectrum underutilization can be subsided if the spectrum holes can be utilized by a set of SU transceivers at the appropriate time and place. Cognitive Radio is one such wireless communication concept which can utilize the unused spectrum opportunistically with least interference to the existing users.

The concept of cognitive radio was first introduced by Mitola III [5]. It is defined in [2] as *Cognitive Radio is an intelligent wireless communication system that is aware of its surrounding environment (i.e. outside world) and uses the methodology of understanding-by-building to learn from the environment and adapt its internal states to statistical variations in incoming RF stimuli by making changes in its operating parameters. (e.g. transmit power, carrier-frequency and modulation strategy) in realtime with two primary objectives in mind :*

- *Highly reliable communications whenever and wherever needed.*
- *Efficient Utilization of Radio Spectrum [2].*

Thus cognitive radios are seen as the perfect fit for the description of secondary users. In simple words, a cognitive radio scans the radio environment, selects the best available spectrum hole based on requirements and most importantly vacates the channel when the licensed user returns. Based on the definition, the major duties of a cognitive radio are explained precisely in [2].

The CR state diagram explains the working of the CR with respect to different states as shown in Fig 1.3. The CR senses the radio environment for vacant channels or spectrum holes; It chooses the best available channel for communication by making changes in its parameters to suit the conditions of the available spectrum. The major tasks of the CR cycle are summarized as follows:

- Spectrum Sensing: CR's sense the radio environment and recognize the unused frequencies or spectrum holes without creating any hindrance to the licensed users. This process has to have accuracy such that there are no missed detections or false alarms about the occupancy of the PU.
- Spectrum Management: When the cognitive radio has found vacant spectrum

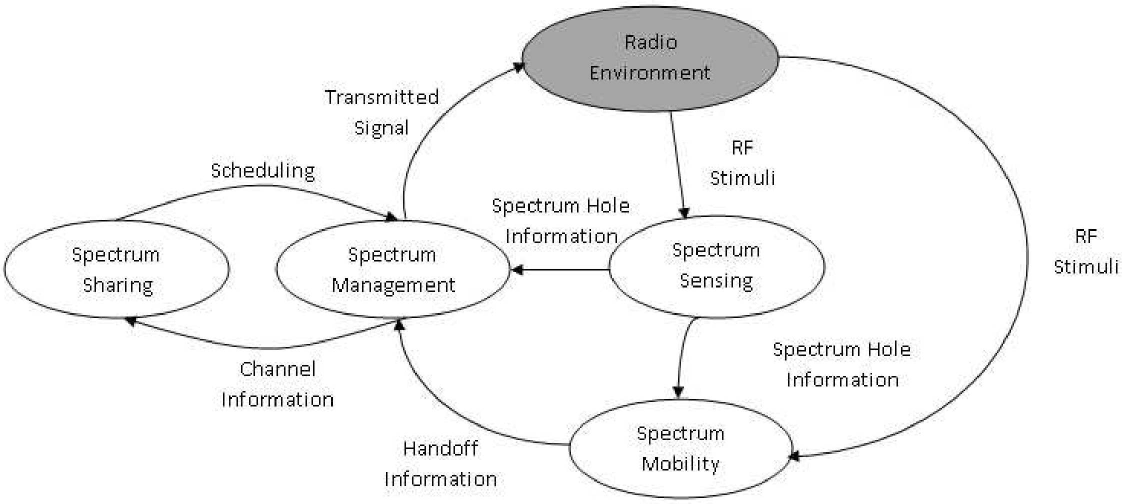


Figure 1.3: Cognitive Radio cycle [6]

bands, the cognitive radio must identify the best possible band according to its communication requirement.

- Spectrum Mobility: When two CRs are communicating with each other, there is a possibility that the PU returns to the active state. In such a case, the CR should be able to leave the band immediately and search another spectrum hole to continue its communication.

- Spectrum Sharing: A fair spectrum sharing method is used when many CRs coexist in the same area.

To summarize, main motive of the CR is to obtain the best vacant frequency band and utilize it for communication. This communication should cause least or no interference to the licensed user. If the licensed user becomes active in its band, the CR should leave the frequency band immediately and search for other spectrum holes to resume communication [1].

1.2 Motivation

From the above discussion, we can say that spectrum sensing is one of the most important components of a CR cycle. Based on spectrum sensing results, the CRs can use the available band for transmission. However, the sensing and transmission times in a CR cycle need to have a certain tradeoff. On one hand, allotting more time for sensing increases the accuracy of sensing results. But, it will decrease the sensing efficiency as the time allotted for transmission will be short. If the sensing time is shorter, the efficiency in terms of transmission gain increases. However, this happens at the cost of decrease in sensing accuracy. This may lead to interference to the licensed user with higher probability.

In most of the literature, all available CRs in the network participate together in sensing. This may not be necessary as well as efficient. There is a certain cost that is associated with sensing. This cost can be referred in terms of time and energy. When more number of CRs sense the spectrum, the sensing cost increases. However, increase in the number of CRs does not increase the sensing performance much in some situations. Hence a subset of CRs from the network can be used for obtaining a certain required sensing performance. While certain CRs are sensing, the other CRs in the network wait for result of sensing thus decreasing the cost of the system. The CRs can either wait or transmit depending on the channel state being 'occupied' or 'unoccupied.'

Hence in our work, we argue that it is not true that using more CRs or sensing more frequently is always a better choice. Sensing is required only when the uncertainty associated with the channel state is high rather than the channel is most possible to be available. If a channel is known highly likely to be occupied after sensing, how soon this channel should be sensed again purely depends on how soon the PU may leave the channel, with a goal to waste the spectrum resource as little as possible. On the other hand, if the channel is known highly likely to be available after sensing, data transmission can be allowed with a duration such that the gain of successful transmission is maximized while the cost of interfering the PU is minimized. When interference occurs, an equivalent sensing decision that the channel is occupied can be obtained with a high confidence. In this scheduling design, after each sensing process, CRs will wait for some time to sense the channel again. We propose a unified framework considering the gain/cost of all possible decision-makings and actions with an objective to maximize the overall gain on average. No periodic sensing is assumed.

A sensing scheduling scheme is designed that maximizes the average gain of transmission over one cycle of sensing and transmission to give optimized operating parameters. The operating parameters include optimal probability of false alarm and miss and waiting times for which the CRs should wait before the channel should be sensed again. The optimal operating parameters also includes the optimal number of CRs that should be used to sense the channel so as to obtain the maximum average gain. This sensing scheduling scheme is further extended to a more realistic scenario where multiple channels are to be sensed in a CR network. The single channel design is used to obtain an optimal parameter profile for each PU channel in the network. The profile is used in the sensing scheduling design that is implemented in multiple channel CR network. The expiring waiting times for each of the channels decides as to which channel should be allocated CRs for sensing. Two approaches, viz. greedy and non-greedy, are proposed to implement the sensing scheduling design.

1.3 Organisation of thesis

The remainder of the thesis is organized as follows: Literature review is presented in Chapter 2. The problem formulation and scheduling design for a single channel network is discussed in Chapter 3. Chapter 4 explains the scheduling design for multiple channels in a multiple CR evironment. Chapter 5 provides experimental results and analysis of the proposed design. Chapter 6 explains the cognitive radio test-bed implemented in the laboratory. Conclusions and future work are given in Chapter 7.

CHAPTER 2

Literature Review

Spectrum sensing and its scheduling has always remained an important component in the CR cycle. Accurate spectrum sensing helps us get to know the presence of PU in the spectrum. This basically includes measuring the radio frequency energy over which the CR is monitoring. Based on the results, the CR decides whether it should start communication with other CR. This chapter will focus on a review of techniques on spectrum sensing, cooperative spectrum sensing and spectrum sensing scheduling.

2.1 Spectrum Sensing Techniques

Spectrum sensing can be widely classified into narrowband spectrum sensing and wideband spectrum sensing. Following are some of the conventional spectrum sensing techniques. Besides these, a large number of sensing methods have been developed using various techniques [7].

Narrowband spectrum sensing

Energy detection is one of the most widely used non-coherent narrowband detection methods. Energy over the narrowband spectrum under consideration is measured. This obtained value is then compared to a predetermined threshold to decide the presence or absence of a licensed user [8] [9]. Due to its simple implementation and non-requirement of prior knowledge, energy detector is one of the favourite methods for spectrum sensing. Though it has a few drawbacks like choice of threshold, inability to differentiate between PU, noise and SU signal, it is still one of the most widely used spectrum sensing technique. Many PU signals are generally coupled or modulated with sine waves, cyclic codes, pulse trains, hopping sequences, etc. which result in built-in periodicity. Such type of modulated signals are called Cyclostationary signals since its characteristics exhibit periodicity. This periodicity is introduced on purpose. With the help of this periodicity, the receiver can estimate the phase of the carrier, pulse timing, etc. It can be used for detection of signals that belong to a particular type [10] [11]. In waveform based sensing, patterns such as preambles, midambles, spreading sequences generally used for synchronization are used for detection. In case of such known pattern, sensing of a channel is possible by correlating the received signal with a copy of itself. However, this is possible only when the pattern is know to the CRs. The decision regarding the presence of the PU is made by comparing the waveform decision metric to a fixed threshold [12]. Radio identification based sensing is one more narrowband sensing method which has been studied in literature. Spectrum characteritic information can be obtained accurately by knowing about the technologies used by the PU and identifying them accurately. This property is exploited for detection by the CR users. In radio identification based sensing, several features are extracted from the received signal. These features are then identified as to which technology they belong to. Using these features, it can be identified whether a PU is present in the sensed spectrum. Features include channel bandwidth, energy, cyclic frequency, etc [7].

Wideband spectrum sensing

The main aspect that needs to be considered in wideband sensing is the large amount of bandwidth that is to be sensed. [13] proposes a wavelet based approach in which the signal spectrum over a wideband is decomposed into elementary building blocks of subbands. These subbands carry relevant information of frequency location and power spectral densities. [14] proposes a wideband detection based on a set of random overlapping filters. Energies at the filter outputs are used as compressed measurements to reconstruct signal energy in each channel. The next approach is using a bank of energy detectors know as the filter bank. Each of the energy detectors are tuned to different frequencies and we can obtain the occupancy report of the total wideband spectrum [15]. [16] explains a compressive wideband spectrum sensing algorithm. It is a process based on the autocorrelation of a compressed version of a received signal. The reconstructed spectrum is then used for detecting the signal occupancy in the wideband spectrum.

2.2 Cooperative Spectrum Sensing

Sensing performed at a single SU is not always reliable or accurate. Sometimes the PU signal may undergo fading and/or shadowing. As a result, the SU might declare the spectrum band as a spectrum hole. This creates interference to the PU. This issue can be resolved by using cooperative spectrum sensing.

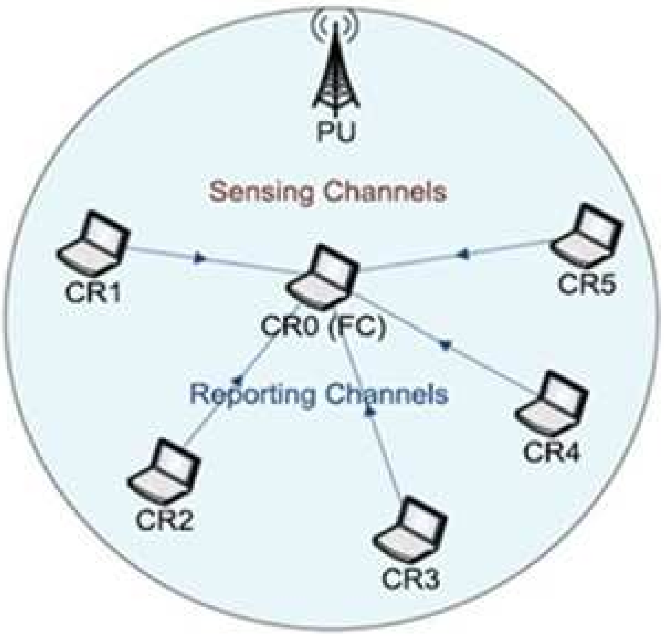


Figure 2.1: Centralized cooperative sensing [17]

Individual CRs perform sensing at the local level and send their results to a fusion center via a dedicated control channel. The Fusion Centre fuses the received results, comes up with a global estimate and diffuses the results back to the CRs. Cooperative spectrum sensing can be widely classified into centralized and distributed methods. Centralized cooperative sensing or fusion as shown in Fig. 2.1 consists of a dedicated fusion centre where all the CR send their local sensing results. The fusion centre will fuse the data to form a global occupancy report of the spectrum. Fig 2.2 shows

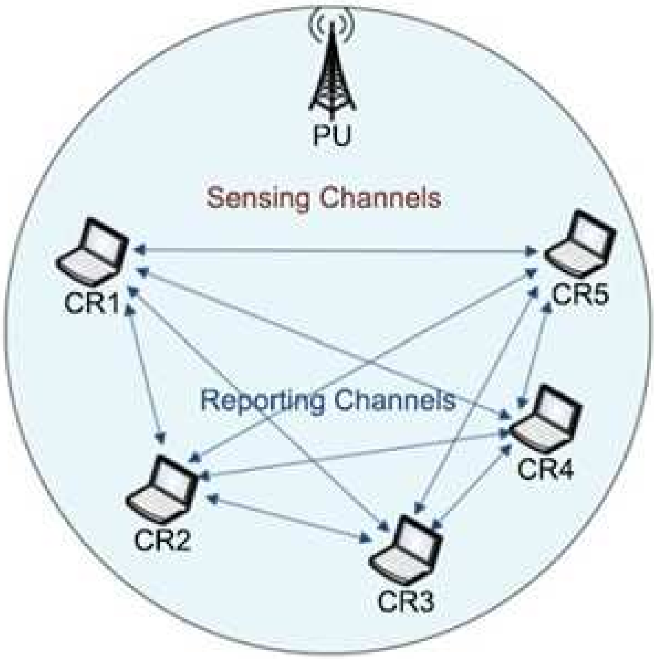


Figure 2.2: Distributed Cooperative Sensing [17]

distributed cooperative sensing in which CRs share their results with each other using reporting channels. Each CR runs a distributed algorithm using its own estimates and the estimates obtained from its neighboring CRs. It's an iterative process. The process continues till the algorithm converges to a global detection estimate. Different algorithms have been derived in order to study distributed cooperative sensing.

Vast number of collaborative spectrum sensing techniques have been exploited in literature [18]-[19]. In [18], energy detectors are adopted at individual CRs and their sensing decisions are transmitted to the fusion center. A linear-quadratic fusion strategy is designed for global decision making. A censoring method is used in [20], where only a selected group of CRs send their decisions to a fusion center. This in turn reduces bandwidth usage during cooperation. In [17], soft decision combining is shown to help further increase the detection accuracy. In [21] and [22] cooperative wideband spectrum sensing techniques are studied in which multiple channels are sensed in one go. Cooperative techniques exploiting cooperative diversity and multiuser diversity have been explained in [19].

2.3 Spectrum Sensing Scheduling

To enable the cogntive radio to communicate, protection of PU is very important as interference to the PU is inacceptable. Therefore, sensing and transmission times need to be determined optimally so as to increase efficiency and decrease interference to the PU. Efficiency can be in terms of trasmission gain or throughput. If the CR senses the channel for a longer period, the efficiency decreases as transmission time reduces. Whereas, if the sensing time is shorter and the transmission period is longer, there is a chance of an inaccurate spectrum sensing decision or change of state of PU during transmission. In both the cases, either the efficiency decreases or the interference to the licensed user increases.

[23] studies the optimal sensing and transmission time control in order to maximize SU usage. the optimal access poilcy is established on a threshold-based structure. When the idle state of the PU is known at a certain time, transmission should not be continued beyond this derived threshold. [24] aims at achieveing a high efficiency and a low interference rate. Normalized spectrum utilization and normalized collision rate are derived as functions of the data transmission time and CR user's traffic model. The data transmission time is then optimized by maximizing normalized spectrum utilization and bounding the normalized collision rate. The tradeoff between sensing

and transmission time is studied in [25] with the objective to maximize sensing efficiency subject to the interference constraints. Sequential sensing is conducted where all CRs sense each individual channel following a least-cost-first-serve criterion. In [26], a spectrum access strategy is explained based on slotted sensing and slotted transmission. Slotted SUs overlap on unslotted PU channels under energy and interference constraints. The channel reuse rate ρ is maximized by keeping a constraint on energy consumption and the interference to the PU. The optimization has constraints on the interference caused during SU transmission and energy consumption.

The above literature talks about the tradeoff between sensing and transmission times. However, a sensing scheduling task comprises of CRs sensing the availability of spectrum, computing the waiting time based on the characteristics of the spectrum band under consideration and schedule the next sensing time based on the results of the above two components. In [27], the channel utilization is maximized while limiting the interference to primary users. The channel utilization refers to successful transmission in a time slot. This channel utilization is maximized under the constraint of interference caused to the PU. Linear programming based on the stationary distribution of PU channels is used in optimization. [28] describes a sensing scheduling approach to improve the channel utilization while limiting the interference to the PU. Utilization and interference are defined in terms of communication duration and interference duration with respect to the entire cycle. [29] explains a cooperative spectrum sensing scheduling problem in cognitive radio networks under energy constraints. The problem of assigning a finite number of CRs to multiple channels is studied. It is modeled as a combinatorial optimization problem with an objective to maximize the successful transmission while minimize the failed ones. [30] also speaks about SU's channel utilization maximization having a constraint on the maximum tolerable interference level. [31] describes efficient scheduling of sensing mechanism's time-frequency assignments for efficient radio utilization. Different time resolutions are allocated to different portions of the spectrum using a backoff algorithm. These time resolutions are allocated to a different set of channels by learning their respective PU activity patterns.

[32] aims at exploring the issue of detection time selection under the constraint of improving the channel efficiency. A numerical optimization algorithm is developed for optimal detection time for uncorrelated samples. [33] focuses on the sensing period optimization that maximizes discovery of spectrum opportunities by sensing period adaptation. Proactive sensing technique is used to seek more bandwidth from different channels in order to transmit packets at a higher data rate. [34] investigates optimal inter-sensing durations to maximize CR user throughput. The sensing time is assumed to be constant and the optimal frame length consisting of sensing and transmission is obtained in order to maximize throughput. The literature in [33] [34] focuses mainly on periodic sensing and detection errors are not considered. The current literature does not explore much how to obtain the optimal number of CRs that can be used for a channel.

The optimality of a sensing scheduling algorithm can be measured in terms of average gain obtained from the algorithm per cycle. This gain can be in terms of transmission opportunities per unit time. Thus the primary user activity state ON-OFF and the decision taken by the SU on the underlying state can be modeled as a semi-markov decision process with a certain state space and action space. Semi-markov decision procesess have been explained in detail in [35]. [35][36][37][38][39][40] explain how to obtain an average cost under a semi-Markov decision process with the specified action space and state space.

CHAPTER 3

Spectrum Sensing Scheduling for a Single Channel

Assume that there are J CRs available in the network, conducting spectrum sensing for opportunistic channel access. PUs have the absolute right to use the channel assigned to them at any time. On one hand, using more CRs to sense a channel can increase decision accuracy. However, this may incur more sensing cost. On the other hand, sensing more frequently leads to better situational awareness regarding channel availability. However, this strategy may reduce the time that can be allocated for actual data transmission. The optimal tradeoff or balance among these considerations depends on several important system factors: (1) Primary user activity pattern: how often and how long a PU occupies a channel; (2) Sensing and decision strategy: how sensing decision is made with multiple CRs and various observing signal to noise ratios (SNRs). Next, the models associated with these factors are described in detail.

3.1 Primary User Activity Pattern Model

The PU activity pattern has a close relation to the performance of a CR network. The PU activity or model can be described in terms of two states ON & OFF i.e. at any time, a channel can be in one of the two states: it is occupied by the PU or it is unoccupied. PU traffic can be modeled in two distinct methods: using either a deterministic model or a stochastic model. This depends on the traffic pattern of the primary channels that are under consideration. Generally, the times the system is in either states follows some fixed but arbitrary distribution. It is commonly assumed that PU accessing the channel follows a Poisson distribution and the time PU occupying the channel follows an exponential distribution [41] [42]. Different accesses are independent of each other. This leads to the general two-state semi-Markov model, a.k.a., an alternating renewal process [25]. The Poisson process implies that the time of PU arrival and the interarrival time between two successive interarrivals are mutually independent. Let τ_I denote the time between two successive arrivals of the PU,

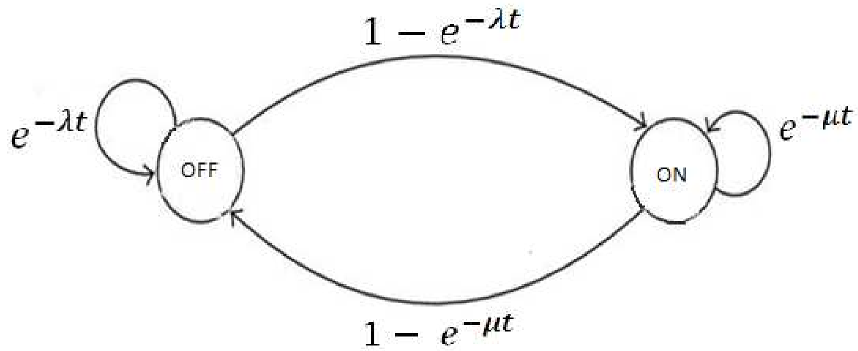


Figure 3.1: Two State PU model

i.e., interarrival time. The probability density function of τ_I is given by,

$$p(\tau_I) = \lambda e^{-\lambda \tau_I} \tag{3.1}$$

where λ is the mean arrival rate of the PU.

The service time is the duration for which the PU occupied a licensed channel. Let μ be the inverse of the average holding time of the PU. Let τ_S denote the duration of a PU occupying its licensed channel, i.e., service time. The probability density function of τ_S is given by [43],

$$p(\tau_S) = \mu e^{-\mu \tau_S} \tag{3.2}$$

Based on the primary user activity models (1) and (2), the marginal probabilities of the channel being unoccupied and occupied can be approximated as

$$P_0 = \frac{\mu}{\lambda + \mu}, \qquad P_1 = \frac{\lambda}{\lambda + \mu} \tag{3.3}$$

respectively.

3.2 Cooperative Sequential Energy Detector

Energy detection is a non-coherent detection method that detects a PU based on the sensed energy. Due to its simplicity and no requirement of *a priori* knowledge of PU signals, energy detection is the most popular sensing technique applied in cooperative spectrum sensing. The detection test is of the following hypothesis

$$\begin{aligned} H_0 : T[n] &= W[n] \qquad\qquad : Signal Absent \\ H_1 : T[n] &= X[n] + W[n] \quad : Signal Present \end{aligned}$$

$n = 1, \ldots, N$ is the observation interval. The noise is assumed to be additive and Gaussian with zero mean and variance σ_n^2. The signal samples are Gaussian with σ_s^2 as the variance [9] Let Y denote the energy measurement at a CR,

$$Y = \sum_N (T[n])^2 \tag{3.4}$$

Let $\tilde{Y}$ be the energy value normalized by the noise standard deviation. It can be shown that when the PU is absent, $\tilde{Y}$ follows a chi-square distribution with N degrees of freedom, where N is the number of samples collected for energy calculation. If sampling rate f_s is used, then the time for taking one energy measurement is $t_s = \frac{N}{f_s}$, which is generally a very small time duration. When the PU is present, it can be shown that $\tilde{Y}$ follows a non-central chi-square distribution with N degrees of freedom and non-centrality $N\gamma$, where γ is the sample SNR. When N is large, chi-square distributions can be approximated by Gaussian distributions [9] [44]. Specifically, we have,

$$\begin{aligned} H_0 : Y &\sim \mathcal{N}(N\sigma_n^2, 2N\sigma_n^4) \\ H_1 : Y &\sim \mathcal{N}(N\sigma_n^2 + N\sigma_s^2, 2N\sigma_n^4 + 4N\sigma_n^2\sigma_s^2) \end{aligned}$$

To simplify the notation, we define $\hat{Y} = \frac{Y - N\sigma_n^2}{\sqrt{2N}\sigma_n^2}$. It can be easily shown that

$$
\begin{aligned}
H_0 : \hat{Y} &\sim \mathcal{N}(0, 1) \\
H_1 : \hat{Y} &\sim \mathcal{N}(\sqrt{\frac{N}{2}}\gamma, 1 + 2\gamma)
\end{aligned}
$$

where $\gamma = \frac{\sigma_s^2}{\sigma_n^2}$.

Assume that j ($j<J$) CRs cooperate in sensing a channel. Instead of decision fusion, all the normalized energy measurements $\hat{Y}_i, i = 1, \cdots, j$, are collected at a fusion center (it can be one of the CRs) for decision making. This is feasible when CRs within the one-hop neighborhood collaborate with each other and this is often seen in practical scenarios [22]. As mentioned before, sensing is required if the uncertainty associated with a channel is high. Here, we adopt the sequential sensing approach.A statistical analysis where number of samples in an observation, is not fixed in advance is known as sequential analysis or sequential testing. The main advantage of this analysis is the conservation of reporting channel bandwidth and reduction in the average observation time. Generally binary hypothesis tests fall into fixed sample test and variable sample test. In a fixed sample test, the null hypothesis H_0 is either accepted or rejected after observing a certain fixed number of samples. In sequential analysis, the number of samples required for making a decision is not fixed, but depends on the actual received samples. The detector can stop collecting more samples, if the actual received samples can provide sufficient information to make a decision.

The idea here is that, if accumulated energy measurements from j CRs are sufficient to meet certain confidence level, a sensing decision is made; otherwise, more measurements are collected. It can be shown that the optimal detector is in the form of the sequential probability ratio test (SPRT) [45]. Sequential probability ratio test (SPRT) is an optimal test that minimizes the average required sample size among all test which achieve the same detection and false alarm probability performance, provided the samples are independent [46]. Specifically, the accumulated log likelihood ratio at the L^{th} step is given by,

$$\begin{aligned} LLR_L &= LLR_{L-1} + \log \frac{p(\hat{Y}_{1L}, \ldots, \hat{Y}_{jL}|H_1)}{p(\hat{Y}_{1L}, \ldots, \hat{Y}_{jL}|H_0)} \\ &= LLR_{L-1} + \sum_{i=1}^{j} \log \frac{p(\hat{Y}_{iL}|H_1)}{p(\hat{Y}_{iL}|H_0)} \end{aligned} \tag{3.5}$$

The energy measurements are assumed to be conditionally independent of each other across all the CRs. Two thresholds a and b are set and the decision rule is as follows,

$$LLR_L = \begin{cases} > a, & \text{decide on } H_1 \\ < b, & \text{decide on } H_0 \\ \text{otherwise}, & \text{take another set of measurements.} \end{cases}$$

This decision rule indicates that if the log likelihood ratio takes extreme values, we are confident on the channel state. Resensing is required only if the uncertainty associated with the channel state is still high. This method can help reduce the number of sensing steps efficiently. Let α be probability of false alarm and β be the probability of missed detection. According the SPRT, the two thresholds are given by [45],

$$a \approx \log \frac{1-\beta}{\alpha}, \quad b \approx \log \frac{\beta}{1-\alpha} \tag{3.6}$$

From eqn. 3.6, the expression for probability of false alarm and probability of miss in terms of tresholds are given as,

$$\alpha \approx \frac{1-e^{b}}{e^{a}-e^{b}}, \quad \beta \approx \frac{1-e^{-a}}{e^{-b}-e^{-a}} \tag{3.7}$$

The number of sensing steps L required for decision making in a sequential test is random. At low SNR, it can be shown that its distributions under both hypotheses are approximately Gaussian [47],

$$H_1 : L \sim \mathcal{N}\left(\frac{4a}{Nj\gamma^2}, \frac{4a}{N^2 j^2 \gamma^4}\right) \tag{3.8}$$

$$H_0 : L \sim \mathcal{N}\left(\frac{-4b}{Nj\gamma^2}, \frac{-4b}{N^2j^2\gamma^4}\right) \tag{3.9}$$

The proof is derived in the appendix. Note that when $L < 1$, L is set to be 1 and the probability mass $P(L < 1|H_i)$ is used for the following calculation.

The corresponding total sensing time is given by Lt_s. Here we assume that the total sensing time is sufficiently small such that the channel state does not change in the sensing stage. In practice, truncated sequential tests can be adopted to impose an upper bound on the sensing time.

3.3 Sensing Scheduling Design

When we have multiple identical CRs sensing one channel, the questions that need to be addressed include (1) How many CRs are needed; (2) When to stop sensing; and (3) How long to wait for next sensing. Let C_s denote the cost associated with each CR taking one energy measurement. This implies that we should not use more than necessary CRs to sense the channel all the time. The total cost due to sensing is given by C_sjL. If decision H_1 is made, CRs wait for T_1 seconds before next sensing. If decision H_0 is made, the channel is available for data transmission and it is scheduled for T_0 seconds before next sensing. Depending on the true underlying state of the channel, there can be various gain/cost associated with each of the above actions.

True channel state is H_1, decision H_1 is made.

In this case, the channel is occupied by the PU at the time of sensing and it is detected correctly. CRs will stop sensing for T_1 seconds. If T_1 is relatively short, the PU does not change its state with a high probability $e^{-\mu T_1}$. There will be no gain or cost in this case. However, if T_1 is relatively large, the PU can leave the channel at any time and the cost of not using the available spectrum is incurred when it happens. The probability that the channel changes its state is $1 - e^{\mu T_1}$ and the duration that the channel is unoccupied converges to P_0T_1. Assume the cost of wasting a channel is C_f per unit time. Then, the total cost within T_1 is given by:

$$\begin{aligned} C_{11} &= C_f[e^{-\mu T_1}(0) + (1 - e^{-\mu T_1})P_0T_1]. \\ &= C_f(1 - e^{-\mu T_1})P_0T_1. \end{aligned} \tag{3.10}$$

True channel state is H_0, decision H_1 is made.

In this case, the channel is available at the time of sensing. However, the wrong decision is made. CRs will stop sensing for T_1. The cost of not using the available spectrum is incurred from the beginning of T_1. However, whenever the PU comes back in between, the cost diminishes. If T_1 is relatively short, the PU does not change its state with a probability $e^{-\lambda T_1}$. The cost persists over this period. The cost becomes 0 whenever the PU comes back and occupies the channel. The associated probability is $1 - e^{\lambda T_1}$ and the available duration converges to P_0T_1. Thus, the cost in this case is given by :

$$C_{01} = C_f \left[e^{-\lambda T_1}T_1 + (1 - e^{-\lambda T_1})P_0T_1\right]. \tag{3.11}$$

True channel state is H_1, decision H_0 is made.

In this case, a missed detection occurs. The action would be to transmit data for T_0 seconds until next sensing. However, collision and interference to the PU occur immediately. The channel state becomes known to be occupied if for example, no acknowledgement is sent by the CR receiver. Hence, CRs will switch to the waiting stage for T_1 seconds. Assume that the cost associated with missed detection is C_m. Then, the cost in this case is given by

$$C_{10} = C_m + C_f(1 - e^{-\mu T_1})P_0T_1. \tag{3.12}$$

True channel state is H_0, decision H_0 is made.

In this case, the channel is scheduled for data transmission for T_0 right after sensing. However, the PU may return at any time within T_0. Here two cases have to be considered. First, the PU does not return and the transmission is successful for entire T_0. In this case, the gain is given by GT_0, where G is the successful transmission gain per unit time. If the PU returns within T_0, collision occurs, transmission is stopped immediately and all CRs wait for T_1 seconds. The gain and cost associated with this case are $Gt, t < T_0$ and $C_{11} = C_m + C_f(1 - e^{-\mu T_1})P_0 T_1$, respectively.

Comparing the above four cases, we can see that the total gain and cost can be different. Besides, the total time duration and the probability of each case are also different. Therefore, we adopt here the total average gain as an objective function. Specifically, the contribution from Case 1 is

$$G_{11} = -(1-\beta)\frac{C_s jL + C_{11}}{Lt_s + T_1}. \tag{3.13}$$

The contribution from Case 2 is

$$G_{01} = -\alpha\frac{C_s jL + C_{01}}{Lt_s + T_1}. \tag{3.14}$$

Case 3:

$$G_{10} = -\beta\frac{C_s jL + C_{10}}{Lt_s + T_1}. \tag{3.15}$$

Case 4:

$$G_{00} = (1-\alpha)\cdot\left[e^{-\lambda T_0}\frac{GT_0 - C_s jL}{Lt_s + T_0} + E_{t,t<T_0}\left(\frac{Gt - C_s jL - C_{11}}{Lt_s + t + T_1}\right)\right]. \tag{3.16}$$

where $E_{t,t<T_0}(\cdot)$ is the expectation with respect to t and $p(t, t < T_0) = \lambda e^{-\lambda t}, t < T_0$. Furthermore, since L is also random,

$$\overline{Gain} = P_0 E_{L|H_0}(G_{00} + G_{01}) + P_1 E_{L|H_1}(G_{10} + G_{11}) \tag{3.17}$$

where $E_{L|H_i}(\cdot)$ denotes the expectation operation with respect to L under hypothesis H_i, $i = 0, 1$. Note that the average is in the sense of both time average and statistical average.

By examining the objective function (13), we can see that it is a function of many variables. Among these, λ, μ, γ, t_s, C_s, C_f, C_m and G are the system parameters and are generally given, while j, α, β, T_0 and T_1 are the design parameters and can be adjusted. Therefore, the sensing scheduling problem becomes the following optimization problem,

$$\max_{\{j,\alpha,\beta,T_1,T_0\}} \overline{Gain} \tag{3.18}$$

where $j = 1, 2, \cdots, 0 < \alpha, \beta < 0.5$ and $T_0, T_1 \in R^+$. Since the objective function is relatively complex and the number of variables is relatively large, genetic algorithms [48] [49] [50] can be adopted to find solutions to this problem.

3.4 Optimization using Genetic Algorithms

Genetic algorithms are an optimization and search technique based on the principles of genetics and natural selection [48]. It is a search technique that replicates the natural evolution process. The genetic algorithm process starts with a population of individuals that are randomly generated. Each individual gives a certain value of the objective function. In each iteration, the fitness of each generated individual is checked against a fitness function. A determined number of individuals are selected from the population on the basis of their fitness. The selected individuals are used to generate new population by operators like crossover and mutation. The newly generated population undergoes the above process in the next iteration till the algorithm converges under pre-determined criteria. In literature, genetic algorithms have been studied for both discrete as well as continuous variables [48] [49] [50]. A few advantages of generic algorithms are optimization of continuous as well as discrete variables, can deal with a large number of variables in a function, simultaneously forms a wide sampling cost surface, provides a list of optimum variables and works well with numerically generated data, experimental data or analytic functions. The main components of this algorithm are as follows:

- Population Generation
- Selection
- Crossover
- Mutation

Population Generation

A genetic algorithm starts with the generation of numerous randomly generated solutions. Each solution is called a chromosome or an individual. The individual consists of all the variables that are used in the optimization function. In our design, the chromosome is as follows:

$$Chromosome = [\alpha \, \beta \, T_0 \, T_1 \, j] \tag{3.19}$$

Let Ag_i be the average gain of the i^{th} chromosome. Such randomly generated chromosomes together constitutes the total population for the genetic algorithm. Average gain values are obtained for each of the configuration in the chromosome.

Selection

After the generation of population and their respective average gain values, the next stage is the selection of individuals that are fit to survive and can generate offspring for the next generation. The individuals are arranged according to the descending order of the average gain. A set of these individuals is selected and the remaining are discarded. This process of selection occurs at every iteration of the genetic algorithm so as to allow the individuals to evolve over the stages. After a fraction of the population is selected, new offsprings are generated through crossover and mutation of the selected individuals. Different methods of selection for crossover include natural selection, roulette selection, tournament selection, etc [48]. Natural selection is one of the most widely used selection methods. A determined percentage of the total population is selected. Before selection, the population is arranged in the decreasing order of the fitness function. After selection, let M_{sel} be the population size that is ready for crossover.

Crossover

Crossover is a genetic algorithm operator that is used to vary the variables in the individuals from one generation to the other. Two parents are drawn from the population of selected individuals. These parents give birth to two offsprings. The main objective of crossover operator is the new offsprings will be better if they take the best genetic characteristics from both the parents. Literature explores different methods of drawing parents from the selected individuals. Each parent selection scheme will result in a different set of parents. Some of the schemes are top to bottom pairing, random pairing, random weighted pairing, tournament selection and roulette wheel selection [48] [50]. We use the gain weighting or roulette wheel technique on the selected individuals to decide the order of individuals for mating. The probability assigned to each individual is directly proportional to the average gain obtained from the individual. An individual with higher gain will have a higher probability of being a parent for the production of next generation of individuals, whereas the individual with a lower gain will have a lower probability of mating. A uniformly distributed random number is selected between 0 and 1. The probability that spans the range of the random number decides the individual to be selected.

The probability of selection is calculated from the average gain of the individual in the population. A normalized gain is calculated for each individual by subtracting the highest gain among the discarded individuals i.e. $(M_{sel}+1)^{th}$ individual and the corresponding average gain is $Ag_{M_{sel}+1}$, from the average gain of all the individuals in the population.

$$Normalized\,Gain_i = Ag_i - Ag_{M_sel+1} \tag{3.20}$$

where $Normalized\,Gain_i$ is the normalized gain of the i^{th} individual.

From the normalized gain, the probability P_i of i^{th} individual to be selected for mating is calculated as follows,

$$P_i = \frac{Normalized\,Gain_i}{\sum_{m=1}^{M_{sel}} Normalized\,Gain_m} \tag{3.21}$$

The roulette wheel approach sorts the individuals in terms of the weight. The weight of the individual with a high gain is more when the spread in gain between the top and the bottom individuals is large. Also, the individuals having similar average gain are weighted equally.

A random point is selected as the crossover point. The variables after this point are subjected to the crossover process. Simple crossover methods are available which exchange variables after the crossover point in between the two selected parents to form two new offsprings. However, the problem with this method is no new information is introduced in the offspring [48]. The continous value generated in the individual is just passed on to the offspring in a different combination. No new genetic characteristics will be introduced. Hence a blending method is used to obtain new variables in the offspring from the variables in the two selected parents. It is at the designer's discretion, to decide which variables should undergo crossover and in what way. Let $V_{offspring1}$ and $V_{offspring2}$ be the variables obtained from the variables $V_{parent1}$ and $V_{parent2}$ of parent 1 and 2 respectively.

$$V_{offspring1} = V_{parent1} - \phi[V_{parent1} - V_{parent2}]$$

$$V_{offspring2} = V_{parent2} + \phi[V_{parent1} - V_{parent2}]$$

Where ϕ is some random number between 0 and 1. This ϕ can be varied for each variable or can be kept constant. Thus new offsprings are generated by crossover operator until the desired population size is reached.

Mutation

Mutation is a genetic algorithm operator which is used to introduce genetic variety in the individuals of the population. Mutation allows to change the value of a component of the individual [49]. Mutation explores the range of components in the individual to avoid the algorithm to get stuck in a local minimum. Due to mutation, the solution may change completely from the previous solution. The main objective of mutation is the introduction of diversity and preserving it.

In continuous GA, the mutation points or the variables to be mutated can be chosen randomly from the entire population space. The mutation rate decides the number of variables that will undergo mutation in the entire population. Increasing the mutation rate increases the freedom of the algorithm to search outside the current region of the variable space. The variable selected for mutation is replaced by a uniform random number lying in the range of the variable.

$$\mathrm{V}_{mut} = U(Minimum\, value, Maximum\, value)$$

Where V_{mut} is the variable that is selected for mutation. In this manner, the determined number of mutations are performed and a new population is generated.

Next Generation

The result of the above process is a new set of individuals that are ready to undergo the same procedure to take the algorithm towards a global optimum. The algorithm is run for the required number of iterations NI. After these iterations, the individual having the highest average gain among all the entire NI iterations is obtained as the optimal configuration.

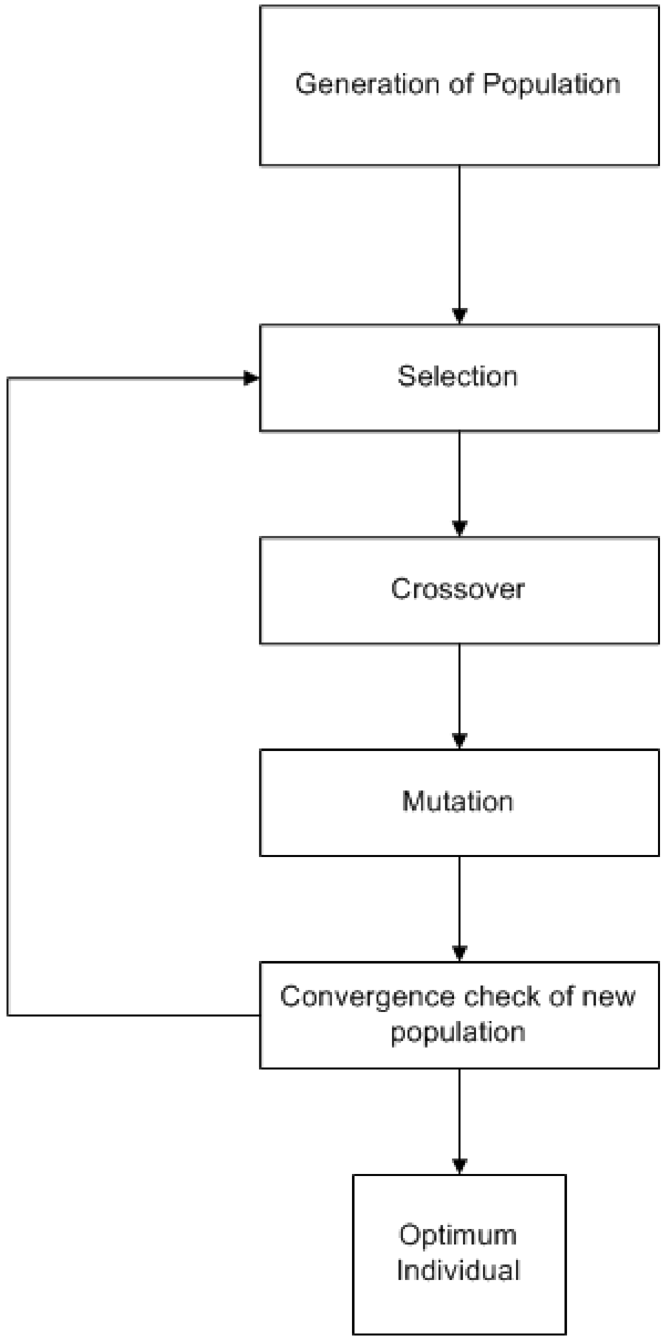


Figure 3.2: Genetic Algorithm Flowchart

CHAPTER 4

Sensing Scheduling for Multiple Channels

A CR network is more efficient when multiple channels are available for communication. The single channel multiple CR formulation gives us the optimum $\alpha, \beta, T_0, T_1, j$ for a channel. But, resources for sensing are limited. Multiple channels present in a CR network is more realistic scnenario and a single channel sensing scheduling design should me extended such that multiple channels can be sensed in the CR network. Hence, when multiple channels are available for a CR network, the available number of CRs should be used optimally for that purpose.

If there are enough CRs available for each channel then the optimal configuration of $\alpha, \beta, T_0, T_1, j$ can be set such that it gives the highest average gain. However, in a situation where the number of CRs is restricted, we argue that optimal performance may still be possible to achieve. All CRs in the network are not sensing at the same time. Hence the CRs that are in the wait state can be used for sensing of spectrum as these CR resources are unused at that point of time. From the single channel multiple CR formulation, we obtain a configuration profile of $\alpha, \beta, T_0, T_1, j$ for the corresponding channel i. However, each channel will have different wait times according to the activity pattern of the channel. This property of different wait times is exploited in the multiple CR multiple channel case. The multiple channel case is an extension to the single channel case.

Scheduling Design

Consider a network of J CRs and M PU channels present in this network. These

M channels will be characterized by their PU activity patterns. It is assumed that these patterns are known to the CRs. The optimal waiting time T_1 and transmission time T_0 for decisions H_1 and H_0 will be known. It is assumed that all the CRs in the network are alike. It is also assumed that each CR can sense only one channel. From the single channel scheduling design, the optimal parameters can be obtained for each of the M channels such that the average gain for that channel is maximized.

Let J_m be the optimal number of CRs for the m^{th} channel. For each channel m, we can obtain an optimal profile consisting of $T_{0,m}(j)$, $T_{1,m}(j)$, $\alpha_m(j)$, $\beta_m(j)$ and $G_m(j)$ for $j = 1, \cdots, J_m$. This profile can be of great use for scheduling in a CR network which consists of multiple channels. Assuming all CRs do not perform sensing simultaneously, it can be said that some CRs are in their waiting state due to the occupied state of the channels. The idle CRs can be exploited for sensing of the channels that require sensing. M channels are present in the network. At any time step k, assume that $M - X$ channels are actually sensing different channels that are assigned to them. X is the number of channels that are in the non-sensing state or waiting state as these channels are either occupied by the PU or CRs are using the channels for secondary transmission. The waiting time for these channels is given by T_x, $x = 1, \cdots, X$.

Assume there are N CRs in the pool that are available for sensing. The problem is formulated as how to assign these N CRs to the X channels that may require sensing. Two approaches to this problem are studied.

4.1 Greedy Approach

The Greedy approach for scheduling design includes assigning all the CRs that are available for sensing to the channel that first requires sensing. Each channel have their own waiting times and these waiting times expire at different time steps. The channel x among X channels whose waiting time T_x expires puts up a request for sensing.

As the request is put up, the available number of CRs are allocated to channel x for sensing. J_x is the optimum number of CRs that gives the maximum average gain over the channel x. However, the number of available CRs N depends on the sensing scheduling of channels. The channels that are already sensed and into waiting state or transmission, have their respective assigned CRs returned to the 'available CRs' pool. Thus the assignment of CRs to channel x will follow the following condition,

$$\text{If } N \geq J_x, \qquad Assign\ \ J_x\, CRs\, to\, channel\, x$$
$$\text{If } N < J_x, \qquad Assign\, N\, CRs\, to\, channel\, x$$

Once the CRs are allocated, the sensing time for each channel is obtained using the distribution of L. The expected value of L is obtained by using the parameters in the profile. The parameters $\alpha_x(j)$ and $\beta_x(j)$corresponding to the selected value of j and the distribution of L gives the average number of sensing steps. Multiplying by t_s we get the average sensing time. Once this sensing time T_s expires, the CRs that are assigned to the channel x go into waiting state $T_{0,x}(j)$ or $T_{1,x}(j)$ depending on the current state of the PU. These waiting CRs now return back to the pool of CRs which can be used for sensing of other channel.

One more condition can persist, where all the available CRs are assigned to some or the other channel for sensing. In such a scenario, if a channel c requests for sensing, it has to wait till the channel with the least remaining sensing time to release the CRs. Thus a penalty is imposed on the average gain obtained for that channel. Consider channel h has the least sensing time $T_{s,h}$ remaining and j_h CRs are alloted to this channel. Thus the next channel c requesting sensing has to wait $T_{s,h}$ seconds for it to start sensing. Thus the average gain decreases over the channel c for time steps which are equivalent to the remaining sensing time $T_{s,h}$. The penalized average gain of the channel c is given as follows:

$$\text{Penalized } \ gain_c = \frac{Average\ gain_c * T}{T + T_{s,h}}$$

T is time taken by channel c for sensing and waiting/transmission together i.e. $T = \bar{L}t_s + T_0$ or $T = \bar{L}t_s + T_1$ and $T_{s,h}$ is the time the channel c has to wait to start sensing.

This is a greedy approach where channel x greedily takes all the available CRs for sensing, as it requires sensing prior to the other channels. In the next time step, the same proceudure repeats by checking how many CRs are available for sensing in the pool and when the next sensing request arrives. However, the drawback here is, there is a chance that there may not be any CRs left for the sensing of the other channels whoes waiting time is expiring and require sensing. There is a possibility that those channel(s) remain unsensed.

4.2 Non-Greedy Ranked Approach

In the greedy approach, the future is not cared for with respect to the availability of CRs for the remaining channels that may require sensing. Assume x requests for sensing and all the available CRs are assigned to this channel. The remaining channels that further request sensing may not have any CRs left for sensing. This will affect the gain of the system as transmission opportunities on the unsensed channels may be lost. Thus the greedy approach is not a feasible method as the overall gain of the entire CR network will be affected.

The next approach which overcomes the problems of the greedy approach is a non-greedy ranked approach. Here, the available CRs will be shared among the channels that may require sensing. This allocation will be done in such a way that the total average gain over the channels is maximized. Assume there are X channels that may require sensing. T_x is the respective remaining waiting time for channel x, $x = 1, \cdots, X$. Instead of assigning the CRs to the channel that first requires sensing, X channels are first arranged in the ascending order of their remaining waiting times. The channels that have their waiting times below a certain threshold η are selected for CR assignment. The channels whose waiting times are above η are not considered for

CR assignment at the current time step. Assume that there are B channels selected from the ranked X channels such that $T_x < \eta$, $x = 1, \cdots, B$

Let $n_1, \cdots, n_B$ be the number of CRs that will be assigned to each channel, respectively. Let $N(k)$ be the number of CRs that are idle or available at the k^{th} time step. Thus the assignment of CRs among B channels has the following constraint,

$$\begin{aligned} \sum_{b=1}^{B} n_b &= N(k) \\ s.t.\ n_b \geq 0 \end{aligned}$$

The $N(k)$ CRs are divided amongst the B channels in such a way that the total average gain should me maximum. For each channel b, an optimal profile is available with the parameters $T_{0,b}(j)$, $T_{1,b}(j)$, $\alpha_b(j)$, $\beta_b(j)$ and $G_b(j)$ such that $j = 1, \cdots, J_b$. This profile will be useful for the assignment as each CR configuration has its resepective average gain for the channel b. Thus the assignment can be formulated as follows,

$$\max_{\{n_1,\cdots,n_B\}} \textstyle\sum_{b=1}^{B} G_b(n_b)$$

where $G_b(n_b)$ is the average gain of the channel b when n_b CRs are used to sense it. Thus we plan for CR assignment of near future sensing requests also.

However, in the next time step $(k+1)$, the number of available CRs can change as the CRs who sense a channel previously may enter the waiting state according to the underlying state of the channel. Also, the number of channels whose waiting time is near to expire might also change. In either of the cases, the CR reassignment design is conducted at each time step considering the update in the number of channels and the number of CRs. As in the greedy approach, sensing time T_s is obtained for each channel. Once the sensing time expires, CRs enter the waiting state for T_1 or the transmission state for T_0. These waiting CRs return back to the pool of CRs available for sensing requests of other channels.

CHAPTER 5

Experimental Results

To evaluate and verify the proposed design for spectrum sensing scheduling, various experiments are conducted and the results are summarized in the following figures. Note that when evaluating the effect of various design parameters, the system parameters are fixed and the average gain is achieved by maximizing over the rest of design parameters. When evaluating the effect of system parameters, all the data points are obtained by optimizing over the design parameters. The system parameters are then varied to observe the effect of the variation on the design parameters.

5.1 Sensing Scheduling for a Single Channel

The genetic algorithm is used to obtain the optimized values of the variables. Natural selection method is used for selection where 50% of the fittest individuals are used for crossover and generation of new individuals. During crossover, the crossover point is selected randomly and the variables after the crossover point undergo changes. The mutation rate is set to 50%. The population size is set to be 100 and 100 generations of individuals are evaluated using genetic algorithm. The individual with the highest average gain in these generations is selected as the optimized individual. The system parameters are initially set to γ=0.05, $\mu = \lambda = 0.01$, t_s=1 and G=30, C_s=0.5, C_f =5, C_m=1. The population is randomly initialized in the following ranges: $T_0 \in$ [0,50], $T_1 \in$ [0,30], $j \in$ [0,25], $\alpha \in$ [0.01,0.3] and $\beta \in$ [0.01,0.3]. The system parameters are now varied in order to evaluate their effects on design parameters.

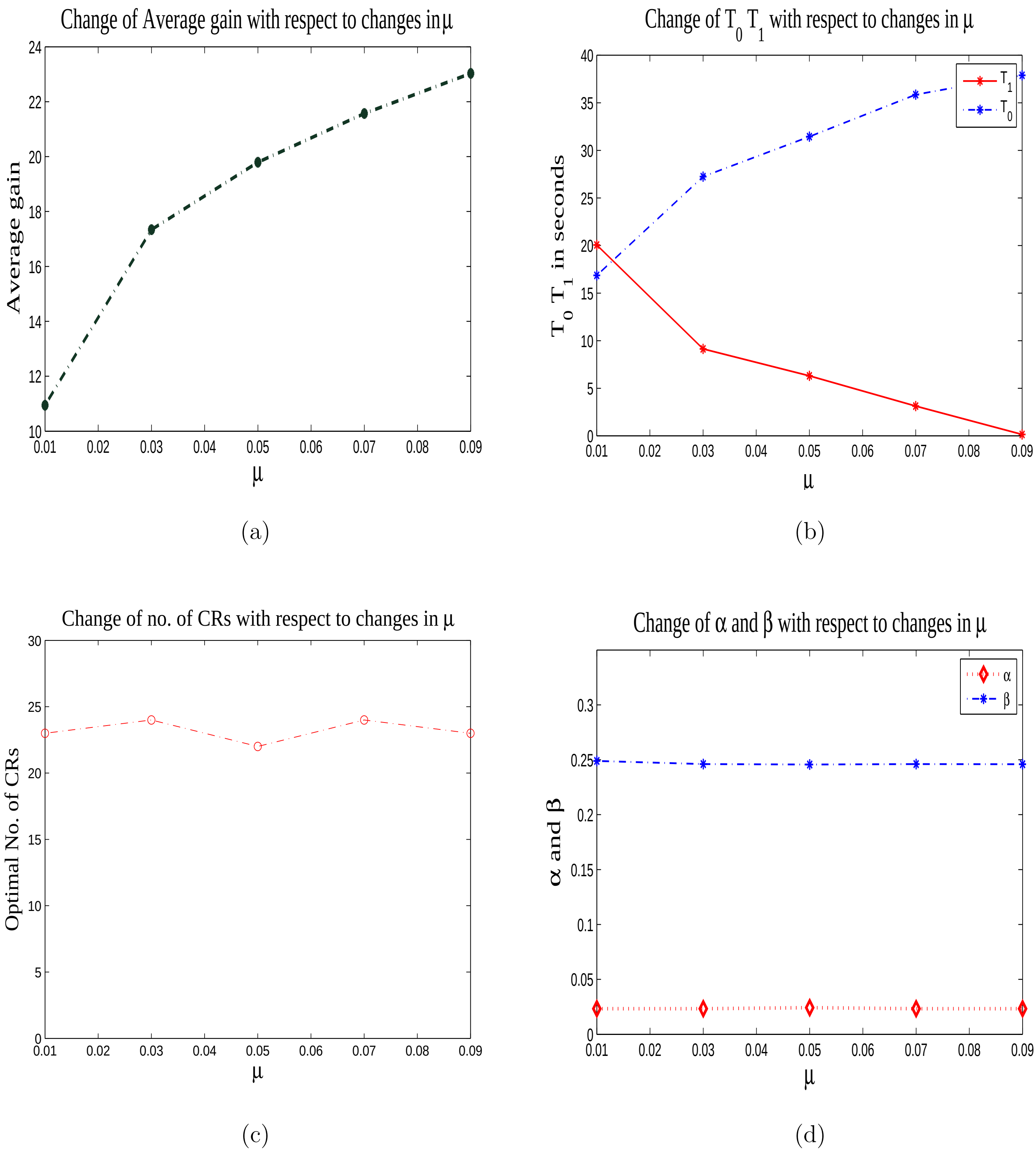


Figure 5.1: Change of Design Parameters with respect to change in μ

5.1.1 Effect of change of μ

μ is the inverse of the average holding time of the PU. When μ varies from 0.01 to 0.09, it indicates that the channel tends to stay occupied for less duration. Hence the channel is more likely to be available. As the channel is more likely to be available, the chances of transmission increase. This boosts the overall average gain of the system. Fig 5.1(a) shows average gain as an increasing funtion of increase in μ. Fig 5.1(b) explains the variation of T_0 and T_1 with respect to μ. As μ increases, the channel remains occupied for less time. Intutively, the time for which the CRs should wait after sensing should decrease in order to avoid missing a transmission opportunity. If this does not decrease, there will be a false alarm cost incurred for a period when the PU has left the channel and the CRs are still in the waiting state. There will be a lost transmission chance which is not desirable. Hence, waiting time T_1 decreases as μ increases which matches our intution. Correspondingly, transmission time T_0 increases as the time for which a PU is occupied decreases in one PU cycle. At high μ, the CRs can trasmit for a longer time as the probability of the PU remaining in the unoccupied state is high. Fig 5.1(c) shows the effect of μ on the number of CRs. It is seen that the optimal number of CRs for different values of μ are almost similar to each other. Thus the change in inverse of mean holding time of the PU does not affect the optimal number of CRs significantly. Fig 5.1(d) shows the α and β values for variations in μ. It is seen that α and β are not sensitive to the variations in μ and the variations are not singnificant.

5.1.2 Effect of change of λ

λ is the average PU arrival rate. As λ increases, the time between two successive inter-arrival decreases i.e. the time of the channel in the unoccupied or OFF state will decrease. Thus the channel is less likely to be vacant in a cycle which brings down the transmission opportunities. This affects the overall average gain negatively.

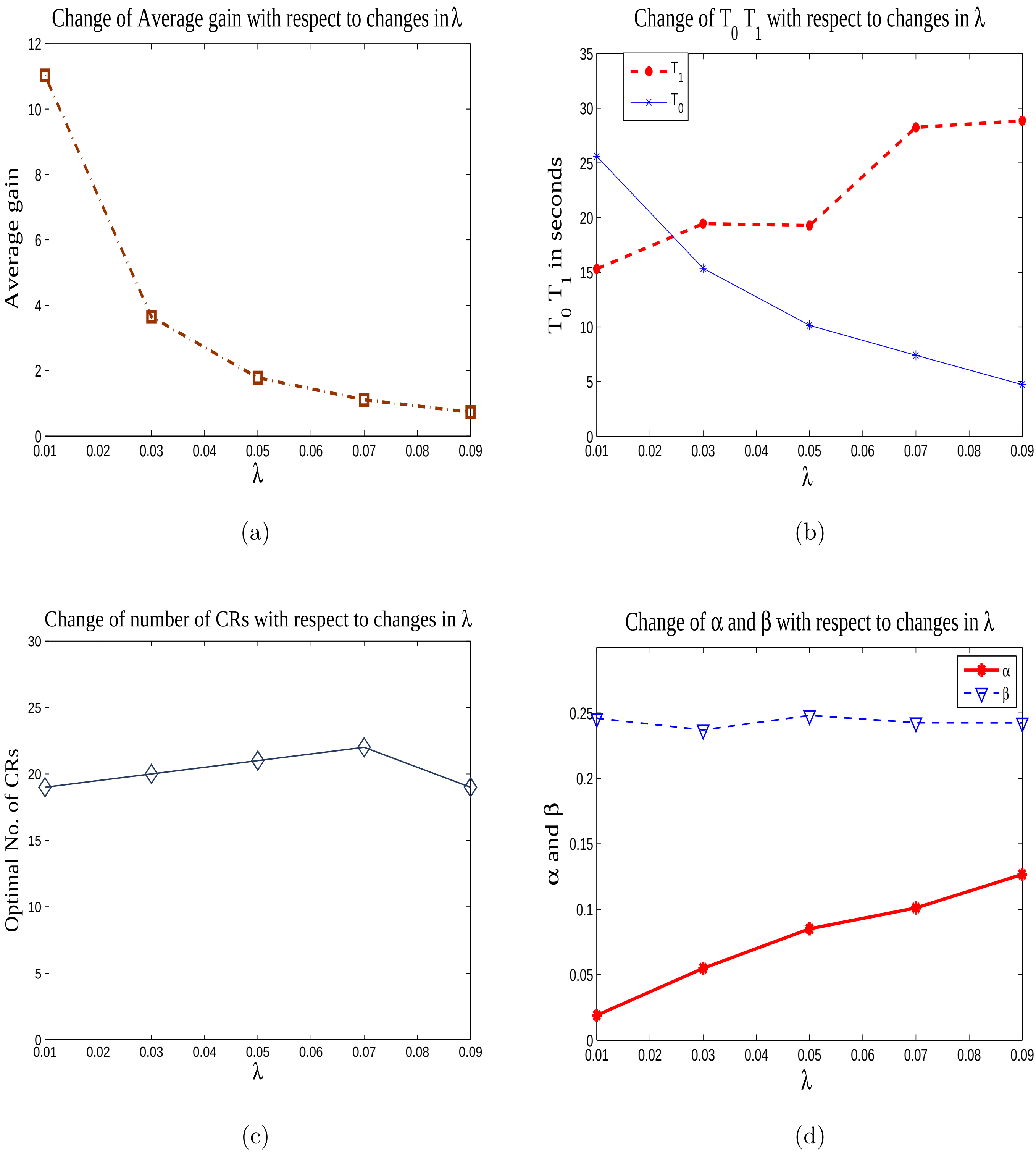


Figure 5.2: Change of Design Parameters with respect to change in λ

Hence the average gain in terms of transmission decreases as λ increases. Fig 5.2(a) shows the variation of gain with respect to change in λ. Fig 5.2(b) shows the variation of T_0 and T_1 with respect to λ. As the interarrival rate increases, the time for which the PU will remain in the unoccupied or OFF state will decrease. Transmission opportunities reduce and hence the optimal transmission time T_0 decrease. If T_0 does not decrease, there is a chance that the CRs will continue transmission which will cause interference to the PU and incur missed detection costs. This will decrease the average gain of the system. As the channel is less likely to be in the vacant state, the possibility of the channel staying in the occupied state in one cycle will be higher. This change is seen in the increase in waiting time T_1 as λ increases. Fig 5.2(c) discusses the number of optimal CRs required for change in λ. It is seen that the optimal number of CRs for a system is very less sensitive to the PU activity pattern. The times for which PU remains in the occupied and the unoccupied state does not affect the optimal number of CRs significantly. Fig 5.2(d) shows the trend of α and β with respect to change in λ. It is seen that changes in β are not significant with increase in lambda. However, increase in λ brings about an increase in the α values. Increase in lambda shows that the PU will remain in the OFF state for less duration thus decreasing the chances of transmission. α is one of the parameter that controls the value of the thresholds a and b. When α increases and β is constant, the two thresholds come closer to each other i.e. a decreases and b increases. This decreases the number of sensing steps to attain the thresholds. Thus sensing time may be low and the possibility of transmission for more duration during the OFF state of the PU increases.

5.1.3 Effect of change of γ

Fig 5.3(a) shows the optimized average gain as a function of SNR. γ is varied from -20 dB to -13dB. Smaller γ leads to more cost due to false alarms and missed detection as

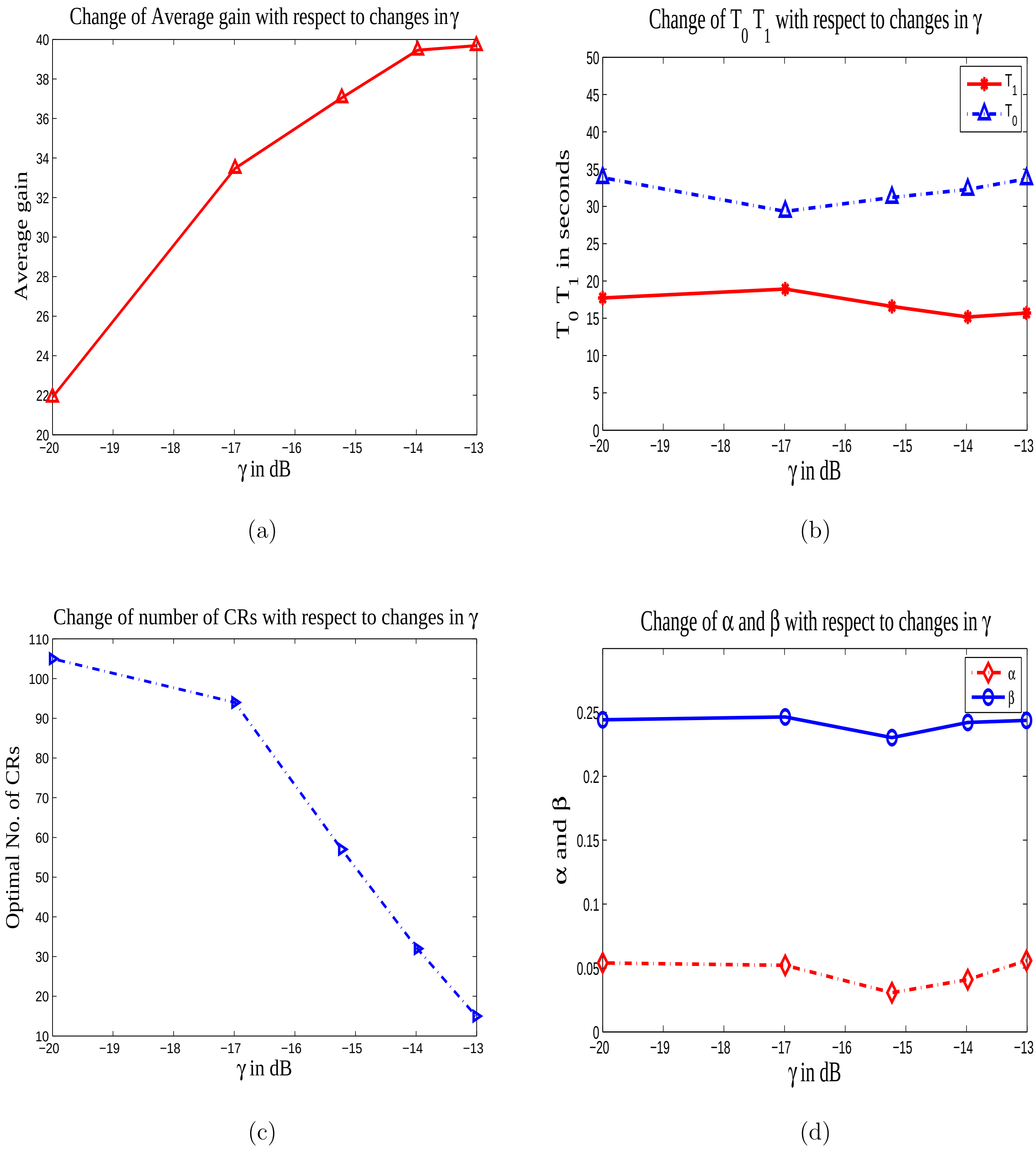


Figure 5.3: Change of Design Parameters with respect to change in γ

noise in the signal is high. The chances of making a wrong decision on the underlying state of the system are high. This in turn, pulls down the overall gain of the system. Note that G and the range of j has been significantly increased for this experiment in order to make the average gain non-negative for γ=-20 dB. G has been increased to 100 and $j \in [0,120]$ It is seen that the optimal number of CRs is also a function of γ. As the signal to noise ratio decreases, more number of CRs will be required to obtain a certain level of accuracy than in case of a higher SNR. Fig 5.3(c) shows the number of CRs required as a function of γ. For each data point, optimized values of α and β are obtained that provide the highest gain. It is seen that the values of α i.e. P_f is closer to the lower range value as lower false alarm probability will render less chances of missed opportunities. Also, it is seen that β is closer to the higher range value of P_m. This is because, if there is a missed detection, immediately the transmission is stopped and the CR will enter the wait state. Hence the missed detection costs are very little. Fig 5.3(d) shows change in the α and β values. It shows that γ is very little sensitive to these values. Fig 5.3(b) also shows the very little effect of γ on the waiting times T_0 and T_1. SNR mainly affects the average gain of the system and the number of optimal CRs that will be required to obtain a decision on the state of the PU for the selected configuration of SNR.

Also, Fig. 5.4 shows change in the average gain as the SNR varies for different PU activity patterns. Note that for this experiment the value of G has been changed to 500 in order to avoid negative gain values for $\mu < \lambda$ case. When μ is greater than λ, the chances of PU remaining unoccupied increases. As PU remains unoccupied for a longer time as compared to the occupied state, the transmission opportunities increases for the CRs. This is reflected in the average gain of the system. It is greater than the average gain for the case when μ is equal to λ. When μ is less than μ, the chances of PU using it licensed frequency is more than that the chances of spectrum hole for transmission. Hence, the average gain in presence of such a PU activity

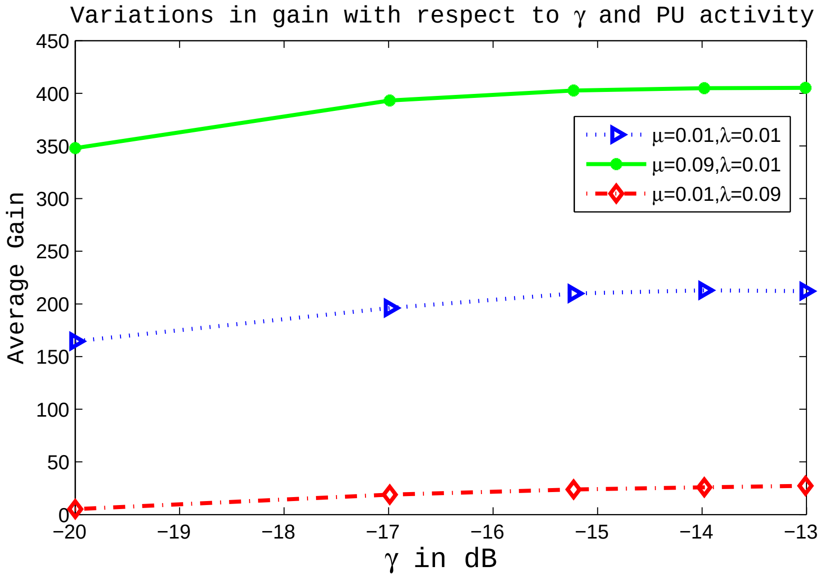


Figure 5.4: Variation of average gain with changes in γ and PU activity pattern

pattern is less than the above two cases.

5.1.4 Effect of change of Costs

Average gain of the system is also a function of the cost associated in the system i.e. cost of sensing, cost of false alarm and cost of missed detection. Different plots show the effect of varations in costs on the average gain of the system. C_m affects the system very little as the CRs go into wait state immediately after collision with the PU after a missed detection. Fig 5.5(a) shows the effect of variation in C_s to the average gain of the system. As the sensing costs increase, the average gain of the system is pulled down. Increased sensing costs also affects the optimal number of CRs. When sensing costs are high, less number of CRs are preferred to be used for sensing. This decrease in the number of optimal number of CRs as shown in the Fig 5.5(c). Also, when the sensing costs boosts it is preferred to sense less time. More sensing operations will increase the cost that brings down the average gain. Hence the wait times T_0 and T_1 are seen to increase with the increase in the sensing costs. This

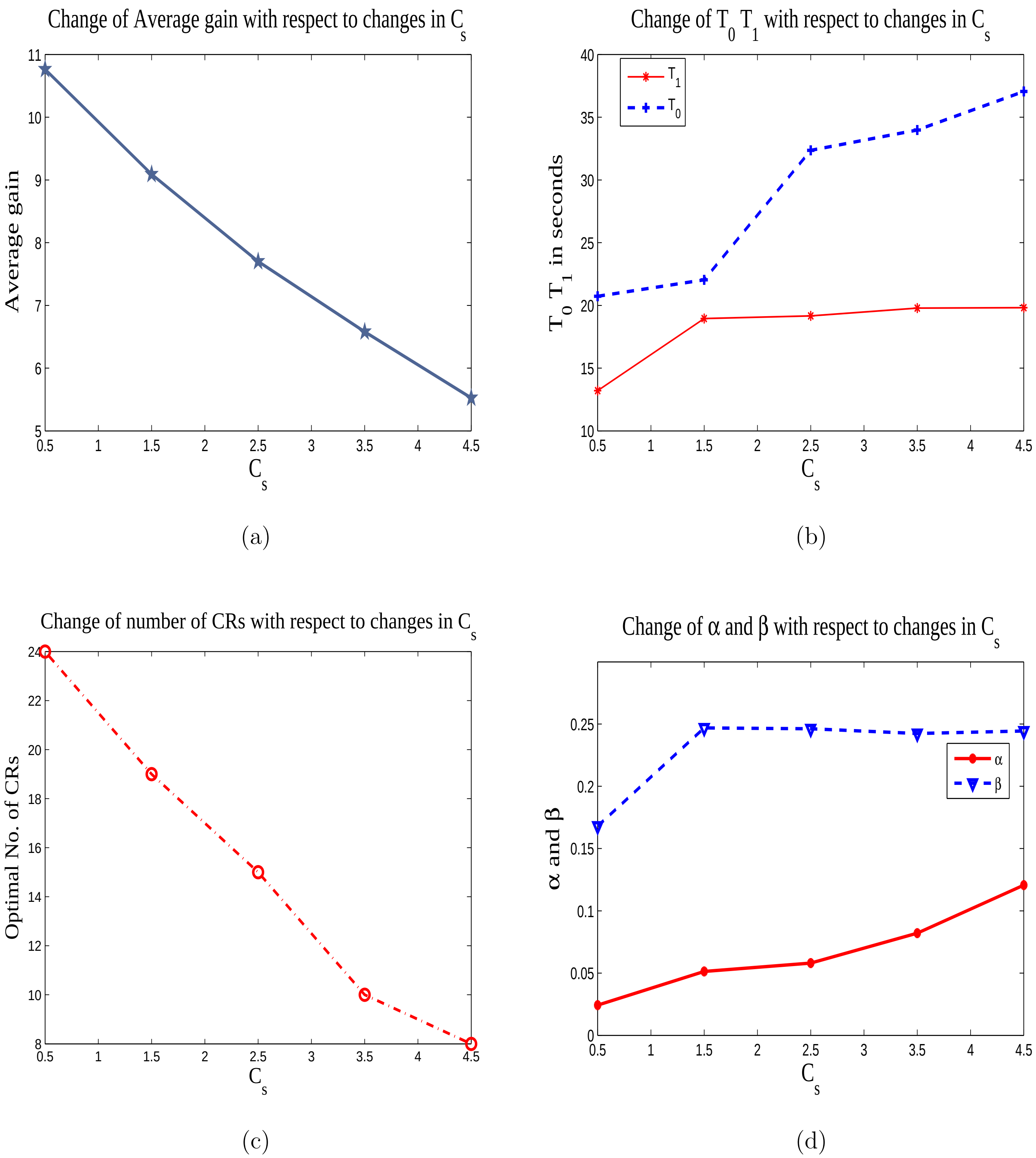


Figure 5.5: Change of Design Parameters with respect to change in C_s

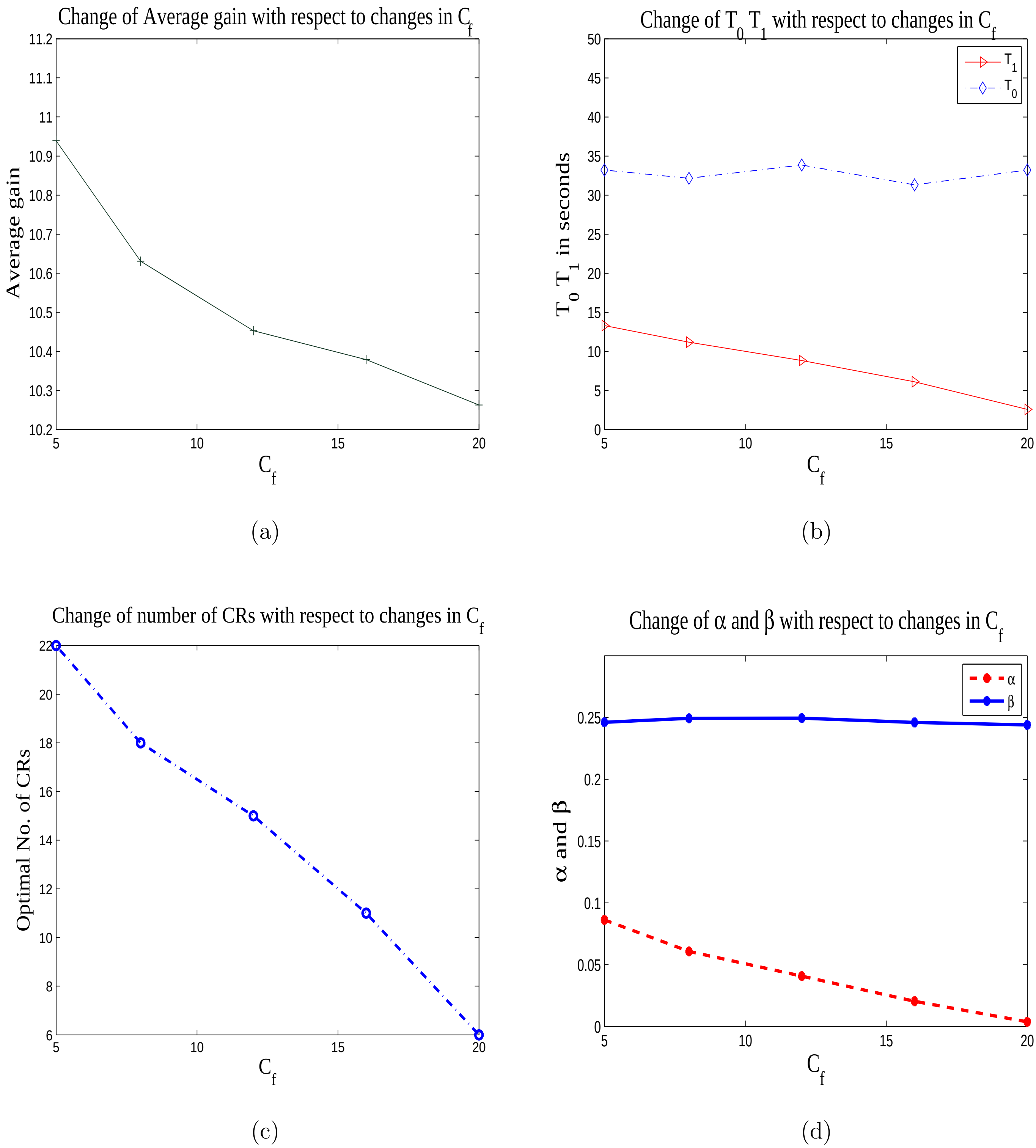


Figure 5.6: Change of Design Parameters with respect to change in C_f

is seen in Fig 5.5(b) which shows increase in waiting times T_0 and T_1 as sensing costs increase. Fig 5.5(d) shows changes in α and β when the cost of sensing is varied. It is seen that when the cost of sensing is increased, the CRs will want to sense for less time. Hence α is seen to increase with increase in sensing cost. β is seen to increase intially and then remain constant. Increase in α and β brings the thresholds for the SPRT closer. As the thresholds are closer, it takes less sensing time to cross either of the thresholds.

Increase in C_f brings about variations in the design parameters. When the cost of false alarm increases, the CRs will try to avoid false alarms as it will increase the overall cost. Increase in false alarm costs pulls down the average gain. The decrease in the average gain with increase in C_f is shown in Fig 5.6(a). The change in C_f is reflected in the value of α in Fig 5.6(d). As C_f is increased, α decreases which indicates more accuracy in the results. CRs tend to make less mistakes with respect to false alarms and thus can avoid that cost of false alarm. As α is decreasing and β is constant, the thresholds a and b go away with increase in α. This leads to more sensing steps, increase in costs and decrease in gain. It is also seen that the waiting time T_1 is seen to decrease with increase in false alarm costs. If T_1 is very high and a false alarm decision is made, the overall cost of the system increases to a greater extent. Hence T_1 is seen to decrease in Fig 5.6(b) so as to reduce the overall cost for high C_f. No significant change is observed in the transmission time T_0. Fig 5.6(c) shows the trend of number of CRs required with change in C_f. It is seen that for higher false alarm costs, less number of CRs assigned to the channel is preferred as it decreases the overall costs of the system.

5.2 Sensing Scheduling for Multiple Channels

A profile containing optimal parameters is generated for each channel that will be sensed in the CR network. The main task here will be to assign CRs to each channel that requires sensing. Two approaches are discussed - greedy and non-greedy approaches. Consider a CR network consisting of 25 CRs and 5 channels. For each of the 5 channels, the profile consisting of $T_{0,m}(j)$, $T_{1,m}(j)$, $\alpha_m(j)$, $\beta_m(j)$ and $G_m(j)$ for $j = 1, \cdots, J_m$, $m = 1, \cdots, 5$ is obtained. Tables 5.1 and 5.2 present the assignment results for the greedy and non-greedy approaches respectively.

5.2.1 Greedy approach

The table 5.1 shows the CR assignment reassignment for the greedy approach. The values in brackets in each block of the table are the waiting times remaining for the respective channel at time step k. Each block consists of the number of CRs that are alloted to the channel that requests sensing. The number of CRs is reflected for the time steps till that channel performs sensing. From the table it is seen that channels request for sensing at different time steps. At k=4, channel 2 requests sensing and 22 CRs are assigned to channel 4. The average gain for channel 2 is found from the profile corresponding 22 CRs used for sensing. In the next step k=5, the remaining 3 CRs are assigned to channel 4. However the channel 1 is also requesting sensing and due to unavailability of CRs, there will be a penalty associated with this channel for the step k=4 to k=7. At step k=7, channel 2 completes sensing and releases the CRs to the available CR pool. The penalty associated with channel 2 decreases the gain for that channel as the total duration of the previous cycle for that channel will be increased by 4 steps. A similar penalty can also be seen for channel 3 due to unavailability of CRs. Once the sensing of channel 2 is complete, the CRs are available for channel 1 and following the condition in the greedy approach CRs were assigned to channel 1. It is also seen at step k=20 that 22 CRs are available. This is because channel 4 completes sensing at the step 20 and the 3 CRs assigned to it were returned back to the pool. The similar process of CR assignment and reassignment continues for 100 steps and the total average gain over these 100 steps is obtained.

5.2.2 Non-Greedy Approach

The non-greedy approach includes reassignment of CRs in such a way that CRs are assigned to channels considering all the near future sensing requests. This can help eliminate the penalty due to any of the channels remaining unsensed. Table 5.2 explains the channel assignment and reassignment using the non-greedy approach. Each block consists of the number of CRs that are alloted to the channel that requests sensing. The number of CRs is reflected for the time steps till that channel performs sensing. The numbers in brackets besides the number of CRs shows the remaining waiting time at the time step k. It can be seen that once the sensing time for a channel completes, the CRs return back to the pool and the number is reflected in the 'available CRs' column. This column shows the number of CRs that are available for the $(k + 1)$ assignment step. It includes the CRs that have joined the pool after ending sensing at the k^{th} step. Step k=2 shows that 6 CRs are allocated to channel 5 and 10 CRs are allocated to channel 1 considering the future requests. The average gains for channel 1 and 5 are found from the profile corresponding 10 CRs and 6 CRs respectively used for sensing. However in further steps it is seen that the channel reassignment may change, due to increase in the available number of CRs or increase in the channels that may request sensing in the near future. The table shows the channel assignments to different CRs with the waiting times left for the channels at each step. This process continues for 100 time steps and the total average gain over these 100 steps is obtained.

5.2.3 Comparison of Total Average gain

The average gain over 100 time steps for both the approaches is compared. It is found that the non-greedy approach fairs better than the greedy approach. In the greedy approach, the total gain of the system is pulled down due to the lack of planning for the future. The penalty of a channel remaining unsensed for a certain time steps lowers the total average gain of the system. This penalty is due to the possibility of loss of transmission opportunities on the unsensed channel for those time steps.

Whereas, on the other side, the non-greedy approach plans for the future. At each step, the available number of CRs are divided among the channels that require sensing in near future. These channels which require sensing are obtained by comparing the waiting times to a threshold. Due to such an assignment, there may be no lost chances of transmission on these channels. Hence the total average gain is greater than the greedy approach. Also, in the next time step, if more number of CRs are available, the reassignment is performed again such that the configuration will give the best total average gain. Table 5.3 displays the total average gain over 100 steps for the two discussed approaches, along with the average gain for ideal approach. In the ideal approach, at each sensing request, optimal number of CRs are allocated to the channel assuming infinite number of CRs are available. This ideal approach gives the highest total average gain.

Table 5.1: CR Assignment-Reassignment for Greedy Approach

Time Step (K)	CRs assigned to requesting channels Ch. 1	Ch. 2 (Remaining	Ch. 3 Waiting	Ch. 4 Time)	Ch. 5	Available CRs at end of step
1	0(2.63)	0(2.28)	0(4.37)	0(2.59)	0(4.71)	25
2	0(1.63)	0(1.28)	0(3.37)	0(1.59)	0(3.71)	25
3	0(0.63)	0(0.28)	0(2.37)	0(0.59)	0(2.71)	25
4	0(-0.36)	22(-)	0(1.37)	0(-0.40)	0(1.71)	3
5	0(-1.36)	22(-)	0(0.37)	3(-)	0(0.71)	0
6	0(-2.36)	22(-)	0(-0.63)	3(-)	0(-0.2819)	0
7	0(-3.36)	22(-)	0(-1.63)	3(-)	0(-1.2819)	22
8	19(-)	0(16.92)	0(-2.63)	3(-)	0(-2.2819)	3
9	19(-)	0(15.92)	3(-)	3(-)	0(-3.2819)	0
10	19(-)	0(14.92)	3(-)	3(-)	0(-4.2819)	19
11	0(29.43)	0(13.92)	3(-)	3(-)	19(-)	0
12	0(28.43)	0(12.92)	3(-)	3(-)	19(-)	0
13	0(27.43)	0(11.92)	3(-)	3(-)	19(-)	19
14	0(26.43)	0(10.92)	3(-)	3(-)	0(22.35)	19
15	0(25.43)	0(9.92)	3(-)	3(-)	0(21.35)	19
16	0(24.43)	0(8.92)	3(-)	3(-)	0(20.35)	19
17	0(23.43)	0(7.92)	3(-)	3(-)	0(19.35)	19
18	0(22.43)	0(6.92)	3(-)	3(-)	0(18.35)	19
19	0(21.43)	0(5.92)	3(-)	3(-)	0(17.35)	19
20	0(20.43)	0(4.92)	3(-)	3(-)	0(16.35)	22

Table 5.2: CR Assignment-Reassignment for Non-Greedy Approach

Time Step	CRs assigned to requesting channels					Available
(K)	Ch. 1	Ch. 2	Ch. 3	Ch. 4	Ch. 5	CRs
		(Remaining	Waiting	Time)		at end of step
1	0(0.65)	0(4.71)	0(4.78)	0(2.87)	0(0.29)	25
2	10(-)	0(3.71)	0(3.78)	0(1.87)	6(-)	9
3	10(-)	0(2.71)	0(2.78)	0(0.87)	6(-)	9
4	10(-)	0(1.71)	0(1.78)	3(-)	6(-)	6
5	10(-)	0(0.71)	0(0.78)	3(-)	6(-)	16
6	0(6.54)	6(-)	9(-)	3(-)	6(-)	1
7	0(5.54)	6(-)	9(-)	3(-)	6(-)	1
8	0(4.54)	6(-)	9(-)	3(-)	6(-)	7
9	0(3.54)	6(-)	9(-)	3(-)	0(5.54)	7
10	0(2.54)	6(-)	9(-)	3(-)	0(4.54)	16
11	0(1.54)	6(-)	0(48.18)	3(-)	0(3.54)	22
12	0(0.54)	0(38.51)	0(47.18)	3(-)	0(2.54)	22
13	10(-)	0(37.51)	0(46.18)	3(-)	0(1.54)	12
14	10(-)	0(36.51)	0(45.18)	3(-)	0(0.54)	12
15	10(-)	0(35.51)	0(44.18)	3(-)	12(-)	0
16	10(-)	0(34.51)	0(43.18)	3(-)	12(-)	10
17	0(6.54)	0(33.51)	0(42.18)	3(-)	12(-)	10
18	0(5.54)	0(32.51)	0(41.18)	3(-)	12(-)	25
19	0(4.54)	0(31.51)	0(40.18)	0(1.42)	0(4.05)	25
20	0(3.54)	0(30.51)	0(39.18)	0(0.42)	0(3.05)	25

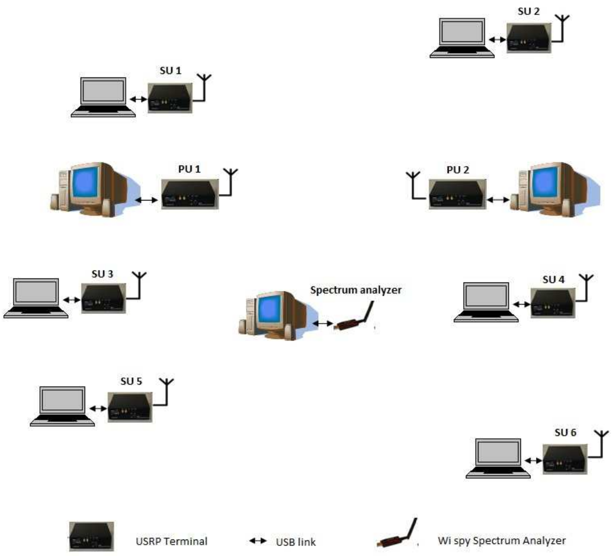
Table 5.3: Comparing the Total Average Gains for the Two Approaches

Experiment Number	Average Gain Greedy Approach	Average Gain Non-Greedy Approach	Ideal case Average gain
1	181.28	265.94	
2	190.36	278.50	
3	188.93	224.48	289.96
4	207.56	269.45	
5	180.44	236.25	

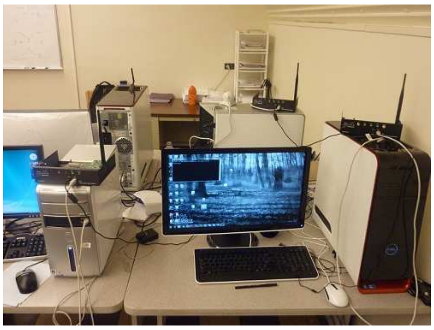
CHAPTER 6

Cognitive Radio Testbed

6.1 Hardware Platform



(a) System architecture

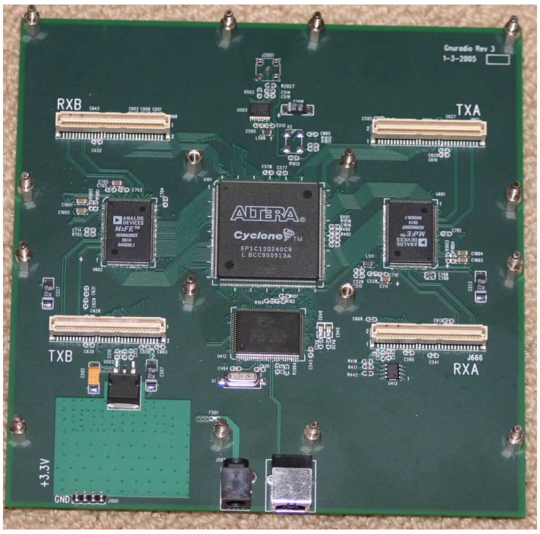


(b) Cognitive radio testbed setup in the lab

Figure 6.1: Cognitive radio environment

The testbed architecture is shown in Fig. 6.1. To simulate a real time scenario we

(a) USRP terminal.



(b) Motherboard of a USRP.

Figure 6.2: The Universal Software Radio Peripheral (USRP) terminal and its major components.

have configured some USRPs to be the primary users and others to be the secondary users. Specifically, two USRPs are configured as primary users. They transmit packets of random content at fixed carrier frequencies. Like primary users, the USRPs do not transmit data all the time and are programmed to transmit data at random intervals and for random lengths of time. The most popular model that can be used in this case is that the arrival rates follow a Poisson distribution while the transmitting duration follows an exponential distribution [51].

Six USRPs are configured as secondary users and are scattered around such that it is still a single hop network. All the secondary users are associated with an ID number which helps them uniquely identify each other. Since they have no licensed spectrum, they opportunistically use any vacant frequency bands. The secondary users are configured to perform the following tasks: 1) Decide if a given frequency band is currently occupied or not; 2) Change the transmitting and receiving parameters at any given time; and 3) Make sure that its operation does not interfere with primary users. Thus, the USRPs acting like secondary users are programmed such that their structures and parameters change according to the channel conditions. There is also a spectrum analyzer which acts as a monitor, providing the ground truth of the state of spectrum utilization.

Details of these hardware components are provided next.

USRP

USRPs are software defined radios which are connected to a computer terminal via a USB cable. To gain all the functionalities of a software defined radio, the USRPs work on the GNU radio platform. GNU radio software [52] is an open source toolkit which allows the construction of radios where all hardware related problems like designing and building the required circuits are converted to software issues. GNU radio has the ability to create blocks that can implement many functions like modulation, demodulation, filtering, etc. In the CR testbed, it performs majority of the processing with minimum amount of processing left for the hardware to perform. In effect, the USRP acts just like an RF front end which sends or receives the samples to/from the host computer via the USB cable. Fig. 6.2, shows a USRP terminal and its major components, i.e., the motherboard and the daughterboard. The daugtherbord is a plug-in device that sits on the motherboard. The motherboard has ADC's, DAC's, an FPGA and USB interface. The daughterboard has the RF front end, LO and mixer. The incoming signal is received by the daughterboard and is down

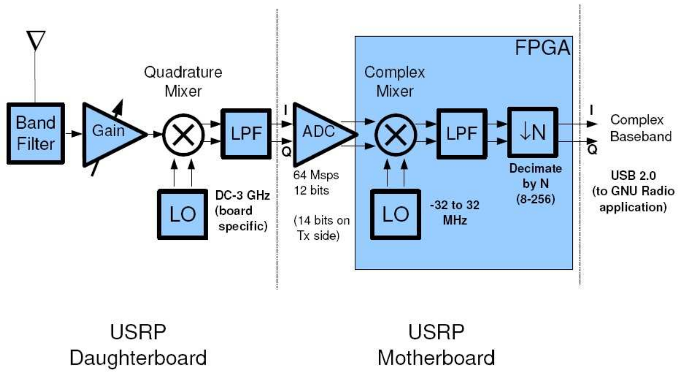


Figure 6.3: Block diagram showing the individual blocks of an USRP

converted to a baseband signal. After the down conversion the signal is sent to the USRP motherboard. Here it is sampled and converted into a bit stream which is then sent to the computer over the USB cable. The GNU radio inside the computer handles these bit streams and performs necessary processing. The same procedure follows in the reverse path wherein the bit stream from the GNU radio is converted to an analog signal in the motherboard and is up converted in the daughterboard. The block diagram of a USRP is shown in Fig. 6.3 which depicts the conversion of the signal into bit streams and vice-versa. By using the GNU radio we are able to design and implement powerful, flexible software radio systems which are the features of a cognitive radio. There are various daugtherbaords available, ranging from DC to 5GHz spectrum and can be changed according to the requirements. In our testbed we have used the XCVR 2450 transceiver board which operates in both 2.4-2.5 GHz and 4.9-5.85 GHz bands.

Monitor

The purpose of the monitor is to view the state of spectrum utilization. We have used a device called Wi-Spy dbx spectrum analyzer [53] which is shown with an antenna in Fig. 6.4. It comes with a USB interface, so it can be plugged into a computer and can be operated using a software called Chanalyzer which is available free of cost. Like the daughterboards this device is capable of analyzing both 2.4 GHz

Figure 6.4: The Wi-spy dbx spectrum analyzer

and 5GHz bands.

Through the Wi-Spy spectrum analyzer we are able get power spectral densities of the existing signals on graphic user interfaces. Thus, we can deduce many features of a spectrum like how good a channel is in terms of noise, the average power in a channel over a period of time, the peak power observed over a period of time etc.. A screen shot of the user interface provided by the chanlyzer software is shown in Fig. 6.5. There are three views available in the spectrum analyzer: the temporal or spectral view, the topographic view and the planar view. To demonstrate the dynamic spectrum access, the most important view is the temporal view as will be explained in Section 4.

6.2 Software/Algorithms

All the USRPs are connected to standard computers where LINUX is running to host the GNU radio software. The GNU radio software comes with programs which can be used for packet transmission and reception and has many reconfigurable options like carrier frequency modulation type, data rate, packet length etc.. To emulate a cognitive radio network, the USRPs are configured to take different roles. In this section, we provide the algorithms and software configuration details that achieve these roles on the USRPs.

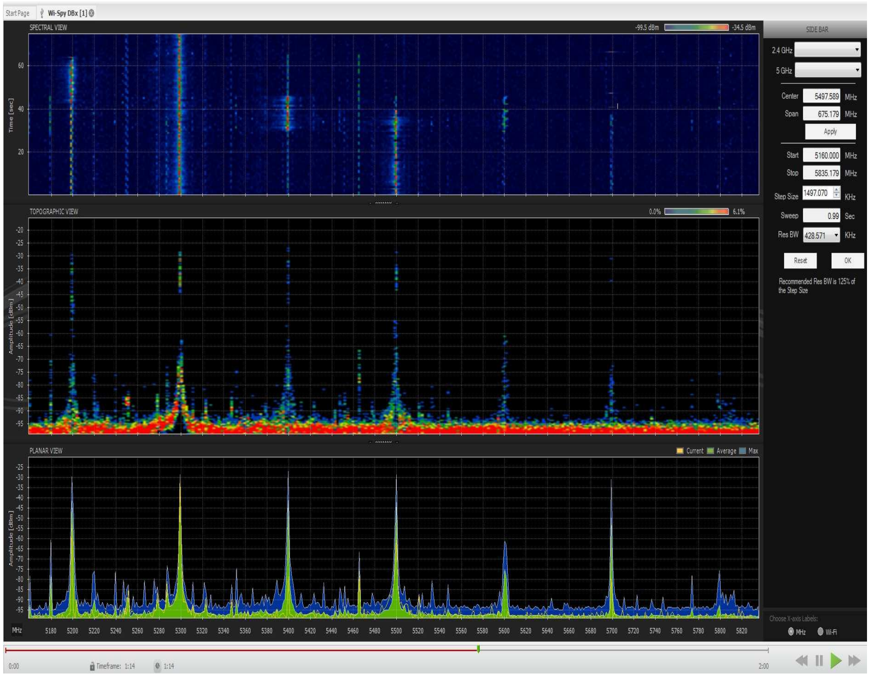


Figure 6.5: Snapshot of the Wi-Spy spectrum analyzer

6.2.1 Spectrum Sensing

Spectrum sensing plays an important role in the cognitive radio cycle. Energy detector is the most popular choice due to its simplicity and the fact that it does not require any prior knowledge about the signals. The basic idea is that the magnitude square of the FFT output gives us the energy contained in a band. If a channel is occupied then it has a higher energy level than an empty band. A value slightly greater than the noise floor is usually taken as the threshold to decide the binary occupancy state of a spectrum. The implementation of the energy detector on USRPs is discussed in [54] [55]. Although the energy detector is popular it has several disadvantages. The noise floor has to be accurately known to choose a proper threshold for detection. Also, the algorithm is very sensitive to sudden changes in the noise floor. More robust algorithms are required. The energy detector is a narrowband sensing scheme. On the contrary, wideband sensing methods which sense a wide band of frequencies in one go make the spectrum sensing more efficient. The ability of GNU radio to communicate with Octave [56] makes it possible to develop more complex and robust algorithms for sensing. Two methods which perform wideband sensing are presented below.

Subspace method for spectrum sensing:

The covariance matrix of the received signal samples has a lot of useful information which can be used for sensing. From its eigenvalues we can deduce many properties of a spectrum like the noise variance, the number of signals and their corresponding frequencies and signal strength. The name “subspace method” comes from the fact that the eigenvalues can be separated into those corresponding to the signal space and those corresponding to the noise space. We first construct the covariance matrix with samples taken from a wide band of interest (BOI). After eigenvalue decomposition, the ordered eigenvalues fall into the signal space and the noise space provided that the dimension of the covariance matrix is greater than the number of signals. A chi-square test statistic can point out the eigenvalues corresponding to the signal space from which we can derive the angular frequencies using the ESPRIT algorithm. One more useful result is that the eigenvalues corresponding to the noise space asymptotically equal noise variance and the ones corresponding to the signal space are signal power plus noise variance asymptotically. [21] proposes such an algorithm along with a cooperative sensing scheme which improves the sensing results.

Regularized least squares method for spectrum sensing:

In this method a matrix $\mathbf{E}$ is created which acts like a frequency mesh similar to a DFT matrix. The received signal can then be represented as a linear function of $\mathbf{E}$. If $\mathbf{x}$ is a vector containing the received samples then we can write:

$$\mathbf{x} = \mathbf{E}\mathbf{h} + \eta \tag{6.1}$$

where $\mathbf{h}$ is a vector of only k nonzero values with k being the number of signals present in the BOI and η is the AWGN noise. If N samples of the signal are collected and the BOI is split into M channels, then $\mathbf{E}$ is $N \times M$ and $\mathbf{h}$ is an $M \times 1$ vector. If $N > M$, $\hat{\mathbf{h}}$ can be obtained by using the least square algorithm. The nonzero elements can be further determined based on the Neyman-Pearson hypothesis testing. If a finer grid is needed then generally we have $M > N$. In this case, the least square solution gives very unstable results. We add a regularization term to the least square solution, wherein the regularization coefficient can be found using an iterative algorithm.

6.2.2 Communication Protocol

Communication protocol is a set of rules and formats that is followed for initiation and exchange of information between communication devices. In our testbed, a channel is reserved exclusively for carrying all the control frames, and is called a control channel. The assumption of a reserved control channel is quite feasible and is discussed in [57]. The protocols associated with non-cooperative narrowband sensing and cooperative wideband sensing are different, the designs of which are presented separately next.

Protocol for Narrowband Sensing: Initially all the secondary users are configured to receive packets on the control channel. When a secondary user 1 (S_1) wants to communicate with secondary user 2 (S_2), the first step of S_1 is to sense the spectrum for empty bands. Once S_1 finds a channel f unoccupied, it sends a *request to send* (RTS) packet to S_2 over the control channel, which includes the receiver ID, the chosen frequency band, frame length of typical secondary user's data packets and optionally another field indicating simplex or duplex communication. When the intended receiver S_2 receives the RTS, it resenses the chosen frequency band to verify that the channel is unoccupied. This dual stage of spectrum sensing eliminates the hidden terminal problem as it is not always true that an empty channel in the vicinity of the transmitter is also empty on the receiver side. If the channel is occupied at the receiver side, a negative *clear to send* (CTS) packet is sent to S_1 and S_1 has to look for other vacant channels. On the other hand, when the channel is termed unoccupied, a positive CTS is sent. Then S_1 and S_2 are ready for data transmission on the chosen channel.

Although the frequency channel is deemed to be available at the beginning of transmission, there is always a possibility of a licensed user coming back. To make sure there is no interference in such cases, the secondary users transmit in a burst mode with a predetermined frame length. Spectrum sensing is carried out between successive bursts to make sure that the primary user has not come back. In the case when a primary user is detected, the transmission is immediately ceased and the transmitter goes back to find other vacant bands. The receiver also manages to go back to the control channel since it is configured to receive frames of a certain frame length but starts to hear packets that it does not understand.

If more than one pair of secondary users exist, then there is contention for the control channel. We use the the IDs of the secondary users to alleviate the problem. Before sending the RTS, the transmitting station is made to wait for a certain period of time proportional to its ID. Thus, the users with higher IDs have lower preference of the control channel. If there is no response to an RTS (might be due to control channel contention or a busy/dead receiving terminal), the transmitter employs the exponential back off algorithm [58] and resends the RTS frame.

Protocol for Wideband Sensing: When a cooperative wideband sensing scheme is used at the secondary user terminals, the above mentioned protocol needs additional requirements. A fusion center comes into the system architecture. Any of the secondary users can easily be reconfigured to exclusively act as the fusion center. The role of a fusion center is to collect individual sensing decisions and generate a global occupancy report of the whole BOI.

The first step of the protocol remains to be spectrum sensing. The difference is that the whole BOI is sensed instead of individual channels. Instead of sensing only when data transmission is required, the secondary user terminals generate a local sensing report at constant intervals which are then updated by the global report generated at the fusion center. When a secondary user wants to transmit data it would already have the available channel information. Thus, the protocol can directly start off with sending an RTS by choosing an appropriate channel frequency in the frequency field. The receiving terminal still performs narrowband sensing via energy detection as it has to only bother about the channel mentioned in the RTS. The second stage of sensing puts a check on the transmitting terminal sending a channel frequency from an outdated channel occupancy report.

The channel occupancy report needs to be updated periodically. The secondary users are synchronized in performing spectrum sensing. If any secondary user is in data transmission, it suspends the transmission and performs wideband sensing. Once the fused global occupancy report is broadcast, it resumes its transmission if the channel is still available. To avoid contention of the control channel in the cooperation stage, we again make the terminals wait according to their IDs. The fusion center is always given the highest priority. The rest of the protocol remains unchanged and since the sensing in the later stages of the protocol concentrate on only one channel, we still use the energy detector.

6.3 Experimental Results

In this section we evaluate the performance of our testbed using two main criteria. The first one is the ability to sense a piece of spectrum and decide the unoccupied channels, i.e., spectrum sensing and second is to check the ability of the whole system demonstrating dynamic spectrum access. Various operating parameters of the cognitive radio network are provided.

As mentioned in Section 2, the daugtherboards and the spectrum analyzer used in our system have the capability to operate on both 2.4 GHz and 5 GHz range. The 5 GHz spectrum is chosen to avoid interference from the Wi-Fi network of the university operating in 2.4 GHz range. To make the primary user signals different from the secondary users, both the primary users transmit GMSK modulated packets of 1600 bytes. The secondary users send out QPSK modulated packets and the data length can be specified in the frame length field of the RTS. All the packets used in our system have the 2 byte header which contains the Cyclic Redundancy Check (CRC) code and a frame tag. The CRC code is used to check the validity of the data bits in the frames and if the CRC check shows any error then the whole packet is discarded.

We present two test scenarios, for non cooperative narrowband sensing and cooperative wideband sensing methods, respectively.

6.3.1 Narrowband Sensing Scheme

The spectrum is divided into six non-overlapping channels with the central frequencies $f_1, f_2, \cdots, f_6$. $f_1 = 5.2$ GHz and the successive channels are separated by 0.1 GHz. The maximum bandwidth that can be processed by the USRP is 8 MHz, thus the channel boundaries can be defined as $f_i \pm 4$ MHz, $i = 1, 2, \cdots, 6$. The control channel is fixed at f_6 and is used exclusively for control channel packets. The two primary users have the exclusive license for channels 1 and 2. Since the primary users don't always transmit, the secondary users can opportunistically use any of the channels 1 to 5. When a secondary user wants to transmit data, the spectrum sensing algorithm is always started from channel 1. Although there are no licensed users for channels 3-5, the secondary users still manage to use channels 1 and 2 opportunistically which in turn improves the spectrum utilization. For narrowband sensing, the energy detector is used. When the energy detector algorithm runs on bands with no signals, the resulting energy value is nearly a constant irrespective of the frequency band chosen. Thus, a common threshold is chosen for detection across all the channels. A 1024 point FFT is used to sweep the 8 MHz for our analysis. The implementation has a bin resolution of about 8 KHz. With a sampling frequency of 8 MHz, the 1024 samples needed for the FFT take only 128μsec to collect. We choose a 1024 $\times$ 100 spectral averaging that takes about 12.8 msec for its complete operation. This is quite reasonable for real time systems.

The performance of the energy detection scheme is good. This can be attributed to the fact that the whole network is set in a 25 ft $\times$ 12.5ft lab room and the USRPs are close to each other. The detection probability is near unity. To demonstrate the working of the dynamic spectrum access system, the spectral view of the network for a duration of 74 seconds is shown in Fig. 6.6. The figure is marked with events A to D. P_2 is using channel 2 during the entire duration and is shown by event A. Event B is S_1 trying to use the spectrum and when it senses that channel 1 is unoccupied, $B1$ shows the control channel information and $B2$ is the actual data transmission on channel 1. C shows the entry of the S_2 with $C1$ being the control channel usage notifying the corresponding receiving terminal that channel 3 is the empty channel sensed and the data transmission occurs at $C2$. Event D shows the spectrum mobility aspect of the system. $D1$ is the event when P_1 comes back to use its licensed spectrum at 5.2GHz (Channel 1). S_1 senses the arrival and ceases transmission immediately. The spectrum is sensed to find that channel 4 is empty and then the control channel information is exchanged at $D2$ and finally data transmission $D3$, is continued at channel 4.

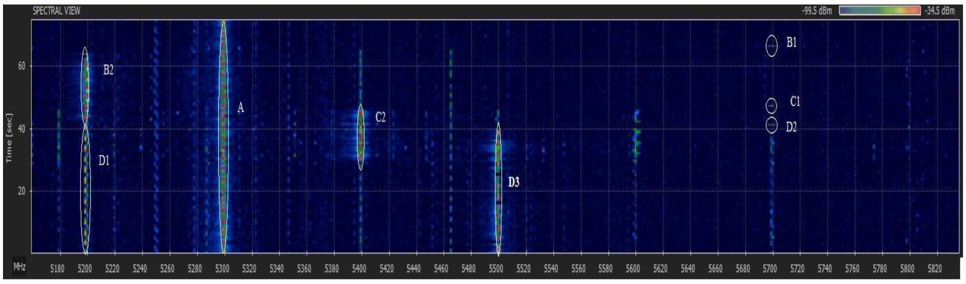


Figure 6.6: Spectral view showing the network traffic for a duration of 74 seconds.

6.3.2 Wideband Sensing Scheme

Due to the system limitations of USRPs, the size of the wide BOI is limited to 8 MHz. We have split the BOI into 8 channels each with a bandwidth of 1 MHz and centered around 5.3 GHz. The control channel is still chosen to be at 5.7 GHz. The length of the binary decision field is of one byte long with each bit corresponding to the one channel. To make the channel occupancy a little more chaotic, the primary users are reconfigured to use different channels at different times and for different durations. Thus all eight channels may have a licensed user. Both the subspace method and regularized least square method perform very well with respect to pointing out the occupied channels.

To demonstrate the working of the wideband sensing scheme, we use the results of the regularized least square technique. Consider a scenario wherein three primary users are concurrently present at channels 1, 3 and 4 respectively. The corresponding carrier frequencies are 5.3 GHz -3.5 MHz, -1.5 MHz and -0.5 MHz. The **h** vector is of length 8. By collecting only 50 samples of the incoming signals the algorithm correctly detects 3 nonzero values of **h** at the corresponding channel numbers. Fig. 6.7 shows the plot of the **h** vector. The amplitude at channel 1 is smaller than the other two since this terminal was far away from the sensing terminal.

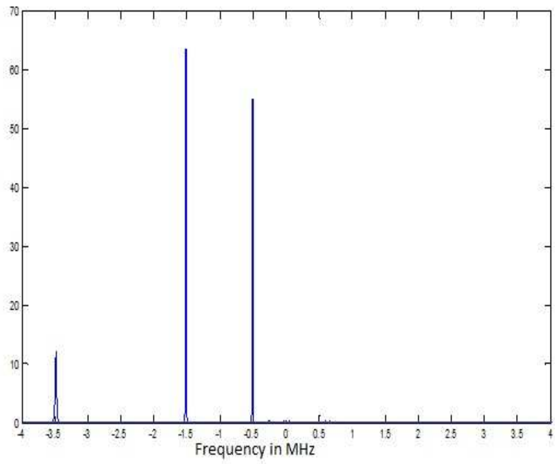


Figure 6.7: Plot of the **h** vector using regularized least squares algorithm.

CHAPTER 7

Conclusions and Future Work

7.1 Conclusions

The sensing scheduling design describes a sequential energy detector based design where several CRs collaborate to sense a channel. This design focuses on maximizing the total average gain per unit time of the system due to spectrum sensing and utilization. After detection, the gain per CR cycle is obtained for various decisions made on the actual state of the PU. Optimized parameters, i.e., number of CRs used for sensing, waiting time when the channel is occupied, transmission time when the channel is inoccupied, P_f and P_m are obtained. Genetic algorithms are applied to obtain the parameters that give the highest average gain. The single channel design is then further extended to a more realistic case where multiple channels are present in a CR network. In a multiple channel network, a channel profile containing the optimal paramters is created for each channel. This profile is used for the CR assignment at the multiple channel level. Two approaches - greedy and non-greedy, focussing on two different conditions for CR assignment are discussed. Experimental results were studied for both the single channel and the multiple channel CR network. Effects of system parameters on the design parameters are observed. In a multiple channel network, it was seen that the non-greedy approach outperforms the greedy approach with respect to total average gain.

The sensing scheduling design was followed by a cognitive radio testbed. The cogntive radio testbed gives us a feel of how actually a CR network would work. This testbed is based on USRPs built by Ettus Research. By configuring the USRPs to play different roles, we are successful in implementing a basic wireless communication network with cognitive abilities. Different sensing and scheduling algorithms can be realized on the testbed to demonstrate their effectiveness in identifying spectrum holes. A communication protocol which caters the needs of a dynamic spectrum access system is also introduced. The system is extended to incorporate collaborative spectrum sensing amongst the secondary users. Experimental results show that the reconfigurability of the secondary users allows them to adapt to the channel occupancy states. Although, the current testbed is focused on spectrum sensing and dynamic spectrum access, it has the ability to carry out extensive research in all fields of the cognitive radio.

7.2 Future Work

In the current multichannel CR network, it was assumed that the CRs and channels are identical. Parameters like estimation of distance between the PU and the SU, shadowing, fading, etc. can be considered during the scheduling design. The distance between the PU and SU can be followed by estimating the direction of the PU at the SU. The scheduling can be designed such that the CRs near to the PU will sense the channel rather than the CRs away from the PU sensing it. We leave this idea for the future research.

Also, the sensing scheduling schemes and other sensing algorithms can be implemented on the cognitive radio testbed. The USRP testbed is compatible with octave. Hence different algorithms may be implemented on the testbed to check the working of a sensing or sensing scheduling method in practise.

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APPENDIX A

Derivation for the distribution of the number of sensing steps

In our formulation we use the SPRT to decide when a PU in a channel is occupied or unoccupied. If the log likelihood ratio after one sensing cycle does not cross upper or the lower threshold a or b respectively, then one more sensing step is taken. It is assumed that the log likelihood ratio crosses the SPRT threholds after L sensing cycles. Hence L has to follow a distribution under the hypotheses H_0 and H_1. The distribution of L can be found using the formulation in [47]. Let us assume the two hypotheses to be,

$$\begin{aligned} H_0 &: \theta = \theta_1 + \Delta/2 \\ H_1 &: \theta = \theta_1 - \Delta/2 \end{aligned} \tag{1}$$

where $\Delta \to 0$. Let θ_0 be the true value of θ. According to [47], α = r($\theta_1 + \Delta$) - r(θ_1) and $\alpha_j = r'(\theta_j)$. For a normal distribution, according to [47] and exponential family, $r(\theta)$ is given by -$\theta^2/2\sigma^2$. Now, the log likelihood ratio where is given by:

$$\log \frac{\frac{1}{\sqrt{2\pi}\sigma} e^{\frac{(X-\theta_1-\Delta/2)^2}{2\sigma^2}}}{\frac{1}{\sqrt{2\pi}\sigma} e^{\frac{(X-\theta_1+\Delta/2)^2}{2\sigma^2}}} = \frac{\Delta(X - \Theta_1)}{\sigma^2} \tag{2}$$

Here $X = \theta_0$ which is the true value of θ. Using [47], mean value is given by,

$$E_{H_1}(L) = \frac{a}{\Delta(\alpha - \alpha_0)} \approx \frac{a}{\Delta(\alpha_1 - \alpha_0)}$$

$$= \frac{a\sigma^2}{\Delta(\theta_0 - \theta_1)}$$
$$= \left(\frac{a\sigma^2}{\Delta(\theta_1 + \Delta/2 - \theta_1)}\right) = \frac{2a\sigma^2}{\Delta^2}$$

For j CRs, the mean value is given by:

$$E_{H_1}(L) = \frac{2a\sigma^2}{j\Delta^2}$$

Similarly, under the hypothesis H_0, the mean value of no. of steps can be calculated and is given by:

$$E_{H_0}(L) = -\frac{2b\sigma^2}{j\Delta^2} \tag{4}$$

According to the theorem 2, under the hypothesis H_1 for a normal distribution the variance of L is given by $a\sigma^2/\Delta(\alpha_1 - \alpha_0)^3$ while, under H_0, the mean of L is given by $b\sigma^2/\Delta(\alpha_0 - \alpha_1)^3$. Therefore under H_1, the variance of L is given by,

$$V_{H_1}(L) = \frac{a\sigma^2}{\Delta(\alpha_1 - \alpha_0)^3} = \frac{a\sigma^2}{\Delta(\frac{\theta_0^2}{\sigma^2} - \frac{\theta_1}{\sigma^2})^3} = \frac{a\sigma^8}{\Delta^4} \tag{5}$$

For j CRs, the variance is given by:

$$V_{H_1}(L) == \frac{a\sigma^8}{j^2\Delta^4} \tag{6}$$

Similarly under hypothesis H_0, we can find the variance of L and it is given by,

$$V_{H_1}(L) = -\frac{b\sigma^8}{j^2\Delta^4} \tag{7}$$

It is assumed that the variance for both the hypothesis is equal to 1 as the assumed SNR is very low. i.e. $1 + 2\gamma \approx 1$. Thus σ^2 in above expressions is equal to 1 and Δ can be obtained as the difference between the means of the two hypothesis, i.e., $\Delta = \sqrt{\frac{N}{2}\gamma}$.

Thus, substituing the values of σ^2 and Δ in the above expressions for mean and varainces for H_0 and H_1 cases, we get,

$$H_1 : L \sim \mathcal{N}\left(\frac{4a}{Nj\gamma^2}, \frac{4a}{N^2j^2\gamma^4}\right)$$

$$H_0 : L \sim \mathcal{N}\left(\frac{-4b}{Nj\gamma^2}, \frac{-4b}{N^2 j^2 \gamma^4}\right) \tag{9}$$

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In cognitive radio (CR) networks, spectrum sensing has gained great importance for opportunistic spectrum access. There are many factors that affect the efficiency of spectrum sensing. High sensing accuracy can help reduce the chance of interference to primary user and improve the spectrum utility. However, high sensing accuracy requires a large amount of sensing resources including multiple collaborative CRs and the sensing duration. We propose a cost based framework for spectrum sensing scheduling, in which all these factors are modeled by certain cost or gain of the system. A sequential energy detector is used for accumulating all energy measurements for sensing. Depending on the decision made, the CRs decide whether to wait as the channel is occupied or to start data transmission as there is a spectral hole. The optimal number of CRs, the sensing accuracy levels and the waiting/transmission time are obtained such that the average gain per unit time including both sensing and wait/data transmission stages are maximized.

Findings and Conclusions:
We provide various experimental results to show the effectiveness of the proposed design and the effects of various parameters on the performance are analyzed. The idea is then extended to a multiple channel CR network. The channel profile generated from a single channel design is utilized for CR assignment to channels that request for sensing. Two approaches, viz., greedy approach and non-greedy approach are designed for scheduling. Then the two approaches are compared on the basis of total average gain obtained from each approaches. The non-greedy approach outperforms the greedy approach with respect to the total average gain.

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