Cooperative Spectrum Sensing Techniques in Cognitive Radios

THESIS

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CERTIFICATE

This is to certify that the thesis entitled "**Cooperative Spectrum Sensing Techniques in Cognitive Radios**" submitted by **V Balaji** ID.No **2011PHXF040H** for the award of Ph.D. degree of the Institute, embodies original work done by him under our supervision.

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Dedicated to my father

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Abstract

Spectrum sensing is the key mechanism in enabling spectrum awareness in Cognitive Radio (CR). By sensing and monitoring the available spectrum, unlicensed cognitive radio users, or secondary users (SUs), can intelligently adapt to the most suitable available communication links in the licensed bands. By exploiting the spectrum holes, they are able to share the spectrum with the licensed primary users (PUs), operating whenever the PUs are idle. CR is capable of making intelligent decisions and their actions are based on observing the wireless connections and then using intelligent algorithms and computational learning to optimize their behavior. CR should intelligently sense the unused spectrum bands and capable of learning without interfering with primary users.

In CR, the most important step is to obtain necessary observations about its surrounding RF environment, such as the presence of primary users and the appearance of spectrum holes. Spectrum sensing enables the detection capability of CR to measure, learn and be aware of the radio's operating environment. The performance of spectrum sensing algorithm degrades due to channel impairments, such as multipath fading, correlated shadowing and receiver uncertainty. To overcome these limitations, Cooperative Spectrum Sensing (CSS) was introduced to take advantage of the spatial diversity of wireless receivers. In recent years, cooperative sensing based on Machine learning has been used to improve the efficiency of learning in CR. Cooperative learning can

help a CR to learn the surrounding environment and improve sensing accuracy.

This thesis aims to develop efficient Cooperative Spectrum Sensing (CSS) algorithm in cognitive radios with high probability of detection and low probability of false alarm to meet the desired objective of efficient utilization of radio spectrum. We consider several simulation scenarios that can be used to evaluate spectrum sensing by single SU unit (local sensing) and multiple SUs in a cooperative setup. The simulation scenario of spectrum sensing algorithms has been formulated to meet the requirements of IEEE 802.22 Wireless Regional Area Network (WRAN) standard.

Firstly, we develop cooperative spectrum sensing algorithms using Machine learning schemes, particularly, using Perceptron Learning, unsupervised clustering approaches. Local sensing phase is carried out using energy detection to scan the complete available channel set from (54-682)MHz divided into 7MHz of channel bandwidth. The local decisions of primary channel activity are modelled as binary hypothesis testing problem where the null and alternate hypothesis corresponds to the presence or absence of primary transmission respectively. For cooperative sensing phase, a centralized decision maker called Fusion Center (FC) is considered where each SU sends its local decision statistics to FC which makes final decision on channel availability. The perceptron module in FC uses local sensing energy vectors as training set to meet the desired target output. The proposed CSS scheme gives improved performance with error rate as low as 0.1.

Due to the dynamic channel environment, feature vectors are scattered in decision boundary which affects the detection accuracy of FC.

To overcome this, we use unsupervised K-means clustering approach which partitions set of training energy vectors into K disjoint clusters. Compared with Perceptron learning, this unsupervised K- means clustering is a promising approach due to its higher detection accuracy with less training and classification delays. The simulation results show that the unsupervised K-means clustering algorithm significantly improves detection accuracy with training and testing delay of 16.8 and 75 milliseconds respectively. However, K-means clustering approach provides an average view on data points which will affect its detection performance under path loss and shadowing environment. To address this issue, we propose Archetypal clustering based CSS scheme which provides an extremal view on data points. It is observed from ROC performance results that Archetypal clustering based CSS scheme achieves the detection probability of 82% to meet the target false alarm probability of 0.1.

Secondly, we discuss the formulation of a Reinforcement Learning (RL) based Cooperative Spectrum Sensing algorithm. The decision making agent, called Fusion Center (FC) observes the state of the RF environment and chooses actions to maximize reward. The simulation results show that the detection probability of RL based CSS scheme is 85-92% which is 5-10% better than the case of without reinforcement learning. It is observed that the algorithm gives the precision accuracy of 88% that is 8-9% of improvement as compared to without RL. Further, in RL based scheme, the decision making agent (FC) undergoes exploration and exploitation trade-off which enhances the cooperative learning and detection capability of cognitive radios.

Finally, we study the formation of coalitional game model for CSS scheme. Coalitional game theory has been used to study user cooperation and design optimal, fair, and efficient collaboration strategies among SUs. Different phases of Coalition Formation (CF) algorithm involving local sensing, adaptive coalition formation, and coalition head selection and coalition sensing phases are discussed.

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List of Abbreviations/Symbols

Term	Definition
CSS	Cooperative Spectrum Sensing
CF	Coalition Formation
DSA	Dynamic Spectrum Access
FC	Fusion Center
FCC	Federal Communication Commission
OSA	Opportunistic Spectrum Access
PU	Primary User
PSD	Power Spectral density
ROC	Receiver Operating Characteristics
RSS	Received Signal Strength
RL	Reinforcement Learning
SU	Secondary User
TRAI	Telecom Regulatory Authority of India
TVWS	Television White Space
UHF	Ultra High Frequency
WRAN	Wireless Regional Area Network

Chapter 1

Introduction

1.1 The spectrum scarcity problem

Frequency spectrum is a limited resource for wireless communications and may become congested owing to the need to accommodate the diverse types of air interfaces used in next generation wireless networks. To meet the growing demands, the Federal Communications Commission (FCC) [Marcus *et al.* 2002] expanded the use of the unlicensed spectral band. However, since traditional wireless communication systems utilize the frequency bands allocated by the regulatory bodies (such as TRAI in India,[of India 2016]) mostly in a static manner, they lack adaptability. Also, studies have shown that some frequency bands in the spectrum are heavily used, while other bands are largely unoccupied most of the time. This sporadic usage of spectrum by licensed user creates 'Spectrum holes' or 'White spaces' [Tandra *et al.* 2009]. The spectrum holes/white spaces are the band of frequencies that are not being utilized by the licensed user at a particular time in a particular geographic area.

The right to access a given spectrum is generally defined by its frequency, space, transmit power, spectrum owner (i.e. licensee), type of use, and the duration of license. Normally, a license is assigned to one licensee, and the use of spectrum by this licensee must conform to the specification in the license (e.g. maximum transmit power, location of the base station etc). In the current spectrum licensing scheme, the license cannot change the type of use or transfer the right to other licensee. This limits the use of the frequency spectrum and results in low utilization of the frequency spectrum. Due to the current static spectrum licensing scheme, spectrum holes or white spaces exist. This has generated a lot of interest among researchers to examine whether these 'holes' can be utilised to increase efficiency.

The investigation on spectrum occupancy measurements conducted by FCC [Marcus *et al.* 2002] and many other regulatory bodies have revealed that such static spectrum allocation leads to inefficient spectrum utilization. Fig.1.1 shows the spectrum occupancy measurement chart over a large portion of the spectrum for New York and Chicago cities in USA. It can be observed here that the spectrum is heavily utilised in certain locations whereas in another location it is less utilised. For example, the spectrum occupancy of UHF TV band 470-512MHz in Chicago city is around 55% whereas the occupancy of same band in New York is around 25%. In [Nekovee 2009], the author presented a quantitative analysis of TV White Spaces (TVWS) availability in the United Kingdom (U.K). The author examined the availability of TVWS channels for 18 major population centres in England, Wales and Scotland. The analysis showed that on an average 150 MHz of TVWS is available. The availability of TVWS in 470-790 MHz for European countries is studied in [Van De Beek *et al.* 2012]. The results show that at an average location in European region, about 56 percent of the spectrum is unused by TV networks. A similar study in Japan can be found in [Shimomura & Oyama 2014]. The study suggests that the metropolitan areas, as well as rural areas, in Japan seem to be a good market for TVWS devices. Since heavily populated areas generally demand additional spectra, TVWS availability in Japan is likely to be more encouraging than that in the USA.

In [Naik *et al.* 2014], the author performed a quantitative analysis of the available TV white space in the 470-590MHz UHF TV band in India. There are a total of 254 Doordarshan TV transmitters located in four zones (East, West, North and South) operating in 470-590MHz of UHF band. Currently, in these zones, 14 out of the 15 channels (channels 21-34) are sparsely used for transmissions. The channels allocated to the transmitters are reused inefficiently or at very large distances. The authors propose a channel allocation scheme such that the minimum number of TV channels is used in each zone, while ensuring that the coverage areas of different transmitters do not overlap. This significant underutilization of wireless spectrum has motivated the need for a new spectrum management paradigm which aims to improve the efficiency of the utilization of licensed spectrum bands.

The major recommendations from FCC, for a new spectrum management policy includes, possibilities to access spectrum dynamically, considering all dimensions (time, frequency and Geo-location) and related issues of spectrum policy. This spectrum management paradigm is referred to as Dynamic Spectrum Access (DSA) or Opportunistic Spectrum Access (OSA) [Akyildiz *et al.* 2006]. Such a dynamic approach has the potential to track and exploit the spectrum opportunities for next generation wireless access networks.

Each nation administers the telecommunications system and specifically the radio spectrum for its geographic dominion through a regulatory agency. Though the form, function, and goals of these organizations vary widely, they generally follow the guidelines of the International Telecommunication Union (ITU) [Russell & Norvig 2003] which is responsible for issues that concern Information and Communication Technologies (ICT). In India, the Telecom Regulatory Authority of India (TRAI) is the national radio regulatory authority responsible for frequency spectrum management, including licensing and caters to the needs of all wireless users (Government and Private) in the country. The development and manufacturing of wireless equipment and spectrum utilization comes from the National

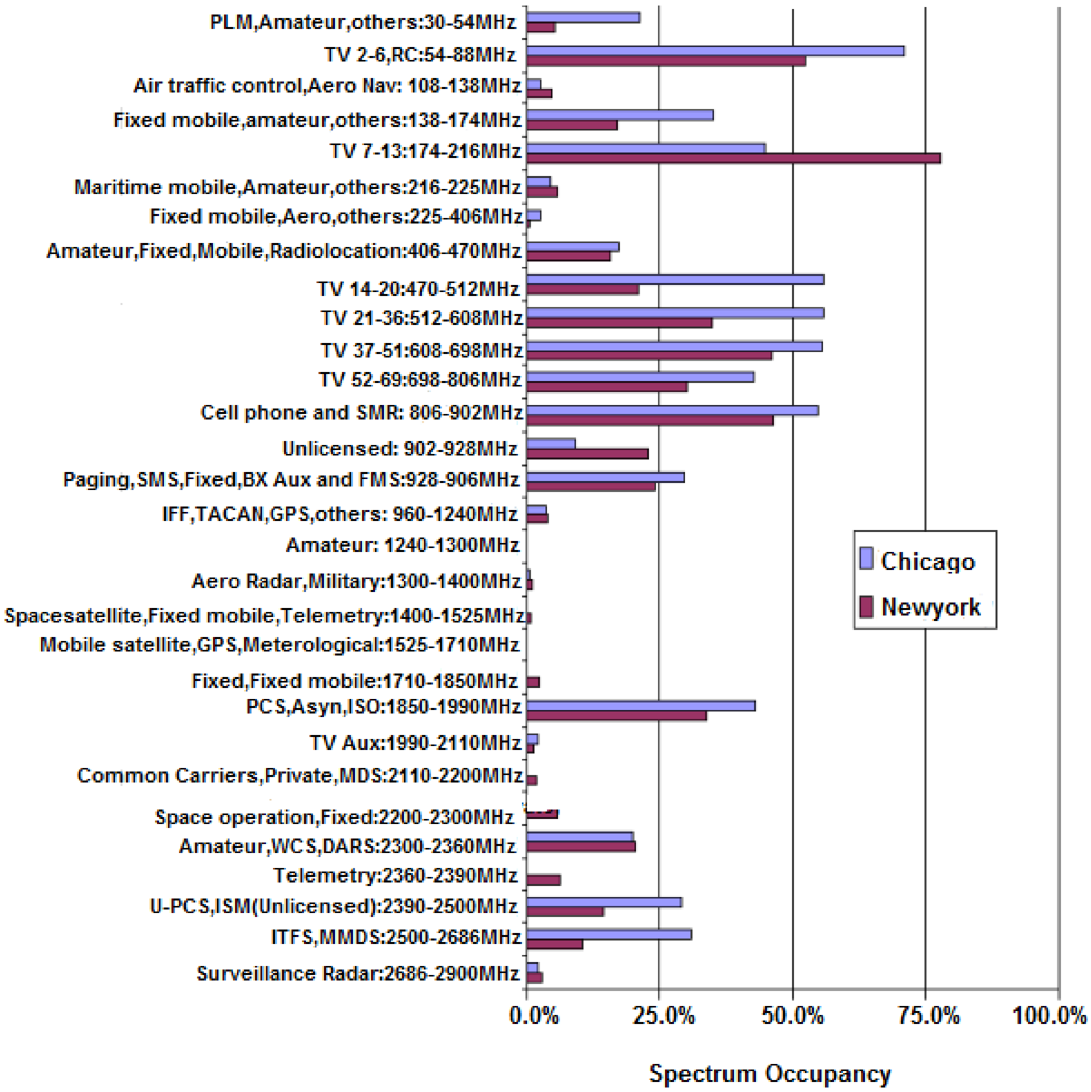

Figure 1.1: Spectrum Occupancy measurement chart (Source: www.itu.int/pub/R-REP-SM.2256-2012)

Frequency Allocation Plan (NFAP), in the country. The National Telecom Policy (NTP-2012) for India promotes the use of white spaces as one of the strategy for spectrum management. The policy aims ’to promote the use of white spaces with low power devices, without causing harmful interference to the licensed applications in specific frequency bands by deployment of Software Defined Radios (SDRs), Cognitive Radios (CRs) to resolve the spectrum management issues in Indian context’ [Sridhar 2011]. In [Dhope *et al.* 2011], the author suggested the potential frequency bands in India for CR deployment are UHF band IV and UHF

Band V. The details of above frequency are as follows:

- **UHF Band IV (470-582)MHz**: There are 14 channels with 8MHz of channel bandwidth. Doordarshan (DD) operates on this band using Digital transmitters from major metros.

- **UHF Band V (582-806)MHz:** In this band, 28 TV channels are available with 8MHz of channel bandwidth. It is used for Defence, BSNL and PPDR (Public Protection and Disaster Relief).

The frequency bands where spectrum utilization is high, as in mobile networks or low signal strength like satellite communication, may not open for CR Technology. Lower frequency bands, Broadcasting, Radar, Armature, radio paging bands are most prominent candidate for CR technology. In [Kumar *et al.* 2015], author presented middle-mile multihop mesh network operates under TV UHF band for providing seamless connectivity between Gram panchayats and village users.

1.2 Emergence of Cognitive Radio

The Cognitive Radio (CR) is the key enabling technology for implementing Dynamic Spectrum Access (DSA) to overcome the spectrum scarcity problem. The idea of CR was first proposed by Joseph Mitola as, 'a technology that extends software radio with radio-domain model based reasoning about RF bands, air interfaces, protocols, spatial and temporal patterns that moderate the use of radio spectrum' [Mitola III & Maguire Jr 1999]. The definition of CR adopted by FCC in 2002 is as [Marcus *et al.* 2002], 'A radio or system that senses its operational electromagnetic environment and can dynamically and autonomously adjust its radio operating parameters to modify system operation, such as maximize throughput, mitigate interference, facilitate interoperability and access secondary markets'.

Simon Haykin [Haykin 2005] addressed some fundamental tasks in cognitive radio namely, 1)Radio-scene analysis, 2)Channel state estimation and predictive modeling, 3)transmit power control and dynamic spectrum management. Further, he suggested a new metric called interference temperature for the quantification and management of interference in a radio environment. From the definition of CR by Simon Haykin [Haykin 2005], it is clear that a CR device must have the attributes such as awareness, intelligence, learning, adaptivity, reliability and efficiency. The realization of CR is based on the combination of knowledge in different domains such as digital signal processing, detection theory in communication, machine learning and communication networks.

The CR must have the features called cognitive capability and reconfigurability. 'Cognitive capability' [Mitola III 2009] implies the following characteristics.

- **Observation**: The radio is capable of acquiring information about its operating parameters.
- **Adaptability:** The radio is capable of changing its RF operating parameters.
- **Intelligence:** The radio is capable of applying information towards a purposeful goal like spectrum sensing, spectrum analysis and spectrum decision environment.

The set of activities required to achieve cognitive capability includes:

- Monitoring the available spectrum band in RF radio environment and capturing spectrum hole information (observe)
- Estimating the captured spectrum signal information by identifying functional relation between measurements and system configurations (orient)
- Evaluating the outcome of orientation phase by gathering knowledge to be exploited in future with the aim of improving decision capability (learn)

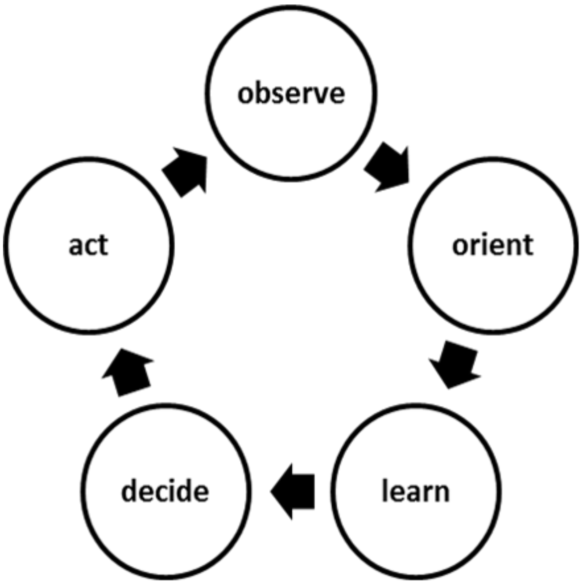

Figure 1.2: Cognitive Cycle

- Choosing appropriate spectrum band according to the spectrum characteristics and user information (decide)
- Performing actions by effectively utilizing available bands (act)

This set of activities, referred to as cognitive cycle, is represented in Fig.1.2. The operational flow of cognition engine and its functionalities are discussed in [Asadi *et al.* 2016].

The 'reconfigurability' enables the CR to adapt to the dynamic RF environment by adjusting RF operating parameters (i.e. operating frequency, bandwidth, modulation scheme, transmission power) with the help of software defined radio (SDR) architecture without changing its hardware components. The SDR architecture [Tabassam *et al.* 2011] helps CR to perform all baseband operations in software which will lead towards interoperability of wireless systems. These RF parameters can be reconfigured at the beginning and/or during the transmission. Ying-Chang Liang et al. [Liang *et al.* 2011] provide a systematic overview of cognitive radio networking by looking at the key functions of Physical, Medium Access Control (MAC) and Network layers involved in Cognitive radio design and explain how these layers are cross related. In Physical layer, they have addressed

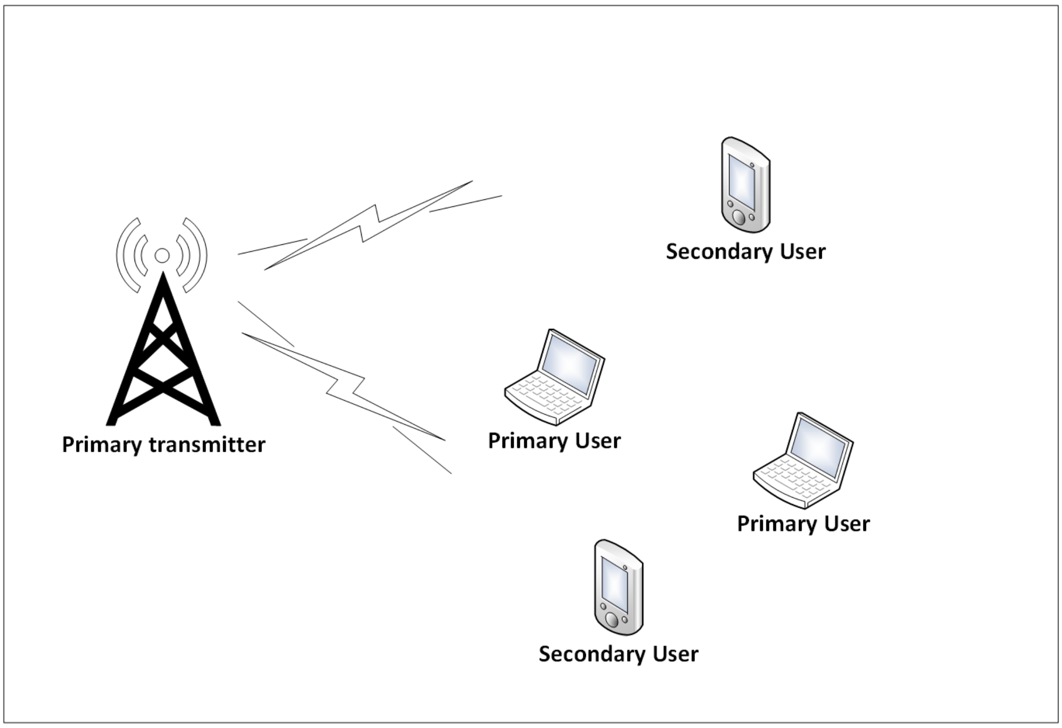

Figure 1.3: Typical CR network

the signal processing techniques in spectrum sensing, cooperative spectrum sensing and transceiver design. For the MAC layer, they reviewed sensing scheduling schemes, spectrum aware access and Cognitive radio MAC protocols. In Network layer, Cognitive radio network tomography, Spectrum-aware routing, and quality-of-service (QoS) control were discussed. In cognitive radio networks, cognitive (unlicensed) users need to continuously monitor spectrum for the presence of primary (licensed) users. An overview of existing CR approaches under practical imperfections are discussed in [Sharma *et al.* 2015]. Some open research issues on CR are described.

1.3 Functional model of CR

In CR terminology [Group *et al.* 2006], the licensed user is called Primary User (PU) who has higher priority and legal rights to access the spectrum band. On the other hand, the Secondary User (SU) is called an opportunistic user who exploits the spectrum band that is not being used by primary users in a particular time, frequency and location. A typical cognitive radio network setup is shown in Fig.1.3.

SU should intelligently sense the unused spectrum bands and must be capable of learning without interfering with primary users. The experience gained through learning makes the CR to optimally reconfigure RF operating parameters and improve decision making capability. To perform this, CR must support the following functionalities as mentioned in [Akyildiz *et al.* 2006]. These sequence of CR operations is schematically shown in Fig.1.4.

Wireless transmitter/receiver: A Software Defined Radio(SDR)based wireless transceiver is the major component with the functions of data signal transmission and reception. In addition, a wireless receiver is also used to observe the activity on the frequency spectrum (i.e.spectrum sensing). The transceiver parameters in the cognitive radio node can be dynamically changed as dictated by higher layer protocols.

Spectrum analyzer: The spectrum analyzer uses measured signals to analyze the spectrum usage to detect the signature of a signal from a licensed user and to find spectrum holes for unlicensed users to access. The spectrum analyzer must ensure that the unlicensed user does not interfered with licensed user if it decides to access the spectrum. In this case, various signal-processing techniques can be used to obtain spectrum usage information.

Knowledge extraction/learning: Learning and knowledge extraction use the information on spectrum usage to understand the ambient RF environment (e.g. the behavior of licensed users gathered during the learning). A knowledge-base of the spectrum access environment is built and maintained, which is subsequently used to optimize and adapt the transmission parameters to achieve the desired objective under various constraints. Machine learning algorithms from the field of artificial intelligence can be applied for learning and knowledge extraction.

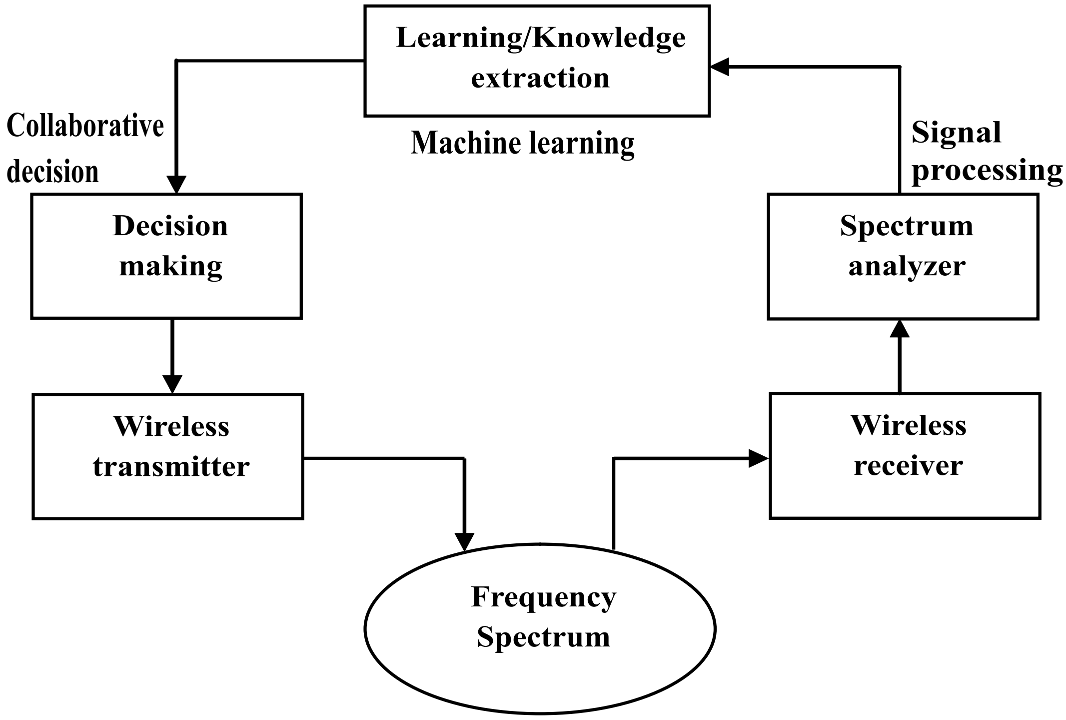

Figure 1.4: Functional model of CR

Decision making: The decision phase helps to choose appropriate spectrum band according to spectrum characteristics and user information. The actions are performed by effectively utilizing spectrum holes. The knowledge gathered at learning phase acts as input to this module. The reconfiguration actions of RF operating parameters are performed during this phase. The above sequence of operations by CR is schematically shown in Fig.1.4.

1.4 Role of Spectrum Sensing in Cognitive Radio

In cognitive radio, the wireless devices can change and tune their transmission or reception parameters in order to achieve efficient wireless communication without interfering with the licensed users. For performing this parameter adaptation, cognitive devices actively monitor several external and internal radio parameters, such as radio frequency spectra, user behavior, and network states. By sensing and monitoring the available spectrum, unlicensed cognitive radio users, or secondary users (SUs), intelligently adapt to the most suitable available communication links in the licensed bands. Hence, by exploiting the spectrum holes they are able to share the spectrum with the licensed primary users (PUs), operating whenever the PUs are idle. Tevfik Yucek et al. [Yücek & Arslan 2009] presented a detailed survey of existing spectrum sensing algorithms for cognitive radio. They studied the various aspects of spectrum sensing problem and introduced multi-dimensional sensing concept. Further, they defined some major challenges associated with spectrum sensing as sensing frequency and duration, decision fusion, hidden terminal user problem, hardware requirements and security. Beibei Wang et al. [Wang & Liu 2011] further extended the survey and studied the recent advances in the research related to cognitive radio. They explain the fundamentals of cognitive radio characteristics, functions, network architecture of cognitive radio system and its applications.

The main aim of spectrum sensing is to detect the presence/absence of Primary User (PU) in order to assign the licensed spectrum (holes) of primary user to the Secondary User (SU). It is mandatory for the SU to identify the spatial-temporally available channels. Further, when the PU occupies a channel, SU using this channel should vacate. In Spectrum analysis stage, the Cognitive Radio (CR) or SU uses RF stimuli and Spectrum holes information to output Channel capacity to Spectrum decision stage. In Spectrum decision stage, with an objective to optimize the SU's transmission performance, SU decides which channel should be used out of many available channels. These aspects of spectrum management [Akyildiz *et al.* 2008] are shown in Fig.1.5.

One of the major challenges of cognitive radio networks is the development of efficient spectrum sensing techniques for the SUs. Spectrum sensing refers to the phase during which the SUs must sense the radio frequencies in order to make a decision on whether to transmit or not, depending on the state of the PUs. The spectrum sensing involves the design of high quality spectrum sensing devices

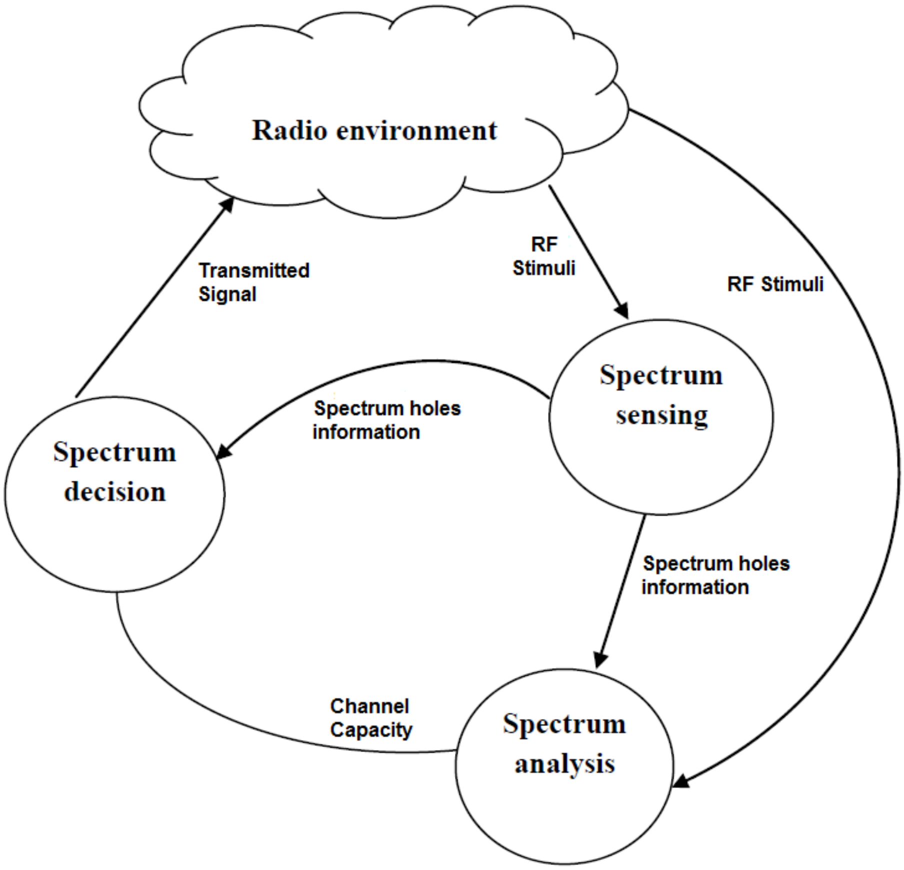

Figure 1.5: Various aspects of Spectrum sensing

and algorithms for exchanging spectrum sensing data between nodes to reliably detect spectral holes for use by the cognitive radio devices without interfering with primary users.

1.5 Primary transmitter detection techniques

In this section, we will discuss some of the most common spectrum sensing techniques for the detection of the primary transmitter in the cognitive radio system. From the perspective of signal detection, sensing techniques can be classified into two broad categories: i)coherent and ii)non-coherent detection. In coherent detection, the primary signal can be coherently detected by comparing the received signal or the extracted signal characteristics with prior knowledge of primary signals. In non-coherent detection, no prior knowledge of the primary signal is required for detection. Another way to classify sensing techniques is based on the bandwidth of the spectrum of interest, i.e., narrow-band or wide-band. In the next sections, we introduce matched filter detection, energy detection, cyclostationary detection and briefly discuss a few other spectrum sensing techniques. A more complete review on various spectrum sensing techniques and design challenges can be found in [Ghasemi & Sousa 2008, Zeng *et al.* 2010].

1.5.1 Matched Filter Detection

Matched filter is a linear filter [Proakis 1995] designed to provide maximum SNR at its output for a given transmitted signal waveform. The mathematical operation of a matched filter is based on convolution (a signal convolved with the impulse response of a filter). The term matched filter is often used synonymously with correlator. It is known as the optimum method for the detection of the primary signal when the transmitted signal is known, since it maximizes the received signal-to-noise ratio (SNR). The main advantage of matched filtering is the short time it requires to achieve a certain detection performance, such as low probabilities of miss-detection and false alarm [Hoven *et al.* 2005], since a matched filter needs less received signal samples. However, matched filtering requires the secondary users to demodulate the received signals. Therefore, it requires perfect knowledge of the primary user's signaling features such as bandwidth, operating frequency, modulation type, order, and pulse shaping as well as accurate synchronization at the secondary user [Cabric *et al.* 2004]. Another significant drawback of matched filter detection is that a secondary user would need a dedicated receiver for every primary user class [Gavrilovska & Atanasovski 2011].

However, in cognitive radio networks, such knowledge is not readily available to secondary users and the implementation cost and complexity of these detectors are high.

1.5.2 Cyclostationary Feature Detection

Another detection method that can be applied for spectrum sensing is the cyclostationary feature detection [Kim *et al.* 2007]. Modulated signals are in general coupled with sine wave carriers, pulse trains, repeating spreading or hopping sequences or cyclic prefixes, which result in built-in periodicity. Cyclostationary features are caused by the periodicity in the signal or in its statistics such as mean and autocorrelation [Yücek & Arslan 2009]. Cyclostationary feature detection is a method for detecting primary user transmissions by exploiting the cyclostationary features [Chen *et al.* 2007] of the received signals since their statistics, mean and auto-correlation exhibit periodicity. This periodicity is typically introduced intentionally in the signal format so that a receiver can exploit it for parameter estimation such as carrier phase, pulse timing, or direction of arrival. This can then be used for detection of a random signal with a particular modulation type in a background of noise and other modulated signals.

Common analysis of stationary random signals is based on autocorrelation function and power spectral density. On the other hand, cyclostationary signals exhibit correlation between widely separated spectral components due to spectral redundancy caused by periodicity. Instead of Power Spectral Density (PSD), Spectral Correlation Function (SCF) is used for detecting signals present in a given spectrum. SCF is also termed as cyclic spectrum. Unlike PSD which is real-valued one dimensional transform, the SCF is two dimensional transform.

The cyclostationary-based detection algorithms can differentiate noise from primary user's signals. This is a result of the fact that noise is wide-sense stationary with no correlation while modulated signals are cyclostationary with spectral correlation due to the redundancy [Gardner *et al.* 1991] of signal periodicity. Therefore, a cyclostationary feature detector can perform better than the energy detector in discriminating against noise due to its robustness to the uncertainty in noise power [Cabric *et al.* 2004]. However, it is computationally complex and requires significantly long observation time. Moreover, it requires the knowledge of the cyclic frequencies of the primary users, which may not be available to the secondary users.

1.5.3 Energy detection

Energy detection [Urkowitz 1967] is a non-coherent detection method that is most commonly used if the receiver cannot gather sufficient information about the primary user's signal. This simple scheme accumulates the energy of the received signal during the sensing interval and declares the primary band to be occupied if the energy surpasses a certain threshold which depends on the noise floor [Digham *et al.* 2007]. Due to its simplicity and the fact that it does not require prior knowledge of the primary user signals, energy detection is the most popular sensing technique among others for spectrum sensing.

The conventional energy detector consists of a pre-filter followed by a square-law device [Kim *et al.* 2010] and a finite time integrator. The pre-filter limits the noise bandwidth and normalizes the noise variance. The output of the integrator is proportional to the energy of the received signal of the square law device. The integrator output is called decision statistic [Urkowitz 1967] or test statistic. The test statistics is finally compared at the threshold device followed by decision device to make the final decision on the presence/absence of transmitted signal. The test statistics may not always be the integrator output, but it can be any function which is monotonic with the integrator output. The conventional energy detection model is shown in Fig.1.6.

The main design parameters of the energy detector are the number of samples and threshold [Kim *et al.* 2010]. However, the performance of the energy detector depends on Signal-to-Noise Ratio (SNR) and noise variance as well, but the designer has very limited control over them since these parameters depend on the behavior of the mobile radio channel. Some of the challenges with energy detec-

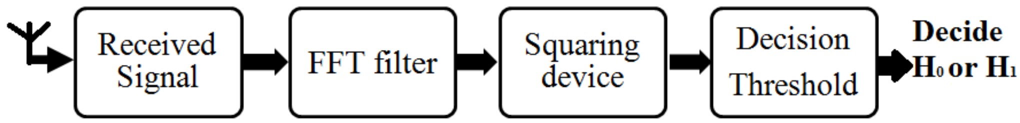

Figure 1.6: Energy Detection model

tion include selection of the threshold, inability to differentiate interference from primary user's transmission and noise, and poor performance under low SNR [Atapattu *et al.* 2010, Tandra & Sahai 2005]. When a system attempts to detect the presence/absence of weak signal in a high noise environment (low SNR), the degree of uncertainty increases. The robustness of energy detector can be quantified in terms of SNR wall [Tandra & Sahai 2008] giving the threshold below which weak signals cannot be detected reliably.

The energy detection has been used for multi-band joint detection in wide-band sensing by employing an array of energy detectors, each of which detects one frequency band [Quan *et al.* 2009]. The multi-band joint detection framework enables secondary users to simultaneously detect primary user's signals across multiple frequency bands for efficient management of the wide-band spectrum resource at the cost of detection hardware.

1.5.4 Other detection techniques

Apart from the above mentioned detection schemes, some alternate sensing techniques are available in the literature [Yücek & Arslan 2009] that include Waveform-based sensing, Multi-taper spectral estimation, Wavelet detection and Compressed sensing. Waveform-based sensing is usually based on correlation with known signal patterns. Known patterns are usually utilized in wireless systems to assist synchronization or for other purposes. Such patterns include preambles, regularly transmitted pilot patterns and spreading sequences. In [Tang 2005], it was shown that waveform-based sensing outperforms energy detector based sensing in reliability and convergence time. Furthermore, it is shown that the performance of the sensing algorithm increases as the length of the known signal pattern increases. Waveform-based sensing, however, is only possible when the target primary user's signal contains known signal patterns.

Multi-taper spectrum estimation was proposed in [Haykin *et al.* 2009]. The algorithm was shown to be an approximation to the maximum likelihood power spectral density estimator, and for wide-band signals, it is nearly optimal. Most important, unlike the maximum-likelihood spectral estimator, the multi-taper spectral estimator is computationally feasible. In [Tian & Giannakis 2006], wavelets are used for detecting edges in the power spectral density of a wide-band channel. Once the edges, which correspond to transitions from an occupied band to an empty band or vice versa are detected, the power within the bands between two edges are estimated. Using this information and the edge's positions, the power spectral density can be characterized as occupied or empty in a binary fashion. The assumptions made however, need to be relaxed for building a practical sensing algorithm. The method proposed in [Tian & Giannakis 2006] was extended in [Tian & Giannakis 2007] by using sub-Nyquist sampling (compressed sensing). Assuming that the signal spectrum is sparse, sub-Nyquist sampling is used to obtain coarse spectrum knowledge in an efficient way. An overview of spectrum exploration and exploitation for CR systems are discussed in [Lunden *et al.* 2015]. The author presented various approaches for spectrum sensing and access policy design in CR networks. Table 1.1 presents a brief comparison of the above mentioned primary transmitter detection techniques.

In this thesis, we adopt the most commonly used energy detection technique for the detection of the primary transmitter. With this technique, secondary users can identify the spectrum access opportunities without requiring prior knowledge of the primary user signal characteristics. Compared to other sensing techniques, energy detection is easier to implement and therefore, is less expensive. It is also

Table 1.1: Brief Comparison of Primary transmitter detection techniques

Detection technique	**Advantages**	**Disadvantages**
Energy detection	Low complexity, No primary knowledge required.	Poor performance for low SNR, Cannot differentiate users.
Matched filter detection	Optimal performance, Low computational cost.	Requires prior knowledge of the primary user signal.
Cyclostationary detection	Robust in low SNR region, Robust against interference.	Requires partial prior information, High computational cost.
Waveform-based detection	Robust in low SNR region, Short measuring time.	Requires prior knowledge of the primary user signal, Susceptible to synchronization errors.
Multi-taper spectrum estimation	Near optimal performance for wide-band Signals, No primary knowledge required.	High implementation complexity.
Wavelet Detection	Effective for wide-band signal detection.	Requires high sampling rate,analog-to-digital converter, High computational cost.
Compressed Sensing	Low sampling rate, Low signal acquisition cost.	Sensitive to design imperfections.

the most general technique for spectrum sensing since it applies to any signal type.

1.6 Performance Evaluation Criteria

A key task in spectrum sensing is to decide whether the spectrum is idle or busy. The spectrum sensing problem is traditionally formulated as a binary hypothesis test [Poor 2013]. The null hypothesis denoted by H_0 corresponds to the absence of the primary user's transmission, i.e., the received signal being only noise. On the other hand, the alternative hypothesis denoted by H_1 indicates that the primary user's transmission is present, i.e., the received signal contains the primary signal along with noise. In case the hypotheses have no unknown parameters, the hypotheses are called simple. If there are unknown or unspecified parameters, then the hypotheses are called composite. As an example, a binary hypothesis test for the received signal of the i^{th} SU at sample index 'n' is given by,

$$x_i(n) = \begin{cases} w_i(n) & H_0 \\ h_i(n) \times s(n) + w_i(n) & H_1 \end{cases} \tag{1.1}$$

where $w_i(n)$ is the additive white-Gaussian noise (AWGN), $s(n)$ is the primary user signal and $h_i(n)$ is the gain of the sensing channel between PU and CR user. In most practical cases, a test statistics 'Y' is computed from the observation vector x = [x(1), x(2), ..,x(N)] containing N observation samples, and detection is based on comparing the test statistics 'Y' to the threshold γ . If the test statistics is greater than the threshold, i.e., Y>γ then H_1 is declared as true. Otherwise, H_0 is declared as true. Two main performance metrics that are crucial in the design of spectrum sensing techniques are the probability of miss-detection, 'P_m', and the probability of false alarm, 'P_f'. The probability of miss-detection is defined as the probability that the detector declares the absence of a primary user (PU) transmission (decide H_0), when PU transmission is actually present (H_1 is true). The probability of false alarm is defined as the probability that the detector declares the presence of PU transmission (decide H_1), when PU transmission is actually absent (H_0 is true). Therefore, we represent the probabilities of miss-detection and false alarm,

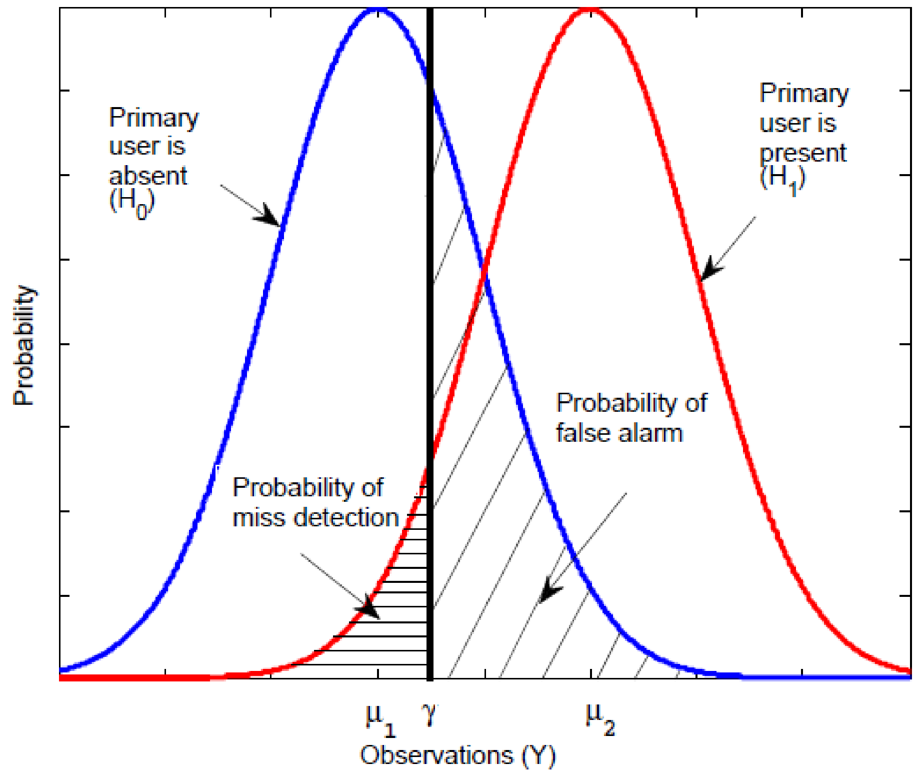

Figure 1.7: Trade-off between Probability of miss-detection and false alarm

respectively, as

$$
\begin{aligned}
P_m &= P(H_0|H_1) = P(Y \leq \gamma|H_1) \\
P_f &= P(H_1|H_0) = P(Y > \gamma|H_0)
\end{aligned}
\tag{1.2}
$$

The trade-off between the probability of false alarm and miss-detection is depicted in Fig.1.7. In the Figure, the likelihood distributions for the absence and presence of the primary user's signal are both assumed to be normally distributed with respective means $\mu 1$ and $\mu 2$ and the variances of the distributions are taken to be equal.

It is clear from the above discussion that we need the probability of detection, P_d=1-P_m, to be high as it indicates the level of protection of the primary users transmissions from the interfering secondary users transmissions. On the other hand, low probabilities of false alarm are necessary in order to maintain high opportunistic secondary throughput, since a false alarm would prevent the unused bands from being accessed by secondary users leading to inefficient spectrum usage.

There are two basic hypothesis testing methods in spectrum sensing: the Neyman-Pearson (NP) test and the Bayes test. In an NP test, the objective is to maximize the detection probability, P_d, given the constraint on the probability of false alarm, P_f . Based on the signal detection problem mentioned in equation (1.1), it can be shown that the NP test is equivalent to the likelihood ratio test (LRT). The LRT test statistics 'Y_{LRT}' is based on the threshold 'γ_{LRT}' [Sklar 2001] is given by,

$$Y_{LRT} = \prod_{n=1}^{N} \frac{P(x(n)|H_1)}{P(x(n)|H_0)} \begin{matrix} >^{H_1} \\ <^{H_0} \end{matrix} \gamma_{LRT} \tag{1.3}$$

In a Bayes test, the objective is to minimize the expected cost called the Bayes risk (BR) given by,

$$BR = \sum_{i=0}^{1} \sum_{j=0}^{1} C_{ij} P(H_i|H_j) P(H_j) \tag{1.4}$$

where C_{ij} and $P(H_i|H_j)$ are, respectively, the cost and the probability of declaring H_i when H_j is true, and $P(H_j)$ is the prior probability of hypothesis H_j, $i, j \in 0, 1$. In other words, the Bayes risk to be minimized is the sum of all possible costs weighted by the probabilities of two incorrect detection cases: false alarm P(H_1 | H_0) and miss-detection P(H_0 | H_1) and two correct detection cases. With the knowledge of the prior probabilities P(H_1) and P(H_0), the LRT of a Bayes test can be represented as,

$$Y_{LRT} = \prod_{n=1}^{N} \frac{P(x(n)|H_1)}{P(x(n)|H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \frac{P(H_0)(C_{10} - C_{00})}{P(H_1)(C_{01} - C_{11})} \tag{1.5}$$

For the particular case of the binary loss function, C_{ii} = 0 and C_{ij} = 1 for $i \neq j$, the Bayes risk, BR, is equal to the probability of error (P_E). Therefore,

$$\begin{aligned} P_E &= P(H_1|H_0)P(H_0) + P(H_0|H_1)P(H_1) \\ &= P_f P(H_0) + (1 - P_d)P(H_1) \end{aligned} \tag{1.6}$$

As mentioned earlier, if the distributions of the received signal under the two hypotheses depend on unknown parameters, then the detection problem becomes a composite hypothesis testing problem.

1.7 Spectrum Sensing requirements in IEEE 802.22 Wireless Regional Area Network (WRAN)

The IEEE 802.22 Wireless Regional Area Network (WRAN) working group [Lei & Shellhammer 2009] has defined sensing requirements and specifications for utilizing unused TV bands called TV white spaces. The standard supports UHF/VHF range of frequencies from 54MHz-698MHz with 6, 7 and 8 MHz of channel bandwidth for worldwide operation. Its objective is to deliver wireless broadband to rural area using a dynamic spectrum access model on spectrum allocated for TV broadcast. The sensing is envisioned to be based on two stages: fast and fine sensing. In the fast sensing stage, a coarse sensing algorithm is employed and the fine sensing stage is initiated based on the fast sensing results. Fine sensing involves a more detailed sensing based on more powerful methods. A base station (BS) can distribute the sensing load among subscriber stations (SSs). The results are returned to the BS which uses these results for managing the transmissions.

The objective of a WRAN system is to maximize the spectrum utilization of the TV channels when they are not used by the primary users. To protect the primary users, whenever the primary users become active, the WRAN system has to vacate that channel within a certain amount of time (say 2 seconds as specified by 802.22

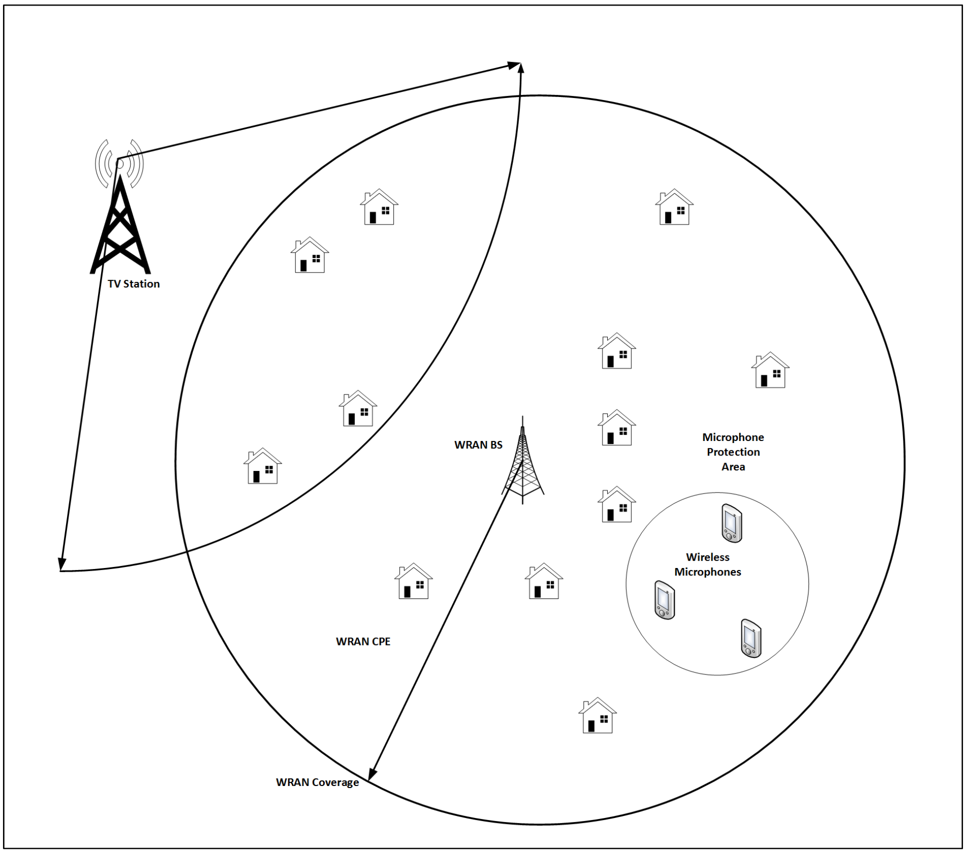

Figure 1.8: Architecture of IEEE 802.22 WRAN

working group). Thus spectrum sensing is of significant importance for cognitive radio systems. WRAN implements a centralized infrastructure, where multiple customer premise equipment (CPE) is serviced by a single base station (BS), and BS communicate with each other through dedicated infrastructure. The proposed network architecture of WRAN [Liang *et al.* 2008a] is illustrated in Fig.1.8. The coverage of each BS is typically 17-30 km, with a maximum of 100 km. The spectrum accessible is in the VHF/UHF range of 54-698 MHz. The incumbent primary users (PU) are analogue and digital TV and low power wireless microphones.

Various cognitive functions are included in WRAN to protect PU and ensure efficient spectrum usage. Both BS and CPE have Geo-location capabilities and BS maintains the location of all associated CPE. The incumbent user database is dynamically updated and contains information of protected primary user operation in surrounding area, such as transmission power limits, protection contour, etc. This information is used to supplement spectrum sensing capabilities. The BS schedules quiet periods for synchronized sensing to ensure sensing results are not corrupted by other SU transmission. Both BS and CPE perform spectrum sensing, while CPE returns sensing information back to BS for central decision. The sensing detector is not specified by the standard, but spectrum sensing must be performed in the current operating spectrum as well as identifying possible backup spectra.

1.8 Potential Applications of IEEE 802.22 WRAN

Opening valuable portion of the TV bands to secondary user access sparks the application proposals for these bands. There is much discussion about which applications will be used in the TV White Spaces (TVWS). Obviously we have rural broadband and super Wi-Fi, but there are many others. In fact, most of the generally used applications for wireless communications could potentially be used in TVWS. However, some applications are more attractive than others when considering commercial and technical aspects [Lei & Shellhammer 2009].

Broadband rural access: In low population rural areas where it is difficult or expensive to deploy a cellular network, an infrastructure based TVWS network as defined in IEEE 802.22 can be deployed. It is a good choice since TVWS can propagate over long distances resulting in a coverage area considerably larger than that of Global System for Mobile Communications (GSM), Universal Mobile Telecommunications System (UMTS), and IEEE 802.16 WiMAX, because IEEE 802.22 BS has a coverage area of 30-100 km in radius.

Smart Utility Networks (SUN), Machine-to-machine communications: Efficient use and management of utilities such as electricity, natural gas and water has lately been more crucial with increasing concerns on ecology and energy resources. In this sense, Smart Utility Networks (SUN) deployed [Sum *et al.* 2011] at houses provide an infrastructure to monitor, control, and possibly enable the best operation mode while decreasing waste of resources as well as decreasing the human cost of stepping in to the utility meters and record readings. Good penetration properties make TVWS cut out for smart metering as these meters are mostly placed in buildings rather than outdoor cabinets. In addition, signals at TVWS propagate in a wider area making the smart metering data collectors deployed by the service providers less dense. Also, Machine-to-Machine (M2M) communications, traffic monitoring, and similar remote monitoring systems can enjoy the great bandwidth introduced by TVWS.

Wi-Fi extension over TVWS (White-Fi): Density of WLANs is increasing day by day, which increases the complexity of channel allocation and inter-Access Point (AP) coordination. This issue is mostly experienced in dense urban areas. White-Fi can remedy this issue by offloading some portion of the traffic from ISM based WLANs to TVWS based WLANs. Similarly TVWS can help traffic offloading from already congested WLANs and 3G/4G networks [Bahl *et al.* 2009].

Home networking: White spaces can be a good enabler for high speed home networking at low power. As many tools and equipments are going wireless in residential places, short range communications via Bluetooth or Wi-Fi may experience distortions and may fall short of providing sufficient Quality of Service (QoS).

Cognitive Femtocells: Motivated by the fact that providing indoor cellular coverage is a burden on the operators; femtocells are proposed to close the coverage gap in indoor areas such as residential areas or small offices. Due to the transmitter and receiver being in close proximity, femtocells provide high data rate at low power levels, which makes them eco-friendly. However, from a technical perspective femtocells are challenging to operate due to macrocell-to-femtocell and femtocell-to-femtocell interference if they share the entire operator's licensed spectrum. Instead, femtocells via cognitive functionalities, dubbed as cognitive femtocells [Al-Rubaye *et al.* 2011], can discover the white spaces and operate through these bands without experiencing inter-tier interference. Similarly, they can coordinate spectrum sharing at the femtocell layer and thus intra-tier interference can be mitigated.

1.9 Thesis Motivation

The Defense Advanced Research Projects Agency (DARPA) funded the NeXt Generation (DARPA-XG) program [Ramanathan & Partridge 2005] to define a policy-based spectrum management framework inside adaptive radios that can sense and share the use of spectrum, with a focus on policy-based negotiation and radio etiquettes that leverage spectrum holes existing in space and time. These XG radios did not have cognitive capabilities, but could serve as potential hosts for policy-adaptive wireless services. Both the XG program and the real spectrum utilization started drawing the attention of Federal Communications Commission (FCC), whose policy makers sponsored a research that confirmed the underutilization of spectrum in time and space. Wireless World Research Forum (WWRF) Working Group 6 [Tafazolli 2006] started to investigate innovative solutions for spectrum and radio resource management (RRM) by exploring CR technology. Their research focus on network reconfigurability, and RRM indicates the potential of CR technology for the next generation wireless access infrastructure.

The IEEE 802.22 working group [Lei & Shellhammer 2009] was formed in the year 2004 to define the Cognitive Wireless Regional Area Network (WRAN) with Physical and MAC layer specifications. The IEEE 802.22 WRAN standard aims to provide fixed wireless access with a typical cell radius of 33km and maximum radius of 100km in rural and remote areas using Cognitive radio (CR) technology in TVWS. It helps to provide broadband access to rural areas with low cost. In most of the existing work, the simulation scenario of CSS algorithm has been based on common theoretical assumptions rather than to meet the operational requirements of WRAN standard.

At the end of 2005, the IEEE launched the Project 1900 standard task group for next generation radio and spectrum management [Murroni *et al.* 2011], with a special focus on applying software defined and cognitive radio technology. As IEEE started 802.22 with a special interest of defining procedures for cognitive operation in TV bands; after three years of preparation, FCC launched the TV band unlicensed service project in 2006 with cognitive radio technology.

The major challenge in cognitive radios for dynamic spectrum access is to ensure that performance of the PU is not compromised due to the activities of SU. The SU should access the primary spectrum without degrading PU performance. Therefore, it is extremely important that each SU should be aware of the RF environment, and existence of primary user. The detection capability of CR should be able to measure, learn and be aware of the radio's operating environment. The spectrum sensing problem in CR consists of three sub-problems [Akyildiz *et al.* 2008],

- Decide which channel to sense (Channel sensing decision making)
- Decide whether the channel is idle/busy based on local observations of the sensed channel (Primary signal detection or channel-state detection)
- Decide collaboratively whether to access the channel or not if it is indeed idle (Cooperative decision making)

From the above discussion, it is apparent that well-designed techniques for spectrum sensing can significantly contribute for improving the decision making capability. However, the performance of the spectrum sensing schemes can be degraded by many factors such as channel impairments; uncertainty due to noise which affects the detection performance of SU. Therefore, it is important to investigate spectrum sensing techniques that can enhance the sensing efficiency by detecting multiple distinct channels within the band of interest [Ghasemi & Sousa 2008].

The research on cognitive radio is highly multidisciplinary which includes, communication theory, signal processing, cooperative communication, machine learning, game theory, network architecture and protocol design. The main focus of this thesis is to develop efficient Cooperative Spectrum Sensing (CSS) algorithm in cognitive radios with high probability of detection and low probability of false alarm to meet the desired objective of efficient utilization of radio spectrum. Three main questions that need to be addressed in every cooperative sensing scheme are as follows [Akyildiz *et al.* 2011]:

- How can cognitive radios cooperate?
- How much can be gained from the cooperation?
- What is the overhead associated with the cooperation?

The core idea of cooperative sensing is to improve sensing performance by exploiting the spatial diversity of SU's.

1.10 Thesis Organization and Contribution

The goal of this thesis is to develop cooperation sensing model that allow the SUs to locally observe the RF environment and collaboratively share its decision over centralized fusion framework. The simulation scenario of cooperative spectrum sensing has been formulated to meet the requirements of IEEE 802.22 WRAN standard. The spectrum sensing framework has been divided into two phases: local sensing phase and cooperative sensing phase.

In the next chapter, we present a brief introduction of cooperative spectrum sensing. We highlight the most important aspects of cooperative spectrum sensing such as cooperation architecture, various fusion schemes and cooperative user selection criteria. We further discuss some of the limiting factors of cooperative spectrum sensing, namely, cooperation overhead and sensing errors.

In Chapter 3 we develop cooperative spectrum sensing algorithms using Machine learning schemes, particularly using Perceptron Learning and unsupervised clustering approaches. The reason for adopting learning algorithm in CSS is because of its ability to dynamically adapt and train at any time, ability to learn features and attributes of the system which is often difficult to formulate analytically. The performance of our proposed algorithms is evaluate in terms of training duration, classification delay and detection accuracy. Local sensing phase is carried out using energy detection to scan the complete available channel set from (54-682)MHz with channel bandwidth of 7MHz. The local decisions of primary channel activity are modelled as binary hypothesis testing problem where the null and alternate hypothesis corresponds to the presence or absence of primary transmission respectively. For cooperative sensing phase, a centralized decision maker called Fusion Center (FC) is considered where each SU sends its local decision statistics to FC which makes final decision on channel availability.

Chapter 4 discusses the formulation of a Reinforcement Learning (RL) based Cooperative Spectrum Sensing algorithm. RL is a trial-and-error machine learning approach in which the decision making agent, called Fusion Center (FC) observes the state of the RF environment and chooses actions to maximize reward. Since reinforcement learning can be used without training data and because it aims to maximize the long-term on-line performance, it is particularly suitable for a cognitive radio network. Specifically, an unlicensed user can use a reinforcement learning algorithm to explore the possible transmission strategies. The Secondary users exploit the knowledge thus obtained to adapt their transmission parameters to achieve the desired objective (e.g. improve sensing accuracy, maximize throughput) while making sure the constraints (e.g. on the interference temperature limit) are satisfied). The optimal solution of the proposed algorithm has been developed using the policy iteration scheme. This RL based CSS algorithm consists of policy evaluation, policy improvement and global decision calculation.

Chapter 5 investigates a comprehensive analytical insight of coalitional game model and its use in cooperative spectrum sensing. In recent years, there is growing interest of adopting game theory models in cognitive radios. The behavior of cooperating CR users in cooperative sensing can be modelled effectively using Game theory. For a realistic environment where several interacting agents take collaborative decision to reach a desired performance under uncertain and dynamic conditions, game theoretic approach is well suited. It provides well defined equilibrium criteria to measure the game optimality under various game settings and highly desirable when centralized control is not available or flexible self-organized approaches are necessary. We have highlighted suitable game model for CSS and presented in-depth analysis of design steps involved in coalition formation. Different phases of Coalition Formation (CF) algorithm involving local sensing, adaptive coalition formation, and coalition head selection and coalition sensing phases are discussed. In CF algorithm, each SU autonomously decides to form or leave a coalition while maximizing its utility in terms of detection probability and the cost incurred by false alarm. To improve the detection performance and respond to PU activity and topology change, CR users merge or split the coalitions if the utility of the merged or split coalitions is larger than the original coalition partitions.

Finally, Chapter 6 concludes the thesis with a summary of accomplished tasks and contributions.

Chapter 2

Cooperative Spectrum Sensing

2.1 An Overview

In cooperative spectrum sensing, information from multiple secondary users is incorporated for the detection of spectrum holes. In the literature, this is discussed as a solution to problems that arise in spectrum sensing due to noise uncertainty, fading, and shadowing since the uncertainty in a single user's decision can be minimized through cooperation [Ghasemi & Sousa 2005]. The main idea of cooperative sensing is to enhance the sensing performance by exploiting the spatial diversity in the observations of spatially distributed secondary users. By cooperation, secondary users can share their sensing information for making a combined decision more accurate than the individual decisions [Akyildiz *et al.* 2011]. The performance improvement due to spatial diversity is called cooperative gain. While this leads to improved detection performance and lower receiver sensitivity requirement, cooperative sensing can incur cooperation overhead. Cooperation overhead refers to any extra sensing time, delay, energy, and operations devoted to cooperative sensing and any performance degradation caused by this process.

2.2 Cooperation architecture

Depending on how the secondary users share their sensing data, several cooperative spectrum sensing architectures for CR networks have been proposed in the literature [Unnikrishnan & Veeravalli 2008, Ganesan & Li 2007, Ye *et al.* 2007]. The most commonly proposed architecture is the parallel fusion architecture, in which all the sensing secondary users send their sensing information directly to a centralized controller called a Fusion Center (FC). This FC then makes a final decision regarding the presence or absence of the primary signal, and broadcasts this information to other secondary users or directly controls the cognitive radio network traffic [Unnikrishnan & Veeravalli 2008]. The parallel fusion architecture is illustrated in Fig.2.1. In this architecture, all the sensing secondary users (SU1, SU2,...,SUN) send their sensing information directly to a centralized controller called a Fusion Center (FC). This FC then makes a final decision regarding the presence or absence of the primary signal, and broadcasts this information to other secondary users through reporting channel.

Another possible sensing architecture involves decentralized sensing architecture which does not solely rely on a fusion center for making the cooperative decision [Ganesan & Li 2005]. In this case, secondary users exchange the sensing observations and converge to a unified decision on the presence or absence of primary users transmissions by iterations. Based on a distributed algorithm, each secondary user sends its own sensing data to other users, combines its data with the received sensing data, and decides whether or not the primary user's transmission is present by using the binary hypothesis criterion as discussed in Sec.1.6 of chapter 1. If the criterion is not satisfied, secondary users send their combined results to other users again, and repeat this process until the algorithm converges and a decision is reached. The decentralized sensing architecture is illustrated in Fig.2.2 using one primary transmitter, seven SUs and one Fusion Center. In this

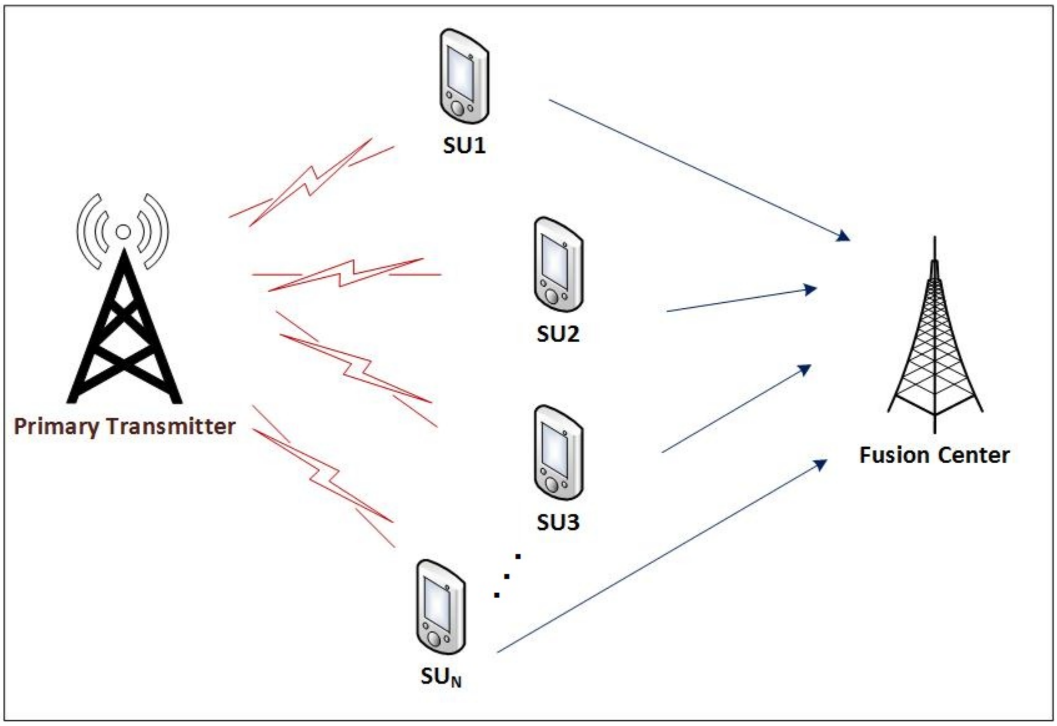

Figure 2.1: Parallel fusion architecture

diagram, it is shown that the SUs form two clusters depending on their spatial location and exchange their local sensing observations to cluster head (SU7 and SU5). Each cluster head collects local observation from a group SUs and reports those results to FC through reporting channel.

2.3 Fusion Schemes

In cooperative sensing, a fusion scheme refers to the process of combining locally sensed data of individual secondary users. Depending on which type of sensing data is transmitted to the fusion center or shared with neighboring users, CSS can employ data or decision fusion schemes. In soft decision schemes (data fusion), secondary users exchange their test statistics calculated from their local observations. On the other hand, in the hard decision schemes (decision fusion); secondary users only exchange their individual binary decisions.

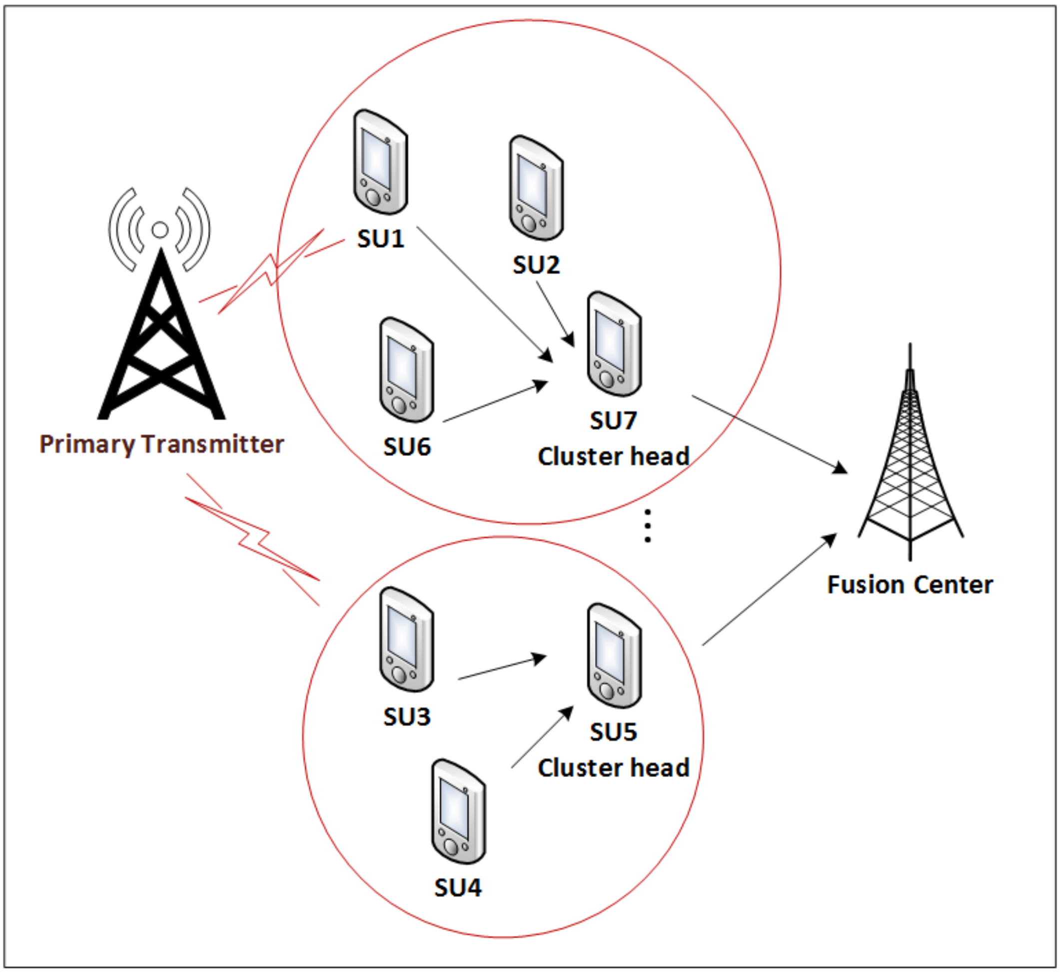

Figure 2.2: Decentralized fusion architecture

2.3.1 Hard Combining and Decision fusion

In the hard combining scheme, the final decision is reached by taking into consideration the individual local decisions reported by each secondary user. When binary local decisions are reported to the fusion center, it is convenient to apply linear fusion rules to obtain the cooperative decision. The main advantage of the hard combining scheme is the reduction of communication overhead. Hard decision combining for CSS has been considered in several works [Zhang *et al.* 2009, Visotsky *et al.* 2005]. The commonly used fusion rules are AND, OR, and majority voting rules which are special cases of the general K-out-of-M rule. Those decision fusion rules can be summarized as below [Akyildiz *et al.* 2011]:

K-out-of-M rule: In this fusion rule, the fusion center decides on the presence of the primary user's transmission if and only if K or more than K secondary users out of the total M cooperating secondary users report the detection of the primary user's signal, where $K \in [1, M]$. Therefore, in the K-out-of-M rule, if K users or more decide in favour of H_1, then the cooperative decision declares that H_1 is true. If the decisions from all the secondary users are independent, the network probabilities of detection and false alarm are, respectively, given by [Quan *et al.* 2008]:

$$P_D = \sum_{k=0}^{M-K} \binom{M}{K+k} (1 - P_{d,k})^{M-K-k} (P_{d,k})^{K+k} \tag{2.1}$$

$$P_F = \sum_{k=0}^{M-K} \binom{M}{K+k} (1 - P_{f,k})^{M-K-k} (P_{f,k})^{K+k} \tag{2.2}$$

where $P_{d,k}$ and $P_{f,k}$ are, respectively, the probabilities of detection and false alarm of $k_t h$ secondary user and $\binom{M}{K+k} = \frac{M!}{(K+k)!(M-K-k)!}$

2.3.2 Majority voting(MV)rule:

In the MV fusion rule, also known as half voting rule, if half or more than half local detectors decide that there is a primary user's transmission; the final decision at the fusion center declares the process of primary user's transmission. Therefore, for the MV rule, the cooperative decision declares H_1 only if half or more than half of the secondary users decide on H_1, i.e., $K = \lceil \frac{M}{2} \rceil$ in equation (2.3), where $\lceil \frac{M}{2} \rceil$ denotes the smallest integer not less than $\frac{M}{2}$. If the decisions from all the secondary users are independent, the network probabilities of detection and false alarm are, respectively, given by,

$$P_D = \sum_{k=0}^{M-\lceil \frac{M}{2} \rceil} \binom{M}{\lceil \frac{M}{2} \rceil + k} (1 - P_{d,k})^{M-\lceil \frac{M}{2} \rceil - k} (P_{d,k})^{\lceil \frac{M}{2} \rceil + k} \tag{2.3}$$

$$P_F = \sum_{k=0}^{M-\lceil \frac{M}{2} \rceil} \binom{M}{\lceil \frac{M}{2} \rceil + k} \left(1 - P_{f,k}\right)^{M-\lceil \frac{M}{2} \rceil - k} \left(P_{f,k}\right)^{\lceil \frac{M}{2} \rceil + k} \tag{2.4}$$

Logical OR rule: In this fusion rule, the fusion center decides on the presence of primary user's transmission if any of the secondary users report the detection of the primary user's transmission. Therefore, for the OR rule, the cooperative decision declares H_1 if any of the secondary users decides on H_1, i.e., setting K = 1 in equations (2.3) and (2.4). It can be seen that the risk of SUs causing interference to the primary users is minimized using the logical OR rule. If the decisions from all the secondary users are independent, the network probabilities of detection and false alarm are, respectively, given by,

$$P_D = 1 - \prod_{k=1}^{M} \left(1 - P_{d,k}\right) \tag{2.5}$$

$$P_F = 1 - \prod_{k=1}^{M} \left(1 - P_{f,k}\right) \tag{2.6}$$

Logical AND rule: In the AND fusion rule, if all local detectors decide that there is a primary user's transmission, then the final decision at the fusion center declares that there is a primary user's transmission. Therefore, for the AND rule, the cooperative decision declares H_1 only if all of the secondary users decide on H_1, i.e., setting K=M in equations (2.3) and (2.4). Using this fusion rule, the probability of false alarm is minimized, but the risk of causing interference to primary users is increased. If the decisions from all the secondary users are independent, the probabilities of detection and false alarm are, respectively, given by,

$$P_D = \prod_{k=1}^{M} P_{d,k} \tag{2.7}$$

$$P_F = \prod_{k=1}^{M} P_{f,k} \tag{2.8}$$

2.3.3 Soft combining and Data fusion

Existing receiver diversity techniques such as equal gain combining (EGC) and maximal ratio combining (MRC) can be utilized for soft combining of local observations or test statistics [Uchiyama *et al.* 2008]. If the channel state information (CSI) between the primary users and the secondary users are perfectly known, the optimal combining strategy, which is MRC, can be used for achieving the highest output SNR. It was shown in [Uchiyama *et al.* 2008] that the soft combining scheme yields better gain than the hard combining scheme. However, there is a significant increase in the cooperation overhead in the case of soft decision based detectors, which requires a wide-band control channel for the soft decision cooperative approach.

The soft information based signal detection method for the single-carrier case and multi-carrier case was investigated in [Ma *et al.* 2008]. In [Peh & Liang 2007], a linear cooperation strategy was developed which is based on the optimal combination of the local statistics from spatially distributed secondary users. In [Ma *et al.* 2008], an optimal soft combination scheme based on Neyman-Pearson criterion was proposed to combine the weighted local observations. The proposed scheme reduces to EGC at high SNR and reduces to MRC at low SNR. Since such a soft combining scheme results in large overhead, a softened two-bit combining scheme was also proposed in [Ma *et al.* 2008] for energy detection. In this method, there are three decision thresholds dividing the whole range of test statistics into four regions. Each secondary user reports the quantized two-bit information of its local test statistics. The performance of this method is comparable to the performance of the EGC scheme with less complexity and overhead.

2.4 Cooperative user selection

The selection of secondary users for cooperative sensing plays a key role in determining the performance of CSS because it can be utilized to improve the trade-off between cooperative gain and cooperation overhead. In [Khan *et al.* 2010], for the case of independent secondary user's observations with energy detection based cooperation, it was shown that cooperating with all users in the network does not necessarily achieve the optimum performance. It was observed that including secondary users experiencing bad channels, in terms of the SNR received at a secondary user, may degrade the performance.

In order to relax the requirement on prior knowledge of the received SNR at each secondary user, the authors in [Lee & Akyildiz 2008] proposed to select the sensing secondary users that have the best detection probabilities with respect to a given false alarm probability. Specifically, the false alarm probability is set to be identical at each secondary user. Therefore, the SU that reports the largest number of 1's is first chosen to participate in cooperative sensing. In [Mishra *et al.* 2006], the optimal number of secondary users, K, which minimizes the total error probability for secondary users with independent local decisions for the general K-out-of-M fusion rule, was found to be approximately half of the total number of secondary users M. A user selection strategy based on a modified deflection coefficient with low complexity was proposed in [Li *et al.* 2012]. The optimal number of secondary users and the user set were obtained in order to provide sufficient protection to the primary users and improve the total throughput of the cognitive radio network.

When cooperating secondary users experience correlated shadowing, selecting independent secondary users for cooperation can improve the robustness of sensing results [Mishra *et al.* 2006]. In [Cacciapuoti *et al.* 2012], a distributed user selection algorithm was developed to address the dynamic changes in the spatial correlation experienced by mobile secondary users and adaptively select uncorrelated secondary users.

2.5 Cooperation overhead

The exploitation of spatial diversity in cooperative sensing results in a significant improvement in detection performance. However, cooperation among secondary users also introduces a variety of overheads that limit or even compromise this improved detection performance. The overhead associated with all elements of cooperative sensing is called cooperation overhead. Cooperation overhead can refer to any transmission cost, extra sensing time, delay, energy and operations devoted to cooperative sensing and any performance degradation caused by cooperative sensing.

Since the sensing time is proportional to the number of samples taken by each individual secondary user, the longer the sensing time is, the better the detection performance will be. However, when each secondary user is equipped with a single radio transceiver, it will be difficult for the secondary users to simultaneously perform sensing and transmission. Therefore, more the time devoted to sensing, less time is available for transmissions thereby reducing the secondary user's throughput, (also known as opportunistic throughput). In addition, the cooperation overhead due to the extra sensing time will generally increase with the number of cooperating users due to the increased volume of data that needs to be reported and processed by the fusion center. This is known as the sensing efficiency problem or the sensing-throughput trade-off [Liang *et al.* 2008b] in spectrum sensing.

The cooperation overhead, in terms of the extra sensing time or reduced opportunistic throughput, will also increase as the delay in finding available channel increases [Yu *et al.* 2012]. In [Kim & Shin 2008], a sensing-period optimization mechanism and an optimal channel-sequencing algorithm were developed to maximize the discovery of spectrum access opportunities and minimize the delay in discovering an available channel when all secondary users participate in sensing an identical channel in each sensing period. Parallel cooperative sensing was proposed in [Xie *et al.* 2010] where the cooperative secondary users are divided into multiple groups and each group senses one channel such that more than one channel is sensed in each sensing period. Since multiple channels are detected in one sensing period, the cooperation overhead associated with the delay in finding an available channel is significantly reduced.

In cooperative sensing, secondary users involve in activities such as local sensing and data reporting that consume additional energy. The energy consumption overhead can be significant if the number of cooperating secondary users or the amount of sensing results to be reported is large. One approach to address this issue is to use censoring to limit the amount of reported sensing data according to certain 'censoring criteria'. Since such criteria are chosen to refrain cooperating secondary users from transmitting unnecessary or un-informative data, the energy efficiency can be improved. In [Sun *et al.* 2007], a simple censoring method was proposed to decrease the average number of sensing bits reported to the fusion center. In this method, the energy detector output of each secondary user is compared to two thresholds and the decision is sent to the fusion center if the energy detector output is between those two thresholds. Otherwise, no decision is made and this sensing output is censored from reporting. The results showed that even though the network probability of false alarm may degrade due to the possibility that the sensing outputs of all secondary users are censored, the amount of reported local decisions can be dramatically reduced. Therefore, the energy efficiency can be traded off with the network probability of false alarm.

Another approach to reduce the cooperation overhead in terms of energy consumption is to minimize the energy consumption with detection performance constraints. In [Pham *et al.* 2010], the energy efficiency problem was addressed by energy minimization under detection performance constraints. This method investigates the trade-off between the two aspects of sensing time. On one hand, longer sensing time consumes more energy at each secondary user. On the other hand, longer sensing time can improve detection performance at each secondary user and reduce the number of cooperating users and the associated energy consumption overhead. Therefore, this method finds the optimal sensing time and the optimal number of cooperating users to balance the energy consumption in local sensing and the energy overhead due to cooperation for a required detection performance.

2.6 Sensing Errors

A secondary user identifies spectrum access opportunities by detecting the presence of primary signals. Sensing errors, in terms of false alarms or miss-detections, occur due to noise and fading. False alarms occur when idle channels are detected as busy, and miss-detections occur when busy channels are detected as idle. In the event of a false alarm, a spectrum access opportunity is overlooked by the secondary user, and eventually wasted if the access strategy trusts the sensing outcome. On the other hand, miss-detections may lead to collisions with primary user's transmissions. Therefore, in spectrum sensing, it is desired to minimize the probability of sensing error (i.e., sum of the probability of false alarm and the probability of miss-detection) which reduces the collision probability with primary user's transmissions and enhances the usage level of vacant spectrum.

A well chosen detection threshold can minimize spectrum sensing errors, provide the primary user's transmissions with enough protection, and fully enhance spectrum utilization. In [Zhang *et al.* 2008], the optimal threshold level for minimizing the probability of sensing error was determined without considering spectrum sensing constraints that may be violated. To alleviate this problem, an adaptive optimal spectrum sensing threshold level was derived in [Oh & Lee 2009] to minimize the probability of sensing error while satisfying spectrum sensing constraints on the probabilities of false alarm and miss-detection. CSS using counting rule was studied in [Jiang & Qu 2008] and the sensing errors were minimized by choosing the optimal probability of false alarm to satisfy a given constraint and the optimal number of cooperating secondary users for both matched filtering and energy detection. CSS with correlated secondary user's local decisions was studied in [Khalid & Anpalagan 2012]. The probability of sensing error was minimized by choosing the optimal assignments for the number of cooperating secondary users, K, in the K-out-of-M fusion rule and the local threshold for a certain correlation index.

Most of the time it is assumed that the local observations and the combining decision are all made at the same time. In reality, this is not always valid and therefore, the CSS scheme should consider the case of asynchronous observations which results in time offsets between local sensing observations and the final decision at the fusion center. In [Zhou *et al.* 2010], a probability-based combination scheme was proposed to combine asynchronous reports at the fusion center. Such a combining scheme considers both detection errors and time offsets between local sensing observations and the final decision. Based on the knowledge of the primary user channel usage model and the Bayesian decision rule, the conditional probabilities of the local sensing decisions received at different times, conditioned on each hypothesis, and their combined likelihood ratio were calculated to make the final decision at the fusion center.

Most of the studies on CSS analyze its performance based on the assumption of perfect knowledge of the average received SNR at the secondary user. However, in practice, this is not always the case. The effect of average SNR estimation errors on the performance of CSS was examined in [Chen & Beaulieu 2009]. In the noiseless-sample-based case, it was found that the probability of false alarm decreases as the average SNR estimation error decreases for both independent and correlated shadowing. In the noise-sample-based case, it was found that there exists a threshold for the noise level. Below this threshold, the probability of false alarm increases as the noise level increases, while above the threshold the probability of false alarm decreases as the noise level increases.

2.7 Multi-channel cooperative sensing

Wideband spectrum sensing, that we also refer to in this thesis as multi-channel or multi-band sensing, faces technical challenges and there is limited work on it in the literature. As mentioned in IEEE 802.22 WRAN, the secondary users need to scan multiple frequency bands (54-682MHz) or use multiple Radio Frequency (RF) front ends for sensing multiple bands. For example, consider a number of digital TV bands. Together they constitute a wide-band spectrum, but divided into different sub-channels. These sub-channels do not even have to be contiguous; some of the sub-channels may be occupied and some may be available. The problem of multi-band sensing is to decide upon which of the sub-channels are occupied and which are available.

In multi-band cooperative sensing, secondary users cooperate to sense multiple narrow bands instead of focusing on one band at a time. In [Quan *et al.* 2009], a multi-band joint detection scheme was proposed for combining the statistics of sensing multiple bands from spatially distributed secondary users. The fusion center calculates the test statistic and makes a cooperative decision in each band. The weight coefficients and detection thresholds of all bands were obtained by jointly maximizing the aggregate opportunistic throughput in each band subject to constraints on the miss-detection and false alarm probabilities. To enable the multi-band sensing at each secondary user, an energy detector is required for each band of interest.

In [Paysarvi-Hoseini & Beaulieu 2011], the authors proposed a multi-band adaptive joint detection framework for wide-band spectrum sensing that collectively searches the secondary transmission opportunities over multiple frequency bands. In this framework, both the sensing slot duration and detection thresholds for each narrow-band detector were jointly optimized to maximize the achievable opportunistic throughput of the secondary network subject to a limit on the interference introduced to primary users. In [Xie *et al.* 2010], a parallel cooperative sensing scheme was proposed to enable the multi-channel sensing by optimally selected cooperating secondary users. Different from the multi-band sensing scheme in [Quan *et al.* 2009, Paysarvi-Hoseini & Beaulieu 2011], each cooperating secondary user senses a different channel. In [Liu *et al.* 2010], the authors proposed a group-based CSS scheme in which the cooperative secondary users are divided into several groups and each group senses a different channel during a sensing period while the secondary users in the same group perform joint detection on the targeted channel. Using the methods described in [Xie *et al.* 2010, Liu *et al.* 2010], multiple channels can be cooperatively sensed in each sensing period. The objective is to maximize the secondary opportunistic throughput while minimizing the sensing overhead such as the sensing time and the number of secondary users required for cooperation.

In this thesis, we focus on multi-channel sensing by cooperating secondary users in which more than one channel can be sensed in each sensing period to leverage the cooperative gain of CSS. In subsequent chapters, we address the problem of improving sensing accuracy in multi-channel cooperative sensing using machine learning techniques. We discuss the framework of Game theory based cooperative spectrum sensing scheme to study, model and analyze the strategic interactions among CR users.

Chapter 3

Decision Fusion Scheme for Cooperative Sensing Based on Perceptron Learning and Clustering Approaches

3.1 Introduction

Learning ability is important for cognitive radios for effective decision making. Learning algorithms [Haykin 2005] are implicitly built into spectrum knowledge acquisitions and decision-making algorithms in the sense that they convert information (current and past observations) into decisions and actions. In Chapter 1, we defined a cognitive radio as an extension of Software Defined Radio (SDR) with built-in cognition and intelligence capability. Being cognitive requires the radio to be able to acquire knowledge and self-comprehend. To be considered as intelligent, it must not only be able to acquire knowledge and comprehend but also be able to apply acquired knowledge. Hence, acquiring knowledge and comprehension (i.e.learning) is at the heart of a cognitive radio's identity[Abbas

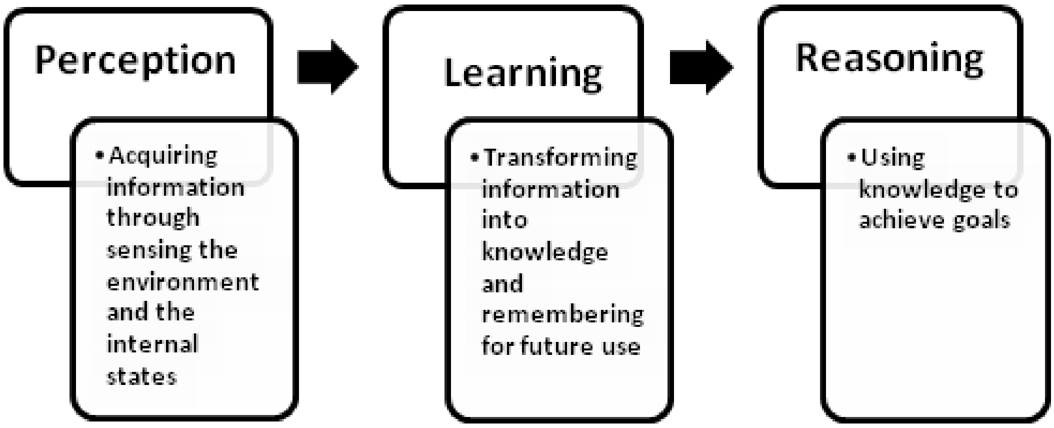

Figure 3.1: Attributes of intelligence

et al. 2015]. In the case of cognition, such learning necessarily needs to include conscious self-learning, while in the case of intelligence, it can be any form of learning. Regardless, it is the ability of learning that is at the heart of a cognitive radio. Intelligence consists of the attributes, such as, perception, learning and reasoning which is shown in Fig.3.1.

A cognitive radio is an intelligent SDR that constitutes attributes of intelligence and cognitive abilities that enable self-learning and self-awareness. In the case of a radio, being conscious, or self-aware, means knowing the internal state and capabilities of the radio, user needs, and the state of its RF environment. The purpose of self-awareness required in a cognitive radio is to ensure that the radio, given its internal state has the ability to autonomously respond to its RF environment and user needs. The experience gained through learning makes the CR to optimally reconfigure RF operating parameters and improve its decision. To perform this, CR must support the following functionalities [Hossain *et al.* 2009]:

- **Spectrum awareness:** It involves sensing the available spectrum bands and monitoring the activities of primary user with the help of spectrum sensing algorithms. These algorithms are used to identify the spectral activity pattern and estimate the characteristics of spectrum holes.

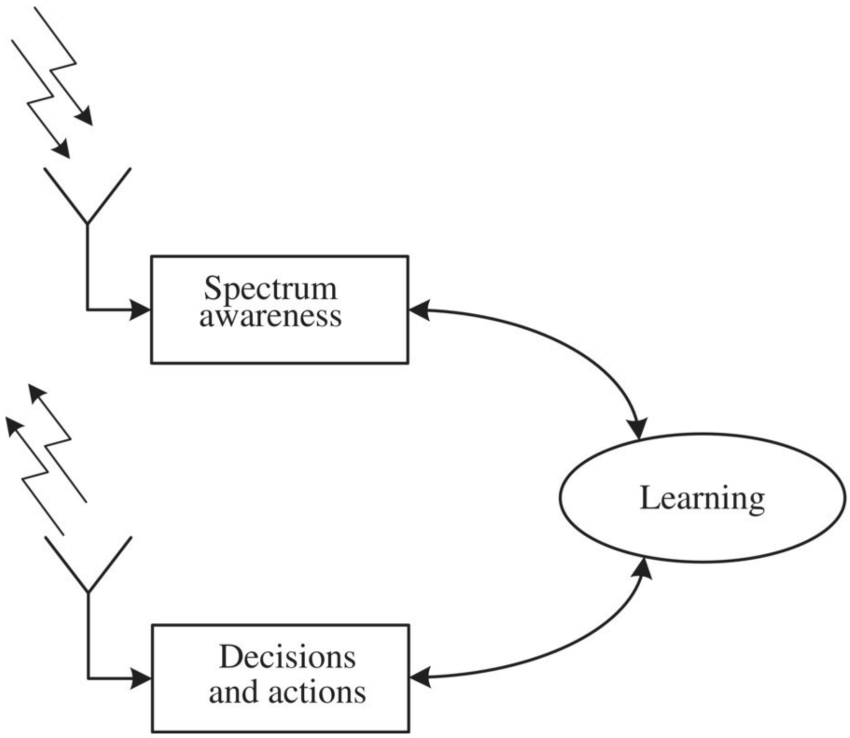

Figure 3.2: Operation of Learning scheme in CR

- **Learning:** This phase acts as a knowledge base between spectrum sensing and decision phase. The gathered knowledge through learning can then be exploited to improve decision capability of CR.

- **Decisions and actions:** The decision phase helps to choose appropriate spectrum band according to spectrum characteristics and user information. The actions are performed by effectively utilizing spectrum holes. The knowledge gathered during the learning phase acts as input to this module. The reconfiguration actions on RF operating parameters are performed during this phase.

The above sequence of operations by CR is schematically shown in Fig.3.2.

In the following sections, we discuss cooperative spectrum sensing algorithms using Machine learning schemes, in particular, using Perceptron Learning and unsupervised clustering approaches. Several simulation scenarios have been considered to evaluate spectrum sensing by single SU unit (local sensing) and multiple SUs in a cooperative setup. The next section discusses Cooperative Spectrum Sensing (CSS) formulation using Perceptron Learning module. Followed by, formulation of unsupervised K-means clustering based CSS scheme in Sec.3.5. The last section of this chapter focus on design of Archetypal clustering based CSS scheme. The randomly deployed SUs form clusters and report their local observation to FC through cluster head. This significantly reduces the classification delay and improves performance under shadowing environment. The reason for adopting learning algorithm in CSS is because of its ability to dynamically adapt and train at any time, ability to learn features and attributes of the system which is often difficult to formulate analytically. The performance of the proposed algorithms is evaluated using training duration, classification delay and detection accuracy.

Local sensing phase is carried out using energy detection to scan the complete available channel set from (54-698)MHz divided into 7MHz of channel bandwidth which gives 92 channels. The local decisions of primary channel activity are modelled as binary hypothesis testing problem where the null and alternate hypotheses correspond to the absence or presence of primary transmission respectively. For cooperative sensing phase, a centralized decision maker called Fusion Centre (FC) is considered where each SU sends its local decision statistics to FC for the final decision on channel availability.

3.2 Spectral density model of received signal

The spectrum estimation [Atapattu *et al.* 2011] can be computed in frequency domain by averaging bins of a Fast Fourier Transform (FFT) using Periodogram approach. The equation for a Periodogram [Simon & Alouini 2005] is given as,

$$S(\omega) = \frac{1}{N} \mid \sum_{n=1}^{N} x(t)e^{-j\omega t} \mid^2 \tag{3.1}$$

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. If we reduce the averaging time, the SNR improves by reducing the noise power. In the application of spectrum sensing, the Periodogram method is superior as it provides a better variance for the set of input data. Variance represents how far apart a particular set of data is spread out in amplitude.

Typically, the variance of the entire FFT data will be larger than the FFT of the data in the segments due to the larger data variations in the entire frame versus the variance of the segments. Because of this, a Periodogram will generally produce a smoother graph and will enable the system to detect and display signals in the presence of noise. The distribution of the total power over a specific range of frequencies is represented by power spectral density, which is the Fourier transform of the autocorrelation function.

3.3 Energy Detection model

As explained in Sec.1.5 of Chapter 1, energy detection scheme accumulates the energy of the received signal during the sensing interval and declares the primary band to be occupied if the energy surpasses a certain threshold which depends on the noise floor. Due to its simplicity and the fact that it does not require prior knowledge of the primary user signals, energy detection is the most popular sensing technique among others for spectrum sensing. However, some of the challenges with energy detection include selection of the threshold for detecting primary users, inability to differentiate interference from primary user's transmission and noise, and poor performance under low signal-to-noise ratio. The decision metric (M_i) for the energy detector can be written as,

$$M_i = \sum_{n=0}^{N} \mid x_i(n) \mid^2 \tag{3.2}$$

where $x_i(n)$ is the received signal of i^{th} SU as defined in equation (1.1) as binary hypothesis testing problem, N is the observation vector. The performance of energy detector can be evaluated by using two probabilities: Probability of detection P_d and Probability of false alarm P_f. It can be formulated as,

$$\begin{aligned} P_d &= P_r(M_i > \lambda / H_1) \\ P_f &= P_r(M_i > \lambda / H_0) \end{aligned} \tag{3.3}$$

where λ is decision threshold which can be selected for finding the optimum balance between P_d and P_f. By setting a desired probability of false alarm and calculating the variance of a data set, the system sets a threshold to indicate signals above the noise level. Each SU processes its received energy and compares with the local threshold. The received signal strength of each SU varies based on its distance from Primary transmitter.

The collection of energy vectors of each SU is represented using a matrix shown below. In this matrix, the row vectors and column vectors are considered as secondary users and number of channels respectively. Each secondary user has an array of values specifying the availability of each of the 92 channels. These are called local decisions.

$$Y_i(t) = \begin{pmatrix} x_1(n) & x_1(n) & \cdots & x_1(n) \\ x_2(n) & x_2(n) & \cdots & x_2(n) \\ \vdots & \vdots & \ddots & \vdots \\ x_N(n) & x_n(n) & \cdots & x_N(n) \end{pmatrix} \tag{3.4}$$

The description of local sensing algorithm is given in Algorithm.1. First, the primary user signal is added with noise according to the distance from the primary user. The noise added signal, '*signal_at_node*' acts as input to different SU's. For the present simulation ten SUs are considered in the model. For each of the 10 secondary users, Periodogram are calculated for '*signal_at_node*', and based on which a Power Spectral Density (PSD) graph is obtained. The channel bandwidth is considered as 7MHz in the frequency range of (54-698MHz) which is scanned in steps of channel width giving 92 channels whose decision can be either 'occupied' or 'available'. The average energy values at each channel are compared to a threshold calculated based on a random probability of false alarm. If the energy value of the channel is greater than the threshold, the channel is specified as 'occupied', otherwise it is 'available'. The signal power estimation (power per unit frequency) has been carried out using Periodogram approach as explained in Sec.3.2. The estimation of Power Spectral Density (PSD) for each SU varies based on the distance coordinates.

Based on the signal estimation, each SU identifies the channel availability by scanning the complete set of primary frequency bands. The FC collects all the sensing information from each SU and makes the global decision. The local channel availability results of individual SUs vary due to variation in Received Signal Strength (RSS) profile. The Fig.3.3 and Fig.3.4 depict this scenario of local observation results of SU5 and SU9. The white spaces between the blue stem shows the spectrum holes detected by individual SU.

3.4 CSS model using Perceptron learning

The CSS model consists of three-step process: local sensing, reporting and data fusion. We consider parallel fusion network model in which groups of spatially distributed nodes observe a physical phenomenon through its local observation and report their observation to a central entity known as Fusion Center (FC). The

Algorithm 1: Local Sensing Based on Energy Detection

```
No_of_Nodes N;
Data: energyDetection()
Result: energy vector
begin
    for user ← 1 to N do
        Signal_at_node ← Primary_user_Signal + AWGN
        L ← size(Primary_User_Signal)
        Threshold ← qfuuncinv(Pf(user))/sqrt(L)+1
        Periodgram_at_node ← periodgrama(Signal_at_node)
        Occupied[length(Periodgram_at_node )] ← 0
        while i < lengthPeriodgram_at_node do
            if Periodgram_at_node i > Threshold then
                Occupide(i) ← 1
            i = i +1
        Channel_width ← 7 MHz
    Energy ← 0
    Sum ← 0
    if Occupide = 1 then
        Sum ← Sum + 1
        Energy ← Energy + Periodgram_at_node (freq)
    if Sum > width/2 then
        Channel ← 1
    else
        Channel ← 0
Data: changeVelocities(velocity_i, velocity_j, X)
begin
    if mod(x,4) = 0 then
        Reverse the Velocity_i
    if mod(x,2) = 0 then
        Reverse theVelocity_i
    else if mod(x,4) = 1 then
        Reverse the Velocity_j
        if mod(x,2) = 0 then
            Reverse the Velocity_i
Data: changeDistances(velocity_i, velocity_j, X, Y)
begin
    X ← X + Velocity_i
    Y ← Y + Velocity_j
    if (X,Y) > (100,100) then
        (X,Y) ← (X,Y) − 2 × ()Velocity_i, Velocity_j
    if (X,Y) > (0,0) then
        (X,Y) ← (X,Y) + 2 × ()Velocity_i, Velocity_j
```

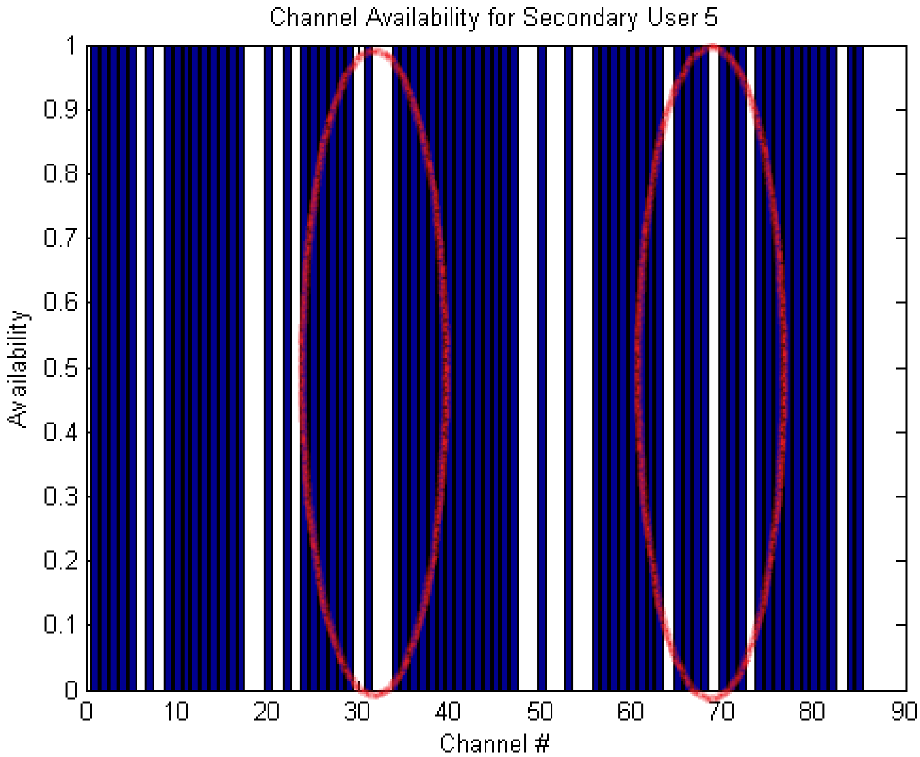

Figure 3.3: Local observation results of SU5

FC combines the reported data by data fusion and makes global decision. All SUs report the estimated energy level (decision vectors) to the Fusion Center (FC) through a reporting channel to make the final decision. We compute the final decision based on the soft combination of the local decisions (weighted average method). The weights corresponding to each secondary user is computed using the energy values as captured by every secondary user. For every channel, we calculate the mean energy value and the weight for each secondary user is the ratio of the corresponding energy value and the mean computed for the channel. This weight essentially captures how variant is the energy levels to the mean in that particular channel. For every channel, the mean value calculated is as follows,

$$mean = \sum_{N=1}^{10} x(n)/N \tag{3.5}$$

where the summation is for all the 10 secondary users. The weight of each sec-

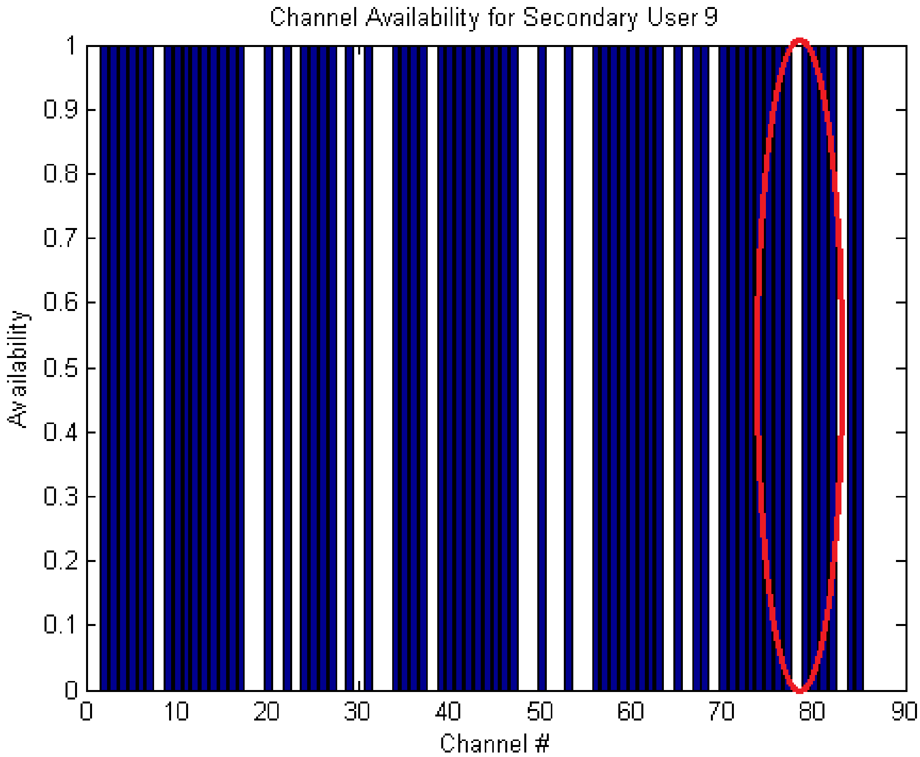

Figure 3.4: Local observation results of SU9

ondary user is determined by using the mean value. The weight assigned to every secondary user is multiplied by the local decision value and the cumulative sum obtained from all the secondary users is used to determine the final decision of the FC. This linear combination of the weights and the local decision vectors produce the Target Output. The model proposed here is then evaluated by comparing its results to the target output of the weighted average method.

The data fusion of CSS scheme is based on Perceptron networks. It is a single-layer binary classifier [He *et al.* 2010], which divides the input space with a linear decision boundary. Perceptrons can learn to solve a narrow range of classification problems and their advantage is a simple learning rule. The goal of the Perceptron is to correctly classify the set of externally applied input stimuli $x1, x2, ..., x_m$ into one of two classes i.e. H_0 or H_1. Each external input is weighted with an appropriate weight $w_{1..m}$ and the sum of the weighted inputs is sent to the hard-limit transfer function, which also has an input of 1 transmitted to it through the

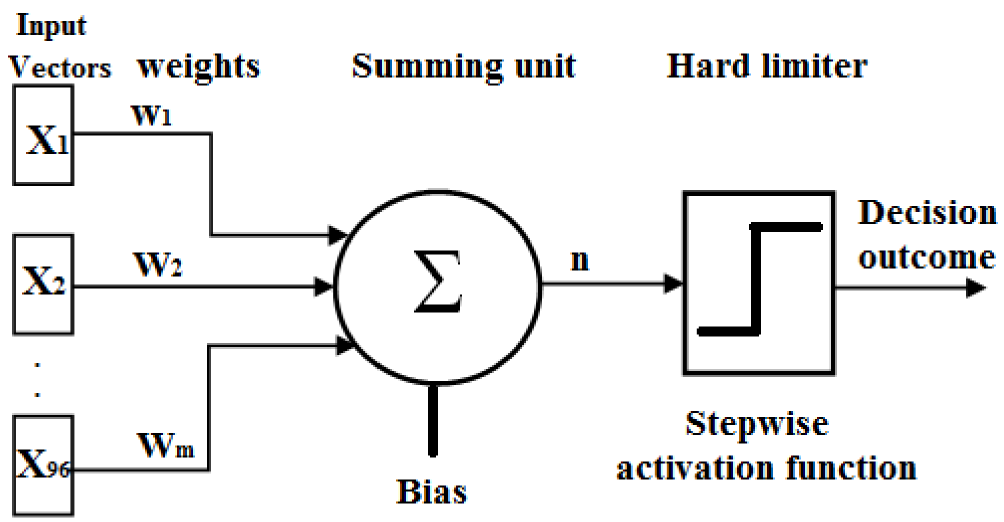

Figure 3.5: Perceptron network

bias. The hard-limit transfer function gives a perceptron the ability to classify input vectors by dividing the input space into two regions (decision boundary). It returns binary decision as H_0 or H_1. The schematic representation of perceptron network is shown in Fig.3.5.

The weight vectors (w) are determined by the method proposed earlier using the mean of the energy values. The bias value (b) is used for shifting the hyperplane [Thilina *et al.* 2013] away from the origin. The hard-limit function determines the network output which gives the final decision of FC about availability of primary channel. The input (n) to the hard-limit function is determined as,

$$n = \sum_{i=1}^{m} w_i x_i + b \tag{3.6}$$

Since the reporting channel is bi-directional, the FC sends its final decision to all SUs. The goal of the perceptron is to correctly classify the set of externally applied stimuli (energy vectors) into one of the two classes H_0 or H_1. The flow chart design of Perceptron learning scheme is given in Fig.3.6. The algorithm steps involved in the proposed CSS scheme are shown below in Algorithm.2.

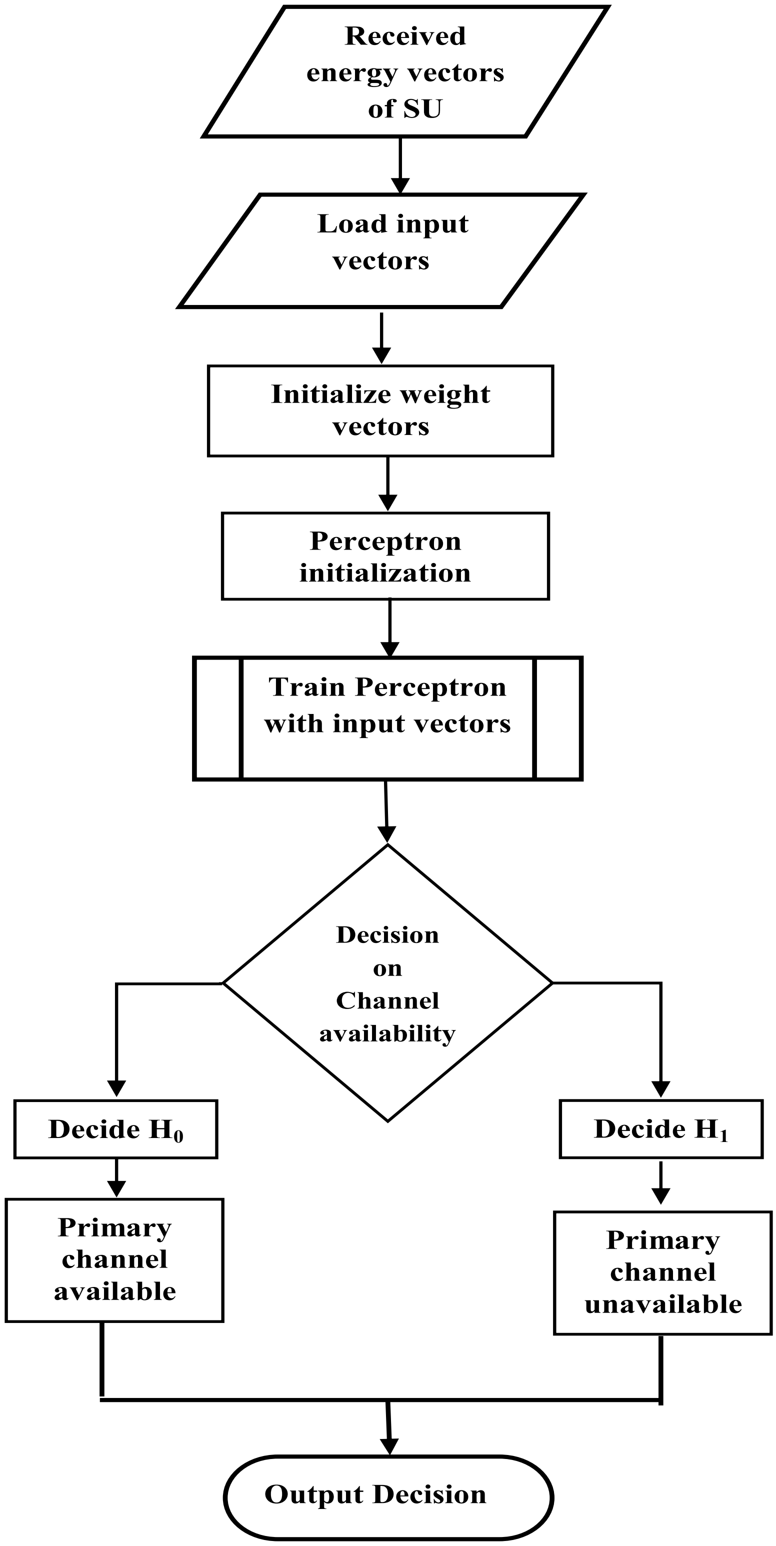

Figure 3.6: Flow chart design of Perceptron module in CSS scheme

The performance of the proposed cooperative sensing scheme has been analyzed with perceptron learning module using MATLAB. We consider a CR sim-

Algorithm 2: Cooperation Spectrum Sensing Scheme

```
Load energy j,i    //Store energy values of j^th secondary user for the i^th band
Load local_decision j,i
begin
    while i < no_of_bands do
        while j < no_of_nodes do
            sum i ← sum i + energy j,i
        avrg i ← sum i / no_of_nodes
        while j < no_of_nodes do
            weight j ← energy j,i / avrg i
            cumulative ← cumulative + weight j × local_decision j,i
        if cumulative > 0 then
            Final_decision i ← 1
        else
            Final_decision i ← 0
        i = i +1
    write Final_decision
```

ulation scenario with one primary transmitter which operates in the frequency range of (54-698) MHz with channel bandwidth of 7MHz. Multiple secondary users (a total of 10) are randomly deployed in a grid topology of area 120×120 Sq.km, using one FC as shown in Fig.3.7. The distance coordinates of each SU varies during each iteration. We have carried out 500 iterations. The value of SNR for each SU changes based on the distance from the primary transmitter.

The channel availability results of each secondary user and FC for band 1 is shown in Fig.3.8 and Fig.3.9 during iteration 6 and 83. The blue bar represents status of primary user band in that region and the red bar represents the decision of FC. These band availability diagrams are based on the local decisions of the corresponding secondary user. Further, it is evident from these figures that the uncertainty of channel availability information may lead to interference to the primary user. Fig.3.10 depicts the channel availability results of FC. The white stem represents the availability of spectrum holes in particular channel. On comparison of Figures.3.8 and 3.9 with Fig.3.10, we can see that the FC provides a

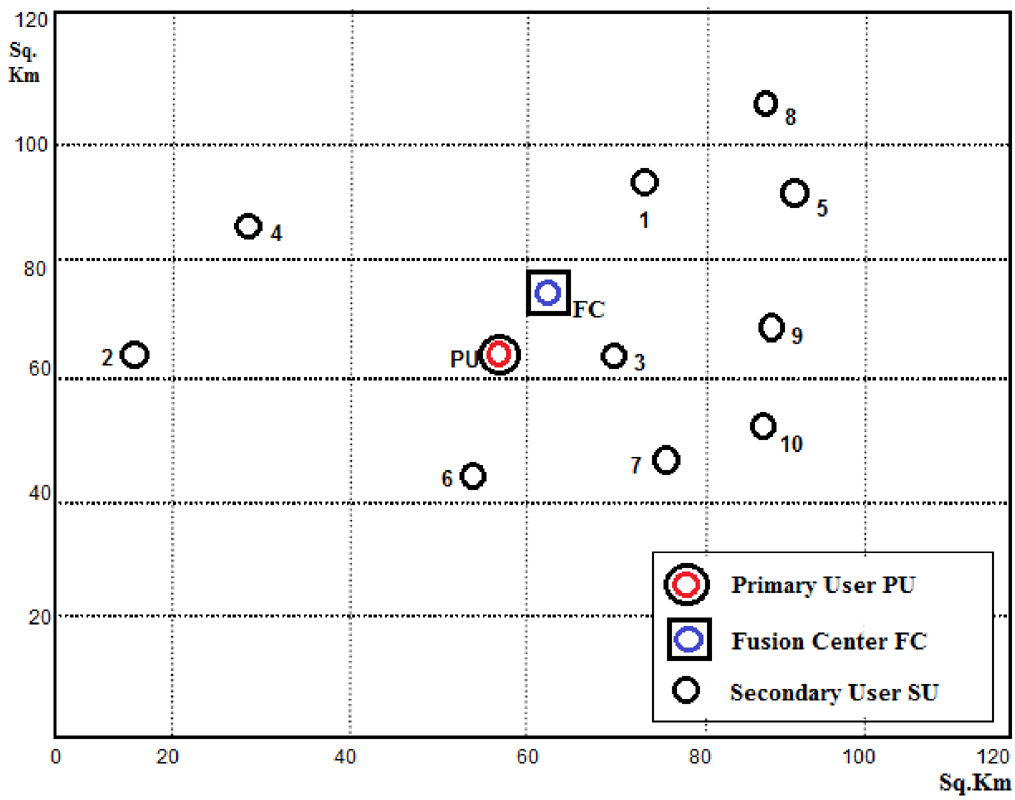

Figure 3.7: Node placement

more accurate channel availability status. The local decisions of the secondary user for some channels are incorrect and the correct decision is communicated to secondary user by the FC.

It can be seen that proposed CSS scheme makes correct decisions by maintaining the target probability of error rate as 0.1. The FC decides the final availability of channel information using perceptron learning module with low error rate. The perceptron module in FC uses 70% of local sensing energy vectors as training set to meet the desired target output. The output obtained from the perceptron model is called the network output. To determine the performance of perceptron learning on CSS scheme, we consider network output versus target output. The target output determines the probability of error rate. Fig.3.11 and Fig.3.12 shows the comparison of the network output with the target output. The highlighted section (marked by arrow) shows the mismatch between the target output and

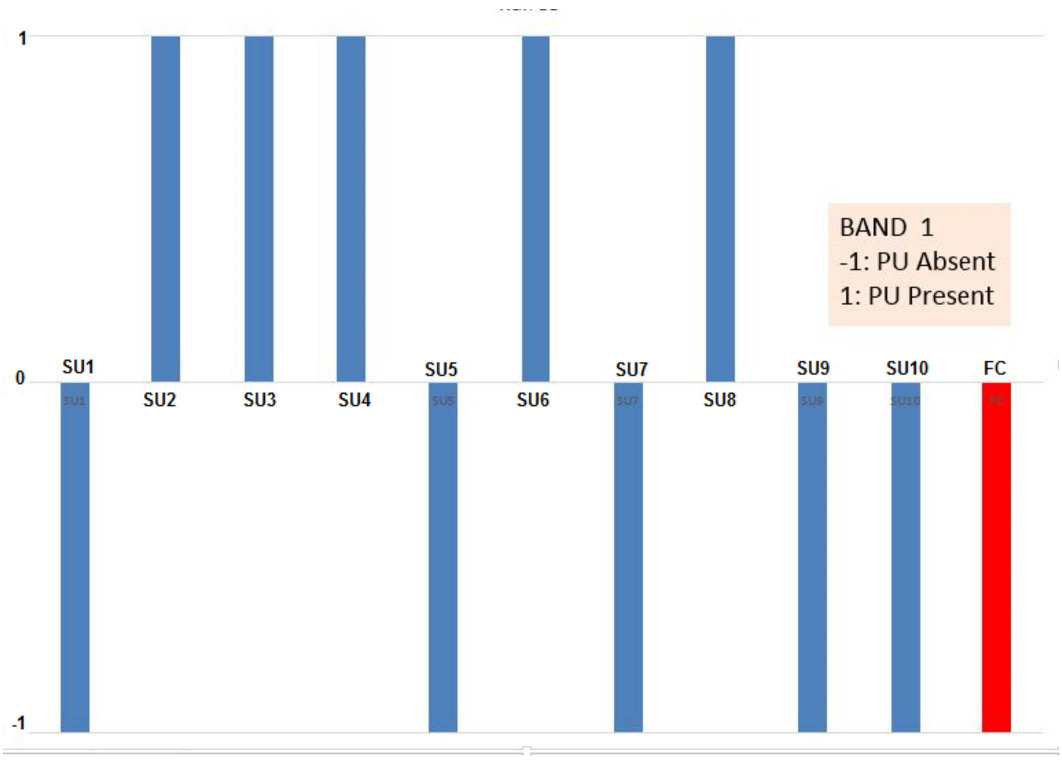

Figure 3.8: Channel availability results of Band 1 during 6th iteration

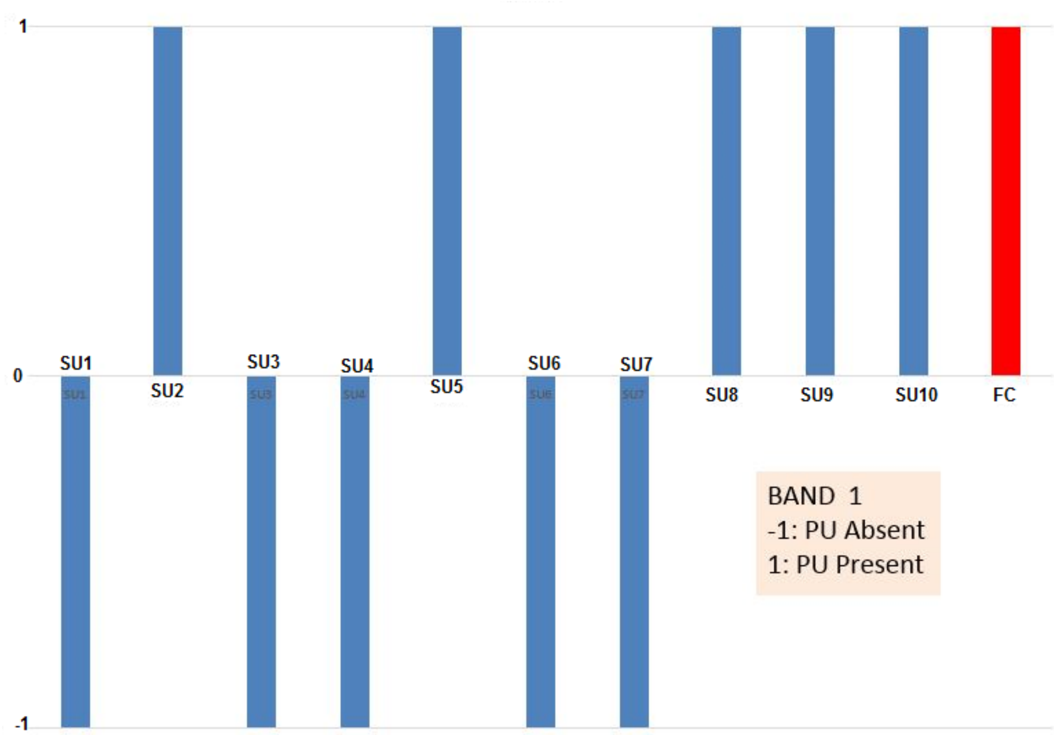

Figure 3.9: Channel availability results of Band 1 during 83rd iteration

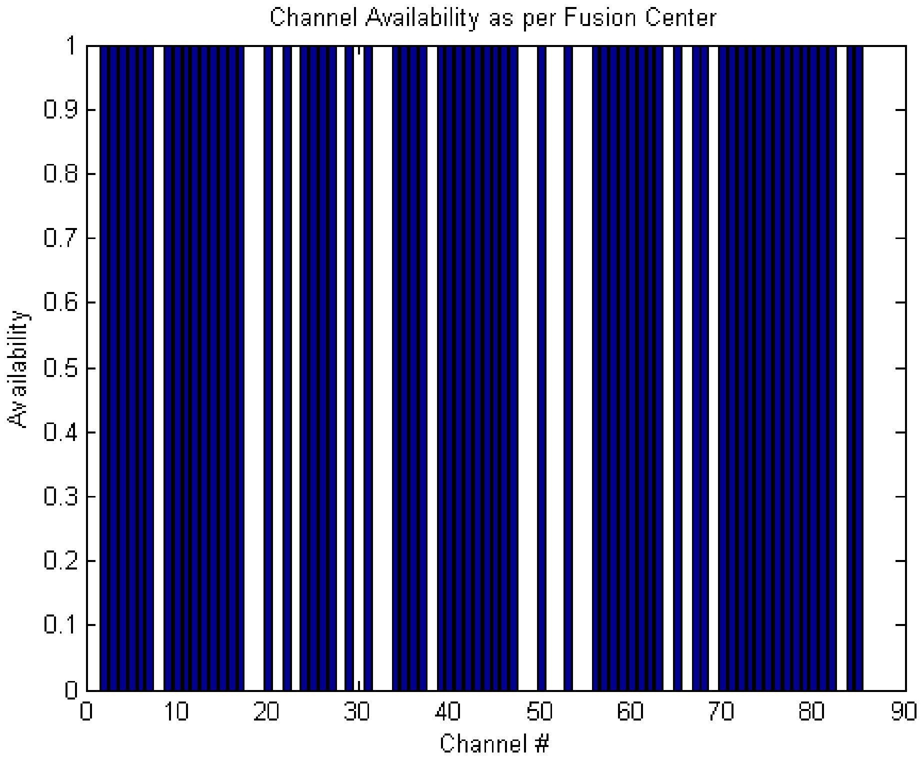

Figure 3.10: Channel Scanning results of FC

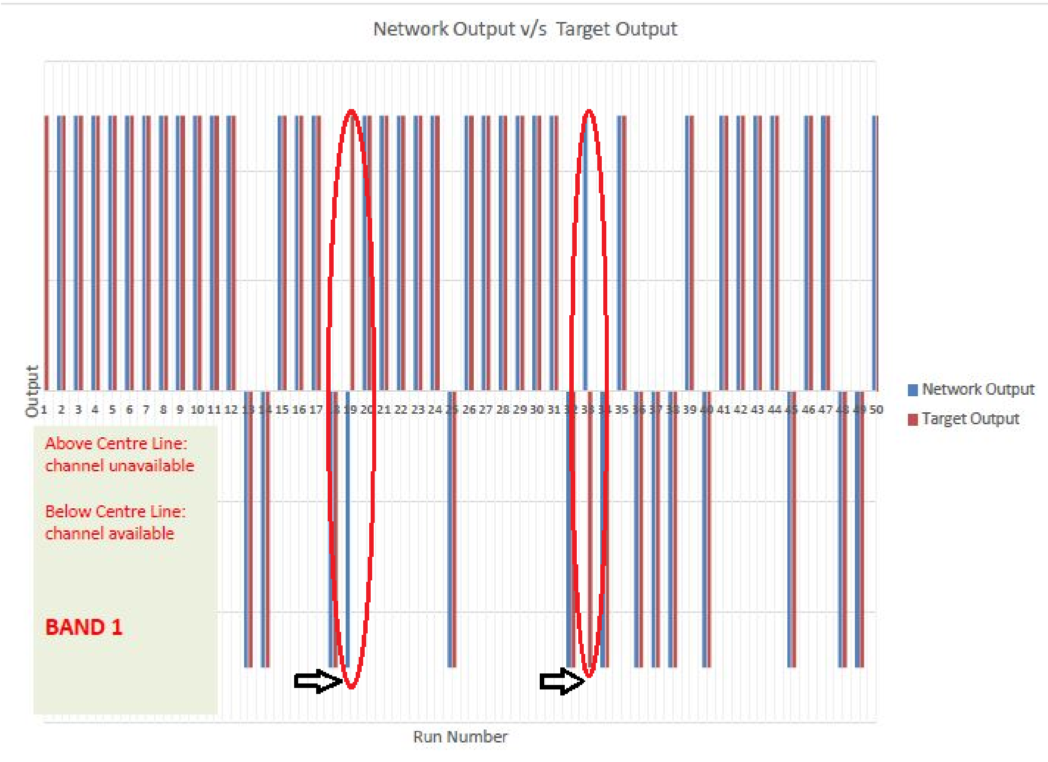

Figure 3.11: Perceptron network output versus target output of Channel 1(Band)

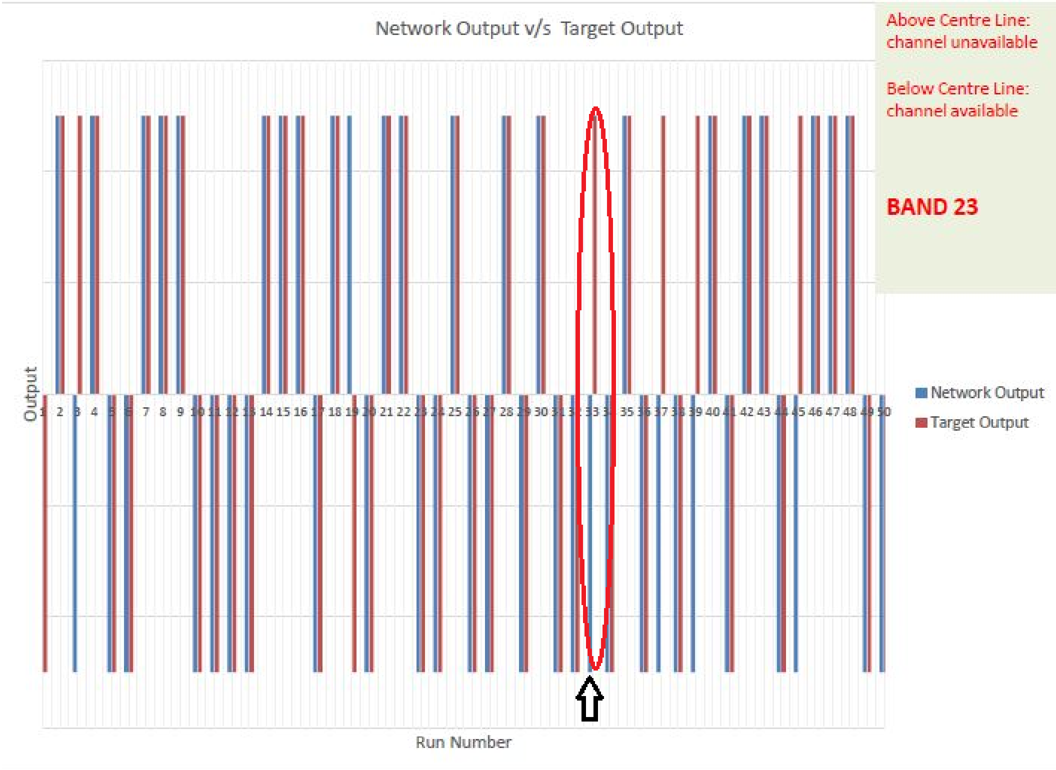

Figure 3.12: Perceptron network output versus target output of Channel 23(Band)

network output and that is an error instance. It was observed that for 50 iterations (different secondary user positions), we have less than 10% error rate. Here, we have depicted the performance for only Channel 1 and Channel 23. The network output of the algorithm meets the target false-alarm rate of 0.1 for all the simulations conducted.

3.5 Unsupervised k-means clustering based Decision fusion scheme

Due to the dynamic channel environment, feature vectors are scattered in decision boundary which affects the detection accuracy of FC. To overcome this, we have developed unsupervised K-means clustering approach which partitions set of training energy vectors into K disjoint clusters. Compared with Perceptron learning, this unsupervised K- means clustering is a promising approach due to

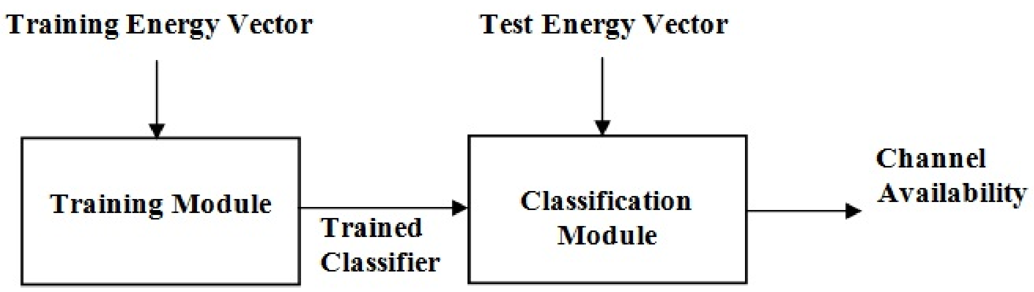

Figure 3.13: Schematic representation of learning module for proposed CSS scheme

its higher detection accuracy and less training and classification delays.

Learning algorithms can broadly be categorized as either Supervised or Unsupervised learning [Bkassiny *et al.* 2013]. Unsupervised learning may particularly be suitable for diverse RF environment to make decisions and actions without prior knowledge. In this framework, we propose to use unsupervised K-means clustering algorithm to make cooperative decisions about channel availability. Before discussing the algorithm, it is necessary to look into the schematic representation of the learning module shown in Fig.3.13. It consists of training module and classification module. The training energy samples are fed in to the training module which provides trained energy vectors to the classification module.

Generally, the training procedure of machine learning takes long time. To overcome this, the training module can be activated only during the initial CR deployment and reactivated if any changes in primary network radio configurations occur. The classification module helps to determine the channel availability with the help of test energy vector. In order to achieve low classification delay, it is necessary to choose suitable classification algorithm with low complexity.

K-means clustering is an iterative, data partitioning algorithm that assigns number of observations to exactly one 'K cluster' defined by centroids, where K is chosen before the algorithm starts. It partitions data into K mutually exclusive clusters, and returns the index of the cluster to which it has assigned each observation. It finds a partition in which objects within each cluster are as close to each other as possible, and as far from objects in other clusters as possible. Each cluster in the partition is defined by its member objects and its centroid. The centroid for each cluster is the point to which the sum of distances from all objects in that cluster is minimized. The centroid of each cluster is used for classification. Once the classifier is trained, it is ready to receive test energy vectors for classification. K-means clustering aims to partition the observed energy vectors in to K clusters (c1, c2,..ck) so as to minimize the distance of vectors within cluster by using distance measure. The partitioned clusters are passed using 'argmin' function as mentioned in equation (3.7).

$$\underset{c_1,c_2,....c_k}{argmin} \sum_{k=1}^{K} \sum_{Y^L \epsilon C_k} \left\| Y^L - \alpha_k \right\|^2 \tag{3.7}$$

where C_k is the set of training energy vectors that belong to cluster K, Y^L is complete training energy vectors, α_k is called Centroid of cluster K and $||.||^2$ is known as Square of Euclidean distance. After training, the classifier receives test energy vector for classification. The classifier classifies based on the following condition,

$$\frac{||Y^* - \alpha_1||}{min_{k=1,2,...K} \, ||Y^* - \alpha_k||} \geq \beta \tag{3.8}$$

where Y^* is known as test energy vector received by classifier, α_k is the centroid for cluster K and β is called threshold to control trade-off between false alarm and detection probabilities. The algorithm works as follows. First, it Partitions the set of energy data into k disjoint clusters. The centroid of first cluster (for which the class is available) is the mean of the data for which class is available. All the other data is divided into separate K clusters such that within squares sum of distances is minimized for all these K clusters. For the given training energy vectors, the data is first divided into two parts. One is for those for which the class is available, and the other for those for which class is unavailable. All the other data is divided

Algorithm 3: Proposed CSS scheme using k-means clustering algorithm

Input energy(i,j) //Stores energy values of j^th SU for the i^th band;
Initialize local decision(j,i);
$Y^L \leftarrow$ Training energy vectors;
$Y^{L,k} \leftarrow C_k$ //partitions training vectors into K disjoint clusters (C);
$\alpha_k \leftarrow \mu_i$ //Initialize centre of cluster to determine Centroid α_k, where $i = 1, 2, .., k$;

for *each cluster k* **do**
  $Y^{L,K} \leftarrow |\alpha_k|^- 1 \sum_{Y^L} \epsilon \alpha_k Y^L, \forall_k = 1, 2, .., k$
  //calculating mean of all training energy vectors in cluster k
  $Distmeasure \leftarrow$ Euclidean $\|$ Cityblock
  // for minimizing distance of energy vectors to local minima
$CH \leftarrow H_0|H_1$
// each SU reports its sensing decision to FC
$CH \rightarrow$ global decision
// FC declares final decision based on suboptimal solution through convergence

into K clusters, where K varies from 1 to 10.

For classification of test energy vectors, the classifier determines if the test energy vector belongs to cluster 1 or other clusters, based on the distance of the test energy vector to the centroids. We have considered two distance measures namely Euclidean and Cityblock. The Euclidean distance examines the root of square differences between coordinates of a pair of objects. Similarly, the Cityblock distance examines the absolute differences between coordinates of a pair of objects. The classifier classifies the test vector as channel unavailable if the distance d is greater than β which is a tunable parameter. The value of this tuning parameter varies from 0.1 to 0.3 which indicates the permissible value of 'P_f' as per IEEE 802.22. The steps involved in unsupervised K-means clustering based CSS scheme is shown in Algorithm 3.

The performance of unsupervised K-means clustering algorithm for CSS scheme has been summarized on Table 3.1 and 3.2 using Euclidean and Cityblock distance metrics.

Table 3.1: Performance Summary of k-means clustering based CSS scheme using Euclidean Distance metric

No of clusters	Training observation	Training Delay	Test observation	Test delay	Detection accuracy
2	1634	0.0097	86	0.0289	69.76
3	1634	0.0117	86	0.0470	69.76
4	1634	0.0157	86	0.0543	69.76
5	1634	0.0168	86	0.0750	69.76

Table 3.2: Performance Summary of k-means clustering based CSS scheme using Cityblock Distance metric

No of clusters	Training observation	Training Delay	Test observation	Test delay	Detection accuracy
2	1634	0.0116	86	0.0369	60
3	1634	0.0119	86	0.0506	60
4	1634	0.0121	86	0.0661	60
5	1634	0.0129	86	0.0757	60

The following observations can be drawn from above summary. The variation of training delay with respect to number of clusters is less under Cityblock than Euclidean. There is less deviation on delay time for test energy vectors under both distance metrics. It is important to note that the detection accuracy remains same under both distance metrics. Also, the rate of detection accuracy satisfies the permissible limit given by IEEE 802.22.

To get an idea of how well-separated the resulting clusters are, we can make a silhouette plot using the cluster indices output from K-means. The silhouette plot displays a measure of how close each point in one cluster is to points in the neighboring clusters. This measure ranges from +1, indicating points that are very distant from neighboring clusters called 'well-formed clusters', through 0, indicating points that are not distinctly in one cluster or another called 'ill-formed clusters', to -1, indicating points that are probably assigned to the wrong cluster called 'outliers'. Silhouette returns these values in its first output. The Silhouette plots using Euclidean distance metric for different values of K are shown in Fig.3.14.

Similarly, the Silhouette plots for Cityblock distance measure are shown in Fig.3.15 for various cluster values. With K = 2 clusters are formed from the data for which the channel is unavailable, the data points are scattered into two clusters

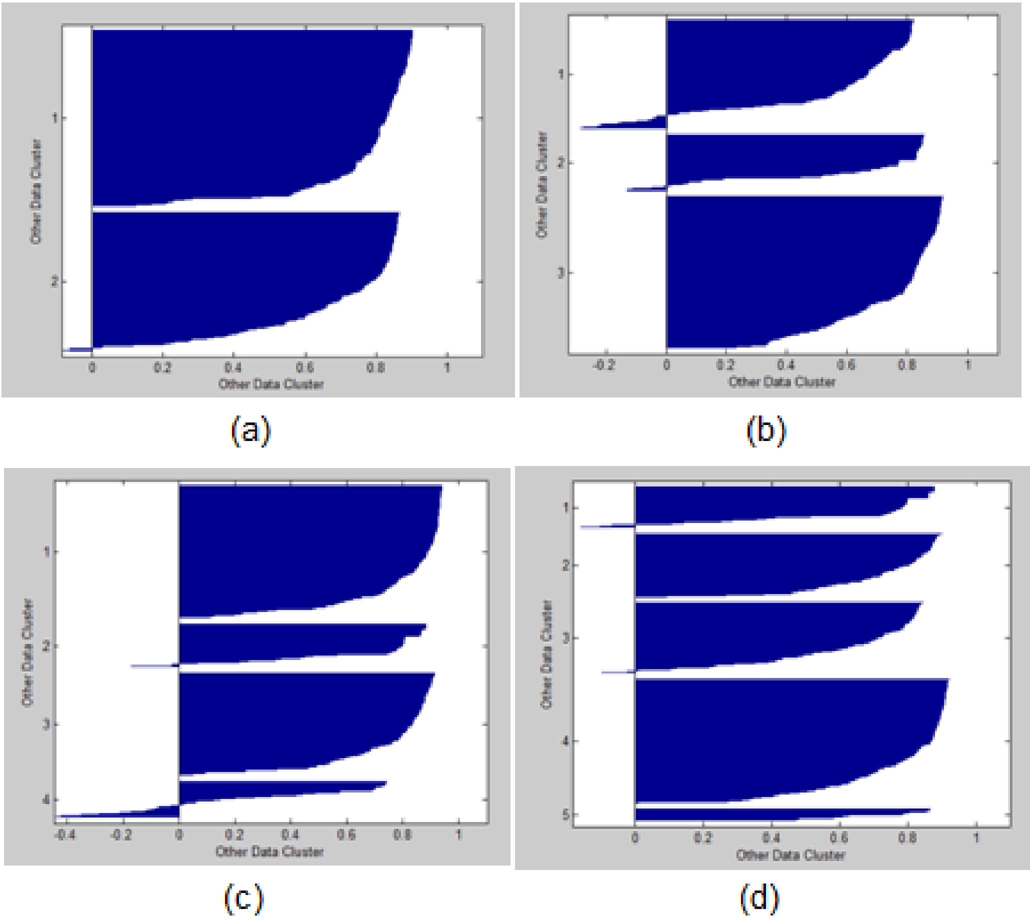

Figure 3.14: Silhouette plot for Euclidean distance measure: a)K=2 b)K=3 c)K=4 d)K=5

as shown above. The Silhouette Graph shows that both clusters are very well-formed with no outliers classified. Also, majority of data points in each of the clusters have their index greater than 0.6, which shows that the clusters have been formed tightly by the data points. With K = 3 clusters are formed from the data for which the channel is unavailable, the data points are scattered into 3 clusters as shown in Fig.3.15. The Silhouette Graph shows that cluster 1 and 2 are well-formed, with cluster 1 having some outliers data points. However, cluster 3 has a large number of outliers, hence cannot be classified as well-formed. With K = 4 clusters are formed from the data for which the channel is unavailable, the data points are scattered into 4 clusters as shown in Fig.3.15.

The Silhouette Graph shows that only cluster 1 and cluster 3 can be thought

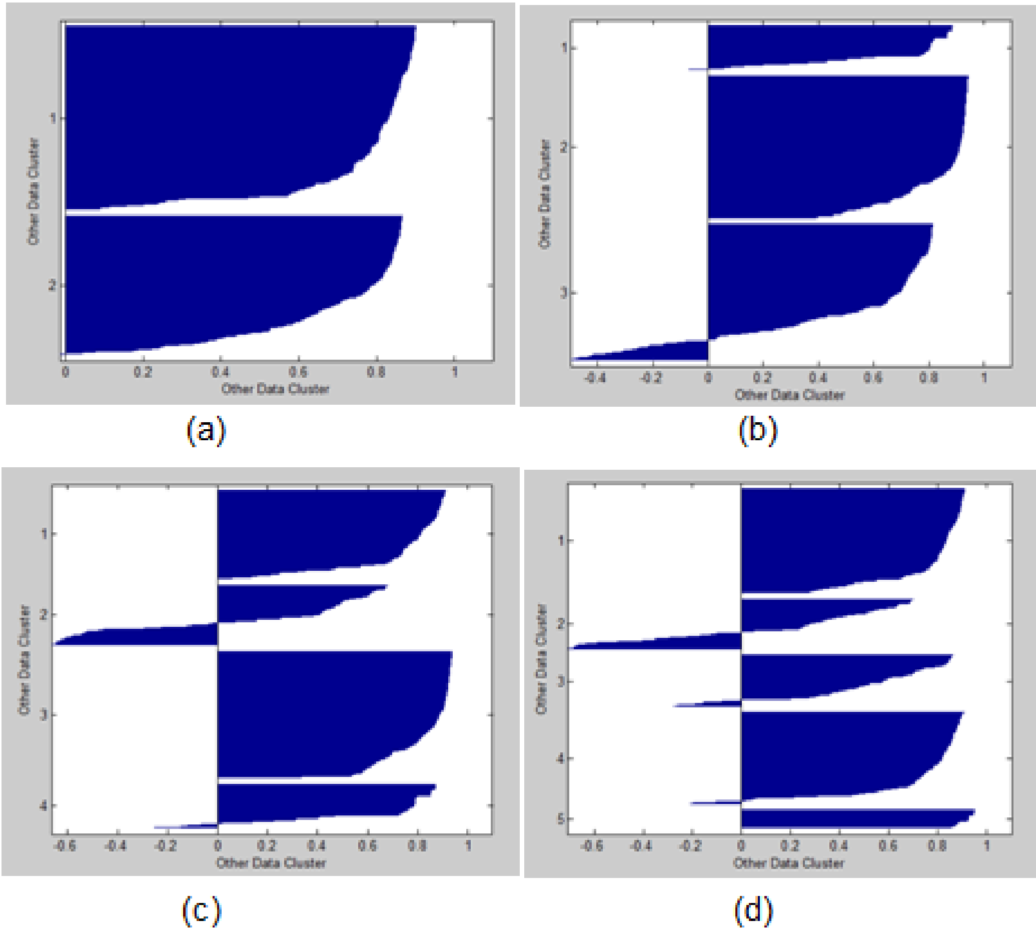

Figure 3.15: Silhouette plot for Cityblock distance measure: a)K=2 b)K=3 c)K=4 d)K=5

as well-formed. However, cluster 2 has large number of data points specified as outliers. Also, cluster 4 is not well-formed because of the outliers shown in the Fig.3.15. With K = 5 clusters are formed from the data for which the channel is unavailable, the data points are scattered into 5 clusters as shown above. The Silhouette Graph shows that only cluster 1 and cluster 5 are well-formed. However, cluster 5 is small as it contains less number of data points. All other clusters have outliers classified within them and hence cannot be thought of as well-formed.

The simulation results show that the unsupervised K-means clustering algorithm significantly improves detection accuracy with training and testing delay of 16.8 and 75 milliseconds respectively. Further, it is observed that unsupervised K-means clustering is a promising approach for CSS due to its high detection performance with low classification delay and training duration. However, k-means clustering approach provides an average view on data points which will affect its detection performance under pathloss and shadowing environment. To address this issue, in the next section, we propose Archetypal clustering based CSS scheme which provides an extremal view on data points.

3.6 Archetypal clustering based CSS scheme

In this section, we discuss the formulation of CSS scheme using Archetypal Clustering approach. Archetypal Analysis is a statistical matrix decomposition technique proposed by Cutler and Breiman [Cutler & Breiman 1994] as a new dimensionality reduction method. It finds the smallest convex hull with k points, which can best represent the input data. This can be further adapted for clustering as the data points can be expressed as a linear combination of these pure types called archetypes. The traditional prototypes, which give a measure of the average of a group, fail to describe the clusters with arbitrary shape. Secondary Users need to be clustered in a way which minimizes the effects of fading and correlated shadowing. An extremal view of the SUs while clustering proves to be more efficient and reliable.

A typical CSS model consists of a Primary transmitter, Fusion Center (FC) and Secondary Users (SUs). The FC takes input from the SUs and predicts if the PU is active or not. The proposed algorithm is a Hierarchical model with two stages of operation. The method requires the SUs to be clustered based on their position. A cluster head is chosen for the coordination between the cluster and the FC. The lower stage of operation is within a cluster, where each cluster head predicts the presence of PU based on the information it receives from the SUs. The cluster head sends its decision to the FC where the second stage operations take place. The FC predicts a global decision by considering all the cluster decisions. The steps involved in the proposed CSS scheme are shown in Algorithm 5.

Algorithm 4: ArchetypalClustering

Input : X (SUs position),K (Number of Archetypes), T(Number of iterations)
Initialize $Z = [z_1, z_2, \dots z_K]$ where z_i are random columns from X
Initialize B such that $Z = XB$
for $t = 1$ to T **do**
  for $i = 1$ to $NoOfNodes$ **do**
    $A_i \in \arg\min_{A \in \Delta_k} \|x_i - ZA\|^2$
  end for
  $RSS = X - ZA$
  for $j = 1$ to K **do**
    $B_j \in \arg\min_{B \in \Delta_n} \| \frac{1}{\|A^j\|^2} R(A^j)^T + z_j - XB\|_2^2$ {A^j refers to the j^{th} row of A}
    $R = R + (z_j - XB_j)A^j$
    $z_j = XB_j$
  end for
end for
for $i = 1$ to $NoOfNodes$ **do**
  $idx_i \in \arg\min_k \|z_k - x_i\|^2$ {Cluster SU based on nearest archetype}
end for
return idx

Cluster Head Decision: The local observation of energy vectors from each SU varies due to path-loss and shadowing effect. The formation of clustering reduces this uncertainty to some extend. The locally predicted decisions of the SU based on the threshold are further processed by the corresponding cluster heads. The cluster heads are determined by clustering the SU's using Archetypal Analysis.

Given a data matrix, Archetypal Analysis decomposes the matrix into a collection of extreme points(archetypes) and coefficient vectors. The coefficient vectors provide a relationship between the data and the archetypes. Consider a matrix which represents the position of SU's $X = [x_1, x_2, \dots x_N] \in R^{n*m}$ where each x_i is a vector denoting the position of i^{th} secondary user. The Archetypes $Z \in R^{m*k}$ are computed under two constraints

1)The data should be approximated by a convex combination of the Archetypes, that is the Residual Sum of Square (RSS) has to be minimized.

Algorithm 5: Archetypal Clustering based CSS Scheme

Initialisation : X (Position of SUs), K (Number of Archetypes), T (Number of iterations)
$threshold$ = qfuncinv(P_{FA})/sqrt(T)+1
$Energy$ = EnergySense($X, PrimarySignal$)
for $i = 1$ to $NoofNodes$ **do**
  if ($Energy_i > threshold$) **then**
    $LocDecision_i = 1$
  else
    $LocDecision_i = 0$
  end if
end for
(idx) = ArchetypalClustering(X, K, T)
for $j = 1$ to K **do**
  $ClusterDecision_j = \bigvee_{i \in ch_j} LocDecision_i$ {ch_j is a set of all SUs which belong to j^{th} cluster }
end for
$FinalDecision$ = Perceptron($ClusterDecision$)
return $FinalDecision$

$$RSS = \|X - AZ^T\|^2 \tag{3.9}$$

2)The Archetypes can be represented as a convex combination of the Data points.

$$Z = X^T B \tag{3.10}$$

Here A is an $n * k$ matrix where $\sum_{j=1}^{k} A_{ij} = 1$ and $A_{ij} > 0$ and $i = 1, \ldots n$. Similarly B is also an $n * k$ matrix where $\sum_{i=1}^{n} B_{ij} = 1$ and $B_{ij} > 0$ and $j = 1, \ldots k$
Combining the two equations we get an optimization problem,

$$\min_{A,B} \|X - XB^T A\| \tag{3.11}$$

The values of matrices A and B are obtained by solving [Chen *et al.* 2014] the equation (3.11) as shown in Algorithm 4. Δ_n refers to a simplex with n dimensions. The Archetype matrix Z computed, is used to cluster the SU. Each SU is assigned to one of the K clusters by determining the closest archetype. The cluster head is

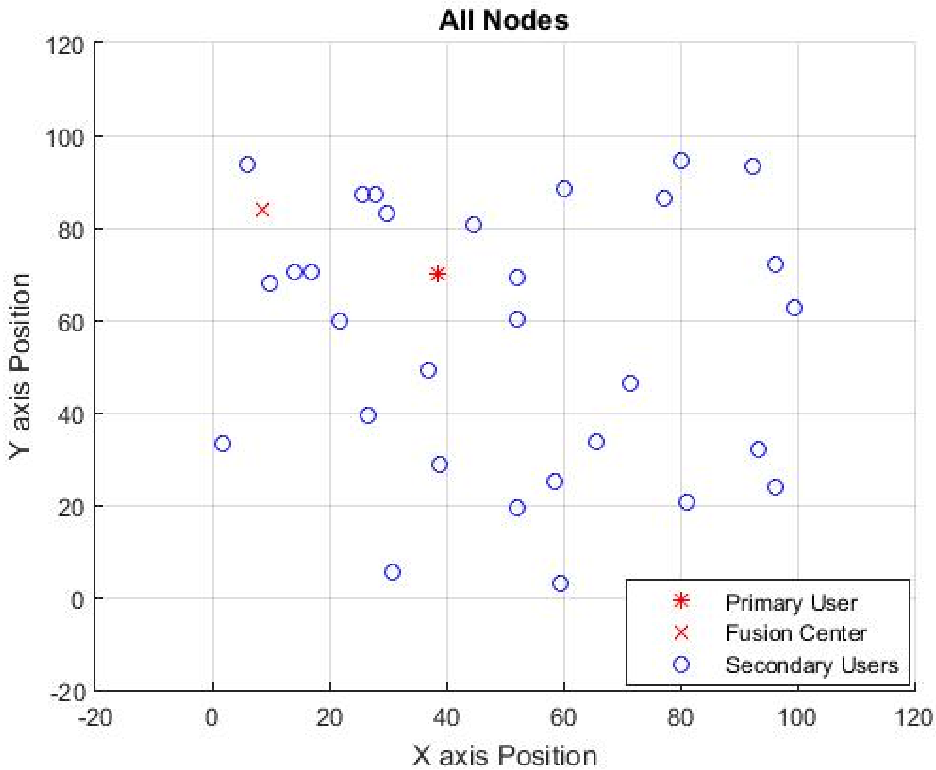

Figure 3.16: Position of SUs

randomly selected among the SUs present in the cluster. The cluster head receives a vector from all the secondary users present in the cluster indicating their local decision. The decision at a cluster is calculated by taking an OR of every bit in the vector. The cluster decision at each cluster head is sent to the Fusion Center(FC).

The implementation of Archetypal model is carried out using SPAMS toolbox [Chen *et al.* 2014]. The performance of the algorithm has been verified with the help of Receiver Operating Characteristics (ROC) curves in MATLAB. CR simulation scenario developed with one primary transmitter and 30 SUs deployed randomly in a grid topology of $100m \times 100m$. The other important simulation parameters are as follows: Number of intervals T is 1000, Number of cluster K is 5, and target P_{FA} is 0.1. The Fig.3.16 shows the snap-shot of CR deployment scenario. The multiple SUs are randomly deployed and the distance coordinates of each SU varies during each iteration. The value of SNR for each SU changes based on the distance from primary transmitter. Each SU identifies the channel

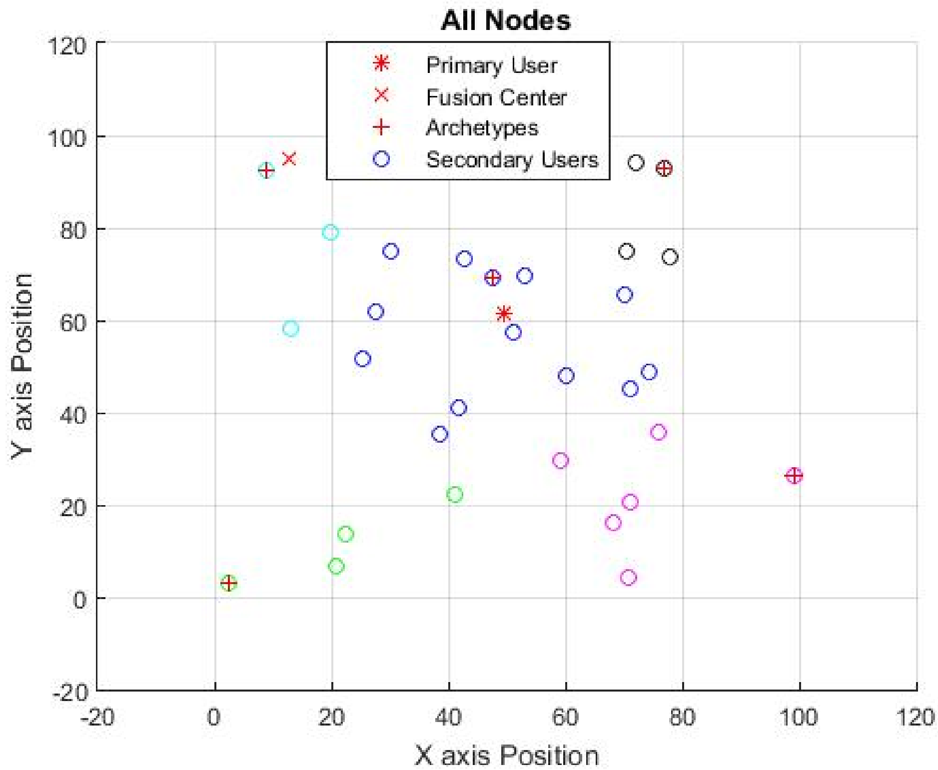

Figure 3.17: Clustering using Archetypal analysis

availability by scanning the complete set of primary frequency bands. The formation of clustering using Archetypal analysis is shown in Fig.3.17. It is observed that the convex combination of Archetypes provides an extremal view of position of SUs.

The ROC curve in Fig.3.18 depicts the detection performance of the proposed CSS scheme. It is noted that Support Vector Machine (SVM) achieves better detection performance compared with Perceptron learning. But its performance is compensated with high computational complexity. Interestingly, the Archetypal clustering gives high detection performance with less computational complexity.

Another ROC curve in Fig.3.19 shows that the sensing performance of Archetypal clustering is higher than K-means clustering scheme. As we stated earlier, the k-means clustering algorithm provides an average view on data points, whereas Archetypal clustering gives extremal view. Therefore, it performs better under pathloss and shadowing environment.

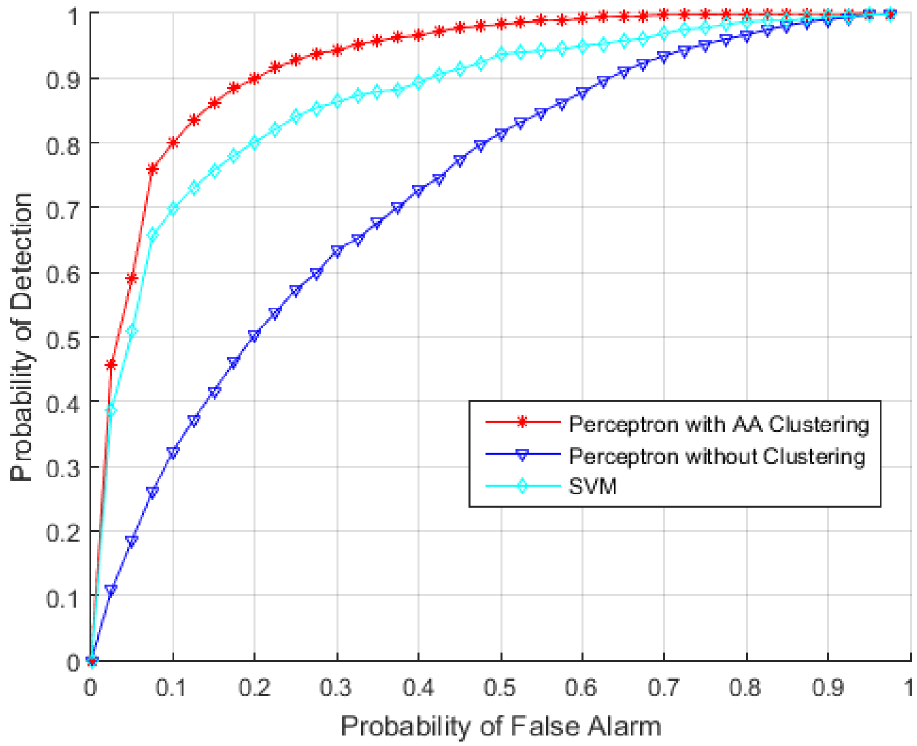

Figure 3.18: ROC Curve in comparison with SVM using 200 training samples for each classifier

Table 3.3: Comparison among different CSS classifiers

Algorithm	Training Duration	Classification Delay	ROC Performance
Perceptron without Clustering	Normal	Normal	Low
SVM with polynomial	High	Normal	Normal
Perceptron with Clustering	Low	Low	High

The graph shown in Fig.3.20 depicts the ROC performance for different number of cooperative SUs (10, 20, 30 and 50). It can be observed that the performance of clustering improves significantly for large number of SUs. Therefore, the detection uncertainty due to more users can be overcome with the help of Archetypal clustering in CSS.

Table.3.3 gives a qualitative comparison of different CSS classifiers used in our simulation. It is observed that the SVM classifier gives better ROC performance, but it takes long training duration due to its high computational complexity. Compared with other two classifiers, perceptron with clustering performs better with low training and classification delay, and high ROC performance.

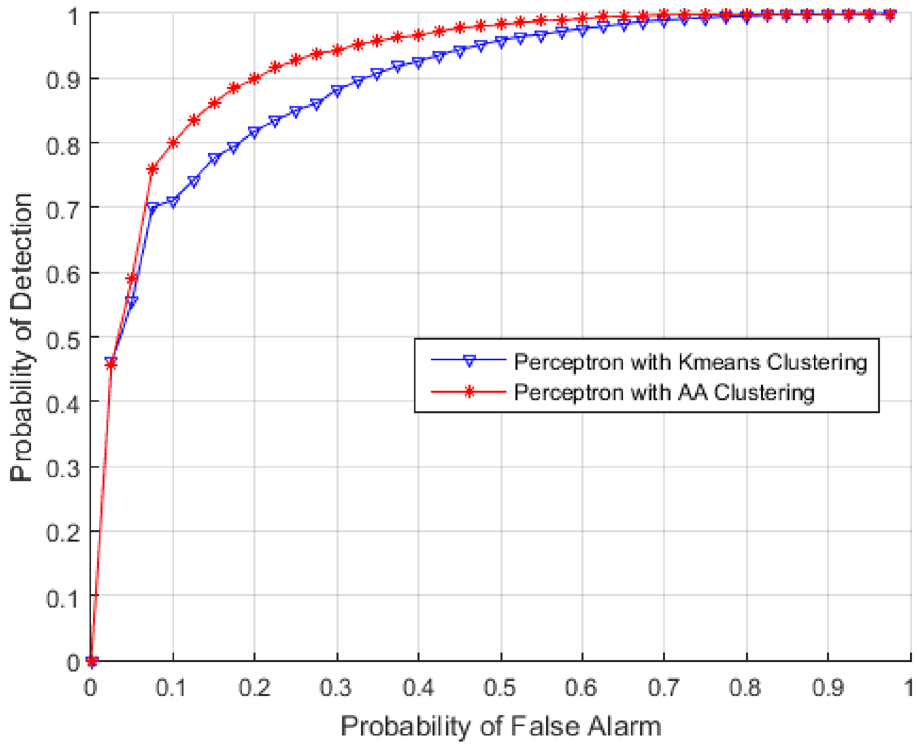

Figure 3.19: ROC Curve in comparison with K-means using 200 training samples for each classifier

It can be observed from ROC performance results that Archetypal clustering based CSS scheme achieves the detection probability of 82% to meet the target false alarm probability of 0.1. It is also noted that Archetypal clustering gives low classification delay and training duration compared with Support Vector Machine (SVM).

Cooperative learning ability is important for cognitive radios for effective decision making. Cooperative learning algorithms are implicitly built into spectrum knowledge acquisitions and decision making algorithms in the sense that they convert information (current and past observations) into decisions and actions. In this chapter, we discussed cooperative spectrum sensing algorithms using perceptron learning scheme and Unsupervised clustering approaches. The received energy vectors of each SU are considered as feature input vectors of cooperative learning module at Fusion Center. The received SNR of each SU varies based on

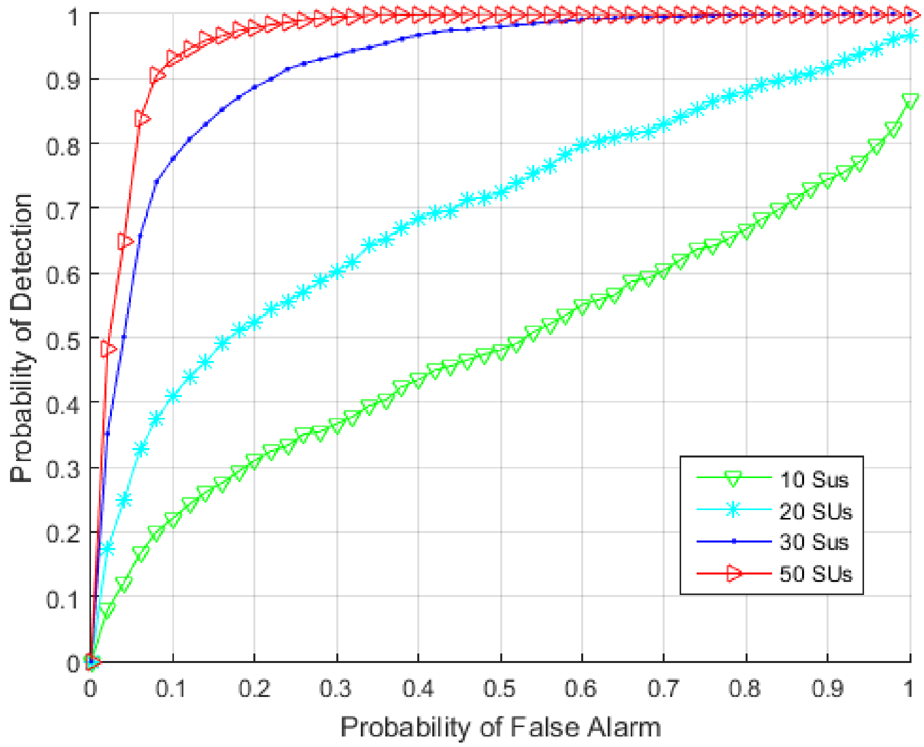

Figure 3.20: ROC Curve of Archetypal Clustering with different number of SUs

distance coordinates. We modelled the CSS scheme under path-loss and shadowing environment. The proposed CSS scheme has the capability to learn from the radio environment to achieve cognitive tasks. Further, it is observed that the cooperative learning module improves the decision capability of FC and significantly reduces the error rate to meet the target false-alarm probability rate to 0.1.

In the next chapter, we present Reinforcement Learning (RL) based CSS scheme with the objective of improving cooperative sensing accuracy by maximizing expected cumulative reward. Using reinforcement learning, the Fusion Center(FC) makes a global decision by interacting with the radio environment which consists of cooperative SUs and primary transmitter.

Chapter 4

Reinforcement Learning based Decision Fusion Scheme for Cooperative Sensing

4.1 An Introduction to Reinforcement Learning

Reinforcement learning [Sutton & Barto 2011] is a type of machine learning technique in which a software agent interacts with the environment and takes decisions to maximize the rewards that it receives from the environment. Reinforcement learning is different from other machine learning algorithms due to the fact that it can adapt to dynamic conditions. The reinforcement learning model contains three main components: states, actions and rewards as shown in Fig.4.1. The entity that is interacting with the environment will be referred to as the agent. The system has a start state and end state, and has many intermediate states in the middle. This transition between states is done by choosing actions at each state based on a state transition probability.

There are many methods which can be used to calculate this probability like the Boltzmann equation [Kaelbling *et al.* 1996], which will be discussed later in

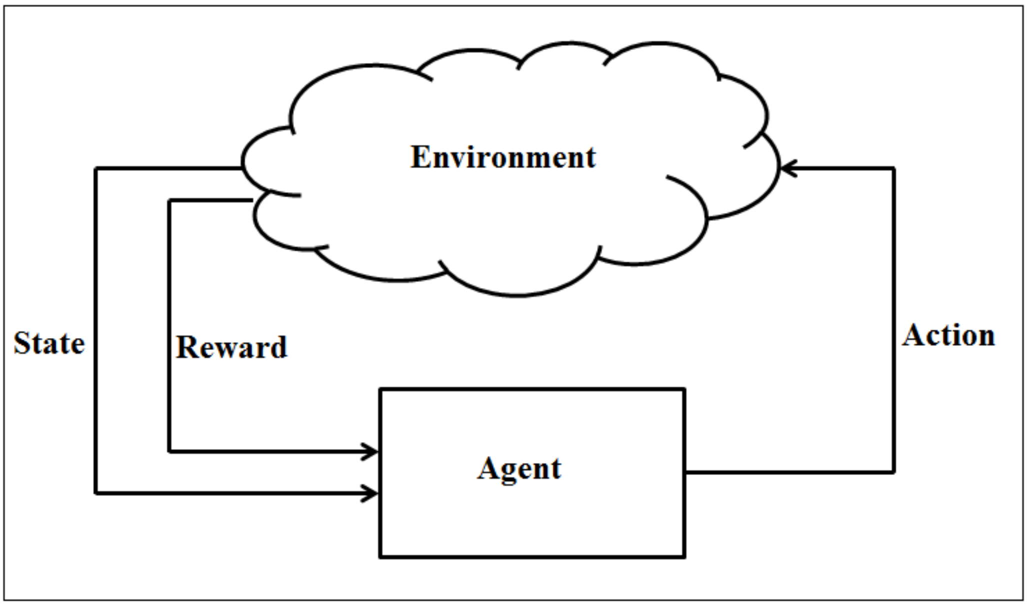

Figure 4.1: Simplified RL model

detail. After executing the actions the agent receives a reward by interacting with the environment. The agent then calculates the value of the actions that it has taken and updates the state transition probability. Therefore the agent takes into account the consequences that it faced after choosing previous actions while making its decision, and in a sense learns from its own mistakes.

4.1.1 Q-learning

Q-Learning [Sutton & Barto 2011] is a dynamic programming based reinforcement learning technique in which we calculate the value of a set of actions using the cumulative reward of all the future states. This value calculation is done through the use of Bellmans equation [Bellman 1956] which is shown below.

$$Q^{\pi}(s) = R(s) + \gamma \sum_{s' \epsilon S} P_{s,\pi(s)}(s') Q^{\pi}(s') \tag{4.1}$$

In equation (4.1) π is the sequence of actions that has been selected with one action for each state. In the above equation $Q^{\pi}(s)$ is the value variable which contains the value obtained by following the policy π. This is calculated by adding the immediate reward with the cumulative values of all future states after taking a particular action. γ is the discount factor given to each of the future states, in order to decrease the weight of reward in the future compared with immediate reward. In the above equation S denotes all possible states that the agent can go to upon taking the action '$\pi(s)'$. $P_{s\pi(s)}(s')$ is the probability of that taking the action stated in the policy at state 's' leads to a transition to state 's'. This probability is known as the state transition probability whereas Q(s') denotes the value at state 's'. Therefore the summation shown above in the equation gives us the total expected reward of taking the action given in the policy π. Bellman's equation is explained in greater detail in [Bellman 1956].

There are two ways [Sutton & Barto 2011] of using this equation for implementing reinforcement learning. The first is value iteration and the second is policy iteration.

4.1.2 Value Iteration

Both Policy iteration and value iteration are stochastic dynamic programming versions of reinforcement learning. Value iteration is when we update the values of each state incrementally by maximizing the expected cumulative reward. In Value iteration the values for all states are initially set to zero and are updated incrementally until the values converge.

Algorithm 6: Value Iteration

Input: array of values for each state - Q, array of rewards for each state - $R(s)$
Initialization $Q(s) \leftarrow 0 \forall$ states S
while Q array has not converged **do**
  for $s = 1$ to $s = S$ **do**
    $Q^{\pi}(s) = R(s) + \gamma \sum_{s'} P_{s,a}(s') Q^{\pi}(s')$ {where $s' \epsilon$ all states reachable from s by choosing action a}
    $\pi(s) = a$
  end for
end while

As can be seen in Algorithm 6, the value will be updated in each iteration by optimizing the previously calculated values. After the value array converges, the $\pi()$ array will contain the optimal policy. In most practical applications of value iteration, the outer loop of this algorithm is run for a fixed number of iterations like 500 or 1000, depending on the characteristics of the system, thereby attaining a suboptimal solution. This is done because the cost of allowing the algorithm to run until the value array converges is very high, therefore we must make a trade-off between the optimality of the solution and the cost of each iteration. The next section covers the second algorithm for reinforcement learning namely, Policy Iteration.

4.1.3 Policy Iteration

Policy iteration is slightly different from Value iteration. In policy iteration we start with a random policy and keep updating the policy with each iteration. This algorithm consists of two steps, the first step is called policy evaluation and the second step involves policy updation. Policy evaluation is the process of calculating the value of the policy, $Q^{\pi}(s)$ in the current epoch by cumulatively adding the expected future rewards. In the policy updation step we use the newly updated value array from the previous step to choose the policy for the next iteration, by choosing the action with the highest value in the value array for each state. The goal of the algorithm is to calculate the optimal policy, therefore we repeat the above steps until the policy stops changing in each iteration i.e. it converges to the optimal policy. Both value iteration and policy iteration use a markov decision process to dictate the state transitions.

As shown in Algorithm 7, the first step updates the value array for the system through the use of Bellman's equation as stated above, while the second step chooses the action for each state that maximizes the value. In the first equation in the loop, we get a system of linear equations with 's' equations, where 's' is

Algorithm 7: Policy Iteration

Input: array of values for each state - Q, array of rewards for each state - $R(s)$, policy $\pi()$ for each state.
Initialization: $Q(s) \leftarrow 0 \forall$ states S
while $\pi()$ array has not converged **do**
$Q^{\pi}(s) = R(s) + \gamma \sum_{s'} P_{s,\pi(s)}(s')Q^{\pi}(s')$ {where $s' \epsilon$ all states reachable from s by choosing action $\pi(s)$}
$\pi(s) = \underset{a}{\operatorname{argmax}} \sum_{s' \epsilon S} P_{s,a}(s')Q^{\pi}(s')$
end while

the number of states, which upon solving gives us the values of all the states. Let us now compare both algorithms and analyze which one is better suited for the task of cooperative spectrum sensing. An important point to note is that this step is the most costly step in policy iteration, since it involves solving a system of linear equations. Therefore as the number of states increases, the complexity involved in this step also increases. Even then we chose policy iteration because policy iteration has been known to converge in fewer iterations than value iteration. Therefore we have to make a trade-off between number of iterations and the complexity of solving a system of linear equations. In conclusion we can state that when there are lesser than 15-20 states the policy iteration is preferred to value iteration as the difficulty of solving the system of linear equations is not too high plus the algorithm converges quicker than that of value iteration. Since we have taken an environment containing 10 cognitive radios, we chose policy iteration for the task of cooperative spectrum sensing.

4.2 Reinforcement Learning for Cooperative Spectrum Sensing

We have chosen the policy iteration technique for the process of Cooperative spectrum sensing due to the reasons stated in the previous section. This section will talk about how this method of policy iteration is adapted to fit the domain of cooperative spectrum sensing.

4.2.1 Elements of RL-Based CSS Scheme

The Markov Decision Process (MDP) [Lo & Akyildiz 2010] for the task of cooperative spectrum sensing is modelled as follows.

States: Each state in the MDP denotes the number of Secondary Users selected for the process of cooperative spectrum sensing. For example, state 1 implies that one SU has been selected for cooperative sensing, 2 implies that 2 cognitive radios have been selected and so on. The total number of states will be equal to the number of SUs that can be selected for spectrum sensing.

Actions: An action initiates a transition from one state to another. These actions are denoted by a_k which can take any value between 1 and 10 where each number denotes the secondary user being chosen in that step. Each of these actions has a particular probability of occurring. The probability of selecting action a_k in the state s_k is given below,

$$P(s_k, a_k = i) = \frac{e^{Q(s_k,a_k)/\tau_n}}{\sum_{j=1}^{n} e^{Q(s_j,a_j)/\tau_n}} \tag{4.2}$$

Equation (4.2) is an adaptation of Boltzmann equation, where τ_n, in the above equation denotes the temperature constant which dictates the extent of exploration vs exploitation of the agent in the MDP. Exploration is the property of the agent to explore more states in order to attain a greater reward. Exploitation is the property of the agent to give a higher weight to the actions with a greater immediate reward. In a sense exploration vs exploitation denotes whether the agent is taking an optimistic or pessimistic approach, if he prefers exploration then he assumes that the he will be able to get a greater $Q(s, a)$ value upon exploring more number of future states and vice versa for exploitation. The temperature variable

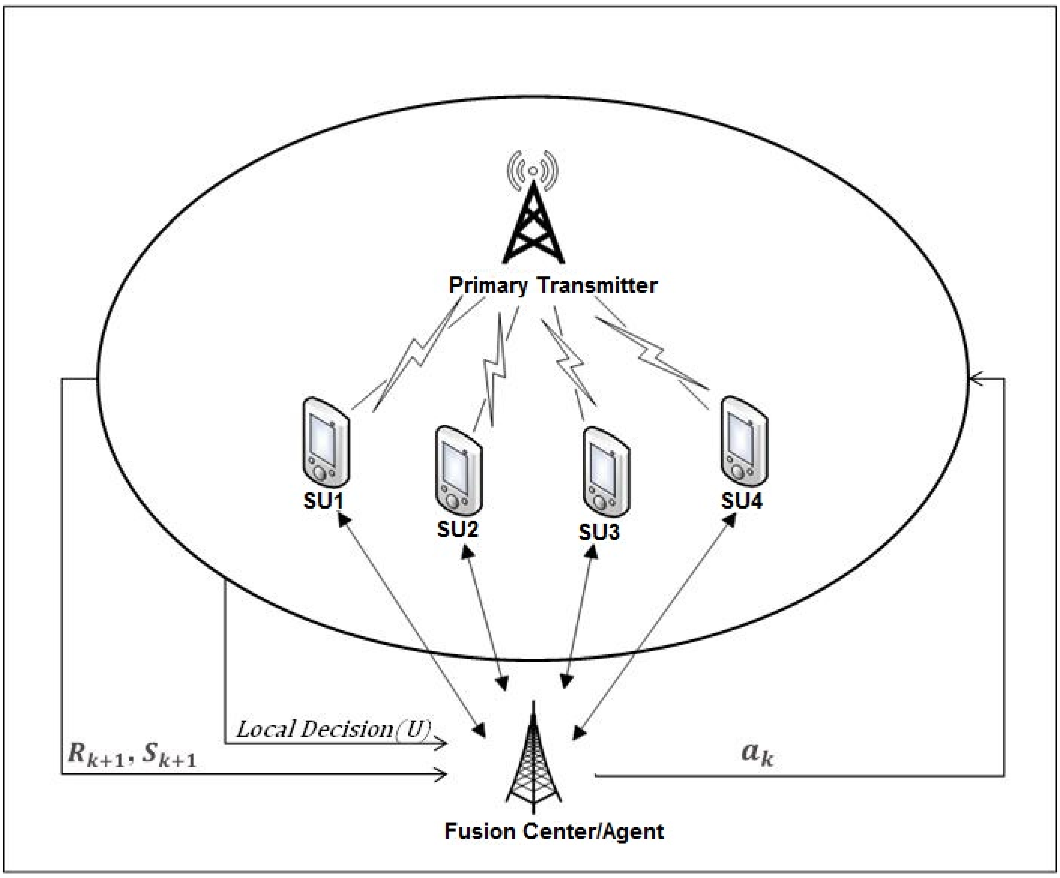

Figure 4.2: RL-Based Cooperative Spectrum Sensing Model

is decreased by a constant linear amount based on the initial τ_n value and the final τ_n value. The probabilities for each state action pair must be recalculated in each iteration as the probability function is dependent on the value array. Equation (4.2) is also known as the action selection strategy.

Reward function: The third and last criteria of an MDP is the reward function. The reward function maps each state transition with a quantifiable reward which denotes how good or bad a particular action was. Each reward depends on the current state of the algorithm and the action taken in that state. The reward function in our problem is based on two criteria. The first is the correlation between users and the second one is the mean ratio, which will be explained in greater detail later in this section.

The first criteria denoted by R_p, is based on correlation and is used to calculate reward as the sum of the correlation of the current SU in question with the previously selected SUs. Given ρ_{ij}, the correlation between two users i and j which calculated for each of the previously selected users(j) and the current state of the MDP k, we can calculate R_p using equation (4.3).

$$R_p = \sum_{m=0}^{k-1} \rho_{ij}(j = \pi(m)) \tag{4.3}$$

where ρ_{ij} is depending on the distance between i and j, d_{ij} and a decaying constant $(1/D_c)$ which is dependent on the characteristics of the environment. This constant is usually around 0.1204 and 0.002 for urban and suburban areas [Goldsmith 2005] respectively. Since we have used a suburban environment during our simulation study we used 0.006 as the decaying constant. Equation (4.4) shows the formula for calculating ρ_{ij}

$$\rho_{ij} = e^{-d_{ij}/D_c} \tag{4.4}$$

R_p is used as the reward in the cases where the correlation is close to zero.

As stated above, we are using two criteria to calculate the reward at each state. The second criteria for calculating reward is chosen to incorporate the effect of the noise experienced by a particular user in its sensing channel in the reward function, which we are going to call R_d. To do this we need to calculate a quantity, called the mean ratio (MN). To calculate the mean ratio of an SU we first calculate the ratio of the transmitted signal to the received signal and take the mean value of this signal. The next step is to calculate the exponential value of this mean. The formula for calculating MN is given below,

$$MN = e^{mean(\frac{[S_t]}{[S_r]})} \tag{4.5}$$

where S_t and S_r are the transmitted and received signals respectively. We have taken the exponential value of the mean to map the output into a higher range. The received signal contains noise and the transmitted signal is pure, therefore the mean ratio value denotes the affect due to noise on each user. Given the mean ratios for each state we can calculate R_d through equation (4.6).

$$R_d = \frac{\sum_{j=0}^{k} MN(s_j)}{\sum_{j=0}^{L-1} MN(s_j)} \tag{4.6}$$

where k is the state in which the user is currently in i.e. the number of SUs that have been selected up till the current state, L is the total number of users present and $MN(s_j)$ is the mean ratio for a user at the state s_j. Now let us discuss how to calculate the actual reward using R_p and R_d. The reward takes into consideration both of the previously stated criteria and calculates the final reward $r_k(s_k, a_k)$ by using the following formula,

$$r_k(s_k, a_k) = \begin{cases} 1 - R_d & R_p = 0 \\ -R_p & R_p \neq 0 \end{cases} \tag{4.7}$$

This reward is then input into Bellman's equation for each state to find the value of all the states as $R(s)$. In our algorithm, we use a slightly modified version of Bellman's equation which is stated below,

$$Q(s, a) = R(s) + \sum_{\forall s'} P(s, a) \sum_{\forall a'} Q(s', a') \tag{4.8}$$

This equation is explained in greater detail in the next section. Our goal is to maximize the reward that we can attain by selecting the optimal set of users that help us maximize this reward by the end of the algorithm. The complete algorithm has been described in following section.

Algorithm 8: Policy Evaluation

Input: $\pi \leftarrow$ initial randomized policy array $Q \leftarrow$ 2D values array
Initialization: $Q(s,a) \leftarrow 0\ \forall$ states and actions, $len \leftarrow length(\pi)$
for $i = 1$ to len **do**
  if $i = len$ **then**
    $R(i) = 1 - R_d(i)$
  else if $correlation$ = 0 **then**
    $R(i) = 1 - R_d(i)$
  else
    $R(i) = -R_p(i)$
  end if
end for
$Q(s,a) = R(s) + \sum_{\forall s'} P(s,a) \sum_{\forall a'} Q(s',a')$
return Q, R

4.3 Algorithm Design of RL-Based CSS Scheme

The optimal solution of the proposed algorithm is based on policy iteration and has been divided into three phases, namely Policy Evaluation, Policy improvement and Calculating Global decision. The general description of the first two phases has already been explained in Section 4.2. This section will describe how these methods are specifically adapted for the task of cooperative spectrum sensing. All three of these sub-algorithms can be seen in algorithms 8, 9 and 10 respectively.

The first step is to initialize a random policy $\pi(s)$ and use it as an input to the RL algorithm. Algorithm 8 then takes the most recent policy and provides it as an input for the reward function to calculate the reward for each state for the given policy. There are a few changes that need to be made to the formula stated in the previous subsection for reward calculation. Firstly if all the nodes have been selected then we must consider $1 - R_d$ for the reward as there are no more users left to select in the next step. If the correlation between the new user with the previously selected users is zero then $1 - R_d$ is used to calculate the reward. The conditions for correlation to be considered as zero will be discussed in next sub-section. If none of these conditions are satisfied, $-R_p$ is used to calculate reward.

Algorithm 9: Policy Improvement

Input: $R \leftarrow$ reward array, $Q \leftarrow$ 2D value array
Initialization: len_st = total number of SUs, len_act = total number of actions, $max = 0$
for $i = 1$ to len_st **do**
  for $j = 1$ to len_act **do**
    if $q(i,j) > max$ **then**
      if $j \notin \pi()$ $||$ $correlation$=0 $||$ distance_PU(j)<60 **then**
        $max = Q(i,j)$
        $maxj = j$
      end if
    end if
  end for
  $\pi(i) = maxj$
  s(i) = $\pi(i)$
end for
For each of the remaining states chose the action with the highest value
return π, s

After calculating the rewards, the current policy needs to be evaluated using these rewards. This is done in the last step of the algorithm. A slight modification has been made to Bellman's equation in this algorithm as mentioned previously. Since we are considering a 2D value array with state-action pairs, when the agent chooses the action a, we cannot only restrict the algorithm to future states. In this case, it is necessary to consider separate states for each state action pair. This is where the inner summation in the last step comes into play. For the state-action pairs that were not a part of the equation in step, the values are calculated simply as the individual reward of selecting an action (a) in that particular state(s).

Algorithm 9 deals with the policy improvement section by using the newly updated value array. In this algorithm we iterate through each action for every state in the value array and chose the action with the highest value function, provided it satisfies a few conditions.

1. That action should not have been selected already as a part of the policy in

this iteration.

2. The users should not be correlated

3. The distance between each SU and primary transmitter should be less than 60 meters.

If these three conditions are satisfied then we will get an optimal set of users which should be used for cooperative spectrum sensing. To complete the policy for the remaining states we just select the actions that have the highest value for each state. Both algorithms 8 and 9 are iterated until the policy converges.

Algorithm 10: Global Decision

```
Input: s ← list of selected nodes, distances
Initialization: nodes ← length(s)
for i = 1 to nodes do
   sum = sum + distances(s(i))
end for
for i = 1 to nodes do
   weight(i) = avg/distance(s(i))
end for
normalize the weight() values
for i = 0 to nodes do
   temp = temp + weight(i)×decisions(s(i))
end for
if temp > 0 then
   d = 1
else
   d = 0
end if
return d
```

Lastly, Algorithm 10 takes a weighted combination of the decisions made by each of the selected users and outputs the final global decision. The weights of each user are calculated using the distances of each Secondary User from the fusion center such that the weights are inversely proportional to the distances and the users closer to the FC are given a higher weight. The complete algorithm for RL-Based Cooperative spectrum sensing can be viewed in Algorithm 11.

Algorithm 11: RL-Based CSS Algorithm

Input: $\pi \leftarrow$ policy, $Q \leftarrow$ 2D value array, distance $\leftarrow$ distances of SUs from FC
Initialization: Randomly select policy π, distances $\leftarrow$ store distances of all SUs from the FC.
while policy has not converged **do**
  [Q,R] $\leftarrow$ Policy Evaluation(π,Q)
  $[\pi, s]$ $\leftarrow$ Policy Improvement(Q,R)
end while
D $\leftarrow$ Global Decision(s,distances)
return D

4.3.1 Simulation Setup and Results

The optimal performance of these algorithms depend on the selection of the optimal set of secondary users. This optimal selection of users is in turn dependant on a few constants which need to be input into the equations as explained in the previous sections.

The positions of the nodes are chosen randomly in a 100×100 grid. Table 4.1 shows one such random deployment of nodes. The deployment of the Primary transmitter is done randomly in the grid between (40,40) to (60,60). The Fusion Center is deployed at a fixed position (55,55). The secondary users are moved by a small random distance in each iteration in such a way that all the users stay inside the 100×100 grid. The deployment of the nodes is shown in Fig.4.3. The circled nodes are the nodes that have been selected for cooperative spectrum sensing by the RL algorithm.

This grid is placed in the first quadrant of the Cartesian coordinate system. We have dictated the activity of the primary transmitter through ON-OFF modelling. Through ON-OFF modelling we have assigned probabilities to the primary transmitter being ON and the primary transmitter being OFF. The probabilities that we have chosen are 0.6 for ON and 0.4 for OFF. The next step is to select the noise parameters for our algorithm. The SNR at each node calculated through the albersheim equation which is explained in greater detail in [Richards 2014]. In short,

Table 4.1: Positions of the nodes

ID	X-coord	Y-coord	Mean-Ratio	Priority
1	47.86	33.86	57.31	5
2	1.76	97.36	29.42	8
3	29.64	13.12	33.02	10
4	37.31	2.44	17.76	1
5	87.55	11.01	59.71	7
6	19.55	58.81	27.69	3
7	57.64	10.43	31.54	9
8	78.57	3.01	30.29	2
9	64.18	84.11	27.51	4
10	9.69	18.70	28.55	6

the albersheim equation takes the probability of detection(P_d) and the probability of false alarm(P_f) as input and gives SNR as output. Based on this equation, we have taken a constant target P_d of 0.9 at each node and a random P_f between 0 to 0.1. As we mentioned in equation (3.3), threshold value(λ) is calculated as a function of the probability of false alarm. In our Noise model we have used log-normal shadowing.

In equation (4.2), we need to chose a temperature value that decreases linearly from T_0 and T_n. We have chosen the values of T_0 as 1 and T_n as 0.001. As stated in equation (4.4) we need to chose an optimal value for the decaying constant, $1/D_c$.The decaying constant that we have chosen is 0.006, to simulate sub-urban conditions in our cooperative sensing environment. In some of the above algorithms we have used a condition called 'correlation=0'. We have assumed that the correlation is said to be zero when the maximum p_{ij} between any of the previously selected users is below 0.8607, which means that any two users whose distance is beyond 25 are assumed to have a correlation of 0.

The overall complexity of the algorithm is O($N \times s^2$) + O($N \times s$) + time complexity of solving a system of linear equations with s equations, where s is the number of states and N is the number of iterations the RL algorithm takes to converge. Therefore the usability of this technique is heavily depending on how many states are present in the problem.

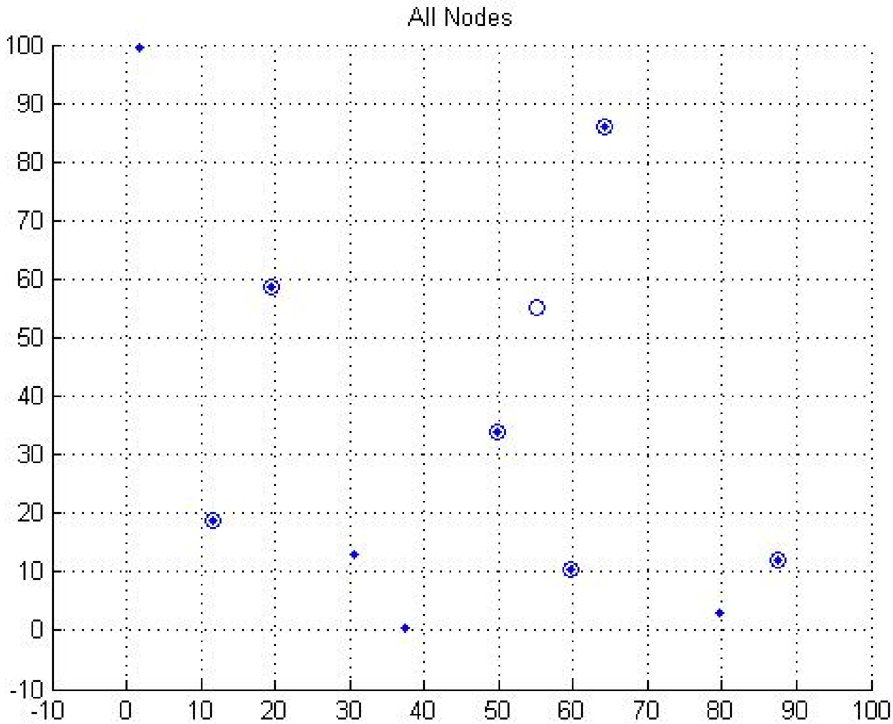

Figure 4.3: Deployment of nodes

We ran the simulation 100 times, each with new positions of the users. In each iteration we attained a final decision from the algorithm on whether the primary users are present or not. We stored all these decisions and compared them to a dataset containing the actual values of whether the primary user was active or inactive. Upon comparing these truth values with the predicted values from our algorithm we got an accuracy between 85-92%.

The graphs displayed in Fig.4.4 and Fig.4.5 explain the performance of our RL-based CSS algorithm. Fig.4.4 shows the ROC curve of the RL-based CSS algorithm and the Energy detection algorithm without RL and compares both techniques. This curve was created by first creating the performance curve and then applying the smoothening function to this curve. The ROC curve of the RL-based CSS shows positive results for the RL-based CSS as it shows a good relationship between the Probability of Detection(P_d) and Probability of False Alarm(P_f). This Figure also allows us to compare the results of the RL-based CSS algorithm with

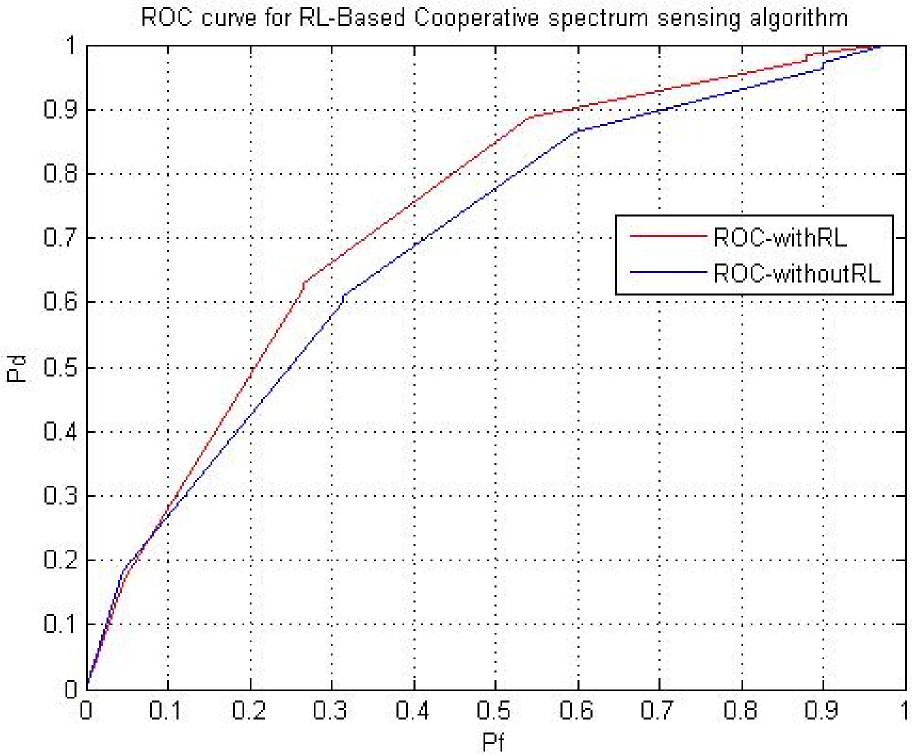

Figure 4.4: ROC curve with and without Reinforcement learning

that of the Energy detection algorithm without reinforcement learning. We can see that the use of RL for the process of Cooperative spectrum sensing leads to an increase in the overall accuracy of the process. The difference in the overall accuracies of the CSS algorithm with and without RL is around 5-10% in favor of the RL-based CSS algorithm.

Fig.4.5 is the precision graph, which shows how the precision changes as more and more primary user ON instances are encountered. The final precision value for the RL-based CSS algorithm settles at around 0.88. The precision is calculated by dividing number of times the primary user ON instances that have been predicted correctly by the total number of primary user ON instances. Every time a primary user ON instance is predicted correctly the precision graph goes up and vice versa. Due to this characteristic this graph is called a saw-tooth graph. As can be seen from the graph, the precision of the RL algorithm settles at a value that is 8-9% greater than that of the algorithm without RL. Therefore, our Reinforcement

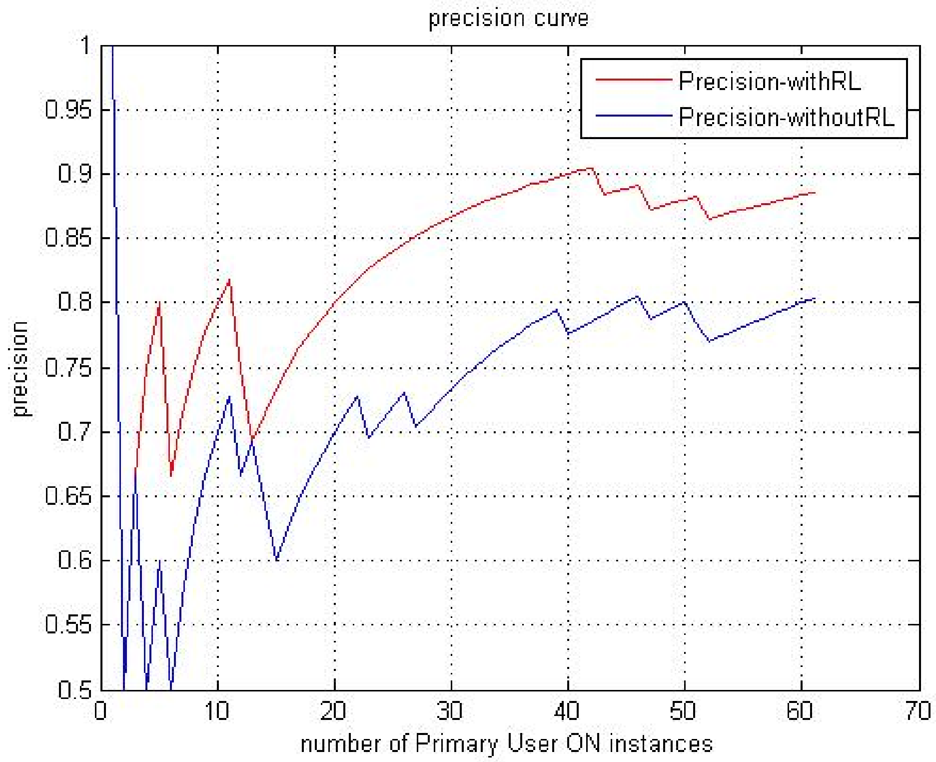

Figure 4.5: Graph showing precision of RL-based CSS algorithm

Learning algorithm is a viable technique for the problem of cooperative spectrum sensing.

In this chapter, we discussed policy iteration based Reinforcement Learning(RL) algorithm for CSS scheme. The optimal solution of the proposed CSS scheme is derived using three phases, such as, policy evaluation, policy improvement and calculating global decision. The secondary users (SUs) are randomly deployed in a multi-path fading/shadowing environment. We carried out 100 iterations and the position of SUs are changing during each iteration. The simulation results shows that the detection probability of RL based CSS scheme is 85-92% which is 5-10% greater than without reinforcement learning. It is observed that the algorithm gives the precision accuracy of 88% that is 8-9% of improvement compare to without RL. Further, in RL based scheme, the decision making agent (FC) undergoes exploration and exploitation trade-off which enhances the cooperative learning and detection capability of cognitive radios.

Chapter 5

Coalitional Game Formation Framework for Cooperative Spectrum Sensing

5.1 Introduction

In a cognitive radio, cooperation among rational users (SUs) can generally improve the network performance due to spatial diversity in a wireless environment. Coalitional game theory has been used to study user cooperation and design optimal, fair, and efficient collaboration strategies among SUs. In this chapter, we study the formation of coalitional game model for CSS scheme.

Game theory provides a formal analytical framework with a set of mathematical tools [Osborne & Rubinstein 1994] to study the complex interactions among rational players. One of the goals of game theory is to predict what will happen when a game is played. The most common prediction of what will happen is called the Nash Equilibrium. Nash equilibrium [Fudenberg & Tirole 1991] is an action profile at which no player has any incentive for unilateral deviation. Throughout the past decades, game theory has made revolutionary impact on a large number of disciplines ranging from engineering, economics, political science, philosophy, or even psychology. In recent years, there has been a significant growth in research activities that use game theory for analyzing communication networks [Han 2012]. This is mainly due to:

- The need for developing autonomous, distributed, and flexible mobile networks where the network devices make independent and rational strategic decisions.
- The need for low complexity distributed algorithms that efficiently represent collaborative scenarios between network entities.

Game theory is the study of the interaction of autonomous agents (players). In a modern wireless network, each node running a distributed protocol must make its own decisions (possibly relying on information from other nodes). These decisions may be constrained by the rules or algorithms of a protocol, but ultimately each node will have some leeway in setting parameters or changing the mode of operation. These nodes, then, are autonomous agents, making decisions about transmit power, packet forwarding, back-off time etc.

The formation of game is made up of three basic components: a set of players, a set of actions, and payoff/utility function. The players are the decision makers in the modelled scenario. In a wireless system [Saad *et al.* 2009], the players are most often the nodes of the network. The actions are the alternatives available to each player. In dynamic or extensive form games, the set of actions might change over time. In a wireless system, actions may include the choice of a modulation scheme, coding rate, protocol, flow control parameter, transmit power level, or any other factor that is under the control of the node. When each player chooses an action, the resulting 'action profile' determines the outcome of the game.

Finally, a preference relationship for each player represents that player's evaluation of all possible outcomes. In many cases, the preference relationship is represented by a utility function, which assigns a number to each possible outcome, with higher utilities representing more desirable outcomes. In the wireless scenario, a player might prefer outcomes that yield higher Signal-to-Noise Ratios (SNR), lower Bit Error Rates (BER), more robust network connectivity, and lower power expenditure. In many practical situations these goals may be in conflict. Appropriately modeling these preference relationships is one of the most challenging aspects of the application of game theory. There is enough literature available on game theory [Han 2012, MacKenzie & Wicker 2001, Benslama *et al.*]and its role in wireless networks. In a game theoretic framework, one can distinguish between two main categories: Non-cooperative and cooperative game theory [77]. While non-cooperative game theory mainly deals with modeling competitive behavior, cooperative game theory is dedicated to the study of cooperation among a number of players.

In this thesis, we restrict our attention to the cooperative game theory, because it mainly deals with the formation of cooperative groups, i.e., coalitions that allow the cooperating player to strengthen their positions in a given game. We use the terms ′coalition′ and ′cooperation′ interchangeably in this thesis.

5.2 Role of Game theory in Cognitive Radio

In cognitive radio networks, network users make intelligent decisions on their spectrum usage and operating parameters based on the sensed spectrum dynamics and actions adopted by other users. The competition and cooperation among the cognitive network users can be well modelled as a spectrum sharing game [Wang *et al.* 2010]. The table below explains the components in a cognitive radio network.

The importance of studying cognitive radio networks in a game theoretic framework is as follows:

Table 5.1: Summary Of Different Coalitional Game model for CSS

Components	**Spectrum Sharing Method**	
	Open Spectrum Sharing	**Licensed Spectrum Sahring**
Players	Secondary users that compete for the unlicensed spectrum	Both primary and secondary users
Actions	Transmission parameters such as transmission rate, power level, access rate, waveforms etc.	Secondary users: which licensed bands they want to use and how much they would pay for leasing the licensed bands Primary users: lease each unused band to SU and charge(price per unit of bandwidth)
Payoff	Transmission parameters such as transmission rate, power level, access rate, waveforms etc.	Monetary gains, e.g., revenue minus cost, by leasing the licensed spectrum

- The network user's (primary and secondary users) behavior and actions can be analyzed in a formalized game structure, by which the theoretical achievements from game theory can be fully utilized.

- Game theory provides various equilibrium criteria for the spectrum sharing problem. To be specific, the optimization of spectrum usage is generally a multi-objective optimization problem, which is very difficult to analyze and solve. Game theory provides us with well defined equilibrium criteria to measure game optimality under various game settings.

- Cooperative game theory which is one of the most important branches of game theory enables us to derive efficient distributed approaches for dynamic spectrum sharing using only local information. Such approaches become highly desirable when centralized control is not available or flexible self-organized approaches are necessary.

Each node in the network that implements the decision step (making it a decision maker) of the cognition cycle is a player in the game. The various alternatives available to a node forms the node's action set and the action space is formed from the Cartesian product of the radio's alternatives. Cognitive radio's observation and orientation steps [Liu & Wang 2010] combine to form a player's utility function. The observation step provides the player with the arguments to evaluate the utility function and the orientation step determines the valuation of the utility function.

The game theory should address the following questions before implementing it on any cognitive radio platform.

- Does the algorithm have a steady state?
- What are those steady states?
- How to determine the desirability of steady states?
- What restrictions need to be placed on the decision update algorithm to ensure convergence?

Though the detailed descriptions of above questions are beyond the scope of this thesis, the readers are encouraged to refer [Liu & Wang 2010] for more details. Neel et al. [Neel *et al.* 2002] examined the applications of game theory models and behavior of several game models and their influence on the structure of cognitive networks. Neel concluded that game theory would be a valuable tool. However, for the analysis of algorithms one must consider convergence behavior and steady state behavior. Neel et al. [Neel *et al.* 2004] discussed extensively the game models for cognitive radios and their analysis. Before formulating any distributed algorithm, it should determine the following: Steady state existence and its characterization, equilibrium efficiency, algorithm convergence properties. The potential and super modular game models allows to know if the steady state can be reached and determines the kinds of adaptations that are assured of convergence, and establish the steady regions. In [Wang & Liu 2011, Wang *et al.* 2010], the authors provide a comprehensive overviews of game theory, and its applications to the research on cognitive radio networks.

5.3 Coalitional Game model: Preliminaries

Cooperative games are modelled using coalitional game structure [Ray 2007]. It describes how a set of players can cooperate with others by forming cooperating groups and thus improve their payoff in a game. Denote the set of players by N and a coalition of players S as non-empty subset of N. Since the players in coalition S have agreed to cooperate together, they can be viewed as one entity and is associated with a value $v(S)$ which represents the worth of coalition S. Then, a coalitional game is determined by N and $v(S)$. Ray [Ray 2007] has mentioned the following key technical terms and its definitions associated with coalitional game model.

Transferable payoff: The value $v(S)$ which is the total payoff that can be distributed in any way among the members of S using some appropriate fairness rule. In [Mathur *et al.* 2006], the authors modeled the receiver cooperation in a Gaussian interference channel as a coalitional game with transferable payoff. The value of the game is defined as the sum-rate achieved by jointly decoding all users in the coalition.

Non-transferable payoff: In some coalitional games, it is difficult to assign a single real number value to a coalition. Instead, each coalition S is characterized by an arbitrary set $v(S)$ of consequences. Such games are known as coalitional games without transferable payoff.

Super additivity: In coalitional games, cooperation by forming larger coalitions is beneficial for players in terms of a higher payoff. This property is referred to as super additive. For example, in games with transferable payoff, the super additivity means the set values of each coalition (say *s1*,*s2*) should be greater than or equal to addition of disjoint values of coalition which is a subset of total number of secondary users *N*. Also, *s1* and *s2* are disjoint if their intersection is empty which is shown in equation (5.1),

$$V(s1 \cup s2) \geq v(s1) + v(s2), \quad s1, s2 \subset N = \emptyset \tag{5.1}$$

Grand coalition: Forming larger coalitions from disjoint (smaller) coalitions can bring at least a payoff that can be obtained from the disjoint coalitions individually. Due to this property, it is always beneficial for players in a super additive game to form a coalition that contains all the players, i.e., the grand coalition. Grand coalition provides the highest total payoff for the players; it is the optimal solution that is preferred by rational players. In cognitive radios, due to multiuser diversity and spatial diversity, it is difficult to form grand coalition. The CSS performance can be improved by forming disjoint (smaller) coalition with Non-transferable payoff.

The core: The idea behind the core is similar to that behind Nash equilibrium of a non-cooperative game: a strategy profile where no player would deviate unilaterally to obtain a higher payoff. It can be seen that the core is the set of payoff profiles that satisfy a system of weak linear inequalities, and thus is closed and convex. The existence of the core depends on the feasibility of the linear program and is related to the proportionality of a game. Since the core is defined by a system of linear equations, the core is a convex region provided it is non-empty. The exact allocation in the core is arrived by means of bargaining between the users. However, there are many players (SUs) in CSS; it is a tedious process to solve for the system of inequalities and finding solution through bargaining.

Shapley value: If the proportionality of a game does not hold, the core will be empty, and will be difficult to find a suitable solution of a coalitional game. Thus, an alternative solution concept that always exists in a coalitional game is necessary. Shapley proposed a solution concept, known as the Shapley value ψ, to assign a unique payoff value to each player in the game. In [Niyato & Hossain 2007], the author presented framework for modeling the spectrum sharing (monetary gains) through solutions derived from Shapley value by assuming the games have non-empty cores, totally balanced and convex in nature.

5.3.1 Demonstration of Steady state

In typical games, players choose their actions in a way that will improve their personal benefit or payoff. Most games reach a state where no user can increase his utility which means all utility have reached equilibrium or stability state. This state is called Nash equilibrium. In most of the game models, the distributed algorithm's steady state is determined by Nash equilibrium (NE) [Osborne & Rubinstein 1994] which is a key concept in game theory. A NE is the state (vector of users utility) at which no player can gain by deviating individually. Without applying more complex game models, a game can be shown to have a NE by applying relevant fixed point theorems [Osborne & Rubinstein 1994]. The basic conditions which needs to be satisfied while demonstrating the steady state or Nash equilibrium are,

- The player set is finite.
- The action sets are closed, bounded, and convex.
- The utility functions are continuous in the action space and quasi-concave.

Nash equilibrium tells us what the equilibrium outcome will be, but it does not answer the question 'How can we get to the equilibrium?'. This is more important in the context of cognitive radio networks, where players may lack the global information to directly predict the equilibrium. Instead, they may start from an arbitrary strategy, update their strategies according to certain rules, and hopefully converge to the equilibrium.

In reality, a very large number of algorithms satisfy these conditions, so demonstrating NE existence is not very insightful as there's almost a default assumption that there will be a steady state for a cognitive radio algorithm and there may be numerous NE in a single game. However, not all games and not all algorithms will satisfy these conditions so there remains some merit in showing that the algorithm will have a steady-state.

Demonstrating that a game has a steady state is not that useful, as it provides no insight into the dynamic behavior of the algorithm. Therefore, steady states (equilibrium) need to be identified. However, without introducing a more advanced game model, such as the coalitional game model, the typical game model does not provide any tools for identifying NE [Ray 2007]. Indeed, to identify an action vector as a NE, an analyst has to verify all possible unilateral deviations from the equilibrium state. Since there can be multiple equilibrium, the process need to be repeated for each of the state, which in turn make the problem NP-complete. Indeed when attempting to identify all NE in a game, analysts are forced to turn to exhaustive simulations which will take days to complete depending on number of players.

5.3.2 Determining steady state desirability

When there is more than one equilibrium in the game, it is natural to ask whether some equilibria outperform others and whether there exists a best, referred as dominant equilibria using optimality framework in such scenarios. Because game theory solves multi-objective optimization problem, it is not easy to define the optimality in such scenarios. For example, when players have conflicting interests with each other, an increase in one player's payoff might decrease others payoffs.

In order to define the optimality, one possibility is to compare the weighted sum of the individual payoffs, which reduces the multi-dimension problem into one-dimension problem. A more popular alternative is to use Pareto optimality, which is a payoff profile that no strategy can make at least one player better off without making any other player worse off. Pareto optimality [Pardalos *et al.* 2008] has been widely used in game theory as well as economics, engineering and social sciences. If there are more than one equilibrium candidates, usually the optimal ones in the Pareto sense are preferred. For example, in the repeated game, a lot of equilibria may exist if certain strategies have been applied. Out of many possible choices, the ones on the Pareto frontier are superior to others. In the bargaining game, Pareto optimality has been used as an axiom to define the bargaining equilibrium in this game.

5.4 Cooperative Sensing as a Coalitional Game

In a cognitive radio network, cooperation among rational users can generally improve the network performance due to the multiuser diversity and spatial diversity in a wireless environment. Coalitional games [Saad *et al.* 2009] prove to be a very powerful tool for designing fair, robust, practical and efficient cooperation strategies for communication networks. Coalitional game theory has been used to study user cooperation and design optimal, fair, and efficient collaboration strategies. Dynamic coalition formation algorithms provide novel collaboration strategies for SUs in a cognitive radio network to improve their sensing performance. The major research challenges [Wang *et al.* 2010] associated with coalitional game approach in cognitive radio networks include, defining a proper payoff function, efficiency of equilibrium, Issues in mechanism design and security. The real challenge for coalitional games will be to characterize equilibria under realistic assumptions. The Fig.5.1 shows CSS as a coalitional game. The

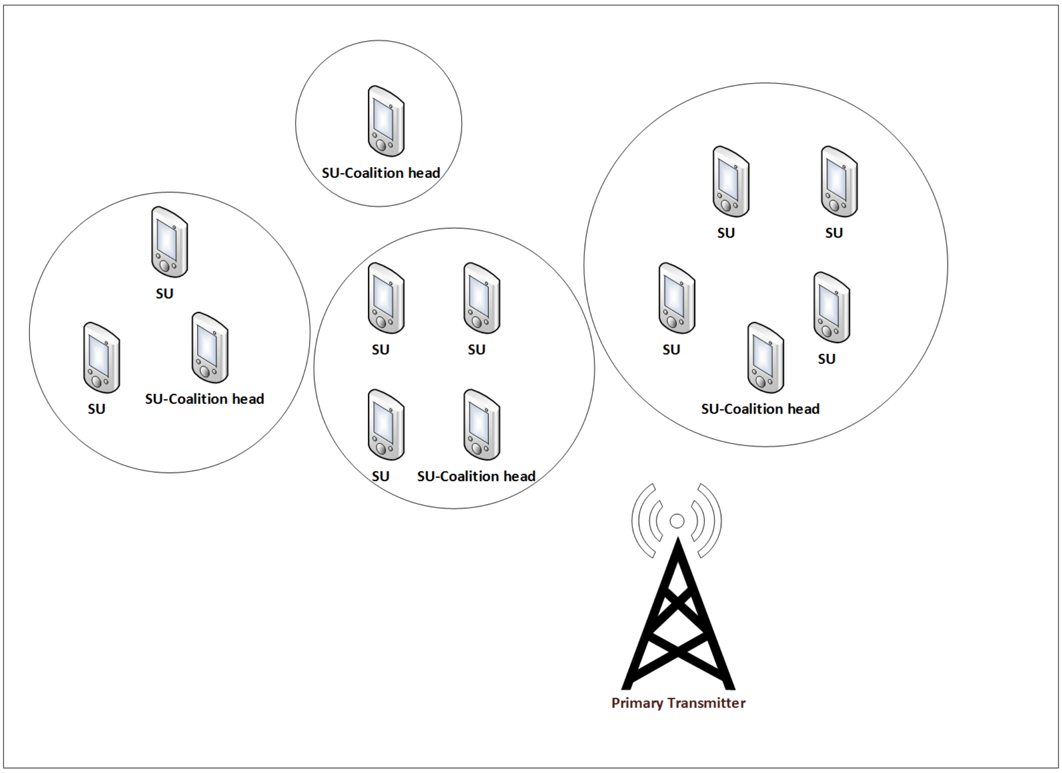

Figure 5.1: Cooperation model as a coalitional game

cooperative sensing is performed in each coalition. To improve the detection performance and respond to PU activity and topology change, CR users merge or split the coalitions if the utility of the merged or split coalitions is larger than the original coalition partitions.

5.4.1 Game formulation and properties

The coalitional game theory provides suitable cooperation strategies for CSS. In [Saad *et al.* 2011], the authors model distributed CSS as a coalitional game with a non-transferable utility (NTU). A coalitional game with NTU is defined by the pair (N,v), where N is the set of players, and v is a mapping such that for every coalition s⊆N, v(S) is a closed convex that contains the payoff vectors that players in S can achieve.

In other words, a coalitional game (N,v) is said to be with NTU if the value or utility of a coalition cannot arbitrarily be apportioned between the coalition's players. Hence, the value of any coalition S can be mapped to a set of payoff vectors. First, we define the value (utility) v(S) of a coalition s⊆N as a function that captures the trade-off between the probability of detection (P_d) and the probability of false alarm (P_f) which are the key metrics for measuring the performance of spectrum sensing. The probability of detection is defined as P_d = Prob{decision=$H_1 \mid H_1$}, which is the probability of correctly detecting the transmission of the PU when this PU is active. Subsequently, the probability of false alarm is defined as P_f=Prob{decision=$H_1 \mid H_0$} which is the probability of deciding that the PU is transmitting while the PU is in fact idle. For this purpose, v(S) must be an increasing function of the detection probability $Q_{d,s}$=1-$Q_{m,s}$ within coalition S and a decreasing function of the false alarm probability $Q_{f,s}$ is given as follows [Saad *et al.* 2011]:

$$v(s) = Q_{d,s} - C(Q_{f,s}) \tag{5.2}$$

where $Q_{d,s}$ and $Q_{f,s}$ are the detection and false alarm probabilities respectively of coalition S, and $C(Q_{f,s})$ is the cost function of $Q_{f,s}$ defined by a logarithmic barrier penalty function which is given by,

$$C(Q_{f,s}) = \begin{cases} -\alpha^2.log(1 - (\frac{Q_{f,s}}{\alpha})^2, & if Q_{f,s} < \alpha \\ +\alpha \qquad\qquad\qquad\quad , & if Q_{f,s} \geq \alpha \end{cases} \tag{5.3}$$

where α is a false alarm constraint per coalition (per SU). The cost function allows incurring a penalty, which is increasing with the false alarm probability. The cost function depends on distance and the number of SUs in the coalition, through the false alarm probability $Q_{f,s}$. Hence, the cost for collaboration increases with the number of SUs in the coalition as well as when the distance between the coalition's SUs increases. Saad et al. [Saad *et al.* 2011] is the first author who has proposed value (worth) of coalition and cost function for CSS game in terms of

$Q_{d,s}$ and $Q_{f,s}$. Here, we consider mobility and battery power of each SU to determine the cost function along with false alarm. To accommodate mobility and battery power of each SU, we modified equation (5.4) and (5.5) as given below:

$$v(s) = Q_{d,s} - C(Q_{f,s}, f_i) \tag{5.4}$$

$$C(Q_{f,s}, f_i) = \begin{cases} -\alpha^2.log(1 - (\frac{Q_{f,s}}{\alpha})^2) & ,ifQ_{f,s} < \alpha \\ +\alpha & ,ifQ_{f,s} \geq \alpha \\ f_i & ,i \leq N \end{cases} \tag{5.5}$$

where f_i indicates the function value of each $SU_{i..N}$. Before formulating coalitional games for CSS, the following properties must be incorporated within each coalition. These properties help to characterize CSS as coalitional game using the trade-off between gain (detection probability) and cost (false alarm). For detailed proof of the below properties, the readers can refer [Liu & Wang 2010].

Property 1: Within each coalition S the SUs report their sensing bits to the coalition head. In its turn the coalition head of S combines the sensing bits using decision fusion OR-Rule to make a final decision on the presence or absence of the PU. The fusion OR Rule can be formulated as follows.

$$\begin{gathered} H_1 : \sum_{k=1}^{N} \triangle_k \geq 1 \\ H_0 : otherwise \end{gathered} \tag{5.6}$$

where k is the number of SUs and Δ_k is binary decision (value) given by each SU. Thus, SUs belonging to a coalition S will transmit or not based on the final coalition head decision. Consequently, the missing and false alarm probabilities of any SU (denoted as i) in each coalition S (notation not clear) are given in (5.7) and (5.8), respectively.

$$Q_{f,s} = 1 - \prod_{i \in S} \left[(1 - P_f)(1 - P_{e,i,k}) + (P_f P_{e,i,k} \right] \tag{5.7}$$

$$Q_{m,s} = \prod_{i \in S} [P_{m,i}(1 - P_{e,i,k}) + (1 - P_{m,i})P_{e,i,k}] \tag{5.8}$$

where $P_{m,i}$, P_f, and $P_{e,i,k}$ are known as probability of miss detection, probability of false alarm and probability of error respectively of individual secondary user SU_i and can be found by using the formulas in [Ghasemi & Sousa 2005]. Here, the probability of error defines the error due to fading on the reporting channel between the secondary user of coalition S and coalition head k. The error over the reporting channel is an important metric that affects the performance of CSS in terms of probability of miss as well as false alarm.

Property 2: The coalition value in the proposed game is given by (5.2) and is a function of $Q_{m,s}$ and $Q_{f,s}$. As per Property 1, the missing probabilities for each $SU_i \in S$ are also given by $Q_{m,s}$ and $Q_{f,s}$ and, thus, the utility of each $SU_i \in S$ is equal to v(S). Hence, the coalition value v(S) cannot be arbitrarily apportioned among the users of a coalition; and the proposed coalitional game has non-transferable utility.

Property 3: For the proposed (N,v) coalitional game, the grand coalition of all the SUs does not always form due to the collaboration false alarm costs; thus disjoint independent coalitions will form in the network.

5.4.2 Coalition formation concepts

Coalition formation has been used in game theory [Ray 2007] to find algorithms for characterizing the coalitional structures that form in a network where the grand coalition is not optimal. Some generic framework for coalition formation is presented in [Saad *et al.* 2008] whereby coalitions form and break through two simple merge and split rules. This framework can be used to construct a distributed coalition formation algorithm for collaborative sensing. Based on this merge and split rules multiple coalitions can merge into a larger coalition if merging yields a preferred collection based on the selected order. Similarly, a coalition would split into smaller coalitions if splitting yields a preferred collection. The comparison relation ($\triangleright$) between collection and partitions based on individual value order which performs comparison based on actual player's utilities. An important example of individual value order is the Pareto order which is defined as follows,

$$R \triangleright S \Leftrightarrow \left\{\emptyset_j(R) \geq \emptyset_j(S), \qquad \vee j \in R, S\right\} \tag{5.9}$$

The definitions of merge and split is as given below [Saad *et al.* 2011],

Merge Rule: Merge any set of coalitions S1, S2,...Sl where

$$\left\{U_{j=1}^{l}\right\} \triangleright \{S_1, ..., S_l\}, \{S_1, ..., S_l\} \rightarrow \left\{U_{j=1}^{l} S_j\right\} \tag{5.10}$$

Split Rule: Split any set of coalitions using split rule where

$$\{S_1, ..., S_l\} \triangleright \left\{U_{j=1}^{l} S_j\right\}, \left\{U_{j=1}^{l} S_j\right\} \rightarrow \{S_1, ..., S_l\} \tag{5.11}$$

Using the above rules, multiple coalitions can merge into a larger coalition if merging yields a preferred collection based on the selected order ($\triangleright$). Similarly, a coalition would split into smaller coalitions if splitting yields a preferred partition. According to Pareto order, coalitions will merge (split) only if at least one SU is able to strictly improve its individual utility through this merge (split) without decreasing the other SUs utilities. By using the merge and split rules combined with the Pareto order, a distributed coalition formation algorithm suited for collaborative spectrum sensing can be constructed.

5.4.3 Coalition head selection

After forming the coalition using merge and split algorithm, the next step is to choose Coalition Head (CH) among the SUs in each coalition. The coalition head collects sensing information from each SU and acts as a fusion center to make a coalition based decision. In order to combine the sensing information and making the final decision, the coalition head uses fusion rule which is mentioned in [Akyildiz *et al.* 2011]. The key question here is, 'how to select coalition head?'. In [Saad *et al.* 2011], the authors propose a convention wherein the SU that has lowest probability of miss (i.e. highest detection) will act as a coalition head. Further, they assume that if more than one SU achieves the minimum probability of miss, then coalition head selected as random among the set of SUs with minimum probability of miss.

In practical cases, the above assumption will create collision among SUs to act as CH. To address the above issue, we have modified the algorithm steps of [Saad *et al.* 2011] and proposed an optimum and effective approach based on leader election algorithm (LEA). There are several LEA approaches available in the literature [Vasudevan *et al.* 2003], and we chose Bully algorithm to select CH. The steps involved in Bully algorithm have been given in Fig.5.2 and it works as follows.

Step 1: There are five nodes in network, in which node 1 detected leader failure and initiated an election (Fig.5.2a).

Step 2: All nodes except the crashed one (node 5) acknowledges with OK message (Fig.5.2b).

Step 3: Now, node 4 which has highest priority and intends to become leader. It sends fresh election message to all nodes 1, 2 and 3 and declares itself s new coalition head (Fig.5.2c). Therefore, the nodes with highest priority is elected as a leader, hence named Bully algorithm.

Our proposed algorithm works as follows. We assume that all the nodes (SU)

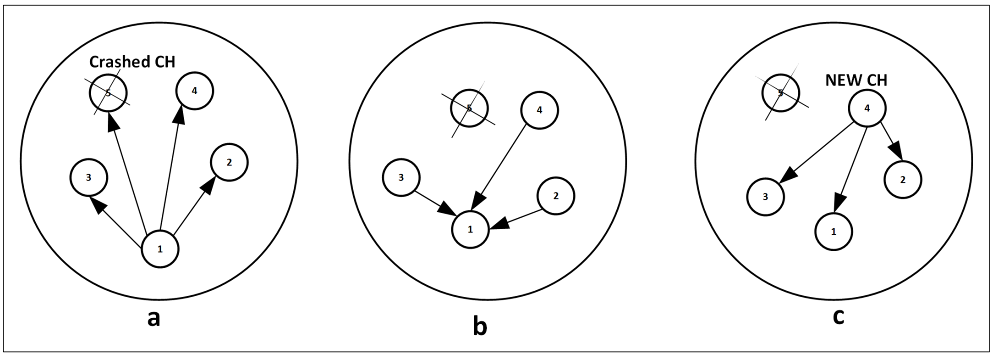

Figure 5.2: Bully algorithm for selecting Coalition Head

in cognitive radio networks reside within the coverage area of each other and each node has one common channel to communicate with its neighbor nodes. There are N channels (i.e. C1, C2, C3...Cn) available in CRN for its operation. Each node in the CRN is assigned a unique identifier (Node ID) in the range 1...N. These ID values are assigned based on parameters such as mobility and energy (battery power) of each SU. The trade-off between these two parameters can be defined using the function below.

$$f_i = (\alpha \times m) + (\beta \times B) \tag{5.12}$$

where α and β are tuning parameters of mobility (m) and battery power (b). These tuning parameters are determined by network topology and number of SUs. The above function woks as follows. Suppose let us assume that α=0.4 and β=0.6. There are two SU's in which SU1 has mobility of 0.3 and 20% (0.2) of battery power. Similarly, SU2 has 0.6 and 0.8 respectively. As per equation (5.12), it gives the values 0.24 and 0.72 respectively for SU1 and SU2. The SU which has highest function value will act as CH (here it is SU2). Each node knows its unique Node ID, but does not know how many other nodes there are and what their IDs are. Nodes are equipped with one transceiver (Transmitter and Receiver) capable of either receiving or transmitting at any given time. Also, each node (SU) performs local sensing to periodically scan the available channel set.

Algorithm 12: Distributed algorithm for Coalition head selection

coalition_head ()
for *each node S* **do**
  $S(D) \leftarrow$ f (Ref.eqn.(10));
  Node S starts scanning on available channel set $C_1, C_2, ..C_n$;
do
  Sel $\leftarrow$ random $(C_1, ...C_n)$;
  Node(S) sends election message along with its f value to all the nodes R in the set Sel;
  Node 'R' does the following: **if** *R(ID)* $\leq f$ **then**
    discard the message;
  else
    If R wants to become the leader, then it sends election messages randomly to next set of Sel nodes;
while *leader is selected*;

When a new node (say SU1) is ready to merge with coalition k in a network, it first checks if a coalition head (leader) already exists or whether some nodes are already trying to become CH. This is done by listening on all available channels through beacon reply. If a CH is detected, node SU1 sends its ID to CH and checks the possibility of itself becoming the leader. After the negotiation is over, either earlier CH will remain as CH and SU1 will be part of this coalition, or SU1 will become the new leader (CH) of the coalition.

5.5 Designing Steps of Coalitional Game model

Based on the coalition formation concepts and properties, a coalition formation algorithm for self organization in wireless networks can be generated. This algorithm will be based on simple rules of merge and split that allow modifying a partition T of N. Multiple coalitions will merge or split, if merging or splitting yields a preferred collection based on a chosen Pareto order. With the Pareto order, coalitions will merge only if at least one user can enhance its individual payoff through this merge without decreasing the other user's payoffs. Similarly, a coalition will split only if at least one user in that coalition is able to strictly improve its individual payoff through the split without hurting other users. A decision to merge or split is, thus, tied to the fact that all users must benefit from merge or split, thus, any merged (or split) form is reached only if it allows all involved users to maintain their payoffs with at least one user improving.

An efficient distributed coalition formation algorithm can be designed using the following phases. In [Saad *et al.* 2011], the author suggested the three phases to formulate coalitional game model and our proposed algorithm accommodates coalition head selection phase along with other three phases which is as given Algorithm 13:

Algorithm 13: Coalition formation for CSS

Initial state :
T $\leftarrow T_1, ..., T_k$; //At the beginning of all time
T $\leftarrow$ N $\leftarrow 1, ..., N$; //with non-cooperative SUs
Local Sensing phase
$s \leftarrow \sqrt{snr} * randn(1, L)$;
$n \leftarrow randn(1, L)$;
$y \leftarrow s + n$;
$energy \leftarrow abs(y)^2$;
$teststatistic \leftarrow (1/L) * sum(energy)$;
if *test statistic* $\geq$ *threshold* **then**
  decide H_1 ;
else
  decide H_0 ;
Adaptive coalition formation
do
  $F \leftarrow merge(T)$;
  Based on the merge rule defined above
  $T \leftarrow split(F)$;
  Based on the Pareto order of split rule
while *Merge and split terminates*;
Coalition Head selection
coalition_head (); //Algorithm 12

Coalitional sensing
$CH \leftarrow H_0|H_1$; //Each SU reports its sensing decision to CH
$CH \rightarrow globaldecision$; //CH declares final decision based on OR rule

The number of coalitions and the average number of users per coalition increase with the network size due to the availability of more partners for forming coalitions. In adaptive coalition formation phase, through distributed and periodic merge-and-split decisions, the SUs can autonomously adapt the network topology to environmental changes such as mobility. The proposed algorithm is a coalition formation algorithm with partially reversible agreements, where the users sign a binding agreement to form a coalition through the merge operation (if all users are able to improve their individual payoffs from the previous state) and they can only split this coalition if splitting does not decrease the payoff of any coalition member (partial reversibility). This partial reversibility through the split operation reduces the complexity of the coalition formation process but can impact the coalition stability.

The above proposed coalitional game model has many benefits to study, model and analyze the cognitive interaction process among secondary users in CR networks. There are many research challenges which need to be addressed in future for effective implementation of coalition formation algorithm for CR networks, which we summaries here below:

Defining proper payoff function: The payoff function defines the objective that a player wants to achieve from playing the game. For example, in spectrum trading (i.e. auction games) the pay off function is defined based on net profit (i.e. the gain from using the spectrum minus the cost of holding the spectrum band). In our proposed work, the pay off function formula is based on detection probability (gain) and false alarm (cost). Here, the challenge is how to choose the weight of the linear function to balance the gain and the cost. Therefore, it is important to choose a meaningful payoff function that can precisely characterize player's objectives.

Performing instantaneous coalition formation is still a challenging task in game theory and it needs to be addressed well in future. One possible solution is to define a period of time (say θ) that specifies the time elapsed between two consecutive runs of the above CF algorithm. There would be a trade-off between the number of runs, i.e.overhead for CF and the adaptation to the dynamics of the environment. Hence, for environments that are static or varying very slowly, θ would be large. Similarly, for highly varying environments, θ would have a small value thus enabling adaptation to rapidly changing environments. This procedure would ensure the convergence of the merge and split algorithm.

In this chapter, we provide a comprehensive analytical insight of coalitional game model and its role in cooperative spectrum sensing. Highlighted suitable game model for CSS and presented in-depth analysis of design steps involved in coalition formation. Different phases of coalition formation algorithm involving local sensing, adaptive coalition formation, and coalition head selection and coalition sensing phases are discussed.

Chapter 6

Conclusion

The demand for radio spectrum has significantly increased due to recent growth in wireless services. The current wireless systems are regulated by fixed spectrum assignment policy where a given spectrum band is assigned to a licensed user on a long term basis and for larger geographic location. In general, a large portion of the assigned spectrum is used by licensed users sporadically with high variance in time. As a result, under the current fixed spectrum assignment policy, the utilization of radio resource is quite inefficient. This limited availability and inefficiency of spectrum usage necessitates a new communication paradigm to exploit the existing wireless spectrum opportunistically.

The growing demand for higher data rates in wireless communications in the face of limited or under-utilized spectral resources has motivated the introduction of dynamic spectrum access (DSA). The Cognitive Radio (CR) is the key enabling technology for implementing DSA to overcome the spectrum scarcity problem. The investigation on spectrum occupancy measurements conducted by FCC and many other regulatory bodies have revealed that static spectrum allocation leads to inefficient spectrum utilization. The study reports of TV white space for countries like USA, UK, Europe, Japan and India are discussed in Chapter 1. Most of the studies suggests that lower frequency bands (used in Broadcasting, Radar, Amateur Radio, Radio paging bands) are most prominent candidates for CR technology. The concept behind DSA is to allow secondary users to exploit these under-utilized spectral resources by reusing unused spectrum in an opportunistic manner without causing harmful interference to the primary users of the spectrum. To achieve this goal, secondary users, equipped with cognitive radios, must sense the spectrum to detect its availability and must be able to detect very weak primary user's signal. Therefore, spectrum sensing plays a crucial role in the successful deployment of cognitive radio networks. To further improve the spectrum sensing performance, efficient cooperative spectrum sensing schemes, that exploits multiuser diversity, need to be employed.

In this thesis we developed cooperation sensing model that allow the SUs to locally observe the RF environment and collaboratively share its decision over centralized fusion framework. The main idea of cooperative sensing is to enhance the sensing performance by exploiting the spatial diversity in the observations of spatially distributed secondary users. By cooperation, secondary users can share their sensing information for making a combined decision more accurate than the individual decisions. The performance improvement due to spatial diversity is called cooperative gain. The spectrum sensing framework has been divided into two phases: local sensing phase and cooperative sensing phase. The simulation scenario of spectrum sensing algorithms has been formulated to meet the requirements of IEEE 802.22 WRAN standard.

In chapter 2, we reviewed some important aspects of cooperative spectrum sensing such as cooperation architecture, various fusion schemes and cooperative user selection criteria. We discussed about parallel fusion and decentralized architecture followed by various fusion schemes called hard combining decision fusion and soft combining data fusion. The selection of secondary users for cooperative sensing plays a key role in determining the performance of CSS because it can be utilized to improve the trade-off between cooperative gain and cooperation overhead. The limiting factors of cooperative spectrum sensing, namely, cooperation overhead and sensing errors have been discussed in Chapter 2. Cooperation overhead can refer to any transmission cost, extra sensing time, delay, energy and operations devoted to cooperative sensing and any performance degradation caused by cooperative sensing. We addressed various approaches available in literature to overcome this cooperation overhead.

In this thesis, we focused on multi-channel sensing by cooperating secondary users in which more than one channel can be sensed in each sensing period to leverage the cooperative gain of CSS. As mentioned in IEEE 802.22 WRAN, the secondary users need to scan multiple frequency bands (54-682MHz) or use multiple Radio Frequency (RF) front ends for sensing multiple bands. Some technical insights and challenges of multi-channel cooperative sensing is covered in last section of Chapter 2.

Cooperative Spectrum Sensing (CSS) algorithms using Machine learning schemes, particularly, using Perceptron Learning and unsupervised clustering approaches are discussed in Chapter 3. The performance of our proposed algorithms is evaluated using training duration, classification delay and detection accuracy. Local sensing phase is carried out using energy detection to scan the complete available channel set from (54-682)MHz divided into 7MHz of channel bandwidth. For cooperative sensing phase, a centralized decision maker called Fusion Center (FC) is considered where each SU sends its local decision statistics to FC which makes final decision on channel availability. It is observed that the cooperative learning module improves the decision capability of FC and significantly reduces the error rate to meet the target false-alarm probability rate to 0.1. We showed that unsupervised K-means clustering algorithm significantly improves detection accuracy with training and testing delay of 16.8 and 75 milliseconds respectively. However, k-means clustering approach provides an average view on data points which will affect its detection performance under path-loss and shadowing environment. To address this issue, we proposed Archetypal clustering based CSS scheme which provides an extremal view on data points. It is observed from ROC performance results that Archetypal clustering based CSS scheme achieves the detection probability of 82% to meet the target false alarm probability of 0.1.

In chapter 4, we discussed the formulation of a Reinforcement Learning (RL) based Cooperative Spectrum Sensing algorithm. We developed policy iteration based Reinforcement Learning(RL) algorithm for CSS scheme. The optimal solution of the proposed CSS scheme is derived using three phases, such as, policy evaluation, policy improvement and calculating global decision. The secondary users (SUs) are randomly deployed in a multi-path fading/shadowing environment. We carried out 100 iterations where the position of SUs are changing during each iteration. The simulation results show that the detection probability of RL based CSS scheme is 85-92% which is 5-10% better than the case of without reinforcement learning. It is observed that the algorithm gives the precision accuracy of 88% that is 8-9% of improvement as compared to without RL. Further, in RL based scheme, the decision making agent (FC) undergoes exploration and exploitaion trade-off which enhances the cooperative learning and detection capability of cognitive radios.

In chapter 5, we investigated the formation of coalitional game model for CSS scheme. Coalitional game theory has been used to study user cooperation and design optimal, fair, and efficient collaboration strategies among SUs. Different phases of Coalition Formation (CF) algorithm involving local sensing, adaptive coalition formation, and coalition head selection and coalition sensing phases are discussed.

Throughout this thesis, we proposed several simulation scenarios that contributed to the efficient design of cooperative spectrum sensing schemes for cognitive radio networks. However, there are some relevant issues that warrant further consideration in the future work. For instance, while studying the performance of the proposed cooperative sensing techniques, it has been assumed that a spectrum access opportunity for secondary users exists when the primary transmitter is inactive. However, secondary users can still share the spectrum when the primary user is transmitting provided that the amount of interference generated at the primary receiver is not harmful. The spectrum sensing problem can then be viewed as deciding whether or not the secondary transmitter is within the guard area. In the case where the secondary user can detect the primary user's transmitter but can still be allowed to transmit, the hypotheses may need to be modified in some reasonable way that accounts for those spatial spectrum opportunities. The probabilities of detection and false alarm will need to be computed using this modified formulation. The proposed cooperative spectrum sensing techniques in this work depend on the values of those probabilities and not on their specific distributions. This suggests that the proposed techniques can still be applied to improve the detection performance. However, further performance analysis and evaluations need to be carried out to assess this performance improvement.

In this thesis, the simulation scenarios of CSS algorithms has been formulated to meet the requirements of IEEE 802.22 WRAN standard. The implementation of these CSS algorithms in CR testbed is important to validate their correctness and performance in real CR environment, which may also allow further refinements on these algorithms. To this end, further research is necessary to investigate the implementation and challenges of CSS based scheme on CR platform.

References

[Abbas *et al.* 2015] Nadine Abbas, Youssef Nasser and Karim El Ahmad. *Recent advances on artificial intelligence and learning techniques in cognitive radio networks*. EURASIP Journal on Wireless Communications and Networking, pages 1–20, 2015.

[Akyildiz *et al.* 2006] Ian F Akyildiz, Won-Yeol Lee, Mehmet C Vuran and Shantidev Mohanty. *NeXt generation/dynamic spectrum access/cognitive radio wireless networks: a survey*. Computer Networks, vol. 50, no. 13, pages 2127–2159, 2006.

[Akyildiz *et al.* 2008] Ian F Akyildiz, Won-Yeol Lee, Mehmet C Vuran and Shantidev Mohanty. *A survey on spectrum management in cognitive radio networks*. Communications Magazine, IEEE, vol. 46, no. 4, pages 40–48, 2008.

[Akyildiz *et al.* 2011] Ian F Akyildiz, Brandon F Lo and Ravikumar Balakrishnan. *Cooperative spectrum sensing in cognitive radio networks: A survey*. Physical communication, vol. 4, no. 1, pages 40–62, 2011.

[Al-Rubaye *et al.* 2011] Saba Al-Rubaye, Anwer Al-Dulaimi and John Cosmas. *Cognitive femtocell*. Vehicular Technology Magazine, IEEE, vol. 6, no. 1, pages 44–51, 2011.

[Asadi *et al.* 2016] Hamed Asadi, Haris Volos, Michael M Marefat and Tamal Bose. *Metacognition and the next generation of cognitive radio engines*. Communications Magazine, IEEE, vol. 54, no. 1, pages 76–82, 2016.

[Atapattu *et al.* 2010] Saman Atapattu, Chintha Tellambura and Hai Jiang. *Performance of an energy detector over channels with both multipath fading and shadowing*. Wireless Communications, IEEE Transactions on, vol. 9, no. 12, pages 3662–3670, 2010.

[Atapattu *et al.* 2011] Saman Atapattu, Chintha Tellambura and Hai Jiang. *Energy detection based cooperative spectrum sensing in cognitive radio networks*. Wireless Communications, IEEE Transactions on, vol. 10, no. 4, pages 1232–1241, 2011.

[Bahl *et al.* 2009] Paramvir Bahl, Ranveer Chandra, Thomas Moscibroda, Rohan Murty and Matt Welsh. *White space networking with wi-fi like connectivity*. ACM SIGCOMM Computer Communication Review, vol. 39, no. 4, pages 27–38, 2009.

[Bellman 1956] Richard Bellman. *Dynamic programming and Lagrange multipliers*. Proceedings of the National Academy of Sciences of the United States of America, vol. 42, no. 10, page 767, 1956.

[Benslama *et al.*] Malek Benslama, Mohamed Lamine Boucenna and Hadj Batatia. *Game Theory and Communication Networks*. Ad Hoc Networks Telecommunications and Game Theory, pages 35–60.

[Bkassiny *et al.* 2013] Mario Bkassiny, Yang Li and Sudharman K Jayaweera. *A survey on machine-learning techniques in cognitive radios*. Communications Surveys & Tutorials, IEEE, vol. 15, no. 3, pages 1136–1159, 2013.

[Cabric *et al.* 2004] Danijela Cabric, Shridhar Mubaraq Mishra and Robert W Brodersen. *Implementation issues in spectrum sensing for cognitive radios*. In Signals, systems and computers, 2004. Conference record of the thirty-eighth Asilomar conference on, volume 1, pages 772–776. IEEE, 2004.

[Cacciapuoti *et al.* 2012] Angela Sara Cacciapuoti, Ian F Akyildiz and Luigi Paura. *Correlation-aware user selection for cooperative spectrum sensing in cognitive radio ad hoc networks*. Selected Areas in Communications, IEEE Journal on, vol. 30, no. 2, pages 297–306, 2012.

[Chen & Beaulieu 2009] Yunfei Chen and Norman C Beaulieu. *Performance of collaborative spectrum sensing for cognitive radio in the presence of Gaussian channel estimation errors*. Communications, IEEE Transactions on, vol. 57, no. 7, pages 1944–1947, 2009.

[Chen *et al.* 2007] Hou-Shin Chen, Wen Gao and David G Daut. *Spectrum sensing using cyclostationary properties and application to IEEE 802.22 WRAN*. In Global Telecommunications Conference, 2007. GLOBECOM'07. IEEE, pages 3133–3138. IEEE, 2007.

[Chen *et al.* 2014] Yuansi Chen, Julien Mairal and Zaid Harchaoui. *Fast and robust archetypal analysis for representation learning*. In Computer Vision and

Pattern Recognition (CVPR), 2014 IEEE Conference on, pages 1478–1485. IEEE, 2014.

[Cutler & Breiman 1994] Adele Cutler and Leo Breiman. *Archetypal analysis*. Technometrics, vol. 36, no. 4, pages 338–347, 1994.

[Dhope *et al.* 2011] Tanuja Satish Dhope, Dina Simunic and Ramjee Prasad. *TVWS opportunities and regulation:-empowering rural India*. In Wireless Personal Multimedia Communications (WPMC), 2011 14th International Symposium on, pages 1–5. IEEE, 2011.

[Digham *et al.* 2007] Fadel F Digham, Mohamed-Slim Alouini and Marvin K Simon. *On the energy detection of unknown signals over fading channels*. IEEE transactions on communications, vol. 55, no. 1, pages 21–24, 2007.

[Fudenberg & Tirole 1991] Drew Fudenberg and Jean Tirole. *Game theory*. 1991.

[Ganesan & Li 2005] Ghurumuruhan Ganesan and Ye Li. *Cooperative spectrum sensing in cognitive radio networks*. In New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005. 2005 First IEEE International Symposium on, pages 137–143. IEEE, 2005.

[Ganesan & Li 2007] Ghurumuruhan Ganesan and Ye Li. *Cooperative spectrum sensing in cognitive radio, part I: Two user networks*. Wireless Communications, IEEE Transactions on, vol. 6, no. 6, pages 2204–2213, 2007.

[Gardner *et al.* 1991] William Gardner*et al.* *Exploitation of spectral redundancy in cyclostationary signals*. Signal Processing Magazine, IEEE, vol. 8, no. 2, pages 14–36, 1991.

[Gavrilovska & Atanasovski 2011] Liljana Gavrilovska and Vladimir Atanasovski. *Spectrum sensing framework for cognitive radio networks*. Wireless Personal Communications, vol. 59, no. 3, pages 447–469, 2011.

[Ghasemi & Sousa 2005] Amir Ghasemi and Elvino S Sousa. *Collaborative spectrum sensing for opportunistic access in fading environments*. In New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005. 2005 First IEEE International Symposium on, pages 131–136. IEEE, 2005.

[Ghasemi & Sousa 2008] Amir Ghasemi and Elvino S Sousa. *Spectrum sensing in cognitive radio networks: requirements, challenges and design trade-offs*. Communications Magazine, IEEE, vol. 46, no. 4, pages 32–39, 2008.

[Goldsmith 2005] Andrea Goldsmith. Wireless communications. Cambridge university press, 2005.

[Group *et al.* 2006] SDR Forum Cognitive Radio Working Group*et al. Cognitive radio definitions and nomenclature*. Rapport technique, January, 2006.

[Han 2012] Zhu Han. Game theory in wireless and communication networks: theory, models, and applications. Cambridge University Press, 2012.

[Haykin *et al.* 2009] Simon Haykin, David J Thomson and Jeffrey H Reed. *Spectrum sensing for cognitive radio*. Proceedings of the IEEE, vol. 97, no. 5, pages 849–877, 2009.

[Haykin 2005] Simon Haykin. *Cognitive radio: brain-empowered wireless communications*. Selected Areas in Communications, IEEE Journal on, vol. 23, no. 2, pages 201–220, 2005.

[He *et al.* 2010] An He, Kyung Kyoon Bae, Timothy R Newman, Joseph Gaeddert, Kyouwoong Kim, Rekha Menon, Lizdabel Morales-Tirado, James Jody Neel, Youping Zhao, Jeffrey H Reed*et al. A survey of artificial intelligence for cognitive radios*. Vehicular Technology, IEEE Transactions on, vol. 59, no. 4, pages 1578–1592, 2010.

[Hossain *et al.* 2009] Ekram Hossain, Dusit Niyato and Zhu Han. Dynamic spectrum access and management in cognitive radio networks. Cambridge university press, 2009.

[Hoven *et al.* 2005] Niels Hoven, Rahul Tandra and Anant Sahai. *Some fundamental limits on cognitive radio*. Wireless Foundations EECS, Univ. of California, Berkeley, 2005.

[Jiang & Qu 2008] Tao Jiang and Daiming Qu. *On minimum sensing error with spectrum sensing using counting rule in cognitive radio networks*. In Proceedings of the 4th Annual International Conference on Wireless Internet, page 62. ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering), 2008.

[Kaelbling *et al.* 1996] Leslie Pack Kaelbling, Michael L Littman and Andrew W Moore. *Reinforcement learning: A survey*. Journal of artificial intelligence research, pages 237–285, 1996.

[Khalid & Anpalagan 2012] Lamiaa Khalid and Alagan Anpalagan. *Cooperative sensing with correlated local decisions in cognitive radio networks*. Vehicular Technology, IEEE Transactions on, vol. 61, no. 2, pages 843–849, 2012.

[Khan *et al.* 2010] Zaheer Khan, Janne Lehtomäki, Kenta Umebayashi and Johanna Vartiainen. *On the selection of the best detection performance sensors for cognitive radio networks*. Signal Processing Letters, IEEE, vol. 17, no. 4, pages 359–362, 2010.

[Kim & Shin 2008] Hyoil Kim and Kang G Shin. *Efficient discovery of spectrum opportunities with MAC-layer sensing in cognitive radio networks*. Mobile Computing, IEEE Transactions on, vol. 7, no. 5, pages 533–545, 2008.

[Kim *et al.* 2007] Kyouwoong Kim, Ihsan Akbar, Kyung K Bae, Jung-Sun Um, Chad M Spooner, Jeffrey H Reed*et al.* *Cyclostationary approaches to signal detection and classification in cognitive radio*. In New frontiers in dynamic spectrum access networks, 2007. DySPAN 2007. 2nd IEEE international symposium on, pages 212–215. IEEE, 2007.

[Kim *et al.* 2010] Kyungtae Kim, Yan Xin and Sampath Rangarajan. *Energy detection based spectrum sensing for cognitive radio: An experimental study*. In Global Telecommunications Conference (GLOBECOM 2010), 2010 IEEE, pages 1–5. IEEE, 2010.

[Kumar *et al.* 2015] Animesh Kumar, Rajeev Kumar, Punit Rathod and Abhay Karandikar. *How much TV UHF band spectrum is sufficient for rural broadband coverage?* In Modeling and Optimization in Mobile, Ad Hoc, and Wireless Networks (WiOpt), 2015 13th International Symposium on, pages 419–426. IEEE, 2015.

[Lee & Akyildiz 2008] Won-Yeol Lee and Ian F Akyildiz. *Optimal spectrum sensing framework for cognitive radio networks*. Wireless Communications, IEEE Transactions on, vol. 7, no. 10, pages 3845–3857, 2008.

[Lei & Shellhammer 2009] Zhongding Lei and Stephen J Shellhammer. *IEEE 802.22: The first cognitive radio wireless regional area network standard*. IEEE communications magazine, vol. 47, no. 1, pages 130–138, 2009.

[Li *et al.* 2012] Xiaohui Li, Wenlong Li and Yongqian Hei. *Joint spectrum sensing and user selection strategy for cognitive radio networks*. In Wireless Communications & Signal Processing (WCSP), 2012 International Conference on, pages 1–6. IEEE, 2012.

[Liang *et al.* 2008a] Ying-Chang Liang, Anh Tuan Hoang and Hsiao-Hwa Chen. *Cognitive radio on TV bands: a new approach to provide wireless connectivity for rural areas*. Wireless Communications, IEEE, vol. 15, no. 3, pages 16–22, 2008.

[Liang *et al.* 2008b] Ying-Chang Liang, Yonghong Zeng, Edward CY Peh and Anh Tuan Hoang. *Sensing-throughput tradeoff for cognitive radio networks*. Wireless Communications, IEEE Transactions on, vol. 7, no. 4, pages 1326–1337, 2008.

[Liang *et al.* 2011] Ying-Chang Liang, Kwang-Cheng Chen, Geoffrey Ye Li and Petri Mahonen. *Cognitive radio networking and communications: An overview*. Vehicular Technology, IEEE Transactions on, vol. 60, no. 7, pages 3386–3407, 2011.

[Liu & Wang 2010] KJ Ray Liu and Beibei Wang. Cognitive radio networking and security: A game-theoretic view. Cambridge University Press, 2010.

[Liu *et al.* 2010] Yi Liu, Rong Yu, Yan Zhang and Shengli Xie. *A group-based cooperative medium access control protocol for cognitive radio networks*. In Quality of Service (IWQoS), 2010 18th International Workshop on, pages 1–9. IEEE, 2010.

[Lo & Akyildiz 2010] Brandon F Lo and Ian F Akyildiz. *Reinforcement learning-based cooperative sensing in cognitive radio ad hoc networks*. In Personal Indoor and Mobile Radio Communications (PIMRC), 2010 IEEE 21st International Symposium on, pages 2244–2249. IEEE, 2010.

[Lunden *et al.* 2015] Jarmo Lunden, Visa Koivunen and H Vincent Poor. *Spectrum exploration and exploitation for cognitive radio: Recent advances*. Signal Processing Magazine, IEEE, vol. 32, no. 3, pages 123–140, 2015.

[Ma *et al.* 2008] Jun Ma, Guodong Zhao and Ye Li. *Soft combination and detection for cooperative spectrum sensing in cognitive radio networks*. Wireless Communications, IEEE Transactions on, vol. 7, no. 11, pages 4502–4507, 2008.

[MacKenzie & Wicker 2001] Allen B MacKenzie and Stephen B Wicker. *Game theory and the design of self-configuring, adaptive wireless networks*. Communications Magazine, IEEE, vol. 39, no. 11, pages 126–131, 2001.

[Marcus *et al.* 2002] Michael Marcus, Jim Burtle, Bruce Franca, Ahmed Lahjouji and Neal McNeil. *Federal communications commission spectrum policy task* *force*. Report of the Unlicensed Devices and Experimental Licenses Working Group, 2002.

[Mathur *et al.* 2006] Suhas Mathur, Lalitha Sankaranarayanan and Narayan B Mandayam. *Coalitional games in Gaussian interference channels*. In Information Theory, 2006 IEEE International Symposium on, pages 2210–2214. IEEE, 2006.

[Mishra *et al.* 2006] Shridhar Mubaraq Mishra, Anant Sahai and Robert W Brodersen. *Cooperative sensing among cognitive radios*. In Communications, 2006. ICC'06. IEEE International Conference on, volume 4, pages 1658–1663. IEEE, 2006.

[Mitola III & Maguire Jr 1999] Joseph Mitola III and Gerald Q Maguire Jr. *Cognitive radio: making software radios more personal*. Personal Communications, IEEE, vol. 6, no. 4, pages 13–18, 1999.

[Mitola III 2009] Joseph Mitola III. *Cognitive radio architecture evolution: annals of telecommunications*. annals of telecommunications-annales des télécommunications, vol. 64, no. 7-8, pages 419–441, 2009.

[Murroni *et al.* 2011] Maurizio Murroni, R Venkatesha Prasad, Paulo Marques, Bernd Bochow, Dominique Noguet, Chen Sun, Klaus Moessner and Hiroshi Harada. *Ieee 1900.6: spectrum sensing interfaces and data structures for dynamic spectrum access and other advanced radio communication systems standard: technical aspects and future outlook*. Communications Magazine, IEEE, vol. 49, no. 12, pages 118–127, 2011.

[Naik *et al.* 2014] Gaurang Naik, Sharad Singhal, Ajit Kumar and Abhay Karandikar. *Quantitative assessment of TV white space in India*. In Communications (NCC), 2014 Twentieth National Conference on, pages 1–6. IEEE, 2014.

[Neel *et al.* 2002] James Neel, J Reed and R Gilles. *The role of game theory in the analysis of software radio networks*. In SDR Forum Technical Conference November, 2002.

[Neel *et al.* 2004] James O Neel, Jeffrey H Reed and Robert P Gilles. *Game models for cognitive radio algorithm analysis*. In SDR Forum Technical Conference, pages 15–18, 2004.

[Nekovee 2009] Maziar Nekovee. *Quantifying the availability of TV white spaces for cognitive radio operation in the UK*. In Communications Workshops, 2009. ICC Workshops 2009. IEEE International Conference on, pages 1–5. IEEE, 2009.

[Niyato & Hossain 2007] Dusit Niyato and Ekram Hossain. *A game-theoretic approach to competitive spectrum sharing in cognitive radio networks*. In Wireless Communications and Networking Conference, 2007. WCNC 2007. IEEE, pages 16–20. IEEE, 2007.

[of India 2016] Government of India. *Telecom Regulatory Authority Of India*. `http://www.trai.gov.in/`, 2016. [Online; accessed 25-January-2016].

[Oh & Lee 2009] Dong-Chan Oh and Yong-Hwan Lee. *Energy detection based spectrum sensing for sensing error minimization in cognitive radio networks*. International Journal of Communication Networks and Information Security (IJCNIS), vol. 1, no. 1, 2009.

[Osborne & Rubinstein 1994] Martin J Osborne and Ariel Rubinstein. A course in game theory. MIT press, 1994.

[Pardalos *et al.* 2008] Panos M Pardalos, Athanasios Migdalas and Leonidas Pitsoulis. Pareto optimality, game theory and equilibria, volume 17. Springer Science & Business Media, 2008.

[Paysarvi-Hoseini & Beaulieu 2011] Pedram Paysarvi-Hoseini and Norman C Beaulieu. *Optimal wideband spectrum sensing framework for cognitive radio systems*. IEEE Transactions on signal processing, vol. 59, no. 3, pages 1170–1182, 2011.

[Peh & Liang 2007] Edward Peh and Ying-Chang Liang. *Optimization for cooperative sensing in cognitive radio networks*. In Wireless Communications and Networking Conference, 2007. WCNC 2007. IEEE, pages 27–32. IEEE, 2007.

[Pham *et al.* 2010] Hai Ngoc Pham, Yan Zhang, Paal E Engelstad, Tor Skeie and Frank Eliassen. *Energy minimization approach for optimal cooperative spectrum sensing in sensor-aided cognitive radio networks*. In Wireless Internet Conference (WICON), 2010 The 5th Annual ICST, pages 1–9. IEEE, 2010.

[Poor 2013] H Vincent Poor. An introduction to signal detection and estimation. Springer Science & Business Media, 2013.

[Proakis 1995] J.G. Proakis. Digital communications. McGraw-Hill, 1995.

[Quan *et al.* 2008] Zhi Quan, Shuguang Cui and Ali H Sayed. *Optimal linear cooperation for spectrum sensing in cognitive radio networks*. Selected Topics in Signal Processing, IEEE Journal of, vol. 2, no. 1, pages 28–40, 2008.

[Quan *et al.* 2009] Zhi Quan, Shuguang Cui, Ali H Sayed and H Vincent Poor. *Optimal multiband joint detection for spectrum sensing in cognitive radio networks*. Signal Processing, IEEE Transactions on, vol. 57, no. 3, pages 1128–1140, 2009.

[Ramanathan & Partridge 2005] Ram Ramanathan and Criag Partridge. *Next generation (xG) architecture and protocol development (XAP)*. Rapport technique, DTIC Document, 2005.

[Ray 2007] Debraj Ray. A game-theoretic perspective on coalition formation. Oxford University Press, 2007.

[Richards 2014] Mark A Richards. *Alternative Forms of Albersheim's Equation*. 2014.

[Russell & Norvig 2003] SJ Russell and P Norvig. *Definitions of software defined radio (sdr) and cognitive radio system (crs)*. Artificial Intelligence: A Modern Approach (2nd ed.), Upper Saddle River, New Jersey: Prentice Hall, ISBN 0-13-790395-2, 2003.

[Saad *et al.* 2008] Walid Saad, Zhu Han, Mérouane Debbah and Are Hjørungnes. *A distributed merge and split algorithm for fair cooperation in wireless networks*. In Communications Workshops, 2008. ICC Workshops' 08. IEEE International Conference on, pages 311–315. IEEE, 2008.

[Saad *et al.* 2009] Walid Saad, Zhu Han, Mérouane Debbah, Are Hjørungnes and Tamer Başar. *Coalitional game theory for communication networks*. Signal Processing Magazine, IEEE, vol. 26, no. 5, pages 77–97, 2009.

[Saad *et al.* 2011] Walid Saad, Zhu Han, Tamer Başar, Mérouane Debbah and Are Ørungnes. *Coalition formation games for collaborative spectrum sensing*. Vehicular Technology, IEEE Transactions on, vol. 60, no. 1, pages 276–297, 2011.

[Sharma *et al.* 2015] Shree Krishna Sharma, Tadilo Endeshaw Bogale, Symeon Chatzinotas, Bjorn Ottersten, Long Bao Le and Xianbin Wang. *Cognitive* *radio techniques under practical imperfections: A survey*. Communications Surveys & Tutorials, IEEE, vol. 17, no. 4, pages 1858–1884, 2015.

[Shimomura & Oyama 2014] Tsuyoshi Shimomura and Teppei Oyama. *Analysis of TV white space availability in Japan*. IEICE Transactions on Communications, vol. 97, no. 2, pages 350–358, 2014.

[Simon & Alouini 2005] Marvin K Simon and Mohamed-Slim Alouini. Digital communication over fading channels, volume 95. John Wiley & Sons, 2005.

[Sklar 2001] Bernard Sklar. Digital communications, volume 2. Prentice Hall NJ, 2001.

[Sridhar 2011] Varadharajan Sridhar. The telecom revolution in india: technology, regulation, and policy. Oxford University Press, 2011.

[Sum *et al.* 2011] Chin-Sean Sum, Hiroshi Harada, Fumihide Kojima, Zhou Lan and Ryuhei Funada. *Smart utility networks in TV white space*. Communications Magazine, IEEE, vol. 49, no. 7, pages 132–139, 2011.

[Sun *et al.* 2007] Chunhua Sun, Wei Zhang and Khaled Ben Letaief. *Cooperative spectrum sensing for cognitive radios under bandwidth constraints*. In Wireless Communications and Networking Conference, 2007. WCNC 2007. IEEE, pages 1–5. IEEE, 2007.

[Sutton & Barto 2011] Richard S Sutton and Andrew G Barto. *Reinforcement learning: An introduction*, 2011.

[Tabassam *et al.* 2011] Ahmad Ali Tabassam, Farhan Azmat Ali, Sumit Kalsait and Muhammad Uzair Suleman. *Building Software-Defined Radios in MATLAB Simulink-A Step Towards Cognitive Radios*. In Computer Modelling and Simulation (UKSim), 2011 UkSim 13th International Conference on, pages 492–497. IEEE, 2011.

[Tafazolli 2006] Rahim Tafazolli. Technologies for the wireless future: Wireless world research forum (wwrf). John Wiley & Sons, 2006.

[Tandra & Sahai 2005] Rahul Tandra and Anant Sahai. *Fundamental limits on detection in low SNR under noise uncertainty*. In Wireless Networks, Communications and Mobile Computing, 2005 International Conference on, volume 1, pages 464–469. IEEE, 2005.

[Tandra & Sahai 2008] Rahul Tandra and Anant Sahai. *SNR walls for signal detection*. Selected Topics in Signal Processing, IEEE Journal of, vol. 2, no. 1, pages 4–17, 2008.

[Tandra *et al.* 2009] Rahul Tandra, Shridhar Mubaraq Mishra and Anant Sahai. *What is a spectrum hole and what does it take to recognize one?* Proceedings of the IEEE, vol. 97, no. 5, pages 824–848, 2009.

[Tang 2005] Haiyun Tang. *Some physical layer issues of wide-band cognitive radio systems*. In New frontiers in dynamic spectrum access networks, 2005. DySPAN 2005. 2005 first IEEE international symposium on, pages 151–159. IEEE, 2005.

[Thilina *et al.* 2013] Karaputugala Madushan Thilina, Kae Won Choi, Nazmus Saquib and Ekram Hossain. *Machine learning techniques for cooperative spectrum sensing in cognitive radio networks*. Selected Areas in Communications, IEEE Journal on, vol. 31, no. 11, pages 2209–2221, 2013.

[Tian & Giannakis 2006] Zhi Tian and Georgios B Giannakis. *A wavelet approach to wideband spectrum sensing for cognitive radios*. In Cognitive radio oriented wireless networks and communications, 2006. 1st international conference on, pages 1–5. IEEE, 2006.

[Tian & Giannakis 2007] Zhi Tian and Georgios B Giannakis. *Compressed sensing for wideband cognitive radios*. In Acoustics, Speech and Signal Processing, 2007. ICASSP 2007. IEEE International Conference on, volume 4, pages IV–1357. IEEE, 2007.

[Uchiyama *et al.* 2008] Hiromasa Uchiyama, Kenta Umebayashi, Takeo Fujii, Kei SAKAGUCHI, Yukihiro KAMIYA and Yasuo SUZUKI. *Study on soft decision based cooperative sensing for cognitive radio networks*. IEICE transactions on communications, vol. 91, no. 1, pages 95–101, 2008.

[Unnikrishnan & Veeravalli 2008] Jayakrishnan Unnikrishnan and Venugopal V Veeravalli. *Cooperative sensing for primary detection in cognitive radio*. Selected Topics in Signal Processing, IEEE Journal of, vol. 2, no. 1, pages 18–27, 2008.

[Urkowitz 1967] Harry Urkowitz. *Energy detection of unknown deterministic signals*. Proceedings of the IEEE, vol. 55, no. 4, pages 523–531, 1967.

[Van De Beek *et al.* 2012] Jaap Van De Beek, Janne Riihijärvi, Andreas Achtzehn and Petri Mähönen. *TV white space in Europe*. Mobile Computing, IEEE Transactions on, vol. 11, no. 2, pages 178–188, 2012.

[Vasudevan *et al.* 2003] Sudarshan Vasudevan, Brian DeCleene, Neil Immerman, Jim Kurose and Don Towsley. *Leader election algorithms for wireless ad hoc networks*. In DARPA Information Survivability Conference and Exposition, 2003. Proceedings, volume 1, pages 261–272. IEEE, 2003.

[Visotsky *et al.* 2005] E Visotsky, S Kuffner and R Peterson. *On collaborative detection of TV transmissions in support of dynamic spectrum sharing*. In New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005. 2005 First IEEE International Symposium on, pages 338–345. IEEE, 2005.

[Wang & Liu 2011] Beibei Wang and KJ Liu. *Advances in cognitive radio networks: A survey*. Selected Topics in Signal Processing, IEEE Journal of, vol. 5, no. 1, pages 5–23, 2011.

[Wang *et al.* 2010] Beibei Wang, Yongle Wu and KJ Ray Liu. *Game theory for cognitive radio networks: An overview*. Computer networks, vol. 54, no. 14, pages 2537–2561, 2010.

[Xie *et al.* 2010] Shengli Xie, Yi Liu, Yan Zhang and Rong Yu. *A parallel cooperative spectrum sensing in cognitive radio networks*. Vehicular Technology, IEEE Transactions on, vol. 59, no. 8, pages 4079–4092, 2010.

[Ye *et al.* 2007] Li Ye*et al.* *Cooperative Spectrum Sensing in Cognitive Radio, Part II: Multiuser Networks*. IEEE Transactions on Wireless Communications, vol. 6, no. 6, pages 2214–2222, 2007.

[Yu *et al.* 2012] Rong Yu, Yan Zhang, Liu Yi, Shengli Xie, Lingyang Song and Mohsen Guizani. *Secondary users cooperation in cognitive radio networks: balancing sensing accuracy and efficiency*. Wireless Communications, IEEE, vol. 19, no. 2, pages 30–37, 2012.

[Yücek & Arslan 2009] Tevfik Yücek and Hüseyin Arslan. *A survey of spectrum sensing algorithms for cognitive radio applications*. Communications Surveys & Tutorials, IEEE, vol. 11, no. 1, pages 116–130, 2009.

[Zeng *et al.* 2010] Yonghong Zeng, Ying-Chang Liang, Anh Tuan Hoang and Rui Zhang. *A review on spectrum sensing for cognitive radio: challenges and so-*

lutions. EURASIP Journal on Advances in Signal Processing, vol. 2010, page 2, 2010.

[Zhang *et al.* 2008] Wei Zhang, Ranjan K Mallik and Khaled Ben Letaief. *Cooperative spectrum sensing optimization in cognitive radio networks*. In Communications, 2008. ICC'08. IEEE International Conference on, pages 3411–3415. IEEE, 2008.

[Zhang *et al.* 2009] Wei Zhang, Ranjan K Mallik and Khaled Letaief. *Optimization of cooperative spectrum sensing with energy detection in cognitive radio networks*. Wireless Communications, IEEE Transactions on, vol. 8, no. 12, pages 5761–5766, 2009.

[Zhou *et al.* 2010] Xiangwei Zhou, Jun Ma, Geoffrey Ye Li, Young Hoon Kwon and Anthony CK Soong. *Probability-based combination for cooperative spectrum sensing*. IEEE Transactions on Communications, vol. 58, no. 2, pages 463–466, 2010.

Publications

Journal Papers

1. V. Balaji, S. Anand, C. R. Hota, and G. Raghurama, 'Spectrum Hole Identification in IEEE 802.22 WRAN using Unsupervised Learning', EAI Endorsed Transaction on Wireless Spectrum, vol.2, no.7, pp.$1-8$, Jan 2016.

2. V. Balaji, P. Kabra, P. V. P. K. Saieesh, C. Hota, and G. Raghurama, 'Cooperative Spectrum Sensing in Cognitive Radios Using Perceptron Learning for IEEE 802.22 WRAN', Elsevier Procedia of Computer Science, vol.54, pp.$14-23$, 2015.

3. V. Balaji, Chittaranjan Hota, and G. Raghurama, 'Spectrum Hole Prediction for Cognitive Radios: An Artificial Neural Network Approach', International Journal of Information Processing (IJIP), (Accepted and to appear in upcoming issue).

4. V. Balaji, Tejas Nagendra, Chittaranjan Hota, and G. Raghurama, 'Distributed Spectrum Sensing in Cognitive Radio Networks using Archetypal Analysis', Accepted in Elsevier Journal of Computers & Electrical Engineering.

5. Pradyumna T, V. Balaji, Chittaranjan Hota, and G. Raghurama, 'Cooperative Spectrum Sensing for Cognitive Radios: A Reinforcement Learning Based Approach', Submitted to Springer Journal of Wireless Networks.

Conference Papers

1. V. Balaji and Chittaranjan Hota, 'Efficient Cooperative Spectrum Sensing in Cognitive Radio Using Coalitional Game model', IEEE International Conference on Contemporary Computing and Informatics (IC3I), pp.$899-907$, Mysore, 2014.

2. V. Balaji, Tejas Nagendra, Chittaranjan Hota, and G. Raghurama, 'Cooperative Spectrum Sensing in Cognitive Radio: An Archetypal Clustering Approach', IEEE International Conference on Wireless Communications Signal Processing and Networking (WiSPNET), March, 2016.

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Brief Biography of the Co-Supervisor

Chittaranjan Hota is a Professor and Associate Dean (Admissions) at Birla Institute of Technology and Science-Pilani, Hyderabad, India. He is also responsible for managing the Information Processing Unit at BITS-Hyderabad that takes care of ICT needs of the entire institute. He was the founding Head of Dept. of Computer Science at BITS, Hyderabad. Prof. Hota did his PhD in Computer Science and Engineering from Birla Institute of Technology & Science, Pilani. He has been a visiting researcher and visiting professor at University of New South Wales, Sydney; University of Cagliari, Italy; Aalto University, Finland and City University, London over the past few years. His research work has been funded by University Grants Commission (UGC), New Delhi; Department of Electronics & Information Technology (DeitY), New Delhi; Tata Consultancy Services (TCS), India; and Progress Software, India. He has guided PhD students and currently guiding several in the areas of Internet of Things, Cyber security, and Big-data analytics. He is recipient of Australian Vice Chancellors' Committee award, recipient of Erasmus Mundus fellowship from European commission, and recipient of Certificate of Excellence from Kris Ramachandran Faculty Excellence Award from BITS, Pilani. He has published extensively in peer-reviewed journals and conferences and has also edited LNCS volumes. He is a member of IEEE, ACM, CSI, IE, and ISTE.