EFFECTIVE APPROACHES FOR SPECTRUM SENSING AND OCCUPANCY ANALYSIS FOR COGNITIVE RADIO NETWORKS

A THESIS

submitted by

JAISON JACOB

for the award of the degree

of

DOCTOR OF PHILOSOPHY

COCHIN UNIVERSITY OF SCIENCE AND TECHNOLOGY

DIVISION OF ELECTRONICS

School of Engineering

Cochin University of Science and Technology.

January 2017

THESIS CERTIFICATE

This is to certify that the thesis entitled "**EFFECTIVE APPROACHES FOR SPECTRUM SENSING AND OCCUPANCY ANALYSIS FOR COGNITIVE RADIO NETWORKS**" submitted by **Jaison Jacob** to the Cochin University of Science and Technology, Kochi for the award of the degree of Doctor of Philosophy is a bonafide record of research work carried out by him under my supervision and guidance at the Division of Electronics Engineering, School of Engineering, Cochin University of Science and Technology. The contents of this thesis, in full or in parts, have not been submitted to any other University or Institute for the award of any degree or diploma.

I further certify that the corrections and modifications suggested by the audience during the pre-synopsis seminar and recommended by the doctoral committee of Jaison Jacob are incorporated in the thesis.

Dr. Babita R. Jose
Research Guide
Assistant Professor
Division of Electronics, SOE
CUSAT, 682 022

Place: Kalamassery
Date:

DECLARATION

I hereby declare that the work presented in the thesis entitled **"EFFECTIVE APPROACHES FOR SPECTRUM SENSING AND OCCUPANCY ANALYSIS FOR COGNITIVE RADIO NETWORKS"** is based on the original research work carried out by me under the supervision and guidance of Dr. BABITA ROSLIND JOSE, Assistant Professor, for the award of degree of Doctor of Philosophy with Cochin University of Science and Technology. I further declare that the contents of this thesis in full or in parts have not been submitted to any other University or Institute for the award of any degree or diploma.

Place: Kalamassery
Date:

Jaison Jacob

ACKNOWLEDGEMENTS

I thank **Almighty** God for giving me the will power and healthy mind in the successful completion of the report.

I place on record my sincere gratitude to my research guide **Dr. Babita Roslind Jose**, Assistant Professor, Division of Electronics, School of Engineering, Cochin University of Science and Technology, for her understanding, patience, advice, guidance and timely help for the completion of this report.

I express my sincere thanks to **Dr. Binu Paul**, Associate Professor & Head of the Department, Division of Electronics, School of Engineering, Cochin University of Science and Technology, for her valuable help and encouragement.

Last but not the least, I am also grateful to my family, all my friends and colleagues for their help and support for preparing the report.

Jaison Jacob

ABSTRACT

Spectrum scarcity is a major issue in an era of ever increasing usage of wireless communication systems. A part of this spectrum scarcity can be attributed to the inefficient spectrum usage among the licensed users. Cognitive radio (CR) is proposed as a solution to the problem of inefficient usage of spectrum. As CR can coexist with the existing licensed primary users, efficient protocols are required for spectrum sensing and allocation of unused spectrum among the secondary users. As can be seen in contemporary literature, for CR to be efficacious a spectrum sensing methodology that overcomes challenges such as fading, shadowing and hidden node problems are inevitable and it is here that cooperative spectrum sensing has a major role to play.

This thesis has initially proposed decision fusion approaches for distributed spectrum sensing. An adaptive weighted combining approach with antenna selection and multiple region encoding has been evolved through various stages of refinement on fusion rules viz. fuzzy rule, SNR rule and intelligent rule. The performance of the rule at various stages and over various parameters are carried out and the performance is compared with other prominent fusion rules in the literature.

In the following sections, a decision fusion approach for external sensing is proposed. 'Cellular automata' has been employed here for developing fusion rules that performs decision fusion as well as to obtain the coverage area of Primary users (PU). Analysis and performance comparison of this approach is carried out and presented.

A comprehensive, prediction based spectrum sensing approach is also proposed to improve the throughput of the system. It consists of a predictor that takes the 'present' and 'prior' information to predict the probability of any channel to be idle. Predictor can generate a rank list of suitable channels for future spectrum sensing. CR will sense only those channels with higher ranking and the final decision will be made with the help of suitable fusion rules. Detailed analysis was carried out and the performance is compared with similar predictors available in literature.

In order to analyse the proposed prediction scheme on real data, a spectrum occupancy measurement was then carried out and the analysis of measured data has been presented. On analysing the spectrum holes, it can be inferred that CRs with different complexity can exist for different types of spectrum holes. In other words, a low end CR device can work in slowly varying spectrum holes and a high end device with multiple protocols can adapt to any type of spectrum holes.

KEYWORDS: Cognitive radio; Spectrum sensing; Cooperative spectrum sensing; Distributed sensing; External sensing; Prediction based spectrum sensing; Decision fusion; Spectrum occupancy; Cellular automata; Bayesian inference; Antenna selection; Energy detection; Rayleigh fading.

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ABBREVIATIONS

UWB	Ultra Wide Band
CR	Cognitive Radio
RF	Radio Frequency
PU	Primary Users
SU	Secondary User
SH	Spectrum Hole
CRN	Cognitive Radio Network
AWC	Adaptive Weighted Combining
SOLC	Soft Optimum Linear Combining
WSN	Wireless Sensor Nodes
GSM	Global System for Mobile
QoS	Quality of Service
AWGN	Additive White Gaussian Noise
AIC	Akaike's Information Criterion
MDL	Minimum Description Length
LRT	Likelihood Ratio Test
ED	Energy Detection
iid	Independent and Identically Distributed
ADC	Analog to Digital Converter
CSS	Cooperative Spectrum Sensing
MRC	Maximum Ratio Combining
SLC	Square Law Combining
SC	Selection Combining
LQ	Linear-Quadratic
MLP	Multi Layer Perceptron
BP	Back Propagation
EWMA	Exponential Weighted Moving Average
DSA	Dynamic Spectrum Access

HMM	Hidden Markov Model
SNR	Signal to Noise Ratio
SEWLC	Soft Equal Weight Linear Combining
FN	Fusion Node
PSD	Power Spectral Density
FC	Fusion Centre
BS	Base Station
WRAN	Wireless Regional Area Networks
CPE	Customer Premise Equipments
PMP	Point-to-Multi-Point
ROC	Receiver Operating Characteristics
BPSK	Binary Phase-Shift-Keying
CA	Cellular Automata
CN	Central Node
DDA	Distributed Detection Algorithm
DFR	Decision/Data Fusion Rules
PDF	Probability Density Function
MAP	Maximum A Posteriori
GA	Genetic Algorithm
CSI	Channel State Information
CCC	Common Control Channel
DoS	Denial of Service
SDR	Software Defined Radio
BF	Beacon Falsification
SEMP	Sensing Effectiveness Maximization Problem
SCAS	Sensing Channel Assignment for Spectrum Sensing
MMP	Min-Miss-detection-Probability
MFP	Min-False-alarm-Probability
AB	Auto-Balance
NE	Nash Equilibrium
ANFIZ	Adaptive Neuro-Fuzzy Inference Systems
MU-OFDM	Multi User Orthogonal Frequency Division Multiplexing
IFC	Interference Channel

MDP	Markov Decision Process
SA	Sub-carriers Allocation
PSO	Particle Swarm Optimisation
PUEA	Primary User Emulation Attacks
SSDF	Spectrum Sensing Data Falsification
WSSN	Wireless Spectrum Sensor Networks
FFT	Fast Fourier Transform

CHAPTER 1

INTRODUCTION

Wireless communications has emerged as one of the largest sectors of the telecommunications industry evolving from a niche business in the last decade to one of the most promising areas for growth in the 21^{st} century (Rappaport *et al.*, 2002). The increasing demand for wireless communication in consumer electronic applications and personal high-data-rate networks indicate a promising commercial potential. Throughput, reliability, service quality and the ever-present availability of wireless services are more and more demanded. The number of devices based on multiple wireless standards and technologies will therefore substantially grow in the future. Not only exciting progress but also new problems will be created with these increasingly widespread wireless communications (Berlemann and Mangold, 2009). Today, availability of spectrum is limited as it is restricted by a radio regulatory regime that emerged over the last one hundred years. Open access to most of the radio spectrum is only permitted with very low transmission powers, in a so-called underlay sharing approach such as ultra wide band (UWB) (Berlemann and Mangold, 2009). Unlicensed spectrum is a small fraction of the entire radio spectrum. Measurement campaigns in various parts of the world have supported the observation that static spectrum access leads to some portions of the spectrum to be overcrowded while some other portions to be underutilised (Patil *et al.*, 2011*a*). Dynamic spectrum access is proposed as a solution to improve the spectrum utilisation. Dynamic spectrum access refers to the time-varying, flexible usage of parts of the radio spectrum subject to regulatory and technical restrictions. Implementation of cognitive capabilities on a software-defined radio will be capable of tapping the potential of dynamic spectrum access (Berlemann and Mangold, 2009).

The term ‘Cognitive Radio’ was initially proposed by Mitolla (Mitola and Maguire, 1999) as “A radio that employs model based reasoning to achieve a specified level of competence in radio-related domains”. Simon Haykin (Haykin, 2005) defines a cognitive radio as “An intelligent wireless communication system that is aware of its surrounding environment (i.e., outside world) and uses the methodology of understanding-by-building to learn from the environment and adapt its internal states to statistical variations in the incoming radio frequency (RF) stimuli by making the corresponding changes in certain operating parameters (e.g., transmit-power, carrier frequency, and modulation strategy) in real-time, with two primary objectives in mind: 1. Highly reliable communications whenever and wherever needed 2. Efficient utilisation of the radio spectrum".

1.1 Motivation

Since most of the spectrum is allocated to various PUs, upcoming services may have to utilise the already allocated spectrum along with unlicensed spectrum in a dynamic manner. Licensed spectrum will be available only when the PU is not occupying the channel. A user that tries to access the spectrum opportunistically is called as secondary user (SU). CRs are the devices employed by an SU. The opportunity in spectrum space is called as spectrum hole (SH). CRs will have to monitor the vacancy in spectrum occupancy across frequency, time, geographical space, code and phase. This is possible only with the help of proper spectrum sensing approaches. Spectrum sensing is the ability to measure, sense and be aware of the parameters related to the radio channel characteristics, availability of spectrum and transmit power, interference and noise, radio's operating environment, user requirements and applications, available networks (infrastructures) and nodes, local policies and other operating restrictions. It is done across Frequency, Time, Geographical Space, Code and Phase (Yucek and Arslan, 2009). A CR is considered as a flexible device that dynamically access the spectrum. The first requirement of a CR is to sense the spectrum hole in the spectrum space. In the case of single node sensing, inaccuracies in detection can be caused by propagation effects such as fading (either fast fading due to multi-path effects, or slow fading due to propagation path blockage or shadowing) and shadowing. Another problem is that of the hidden terminal; this is being defined as an undetectable terminal that will suffer as the result of any interference from the cognitive system.

Cooperative spectrum sensing is proposed in literatures as a solution to issues that arise in spectrum sensing due to noise, fading, shadowing and hidden terminals (Yucek and Arslan, 2009; Harrold *et al.*, 2008). Here the neighbouring CR nodes collaborate to make a more accurate decision on the spectrum opportunity. Each CR node makes their own spectrum sensing and the result is shared among its neighbours. Final decision will be made by each CR by using suitable fusion rules. All the nodes in the field undergo random shadowing and fading. Hence the coverage area of a PU may have random variations at the boundaries. Also some of the PU may be mobile in nature and hence the position of the PU need not be fixed always. That means the CR nodes and their neighbours need not be under the coverage area of a PU always. There will be random variations in scenario. A decision fusion rule needs to accommodate such changes so that the cooperative decision will be correct. A CR device has to sense a large range of spectrum to find the proper spectrum hole. It can reduce the spectrum sensing task if it can predict the probability of occupancy of a channel by a PU. Those channels with higher probability of occupancy may be omitted from spectrum sensing task. This will improve the throughput of the system. It is always helpful for a CR to have the general knowledge about the spectrum occupancy status in its geographical area. This information can be used as a prior for prediction purposes. This dissertation proposes schemes that help to improve the throughput of the cognitive radio network (CRN) through efficient decision fusion approaches for various network scenarios and prediction based spectrum sensing approaches. In this thesis, we focus more on to distributed sensing and external sensing schemes under cooperative sensing. We have proposed an adaptive weighted combining (AWC) rule for decision fusion under distributed sensing. It is able to adapt to the changes in scenarios occurred due to a CRs position in the field with respect to primary transmitters. It has been evolved through various stages of modifications and analysis. This rule out performs other rules such as soft optimum linear combining (SOLC) and fuzzy based approaches. We have also proposed a cellular automata (CA) rule for external sensing scenario where an external entity aggregate the sensing results of wireless sensor nodes (WSN) deployed in the field. This entity also aims at forming the coverage area of a PU within a large area.

Since prediction based spectrum sensing will reduce the spectrum sensing efforts to a large extent, we have proposed a spectrum prediction approach using Bayesian Inference. It uses recent sensing results along with history of the spectrum occupancy (prior) to make the prediction. In order to obtain real data as spectrum occupancy history, we have also conducted a spectrum measurement over the frequency range 50 MHz - 4.4 GHz and its utilisation is analysed. Low computation complexity of proposed fusion rules, prediction approaches and properties of CA and its massive parallelism of information processing, will make these approaches a favourite choice for low power VLSI implementation of Decision fusion blocks in their respective sensing scenarios of cognitive radio.

1.2 Author's Contributions

This thesis commences with an overview of the related research in the field of spectrum sensing for cognitive radio and discusses the relevance of this research in the light of the cited previous research works. The primary technical contribution of this thesis is in developing and analysing fusion rules for decision fusion in CSS, particularly in the network categories such as distributed sensing and external sensing. The research then progresses to suggest a comprehensive CSS framework which is based on prediction based sensing. A Bayesian inference approach for spectrum-hole prediction is also proposed and analysed. A spectrum occupancy measurement and analysis is then carried out to validate the performance of the Bayesian predictor on real data. This is followed by few suggestions for future work. The main contributions and the papers on which these are based are listed below. ['**C**' represents International conferences and '**J**' represents lists in International Journals]

C1. Jaison Jacob, Babita R. Jose, J. Mathew, "A Fuzzy Approach to Decision Fusion in Cognitive Radio" International Conference on Information and Communication Technologies (ICICT 2014), CUSAT , Kochi. India. December 2014. pp. 425-431.

Author's contribution: A fuzzy rule for decision fusion is proposed for distributed sensing under cooperative sensing. As signal-to-noise ratio (SNR) of the CR is a key parameter that reflects the strength of the signal, SNR and signal strengths of the neighbours are used as the inputs of the fusion rule. Testing and analysis of this rule was carried out using energy detection under Rayleigh fading channel. The effectiveness of the proposed rule was compared with classical fusion rules such as 'AND' & 'OR' rules. Comparison of both Probability of detection (P_d) and Probability of false alarm (P_f) vis-a-vis SNR was carried out. The 'time consumed' for a decision fusion was reckoned as the computational overhead for this rule. Even though the detection performance was very good, time consumption of fuzzy rule was quite high. The author formulated appropriate theory, did the simulations, wrote the manuscript and presented the findings and inferences in the conference (C1).

C2. Jaison Jacob, Babita R. Jose, "Performance Evaluation of a Cooperative Spectrum Sensing Algorithm for Cognitive Radio " Proceedings of International Workshop on Embedded Computing & Communication Systems (IWECC-11), Kochi, December 2011, pp. 18-22.

Author's contribution: Fuzzy rule is quite time consuming and to overcome this limitation, we propose a new fusion rule for distributed sensing (under cooperative sensing) based on weighted combining methodology. Apart from SNR, self-weighting factor and positive weighting factor were also included in the weighted combining. The performance of the rule was analysed under shadowing using the 'path loss' model. Various scenarios of channel conditions such as rural, urban and dense urban were considered for the analysis. Effect on the 'probability of detection' on account of each of the likely dependencies viz. the number of sharing nodes, varying environmental parameters, self-weighting factor, positive weighting factor, receiver density etc. were analysed. Best possible weighting factors that gave the right decision was then assessed and estimated. The author formulated appropriate theory, did the simulations, wrote the manuscript and presented in a conference (C2).

J1. Jaison Jacob, Babita R Jose, J. Mathew, "Fusion Rule for Cooperative Spectrum Sensing in Cognitive Radio" Journal of Circuits, Systems & Signal Processing (CSSP), Springer , on line: Dec. 2015, Print: September 2016, Vol. 35, Issue 9, pp. 3418 - 3430, (Indexed in Science Citation Index Expanded (SCIE), Impact factor 1.178).

Author's contribution: In literature, it was widely considered that all the CRs are located within the coverage area of a PU under consideration. However, it was felt that decision fusion at the boundaries of the coverage area of a PU also needs to be reckoned. Therefore, a new scenario was considered for analysis and an AWC approach was proposed to handle such a scenario. Here the weights would be adapted based on the location of the CRs with respect to the Primary Transmitter. A fusion rule that considers the location of the nodes with respect to a PU was proposed here. Performance of this rule (named as 'Intelligent rule') was analysed using energy detection model under Rayleigh fading as well as path loss model under shadowing. Its performance was also compared with other rules. The author formulated appropriate theory, did the simulations, wrote the manuscript and published in a journal (J1).

J2. Jaison Jacob, Babita R Jose, J. Mathew, "An Antenna Selection Scheme with MRE and AWC for Decision Fusion in Cognitive Radio ", Transactions on Emerging Telecommunications Technologies (ETT), John Wiley & Sons Ltd, 2017. (Indexed in Science Citation Index Expanded (SCIE), Impact Factor: 1.295).

Author's contribution: In order to make the decision rule more efficacious, the adaptive weighted combining approach was enriched with an antenna selection approach (with multiple regions encoding scheme). The performance of this rule was then contrasted with other optimal rules and HDC rules in related literature. Four plots were analysed, viz. P_f versus P_d, P_f versus P_m, P_d versus 'N' (N - no. of neighbouring nodes) and computational complexity. On analysing the result of spectrum sensing, this enriched approach was observed to have given a better performance compared to the other rules. The author formulated appropriate theory, did the simulations, wrote the manuscript and published in a journal (J2).

C3. Jaison Jacob, Babita R. Jose, "Cellular Automata Approach for Spectrum Sensing in Energy Efficient Sensor Network Aided Cognitive Radio", Proceedings of International Conference on Eco-friendly Computing and Communication Systems (ICECCS-2012), Kochi, August 2012 , pp. 54-61

J3. Jaison Jacob, Babita R. Jose, J. Mathew, " Cellular Automata Approach for a Low Power Fusion Center to Evaluate Spectrum Status and Coverage Area in Cognitive Radios", Journal of Low Power Electronics, October, 2013; Volume 9, Issue 3, pp. 332-339, American Scientific Publishers, (Impact factor 0.485).

Author's contribution: In external sensing, an external agent performs the sensing and broadcasts the channel occupancy information of PUs to SUs. Sensors deployed in the field perform sensing and transfer the information to the central server and decision is taken at the server. These papers have proposed CA based approaches for decision fusion. CA is a discrete model used in wide variety of applications. CA based architectures have already proved its utility in the low power and high speed VLSI designs. Proposed CA schemes are able to form the coverage area of a PU through decision fusion. It was analysed using path loss model and its performance was compared with fuzzy based methods and weighted combining methods. Performance on coverage area formation, probability of detection (P_d), false alarm rate and computational cost were analysed. Proposed approaches were performing well in comparison with other methods. The author formulated appropriate theory, did the simulations, and wrote the manuscript. The concise version is presented in the conference (C3) and extended version is published in the journal (J3).

C4. Jaison Jacob, Babita R Jose, J. Mathew, "Spectrum Prediction in Cognitive Radio Networks: A Bayesian Approach", 8th International Conference on Next Generation Mobile Apps, Services and Technologies (NGMAST-2014), Oxford, UK, September 2014, pp. 203-208.

J4. Jaison Jacob, Babita R Jose, J. Mathew, "Bayesian Analysis of spectrum occupancy prediction in Cognitive Radio", Int. Journal, Smart Science, May 2016, Volume 4, Issue 2, pp. 52-61 Taylor & Francis publication. (Indexed in the Emerging Sources Citation Index.)

Author's contribution: In order to save sensing time, a spectrum sensing approach that rules out certain channels from the sensing exercise and reckons some other channels in the sensing exercise is proposed. Such an exclusion or inclusion of channels from the scope viz. skipping a channel from sensing if there is a higher probability for a channel to be busy and looking out for channels with less chance of being busy is based on empirical evidence and observed trends. Following such an approach, if spectrum sensing is limited to only those channels which are having higher probability of being idle, CR can save lot of time in sensing activity and more time can be spent on utilising that channel. In this thesis, a prediction based spectrum sensing approach for CR systems is proposed to improve the throughput of the system. It consists of a predictor that takes the 'present' and 'prior' information to predict the probability of any channel to be idle. Predictor can generate a rank list of suitable channels for future spectrum sensing. Two approaches based on Bayesian inference are proposed to predict the future probability. Analysis of the predicted probability by both the methods were carried out. Channel ranking was formed based on these methods and they were compared with other prediction approaches such as EWMA, HMM and Neural Network. On analysis it was found that the amount of data required under 'prior' and 'present' was relatively low for the Bayesian approaches. These analysis and comparisons were done on both synthetic as well as real data. Real data was obtained through spectrum measurement. The author formulated appropriate theory, did the simulations, and wrote the manuscript. The concise version was presented in the conference (C4) and extended version was published in the journal (J4).

C5. Jaison Jacob, Babita R Jose, "Spectrum Occupancy Measurement and Analysis in Kochi-India from a Cognitive Radio Perspective", 6th International Symposium on Embedded computing & system Design (ISED), December 2016, Patna.

Author's contribution: In order to analyse the performance of the predictors, a spectrum occupancy measurement in the 50 MHz to 4400 MHz range was carried out and its analysis was also done. Spectrum hole patterns from the spectrum occupancy measurement were used for analysing the predictors. Analysis on spectrum occupancy, hourly utilisation, received energy levels etc. were carried out. On analysing the spectrum occupancy, it was found that Global System for Mobile (GSM) downlink channels were heavily utilised and others were lightly utilised. On analysing the spectrum holes, it could be inferred that CRs with different complexity could work in different types of spectrum holes. It could also be inferred that high end devices with multiple protocols could adapt to any types of spectrum holes with ease. At the same time, there is a possibility that a low end CR device specific to the type of spectrum hole can exist and perform. The author prepared the measurement set up, did the data collection and analysis, wrote the manuscript and submitted in a conference (C5).

1.3 Thesis Outline

Chapter 1 presents the introduction, motivation and author's contribution.

Chapter 2 illustrates the background concepts related to this thesis. Present allocation and usage of radio spectrum today and a probable usage pattern of tomorrow are discussed. Cognitive Radio is presented as a potential device that can handle the future spectrum usage in an opportunistic manner. Spectrum sensing aspects and several methods used in this context are discussed. Spectrum sensing challenges and possible solutions under various scenarios are reviewed. Relevance of this thesis under the background mentioned is presented.

In Chapter 3, fusion rules for decision fusion in a distributed sensing scenario is proposed and analysed. A fuzzy rule is proposed initially and on observing its weakness, an SNR based weighted combining approach is proposed and analysed. A realistic scenario is suggested and an adaptive weighted combining is proposed as a modification to SNR rule to suit this scenario. Its performance has been analysed. In order to improve its performance further, an antenna selection with multiple region encoding is proposed and its performance is compared with optimal fusion rules in the literature.

In Chapter 4, a CA based fusion rule is proposed for an external sensing scenario, where an external agency take care of the spectrum sensing task and share the result with the CRs in the field. It will also provide the coverage area of a PU. Its performance is analysed and compared with other fusion rules as well. Considering the properties of CA and its massive parallelism of information processing will make it a favourite choice for low power VLSI implementation of Decision fusion blocks for an external sensing scenario in cognitive radio.

Chapter 5 proposed a general frame work for prediction based spectrum sensing strategy for throughput enhancement in a CR system. A Bayesian approach is proposed for predicting the probability of a channel being idle during the next time slot so that a ranking of channels can be formed. This information will help the CRs to prioritize channels for spectrum sensing according to the rank of the channels. Its performance was analysed using artificial as well as real data. In order to analyse the performance of the predictors with real data a spectrum measurement was carried out and the analysis of spectrum occupancy and spectrum hole are presented here

Chapter 6 summarizes the work presented in this thesis.

CHAPTER 2

BACKGROUND AND LITERATURE REVIEW

2.1 Introduction

In future, mobile terminals will be able to communicate with various heterogeneous systems that are different by means of algorithms used to implement baseband processing and channel coding (ITU-R, 2008). As the number of wireless devices, innovative services, and mobile users continues to grow, more and more spectrum resources will be needed to guarantee desired quality of service (QoS) (ITU-R, 1994). In order to overcome the problem of spectrum scarcity and to support all the incoming services, the communication terminals need to be intelligent enough to grab the spectrum opportunities. Current research is investigating different techniques of using a new type of radio to reuse locally unused spectrum so as to increase the total system capacity. The research also aims to develop efficient algorithms to maximize the QoS for the secondary (unlicensed) users while at the same time minimizing the interference to the primary (licensed) users. Cognitive radios have been proposed as a means to implement efficient reuse of licensed spectrum. However, there are many challenges across all layers of a cognitive radio system design, right from its application to its implementation (Hayar *et al.*, 2007). A review of existing activities carried out in this direction is presented in the following sections.

2.2 Radio Spectrum Today and Tomorrow

Radio spectrum is a public resource used for a wide variety of services. Utilising radio spectrum usually means emitting electromagnetic radiation at radio frequencies (between 30 kHz and 300 GHz). Regulating radio spectrum is of great significance as it is needed for economic, societal and technological reasons (Berlemann and Mangold, 2009). Spectrum regulation will ensure smooth usage of the spectrum without any interference to the users. New frequencies need to be allocated for new services.

Video streaming over wireless networks is convincing for many applications, ranging from home entertainment to surveillance to search-and-rescue operations. Though the demand for such services is growing day by day, there is no growth in the available spectrum. On analysing the usage of the allocated spectrum, it is observed that a large portion of the frequency channels are having very limited usage. At the same time, a few channels are heavily utilised.

Dynamic spectrum access and spectrum sharing are tools that provide regulators with the flexibility needed in order to achieve a more efficient spectrum usage. Secondary users operate with a lower regulatory priority and have to defer to primary users by vacating spectrum immediately when primary users need the radio resources. Spectrum usage rights can be transferred in different ways such as lease, sale, etc. The right to access spectrum at a certain future point of time for a predefined duration can be transferred for a pre-agreed price. Underlay and overlay spectrum sharing are the two approaches proposed for spectrum sharing. Once the regulatory constraints are met, there is a need for a radio that adapts to the situation and work like a secondary user. Cognitive radio is proposed as a solution for this. It is a software defined radio with cognitive capabilities.

2.3 Cognitive Radio

The need for higher data rates is increasing as a result of the transition from voice-only communications to multimedia type applications. Given the limitations of the natural frequency spectrum, it becomes obvious that the current static frequency allocation schemes can not accommodate the requirements of an increasing number of higher data rate devices. As a result, innovative techniques that can offer new ways of exploiting the available spectrum are needed. Cognitive radio appears to be a potent solution to this spectral congestion problem as it ensures opportunistic usage of the frequency bands that are not heavily occupied by licensed users (Yucek and Arslan, 2009; Gao *et al.*, 2010). CR is formally defined by the FCC (FCC, 2002) as a radio that can change its transmitter parameters based on interaction with its environment. The ultimate objective of cognitive radio is to obtain the best available spectrum through cognitive capability and reconfigurability. Tasks required for adaptive operation are spectrum sensing,

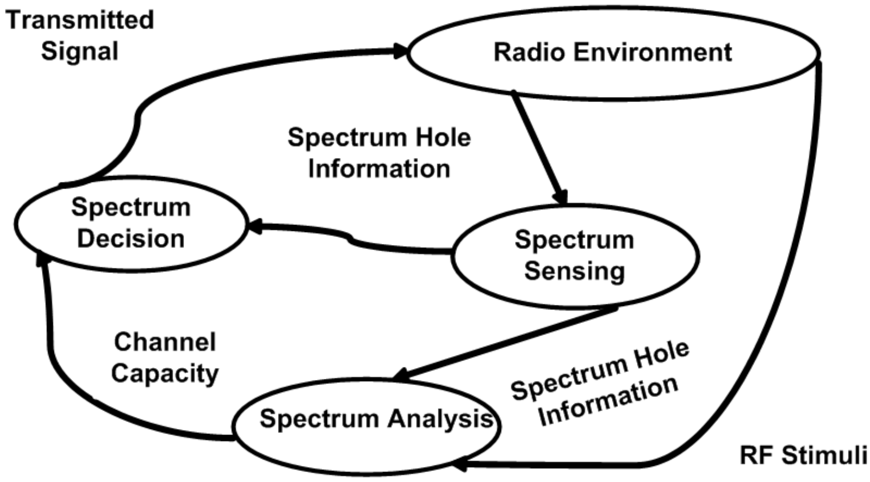


Figure 2.1: Cognitive cycle

spectrum analysis and spectrum decision (Haykin, 2005; Mitola, 2000; Akyildiz *et al.*, 2006).

One of the most important components of the cognitive radio concept is the ability to measure, sense, learn, and be aware of the parameters related to the radio channel characteristics, availability of spectrum and power, radio's operating environment, user requirements and applications, available networks (infrastructures) and nodes, local policies and other operating restrictions (Yucek and Arslan, 2009).

A basic cognitive cycle comprising of spectrum sensing, spectrum analysis and spectrum decision making is shown in Fig. 2.1. In cognitive radio terminology, primary users can be defined as the users who have higher priority or legacy rights on the usage of a specific part of the spectrum. On the other hand, secondary users which have lower priority, exploit this spectrum in such a way that they do not cause interference to primary users. Therefore, secondary users need to have cognitive radio capabilities such as sensing the spectrum reliably to check whether it is being used by a primary user and to change the radio parameters to exploit the unused part of the spectrum (Yucek and Arslan, 2009).

2.4 Spectrum Sensing

Spectrum sensing is the ability to measure, sense and be aware of the parameters related to the radio channel characteristics, availability of spectrum and transmit power, interference and noise, radio's operating environment, user requirements and applications, available networks (infrastructures) and nodes, local policies and other operating restrictions. It is done across frequency, time, geographical space, code and phase.

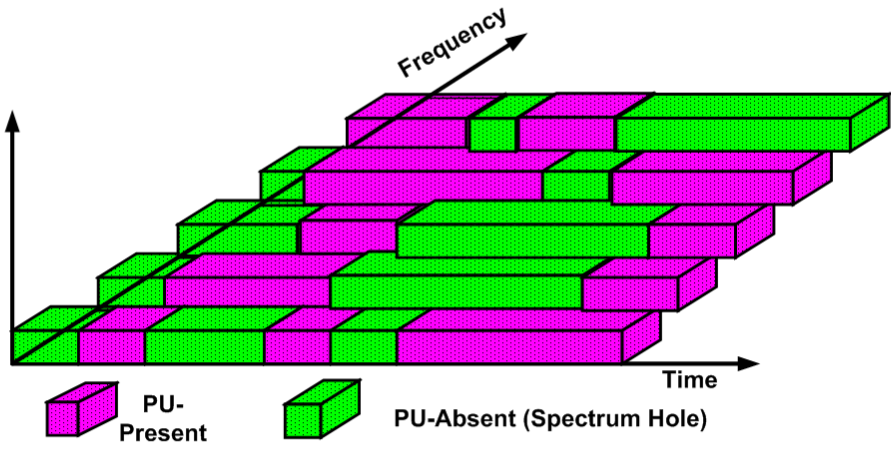


Figure 2.2: Conceptual example of opportunistic spectrum utilisation

The first requirement of a CR is to sense the spectrum hole in the spectrum space. A spectrum hole or white space is shown in Fig. 2.2. In short, the goal of spectrum sensing is to decide between two hypotheses H_0 and H_1

$$Y(t) = \begin{Bmatrix} n(t).....H_0(SpectrumHole) \\ h \times s(t).......H_1(Occupied) \end{Bmatrix} \quad (2.1)$$

where Y(t) is the complex signal received by the cognitive radio device, s(t) is the transmitted signal of the primary user, n(t) is the additive white Gaussian noise (AWGN), and 'h' is the complex gain of the ideal channel.

The biggest challenge related to spectrum sensing is to develop sensing techniques that are able to detect very weak primary user signals while at the same time being sufficiently fast and low cost to implement (Kang *et al.*, 2008; Zhang *et al.*, 2009; Hoang *et al.*, 2010). Various sensing methods proposed for spectrum sensing are based on Energy Detector, Cyclostationarity, Radio Identification, Waveform, and Matched Filtering (Yucek and Arslan, 2009). A study on the performance of energy detection algorithms for spectrum sensing in cognitive radio is presented in (Eerla, 2011). Analysis of probability of false alarm versus probability of detection, and SNR versus probability of detection are carried out. The performance of dynamic threshold on spectrum detection techniques (matched filter detection, energy detection) in cognitive radio systems are also analysed. It concludes that the detection performance can be improved by using dynamic threshold based spectrum detection algorithm in cognitive radio systems. Energy detection based on fixed threshold are sensitive to noise uncertainty. A fractional change in average noise power causes decrease in the performance quickly. When compared to a fixed threshold approach, dynamic threshold will improve the spectrum sensing performance. Matched filter is also not sensitive to noise uncertainty.

Detectors that rely on a specific structure of sample covariance matrix are presented by (Zeng and Liang, 2009*b*; Axell *et al.*, 2012). Properties of the covariance matrix are also exploited for detection by (Zeng and Liang, 2009*b*) and (Zeng and Liang, 2009*a*), without knowing the structure. Some communication signals, for example when the signal is received by multiple antennas (Bianchi *et al.*, 2011; Wang *et al.*, 2010; Taherpour *et al.*, 2010), impart a specific known structure to the covariance matrix. This property is exploited here for spectrum sensing. Detection without any knowledge of the transmitted signal is usually referred to as blind detection. Blind detectors are commonly based on information theoretic criteria, such as Akaike's information criterion (AIC) or the minimum description length (MDL) (Wax and Kailath, 1985; Wang and Tao, 2010; Chiani and Win, 2010; Haddad *et al.*, 2007). If the spectral properties of the signal to be detected are known, and the signal has otherwise no usable features that can be efficiently exploited, then spectrum estimation techniques like filter bank based detectors may be preferable (Haykin, 2005; Haykin *et al.*, 2009; Farhang-Boroujeny, 2008; Thomson, 1982). Wide band spectrum sensing is addressed with multi band sensing methods (Hossain and Champagne, 2011; Quan *et al.*, 2009; Fan *et al.*, 2011) and compressive sensing methods (Tian and Giannakis, 2007; Tian, 2008; Wang *et al.*, 2009; Zeng *et al.*, 2011). likelihood ratio test (LRT) is proposed by (Kay, 1998).

The energy detection (ED) based approach is the most common way of spectrum sensing in high SNR conditions since it does not require any priori knowledge of primary signals and has much lower computational and implementation complexity (Zeng and Liang, 2009*b*; Axell *et al.*, 2012; Zeng and Liang, 2009*a*; Bianchi *et al.*, 2011; Wang *et al.*, 2010; Taherpour *et al.*, 2010; Wax and Kailath, 1985; Wang and Tao, 2010; Chiani and Win, 2010; Haddad *et al.*, 2007; Haykin *et al.*, 2009; Farhang-Boroujeny, 2008). However, energy detection requires perfect knowledge of noise power. Wrong estimation of the noise power leads to 'SNR wall' and high probability of false alarm (Cabric *et al.*, 2006; Sahai and Cabric, 2005; Sonnenschein and Fishman, 1992; Tandra and Sahai, 2005; Shellhammer and Tandra, 2006). Due to noise uncertainty, the estimated noise power could be inaccurate. Hence sensitivity to noise uncertainty is the main drawback of energy detection method. Furthermore, while energy detection is optimal for detecting independent and identically distributed (iid) signal (Kay, 1998), it is not optimal for detecting correlated signal, which is the case for most practical applications. LRT is proved to be optimal, but in practice, it has some difficulty in implementation (Zeng and Liang, 2009*b*). It needs exact channel information and distribution of PU's signal and noise. Obtaining channel information and distribution of signal and noise, before the detection process is difficult. MF-based method requires accurate synchronization and perfect knowledge of the channel responses from the primary user to the receiver (Cabric *et al.*, 2006; Chen *et al.*, 2007). Otherwise its performance will be reduced dramatically. It can be made possible only with the cooperation of the primary users. Cyclostationary detection method needs to know the cyclic frequencies of the primary users, which may not be realistic for many of the spectrum reuse applications. Furthermore, this method demands excessive analog to digital converter (ADC) requirement and signal processing capabilities (Sahai and Cabric, 2005).

2.4.1 Spectrum Sensing Challenges

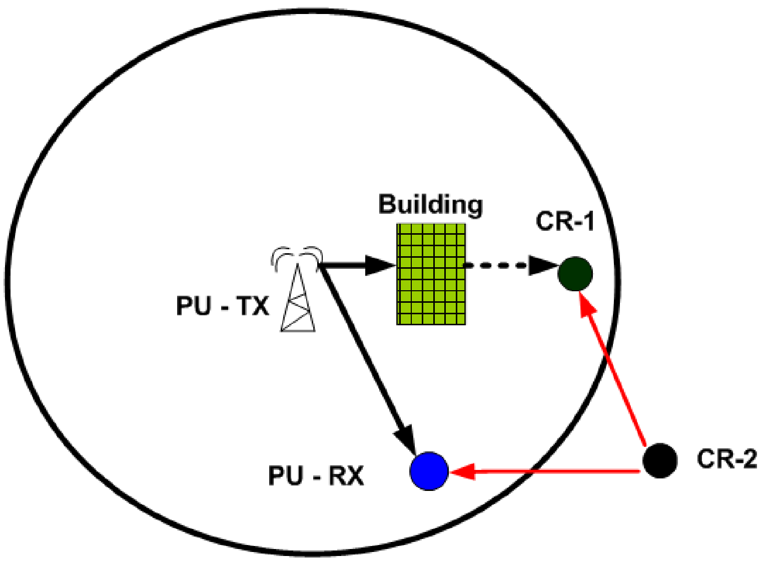


Figure 2.3: Shadowing and hidden terminal problem

In the case of single node sensing, inaccuracies in detection can be caused by propagation effects such as fading (either fast fading due to multi path effects, or slow fading due to propagation path blockage or shadowing). Another problem is that of the hidden terminal; this is defined as an undetectable terminal that will suffer as the result of any interference from the cognitive system. Fig. 2.3 shows that CR_1 is under shadowing as it is blocked by a building. CR_2 is located outside the coverage area of the PU. CR_1 and CR_2 will sense that the PU is absent and if they start communication, it is going to interfere with Primary Receiver. In other words PU_{RX} is a hidden terminal for CR_2.

2.4.2 Cooperative Spectrum Sensing

Cooperative spectrum sensing (CSS) is proposed as a solution to overcome the challenges of spectrum sensing. In this case, CRs will share their sensing result and a final decision will be taken after combining the collected information using suitable fusion rule. Activities under cooperative sensing are classified into three categories (Yucek and Arslan, 2009).

1. Centralized sensing:-A central unit collects sensing information from cognitive devices, identifies the available spectrum, and broadcasts this information to other cognitive radios or directly controls the cognitive radio traffic.
2. Distributed sensing:-Cognitive nodes share information among each other but they make their own decisions as to which part of the spectrum they can use.
3. External sensing:- An external agent performs the sensing and broadcasts the channel occupancy information to cognitive radios.

Centralized sensing is similar to the existing mobile communication systems and hence the infrastructure requirement is high. We have focused on distributed sensing and external sensing.

2.4.3 CSS in Distributed Sensing

Cooperative sensing assumes importance because of the fading and shadowing experienced by the CRs. Distributed sensing helps the CRs to form ad hoc local networks anywhere at any time based on the need. In CSS, CRs will share their sensing result and a final decision will be made after combining the collected information using a suitable fusion rule. Process of making a decision by applying a fusion rule on the collected independent decisions is called decision fusion.

Observations of a single CR are not always trustworthy because single node sensing usually gets affected with channel conditions such as noise, fading and shadowing.

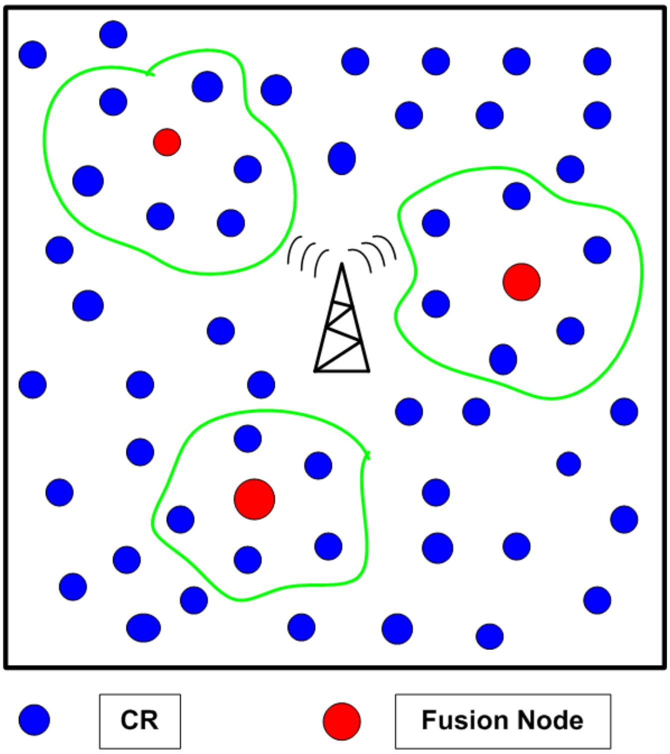


Figure 2.4: General scenario in distributed sensing

Hidden terminals may also get affected with secondary networks if the sensing is wrong. Such a situation can be overcome with cooperative spectrum sensing (Yucek and Arslan, 2009; Ejaz *et al.*, 2013). In cooperative sensing, each node shares its sensing result with its neighbours as shown in Fig. 2.4 and a final decision is made by the fusion node after decision fusion. Generally all CRs perform decision fusion similar to the three fusion nodes, as shown in Fig. 2.4. In order to reduce the sensing overhead, cluster based approaches are also proposed in literatures.

Neighbours' data can be fused using either hard decision combining or soft decision combining. 'K-out-of-M', 'AND' and 'OR' fusion rules are rules under hard decision combining. Weighted combining approach is also seen in literature. When the number of sharing nodes are large, soft decision combining is used. Maximum ratio combining (MRC), square law combining (SLC) and selection combining (SC) are some of the soft data fusion schemes proposed in literature (Han *et al.*, 2010*a*; Simon and Alouini, 2005; Sun, 2011). A weighted combining rule is proposed by (Harrold *et al.*, 2008) for decision fusion. It also considers the history of spectrum occupancy status for the decision fusion. Magnitude of the weights used in this case would be inversely proportional to the distance between a node and its neighbours. Analysis about the impact of weights on the decision fusion is also presented. A fuzzy approach that collects 2-bit decision (which indicates the linguistic variable as 'low', 'medium', or 'high') from its neighbours, to make a cooperative decision is presented in (Matinmikko *et al.*, 2009). Another fuzzy approach that collects received power from its neighbours for decision fusion is also seen in the literature (Taghavi *et al.*, 2011). Here the fuzzyfication of the received power is done during fusion. (Kyperountas *et al.*, 2010) has presented a soft linear combining along with soft optimal linear combining. A method based on a deflection criterion, named as linear-quadratic (LQ) fusion strategy is proposed by (Unnikrishnan and Veeravalli, 2008). Correlation between the nodes is considered here for fusion.

Existence of a large number of cognitive networks is highly probable in the future communication systems. However, the CSS mechanism generates a large amount of traffic overhead since each SU needs to transmit its own decision. Therefore collaboration of users needs to be refined and optimised (Arshad *et al.*, 2010; Ghasemi and Sousa, 2007). An energy efficient transmission scheme is proposed by (Xia *et al.*, 2009). Clustering technique is adopted to save energy consumed in reporting results and exchanging information. All cognitive nodes are separated into a few clusters and report local decisions to cluster heads to make cluster decisions through some data fusion method. Cluster decisions are forwarded to the common receiver to decide whether the spectrum of interest is idle or not. Simulation results demonstrate that the proposed method shows significant energy saving from 35% to 95% compared with the conventional scheme. Unlike each node do the distributed sensing in (Harrold *et al.*, 2008) only the cluster head is performing the distributed sensing. An analysis of power consumption, power consumption ratio and the delay performances are compared with respect to cluster size.

In order to decrease the average number of bits required for transmission, a censoring approach with quantization is presented in (Sun *et al.*, 2007). In quantized data fusion, received energy level is classified into various bands and hard combining is performed. (Ma *et al.*, 2008) proposed an optimal soft combining and its performance is compared with softened 2-bit hard combining and quantized data fusion. A genetic algorithm based weighted optimization strategy is proposed by (Arshad *et al.*, 2010) for soft decision combining.

A theorem to reveal the optimum threshold for general data fusion rules(DFR) is given by (Han *et al.*, 2010*b*). Then three novel DFRs and related three algorithms are proposed to efficiently obtain the optimum decision threshold for different objectives. It is shown through simulations that the proposed DFRs have improved the performance of the system. Following rules named min-false-alarm-probability (MFP) rule, min-miss-detection-probability (MMP) rule and auto-balance (AB) rule are defined and analysis of various parameters are being carried out to obtain optimum decision threshold. The final numerical results confirm the evident improvement on related optimization objective by proposed DFRs.

Multiple antennas based spectrum sensing approaches are proposed by (Taherpour *et al.*, 2010; Singh *et al.*, 2012) and these approaches showed that by using multiple antennas at the CRs, it is possible to significantly improve reliability of spectrum sensing with extremely low interference levels to the PU and very low (much less than 0 dB) signal-to-noise ratio of the PU-CR link. A multiple antennas assisted blind spectrum sensing method is proposed by (Shen *et al.*, 2012), that does not need any information of primary user and the noise power.

Double threshold methods in energy detector to perform spectrum sensing are presented in (J. Zhu and Zhang, 2008; Bagwari and Tomar, 2014; Jiang *et al.*, 2013). Its analysis were done in AWGN channel and has shown significant improvement in detection performance. All the above approaches assume that these nodes are located within the coverage area of the PU. A realistic scenario may have nodes located outside the coverage area also.

2.4.4 CSS in External Sensing

Another technique for obtaining spectrum information is external sensing. In external sensing, an external agent performs the sensing and broadcasts the channel occupancy information to SUs (Yucek and Arslan, 2009). Spectrum sensing mechanism is deployed in the field to sense the spectrum continuously and the results are communicated to a CN that processes the information and makes a decision on the spectrum holes. This system will help to have relatively simple and low power design for CR terminals with an extended battery life. In external sensing, a central controller manages the spectrum sensing through its sensor network. Various types of spectrum sensing schemes are reported in (Yucek and Arslan, 2009). In (Visotsky *et al.*, 2005), sensing results are combined in a central node for detecting TV channels. Hard and soft information combining methods are used for reducing the probability of missed opportunity. In (Lundén *et al.*, 2007), users send a quantized version of their local decisions to central unit (fusion center). Then, a likelihood ratio test over the received local decisions is applied. Bandwidth requirement for reporting will be high in the case of a large number of users. In order to reduce the sharing bandwidth, local observations of cognitive radios are quantized to one bit (hard decision) in (Sun *et al.*, 2007). Architecture with sensor network is proposed by (Cordeiro *et al.*, 2005*b*). In (Harrold *et al.*, 2008), decision is formed based on the result of a weighted summation of the neighbouring node's results. It includes several weighting factors such as weighting according to distance to neighbouring nodes, increased influence of positive results and increased influence of a node's own result. It considers the results of previous time instants also. Analysis of this is done with respect to the number of neighbouring nodes considered and the weights assigned to neighbour's results.

This thesis has proposed a CA based approach for decision fusion in external sensing. Application of CA in decision fusion is seldom found in the literature, but it is used in a variety of applications. Theory of cellular automata with regular configuration and its application is discussed in (Cattell *et al.*, 1999). Application of CA in image processing is demonstrated in (Rosin, 2006). Its application into VLSI implementation is discussed in (Corno *et al.*, 2000; Chuanwu and Libin, 2005; Bhattacharjee *et al.*, 1996; Tsalides *et al.*, 1991). VLSI implementation of a test pattern generator based on CA is proposed in (Corno *et al.*, 2000) and it yields 34$\%$ reduction in power consumption without affecting the fault coverage. Pseudo-random sequence generators using cellular automata and LFSR are implemented on a CPLD and its performance is compared in (Chuanwu and Libin, 2005; Tsalides *et al.*, 1991). It has shown that the locality of signal path of cellular automata contributes higher speed than the LFSR. VLSI architecture for cellular automata based parallel data compression is given in (Bhattacharjee *et al.*, 1996). The experimental results confirm its superiority in terms of compression ratio over UNIX Compress and GZIP packages.

In literature (Yucek and Arslan, 2009; Harrold *et al.*, 2008; Han *et al.*, 2010*a*), it is seen that the fusion rules employed for decision fusion in external sensing are same as that of distributed spectrum sensing. However the spectrum holes in a geographical area is not assessed for analysis. Coverage area of a PU is an important factor when we consider a heterogeneous system with a larger geographical area. This thesis has made an attempt to obtain coverage area and spectrum holes in both time and geographical space in an external sensing scenario.

2.4.5 Prediction-based Spectrum Sensing

Various methods are proposed in the literature to sense the spectrum hole. A CR user develops a spectrum pool consisting of all the spectrum holes in a range of frequencies and chooses the optimum one for its future usage. Channel capacity can be increased using proper spectrum sharing policy. CR users are supposed to operate within very small time slots for both spectrum sensing and for communicating with other users. Spectrum sensing, spectrum decision and spectrum sharing will lead to considerable time delays. If it takes more time for these activities then the time available for data communication will be less and the throughput of the system will also come down. Spectrum prediction will be an alternate approach to save sensing time. If there is a higher probability for the channel to be busy, CR can skip that channel for sensing purpose. It can look for channels with less chance of being busy for spectrum sensing. Prediction methods are used to predict the usage behaviour of a frequency-band based on channel usage patterns of PU so that a CR can decide whether or not to move to another frequency band. Spectrum prediction in CR networks is a challenging problem that involves several sub topics such as channel status prediction, PU activity prediction, radio environment prediction and transmission rate prediction (Xing *et al.*, 2013). Prediction-based spectrum sensing, (Akbar and Tranter, 2007) prediction-based spectrum decision, and prediction-based spectrum mobility (Tumuluru *et al.*, 2012) have been presented in the literature. Several prediction methods also have been proposed in literature. Predicting the duration of spectrum holes of PU using hidden Markov model (HMM) is proposed in (Tumuluru *et al.*, 2012). The authors have assumed that the channel state occupancy of primary users are to be Poisson distributed and based on the prediction, a CR can continue to use a channel or can be relinquished. A linear filter model followed by a sigmoid transform is used by (Jianli *et al.*, 2011) for spectrum prediction where spectrum occupancy is characterized as binary time series. The authors have considered two types of spectrum occupancy schemes, viz. deterministic and non-deterministic. These models have been used to provide predicted information to SU's 'next-step decision'. Multilayer perceptron (MLP) based approaches for spectrum prediction are presented in (Chen *et al.*, 2011; Griffiths *et al.*, 2008). The parameters of the MLP predictor are updated using back propagation (BP) algorithm. Exponential weighted moving average (EWMA) approach is proposed in (Shi *et al.*, 2008). Here it uses the previous status of spectrum occupancy to predict the probability of the next state. A modified HMM method for channel state prediction is proposed in (Akbar and Tranter, 2007) and its performance is compared with 1-NN approach. Implementation of hidden Markov model (HMM) spectrum prediction algorithm is presented in (Black *et al.*, 2012) with some analysis. Beta distribution is considered by (Marshall, 2008) to represent the channel occupancy pattern of PU and it is validated by (Ghosh *et al.*, 2010).

Spectrum Occupancy Analysis

Prior information on the spectrum occupancy status is a very useful data for prediction based-spectrum sensing. Also a proper understanding of current spectrum usage can be extremely useful, not only to the research community in order to develop spectrum usage models, but also to policy makers in order to define adequate Dynamic Spectrum Access (DSA) policies for improving the exploitation of the currently underutilised spectral resources (Martian *et al.*, 2010*b*). In order to determine the spectrum utilisation, several spectrum measurement campaigns covering wide frequency ranges as well as some specific licensed bands have already been performed in many countries under diverse locations and scenarios (Martian *et al.*, 2010*b*; López-Benítez and Casadevall, 2010; McHenry *et al.*, 2006; Wellens *et al.*, 2007; Islam *et al.*, 2008; Martian *et al.*, 2010*a*; Patil *et al.*, 2011*b*; Jayavalan *et al.*, 2014; Marţian *et al.*, 2010; Naik *et al.*, 2014; López Benítez and Casadevall Palacio, 2010). Analysis of spectrum occupancy in various dimensions is also being carried out. Measurements of the radio environment can provide valuable insights into current spectrum usage. This information will be very useful for dynamic allocation of frequencies for future communication systems. Prior knowledge on the usage pattern of PU will help to develop spectrum usage models and more efficient CR techniques. Accuracy of usage pattern is a concern when the PU signal level is weak. Choice of suitable thresholds for energy detection is also an important task. It is seen in (Martian *et al.*, 2010*a*) that measured occupancy varies with the threshold used. It is also observed that the average noise floor in a frequency band is varying with time. It is also seen that average noise level is varying with frequency as it moves from one end to the other end of the spectrum.

2.5 Spectrum Analysis and Decision Making

Objective of spectrum analysis is to find out the optimal communication protocol and changing frequency or channel, based on the situation of several factors in the external and internal radio environment. It is also called as channel estimation. It analyses the radio environment such as radio frequency spectrum usage by neighbouring devices, user behaviour and network state. Spectrum analysis will help to take proper spectrum decision so that resource utilisation of the CR system becomes optimum. Spectrum decision making aims at reconfiguring the protocol and channel, in order to adapt to changing environment. A CR will have to adjust the output power or transmission parameters (such as modulation formats, variable symbol rates, and different channel coding schemes) and characteristics. It is expected that CR will have multiple antennas for interference reduction, capacity increase and range extension.

(Subramanian and Rimal, 2011) have proposed resource allocation algorithms for CR and have carried out its performance comparisons. These algorithms attempt to maximize the total throughput of the CR system (secondary users) subject to the total power constraint of the CR system and tolerable interference from and to the licensed band (primary users). It was assumed that a base station is serving as both primary and secondary user. Keeping the interference threshold constant, impact of average data rate on the total power requirement was analysed. They have observed that average data rate increased with the increase in CR power till the power constraint is maintained, after which it ceased to increase and became constant. Keeping the power constant, impact of average data rate on the interference threshold was also analysed. They have further observed that the data rate increases with the increasing threshold because there was still some room for interference to occur. Particle swarm optimization (PSO) algorithm and genetic algorithm (GA) were implemented for resource allocation and its comparisons were carried out. It has been concluded that PSO algorithm is best suited for dynamic resource allocation in cognitive radio systems where the resources are allocated in a dynamic environment within the given constraints of power and interference in a very optimal manner.

Another resource allocation work that tries to optimize bit rate, power efficiency and spectrum usage is proposed by (Venkata, 2011). He has proposed a two-step scheme with low computational complexity, in which sub-carrier and power allocation are optimized separately. Simulation results show that when performing channel estimation with a larger number of training symbols, the sum capacity is largely increased. The system performance will degrade when the transmitter has only the partial channel state information (CSI). In order to maintain the system performance, an appropriate transmission schedule based on partial CSI is needed. However, the optimal resource allocation in multi user orthogonal frequency division multiplexing (MU-OFDM) systems based on partial CSI is still an open issue. The effects of partial CSI on the resource allocation problem in MU-OFDM based cognitive radio systems is analysed. Based on obtained partial CSI at the transmitter, the average BER should satisfy the given BER target during transmission. As the function of average BER is too complex, a Nakagami- distribution is used to approximate the original function. A simple function, which is closer to the original function, is then derived. The resource allocation problem in MU-OFDM based cognitive radio systems is computationally complex. In order to make the problem tractable, a simple sub-carriers allocation (SA) algorithm is applied for sub-carrier allocation. Then memetic algorithm is applied to solve the bits allocation problem. Simulation shows that partial CSI has great impact on the wireless transmission. In addition, due to user diversity, the total bit rate decreases when the data rate requirements become less uniform.

Game theory based resource allocation algorithm is proposed by (Leshem *et al.*, 2012). They use the well known game theoretic Gale-Shapley stable marriage theorem from game theory as a basis for spectrum allocation in cognitive radio networks. They also provide tight lower and upper bounds on both the stable allocation and the optimal allocation performance. A novel opportunistic multichannel medium access control technique that achieves stable allocation within a single CSMA contention window is also proposed. In order to overcome practical implementation issues, they have also proposed new algorithms which have lower implementation complexity.

A method to predict the data rate in cognitive radio system is proposed by (Hiremath, 2010). Capability of radio configuration is indirectly estimated here. Future of wireless communications will be characterized by highly varying environments with multiple available radio access technologies exhibiting diverse features. Therefore in such an unfamiliar landscape, cognitive radio systems are expected to play an exceptional role by adding an inherent ability to perceive, think, decide, learn and adapt to the changing environmental conditions. In order to behave as an intelligent radio, CR needs learning techniques based on artificial intelligence techniques. (Hiremath, 2010) has proposed an adaptive neuro-fuzzy inference Systems (ANFIS) learning technique in channel estimation stage of cognitive radio to predict data rate of particular radio configuration. By predicting data rate of particular radio configuration, proposed ANFIS based technique can facilitate the cognitive terminal in making its decision regarding the configuration in which it should operate (selecting the best among a set of candidates).

Capacity of a partially cognitive radio is represented with a mathematical model by (Chung *et al.*, 2012). In this setup, the transmitter of the cognitive radio has only a portion of legitimate user's message. As the extent of cognition reduces, the channel becomes a conventional interference channel. As the extent of cognition increases, the channel resembles an interference channel with degraded message sets. Thus, the partially cognitive radio model lies in between these two extremes and encompasses both as special cases. For the general discrete memoryless interference channel (IFC) setting, an outer bound for the capacity region and achievable rate region under assumptions of 'weak' interference is obtained. An outer bound on the capacity region of a Gaussian partially cognitive radio channel is also obtained. An achievable region is obtained by combining Han-Kobayashi coding strategy and dirty paper coding for the Gaussian channel.

A robust, distributed power control algorithm designed with low implementation complexity for CR networks through reinforcement learning is proposed by (Zhou *et al.*, 2012). It does not require the interference channel and power strategy information among CR users (and from CR users to PUs). A design of algorithms for rendezvous without using any centralized controller or common control channel (CCC) is proposed by (Liu *et al.*, 2012). A two step (hybrid) scheduling method is proposed by (Li and Nosratinia, 2012) that pre-select a set of secondary users based on their interference on the primary, and from among them selects the user(s) that yield the highest secondary throughput.

2.6 CRN Security

There are two types of architectures in CRN, centralized and distributed. And there are two types of access behaviours, cooperative and non-cooperative. The centralized and cooperative types are more vulnerable. In the cooperative approach, attacking one node and taking control of that node will impact the network because it will send spoof packets to other nodes. In centralized approach, if the attacker can manipulate the common control channel, then this makes the whole network under control of the attacker. On the other hand, in distributed and non-cooperative approaches, effect of attacking a node will not propagate to other nodes (Saifan, 2010).

Security threats that raise from the use of cognitive technology is described by (Fragkiadakis *et al.*, 2013). They fall into two categories. First category represents threats to PUs and cognitive users. Malicious cognitive users can cause severe denial of service (DoS) attacks in primary networks through interference. The second category of security threats are those related to CRNs and the respective attacks against them. Primary user emulation attacks (PUEA), spectrum sensing data falsification (SSDF) attacks, CCC attack, beacon falsification (BF) attacks, cross layer attacks and software defined radio (SDR) attacks are the various types of possible attacks listed. There are also many proposals described to overcome these threats. But there is opportunity to contribute more in this area to prevent possible threats. Counter measures for Most Active Band attack is proposed by (Hu *et al.*, 2012).

Anti-jamming defence for a cognitive radio network with multiple available channels is investigated in (Wu *et al.*, 2012), by modelling the interaction between a secondary user and attackers as anti-jamming games and studying the optimal strategy and the equilibrium of the games. In the scenario where both the secondary user and attackers are equipped with a single radio and access only one channel at any time, the secondary user pro-actively hops between channels as a defence strategy. It is shown that the Markov decision process (MDP)-based hopping is a good approximation to the game equilibrium. Moreover, in order to gain knowledge about the adversaries, learning schemes are proposed for the secondary user, based on maximum likelihood estimation and Q-learning. Extending the anti-jamming problem to the scenario where the multi-radio secondary user can access multiple channels simultaneously, they have redefined the game with randomized power allocation as the defence strategy. The defence strategy obtained from the Nash equilibrium is optimal in the sense that it minimizes the worst-case damage caused by attackers.

A spectrum pricing strategy for CRN is proposed in (Kasbekar and Sarkar, 2012), where multiple primary and secondary users in a region and primaries can lease out their unused bandwidth to SUs in exchange for a fee. This gives rise to price competition among the primaries, wherein each primary tries to attract SUs by setting a lower price for its bandwidth than the other PUs. They have analysed price competition among multiple primaries in a CRN in the presence of spatial reuse in the symmetric setting in which each primary has unused bandwidth with the same probability. It is proved that there exists a unique symmetric Nash equilibrium (NE) in this case, and have characterized this symmetric NE as a solution of a set of non-linear equations. It is assumed that each primary knows the statistical distribution governing the bandwidth availabilities of other primaries and the number of SUs at each node. Characterization of the NE when primaries have imperfect knowledge of the above distributions, and seeking to enhance their knowledge using learning strategies, remains open. Finally, they have only characterized the NE strategies in a one-shot game. Primaries may play this game repeatedly and may use their experience from previous slots and a learning algorithm to choose their strategy in the current slot. An investigation into whether the symmetric NE for the one-shot game constitutes a steady-state outcome of some natural learning algorithms in such a setting is an interesting direction for future research.

Application of WSN for spectrum sensing in CR is proposed by (Akan *et al.*, 2009). Application of wireless sensor network is also proposed by (Gao *et al.*, 2010). In traditional spectrum sensing schemes, SUs are responsible for the spectrum sensing which could be very time and resource consuming. It leads to a great deal of inefficiency in spectrum usage and introduces many practical challenges. To tackle these challenges and leverage the spectrum opportunity more efficiently, a new system that provides a spectrum sensing service for SUs using dedicated wireless spectrum sensor networks (WSSNs) is proposed here. They have studied the sensing channel assignment for spectrum sensing using WSSNs in CRNs and formulated the problem as the sensing effectiveness maximization problem (SEMP) and proved that SEMP is NP-complete.

Based on the key factors influencing the performance for single channel sensing, sensing channel assignment for spectrum sensing (SCAS) algorithm is proposed. Evaluation results show that for both the scenarios of given deployments and manual deployment, SCAS is able to sense more channels. The improvement on the sensing effectiveness is up to 300% comparing to other simple alternatives. This demonstrates that SCAS hits a better trade-off between the sensed channel number and the accumulated sensing effectiveness that can be achieved. The assumption made in the formulation may not always be valid in reality. A more practical channel utilisation situation in a large scaled field may be considered. Also a more comprehensive model for describing the actual usage of a PU channel may be included.

2.7 Relevance of Proposed Work

Cooperative spectrum sensing has been widely accepted as the solution to overcome false sensing due to fading, shadowing etc. Many fusion rules are proposed in the literature for decision fusion under cooperative sensing. The network scenario considered in all the cases, assumes that all the CRs are under the coverage area of a PU for the channel under consideration. Probability of detection and false alarm rate are also defined for such a scenario. It is also noted that location of the nodes (either a fusion node or a neighbour node) with respect to the PU is not given much attention. It is felt that knowledge about the coverage area of a PU can have significant contribution in making a right decision. i.e., distance between T_x and R_x also needs to be considered for decision making. Aggregating the neighbours result need not guarantee right decision every time under CSS. Location of the fusion node and its neighbours with respect to PU also needs to be considered in setting proper weightage to individual results. Given the need for a cost effective system, two categories of CSS viz. distributed sensing and external sensing are given importance in this work.

Under this situation, we have proposed a scenario that faithfully represents a realistic network under distributed sensing and proposed a decision fusion approach that will adapt according to the situation and carry out more accurate decision fusion. This approach is evolved through various stages of modification and analysis. Its performance is compared with optimal rules available in the literature and presented in chapter 3. As far as decision fusion is considered, process involved in centralized sensing and external sensing is similar and difference is present only in its administration. In fact coverage area of all the PUs in the field with respect to time have to be available at the server so that this information can be shared with CRs in the field. We have proposed and analysed a cellular automata approach for decision fusion under external sensing, that gives a realistic picture about the coverage area of a PU. It is presented in chapter 4. Prediction based spectrum sensing is available in the literature as a new development. History of spectrum occupancy pattern of PUs are used here to predict the best available channels for the next time slot, so that spectrum sensing can be limited to only few channels. This will improve the throughput of the network. We have proposed a Bayesian approach for spectrum prediction and its performance is analysed with the real data obtained from the spectrum measurement carried out in this regard. Along with Bayesian predictor, an analysis of spectrum occupancy for a range of 50 MHz-4.2 GHz is also presented in chapter 5.

2.8 Chapter Summary

In this chapter, we have presented an overview of the related research in the field of spectrum sensing for cognitive radio. Scarcity in electromagnetic spectrum is highlighted by stating the present licensing policy of the spectrum and the spectrum allocation for various applications. Since the utilisation of spectrum is very less, dynamic reuse of the spectrum is proposed as the spectrum strategy for tomorrow. Cognitive radio is introduced as the potential device that can perform this dynamic usage of the spectrum. Spectrum sensing is an important task in this regard and CSS is proposed as one of the best methods to obtain the right sensing. Decision fusion is a task to be carried out to finalize the presence of a PU. Previous works in the area of fusion rules and prediction based spectrum sensing are also analysed. Finally the relevance of our proposed work in the light of previous research works is presented.

CHAPTER 3

DECISION FUSION IN DISTRIBUTED SENSING

3.1 Introduction

Dynamic spectrum sharing by primary and secondary users will be an essential component of any spectrum usage policy, in order to provide new services and technologies in a wireless communication scenario. This is relevant because at present, most of the available spectrum is licensed to primary users. Considering the spectrum utilisation at various frequency bands, there appears to be an opportunity to reuse the unused spectrum for future uses. Current research is investigating different techniques of using cognitive radio to reuse locally unused spectrum so as to increase the total system capacity. Various methods are proposed in the literature to sense the spectrum occupancy status of PUs. The biggest challenge related to spectrum sensing is in developing sensing techniques which are able to detect very weak primary user signals while being sufficiently fast and low in cost to implement.

Considering the signals at low SNR and the channel conditions it is felt that Fuzzy approaches may give a reasonable decision fusion under CSS. From the literature (Matinmikko *et al.*, 2009; Taghavi *et al.*, 2011), it is seen that fuzzy approaches tend to give a better detection level at low SNR. Since SNR of the CR is a key parameter that reflects the strength of the signal, a Fuzzy rule for decision fusion (with SNR and signal strengths of the neighbours as the inputs) was proposed and analysed in Section 3.2. On analysing the performance of this rule, it was found that even though the probability of detection was very good, computational time is much high. This may not be desirable in CR systems as it may reduce the throughput of the system.

Another option is a weighted combining approach with SNR as one of the key component and this is analysed in Section 3.3. The performance of the rule was also analysed under various scenarios of channel conditions. While dealing with the scenarios, it was felt that the decision fusion at the boundaries of the coverage area of a PU also needed to be analysed. Hence a new scenario was considered for analysis with an adaptive weighted combining approach. The analysis and observations are presented in Section 3.4.

In order to further improve the performance of the system an antenna selection approach with multiple region encoding scheme for SU reporting is included along with the adaptive weighted combining and presented in Section 3.5. Its performance is also analysed and compared with other optimal rules available in the literature.

3.2 A Fuzzy Approach to Decision Fusion under CSS

3.2.1 System Model

In this work, it is considered that a CR network consists of one PU and a large number of CRs in the field. It is assumed that the PU operates only on a particular channel and the CR terminals are trying to find out the spectrum holes in that channel. Each node performs spectrum sensing and the received signal energy level is shared among its neighbours. With the help of suitable fusion rule, final decision is made after decision fusion. Proposed fusion rule (Fuzzy approach) is given in Section 3.2.2.

It is assumed that data from PU is BPSK modulated and transmitted over a channel where it gets affected by white Gaussian noise and Rayleigh fading. CR terminals act as the receiver that checks the presence of PU's signal in the specified band. Energy detection method (Nallagonda *et al.*, 2012) is used to detect the received signal at the receiver end and is shown in Fig. 3.1. It is a non-coherent detection method that detects the primary signal based on the sensed energy. Due to its simplicity and no necessity of prior knowledge about PU, energy detection has become the most popular sensing technique.

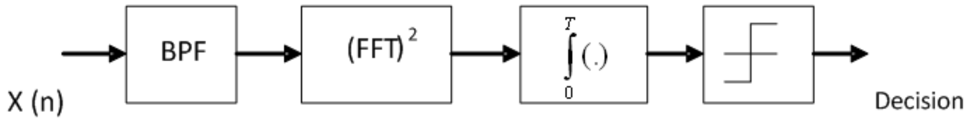


Figure 3.1: Energy detector

In order to measure the energy of the received signal, the output of band pass filter with bandwidth 'W' is squared and integrated over the observation interval 'T'. Finally the output of the integrator is compared with a threshold to detect whether the primary or licensed user is present or not. It can also be computed in frequency domain by averaging bins of a fast Fourier transform (FFT). In this, the processing gain is proportional to FFT size 'N' and the averaging time 'T'. Increase in the size of FFT improves the frequency resolution which is helpful in detecting narrow band signals. Likewise a decrease in averaging time will improve the SNR by reducing the noise power. It estimates the presence of the signal by comparing the energy received with a known threshold derived from the statistics of the noise.

3.2.2 Proposed Fuzzy Rule

Spectrum sensing part in CR systems identifies the presence of the PU. A geographical area consisting of a single PU and a random number of CR terminals are considered here. It is assumed that all the CR terminals are within the coverage area of the PU. In CSS, each CR consider its neighbours data also for making a final decision.

Here in the first phase, depending on the received energy at each node CRs make an individual decision on the spectrum status as 'Low', 'Medium' or 'High'. In the second phase it performs CSS by taking these individual decisions from its neighbours. Fuzzy logic is used for decision fusion. Main highlight of this method is that it considers the SNR of the decision making node also in the decision making process. Each CR terminal periodically observes the power of the received PU signal and records the SNR at the respective instants as well. For a CR to make a final decision about the status of the PU, it considers its own data of power & SNR and power from two of its nearest neighbours. Thus a total of four inputs are considered for decision making. Model of a fuzzy fusion center is shown in Fig. 3.2, where CR1 corresponds to decision making node and CR2 and CR3 are its neighbours. For fuzzification of power and SNR, three membership functions are defined for each inputs. Membership functions that are widely used in the literature are considered here. The membership functions represent three levels viz. 'Low', 'Medium' and 'High' and are as shown in Fig. 3.3. These levels were set after analysing the range of the received signal parameters, from the channel model considered for simulation, after numerous trials.

However, the output is a binary parameter which denotes the presence of the PU by '1' and the absence of the PU by '0'. The fuzzy rule base contains 'IF-THEN' clauses

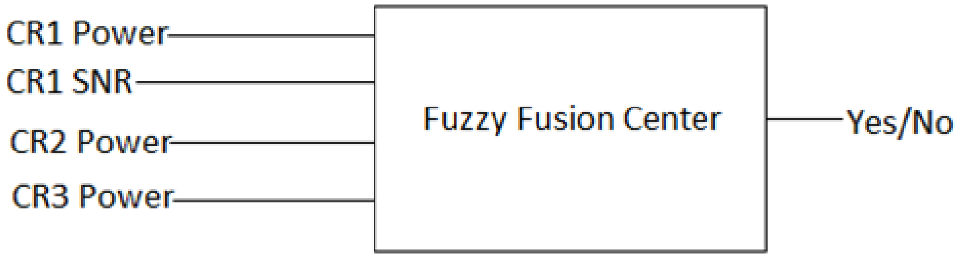


Figure 3.2: Fuzzy fusion center

which are designed in such a way that the priority of node's own decision gets priority based on its SNR value. For example, if the CR terminal detects high power and high SNR, then the output is '1' regardless of the data on power that has been collected from the neighbours. The rule base is defined for all the possible combination of inputs. With four inputs and three possible levels for each input, there are 81 possible combinations. A part of the rule base is shown in Table 3.1.

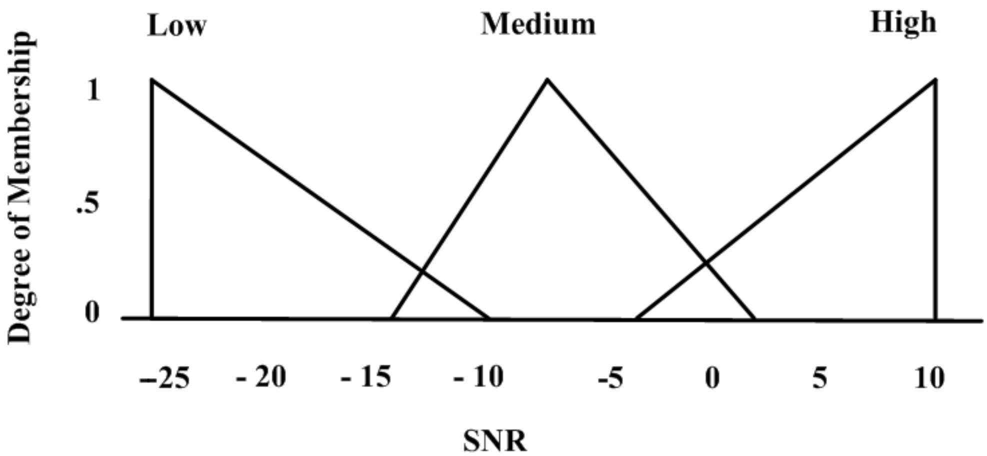


Figure 3.3: Membership function [SNR]

Table 3.1: Fuzzy rule base

Power CR-1	SNR CR-1	Power CR-2	Power CR-3	Output
Low	Low	Low	Low	No
Low	Low	Medium	High	No
Medium	Low	Medium	Low	No
Medium	High	High	High	Yes
High	Medium	Medium	Medium	Yes
High	High	High	High	Yes

3.2.3 Results and Discussion

The proposed Fuzzy rule is evaluated by a simulation done in Matlab. It is considered that a PU located at the center of an area under consideration and 25-50 CR terminals are positioned randomly around the PU. One of the CR terminals is selected randomly and the power and SNR of that CR terminal are recorded. The powers received by the neighbouring two CR terminals which lie nearest to the selected terminal are fetched by the selected CR. The four parameters, power and SNR of CR1, power of CR2 and power of CR3 are the input parameters for the fuzzy based decision making stage. For simulation, similar SNR is considered for all the nodes which are located nearby. Here each node will calculate the energy of the received signal and based on the two threshold values it decides on the output as 'Low', 'Medium', or 'High'. This information is passed on to neighbouring nodes as two bit information. Each node will take the result of two neighbouring nodes, own decision and SNR to make final decision. Performance of this proposed decision fusion method (named as Fuzzy-SNR) is evaluated at various SNR values and it is compared with 'OR'- rule, 'AND'- rule and single node decision. False detection refers to the situation in which the spectrum is free (PU is not using the spectrum) but the decision made by the system indicates that the spectrum is in use by the PU. The probability of false detection was computed by running the program 100 times and counting the number of times the PU was falsely detected when it was not using the spectrum. In order to use 'AND rule' and 'OR rule' the two bit decision is converted into single bit decision by setting 'Low' as not sensed and others as sensed. Performance comparison on probability of false detection is shown in Fig. 3.4.

The probability of false detection was observed for SNR values between -25 dB and 10 dB, and the fuzzy based system returned the probability of false detection as almost 0 in the given range of SNRs, which is ideal. It is found that at lower SNRs also, this proposed method gives a good result. Above results are obtained based on fixed threshold pairs for all the cases. Change in thresholds might give a change in the result. These threshold values were chosen based on the average range of energy level received at the receiver.

Successful detection refers to the situation in which the spectrum is being used by the PU and the decision made by the CR is correct, indicating that the spectrum is in use by the PU. The probability of detection was computed in the same way as

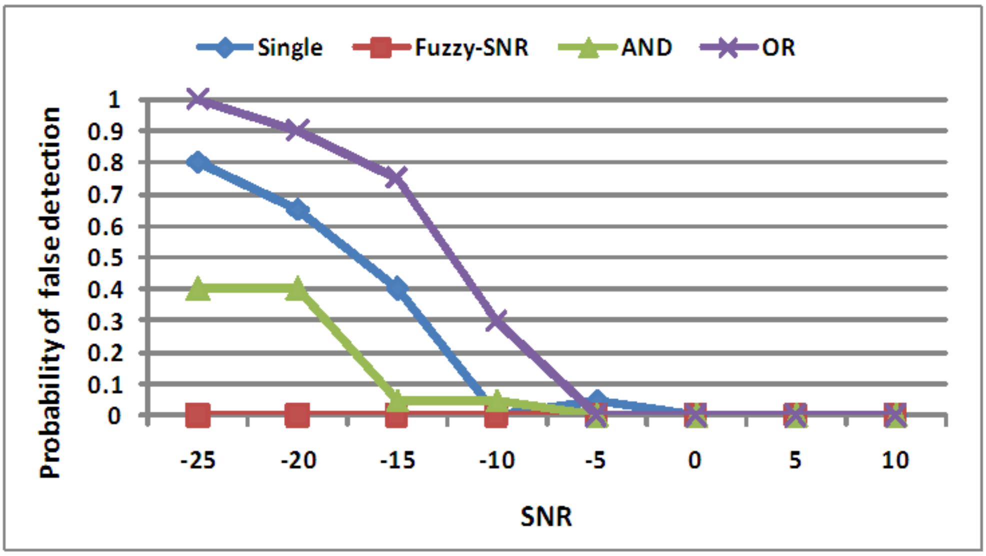


Figure 3.4: Probability of false detection

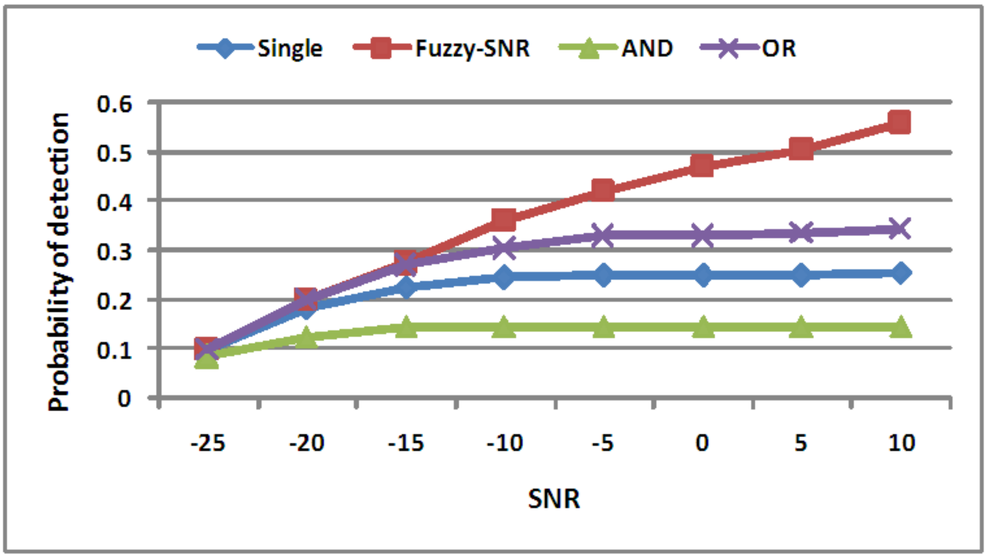


Figure 3.5: Probability of detection

that of probability of false detection and the same thresholds were used. Performance comparison is presented in Fig. 3.5. Even though the detection rate depends on the Rayleigh channel parameters used and the filtering process, relative performance of fuzzy based method is giving a better detection rate.

In both the cases the performance of our proposed fuzzy based approach is better. Conversion of two bit decision to one bit decision for the implementation of 'AND rule' and 'OR rule' are supposed to help either probability of false detection or probability of detection. And it is seen that the proposed fuzzy based approach is giving a better result compared to other cases. This is because of the fuzzy nature in the decision making that gives a favourable outcome. Effect of SNR has also contributed in giving a better result.

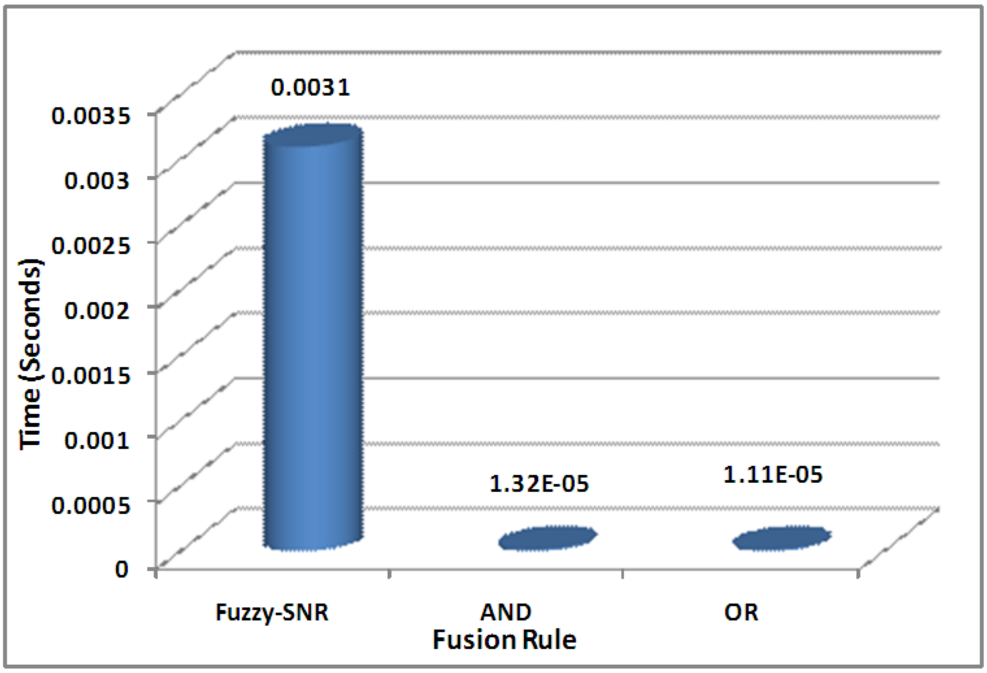


Figure 3.6: Time taken to perform decision fusion. [Machine spec: Intel(R) Core (TM) 2 Duo CPU, T7250 @ 2.00 GHz, 777 MHz,1.95 GB RAM]

Overall performance can be even improved with the choice of an optimum threshold. A comparison on the time taken for data fusion is analysed in Fig. 3.6. It shows that the performance of fuzzy rule consumes more time compared to other rules. This is because of the size of the rule base, which is to be evaluated for taking a decision.

3.2.4 Section Summary

A modified fuzzy approach is proposed for decision making in cooperative sensing. It has been simulated under AWGN channel with Rayleigh fading. BPSK modulated bit stream is transmitted through the channel and at the receiver energy detector is used to sense the status of the spectrum. SNR of the receiver is included here in making a decision fusion at the CR. It was found that the performance of the proposed fuzzy based approach is giving a better performance compared to other methods considered. However, the system has its disadvantages. Due to its wide range of possibilities the computation time for a fuzzy decision is high compared to other systems. Furthermore, increase in number of inputs will increase the number of rule base exponentially, which is a cumbersome task to the system designer. In order to use this for cognitive radio applications, fast approaches need to be developed. Inclusion of other inputs such as distance between sharing nodes will help this rule to perform even better in all scenarios.

3.3 SNR Based Rule for Decision Fusion

It was observed that proposed Fuzzy-SNR approach was relatively doing well, from the point of view of probability of detection. But the computational complexity was high. Better throughput can be achieved only if the spectrum sensing time is small. To overcome the limitation of the Fuzzy-SNR rule, a weighted combining approach is proposed and analysed in this section. The performance of the rule was analysed under shadowing using the 'path loss' model. Various scenarios of channel conditions such as rural, urban and dense urban were considered for the analysis. Effect on 'the probability of detection' on account of each of the likely dependencies viz. the number of sharing nodes, varying environmental parameters, self-weighting factor, positive weighting factor, receiver density etc. were analysed. Best possible weighting factors that gave the right decision were then assessed and estimated.

3.3.1 System Model

In this section a CR network consisting of 'M' primary users and 'N' CR users are considered. It is assumed that one licensed frequency channel is allocated to each primary user. It is also assumed that there are M orthogonal frequency channels and cross channel interference is negligible. Each CR user knows the total number of frequency channels in the network and communicate each other periodically. The interference to a primary user by a CR user occurs only when the CR user transmits over the channel that is being used by that primary user. A simulation set up based on path loss model is considered to analyse the effect of single node sensing and distributed sensing at channel conditions such as rural, urban and dense urban. All the estimations are based on the practical link budget design using path loss model presented by (Rappaport *et al.*, 1996). The model was designed for simulation of primary signal transmitters, and CR receivers within a 2-dimensional square spatial area with Cartesian co-ordinates. The number of transmitters and receivers are also variable. Typical values used were 5 transmitters, 100 receivers, within an area of 1 - 4 sq. km.

Propagation path loss according to distance from the transmitter was defined according to the equation 3.1 as given by (Harrold *et al.*, 2008).

$$PL_{dB} = 10nlog_{10}d + 20log_{10}\left(\frac{4\pi}{\lambda}\right) + X_{dB} \tag{3.1}$$

where PL (dB) = Path loss in dB, n = Path loss exponent, d = Distance from transmitter in meters, λ = Wavelength of transmitted signal in meters, X (dB) = Shadowing factor. Thus the received power P_r (in dBW) at a receiver at a distance 'd' meters from a transmitter with transmit power P_t (in dBW) will be

$$P_{r(dBW)} = P_{t(dBW)} - PL_{(dB)} + G_{r(dBi)} \tag{3.2}$$

where G_r represents the receiver antenna gain (typically 2 dBi was used). This value of received power for each receiver is used in the sensing calculations. A suitable value for 'n', the path loss exponent, was required for various types of environment. In realistic scenarios this value will vary according to the following Table 3.2 as given in (Rappaport *et al.*, 1996).

Table 3.2: Typical values of Path loss exponent used for simulation

Environment type	Value of Path loss exponent
Free Space LOS (rural)	2
Urban	2.5 - 3.5
Dense Urban	3.5 - 5

The parameter 'X' in equation 3.1 is a factor which models the shadow fading effects. It is implemented as a log-normal random variable as shadow fading has been proven to exhibit a log-normal distribution due to the differences in the density of objects blocking the line of sight path between receivers at different locations. The log-normal distribution describes the random shadowing effects which occur over a large number of measured locations which have the same T-R separation (Rappaport *et al.*, 1996). The value of 'X' depends on its standard deviation 'σ' (quoted in dB, since 'X' is log-normal in distribution), which typically varies between 6 - 10 dB across different environments according to (Harrold *et al.*, 2008; Algans *et al.*, 2002) as given in the Table 3.3.

We have considered the standard broadcasting systems such as VHF TV and FM Radio, and mobile communication systems (GSM) used in India. The parameters of the

Table 3.3: Typical values of σ for different environments

Environment type	Shadowing standard deviation
Suburban	6 dB
Urban Microcell(d $<$ 1 km)	8 dB
Urban Macrocell(d $>$ 1 km)	10 dB

main primary systems used in the simulations are given in the following Table 3.4

Table 3.4: Main primary systems simulated

System	System Type	Tx. Power	Frequency	BW
1	Analog TV (PAL) DD National	40 dBW	203.25 MHz	7 MHz
2	Analog TV (PAL) DD News	40 dBW	217.25 MHz	7 MHz
3	GSM -900 Band Cell	10 dBW	935.20 MHZ	200 kHz
4	FM Radio Kochi - A	38 dBW	102.30 MHz	200 kHz
5	FM Radio Kochi - B	40 dBW	107.50 MHz	200 kHz

Model Verification

Fig. 3.7 is an example of calculated received power vs distance from an analog TV transmitter (according to equation 3.2), in order to verify the path loss parameters of equation 3.1 with n = 4.5, $\sigma = 10\ dB$, Gr = 2 dBi. The random fluctuations are due to the log-normal shadowing effects, and the overall regression in received power with increased distance is due to the path loss, the slope of which is determined by the path loss exponent. This can also be compared with experimentally gathered path loss data as in (Rappaport *et al.*, 1996).

3.3.2 Spectrum Sensing Strategy

Single Node Sensing

The basic sensing function at each receiver was implemented by setting a decision threshold in decibels relative to the noise floor. Each receiver will calculate the received power at the specific time steps and if the calculated power is greater than the noise floor, which is related to the bandwidth of the channel, then the channel is considered as sensed. Noise floor is calculated as N(dB)=$10\log_{10}$(kTB)+NF, where k-Boltzmann constant, T-Temperature (Kelvin), B-Bandwidth (Hz), NF-Receiver Noise Figure(dB).

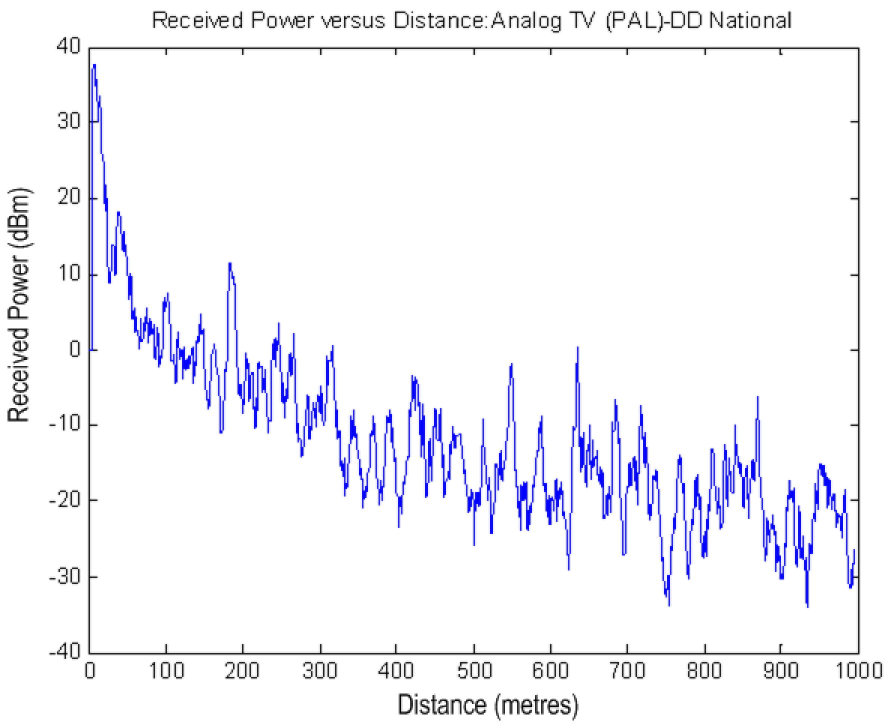


Figure 3.7: Calculated received power vs distance from an analog TV transmitter

Distributed Sensing

Here the decision is made based on the single node sensing information collected from various cognitive receivers. A limit is set on the number of neighbouring nodes to share information with. The effect of varying the number of neighbouring nodes is explored in the different environments. Each node will broadcast its current set of results (single node sensing data and the SNR) within its group which is based on the distance between each receivers. Individual nodes will use these data and their own data to determine the existence of the primary user. A weighting factor is applied to each neighbouring nodes according to the SNR level at each node. All the data are given a specific weightage based on its relevance. A majority polling system is used to determine the likelihood of a primary user. The final sensing algorithm can be represented as in equation 3.3.

$$Y = \sum_{n=1}^{n=N} Q_n S_n + XW \tag{3.3}$$

where N - Number of neighbouring nodes considered, Q_n - Sensing result from neighbouring node 'n' received as 1 or -1, S_n = snr*positive weight [Weighting factor according to the SNR of neighbouring node 'n' and the positive weight], X - Node's own result, W-Weighting applied to the nodes own result, Y - Final result, where a positive value indicates that a signal has been detected, and a negative value indicates that no signal has been found. Since SNR is used to form the weight vector, it is expected that false results will get a reduced weight.

3.3.3 Results and Discussion

In this section, the performance of the proposed distributed spectrum sensing strategy is analysed through Matlab simulation. Five primary systems were considered for simulation. The number of CR users considered is 100. For the sake of simplicity, all transmitters are located at the center point. Receivers are located with a random distribution within an area of 1 - 4 sq.km. It is assumed that each receiver moves in a random direction to a specific distance at each time instance.

Effects of Environmental Changes on Probability of Detection

A distribution of 100 receivers in an area of 4 sq. km. was considered in each case. The results were obtained for various environmental parameters as defined, in Table 3.5

Table 3.5: Scenarios defined to simulate
effects of varying Environmental parameters

Scenario	n (PLE)	σ (dB)
Rural	2	6
Urban	3	8
Dense Urban	4	10

Single node sensing result shown in Fig. 3.8 indicates 100% detection in the rural environment. It can be said that this will be true in real scenarios also since the shadowing effect will be less in a rural environment.

In the case of urban environment only FM channels are sensed properly. This is because the noise floor of FM channels are less compared to TV channels. Low transmission power of GSM transmitter also contributed to its low detection rate.

In a dense urban environment, 100% accuracy is not obtained in any of the primary systems. It is clear that path loss, shadowing and noise level are contributing to the poor sensing in this environment. Benefit of CSS under distributed sensing can be seen in Fig. 3.9. Improved detection rate could be observed in all systems and across all

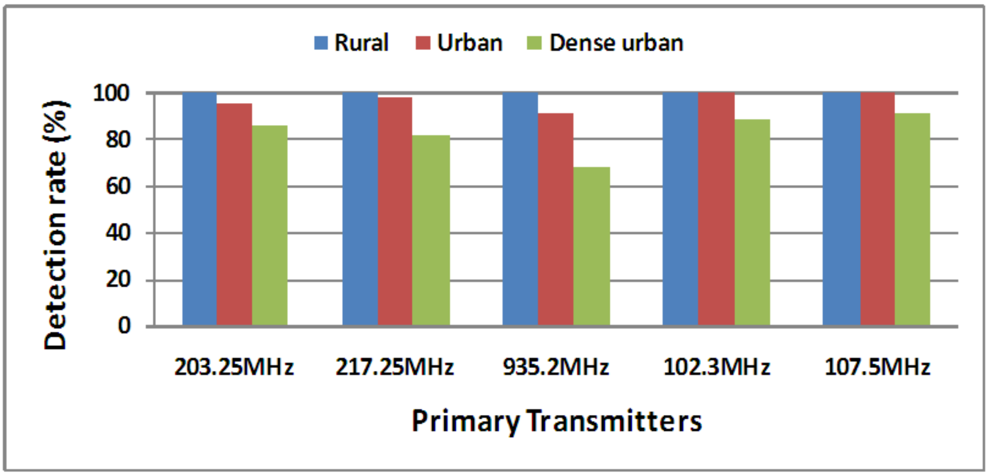


Figure 3.8: Single node sensing result

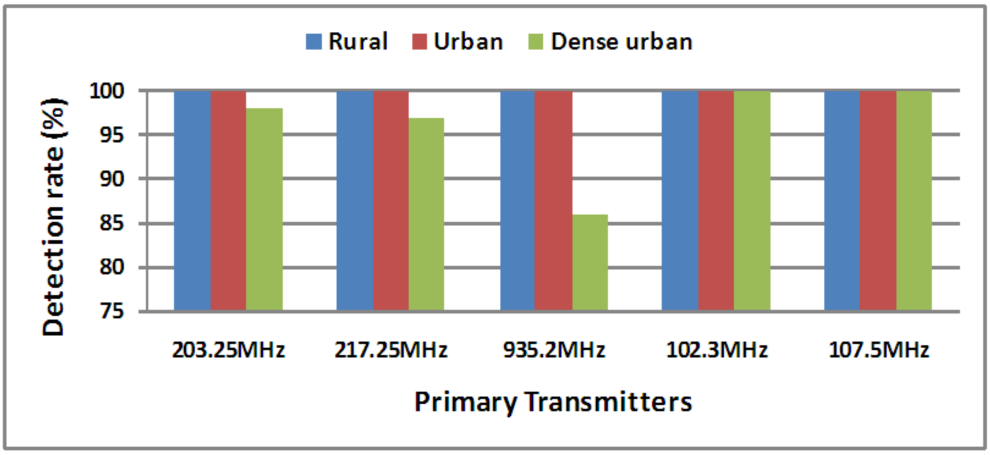


Figure 3.9: Distributed sensing result

environments. It can be concluded that the proposed distributed sensing method is a reliable technique for detection of most types of primary users. In order to improve reliable detection for low power PU's, the density of CR terminals within the PU's transmission range needs to be analysed.

Effects of Increasing Number of Sharing Nodes

It seems logical to assume that increase in the number of neighbouring nodes considered for decision fusion would offer improvements in probability of detection. 100 receivers within a coverage area of 2 sq. km. under dense urban environment were considered for simulation. The effect of number of sharing nodes is demonstrated in Fig. 3.10.

Increasing the number of sharing nodes offers increased performance in all cases with 100% reliability with 16 sharing nodes for 4 out of the 5 cases. Improvements can

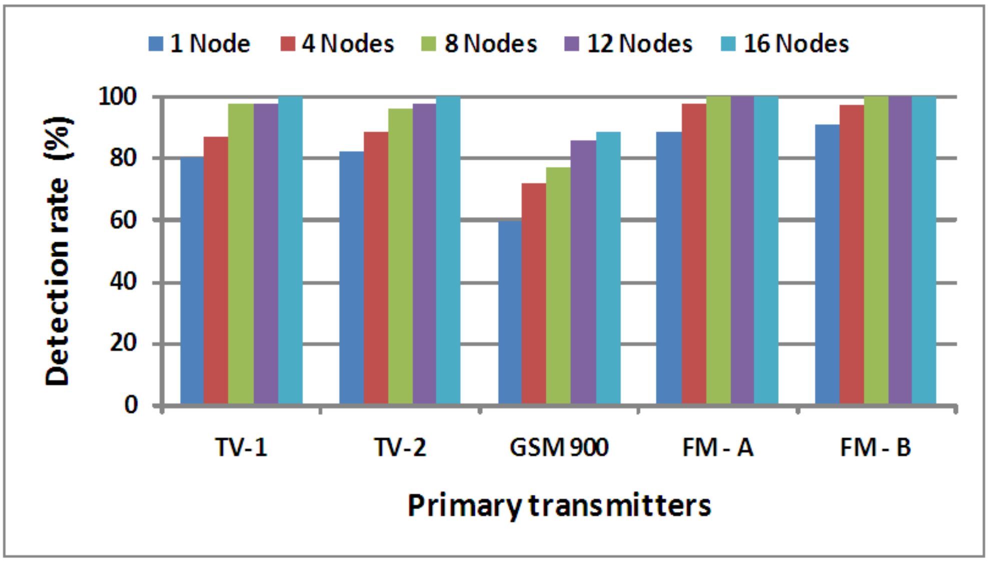


Figure 3.10: Effect of increasing the number of sharing nodes

be seen in the GSM cell also. It is true that TV and FM channels have enough power to provide sufficient coverage in the area considered. But in the case of GSM, the power is not sufficient to cover larger area. It is also found that in the case of high power primary systems, less number of sharing nodes are required for a better result. It is desirable that in case of low power primary systems, more number of nodes may be used to get a better result. It is understood that as the number of sharing nodes increases, processing time will also get increased.

There is a chance that one CR user may be located outside the coverage area and its neighbours located within the coverage area. The effect of neighbours may generate a false positive for the node located outside the coverage area and vice versa. Such a case is considered in the next section.

Effect of Increasing the Self Weighting Factor

An area of 2 sq. km. is considered here. It is seen that in the case of low power GSM cell, distributed sensing helps a lot to improve the detection rate. As the self weighting factor increases, it is seen that detection rate decreases with increase in self weight. Detection rate of the low power GSM cell with increase in self weight is shown in the Fig. 3.11. It is clear that in distributed sensing, the results of the neighbouring nodes also need to be given its due weightage. In this simulation, weight for a neighbour's positive result was kept a value just above '1' . Since the area considered is small, all

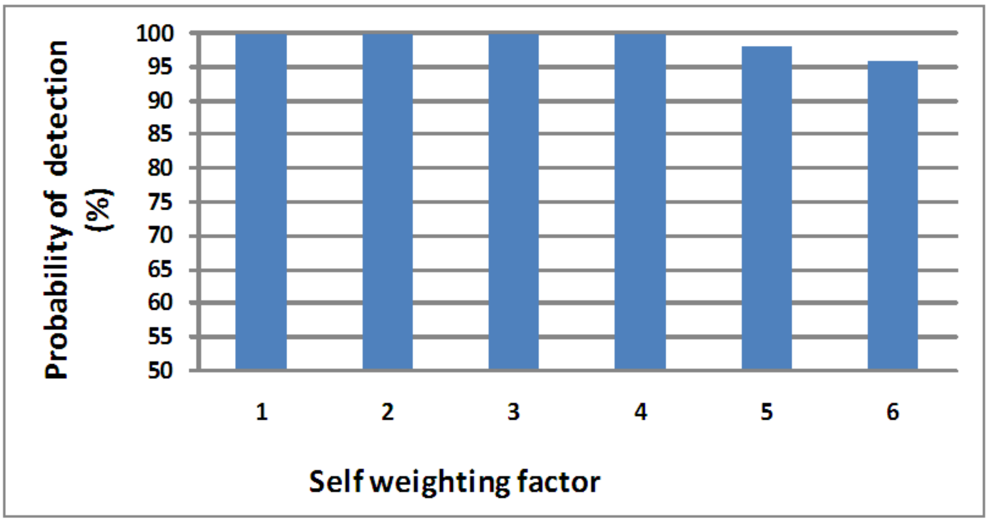


Figure 3.11: Effect of increasing the self weighting factor

the users are in the coverage region. So the increase in self weight may lead to reduction in detection rate.

If the decision making CR is outside the coverage region of a PU and some of its neighbours are within the coverage area, then reduced self weight may lead to a false positive detection for that CR. CRs located outside the coverage area of a particular PU have the opportunity to communicate among themselves without affecting that PU.

Effect of Increasing Receiver Density

An area of 4 sq. km. is considered here. A dense urban scenario is considered to observe the effect of receiver density on the probability of detection. A low power primary transmitter GSM and a high power TV broadcast transmitter are considered. Fig. 3.12 shows that in the case of low power transmitter, there is an improvement in the probability of detection initially and as the receiver density increases above 100, the improvement is marginal. As per Fig. 3.13 the detection rate for a high power transmitter has no impact on the number of CR terminals within a 4 sq. km.

Effect of Increasing Positive Weighting Factor

Positive weighting factor is an additional weight that is given only to neighbour's positive results during decision fusion. Impact of positive weighting factor on the probability of detection is explored in a dense urban scenario for a high power TV transmitter

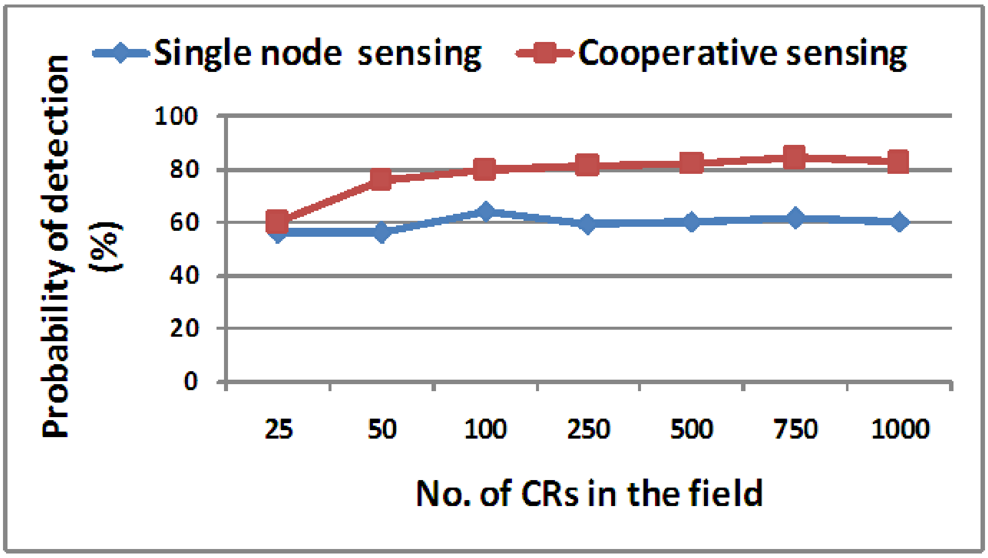


Figure 3.12: Effect of increasing the receiver density for a low power GSM transmitter

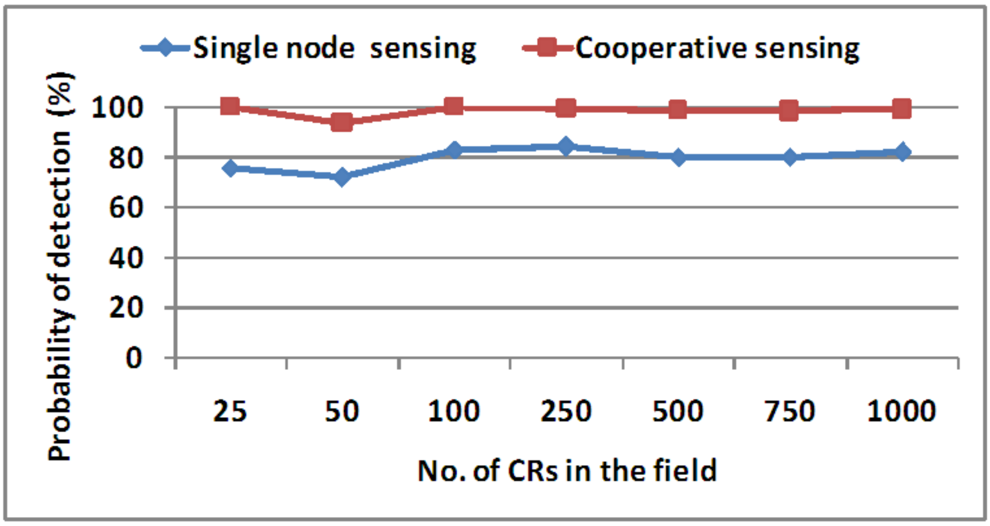


Figure 3.13: Effect of increasing the receiver density for a high power TV transmitter

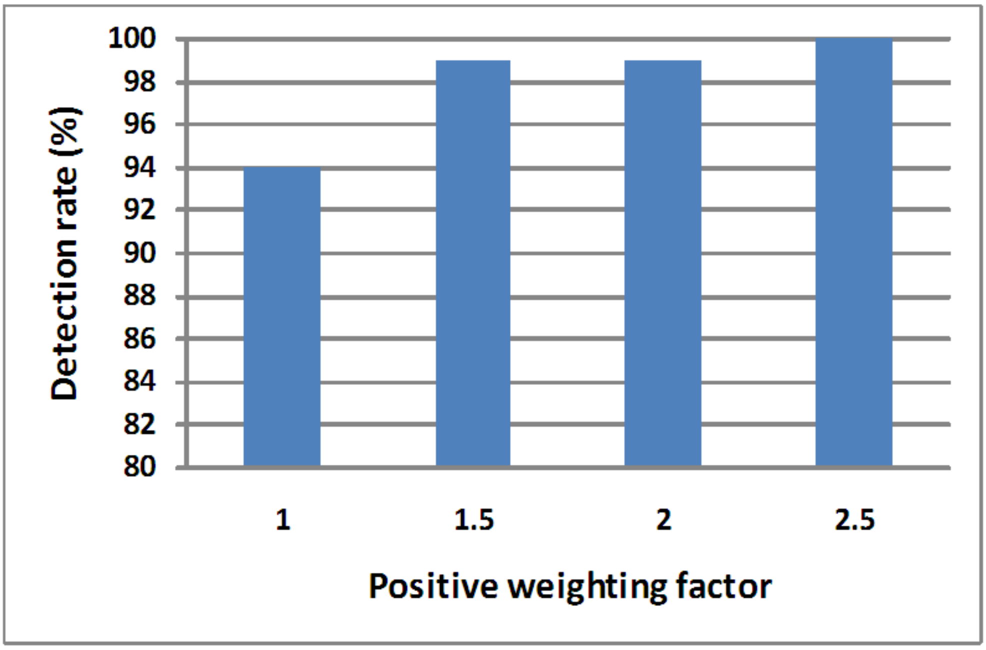


Figure 3.14: Effect of increasing positive weighting factor

and shown in Fig. 3.14. It is observed that detection rate is improved with positive weighting factor.

But this will be true only if the transmitter has sufficient power to cover the area under consideration. In the case of low power transmitters whose coverage area is small, this may lead to false positives. That is, the neighbour's result will force a false positive decision on a CR which is located outside the coverage area of a low power transmitter.

3.3.4 Section Summary

In this section, analysis of a cooperative spectrum sensing algorithm based on weighted combining proposed for cognitive radio has been carried out. Each CR performs decision fusion after collecting 'SNR' and individual decision from its neighbours. Path loss and shadowing have been considered while modelling the channel. It was found that false negatives were increasing as the analysis was moved from rural to dense urban environment. These inaccuracies could be minimized through the proposed CSS strategy. Effect on 'the probability of detection' on account of each of the likely dependencies viz. the number of sharing nodes, varying environmental parameters, self-weighting factor, positive weighting factor, receiver density etc. were analysed.

It has been found through simulation across various environments (rural, urban and dense urban) that the proposed method is highly effective in minimizing interference to the primary systems by sensing the presence of primary users properly. It was found that a high degree of detection probability could be obtained for the TV and FM broadcast systems than for GSM systems under the same environmental parameters, largely due to the higher transmission powers involved in broadcast networks. The values assigned to the weighting factors will also affect the probability of detection within the PU's coverage area. There is a scope to further optimize the weight vectors for a better result.

3.4 Adaptive Weighted Combining for CSS under Distributed Sensing

It was seen in Section 3.3 that proposed SNR rule, based on weighted combining was giving improvement in the probability of detection under CSS. In this section an attempt is made to modify this rule to make it suitable for all the scenarios that may arise for a CR network. Both the proposed approaches described in Sections 3.2 and 3.3 were analysed, on the assumption that all the CRs are located within the coverage area of a PU under consideration. However, it was felt that decision fusion at the boundaries of the coverage area of a PU also needs to be reckoned. Therefore, a new scenario is considered for analysis and an adaptive weighted combining approach is proposed to handle such a scenario. Here the weights would be adapted based on the location of the CRs with respect to the Primary Transmitter. A fusion rule that considers the location of the nodes with respect to a PU is proposed here. In this section, the performance of this rule, named as 'Intelligent rule' is analysed using energy detection model under Rayleigh fading as well as path loss model under shadowing. Its performance is also compared with other rules.

3.4.1 System Model

Consider a CR network consisting of 'M' primary transmitters with respective primary receivers and 'N', CR users in the field. Each PU is allocated specific channels for

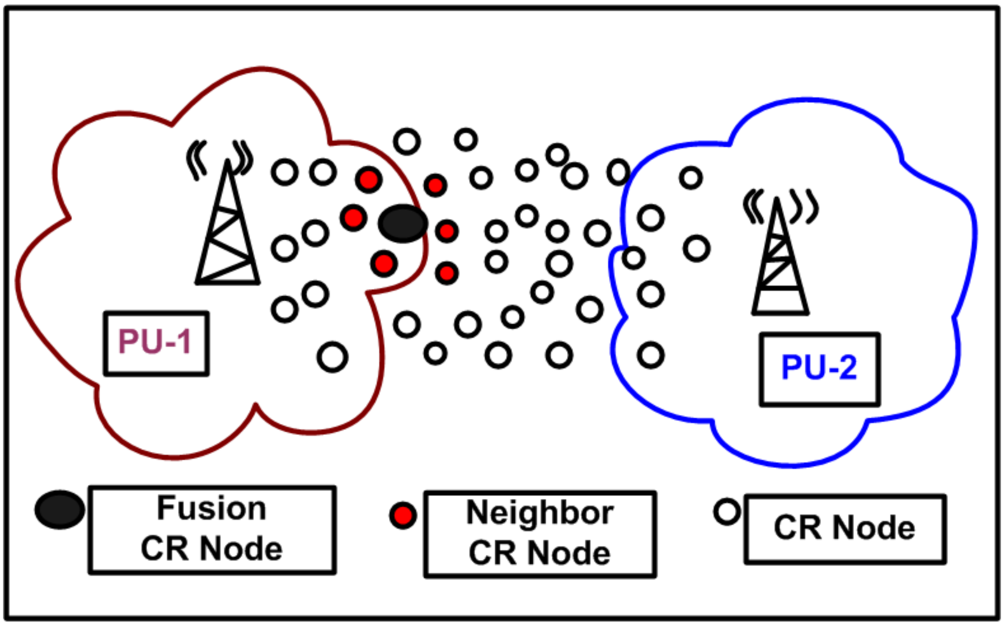


Figure 3.15: Scenario-1: Fusion node is located at the boundary of PU's coverage area

communication. During the absence of PUs, CRs can communicate among themselves over the above channels. The CRs have to relinquish the channels as soon as the PU starts its transmission. Any interference to PU from CR is not tolerated. Time division approach is followed here and CRs are required to sense the presence of a PU at the beginning of each time slot. If the PU is absent, CR will occupy the channel for the remaining period of the time slot. Duration of the time slot is decided in such a way that the channel state will be constant during the slot. In other words, the PU will not start its transmission at the middle of the time slot. Spectrum sensing is an important task to be performed in such a way that all the nodes should have the right decision. In a real situation channel conditions for each CR nodes will be independent. They may undergo independent fading and shadowing. It is hard to detect signals of low SNR for desired performance. Missed detection will prompt the CR to start communication with other CRs. Improper spectrum sensing will cause interference to primary users. Cooperative spectrum sensing is proposed as a solution to overcome this issue. It is expected that various nodes in a terrain may experience random fading and shadowing. If nearby nodes share their sensing result with others, each node can make a final decision on the spectrum status by aggregating the results from a group of neighbouring nodes using a suitable fusion rule. This will ensure proper spectrum sensing and low interference to primary users.

Scenarios as shown in the Fig. 3.15 & 3.16 are considered here for analysis. All CRs

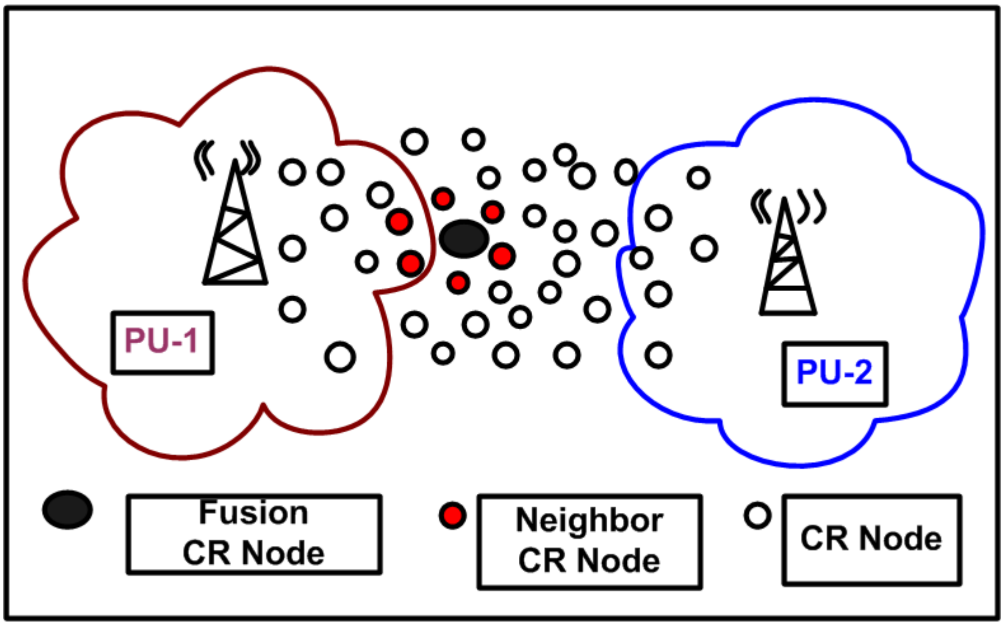


Figure 3.16: Scenario-2: Fusion node is located just outside the boundary of PU's coverage area

are not located under the coverage area of PU-1 or PU-2. Some are outside the coverage area of both PU-1& PU-2. In this work only one PU and many CRs are considered for proper analysis of the scenario. Hence each CR node will perform the spectrum sensing and a one bit decision on the sensed result will be shared to neighbours. The term PU will include both primary transmitter and receiver. In duplex networks, primary receivers will transmit in another channel with respect to transmitter and in the case of simplex networks like TV etc., emitted features like leakage power from the Local oscillator of the receiver etc., may also be sensed (Zou and Chigan, 2011). The coverage area of a PU need not be perfect circle in practical situations. According to (Goldsmith, 2005) contours of a constant received power from a transmitter form an amoeba-like shape, due to the random shadowing variations about the path loss. A distributed sensing scenario is considered here, where each node will get the sensing result from the neighbours and fusion of data is done at each node. In Fig. 3.15 small circle with black filling is considered as the node who does the fusion (hereafter it will be called fusion node) and the smaller red filled circles represent neighbours whose results are used for decision fusion. This is applicable for each CR. Based on the position of the node and its neighbours each decision fusion needs to be correct. In Fig. 3.15 fusion node is located within the boundary of PU-1 and some of its nearest neighbours are located inside the coverage area and some are located outside the coverage area. In Fig. 3.16 fusion node is located outside the coverage area. Normally CRs in the field may not understand whether it is outside or inside the coverage area, when it is closer to the boundary, as its spectrum sensing may vary with time due to random shadowing and fading. If a neighbour node is located outside the coverage area of the PU then there is a chance that this Fusion Node (FN) also may be closer to the boundary. Hence inputs from all directions are necessary to make a suitable decision. In both scenarios the neighbours are located at all the directions. Here the fusion rule needs to be intelligent enough to make a right decision.

In the literature, such a scenario is not given much importance. In most of the analysis of fusion rules, both fusion node and the neighbours are considered to be within the coverage area of a PU. Also the SNR considered for all the nodes at a time instant is same. And all the parameters associated with detection, false alarm rate etc. are defined under the assumption that all nodes are within the coverage area of a PU. In a real scenario all the CRs in the field are expected to undergo independent fading. The spatial location from the PU also will be different.

An attempt is made to model the scenario with CRs having independent conditions with respect to its spatial location, fading, SNR and mobility. In this section an intelligent fusion rule is proposed as a modification to the fusion rule presented in Section 3.3. Its performance is analysed under the scenarios shown in Fig. 3.15 & 3.16.

Performance of the proposed fusion rule is analysed with the simulation setup prepared according to the energy detection approach in (Digham *et al.*, 2007) as well as the practical link budget design using path loss models given in (Rappaport *et al.*, 2002).

Decision Fusion in Cooperative sensing

Cooperative sensing has become important because of the fading and shadowing experienced by the CRs. A fusion rule is already proposed in equation 3.3 for cooperative spectrum sensing, which uses SNR at the node as the weighting factor along with a self weight. In order to improve the performance of fusion rules under the scenarios shown in Fig. 3.15 & Fig. 3.16, a modification is proposed to equation 3.3 by including the feature of location awareness. It is stated as follows.

$$Y = \sum_{n=1}^{n=N} R_n Q_n S_n + R_s X W \tag{3.4}$$

where R_n is the weight factor according to the location of the node, R_s is the weight for the fusion node. The fusion node can choose the values of $R_n \& R_s$ intelligently, based on its own location with respect to a PU and its neighbours location with respect to itself. It is assumed that the nodes are having the location awareness and they share the details of their location, SNR at each instant and single node sensing result to the neighbours. It is also assumed that the nodes have clear knowledge of where exactly the PU is located. Hence a fusion node can infer three cases about its own location, based on the distance measure. Case-1: Within the coverage area, Case-2: Outside the coverage area, Case-3: Within or outside the coverage area. But in practice, the coverage area is not constant and rather varies with fading etc. Hence fusion rule for decision fusion must have provision to accommodate the dynamic changes in the coverage area. Neighbours also will be considered in two groups. Nodes closer to PU than FN are in group-I (G_1) and others are in group-II (G_2). Fusion node can choose the weights R_n and R_s according to following equations 3.5, 3.6 $\&$ 3.7. For Case-1 and Case-2

$$R_{ni} = \left\{ \begin{array}{c} 1 + \Delta_1, L_i \in G_1 \\ 1 - \Delta_2, L_i \in G_2 \end{array} \right\} \tag{3.5}$$

$$R_s = 1 + \Delta_1 \tag{3.6}$$

where R_{ni} is the R_n for the i^{th} neighbouring node, L_i is the location of the i^{th} node, R_s is the self weight for the FN and $\Delta_1, \Delta_2 \in [0 - 1]$.

For Case-3, R_s = 1 and R_n can be chosen as

$$R_{ni} = 1 + \Delta_1 \tag{3.7}$$

Presence of R_n and R_s in equation 3.4 will help to reduce the unwanted influence of neighbours to make a decision which may false negative or false positive and this will help this rule to perform better than SNR rule. If the knowledge about location of the PU is not available, these nodes can infer a reasonable estimate of the location of the PU, based on the periodic data it collects from its neighbours. Location inference is not dealt here. The performance of the proposed decision fusion approach is compared with 'majority rule' and two variants of fuzzy approaches. In majority rule, if the single node result from majority of the nodes under consideration are true then the fusion nodes decision is 'Yes', otherwise it will be 'No'. In the fuzzy approach, proposed in (Matinmikko *et al.*, 2009) a two bit fuzzy decision represents the range of the received power which is communicated to fusion node and decision fusion is carried out. According to (Taghavi *et al.*, 2011), the nodes transmit the received power to the fusion node to make a decision. Fuzzification of data is done during the fusion process.

3.4.2 Analysis under AWGN and Rayleigh Fading

In this section, simulation setup to analyse the performance of the fusion rule under the scenario shown in Fig. 3.15 is discussed. Energy detection mechanism is employed here to simulate the environment. An AWGN channel with Rayleigh fading is considered for the environment. According to (Digham *et al.*, 2007) the received BP waveform at an SU can be represented as

$$r(t) = \left\{ \begin{array}{l} Re[hS_{LP}(t) + n_{LP}(t)] \exp^{j2\Pi fct}, ...H_1 \\ Re[n_{LP}(t)] \exp^{j2\Pi fct}, ...H_0 \end{array} \right\} \tag{3.8}$$

where r(t) is the received signal, h corresponds to gain of the slow varying fading channel, fc is the carrier frequency, H_0 and H_1 and refer to the two hypotheses of signal presence and signal absence, respectively. S_{LP} is an equivalent LP representation of the unknown signal and n_{LP} an equivalent LP AWGN process with a zero mean and a known flat power spectral density (PSD). At the receiver this signal is pre-filtered by an ideal BP filter and its output is squared and integrated over a time interval 'T' to produce a measure of energy of the received waveform. The output of the integrator denoted by 'y' acts as a test statistic to test the two hypotheses H_0 and H_1. For AWGN channels, the local false alarm probability and detection probability are given as

$$P_f = \frac{\Gamma(\frac{N}{2}, \frac{\lambda}{2\sigma^2})}{\Gamma(\frac{N}{2})} \tag{3.9}$$

$$P_d = Q_{\frac{N}{2}}(\sqrt{\frac{a\gamma}{\sigma^2}}, \sqrt{\frac{\lambda}{\sigma^2}}) \tag{3.10}$$

where N is the number of samples, σ^2 is the variance of 'y', λ is the threshold for energy detection, $\Gamma(.,.)$is the incomplete gamma function and $Q_{N/2}(.,.)$ is the generalized Marcum Q-function. According to (Arshad *et al.*, 2010), when the SU is in a fading channel, the channel gain h_i for an i^{th} user is varying due to the fading and P_d^i becomes conditional probability dependent on instantaneous SNR γ^i. Average probability of detection can be obtained by averaging instantaneous P_d^i over fading statistics. As expected, P_f^i is independent of γ^i and remains static. In this simulation, threshold for energy detection is calculated from P_f in the equation 3.9. Verification of these models is already there in the literature. This work aims to form a simulation setup that truly represents the scenario shown in Fig. 3.15 and to find out the probability of detection under various probabilities of false alarm.

In this setup the channel is modelled by considering one PU and 7 SUs randomly located on the same plane and where transmitted signal from the PU reaches the SUs through independent path. This means that each SU will undergo independent fading and SNR. It is also assumed that increase in distance between PU and SU will lead to decrease in SNR at receivers. Normally in literature, verification of this type of models is done by keeping the SNR constant. Out of 7 SUs considered for simulation, one is fusion node and the others are neighbours. As shown in Fig. 3.15, neighbours are categorized into two groups. One group is located closer to PU than the fusion node and the second group is located farther from this fusion node with respect to PU. The weight R_n has to be high for group-I and small for group-II. This has to be reversed when the fusion node is located just outside the boundary of the coverage area. Since the nodes are smart enough to have location awareness, they can also vary the weights while adapting to the situation. Fig. 3.17 shows that when all the nodes are having high SNR there is no need for a cooperative decision making. Fig. 3.18 shows that at lower SNR, the probability of detection is coming down and the majority rule for decision making is performing very poor while the SNR rule and Intelligent rules are giving a slightly better performance. But it is sure that above case, considered for Fig. 3.17 is far from reality.

In order to match with the scenario in Fig. 3.15, a random SNR value between -5 dB to +1 dB is chosen for fusion node, -5 dB to 10 dB and -15 dB to -3 dB for group-I and group-II respectively. Through iteration under various values of probability

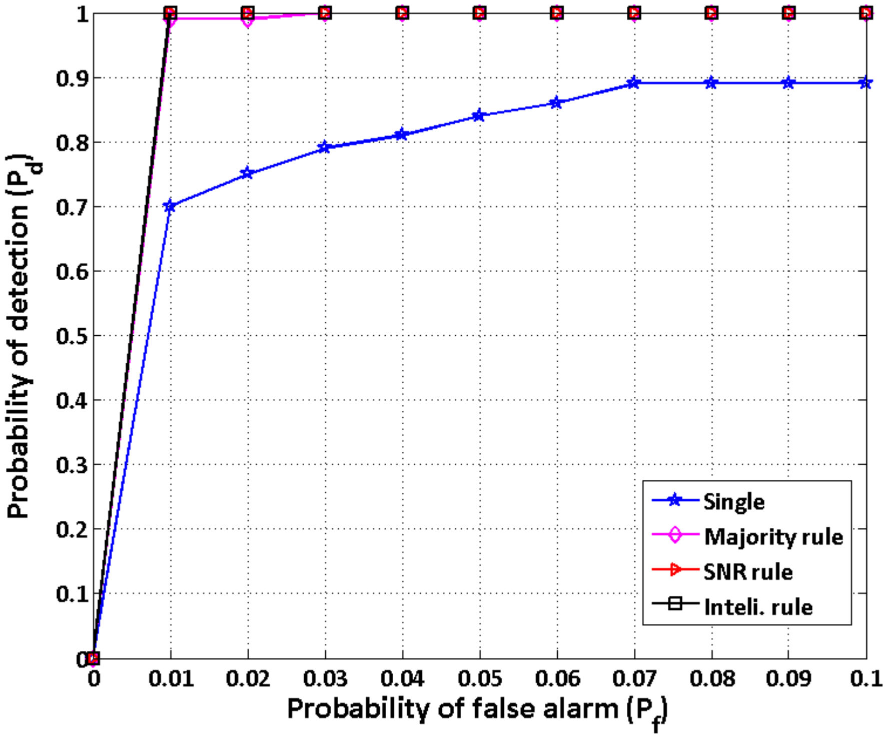


Figure 3.17: P_f vs P_d plot when all nodes with equal SNR for all nodes (SNR=5 dB)

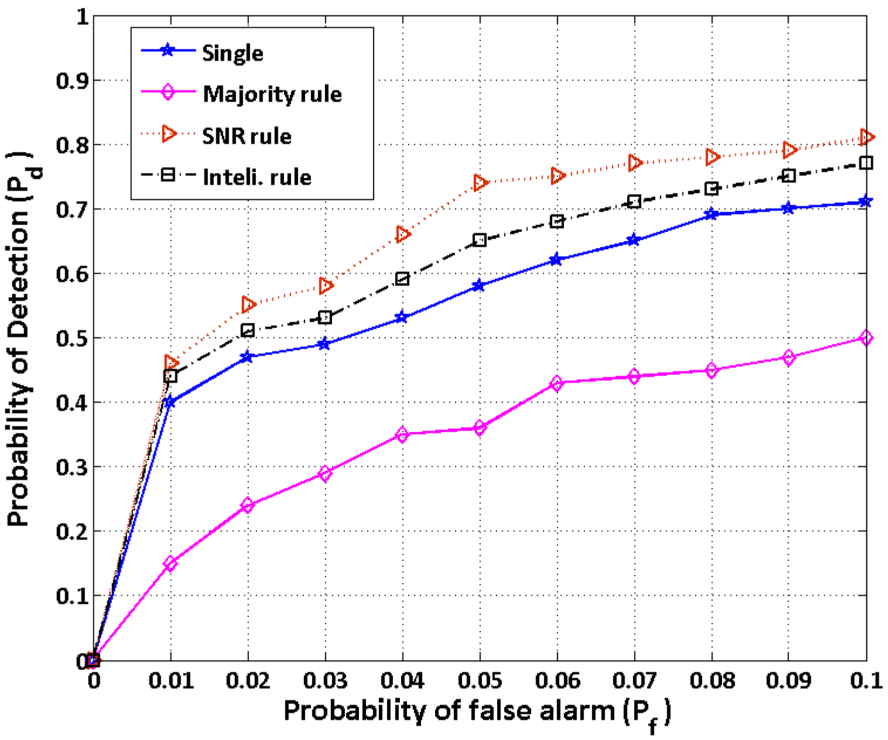


Figure 3.18: P_f vs P_d plot when all nodes with equal SNR for all nodes (SNR=-5 dB)

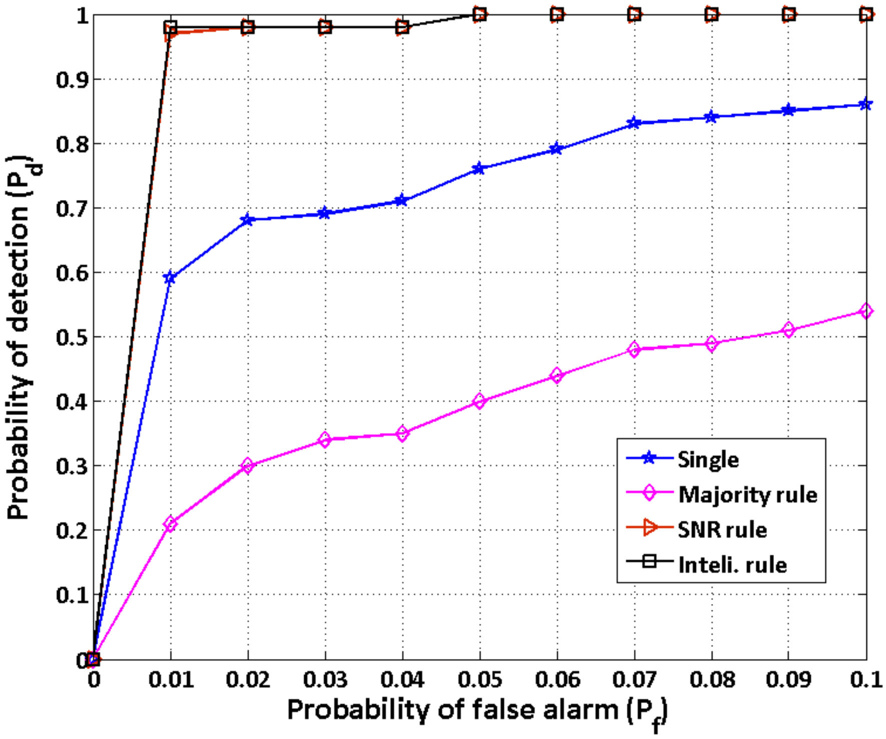


Figure 3.19: P_f vs P_d plot when the number of nodes within group-I- fusion node - group-II follows a pattern 5-1-1

of false alarm rate, probability of detection is calculated and displayed in Fig. 3.19 to 3.22. Since random SNR and fading is considered in each case, single node result has variations from figure to figure. In all the four cases, the performance of three fusion rules are compared with respect to single node result. It is seen from Fig. 3.19 to 3.22 that performance of the majority rule is getting deteriorated with increase in the number of neighbours in group-II. 'AND' rule and 'OR' rule are not considered here, as it may give extreme results. But it can be considered, when all the nodes are considered to be well within the coverage area of a PU. Here it is considered that the fusion node is relatively within the coverage area and the neighbours are located within and outside the boundary of the coverage area. Always there is some amount of fuzziness present, regarding the boundary of PU's coverage area.

Performance of 'SNR rule' and its modification 'Intelligent rule' is compared in Fig. 3.19 to 3.22. 'SNR rule' is giving very good detection rate compared to 'Majority rule'. This is because SNR is included in the fusion rule for decision fusion. It is seen that as the number of nodes in group-II increases, 'Intelligent rule' is more effective. This is attributed to the adaptive weights used in that rule. The weight is chosen in

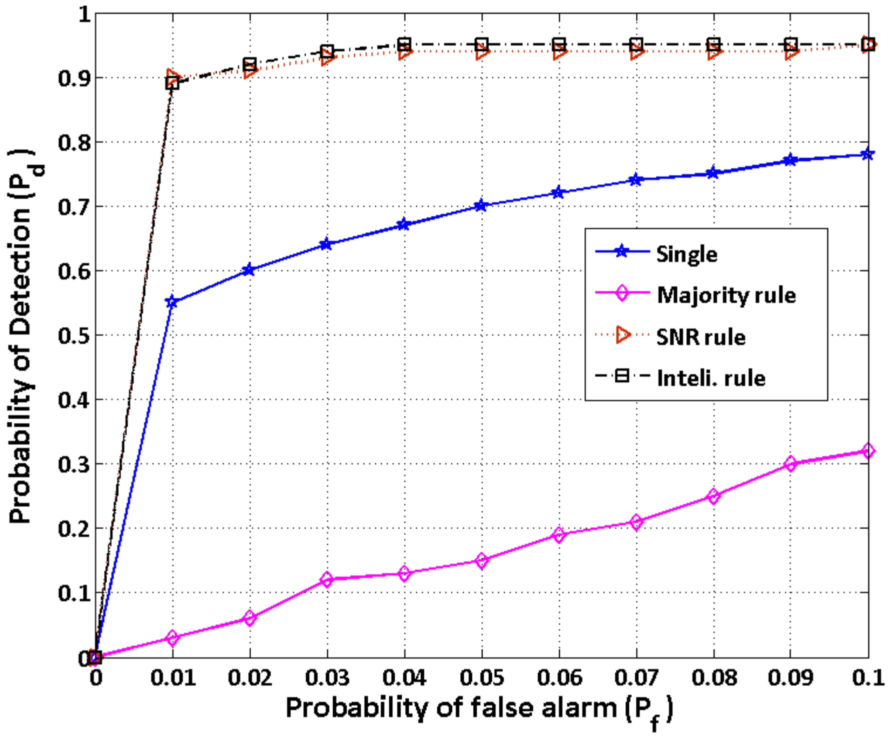


Figure 3.20: P_f vs P_d plot when the number of nodes within group-I- fusion node - group-II follows a pattern 3-1-3

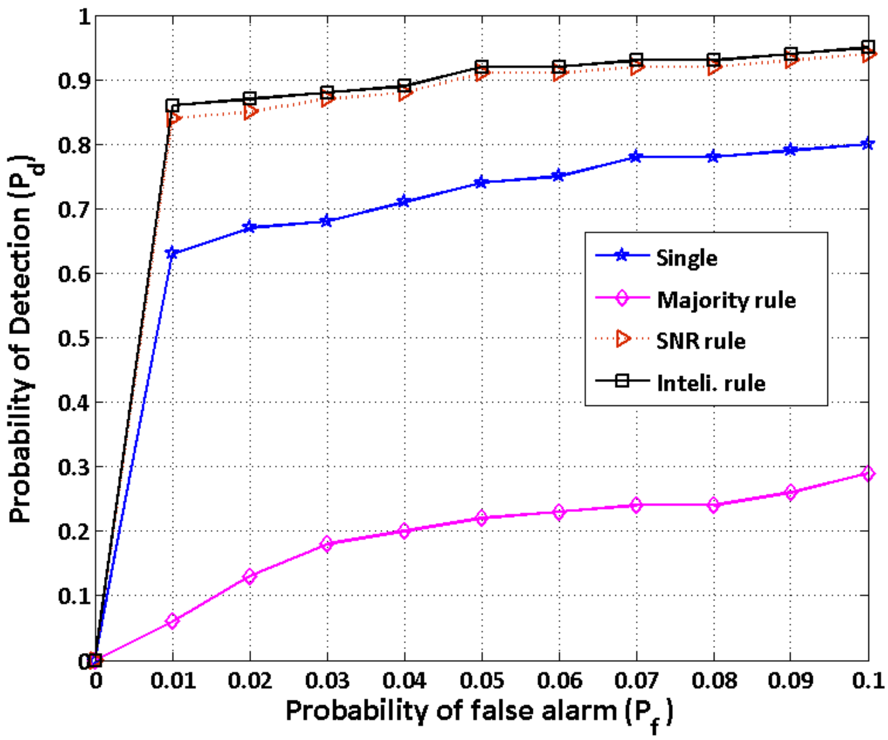


Figure 3.21: P_f vs P_d plot when the number of nodes within group-I- fusion node - group-II follows a pattern 2-1-4

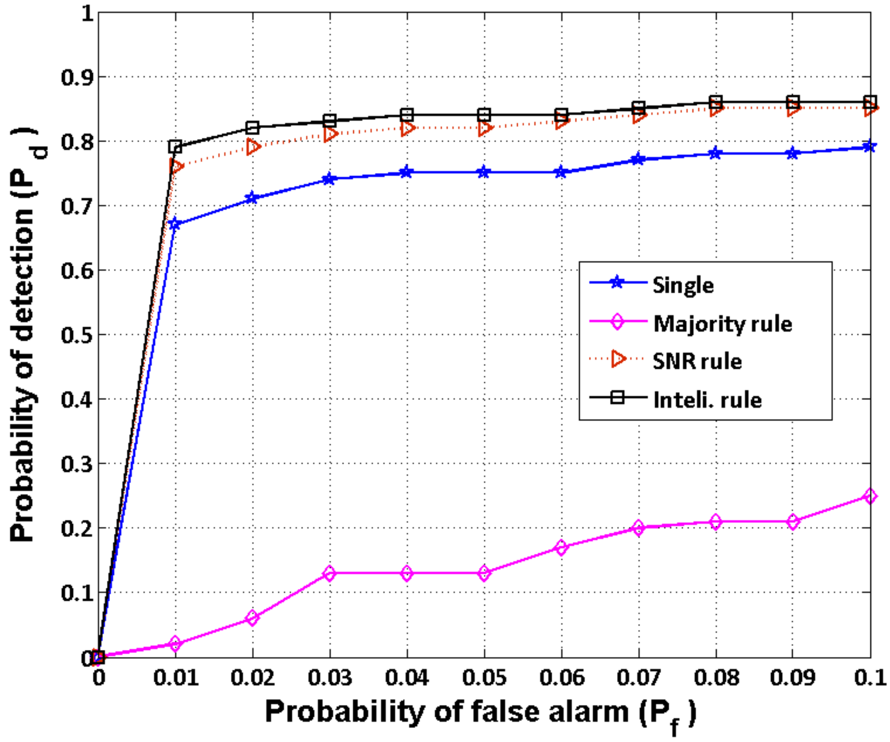


Figure 3.22: P_f vs P_d plot when the number of nodes within group-I- fusion node - group-II follows a pattern 1-1-5

such a way that if the fusion node is closer to PU, the weights for group-I will be larger than group-II. This will ensure that false negatives will be reduced. As the fusion node moves away from a PU, the weight for group-I decreases and that of group-II increases. This will reduce the false positives. It shows that 'Intelligent rule' approach will work well for a realistic scenario as it is adaptively adjusted to the need of the fusion node.

3.4.3 Analysis under Shadowing

In order to analyse the fusion rule under shadowing, a different approach as per the practical link budget design using path loss model in (Rappaport *et al.*, 1996) is used. Propagation path loss according to distance from the transmitter is defined according to the equation 3.1 as mentioned in (Harrold *et al.*, 2008). The received power P_r (in dBW) of a receiver at a distance d meters from a transmitter with transmit power P_t (in dBW) is calculated according to equation 3.2

A binary hypothesis model for transmitter detection, i.e., the model of signals received by the SU, is defined as

$$P_r = \left\{ \begin{array}{c} P_n \text{ , } in\ case\ of\ \ H_0 \\ P_s + P_n \text{ ,} in\ case\ of\ H_1 \end{array} \right\} \tag{3.11}$$

where P_n is the noise power and P_s is the signal power, H_0 indicates only noise and H_1 indicates the presence of PU. Dense urban scenario with path loss exponent n=4.5 and shadowing standard deviation 10 dB is considered for simulation. PU is located at the center and the CR nodes are located around it. Received power of each node is calculated based on the equation 3.2. And this received power is compared with noise power (noise floor) to make a decision on 'sensed' or 'not sensed '. Once this individual decision is made, final decision is achieved with the help of fusion rules. This model is used to get more clarity on the boundary of a PU. The model is designed for simulation of primary signal transmitter and CR receivers within a 2-dimensional square spatial area with Cartesian co-ordinates. Fig. 3.23 shows the arrangement in the field with PU at the center as black dot and the CRs are located around it. CRs with 'sensed' status are marked as '$\bullet$' in blue colour and CRs with 'Not sensed' status are marked as '$\circ$' in red colour. Fig. 3.23 shows the single node sensing result as per equation 3.2 and Fig. 3.24 is an example of a result after cooperative sensing where 'Intelligent rule' is used for decision fusion. A black circle is the calculated coverage area of the PU by considering the transmission power of the PU, noise floor and the average shadowing. In reality the coverage area will fluctuate around this black circle as mentioned in (Goldsmith, 2005). Coverage area is expected to fluctuate between the inner fade range shown by inner circle and the outer fade range shown by the outer circle.

Under such a situation, probability of detection, rate of false alarm and rate of false positive are to be defined with respect to the coverage area of the PU. Coverage area of the PU need not be a definite area always. It will be varying due to random shadowing. The region inside the inner fade range is where all nodes should sense the PU and the region outside the outer fade range is where none of the nodes should sense the PU. In the region between inner and outer fade range, nodes may get a 'sensed' or a 'not sensed' status. Hence for this setup, we have defined the detection rate as the percentage detection within the average fading region. False alarm rate is defined as the percentage 'not sensed' within the average fade region and false positive is defined as the percentage 'sensed' outside the outer fade range.

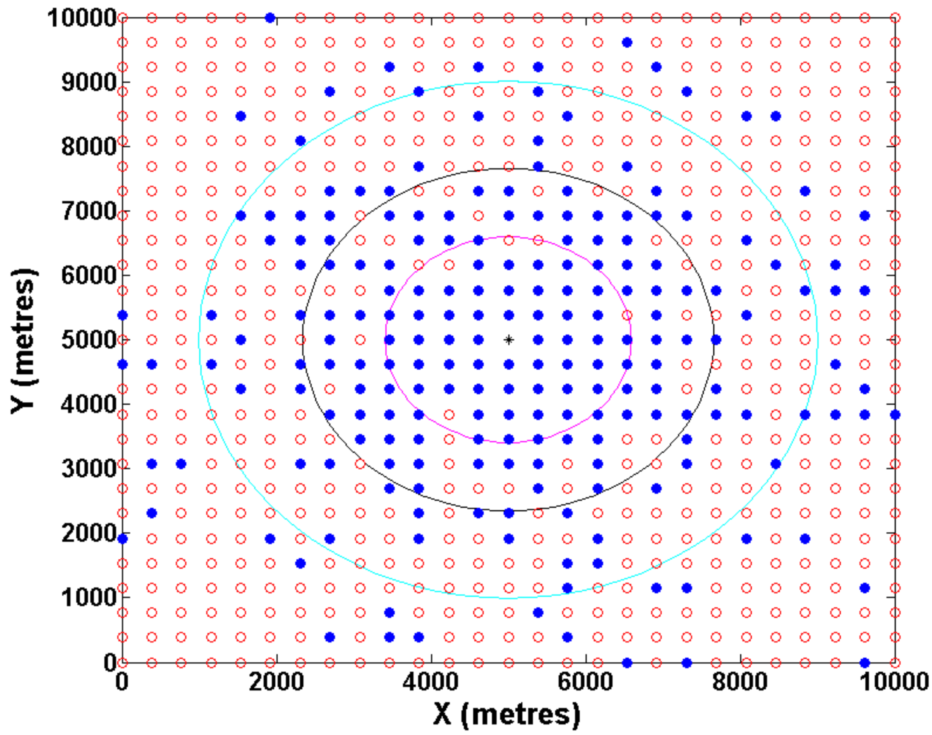


Figure 3.23: Single node sensing

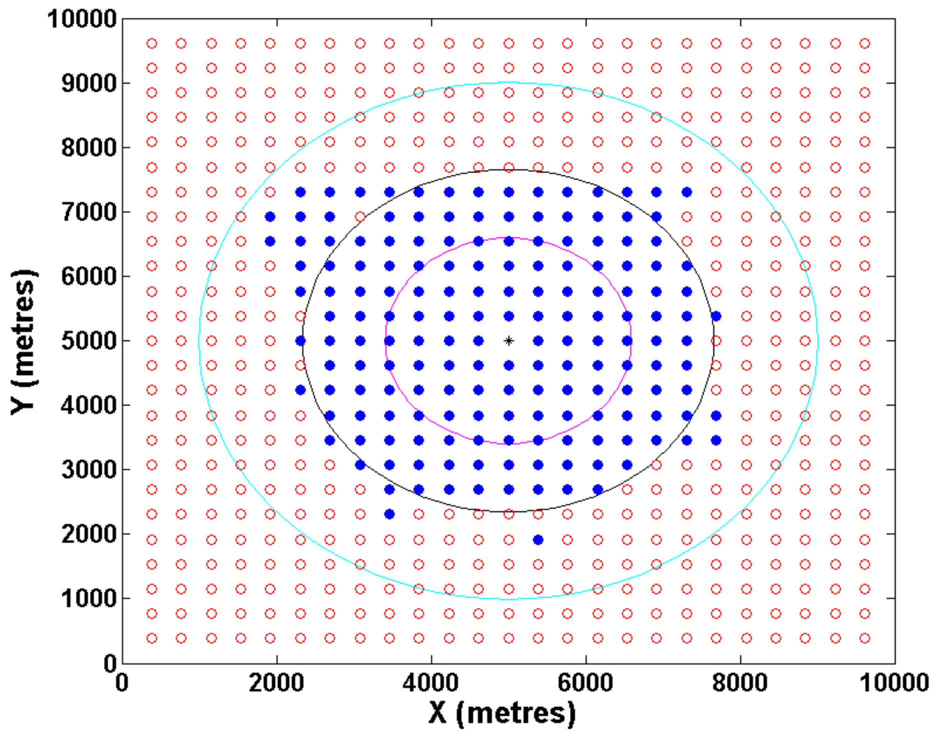


Figure 3.24: Cooperative sensing

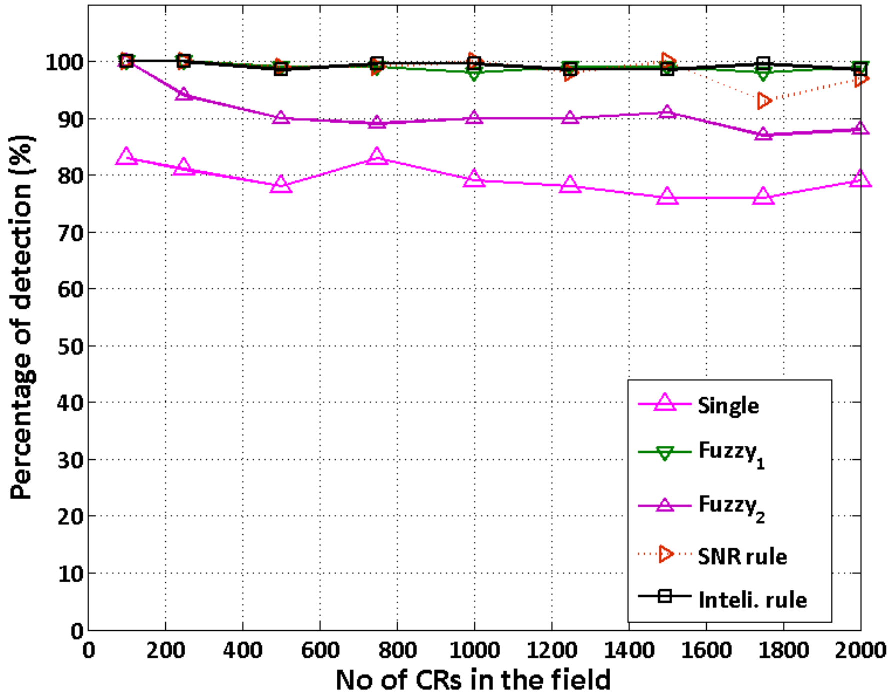


Figure 3.25: Performance comparison of Intelligent fusion rule with SNR rule and Fuzzy rules on detection rate

Comparison is made between the proposed Intelligent rule with SNR rule in Section 3.3 and fuzzy based rules (named as Fuzzy_1 and Fuzzy_2) proposed in literature. The rule proposed by (Taghavi *et al.*, 2011) is named as Fuzzy_1 and in this approach, the CRs transmit the received power to the neighbours for decision fusion. Fuzzification of data is done during the fusion process. The rule proposed by (Matinmikko *et al.*, 2009) is named as Fuzzy_2 and in this approach, a two bit decision from a CR that indicates the linguistic variable as low, medium and high, is transmitted to its neighbours for decision fusion. These fuzzy inputs are given to a fuzzy controller and a decision is made according to the fuzzy rule base available in the node.

We have considered a mobile tower with 935 MHz and 10 dB power as the PU. Shadowing environment is simulated and the received power is compared with the noise power to make a single node spectrum sensing. We have considered a 10 km x 10 km area for this set up and the Fig. 3.25 gives the comparison of single node performance and cooperative sensing. It shows that the detection rate is very good for all the rules except Fuzzy_2. Number of CRs in the field does not have much impact on the detection rate. Fig. 3.26 gives the false negative performance. False alarm rate is high for Fuzzy_2 and it is very less for 'Intelligent' approach. Fuzzy_1 and SNR approaches are giving

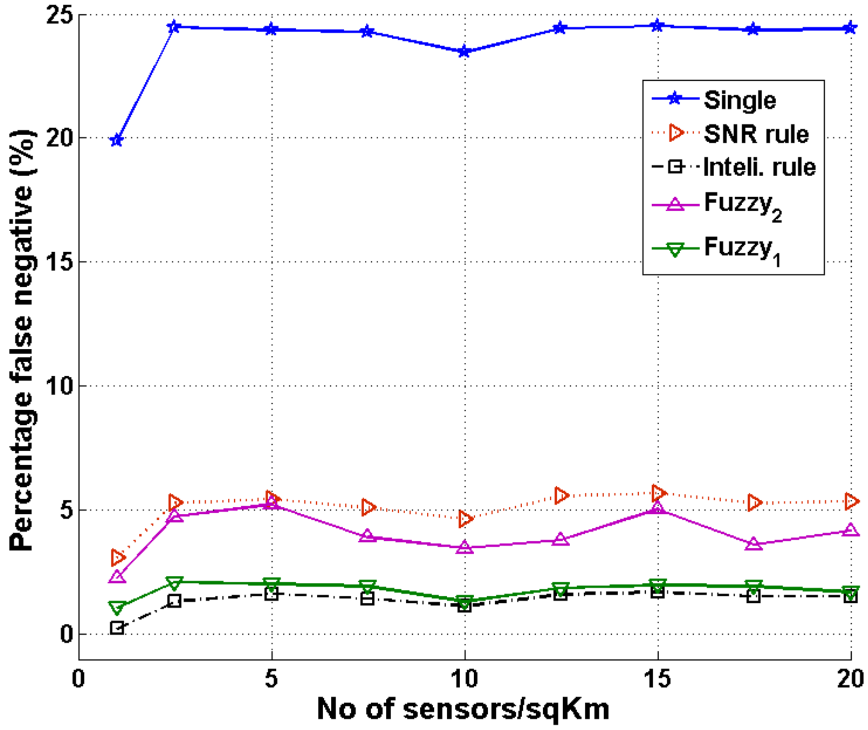


Figure 3.26: Performance comparison of Intelligent fusion rule with SNR rule and Fuzzy rules on false negative

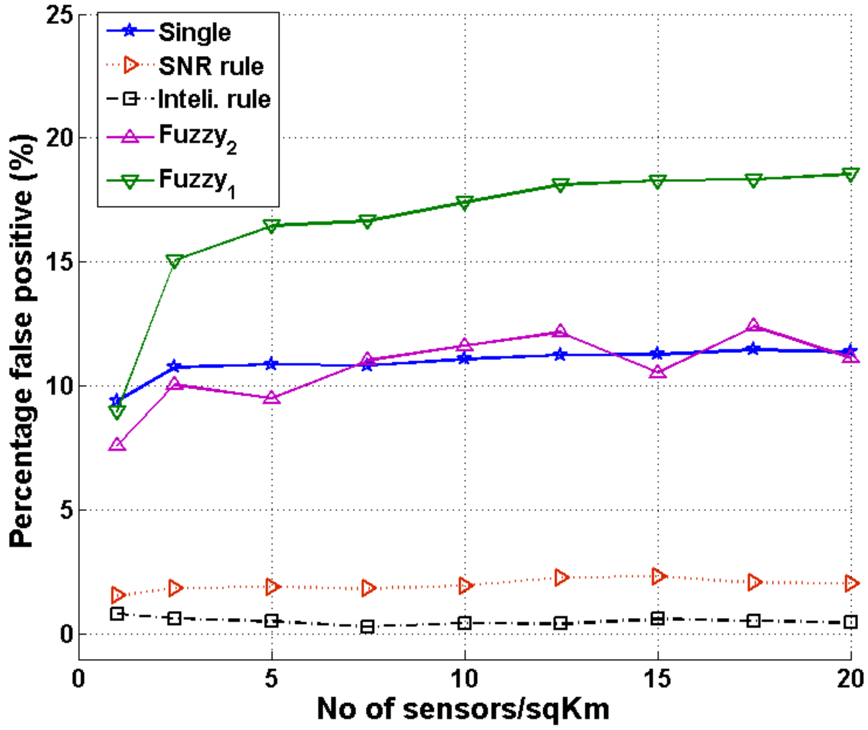


Figure 3.27: Performance comparison of Intelligent fusion rule with SNR rule and Fuzzy rules on false positive

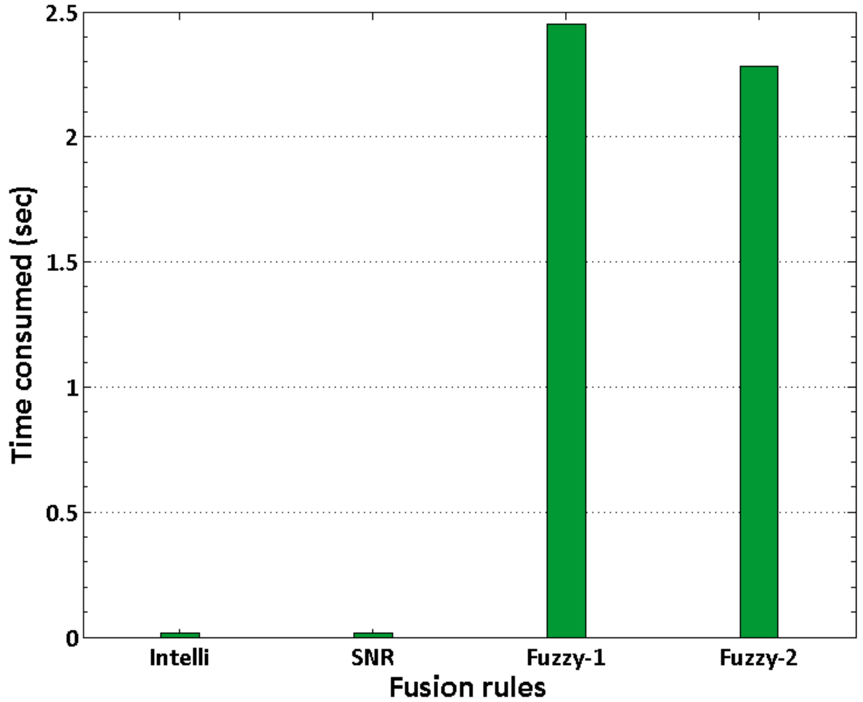


Figure 3.28: Time consumed by various rules for decision fusion. [Machine spec: Intel(R) Core(TM)2 Duo CPU, T7250 @ 2.00 GHz, 777 MHz,1.95 GB RAM]

medium performance. When it comes to false positive case Fuzzy$_1$ is having the worst performance. It is seen in Fig. 3.27 that there is slight increase in the number of false positives with increase in the number of CRs in the field. False positive performance of 'Intelligent' rule approach is almost zero. This is because of the adaptive weight pattern that can be used for decision fusion. Computational complexity is measured by calculating the time consumed by the fusion rules to make decision for 500 CR terminals. Fig. 3.28 shows that 'SNR' rule is having the least computational time and the 'Intelligent' rule has consumed slightly more time. This is because of the additional multiplication due to the region weight added with SNR rule. Fuzzy based approaches are consuming significantly more time compared to SNR based rules.

3.4.4 Section Summary

In this section, a realistic network scenario is proposed for CRs, where the fusion node is located at the boundary of a PU's coverage area. An adaptive weighted combining approach as a modification to 'SNR rule' in Section 3.3 is also proposed. Performance of these fusion rules were analysed under two simulation setup that models the scenarios in

Fig. 3.15 & Fig. 3.16 meaningfully. Analysis of these rules were carried out in Rayleigh fading and shadowing under two separate channel models respectively. Performance of the proposed rules are compared with 'Majority' rule, Fuzzy_1 rule and Fuzzy_2 rule. Criteria such as detection rate, false negative, false positive and computational complexity are considered for comparison. It is found that the proposed 'Intelligent' rule is having a better performance under the scenario considered. This rule can be optimized further with adaptable and optimized weights.

3.5 Antenna Selection with MRE and AWC for Decision Fusion

It was seen in Section 3.4 that proposed 'Intelligent rule' is performing well in the realistic scenarios considered for analysis. In this section, an attempt is made to further improve the performance of the spectrum sensing scheme by modifying the single node reporting strategy and the 'Intelligent rule'. Main contribution of this section is that an antenna selection scheme with multiple region encoding for single node reporting and an adaptive weighted combining fusion rule for fusion node are proposed. Its analysis is carried out in a realistic scenario and its performance is compared with other prominent approaches in the literature.

3.5.1 System Model

In this model, a CR network consisting of 'N' primary users and 'M' Cognitive users where the CRs utilise the same spectrum allocated to PUs whenever the spectrum is unused by any PU. It is also considered that the secondary network is performing CSS at specified time slots. Cognitive radio network under CSS (distributed sensing) has to sense a portion of the spectrum of bandwidth 'W' in order to detect the existence of the PU. It is assumed that each CR is equipped with an energy detector and is able to perform local spectrum sensing independently. In CSS, every SU performs spectrum sensing and a local decision on the presence of a PU is made. All SUs in the network share its soft (local measurement) or hard (1-bit) decision with its neighbours. In distributed sensing, each SU behaves as a fusion center (FC) and a final decision is taken.

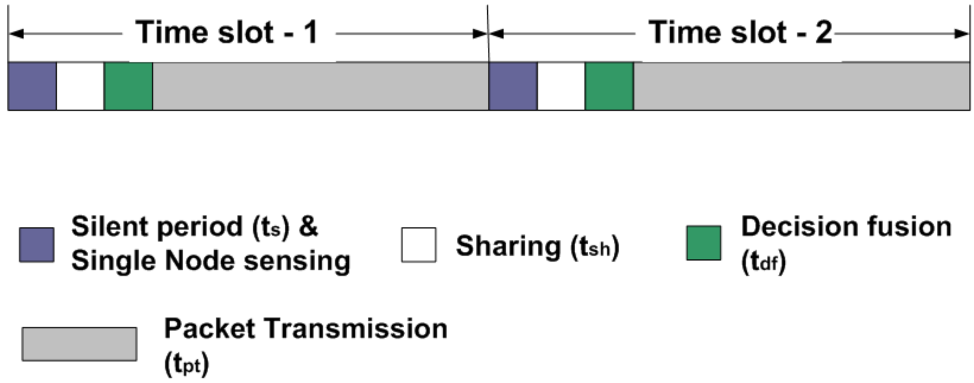


Figure 3.29: Timing sequence for a practical implementation of CSS

In a cluster based network, SUs share its individual decision with a common receiver in the cluster called FC and the FC makes the final decision and shares it within the cluster. In both cases, fusion center has to collect its neighbours' decision and a final decision will be taken after decision fusion.

Cooperative sensing can be practically carried out in sequence as shown in Fig.3.29. It is assumed that one licensed frequency channel is allocated to each primary user and control channels are available for the CRs to share its decision with the fusion center. Also the cross channel interference is considered to be negligible. CSS and data transmission are carried out in cycles of equal time slots. Duration of the time slot is fixed in such a way that interference to a PU will be negligible even if the PU has arrived at the middle of the time slot. At the beginning of each time slot all the CRs will be silent for a duration 't_s', so that only the signals from PU will be present. During 't_s', spectrum sensing is also carried out by each CR. During 't_{sh}' , individual sensing result from each node is shared among its neighbours. 'Decision fusion' is performed during 't_{df}' and remaining time within a slot is allocated for data transmission by the concerned CRs. This process will be repeated in every time slot.

It is also considered that PUs and CRs are randomly placed in the field in such a way that coverage area of the PUs will not overlap. Fig. 3.30 shows that some CRs are located totally outside the coverage area of PUs. In a practical situation where shadowing is present, the coverage area is not a perfect circle. It will form an amoeba-like shape due to the random shadowing variations about the path loss (Goldsmith, 2005). Black circle in Fig. 3.30 performs decision fusion (fusion node) and red circles are its neighbours. Single node sensing results from FN and its neighbours are fused to make a final decision. Every node in the field performs decision fusion by considering results

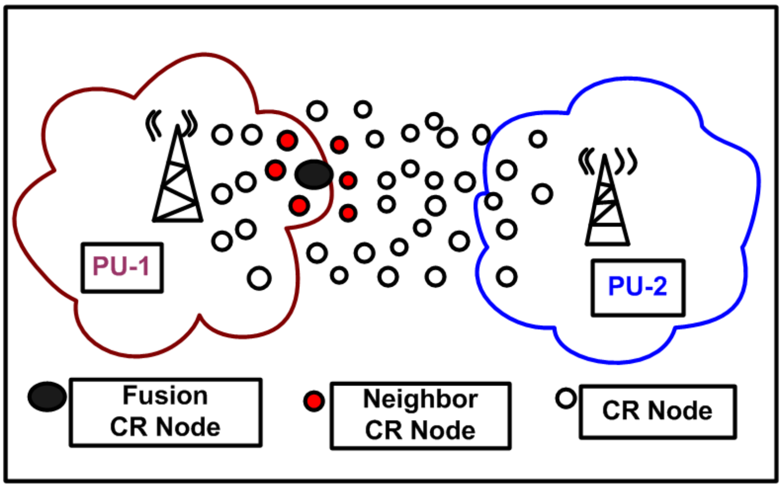


Figure 3.30: Distribution of CRs in the field considered for this work

from its neighbours. For some nodes, all of its neighbours are within the coverage area of a PU, but in some cases some of its neighbours are located outside the coverage area as in Fig. 3.30. Decision fusion should be correct in both the conditions. Our focus is to improve decision fusion in the second case where wrong influence of the neighbours needs to be limited. In this discussion, a CR terminal is referred with following terms, such as nodes, neighbour nodes, fusion nodes, CR nodes etc. based on their functionality. In other words, all such terms are the synonyms for a CR terminal. It is assumed that all the CRs are equipped with multiple antennas and location awareness mechanisms. For the scenario in Fig. 3.30, fusion rule should be able to identify such a situation and priority of the neighbours needs to be adjusted. It is assumed that each node is aware about its position in the field and shares this information with its neighbours. This will help each node to prioritize neighbours' result during decision fusion.

In literature, in most of the cases, fusion rules are proposed and analysed under a scenario where all the CRs are within the coverage area of a PU and the SNR is uniform for all nodes. Parameters such as detection rate, false alarm rate etc. are also defined and evaluated for the same scenario. A realistic scenario may look similar to that of Fig. 3.30 where spatial location of CR nodes with respect to PU will be different for all the CRs.

The proposed model can also be practically implemented in line with IEEE 802.22, cognitive wireless regional area networks (WRAN) standard, where the system specifies a fixed point-to-multi-point (PMP) wireless air interface similar to cellular system. In WRAN, the base station (BS) controls the medium access in its cell and transmits in the downstream direction to the various customer premise equipments (CPE), which respond back to the BS in the upstream direction. In order to ensure proper incumbent protection, BS also manages a unique feature of 'distributed sensing', where the BS and CPEs perform spectrum sensing during the quiet periods and are consolidated at the BS. Quiet periods are derived with respect to the packet structure (IEEE-802.22, 2011; Cordeiro *et al.*, 2005*a*).

Proposed system model can be easily fitted in cognitive WRAN. Spectrum sensing (fast sensing) carried out by BS and CPE during the quiet period is similar to single node detection by each CR in the proposed system. BS performs consolidation of the sensed data from all CPEs, and it is equivalent to the activity of fusion node in the proposed system. Hence BS can easily use the AWC rule to make a final decision on the spectrum occupancy status. CPEs can make use of the proposed SU reporting process for sensing as well as to report the result to BS.

If the BS has to manage a scenario as proposed in Fig. 3.30, where some of its cluster members are outside the coverage area of a PU, decision for those members can be obtained by suitable selection of neighbouring nodes and suitable choice of adaptive weight factor according to the location of those nodes.

The spectrum sensing problem can be considered as a binary hypothesis testing problem with two possible hypothesis H_0 and H_1 (Arshad *et al.*, 2010). An AWGN channel with Rayleigh fading is considered for the environment. Received BP waveform at an SU is represented according to (Digham *et al.*, 2007) as equation 3.8

Received signal is filtered and the energy is calculated by squaring it and integrating it over a time interval 'T'. The output of the integrator acts as the test statistic 'y' . It is assumed that the noise at each sample is Gaussian with zero mean and unit variance and is independent of the primary signal under H_1 and the instantaneous SNR varies from observation period to period. The received energy is calculated according to (Ma *et al.*, 2008) as

$$y = \sum_{t=1}^{N} |x(t)|^2 \tag{3.12}$$

For an AWGN channel, probability of false alarm and probability of detection are given as in equation 3.9 and equation 3.10.

In this simulation, threshold for energy detection is calculated from P_f in the equation 3.9. Probability of detection under a Rayleigh fading channel is given by (Digham *et al.*, 2007) as

$$P_{d,Ray} = e^{-\frac{\lambda}{2\sigma^2}} \sum_{i=0}^{\frac{N}{2}-2} \frac{(\frac{\lambda}{2\sigma^2})^i}{i!} + (\frac{2\sigma^2 + a\gamma}{a\gamma})^{\frac{N}{2}-1} \left[e^{-\frac{\lambda}{2\sigma^2 + a\gamma}} - e^{-\frac{\lambda}{2\sigma^2}} \sum_{i=0}^{\frac{N}{2}-2} \frac{(\frac{\lambda a\gamma}{2\sigma^2(2\sigma^2 + a\gamma)})^i}{i!} \right] \tag{3.13}$$

In this section, a CR terminal is variously referred to as nodes, neighbour nodes, fusion nodes, fusion center, CR nodes etc., based on its functionality. All these terms are synonymous to a CR terminal. It is considered that all the CRs are equipped with multiple antennas and location awareness mechanisms. It is considered that all the nodes are experiencing Rayleigh fading. The proposed system for cooperative sensing has two parts. An antenna selection with multiple region encoding is performed at each SU as part of single node sensing and an adaptive weighted combining is performed during the fusion process. Details are given in the following sections.

3.5.2 SU Reporting Process

In this section, an antenna selection scheme with multiple region encoding is proposed. Modified version of antenna selection approach in (Wang *et al.*, 2011) and double threshold approach in (J. Zhu and Zhang, 2008) are combined here to model the single node reporting scheme for the SU. Proposed scheme for single node reporting is given in Fig. 3.31. It is assumed that secondary user employs 'K' antennas and one RF chain. Assume that each SU will have a sensing duration of 'T' and 'N' samples will be collected during 'T'. Time is divided into mini slots of T/K duration and at each mini slot, N_1= N/K samples from each antenna will be collected sequentially to form 'N' samples. This is done to get the benefit of antenna diversity. Energy 'y' of these 'N' samples are calculated and sent to the encoding block. This antenna diversity scheme will improve the probability of detection $P_{d,AD}$ at each node. It can be obtained from (Liang *et al.*,

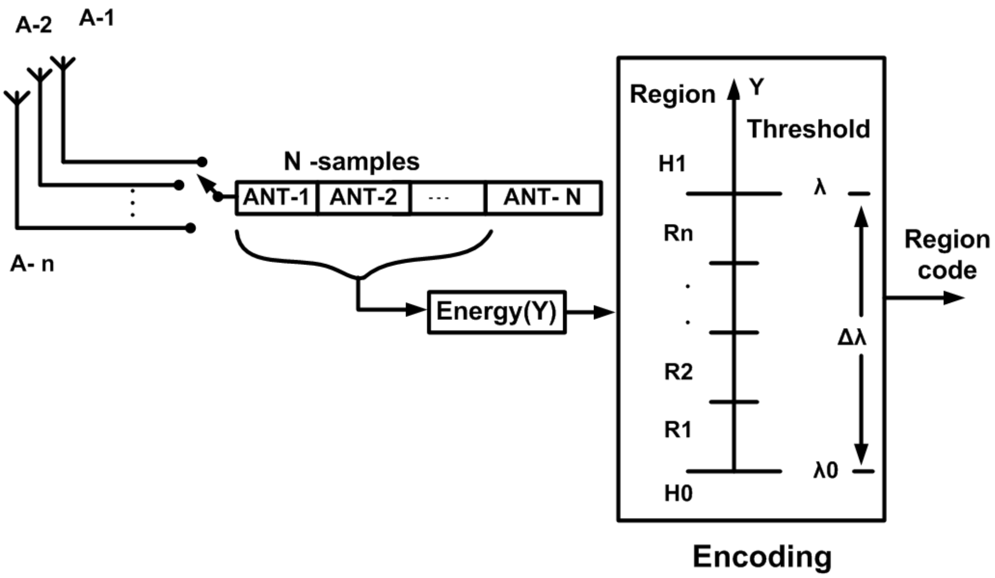


Figure 3.31: Antenna selection scheme with multiple region encoding

2008) as

$$P_{d,AD} = Q(\frac{1}{\beta}(Q^{-1}(P_f) - \gamma\sqrt{N_1}\sum_{i=1}^{K} g_i|h_i|^2)) \tag{3.14}$$

where $\beta = Q(\sqrt{1 + \frac{2\gamma}{K}\sum_{i=1}^{K}|h_i|^2})$, Q(.) is the complementary distribution function of the standard Gaussian, $g_i \geq 0$ is the weighting factor associated with the i^{th} mini slot and h_i's are zero-mean, unit variance complex Gaussian random variables that represents channel coefficients. Here the first threshold 'λ' for the energy detection is calculated in the usual way based on a specific P_f fixed for a system. P_d depends on the instantaneous SNR of the SU. Under a fading channel, the P_d will be different from that of an AWGN channel. The distribution of received energy in this case will be the same. Second threshold 'λ_0' is calculated based on the parameter defined as Δ = P{$\lambda_0 < y < \lambda | H_0$ }. From equation 3.9, it can be written as

$$\Delta = \frac{\Gamma(\frac{N}{2}, \frac{\lambda_0}{2\sigma^2})}{\Gamma(\frac{N}{2})} - \frac{\Gamma(\frac{N}{2}, \frac{\lambda}{2\sigma^2})}{\Gamma(\frac{N}{2})} \tag{3.15}$$

By setting the value of 'Δ', length of the region $\Delta\lambda = \lambda - \lambda_0$ can be varied. In this system '$\Delta\lambda$' is divided into multiple regions of equal size referred as $R_1, R_2, ...R_n$ as shown in Fig. 3.31. This will help the node to assign suitable codes to the received energy. Encoding of the result is as follows.

If the received energy 'y' is in the H_0 region or at the H_1 region, then the node will assign '-1' or '+1' respectively to the decision. If the energy 'y' falls in the region R_1 to R_n, a fractional value between -1 and 1 is awarded in such a way that $-1 < R_1 < R_2 < ... < R_n < 1$. For example, if '$\Delta\lambda$-region' is divided into two regions, there will be a total of four regions named H_0, R_1, R_2 and H_1 and -1,-0.5,+0.5,+1 will be their respective weights. Depending on the strength of the signal any value from -1,-0.5, +0.5, +1 will be sent out as the single node's result. The SU is supposed to transmit this value as the sensing result to its neighbours. During decision fusion, this value is combined with suitable fusion rules and final decision is made. Considering the transmission overhead in sending the single node sensing values, each region can be encoded with an 'n-bit' decision, where n= [1,2...]. This includes the 'H_1' region and 'H_0' region. Depending on the number of regions available, 'n' can take a suitable value. During fusion, proper value can be included in place of the corresponding code. In our simulation, we have considered a 3-bit encoding to represent these regions.

3.5.3 Decision Fusion

Single node sensing may lead to false decision especially when the SNR level is low. Noise level in the channel, shadowing and fading can cause low SNR. Another challenge in spectrum sensing is hidden node problem. These problems can be overcome with cooperative spectrum sensing (Harrold *et al.*, 2008). Researches show that CSS is able to give a very good performance under fading and shadowing. Here all the nodes will do spectrum sensing and share its decision or the measured energy to its neighbours. Every node will make a final decision by fusing these information (Kyperountas *et al.*, 2010). In order to improve the detection probability at lower SNRs, an adaptive weighted combining is proposed below. Performance comparison of the proposed combination of SU reporting and fusion rule with other fusion rules is given in Section 3.5.4.

Adaptive Weighted Combining (AWC)

To overcome the effect of fading and shadowing cooperative spectrum sensing needs to be carried out. In order to get a reliable performance over the scenario shown in

Fig. 3.30 intelligent rule in equation 3.4 is modified and given in equation 3.16 . It is assumed that each SU is having the location awareness and it is communicated to the neighbours also. Each node is expected to send details about location, experienced SNR and node's own sensing result to its neighbours. Each node will collect details of N neighbours and this will be combined with node's own weight. The proposed AWC rule is stated as follows.

$$Y_{AWC} = \sum_{n=1}^{n=N} R_n \gamma_n Q_n + R_s \gamma_s W_s Q_s \tag{3.16}$$

where R_n is the adaptive weight factor according to the location of the node, 'γ_n' - SNR at the node, Q_n- single node decision value generated at SU reporting process, R_s is the adaptive weight for the fusion node, 'γ_s'- SNR at the fusion node, Q_s- single node decision value of fusion node and W_s - Self weight for the fusion node. Decision of a spectrum hole is taken as

$$Y_{AWC} \underset{H_0}{\overset{H_1}{\gtrless}} 0 \tag{3.17}$$

The fusion node will choose the values of R_n, R_s according to its own location with respect to a PU and its neighbour's location with respect to itself. Nodes which are closer to PU than fusion node will have $R_n = 1 + \Delta_1$ and others will have $R_n = 1 - \Delta_2$ where $\Delta_1, \Delta_2 \in [0 - 1]$. It is assumed that locations of the PUs are known to the CRs. Otherwise, nodes can infer it by following the signal strength of its neighbours. W_s is used to give a higher weightage to node's own decision when it aggregate the data. It will also help to reduce the wrong influence from the neighbours. 'SNR' is used along with all the decisions to ensure that false positives are reduced. If the single node result is broadcast in the encoded format as mentioned in the previous section, proper decoding will be done at the fusion node before fusion process. Proposed approach is compared with other prominent fusion rules in the literature. A brief description of other rules used for comparison is also presented below.

Soft Optimal Linear Combining (SOLC)

Soft optimal linear combining is presented in (Kyperountas *et al.*, 2010). Energy of each node is weighted combined here and compared against a threshold to make a decision. With soft linear combining, the test statistic at the fusion center corresponds to

$$y_f = \sum_{I=1}^{M} w_i u_i = \mathbf{w}^T \mathbf{u} \tag{3.18}$$

where $\mathbf{w} = [w_1, w_2, ...w_M]^T$is the weight vector and $\mathbf{u} = [u_1, u_2, ...u_M]^T$ is the energy from 'M' neighbouring nodes with 'N' samples with standard deviation of noise 'σ' and SNR at the receiver 'γ'. Since y_f is a sum of Gaussian distributions, then it also follows a Gaussian distribution. Test to determine whether a primary is present or not is:

$$y_f = \frac{\overset{H_1}{>}}{\underset{H_0}{<}} \lambda_f \tag{3.19}$$

Threshold (λ_f) can be calculated from the P_{fa} of the fusion center as

$$\lambda_f = Q^{-1}(P_{fa}) \sqrt{Var\{y_f/H_0\}} + E\{y_f/H_0\} \tag{3.20}$$

Weight vector can be calculated as

$$\mathbf{w} = sign(\mathbf{g}^T \mathbf{w}_1)\mathbf{w}_1 \tag{3.21}$$

Where

$$\mathbf{w}_1 = \frac{\mathbf{L}_{H_1}^{-1/2} \mathbf{L}_{H_1}^{-T/2} \mathbf{g}}{||\mathbf{L}_{H_1}^{-1/2} \mathbf{L}_{H_1}^{-T/2} \mathbf{g}||} \tag{3.22}$$

$$Var\{y_f/H_0\} = \mathbf{w}^T \mathbf{L}_{H_0} \mathbf{w} \tag{3.23}$$

$$E\left\{y_f/H_0\right\} = \mathbf{s}_{H_0}^T\mathbf{w} \tag{3.24}$$

$$\mathbf{s}_{H_0}^T = [\sigma_1^2, \sigma_2^2, ...\sigma_M^2]^T \tag{3.25}$$

$$\mathbf{L}_{H_0} = 2diag(\mathbf{s}_{H_0})/N \tag{3.26}$$

$$\mathbf{L}_{H_1} = 2diag(\sigma_1^4(1+2\gamma_1), \sigma_2^4(1+2\gamma_2)....\sigma_M^4(1+2\gamma_M))/N \tag{3.27}$$

$$\mathbf{g} = [\sigma_1^2\gamma_1, \sigma_2^2\gamma_2, ...\sigma_M^2\gamma_M]^T \tag{3.28}$$

Soft equal weight linear combining (SEWLC) employs straightforward averaging of the received soft decision statistics. The test statistic at the fusion center for equal weight combining corresponds to equation 3.18 with $\mathbf{w} = [1, 1, ...1]^T$.

3.5.4 Results and Discussion

Simulation framework is formed in MATLAB tool, to model the proposed scenario, including propagation channel, received signal from the PU and CSS. It is considered that CRN is formed by locating a large number of CRs in a 2D plane, with a PU located at the center of it. The primary signal is considered to be deterministic and BPSK (binary phase-shift-keying) modulated. Noise is real Gaussian with mean '0' and variance '1'. Rayleigh fading channel with slow fading is considered in the simulation. Transmitted signal from the PU reaches the SUs through independent path. That means, received signal at each CR undergoes independent fading and SNR. Focus in our proposed scenario is the nodes that are located near the boundary of PU's coverage area. This is modelled by assigning appropriate SNRs within a range of +5 dB to -25 dB to the nodes. One PU, one fusion node and six neighbour nodes (7 CRs in total) were considered for most of the performance evaluation. In some cases, up to eight neighbours were considered. Energy detection model is used for performing the spectrum sensing. During CSS each CR performs individual spectrum sensing as per SU reporting process and the CR that functions as fusion node performs decision fusion with the help of AWC rule. This has been repeated over 10000 times at each case and average of the evaluation is presented.

As receiver operating characteristics (ROC) curve illustrates the performance of a binary classifier system, simulation framework is validated by plotting ROC curves (plots of P_d versus P_f and P_m = 1 - P_d versus P_f) of local spectrum sensing using both theoretical results as well as Monte Carlo simulations. The performance of the proposed approach and the related works were also compared using ROC curve.

As low computational overhead can ensure fast spectrum sensing which is the key in improving the throughput of the secondary network, the parameters that influence the time were thoroughly analysed. These include factors such as number of neighbours included for decision fusion, complexity of fusion rule, time consumed for decision fusion etc.

In order to represent the scenario mentioned in Fig. 3.30, it has been assumed that an SU considered as the fusion node, is located near to the boundary of the coverage area of a PU and that its neighbours are located around it. CRs are positioned in such a way that some are closer to PU than the FN and are called group-I (G_1) where as those node that are away from PU with respect to FN are called group-II (G_2). A realistic scenario is formed by assigning random SNR values from a range-1 (R_1) to G_1, range-2 (R_2) to FN and range-3 (R_3) to G_2, such that SNR of R_1 >R_2 >R_3 . These ranges would be overlapping each other at its boundaries.

Evaluation of our proposed approach is carried out in the following section. Since other fusion rules are compatible for single threshold scheme, the same single threshold scheme is used for the evaluation of other fusion rules.

Comparison with Prominent Fusion rules in the Literature

Generally, probability of detection depends on the SNR and fading conditions of the FN and the neighbouring nodes. Location of each node with respect to PU and with the FN has significant impact on the P_d. As per the scenario considered, FN is located near to the boundary of the PU's coverage area. It means some of its neighbours may be located outside the coverage area of the PU. A fusion rule should be in such a way that false influence from the neighbours needs to be avoided. Adaptive weight assignment ('R_s'

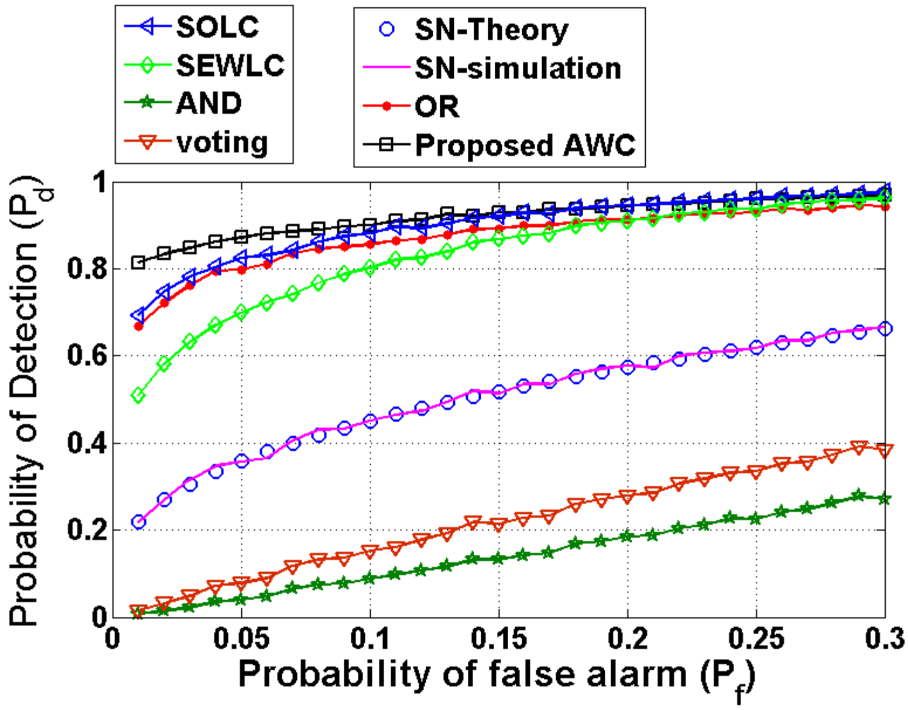


Figure 3.32: P_f vs P_d plot of proposed AWC, SOLC (Kyperountas *et al.*, 2010), SEWLC (Kyperountas *et al.*, 2010), AND, OR and VOTING fusion rules under Rayleigh fading with $\Delta = 0.4$ and unbalanced (Majority of nodes in G_2) case with SNR dB [-4 -5 -7 -18 -16 -19 -20]

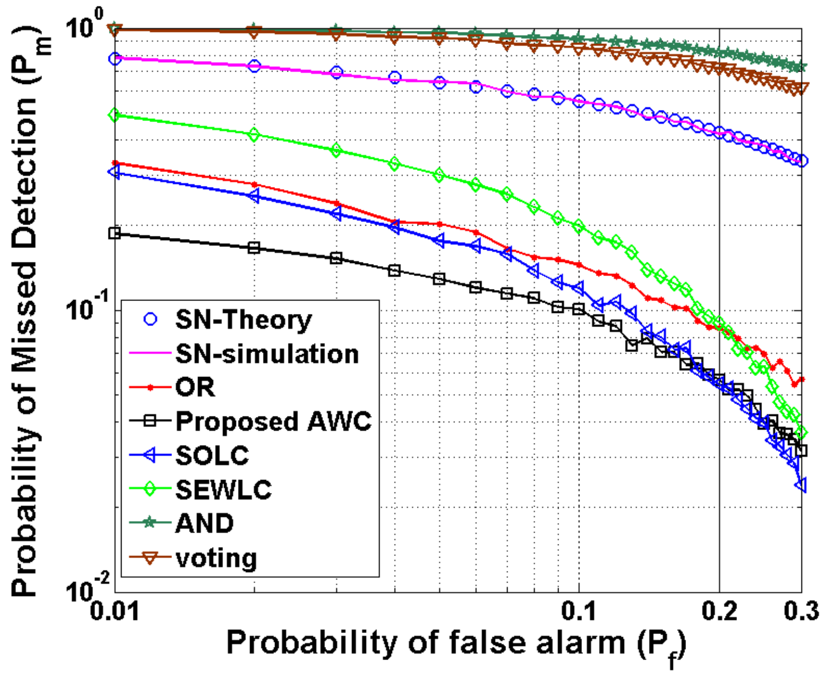


Figure 3.33: P_f vs P_m plot of proposed AWC, SOLC (Kyperountas *et al.*, 2010), SEWLC (Kyperountas *et al.*, 2010), AND, OR and VOTING fusion rules under Rayleigh fading with $\Delta = 0.4$ and unbalanced (Majority of nodes in G_2) case with SNR dB [-4 -5 -7 -18 -16 -19 -20]

according to the location of neighbours) by the FN under AWC fusion rule will cater the above issue.

Comparison of proposed approach with Soft Optimized Linear Combining, Soft Equal Weight Linear Combining, Voting rule, AND-rule and OR-rule is presented in Fig. 3.32 and Fig. 3.33. This performance is obtained for Δ =0.4, No. of antennas M = 4, and a neighbour concentration G_1-FN-G_2 = 2-1-4. It is plotted as the average of 10000 iterations with SNR (dB) of each node fixed at SNR (dB) = [-4 -5 -7 -18 -16 -19 -20] respectively during simulation. These parameters are chosen to faithfully represent the scenario mentioned in Fig. 3.30

It is seen from the P_d-P_f plot in Fig. 3.32 that the detection rate of the proposed approach is nearly 10% better with respect to SOLC (best among the five) at P_f = 0.01 and gradually becomes equal at P_f = 0.15 and it maintains it as P_f goes up. This is achieved by reducing the influence of Group-II nodes through adaptive weight assignment. As the P_f increases, all rules will reach to P_d = 1. It was seen in our simulations that this rule performs better at low average SNRs. At higher SNRs, its performance is equal to other rules. Even though the probability of detection of 'OR' rule is quite high, it is known that its false alarm rate is also high at low SNR values, which is an unwanted quality. Fig. 3.33 gives the probability of missed detection. It is seen that when $P_f < 0.2$, proposed approach is giving the least missed detection and after that, SOLC is giving the least value but closer to AWC. At lower values of P_f, the number of nodes falling in the '$\Delta\lambda$ region' may be more and as the P_f increases, the number of nodes in this region will become less. Hence the effect of region encoding is getting reduced as P_f increases. This may be the reason for the proposed rule performing well at lower P_f.

Relative performance of fusion rules with single node sensing needs to be considered for performance evaluation. Detection performance depends on the channel conditions of all the nodes. At higher SNRs, the performance of all fusion rules will be very good. But as the SNR comes down, detection rate also gets affected and only a good fusion rule will be able to maintain respectable detection levels.

Probability of detection as a function of number of nodes (N) is presented in Fig. 3.34. A balanced case (ie, no of neighbours in G_1 and G_2 are equal) is considered for uniformity. Average SNR level considered here is slightly greater than that of Fig. 3.32.

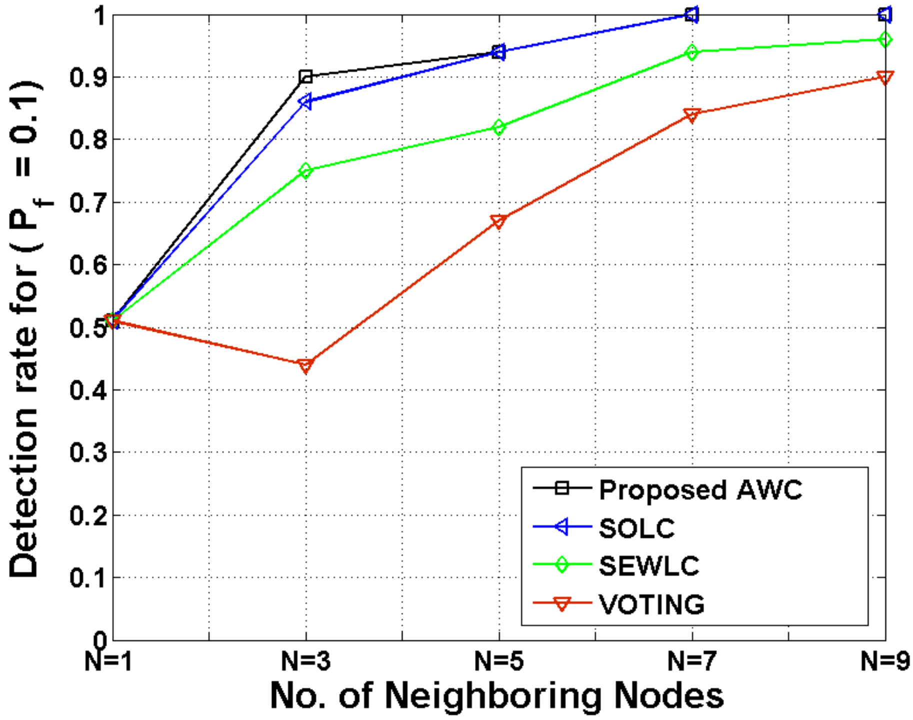


Figure 3.34: Probability of detection of proposed AWC, SOLC (Kyperountas *et al.*, 2010), SEWC (Kyperountas *et al.*, 2010) and VOTING (2 - out of - N) as a function of the number of users at $P_f = 0.1$ and balanced (Equal number of nodes in G_1 and G_2)

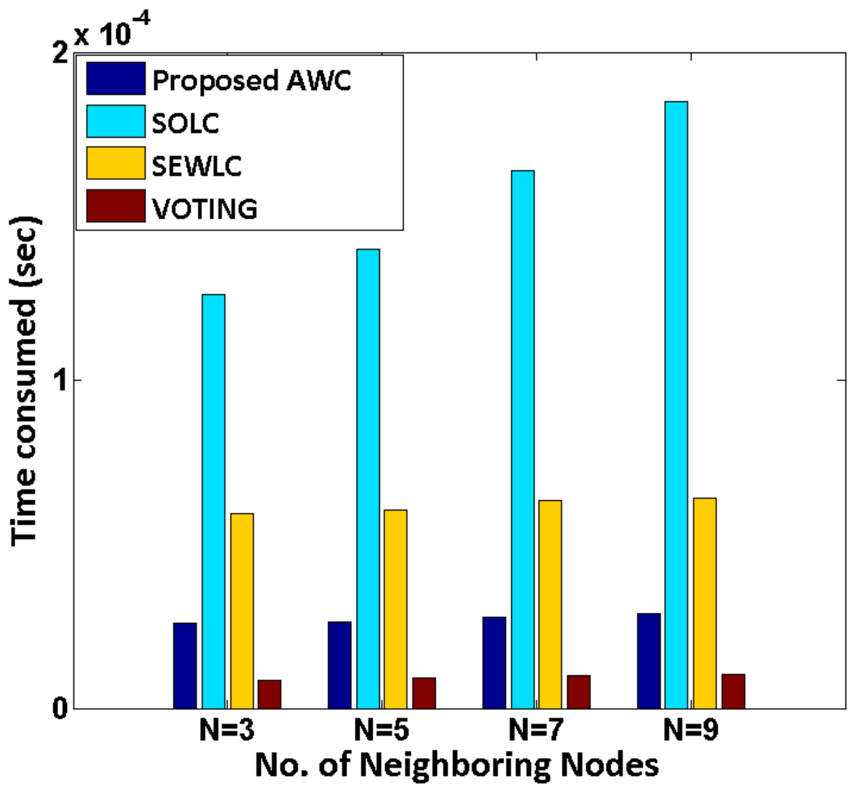


Figure 3.35: Average time consumed by all rules to make a decision vs No. of nodes (N). [Machine spec: Intel(R) Core(TM)2 Duo CPU, T7250 @ 2.00 GHz, 777 MHz,1.95 GB RAM]

When there are equal number of nodes in G_1 and G_2, average SNR is high and hence there is a steady increase in the P_d with increase in 'N'. At lower P_f, AWC is giving high P_d and at higher P_f, SOLC (Kyperountas *et al.*, 2010) is coming closer to AWC. At N = 7 these rules are giving reasonably good P_d. Low performance of voting rule at N=3 indicates that voting rule needs more neighbours for giving a better result under the scenario considered.

Fig. 3.35 compares the computational complexity of the fusion rules as a function of number of nodes involved in the decision fusion. Computational complexity of these approaches were compared as the time consumed in making a decision and it was found that proposed approach consumed only 20% of the time than that of SOLC approach. It can be seen that voting rule has got the lowest time consumption as it has very limited computation requirements. AWC has reasonably low computational requirements as it has 2N+3 multiplications followed with N additions and one comparison for an 'N' neighbour scenario. Since each antenna is sampled for a time slot within the time duration allocated for sensing, computational complexity for energy detection is similar to that of a single antenna system. SOLC marks the highest computational complexity. In the case of SOLC, it has to calculate the weight vector and the threshold for each decision fusion.

Impact of 'Δ' on the Probability of Detection

The value of 'Δ' plays a significant role in the detection performance of the fusion node. It can take values greater than zero. When it is zero, it is similar to a single threshold system with AWC fusion rule. P_f vs P_d plot of AWC rule for various values of 'Δ ' is shown in Fig. 3.36. It is seen that detection rate is improving with increase in the value of ' Δ '. As ' Δ ' comes down, the detection performance is coming closer to a single threshold system.

Impact of Number of Users on the Probability of Detection

Importance of the number of nodes in cooperative spectrum sensing is a key factor to be considered. Usually increase in number of users considered for decision fusion will increase the detection probability. But it will increase the computational overhead and

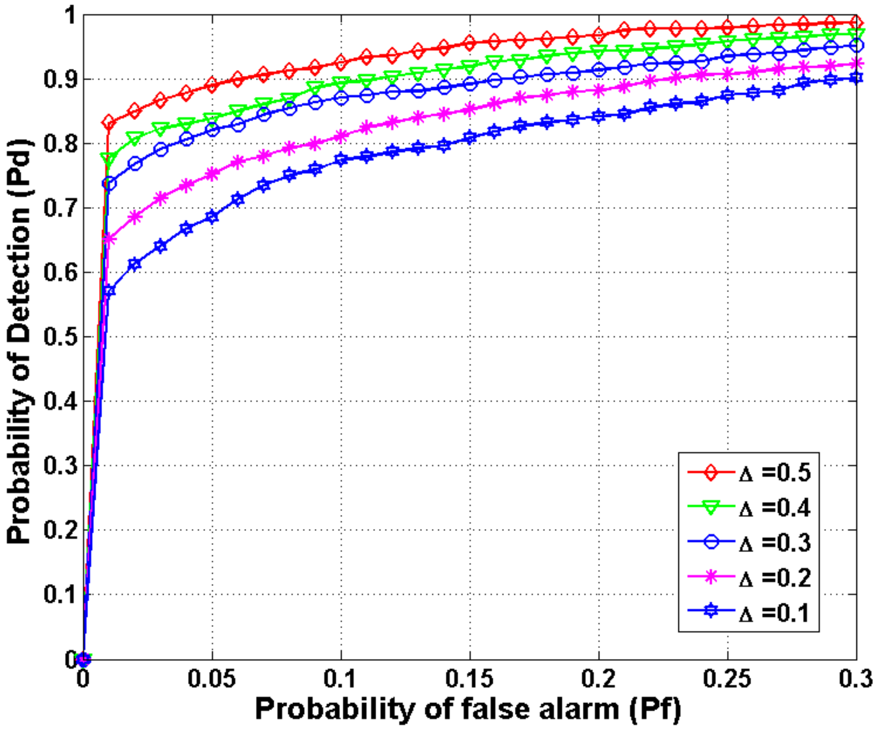


Figure 3.36: P_f vs P_d plot under various values of Δ for cooperative sensing with proposed scheme in a Rayleigh fading channel.

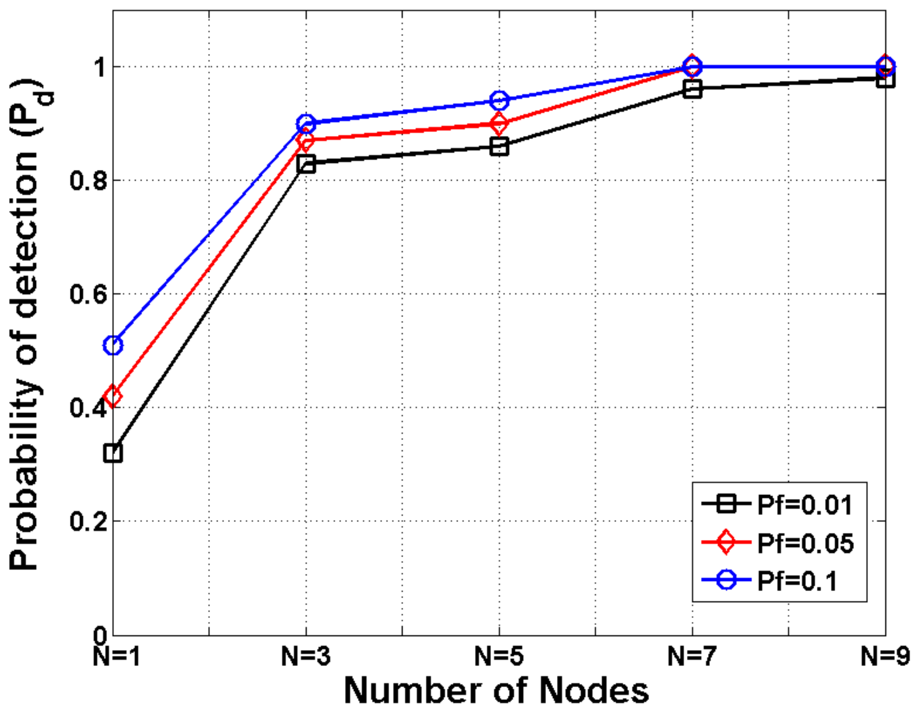


Figure 3.37: Probability of detection as a function of the number of users in a balanced (Equal number of nodes in G_1 and G_2) case, at various values of P_f

also be a threat to strict time constraints in spectrum sensing. Fig. 3.37 evaluates the detection performance of AWC fusion rule as a function of the number of cooperating users for decision fusion, for system targets P_f of 0.01, 0.05 and 0.1. It can be seen that detection rate increases with N, and at N=7 it is giving a better performance for P_f = 0.05.

3.5.5 Section Summary

This section has considered a scenario that poses challenges to cooperative sensing. An antenna selection scheme with multiple region encoding for single node detection and an adaptive weighted combining fusion rule for fusion node were also proposed to manage this scenario. Its performance is analysed under Rayleigh fading channel and it is found effective at the scenario highlighted above. Performance of this approach is compared with fusion rules such as voting rule, SOLC and SELC that are presented in (Kyperountas *et al.*, 2010). On analysing various parameters associated with these rules, it is found that AWC is giving a better performance in all respects. A possible extension of this work is to optimize the regional weights to further fine tune its performance.

3.6 Chapter Summary

In this chapter, an effective decision fusion approach for distributed sensing is evolved through various stages of analysis and modifications. A fuzzy based approach was proposed initially and its analysis was carried out using energy detection under Rayleigh fading channel. Its performance was compared with classical fusion rules such as 'AND' & 'OR' rules. Analysis of P_f and P_d with respect to SNR and 'time consumed' for a decision fusion were carried out. Even though the detection performance was very good, time consumption of fuzzy rule was quite high.

For quick decision making, a weighted combining approach with SNR as its key component was proposed and its analysis was carried out using path loss model under shadowing. In both the above cases, the assumption was that all the CRs are located within the coverage area of PU under consideration. A realistic scenario with CRs at the boundaries of PUs is suggested and the SNR-rule is modified to adapt to the situation. It is named as 'Intelligent rule' and its performance was analysed using energy detection model under Rayleigh fading as well as path loss model under shadowing.

In order to improve its performance further, antenna section scheme and multiple region encoding for SU reporting are added to the 'Intelligent rule'. Its performance is compared with other optimal rules and fuzzy rules in the literature. Analysis on P_f versus P_d, P_f versus P_m, P_d versus 'N' (no. of neighbouring nodes) and computational complexity were carried out. On analysing the various parameters associated with this evolved approach, it is found that it is giving a better performance in all respects.

CHAPTER 4

DECISION FUSION IN EXTERNAL SENSING

4.1 Introduction

Efficient spectrum sensing is an important requirement for the success of the cognitive radio system. In an external sensing scenario, an external agent performs the sensing and broadcasts the channel occupancy information of Primary Users to Secondary Users. Cellular automata (CA) is a discrete model used to develop wide variety of applications. CA based architectures have already proved its utility in the low power and high speed VLSI designs.

In this section, a novel data fusion approach based on CA is proposed for external sensing where wireless sensors are deployed in the field to form the spectrum sensing network. Individual sensing result from the sensors are sent to the central node (CN) for performing the decision fusion. Final decision on spectrum occupancy status will be shared with CRs on demand.

Proposed approach is evaluated for its ability to form the coverage area of PU, probability of detection, false alarm rate and computational cost. Its performance is also compared with fuzzy based methods and a weighted combining method.

4.2 System Model

We consider a scenario where an external agency is providing the spectrum hole information to the SUs. The external agency obtains this information through the wireless sensors deployed in the field. We assume that low power sensors with low installation cost are deployed in the field and necessary networks and protocols to transfer all the sensed data to a CN are available. After processing the data, CN will have the information about the channel occupancy status and coverage region of a particular PU. We also assume that these sensors will undergo fading and random shadowing and for this

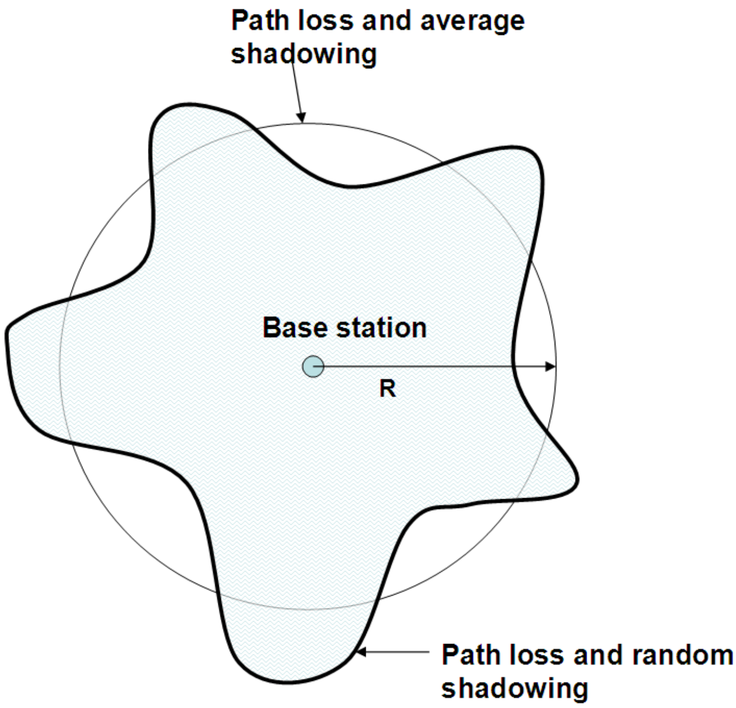


Figure 4.1: Cell coverage area

reason, the sensor output may not be correct always. A simulation set up was formed in Matlab to model and evaluate the system. It is considered that the sensors are arranged in a 2-D grid within an area of 100 sq. km. And the transmitter is located at the center. Transmit power is chosen in such a way that sensors will be present within and outside the coverage area of the transmitter. All the sensing results are transferred to a central node through the network. At the CN these data are processed with the proposed method to obtain spectrum occupancy status and coverage area. Now this can be broadcast or can be provided on demand.

Our estimations are based on the practical link budget design using path loss model (Rappaport *et al.*, 2002). The cell coverage area in a cellular system is defined as the expected percentage of locations within a cell where the received power at these locations is above a given minimum. The transmit power at the base station is designed for an average received power P_r at the cell boundary. However multi-path and shadowing will cause some locations within the cell to have received power below $P_r$min, and others will have received power exceeding $P_r$min (Goldsmith, 2005). This is illustrated in Fig. 4.1. Propagation path loss according to distance from the transmitter was defined according to the equation 3.1 as mentioned in (Harrold *et al.*, 2008) and the received power P_r (in dBW) of receiver at a distance 'd' meters from a transmitter with transmit power P_t (in dBW) was estimated based on equation 3.2

As a dense urban scenario has been considered, the values of path loss exponent 'n' and 'σ' are considered as 4.5 and 10 respectively (Harrold *et al.*, 2008). It is chosen because of the reason that difference in the performance of various approaches will be observable only in dense urban scenario. In this dense urban scenario, sensors are stationary at the ground level and moving objects (vehicles etc.) around it are causing random shadowing.

4.3 Decision Fusion

In the case of external sensing, the CN should have clear information about the spectrum holes in the time-frequency space as well as geographical space. Spectrum hole in the time-frequency space can be obtained through simple fusion rules at the central node. Since we consider smaller transmit power and larger area for spectrum sensing, there will also be spectrum holes in the geographical space. Data fusion process at the central node should have the capability to obtain the presence of PU and the coverage area of each PU. It is expected that same channels will be used by different PUs at different geographical spaces. In this section, a CA-based approach for decision fusion is proposed and is expected to give a better result with less computation. Two rules based on the popular neighbourhood used in CA are proposed and its performance is compared with data fusion rules proposed in (Harrold *et al.*, 2008; Matinmikko *et al.*, 2009; Taghavi *et al.*, 2011). All the above five rules are implemented and its performance is compared. Brief description on all the above rules are given in the following section.

4.3.1 Overview of CA

A cellular automaton consists of a regular lattice of cells. Each cell takes on 'k' possible values, and is updated in discrete time steps according to a rule ' f ' that depends on the value of the cell in some neighbourhood around it. There are several possible lattices and neighbourhood structures for two-dimensional cellular automata (Packard and Wolfram, 1985). The value a(i,j) of a cell at position (i, j) in a two-dimensional cellular automata with a rule that depends only on nearest neighbours thus evolves according to equation 4.1

$$a_{i,j}^{t+1} = f[a_{i,j}^{t} + a_{i,j+1}^{t} + a_{i,j-1}^{t} + a_{i+1,j}^{t} + a_{i-1,j}^{t}] \tag{4.1}$$

The function '$f_{i,j}$' is called the cell rule for cell '$a_{i,j}$'. The transition function 'f' is linear if and only if each of the '$f_{i,j}$' are linear (Cattell *et al.*, 1999). The identical rule contained in each cell is essentially a finite state machine, usually specified in the form of a rule table with an entry for every possible neighbourhood configuration of states.

In this system, each sensor deployed in the field is considered as a cell in the cellular space and the single node result of each sensor is considered as a set of cellular states. In a sensor network, the sensing result of each node at a particular time instant will be transferred to CN and processing is done there to establish the presence and coverage area of a PU. Single node result available at CN will form a 2-D grid and the state of each cell will update its state with respect to the states of its neighbours, based on the cell rule. This rule can be applied repeatedly until there is no change in the cell states. It may be also applied repeatedly for certain number of times. Different rules may also be applied over it in a serial order. Popular neighbourhoods used in 2-dimensional CA are Moore neighbourhood and Von Neumann neighbourhood. Rules are devised for these neighbourhoods and are given below.

4.3.2 Proposed CA-based rules for Decision Fusion

In this scenario, the spectrum decision by the nodes are assigned state '1' for sensed and state '0' for not sensed. States are represented in white for state '1' and in black for state '0'. Eight neighbours are considered for Moore neighbourhood and four neighbours are considered for Von Neumann neighbourhood. Each node's result will change to any one of the state, based on the state of the neighbours. The rule is represented here as a pattern with white and black cells. Rule consists of a specific number of patterns and if the state of a cell and its neighbours matches with the pattern, the central cell will change its state to the specific state as represented in the rule. Since eight neighbours are present, there can be 2^9 combinations possible. The rule is defined in such a way that for certain combinations, the central node will change its state to white or black and for certain other rules it will not change its state.

For CRN with external sensing, sensors deployed in the filed form a 2-D grid and result from the sensors are collected at the server. When this data is represented with respect to their position in the field, it will form a 2-D CA with two possible sates. Each cell in the CA will change its state to ‘sensed’ or ‘not sensed’ with respect to the transition rule. It was found that CA performs well in image processing. This has motivated us to propose two rules for external sensing, as given below.

Rule set 1 : CA$_1$ [based on Moore-neighbourhood]

Some of the rules (patterns) for the decision making are given below. The central pixel will go to its state ‘1’ if each cell and its neighbourhood are same as the mask. Here white indicates state ‘1’ (sensed) and black indicates the state ‘0’ (not sensed). This can be applied repeatedly until no further change happens to the cellular space or to a specific number of times. Moore’s neighbourhood based rules are given in Fig. 4.2. Here the transition of the central cell will be based on the eight neighbouring cells.

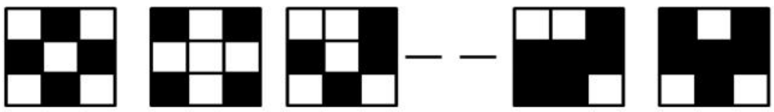


Figure 4.2: Rule set 1

This rule can also be stated as follows:-R$_1$ $\rightarrow$ Live (sensed) cell stays alive (sensed) if 3 or more of its neighbours are alive, else it changes the state. Dead (not sensed) cell will come to life if 4 or more of its neighbours are alive, else it stays in the same state.

Rule set 2 : CA$_2$ [based on Von-neighbourhood]

Von Neumann neighbourhood based rules are given in Fig. 4.3. Four adjacent neighbours are considered for the transition of the central cell. In the case of all the patterns shown here, the central pixel will remain in its state or otherwise it will change its state.

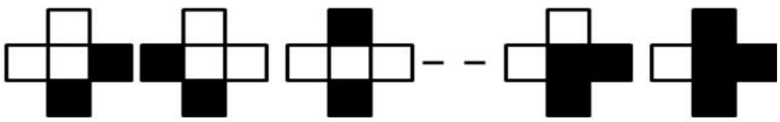


Figure 4.3: Rule set 2

This rule can also be stated as follows:-R$_2$ $\rightarrow$ Live (sensed) cell stays alive if 2 or more of its neighbours are alive, else it changes its state. Dead (not sensed) cell will come to life if 2 or more of its neighbours are alive, else it will stay in the same state.

4.3.3 Fuzzy based Information Combining

Fuzzy based approaches for distributed sensing is proposed in (Matinmikko *et al.*, 2009; Taghavi *et al.*, 2011). In fuzzy logic, each input can be labelled by a linguistic term, where a linguistic term is a word such as 'low', 'medium', 'high' etc. so that, the input is defined as a linguistic variable. Each linguistic variable is associated with a term set T(x), which is the set of names of linguistic values of x. Each element in T(x) is a fuzzy set. A fuzzy set F in a universe of discourse U is characterized by a membership function μF which takes values in the interval [0,1]: μF :U $\rightarrow$[0,1]. According to (Matinmikko *et al.*, 2009) two bit decision is transmitted to the CN for decision making. It indicates the linguistic variable as low, medium and high. These fuzzy inputs are given to a fuzzy controller and a decision is made according to the fuzzy rule base available in the central node. This method is named as Fuzzy_2 for future reference. It is implemented in (Matinmikko *et al.*, 2009) as a two input case with a rule base of size eight. In other words, a node will consider two of its neighbour's inputs to make a decision. We have extended this to 4 neighbours with a rule base of 95. It is implemented on the external sensing scenario and its performance is then evaluated. In (Taghavi *et al.*, 2011) the nodes transmit the received power to the central node to make a decision. This method is named as Fuzzy_1 for future reference. The range of received power varies with respect to transmit power, the distance of the node from the transmitter and the level of fading. Membership functions are formed within this range with respect to the threshold of detection. We have implemented this as a 4 neighbour case with a rule base of 95. Further increase in the number of neighbours will increase the size of the rule base.

4.3.4 Distributed Detection Algorithm

A distributed detection algorithm (DDA) is proposed by (Harrold *et al.*, 2008) to combine the neighbouring node's result to make a cooperative decision. This decision algorithm can be represented by equation 4.2. Here it performs a weighted combining of the neighbour's results. Weight is decided according to the neighbour's distance from the centre node. It also considers the results in the previous time steps and assigns a self weight to the node's own result. Above rule is applied in this external sensing context with a single time step and its performance is compared with the proposed CA based fusion methods. We have considered 8 neighbours for the implementation of this algorithm.

$$Q = [X_1..X_N][D_1..D_N]' + [Y_1..Y_M][T_1..T_M]' + SZ \tag{4.2}$$

where 'X_N' is the sensing results from neighbouring node, 'D_N' is the weight according to the distance, 'Y_M' is the result from 'M' time steps, 'T_M' is the weight according to previous time steps, 'S' is the self weight and 'Z' is the node's own result.

4.4 Results and Discussion

In this section, we evaluate the performance of the proposed CA based approach and the methods proposed in (Harrold *et al.*, 2008; Matinmikko *et al.*, 2009; Taghavi *et al.*, 2011). We do the comparison using the performance measures such as coverage area that can be formed, probability of detection, percentage of false positive, percentage of false negative and the time taken for computation. We have considered the standard mobile communication systems (GSM 900 MHz band) used in India. Wireless sensors are considered to be installed in a 2-D grid within an area of 100 sq. km. as shown in the Fig. 4.4. Sensors with positive results (sensed) are marked '$\bullet$' and those with negative results are marked as '$\circ$'. Irrespective of the location of the transmitter, sensing will take place and the coverage area will be formed with respect to the transmitter. We have chosen the area, the location of the transmitter and transmit power in such a way that the area under consideration will have sensors located within and outside the coverage area of the transmitter.

4.4.1 Coverage Area

Coverage area is the region where the received power from a PU will be above the noise floor. Fig. 4.4 to Fig. 4.9 show the single node result and the results after data fusion based on the various algorithms mentioned. The central circle in Fig. 4.4 indicates the calculated coverage area based on path loss and average shadowing. The other two circles are named as the outer fade boundary and the inner fade boundary. In other words, due to random shadowing, the coverage area may fluctuate about the central circle between this interval. It was calculated from equation 3.2 by choosing appropriate values for standard deviation σ (quoted in dB) of the shadowing. Typically σ varies between 6 - 10 dB across different environments.

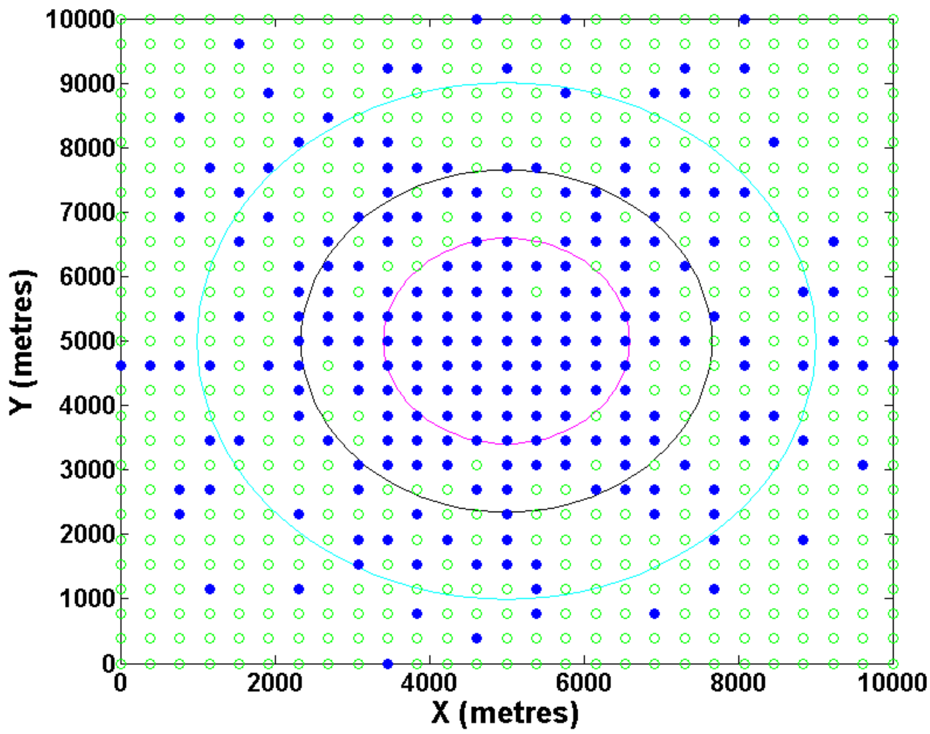


Figure 4.4: Coverage area formed by single node result

Fig. 4.4 shows that, in the single node result, some nodes located even outside the outer fade region give the status 'sensed' and some nodes located within the inner fade region give the spectrum status as 'not sensed'. Also there is no indication about the coverage area of the transmitter. This is because of the multipath fading and shadowing occurring in the terrain. After applying the decision fusion rules (DFR) it is seen that the nodes with status 'sensed' is concentrated towards the transmitter at the centre. It is observed in the Fig. 4.5 that the result obtained through the proposed CA_1 algorithm is in

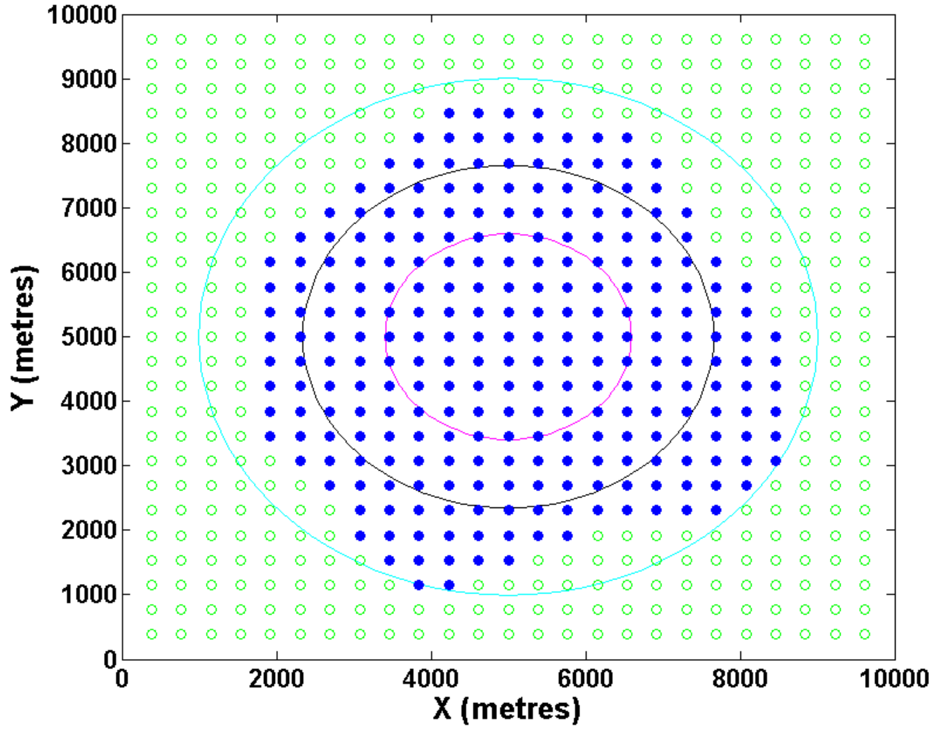


Figure 4.5: Coverage area formed by proposed CA_1

line with the expectation in (Goldsmith, 2005). All the 'sensed' nodes are located closer to the transmitter and it forms an amoeba like shape around the transmitter. Even in a scenario where the transmitter is moving, this DFR is expected to give a clear boundary of the PU at each instant. This is mainly because of the locality of cellular automata interactions. Choice of suitable rule will make the single node result to converge into a reasonable PU boundary. It is seen from Fig. 4.6 to Fig. 4.9 that even though the area is reduced, the proposed CA_2 also gives better coverage area information compared to algorithms (Harrold *et al.*, 2008; Matinmikko *et al.*, 2009; Taghavi *et al.*, 2011). All the non CA fusion rules are not able to provide a reasonable coverage region which is very important in the case of external sensing or centralized sensing. It is clear that CA_1 performs better than CA_2 because of the higher number of neighbours considered in CA_1

4.4.2 False Negative

In this analysis, negative sensing result of the sensors which are located inside the average coverage region is considered as false negative. Percentage error is calculated as

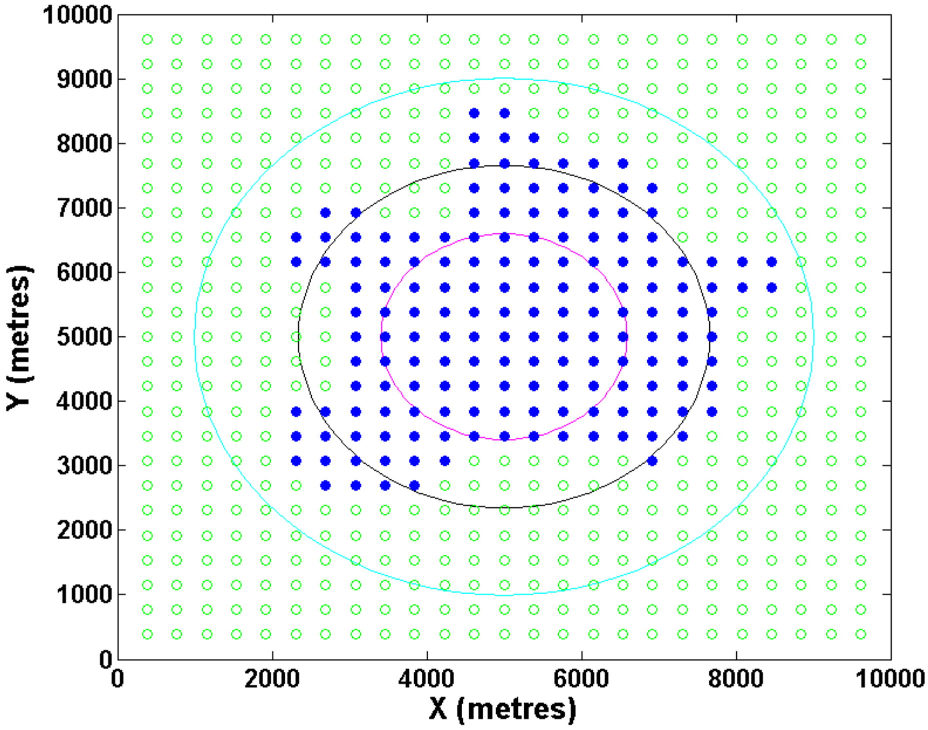


Figure 4.6: Coverage area formed by proposed CA_2

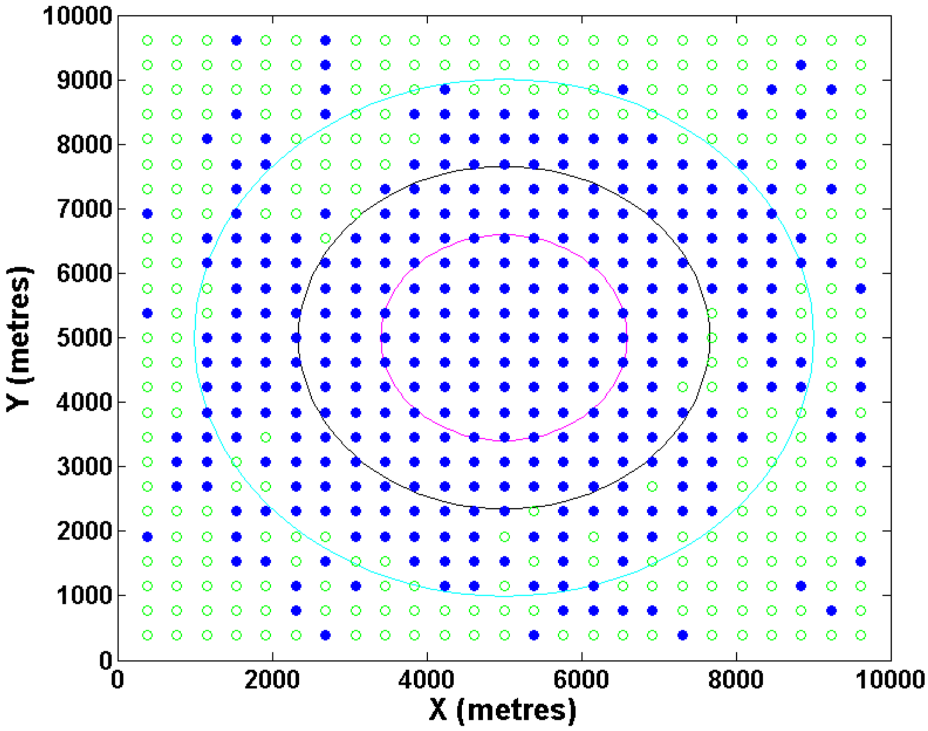


Figure 4.7: Coverage area formed by $Fuzzy_1$

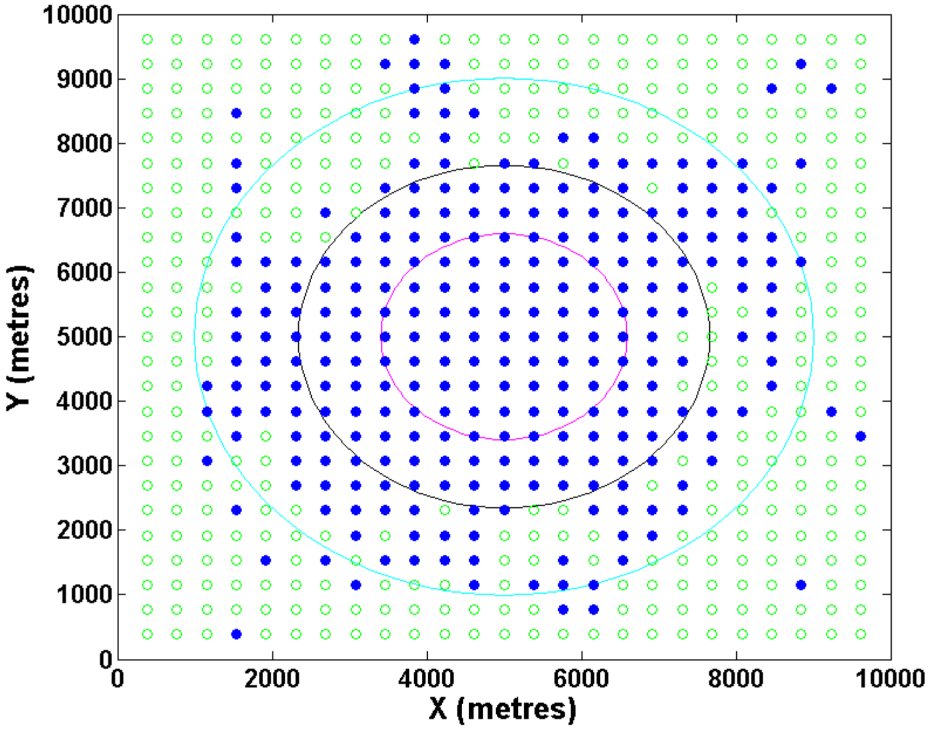


Figure 4.8: Coverage area formed by Fuzzy$_2$

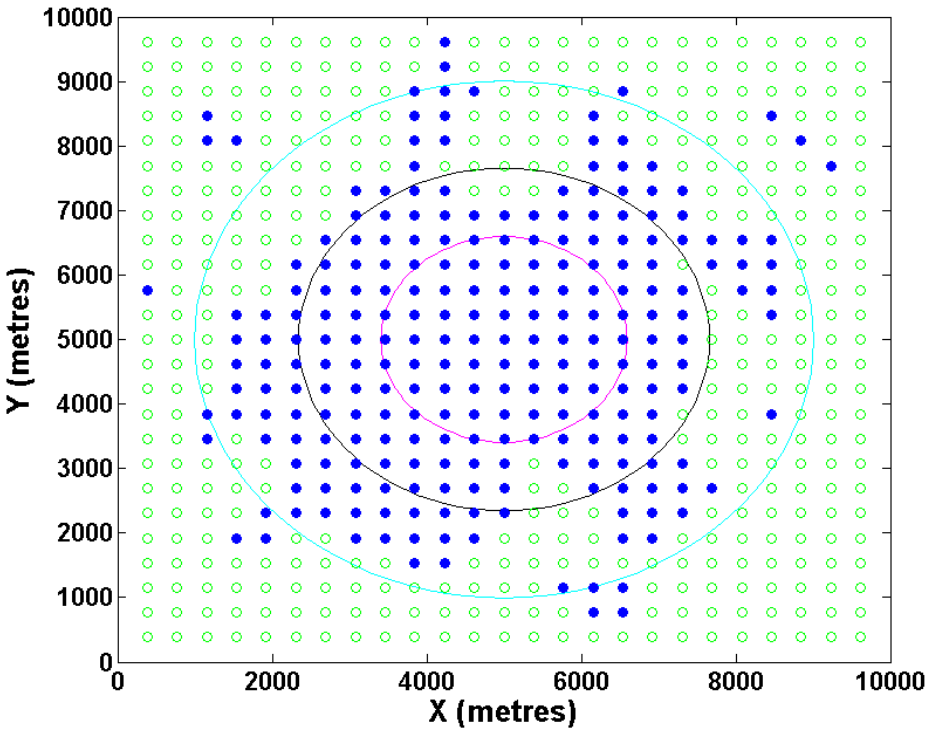


Figure 4.9: Coverage area formed by DDA

the ratio of the false negative and the total number of sensors located inside the average coverage region. Analysis on the percentage error versus number of receivers is shown in Fig. 4.10. It has been assessed by taking the average of 100 readings in each sensor density. It is seen that the percentage of false negative is almost zero for the CA_1 DFR. This is because of the locality of cellular automata interactions with more neighbours. It is also seen that sensor density doesn't have much impact on the false negatives. However a higher concentration will always give better resolution of the coverage area. CA_2 DFR is giving the highest false negative compared to other rules and this may be due to the small size of the neighbourhood. Others are giving less than 5% false negatives.

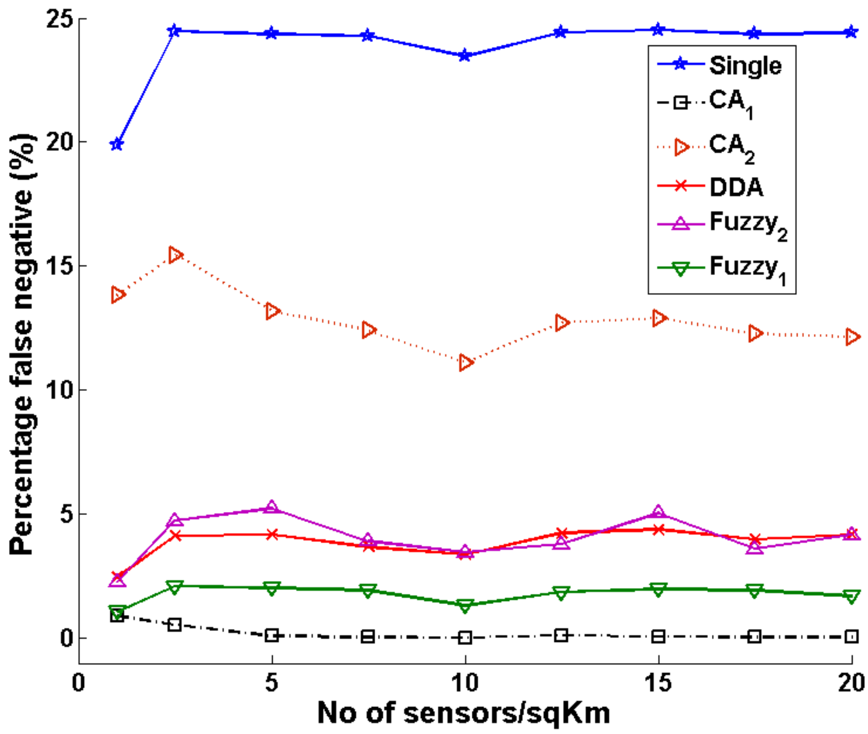


Figure 4.10: False negative performance

4.4.3 False Positive

In this analysis, positive sensing result of the sensors which are located outside the outer fade region is considered as false positive. Percentage error is calculated as the ratio of the false positive and the total number of sensors located outside the outer coverage region. It is seen from Fig. 4.11 that the percentage of false positive is almost zero for the CA based DFRs. CA_2 has got the least value of false positive. And the number of sensors needed to give acceptable result is around 3 to 4 per sq. km. All the other DFRs give a higher percentage of false positives and sensor density doesn't have much impact on the false positives. Fuzzy based methods are giving the lowest level of performance. And the $Fuzzy_1$ gives a poor performance than single node result. DDA gives a better show than the fuzzy methods.

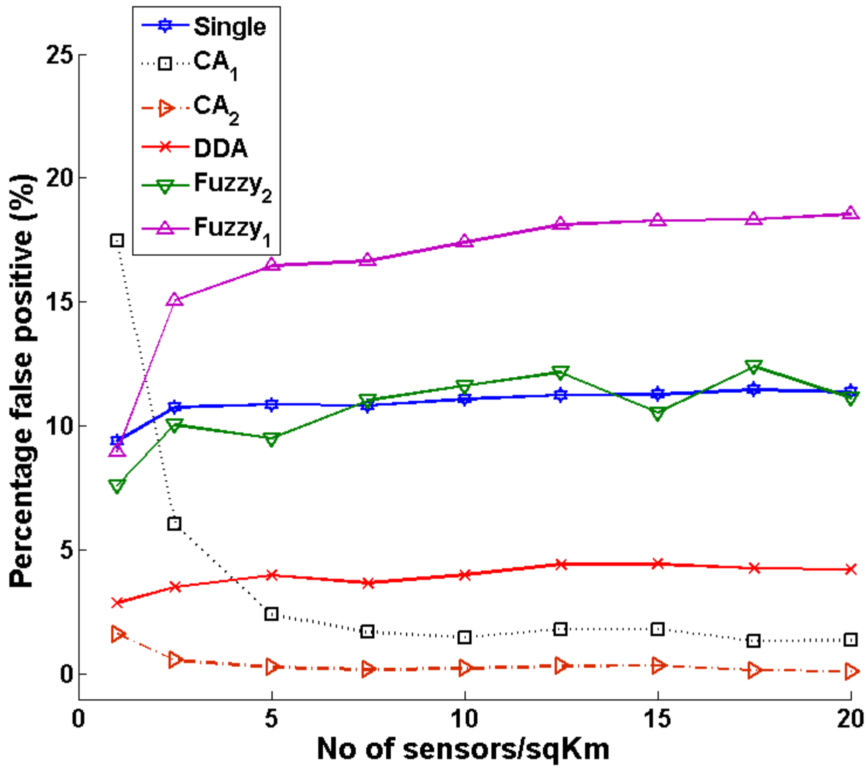


Figure 4.11: False positive performance

On analysing the false positives and false negatives, it is seen that DFRs with low false negatives are having high false positives and vice versa. Only in the case of CA_1 false alarm rate is relatively low.

4.4.4 Detection Rate

The detection rate of each algorithm is compared in Fig. 4.12. In this case, the power level of the transmitter is chosen in such a way that all the nodes under consideration will come under the coverage area of the transmitter. It was found that at all sensor densities the single node result was around 60%. In this case also, the CA_1 is giving the best performance at all sensor densities. This is possible because of the locality of cellular automata interactions and its complex global properties. $Fuzzy_1$ is positioned just below CA_1 and the $Fuzzy_2$ gives the lowest performance. DDA has obtained a detection rate above 95% and CA_2 has a detection rate around 92%. The dip in the detection rate with increase in sensor density may be due to the random nature of the shadowing.

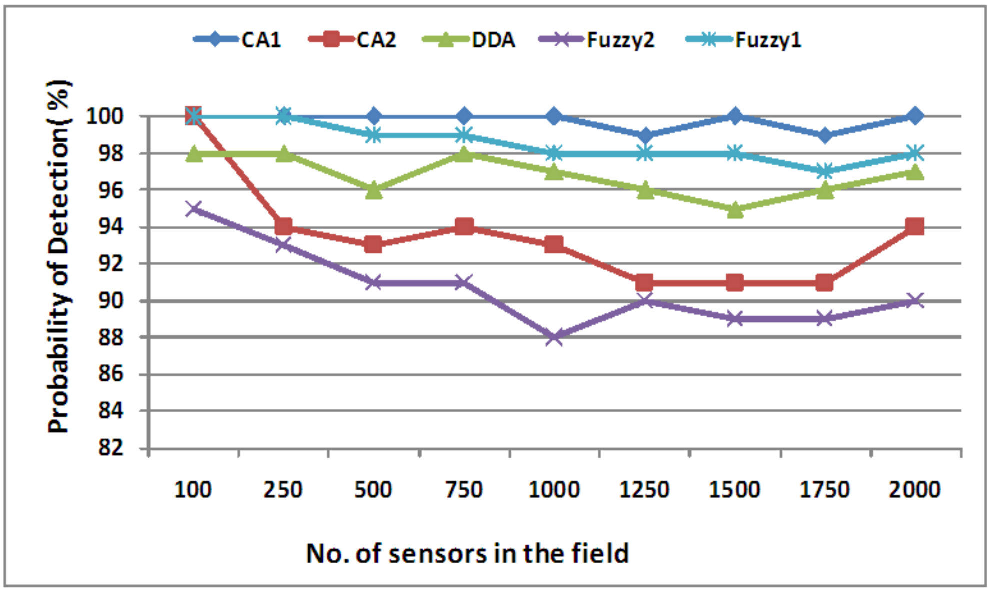


Figure 4.12: Detection rate of all the algorithms at various sensor density

4.4.5 Computational Complexity

A comparison of the time taken by each algorithm for a specific number of sensors under consideration is given in Fig. 4.13. A total of 100 sensors are considered for computing the coverage area of a PU. Time taken by each algorithm when it runs in Matlab is considered for comparison. For an N x N grid, the amount of calculations involved to obtain the above result is as follows. CA_1 can be implemented with $32N^2$ additions and $4N^2$ comparisons. DDA needs $9N^2$ multiplications, $8N^2$ additions and $4N^2$ comparisons. And CA_2 takes only $16N^2$ additions and $4N^2$ comparisons. It shows that the computational complexity is very less for CA based approaches and the fuzzy based approach needs more time to complete the calculation. It clearly indicates that the energy requirement at the CN is relatively less if CA_1 rule is employed for information fusion.

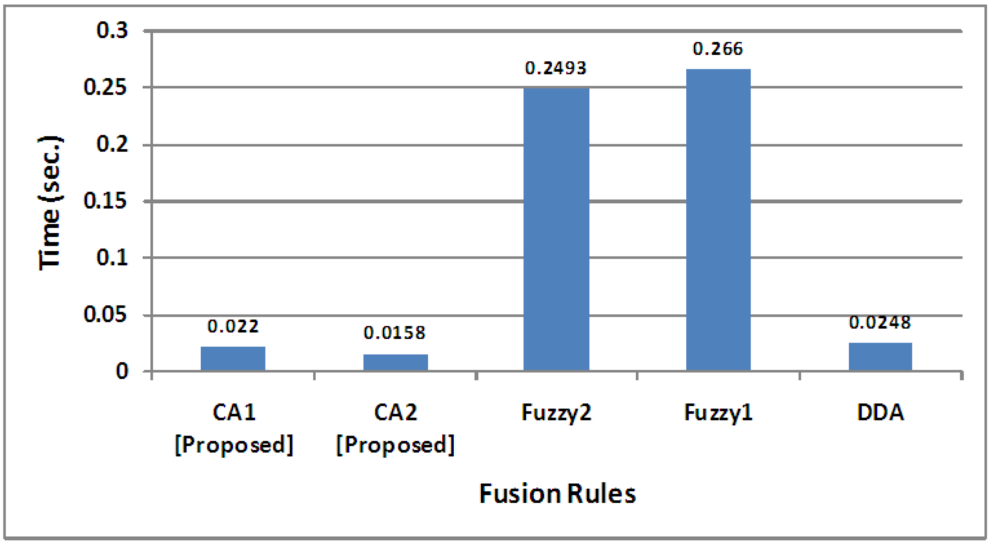


Figure 4.13: Time consumed to perform decision fusion. [Machine spec: Intel(R) Core(TM)2 Duo CPU, T7250 @ 2.00 GHz, 777 MHz,1.95 GB RAM]

4.4.6 Low power VLSI Implementation

Now it is clear from the Matlab simulation that CA based DFR is giving the best performance in all the parameters considered for performance evaluation of various DFRs. Cellular automata has the characteristic of simplicity of basic components, locality of cellular automata interactions, massive parallelism of information processing and also exhibits complex global properties. These ensure that cellular automata have higher speed and more potential applications in building VLSI blocks for decision fusion in external sensing scenario. Considering the VLSI implementation of CA based architectures in (Corno *et al.*, 2000; Chuanwu and Libin, 2005; Bhattacharjee *et al.*, 1996) and its advantages of lower power consumption and higher speed, CA_1 DFR can be a potential candidate for low power VLSI design of DFR for cognitive radio.

4.5 Chapter Summary

In this section, an external sensing scenario using wireless sensor networks for cognitive radio is considered. As there will not be any limit on the expected number of SUs in the field, it is better to have the overheads such as spectrum sensing, information combining and decision making on the availability of PUs, taken off from the SUs and given to an external agency. Hence there will be large savings in energy at the SU end. Hence the battery of such mobile SUs may get a longer life. We have proposed two rules under CA based approach and its performance is then evaluated with available distributed sensing algorithms such as DDA (Harrold *et al.*, 2008), Fuzzy_2 (Matinmikko *et al.*, 2009) and Fuzzy_1 (Taghavi *et al.*, 2011). Performance evaluation of all the algorithms is carried out. Coverage area of a transmitter is an important aspect when a CN monitors a larger area. CA based approaches are giving a realistic coverage area. CA_1 is exceptionally well in forming the coverage area. From all the other algorithms it was very difficult to derive a proper coverage area. False alarm rate of CA_1 is very low compared to other algorithms. Probability of detection is very high for CA_1 algorithm. It is also proved that CA based approach is the most computationally efficient algorithm among the five and hence it is energy efficient. The properties of CA and its massive parallelism of information processing will make it a favourite choice for low power VLSI implementation of decision fusion blocks for an external sensing scenario in cognitive radio. This approach may also be extended to distributed sensing where the nodes are randomly distributed.

CHAPTER 5

PREDICTION-BASED SPECTRUM SENSING

5.1 Introduction

Spectrum prediction will be an alternate approach to save sensing time. If there is a higher probability for the channel to be busy, CR can skip that channel from sensing purpose. It can look for channels with less chance of being busy for spectrum sensing. Prediction methods are used to predict the usage behaviour of a frequency band based on channel usage patterns of PU so that a CR can decide whether or not to move to another frequency band. Spectrum prediction in cognitive radio networks is a challenging problem that involves several sub topics such as channel status prediction, PU activity prediction, radio environment prediction and transmission rate prediction (Xing *et al.*, 2013). Prediction based spectrum sensing (Chen *et al.*, 2011), prediction based spectrum decision and prediction based spectrum mobility (Akbar and Tranter, 2007) have been presented in the literature.

In this chapter, a comprehensive prediction-based spectrum sensing framework for cooperative sensing is proposed. This includes spectrum prediction, spectrum sensing and decision fusion as the building blocks. This chapter further proposes two spectrum prediction approaches using Bayesian Inference that predict the probability of a channel's next state (busy/idle). Further analysis is done to study the impact of various parameters associated with them. This channel prediction will help to select suitable channels for spectrum sensing, from a rank list prepared based on the probability of channel being idle. It is seen that channel ranking using Bayesian approaches closely follow actual ranking. Proposed approaches are compared for their prediction performance and the computational complexity with other approaches based on EWMA, HMM and Neural Network which are already available in the literature.

In order to validate the proposed prediction-based spectrum sensing using real data, a spectrum occupancy measurement is carried out. Spectrum hole pattern obtained through this process is used to compare the performance of this approach with other prediction approaches. Analysis of spectrum occupancy for selected bands of electromagnetic spectrum is also presented in this chapter.

5.2 Proposed Spectrum Sensing Model

In line with IEEE 802.22 cognitive wireless regional area networks (WRAN) standard, we have proposed a sensing scheme in Chapter 3 for distributed sensing. (Pei *et al.*, 2011) had also suggested an optimal sensing strategy for CRN that focuses on energy efficient design of sequential channel sensing. It gives emphasis to sensing-access strategies and the sensing order. Sensing strategy also specifies when to start and stop the transmission. Power level for transmission is specified by the access strategy and sensing order specifies the sequence of channel sensing. Their objective is to design the sensing-access strategies together with the sensing order to maximize the energy efficiency of the sequential channel sensing process. They have estimated the optimum sensing time duration for energy efficient sensing. Their approaches could also reduce the computational complexity in channel search.

In order to reduce the computational complexity further, we have proposed a ranking scheme for channel search. Prediction based spectrum sensing for channel search is employed so that the CR needs to sense only the highly ranked channels. This will save time in channel search and hence saves energy. The proposed spectrum sensing model is presented in Fig. 5.1. Here each CR is expected to have a rough idea about the percentage occupancy of each channels. This is made possible by consulting with the spectrum occupancy measurement, already carried out by other sources. Spectrum occupancy measurement block is shown with dotted lines to convey that it is not a part of the CR. This will act as a prior information for the predictor block. Predictor will combine the recent information and 'prior' to predict the probability of occupancy of the channel in the coming time slot. Channels with higher probability of being idle are ranked and only those channels with higher ranking are considered for spectrum sensing. Since only potential channels are considered for spectrum sensing, there will be considerable saving in time. After single node sensing, final decision is taken by fusing the node's own result with neighbour's results. Fusion rule plays an important role in making right decision. The control unit with its cognitive capability can choose

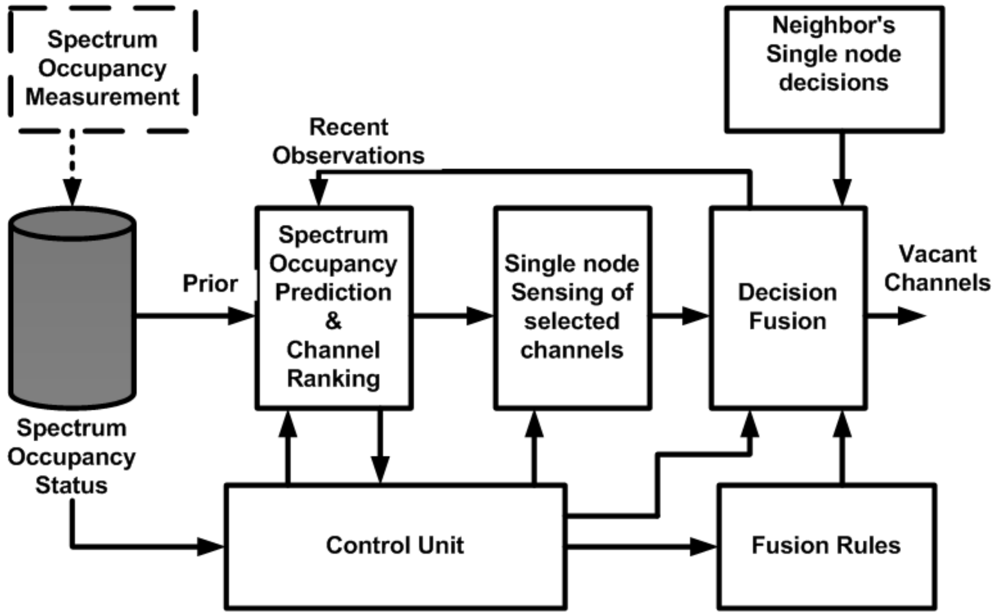


Figure 5.1: Proposed prediction-based spectrum sensing model for cooperative sensing

the various modalities of each block.

5.3 Spectrum Prediction through Bayesian Inference

This section explores the possibility of employing Bayesian inference in prediction based spectrum sensing. Prediction based spectrum sensing needs a fast predictor to work within the specified time constrains and at the same time, it has to be reliable. Bayesian predictors consider present and prior information to make a prediction and it can also be fast. Two fast approaches based on Bayesian inference are proposed here to predict the probability of a channel state (busy/Idle) in the coming instant. These approaches were analysed and its performance is compared with similar prediction methods based on statistical approach, Neural Network and Hidden Markov model. Major contribution of this work is its low computational complexity and its adaptability to real scenario.

5.3.1 System Model

Here the trend of the spectrum occupancy of each channel is assumed to be available to the CR as a record and it is called as ‘prior’. It is obtained through spectrum measurement by an external system. Spectrum measurement block is shown with dotted lines

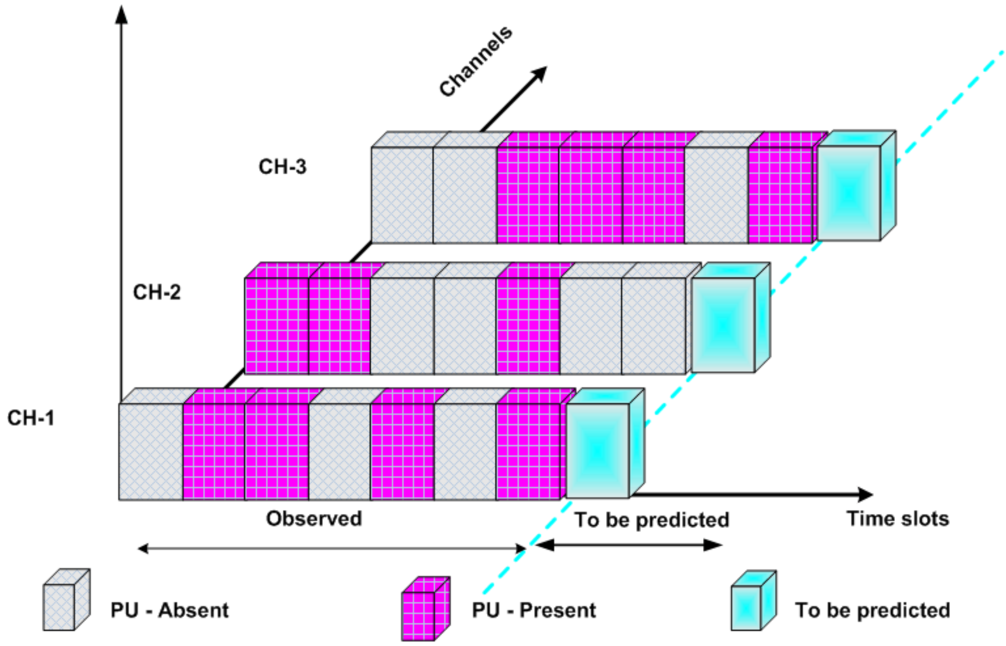


Figure 5.2: System model for opportunistic utilisation of spectral holes used in this section

to convey that the measurement is done outside the CR. A spectrum prediction unit can combine the prior and recent observations to predict the probability of the next state of a channel to be Idle/busy. This information will allow the CR to have a channel ranking so that the CR needs to perform spectrum sensing only to selected channels. Channels which are predicted to have higher probability to be busy can be omitted. Cooperative spectrum sensing can be performed later to arrive at the list of vacant channels. Rest of the section is given more focus to spectrum prediction approaches and their analysis.

We have considered that a PU operates on a specific frequency band and each channel is occupied by various primary users. Time is divided into different slots of specific duration and it is assumed that the channel is stable within the time slot; i.e., a channel state is constant for one slot and if a PU is not detected during the initial period of the slot, an SU can use the time slot for the remaining duration of the slot without causing any interference to the PU. Typically, the duration of the time slot is one millisecond or smaller. Spectrum occupancy status of PUs is represented as ‘present’ or ‘absent’ in a specific time slot. Grey boxes in Fig. 5.2 represent the absence of a PU and magenta boxes represent the presence of a PU in the respective time slots. Spectrum sensing is an important task to be performed by each SU to sense its opportunity to use vacant slots.

It is required to perform spectrum sensing in the initial period of the time slot followed with data transmission or reception. Spectrum prediction will help to skip some channels from spectrum sensing. Spectrum predictor takes the status of 'N' previous time slots into account and tries to predict the next state. The cyan block in Fig. 5.2 represents the time slot to be predicted by the CR by utilising the spectrum occupancy status in the previous time slots. It is assumed that the spectrum sensing by the CR terminals are correct. Proposed spectrum prediction approach based on Bayesian inference and a brief description about some of the prominent prediction approaches from the literature are discussed in the following section.

5.3.2 Bayesian Model for Spectrum Prediction

Bayesian Inference is an approach of inference where Bayes' rule is used to update the probability distribution of a hypothesis when additional evidence data is learned. In cognitive radio networks, a CR user can compute a probability distribution (also known as prior) of a system parameter θ, such as the spectrum occupancy status of a PU, denoted by P(θ), from the observations made and subjective assessment. Through spectrum sensing, some data X = [x_1, x_2,...x_N] are observed for 'N' time slots. Then, a likelihood function of parameter θ, is calculated by CR user, denoted by L(θ), as the probability of the observed data given that parameter. After acquiring the prior probability distribution and the likelihood function, Bayesian inference can be used to derive the posterior probability distribution of the system parameter θ conditioned on the data X = [x_1,x_2,...x_N]; (Xing *et al.*, 2013). Bayes' rule is given as

$$P(\theta/X) = P(X/\theta).P(\theta)/P(X) \tag{5.1}$$

The posterior probability is proportional to the product of the prior probability and another term P(X/θ), the probability of the data given the parameter, commonly known as the likelihood. Likelihoods are the critical bridge from priors to posteriors, re-weighting each parameter by how well it predicts the observed data. Different choices of the prior P(θ), will lead to different inferences about the value of θ. The posterior distribution over θ contains more information than a single point estimate. It indicates not just which values of θ are probable, but also how much uncertainty is there about those values. However, there are two methods that are commonly used to obtain a point estimate from a posterior distribution. The first method is 'Maximum A Posteriori' (MAP) estimation: choosing the value of θ that maximizes the posterior probability. The second method is computing the posterior mean of the quantity which is a weighted average of all possible values of the quantity, where the weights are given by the posterior distribution. System scenario is formulated to match with Bayesian problem and is presented as approach 1. In approach 2, posterior mean is employed to predict the probability of a 'busy' next state. In the following discussion, term 'history' is used to represent the prior information. This is the average occupancy of the channel in the past. And 'recent observation' is used to estimate the Likelihood.

Approach 1

According to Bayes' rule, the posterior probability is proportional to the product of the prior probability and the likelihood. In this approach, the prior is the probability of channel occupancy by a PU in a particular channel based on large data observed already. Likelihood function is the probability of busy next state given a busy previous state. This is calculated from the data observed recently. Posterior probability is the probability of a busy next state (to be sensed) given a previous busy state. The prior is calculated by observing the spectrum occupancy status of PU for 'M_1' previous time slots. Let 'S_p' be the number of busy slots and 'N_p' be the number of idle slots from the spectrum occupancy status of the PU. Prior probability of the channel being busy is given by

$$P(S) = S_p/M_1 \tag{5.2}$$

Hence the prior probability of channel being idle is,

$$P(N) = 1 - P(S) \tag{5.3}$$

where 'S' stands for 'sensed state' or 'busy state' of a PU within a time slot and 'N' stands for a 'Not sensed state' or 'Idle state '. Let 'X' be the recently obtained result with 'M_2' observations such that $M_1 >> M_2$ and 'S_r' is the number of cases where both next and previous states are busy. And 'N_r' is the number of cases where both next and the previous states are idle. Let P(C/S) be the probability of previous state being busy given the next state is also busy, P(D/S) be the probability of previous state being idle given the next state is busy, P(C/N) be the probability of previous state being busy, given the next state is idle, and P(D/N) be the probability of previous state being idle, given the next state is also idle. Now the probability of the next state to be busy, given the previous state is also busy can be calculated as

$$P(S/C) = P(C/S).P(S)/P(C) \tag{5.4}$$

where

$$P(C) = P(C/S)P(S) + P(C/N).P(N) \tag{5.5}$$

And the probability of next state to be busy, given the previous state is idle can be calculated as

$$P(S/D) = P(D/S).P(S)/P(D) \tag{5.6}$$

where

$$P(D) = P(D/S)P(S) + P(D/N).P(N) \tag{5.7}$$

This approach is implemented as case-I and its variants are also implemented as case-II and case-III. Differences between three cases are given below.

Case - I: Next state is predicted by looking only at the present state and the previous statistics. In this case if you want to process N cases, you need to have N+1 observations. Here the calculations are as mentioned above. Here the present state may be either 'S' or 'N'

Case - II: A state is predicted considering the two previous states and statistics of the observed duration. In this case $N + 1^{th}$ state is predicted by considering the pattern of $N - 1^{th}$ and N^{th} states and the previous statistics. Hence the present states may be having any one combination from 'SS', 'SN', 'NS', 'NN' .

Case -III : A state is predicted considering three previous states and statistics of the observed duration. In this case $N + 1^{th}$ state is predicted by considering the pattern of $N - 2^{th}$, $N - 1^{th}$ and N^{th} states and the previous statistics. Here the present states will have eight combinations 'SSS', 'SSN', 'SNS', ...'NNN' .

Approach 2

Let us consider that the spectrum sensing by a CR in specific number of time slots follow a binary pattern represented as 'sensed(S)' and 'not sensed(N)'. It is assumed that sensing result in each time slot is arrived independently from a Bernoulli distribution with parameter θ. It may looks like SSNNNNNSSNSSSSN... . By looking into the recent sensed results, the probability of a busy('S') state in the next time slot is to be predicted. The belief about the arrival of PU is called 'prior', which is formed based on the history of its arrival pattern. It is considered that this sequence forms a beta distribution. Let X be the observed result with S_p and N_p as the number of 'sensed' or 'not sensed' respectively, from the history considered. Similarly S_r and N_r are the details about the recently observed results. Using a beta prior with the Bernoulli likelihood, posterior distribution can be obtained based on (Griffiths *et al.*, 2008) as

$$P(\Theta/X) = \frac{(Sp + Np + Sr + Nr + 1)!}{(Sp + Sr)!(Np + Nr)!}\Theta^{Sp+Sr}(1 - \Theta)^{(Np+Nr)} \tag{5.8}$$

which is a Beta (Sp+Sr+1, Np+Nr+1) distribution. A point estimate of θ from this distribution is obtained through the MAP estimate of θ is given as

$$\hat{\theta} = \frac{Sp + Sr}{Sp + Sr + Np + Nr} \tag{5.9}$$

and the posterior mean of the distribution is calculated as

$$\bar{\theta} = \frac{Sp + Sr + 1}{Sp + Sr + Np + Nr + 1} \tag{5.10}$$

Probability of the channel being busy can be estimated from equations 5.9 or 5.10. There will be slight difference between the two results. In a practical situation, a CR is expected to have the prior probability about a PUs arrival based on the history and this will be updated regularly. Likelihood of the data can be calculated from the recent observations. In practical cases, N_p and S_p need not be available in certain cases and it may be available as only a prior probability. Since denominator of equation 5.1 normalizes the posterior probability, posterior probability can be calculated as the product of prior and likelihood.

5.3.3 EWMA-based Prediction Approach

Exponential weighted moving average (EWMA)-based approach is presented by (Shi *et al.*, 2008). The authors have considered channel occupying probability $\pi(t)$ as Wiener process, which has the following two properties (Hull, 2006). The change of $\pi(t)$ during a small period of time Δt is

$$\Delta\pi = \epsilon\sqrt{\Delta t} \tag{5.11}$$

where $\Delta(t)$ can be defined as the prediction interval, and ϵ follows standardized normal distribution (a normal distribution with mean '0' and standard deviation '1'). The value of $\Delta\pi$ for any two different prediction interval Δt are independent. Hence, the mean and standard deviation of $\Delta\pi$ is 0 and Δt respectively. In a prediction time interval Δt, the change $\Delta\pi$ in the value of π(t) can be defined as

$$\Delta\pi = \mu\Delta t + \epsilon\sigma\sqrt{\Delta t} \tag{5.12}$$

where ϵ is a variable which follows standardized normal distribution. Thus $\Delta\pi$ has a normal distribution with mean and standard deviation $\mu\Delta$t and $\sigma\sqrt{\Delta t}$, respectively. μ and σ are known as the expected drift rate and the standard deviation rate of $\Delta\pi$ (Hull, 2006). Drift rate can be calculated by equation 5.13 and the estimator $\widehat{\mu}$ of μ and $\widehat{\sigma}$ of σ are given by equations 5.14 and 5.15

$$\mu(t) = \pi(t) - \pi(t-1) \tag{5.13}$$

$$\widehat{\mu} = \frac{\pi(t) - \pi(t-m)}{m} \tag{5.14}$$

$$\widehat{\sigma} = (1-\lambda)\sum_{i=0}^{m-1} \lambda^i(\mu(t-i) - \widehat{\mu} \tag{5.15}$$

5.3.4 Neural Network Approach for Spectrum Prediction

In line with the neural network presented in (Tumuluru *et al.*, 2012; Jianli *et al.*, 2011), we have implemented a neural network predictor, for comparing its computational complexity and prediction performance with the proposed Bayesian approaches. A multilayer perceptron (MLP) network consisting of an input layer and two hidden layers (each with 15 neurons) was implemented. The output layer consists of a single neuron. The network has 'N' inputs and one output. The parameters of the MLP predictor are updated using the back propagation (BP) algorithm. Spectrum sensing results are applied to the network as a binary sequence. For training the network, a sequence of 'N' inputs, say $x_n, x_{n-1}, x_{n-2}, x_{n-3}, ...x_{n-(N-1)}$ are applied and x_{n+1} is supplied as the desired response. This way the training is carried out with sufficient number of sequences and later it is used for prediction.

5.3.5 Discrete Time Hidden Markov Model

An HMM based approach is presented in (Akbar and Tranter, 2007) for spectrum prediction in cognitive radio. The sequence of spectrum states is modelled through the use of a two-state Markov chain with the spectrum in either state $S_t = 1$ or $S_t = 0$. A Markov chain has the property that the probability of future states is dependent only on the past 'm' states where 'm' is the order of the Markov chain. The parameters of the HMM are updated using the Baum-Welch algorithm. This algorithm uses the observed sequence of spectrum states to infer the underlying HMM transmission matrix. Assuming perfect sensing for the CR, the case of the emission matrix is not considered. This method is also implemented for comparing its computational complexity and prediction rate with proposed Bayesian approaches.

5.3.6 Results and Discussion

In this section, performance analysis of the proposed Bayesian approaches is carried out first and its performance is compared with other methods mentioned above. Evaluation of the proposed approaches is carried out by a simulation done in Matlab. For the analysis of predictors different data distributions have to be used. Beta distribution has the flexibility to form various types of distributions by changing its parameters. Hence binary data with Beta(α, β) distribution is used to represent spectrum occupancy pattern of a PU. Both prior and recent observations are extracted from same distribution and based on this data, probability of the next state is predicted using the methods presented above. Also the effect of various parameters on the predicted probability is analysed.

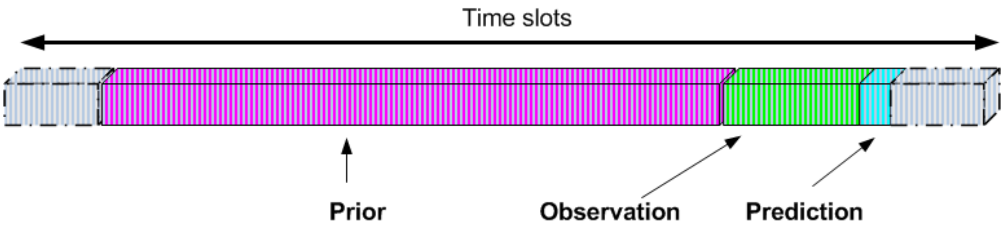
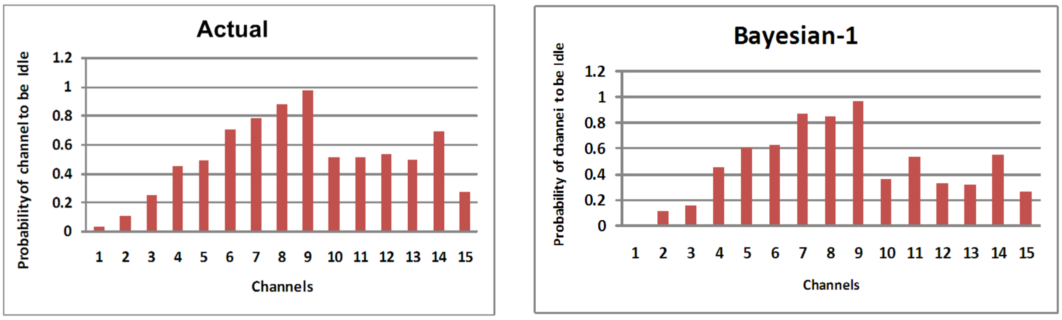


Figure 5.3: Channel time slots and its Bayesian model parameters

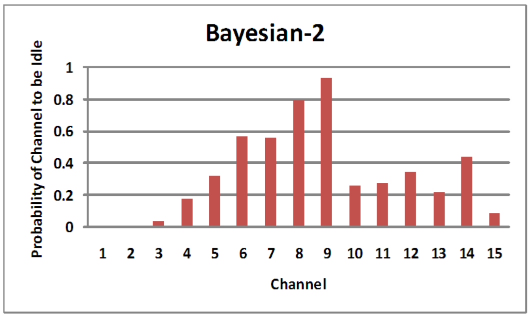
As shown in Fig. 5.3, consecutive blocks of data for prior and observation are selected and the probability of next busy state is predicted. For simulation, the number of time slots considered for prior should be large. In a practical situation, a CR will only have the estimate of the prior.



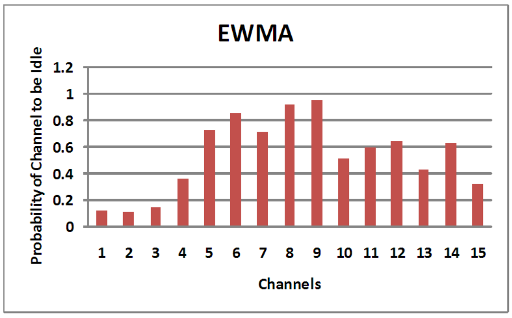
(a) (b)

Figure 5.4: Predicted probability of 15 channels (a) Actual (b) Bayesian-1

In order to reduce the computational complexity, the quantity of data considered as recent observation needs to be small. The cyan block shown in Fig. 5.3 as prediction is of one time slot duration and its probability needs to be predicted. Comparison of predicted probability is dealt first. A comparison of prediction by Bayesian approaches and EWMA approach for 15 channels are given in Fig. 5.4 and Fig. 5.5. Probability of 'next state to be idle' is calculated here. Actual probability is calculated from the known data. It can be seen that prediction by Bayesian approaches are very close to actual probability. Relative difference in the predicted probability between channels are



(a)



(b)

Figure 5.5: Predicted probability of 15 channels (a) Bayesian-2 (b) EWMA

almost closer to actual values. Number of recent observations ‘N’ considered for this prediction is 12. All the 15 channels were drawn from different beta distributions.

Next the prediction over 25-50 consecutive time slots for various approaches are presented. In order to predict consecutive time slots, specific size of the prior and observation blocks are moved forward for ‘n’ number of times over the time slots and the predicted values are plotted in Fig. 5.6 and Fig. 5.7. In practice, each SU will have the recent observations and a subjective estimate of PUs arrival rate. From this a node will infer the probability of the next busy state.

Fig. 5.6 shows the comparison of predicted probability of three cases of Bayesian-1 approach with the actual probability. This observation is arrived at with data distribution of $\beta(0.5, 0.5)$ and observation block size of 30. Three cases of Bayesian-1 approach are showing similarity among themselves and their magnitudes are increasing as it moves from case 1 to 3. It is seen that the Bayesian estimate is moving around the actual probability. It was observed in our trials that as the size of the observation block increases, variation of Bayesian estimate from the actual has become smaller and smaller. Since uniform data distribution is considered, actual probability in this context is around 0.5. Case-1 is showing more similarity with actual probability than other cases. On observing the direction of transition with respect to previous step at each time instance in the graph, evidence of correlation can be established between actual and Bayesian approaches.

Comparison of Bayesian-2 approach is shown in Fig. 5.7. In this case $\beta(2,1)$ distribution is used for analysis. EWMA approach is also compared here with Bayesian-2 approach. It is found that both Bayesian and EWMA patterns try to follow the actual

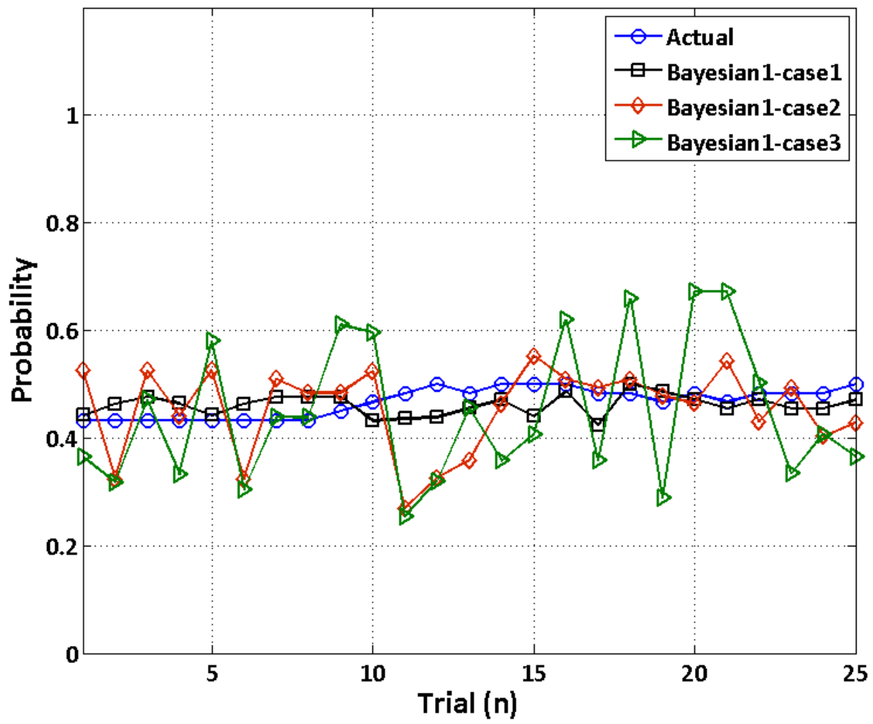


Figure 5.6: Comparison of predicted probabilities for three cases of Bayesian-1 and actual

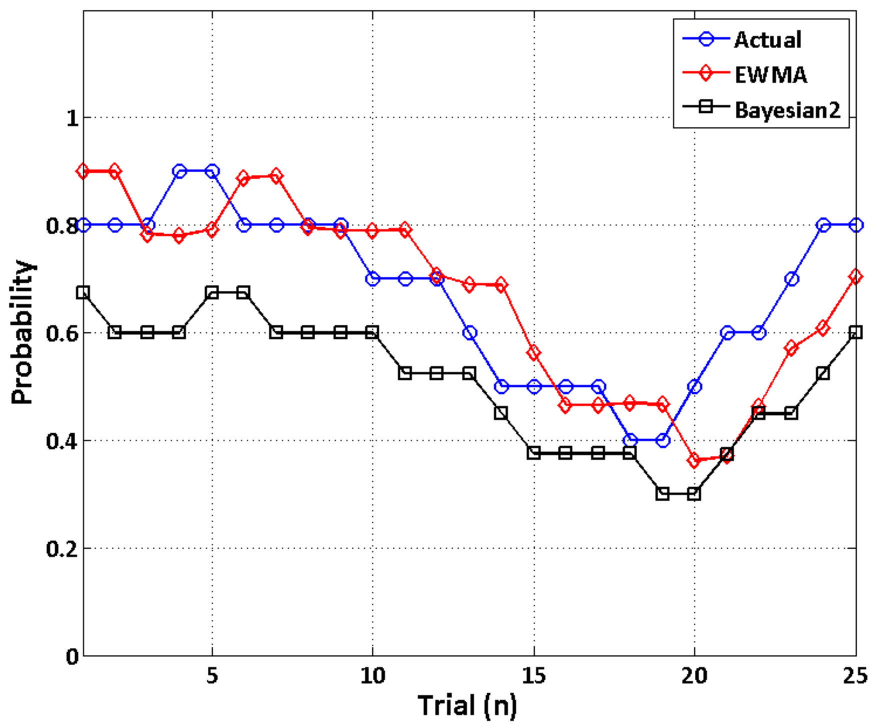


Figure 5.7: Comparison of predicted probabilities of Bayesian-2 and actual

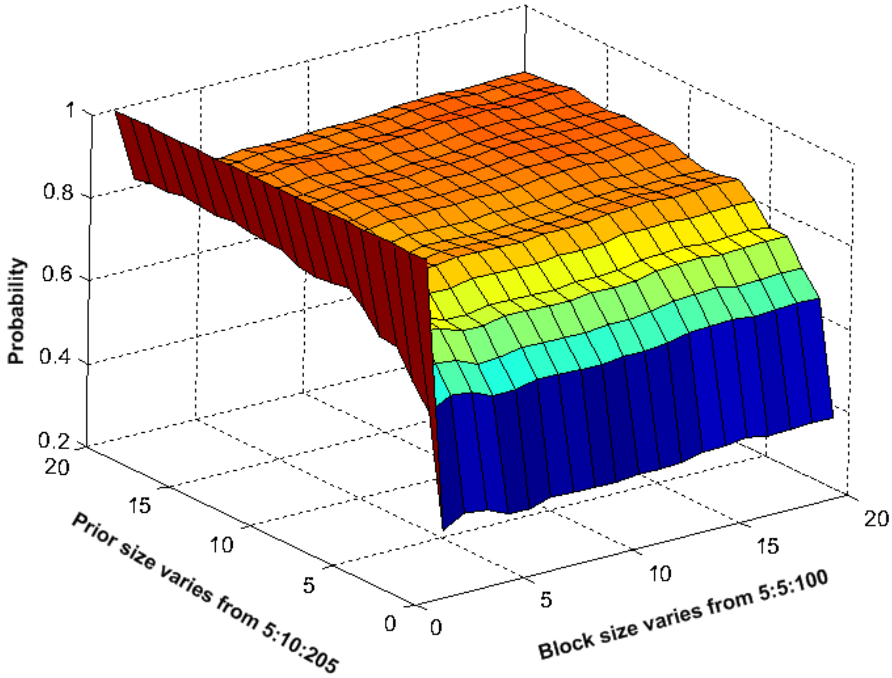


Figure 5.8: Predicted Probability under varying prior size and observation block size for Bayesian-1 approach for 'sensed' state

probability pattern. Considering the magnitude of the predicted value at each time slots, EWMA looks closer to actual than Bayesian-2. But it can be seen that, this difference is in the average value of the plot. On observing the transition pattern, Bayesian approach follows the actual transition pattern with one time slot delay and the EWMA follows the actual pattern with two time slot delay. Hence it can be considered that Bayesian-2's output is closer to the actual probability. It shows that Bayesian approach is a better choice for spectrum prediction in cognitive radio.

In all the Bayesian cases, there is a possibility to vary the number of data considered for prior and number of data considered for observation. In the next part, the effect of prior size and observation block size on the prediction value is analysed. A typical case with known next state and its respective prediction by various methods are shown below. Two cases of next state ('sensed' and 'not sensed') with their respective prediction are shown in Fig. 5.8 to 5.13.

Here the aim is to find the minimal size of the prior block and observation block for a reliable prediction. In all these cases, scale used for x-axis is 1:5 and that of y axis is 1:10. Fig. 5.8 & 5.9 shows that Bayesian-1(case-1 is considered) is giving a stable result with a block size of around 10 and that of prior is around 100. Generally larger block

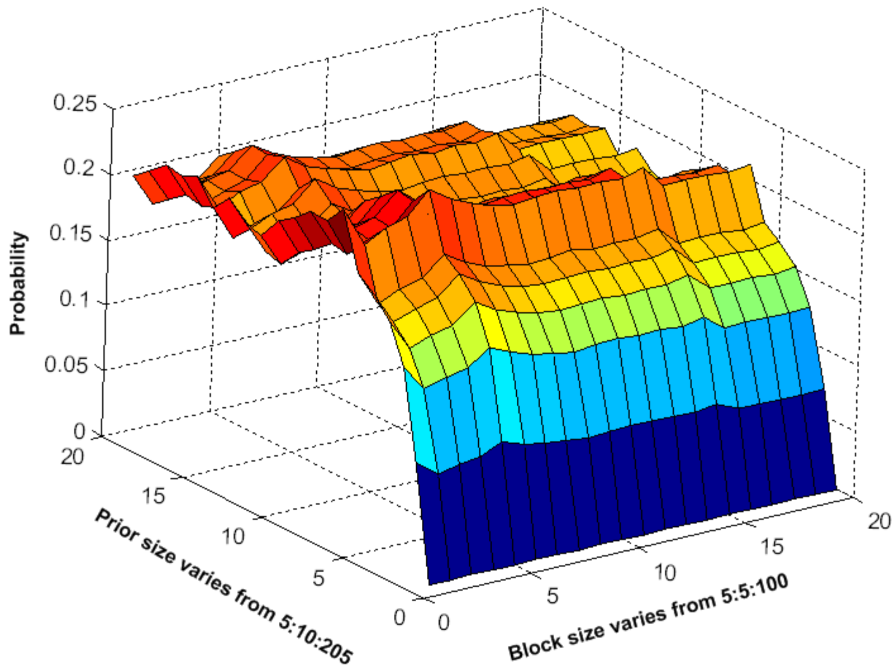


Figure 5.9: Predicted probability under varying prior size and observation block size for Bayesian-1 approach for 'not sensed' state

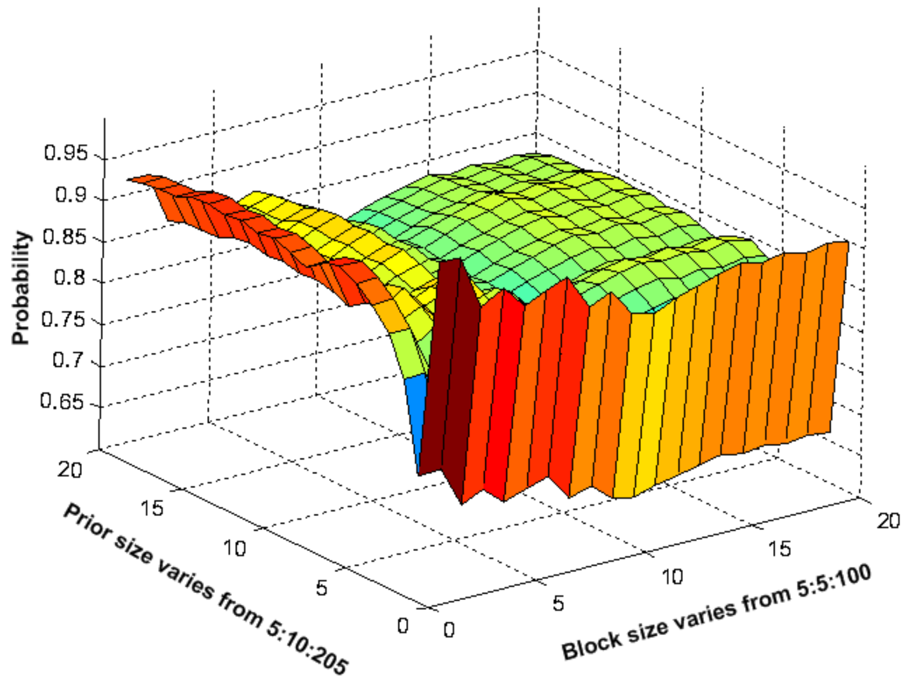


Figure 5.10: Predicted probability under varying prior size and observation block size for Bayesian-2 approach for 'sensed' state

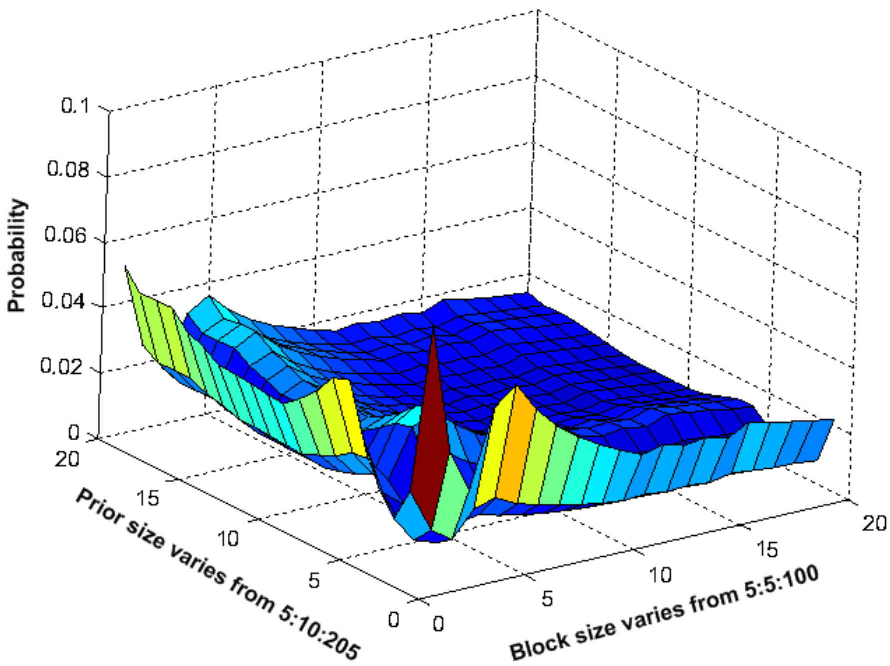


Figure 5.11: Predicted probability under varying prior size and observation block size for Bayesian-2 approach for ‘not sensed’ state

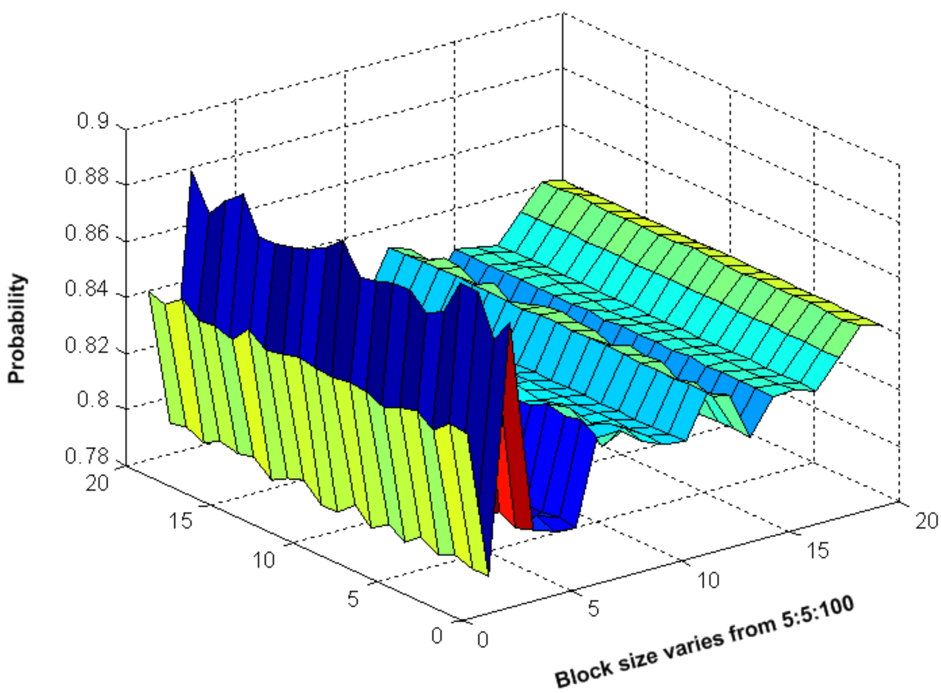


Figure 5.12: Predicted Probability under varying observation block size for EWMA approach for ‘sensed’ state

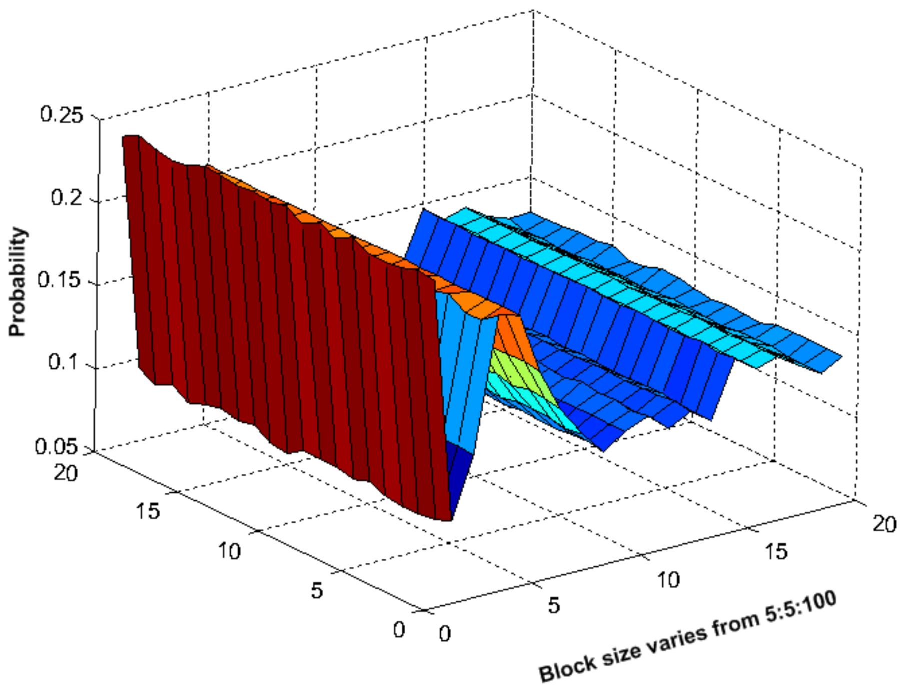


Figure 5.13: Predicted probability under varying observation block size for EWMA approach for 'not sensed' state

size for a prior will give a stable result. Fig. 5.8 & 5.9 shows that Bayesian-2 approach require slightly more block size as that of Bayesian-1. Slightly larger block size for prior is also required here. In Fig. 5.12 & 5.13 EWMA approach is analysed only on the block size under consideration and it is repeated more times to make it similar to other approaches. It is found that EWMA needs more data to get a stable prediction.

All the above analyses were carried out with the help of different data generated under various beta distributions. In order to match with a real situation, we have performed spectrum occupancy measurement of GSM-900 band using NI-USRP. 24 hours measurement of spectrum occupancy in each time slot, per channel is obtained. Duration of time slot was around 1 sec. The 'ON', 'OFF' status of PU in each time slot is represented with '1s' and '0s '. This data of nine channels are used for comparing the performance of proposed Bayesian approaches with other methods.

Channel ranking, based on the probability of the channel being idle, is used to compare the performance of proposed Bayesian method with approaches based on EWMA, HMM and Neural Network. All the methods tries to rank the channels after observing spectrum occupancy status of 'N' recent time slots. They also use an estimate of prior data for the ranking. This estimate is taken only once and it may be updated later, but

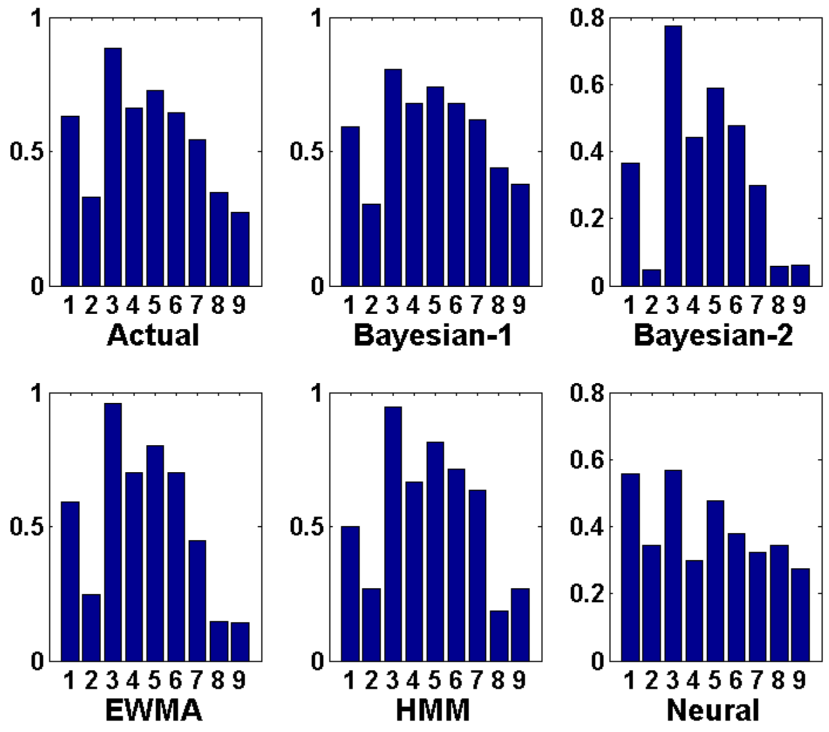


Figure 5.14: The channel ranking based on prediction of the probability of channel being idle for an observation size N=20

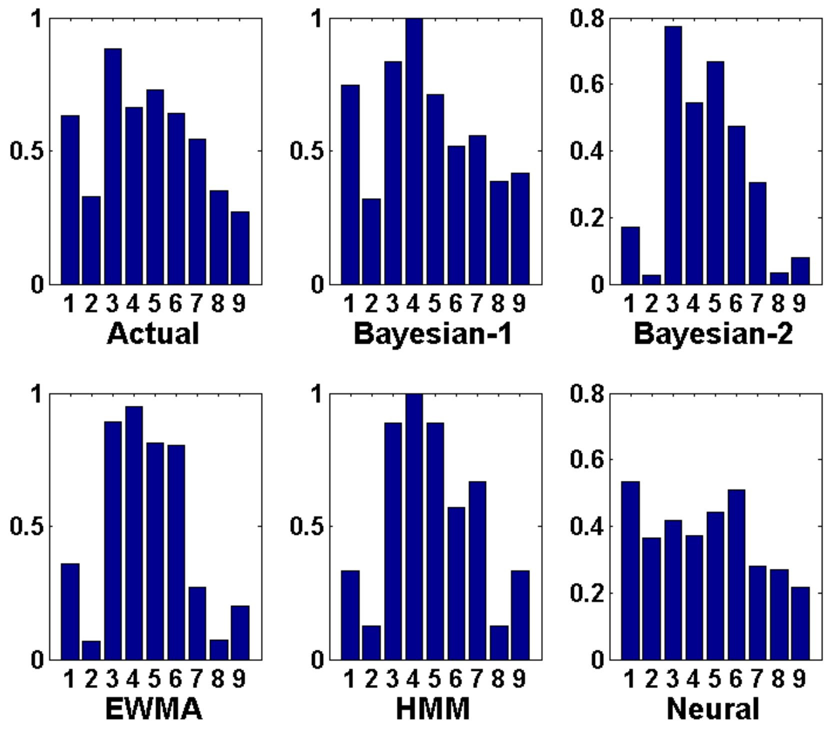


Figure 5.15: The channel ranking based on prediction of the probability of channel being idle for an observation size N=10

not on a regular basis. 'N' recent observations will be considered regularly to prepare the ranking. This is to reduce the time consumption. Channel ranking carried out by all the methods are shown in Fig. 5.14 and 5.15. X-axis in each subplot is the channel number and the Y-axis gives the predicted estimate. The estimate with higher value is the best channel with higher probability of being idle. N=20 is used for Fig. 5.14 and N=10 is used for Fig. 5.15. Actual ranking is obtained from the data used for simulation. When N=20, ranking by Bayesian-1 is almost closer to actual ranking. Estimates by Bayesian-2, EWMA and HMM are giving similar pattern, but slight deviation from the actual pattern. Even though they use 'prior', it seems the effect of recent observation is dominant in the estimate. Ranking pattern by neural net is giving more deviation from the actual. When N =10, neural net is showing a closer relation with actual case than the previous case. But ranking pattern by other methods are showing deviation from the actual pattern. This is because of the insufficient size of the 'N'. During experiment it was seen that N>15 was giving a good result for Bayesian-1 and as 'N' increases Bayesian-2, EWMA and HMM were giving a closer estimate to the actual case.

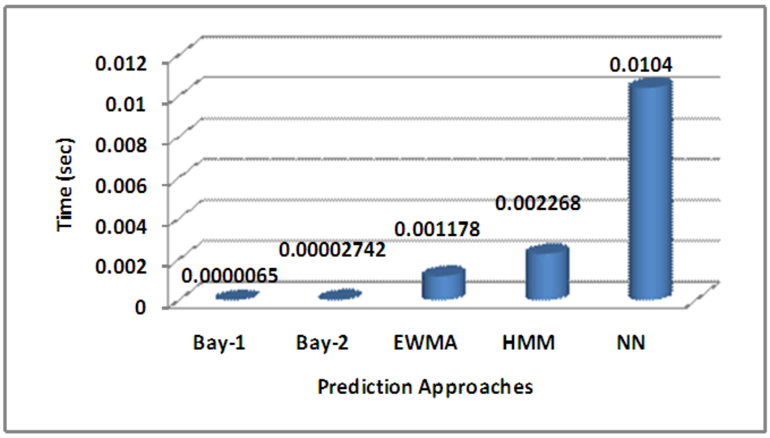


Figure 5.16: Time consumed by all the approaches for one state prediction. [Machine spec: Intel(R) Core(TM)2 Duo CPU, T7250 @ 2.00 GHz, 777 MHz, 1.95 GB RAM]

Analysis of computational complexity is carried out and the result is shown in Fig. 5.16. These approaches were run on an Intel core-2 Duo CPU with 2 GHz clock and the time elapsed for each method is tabulated and compared. In the case of NN and HMM approach, training time is not considered for comparison. Fig. 5.16 clearly shows that Bayesian approaches are less expensive in terms of computational cost. Considering the time required for spectrum sensing and time available for data transmission within a specific slot as in Fig. 5.3, a successful prediction is going to improve the throughput of the system. Low prediction time and higher detection rate of Bayesian approaches can make it a useful candidate for cognitive radio system.

5.3.7 Section Summary

Spectrum prediction is a very useful task that improves the efficiency of spectrum sensing and it will lead to increase in the throughput of the CR system. In this section, we proposed some Bayesian approaches for spectrum prediction and their analysis is carried out. This predicted probability can be used to rank the channels so that channels with lower rank can be skipped from spectrum sensing. Performance of proposed methods are carried out on generated data as well as on real data obtained through spectrum measurement. Its performance is compared with existing approaches such as EWMA (Shi *et al.*, 2008), Neural Network (Jianli *et al.*, 2011), HMM (Akbar and Tranter, 2007). Considering the prediction performance and computational cost, Bayesian approaches are giving a better performance and it is found that they are the promising approaches to improve the throughput of the system.

5.4 Spectrum Occupancy Measurement and Analysis

In the context of cognitive radio, spectrum occupancy estimate of a geographical region is very important to establish strategies to utilise the unoccupied spectrum. Most of the spectrum occupancy measurement performed till date are based on measurements in outdoor high points. In this work, spectrum occupancy is measured using an indoor setup. Here the focus is to find the utilisation of the licensed spectrum in the region, Kochi, India. Spectrum holes in the frequency domain is presented through the overview of the spectrum occupancy over the range 50 MHz - 4400 MHz. Spectrum hole in the frequency - time domain is presented through detailed measurement at frequencies where activity is noticed. Average duty cycle of specific channels and specific bands are presented. Analysis shows that CRs with different complexity can work at different types of spectrum holes. That means, a high end device with multiple protocols can adapt to any type of spectrum holes and always there is a possibility that a low end CR device specific to the type of spectrum hole can also exist.

5.4.1 Measurement Setup and Methodology

Measurements were conducted at Rajagiri School of Engineering and Technology (RSET), Kochi, Kerala, India. The indoor measurements were performed inside the laboratory located on the top floor of the building where exists excellent signal strength for all the transmitters located nearby. The district headquarters and major towers of TV, FM and Mobile towers are located near to the measurement location. NI USRP with Lab view platform was used for the measurement setup. The sensing setup consisted of NI-USRP-2920 and NI-USRP-2922 with omni directional antenna that performed the measurement and a computer loaded with LabVIEW that recorded the data along with its time and frequency information to perform further analysis. Detailed analysis is presented in Section 5.4.3

5.4.2 Occupancy Metrics

General metrics used in this work for the spectrum occupancy measure is as mentioned in (López Benítez and Casadevall Palacio, 2010). Power Spectral Density (PSD) samples collected by the PSD block of USRP over a time span 'T' and along a frequency span 'F' is represented by a matrix P of N_T by N_F size

$$P = P[t_i, f_j] \tag{5.16}$$

where each matrix element P(t_i, f_j) represents the PSD sample captured at time instant t_i (i = 1, 2, .. , N_T) and frequency point f_j (j = 1, 2, .. , N_F). Energy detection is used to detect the PU. Here the received signal energy is compared to a predefined decision threshold 'λ' chosen adaptively with respect to noise floor. If the signal energy is greater than the threshold, PU is said to be present. Otherwise, the measured frequency channel is said to be idle. Following this principle, a binary spectral occupancy matrix E[t_i, f_j] is defined, where each element E(t_i, f_j)$\in [0, 1]$ is computed as

$$E(t_i, f_j) = \left\{ \begin{array}{l} 0, M(t_i, f_j) < \lambda_j \\ 1, M(t_i, f_j) \geq \lambda_j \end{array} \right\} \tag{5.17}$$

Average usage or average duty cycle D_j of a frequency f_j is calculated as the average of the i^{th} column of E.

$$D_j = \frac{1}{N_T} \sum_{i=1}^{i=N_T} E(t_i, f_j) \tag{5.18}$$

Average duty cycle of a band of frequencies is computed by averaging the duty cycle D_j of all the N_F frequency points measured within the band:

$$D = \frac{1}{N_F} \sum_{j=1}^{j=N_F} D(j) \tag{5.19}$$

5.4.3 Spectrum Occupancy Analysis

This section presents the activity in the spectrum space ranging from 50 MHz to 4400 MHz. Initially an overview of spectrum occupancy over the entire range based on measurements taken for around 128 instances at a stretch is presented. This is followed by detailed measurement of 24 hours duration over specific bands, where more activity is observed. This work focuses on FM radio band, VHF TV band, GSM-900 band, GSM-1800 band, 3G and Wi-Fi. It is observed that spectrum occupancy is seen in certain other frequency bands also.Samples are taken at 1 second interval. Threshold was set 6 dBm above the average noise floor. It was verified through conducting trials over unoccupied channels that, this threshold was giving a probability of false alarm, $P_f \leq 0.1$. It was observed that average energy level of the noise shows slight variation with respect to frequency bands. And in some bands like FM, the signal level is so strong that even a higher threshold also will give a correct result. But in the case of GSM, both weak and strong signals are present. The measurement setup was configured to give spectrum occupancy details of 10 MHz at a time. These results were combined to obtain PSD plots for all the bands. Average duty cycle of each channel and the respective band are calculated according to equations 5.18 and 5.19. Since GSM and FM channels are of 200 kHz band width, during detailed measurement each frequency band was divided into 200 kHz channels and the average occupancy of various bands were calculated. Fig. 5.17 gives an overview of the spectrum occupancy in 50 MHz to 200 MHz band. Some activity is seen in 50 MHz-75 MHz band followed with activity in the FM band. No activity except some spikes are visible in the 110 MHz - 200 MHz

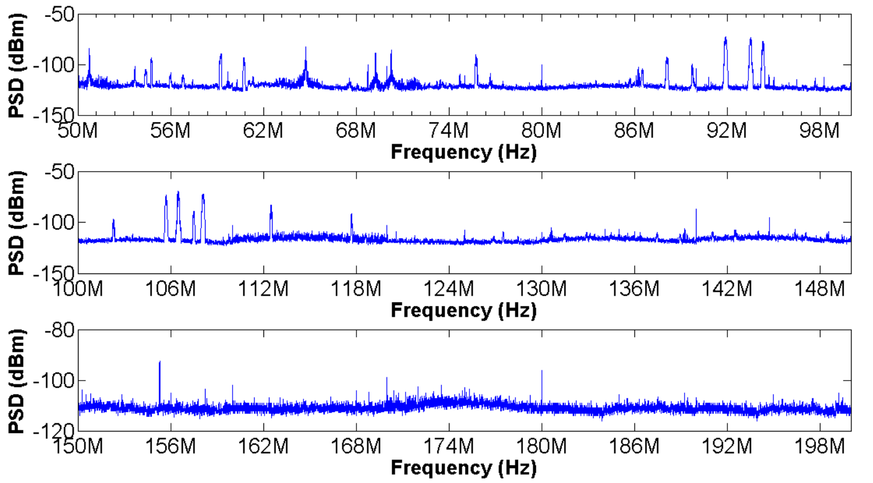


Figure 5.17: Spectrum activity in the 50 MHz - 200 MHz

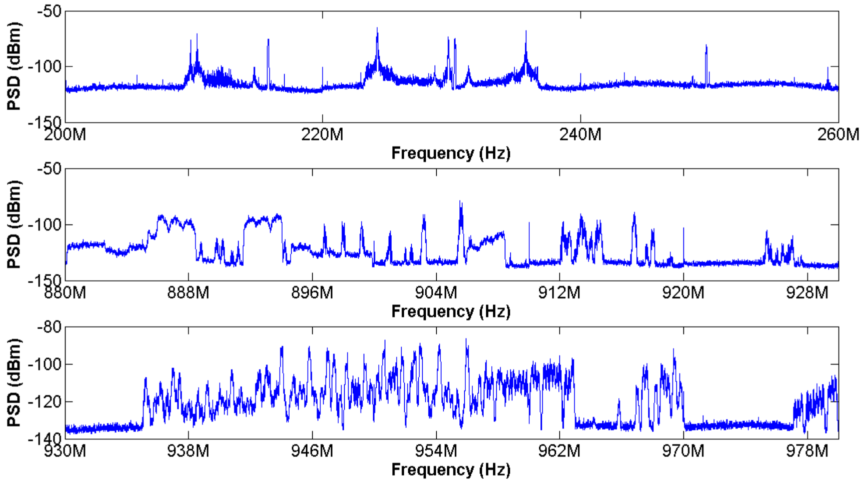


Figure 5.18: Spectrum activity in the VHF TV and GSM-900 band

frequency range. All the FM radio channels in Kochi, viz. 91.9 MHz, 93.5 MHz, 94.3 MHz, 102.3 MHz, 107.5 MHz etc. and other channels clearly appear in the plot.

Spectrum occupancy in the VHF TV band and GSM-900 bands are shown in Fig. 5.18. Transmission of TV channels from Kochi such as DD-National (224.25 MHz) and DD-News (210.26 MHz) are clearly captured. For GSM-900, an extended frequency band from 880 MHz - 980 MHz is shown in the figure. This has been included to show the spectrum occupancy in the nearby frequencies of GSM uplink and downlink. GSM-900 band appears to be heavily used. No activity is found in frequency band between 980 MHz to 1700 MHz, and hence it is not shown. Spectrum activity between 490 MHz - 870 MHz is presented in Fig. 5.19. Some activity is seen in 715 MHz - 725 MHz and 790 MHz - 810 MHz band. As per the spectrum allocation table, some portion is allo-

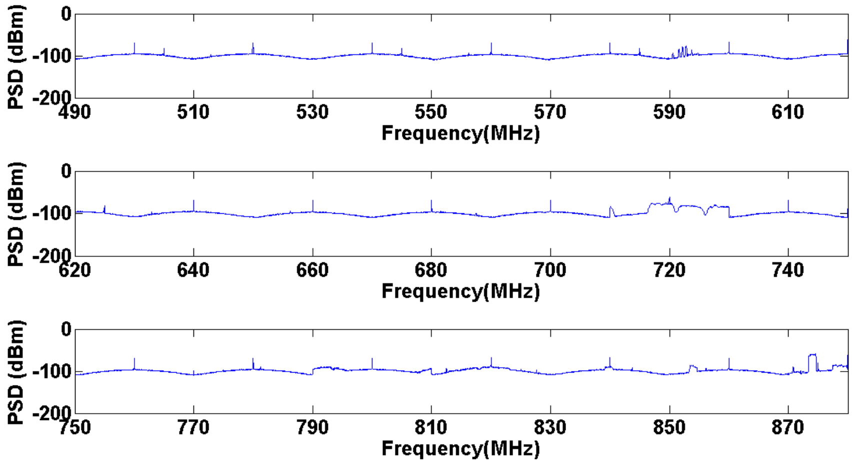


Figure 5.19: Spectrum activity in the 490 MHz - 870 MHz band

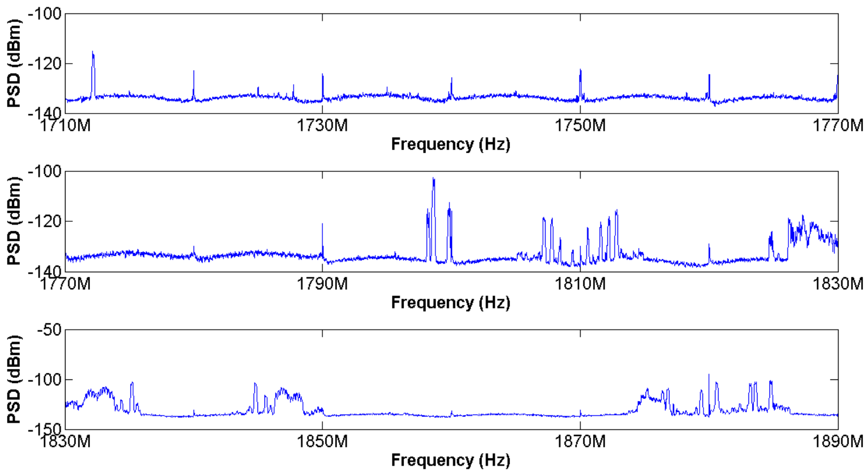


Figure 5.20: Spectrum activity in the GSM-1800 band

cated to UHF TV and some are not allocated, whereas some are for mobile applications including CDMA.

Fig. 5.20 shows the spectrum occupancy within 1710 MHz - 1890 MHz. GSM-1800 band is located within this range. Only limited activity is visible in the uplink whereas relatively more activity is seen in the downlink. This could be because the measurement setup is located at one side of the mobile tower. All the downlink signals from the tower are available at the measurement setup and the signals from the mobile phones located away from the tower do not give significant signal strength at the measurement setup. While monitoring the real time measurement, some patterns similar to channel occupancy were observed along with the noise floor though with feeble amplitude. Such signals may not get recorded as channel occupancy of a user. Fig. 5.21 gives the

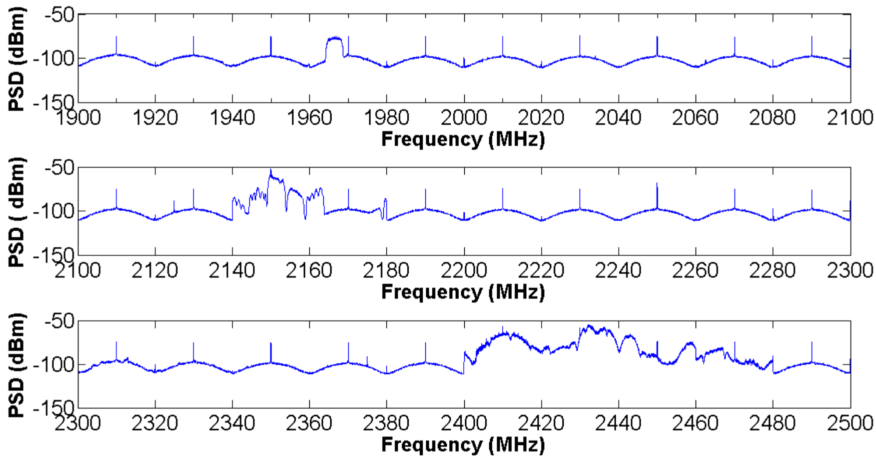


Figure 5.21: Spectrum activity in the 3G and WiFi band

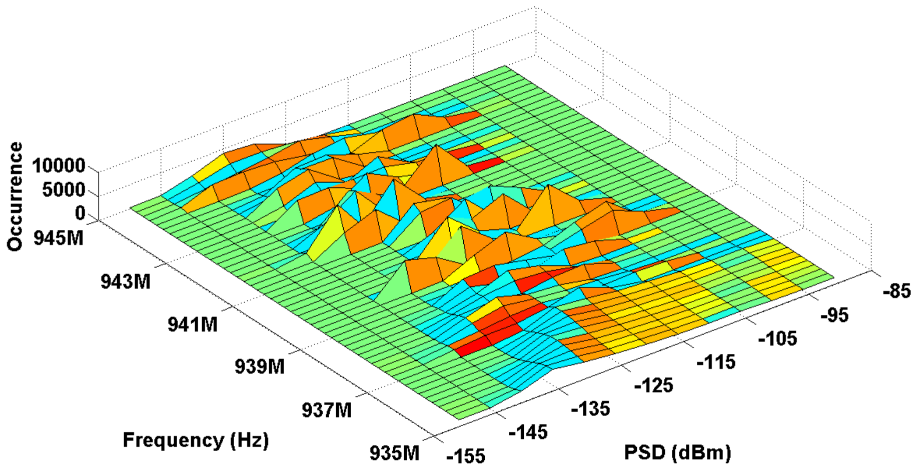


Figure 5.22: PDF of received energy for GSM-900 downlink

spectrum activity in the 3G band and Wi-Fi band. 3G uplink is seen in 1900 MHz and downlink in 2100 MHz band. More activity is seen in 2100 MHz band. This is also because of the presence of the tower near to the measurement location. Activity was also observed on the entire range of the Wi-Fi band (2400 MHz - 2500 MHz).

Histogram of the PSD of the received signal at various bands are displayed in Fig. 5.22 to Fig. 5.29. The distribution of PSDs throughout 24 hours for each 200 kHz band is presented here. It gives the Probability Density Function (PDF) of the received energy for a band of frequencies at the receiver. This was obtained from around 10000 samples collected over 24 hours. At a time 10 MHz band was observed. Each band was divided into 50 channels of 200 kHz each. Necessary offsetting in the re-

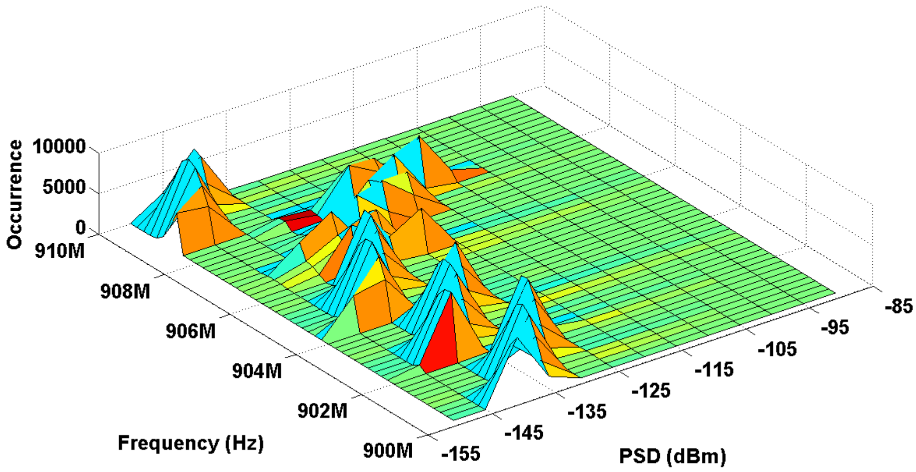


Figure 5.23: PDF of received energy for GSM-900 uplink

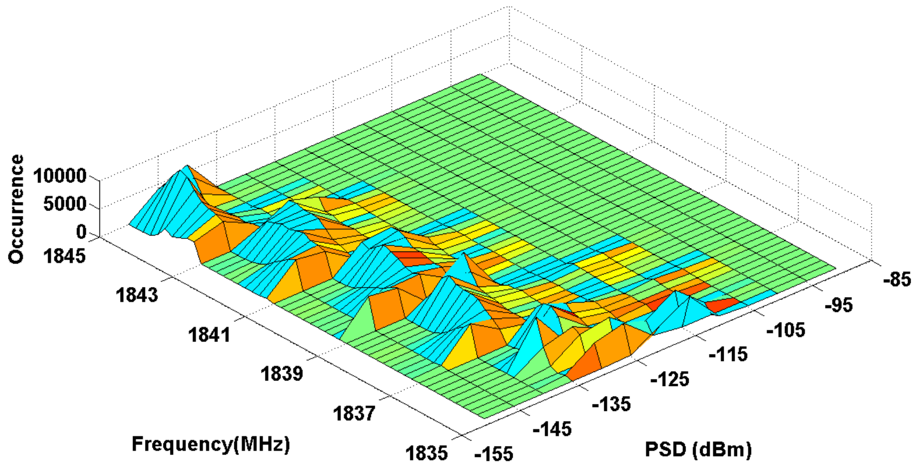


Figure 5.24: PDF of received energy for GSM-1800 downlink

ceived data was done to receive a complete channel. This is done to avoid the guard bands allocated in FM and GSM bands. Since FM and GSM use 200 kHz channels, our measurement setup is configured like that. Same setup is used for other bands also. A histogram of received energy levels of a particular channel over the range of -155 dBm to -85 dBm is plotted here. 10 MHz band details from GSM-900 downlink, GSM-900 uplink, GSM-1800 downlink, GSM-1800 uplink, FM, VHF-TV, 3G and Wi-Fi are presented in Fig. 5.22 to Fig. 5.29. It is obvious that more the usage, more the energy in the high energy bins. It is clear that the TV signals are having highest energy followed by the FM stations. This is of course due to the high power transmitters at TV stations. It is also seen that GSM 900 downlink is giving stronger signals at the receiver. Compared to downlink signals, uplink signals are weak as these are originated from the mobile

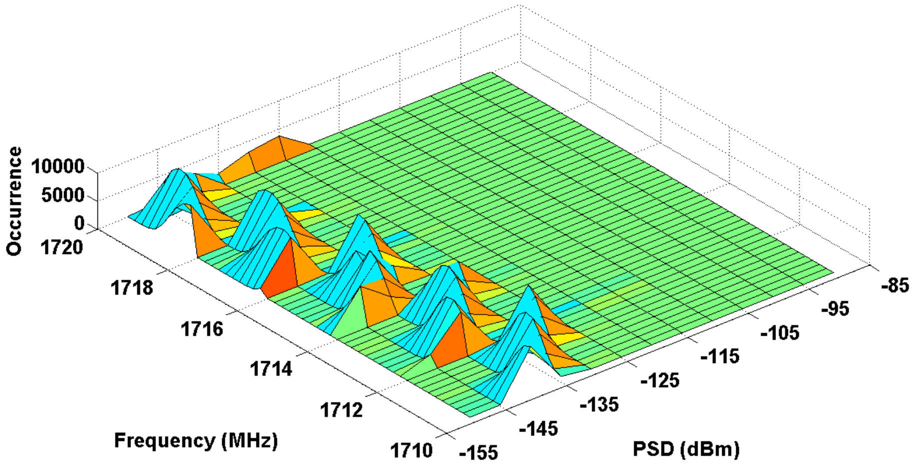


Figure 5.25: PDF of received energy for GSM-1800 uplink

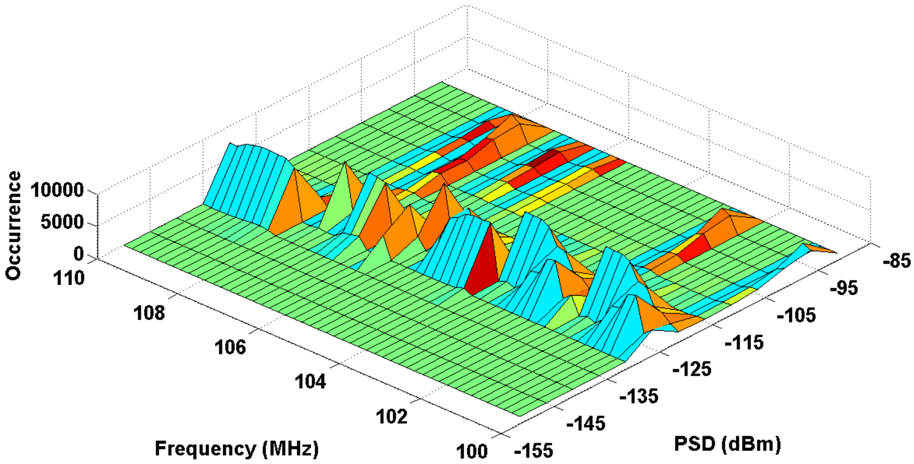


Figure 5.26: PDF of received energy for FM band

phones located within the cell boundary. The received energy of the GSM-900 downlink appears to be stronger and GSM-1800 uplink is found to be the weakest among GSM signals.

In order to calculate the average duty cycle of a channel, 24 hours measurement was conducted on each channel. Spectrum utilisation of all the channels in the FM band(88 MHz - 108 MHz), GSM uplink band(880 MHz - 915 MHz) and GSM downlink band(935 MHz - 960 MHz) were carried out as per equation 5.18 and presented in Fig. 5.30. In the FM band, only nine channels have significant usage and the average duty cycle of the band is only 8.6%. This is because only nine channels may have operation license in this region. Most of these primary users, utilise the channel 100%, while for others the utilisation is almost 80%. It is observed that these FM stations

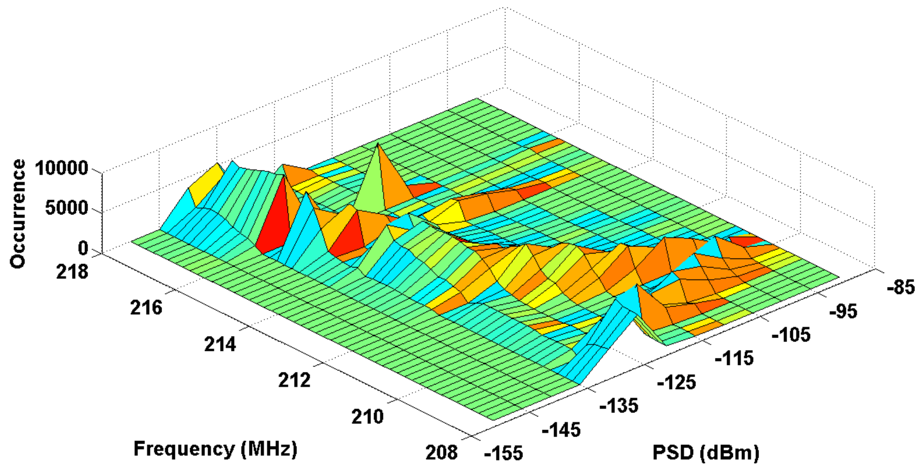


Figure 5.27: PDF of received energy for VHF TV band

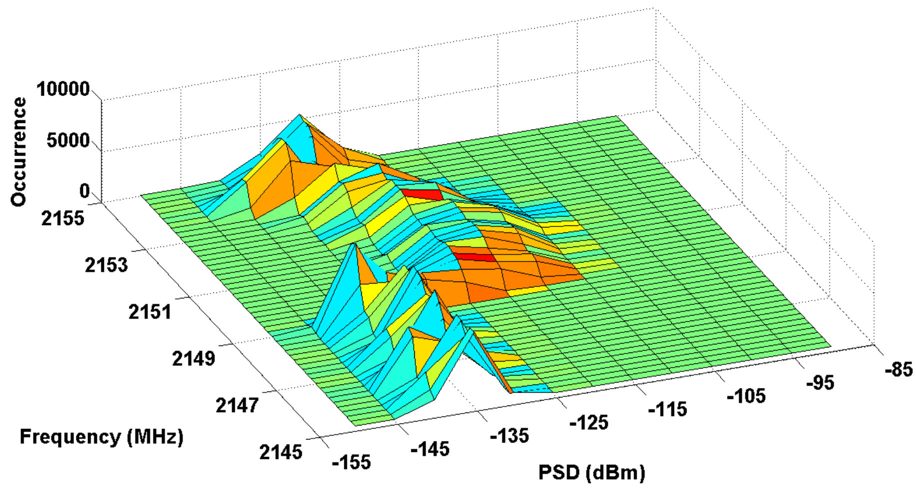


Figure 5.28: PDF of received energy for 3G downlink

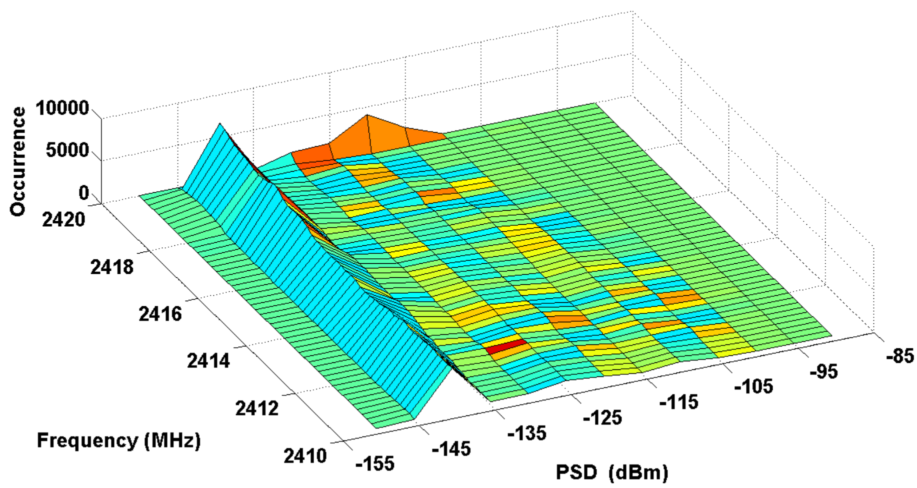


Figure 5.29: PDF of received energy for Wi-Fi

were switched off for a specific duration. Sub-plots 2 and 3 of Fig. 5.30 show the channel utilisation of GSM-900 band. It is seen that GSM-900 downlink channels are heavily utilised. Almost 61 percent utilisation is observed for this band. The uplink band is observed with only 17 percentage utilisation. Significant gap is observed in the utilisation of uplink and downlink channels. This is because of the presence of GSM tower closer to the measurement setup than the mobile phones. Uplink channel is used by the mobile phones and the mobile concentration near to the measurement setup are likely to be less.

Channel utilisation of GSM-1800 band is provided in Fig. 5.31. Here all the channels in this band were observed and the average duty cycle was plotted. As usual, GSM-1800 downlink is showing higher utilisation than its uplink channel. This may be due to the same reason as that of GSM-900 band. Comparing the two GSM bands, GSM-900 is heavily utilised than GSM-1800 band. Hence spectrum opportunity is more with GSM-1800. Only in the above three bands, analysis is done for the entire channels in a band. In all other bands, we have conducted similar analysis on specific 10 MHz regions over the respective bands. Based on this, spectrum usage pattern of all the services over 24 hours duration is presented here. Hourly usage pattern of GSM-900 band is presented in Fig. 5.32. Two 10 MHz ranges are analysed here. It is observed that certain channels are used round the clock. This may include control channels. Certain channels have a random usage with less usage between 12 am - 5 am. This may be because of less active users during that time. Hourly usage pattern of GSM-1800 band is presented in Fig. 5.33. Some channels are steadily used and some have random usage with minimum usage during 12 am - 5 am. It is observed that some channels have heavy usage between 2 am - 8 am and a few channels are less utilised between 1 pm-4 pm. And some channels are not at all used. Hourly usage of a VHF TV channel is presented in Fig. 5.34. It is very clear that it has a steady usage throughout its operation with no transmission between 12 am - 5 am. Some activity is visible in a small band in subplot-1 of Fig. 5.34. It may be an activity of a third party. Two Video channels along with its audio carrier is clearly visible in the subplots. In this case, the spectrum hole is very clear. But there is some space visible between video signals and audio carrier that cannot be used while the transmission is on. In VHF TV, this channel is vacant between 12 am - 5 am. In the case of FM channels some channels were used round the clock and a few channels were switched off for a specific period. Hourly usage pattern of 3G

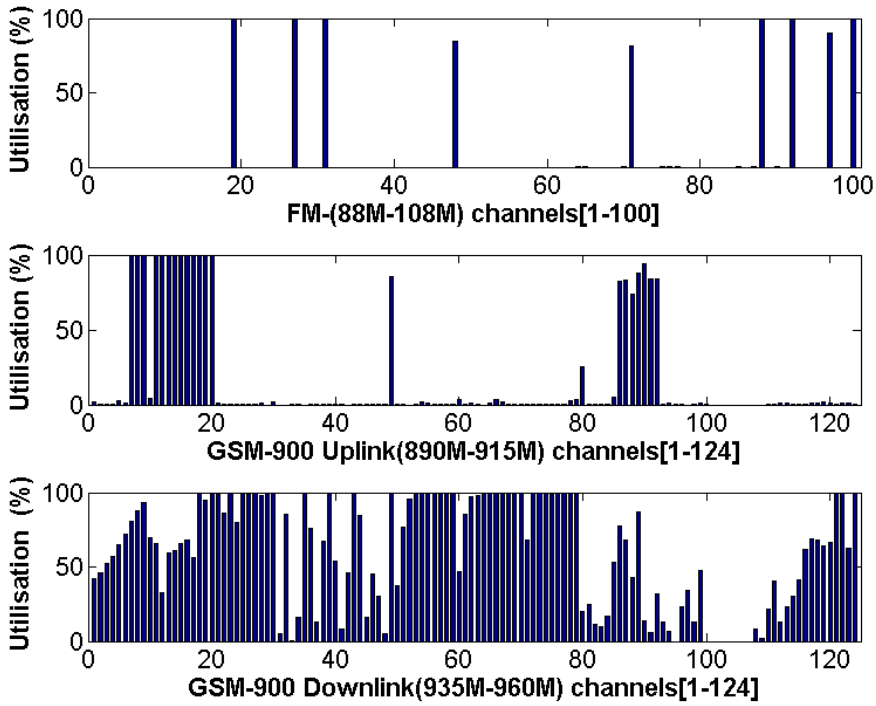


Figure 5.30: Channel utilisation in FM band and GSM-900 band

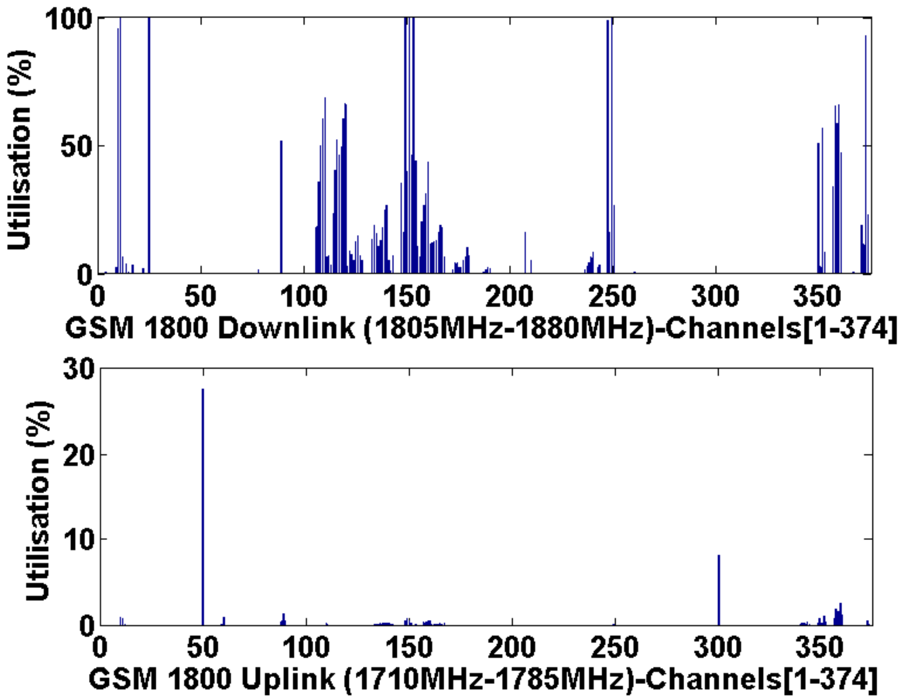


Figure 5.31: Channel utilisation in GSM-1800 band

service and Wi-Fi is presented in Fig. 5.35. A sample 10 MHz range is considered here from this band where activity is seen. In 3G and Wi-Fi, channel band width is more than 10 MHz and this analysis will give only an indication about this band's nature.

For Wi-Fi in 2410 MHz - 2420 MHz, the usage is less than 50 during the peak hours 8.30 am - 4.30 pm and the usage is near to zero during other timings. This is because of the higher usage during working hours of the institution. For 3G service the usage pattern looks constant throughout the time with slight deviation with respect to time. This may be due to the data usage with optimized routing.

Spectrum hole pattern of 50 GSM downlink channels over 200 time slots are shown in Fig. 5.36. Spectrum hole is represented with white colour and spectrum occupancy is indicated by black colour. From the cognitive radio perspective, availability of spectrum holes and its pattern is important for the planning of CR systems. It is seen that some channels are heavily used and some channels are totally free. On analysing the hourly usage, it was observed that some spectrum hole patterns have time dependency and some are random. That is, a large number of channels follow various types of utilisation patterns. On analysing the spectrum holes, it was seen that a lot of spectrum holes are available in geographical space. That is, out of 50 MHz - 4.4 GHz, spectrum occupancy is seen in very low percentage of the spectrum space. It may be because of the under utilisation of the band by the PU and also because some bands are unallocated in this specific region.

Spectrum utilisation in various bands is presented in Fig. 5.37. Spectrum occupancy is calculated as per equation 5.19. In the case of FM, GSM-900, GSM-1800 and Wi-Fi, spectrum occupancy is calculated with 24 hours data. And in other cases, the spectrum occupancy is calculated with a few samples in the time scale and all the samples in the frequency range. On observing the spectrum utilisation and spectrum holes in space, frequency and time, it is felt that a Cognitive radio can utilise the spectrum more efficiently. Also there can be CRs of various complexities. That means, at certain spectrum holes, CRs with lighter complexity can work effectively. These nodes need not have stringent time constraints in spectrum sensing and effective communication. But for spectrum holes which are agile in its occurrence, a CR with complex algorithms and strict time constraints is required. Hence it gives out an opportunity that a stable CR device can work in various modes according to the environment. Such an opportunity

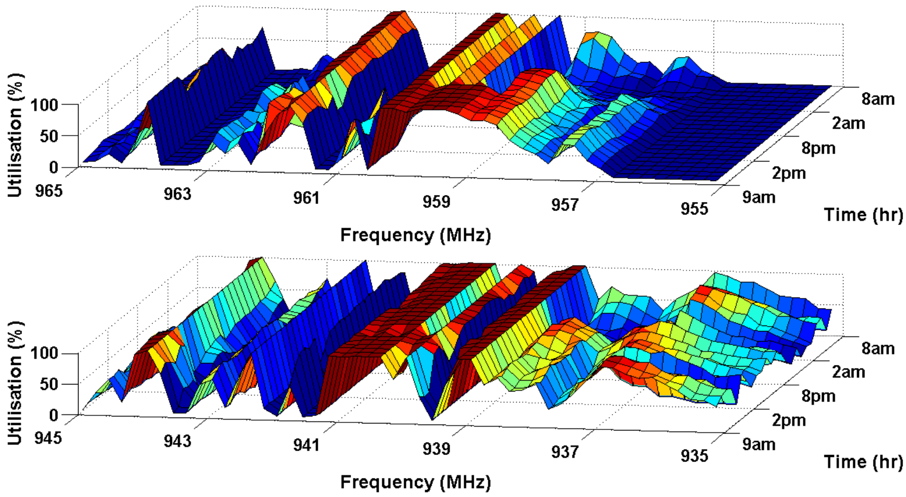


Figure 5.32: Channel utilisation of GSM-900 band over 24 hours

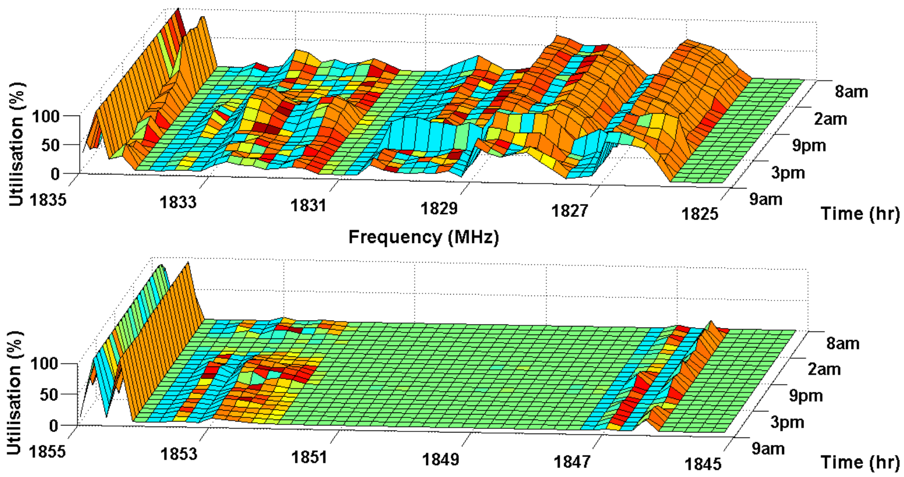


Figure 5.33: Channel utilisation of GSM-1800 band over 24 hours.

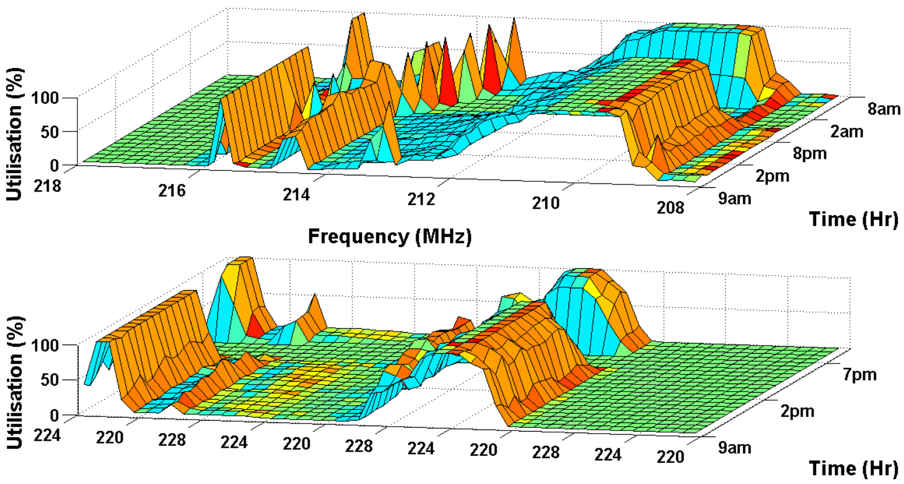


Figure 5.34: Channel utilisation VHF TV band over 24 hours.

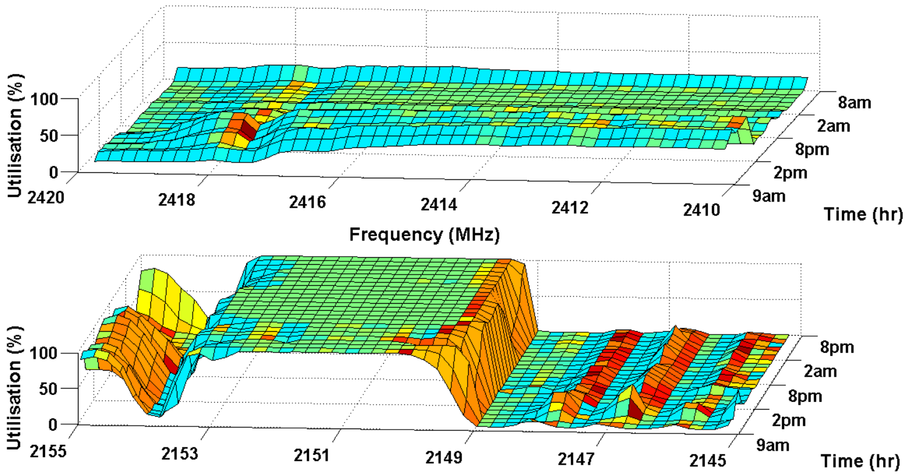


Figure 5.35: Channel utilisation of 3G and Wi-Fi over 24 hours.

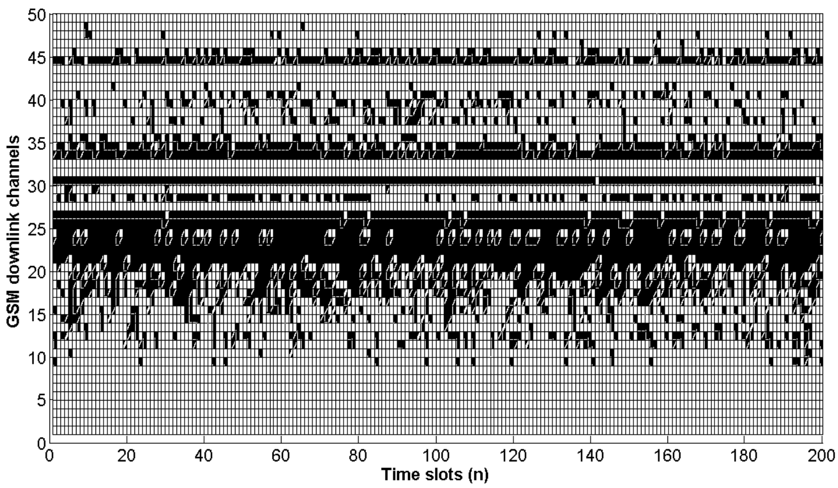


Figure 5.36: Spectrum hole pattern in GSM band

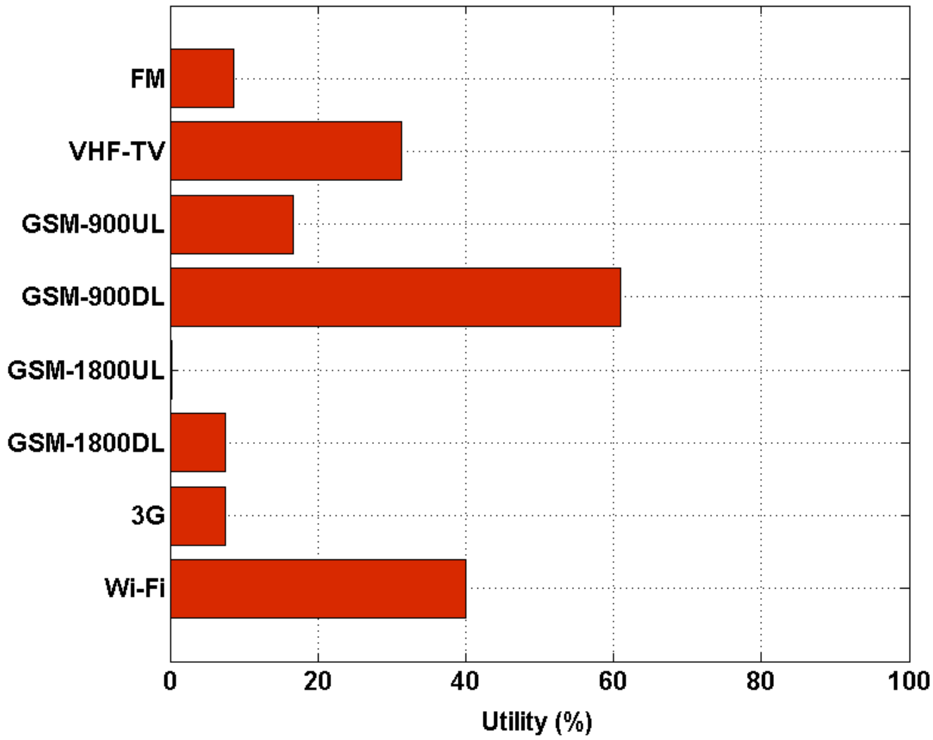


Figure 5.37: Overall spectrum utilisation

will help the device to be more energy efficient in its operation.

5.4.4 Section Summary

Scarcity of electromagnetic spectrum has led us to think about dynamically utilising this scarce resource. The utilisation of licensed spectrum is found to be very poor at certain bands. It also varies with the geographical location. This has opened spectrum opportunity in frequency, time and space. In this work spectrum occupancy pattern of Kochi city (Kerala, India) was measured and its analysis is presented. NI-USRP-2920, 2922 with LABVIEW has been used to build the measurement setup. Spectrum activity within the range of 50 MHz to 4400 MHz is outlined and the average utilisation of the spectrum at specific band is also estimated and presented.

5.5 Chapter Summary

If the spectrum sensing is limited to only those channels which are having higher probability of being idle, CR can save lot of time in sensing activity and more time can be spent on utilising that channel. In this chapter, a prediction based spectrum sensing approach for CR systems is proposed to improve the throughput of the system. It consists of a predictor that takes the 'present' and 'prior' information to predict the probability of any channel to be idle. Predictor can generate a rank list of suitable channels for future spectrum sensing. Two approaches based on Bayesian inference are proposed here to predict the future probability. Analysis of the predicted probability by both the methods are carried out. Channel ranking is formed based on these methods and they are compared with other prediction approaches such as EWMA, HMM and Neural Networks. On analysis it is found that amount of data required under 'prior' and 'present' is relatively less for Bayesian approaches. These analysis and comparisons were done on both synthetic as well as real data. Real data was obtained through spectrum measurement.

In order to analyse the performance of the predictors a spectrum occupancy measurement and analysis was carried out and presented in this chapter. Obtained spectrum hole details were used for analysing the predictors. On analysing the measured data it was found that GSM downlink channels are heavily utilised and others are lightly utilised. Analysis of spectrum occupancy, hourly utilisation, received energy levels etc., were carried out. On analysing the spectrum holes, it can be inferred that CRs with different complexity can work at different types of spectrum holes. That means a high end device with multiple protocols can adapt to any types of spectrum holes and always there is a possibility that a low end CR device specific to the type of spectrum hole can also exist.

CHAPTER 6

CONCLUSIONS AND FUTURE WORK

This chapter sums up the objective, highlights of the major contributions and results of the research work carried out. Followed by few suggestions for future work.

6.1 Summary of the Thesis

In the upcoming era of dynamic spectrum allocation, CR needs to be fully operational. A major task of CR is to find the vacant channels in the spectral space and that too with proper precision. This thesis aims at providing solutions to challenges faced in the spectrum sensing domain. The thesis has started with an overview of the related research in the field of spectrum sensing for cognitive radio. Scarcity in electromagnetic spectrum and the ramifications thereof are highlighted in the context of the present spectrum licensing policy and the spectrum allocation for various applications. As the utilisation of spectrum is very low, dynamic reuse of the spectrum is proposed as the spectrum strategy for tomorrow. Cognitive radio is introduced as the potential device that can perform this dynamic usage of the spectrum. Spectrum sensing is an important task in this regard and CSS is proposed as one of the best method to obtain the right sensing. Decision fusion based on fusion rules is a task to be carried out to finalize the presence of a PU. Therefore, previous work in the area of fusion rules and prediction based spectrum sensing are analysed. The relevance of the proposed work, in light of previous research work in this area is also presented.

This thesis initially proposes decision fusion approaches for distributed spectrum sensing and external sensing. This is followed by a comprehensive prediction based spectrum sensing approach that can improve the throughput of the system.

An effective decision fusion approach for distributed sensing is evolved through various stages of analysis and modifications. Initially, a fuzzy based approach (named as Fuzzy-SNR) was proposed and an analysis thereof was carried out using energy detection under Rayleigh fading channel. Its performance was compared with classical fusion rules such as 'AND' & 'OR' rules. Analysis of P_f and P_d with respect to SNR and 'time consumed' for a decision fusion were then carried out. Even though the detection performance was very good, time consumption of fuzzy-SNR rule was noted to be quite high. For a fast decision making, a weighted combining approach with SNR as its key component was therefore proposed and analysed using path loss model under shadowing. For the above cases, the assumption was that all the CRs are located within the coverage area of a PU under consideration. A realistic scenario with CRs located at the boundary of PUs is suggested and the SNR-rule is modified to adapt to the situation. It is named as 'Intelligent rule' and its performance was analysed using energy detection model under Rayleigh fading as well as path loss model under shadowing. In order to improve its performance further, antenna selection scheme with multiple region encoding for SU reporting was added to the 'Intelligent rule'. Its performance was compared with other optimal rules and fuzzy rules from the literature. Analysis of P_f versus P_d, P_f versus P_m, P_d versus 'N' (no. of neighbouring nodes) and computational complexity were carried out. On analysing various parameters associated with this evolved approach, it is found that this approach is giving a better performance in all respects.

For the external sensing scenario (which uses wireless sensor networks for spectrum sensing and a centralized node that aggregate the sensor results to form the final decision), CA based approach is proposed for decision fusion and to form the coverage area of PUs. This approach will reduce the task of CR and hence the battery of such mobile SUs may get a longer life. Two fusion rules named 'CA_1' and 'CA_2' are proposed under CA scheme and its performance is compared with available distributed sensing algorithms such as DDA (Harrold *et al.*, 2008), $Fuzzy_2$ (Matinmikko *et al.*, 2009) and $Fuzzy_1$ (Taghavi *et al.*, 2011). Performance comparison of all the algorithms were carried out. Coverage area of a transmitter is an important aspect when a CN monitors a large area. CA based approaches are giving a realistic coverage area. 'CA_1' perform exceptionally well in forming the coverage area. With all the other algorithms, it was very difficult to derive a proper coverage area. False alarm rate of 'CA_1' is very low compared to other algorithms. Probability of detection is very high for 'CA_1' algorithm. It is also proved that CA based approach is the most computationally efficient algorithm among the five and hence it is energy efficient. Considering the properties of CA and its massive parallelism of information processing, CA will be a favourite choice for low power VLSI implementation of decision fusion blocks for an external sensing scenario in cognitive radio.

If the spectrum sensing is limited to only those channels which are having higher probability of being idle, CR can save a lot of time in sensing activity and resultantly more time can be spent on utilising that channel. A prediction based spectrum sensing approach for CR systems is also proposed to improve the throughput of the system. It consists of a predictor that takes the 'present' and 'prior' information to predict the probability of any channel to be idle. Predictor can generate a rank list of suitable channels for future spectrum sensing. Two approaches based on Bayesian inference are proposed here to predict the future probability. Analysis on the predicted probability by both the methods are carried out. Channel ranking is formed based on these methods and they are compared with other prediction approaches such as EWMA, HMM and Neural Network. On analysis it was found that the amount of data required under 'prior' and 'present' is relatively less for Bayesian approaches. These analysis and comparisons were done on both synthetic as well as real data. Real data was obtained through spectrum measurement.

In order to analyse the performance of the predictors a spectrum occupancy measurement and its analysis was carried out and presented. Obtained spectrum hole details were used for analysing the predictors. On analysing the measured data it was found that GSM downlink channels are heavily utilised and others are lightly utilised. Analysis of spectrum occupancy, hourly utilisation, received energy levels etc. were carried out. On analysing the spectrum holes, it can be inferred that CRs with different complexity can work at different types of spectrum holes. In other words, a low end CR device can work in slowly varying spectrum holes and a high end device with multiple protocols can adapt to any types of spectrum holes.

6.2 Future Work

For decision fusion in the distributed sensing scenario, proposed fuzzy approach in this thesis, has considered all the possible rules for its decision making. It has led to high computational complexity. Since the detection rate is a promising factor, the possibility of reducing the computational complexity can be explored by restricting the number of rules or by any faster implementation approach. There is a scope in further optimising the membership functions and fuzzy rules.

In the proposed adapted weighted combining for decision fusion, weights for various components were finalized based on various trials carried out with respect to specific scenarios. These weights can be optimized with the help of optimization algorithms.

For decision fusion in the external sensing scenario, CA based fusion rules are proposed in the thesis. These rules were developed based on heuristic approaches. Based on the number of neighbours considered and the state of each neighbours, a large number of rules or its combinations are possible in CA. Possibility of finding better rules from the large rule base can be explored with the help of evolutionary algorithms such as Genetic Algorithm.

Since CA based structure are suitable for low power VLSI integration, implementation of this approach as a low power VLSI core can be explored. This approach may also be extended to distributed sensing where the nodes are randomly distributed.

Outdoor propagation models were considered for the analysis of all the above fusion rules. CR devices are expected to be present in numerous scenarios and to operate in various frequency bands, indoor propagation models and other channel models may also be tried out for the analysis.

For the prediction based spectrum sensing presented in this thesis, Bayesian inference is considered for proposing the predictor. In order to further improve the performance, possibility of modelling this scenario using recursive Bayesian approach can be explored.

All the approaches considered in this thesis were analysed with the help of Matlab simulations. Physical verification of all the approaches can be carried out by setting up a network with the help of a software defined radio platform.

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CURRICULUM VITAE

Name:	**Jaison Jacob**
Gender:	Male
Date of birth:	10. April 1972

Educational Qualifications

- June 1989 - May 1993
  B. E. (Bachelors of Engineering) degree in Electronics
  Babasaheb Ambedkar Marathwada University , Aurangabad
  Maharashtra,India.
- August 2004 - June 2006
  M.E. (Master of Engineering) degree in Applied Electronics
  Karunya University, Coimbatore
  Tamilnadu, India.
- November 2011 - Present
  Doctor of Philosophy (Ph.D)
  Division of Electronics, SOE
  Cochin University of Science & Technology
  Reg Date : 25-11-2011

Experience

- April 1994 to May 2000
  Senior Customer Engineer
  Modi Xerox Ltd, Ernakulam.
- July 2000 to May 2002
  Lecturer in Electronics
  Cochin University School of Engineering,
  Kuttanad , Aleppey.
- June 2002 to Till Date
  Assistant Professor in the Dept. of ECE.
  Rajagiri School of Engineering and Technology, Rajagiri Valley , Kochi-39