THE DESIGN AND IMPLEMENTATION OF COOPERATIVE SPECTRUM SENSING ALGORITHM IN COGNITIVE NETWORKS

by

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DISSERTATION

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DEDICATION

This work is dedicated to my two sons, Amogelang and Gracious who put a smile on my face and gave me courage and hope when things got harder and tougher,

To my mother, Tlouyamma Johanna, who encouraged me in an event where I lost hope in my studies.

To my three younger brothers and Uncle, who supported me through thick and thin throughout my studies.

DECLARATION

I ....**Tlouyamma Joseph**................., declare that a work presented in this dissertation is my own original research work and that, works done by other researchers or quotes extracted from any other source have appropriately been referenced. And I further declare that this work, Titled THE DESIGN AND IMPLEMENTATION OF COOPERATIVE SPECTRUM SENSING ALGORITHM IN COGNITIVE NETWORKS has not been submitted in any other university or institution of higher learning.

Signed: ……………………………………. Date…………………………………...

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ABSTRACT

A Major concern in the past years was the traditional static spectrum allocation which gave rise to spectrum underutilization and scarcity in wireless networks. In an attempt to solve this problem, cognitive radios technology was proposed and this allows a spectrum to be accessed dynamically by Cognitive radio users or secondary users (SUs). Dynamic access can efficiently be achieved by making necessary adjustment to some MAC layer functionalities such as sensing and channel allocation. MAC protocols play a central role in scheduling sensing periods and channel allocation which ensure that the interference is reduced to a tolerable level. In order to improve the accuracy of sensing algorithm, necessary adjustments should be made at MAC layer. Sensing delays and errors are major challenges in the design of a more accurate spectrum sensing algorithm or MAC protocol. Proposed in this study, is a scheme (EXGPCSA) which incorporate sensing at the MAC layer and physical layer. Energy detector was used to detect the presence of primary users (SU). A choice of how long and how often to sense the spectrum was addressed at the MAC layer. The focal point of this study was on minimizing delays in finding available channels for transmission. EXGPCSA used channel grouping technique to reduce delays. Channels were divided into two groups and arranged in descending order of their idling probabilities. Channels with higher probabilities were selected for sensing. Three network scenarios were considered wherein a group of SUs participated in sensing and sharing their spectral observations. EXGPCSA was designed such that only SUs with higher SNR were allowed to share their observations with other neighbouring SUs. This rule greatly minimized errors in sensing. The efficiency of EXGPCSA was evaluated by comparing it to another scheme called generalized predictive CSA. A statistical t-test was used to test if there is significant difference between EXGPCSA and generalized predictive CSA in terms of average throughput. A test has shown that EXGPCSA significantly performed better than generalized predictive CSA. Both schemes were simulated using MATLAB R2015a in three different network scenarios.

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ABBREVIATIONS

ACK – Acknowledgement

AS MAC – Ad hoc secondary network Medium Access Control

ASP – Allocated-Group Sensing Policy

CCC – Common Control Channel

CogMesh – Cognitive Wireless Mesh Networking

CR – Cognitive Radio

CRAHNs – Cognitive Ad hoc Radio networks

CSA – Channel Selection Algorithm

CSIR – Centre for Scientific and Industrial Research

CSMA MAC – Carrier Sense Multiple Access Medium Access Control

CTS – Clear To Send

DC MAC – Decentralized cognitive Medium Access Control

DCTS – Distributed Consensus Time Synchronization

DOSS – Dynamic Open Spectrum Sharing

DSP – Distinct-sensing policy

ECRQ MAC – energy efficient Cognitive Radio Medium Access Control for QoS provisioning

EXGPCSA – Extended Generalized Predictive Channel Selection Algorithm

FCC – Federations of Communication Commission

FIFO – First in First Out

GHz – Giga Hertz

GSM – Global System for Mobile Communication

HC-MAC – Hardware-Constrained Cognitive Medium Access Control

ICT – Information Communication Technology

IDE – Integrated development Environment

IEEE – The Institute of Electrical and Electronics Engineers

LTE – Long Term Evolution

MAC – Medium Access Control

MATLAB – MATrix LABoratory

MHz – Mega Hertz

MRC – Maximal Ratio Combining

NS3 – Network Simulator 3

OMNET++ – Objective Modular Network Testbed in C++

OP MAC – Opportunistic Medium Access Control

OSA – opportunistic spectrum access

OSI – Open Systems Interconnection

PAD MAC – PU Activity-aware Distributed Medium Access Control

PBWAM – Penalty-Based Weights Adjustment Mechanism

PDF – Probability Density Function

PSD – Power Spectral Density

PU – Primary User

RSP – Random Sensing Policy

RTS – Request To Send

SC – Selection Combining

SDCSS – Semi-Distributed Cooperative Spectrum Sensing

SLC – Square Low Combining

SNR – Signal-to-Noise Ratio

SRAC – Single Radio Adaptive Channel

SU – Secondary User

SYN MAC – Synchronized Medium Access Control

TCP/IP – Transmission Control Protocol/ Internet Protocol

TTDMA – Truncated Time Division Multiple Access

TV – Television

TVWS – Television White Spaces

WLAN – Wireless Local Area Network

CHAPTER 1 - INTRODUCTION

1. Introduction

Different parts of the spectrum have been traditionally defined to be used by different wireless technology (GSM, WLAN, TV, Military, emergency services or LTE). Unfortunately, due to an increased usage of mobile communication devices, some spectrum bands are crowded while others are hardly used because of fixed spectrum allocation. This leads to spectrum inefficiency problem shown in figure 1.1. Primary traffic is the activity of the licensed users in the spectrum. This is the actual data transmission by the licensed users. Unfortunately, data transmission is not performed at all times by licensed users. There are times when the spectrum is idling or unutilized. This poses a great challenge where these four channels are hardly used while other channels meant for services such as wireless mobile devices (GSM, LTE, etc.) are crowded. The spectrum is inefficiently used while there is a need for more data transmission to meet high demand in the wireless mobile communication.

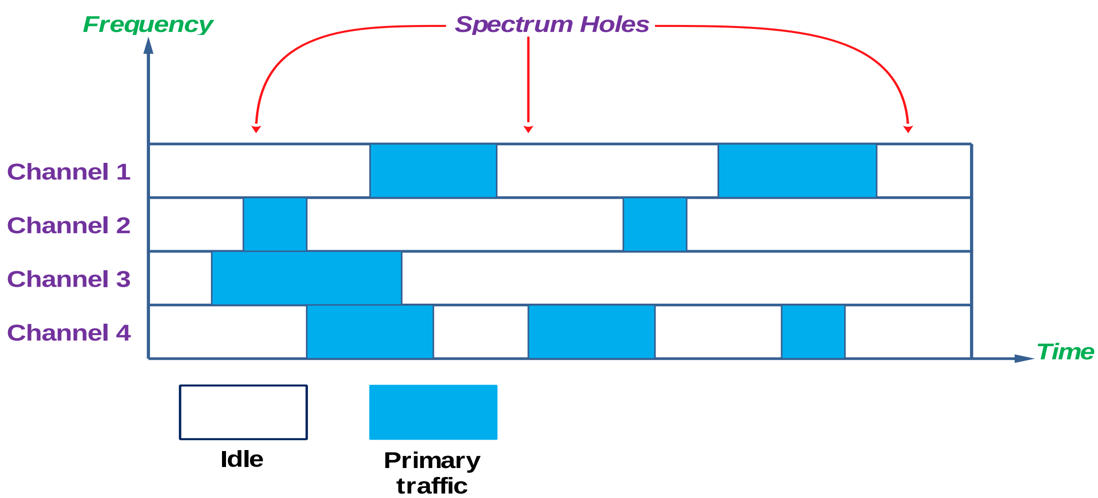

Figure 1. 1: Fixed spectrum allocation in TV white spaces

In order to solve this problem, cognitive radio (CR) technology is used to efficiently exploit the spectrum white spaces or holes. CR is a radio that is capable of learning the environment in which it operates and changes its transmission parameters based on the status (channel occupancy information) of the spectrum band. Federal Communications Commission (FCC) assigned certain portion of the spectrum to licensed users or primary users (PU) for data transmission. Licensed users and Primary users (PU) are used interchangeably throughout this study. A diagram in figure 1.2 shows a dynamic network environment where SUs opportunistically transmit their data in the channels assigned to PUs. Data transmission has to be done after sensing to avoid interference with PUs.

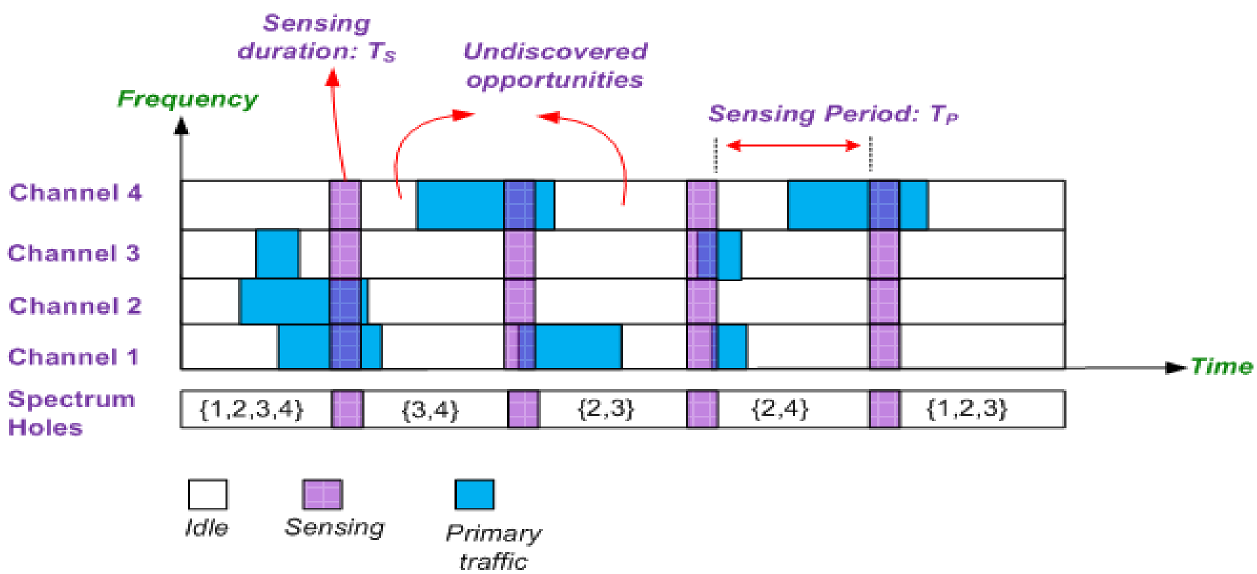

Figure 1. 2: Dynamic spectrum allocation in TV white spaces [1]

In order to lessen high demand in mobile data communication, FCC approved the co-existence of secondary users (SU) with PUs in the bands assigned to licensed users where idle channels could be utilized by SUs as shown in the figure 1.2. Since PUs are legitimate users of the spectrum, they must not be interfered with by SUs. SUs must have the capability to sense the spectrum before transmitting data and if PUs are transmitting, SUs should adjust their transmission power levels or switches to unoccupied spectrum band to avoid interference. This makes spectrum sensing to be one of the most important aspects of CR technology.

There are two approaches to spectrum sensing in CR networks. That is, sensing at physical layer and MAC layer. Sensing a spectrum at the physical layer makes adaptation of modulation schemes and parameters for detecting and measuring the signals transmitted by PUs from different channel while MAC layer sensing makes a decision as when SUs have to sense which channels [2]. MAC layer is responsible for searching of channels and transmissions, and scheduling time slots for sensing. MAC has received far less attention as compared to the physical layer sensing. Spectrum sensing function belongs to physical layer but the coordination and scheduling of SUs is the responsibility of MAC protocol.

Proper coordination and scheduling of SUs lead to better utilization of spectrum resources. A key technology in efficient use of the spectrum is spectrum sensing. Sensing must be performed accurately to avoid interference and degradation of performance. Secondly, a seamless communication must be maintained during spectrum mobility. If a PU is detected in the current band a SU is transmitting in, SU will have to move to a new band to continue with its data transmission. This movement is made possible by spectrum mobility function. A perfect timing has to be performed during spectrum handoff. Spectrum handoff happens when SU ceases its transmission from one spectrum to the other.

The major causes of delays in data transmission in cognitive radio networks are cooperative sensing and sharing of the sensed results. In this study we address these challenges in order to maximize the throughput of SUs. Hence, we proposed a channel selection algorithm to intelligently select channels that are free from PU and ready to be used opportunistically by SUs for data transmission. The channels with the highest probability of being free from PUs are selected for sensing. Delays incurred during cooperative sensing will be dealt with through sensing multiple channels at the same time (parallel sensing) and the use of probabilistic models to model delays in sensing and sharing of spectral observations. It should be noted that SUs share their sensed results through fusion node not directly amongst themselves.

In order for SUs to reliably detect the presence of PUs in the channel and reduce sensing delays, we incorporate cooperative spectrum sensing and set a rule which ensures that only cooperating SUs with higher Signal-to-Noise Ratio (SNR) share their sensed results. For this, we proposed an algorithm called extended generalized predictive channel selection algorithm (EXGPCSA). This algorithm is an improved version of an existing algorithm called generalized predictive channel selection algorithm [3].

1.1. Problem Statement

The emergence of wireless devices has led to an increase in demand for radio frequency spectrum against the backdrop of poor utilization of licensed spectrum and overcrowding in unlicensed bands. The cognitive radio technology has been proposed as the solution to the scarcity of the spectrum. It is envisioned that cognitive radio technology will improve the utilization of the spectrum by opportunistically utilizing the unused spectrum.

The ability to effectively exploit these opportunities depends on cooperative spectrum sensing, which is one of the key technologies in cognitive radio networks. The challenge is to cooperatively sense the whole radio frequency spectrum and share sensed or collected information amongst cognitive radio users in a wide geographic area within a short observation time. Longer observation times imply performance degradation and spectrum underutilization.

There is therefore a need to optimize the sensing times with the data transmission times. A well designed cooperative algorithm can significantly contribute to achievable end-to-end throughput or cooperative gain. Unfortunately, cooperative sensing incurs higher cooperative overheads and this impact negatively on the efficiency of sensing algorithms. Factors contributing to overheads are operations performed during cooperative sensing (sharing and comparing of cooperatively sensed information) and extended sensing and decision time. To achieve higher cooperative gain, optimization of the above factors will be critical. Spectrum sharing, spectrum decision and spectrum access processes increase further delays in the cognitive cycle and they do require optimization to improve end-to-end achievable throughput.

Distributed sensing and gathering of distributed sensed information is a challenging task in Ad hoc networks; a network set up without a centralized coordination and maintenance. A frequent change in topology leads to sensing errors and PU interference. Sensing delays, sensing errors and PU interference affect the performance of distributed sensing algorithm; as such correct measures may be considered for optimization. However, interference cannot be avoided, but may be reduced to a tolerable level through distributed cooperative sensing. Hence, we are motivated to design and implement a cooperative sensing algorithm which reduces sensing delays, sensing errors and mitigates the interference between SUs and PUs.

1.2. Study Aims

The main aim of this study is to minimize delays in finding available channels for transmission. We aim to develop cooperative sensing algorithm to reliably detect changes in cognitive radio environment, minimize sensing delays by optimizing sensing time and implementing channel selection algorithm to maximize achievable throughput, thereby minimizing delays in finding available channels for transmission. The main objectives of this study are:

- To develop a spectrum sensing algorithm which will minimize the overheads associated with cooperative spectrum sensing.
- To determine the appropriate technique to be implemented by SUs when they collaborate in reporting channel occupancy information.
- To reduce delays incurred when cooperatively sensing a radio frequency spectrum.
- To mitigate PU interference through the implementation of cooperative sensing algorithms.
- To reduce the probability of false alarm while increasing hit probability.
- To detect changes in the radio environment faster through the implementation of cooperative sensing.
- To determine the optimal sensing time to facilitate timely spectrum access decisions.

1.3. Hypothesis

H_1: channel selection algorithms can be optimized through the use of probabilistic models such that SUs select channels that are free from PUs with minimal delays.

H_0: channel selection algorithms may incur more delays depending on how channels are ordered for sensing and selection and the choice of probabilistic model.

1.4. Research Questions

Challenges involved in cognitive radio environment have led to the formulation of the following questions which will be addressed by this study. A dynamic nature of cognitive radio networks gives rise to different challenges which need to be addressed by research community. We contributed to this community by formulating the following research questions:

- What factors should be considered in the design of a cooperative sensing algorithm optimized to minimize sensing delay and reduce interference?
- How much cooperative gain can be achieved through cooperative sensing?
- To what extent can cooperative spectrum sensing algorithm address the challenges of CR networks such as sensing delays, sensing errors and effective utilization of the spectrum?

1.5. Motivation of the study

An extent to which wireless devices are in use today has put strains on finite spectrum. Hence, FCC allowed coexistence of PUs and SUs in the spectrum assigned to PUs. The coexistence of the users in the spectrum has led to a number of challenges. These challenges amongst others are; interference between users of the spectrum, waiting time of SUs to sense and transmit data (delays in sensing and transmitting data) and spectrum mobility. These issues and others need to be addressed to alleviate spectrum underutilization or spectrum scarcity problem. Hence this has motivated us to investigate sensing delays to allow faster data transmission.

1.6. Literature Review

The exponential ON/OFF time distributions for the PU's channel occupancy information were assumed in most channel selection algorithms in literature. Such assumptions might be very useful for improving the performance but cannot be evaluated in a realistic network environment. A study in [3] proposed heavy tailed PU OFF time distributions which represent a realistic network environment. It used a CSA to intelligently select channels to be sensed. This scheme has shown to reduce channel switching and energy consumption.

A major drawback of this scheme is that, channels are sensed sequentially and that greatly limits the amount transmission opportunities that can be discovered at a particular time interval. Kim et [25] used the knowledge of the sensing results obtained from the previous sensing slot to predict future availability of the channel. The historic sensing results were then used to order channels for sensing. The study focused mainly on sensing and channel selection but did not clearly define how aggregation is performed.

1.7. Research Methodology

Most MAC layer studies in literature used Matlab simulation tool to evaluate the efficiency of CSA or MAC layer protocols due to its simplicity in designing and implementing new algorithms. Tools such as NS-2 and NS-3 have libraries defined to support cognitive radio but can be very difficult to deploy. We choose to simulate our proposed algorithm using Matlab and other tools in future to have a fair comparison in terms of the performance.

Matlab R2015a was installed in a machine running windows 7 64 bits operating system. A directory was set for m files used for simulations in three network scenarios where 10, 20 and 30 SUs were considered. The following performance matrices were used to evaluate the efficiency of the proposed scheme:

- Probability of false alarm
- Probability of detection
- Sensing delays
- Service time
- Channel switching rate
- Throughput

1.8. Contributions

A proposed study, EXGPCSA is an extension to existing algorithm called generalized predictive CSA. There were adjustments done to optimize generalized predictive CSA. These adjustments form part form of contributions. Table 1.1 shows the contributions of our study. A complex approach was incorporated into existing work and yet managed to enhance the performance. This complexity was brought in by collaborative sensing and parallel sensing. These are the major contributions of this study.

Table 1. 1: Major contributions of this study

Attributes	Generalized predictive CSA	EXGPCSA (Proposed Scheme)
Cooperation of SUs	Partial with no specific rule on which SUs should share their observations	Full cooperation with a rule that forces SUs with higher SNR to participate in cooperation
Coordination amongst SUs to mitigate self-interferences	No specific coordination	Coordination was enforced using Carrier Sense Multiple Access with Collision Avoidance(CSMA/CA)
Channel sensing and grouping techniques	Channels are grouped in descending order of their idling probabilities. And channels with the highest probabilities are selected for sensing. There is only one group and sensing is sequential.	Channels are grouped into two groups and ordered in descending order of their idling probabilities. And channels with the highest probabilities are selected for sensing. There is only two groups and parallel sensing is possible
Modelling ON/OFF periods	Probability density function (PDF) with exponential distribution.	Probability density function (PDF) with exponential distribution and Hidden Markov Models.
Queue Modelling	No specific model used for controlling queues	M/M/1 queuing model using exponential probability density function and Poisson distribution

The following are the contribution of this work.

Joseph Tlouyamma, Mthulisi Velempini & Sabelo Dlamini, "Delay analysis of parallel distributed cooperative spectrum sensing in Cognitive Radio Ad Hoc Networks", SATNAC 2016, pp 68.

The paper analyzes delays incurred in a distributed environment where SUs cooperatively sense the spectrum. A framework suitable for CR environment was developed and presented in this paper.

Tlouyamma, Joseph, Mthulisi Velempini, and Sabelo Velemseni Dlamini. "Modelling and theoretical analysis of cooperative spectrum sensing performance." In *Advances in Computing and Communication Engineering (ICACCE), 2016 International Conference on*, pp. 81-84. IEEE, 2016.

The reliability and efficiency of any spectrum sensing algorithm depend on sensing and sharing strategies. This paper proposed a sensing policy, channel grouping, and sensing technique to efficiently utilize the spectrum bands. The analysis was made by comparing cooperative and non-cooperative sensing. SUs in cooperative environment had higher achievable throughput compared to non-cooperative SU.

Tlouyamma, Joseph, Mthulisi Velempini, and Sabelo Velemseni Dlamini. "Delay minimization in spectrum sensing in cognitive radio networks." In *AFRICON, 2017 IEEE*, pp. 204-208. IEEE, 2017.

This paper focused on minimizing delays in finding available channels. The Probability density function with exponential distributions and hidden Markov models were used to model ON/OFF time distributions. The channel selection algorithm which intelligently selects channels with higher likelihood of idling is presented. These channels were sensed in sequential order and it has shown to minimize delays.

1.9. Dissertation outline

An outline of the other remaining chapters is as follows: presented in chapter 2 is a background in cognitive radio environment, mainly focusing on the data transmission in TVWS. Chapter 3 reviews work done in literature exploring gaps and limitations. Tools, models and algorithms used to simulate a proposed scheme are discussed in chapter 4. The results obtained through these simulations are presented and analyzed in chapter 5. Chapter 6 concludes our work and presents recommendations for future work.

CHAPTER 2 - BACKGROUND

2. CR networks and data transmission in Television vision white spaces (TVWS): An overview

Limpopo province, like many other parts of the world, is marked by a number of rural areas. Many schools in such rural areas are not having information communication and technology (ICT) infrastructure to connect to the Internet. This happens at critical times when e-learning is inevitable. The South African department of communications took an initiative in December 2014 by issuing a national broadband policy called Connect SA [4].

This policy recognizes the scarcity of the spectrum and sets a number of important issues regarding the usage of the spectrum. These include amongst other things, the identification of idling spectrum (a spectrum that is free from PU), enabling coexistence of SU and PU while giving maximum protection to PU and unutilized spectrum reassignment [5]. The policy also takes into considerations the requirements for public access technologies. The coexistence of PUs and SUs is discussed in this chapter in the context of TVWS.

The rest of the chapter is outlined as follows: section 2.1 discusses data transmission in the TVWS and section 2.2 looks into spectrum sensing taking into consideration, in-band and out of band sensing. This section also briefly discusses the workings of reactive and proactive modes of sensing and is concluded by presenting methods of sensing where cooperative and individual sensing are discussed. Presented in section 2.3 is sequential and parallel sensing while 2.4 looks deeper into the aggregation of data taking into account the hard fusion and soft fusion rules. Section 2.5 presents detection a technique focusing on energy detection and section 2.6 concludes the chapter.

2.1. Data transmission in TVWS

Ultra-high frequency (UHF) is a portion of the spectrum assigned to PU operating between 470–694 MHz. PUs are those licensed devices, which operate in the television (TV) bands. There are times when TV bands are not used at a given geographical location [6]. Several studies were conducted in South Africa by Council for Scientific and Industrial Research (CSIR) have shown that there is a huge amount of spectrum to be used especially in the bands assigned to (TV) [7], [8], [9] [10], [11]. The spectrum can be assigned dynamically such that unutilized bands can be used by SU. These can be done by keeping a level of interference to PU low. In other words, SU will have to occasionally sense the spectrum in order to detect the presence of PU signal. A transmission of SU will be carried out in another channel in case PU is detected in the current channel SU is transmitting in. A concept of spectrum sensing is explained in details in section 2.2.

2.2. Spectrum sensing

The detection of PU in the TV bands depends on the ability of SU to sense the spectrum. Sensing is one of the most important functions of CR since it protects PU from interference by SU. In order for SU to transmit in the bands assigned to TV, they have to first sense the spectrum to detect the presence of PU.

The presence of the PU in band means SU will have to search other channels in which there is no sign of PU signal. Since PUs are legitimate users of these bands, they are allowed to transmit whenever they have data packet to transmit. So it is important that SU periodically sense the spectrum to check its current transmission status. They must be able to sense the spectrum in the current channel they are transmitting in (In band sensing) and other channels in the spectrum (Out-of-band sensing).This is discussed in the next subsections. Figure 2.1 differentiates In-band and out-of-band sensing and shows configuration parameters coordinated by sensing. These are necessary to avoid interferences and ensure faster discovery of transmission opportunities.

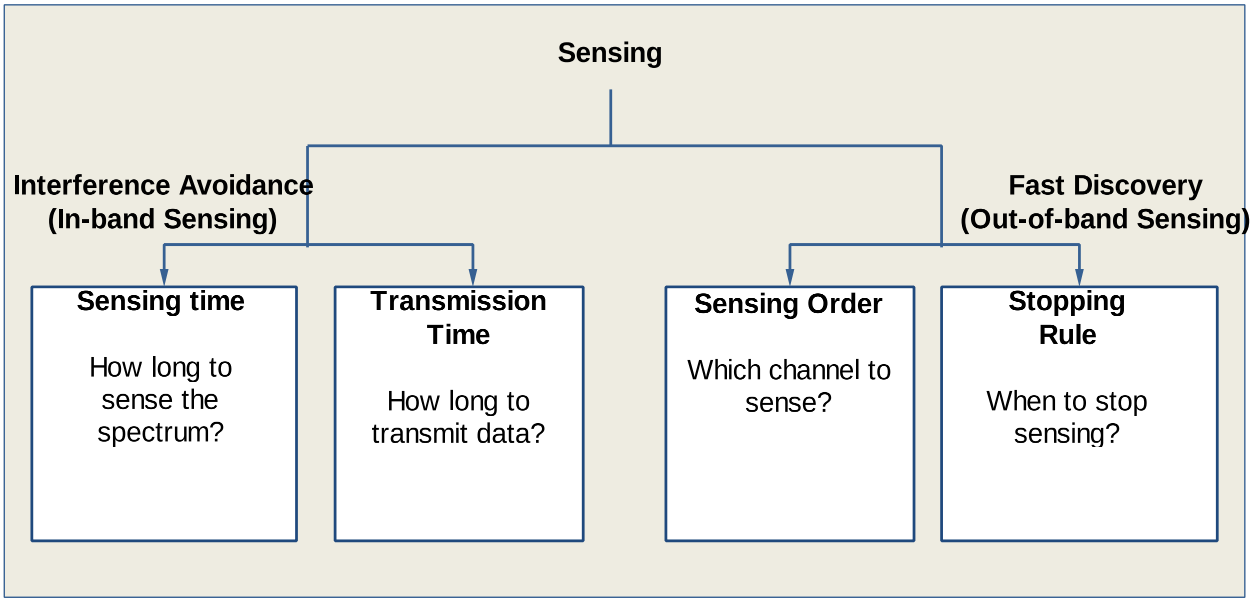

Figure 2. 1: configuration parameters coordinated by sensing [12]

2.2.1. In-band sensing

In band sensing occurs when SU sense a channel(s) or band(s) they are currently transmitting in. A transmission is halted whenever this sensing happens such that PU coming back into the channel can be detected. If ever there is evidence of PU signal in the channel, SU will then have to sense foreign channels (i.e., performing out of band sensing). The efficiency of a spectrum sensing algorithm depends on how well we answer the questions in figure 2.1.

There are two questions considered when performing In-band sensing: how long to sense the spectrum. How often to sense the spectrum is very important since it is the process through which interferences are avoided. Periodically sensing the spectrum allows the detection of PU that has just come to use the channel. Another question to be addressed is how long to transmit data. The longer transmission times will ultimately lead to high interferences since PUs may want to start their transmission before SUs finish transmitting their data.

2.2.2. Out-of-band sensing

This kind of sensing is performed when SUs have vacated the channel in which they were transmitting in and sensing other bands to continue with its transmission. Vacating a channel might mean that there is a PU that came in or quality of services of a particular application is not met. The criticality of out-of-band sensing lays in the fact that there should be no interference to PU already transmitting in those channels. Channels are searched until free a channel is available. Figure 2.1 also asks some critical questions in the interest of better performance. Which channels to sense and when to stop sensing? It takes considerable amount of time to search for idle channels in the spectrum. It is critical that this time is reduced in order to maximize the end-to-end throughput of SUs.

2.2.3. Mode of sensing

A spectrum can be sensed proactively or/and reactively. In proactive sensing, a spectrum is sensed periodically such that a clear map about the spectrum availability is known. Since the observations about the spectrum are readily available whenever users have data packets to transmit, the transmission is likely to be faster. But periodic sensing comes at a costly price, overheads and high usage of bandwidth in exchange of control packets.

On the other hand, reactive sensing occurs whenever SUs are having a data to transmit and the channel occupancy information is not known. They first sense the spectrum to check the availability of any channel to be used to transmit. A packet is transmitted whenever a channel is found. SU sense only when there is something to transmit. The advantage of this approach is that the spectrum is not unnecessarily flooded with control packets even when there is no packet to transmit. Unfortunately, it incurs more delays since the spectral map is unknown prior to a packet being ready.

2.2.4. Method of sensing

There are two ways in which spectrum can be sensed; individually and cooperatively. Individual sensing involves a single user collecting the information about spectrum availability without having to share it with other users in the network. Users in this case refer to SUs. The decisions are made based on individually sensed results. These results are in many cases not accurate or even reliable due to a number of factors such security issues, hidden terminal problem, shadowing, multi-path fading, etc. The problems alluded to above can better be dealt with by cooperative sensing.

In cooperative sensing, individual SUs perform local spectrum sensing and share local observations with their neighbours. Based on global spectral observations, users decide which channels are free for data transmission. Cooperation amongst users ensures accurate and reliable sensed results; however, cooperation incurs overheads and delays due to exchange of control packets.

2.3. Sequential and parallel sensing

Sequential sensing is depicted in figure 2.2. This shows a scenario where SU sequentially senses the spectrum in search of available channels for transmission. An algorithm is implemented such that all SUs sense channel 1 and if it idles, data is transmitted. If not, sensing is performed on channel 2, and so on, in that order until an idle channel is found.

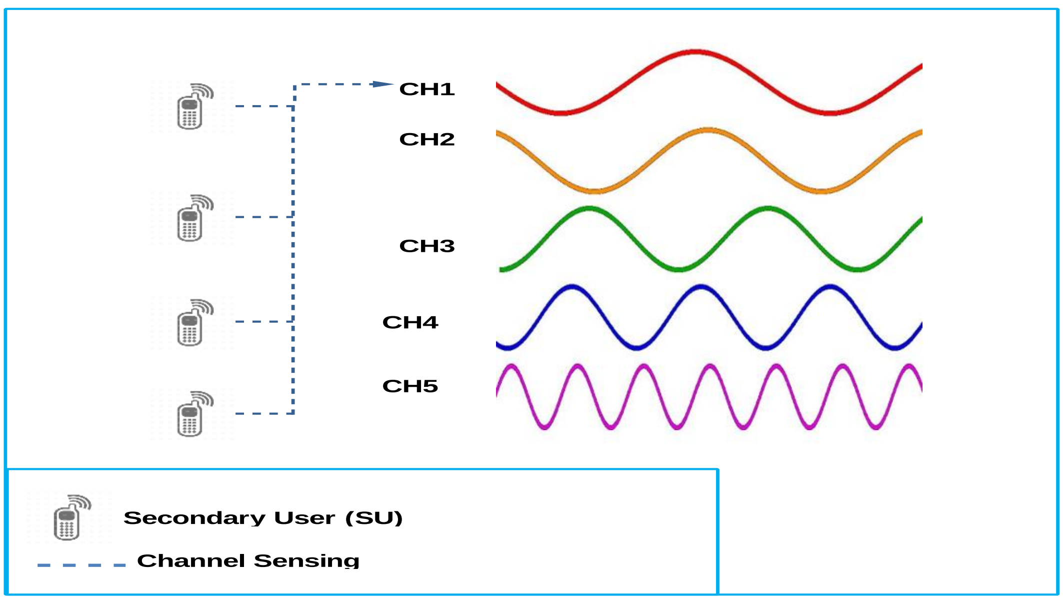

Figure 2. 2: sequential sensing

Such algorithms are designed such that all SUs search for idling channels in sequential order. This greatly limits the number of channels to be discovered at a particular point in time; hence, it incurs delays in data transmission. This approach is simple to implement but runs a risk of being inefficient while there is a need for more discovery of opportunities to meet high demand for data transmission.

Another approach to sensing is parallel sensing. This is a case where multiple channels can be sensed at the same time. Greater discovery of transmission opportunities is possible since there could be more than one channel idling. If multiple channels are sensed and found to be idling, multiple SUs can transmit in different channels without causing self-interference. It should be noted that self-interference should be dealt with separately through SU coordination. Figure 2.3 shows two ways in which different channels can be sensed simultaneously.

Channel grouping technique is considered in Figure 2.3 (a). A network is set up in such a way that SUs are able to sense channels in different groups at the same time. This approach has an advantage of minimizing delays in finding available channels since multiple channels can be discovered simultaneously. The main challenge here could be deciding which SU to sense in which group. If well implemented, this promises to be an ideal solution to CR network.

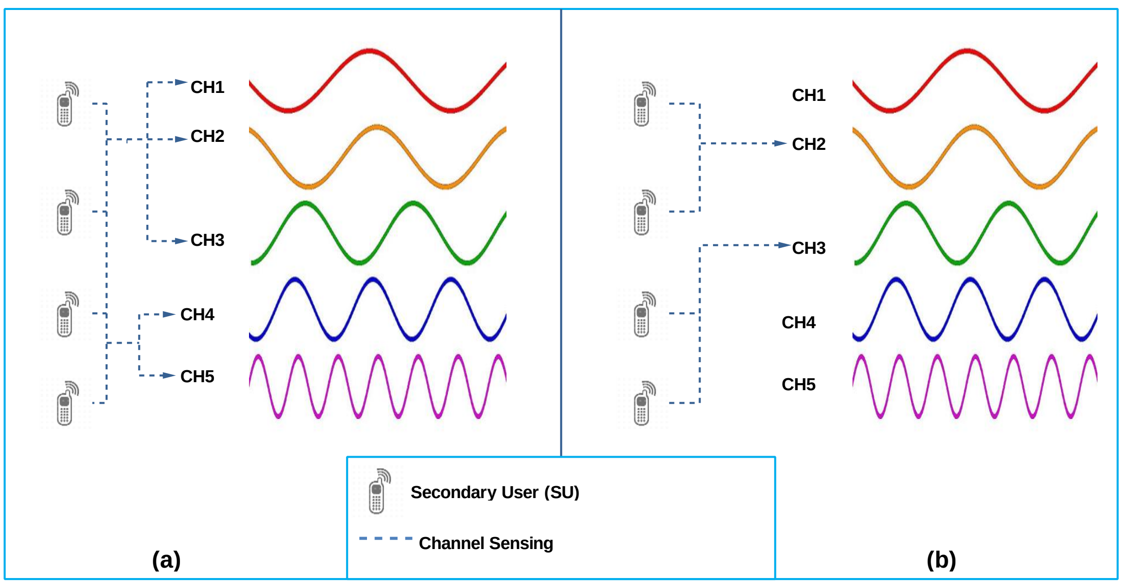

Figure 2. 3: Parallel sensing. (a) Channel grouping and (b) SU grouping

In cognitive radio network, more effort is put in maximizing the throughput of SU and one way to do this is minimizing delays in finding available channels. An approach in figure 2.3 (b), considers the grouping of SUs. SUs are grouped and assigned to sense different channels at the same time. This also allows maximum discovery of opportunities but is very impractical given a dynamic environment these devices are operating in. Another challenge could be posed when SUs leave a group they are assigned to due to mobility. An adaptable algorithm is required in this case.

2.4. Data aggregation

SU in cognitive radio network may be setup in a way that some of them are involved in making decisions about the availability of channels. Nodes involved in decision making aggregate sensing results from neighbours in order to make a final decision. There are two rules involved in fusing or aggregating sensing results; Hard and soft fusion rule. These are explained in the next subsection.

2.4.1. Hard fusion rule

Using this fusion rule, individual SUs send one bit decision to the data fusion centre. The idea is to make a decision about the absence or presence of PU signal. One bit decision can either be 1 or 0. 1 represents the presence of PU signal (i.e. the energy of the received signal is greater than a predefined threshold) while 0 indicates the absence of PU signal in the channel. In this case, decisions made by individual SUs are quantized to one bit (0 or 1).

A major advantage of this approach is that it uses less bandwidth [13]. OR, AND or majority rules are three basic rules used in hard fusion. OR rule makes a decision that the spectrum is available if any of the SUs reports a bit 0. In an AND rule, a channel is free from PU only if all SUs report a bit 0. The third rule is the majority rule in which a channel is marked idling only if at least N out of M SUs report a bit 0 where $1 \leq N \leq M$.

2.4.2. Soft fusion rule

In soft data fusion, SUs involved in sensing the spectrum forward their observations to the fusion centre without having to perform local decision. Selection combining (SC), maximal ratio combining (MRC) and square low combining (SLC) are some of the rules used to combine sensing results to make a final decision. Although this method gives better performance, the usage of control channel demands more bandwidth [14]. Overheads incurred by soft fusion rule are much higher compared to hard fusion [15].

2.5. Detection techniques in Cognitive Ad hoc Radio networks (CRAHNs)

There are three ways in which PU detection techniques can be classified [16]: PU transmitter detection, interference temperature and PU receiver detection. In PU transmitter detection, SUs are aimed at detecting a weak signal from transmitting PUs. A basic idea behind interference temperature detection technique is that the upper interference limit is set up for a given frequency band. Such SUs do not cause the interference in a specific frequency bands. PU receiver detection is based on the detection of PUs that are receiving data packets within the transmission range of SUs.

This method or technique is only feasible in detecting the TV receivers. Most studies in literature focused on PU transmitter detection for detecting the presence of PUs in CRAHNs. In PU transmitter detection, in order to differentiate between occupied and unoccupied spectrum bands, SUs must be able to detect their own signal from PU transmitter. In order to detect the presence of PU signal through sensing, the following model is used.

$$r(x) = \begin{cases} n(x) & H0 \\ s(x) + n(x), & H1 \end{cases}$$

where $r(x)$ is a received signal from SU, $n(x)$ is a zero-mean additive white Gaussian noise (AWGN) and $s(x)$ is the actual PU signal. H0 is a null hypothesis that there is no transmitting PU in the channel and an alternative hypothesis, H1 states that a particular channel is occupied. To detect PU signal in the frequency band, energy detection, matched filter and cyclo-stationary feature detection are used in literature [17]. We will only consider energy detection in subsection 2.5.1.

2.5.1. Energy detection

In energy detection, the detection of PU signal is based on the energy of the signal detected. The received signal $r(x)$ is then squared, integrated and compared with a threshold in order to decide on the presence/absence of PU signal. Energy detection is very easy to implement since the characteristics of PU signal are not required. However, this detection technique has some shortcomings. If SU needs to detect a signal with low signal-noise-ratio (SNR), energy detection incurs more delays in detection time.

Furthermore, the dependence of energy detection on SNR makes its performance to be influenced by uncertainty in noise power. Energy detection will not be able to reliably detect a signal if ever a noise power is uncertain since SNR is below SNR wall [18]. In figure 2.4, the process of detecting a signal using energy detection is depicted. This approach has been extensively used in literature due to its simplicity in deployment.

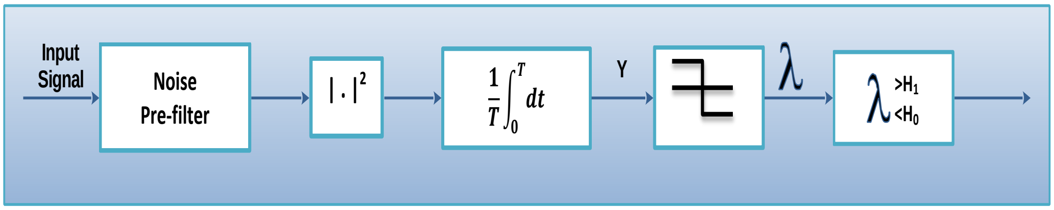

Figure 2. 4: Block diagram for energy detection [19]

When detecting energy in the signal, an input signal is filtered before its absolute value is squared as shown in figure 2.4. The next step is to integrate a signal over the T observation interval and form a test statistic. A test statistic will then be compared to threshold to check if there is transmission in the channel. There is a signal in the channel if $lambda$ is greater than $H_{1;}$ else if $lambda$ is less than H_0, then there is no signal.

2.6. Conclusion

One of the requirements for CR users operating in the licensed bands is the ability to detect the licensed user's transmission signal. This ability must be accompanied by a number of techniques to maximize the throughput of CR users or SUs, while allowing licensed user or PUs to transmit without interferences. This chapter discussed different approaches and techniques that are necessary for cognitive radio environment.

CHAPTER 3 - LITERATURE REVIEW

3. Introduction

Cooperative sensing has attracted the attention of most researchers in the past few years as cited in most of the studies below and a few design issues of cooperative sensing algorithms have been addressed. Reliable sensing of the spectrum is very important to avoid interferences in data transmission and this is not an issue in cooperative spectrum sensing. Although cooperative sensing has many benefits, its major drawback is delays incurred when SUs collectively share their observations about the spectrum.

There are a number of factors that have been investigated in literature and shown to cause delays in cooperative spectrum sensing. Information about these factors was gathered and will further be used in our proposed study to reduce delays incurred in sensing and data transmission.

This chapter is structured as follows: discussed in section 3.1 are cooperative spectrum sensing schemes and section 3.2 further looks into distributed cooperative spectrum sensing algorithms, section 3.3 presents data fusion rules used in literature to reduce delays in data transmission, section 3.4 digs deeper into how sensing periods have been optimized in literature to reduce delays and enhance greater achievable throughput of SUs. Section 3.5 discusses channel selection algorithms used in literature to intelligently select available channel for data transmission and section 3.6 concludes the chapter.

3.1. Cooperative spectrum sensing

To improve the performance of spectrum sensing algorithms and reliability of sensing results, most studies proposed cooperative spectrum sensing where SUs collaborate in finding channels [20]-[25]. The main motives behind these studies are that the performance of sensing algorithms is in practice, compromised by problems such as multi-hidden terminal problem, multi-path fading, and receiver uncertainty and shadowing. Cooperative spectrum sensing algorithms are used to efficiently exploit the spatial diversity of SUs.

In [20], cooperative gain, cooperation overheads and cooperation methods are investigated. Method of cooperation is fully analyzed using elements of cooperative sensing such as control channel and reporting, data fusion, sensing technique, cooperation models, knowledge base, hypothesis testing and user selection. Factors leading to cooperative overheads and cooperative gain are also presented in this study. The following factors were considered; cooperation efficiency, wide band sensing, sensing time and delay, security, mobility, energy efficiency and channel impairment.

In [24], sensing the spectrum is considered in the context of cooperative spectrum sensing in which two SUs collaborate using amplify and forward protocol. SUs relay signal without any further processing. This scheme has shown to achieve full diversity but more delays are incurred due to relaying of signal from one SU to another.

Most studies in cooperative spectrum sensing considered sequential sensing of the spectrum in which SUs cooperate in sensing a single channel in a given time slot or sensing period [24, 25]. This greatly limits the number of channels to be discovered in a sensing period, hence incurs delays. There is a need to discover more opportunities in one sensing period to meet high demand in wireless communication.

Authors in [26] proposed sequential algorithm for maximization of achievable throughput of SUs in multi-channel CR network. The time it takes SUs to sense the spectrum has been considered using effective rate criterion where trade-offs between sensing time and sensing accuracy are captured. Constrained dynamic program is formulated in this study for optimal stopping policy. This policy determines when to stop sensing and ensures optimal channel access policy to choose a set of available channels for transmission of data.

The optimization of sensing accuracy and efficiency has been proposed in [26] where authors designed hybrid cooperative spectrum sensing algorithm in which parallel and sequential sensing are combined. Using sequential and parallel sensing, a certain number of SUs cooperate in sensing one channel while other SUs sense other channels. Authors considered advantages of both parallel and sequential sensing in developing their scheme. Accuracy of sequential sensing ensured that missed detections are minimized. An ability of parallel sensing to discover more opportunities within minimal time possible ensured that less delay is incurred in data transmission. This study is closely related to our proposed study except that the author’s main focus was not on spectrum sensing delay minimization.

To improve reliability and accuracy, cooperative sensing is deployed in [27] where cooperative overheads are reduced by improving the accuracy of local spectrum sensing. The study proposed two-stage local spectrum sensing approach. In the first stage, each SU measures its local environment for the availability of channels and in the second stage; the results are combined using fuzzy logic in order to detect the presence of PU in the spectrum.

Maximum ratio combining in the presence of reporting channels and Rayleigh faded sensing has been evaluated in [28]. To improve the performance of cooperative spectrum sensing, authors proposed double threshold and censoring. Spectrum sensing is performed in two stages in order to use bandwidth efficiently and minimize overheads. In the first stage, SUs perform double threshold spectrum sensing and only SUs selected will be allowed to send one bit decision to common receiver to decide if the channel is idling or occupied.

In the second stage, censoring is performed to check the quality of reporting channel. When censoring is based on threshold, SUs with reporting channel coefficient value being greater than a set threshold value are selected to send their observations to a common receiver. The approach has been shown to increase detection probability while minimizing overheads by selecting few SUs with good reporting channels.

To achieve greater throughput, a group of SUs must cooperate in sensing multiple channels within one sensing time slot or period [29]. This is achieved through parallel sensing technique. Reliable combining of sensing results and selection of cooperating SUs are studied in [29]. The tradeoff between accuracy and efficiency in cooperative spectrum sensing has been addressed through independently selecting heterogeneous SUs for parallel sensing such that different groups of SUs can sense multiple channels simultaneously.

In an effort to further enhance the performance of cooperative spectrum sensing, fusion of local observations of heterogeneous SUs is addressed, taking into consideration the reliability of those local observations. When decisions of SUs are correlated, the K-out-of-M fusion rule is derived. The probability of sensing errors was minimized by this fusion rule for a certain degree of correlation between local decisions or observations. A major limitation of this scheme is overheads when M increases and will ultimately cause delays in data transmission.

The main design objective of the study in [30] was to limit the interference of PUs while ensuring maximum throughput of SUs. Three components have been integrated in the joint design: spectrum sensor, access strategy and sensing strategy. Spectrum sensor ensures that more spectrum opportunities are identified. Authors used receiver operating characteristics of spectrum sensor to capture the trade-off between miss detection and false alarms.

Access strategy determines whether to access the channel based on sensing outcomes that are erroneous or imperfect. As proposed in this study, SUs access the channels when the sensing outcomes indicate that the channel is idling or else access is denied to avoid collision with PUs. Sensing strategy decides which channel to sense in each time slot. Authors proposed multi-channel sensing scheme in which SUs can sense and access many channels at the same time. The study further provided examples to investigate the trade-off between transmission time and sensing time, and how MAC layer sensing interacts with physical layer sensing.

The separation principle of joint design opportunistic spectrum access has been presented in [30]. This chooses the spectrum access policy and spectrum sensing policy that maximizes the achievable throughput of SUs subject to interference constraint. Sensing and transmission delays were not investigated in this paper yet there is a need for it.

Authors in [31] proposed Signal-to-Noise ratio (SNR)-based weighted cooperative spectrum sensing scheme in CR networks. Weights based on the SNR are assigned to every cooperating SUs and a SU with higher SNR received from PU signal will have major contribution towards final decision. Contrary to this, a study in [32] indicated that SNR cannot be the best option for assigning weights since there is a certain threshold, the SNR wall in which the performance of SUs cannot be improved at all.

SUs in CR networks must have the capabilities to adapt to their time varying environment. To enhance this adaptability, authors in [33] proposed a Penalty-Based Weights Adjustment Mechanism (PBWAM) for cooperative spectrum sensing. Past experience of SUs is not considered when designing this algorithm because of time varying nature of SUs environment. The weight factors of the proposed algorithm are adjusted based on the recent decision of each cooperating SU. The computation of the final results is made by cooperating SUs using fusion of soft decision. Although the proposed algorithm has shown to minimize the effects of sensing errors, authors did not investigate the effects of delays in exploring the spectrum for detecting the presence of PUs.

Authors in [34] proposed cooperative MAC framework which integrates spectrum sensing methods at physical layer into cooperative MAC protocol. Incorporated in the framework is the deterministic sensing policy called Allocated-group sensing policy (ASP). ASP uses dynamic ID number approach to efficiently identify spectrum opportunities. This policy has shown effectiveness compared to other two sensing policies which are Random sensing policy (RSP) and Distinct-sensing policy (DSP).

ASP increases the average number of sensed channels by allowing SUs to sense different groups of channels. The major drawbacks of this policy are delays and overheads incurred when the number of cooperating users increases. There is no specific number of cooperating users to sense a particular channel which might lead to over-sensing of channels in a particular group and these would compromise SU's throughput**.**

Proposed in [35] is a scheme in which SUs can cooperatively sense channels in parallel. Their scheme allowed selected cooperative SUs to sense multiple channels. The results have shown a significant improvement on sensing efficiency. This study determines key design parameters: a threshold value and optimum number of channels that can be sensed by a given number of SUs simultaneously. Although numerical results show the maximization of throughput was achieved and delays minimized, given the observation in [36] channel grouping can further improve the efficiency of the scheme. The author in [36] studied a similar problem but incorporated channel grouping technique. However, the sensing strategy was not emphasized.

3.2. Distributed cooperative spectrum sensing

Considering scalability and cost effectiveness, most studies considered distributed cooperative spectrum sensing [37]-[40]. Gradient-based distributed cooperative spectrum sensing is proposed in [37]. Television (TV) signals are considered PUs in this study. The calculation of a gradient is based on the components including energy sensed by SUs and received from cooperating nodes. Change in energy sensed by SUs is the resultant of change in gradient field. SUs share observations with their neighbours to reach a consensus point and compare this point to predetermined threshold to detect the presence of PU signal.

The advantage of gradient-based distributed cooperative spectrum sensing is that there is no requirement for prior knowledge of network topology. Reliability in sensing, energy consumption and convergence time were considered in evaluating effectiveness of the proposed scheme. Although authors proposed an algorithm which performs better in terms of three metrics mentioned above, the study lacks clarity on how much delays are incurred during sensing and data transmission.

A cluster and forward based energy efficient distributed spectrum sensing scheme is studied in [38]. SUs are clustered according to their geometric location and with each cluster having cluster head. Decisions of SUs can only be send to cluster head if the contributing factor is positive. Major sensing decisions from neighbors will be known to each SU at the end of each round. SUs will be able to readjust their contributing factors using information received from their neighbours. The information collected through cluster head from SU is sent to fusion centre for final decision making. Fusion centre in this case is one of cluster heads. Final decision from fusion centre will be sent back to cluster head and to SUs.

A cluster-based decentralized cooperative spectrum sensing approach which uses past sensing decisions is proposed [39]. SUs are grouped in clusters and each SU has the capability of making decision about which channel to sense using past sensing decision. Each SU shares its spectrum observations with its neighbours and serves as a fusion centre for a final decision. A major drawback of this approach is that authors did not consider overheads involved in exchange of control message. This is the case when all SUs are used for decision making. Cooperative overheads are increased with the number of cooperating SUs and the achievable throughput of SUs is compromised. In our study we are using the same approach as in [39] except that we incorporate parallel sensing to minimize delays.

In his work, an author focused on time synchronization and cooperative spectrum sensing [40]. To effectively share control messages over control channel, SUs must be synchronized to the same time reference. Discrete time second- and high-order distributed consensus time synchronization (DCTS) algorithm has been proposed in this study. For each iteration of DCTS, SUs decode and process messages with time stamps received from their neighbours.

It should be noted that in the M-*th* order DCTS algorithm, each secondary user needs to store time information from all its neighbours for the past M − 1 iterations as well as the current iteration [40]. This is not the case with first-order DCTS where the information about current time is processed in the current iteration. Any distributed iteration algorithm is measured by the speed at which it converges.

Optimal convergence rate and convergence region were investigated and this study claims that optimal rate of convergence of second- and high order DCTS algorithm is better than that of first order DCTS algorithm in terms of addressing the problem of global timing synchronization Cognitive Radio Ad Hoc Networks (CRAHN). Delays incurred when SUs exchange local time information were investigated.

In [41], a cluster and forward scheme in which SUs are clustered based on their geometric location has been proposed. All SUs within a cluster forward their local observations to the cluster heads. Cluster heads would then make a decision based on the trustworthiness of received local observations.

The study has shown that the increase in the number of clusters ultimately leads to the system running in parallel and delays will be minimized. Unfortunately, overheads incurred due to increase in number of clusters will be alarmingly high. The trade-off between overheads due to many clusters and delays should be taken into consideration when efficient cluster-based distributed spectrum sensing is to be designed.

Decentralized cognitive MAC (DC MAC) algorithm with reactive sensing was proposed in [42]. Slotted time CSMA was proposed in DC MAC as the method of accessing the channel. The slot information is synchronized. Ad hoc secondary network (AS MAC) was proposed in [43] and a proactive scheme was proposed with channel access based on slotted time.

Authors in [42] and [43] did not evaluate the tradeoffs between proactive and reactive sensing, but only concentrated on the performance of the scheme they had chosen.

In [44], energy efficient Cognitive Radio MAC for QoS provisioning (ECRQ MAC) has been proposed. This protocol has been designed to integrate sensing at PHY layer and the allocation of timeslot to channels at MAC layer. ECRQ MAC has shown to increase throughput in case the network traffic is high and also allows SUs to make use of unutilized spectrum bands in a way that reduced the level of interference to primary users. ECRQ is the improved version of ECR.

The major disadvantage of ECR MAC protocol is that spectrum sensing occurs after channel-timeslot negotiation and synchronization, which may lead to out of date spectrum sensing results. ECRQ has been designed to solve this problem. A major drawback of ECRQ is high reconfiguration overhead and the interference to PU is not properly addressed. SYN MAC protocol has been proposed in [45] and addresses multi-hidden terminal problem by using two radios in which one is dedicated to channel sensing and the other to data transmission. Sensing errors and PU interference were not properly addressed. These problems also apply to DOSS [46], HC-MAC [47] and SRAC [48].

In [49] OSA Mac has been proposed for multi-channel environment in which secondary users monitor or sense the spectrum to discover opportunities. Multi-hidden terminal problem, sensing errors and interference to PUs were addressed and also provided Quality of Service provisioning. OSA solves interference problem using four-way handshake; RTS/CTS/DATA and ACK as used in IEEE 802.11 standards. OSA uses a single radio for sensing and data transmission. So there is a delay in data transmission since sensing and data transmission cannot be performed at the same time. A major drawback in OSA is that, channel selection is performed before channel sensing.

OP MAC, proposed in [50], has been designed to improve coexistence of PUs and SUs in CR networks. SUs cooperate in sensing channels, reporting channel occupancy information and exchanging control messages in order to solve multi-hidden terminal problem and Common Control Channel problem. The main disadvantage of CCC is the fact that it is prone to Denial of service attacks or saturation problems especially when the number of communicating devices increases. Sensing errors and interference to PUs were not addressed in this protocol.

CogMesh proposed in [51], is a distributed MAC protocol which has been designed to achieve better coordination of SUs through the use of dynamic local common control channel. A major challenge with this protocol is that sensing errors, multichannel hidden terminal problem and PU interference were not addressed.

The throughput of CR networks and the impact of the interference on PUs in a multichannel Opportunistic Spectrum Access (OSA) in which centrally coordinated and random channel assignment were compared in [52]. Processes of sensing spectrum were not considered. This kind of problem is also studied in [53] in which Authors considered PU and SU networks in multichannel and distributed Ad hoc networks. Unfortunately, zero delays in the processes of sensing the spectrum using genie-aided channel selection were assumed.

The assumption was that the receiving node knew the exact channel the sending node would utilize to transmit data for every time slot. A microscopic model was developed and analyzed in [54]. The synchronization between SU and PU, and sensing period in every time slot was investigated in this study. Delays incurred when scanning for available channels were evaluated using Markov analysis. The study only considered a case where SUs sense the spectrum non-collaboratively. This is prone to unreliable or inaccurate sensing results.

Authors in [55] proposed Truncated Time Division Multiple Access (TTDMA) that support efficient distribution of sensing outcomes in K out of N fusion rule. In this approach, Fusion centre needs to wait until all reporting bits are received, but the operation of reporting to can be stopped once Kth one bits representing the presence of PU signal are received. The main aim here was to reduce overheads associated with channel reporting, but delays associated with sensing and exchanges of reporting information were not considered in this study. TTDMA has shown to be a promising future design option for cooperative spectrum sensing process especially when k does not change frequently. Proposed in [56] is the PU activity-aware distributed MAC (PAD-MAC) protocol.

This protocol has been designed for heterogeneous multichannel cognitive radio networks to facilitate the proper selection of best channel for each SU. PAD-MAC allows SUs to exploit the spectrum for the duration of estimated idle time slot and also allows predictive and faster switching of channels in case the PUs are detected in the spectrum bands. Idling channels are allocated to each SU based on cross layer design where physical layer sensing is deployed to monitor usage patterns of PU signal and idling channels at any time. MAC layer sensing has been used to mitigate the interference amongst SUs themselves and SU to PU interference.

Although best channel selection technique has been proposed through PAD-MAC, delays in selecting these channels were not investigated. Authors in [57] investigated adaptive retry time based MAC layer spectrum sensing scheme in which adaptive retry time algorithm is proposed to allow SUs to efficiently sense the spectrum. A spectrum sensing retry time is varied according to the number of channels and sensing time at the physical layer [57].

This study also proposed modified optimal channel sequencing algorithm, which arranged channels, based on their idling probability in descending order. The study has shown significant reduction in channel switching delays but unfortunately no considerations were taken into account to deal with sensing and transmission delays which is the main focus of our study.

Analytical and optimization framework for semi-distributed cooperative spectrum sensing (SDCSS) has been proposed to maximize achievable throughput of SUs [58]. SDCSS was integrated with p-persistent CSMA MAC protocol to optimize sensing and access parameters of the proposed algorithm. The study has shown to maximize the achievable throughput thereby allowing SUs to sense channels in parallel.

3.3. Data fusion rules

One of the challenges in cooperative sensing is how to combine sensing results. Performances of hard combination rules such as AND, OR and M out of K rules and soft combination rules such as equal gain combination, linear weighted combination and maximal ratio combination are investigated in [59]. In hard combination, decisions are combined directly from SUs after being converted into 1 or 0. Each SU forwards its binary decision to fusion node in the form of 0 or 1 where 0 indicates absence and 1 presence of PU.

This study proposed optimum number of SUs to cooperate in hard combination such as M out of K, AND and OR rules. In soft combination, the detection probabilities of equal gain combination and maximal ratio combination in terms of Signal-to-Noise Ratio were compared. Maximal ratio combination has shown better performance than equal gain combination. Proposed in [60] is the detection model considering full duplex transmitting SU for sensing and transmitting at the same time. For the improvement of spectrum utilization, authors proposed adaptive sensing window.

This study has shown that significant improvement in spectrum utilization can be achieved by simultaneous spectrum sensing with adaptive window as compared to periodic sensing. Our study considers parallel sensing in which SUs cooperate in sensing the spectrum simultaneously to achieve higher throughput and minimize delays.

Cooperative spectrum sensing using hard fusion combination is studied in [61]. Hard decision fusion scheme using AND and OR logical rules is studied and compared. Using AND logical rule, PU signal is present if all SUs send one bit decision. The detection of PU signal in the spectrum is true if any SU reports one bit decision to the fusion node implementing OR logical rule. OR logical rule yielded better performance compared to AND logical rule because PU signal is detected whenever at least one SU reports one bit decision when using OR rule.

Many opportunities would be missed when implementing AND logical rule on decision making since it is not always the case that all SUs would have one bit as a decision. The study also indicated that better performance is realized with increase in the number of cooperating SUs, although there is a trade-off between performance and complexity of the architecture. This study shows that the way data is aggregated can cause delays in data transmission especially when a number of cooperating SUs increases.

The manner in which local observations are aggregated is very important in cooperative spectrum sensing. Proper aggregation techniques lead to more reliable and accurate sensing outcomes which in turn allow greater discovery of opportunities. Proposed in [62] is the majority or half voting rule in which a channel is unavailable if N out of K SUs votes that indeed a channel is occupied by PU where N > (K/2). In special case where N=K and N=1, AND rule and OR rule were applied. The assumption made from this study was that all SUs participating in decision making must have the threshold. This requirement in reality is very hard to meet.

A study in [63] proposes a fusion scheme and the optimization of cooperative sensing by choosing a value of *K* that maximizes SU's throughput. Authors used K-out-of-N fusion as basis to the formulation of optimization problem and a parameter k was chosen as optimization variable. To obtain optimal sensing time and value of k, an iterative algorithm was proposed.

3.4. Sensing period optimization

In order to minimize delays in locating available channels and discover more opportunities, authors in [64] used sensing period adaptation and optimal channel ordering in which a proactive mode of sensing is implemented. The proposed scheme discovered up to 20% of opportunities better than other previously proposed schemes without sensing period adaptation.

A proposed channel ordering has shown to reduce delays in finding available channels by half a percentage of delays incurred when deploying a scheme without channels ordering. This scheme has been evaluated over a wide range of channels and it has yielded a consistent performance even though authors outline in detail how a proposed scheme will perform in distributed environment.

Important MAC layer issues have been addressed in [65]. Sensing period adaptation for maximization of discovery of opportunities and minimization of delays in finding idle channels has been studied. Optimal channel sequencing algorithm and optimal sensing period mechanism have been developed in this study. For sensing period optimization, proactive sensing is implemented by SUs where individual channels are periodically sensed with their own sensing period. A set of N sensing periods were considered for optimization to maximize the discovery of transmission opportunities. This mechanism provides optimal sensing time, which addresses sensing overheads caused by frequent sensing and undiscovery of opportunities due to blindly increasing sensing periods or infrequent sensing.

A study also proposed optimal channel sequencing algorithm in which SUs sense N-1 channels in descending order of the probability that a particular channel would be idling at a certain times. Optimal sensing periods have shown to discover up to 22% transmission opportunities while optimal channel sequencing algorithm reported delays ranging from 0.08 to 0.35 seconds which is much faster compared to Non-optimal schemes.

The performance of MAC layer sensing in cognitive radio networks has been assessed and investigated in [66]. In the assessment of performance of MAC layer sensing schemes, two metrics were used: The delays in finding idling channels and available channel usage considering proactive and reactive modes of sensing. There were schemes considered for assessment of proactive sensing: adaptive and non-adaptive schemes. Proactive sensing with adaptive periods has shown better performance compared to non-adaptive sensing scheme. A major drawback of adaptive sensing scheme is high computational cost to be performed by SUs.

Authors in [67] also address the spectrum inefficiency problem by proposing schemes based on sensing- period adaptation and channel selection. This study addressed the cross layer issues of spectrum sensing by considering the optimization of the sensing time for MAC layer sensing. A model has been developed to improve the utilization of channels thereby ensuring that idle channels are used more efficiently and the underlying ON/OFF channel usage patterns are carefully monitored. Maximum channel utilization has been achieved through the implementation of improved optimization algorithm. This scheme has shown better performance over non-adaptive schemes.

MAC layer sensing had a limited number of publications. A non-adaptive proactive sensing algorithm has been proposed in [68]. This algorithm makes use of pre-determined sensing periods and in this approach; they did not consider how the delay in locating a channel can be minimized (The assignment of sensing periods are not optimal since the chance of discovering opportunities were not maximized).

Investigated in [69] is the tradeoff between proactive and reactive sensing and derived an energy-efficient sensing mode selection algorithm. Proactive sensing with channel ordering seemed to be performing better in terms of reducing delays and discovering opportunities. Adaptive retry time algorithm and modified optimal channel sequencing algorithm were proposed in [69].

Adaptive retry algorithm changes sensing periods depending on the number of channel and the time it takes to sense the spectrum at the physical layer. On the other hand, in modified optimal channel sequencing algorithm, PU channels are arranged in descending order depending on the idling probability. These two algorithms have shown an improvement in the channel utilization and the significant reduction of the average channel switching latency from 35.65% to 65.11%.

Cooperative spectrum sensing framework has been proposed in [70] where SUs simultaneously perform spectrum sensing and data transmission over two different parts of PU spectrum bands. Authors derived optimal fusion scheme and optimal Multi-mini-slot sensing scheme to mitigate delays in data transmission.

A total sensing duration has been divided into N mini slot. Sensing time for each mini-slot is derived by dividing total sensing duration by N. Simulation results have shown that collecting sensing results from multiple mini-slots reduced delays. A major limitation to this approach is overheads involved in combining sensing results collected from Mini-slots.

An author in [71] considered tradeoff between reactive and proactive sensing in a varying network environment. Idling channel search delays were investigated in uncongested and highly congested network environments. Comparative results show that proactive sensing reduces idling channel delays in highly congested network environment whereas reactive sensing is at its best in uncongested network.

A study further investigated adaptive and non-adaptive period sensing scheme in proactive sensing. Results show that adaptive sensing discovers a large number of channels to be utilized by SU and is more consistent in finding available channels as compared to non-adaptive proactive sensing scheme. The author did not consider the impact of interference to PUs when reactively and proactively sensing the spectrum which might lead to transmission delays where the level of interference is high.

3.5. Channel selection algorithms in CR networks

A study [72] proposed extended predictive channel selection algorithm in which the probability of the channel being free was calculated for hyper-exponential OFF times. This study has shown a significant reduction in channel search time and channel switching rate. The cooperation has been considered in greater details in this paper, which is more likely to have impact on delays.

A fully distributed channel selection algorithm has been designed to facilitate the coexistence of LTE devices or systems in the unlicensed 5 GHz band [73]. A Game theory and Q-learning approaches were used and their implementations were compared in as far as performance is concerned. The effectiveness of this study was evaluated in terms of the signaling requirement, convergence time as well as the effect of errors in the estimation of throughput.

3.6. Conclusion

This chapter discussed some of the work done in literature focusing on cooperative sensing, data aggregation, sensing period optimization as well as channel selection algorithms. Most of the studies reviewed emphasized the importance of data aggregation and channel grouping for minimizing delays in finding available channels. To achieve reliable sensing results and resolve other problems such as shadowing, hidden terminal problems, etc., most studies proposed cooperative sensing and sensing period optimization. The gaps in literature were identified and will be addressed by this study.

CHAPTER 4 -METHODOLOGY

4. Introduction

Identification of key technologies to be incorporated in the development of any algorithm is very critical. Different Integrated development tools (IDTs) are suitable for different tasks. So it is necessary to understand which simulation tool best supports the development of algorithms in different layers of TCP/IP or OSI model. Some algorithms may be efficient when deployed using one tool and may experience performance degradation when simulated in another simulation tool.

In this chapter, we first investigate the suitability of different simulation tools to simulate MAC layer protocols. This brief investigation will be based on the tool's ability to support cognitive radio framework and the accuracy as well as the ability to implement a new algorithm.

Sections in this chapter are outlined as follows: Section 4.1 generally discusses simulation tool and the environment in which simulations were carried out. Three simulation tools were investigated in this section and their selection justifications and limitations are discussed. This section also presents different network scenarios under which the simulations were carried out. Presented in section 4.2 are models and algorithms used to develop and evaluate the efficiency of a proposed scheme. Section 4.3 presents the parameters and performance metrics used to measure the performance of the EXGPCSA. Section 4.4 discusses models used in queueing theory to model service time and the rate at which packets arrive at fusion node and finally, section 4.5 concludes the chapter.

4.1. Simulation tools and environment

The rate at which spectral opportunities are discovered partially determines the efficiency of the spectrum sensing algorithm. Many network simulators have been developed to help the researchers to evaluate their algorithms and/or protocols. A best network simulator in the context of spectrum sensing can be determined by its flexibility in employment of custom MAC and physical layer algorithms, support of default communication protocols and the ability to employ custom sensing algorithms.

In this chapter, we investigate few simulation tools and select the most appropriate and easy to use tool to be used for simulating EXGPCSA. We consider the following tools for our investigation: MATLAB, Network simulator (NS) -2 and OMNET++. These simulation tools will be compared using the following aspects: a support for cognitive framework, accuracy and the ability to employ new protocol.

4.1.1. Tool choice Justification and Limitations

Different simulation tools have varying capabilities which are suitable for different network layers. A choice of appropriate tool will ultimately influence the performance of the proposed algorithm. Hence a choice of a simulation tool has to be done carefully. In this section, we explore limitations of three tools that are investigated in this chapter.

4.1.1.1. Support for Cognitive framework

Only NS-2 supports cognitive radio network framework whereas a framework can be easily developed in OMNET++ and MATLAB. The ability of NS-2 to support cognitive radio networks serves as an advantage to researchers who develop their protocols in layers such as Network layer. It is difficult to develop a protocol at the MAC layer using this tool. OMNET++ and MATLAB do not have libraries for cognitive radio networks but developing algorithms for this type of environment is much easier.

4.1.1.2. Accuracy and ability to implement a new protocol

The accuracy of NS-2 is low compared to MATLAB and OMNET++ and the implementation of a new protocol is possible, but very difficult [74]. It is much easier to implement new protocol in OMNET++ and MATLAB since they have better support for MAC layer protocols. A comparative study has been conducted in [74] where the effectiveness of NS-2 and OMNET++ was assessed based on the time it takes each network simulator to simulate large network. A study considered a comparison of these two simulation tools in a distributed environment and OMNET++ outperformed NS-2 in all network scenarios. According to this study, the best simulation tool to serve cognitive radio is OMNET++.

4.1.1.3. Limitations

NS-2 is widely used by the research community to develop algorithms mostly in Network layer for routing protocols [75, 76, 77, and 78]. Modeling technique and scripting language used in this tool are somewhat difficult to write and understand. It also offers no graphical user interface for better experience in interacting with a tool. Everything is done on a command line and script files. Large networks built using OMNET++ converge faster and is much easier compared NS-2. Unfortunately there are few sources in literature in which this tool was used. This poses a great challenge when one investigates which network environment a tool can best be suited for. One major drawback of MATLAB is that it is not freely available. One needs to have a license to utilize it.

4.1.2. MATLAB simulation tool

Our algorithms will be implemented using MATLAB and/or OMNET++ simulation tools particularly because of their support for MAC layer protocols or an ease with which MAC frameworks can be developed. The efficiency of an algorithm to be developed will first be evaluated in MATLAB and also simulated on OMNET++ only if MATLAB results are not satisfactory. In case simulations carried out in MATLAB provide satisfactory results, our future work will focus on evaluating the same algorithm in OMNET++ for comparative study. The choice of MATLAB as our primary tool is because a tool has widely been used in most of the studies that are related to our work [79, 80, 81, 82, and 83].

The following simulation process will be carried out in MATLAB and the relationships between processes are depicted in figure 4.1.

1. **Initialization** – the first step is to initialize sampling frequency, carrier frequency bands and message frequency for each user.
2. **Modulation** – we use amplitude modulation to modulate data from the user.
3. **Adder** – Addition of all the modulated signals to produce a transmitting signal.
4. **Period gram** – power spectral density (PSD) will be estimated using period gram.
5. **Unused slot allocation** – arriving new users are allocated to the first spectrum hole.
6. **Emptying a slot** – specific slots are emptied when all slots are occupied.

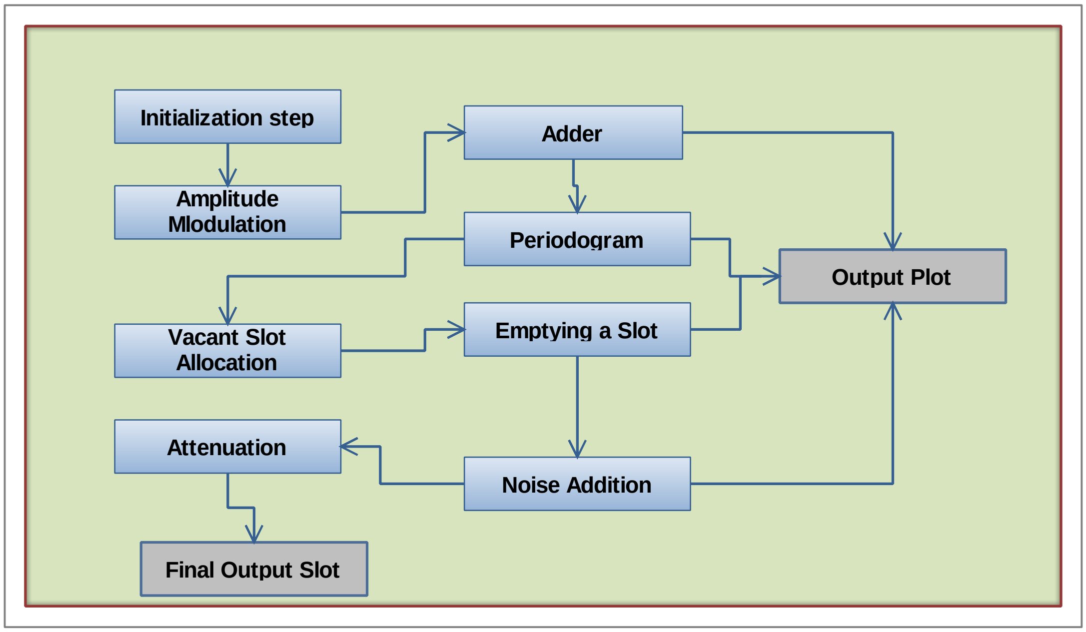

Figure 4. 1: Implementation of Cognitive Radio System using MATLAB

4.1.3. Environmental setup

Simulation was run on MATLAB for 200 seconds to simulate three network scenarios. The first simulation is carried out with 10 SU distributed across an area coverage of 1000m x 1000m.

SUs collaboratively sense the spectrum in search of vacant channels to transmit their data packets. To increase reliability and alleviate other problems such as shadowing and hidden terminal, our network is set up in a way that SUs are able to collaboratively sense and share their observations.

In the second network scenario, number of SUs has been increased to 20 and this allows us to investigate the rate at which delays in finding idle channels are increased as the network grows. Although it is very clear that delays increase when a network is scaled up, the main aim is to minimize it through the use of intelligent channel selection algorithm which incorporates probabilistic models as its knowledge base.

The third simulation was carried out in a network environment where a network had 30 SUs. Nodes or SUs were allowed to move slowly in area coverage of 1000m^2. This is the largest network to be simulated in this study.

Three network scenarios 10, 20 and 30 SUs were varied to evaluate the efficiency of our proposed algorithm as the number of SUs increases in a network. We expect our scheme to accurately detect changes in the network environment while incurring delays due to the high number of SUs cooperating. We simulated SUs in a network which is dynamic, but we assume that the mobility of SUs in a network is slow and cannot partition a network during the simulation.

4.2. System Models and Algorithms

A scientific way of solving complex problems is through models and algorithms which ensure better understanding of a problem at hand and derivation of better solutions. Hence, presented in this section are models, algorithms and parameters necessary to design and evaluate the efficiency of a proposed scheme.

4.2.1. Receiver/Transmitter operation

We consider a group of SUs communicating in a simple multi-hop CRN. Each SU is equipped with a single radio for both sensing and transmission. Unfortunately, sensing and data transmission cannot be performed simultaneously. All SUs stop their transmissions when sensing the spectrum. This is one of the requirements in the 802.22 IEEE standards. This gives SUs time to detect the presence of PU signal.

To properly manage the coordination of SUs, we use listen before talk strategy in which a transmitter listens to the medium or wireless channel before transmitting data packet. To avoid interference amongst transmitters (SUs), Clear-to-Send (CTS) and Request-to-Send (RTS) control packets are flooded to the network. RTS is meant to check if there is any other transmitter using wireless channel. If a channel is currently being occupied, transmitter backs off for a random amount of time before trying again. CTS data packet is used to alert the transmitter that there is a free data channel between the current transmitter and the receiver.

The transmitter-receiver pair start data exchange after CTS has been received by the transmitter. Once a data packet has successfully been received at the destination, the receiving SU will acknowledge the receipt of data packet by sending an ACK packet. Transmitting SU will have to transmit the same data packet if no ACK packet has been received. Common control channel (CCC) is used for exchange of control packets.

A flow diagram in figure 4.5 provides detailed information of how our algorithm was designed and implemented. It shows how different components were linked together and the flow of sensing data or transmission of data.

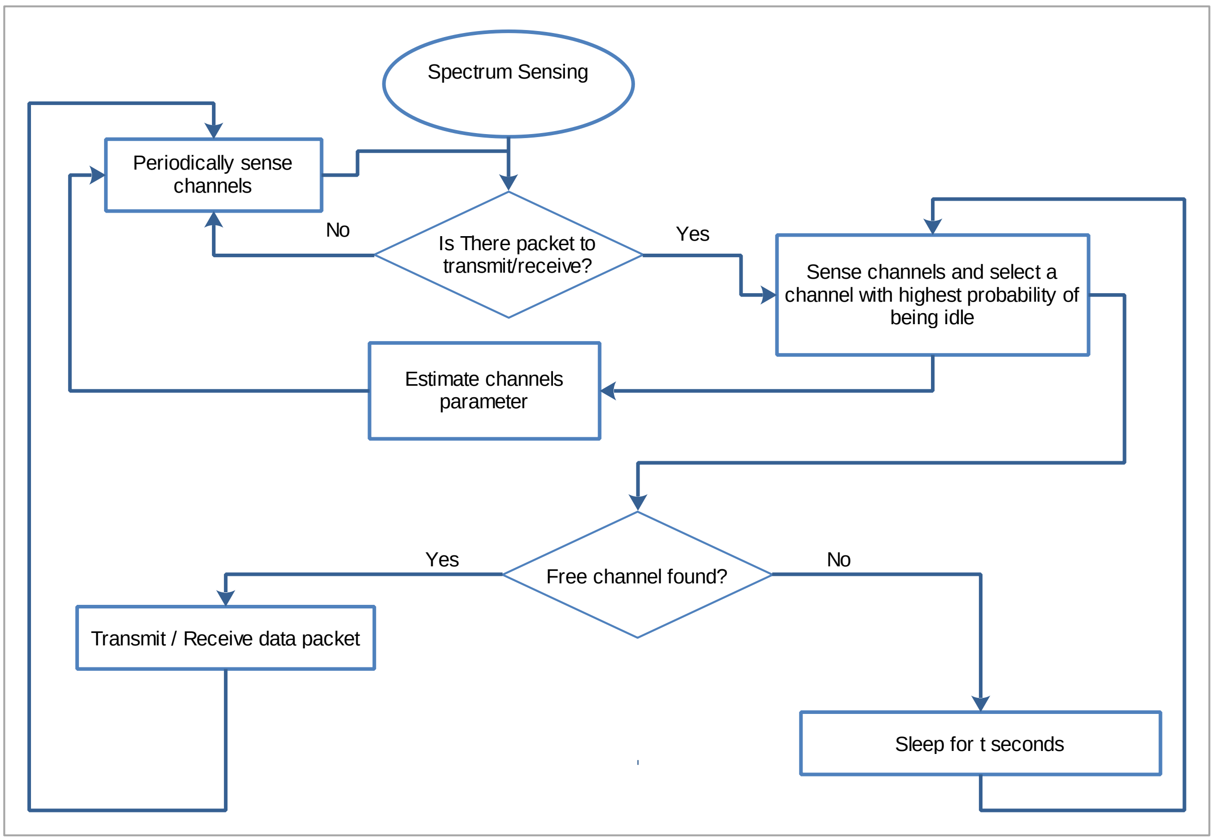

Figure 4. 2: Sensing strategy flow diagram

The frame structure shown in figure 4.6 is composed of two main phases: sensing and transmission. Sensing has extensively been modeled in section 4.2.3. We model sensing using PDF assuming ON/OFF time distributions. Transmission phase is explained above and figure 4.5 shows the SU sensing strategy. A channel is periodically sensed to ensure faster data transmissions. Since data transmission is performed immediately after an opportunity is discovered, it is very critical to find an opportunity as fast as possible to allow faster packet transmission. Hence, a channel selection algorithm (*algorithm 3*) will be implemented to fast track channels and pick the one with the highest probability of being free.

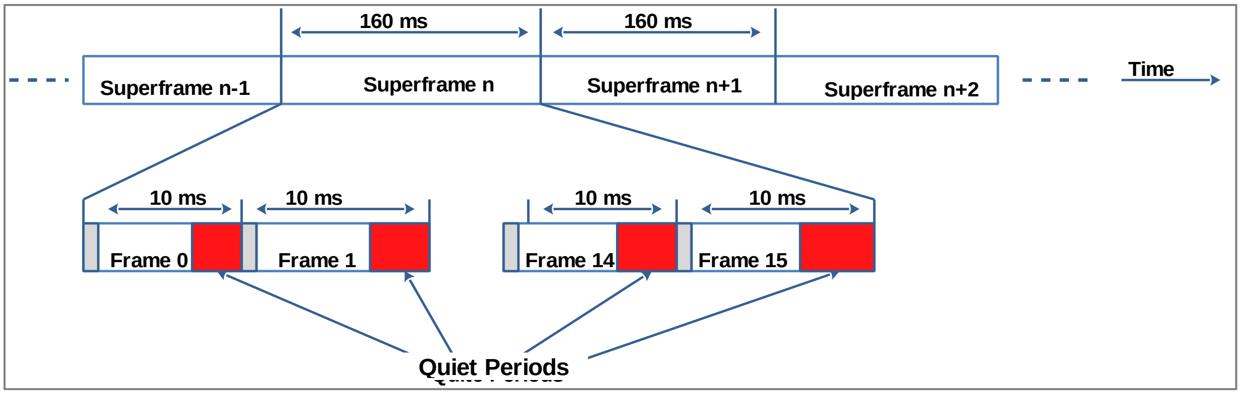

Figure 4. 3: SU frame structure [84]

4.2.2. Cooperative sensing

Before we delve into how SUs cooperate and how the whole system works, there are few assumptions we make. Although mobility in CR networks is inevitable, we assume slowly moving SUs such that a network is not portioned during simulation. SUs are assumed to always have data packets to send and have to first search for idle channels.

Cooperative sensing is performed by a group of SUs in a distributed CR network. There are N SUs in area coverage of 1000m^2. SU individually senses and selects a channel using algorithm presented in section 4.2.4 (algorithm 2). Cooperative sensing is performed in the following three steps; first, SUs individually sense the frequency bands. They performed what is known as local sensing. Since we are using hard fusion rule, each SU sends one bit to a fusion node for decision making. In other words, each SU makes a local decision about the availability or unavailability of the spectrum band.

A decision can either be 1 or 0 where 1 represents unavailability of the spectrum and 0 means the spectrum is available to be utilized by SUs. Secondly, individual SUs report their observations about the spectrum to the fusion node using common control channel (CCC). Only SUs with higher SNR are allowed to report their sensing results.

Fusion node receives one bit sensing results from each SU involved in cooperation. This will greatly reduce communication overheads and bandwidth usage. Each SU maintains a table or vector containing sensed results together with a channel number from which results are obtained. A table is maintained after SUs have sensed and made local individual decision about the spectrum. Figure 4.7 shows an example of how this works. In this study, we considered channels labelled 1 to 6 and these channels are used by both SUs and PUs. Once the results about the availability/unavailability of channels are obtained, SUs share a recent results or vector directly with fusion node (node 1). C_i and r_i are channels sensed by SU and the sensing results obtained from that channel at an index i respectively.

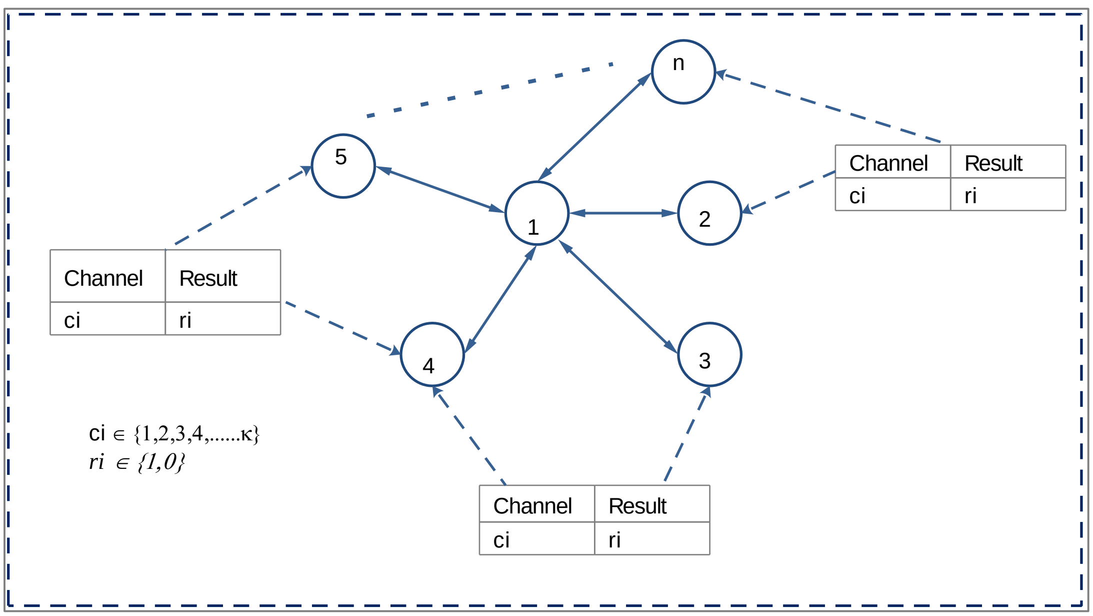

Figure 4. 4: Cooperative sensing and sharing

Finally, fusion node aggregates sensing results stored in the vector to make a final decision. Fusion node combines the results from neighbouring SUs and maintains a table in its buffers to the last twenty-four sensing results. This is done to keep history of the previously sensed results. This is very critical for the estimation of channel parameters. We limited a history to twenty-four sensed results to avoid buffer overflow. A history is referred to as the previous state of the channel before the current state. A fusion node will keep previous four states for each channel since the estimation is based on history. E.g. {ON, ON, OFF, OFF} which is equivalent to {1, 1, 0, 0}.

We looked at the easiest and fastest way of aggregating data to ensure faster data transmission. After spending considerable amount of time going through what a research community has done, we came to a conclusion that OR aggregate rule can be used. Some of the benefits of this rule are higher detection and faster data aggregation. Using this rule, the probabilities of detection and false alarm were calculated as follows:

$$P_{dec} = 1 - (1 - p_d)^k \tag{4.1}$$

Where P_d, the probability of detection for each SU and k is is the number of participating SUs

and

$$P_{fa} = 1 - (1 - p_f)^k \tag{4.2}$$

Where P_f, the probability of false alarm given by each SU and k is the number of SUs.

A major drawback of OR aggregation rule is the fact that the probability of false alarm increases with the increase in the probability of detection. However, this cannot be a hindrance since minimization of delays in finding available channel is a major focus of this study. Although other aggregation rules such as AND or N-out-M may be used, they incur more delays and give lower detection probabilities compared to OR rule.

Algorithm 1: Used by Secondary users during sensing

1. *sense channel c*
2. *use channel selection algorithm (*Algorithm 3*)*
3. *each SU generate sensing results*
4. *then*
5. c_i = *channel number*
6. r_i = *sensing results*

Algorithm 2: To be used by aggregating node

1. *P_outcome* $(O_1) = 0$
2. *A_outcome* $(O_0) = 0$
3. *correctResult = 0*
4. *finalResult = 0*
5. *receive result array from SUs*
6. *compare data from result arrays*
7. *if* $c_i = c_i+1$ *and* $r_i = 1$
8. *then*
9. *P_outcome ++*
10. *else*
11. *if* $c_i = c_i+1$ *and* $r_i = 0$
12. *then*
13. *A_outcome++*
14. *if P_outcome > A_outcome*
15. *then*
16. *correctResult = P_outcome*
17. *else*
18. *if A_outcome = P_outcome*
19. *then*
20. *correctResult = A_outcome*
21. *else*
22. *if A_outcome = P_outcome*
23. *then*
24. *decide based on SU's history*
25. *end*
26. *finalResult = correctResult*
27. *if* c_i *is unique*
28. *then*
29. *finalResult = correctResult*
30. *End*

P_outcome in this algorithm is used to hold the results indicating that the PUs in the spectrum are present while the results that the channels are free from PUs are stored in *A_outcome*.

4.2.3. Channel Model.

We consider N channels being opportunistically accessed by SUs where each channel is licensed to PU. The ON times (SU's channel usage time)/OFF times (PU's inter-arrival time) on a channel c are modelled using probability density functions (PDF) represented by $f_X^{\,c}$ and $f_Y^{\,c}$ respectively. The assumption is that the distributions of ON/OFF time are independent and not the same. This is validated in [85].

As shown in figure 4.8, SUs are required to search for a channel starting at t_s for t duration. The lengths of ON and OFF periods are represented by X^c and Y^c respectively. If we assume that these periods are exponentially distributed, then

$$f_{X^c}(x) = \mu_{x^c} e^{-\mu_{x^c} x}, \quad \forall\, \mu_{x^c} = \frac{1}{EX^c(x)} \tag{4.3}$$

and

$$f_{Y^c}(y) = \mu_{y^c} e^{-\mu_{y^c} y}, \quad \forall\, \mu_{y^c} = \frac{1}{EY^c(y)} \tag{4.4}$$

where μ is a rate parameter and $\mu \geq 0$, $EX^c(x)$ and $EY^c(y)$ are mean values of the distribution,

$f_{X^c}(x)$ is the PDF of the ON periods on channel c and

$f_{Y^c}(y)$ is the PDF of the OFF periods on channel c.

To find Mean values of ON periods,

$$EX^c(x) = \int_0^\infty f_{x^c}(x)dx \tag{4.5}$$

$$= \int_0^\infty \mu_{x^c} e^{-\mu_{x^c} x} dx$$

$f_{x^c}(x)$

To evaluate the integral using integration by parts, we then

have

$$EX^c(x) = \frac{1}{\mu}$$

similarly for OFF periods

$$EY^c(y) = \int_0^\infty f_{y^c}(y))dy \tag{4.6}$$

$$= \int_0^\infty \mu_{y^c} e^{-\mu_{y^c} y} dy$$

Applying integration by parts we get,

$$EY^c(y) = \frac{1}{\mu}$$

PUs utilize a channel c for an infinite time period t for its data transmissions and we define u^c as channel c's utilization factor. u^c is a fraction of t in which channel c has been utilised by its PUs. Using (4.5) and (5.6) we derive channel utilization factor as follow,

$$u^c = \frac{\int_0^\infty \mu_x c e^{-\mu_x c x} dx}{\int_0^\infty \mu_x c e^{-\mu_x c x} dx + \int_0^\infty \mu_y c e^{-\mu_y c y} dy}$$

$$= \frac{EX^c(x)}{EX^c(x) + EY^c(y)} \qquad (4.7)$$

Substituting equations (4.5) and (4.6) into (4.7), we have u^c = ½.

Figure 4.8 models ON/OFF time distributions. The length of ON periods are represented by $X_n{}^c$ or x while OFF periods are shown by $Y_n{}^c$ or y . x' represent the missed opportunities while y' shows correctly detected PUs. Sensing of the spectrum is done for t ms and no transmission can be done during this time. Blindly selecting t may have a negative impact of the usage of the spectrum. Having smaller t may incur higher sensing overheads while on the other hand making t large enough might lead to missing of transmission opportunities. On periods are always followed by OFF periods and this forms a cycle Z_1. It is very important to identify the beginning and the end of Z_1 which forms a complete cycle. Within this cycle, it can then be predicted that a channel is either ON or OFF.

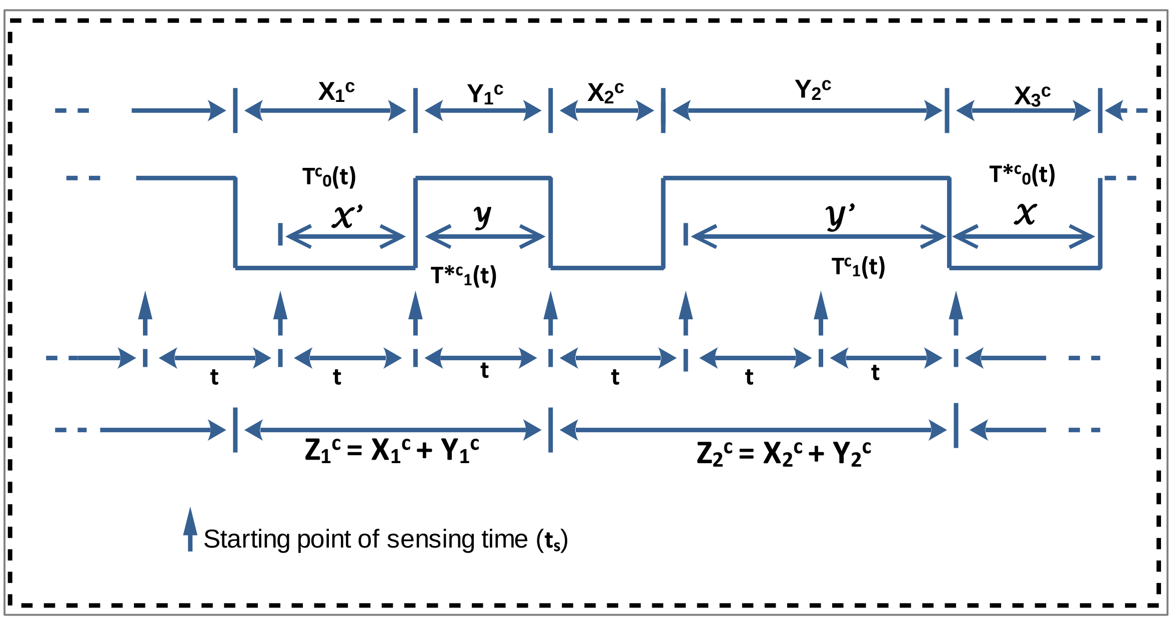

Figure 4. 5: ON/OFF time distributions with complete cycle $Z_K{}^c$

Next we look at how much opportunities are missed by SUs. In figure 4.8, there is a missed opportunity in period Z_1^c. i.e. $T^c_0(t) = 1 - x'$. In order to reduce missed opportunities, we adopt proactive sensing with adaptive sensing period proposed in [86]. This will be incorporated into our proposed channel selection algorithm detailed in section 4.2.4.

4.2.4. Proposed Channel Selection Algorithm.

There are two classifications of channel selection algorithm in multichannel cognitive radio network MAC protocols; (i) ON/OFF distributions based channel selection algorithm where channel statistics are known in advance or can be estimated at the run time. These types of algorithms rely heavily on the first and second order statistics of ON/OFF time distributions and it's often very difficult to predict the distributions of ON/OFF times at the run time and (ii) learning-based channel selection algorithm in which channel usage pattern is not known to SUs but they have to learn usage patterns or parameters.

The ON/OFF distributions based channel selection algorithm performs better in terms of estimating channel usage pattern and finding idle channels with minimal delay [85]. For this reason, our study focuses on modifying a channel selection algorithm which is based on ON/OFF time distributions studied in [87].

In this study, we address two key issues; (i) we determine how SUs can efficiently and effectively select channel for sensing. From figure 4.9 there are N SUs sensing N channels. SUs should sequentially sense all channels until an idle channel is found. In this case a question may be; how long, on average does it take SUs to find an idling channel. If SUs can intelligently locate channels with the highest probability of being idle, then sensing delays can be greatly minimized. We will achieve this by implementing channel selection algorithm to intelligently select channels free of PUs.

In (ii) we optimize T_p^c, which is sensing period on channel c such that less transmission opportunities are missed. The shorter the T_p^c , the more the overheads are incurred, and this will ultimately lead to compromised throughput while on the other hand blindly increasing T_p^c will lead to more opportunities being missed. Much of our attention will not be on T_I^c (sensing interval on channel c) since it is mainly determined by the physical layer as per 802.22 standards. We will therefore make few assumptions for most of physical layer parameters.

Shown in figure 4.9 is how SUs sense and select channels. T_I^c is the sensing time or interval and T_P^c is the sensing period. It is very critical to consider how long and how often to sense the spectrum. Hence this was considered during the design of our algorithm. An algorithm for sensing multiple channels at the same time was designed. This algorithm is explained and presented below.

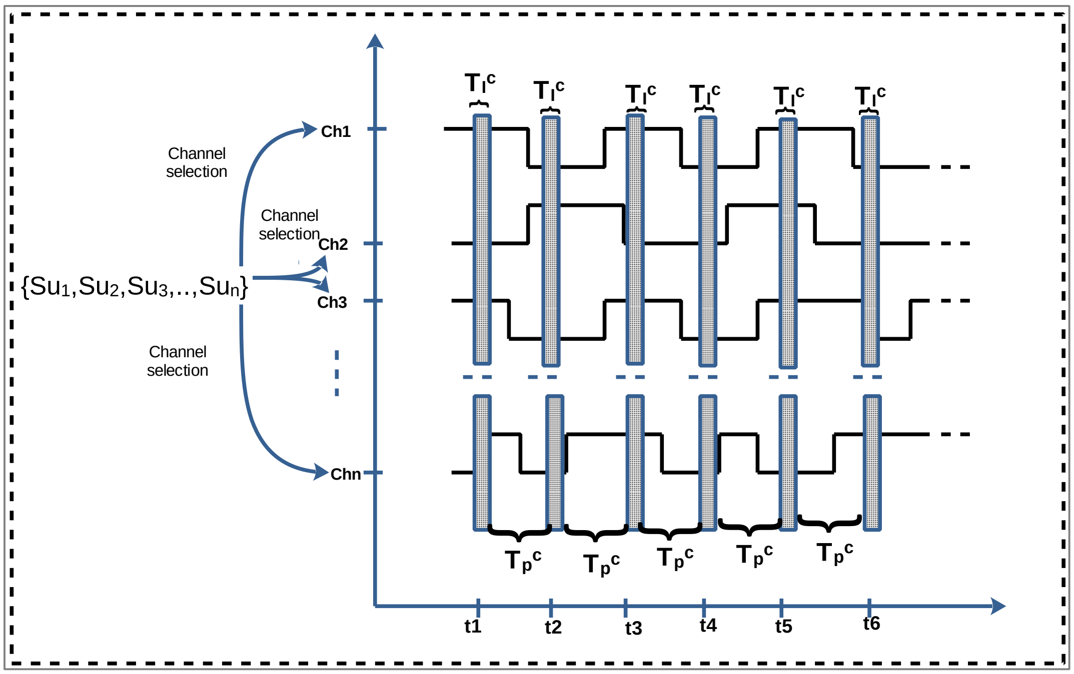

Figure 4. 6: graphical representation of SU channel selection

We have taken a probabilistic approach to predict the state of a channel at a particular point in time. To efficiently predict using probabilities, we allow SUs to maintain a believe vector, $\boldsymbol{V}_{p(\mathbf{c})}(t)$ which has N dimensions in two sets or groups and if we let $\boldsymbol{O}_{p(\mathbf{c})}$ and $\boldsymbol{q}_{p(\mathbf{c})}$ be the probabilities that channels are free from PU, then a believe vector containing this probabilities in descending order is defined as follows:

$$\boldsymbol{V}_{p(\mathbf{c})}(\mathbf{t}) = \{\{\boldsymbol{O}_{p(\mathbf{1})}, \boldsymbol{O}_{p(\mathbf{2})}, \boldsymbol{O}_{p(\mathbf{3})}, \ldots, \boldsymbol{O}_{p(\mathbf{N})}\}, \{\boldsymbol{q}_{p(\mathbf{1})}, \boldsymbol{q}_{p(\mathbf{2})}, \boldsymbol{q}_{p(\mathbf{3})}, \ldots, \boldsymbol{q}_{p(\mathbf{N})}\}\} \quad (4.8)$$

The elements of $\boldsymbol{V}_{p(\mathbf{c})}(t)$ are arranged such that

$\boldsymbol{O}_{p(1)} > \boldsymbol{O}_{p(2)} > \boldsymbol{O}_{p(3)}, >\ldots, \boldsymbol{O}_{p(N)}$ and $\boldsymbol{q}_{p(1)} > \boldsymbol{q}_{p(2)} > \boldsymbol{q}_{p(3)}, >\ldots, \boldsymbol{q}_{p(N)}$.

Using this $\boldsymbol{V}_{p(c)}(\boldsymbol{t})$ (believe vector), SUs will select a channel with the highest probability of being free from each group. This is equivalent to say:

$$\mathbf{c}^*(\boldsymbol{t}) = \{\arg\{\max_{1\leq \boldsymbol{c}\leq N} \boldsymbol{V}_{p(\boldsymbol{c})}(\boldsymbol{t})\}, \arg\{\max_{1\leq \boldsymbol{c}\leq N} \boldsymbol{V}_{q(\boldsymbol{c})}(\boldsymbol{t})\}\} \qquad (4.9)$$

If a channel with the highest probability i.e., c* has been sensed and is occupied, SUs sense the next channel with the highest probability and this is done repeatedly until a free channel is found. An idle channel is then used by SUs for ***t*** duration. In order to avoid interference SUs have to sense a channel for ***t*** duration as shown in figure 4.8.

Algorithm 3: channel selection Algorithm

---

1. *Use results from slot i-1*
2. *if* $q_{p(c)} = p_1(i\text{-}c)$
3. *then*
4. *Sensing_results = 1*
5. *else if* $q_{p(c)} = p_0(i\text{-}c)$
6. *then*
7. *sensing_results=0*
8. *use* $c^*(t)$
9. *select* $\{arg\{\max_{1\leq c\leq N} V_{p(c)}(t)\},\ arg\{\max_{1\leq c\leq N} V_{q(c)}(t)\}\}$
10. *if channel* $c^* = 0$
11. *then*
12. *SU packet transmission*
13. *else if channel* $c^* = 1$
14. *select another channel with* $\{arg\{\max_{1\leq c\leq N} V_{p(c)}(t)\},\ arg\{\max_{1\leq c\leq N} V_{q(c)}(t)\}\}$

Figure 4.10 presents a two state markov model. This is used to predict the future state of the channels. SUs should be able to predict the next channel transition state for them to make an informed decision about whether the channel is likely to be available or not.

There are two states (0/1) and four state transitions as shown in figure 4.10. At a particular point in time, a channel can be in exactly one state or may be transiting from one state to the next. We will use probabilistic approach in predicting a current and future state of the channel. For example, what is the probability that a channel c is idling after being occupied by PUs for t duration? If we can correctly determine this probability, then idle channel search time can greatly be reduced. Probabilities are defined as follows:

$P_{00}(X^c)$ - a probability that a channel c remains idling

$P_{01}(Y^c)$ - a probability that a channel c started in an idling state before changes its state

$P_{11}(Y^c)$ - a probability that a channel c remains busy

$P_{10}(X^c)$ - a probability that a channel c begins in busy state before transiting into idling state

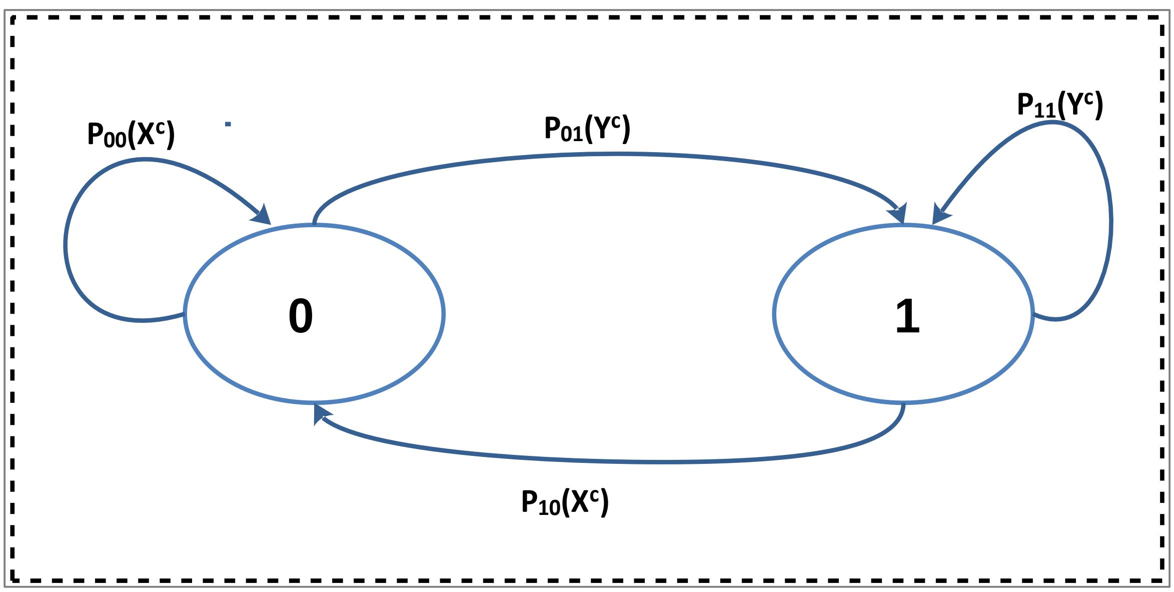

Figure 4. 7: presentation of state transition probabilities

These probabilities are modeled using four state Markov chain where $S_c(t)$ is the state of a channel c at time t and the sensed result obtained from state $S_c(t)$ is given by $\bar{S}_c(t)$ and $S_c(t) = P_{00}(X^c)= P_{01}(Y^c)= P_{11}(Y^c) = P_{10}(X^c)$. {0 if channel c is free, 1 if channel c is busy}є$S_c(t)$ and {0 if channel c sensed free, 1 if channel c sensed busy } є $\bar{S}_c(t)$. To maximize SU throughput, it will be necessary to accurately detect the presence of PUs while reducing false alarms. To achieve this, we consider four states of Markov chain:

State 1: If channel c is correctly sensed as free; i.e, $S_c(t)$ =0 and the results obtained are such that $\bar{S}_c(t)$=0, then SUs transmit data packets since there will be no interference.

State 2: If $S_c(t)$ =0 and $\bar{S}_c(t)$ =1, because the channel c idles and the results give the opposite, this is the state under which a false alarm occurs. More opportunities will be missed and SU throughput will be compromised.

State 3: Here, we consider a case where $S_c(t)$ =1 and $\bar{S}_c(t)$ =0, since decisions are taken based on sensed results, this leads to miss detection. This affects both SU and PU throughput.

State 4: If $S_c(t)$ =1 and $\bar{S}_c(t)$ =1, then we correctly detected PU signal in channel c. In this case there will be no interference since SU will sense and switch to the next available channel for transmission. This is also one of the requirements (interference avoidance) of SU in CR networks.

It is very critical to identify $P_{10}(X^c)$ since this will ensure maximum utilization of transmission opportunities. Identifying opportunities when they begin will ensure efficient utilization of the spectrum and maximum throughput of SUs. It is also important to identify a start of busy period $P_{01}(Y^c)$. This is very critical for collision avoidance since detecting the PUs signal when they start occupying a channel would mean that a SU should vacate a channel and starts its transmission on the next available channel.

4.3. Simulation Parameters and Performance Metrics

In analyzing our results, the following metrics will be considered:

1. The probability of detection vs Signal-to-Noise ratio
2. The probability of arriving in a given time window vs Number of packets
3. Probability of service time>=t vs Service time
4. Probability of detection vs Probability of false alarm
5. Sensing delays vs Inter-sensing interval
6. Channel switching rate vs Inter-sensing interval

7. Throughput vs Inter-sensing interval

Probability of detection: an optimization of threshold level has shown to increase the probability of detection while minimizing sensing errors (probability of miss detection and probability of false alarm) [87]. Next we determine the threshold level which serves a constraint for the detection probability and probability of false alarm. We choose a test statistic $\boldsymbol{T_L}$ for energy detection such that false alarm occurs whenever $\boldsymbol{T_L}$ is greater than $\boldsymbol{T_h}$ where $\boldsymbol{T_h}$ is the threshold level.

Both test statistic and threshold values are given by:

$$T_L(y) = \frac{1}{L}\sum_{n=1}^{L} |y(n)|\hat{}2 \qquad (4.10)$$

Where $\boldsymbol{L}$ is the number of samples and $\boldsymbol{y}(\boldsymbol{n})$ is the received signal sample of a SU.

and

$$T_h(x) = \frac{1}{\sqrt{\alpha L}}\int_x^{\infty} exp(x/2)\, dx + 1 \,, \quad \forall\ \alpha \epsilon \{1,2,3\} \qquad (4.11)$$

Delay in finding idle channels: This is given by $D_c = D_s + W_t$ where D_c is the delay in finding available channel, D_s is the searching time and W_t is the waiting time.

The average delay will then be given by

$$Av_D(t) = \frac{1}{n}\int_0^{\infty} D_c\,(t)dt$$

where n is the number of SU in a network.

Channel switch rate: the rate at which channels are switched $\boldsymbol{C_R(t)}$ is calculated as a fraction of number of channel switches of SU sender to the time period $\boldsymbol{t}$.

Throughput: the throughput of SUs $\boldsymbol{T(t)}$ is calculated by taking a ratio of the product of successfully transmitted data frames and the size of frames in bits to the total time $\boldsymbol{t}$ elapsed during simulation. The throughput of SUs is given in [72] by:

$$T(t) = \frac{F_N(t) * Frame\ size[bits]}{t} \qquad (4.12)$$

Where $\boldsymbol{F_N}(\mathbf{t})$ is the number of successfully transmitted frames until time $\boldsymbol{t}$. The average throughput of SUs is then given by:

$$\lim_{n\to\infty} T(t) = \lim_{n\to\infty} \frac{F_N(t) * Frame\ size\ [bits\ ]}{t} \qquad (4.13)$$

Table 4.1 presents the simulation parameter used to simulate EXGPCSA. These parameters were set for all network scenarios and simulated under a very dynamic environment to mimic the actual cognitive radio network environment.

Table 4. 1: Simulation parameters

Parameters	**values**
IEEE standard	802.22
Network Grid	1000m x 1000m
Network simulator	MATLAB R2015a
Simulation Time	200 sec
Transmission range	Maximum 1000m
Traffic type	Periodic
Number of Secondary nodes Ns	10, 20, 30
Number of Radios	1
Load on the network	80%
Super frame	160ms
Frame size	10ms
Modulation scheme	Amplitude modulation
Maximum transmission power for Secondary nodes	1 µW
Collaborative sensing	OR
Operating System	Windows 7 OS

4.4. Modeling arrival rate and service times using queueing theory.

Sending sensing results to the fusion node causes queues and ultimately compromises performance if not well managed. Sensing results cannot all be aggregated at the same time, hence queues are formed. They have to be buffered before aggregated, which raises a question of how long they will be buffered and at what rate they are arriving for buffering. The other issue to be considered is; how long does it take a fusion node to aggregate data or sensing results? Answers to these questions are provided through the application of a queueing theory. We make the following assumptions:

1. Packets join a queue on the first come first out (FIFO) basis
2. Fusion node has infinite buffers
3. The inter-arrival time of packets at the fusion node takes on exponential probability distribution with an average arrival rate of n packets arrival per unit time
4. The service time of packets at the fusion node takes on exponential probability distribution with an average service rate of m completion of service per unit time

We used two commonly known distributions, exponential and Poisson to evaluate the performance of EXGPCSA and generalized predictive CSA in terms of service time and arrival rate. The exponential distribution was used to model service times. This distribution is defined by:

$$f(t) = e^{\lambda * t} \tag{4.14}$$

For $\lambda = mean(t)$ and t a service time

A Poisson distribution was used to model sensing results arrival rate and it is given by the following function:

$$f(y) = \frac{e^{\mu} y^{\mu}}{y!} \tag{4.15}$$

Where μ is the average arrival rate.

4.5. Conclusion

We have investigated three simulation tools and selected MATLAB as a primary tool to simulate our proposed algorithm. A choice of this tool is based on its simplicity to develop MAC layer protocols. This tool was used to simulate cooperative SUs in a cognitive radio environment. There are three network scenarios under consideration and the performance metrics used to evaluate our proposed scheme are probability of detection, sensing delay, channel switching rate and throughput. These metrics were used to evaluate how much performance we can achieve in all network scenarios.

This chapter also discussed some of the most important models and algorithms to enable the implementation of our proposed scheme. We looked at how SUs can share sensing results while considering a trade-off between overheads and efficiency. A proposed cooperative algorithm (EXGPCSA) reduces cooperative overheads by selecting certain SUs to be involved in decision making, mainly, SUs will the highest SNR. It should be noted that overheads are not the main focus of this study; however this has indirectly been addressed through the selection of certain SU for cooperation.

We also proposed a channel selection algorithm in which SUs intelligently select a channel that is likely to have the highest likelihood of idling. This is achieved through assigning probabilities to channels and orders them in descending order of their probabilities. These ensure the reduction of delays in locating idle channels while maximizing achievable throughput. The performance of algorithms presented in this chapter is evaluated in the next chapter.

CHAPTER 5 - RESULTS AND INTERPRETATIONS

5. Introduction

MATLAB simulation tool, as discussed in chapter 4, was used to evaluate the efficiency of EXGPSCA. There are three scenarios considered for EXGPCSA. Simulations were run for 200 seconds for all three network scenarios. The probability of detection, delay in finding available channels, channel switching rate, and throughput were considered as performance metrics to evaluate the efficiency of EXGPSCA. The T-test statistical technique was conducted for the comparison of the average throughput. This technique was used to test if there is a significant difference between our proposed scheme (EXGPSCA) and Generalized predictive CSA. A test has only been considered for a network scenario where there are 30 SUs since t-test is suitable for sample size of 30 or above.

5.1. Simulation results and interpretations

A simulation diagram presented in figure 5.1 portrays the actual cooperative sensing and sharing of observations in cognitive radio network deployed in 1 000 m^2 grid area.

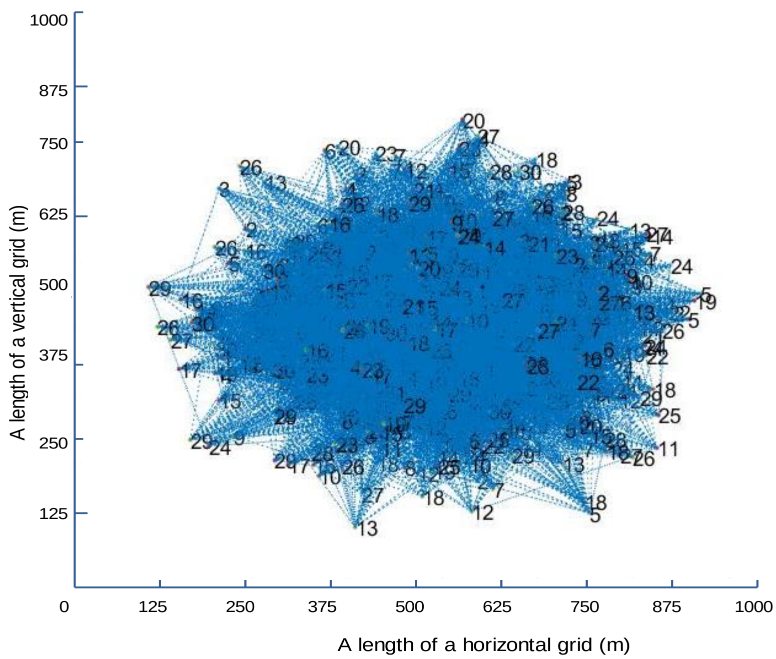

Figure 5. 1. Collaborative sensing and sharing in cognitive radio network environment

The maximum transmission range in this network is 1 000 meters such that all SUs are within transmission rage. SUs, as it can be observed from figure 5.1; SUs are denoted by numerical labels from 1 to N where N is the highest number of SUs in network. In this case, there are 30 SUs simulated in this network environment. Other two scenarios were not shown but they were also simulated under the same network setup. Links were established between SUs to allow sharing of sensed results and data transmissions. Since CR network is characterized by mobility of nodes, SUs were moving from one point to the next during the simulation. For example, a link connecting a node 29 to another 29 on the left hand side of the grid shows that node 29 has moved to a new location. A node or SU can change its location several times during a simulation. A fusion node, which is also a SU, is mobile but the assumption is that it moves slowly to keep a network stable. To reduce communication overheads, only one SU was chosen as fusion node. All SUs send their observations to the fusion node except the ones with lower SNR. All simulation results in this study were obtained from the type of network environment shown in figure 5.1 where mobility and interferences are inevitable. This type of a network is prone to interferences, cooperative sensing delays and sensing errors that affect the SUs throughput.

Figure 5.2 presents a set of results where (a) we investigated SNR for different probabilities of false alarm while on the other hand, (b) we compared three collaborative rule; OR, N-out-M and AND rules. It can be observed from figure 5.2(a) that the chances of detecting a PU signal increases with the increase in SNR as the probability of false alarm decrease. The higher the SNR, the better are the chances of detecting the PU signal.

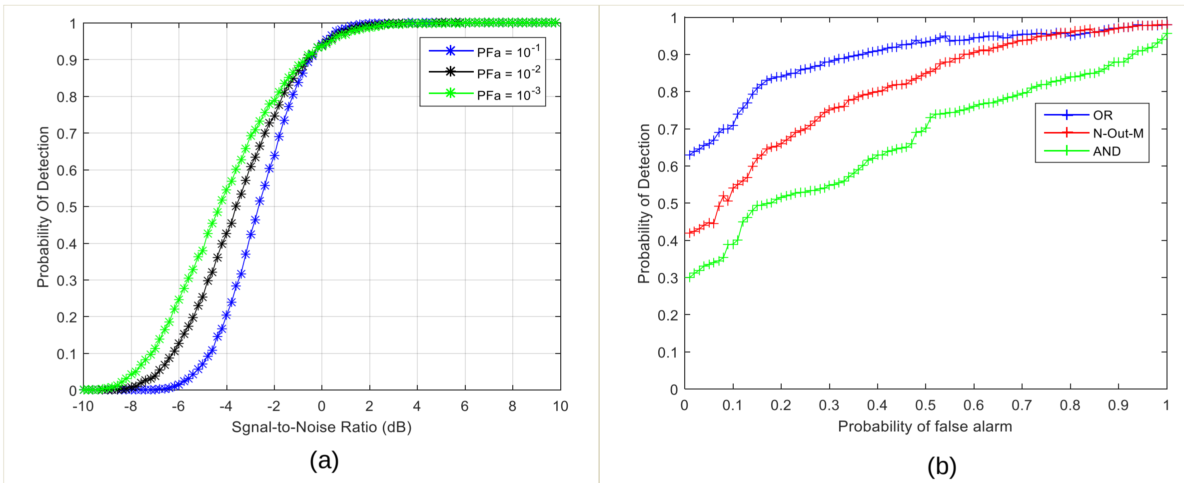

Figure 5. 2: (a) SNR for the selection of cooperating SU. (b) Comparison of collaboration rules for better detection probability

It was observed that there is at least 60% chance of detecting PU signal for any SNR above -2dB, hence this serves as the minimum requirement for collaborative sensing. That is, only SUs with higher SNR (equal or above -2dB) are allowed to forward their observation to the fusion centre. The main motive of setting this threshold is that SUs with lower SNR often inaccurately detect PU signal which leads to interference. The threshold therefore mitigates interference amongst PUs and SUs and it also ensures maximum utilization of SUs bandwidth.

On the other hand, figure 5.2 (b) compares the collaborative rules (OR, AND and N-out-M). It is clear that the OR rule has higher chances of detecting the transmission of PU than other rules. Given the OR rule, the decision that the channel is occupied is made based on one of the SUs reporting the presence of PU. Considering this fact, more opportunities could be missed in the presence of malicious SUs. Hence, the assumption is that there are no security threats in the network.

To ensure reliable sensed results to be aggregated using OR rule, a rule was set to allow only SUs with $SNR \geq -2dB$ to share their observations. A major drawback of OR aggregation rule is that, it increases the probability of detection while at the same time the probability of false alarm increases. The other aggregation rules AND and N-out-M achieved lower detection probabilities compared to OR rule because they employ complex data aggregation methods.

The complex data aggregation techniques incur delays and compromise the chances of detecting PU signal. In N-out-M, a number of nodes making observations are taken into account when deciding on the presence of PU in the signal. The advantage of using N-out-M rule is that the number of N could be chosen such that the probabilities of false alarm and detection stay in an acceptable domain AND rule has a benefit of reducing probability of false alarm; unfortunately it also reduces the probability of detection.

The likelihood of detecting PU in the channel when aggregation rules (OR and N-out-M) are employed is lower as it is evident in figure 5.2 (b). An advantage of such systems is the accuracy at which a signal can be detected. For all of our simulations, OR collaboration rule was implemented since it gives higher detection probabilities and incurs less delay in data aggregation. It should be emphasized that the main focus of this study is to minimize delays in finding the next available channel. Hence OR rule is more applicable to our proposed scheme.

Figure 5.3 analyses generalized predictive CSA and EXGPCSA in terms of packet arrival rates and the packet service rates. It is critical to evaluate the performance of the fusion node which performs a critical task of aggregating and making decision about the availability of the spectrum. Hence, two schemes are evaluated on the ability to aggregate or service packets within the shortest possible time. In figure 5.3 (a), 2 to 3 packets have the highest chances of arriving within 1 second time window for generalized predictive CSA while given the same amount of time, EXGPCSA has the highest chances of 4 and 5 packets arriving. This means that the rate at which packets arrive at the fusion node is higher for EXGPCSA than generalized predictive CSA.

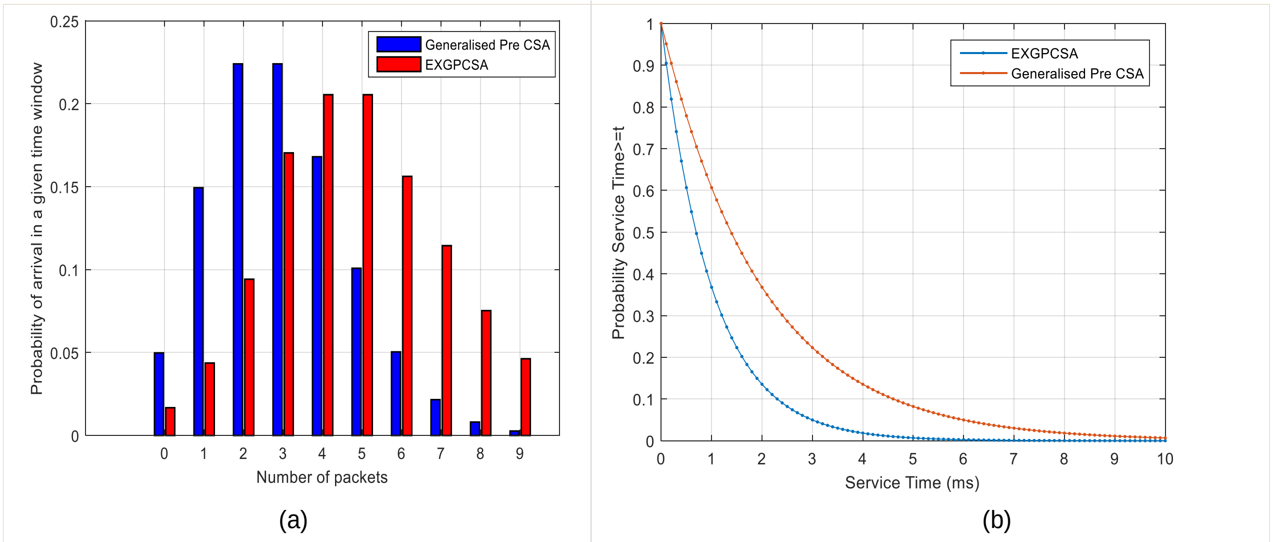

Figure 5. 3 :(a) Packet arrival rate per second. (b) The probability that service time is greater than time t.

The processing or aggregating of packets should be faster for EXGPCSA to prevent buffer overflow. It can be observed from figure 5.3 (b) that EXGPCSA has lower service time and packets are aggregated within 5 milliseconds. This contributes to the results presented in figures 5.4(b), 5.6 (b), and 5.8(b) which show the delays in finding available channel. The time taken by a fusion node to aggregate data contributes to overall delays in finding the available channel for transmission. The rate at which packets arrive at the fusion node for generalized predictive CSA is slower compared EXGPCSA. The maximum service time for EXGPCSA is twice lower than the generalized predictive CSA which meets the objectives of our scheme.

Figure 5.4 depicts two performance metrics, probability of detection and delays in finding available channels with varying inter-sensing intervals. A simulation was carried out with 10 SUs in a network. The results in figure 5.4 (a) show the probability of detection with $SNR = -2dB$. It is clear that the probability of detection increases as the probability of false alarm increases and that the detection probability of EXGPCSA improves with the increase of $\boldsymbol{\alpha}$.

A noticeable increase can be observed for probability of false alarm below 50% in which EXGPCSA kept the probability of false alarm constant while increasing the probability of detection. This shows that changing a value of threshold can somehow have impact on the detection of PU signal. The relationship between $\boldsymbol{\alpha}$ and the threshold was discussed in chapter 4 in detail. Our proposed scheme maintained high level of detection through the implementation of a rule set to allow only SUs with higher SNR to participate in collaborative detection and by varying the value of $\boldsymbol{\alpha}$.

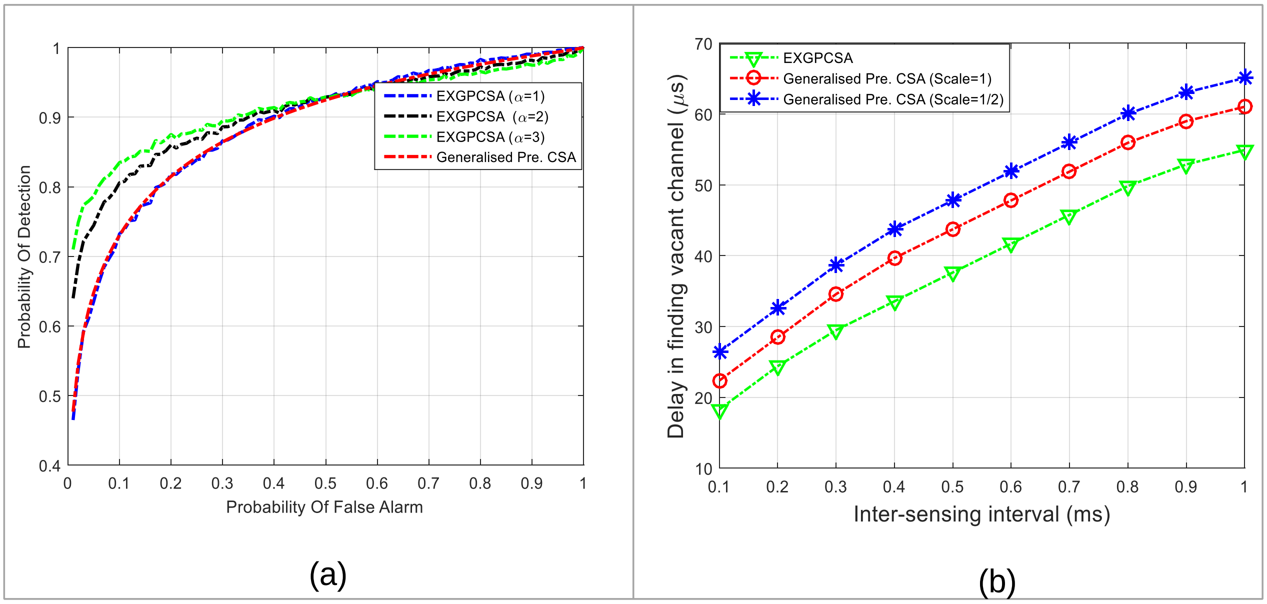

Figure 5. 4: 10 cooperative SU transmitting over 6 channels: (a) ROC for the hard fusion rules with SNR = -2dB and energy detection over 1000 samples. (b) Delay in finding idle channels.

It is important to keep probability of false alarms low and increase probability of detection to enhance performance. In figure 5.4 (b), inter-sensing intervals were varied to investigate the behaviour of two schemes in terms of delays. It can be seen from (b) that delays in finding next available channel for transmission increases with the increase in the inter-sensing interval. It should be noted that a channel sensed for 0.1ms will always have lower delays, but does not guarantee accurate and reliable results since the observations were gathered for a short period of time. It is therefore important to trade-off between increasing/decreasing delays and maximizing throughput. For example, if delays are very low, the chances of sensing results to be inaccurate are very high and this could lead to interferences, which imply that a throughput is compromised.

On the other hand, having more sensing delays is undesirable either since SUs spend much of their time sensing the spectrum which means that some of the transmission opportunities may be missed. In all such cases the throughput will also be affected. Generally, EXGPCSA has lower delays compared to generalized predictive CSA. A good performance was achieved through channel grouping technique where sensing multiple channels at the same time is possible. Presented in figure 5.5 are the SUs individual throughputs and the average throughputs simulated in a network with 10 SUs.

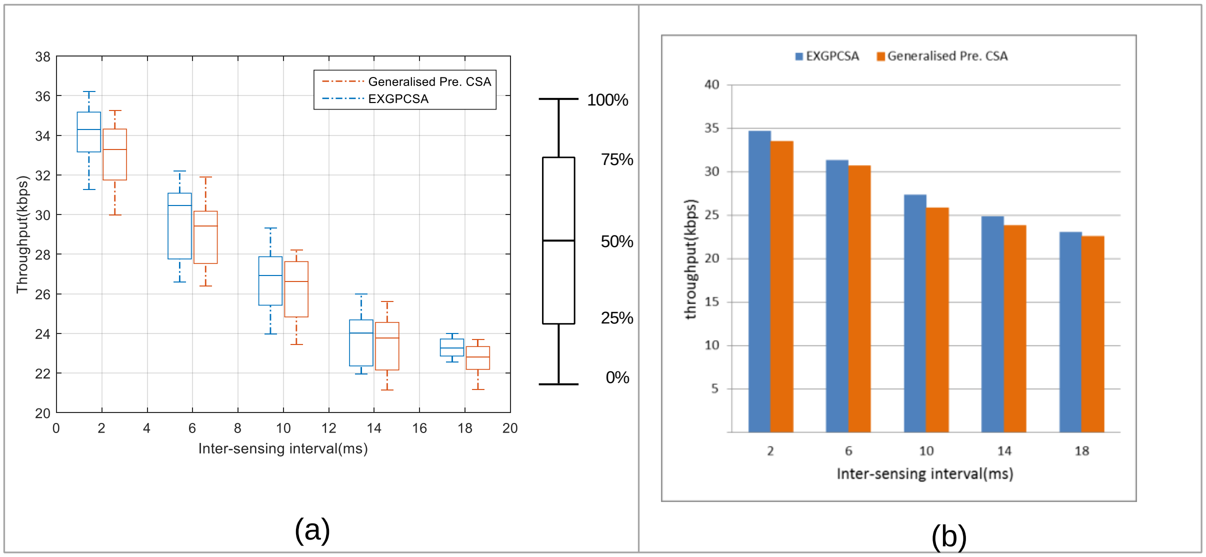

Figure 5. 5: (a) Box and whisker plot representing individual throughput of 10 SUs in a network. (b) Average throughput of 10 SUs in a network

Figure 5.5 looks at the SUs throughput, which is one of the measures of how efficient EXGPCSA is compared to generalized predictive CSA. The two diagrams in (a) and (b) present the variability of individual throughput in different sensing intervals and the average throughput of SUs respectively. In figure 5.5(a), a throughput is presented using box-and-whisker plot. Here a comparison is made in terms of percentage of SUs recording higher throughput in one scheme than the other. The smaller the box-and-whisker implies that the individual throughput converge closer to the mean. Hence a scheme is consistent since different SUs are generating throughputs which are closer to each other.

It can be observed that 50% of SUs achieved individual throughputs of a 34.5 kbps for EXGPCSA whereas only 25% of SUs in Generalized Predictive CSA had individual throughputs of 34.5 kbps within 2 milliseconds inter-sensing interval. The same trend is evident for 18 milliseconds inter-sensing interval with average above 23 kbps for two schemes.

We also notice better performance when inter-sensing is increased to 6 milliseconds in which more than 50% of SUs in EXGPCSA recorded individual throughputs of above 30.66 kbps while the same individual throughputs were achieved by 25% of SUs in generalized predictive CSA. EXGPCSA also performed better for 10, 14 milliseconds even though the performance is marginal. It should be noted that box-and-whiskers for both schemes are much shorter in the 18 milliseconds inter-sensing intervals. All SUs in both schemes recorded throughput, which is closer to one another.

This is because 18 milliseconds are large enough to accurately detect PU signal in the channel but give poor throughput. Shown in figure 5.5 (b) are average throughput when SUs are set to sense the spectrum with different sensing intervals. The mean throughputs drop when inter-sensing intervals increase. One of the reasons why throughput drops is that, increasing sensing time delays data transmission since transmission should be done after sensing.

In figure 5.6, the number of cooperating SUs has been increased to 20. One thing that can be observed from figure 5.6(a) is that the detection probability has increased compared to results in figure 5.4(a). Probability of false alarm is kept constant while the probability of detection is increased. Since only SUs with higher SNR were considered in sharing their results, there has been elimination of sensing errors including keeping probability of false alarm constant. Hence, this has drastically increased the chances of detecting PU signal.

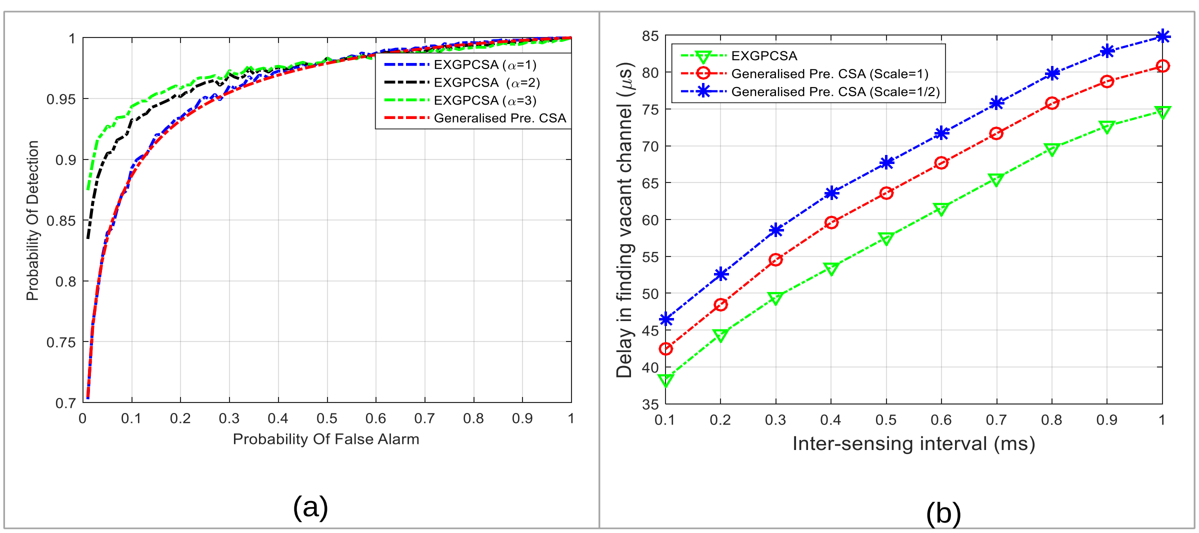

Figure 5. 6: 20 cooperative SU transmitting over 6 channels: (a) ROC for the hard fusion rules with SNR = -2dB and energy detection over 1000 samples. (b) Delay in finding idle channels.

Considered in figure 5.6(b) is an investigation of how the sensing delays affect the performance as the network increases. Comparing results in figure 5.6(b) to figure 5.4(b), we see that the sensing delays have increased with the increase of SUs in a network and also with the increase in inter-sensing interval. The sensing delays in EXGPCSA remained relatively low compared to Generalized predictive CSA. This is because with EXGPCSA, sensing is performed in different channels at the same time hence searching time is reduced. This allows more opportunities to be discovered and ultimately gives higher throughput.

Figure 5.7 gives the individual and average throughputs in a network designed for 20 SUs. The individual throughputs in figure 5.7(a) decrease as we increase the inter-sensing interval. Each time SUs spend more time in sensing one channel, they may miss opportunities in other idling channels since there is no guarantee that the currently sensed channels are idling. This results in performance degradation.

The general performances of two schemes have declined compared to the case of 10 SUs in figure 5.5. This is due to the fact that increasing users in a network means higher contention rates and interferences which ultimately affect the throughput. When inter-sensing interval is set to 2 milliseconds, 50% of SUs had the throughputs of above 30.68 kbps for the EXGPCSA whereas Generalized predictive CSA had fewer SUs (about 37.5%) achieving a throughputs of above 30.68 kbps.

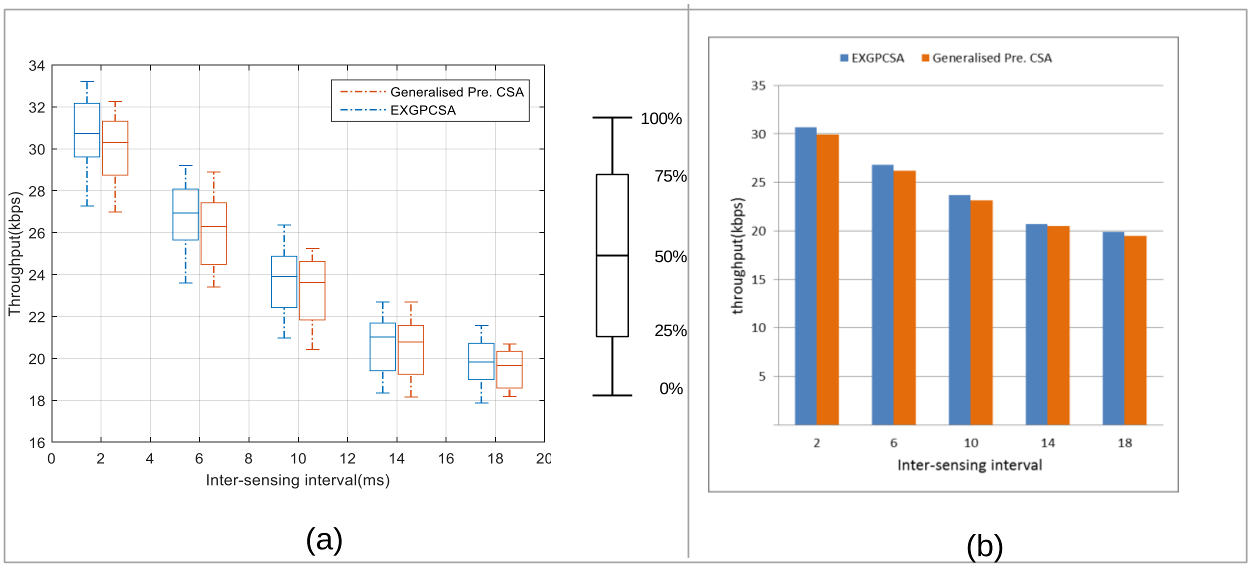

Figure 5. 7: (a) Box and whisker plot representing individual throughput of 20 SUs in a network. (b) Average throughput of 20 SUs in a network

Similar trends are evident for 6, 10, 14 and 18 inter-sensing intervals. EXGPCSA, on average performs better than Generalized predictive CSA.

The probability of detecting the presence of PUs has tremendously increased with the increase in cooperating SUs as shown in figure 5.8(a). EXGPCSA has the highest chances (above 95%) of detecting PU signal in the spectrum. When there are more SUs collaboratively sensing the spectrum, the detection always increases since they share a spectral map of which channels are available for transmission or which ones are occupied. But this comes at a price as shown in figure 5.8(b). Whenever the number of cooperating SUs increases, delays due to sharing and aggregating are incurred. EXGPCSA incurred lesser delays in finding the available channels for transmission.

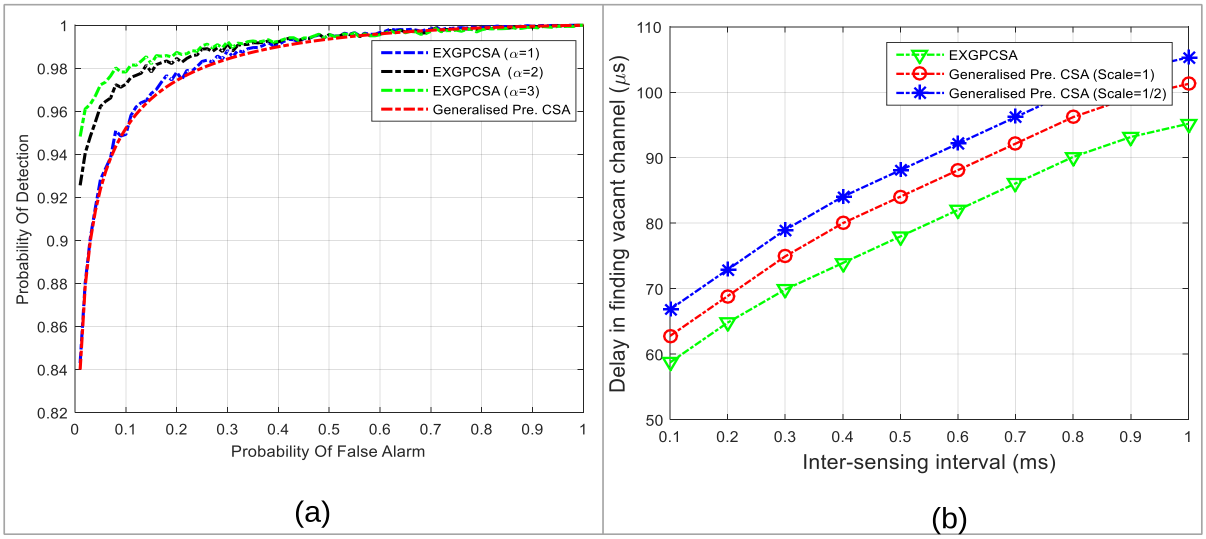

Figure 5. 8: 30 cooperative SU transmitting over 6 channels: (a) ROC for the hard fusion rules with SNR = -2dB and energy detection over 1000 samples. (b) Delay in finding idle channels.

From statistical point of view, it is not enough to evaluate the efficiency of two schemes by comparing means or throughputs. It is very critical to test if there is significant difference between two means. Figure 5.9 was used to test if EXGPCSA is significantly better than generalized predictive CSA in terms of average throughput. Statistical mean test is used to test significant difference between two schemes. In order to successfully perform the test, the following assumptions were made:

1. Homogeneity of standard deviation
2. Throughputs are normally distributed
3. Each throughput value is sampled independently

and we let

μ_{EG} : Population mean throughput for 30 SU (EXGPCSA)

μ_{GP}: Population mean throughput for 30 SU (Generalized Predictive CSA)

Hypothesis:

H_0: $\mu_{EG} - \mu_{GP} \leq 0$

H_1: $\mu_{EG} - \mu_{GP} > 0$

Rejection Region:

Using a significance level of $\alpha = 0.05$, we reject H_0 if t Stat > t Critical one-tail value and otherwise accept H_1. This is equivalent to saying that there is significant difference between the two schemes in terms of average throughput. In other words, EXGPCSA has performed far much better than the generalized predictive CSA. We analyze mean throughput by varying inter-sensing interval. This analysis is very critical to investigating optimal sensing interval or an inter-sensing interval which results in the highest throughput.

The analysis below is derived from using statistical t-test results in $Appendix\ A$ and it is based on figure 5.9. For this analysis, 2, 6, 8, 14 and 18 millisecond inter-sensing intervals were considered separately. The main idea behind this analysis is to investigate in which inter-sensing interval EXGPCSA performed significantly better than generalized predictive CSA. This is particularly important for selecting optimal sensing interval.

In $Appendix\ A$, $Table\ 3$, we see that a test value (t stat) is greater than t critical one-tail value when sensing is done for 2 milliseconds. This gives enough evidence to support the fact that the EXGPCSA has performed significantly better than generalized Predictive CSA. Generally, EXGPCSA performed much better since about 25% of SUs recorded the throughput of above 29 kbps than generalized predictive CSA. It can also be seen from figure 5.9(b) that the average throughput is significantly higher for EXGPCSA.

A t stat is less than t critical one-tail value, which means that even if the average throughput of the EXGPCSA is slightly higher (shown in figure 5.9(b)), the difference is not statistically significant (refer to $Appendix\ A$, $Table\ 4$). The main cause here maybe is the uncertainty in wireless networks and bad channel conditions hence the throughput also dropped compared to previous inter-sensing interval. From the figure 5.9(a), we see that 50% of individual SUs for EXGPCSA had a throughput of at least 24 kbps while Generalized Predictive CSA had about 27% of individual SUs generating the throughputs of above 24 kbps. EXGPCSA yielded better performance in terms of the number of SUs achieving higher throughput. But there is less evidence to prove that EXGPCSA performed better than generalized CSA for 6 milliseconds inter-sensing interval.

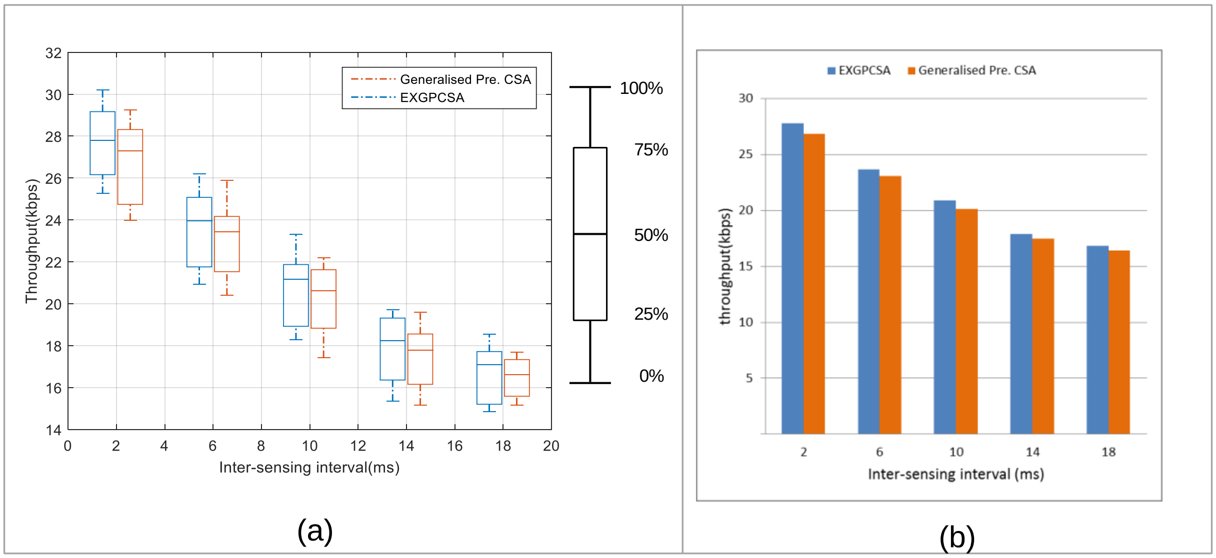

Figure 5.9: (a) Box and whisker plot representing individual throughput of 30 SUs in a network. (b) Average throughput of 30 SUs in a network

A test value (t Stat) is greater than t Critical one-tail value as shown in $Appendix\ A$, $Table\ 5$ which clearly gives enough evidence to conclude that EXGPCSA performed significantly better than Generalized Predictive CSA. This was achieved through increasing inter-sensing interval to 10 milliseconds. It can also be seen from the figure that the EXGPCSA had 25% of SUs recording individual throughputs of above 22 kbps when on the other hand, Generalized Predictive CSA had about 12.5% of SUs recording individual throughput of above 22 kbps.

Since a test value is less than t Critical one-tail value for 14 milliseconds sensing interval, it implies that there is no significant difference in average throughputs between two schemes (refer to $Appendix\ A$, $Table\ 6$). Even though the EXGPCSA has higher average throughput than Generalized Predictive CSA but the difference is marginal.

With reference from $Appendix\ A$, $Table\ 7$ where inter-sensing interval is 18 milliseconds, test value is less than t critical one-tail and this gives enough evidence to conclude that there is no significant difference between two schemes. About 25% of SUs had an individual throughput of 17.8 kbps for EXGPCSA when on the other hand 100% of SUs for Predictive Generalized scheme had individual throughput of below 17.8 kbps.

We used statistical test to mainly check if the difference between two schemes is significant. From the analysis, EXGPCSA significantly performed better than generalized predictive CSA for 2 and 10 milliseconds inter-sensing intervals. According to IEEE 802.22 standards, sensing can be done for 2 ms for fast sensing and 25 ms for fine sensing. Since 2 ms sensing interval gives the highest throughput, incurs lower delays in finding free channels and also supported by IEEE 802.22 standard, it was chosen as optimal sensing interval.

Figure 5.10 shows the rate at which channels are switched when inter-sensing intervals are increased. SUs switch from one channel to the other in search of a free channel for transmission. It is desirable to have few channel searches before finding next available channel.

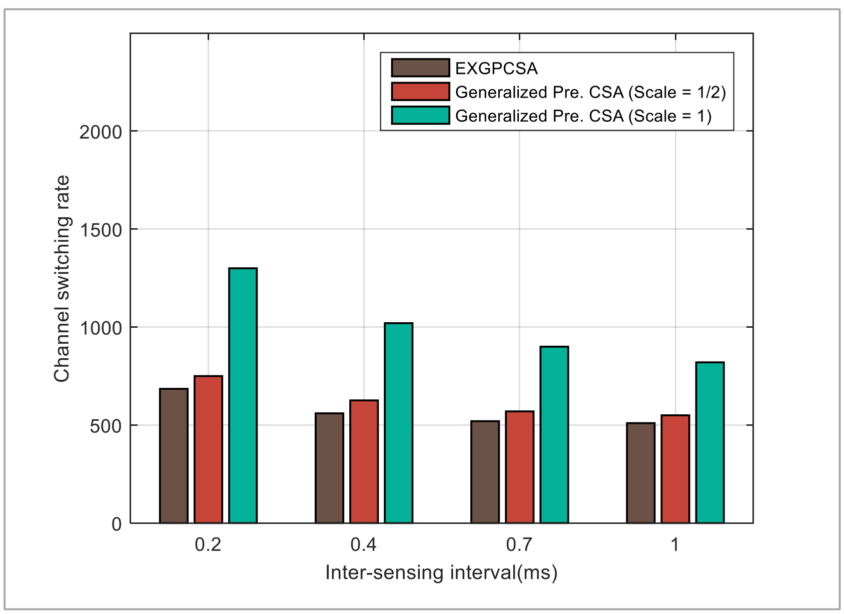

Figure 5. 10: The rate at which channels are switched in a cognitive radio network

Channel switching rate remains higher when inter-sensing interval is small. This is due to the fact that sensing is performed within a very short period of time which causes high overheads and more channel switches. Knowing the channels that are likely to be idling reduces channel switches and delays. Hence EXGPCSA uses channel selection algorithm which intelligently selects channels to be sensed. This greatly reduces the number of channel switches since only channels with the highest probabilities of being free are selected for sensing.

In figure 5.10, channel-switching rate declines with the increase in inter-sensing interval. When sensing interval increases, the accuracy of sensing results also increases but this does not directly influence channel switching. Channel switching is affected by the choice of channels to be sensed. An ability of EXGPCSA to intelligently select channels for sensing ensured lower channel switching especially when increasing sensing period. Unnecessary sensing of occupied channels was avoided, hence lesser channel switching. This was made possible by selecting and sensing channels with the highest probabilities of being free.

All the results obtained thorough simulations show that EXGPCSA had an upper hand over generalized predictive CSA in terms of performance. To achieve that performance, there were extensions or adjustments made to existing generalized predictive CSA. These were channel grouping and selection technique, self-coordination, collaborative sensing and enforcing cooperative rule. Incorporating all these has given EXGPCSA a major performance boost.

Collaborative sensing ensured that reliable sensed results or observations were shared amongst SUs in a network. But not all the sensed results were shared. With cooperative or collaborative rule, only SUs with higher SNR were allowed to share their observations. This is because better detection is achieved with higher SNR. The simulation results show that EXGPCSA had the highest detection rate than its counterpart and that was gained through setting up collaborative rule. Sensing errors were minimized in this since higher SNR implied better detection.

It should be noted that delays in finding next available channels for transmission directly influence the throughput. In EXGPCSA, delays were taken care of through channel grouping in which channels were divided into two groups and ordered in the descending order of their probabilities. This gave boost to SU throughput.

Our study also considered the contention of SUs thereby deploying CSMA/CA since contention causes collisions and thus affects a SU throughput. We dealt with interferences from two different levels; the interferences amongst SUs themselves as well as the interferences between SUs and PUs. Hence, EXGPCSA managed to gain higher achievable throughput.

5.2. Conclusion

A simulation was carried out in three different network scenarios. That is, 10, 20, 30 SUs respectively. In each network scenario, the probability of detection, delays in finding available channels, throughput and channel switching rate were used to evaluate the efficiency of EXGPCSA. Delays in finding the available channel remained reasonably low for EXGPCSA compared to generalized predictive CSA. In both schemes, delays increased with the increase in the number of cooperating SUs. EXGPCSA performed exceptionally well due to the deployment of channel grouping technique.

This has substantially reduced delays. Lesser delays implies that opportunities can be discovered faster and have positive impact on the throughput. As would be expected, EXGPCSA had better performance in terms of throughput due to lesser delays in finding available channels. Unfortunately as delays increased, throughput dropped with the increase in inter-sensing interval. This can be observed in all network scenarios for both schemes. Whilst on the throughput, a statistical t-test was conducted to check if there is a significant difference between EXGPCSA and Generalized predictive CSA.

This test was performed for average throughput. The test has revealed that EXGPSCA has performed significantly better when sensing was done for 2ms and 10ms. In all other sensing intervals, EXGPCSA had higher average throughputs but the difference is marginal. The probability of detection, on the other hand has tremendously increased with the increase of the size of the network. Having more SUs cooperating ensured the higher chances of detecting PU signal in the channels.

Lastly, channel switching rate has been considered for a network scenario where there were 30 cooperating SUs. EXGPCSA has given the lowest channel-switching rate compared to generalized predictive CSA. To reduce channel switching rate, EXGPCSA uses an ‘intelligent’ algorithm which selects channels with the highest chances or probabilities of being free from PU signal. A performance of the fusion node was also evaluated in terms of service time and packet arrival rate.

EXGPCSA has shown to aggregate sensing results within shortest time possible compared to generalized predictive CSA. Since the selection of channels to be sensed is not random but certain criteria, the number of channel switches is reduced. Generally, EXGPCSA has performed way better than generalized predictive CSA.

CHAPTER 6 - CONCLUSION AND FUTURE WORK

6. Introduction

Our study mainly focused on few issues in spectrum sensing where we dealt with delays in finding available channels and cooperative sensing. In this section, we summarize the findings of our study and also propose future work that is in line with what has already been done in this study. A section on future work may be seen as a way of presenting gaps in the current study.

6.1. Summary of Findings

In this study, we designed a cooperative cognitive radio ad hoc network and ran our simulations in MATLAB version R2015a. A network was setup for three scenarios, that is, 10, 20 and 30 SUs and a time set for simulation was 200 sec. The primary objective in setting up this network was to evaluate the efficiency of our scheme when a number of nodes increase.

SUs in this network cooperated in sensing and sharing of the spectral map to reduce interferences with PUs. To ensure reliability and accuracy, a rule was set to allow only SUs with higher SNR to share their sensed results. A major focus of this study was on minimizing delays especially in finding available channels. Hence OR aggregate rule was used to combine sensed results as it is known from literature to aggregate data faster than other aggregation rules.

We proposed a scheme called EXGPCSA which is an extension of generalized predictive CSA. Generalised predictive CSA outperformed most of the other schemes in literature; hence we found it important to conduct performance comparison of this scheme with EXGPCSA. The techniques used for channel sensing and selection in generalized predictive CSA have given it upper hand over other CSA schemes. Using that to our advantage, we have gone a little further to optimize generalized predictive CSA by modifying how channels are sensed and selected.

Two schemes were evaluated in different network scenarios using the following performance metrics: the probability of false alarm, probability of detection, probability that a service time will be greater than time t, channel switching rate, probability of arriving in a given time window, delays in finding next available channels, individual throughput and average throughput.

The results obtained show that EXGPCSA has significantly performed better than generalised CSA. A measure of significance was done using statistical analysis tool for mean comparison, a t-test. A t-test was conducted to compare average throughputs of EXGPCSA and generalised predictive CSA in 5 different inter-sensing intervals. This test has shown that there is significant difference between two average throughputs for both schemes especially for 2ms and 10ms. A test ascertains that EXGPCSA significantly performed better that generalized predictive CSA for some sensing intervals.

EXGPCSA managed to maintain consistent performance throughout all simulation scenarios carried out in a cluster head-based CR networks. The manner in which channels were grouped and selected for sensing significantly improved the performance of EXPCSA. Carefully choosing collaborating SUs did not only prevent shadowing or hidden terminal problem but also ensured that accurate sensing results are shared amongst CR users in a network.

Collaboration and aggregation techniques were employed in this study substantially improved the detection of licensed users or PUs. It can be observed that the detection increases each time a network is scaled up. A flip side of this is the results obtained for throughput. The throughput dropped when the number of nodes in a network increased. But this is normal in wireless radio networks where factors such interferences, distance between devices, multi-path fading, the limitations of channels in the spectrum, signal characteristics, usage and load of the network, etc. affect the performance of the network. In the presence of some of this wireless network uncertainties, EXPCSA outperformed its counterpart (generalise predictive CSA) in all environments set for simulation.

6.2. Future work

The dynamic nature of cognitive radio ad hoc network makes it difficult to design spectrum sensing algorithm that can effectively exploit spectral opportunities. Our study has put some constraints on the mobility of SUs in a network especially fusion node. We made an assumption that fusion node does not move or moves slowly during the simulations such that it will always be within communication range of other SUs. This is not possible in the actual deployment of cognitive radio devices. In future, this issue needs to be taken into consideration and factor in the mobility of SUs in the cognitive radio environment.

Most studies in literature focused on centralized collaborative spectrum sensing algorithms to mitigate interference between PUs and SUs and resolve hidden terminal problems experienced in individual sensing. But in CR network, communication devices do not always belong to a single service provider and as a result there may be no need for central entity for decision making as these can lead to an increased network complexity and communication overhead.

Our study mimics centralized network architecture in the sense that we have N fusion nodes acting as central entity where SUs forward their observations for decision making. Unfortunately, a major challenge in such network architecture is a single point of failure. Considering all challenges mentioned above, it would be critical to have purely designed decentralized network architecture to allow SUs to dynamically sense and share sensed results or observations obtained from a wide geographic area.

Lastly, our scheme was evaluate under assumption that there were no security issues. This is unrealistic in the real CR network environment. There will always be security issues that are aimed at degrading a network performance. The behaviour of EXGPCSA will be evaluated under the presence of malicious SUs. Incorporating security features in our proposed scheme will ultimately make it to be a suitable candidate to deploy in real network environment.

6.3. Conclusion

A robust approach was taken in designing and implementing EXGPCSA in which the collaborative sensing, parallel sensing and data aggregation rules were considered. This approach is very complex in nature and required necessary techniques to achieve better performance. Hence a channel selection technique and sensing strategies were deployed to intelligently allow SUs to adapt to their environment. EXGPCSA consistently achieved better results compared to generalized predictive CSA. Statistical t-test shows that the average throughputs of two schemes are significantly different for some sensing intervals. We can therefore, conclude that EXGPCSA significantly performed way better generalized predictive CSA.

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APPENDIX A: Performing t-test on Average throughput of 30 SUs

Table 5. 1: 2 milliseconds inter-sensing interval

	EXGPCSA	*Generalized Pre. CSA*
Mean	27.77968	26.81676
Variance	3.368970842	3.962675787
Observations	30	30
Pooled Variance	3.665823314	

Hypothesized Mean Difference	0
df	58
t Stat	1.947825613
P(T<=t) one-tail	0.028140602
t Critical one-tail	1.671552762
P(T<=t) two-tail	0.056281204
t Critical two-tail	2.001717484

Table 5. 2**:** 4 milliseconds inter-sensing interval

t-Test: Two-Sample Assuming Equal Variances		
	EXGPCSA	*Generalized Pre. CSA*
Mean	23.6887	23.08324
Variance	3.625190977	3.885927
Observations	30	30
Pooled Variance	3.755558942	
Hypothesized Mean Difference	0	
df	58	
t Stat	1.210023472	
P(T<=t) one-tail	0.115589222	
t Critical one-tail	1.671552762	
P(T<=t) two-tail	0.231178444	
t Critical two-tail	2.001717484	

Table 5. 3: 10 milliseconds inter-sensing interval

t-Test: Two-Sample Assuming Equal Variances		
	EXGPCSA	*Generalized Pre. CSA*
Mean	20.9198	20.14164
Variance	3.210094854	3.257137
Observations	30	30
Pooled Variance	3.233616012	
Hypothesized Mean Difference	0	

df	58
t Stat	1.675985701
P(T<=t) one-tail	0.049562091
t Critical one-tail	1.671552762
P(T<=t) two-tail	0.099124182
t Critical two-tail	2.001717484

Table 5. 4: 14 milliseconds inter-sensing interval

t-Test: Two-Sample Assuming Equal Variances		
	EXGPCSA	*Generalized Pre. CSA*
Mean	17.86352	17.48408
Variance	2.271642519	1.739302198
Observations	30	30
Pooled Variance	2.005472358	
Hypothesized Mean Difference	0	
df	58	
t Stat	1.037720511	
P(T<=t) one-tail	0.151853609	
t Critical one-tail	1.671552762	
P(T<=t) two-tail	0.303707219	
t Critical two-tail	2.001717484	

Table 5. 5**:** 18 milliseconds inter-sensing interval

t-Test: Two-Sample Assuming Equal Variances		
	EXGPCSA	*Generalized Pre. CSA*
Mean	16.84432	16.4175
Variance	1.692218108	0.813737952
Observations	30	30
Pooled Variance	1.25297803	
Hypothesized Mean Difference	0	
df	58	
t Stat	1.476789728	
P(T<=t) one-tail	0.072570675	
t Critical one-tail	1.671552762	
P(T<=t) two-tail	0.145141349	
t Critical two-tail	2.001717484	