USER SELECTION AND DENSITY BASED DECISION METHOD FOR COOPERATIVE SPECTRUM SENSING IN COGNITIVE RADIO NETWORKS

by

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ABSTRACT

USER SELECTION AND DENSITY BASED DECISION METHOD FOR COOPERATIVE SPECTRUM SENSING IN COGNITIVE RADIO NETWORKS

Radio spectrum is one of the scarce source and its importance is increasing in recent years due to rapidly developing new technologies. Today's wireless networks use fixed spectrum assignment policy which causes inefficient utilization of this limited source. Therefore, new technologies are needed to use the spectrum in a more efficient manner. One of the promising technology that aims to use the spectrum dynamically is *Cognitive Radios (CRs)*. *Cognitive Radio Networks (CRNs)* aim to use the spectrum dynamically by sensing the spectrum and if any gap is detected than they will provide their customer to use this spectrum band. Spectrum sensing plays significant role for the implementation of CRNs. The focus of this thesis is spectrum sensing problem in CRNs. In this work, spectrum sensing problem is investigated as a binary signal detection problem, which aims to find if a signal is present or not. The signal to be detected can be either known or unknown characteristics depending on the application. The signal is considered to be completely unknown from the *Secondary User (SU)* receiver side throughout the thesis. For this reason, energy detector is preferred as a detection method. Energy detectors (radiometers) are often used due to their implementation simplicity and good performances. The detection is based on some function of the received samples which is compared with a threshold. If the threshold is exceeded, it is decided that signal is present. Since sensing is very crucial at CRNs, cooperative user selection algorithms and decision methods are proposed to improve the performance of the detector. Two cooperative user selection algorithms based on SUs' and *Primary User's (PU's)* locations are proposed. Besides, two centralized cooperative decision methods are also proposed and evaluated with the cooperative user selection algorithms. One of the proposed cooperative decision methods is based on SUs' decision

density at each region and the other one is based on weighting SUs' decisions according to their regions. Performance of these methods are evaluated using indoor and outdoor propagation models. One of the main goals here is to show that with the proposed cooperative selection algorithms, performance is improved when compared with random and worst selection of SUs. The other one is to illustrate further improvement in sensing performance is also achieved with the proposed centralized cooperative decision methods, compared to non-cooperative and cooperative schemes like majority rule and hard decision. The success of these methods are verified through simulations.

ÖZET

BİLİŞSEL RADYO AĞLARINDA İŞBİRLİKÇİ SPEKTRUM ALGILAMA İÇİN KULLANICI SEÇİMİ VE KULLANICI YOĞUNLUĞU BAZLI KARAR VERME ALGORİTMASI

Radyo spektrumu sınırlı kaynaklardan biridir ve hızla ilerleyen yeni kablosuz teknolojiler ile birlikte son yıllarda önemi artmaktadır. Günümüzdeki kablosuz ağlar, bu sınırlı kaynağın verimsiz kullanılmasına sebep olan sabit spektrum atama kuralını kullanmaktadır. Bu sebeple, spektrumun çok daha verimli kullanılmasını sağlayacak yeni teknolojilere ihtiyaç vardır. Bilişsel radyolar, spektrumun dinamik olarak kullanılmasını amaçlayan, gelecek vaadeden teknolojilerden biridir. Bilişsel radyo ağları spektrumu dinamik olarak kulanmayı, spektrumu algılayarak ve eğer bir boşluk bulurlarsa, bu spektrum bandını müşterilerinin kullanmasını sağlayarak amaçlamaktadırlar. Bilişsel radyo ağlarının hayata geçirilmesinde spektrum sezimi önemli rol oynamaktadır. Bu tezin odak noktası, bilişsel radyo ağlarındaki spektrum sezme problemidir. Bu çalışmada, spektrum sezme problemi, amacı sinyalin varlığını ya da yokluğunu tespit etmek olan ikili sinyal algılama problemi olarak incelenmiştir. Algılanmak istenen sinyal, uygulamaya bağlı olarak bilinen ya da bilinmeyen niteliklere sahip olabilmektedir. Tezde, algılanmak istenen sinyalin ikincil kullanıcının alıcısı tarafından bilinmediği kabul edilmiştir. Bu sebeple, enerji dedektör algılama yöntemi olarak tercih edilmiştir. Enerji dedektörleri, uygulama kolaylıkları ve iyi performansları sebebiyle oldukça sık kullanılmaktadırlar. Algılama, alınan örneklerin bir eşik değeri ile karşılaştırıldığı bazı fonksiyonlara dayanmaktadır. Eğer eşik aşılırsa, sinyal mevcut kararı verilir. Algılama bilişsel radyo ağlarında çok önemli olduğundan, dedektörün performansını artırmak için, bu tezde işbirlikçi kullanıcı seçimi algoritmaları ve karar verme yöntemleri önerilmiştir. İkincil ve birincil kullanıcılarının konumlarına dayanarak iki işbirlikçi kullanıcı seçimi algoritması sunulmuştur. Ayrıca, iki merkezi işbirlikçi karar verme yöntemi de önerilmiştir ve bu yöntemler işbirlikçi kullanıcı seçim al-

goritmaları ile değerlendirilmiştir. Önerilen işbirliği yöntemlerinden biri, ikincil kullanıcıların her bir bölgedeki karar yoğunluğuna, diğeri ise ikincil kullanıcıların kararlarının bulundukları bölgelere göre ağırlıklandırılmasına dayanmaktadır. Bu yöntemlerin performansı açık ve kapalı alanlardaki yayılma modelleri ile değerlendirilmiştir. Buradaki ana hedeflerden biri, önerilen işbirlikçi seçim algoritmaları ile performansın rastgele ve en kötü seçim algoritmalarına göre geliştiğini göstermektir. Diğeri ise, önerilen merkezi işbirlikçi karar verme yöntemleri ile performansdaki iyileşmenin işbirlikçi olmayan ve işbirlikçi olan çoğunluk ile zorunlu karar verme yöntemlerine kıyasla daha da arttığını göstermektir. Bu yöntemlerin başarımları benzetim çalışmaları ile doğrulanmıştır.

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Co_{SU}^{Equ}	Group of SUs chosen for cooperation with equal selection
Co_{SU}^{Prob}	Group of SUs chosen for cooperation with probabilistic selection
Co_{SU}^{Rand}	Group of SUs chosen for cooperation randomly
Co_{SU}^{Worst}	Group of SUs chosen for cooperation with worst selection
DR^i	Detection ratio of region i
DR^{total}	Total Detection Ratio
d	Transmitter-Receiver separation distance
d_0	Close-in reference distance which is determined from measurements close to transmitter
f_c	Center frequency
H_0	Null hypothesis, means PU does not exist
H_1	Alternative hypothesis, means PU exists
h	Amplitude gain of the channel between primary user and secondary user
$I_\upsilon(.)$	υth-order modified Bessel function of the first kind
k	Number of regions
N_{CoopSU}	Number of cooperating SUs
N_{CoopSU}^i	Number of cooperating SUs at i^{th} region
$N_{CoopSU^{det}}^i$	Number of cooperating SUs at i^{th} region who decides PU is present
n	Path loss exponent
n_i	Number of SUs at region i
$n(t)$	Signal representing Additive White Gaussian Noise
P_d	Probability of Detection
P_{fa}	Probability of False Alarm
PU_{Loc}	Primary user location
$Q_N(a, b)$	Generalized marcum Q function
$Rand(x; y)$	A function which selects y number of users from table x randomly

R^i	i^{th} region of CBS
R^i_{SU}	A table in which SUs' locations at i^{th} region are recorded
R^{PU}	PU's region
$R^{\alpha}_{y}(\tau)$	Cyclic Autocorrelation Function
$r(t)$	Input signal of Bandpass Filter
$r_f(t)$	Output signal of Bandpass Filter
$S(f,\alpha)$	Cyclic Spectral Density function
SU_{Weight}	Secondary user weight
$s(t)$	Transmitted signal of the primary user
T	Observation interval
W	Bandwidth
W_{R_i}	Weight of i_{th} region
W_{SU_i}	Weight of each SU at region i
w_n	Weight of each user
X^2_{2N}	Central chi-square distribution
$X^2_{2N}(2\gamma)$	Non-central chi-square distribution
Y	Output of the energy detector, decision metric
Y_n	Output of the energy detector
Y_{WC}	Weighted sum of the N number of secondary users' measurements
$y(n)$	Output signal of energy detector
$y(t)$	Signal received by secondary user
α	cyclic frequency
γ	Instantaneous Signal to Noise Ratio of secondary user
$\Gamma(.)$	gamma function
λ	Threshold
AF	Amplify and Forward
AWGN	Additive White Gaussian Noise
BS	Base Station
BPF	Band Pass Filter

CAF	Cyclic Autocorrelation Function
CBS	Cognitive Base Station
CC	Central Controller
CDMA	Code Division Multiple Access
CogMT	Cognitive Mobile Terminal
CPE	Customer Premise Equipment
CR	Cognitive Radio
CRN	Cognitive Radio Network
CSD	Cyclic Spectral Density
DAS	Distributed Antenna System
DFS	Dynamic Frequency Selection
DSA	Dynamic Spectrum Access
DySPAN	Dynamic Spectrum Access Networks
EGC	Equal Gain Combining
FCC	Federal Communications Commission
FSA	Fixed Spectrum Allocation
GLR	Generalized Likelihood Ratio
GSM	Global System for Mobile communications
IEEE	Institute of Electrical and Electronics Engineers
NetLab	computer Networks research Lab
OFDM	Orthogonal Frequency Division Multiplexing
QOS	Quality of Service
PSD	Power Spectral Density
RF	Radio Frequency
Satlab	Satellite Networks Research Laboratory
SB	Spectrum Broker
SC	Selection Combining
SSC	Switch and Stay Combining
SDR	Software-Defined Radio
SM	Spectrum Manager
SNR	Signal to Noise Ratio

TPC	Transmit Power Control
WGC	Weighted Gain Combining
WRAN	Wireless Regional Area Network
xG	Next Generation

1. INTRODUCTION

Telecommunication technology has been improving very rapidly in recent years and the new coming technologies have not been replaced with the older technologies immediately. Sometimes new technologies are used together with the older ones for a long period in order to serve different usage areas. Besides, newer technologies in wireless networks want to allocate a spectrum band to work with. This causes problems in sharing one of the limited resources, the wireless spectrum.

James H. Snider, a senior fellow at the Washington based New America Foundation think tank group, said: “This is the most valuable natural resource for America’s information infrastructure. The tragedy is that the public doesn’t know about it and doesn’t give a damn. There are hundreds of lobbyists that spend their waking hours just thinking of how to acquire public airways without paying for them and they’ve been very successful” [1].

Up to now spectrum has been allocated by wireless networks sporadically. For instance, today’s wireless networks are characterized by a fixed spectrum assignment policy which causes gaps in spectrum [2]. Actual measurements show that at least 70% of spectrum is unused. In order to overcome the problem of scarcity in the spectrum due to the limited available spectrum bands and inefficiency in the spectrum usage, a new paradigm for wireless communication has been suggested, *Cognitive Radio (CR)*, which is formerly known as *Next Generation (xG)* Networks or *Dynamic Spectrum Access (DSA)*. According to the *Federal Communications Commission (FCC)*: “We recognize the importance of new cognitive radio technologies, which are likely to become more prevalent over the next few years and which hold tremendous promise in helping to facilitate more effective and efficient access to spectrum” [3].

1.1. Contribution of the Thesis

We propose two user selection algorithms and two cooperative decision methods to improve the performance of detection in cognitive radio networks. The contribution of this thesis can be summarized as follows:

- *Cognitive Radio Network (CRN)* architecture is implemented in order to evaluate performance for outdoor and indoor environments.
- For given CRN architecture, two cooperative user selection algorithms are proposed to improve detection performance at the *Cognitive Base Station's (CBS's)*. Performances of these proposed methods' are compared with random, worst, and best selection cases for each cooperative decision methods.
- For CBS final decision, two centralized cooperative decision methods are proposed based on SUs' and/or PU's location information knowledge. The performance of these methods' are compared with non-cooperative and cooperative cases.
- A CRN air interface simulator is implemented to evaluate performance of each selection algorithm with each decision method.

1.2. Organization of the Thesis

In this thesis, cognitive radio and spectrum sensing overview are introduced in Chapter 2. Moreover, cooperative decision rules in the literature and IEEE 802.22 specifications including geo-location database and spectrum sensing are presented.

Chapter 3 explains spectrum sensing problem in CRNs. *Institute of Electrical and Electronics Engineers (IEEE)* requirements in IEEE 802.22 and necessity of new spectrum sensing methods are explained. Two user selection algorithms for cooperative sensing at CRNs are proposed in Section 3.2. Furthermore, in Section 3.3, two cooperative decision methods are proposed which are based on centralized decision architecture.

In Chapter 4, a CRN simulator is implemented to evaluate the performances of decision methods and selection algorithms. With the help of this simulator, each selection algorithm is analyzed with each decision method to find the pair with the best performance. Furthermore, network architecture is considered for spectrum sensing environment in CRNs. Details of the network architecture considered for simulation are also given. Network architecture is composed of one CBS, one PU for each channel and multiple SUs sensing that channel. Sensing environment for outdoor is considered as one sector of base station like in *Global System for Mobile communications (GSM)*. Indoor environment details can be found in literature as *Distributed Antenna Systems (DAS)*.

Finally, Chapter 5 presents our conclusions and possible future research directions.

2. BACKGROUND INFORMATION

2.1. Cognitive Radio Overview

The idea of cognitive radio was first presented officially in an article by Joseph Mitola III and Gerald Q. Maguire, Jr. [4]. Initially cognitive radio was thought as a *Software-Defined Radio (SDR)* extension. But then researches about this issue have focused on Spectrum Sensing Cognitive Radio which differentiates it from SDR. The main goal of cognitive radio is to provide open spectrum sharing without causing any interference. This will be done by finding spectrum holes with spectrum sensing. Spectrum hole concept is illustrated in Figure 2.1. The problem in Spectrum Sensing Cognitive Radio is that the design of high quality spectrum sensing devices and algorithms are not very simple to solve. It has been shown in [5] that a simple energy detector cannot guarantee the accurate detection of signal presence. However, it has also been shown that increasing the number of cooperating sensing nodes decreases the probability of false detection, thus improving the spectrum sensing performance [6].

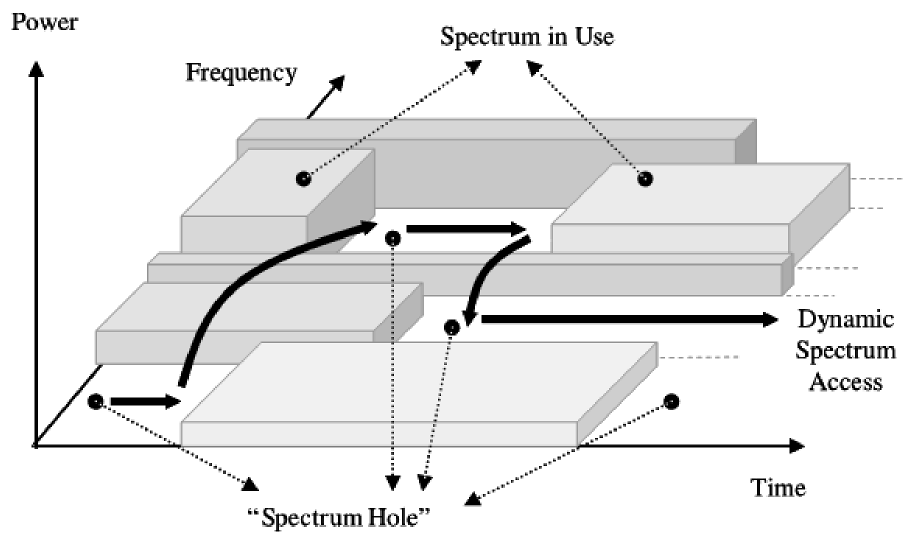

Figure 2.1. Spectrum Hole Concept

[2]

Looking from the point of spectrum allocation for cognitive radio, it is seen that the spectrum bands up to $60GHz$ are allocated by *Federal Communications Commission (FCC)* for multiple users. But the spectrum bands from $3GHz$ to $6GHz$ are used much more frequently. Although spectrum is allocated up to $60GHz$, it is almost unused which can be seen from Figure 2.2. TV band is considered promising for the use of cognitive radios. Moreover, higher frequencies are also attractive for this purpose. Cognitive radios manage the spectrum by providing unlicensed users to share the spectrum with primary users without causing interference problem. Therefore, this gap of spectrum or the parts which are used randomly in the spectrum bands will play a significant role when establishing cognitive radio.

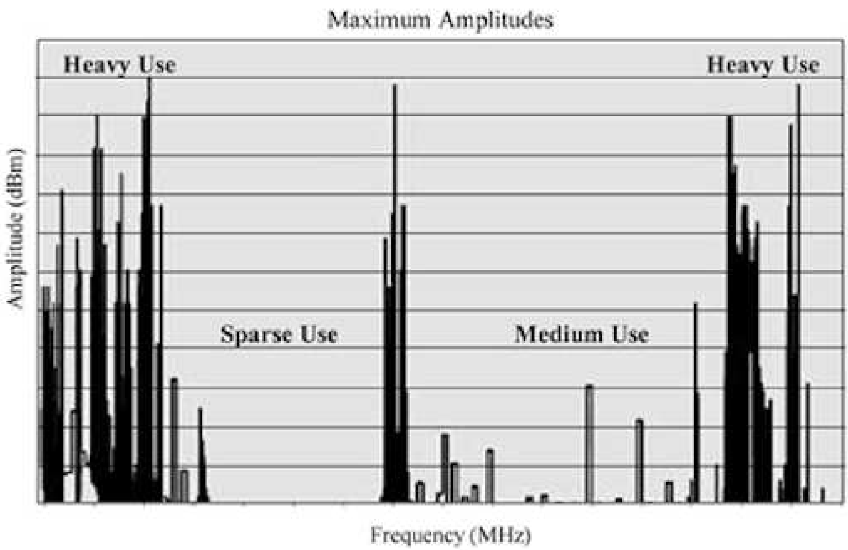

Figure 2.2. Spectrum Utilization

[2]

In the near future, the applications of CR are desired to be emergency networks, next generation wireless networks and heterogeneous wireless networks. The next generation wireless networks will be based on cooperative and collaborative wireless networks, in which nodes are communicating in different band allocations, in order to improve the performance and bandwidth efficiency. Roaming in heterogeneous wireless networks is limited due to the bandwidth inadaptability caused by the fact that today's wireless networks are based on a fixed spectrum. Therefore, CR is thought to be a primary solution to overcome this problem.

Cognitive radio promises a low cost, highly flexible alternative to the classic single frequency band, single protocol wireless device. By sensing and adapting to its environment, such a device is able to fill the voids in the wireless spectrum and dramatically increase spectral efficiency [7].

The main functions of *Cognitive Radios (CR)* can be summarized as follows [2]:

Spectrum Sensing: The most important requirement of cognitive radio is to detect the unused spectrum and share it without causing interference to other users.

Spectrum Management: The aim is to capture the best available spectrum to meet users' *Quality of Service (QoS)* requirements over all available spectrum bands.

Spectrum Mobility: Cognitive radio networks aim to use the spectrum in a dynamic manner by allowing the radio terminals to operate in the best available frequency band.

Spectrum Sharing: One of the major challenges in open spectrum usage is the spectrum sharing. It is similar to generic *Media Access Control (MAC)* problems in existing systems.

In [8], FCC has identified the following features that cognitive radios can incorporate to enable a more efficient and flexible usage of the spectrum:

- Frequency Agility: The radio is able to change its operating frequency to optimize its use in adapting to the environment.
- *Dynamic Frequency Selection (DFS)*: The radio senses signals from nearby transmitters to choose an optimal operation environment.
- Adaptive Modulation: The transmission characteristics and waveforms can be reconfigured to exploit all opportunities for the usage of spectrum.

- *Transmit Power Control (TPC)*: The transmission power is adapted to full power limits when necessary on one hand and to lower levels on the other hand to allow greater sharing of the spectrum.
- Location Awareness: The radio is able to determine its location and the location of other devices operating in the same spectrum to optimize transmission parameters for increasing spectrum re-use.
- Negotiated Use: The cognitive radio may have algorithms enabling the sharing of spectrum in terms of prearranged agreements between a licensee and a third party.

Cognitive functionality is presented in Figure 2.3.

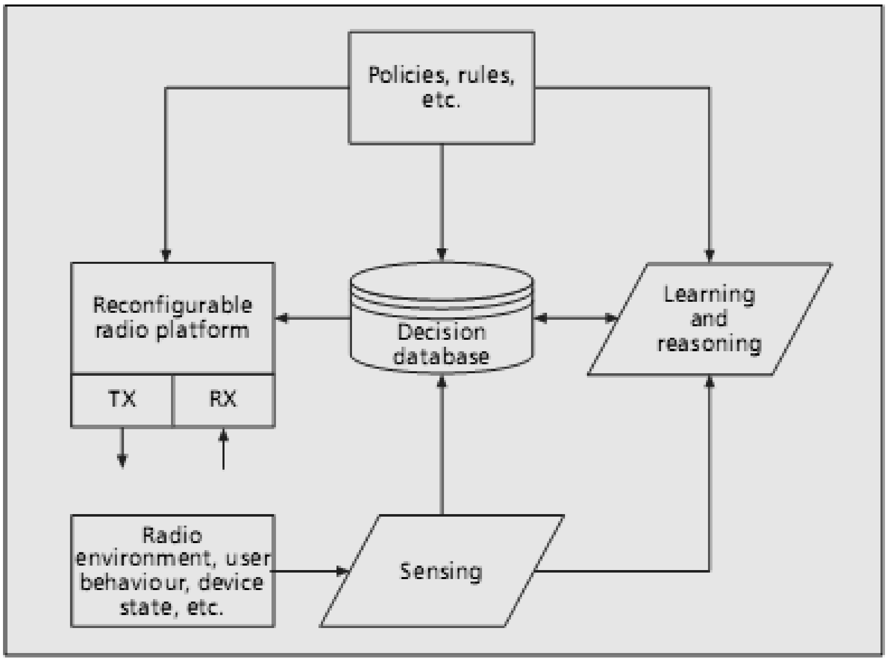

Figure 2.3. Cognitive Radio Functionality
[9]

2.1.1. Spectrum Sensing

Spectrum sensing issue in CRNs can be analyzed in two different detection requirements namely, PU detection and *Quality of Service (QoS)* detection. Moreover, spectrum sensing can be classified according to sensing band specifications like In-Band and Out-of-Band detection [10].

2.1.1.1. PU vs QoS Detection. Major aim of SU is to detect the PU whenever it appears in the spectrum band. If any PU is detected, SU should leave the band and hop to another where PU does not exist. Since PU detection has an important role in CRN, challenging problems related to PU detection are awaiting the best solutions. Challenges of PU detection can be given as:

- decreasing false alarm probability while increasing detection probability
- decreasing sensing time required for correct decision
- increase throughput

Cooperative sensing is one of the proposed methods to improve these requirements. QoS detection has smaller importance when compared with PU detection in CRNs. Hence, very limited studies are found on this topic in the literature. QoS detection goal is to satisfy SUs' channels with better QoS parameters. To achieve this, SUs sense in band and out of band channels and hop if they found channels with better QoS. The following schemes are proposed for this kind of detection:

- Long Term Sensing: This type of sensing can be deduced by data like PU presence duration of the band, hopping times of SUs from the band to another. Information gathered from long term sensing can help to estimate channel characteristics more precisely, hence has a contribution to estimate QoS of the channel.
- Short Term Sensing: Shadowing, fading, secondary user density information can provide necessary data for instant QoS of the channel.

2.1.1.2. In-band vs Out-of-band Sensing. All CRs independently sense their own spectrum at in-band sensing which is also known as own band sensing. On the other hand, for out-of-band sensing, all SUs need to sense the spectrum that they can hop to whenever PU is detected or QoS of the channel does not match with their requirements. This type sensing can be named also as hopping band sensing.

Hopping band detection may not be needed for all SUs. There can be other ways to hop to another channel whenever needed. One of them is keeping backup channels in order to provide SUs whenever they need. However, since it is difficult to keep a backup channel for all users, this is not feasible. The second way is using cooperative sensing methods, which CR1 can learn information about CR2's channel and vice versa. Hence, CR1 does not need to sense the whole spectrum bands but only sense its own spectrum and possibly one another band to hop to and provide information to nearer SUs.

Spectrum sensing in CRNs is an attractive issue because of its necessity to sense PU presence. Therefore, methods used for sensing should also be investigated to give a complete picture for sensing function of CRNs. For this reason, we give more detailed information about spectrum sensing and spectrum sensing methods in Section 2.2.

2.1.2. Spectrum Management

Spectrum consists of unoccupied bands, licensed and unlicensed bands. Characteristics of spectrum bands vary not only with time but also with space. Therefore, in order to choose the best band with specified qualifications from all available spectrum bands, new dynamic spectrum management functions are needed. In [2], these functions are classified into three categories as spectrum sensing, spectrum analysis and spectrum decision. Spectrum sensing is related to physical layer functionality of the cognitive radio and given in the previous section. Spectrum analysis includes classifying spectrum bands according to their characteristics such as primary user activity, operating frequency, bandwidth, channel error rate, path loss, interference, etc. On the other hand, spectrum decision function provides choice of the suitable spectrum band according to cognitive radio's QoS requirements and spectrum characteristics [2]. In [11] five spectrum decision rules are proposed that tradeoff performance between complexity of implementation and communication cost. [12] focuses on spectrum pricing and spectrum allocation algorithms in the context of design of spectrum brokers for macro-cellular networks. The problem is investigated considering *Code Division Multiple Access (CDMA)* networks.

2.1.3. Spectrum Mobility

Spectrum mobility concept includes that cognitive user has right to change its operating frequency either due to primary user presence or in order to get the channel with better QoS requirements. To achieve this, a new type of handoff mechanism is introduced namely spectrum handoff. There are lots of challenging issues awaiting solutions on spectrum handoff in cognitive radio networks. One of them is to design new mobility and connection management approaches to reduce delay and loss during spectrum handoff [2].

2.1.4. Spectrum Sharing

Spectrum sharing techniques can be classified according to access technique, architecture and allocation behavior. Spectrum sharing can be overlay and underlay according to access technique; distributed and centralized according to architecture, and cooperative and non-cooperative according to allocation behavior. This classification is visualized in Figure 2.4.

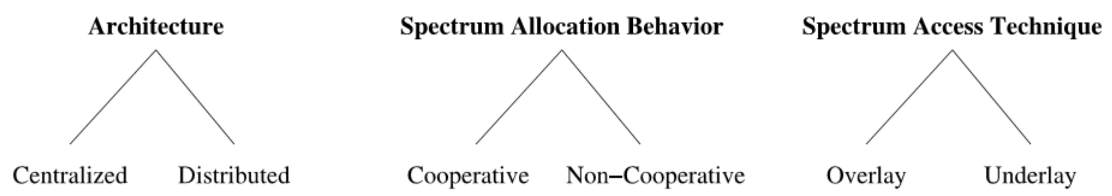

Figure 2.4. Classification of Spectrum Sharing based on Next Generation Architecture [2]

We will investigate overlay and underlay techniques in the following subsection.

Architecture and spectrum allocation behavior parts will be explained in the context of spectrum sensing and spectrum sensing methods section.

2.1.4.1. Overlay vs Underlay Techniques. Overlay technique allows next generation users to allocate the spectrum band which has not been allocated at that time or place by primary user. Main advantage is that interference with PU is minimized. However, it is difficult to find free spectrum portions always. Hence, it may cause frequent handoff due to PU presence [2].

With underlay technique, SU can allocate the same band at the same time with PU by providing less power in order not to interfere with PU. Hence PU considers this signal as noise. Advantage is that handoff frequency may decrease since SU does not need to vacate the channel when PU exists. Contrary to the overlay technique, interference with PU increases. In [2], it is stated that underlay techniques requires more complex spread spectrum techniques. Besides, they use increased bandwidth compared to overlay techniques. The effects of underlay and overlay approaches in a cooperative sensing are investigated in [13]. It is shown that when interference among users is high, the overlay approach becomes more efficient than underlay.

2.2. Spectrum Sensing and Spectrum Sensing Methods

Spectrum Sensing is one of the crucial topics in CRNs. Spectrum sensing method can be analyzed in terms of different aspects as can be seen from Figure 2.5.

From these various aspects, we focus on enabling algorithms, especially energy detection method and cooperative sensing. Besides, we use geo-location database's information partially for our proposed selection and decision methods. In this section, spectrum sensing methods and cooperative sensing issue in CRNs will be introduced in detail. Spectrum sensing methods can be classified as follows in a similar manner with Figure 2.5.

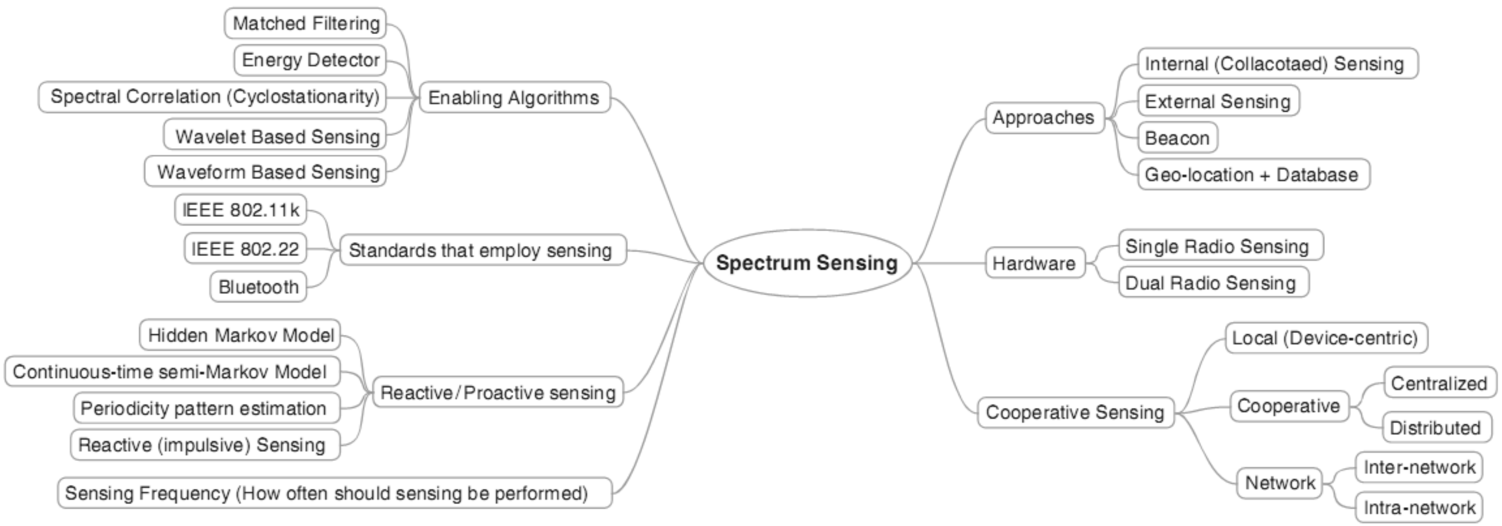

Figure 2.5. Various Aspects of Spectrum Sensing in Cognitive Radio Networks

[14]

1. Transmitter Detection
   - Matched-filter Detector
   - Cyclostationary Detector
   - Energy Detector
2. Non-cooperative vs Cooperative
   - Centralized
   - Distributed

In the following subsections these items will be explained in detail.

2.2.1. Transmitter Detection Methods

Transmitter detection is based on detection of the weak signal from a primary transmitter using local observations of secondary users. The transmitter detection model can not prevent the hidden terminal problem. Besides, SU may not be able to detect the transmitter due to the shadowing as shown in Figure 2.6. For such cases, cooperative sensing can be used with transmitter detection methods to detect PU.

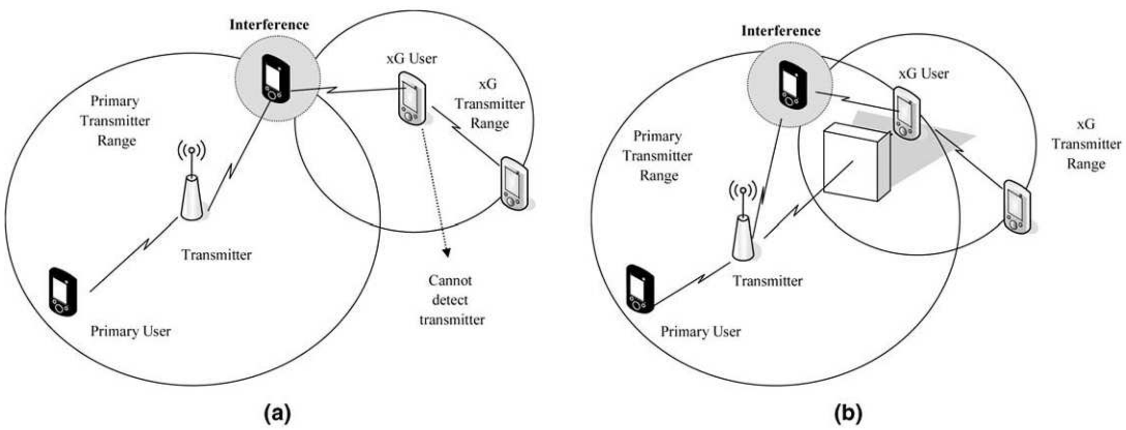

Figure 2.6. Transmitter Detection Problem:(a)Receiver Uncertainty (b)Shadowing Uncertainty

[2]

Basic hypothesis model for transmitter detection can be defined as follows [15]:

$$y(t) = \begin{cases} n(t) & H_0, \\ hs(t) + n(t) & H_1 \end{cases} \tag{2.1}$$

where $y(t)$ is the signal received by the secondary user, $s(t)$ is the transmitted signal of the primary user, $n(t)$ is *Additive White Gaussian Noise (AWGN)* and h is the amplitude gain of the channel between primary user and secondary user. H_0 is known as null hypothesis which means primary user does not exist for the specified spectrum band. H_1 is known as alternative hypothesis which indicates that primary user signal is present.

When transmitter detectors are considered, spectrum sensing techniques fall into three categories generally: energy detector [16], coherent detector [17], and cyclostationary feature detector [18]. If the secondary user has limited information about primary signal, then energy detector is optimal [5]. If certain primary signal features are known to the secondary users such as pilots, preambles, or synchronization messages, then the optimal detector is the matched filter.

2.2.1.1. Matched-filter Detector. When primary user's signal is known by secondary users (i.e. modulation type, pulse shape packet format), then the best detection method is matched-filter [5]. Its main advantage is that with the help of coherency, it requires less time to achieve a certain probability of false alarm or probability of missed detection [2]. On the other hand, since it requires perfect knowledge of the signal, inaccurate information results in wrong decision, hence poor performance. Moreover, cognitive radio requires receivers of all signal types which increases implementation complexity of sensing device [19]. This also results in large power consumption due to necessity of various receiver algorithms to be executed.

2.2.1.2. Cyclostationary Feature Detector. Cyclostationary feature detectors differentiate the primary signal's energy from the local noise energy by exploiting certain periodicity exhibited by the mean and autocorrelation of a particular modulated signal [20–25]. Cyclic correlation function is used for detecting signals present in a given spectrum rather than *Power Spectral Density (PSD)* [22]. The *Cyclic Spectral Density (CSD)* function of the received signal given in Equation (2.1) can be calculated as [26]

$$S(f, \alpha) = \sum_{\tau=-\infty}^{\infty} R_y^{\alpha}(\tau) e^{-j2\pi f \tau}. \tag{2.2}$$

where

$$R_y^{\alpha}(\tau) = E[y(n+\tau) y^*(n-\tau) e^{-j2\pi\alpha n}] \tag{2.3}$$

$R_y^{\alpha}(\tau)$ is the *Cyclic Autocorrelation Function (CAF)* and α is the cyclic frequency. If the peak values of the cyclic frequency are equal to transmitted signal's fundamental frequencies, then the CSD function outputs peak values. Cyclic frequencies can be assumed to be known [20–25] or they can be extracted and used as features for identifying transmitted signals [23].

2.2.1.3. Energy Detector. A common method for detection of unknown signals in noise is energy detector (radiometry). Energy detection method can be used to determine primary user presence in CRNs. The structure of the energy detector is shown in Figure 2.7. An input band-pass filter selects the center frequency, f_c, and the bandwidth of interest, W. This filter is followed by a squaring device to measure the received energy and an integrator which determines the observation interval, T. If the secondary user wants to make decision individually on the signal presence or absence, the output of the integrator will be compared with a threshold. In this case, each secondary user decides on the primary user presence individually. The main advantage of energy detectors is implementation simplicity. Furthermore, it is the optimal detector when PU information is insufficient, for example, if the power of the random gaussian noise is only known by the receiver [5]. However, this non-cooperative method requires a long integration time to achieve a reliable decision.Besides, performance of energy detector is vulnerable when noise power is not predictable.

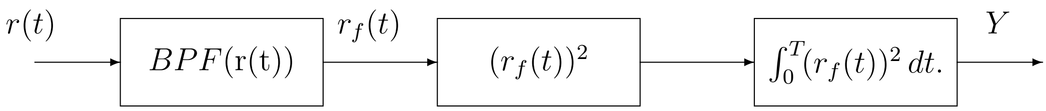

Figure 2.7. Block Diagram of Energy Detector

Using Equation (2.1), decision metric for energy detector can be written as

$$Y = \sum_{n=0}^{N} |y(n)|^2. \tag{2.4}$$

where $y(n)$ is received signal and Y is the output of the energy detector. If noise is modeled as *Additive White Gaussian Noise (AWGN)* with zero mean and unit variance, then decision metric Y follows chi-square distribution with $2N$ degrees freedom, X_{2N}^2 and hence, can be modeled as [27, 28]

$$Y = \begin{cases} X_{2N}^2 & H_0 \\ X_{2N}^2(2\gamma) & H_1 \end{cases} \tag{2.5}$$

where γ is instantaneous *Signal to Noise Ratio (SNR)* of secondary user, X_{2N}^2 and $X_{2N}^2(2\gamma)$ are central and non-central chi-square distributions respectively with non-centrality parameter of 2γ. *Probability Density Function (PDF)* of Y can be written [27] as

$$f_Y(y) = \begin{cases} \frac{1}{2^N \Gamma(N)} y^{N-1} e^{\frac{-y}{2}} & H_0 \\ \frac{1}{2}\left(\frac{y}{2\gamma}\right)^{\frac{N-1}{2}} e^{-\frac{2\gamma+y}{2}} I_{N-1}(\sqrt{2\gamma y}) & H_1 \end{cases} \tag{2.6}$$

where $\Gamma(.)$ is the gamma function and $I_v(.)$ is the vth-order modified Bessel function of the first kind [29]. Using Equation (2.6), probability of false alarm and detection can be calculated as

$$P_d = Pr(Y > \lambda | H_1) = \frac{\Gamma(N, \frac{\lambda}{2})}{\Gamma(N)} \tag{2.7}$$

$$P_f = Pr(Y > \lambda | H_0) = Q_N(\sqrt{2N}, \sqrt{\lambda}) \tag{2.8}$$

where $Q_N(a, b)$ is the generalized marcum Q function and λ is the threshold [30].

The performance of energy detector based sensing over Rayleigh, Nakagami, and Ricean fading channels is investigated in [28]. Closed form expressions for probability of detection under AWGN and fading channels are derived. Average probability of detection for energy detector based sensing algorithms under log-normal shadowing and Rayleigh fading channels are derived in [31]. The effect of quantization error for energy detector based sensing algorithms is evaluated in [32]. Furthermore, with the proposed detector in a sequential detection structure, it is shown that decision time needed by the detector is shortened.

2.2.2. Non-Cooperative Sensing vs Cooperative Sensing

In cooperative methods, SUs use and share the information between them directly or through central controller. In contrast to cooperative methods, in non-cooperative methods, SU tries to detect PU independent from other SUs' observations. In Chapter 9 of [14] cooperative sensing and non-cooperative sensing are compared. This comparison is summarized in Table 2.1. Cooperative sensing can be distributed or can have a centralized architecture.

2.2.2.1. Distributed Cooperative Sensing. Secondary users share their sensing information with each other in a distributed architecture. Advantages of distributed sensing over the centralized one are implementation simplicity and low transmission rates (zero or one). On the other hand, it is not an optimum detection method. In [34] and [35],

Table 2.1. Local versus Cooperative Sensing

[14]

Sensing Method	Advantages	Disadvantages
Non-cooperative Sensing (Local Sensing)	Computational and Implementation Simplicity	Hidden Node Problem, Multipath and Shadowing
Cooperative Sensing	Higher accuracy (Close to optimal), Reduced Sensing Time [33], Shadowing effect and hidden node problems can be prevented	Complexity (complexity of sensor, complexity of within system cooperation, complexity of among-system cooperation), Traffic overhead, The need for a control channel

distributed collaborative algorithms are proposed for two user and multiuser networks respectively. For the former one, the collaboration is performed between two secondary users and the user closer to primary transmitter, cooperates with the user far from the primary user. An algorithm for pairing secondary users is also proposed in this work.

2.2.2.2. Centralized Sensing. In the centralized architecture, CBS or central controller has a role to collect all secondary users' information to detect spectrum holes. In [36], a centralized architecture is used to mitigate the fading effects of the channel and increase detection performance. In [37], sensing results are combined in a central node for detecting TV channels. Hard and soft information combining methods are investigated for reducing the probability of missed opportunity. Multi node spectrum sensing using centralized structure is also studied in [38]. In this article, measurements from SUs are combined at the fusion center and combined using measurement, hard decision and log likelihood combining techniques.

2.3. Cooperative Decision Rules

Cooperative decision rules provide CBS or central controller to finalize the decision according to information taken from individual users. In the literature, these decision rules vary according to detector type and architecture of the network. In this following subsection, we investigate majority rule based combining, hard decision combining, and weighted combining.

2.3.1. Majority Rule Based Combining

CBS collects SUs' decisions from *Cooperative Secondary User Group (CoSUG)*. CBS makes final decision according to majority rule (voting rule) which can be defined as in Table 2.2. According to this rule, majority of the secondary users' decision is considered as a final decision.

Table 2.2. Majority Rule Based Combining

IF	No of SUs in CoSUG sense PU exists >= No of SUs in $CoSUG/2$ THEN
	CBS Final Decision=1 $--$ >PU is Present
ELSE	
	CBS Final Decision=0 $--$ >PU is not Present
END	IF

2.3.2. Hard Decision Combining

Previous studies on cooperative detection for DSA with hard decision combining [15, 37] use energy detection. The threshold is fixed and same for all SUs in these works. The disadvantage is that this cooperative scheme is suboptimal [39]. However, decision rules are simple and easy to implement. In hard decision combining, CBS collects SUs' decisions from CoSUG. CBS decides final decision according to hard decision rule which can be defined as in Table 2.3. In hard decision rule, if any of the secondary users's decision is PU present, then final decision is also PU present.

Table 2.3. Hard Decision Combining

IF	Any of SUs in CoSUG sense PU is present THEN
	CBS Final Decision=1 −− >PU is Present
ELSE	
	CBS Final Decision=0 −− >PU is not Present
END	IF

2.3.3. Weighted Combining

CBS weighs and combines the measurement values of the SUs' individual decisions or detections results in weighted combining. Using the predefined threshold, a global decision is generated. The test statistic Y_{WC} is the weighted sum of the N number of SUs' measurements given in [38] as

$$Y_{WC} = \sum_{n=1}^{N} w_n Y_n \tag{2.9}$$

where Y_n is the output of the energy detector and w_n is the weight of each secondary user. If w_n is given one for each SU then it is named as *Equal Gain Combining (EGC)*, otherwise *Weighted Gain Combining (WGC)*. In [38], weights are given according to SUs' SNR levels.

2.4. IEEE 802.22

A cognitive radio observes its environment and adapts by changing its transmission characteristics. Dynamic spectrum access is the specific area of cognitive radio systems which aims to use the unused part of the spectrum at that time or space. IEEE began holding annual conference on *Dynamic Spectrum Access Networks (DySPAN)* in

2005 [40]. Two methods used with IEEE 802.22 for cognitive radio to be aware of its spectral environment are geo-location/database and spectrum sensing.

2.4.1. Geo-location Database

Cognitive radio users have privileges to use the specified band temporarily in the absence of primary users. This can be achieved by using overlay and/or underlay spectrum access techniques. Three techniques related to dynamic spectrum management in cognitive radio networks that FCC proposes are Listen-before-talk, Geo-location database, and Local Beacon techniques [39]. In [39], it is stated that a recently formed IEEE 802.22 working group for the *Wireless Regional Area Networks (WRANs)* follows the vision of FCC about this topic. The geo-location database and local beacon techniques utilize the location information which is very useful for sensing and management of cognitive radios. In geo-location database both licensed and unlicensed users provide their location information to FCC database. Unlicensed users check their locations with the FCC database and request for the channel from CBS if at that location the channel is available. In this scenario, CBS gives right to use the channel to corresponding SU and broadcasts the geo-location database. The reliability of location estimation techniques and FCC database determine the system performance [39]. An example of the geo-location database can be seen in Table 2.4.

Table 2.4. A local Geo-location Database

[39]

User Type	Unlicensed	Licensed	Licensed
Waveform	WLAN AP	WIMAX MS	CDMA MS
Location Estimation Method	GPS	GPS	GPS
Datum	WGS-84	WGS-84	WGS-84
Date Format	mmddyyyy	mmddyyyy	mmddyyyy
Date	12012006	12012006	12012006
Time Source	GPS	GPS	GPS
Local Time Format	hhmmss AM/PM Zone	hhmmss AM/PM Zone	hhmmss AM/PM Zone
Local Time	092307 AM US EST	092307 AM US EST	092307 AM US EST
Dimension accuracy unit	meter	meter	meter
Altitude unit	meter	meter	meter
Frequency unit	MHz	MHz	MHz
Longitude	82 24 34 W	82 24 34 W	82 24 34 W
Longitude accuracy	4	4	4
Latitude	28 31 16 N	28 31 16 N	28 31 16 N
Latitude accuracy	3	3	3
Altitude	10	14	7
Altitude accuracy	3	1	2
Center frequency	2415	3475	1900
Absolute bandwidth	20	10	1.25

In Figure 2.8, it is seen how location information can be used in sensing and hence cognitive radio functionality.

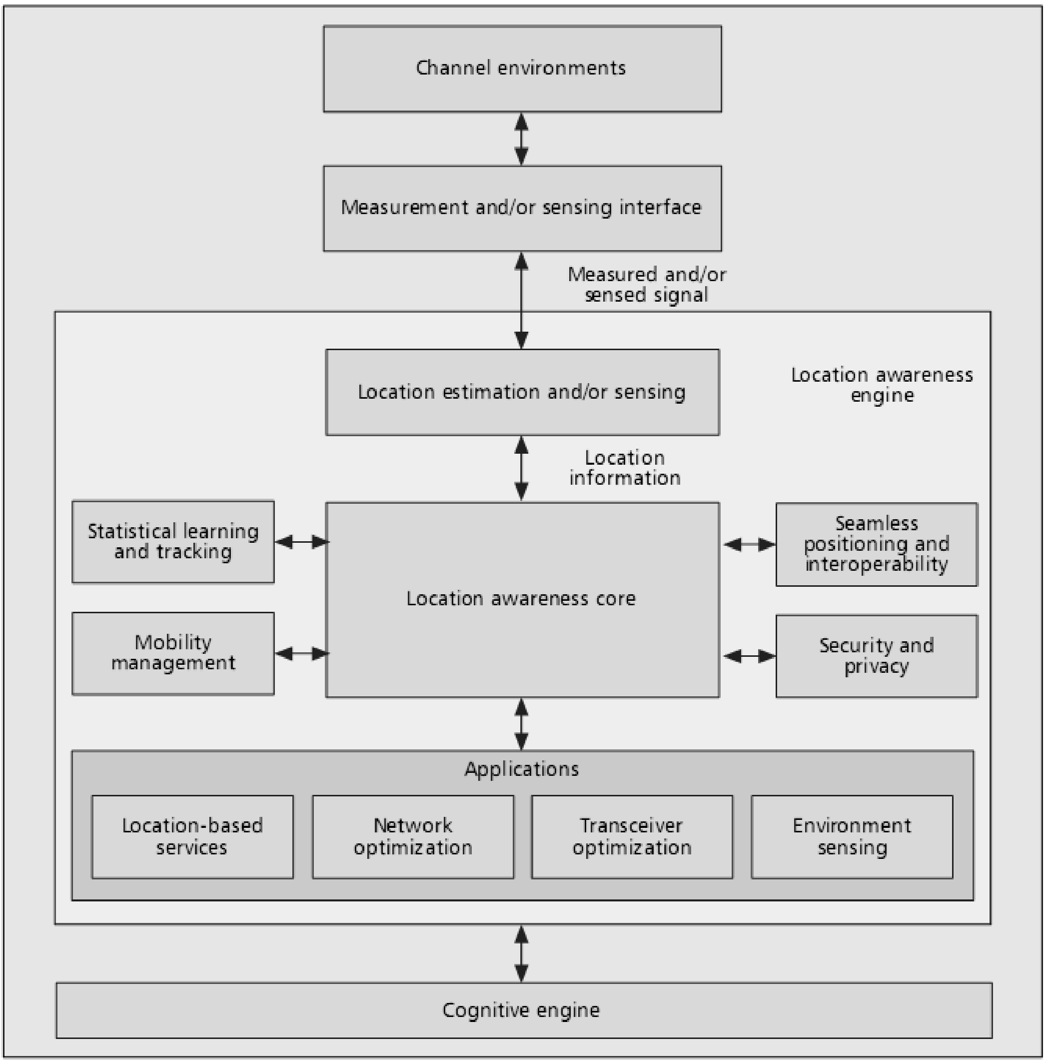

Figure 2.8. Location and Sensing

[39]

In this thesis, we use a system model similar to geo-location database. We assume that SUs' locations are available in CBS database. Hence, proposed algorithms use this information when selecting SUs and combining SUs' decisions. Since reliability of this database may change, decisions made only with the help of this database seem to be not sufficient. For this reason, using this database with sensing algorithms for spectrum decision can be more useful rather than using only this database's information.

2.4.2. Spectrum Sensing

Spectrum sensing is the mandatory feature of IEEE 802.22. In IEEE 802.22, not only CBS but also *Customer Premise Equipments (CPEs)* should also sense. IEEE 802.22 requirements for sensing are classified as: channel detection time, probability of false alarm, probability of detection and sensing receiver sensitivity. The required probability of detection is 0.9 and probability of false alarm is 0.1 for all devices [41].

IEEE 802.22 spectrum sensing framework consists of four elements namely, per-channel sensing to provide low cost device, quiet periods to prevent SUs' signals to mix with PU's signal, standardized reporting and implementation independence. Quiet periods are synchronized by CBS. CBS informs SUs and other CBSs to perform quiet periods in a scheduled manner. With the standardized reporting, SUs report their sensing information to CBS and final decision is made by CBS. No specific spectrum sensing technique is determined in IEEE 802.22 [41]. Additional information about spectrum sensing in IEEE 802.22, can be found in articles [9, 42, 43].

2.5. Related Works in the Literature

Cognitive radio is a new topic to survey and has not got any finalized standard which makes it an attractive working area in recent years. Researches on cognitive radio should have to make some assumptions due to its non-standardized structure. As mentioned in previous sections, spectrum sensing is one of the significant roles of cognitive radio devices or network elements. There are various studies in the literature on spectrum sensing functionality of cognitive radio networks.

In cognitive radio networks, especially energy detector method is preferred due to its simplicity. Energy detection is an old issue that has been worked for several years. In practice, it is difficult for a cognitive radio to have a direct measurement of the channel between a primary receiver and a transmitter. Thus, the most recent studies focus on primary transmitter detection based on local observations of cognitive radios [27]. In [27, 28, 32], energy detection method is used with cooperative sensing methods.

In [28], energy detector method is used and closed-form expressions for the probability of detection and false alarm is obtained for Rayleigh, Nakagami and Rician fading channels with *Additive White Gaussian Noise (AWGN)*. Moreover, diversity techniques including, *Selection Combining (SC)*, *Equal Gain Combining (EGC)* and *Switch and Stay Combining (SSC)* are compared with no diversity scheme. It is shown both numerically and with simulations that diversity schemes has better probability of missed detection vs probability of false alarm curves compared to no diversity scheme. This gain is quantified approximately one order of magnitude for both SC and SSC schemes, and approximately two orders of magnitude for the EGC scheme.

[32] benefits from works of [27] and [28]. In [32], spectrum sensing information is gathered from all secondary users and then decision is made by a central controller. In an optimum detector, all observations about PU presence should be taken into consideration in order to make a final decision and knowledge of some parameters should be known. In order to provide this, *Generalized Likelihood Ratio (GLR)* test is used. Maximum likelihood estimation of unknown parameter in a GLR detector is used. With the use of sequential detection structure, spectrum sensing time is shortened. Besides, the effects of Rayleigh fading channels and shadowing are considered. Moreover, quantization error on sensing performance is demonstrated by simulations. In order to transmit signal sensed by each secondary user, a common control channel is used. This channel is chosen from reliable low capacity channels.

In [28] and [32], signal sensed by each SU is transmitted directly to central controller. This type of transmission requires high channel bandwidth between SU and central controller. Instead of this, another approach is that each secondary user transmits one bit of information including its own decision to central controller and central controller decides PU presence. In [44] level of cooperation is considered and following three level of cooperations are defined. Level of cooperation depends on control channel bandwidth and quality of the detector. Level of cooperations are as follows:

1. Low bandwidth control channel, energy detector radios:
   - Sends one bit of information about sensed signal.
   - Low SNR cause SNR wall problem.
   - No prior information about correlation structure of the signal is required.
2. Low bandwidth control channel, detectors utilizing signal statistics:
   - Cyclostationary detectors can be used for this cooperation scheme.
   - Utilize correlation in the signal
3. High Bandwidth Control channel, all possible detectors:
   - CR can exchange entire raw data, i.e. signal sensed is transmitted to *Central Controller (CC)* and CC decides.
   - Tightly synchronized radios collectively can overcome SNR wall.

The first one "Low bandwidth control channel, energy detector radios" is taken into consideration for simulations. Spectrum sensing issue is investigated under decision schemes of hard versus soft decisions. Different from other works untrusted users are also mentioned. Besides, shadowing correlation is studied. These topics are grading with impact of number of users.

Cooperative sensing is also studied in [15, 33, 36]. In [15], collaborative sensing is used to detect PU presence as in [44]. Each SU first decides on the presence of PU by comparing sensing information with a threshold. Then, each SU transmits this information to other SUs. For combining SUs' decisions, fusion rule is used. This rule is also known as OR logic which combines information from SUs and decides PU is present if any SU's decision is like that. In [33] and [36], cooperative sensing is proposed and *Amplify and Forward (AF)* method is used. In these works, Rayleigh fading is used and it is shown that required time for spectrum sensing is decreased by cooperation. In [33], it is shown that detection reliability and SNR is increased for cooperative methods if users' signals are correlated (if two SUs signals are summed for cooperation). This cooperation method is differentiated from articles [45, 46] since it needs wideband control channel. Voting rule based decision for cooperative sensing is applied in [45]. The rule is based on counting number of sensor nodes which votes for presence of PU and compares it with a given threshold. In [46], two decision combining methods are used namely, hard decision also known as AND logic and soft decision using likelihood ratio test. It is shown that soft decision gives better performance over hard decision.

3. SPECTRUM SENSING PROBLEM IN COGNITIVE RADIO

Spectrum sensing is one of the significant problems in cognitive radio to be improved. In this section, first we give the problem definition of spectrum sensing in CRNs. Next, in order to improve sensing performance of the detector, two proposed cooperative SU selection methods namely, Equal and Probabilistic Selection algorithms are introduced. Finally, for cooperative sensing performance improvement, two decision methods are proposed. The first decision method is based on SU decision density in a region and the second one uses weight of SUs in each region.

3.1. Problem Definition

Cognitive radio's major aim is to detect primary users while not causing interference to licensed users. For this reason, spectrum sensing has a significant role which cognitive radio device should perform. IEEE 802.22 requirement for probability of detection is 0.9 and probability of false alarm is at most 0.1. Besides these detection performance metrics, sensing time is also crucial to vacate the channel and hop to an other in a specified time. In order to meet these requirements, various sensing techniques are proposed. However, in most cases there is a tradeoff between detection performance of the sensing method and its complexity. Complexity of some methods are even increasing with the number of nodes. Since power consumption and sensing time are very important for CPEs, it is also crucial to find simpler and more efficient methods which can also provide good performance. In other words, there is a necessity on improvement of sensing methods without increasing complexity. For these reasons, we propose secondary user selection and cooperative decision methods to improve sensing performance in cooperative architectures without increasing complexity of the system.

3.2. Proposed User Selection Algorithms for Cooperative Sensing

In cooperative cognitive radio networks, CBS or CC selects cooperative users to make them sense the specific channel. Hence, chosen SUs sense that channel and send their information to CBS. Then, CBS makes the final decision according to these data. In order to make the best decision, SUs which can provide best data should be chosen. However, since there is not any information about PU, CBS can not choose SUs which can provide the best data. To guarantee reasonable value of SUs with best data to be chosen, two user selection algorithms namely, Equal and Probabilistic Selection are proposed in this section. These selection methods use the information of secondary users' locations. This information can be provided from one of the known future geo-location database in CRNs or other location estimation methods. Different from geo-location database structure, not only SUs' and PU's locations are used for decision but also spectrum sensing methods are used to find spectrum holes.

Assumptions:

1. SUs' locations are known in region base for two proposed algorithms. Exact locations need not to be known.
2. For Probabilistic Selection Algorithm, other than SUs' locations, PU's location is also known in a probabilistic manner. As in the SU case, exact PU's location is not used. Instead, PU existence probability for a given region is used.

3.2.1. Equal Selection Algorithm

CBS learn SUs' locations from geo-location database. Locations need not to be known exactly but CBS knows in which region SU is. CBS chooses SUs from each region with equal probability to guarantee SUs with best SNRs to be chosen for cooperation. Mathematical model that we use for this selection is given as

$$Co_{SU}^{Equ} = [Rand(R_{SU}^{1}; \frac{N_{CoopSU}}{k})Rand(R_{SU}^{2}; \frac{N_{CoopSU}}{k})...Rand(R_{SU}^{k}; \frac{N_{CoopSU}}{k})]. \quad (3.1)$$

where Co_{SU}^{Equ}=Group of SUs chosen for cooperation, R_{SU}^{i} is a table in which SUs' located at i^{th} region are recorded, N_{CoopSU}= Number of Cooperating SUs, k=Number of Regions and $Rand(x;y)$ is a function which selects y number of users from table x randomly.

3.2.2. Probabilistic Selection Algorithm

CBS learns SUs' locations from geo-location database. Locations need not to be known exactly but CBS knows in which region SU is for this type of selection too. Moreover, CBS has a priori information about PU presence probability in its regions of coverage similar to SUs' locations. The only difference is that CBS knows in which region SU is exactly, however PU's region with a probability.

CBS chooses SUs to cooperate from each region proportional to PU presence probability of the region. As can be seen from Equation (3.2), the probability of PU presence in i^{th} region of CBS is

$$Pr\{PU_{Loc} = R_i\} = \gamma_i \tag{3.2}$$

where PU_{Loc}=Primary user location, R^i=Region i of CBS.

Using probabilities of Equation (3.2), proposed probabilistic selection method is given in the Equation (3.3) as

$$Co_{SU}^{Prob} = [Rand(R_{SU}^{1}; N_{CoopSU} \times \gamma_1) Rand(R_{SU}^{2}; N_{CoopSU} \times \gamma_2) ... Rand(R_{SU}^{k}; N_{CoopSU} \times \gamma_k)]. \tag{3.3}$$

where Co_{SU}^{Prob}=Group of SUs chosen for cooperation with probabilistic manner, R_{SU}^{i} is a table in which SUs located at i^{th} region are recorded, N_{CoopSU}= Number of cooperating SUs, k=Number of regions and $Rand(x;y)$ function selects y number of users from table x randomly.

Performances of these two proposed methods are compared with Best, Worst and

Random Selection Algorithms. Simulation details and results are given in Chapter 4.

3.3. Proposed CBS Decision Algorithms

After collecting decisions from each SU, CBS should use an intelligent method to make a final decision. Methods like majority or hard decision rules may even degrade the performance of the system when some cooperative secondary users are exposed to bad channel conditions. In this section, we propose two decision combining methods which can be used by CBS in CRNs. The first method compares SUs' decision with SUs' location and make final decision accordingly. This method is named as SU Density Based Decision since SUs' decisions are more valuable when other SUs in that region obtain same information. In other words, rather than using majority of whole SUs in CoSUG, majority of SUs in each region is taken into consideration. The second method not only uses SUs' locations but also uses PU's location with a probabilistic manner. CBS weighs SUs' decisions proportional to the regions' probability.

3.3.1. Cooperative Decision using SU Density Based Combining

CBS collects SUs decisions from CoSUG (Cooperative SU Group). CBS makes final decision comparing SUs' decisions density according to SUs' locations. Since CBS knows in which region the SU is, cooperating SUs can be categorized according to their regions. Detection ratio of each region is calculated as

$$DR^i = \frac{N^i_{CoopSU^{det}}}{N^i_{CoopSU}}. \tag{3.4}$$

where N^i_{CoopSU}=Number of cooperating SUs at i^{th} region, $N^i_{CoopSU^{det}}$=Number of cooperating SUs at i^{th} region who decides PU is present and DR^i=Detection ratio of region i. And total detection ratio is

$$DR^{total} = \sum_{i=1}^{k} DR^i. \tag{3.5}$$

where k=Number of regions and DR^{total}=Total Detection Ratio.Then, SU density based decision algorithm can be figured out as in Table 3.1.

Table 3.1. SU Density Based Combining

IF	Detection Ratio of any Region >= Threshold THEN
	CBS decides PU is detected
ELSE	IF Total Decision Ratio >= Threshold THEN
	CBS decides PU is detected
ELSE	
	CBS decides PU is not detected
END	IF

3.3.2. Cooperative Decision using Weighted Combining

CBS collects SUs' decisions from CoSUG (Cooperative SU Group). CBS assigns SUs' weights according to their regions and PU presence probability in that region. CBS calculates SU's weighted decisions according to weights assigned to them. Finally, CBS makes final decision if total PU presence probability collected from SUs in CoSUG greater than specified threshold.

PU presence probability in the region which is given as in the Equation (3.2) are obtained from centralized database like geo-location database. Regions' weights are calculated according to this probability as in the Equation (3.6).

$$W_{R_i} = \gamma_i. \tag{3.6}$$

where W_{R_i} is weight of i_{th} region and γ_i is obtained from Equation (3.2) as PU presence probability.

Hence each SUs' weights at region i is

$$W_{SU_i} = \frac{W_{R_i}}{n_i} \tag{3.7}$$

where W_{SU_i} is the weight of each SU at region i and n_i is number of SUs at region i.

In order to guarantee that all SUs' decisions are taken into consideration, we use the algorithm given in Table 3.2 when weighting SUs. Hence, although PU presence probability for a region is zero, we will not ignore decisions of SUs at that region. The pseudo code for this algorithm can be defined as

Table 3.2. Weighted Rule Based Combining

IF	PU Presence Probability at Region $j <= 0.1$ THEN
	Weight of Region $j = 0.1$
	Weight of other Regions are $\frac{\gamma_i}{\sum_{i=1}^{k} \gamma_i - \gamma_{i=j}} \times 0.9$
ELSE	
	Weight of each Region $=\gamma_i$
END	IF

If none of the regions probability is smaller than 0.1, then CBS considers γ_i to give weights for SUs. If any probability of PU presence is smaller than 0.1 value, CBS assigns 0.1 for that region and assigns corresponding probabilities for remaining regions according to their PU presence probability ratio to each other.

4. SIMULATION RESULTS

In this chapter, simulation results obtained for two proposed selection algorithms and two proposed decision methods are introduced. Proposed selection algorithms' performances are compared with random, worst and best selection cases. On the other hand, proposed decision methods are also compared with Hard Decision and Majority Rule Based Decision Methods.

4.1. Cognitive Radio Network Structure

Cognitive radio network is composed of various elements including cognitive base stations and secondary users in the literature. In this thesis, we explain cognitive radio network architecture used for simulations in two parts. Firstly, cognitive radio elements in cognitive radio network are presented. Secondly, cognitive base station's decision cycle is analyzed for non-cooperative and cooperative cases.

4.1.1. Cognitive Radio Network Elements

Network elements used throughout simulations can be introduced as

- PU=Primary User, is the licensed user of the corresponding channel.
- SU= Secondary User-(Cognitive Radio User-CRU) is the unlicensed user who uses the channel under the constraints of the network.
- CBS= Cognitive Base Station, Secondary Users' Base Station
- CRN= Cognitive Radio Network is known as the secondary network composed of SUs and CBS.
- CoSUG= Cooperative SU Group - Group of SUs which are chosen for cooperation.

In the network topology which is given in Figure 4.1, one PU and $l = 11$ number of SUs are considered. PU and SUs are scattered to the $k = 3$ regions randomly. CBS's one sector is considered for the CRN and partitioned into three nearly equal regions.

One of the possible CoSUG chosen randomly is consisted of four members, SU5, SU7, SU8, and SU11 as illustrated with a circle in the Figure 4.1.

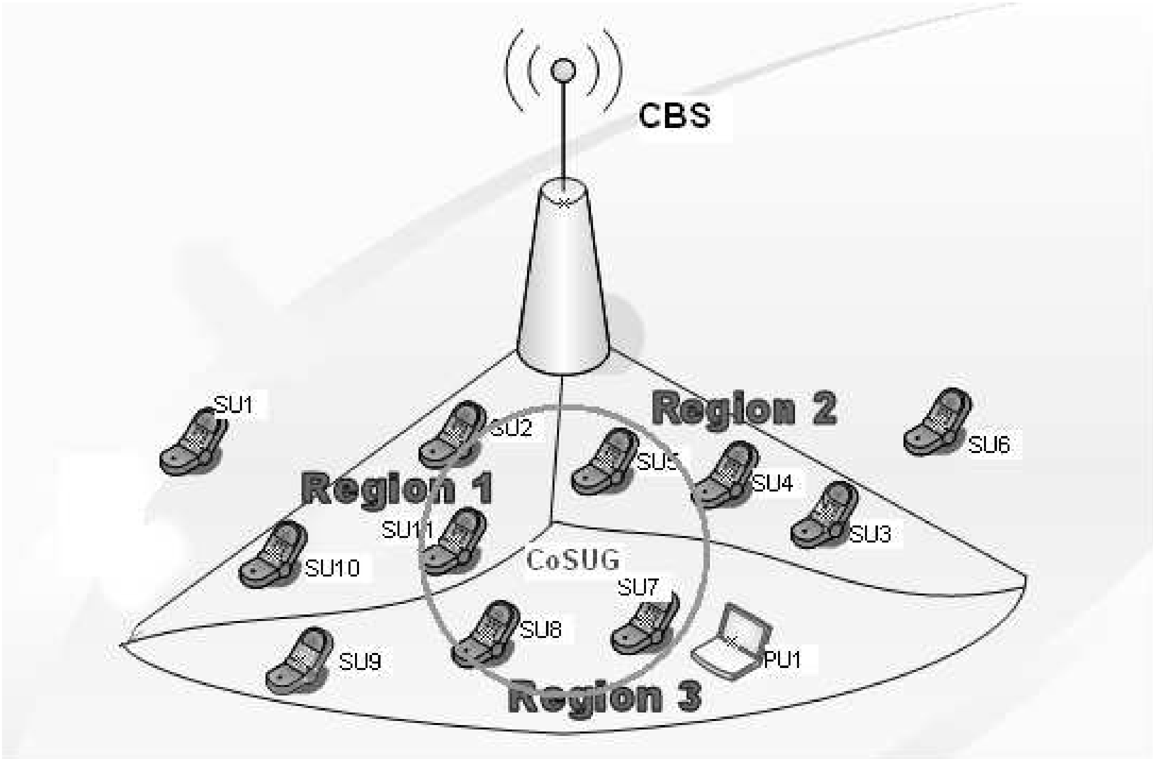

Figure 4.1. Cognitive Radio Network Architecture, $k = 3$ regions, $l = 11$ SUs, CoSUG with four members

4.1.2. CBS Decision Cycle

CBS decision cycle is varying according to non-cooperative and cooperative cases. In the following sections, CBS decision cycle for these two cases is introduced.

4.1.2.1. Non-Cooperative Case.

- CBS or SU chooses channels from available ones depending on the network structure. Former one is for centralized networks, the latter one is for distributed networks.
- For centralized case, CBS assigns channels to each SU to sense.

- SUs individually sense channels assigned to them.
- CBS gives right to use the channel to corresponding SU, if SU at that channel does not sense any PU.

Advantage of this method is its simplicity. CBS does not have any responsibility to synchronize and manage cooperative users. However, for distributed network since SUs individually sense and get channels to use, SUs have higher probability to have collision.

4.1.2.2. Cooperative Case.

- CBS selects SUs to cooperate from SUs attached to itself at that time instant. CBS can select SUs according to proposed algorithms defined in the cognitive radio user selection section.
- CBS chooses one channel to sense and informs CoSUG about this channel to gather individual decisions from each of them.
- SUs in CoSUG individually sense the channel assigned to them.
- CBS collects cooperative SUs' decisions. CBS calculates the final decision according to proposed methods defined in details at cooperative decision section.
- CBS informs CoSUG about this decision and assigns other channels to sense.

4.2. Simulation Environment

Simulation environment consists of four parts namely, network topology, channel information, user selection algorithms and cooperative decision methods. In the network topology part, cognitive radio network architecture used in simulations are explained. Channel details between SUs and PU considered throughout the simulations are introduced at channel information section. User selection and cooperative decision methods used for comparison are given at user selection algorithms and cooperative decision methods sections respectively.

4.2.1. Network Topology

The network topology considered for proposed algorithms consists of one PU and l number of SUs. In CRN network, PU and SUs are scattered to the k regions randomly. These regions are assumed to have similar characteristics. However, it is assumed that there are obstacles between regions which results in signal power to be weakened through regions. In simulations $l = 100$ and $k = 3$ is considered for outdoor environment; $l = 50$ and $k = 3$ is considered for indoor environment.

Outdoor environment is considered as one sector of the cognitive base station with radius equal to $30km$ and angle equal to 120^o. In this sector, there are three regions in which SUs and PU is scattered. Air interface characteristics of these regions are similar. Between these regions, there are obstacles which cause signal power to be weakened. Hence, signal is weakened only with path loss in the region. However, signal is weakened due to path loss plus obstacle between regions. Values of parameters related to air interface is tabulated in channel information section. Illustrations of this network topology is given in Figure 4.2.

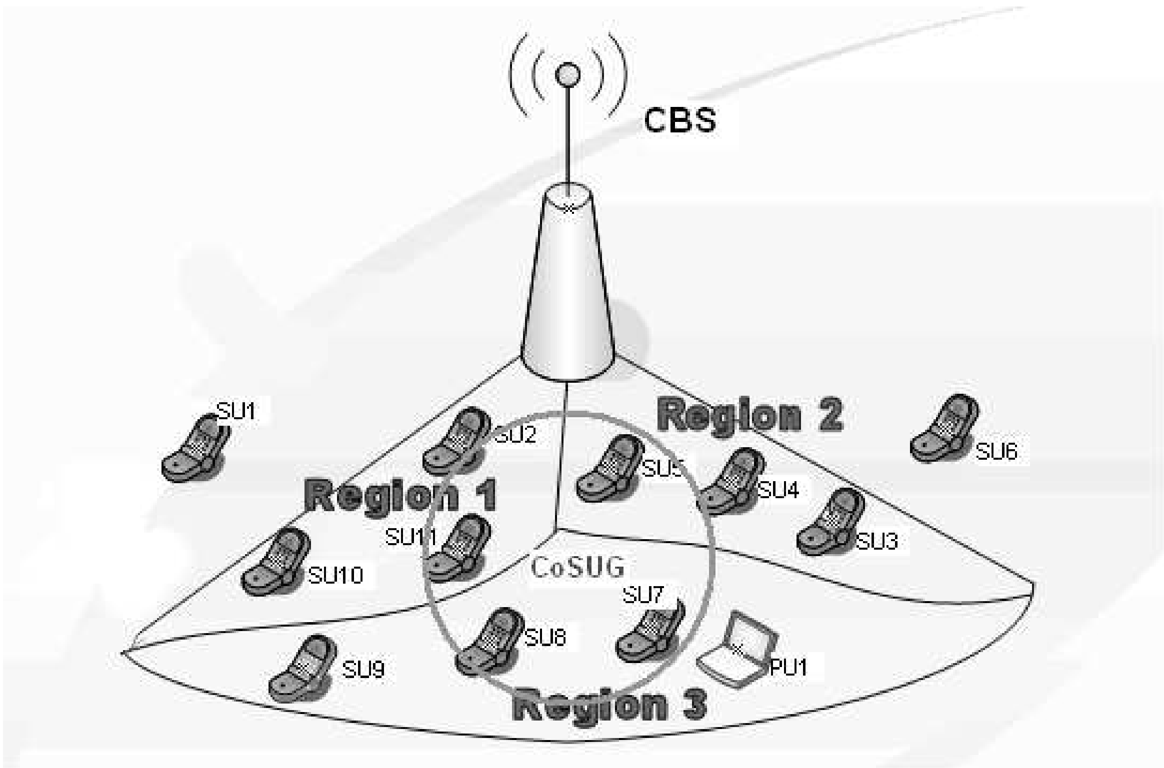

Figure 4.2. Cognitive Radio Network Architecture - Outdoor

Indoor environment is considered as a rectangle which has 900m width and 300m height as can be seen from Figure 4.3. The environment also consists of three regions which has equal dimensions, as 300×300. Besides, air interface characteristics of these regions are similar to outdoor environment case where obstacle exists between regions. These regions can be assumed to be the part of the large shopping center or floors of the large building. CBS knows in which region SU is. Location information can be obtained with the help of *Distributed Antenna Systems (DAS)*. DAS is a way to efficiently distribute wireless connections inside a large building where columns and layers of concrete can interfere with wireless signals. DAS can be used to get rid of "dead zones" by routing *Radio Frequency (RF)* signals through fiber or copper cabling from a single base station to multiple antennas located throughout the building [47].

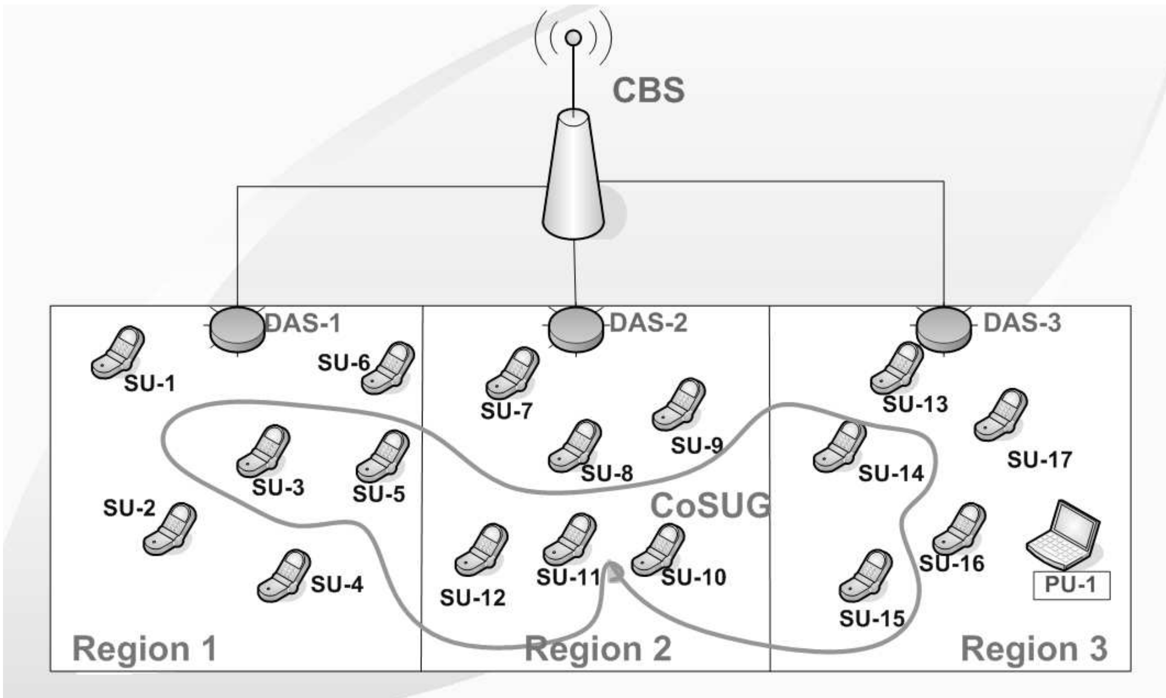

Figure 4.3. Cognitive Radio Network Architecture - Indoor

4.2.2. Channel Information

In each of these regions, Rayleigh fading exists at channel between PU and SU. Moreover, AWGN exists in the channel. SNR is considered differently for indoor and outdoor environments. Primary user signal is weakened due to both path loss model given in Equation (4.1) which is taken from [48] and obstacles between regions.

$$\overline{PL}(dB) = \overline{PL}(d_0) + 10nlog(\frac{d}{d_0}) \tag{4.1}$$

where n is the path loss exponent which indicates the rate at which the path loss increases with distance, d_0 is the close-in reference distance which is determined from measurements close to transmitter, and d is the *Transmitter-Receiver (T-R)* separation distance. The bars in the equation indicates ensemble average of all possible path loss values for a given value of d.

Parameters for path loss model and signal power weakened due to obstacles are given in Tables 4.1 and 4.2.

Table 4.1. Path Loss Exponents for Different Environments [48]

Environment	Path Loss Exponent
Free space	2
Urban area cellular radio	2.7 to 3.5
Shadowed urban cellular radio	3 to 5
In building line-of-sight	1.6 to 1.8
Obstructed in building	4 to 6
Obstructed in factories	2 to 3

Parameters used in simulations for outdoor and indoor environment models can be found in Tables 4.3 and 4.4. Channel between SU and CBS is considered as a perfect channel, i.e SU's one bit information is perfectly transmitted to CBS.

Table 4.2. Average Signal Loss Measurements

[48]

Material Type	Loss	Frequency
Concrete block wall	13dB	1300 MHz
Loss from one floor	20dB to 30dB	1300 MHz
Loss from two floors or one floor and a wall	40dB to 50dB	1300 MHz

Table 4.3. Outdoor Parameters

Parameter	Value
Fading	Rayleigh Fading
Noise	AWGN with zero mean, unit variance
Number SUs	100
Number of Cooperative SUs	10
Number of PU	1
d_0	$1.75km$
n	2
SNR at d_0	$10dB$
Max Power Loss	$50dB$
Environment	One sector of BS with $r = 30km$ θ=120^o
Loss due to obstacle between regions 1 and 2 or 2 and 3	$20dB$
Loss due to obstacle between regions 1 and 3	$30dB$

Table 4.4. Indoor Parameters

Parameter	Value
Fading	Rayleigh Fading
Noise	AWGN with zero mean, unit variance
Number SUs	50
Number of Cooperative SUs	10
Number of PU	1
d_0	$100m$
n	6
SNR at d_0	$0dB$
Max Power Loss	$70dB$
Environment	Rectangle with $x = 900m$, $y = 300m$
Loss due to obstacle between regions 1 and 2 or 2 and 3	$50dB$
Loss due to obstacle between regions 1 and 3	$60dB$

4.2.3. User Selection Algorithms

Proposed user selection algorithms namely, Equal and Probabilistic Selection Algorithms presented in Chapter 3 are compared with user selection algorithms listed below:

- Random Selection Algorithm
- Worst Selection Algorithm
- Best Selection Algorithm

4.2.3.1. Random Selection Algorithm. CBS does not know any information about PU and SUs. CBS chooses SUs to cooperate randomly. Random Selection Algorithm can be defined as

$$Co_{SU}^{Rand} = [Rand(R_{SU}; N_{CoopSU})]. \tag{4.2}$$

where Co_{SU}^{Rand}=Group of SUs chosen for cooperation randomly, R_{SU} is a table of SUs, N_{CoopSU}= Number of cooperating SUs and $Rand(x; y)$ is a function which selects y number of users from table x randomly.

4.2.3.2. Worst Selection Algorithm. In the Worst Selection Algorithm, CBS chooses SUs from the most far region where PU is present. Hence, SUs with worst SNR levels are chosen.

$$Co_{SU}^{Worst} = [Rand(R_{SU}^{w}; N_{CoopSU})]. \tag{4.3}$$

where Co_{SU}^{Worst}=Group of Worst SUs chosen for cooperation, R_{SU}^{w} is chosen from CBS' regions of coverage from 1,2,...i,...k satisfying

$$max(distance(R^{i} - R^{PU})) \tag{4.4}$$

4.2.3.3. Best Selection Algorithm. In the Best Selection Algorithm, CBS chosen SUs from the region where PU is present or at least the nearest region to PU's region. Hence, SUs with best SNR levels are chosen.

$$Co_{SU}^{Best} = [Rand(R_{SU}^{b}; N_{CoopSU})]. \tag{4.5}$$

where Co_{SU}^{Best}=Group of Best SUs chosen for cooperation, R_{SU}^{b} is chosen from CBS' regions of coverage from 1,2,...i,...k satisfying

$$min(distance(R^{i} - R^{PU})) \tag{4.6}$$

For the Best and Worst Selection Algorithms, if N_{CoopSU} is greater than the number of SUs at selected region, then the next candidate region (next the most far or nearest region) satisfying equations (4.4) or (4.6) will be chosen respectively.

4.2.4. Cooperative Decision Algorithms

Proposed SU Density Based Decision Method and Weighted Combining Decision Method are compared with individual decisions of SUs (Non-Cooperative Method), Majority Rule and Hard Decision Methods (Cooperative Methods) which are stated in Chapter 2.

4.3. Simulation Results

Simulations illustrated in this thesis include comparison of selection algorithms and comparison of decision methods. In this part, all selection algorithms are compared for each decision method both for indoor and outdoor environments. Besides, all decision methods are also compared for each selection algorithms. Hence, pair with best performance which can be used as a selection and decision method is illustrated and explained in following sections.

4.3.1. Comparison of Selection Algorithms in Outdoor Environment

Simulation results which are taken from outdoor environment are given in this part. Proposed secondary user selection algorithms, namely Equal and Probabilistic Selection Algorithms are compared with Random, Best and Worst Selection Algorithms which are explained in details in Chapters 3 and 4. As can be seen from simulations below, user selection algorithms are compared for all decision methods used, in a separate figure.

In Figures 4.4 and 4.5 selection algorithms are compared using Hard Decision and Majority Rule as a decision method respectively. In order to observe performances of the selection methods for Hard Decision Method, Figure 4.4 is provided. When Hard

Decision Method is used, proposed Probabilistic and Equal Selection Algorithms give better results compared with the Worst and Random Selection cases. However, it can be seen from Figure 4.4 that Hard Decision Method does not meet requirements of IEEE 802.22.

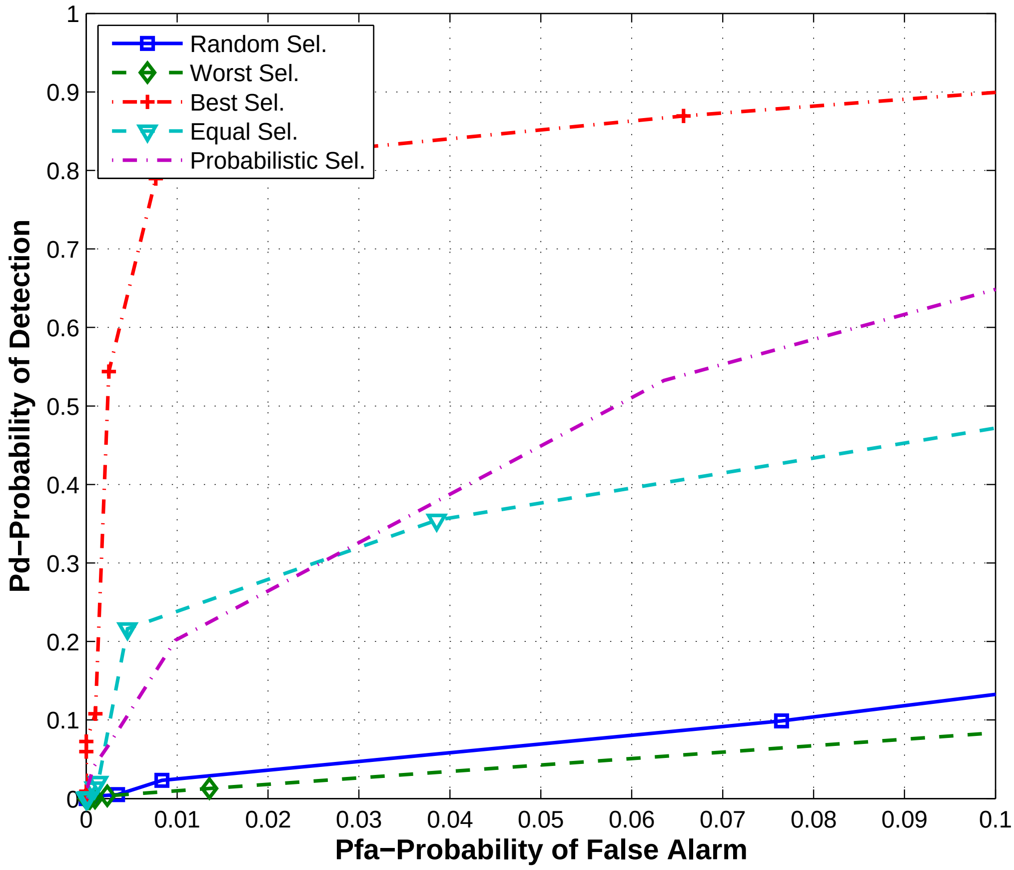

Figure 4.4. Comparison of Selection Algorithms using Hard Decision Method

On the other hand, the best performance is obtained from Probabilistic Selection Method when considering the Majority Rule Method as decision. It can be seen from Figure 4.5 that targeted probability of detection and false alarm values ($Pd = 0.9, Pfa = 0.1$) are nearly succeeded. Best selection algorithm for Majority Decision Method is Probabilistic Selection Algorithm. The Equal Selection Algorithm achieves much better performance than Random and Worst Selection Algorithms. Probabilistic Selection Algorithm provides better performance than Equal Selection since it needs additional information of PU presence probability. This information provides more user to be chosen from PU's location (more SUs with better SNR values). Since Majority Rule is based on decisions of majority of the CoSUG, Probabilistic Selection performs better than Equal Selection Method unless probability of PU's presence is equal for each region. In this case, Probabilistic and Equal Selection Methods give similar performances.

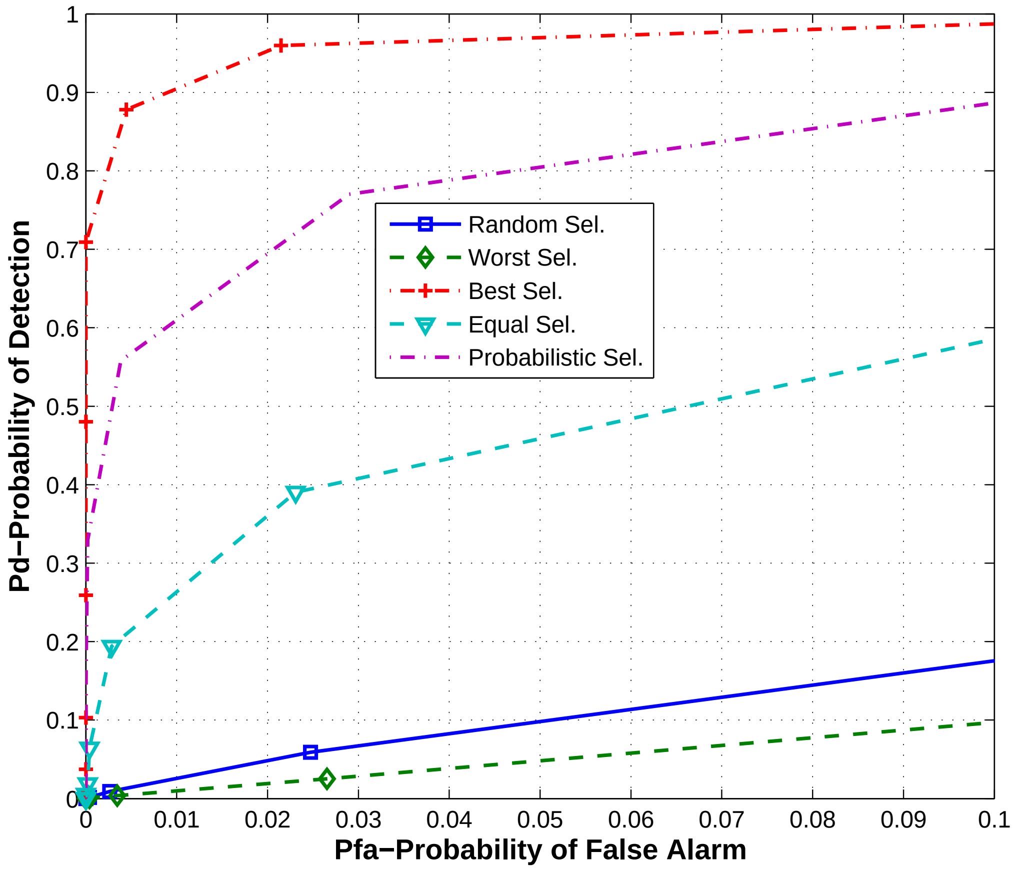

Figure 4.5. Comparison of Selection Algorithms using Majority (Voting) Method

In Figures 4.6 and 4.7 selection algorithms are compared using proposed Weighted and SU Density Based Decision Methods respectively. When Weighted Combining Decision is considered, Equal and Probabilistic Selection Methods perform better than Worst and Random Selections. Equal Selection Method fits best for Weighted Decision Method. With Probabilistic Selection Algorithm, number of users chosen from each region are proportional to PU's presence probability of the region. With Weighted Decision Method, weights of regions are also proportional to PU's presence probability of the region. For instance, if PU's presence probability of a region is 0.6 and number of cooperative user is ten, then number of users chosen from this region is six, region's weight is 0.6 and each SU's weight in the region is 0.1 from

$$SU_{Weight} = \frac{0.6}{6} \tag{4.7}$$

This result is same as giving equal weights to SUs. Therefore, it should be noted that using Weighted Decision Method with Probabilistic Selection Algorithm does not have contribution to performance as Weighted Decision Method-Equal Selection pair. The reason is that when Weighted Decision Method is used with Equal Selection Algorithm, SUs in each region can have different weights. However, if Probabilistic Selection Algorithm is used with Weighted Decision Method then weights of users will be equal or nearly equal as explained in Equation (4.7).

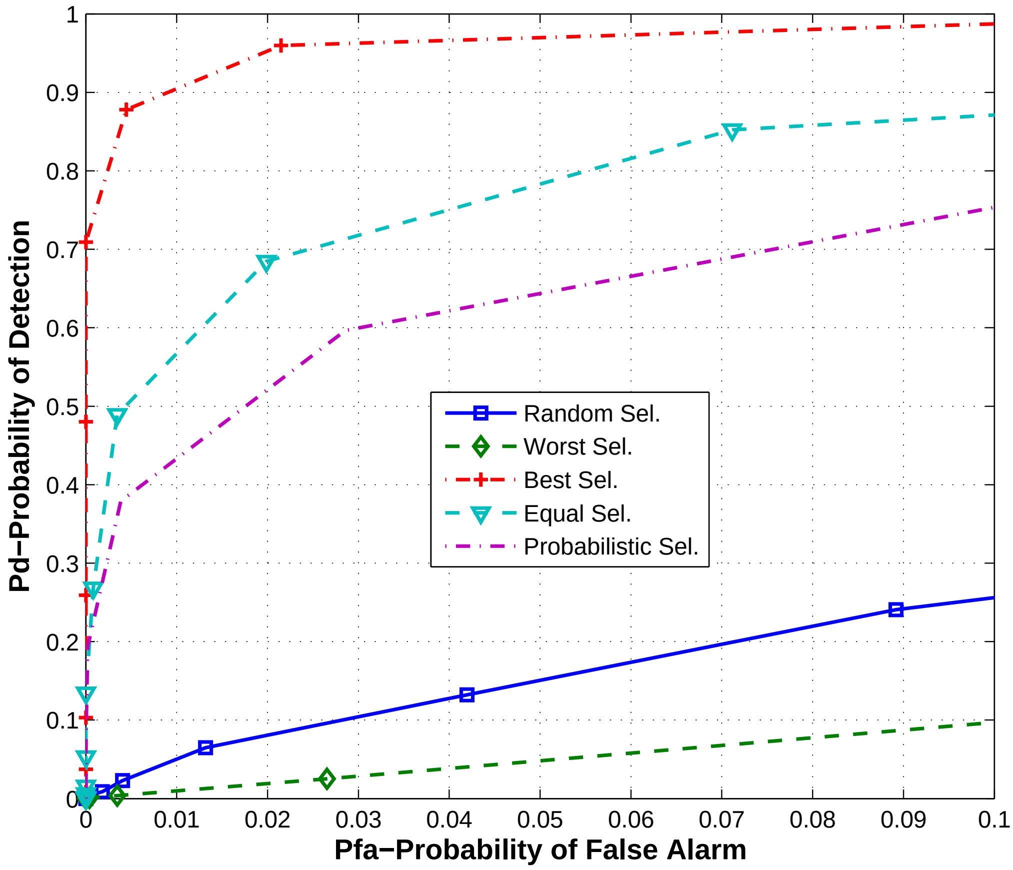

Figure 4.6. Comparison of Selection Algorithms using Weighted Combining Decision Method

In Figure 4.7, it is observed that Equal Selection Algorithm performs extremely good performance when used with SU Density Based Decision Method. The performance of this pair reaches best selection performance and provides probability of false alarm and probability of detection values of IEEE 802.22. SU Density Based Decision Method evaluates SUs' decisions according to their regions. In other words, majority of users in each region is considered separately. For this region, it is important not to choose unbalanced number of users from regions which may result in misleading decisions. For instance, if one user exists in the region, then CBS considers this user's decision because of high detection ratio of the region (equal to one). This decision can not be reliable since only one user's information is considered. Therefore, equal selection of SUs from each region increases performance of the SU Density Based Decision Method.

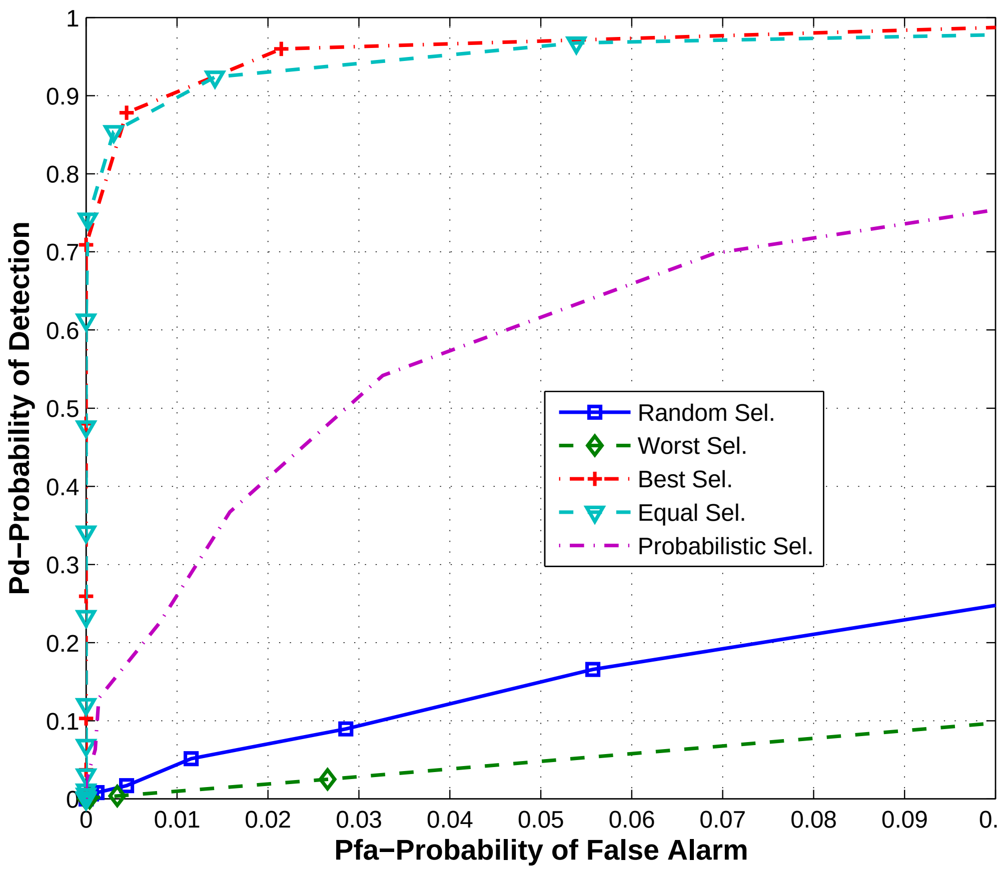

Figure 4.7. Comparison of Selection Algorithms using SU Density Based Decision Method

4.3.2. Comparison of Decision Methods in Outdoor Environment

At this part, proposed decision methods namely, SU Density Based Decision and Weighted Combining Decision Methods are compared with Majority and Hard Decision Methods for all selection algorithms described in Chapters 3 and 4.

In Figures 4.8, 4.9 and 4.10, decision methods are compared using Random, Worst and Best Selection Methods respectively. It is seen in Figure 4.8 that SU Density Based Decision and Weighted Combining Decision performs better than Majority and Hard Decision Methods when Random Selection is used. For Worst and Best Selection cases as in Figures 4.9 and 4.10, proposed methods do not have much contribution to sensing performance when compared with Majority Method. On the other hand, these proposed methods have slight contribution to performance when compared with Hard Decision Method. These three figures are simulated for comparison with Figures 4.11 and 4.12.

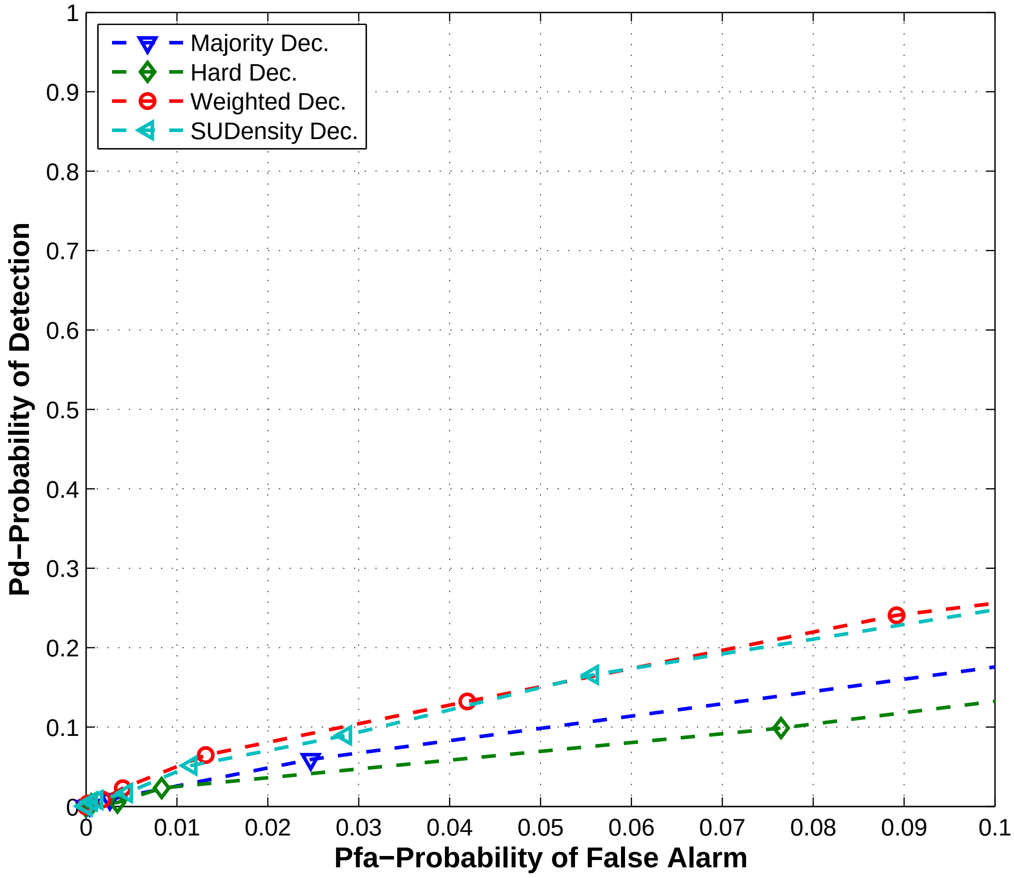

Figure 4.8. Comparison of Decision Methods using Random Selection of SUs

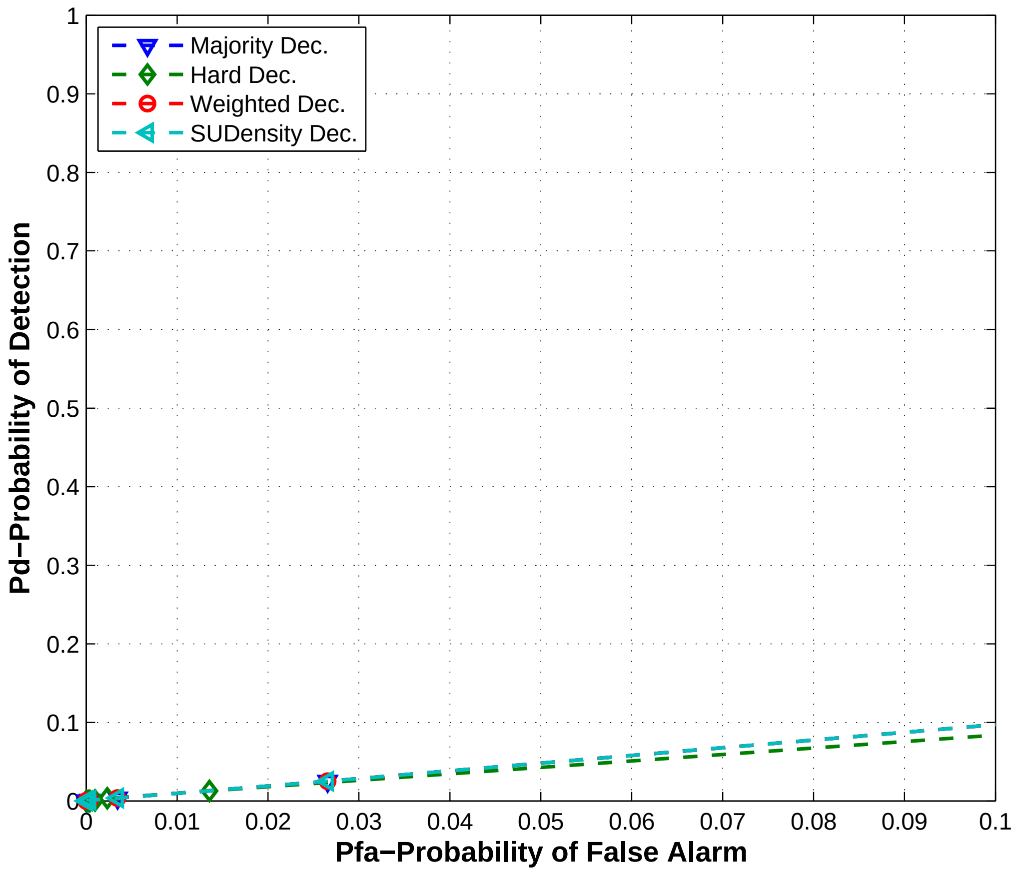

Figure 4.9. Comparison of Decision Methods using Worst Selection of SUs

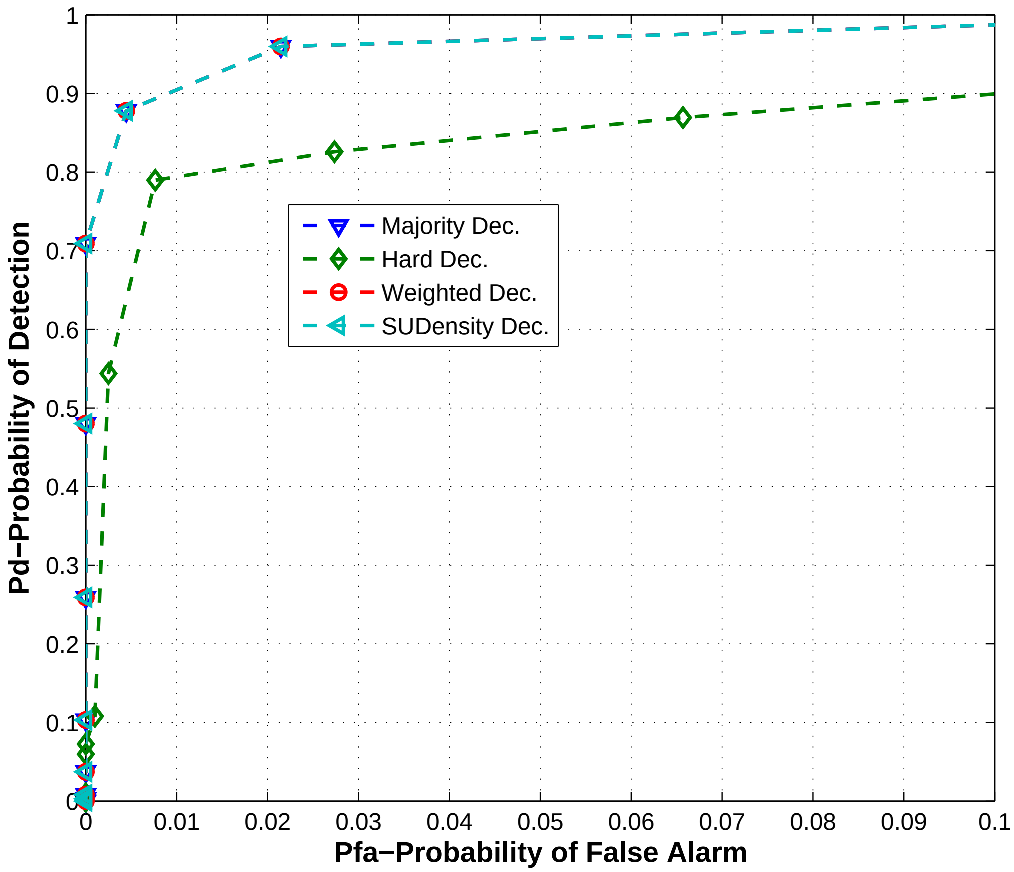

Figure 4.10. Comparison of Decision Methods using Best Selection of SUs

In Figures 4.11 and 4.12, decision methods are compared using proposed Equal and Probabilistic selection algorithms respectively. When Equal Selection is used, increase in performance for SU Density Based and Weighted Combining Decision Methods can be seen in Figure 4.11. Weighted Combining Decision Method improves the detection performance compared with Majority Method. On the other hand, performance improvement with SU Density Based Decision Method is much better than Weighted Combining Method. As stated in selection algorithms figures, Equal Selection-SU Density Based Decision pair provides best performance of all.

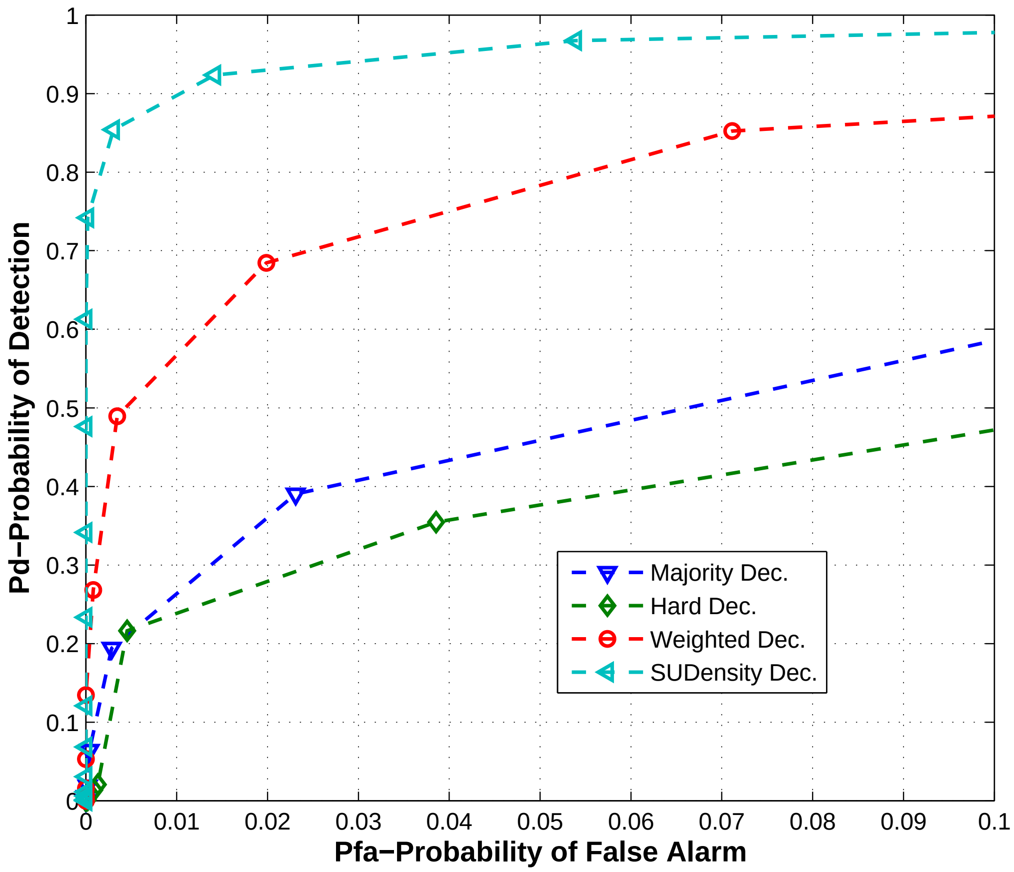

Figure 4.11. Comparison of Decision Methods using Equal Selection of SUs

If Probabilistic Selection Method is used, then Majority Method will be the decision rule which should be chosen to achieve good performance. Performance can be seen from Figure 4.12. However, this pair's performance is not as well as Equal Selection-SU Density Based Decision pair.

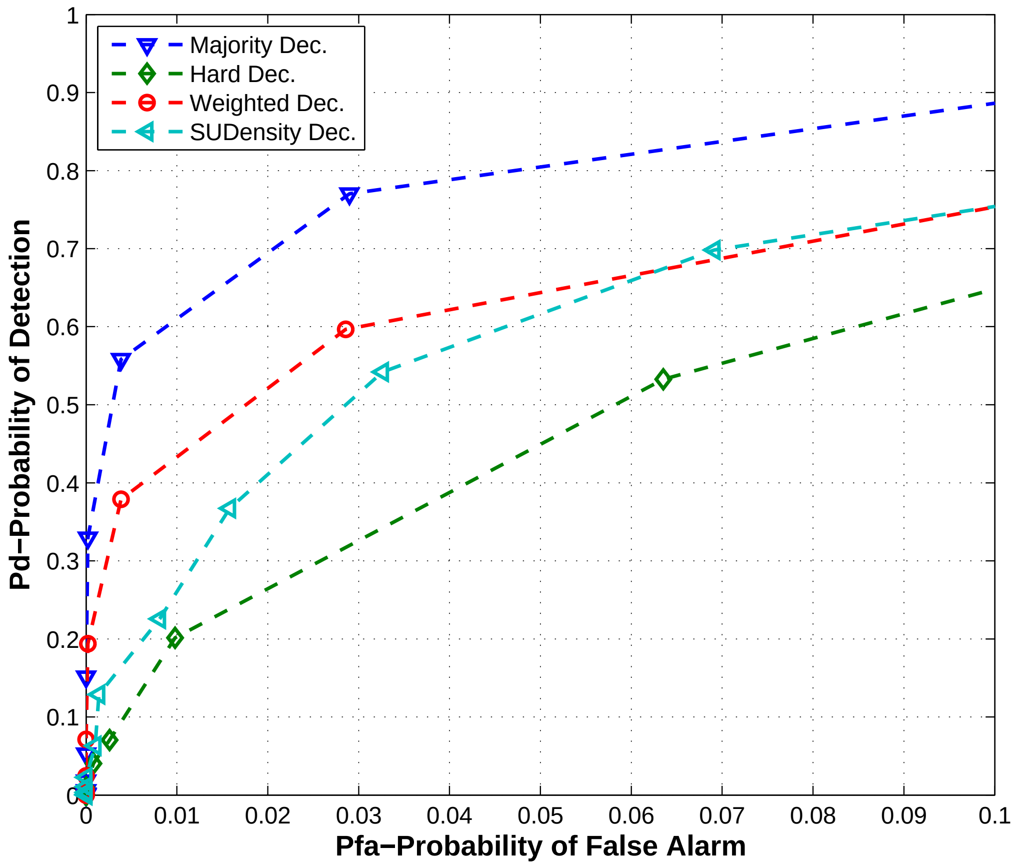

Figure 4.12. Comparison of Decision Methods using Probabilistic Selection of SUs

4.3.3. Comparison of Selection Algorithms in Indoor Environment

As in the outdoor environment, proposed secondary user selection algorithms, namely Equal and Probabilistic Selections are compared with Random, Best and Worst Selections which are explained in Chapters 3 and 4. Besides, user selection algorithms are compared for all decision methods at indoor environment.

In Figures 4.13 and 4.14, selection algorithms are compared using Majority and Hard Decision Methods respectively. Simulation results are similar with outdoor network case. In order to observe performances of selection algorithms using Hard Decision Method, Figure 4.13 is given. When Hard Decision Method is used, proposed Probabilistic and Equal Selection Algorithms give better results than the Worst and Random Selection Algorithms.

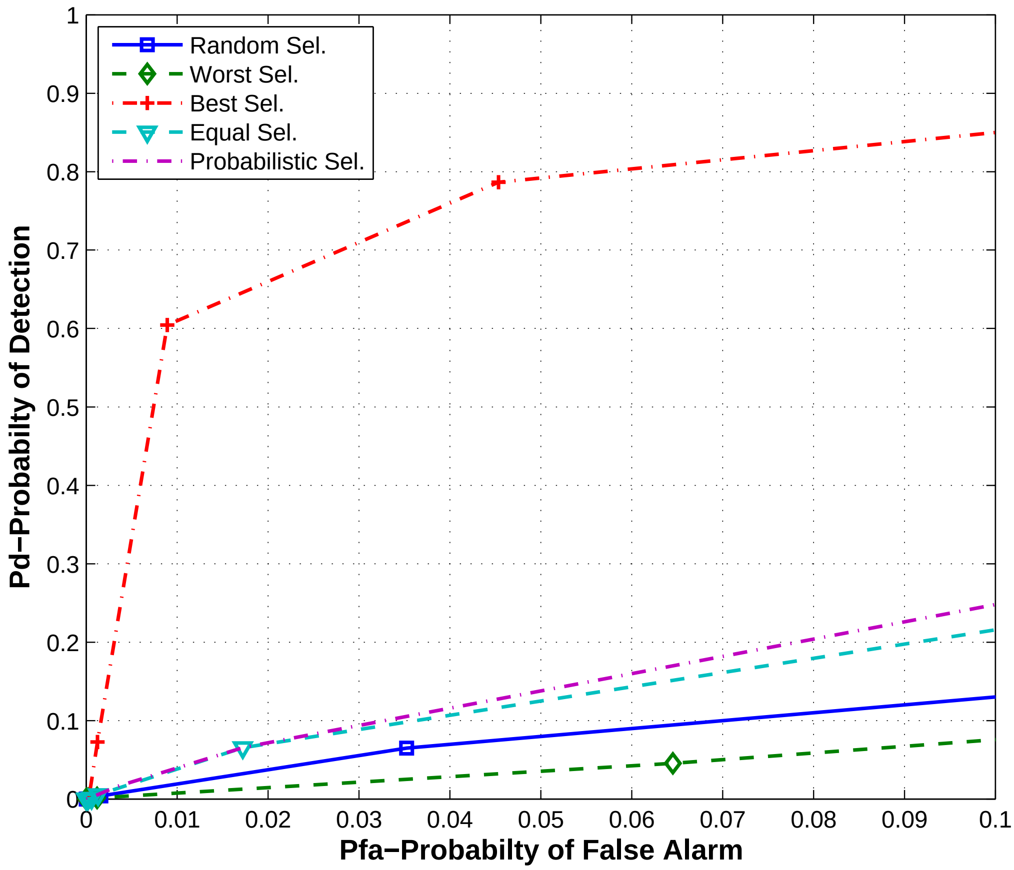

Figure 4.13. Comparison of Selection Algorithms using Hard Decision Method

Performances of user selection algorithms are compared using Majority Method in Figure 4.14. Probabilistic and Equal Selection Algorithms have better performances than Random and Worst Selection for this type of decision method too. However, expected probability of detection and false alarm values (0.9 and 0.1 respectively) can not be achieved with Majority Based Decision and proposed selection algorithms.

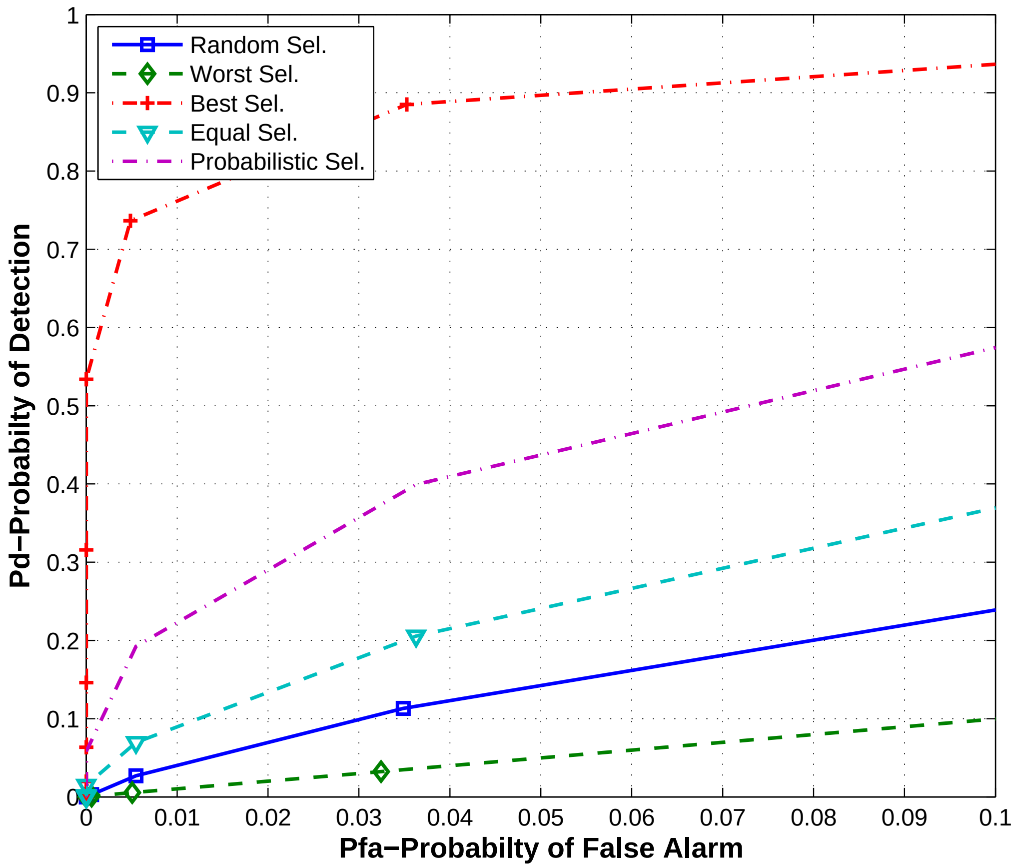

Figure 4.14. Comparison of Selection Algorithms using Majority (Voting) Method

In Figures 4.15 and 4.16, selection algorithms are compared using proposed Weighted Combining and SU Density Based Decision Methods respectively. Compared to Random and Worst Selection cases, increase in probability of detection is achieved when Weighted Combining Decision is used. This is shown in Figure 4.15.

It is shown in Figures 4.15 and 4.16 that Equal Selection Method performs well for both decision methods. Equal Selection achieves extremely good performance when used with SU Density Based Decision Method.

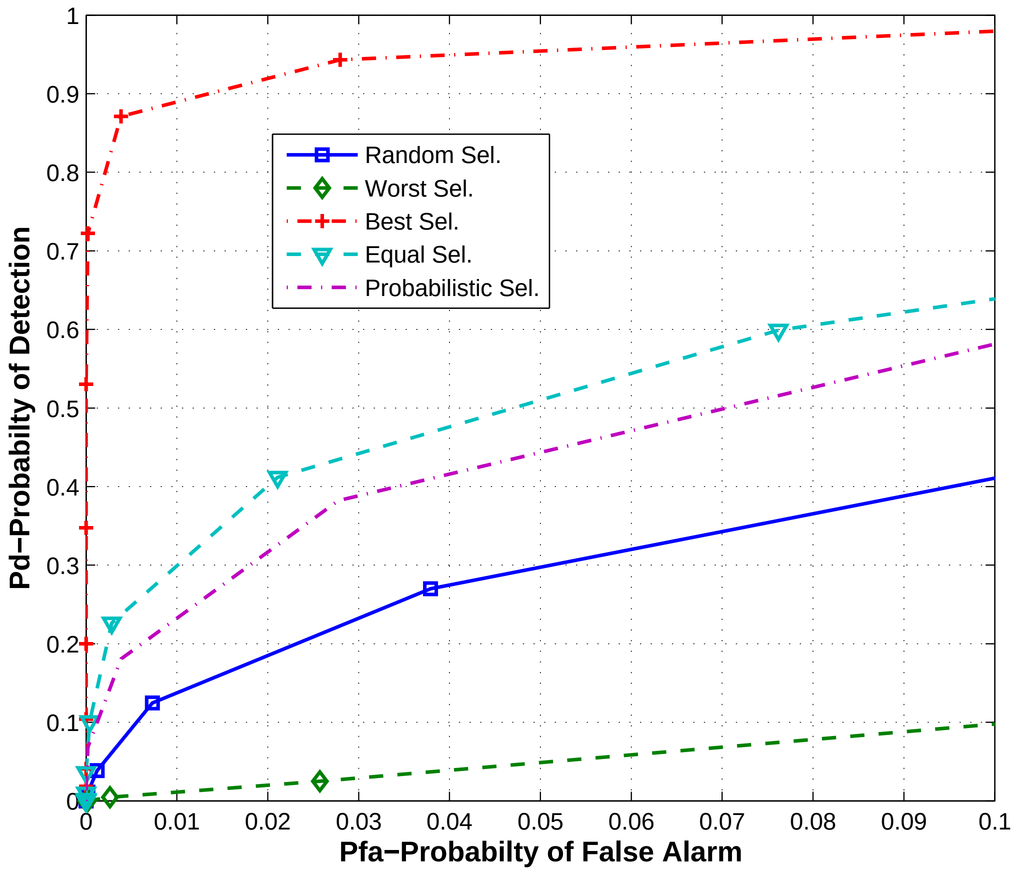

Figure 4.15. Comparison of Selection Algorithms using Weighted Combining Decision Method

Figure 4.16 shows that usage of SU Density Based Decision Method with Equal Selection Algorithm gives the best performance in indoor environment as in outdoor case. Hence, this pair proves its performance for indoor and outdoor environments. As explained at outdoor part, equal selection of users from each region improves the performance of SU Density Based Decision Method.

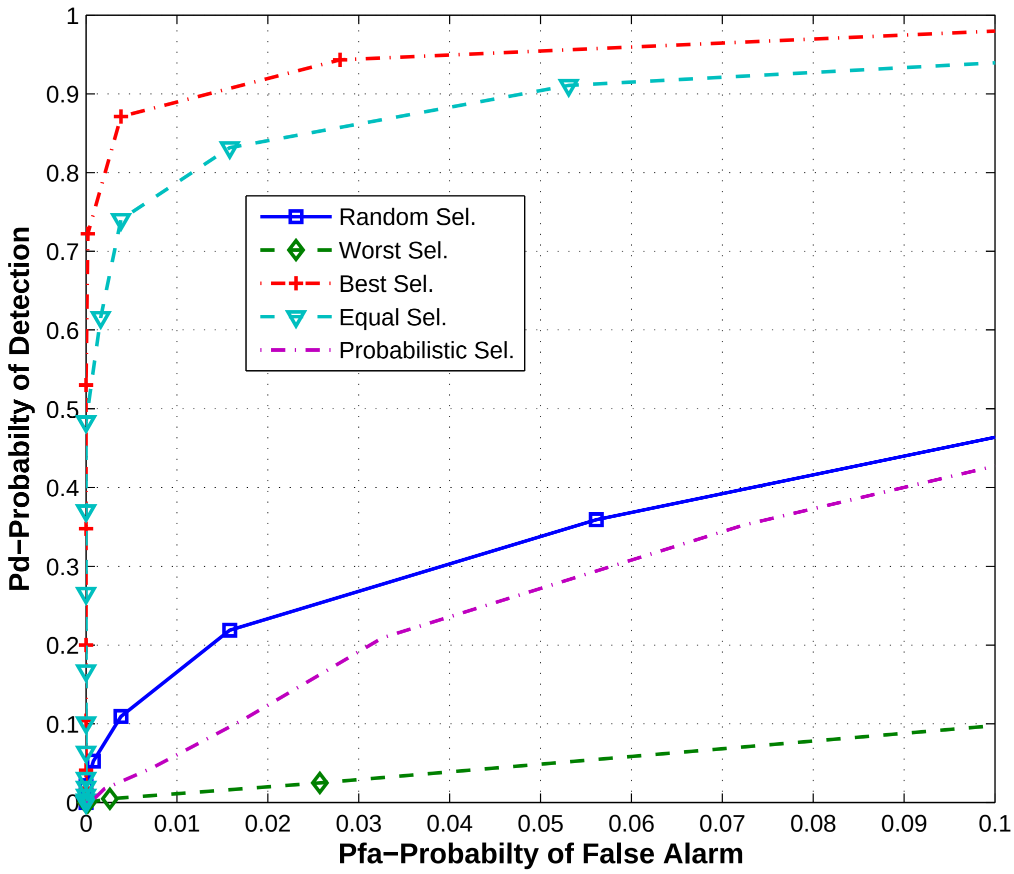

Figure 4.16. Comparison of Selection Algorithms using SU Density Based Decision Method

4.3.4. Comparison of Decision Methods in Indoor Environment

At this part, proposed decision methods, namely SU Density Based Decision and Weighted Combining Methods are compared with Majority and Hard Decision Methods. In Figures 4.17, 4.18 and 4.19 decision methods are compared using Random, Worst and Best Selection Algorithms respectively.

As can be seen from Figure 4.17, when Random Selection Algorithm is used, SU Density Based Decision should be chosen in order to obtain the best performance. Weighted Combining Decision Method also improves the performance compared to other methods. However, IEEE 802.22 specifications can not be achieved with selection-decision pairs simulated in Figure 4.17.

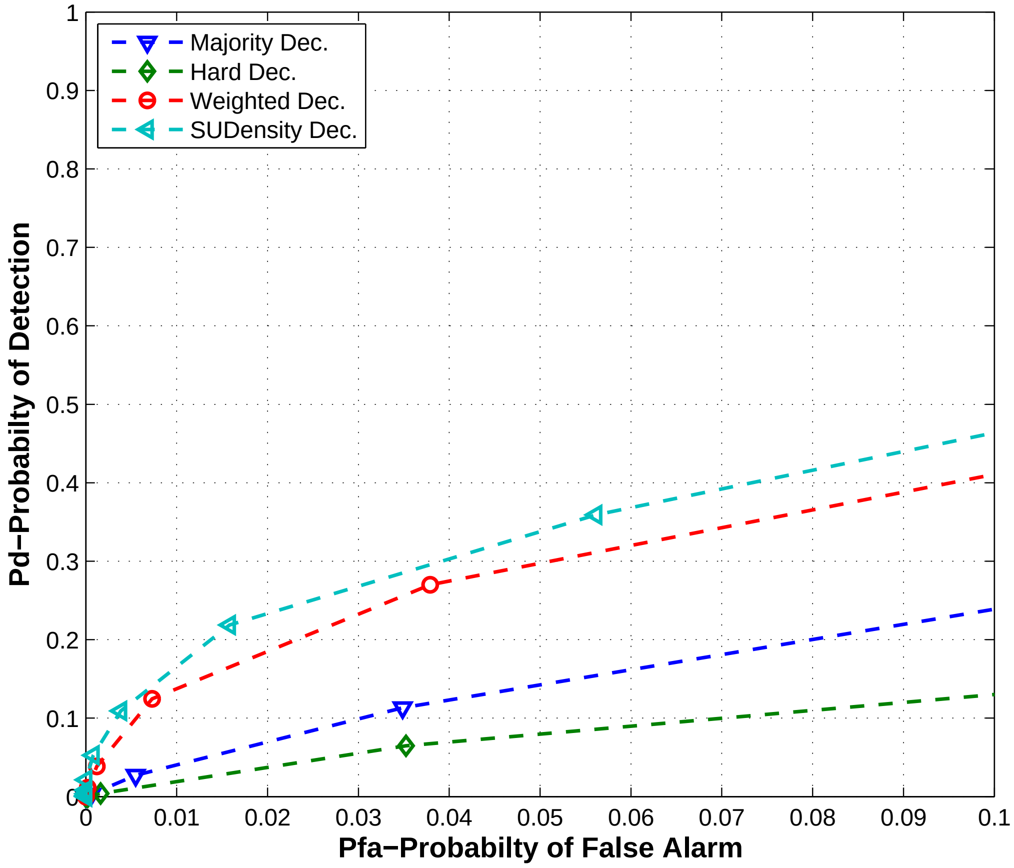

Figure 4.17. Comparison of Decision Methods using Random Selection of SUs

If Worst Selection Algorithm is used as in Figure 4.18, proposed selection methods do not have a reasonable contribution to performance. Since decision methods performances are limited with data obtained from secondary users, bad information taken from secondary users results in bad performance.

In Figure 4.19, it can be seen that if users with best SNR levels are chosen for cooperation then proposed decision methods show better performance than other decision methods.

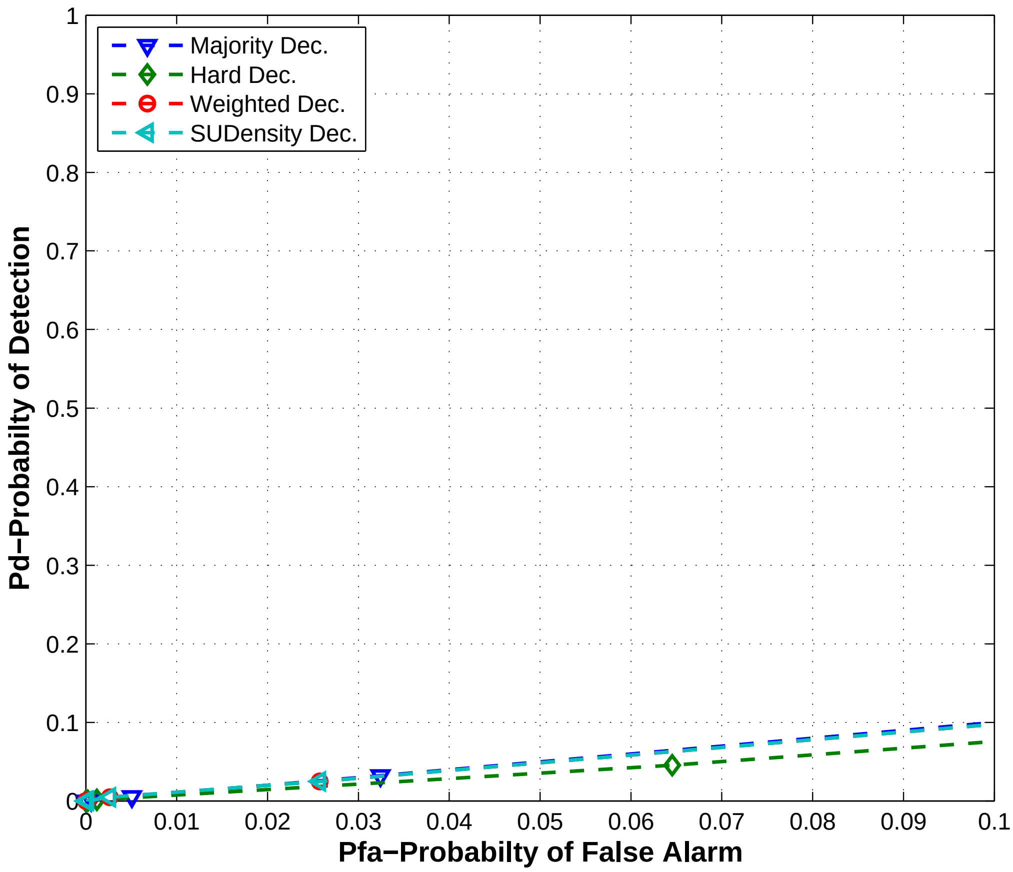

Figure 4.18. Comparison of Decision Methods using Worst Selection of SUs

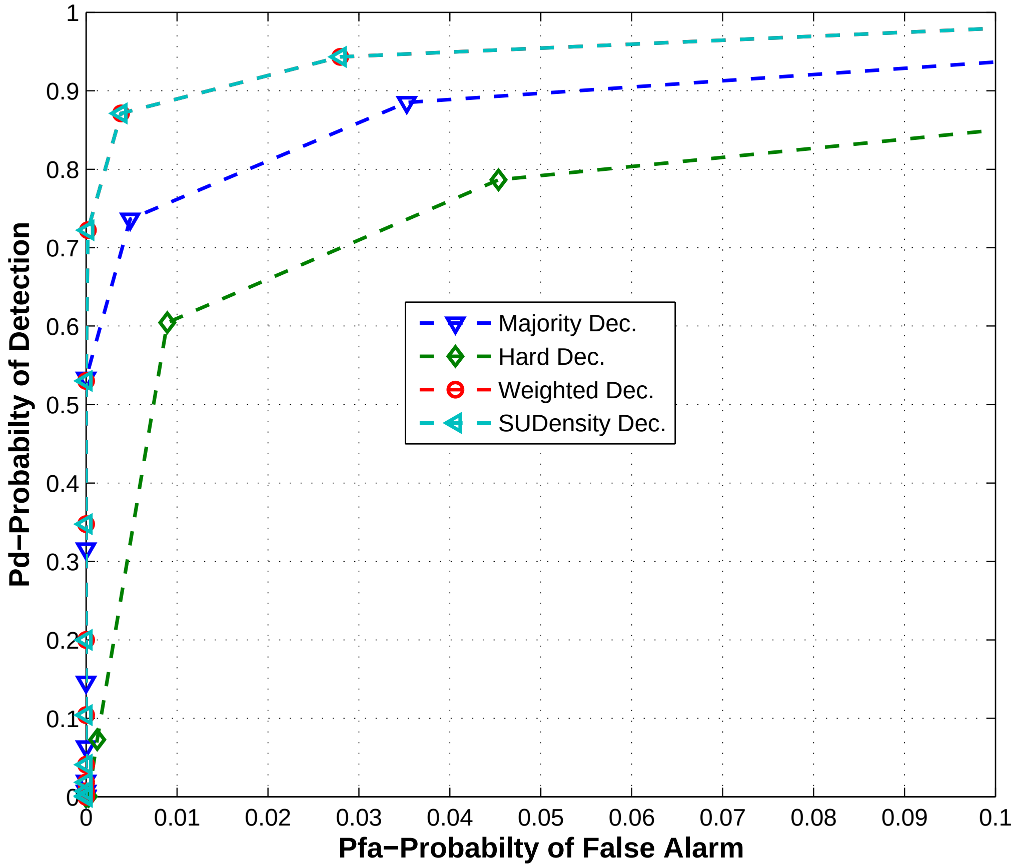

Figure 4.19. Comparison of Decision Methods using Best Selection of SUs

In Figures 4.20 and 4.21 decision methods are compared using proposed Equal and Probabilistic Selection Methods respectively. Indoor environment is similar to outdoor for equal selection case. It can be seen from Figure 4.20 that Weighted Combining and SU Density Based Decision with Equal Selection Algorithm perform better than Majority Method. On the other hand, Probabilistic Selection Algorithm has not got a reasonable contribution for improvement of the performance at indoor environment when used with SU Density Based Decision Method. As previously stated, performance of Weighted Combining Decision is similar to Majority Method when it is used with Probabilistic Selection Algorithm. On the other hand, it can be seen from Figures 4.14 and 4.21 that Probabilistic Selection has contribution to Majority Decision's performance when compared to other selection methods. However, Probabilistic Selection does not improve the performances of Weighted and SU Density Based Decision Methods as Majority Method.

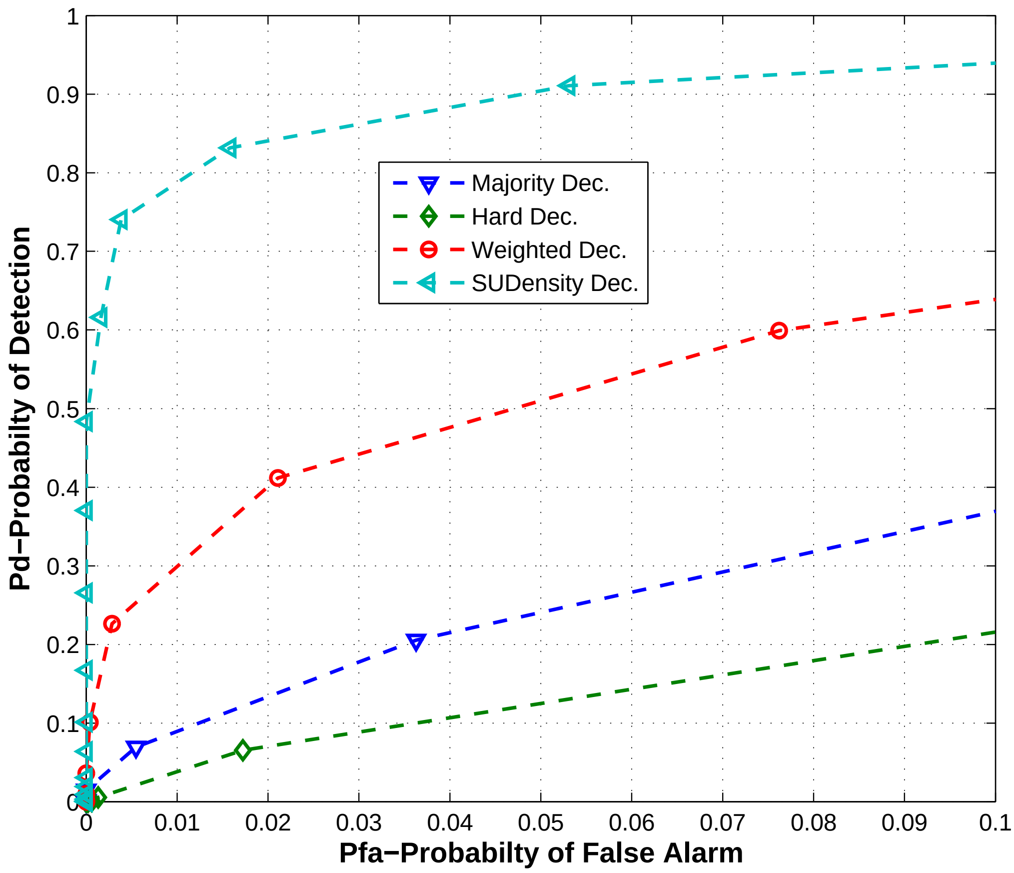

Figure 4.20. Comparison of Decision Methods using Equalized Selection of SUs

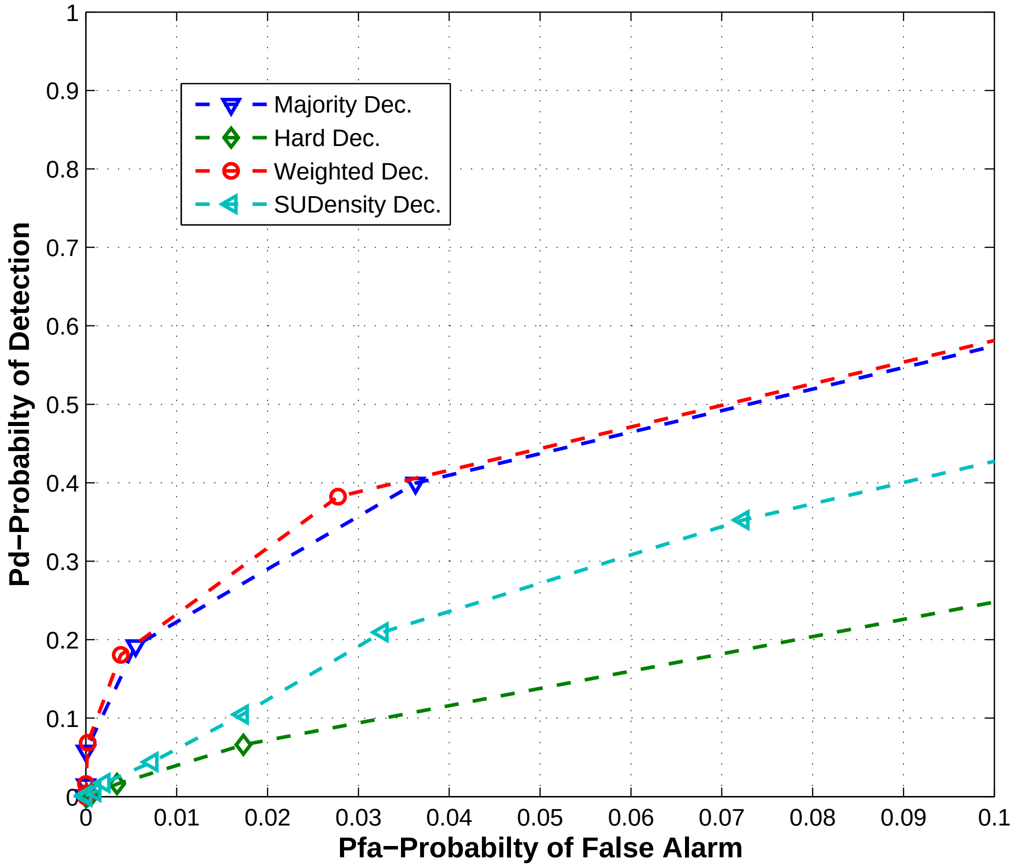

Figure 4.21. Comparison of Decision Methods using Probabilistic Selection of SUs

When indoor and outdoor simulations are considered, it can be deduced that Equal Selection-SU Density Based Decision pair improves the performance of the energy detector reasonably. This pair provides IEEE 802.22 specifications even for secondary users with low SNRs. The second pair is chosen as Equal Selection and Weighted Decision when both environment results are evaluated. Majority Decision with the use of Probabilistic Selection Algorithm has also contribution when compared random selection case. However, if CBS has information about SUs' and PU's location as in probabilistic selection case, it is better to use the first pair, Equal Selection-SU Density Based Decision rather than Probabilistic Selection-Majority Decision pair.

5. CONCLUSIONS AND FUTURE WORK

In this study, outdoor and indoor sensing models of cognitive radio networks are considered. Spectrum sensing is performed by energy detector for each individual secondary user node and user decisions are combined at CBS according to decision algorithms in the network architecture. Cooperative user selection algorithms and cooperative user decision methods are simulated over cognitive network architectures defined. Performances of cooperative user selection algorithms and cooperative user decision methods are compared by simulating each user selection with each decision method.

Firstly, we verify models for indoor and outdoor environments. Then, we evaluate performances of proposed selection and decision methods with users which experiences different SNRs due to path loss and obstacles between regions. Proposed Equal User Selection Algorithm and SU Density Based Decision Method achieve IEEE 802.22 specifications of 0.9 for probability of detection and 0.1 for probability of false alarm. This pair improves performance of the system when compared with random selection and majority based decision methods. Proposed methods are simple to implement since they do not include complexity and complexity of the system does not increase with the increasing number of nodes. For future work, detection time performances of these methods can also be studied. Besides, since proposed methods are independent from individual detection of secondary users, these methods can also be evaluated for other detection methods like likelihood energy detector or matched filter detector.

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