A Compressive Sensing Approach to Analyze the Performance of Wideband Cognitive Radio Networks

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Declaration

This is to certify that the thesis work entitled "*A Compressive Sensing Approach to Analyze the Performance of Wideband Cognitive Radio Networks*" has been carried out by *S.M. Bulbul Ahammed* in the Department of *Electronics and Communication Engineering*, Khulna University of Engineering & Technology, Khulna, Bangladesh. The above thesis work or any part of this work has not been submitted anywhere for the award of any degree or diploma.

Signature of Supervisor	Signature of Candidate

Approval

This is to certify that the thesis work submitted by *S. M. Bulbul Ahammed* entitled "*A Compressive Sensing Approach to Analyze the Performance of Wideband Cognitive Radio Networks*" has been approved by the board of examiners for the partial fulfillment of the requirements for the degree of *Master of Science in Electronics and Communication Engineering*, Khulna University of Engineering & Technology, Khulna, Bangladesh in April 2018.

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Abstract

In the field of wireless communication systems, Cognitive Radio (CR) technology is the talk of the time for the best utilization of spread spectrum frequency. In the Wideband range, traditional Narrowband Sensing methods are not suitable to apply for performing Wideband Spectrum Sensing, as of making a single binary decision (Primary User present or absent) in the entire Wideband signal, thus cannot locate individual spectral opportunities that rely within the Wideband Spectrum. The Compressive Sensing (CS) can recover sparse signals at Sub-Nyquist rates and it depends on this principle of sparsity, so that a brief representation of the signal is possible when expressed in a suitable form. This research work has proposed a model of CR receiver sensing module which can be able to estimate a significant part (which is highly sparse among the segments of the spectrum) of the entire Wideband Spectrum with lower computational complexity. This proposed work aims to analyze the compression ratio, i.e., M/N, with different number of Primary User (PUs) present in the wideband frequency from the Receiver Operating Characteristics (ROC) curves. Additionally, it is also analyzed that how the compression ratio, M/N characteristics varies with signal-to-noise ratio (SNR) in the wideband frequency from the ROC curves. This work investigates the probability of detection, P_d versus SNR for a fixed M/N and the throughput of a CR network against sensing period for a fixed frame length and vice versa. This proposed work also aims to find the requirement of less computational complexity and physical memory. Eventually, from the wide investigations through our proposed research work, it is found that the proposed method provides better throughput for fixed frame length as well as fixed sensing period in the field of CR network. The achievable rate of a CR node varies with the sensing slot duration as well as frame duration the throughput is greater for shorter sensing time period. It can hopefully state in the final point that the proposed method proves its significance in CR system.

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List of Acronyms

AWGN	Additive White Gaussian Noise
AIC	Analog-to-Information Converter
ADC	Analog-to-Digital Converter
BP	Basis Pursuit
BPF	Band-Pass Filter
CR	Cognitive Radio
CM	Cognitive Manager
CRN	Cognitive Radio Network
CS	Compressive Sensing
CRAMNET	Cognitive Radio Assisted Mobile Ad Hoc Network
DFT	Discrete Fourier Transform
DSP	Digital Signal Processing
FCC	Federal Communications Commission
MAC	Medium Access Control
MP	Matching Pursuit
OSA	Opportunistic Spectrum Access
OMP	Orthogonal Matching Pursuit
PDF	Probability Density Function

List of Acronyms

PU	Primary User
RD	Random Demodulator
ROC	Receiver Operating Characteristics
RMS	Root Mean Square
RF	Radio Frequency
SU	Secondary User
VHF	Very High Frequency

Chapter 1

Introduction

1.1 Motivation

In wireless communication systems, Cognitive Radio (CR) is one of the most important modern techniques which utilizes the unused spread spectrum effectively. Nowadays, spectrum scarcity is a big issue in the field of mobile communication [1]. The CR is a reliable solution to this problem. The CRs are considered for using the licensed spectrum without causing harmful interference to the primary users (PUs) [1-2]. Spectrum sensing is an ability of Secondary Users (SUs) to independently detect spectral opportunities without any assistance of PUs.

Wideband Spectrum Sensing methods targets to sense a frequency bandwidth that exceeds the coherence bandwidth of the channel [2]. In the wideband range, traditional narrowband sensing methods are not possible to apply for performing wideband spectrum sensing, as of making a single binary decision (PU present or absent) in the entire wideband signal, thus cannot locate individual spectral opportunities that lie within the wideband spectrum [3]. The wideband spectrum sensing can be mainly categorized into two kinds: i) Nyquist rate wideband sensing and ii) sub-Nyquist rate wideband sensing [4-5]. The first approach is the one which processes digital signals are taken at or above the Nyquist rate, while the later scheme deals acquiring signals using sampling rate lower than the Nyquist rate.

1.2 Problem Statements and Scope

The compressive sensing (CS) can recover sparse signals at sub-Nyquist rates and it depends on this principle of sparsity, so that a brief representation of the signal is possible when expressed in a suitable form. Wireless communication signals in open-spectrum networks are typically considered as sparse in the frequency domain, allowing using compressive sensing to remove the sampling problem [4-6]. Though the CS is a powerful and efficient technique, it has a side effect that it results increased computational complexity. The signals require low energy for processing at both the transmitter and receiver sites which is supportive to move forward the complexity. Since the sampling rate is less than the Nyquist rate, the CS is a method that estimates signals using less evaluations comparing to conventional sampling [6]. Therefore, a scope is arisen to develop methodology based on CR receiver sensing model for estimating the entire wideband spectrum with lower computational complexity.

1.3 Contribution of this Thesis Work

This research work presents a model of CR receiver sensing module which estimates a significant part (which is highly sparse among the segments of the spectrum) of the entire wideband spectrum thus making computational complexity lower. As soon as the wideband signal under goes to different band pass filters (BPFs) that pick out the present value of radio frequency (RF) band and divide the whole wideband spectrum into several frequency bins (FBs). Capitalizing the presence of sparsity in wideband spectrum, the thesis aims to ascertain the highly-sparse frequency bin (HSFB) through average energy classification of each FB. The energy estimation of a single FB is performed by taking random sub-Nyquist rate samples. The HSFB exploits several indications; *First*, it ensures of having minimum number of active PUs which substantially exploit maximum opportunistic accessibility for a CR user. *Second*, the more the sparsity, the better would be the spectral estimation which pays improved detection performance and, the detection performance is discovered employing the popular energy detector method. Third, achievable throughput performance of a static frame duration as well as static sensing length are compared to a traditional spectrum sensing methodology subsequent to a single RF chain with CS method. Finally, spectral estimation of a single HSFB rather than entire wideband would ask minor computational complexity.

As a result, the main contributing objectives of this work can be summarized by the following key points:

- To explore the computational complexity as well as volume of the physical memory requirement.
- To examine the probability of detection versus signal-to-noise ratio (SNR) for a fixed the compression ratio, i.e., M/N (%) and calculate the energy estimator performances with respect to the M/N (%).
- To investigate the throughput of a CR network against sensing period for a fixed frame length and vice versa.
- To analyze the M/N (%) with different SNR in the wideband frequency from the receiver operating characteristics (ROC) curves.
- To analyze the M/N, with different number of PUs present in the wideband frequency from the ROC curves.

1.4 Thesis Outline

In Chapter 1, an introduction to the topics discussed in this work is presented. In particular, Chapter 1 details the context of this thesis and emphasizes the main contribution of this Thesis Work.

In Chapter 2, the state of art schemes of CR systems are described. This chapter focuses on the difference types of spectrum sensing techniques. Various compressive sampling techniques are also brought into discussion. Different types of fading channel are also considered here.

In Chapter 3, Signal model and System model of this thesis work are described. It includes deliberation of theory and problem evaluation.

In Chapter 4, describes the Compressive sensing techniques are implemented in MATLAB and their simulation results are presented. The results are methodically investigated and analyzed.

In Chapter 5, the overall conclusion of the thesis work. In addition, this chapter provides some recommendations and possible future direction of research in CR network.

Chapter 2

State of the Art and Literature Reviews

2.1 Introduction

Previous research works those are closely related to this thesis have been discussed in this chapter with their specifications, proposed techniques and the limitations. In addition, the main contributions and the dissimilarities contrast to the other works have also been mentioned here. This chapter also covers different notions, definitions, and parameter clarifications as the basic states of the art.

CR is a form of wireless communication where a transceiver can intelligently detect the channels for communication which are in use and which are not in use, and move into unused channels while avoiding occupied ones. This optimizes the use of available radio-frequency spectra while interference is minimized to other users. Spectrum scarcity problems happen due to the spread of various wireless devices and technologies engaging static frequency access and to cope up with this demand, CR is a solution of enormous outlook. There are mainly two techniques that are widely used by the CR to detect the spectrum holes. These are Narrow band and Wide band Spectrum sensing. In this chapter, various spectrum sensing techniques have been described. Various fading channels and different types of compressive techniques are taken into account. Besides there are various issues and challenges that are being faced by the CR while detecting the unused spectrum are also discussed.

2.2 Literature Review

Wide band spectrum sensing techniques are getting tremendous attention among the current researchers regarding CR Network [7]. In [8], a traditional filter-bank based approach was presented for wideband spectrum sensing in a multi-carrier communication environment. It has been shown to have a higher spectral dynamic range than conventional power spectrum estimation approach. Another filter-based method has been discussed for wideband spectrum sensing in [9] and here the filter outputs has been considered for channel energy vector recovery via a CS scheme. In [10], the authors proposed a multiband joint detection scheme in order to detect the active PUs over multiple frequency bands. Also, the pleas subsequent to a wavelet based approach were employed to detect and classify the wideband RF signals [11]. In [12], an estimation of the RF spectrum based on CS scheme was proposed for authors have claimed this scheme outperforms in some practical conditions. In particular, authors in [12] introduced the auto-correlation of the compressed signal to estimate the spectrum of the sparse signal. In most of the papers, the authors are devoted to estimate the whole wideband spectrum to find a spectrum hole for opportunistic access of CRs [13, 14]. To estimate the whole wideband in CS domain implies computational burden as well as it requires more memory space to store signal vector and hence prohibitive energy cost. To avoid the estimation of wideband spectrum, our emphasis is to reconstruct a significant portion (which is more sparse than the other part of spectrum) of it, as a result of making computational complexity significantly lower. As soon as the wideband signal undergoes at different BPFs, it selects the RF band of interest and divide the whole wideband spectrum into several frequency bins (FBs). Sparsity is one of the fundamental requirements for spectral recovery that has already been proposed in CS theory [15, 16].

In [17] authors have proposed a method for wideband cognitive receiver sensing unit which can estimate a highly sparse segment of wideband based on compressed sensing with compared to entire wideband spectrum. The proposed model is capable to reduce computational complexity and improve detection performance. In this work, the performances of sparsity had been measured based on the SNR profile but PU presented in each FB based analysis had not been considered. In addition, this work measured the performance considering standard energy estimation of the frequency bins but this value may be changed in applied approach. Another model based on CR receiver wideband sensing unit is proposed in [18] where an important percentage of the wideband spectrum has been estimated through CS rather than recovering the total wideband spectrum. This model requires reduced sensing time and lesser computational burden in signal detection and therefore, throughput rate increases.

Therefore, some questions are still unknown. Previous research works considered the energy of the active PU's signals as standard or theoretical value. But, the real-world scenario is not the same as they considered. Therefore, the actual performance of the network should be calculated considering the real-world approach simulation. On the overall discussion, an acute opportunity arises to search further the actual performance measurement of CSN of filter based spectrum estimation in applied environment simulation which helps to find the actual performance of the network in practical field.

2.3 History of Cognitive Radio

The concept of CR was first proposed by Joseph Mitola III in a seminar at KTH (the Royal Institute of Technology in Stockholm) in 1998 and published in an article by Mitola and Gerald Q. Maguire, Jr. in 1999.It was a novel approach in wireless communications, which Mitola later described as: The point in which wireless personal digital assistants (PDAs) and the related networks are sufficiently computationally intelligent about radio resources and related computer-to-computer communications to detect user communications needs as a function of use context, and to provide radio resources and wireless services most appropriate to those needs.

CR is considered as a goal towards which a software-defined radio platform should evolve: a fully reconfigurable wireless transceiver which automatically adapts its communication parameters to network and user demands. Regulatory bodies in the world (including the Federal Communications Commission in the United States and Ofcom in the United Kingdom) found that most radio frequency spectrum was inefficiently utilized. Cellular network bands are overloaded in most parts of the world, but other frequency bands (such as military, amateur radio and paging frequencies) are insufficiently utilized. Independent studies performed in some countries confirmed that observation and concluded that spectrum utilization depends on time and place. Moreover, fixed spectrum allocation prevents rarely used frequencies (those assigned to specific services) from being used, even when any unlicensed users would not cause noticeable interference to the assigned service. Therefore, regulatory bodies in the world have been considering allowing unlicensed users in licensed bands if they would not cause any interference to licensed users. These initiatives have focused CR research on dynamic spectrum access.

The first phone call over a cognitive-radio network was made on Monday, 11 January 2010 in the Centre for Wireless Communications at the University of Oulu using CWC's cognitive-radio network, CRAMNET (Cognitive Radio Assisted Mobile Ad Hoc Network), which was developed by CWC researchers.

2.4 Cognitive Radio (CR)

A CR is an intelligent radio that can be programmed and configured dynamically.CR can efficiently utilize the unused Spectrum for secondary usage without interfering a primary licensed user. CR have the capabilities to sense the operating radio environment, learn and reconfigure its radio parameters in real time according to environment creating a form of mesh network, are seen as a promising technology.

2.5 Characteristics of CR

There are two main characteristics [19] of the CR and can be defined as

- ***Cognitive capability:*** Cognitive Capability defines the ability to capture or sense the information from its radio environment of the radio technology. Joseph Mitola first explained the cognitive capability in term of the cognitive cycle "a CR continually observes the environment, orients itself, creates plans, decides, and then acts"
- ***Reconfigurability:*** Cognitive capability offers the spectrum awareness;

Reconfigurability refers to radio capability to change the functions, and enables the CR to be programmed dynamically in accordance with radio environment (frequency, transmission power, modulation scheme, communication protocol).

2.6 The Cognitive Radio Network Architecture

Some part of the wireless spectrum is licensed for different tasks and few bands are still unlicensed. Based on this there are two main Network groups, the primary networks and the CR networks (the next generation networks).

2.6.1 Primary Network

The primary networks have special rights to specific bands. The primary network includes then primary user and the primary base-station.

- **Primary Users (PU)***:* PUs also called licensed users, operate in specific spectrum bands. This operation is entirely controlled only by the primary base-station. This PUs does not require any further enhancements for the coexistence of the primary base stations and the PUs.

- **Primary Base Station**: The primary base station has a fixed infrastructure. Primary networks do not have the ability of CR for sharing the spectrum with cognitive users but it can be requested to have both legacy and CR protocols for primary network access of CR users.

2.6.2 Cognitive Radio Network

CR networks do not have the permission to operate in the required band. The CR networks can be deployed both with infrastructure and without infrastructure networks. The components of the network are as follows:

- **CR user**: The CR user (the unlicensed user) has no spectrum license, so extra functionalities are needed for sharing the spectrum band. These users are also known as secondary user (SU).

- **CR base-station**: The CR base-station (the unlicensed base station) has a fixed infrastructure component with CR abilities. CR can access the different networks by providing the single hop network connection to CR user. Single hop connection is used to reduce the propagation delay; it has now become essential to have single hop network connection which connects the user terminals. The CR networks operate both in licensed and unlicensed bands (mixed spectrum environment). There are three access types are:

- **CR Network Access**: The CR users can access the CR base-station not only the licensed bands but also the unlicensed spectrum bands.

- **CR ad hoc Access**: The CR users communicate with different CR users through the ad-hoc connection on licensed and unlicensed bands.

- **Primary Network Access**: The licensed bands are means for the CR users through which they access the primary base-station.

2.7 Functions of CR

There are four major functions of CR. Fig. 2.1 shows the basic Cognitive cycle.

2.7.1 Spectrum Sensing

The first step of spectrum sensing is that it determines the presence of PU on a band. The CR is able to share the result of its detection with other CR after sensing the spectrum. The goal of spectrum sensing is to find out the spectrum status and activity by periodically sensing the target frequency band. Particularly, a CR transceiver detects the spectrum which is unused or spectrum hole and also determines method of access without interfering the transmission of licensed. Two types of spectrum sensing are there; it may be either centralized or distributed. In the centralized spectrum sensing, a sensing controller senses the target frequency band, and share the information with other nodes in the system.

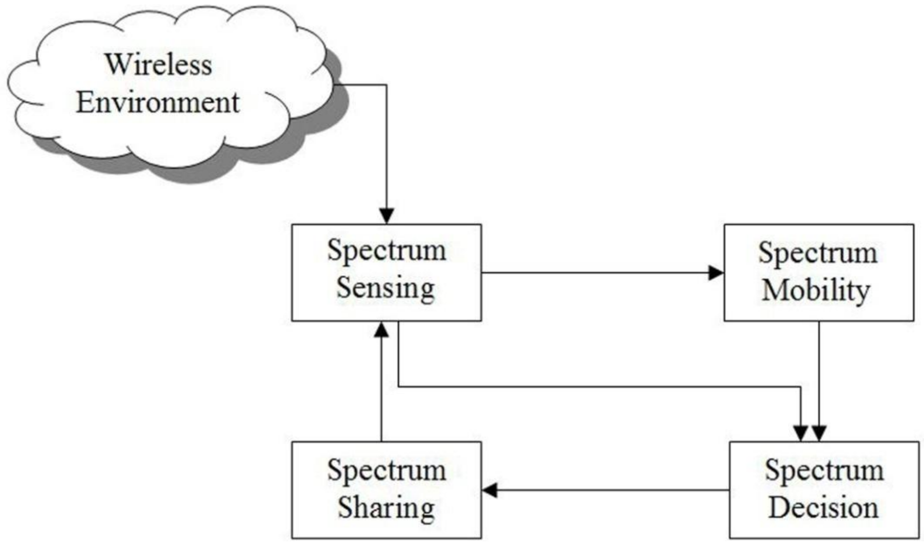

Fig. 2.1 Basic diagram of cognitive cycle

2.7.2 Spectrum decision

Spectrum decision provides the fair spectrum scheduling method among coexisting users. The available white space or channel is immediately selected by CR if once found. Spectrum decision refers to a CR decides the data rate, determines the transmission mode, and the transmission bandwidth. Then, the appropriate spectrum band is selected according to the spectrum characteristics and user requirements.

2.7.3 Spectrum Sharing

Cognitive Radio assigns the unused spectrum (spectrum hole) to the CR as long as PU does not use it. This property of CR is described as spectrum sharing.

- ***Underlay Spectrum Sharing:*** Underlay spectrum sharing is the availability of the radio spectrum access with minimal transmission power that the interference temperature above its pre-designed thresholds wouldn't be raised. To spread the unlicensed signal over a large band of spectrum in underlay spectrum sharing the licensed radio device can identify undesired signal which is below the noise and interference floor [20].

- ***Overlay Spectrum sharing:*** Unlicensed users can utilize a spectrum band for the fraction of time where this band is under-utilized by the licensed users in Overlay Spectrum sharing technique.

2.7.4. Spectrum Mobility

When a licensed (Primary) user is detected the CR vacates the channel. This property of CR is described as the spectrum mobility and also called handoff [21]. This is the process that allows the CR user to change its operating frequency. CR networks try to use the spectrum dynamically to operate in the best available frequency band and maintain the transparent communication. Spectrum sensing is an important and a sensitive job out of these four functions in CR since interfering with other users is illegal.

2.8 Spectrum Holes

A huge portion of the radio spectrum is allocated but rarely used in most of the locations and time. The portions of the spectrum which are temporarily unused by the licensee, are called the spectrum holes or spectrum white spaces or vacant spaces [21]. The spectrum holes can be distinguished by either frequency or time according to the communication environment. CR is a form of wireless communication where a transceiver can intelligently detect the channels for communication which are in use and which are not in use, and move into unused channels while avoiding occupied ones. This optimizes the use of available radio-frequency spectra while interference is minimized to other users. This is a paradigm for wireless communication where transmission or reception parameters of network or node are changed for communication avoiding interference with licensed or unlicensed users. A spectrum hole (Fig. 2.2) is generally a concept of spectrum as non-interfering, considered as multidimensional areas within frequency, time, and space. For secondary radio systems, the main challenge is to be able to sensing spectrum hole when they are within such frequency bands.

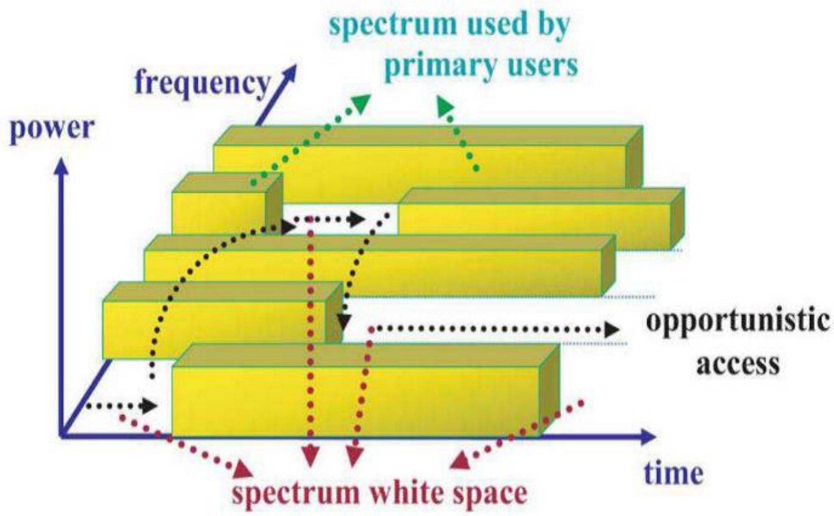

Fig. 2.2. Spectrum used by licensee [21]

- ***Spectrum hole in time domain*** A radio spectrum that is not currently being used by a primary users for a certain period of time.

- ***Spectrum hole in frequency domain*** It is a contiguous frequency band in which functions of the cognitive radio do not cause any harmful effects to the PUs.

- ***Spectrum hole in spatial domain*** This is a frequency band in a specific geographic location area where the primary users transmission is being employed. Additionally, spectrum holes may also be classified as follows:

- ***White Spaces*** In white spaces, license bands are not present at that time, only natural noises such as broadband thermal noise and impulsive noise are exit.

- ***Gray Spaces*** Gray spaces which partially filled by low power interferers.

- ***Black Spaces*** Those places are occupied by the PUs.

According to the space classification, a CR can transmit in the gray and white spaces, but it is forbidden to work in the black space once the PU is active.

2.9 Techniques of Spectrum Sensing for CR

Radio spectrum is classified as black spaces, grey spaces and white spaces based on the usage of it [22]. CRs take the advantages from grey and white spaces by opportunistic use. To reuse the spectrum, spectrum sensing is necessary and there are different approaches for CR to grasp the spectrum sensing issues. Based on the band of interest, spectrum sensing techniques can be classified as narrow band and wide band. The CR is liable to identify the presence of PU transmission hence it is called transmitter based detection or stand-alone detection which is addressed for military and many civilian applications for signal detection, automatic modulation classification, to locate radio source and to perform the jamming activities in communication networks. As, no collaboration is apparent among the CRs hence this method cannot identify hidden PUs. In this section, some of the most common transmitter based sensing schemes are addressed. Fig. 2.3 shows different types of Spectrum Sensing Technique.

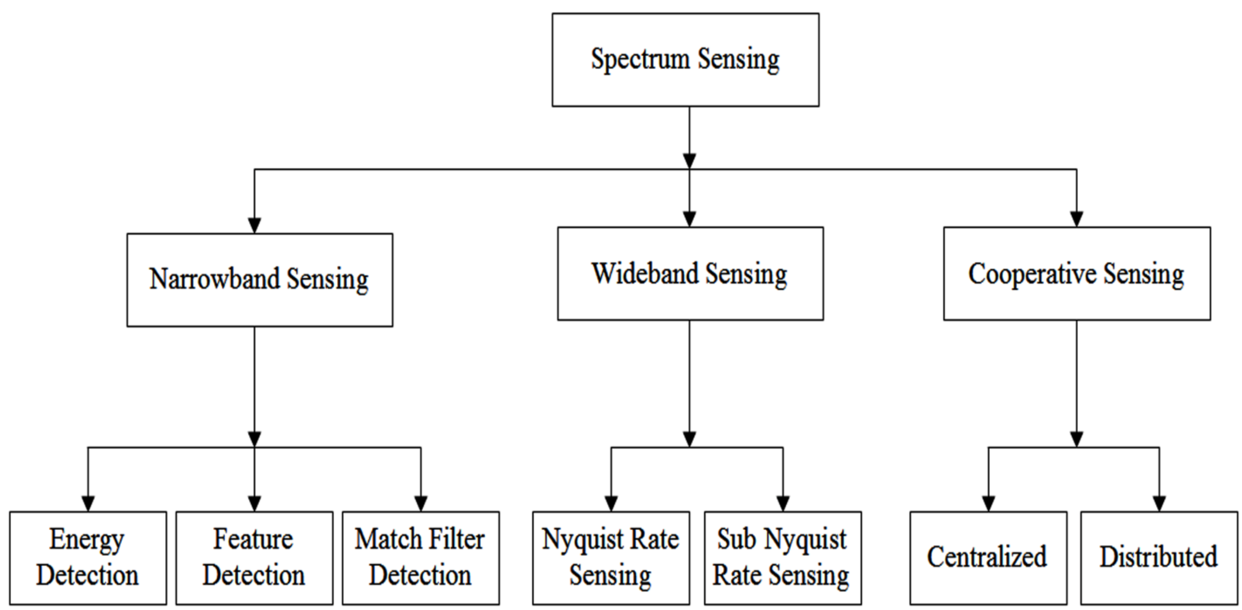

Fig. 2.3. Different Types of Spectrum Sensing Technique

2.9.1 Narrowband Sensing

The most efficient way to sense spectral opportunities is to detect active primary transmitters in the vicinity of CRs. Here, the term "narrowband" implies that the bandwidth of interest is less than the coherence bandwidth of the channel. We would like to address a number of narrowband spectrum sensing methods in the following:

2.9.1.1 Energy Detection

A well-known method for spectrum sensing is based on energy detection (ED) where received PU signal energy is measured in a specific time period of a particular frequency band of interest. This technique comprises low computational and implementation complexities, thus leads to its popularity. In addition, the notable advantage of this scheme is that it does not require any prior information about the PUs transmission [23]. While the signal received at CR node, the PU status is determined by comparing the output of the ED with a threshold which depends on the noise floor. The performance of the detection algorithm can be determined by two probabilities as the probability of detection, P_d and probability of false alarm P_f. ED is considered a non-coherent detection method where knowledge of noise variance is adequate for choosing threshold to obtain a predetermined false alarm rate. Meanwhile, to design a standard CR system higher value of detection probability as well as lower value of false alarm probability is anticipated. The decision threshold can be selected for finding an optimum balance between and however this requires knowledge of noise and detected signal powers. The noise power can be estimated, while the signal power is difficult to predict as it changes depending on the transmission characteristics and the distance between the CR and PU. A major drawback is that it has poor detection performance under low SNR scenarios and cannot differentiate between the signals from PUs and the interference from other CRs.

2.9.1.2 Feature Detection

Another promising spectrum sensing technique is based on feature detection. A feature is unique and inherent characteristics of the PUs signal and it is drawn as pilot signal, segment sync, field sync, and also the instantaneous amplitude, phase and frequency [24]. In practice, these features are commonly perceived many signals employed in wireless communication and radar systems. Cyclostationary feature detection method detects and distinguishes between different types of PU signals by exploiting their Cyclostationary features. Nowadays, analog to digital conversion has made the use of signal transformation practical in order to discover a specific feature. The fundamental and promising feature detection technique is based on the cyclic feature. Cyclostationary feature detector can overcome the energy detector limits in detecting signals in low SNR environments. In fact, signals with overlapping features in the power spectrum, can have non-overlapping features in the cyclic spectrum.

2.9.1.3 Matched Filtering

Matched-filtering is known as the optimum method for detection of primary users when the transmitted signal is known. The main advantage of matched filtering is the short time to achieve a certain probability of false alarm or probability of misdetection. In fact, the required number of samples grows as O (1/SNR) for a target probability of false alarm at low SNRs for matched filtering. However, matched-filtering requires cognitive radio to demodulate received signals. Hence, it requires perfect knowledge of the primary users signaling features such as bandwidth, operating frequency, modulation type and order, pulse shaping, and frame format. Moreover, since cognitive radio needs receivers for all signal types, the implementation complexity of sensing unit is impractically large [25]. Another disadvantage of match filtering is large power consumption as various receiver algorithms need to be executed for detection.

2.9.1.4 Covariance based Detection

Another narrowband spectrum sensing is based on covariance based detection which exploits the inherent correlation in received signals at the CR terminal ensuing from the time dispersive nature of wireless channel and oversampling of received signal.

Usually covariance based detection does not require any prior information about the PU signal or noise [26].

2.9.1.5 Eigenvalue Based Detection (EBD)

This approach is generally known as covariance based detection, EBD being its one special case Where the Eigen values of received signal sample covariance matrix are used for PU signal detection. It is indicated that number of significant Eigen values is directly related to presence or absence of data in received PU signal and may be exploited to identify the PU occupancy status.

2.9.2 Wideband Sensing

Wideband spectrum sensing techniques aim to sense a frequency bandwidth that exceeds the coherence bandwidth of the channel (e.g., 300 MHz - 3 GHz). In the wideband regime, traditional narrowband sensing methods cannot be casted off directly for performing wideband spectrum sensing, as of making a single binary decision (PU present or absent)in the entire wideband signal, thus cannot locate individual spectral opportunities that lie within the wideband spectrum. Wideband spectrum sensing can be broadly categorized into two types; Nyquist rate wideband sensing and sub-Nyquist wideband sensing. The former type processes digital signals taken at or above the Nyquist rate, while the latter acquires signals using sampling rate lower than the Nyquist rate. In the rest of this paper, an overview of the state-of-the-art wideband spectrum sensing algorithms will be provided.

2.9.2.1 Nyquist Rate Wideband Sensing

A conventional approach of wideband multicarrier signal sensing is to directly acquire the entire signal using a standard ADC and then use DSP algorithms to detect spectral opportunities to CRs .A promising solution for the multicarrier wideband sensing would be the filter bank schemes as presented in. A special class of filter banks (prototype filters) was proposed to detect the opportunity in the wideband spectrum. Besides, those filter banks can be used for the multi-carrier communications for the CR nodes. The baseband can be directly estimated through using a proto type filter, and other bands can be obtained through modulating the proto type filter.

- Moreover, a wavelet approach to efficient spectrum sensing algorithm is proposed where the wideband spectrum has decomposed into a train of consecutive sub bands, where the power spectral property is regular within each sub band but exhibits discontinuities and irregularities between adjacent sub bands.

- Furthermore, a novel multiband joint spectrum detection was introduced which jointly detects the PU occupancy status over multiple frequency bands rather than over one band at a time where the spectrum sensing problem was considered as a class of optimization problems. The whole wideband spectrum was then divided into successive sequences of narrowband spectrum. This strategy allows CRs to take maximum advantage of the unused spectra and limit the subsequent interference.

2.9.2.2 Sub-Nyquist Rate Wideband Sensing

The high sampling rate as well as obligation of diverge DSP utensils in Nyquist systems set limit to explore in wideband sensing hence, sub-Nyquist approaches are drawing more and more attention in both academia and industry [27] Sub-Nyquist wideband sensing refers to the procedure of acquiring wideband signals/spectrums using sampling rates lower than the Nyquist rate and detecting spectral opportunities in the wideband. Two important types of sub-Nyquist wideband sensing are illustrated so far in the open literatures; wideband Compressive Sensing (CS) and wideband multi-channel sub-Nyquist sensing. In the sub sequent paragraphs, we will deliver some discussions and comparisons regarding these wideband sensing algorithms.

A. Compressive Sensing

CS (also known as compressive sampling or sparse sampling) is a signal processing technique for efficiently acquiring and reconstructing a signal, by finding solutions to underdetermined linear systems. This is based on the principle that, through optimization, the sparsity of a signal can be exploited to recover it from far fewer samples than required by the Shannon-Nyquist sampling theorem. The first requirement for compressed sensing is the existence of a sparse signal representation. We need to know *a priori* that the signal we are acquiring has relatively few nonzero coefficients in some transform domain.

CS, which declares that one, can recover sparse signals at sub-Nyquist rates [28]. CS depends on this principle of sparsity, so that a brief representation of the signal is possible when expressed in a suitable form. Wireless communication signals in open-spectrum networks are typically sparse in the frequency domain, allowing using compressive sensing to remove the sampling problem. Though CS is a powerful and efficient technique, it has a side effect that it results increased computational complexity. The signals requires low energy for processing at both the transmitter and receiver sites which is supportive to move forward complexity since the sampling is done less than the Nyquist rate, so Compressive sensing is a method to estimate signals using less evaluations comparing to conventional sampling. Assume that P is to be measured which is an $N \times 1$ vector. Mathematically, P can be viewed as

$$P = \Psi s \tag{2.1}$$

where Ψ is a basis in which P is sparse and the $N \times 1$ vector s can be represented by P in the basis Ψ and has $L_s \ll N$ non zero elements.

From the basic of Compressive sensing theory we can say that P can be correctly estimated from $Z \ll N$ evaluations of the signal. Assume that we use a set of Z linear combinations of the signal. The measurement vector y can be given by

$$Q = \Phi P \tag{2.2}$$

where Φ is the sensing matrix. So, P can be estimated from Q if we take appropriate value of Z and Φ and use the sparsity of the representation of P in the Ψ basis. N, L_s and a estimate of similarity between the sensing matrix Φ and the basis matrix Ψ determines the value of Z. Then, using ℓ_1 norm minimization the sparse vector s can be recovered from the measurement vector y as follows

$$\hat{s} = \arg_s \min ||s||_1 \text{ Subject to } Q = \Phi\Psi s \qquad (2.3)$$

This is a convex optimization problem that conveniently reduces to a linear program known as basis pursuit (BP).

B. Multi-channel sub-Nyquist Wideband Sensing

Conventional CS scheme for analog signals require prior information about the signal sparsity pattern. The spectral estimation becomes more challenging without having the spectral support i.e., blind sub- Nyquist sampling of multiband signals. There is a mixed analog-digital spectrum sensing method also known as modulated wideband converter (MWC) that has multiple sampling channels, with the accumulator in each channel replaced by a general low-pass filter. Very few numbers of measurements are required for the digital operations in support recovery, thus introducing a short delay and making computationally efficient. When the signal support set is identified, numerous real-time computations are possible with this scheme. The multi-channel structure in MWC provides robustness against the noise [29]. Another multi-channel sub-Nyquist sampling approach employs multi-coset(MC) sampling which incorporates the advantages of CS when the frequency power distribution is sparse, but applies to both sparse and non-sparse power spectra.

2.9.3 Cooperative Sensing

Cooperation is proposed in the literature as a solution to problems that arise in spectrum sensing due to noise uncertainty, fading, and shadowing. Cooperative sensing decreases the probabilities of misdetection and false alarm considerably. In addition, cooperation can solve hidden primary user problem and it can decrease sensing time [30]-[31]. Challenges of cooperative sensing include developing efficient information sharing algorithms and increased complexity. In cooperative sensing architectures, the control channel (pilot channel) can be implemented using different methodologies. These include a dedicated band, an unlicensed band such as Industrial, Scientific and Medical (ISM) Radio Band and an underlay system such as Ultra Wide Band (UWB). Depending on the system requirements, one of these methods can be selected. Control channel can be used for sharing spectrum sensing results among cognitive users as well as for sharing Cooperation can be among cognitive radios or external sensors can be used to build a cooperative sensing network. In the former case, cooperation can be implemented in two fashions: centralized or distributed.

2.9.3.1 Centralized Sensing

The centralized control model is one in which the management of spectrum opportunities is controlled by a single entity or node which has been referred to as the spectrum broker. The spectrum broker is responsible for deciding which spectrum opportunities can be used and by which radios in the network. A central broker may use sensors from the distributed nodes or may use other means for sensing and spectrum awareness. One application of centralized control is real-time spectrum markets.

2.9.3.2 Distributed Sensing

The second opportunistic spectrum access or flexible spectrum usage control model is the distributed control model. In this model the interaction is "peer-to-peer". In other words the cognitive radio or policy based adaptive radio nodes in the network are collectively responsible for identifying and negotiating use of underutilized spectrum. For some scenarios, the distributed control may be between co-operative radio access networks. There are also some other sensing technique such as-External Sensing and Interference-based Detection.

2.10 Different Technique of Compressive Sensing

Compressed Sensing has provided many methods to solve the sparse recovery problem and thus its applications. There are two major algorithmic approaches to this problem. The first relies on an optimization problem which can be solved using linear programming, while the second approach takes advantage of the speed of greedy algorithms. Both approaches have advantages and disadvantages which are discussed throughout this chapter along with descriptions of the algorithms themselves. First we discuss Basis Pursuit, a method that utilizes a linear program to solve the sparse recovery problem.

2.10.1 Basis Pursuit

Basis pursuit is the mathematical optimization problem of the form:

$$\min_{\mathbf{x}} \|x\|_{\mathbf{1}} \quad \text{Subject to} \quad y = Ax. \tag{2.4}$$

where x is a $N \times 1$ solution vector (signal), y is a $M \times 1$ vector of observations (measurements), A is a $M \times N$ transform matrix (usually measurement matrix) and $M < N$. It is usually applied in cases where there is an underdetermined system of linear equations $y = Ax$ that must be exactly satisfied and the sparsest solution in the L_1 sense is desired. One major approach, Basis Pursuit, relaxes the l_0 minimization problem to an l_1 -minimization problem [32]. Basis Pursuit requires a condition on the measurement matrix φ stronger than the simple infectivity on sparse vectors, but many kinds of matrices have been shown to satisfy this condition with number of measurements m.

2.10.2 Orthogonal Matching Pursuit

Orthogonal Matching Pursuit Algorithm (OMP) is a greedy compressed sensing recovery algorithm which selects the best fitting column of the sensing matrix in each iteration [33]. A least squares (LS) optimization is then performed in the subspace spanned by all previously picked columns. This method is less accurate than the Basis pursuit algorithms but has a lower computational complexity. The Matlab function has three inputs: Sparsity K, measurements vector y and sensing matrix A. The output of this function is the recovered sparse vector x.

2.11 Issues and Challenges in Spectrum Sensing

There are various types of challenges and issue that are required to be while detecting the spectrum holes by the CR networks. Some of the issues and challenges are discussed in details as follows [34].

- **Channel Uncertainty:** In wireless communication networks, uncertainties in received signal strength arises due to channel fading or shadowing which may wrongly interpret that the primary system is located out of the SUs interference range as the primary signal may be experiencing a deep fade or being heavily shadowed by obstacles. Therefore, CR have to be more sensitive to distinguish a faded or shadowed primary signal from a white space. Any uncertainty in the received power of the primary signal translates into a higher detection sensitivity requirement [35-36].
- **Noise Uncertainty:** The detection sensitivity can be defined as the minimum SNR at which the primary signal can be accurately (e.g. with a probability of 0.99) detected by the CR and is given by

$$\gamma = \frac{P_p(D+R)}{N} \tag{2.5}$$

where N is the noise power.

P_p is transmitted power of the PU.

D is the interference range of the SU.

R is maximum distance between primary transmitter and its corresponding receiver

- **Combined Interference Uncertainty:** In future, due to the incredible deployment of secondary systems, there will be increased possibility of multiple CR networks operating over the same licensed band. As a result, spectrum sensing will be affected by uncertainty in aggregate interference. Though, a primary system is out of interference range of a secondary system, the aggregate interference may lead to wrong detection. This uncertainty creates a need for more sensitive detector, as a secondary system may harmfully interfere with primary system located beyond its interference range, and hence it should be able to detect them [37].
- **Hidden Primary User Problem:** The hidden PU problem can be caused by many factors including severe multipath fading or shadowing observed SUs while scanning for PUs transmissions. The following Fig. 2.4 shows an illustration of a hidden node problem where the dashed circles show the operating ranges of the PU

and the CR device. Here, CR device causes unwanted interference to the PU (receiver) as the primary transmitter's signal could not be detected because of the locations of devices.

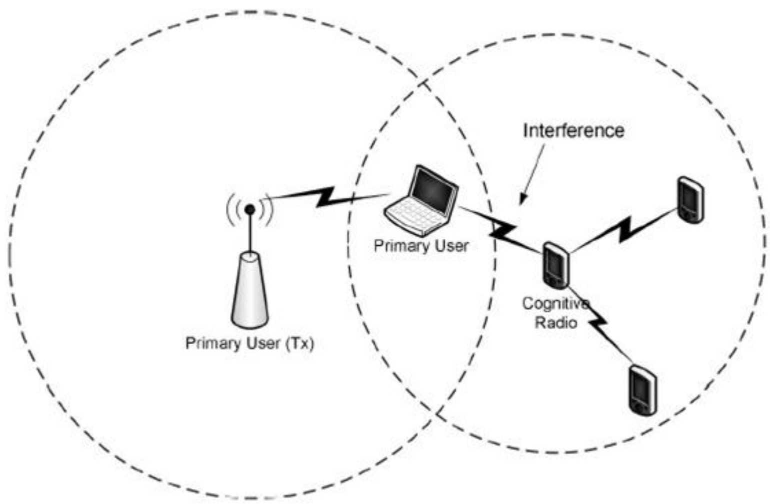

Fig. 2.4 Hidden terminal problems in CR Networks [38]

- **Sensing Interference Limit:** Primary goal of spectrum sensing is to detect the spectrum status i.e. whether it is idle or occupied, so that it can be accessed by an unlicensed user. The challenge lies in the interference measurement at the licensed receiver caused by transmissions from unlicensed users. First, an unlicensed user may not know exactly the location of the licensed receiver which is required to compute interference caused due to its transmission. Second, if a licensed receiver is a passive device, the transmitter may not be aware of the receiver. So these factors need attention while calculating the sensing interference limit.

- **Sensing Duration and Frequency:** PUs can claim their frequency bands anytime while CR is operating on their bands. In order to prevent interference to and from primary license owners, CR should be able to identify the presence of PUs as quickly as possible and should vacate the band immediately. Hence, sensing methods should be able to identify the presence of PUs within certain duration.

This requirement poses a limit on the performance of sensing algorithm and creates a challenge for CR design.

2.12 Fading Model

Fading is the fluctuations in the amplitude of a radio signal over a short period of time or travelled distance. It is caused by interference between two or more versions of the transmitted signal which arrive at the receiver at slightly different times.

2.12.1 Non- Fading Additive White Gaussian Noise (AWGN) Channel

In this model, the channel noise is assumed to have Gaussian nature and is additive. Compared to other equivalent channels, the AWGN channel does the maximum bit corruption and the systems designed to provide reliability in AWGN channel is assumed to give best performance results in other real-world channels. But the real performance may vary. The AWGN channel is a good model for many satellite and deep space communication links. In serial data communications, the AWGN mathematical model is used to model the timing error caused by random jitter. The distortion incurred by transmission over a lossy medium is modeled as the addition of a zero-mean Gaussian random value to each transmitted bit.

2.12.2 Rayleigh Fading

For a large number of paths, the impulse response can be modeled as zero mean complex-valued Gaussian process to model fading channel. This channel is known as Rayleigh fading channel. It is best suited for flat fading signal and can be figured from sum of two Gaussian noise signals. It is used in urban areas where there are no line of sight (LoS) components. When the baseband components of $h(t)$ are independent the probability density function(PDF) of the amplitude $R = |h| = \alpha$ assumes Rayleigh PDF described in [39].

$$f(R) = \frac{R}{\sigma^2} e^{\frac{-R}{2\sigma^2}} \tag{2.6}$$

where, $2\sigma^2 = ER^2$ and $R \geq 0$. The PDF is independent of amplitude.

2.12.3 Rician Fading

Rician fading will present strong dominant component. It can be figured using two Gaussian components of one with zero mean and other with non-zero mean. It is best suited in sub-urban areas. The baseband signal for Rician channel in [40] is as follows:

$$h = ae^{j\varphi} + ve^{j\theta} \tag{2.7}$$

where, α depicts the power of line of sight component and are mutually independent and uniform and their limit. The PDF of Rician fading is given by the following equation in[40] .

$$f(R) = \frac{R^2}{\alpha^2} e^{\left(\frac{R^2+v^2}{2\alpha^2}\right)} I_0\left(\frac{R^2}{\alpha^2}\right), R \geq 0 \tag{2.8}$$

where, $E\alpha^2 = 2\sigma^2$ is the Bessel function of order zero. The relation between the power of Rician component and Rayleigh component can be explained by rice factor K.

$$K = \frac{v^2}{2\sigma^2} \tag{2.9}$$

Rician distribution acquits like Rayleigh component if $v = 0$.

2.12.4 Nakagami Fading

The Nakagami-m distribution is considered as one of the most important models among all the statistical ones that have been proposed to characterize the fading envelope due to multipath fading in wireless communications. It is applicable for empirical fading data. It is used to model signal for excessive to temperate fading case by properly setting the value of Nakagami parameter m. If the signal amplitude follows a Nakagami distribution, then the PDF of R follows a gamma distribution. The Nakagami PDF in [41] is as follows

$$f(R) = \frac{2}{\tau(m)} \left(\frac{m}{2\sigma^2}\right)^m R^{2m-1} e^{\frac{mR^2}{2\sigma^2}}, R \geq 0 \tag{2.10}$$

where, $2\sigma^2 = ER^2$ and $\Gamma(m)$denotes the gamma function.

As special cases, Nakagami-m fading i.e., for m=0, AWGN and for m=1, Rayleigh fading and one-sided Gaussian distribution for m = 1/2. This basically means that, if m < 1, the Nakagami-m distributed fading is more severe than Rayleigh fading, and for values of m > 1, the fading circumstances are less severe. For the values of m > 1, the Nakagami-m distribution closely approximates the Rician distribution, and the parameters m and the Rician factor K (which determines the severity of the Rician fading) can be mapped via the equation of $m = \frac{(1+k)^2}{(1+2k)}$, when $K \geq 0$.

2.13 Sparse Signal and Sparsity

Sparse Signal is a signal which contains only a small number of non-zero elements compared to its dimension. Analog to Information Converter (AIC) is the front end of compressive sampling systems that is able to capture linear combinations of signal measurements at sub Nyquist rate. Wide-band Spectrum Sensing is an important stage in the CR technology at which the PU shall detect a wideband spectrum to identify vacant channels for opportunistic use.

In numerical analysis , a sparse matrix or sparse array is a matrix in which most of the elements are zero. By contrast, if most of the elements are nonzero, then the matrix is considered dense. The number of zero-valued elements divided by the total number of elements (e.g., m × n for an m × n matrix) is called the sparsity of the matrix.

$$\begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

The above sparse matrix contains only 9 nonzero elements, with 26 zero elements. Its sparsity is 74%, and its density is 26%.

Chapter 3

Methodology and Problem Formulation

3.1 Introduction

This chapter describes the methodologies regarding this thesis work, in details. The technical details with their mathematical and metaphorical approaches have been discussed in this chapter. In addition, the different mathematical and computational particulars regarding different performance measure metrics are also given as necessity. Therefore, this chapter helps to explore the procedural details of the methodologies and the problem formulation concerning this research work.

3.2 Signal Model

Our objective is to decide the PU signal occupancy state of a band of interest within a FB and the band is denoted by $l\ (l = 1, 2, \ldots, L)$. To do so, the test statistic of detecting the occupancy status of PU in a band of interest is measured as $\mathcal{H}_{0,l}$(absences of a PU) and $\mathcal{H}_{1,l}$(presence of a PU). That is, we test the following binary hypotheses:

$$\hat{X}[l] = \begin{cases} W[l], & \mathcal{H}_{0,l} \\ H_l S[l] + W[l], & \mathcal{H}_{1,l} \end{cases} \tag{3.1}$$

where, $\hat{X}$ is the spectrum of the band of interest estimated through the promising l_1-minimization scheme, discussed in [42-43]. H_l Stands for the discrete frequency response between the PU and the CR, $S[l]$ is the primary signal transmitted within a PU band l along with complex additive white Gaussian noise (AWGN) $\mathrm{W}[l]$ of zero mean and unity variance. An energy detector performance does not depend on the a-priori information of PU signal and is less complex to implement [44], thus make it popular in practice;

therefore, the signal energy is calculated over an interval of J samples by

$$E[l] = \sum_{j=0}^{J-1} \left|\hat{X}_j[l]\right|^2, l = 1, 2, \dots, L \tag{3.2}$$

where, $\hat{X}_j[l]$ indicates the j-th sub-channel spectral estimation considered by the CR and the decision parameter of the ED is given by

$$E[l] \underset{\mathcal{H}_{0,l}}{\overset{\mathcal{H}_{1,l}}{\gtrless}} \lambda_l \ , l = 1, 2, \dots, L \tag{3.3}$$

where, λ_l is the decision threshold of a PU sub-channel of interest inside a FB. Following [44], the signal energy can be described as

$$E[l] \backsim \begin{cases} \chi_{2j}^2, & \mathcal{H}_{0,l} \\ \chi_{2j}^2(2\gamma[l]), & \mathcal{H}_{1,l} \end{cases} \tag{3.4}$$

where, $\gamma[l]$ denotes the signal-to-noise ratio (SNR) at the CR of a frequency band, and χ_{2j}^2 and $\chi_{2j}^2(2\gamma[l])$ denote central and non-central chi-square distributions, respectively. Both distributions have degrees of freedom equal to *2j*. For simplicity, we assume that the primary radios deploy uniform power transmission strategy. The probability of detection, P_d and the probability of false alarm, P_{fa} can be calculated as in [44]

$$P_{fa,l} = Pr(E[l] > \left(\lambda_l \middle| \mathcal{H}_{0,l}\right) = \frac{\Gamma\left(J, \frac{\lambda_l}{2}\right)}{\Gamma(J)} \tag{3.5}$$

$$P_{d,l} = Pr(E[l] > \left(\lambda_l \middle| \mathcal{H}_{1,l}\right) = Q_J\left(\sqrt{2\gamma[l]}, \sqrt{\lambda_l}\right) \tag{3.6}$$

where, $\Gamma(u)$ is the gamma function, $\Gamma(u, x)$ is the incomplete gamma function, and $Q_J(u, x)$ denotes the generalized Marcum Q-function.

3.3 Probability of Detection Over Fading Channels

In this section, we derive the detection probability over Rayleigh and Nakagami fading channels [44]. Our expressions are in closed form and are based on a different approach by averaging the conditional P_d in the AWGN case as given by (3.6) over the SNR fading distribution. Of course, P_f of (3.5) will remain the same under any fading channel since P_f is considered for the case of no signal transmission and as such is independent of SNR.

3.3.1 Rayleigh Channels

If the signal amplitude follows a Rayleigh distribution, then the SNR γ follows an exponential PDF given by

$$f(\gamma) = \frac{1}{\bar{\gamma}} \exp\left(-\frac{\gamma}{\bar{\gamma}}\right), \ \gamma \geq 0 \tag{3.7}$$

The average P_d in this case, $\bar{P}_{dRay}$ can now be evaluated by averaging (3.6) over (3.7) while making the change of variable $x = \sqrt{2\gamma}$ yielding

$$\bar{P}_{dRay} = e^{-\frac{\lambda}{2}} \sum_{n=0}^{j-2} \frac{1}{n!} (\lambda/2)^n + \left(\frac{1+\bar{\gamma}}{\bar{\gamma}}\right)^{j-1} \left[e^{-\frac{\lambda}{2(1+\bar{\gamma})}} - e^{-\frac{\lambda}{2}} \sum_{n=0}^{j-2} \frac{1}{n!} \frac{\lambda\bar{\gamma}}{2(1+\bar{\gamma})} \right] \tag{3.8}$$

The normalized incomplete gamma function $P(u, x) = \gamma(u, x) / \Gamma(u)$ can be expressed in its series form setting $d^2 = \bar{\gamma}$,

3.3.2 Nakagami Channels

If the signal amplitude follows a Nakagami distribution, then the PDF of γ follows a gamma PDF given by

$$f(\gamma) = \frac{1}{\Gamma(m)} \left(\frac{m}{\bar{\gamma}}\right)^m \gamma^{m-1} \exp\left(-\frac{m}{\bar{\gamma}}\gamma\right), \ \gamma \geq 0 \tag{3.9}$$

where m is the Nakagami parameter. The average P_d in the case of Nakagami channels $\bar{P}_{dNak}$ can now be obtained by averaging (3.6) over (3.9) and then using again the change of variable $x = \sqrt{2\gamma}$ yielding

$$\bar{P}_{dNak} = \alpha \int_0^\infty x^{2m-1} \exp\left(-\frac{mx^2}{2\bar{\gamma}}\right) Q_j\left(x, \sqrt{\lambda}\right) dx, \tag{3.10}$$

where,

$$\alpha = \frac{1}{\Gamma(m) 2^{m-1}} \left(\frac{m}{\bar{\gamma}}\right)^m \tag{3.11}$$

Evaluating the integral in (3.10) as described in Appendix A, $\bar{P}_{dNak}$ can be written as

$$\bar{P}_{dNak} = \alpha \left[G_1 + \beta \sum_{n=0}^{j-2} \frac{\left(\lambda/2\right)^n}{2(n!)} 1F_1\left(m; n+1; \frac{\lambda}{2} \frac{\bar{\gamma}}{m+\bar{\gamma}}\right)\right] \tag{3.12}$$

where $1F1(.;\ .;\ .)$ is the confluent hyper geometric function $(\equiv\Phi(.,\ .;\ .))$

$$\beta = \Gamma(m) \left(\frac{\mathbf{2\bar{\gamma}}}{\mathbf{m+\bar{\gamma}}}\right)^m e^{-\lambda/2}, \tag{3.13}$$

and

$$G_1 = \int_0^\infty x^{2m-1} \exp\left(-\frac{mx^2}{2\bar{\gamma}}\right) Q\left(x, \sqrt{\lambda}\right) dx, \tag{3.14}$$

where, $Q\ (.,\ .) = Q_1\ (.,\ .)$ is the first-order Marcum Q-function.

APPENDIX A:

EVALUATION OF $G_M = \int_0^\infty x^\rho e^{-p^2x^2/2} Q_M(ax, b) dx$

With the aid of [Eq. (3.10)], G_M can be recursively evaluated as

$$G_M = G_{M-1} + C_{M-1} F_M, \quad \text{for } \rho > -1, \tag{3.15}$$

where,

$$C_{M-1} = \frac{\Gamma\left(\frac{\rho+1}{2}\right)\left(\frac{b^2}{2}\right)^{M-1} e^{-b^2/2}}{2(M-1)!\left(\frac{p^2+a^2}{2}\right)^{\frac{\rho+1}{2}}} \quad \text{and} \tag{3.16}$$

$$F_M = F_1\left(\frac{\rho+1}{2}; M; \frac{b^2}{2} \frac{a^2}{p^2+a^2}\right) \tag{3.17}$$

One can evaluate G_M iteratively as follows

$$\begin{aligned} G_M &= G_{M-1} + C_{M-1} F_M \\ &= G_{M-2} + C_{M-2} F_{M-2} + C_{M-1} F_{M-1} \\ &\ \vdots \\ &= G_1 + \sum_{n=1}^{m-1} C_n F_{n+1} \end{aligned} \tag{3.18}$$

3.4 CS via Analog to Information Converter (AIC)

In this section, a flavor of promising AIC have illustrated for spectrum sensing architecture as shown in Fig. 3.1, this model consists of a pseudo-random number generator, a mixer, an accumulator, and a low-rate sampler. The pseudorandom number generator produces a discrete-time sequence that demodulates the signal $x(t)$ by a mixer. The accumulator is used to sum the demodulated signal for $\frac{1}{\omega}$ seconds, while its output signal is sampled using a low sampling rate. After that, the sparse signal can be directly reconstructed from partial measurements using CS algorithms. The baseband (at CR receiver) signal $x(t)$ is sampled by using an AIC.

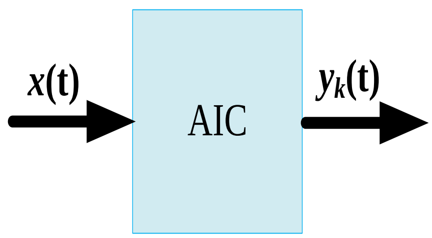

Fig. 3.1 AIC for the CS acquisition scheme

An AIC is conceptually similar to an ADC operating at Nyquist rate followed by compressive sampling. Let the output of the ADC is the sampled signal of $x(t)$, denoted by:

$$x_k = [x_{kN} \;\; x_{kN+1} \;\; \ldots . x_{kN+N-1}], \;\; k = 0,1,\ldots,K \tag{3.19}$$

is a $N \times 1$ vectors and the size of the measurement matrix Φ_A is $M \times N$, such that

$$y_k = \Phi_A x_k \tag{3.20}$$

Hence, output of the AIC denoted by the size of $M \times 1$ vectors

$$y_k = [y_{kM} \;\; y_{kM+1} \ldots \ldots . y_{kM+M-1}], \;\; k = 0,1,\ldots,K \tag{3.21}$$

Eventually, recovery of the compressive sampling can be done by solving mixed l_1 *–norm optimization* problem as equation in (2.3).

3.5 System Model

In this section, we use a system model which is shown in Fig. 3.2. Here, the CR receiver has been employed with a BPF bank. Let the wideband signal, $x_c(t)$ of bandwidth ωHz is mutually shared among the PUs to a primary communication system and some part of the bandwidth is available for opportunistic accessing to the CRs in a particular geographic location and time. Let the CR receiver has accommodated K number of identical BPFs, the outputs of the BPFs are denoted by x_k and each one has a bandwidth of equal size $w_k = w/K$ Hz, where, $k = 0, 1, 2 \ldots K$. Then the average energy of each BPF is calculated and compare those average energies E_k (k=1, 2....K) at the energy estimate and compare block. While calculating the average energy of each BPF, the comparator also restores that BPF which contains minimum average energy E_k(min). In this model, an energy detector (ED) approach is used to find an inactive PU sub-channel for opportunistic use of a CR.

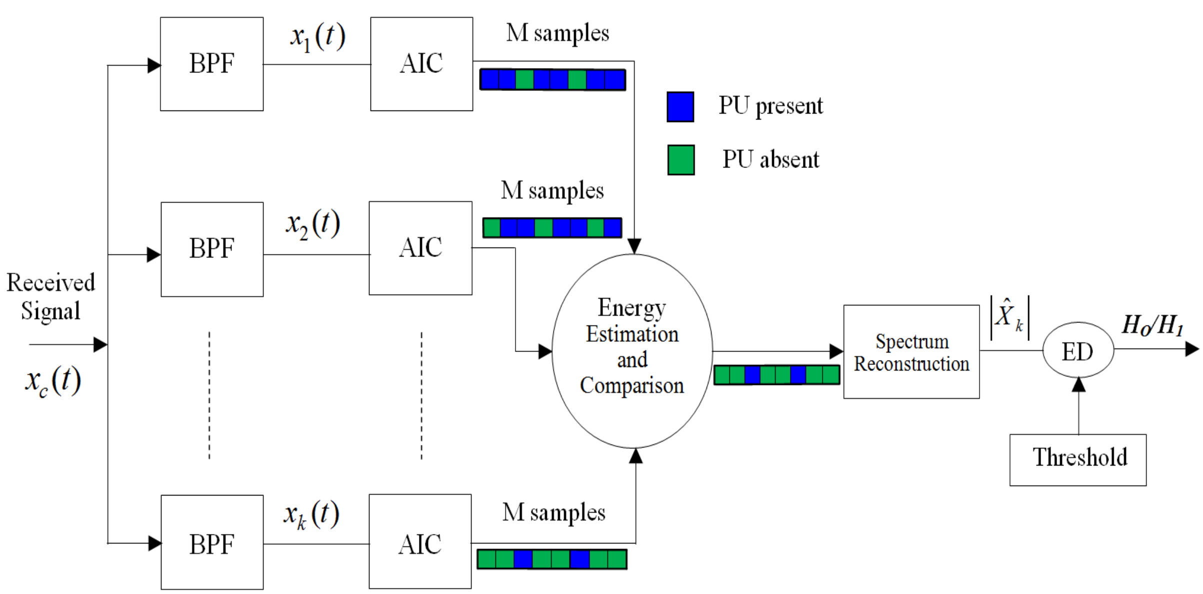

Fig. 3.2 Schematic illustration of the filter based spectrum estimation via compressive sensing.

The HSFB indicates minimum number of PUs actively present which substantially provides maximum opportunistic accessibility to a CR user. Besides, the theory of CS tells that the more the sparsity, the better would be the spectral estimation which contributes better detection performance. In this proposed system model, we have deployed an energy estimator that functions to estimate the energy and compare the energy level of different frequency bins. The accuracy estimation of energy estimator is performed based on the Compression Ratio, M/N (%) of the proposed system. Nonetheless, the Compression Ratio, M/N (%) of this system is considered from 1% to 25% in order to calculate the accuracy of the system's energy estimator. Eventually, the estimated accuracy of the proposed approach is actually the simulated outcomes of the energy estimators. In addition, the comparator model passes the frequency bin which poses the minimum energy.

3.6 Achievable Throughput of a Stand-Alone CR Terminal

Fig. 3.3 shows the frame structure designed for a CR network with periodic spectrum sensing where each frame consists of one sensing slot and one data transmission slot [45-46].

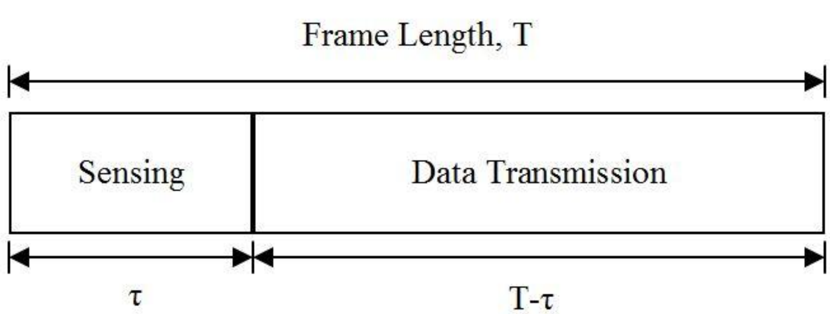

Fig. 3.3 Structure of a typical frame of a CR data transmission

Suppose the sensing duration is τ and the frame duration is T. Denote C_0 as the throughput of the secondary network when it operates in the absence of primary users and C_0 can be written as $C_{0} = log_2(1+SNR_s)$, where SNRs denote signal to noise ratio of a

CR link. Inside an interoperable network, we also consider PU data transmission, CR data transmission and reception are Gaussian, white in nature and independent to each other. For a particular band of interest $P(H_0)$ signifies the probability for which the PU data transmission is absent. Therefore, optimal achievable rate can be found by

$$R(\tau) = C_0 P(H_0)\left(1 - \frac{\tau}{T}\right)(1 - Q(\alpha + \sqrt{N}\gamma) \tag{3.22}$$

where,

$$\alpha = \sqrt{2\gamma + 1}\, Q^{-1}(P_d) \tag{3.23}$$

From equation (3.10), it has been noticed that the achievable rate of a CR node varies with the sensing slot duration as well as frame duration, e.g., the throughput is greater for shorter sensing time period τ with a fixed frame length T. Hence, we try to sort out a trade-off between the sensing length and frame length. As the miss detection probability, P_m can obligate with the possibility of data collision (a collapse of achievable throughput) with the PU transmission while the probability of false alarm, P_{fa} recommends the CR to stop packet transmission during the frame interval though PU channel is idle at that instant which also decrease the throughput performance. We assume MAC layer of CR network guarantees that only one CR can have the accessibility of a PU sub-channel at a particular time to avoid the collisions among the CR nodes inside the network. Therefore, collisions can only be possible between the CR and the PU.

3.7 Signal to Noise Ratio (SNR)

SNR is a measure used in science and engineering that compares the level of a desired signal to the level of background noise. It is defined as the ratio of signal power to the noise power, often expressed in decibels. A ratio higher than 1:1 (greater than 0 dB) indicates more signal than noise. SNR is sometimes used informally to refer to the ratio of useful information to false or irrelevant data in a conversation or exchange. SNR is defined as the ratio of the power of a signal (meaningful information) and the power of background noise (unwanted signal):

$$SNR = \frac{P_{signal}}{P_{noise}} \tag{3.24}$$

where, P is average power. Both signal and noise power must be measured at the same and equivalent points in a system, and within the same system bandwidth. If the variance of the signal and noise are known, and the signal is zero-mean:

$$SNR = \frac{\partial^2{}_{signal}}{\partial^2{}_{noise}} \tag{3.25}$$

If the signal and the noise are measured across the same impedance, then the SNR can be obtained by calculating the square of the amplitude ratio:

$$SNR = \frac{P_{signal}}{P_{noise}} = (\frac{A_{signal}}{A_{noise}})^2 \tag{3.26}$$

where, A is root mean square (RMS) amplitude (for example, RMS voltage). Using the definition of SNR:

$$SNR_{dB} = 10log\frac{P_{signal}}{P_{noise}} \tag{3.27}$$

3.8 Computational Complexity of the Proposed Method

In this part, we try to analyze the computational complexity of this CR receiver block expressed in Fig. 3.2. As the sub-sampled Fourier matrix (it is customized by pooling of m rows selected uniformly at random from the DFT matrix) is applied to the signal recovery so it requires $\mathcal{O}(NlogN)$ operation (precisely, the computational burden is equal to the *no. of iterations* $\times N \times logN$, where no. of iterations is not usually easy to bound, but in worst-case, it can be bounded by N). By using K number of filters, the computational complexity is reduced in the order of $\mathcal{O}(\mathrm{KlogK})$ and it requires $\mathcal{O}\left(\frac{N}{K}log\frac{N}{K}\right)$. Besides, we have to take care of estimating the average energy of each FB in a static manner which is in the order of $\mathcal{O}(2\beta - 1) \approx \mathcal{O}(2\beta)$where$\beta = \mathrm{M/N}$. To set large α exploits better estimation of suitable FB and let $\mathcal{O}(2\beta) = \mathcal{O}(P)$. There is one additional term to work out, used for comparison of the average energy that depends on the number of filters $\mathcal{O}(\mathrm{K})$. As a result, in the proposed method the computational burden is in the order of

$$\Omega = \mathcal{O}\left(P + K + \frac{N}{K} log \frac{N}{K}\right) \approx \mathcal{O}\left(P + \frac{N}{K} log \frac{N}{K}\right) \tag{3.28}$$

where$K \ll P$ and $K \ll N$. A detail study of complexity order deviation with no. of BPFs is clarified in Fig. 3.2. Another important entity is to notice the memory space needed for the proposed CR receiver sensing block; there are two terms to consider usually $\mathcal{O}(N)$ bits of memory spaces to be required for the recovered spectrum of length N and the later is $\mathcal{O}(\mathrm{M} \times \mathrm{N})$ for the measurement matrix to store. However, memory space requirement is greatly reduced by the sensing matrix as in the proposed method the space requirement is divided by the K-th square of $\mathcal{O}(M \times N)$ i.e.$\mathcal{O}\left(\frac{M}{K} \times \frac{N}{K}\right) = \mathcal{O}\left(\frac{MN}{K^2}\right)$. However, we have to spend a few static memory spaces due to the average energy estimation of the random samples comes out from the RD which is at the order of $\mathcal{O}\left(\frac{1}{2}P\right)$ and this term depends on the compression ratio M/N considered for the average minimum energy $E_{k(min)}$. Hence, the expression of the total memory spaces required for the proposed method is

$$\Upsilon = \mathcal{O}\left(\frac{1}{2}P + \frac{N}{K} + \frac{MN}{K^2}\right) \tag{3.29}$$

which is greatly influenced by the number of filters. It shows similar characteristics with the computational burden and the analytical figure is not provided here due to page limit. As computational burden decreases with the increasing number of filters K and so this does not necessarily mean that high values of K always increase the sparsity in some basis. If K is excessively large, the sparsity is reduced in substantial order and hence spectral recovery would be ambiguous to resolve.

Thus, selection of higher values of K have two complications; one is budget constraints for designing such type of CR receiver and another is too high value of K do not convey suitable sparsity. Therefore, there should be a trade-off to choose the value of K where sparsity and cost find a best possible way out.

3.9 Concluding Remarks

The aforementioned methodologies and mathematical approaches have been implemented in simulation software Matlab 2016a and the corresponding outcomes from this analytical software have been shown and discussed in the next chapter, Chapter 4.

Chapter 4

Performance Analysis and Simulation Results

4.1 Introduction

All the results concerning this research work have been presented in this chapter. The main contribution and the significance of this work have been presented with graphical and numerical approaches. This chapter presents the significant outcomes with chronological approaches so that this research work can be easily understandable and shows how these contributions can be helpful to improve the quality of CR.

4.2 Detection Performance of Compression Ratio, M/N (%)

We consider, at baseband, the wideband received signal $x_c\ (t)$ falling in the range of 1~64 Δ Hz can accommodate a maximum of 32 non-overlapping PU's sub-bands. The bandwidth B of each sub-band is set to 2Δ Hz and encoded as $ch_l|_{l=1}^{32}$, where, Δ is the frequency resolution and ch is the channel. The $x_c\ (t)$ at the CR node is as follows:

$$x_c(t) = \sum_{n=1}^{N} \sqrt{(E_n B_n)}.\sin c(B_n(t-\delta)).\cos(2\pi f_n(t-\delta)) + z(t) \tag{4.1}$$

where, $sinc(x) = sin(\pi x)/\pi x$, δ denotes a random time offset within sampling branches, $z(t)$ is the Additive White Gaussian Noise of unit variance. In simulations, are considered the maximum number of BPFs as $K = 4$ so the bandwidth of each x_k is $w_k = 16$ Δ Hz, i.e., a single FB can comprise a maximum of $w_k/B = 8$ PUs having no sparsity. A total of 16 PU bands with different carrier frequencies $f_n|_{n=1}^{16}$ present inside the wideband W when probing the burst of transmissions. The distributions of the active PUs in various FBs are $x_k|_{k=1}^{4} = \{6, 5, 3, 2\}$ with dissimilar sparsity levels. The number of Nyquist rate samples N

is taken from HSFB for an observation time T. The average energy estimations of various FBs are performed by increasing the M/N. The discrete Fourier transform (DFT) is selected as the sparsifying basis to form the measurement matrix, and is used to solve the l_1-minimization scheme leading to HSFB spectrum estimation. Centered on the HSFB spectrum, the detection performance is tested for a band of interest of PU by varying the M/N from 1% to 25%.

4.2.1 M/N (%) vs. P_d with different Number of PUs present

Fig. 4.1 illustrates the influence of the compression ratio M/N (%) on the PU detection performance by setting P_{fa}= 0.01 The Fig. 4.1 satisfies the theory of compressed sensing as highly sparse signals provides better spectral estimation and hence the probability of detection.

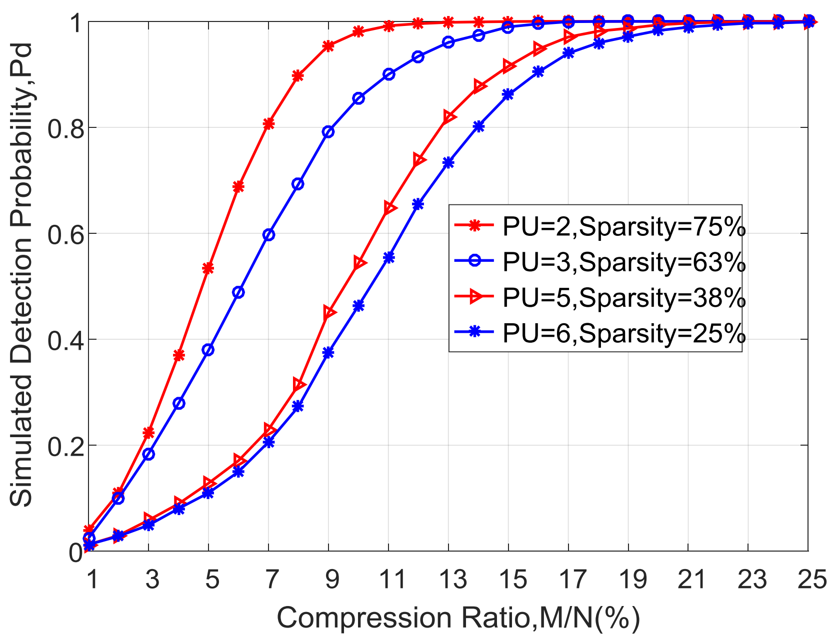

Fig. 4.1 compression ratio, M/N (%) vs. detection probability (P_d) with different number of PUs presented in the Wideband Frequency.

To make simulation environment relaxed, we consider frequency resolution Δ is 2 MHz so the signal has a global bandwidth of $W = 64$ MHz. In this setting, the number of Nyquist samples, $N = 1024$ if the band was sampled at Nyquist rate for $T = 32\mu s$. For the analysis of P_d of the band of interest of PU, the Compression Ratio, M/N (%) has been varied from 1% to 25%. The numbers of PU presence in this analysis were considered as 2, 3, 5, and 6. The analysis is performed by Monte-Carlo simulation through MATLAB 2016b. From the result of P_d versus M/N (%) has been analyzed for each number of PU and the result is given in Fig. 4.1.

We found that in case of lower number of PU (2 and 3) presence, the highest number of P_d has been achieved with respect to lower M/N (%) such as with 10% to 15%. On the other hand, due to the presence of higher No. of PU (for 5 and 6), the P_d reaches at the highest value (almost 1) while the M/N (%) is needed within 20% to 25%. Therefore, this result clarifies the effect of PU on the characteristics of P_d versus M/N (%). According to the presence of the number of PU, the value of sparsity varies. Since 2 PU are presented, therefore other 6 channels are free because each FB consists of 8 channels. Therefore the sparcity will be ((8-2)/8)*100%=75%. From this relationship, it is easily understandable that with the increment of the number of PU the sparsity will be decreased.

4.2.2 M/N (%) vs. Accuracy of the Energy Estimator

As we have discussed the methodology in previous chapter, the accuracy of the energy estimation has been examined with respect to the variation of the M/N (%) regarding the proposed system. The outcomes of this analysis are illustrated in Fig. 4.2. The numerical values are also presented which is given in Table 4.1. From both graphical and numerical results, it is easily observable that with the increment of the value of M/N (%), the accuracy of the energy estimator is increasing. Therefore, it is claimed that with higher rate of compression the energy estimation can work more accurately.

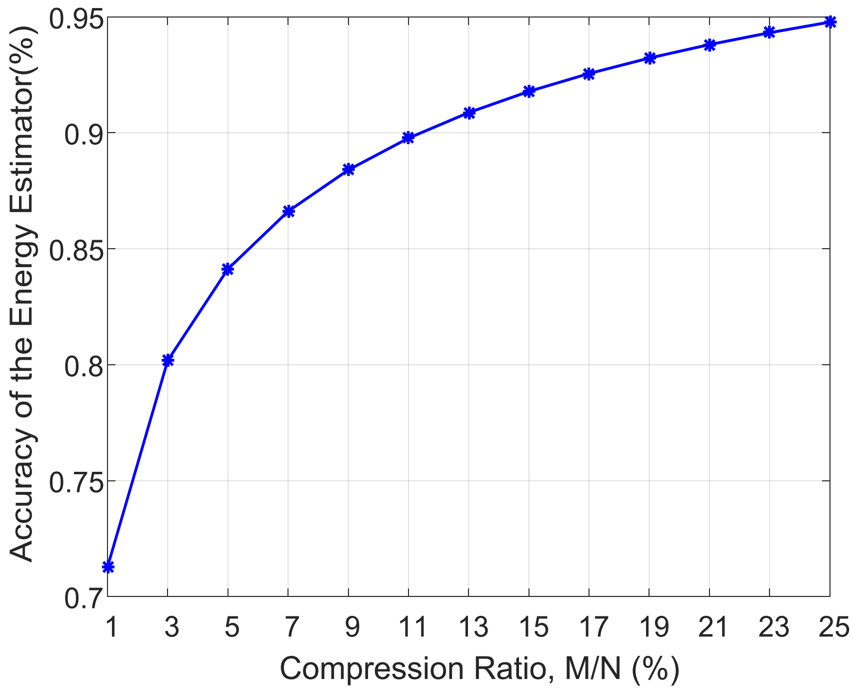

Fig. 4.2: compression ratio, M/N (%) vs. accuracy (%) of the energy estimator in the wideband frequency.

Table 4.1 Different compression ratio, M/N (%) and their corresponding accuracy (%) of Energy Estimator.

Compression Ratio, M/N (%)	**Accuracy of the Energy Estimator(%)**	**Compression Ratio, M/N (%)**	**Accuracy of the Energy Estimator(%)**
1%	0.71%	15%	0.91%
3%	0.80%	17%	0.92%
5%	0.84%	19%	0.93%
7%	0.86%	21%	0.935%
9%	0.88%	23%	0.94%
11%	0.89%	25%	0.95%
13%	0.90%		

4.2.3 M/N (%) vs. $\boldsymbol{P_d}$ with different SNR values. (Estimated Result)

The effect of SNR on the characteristics of detection probability, P_d versus compression ratio, M/N(%) is analyzed and reported in Fig. 4.3. In this analysis, three different SNR's are considered those are 4dB, 8dB, and 12dB in number. From the results, we can observe that the higher value of SNR assists to reach the highest P_d with lower M/N (%). On the other hand, lower SNR needs high M/N (%) to reach at the highest P_d. It is also mentionable regarding this result that this analysis is performed under AWGN channel. Similarly, analogous analysis is also performed under Rayleigh channel in Fig. 4.4. From this result we have found that almost similar pattern of understanding comes with compared to the previous result. Both these information are analyzed based on theoretical aspects.

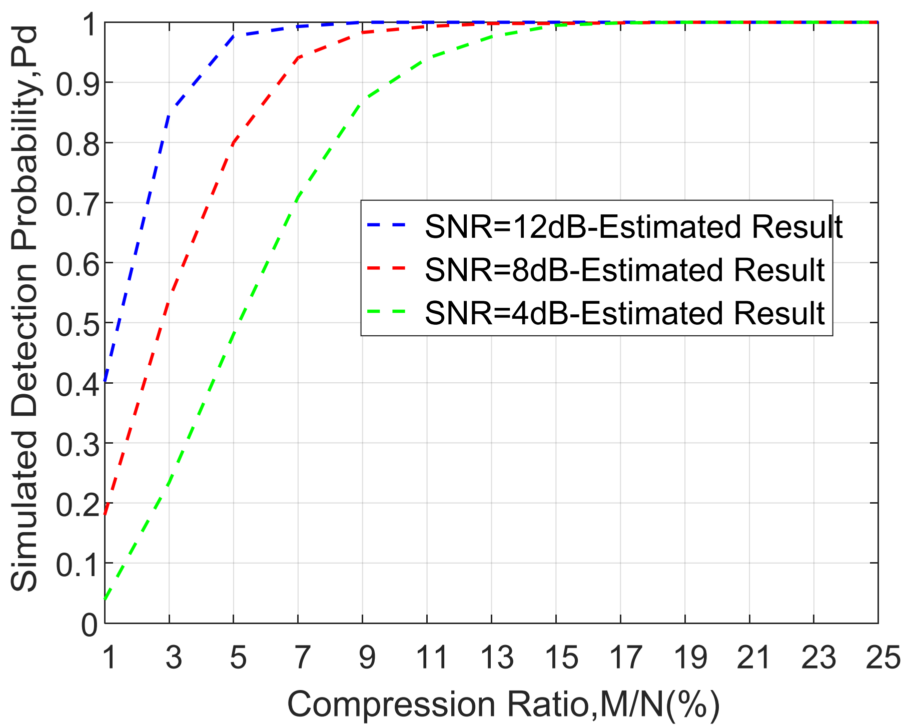

Fig. 4.3: ROC curve for compression ratio, M/N (%) vs. detection probability, P_d with different SNR values in the Wideband Frequency under AWGN channel (Estimated Result).

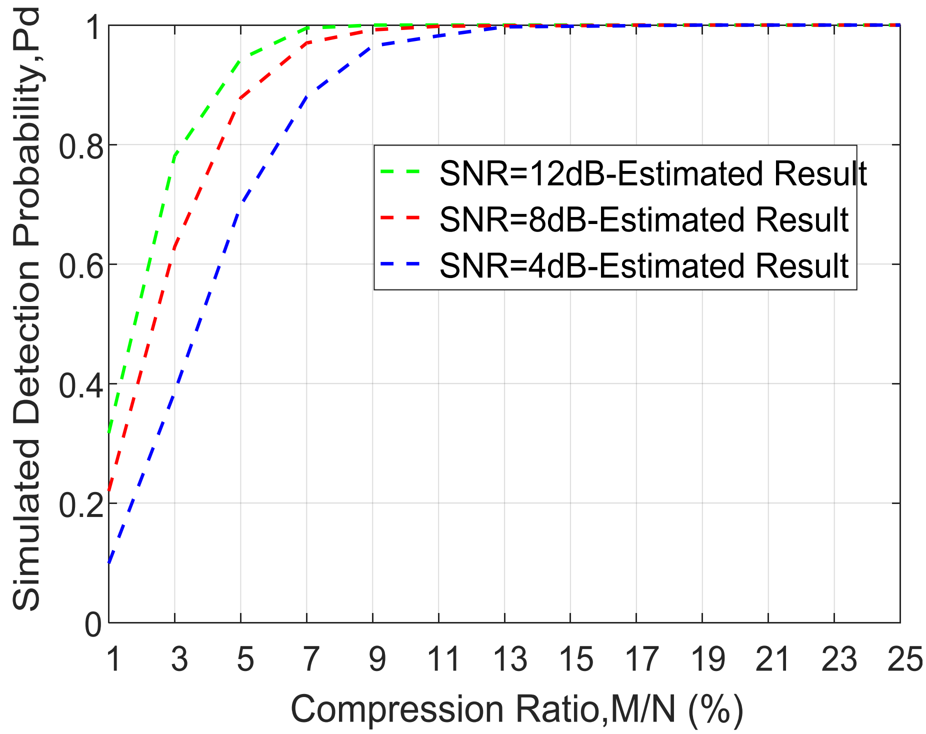

Fig. 4.4: ROC curve for compression ratio, M/N (%) vs. detection probability, P_d with different SNR values in the Wideband Frequency under Rayleigh channel (Estimated Result).

4.2.4 M/N (%) vs. $\boldsymbol{P_d}$ with different SNR values. (Simulated Result)

Based on the estimated results same analyses are also examined for the simulated conditions. Due to investigate the simulated results of detection probability, P_d the performance of probability is calculated by multiplying accuracy of energy estimator and estimated value of P_d for different SNR values with respect to compression ratio, M/N (%) The practical results under AWGN and Rayleigh channel condition are given in Fig. 4.5 and Fig. 4.6. These results depicts that the simulated results follow the pattern of the estimated results but the numerical values of simulated results are slightly lower than that of estimated results.

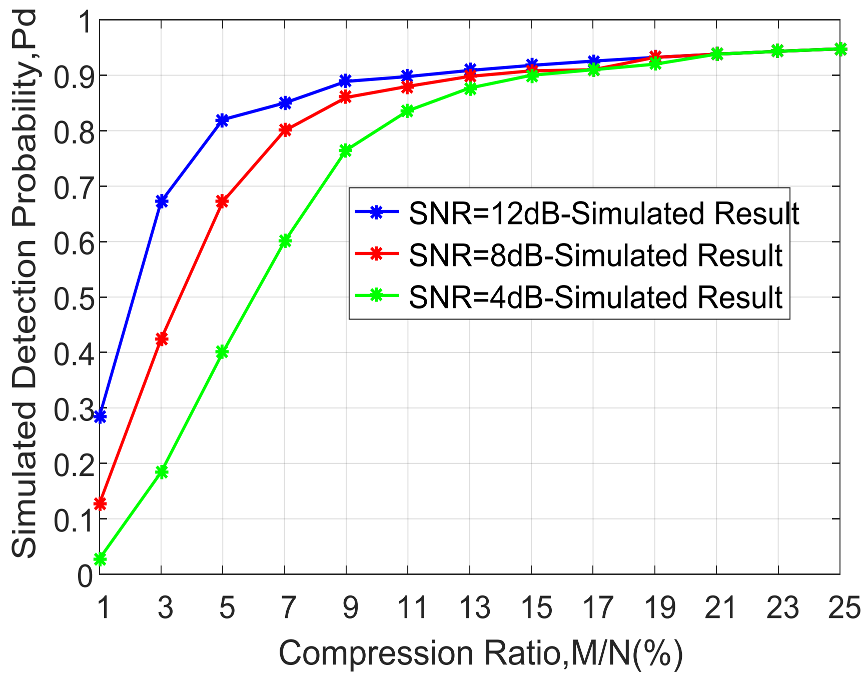

Fig. 4.5: ROC curve for compression ratio, M/N (%) vs. detection probability, P_d with different SNR values in the Wideband Frequency under AWGN channel (Simulated Result).

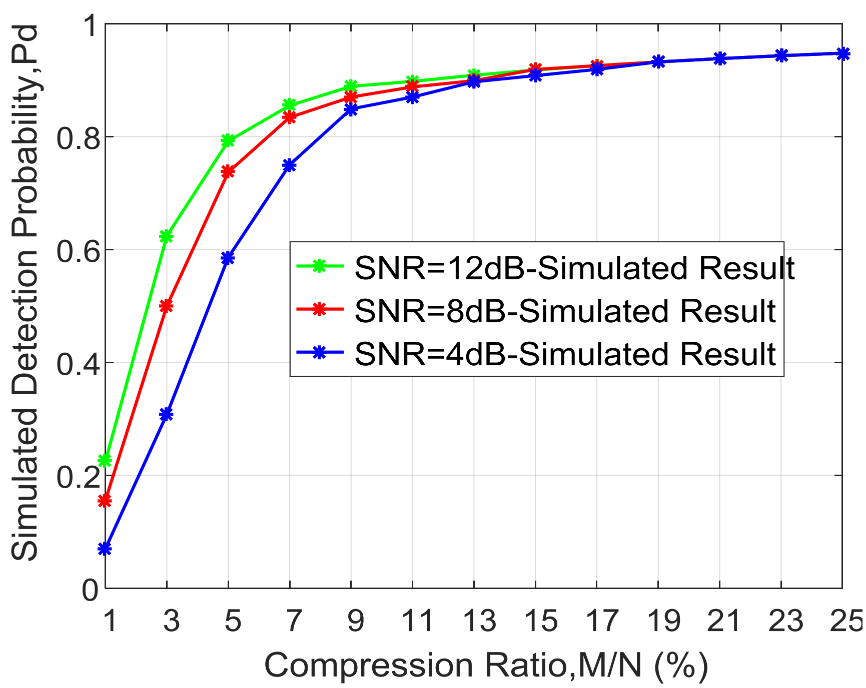

Fig. 4.6: ROC curve for compression ratio, M/N (%) vs. detection probability, P_d with different SNR values in the Wideband Frequency under Rayleigh channel (Simulated Result).

4.2.5 Comparison of ROC curve between Estimated & Simulated Result

To compare the results of Estimated and Simulated outcomes, Fig. 4.7 and Fig. 4.8 are presented for the AWGN and Rayleigh channel condition, respectively.

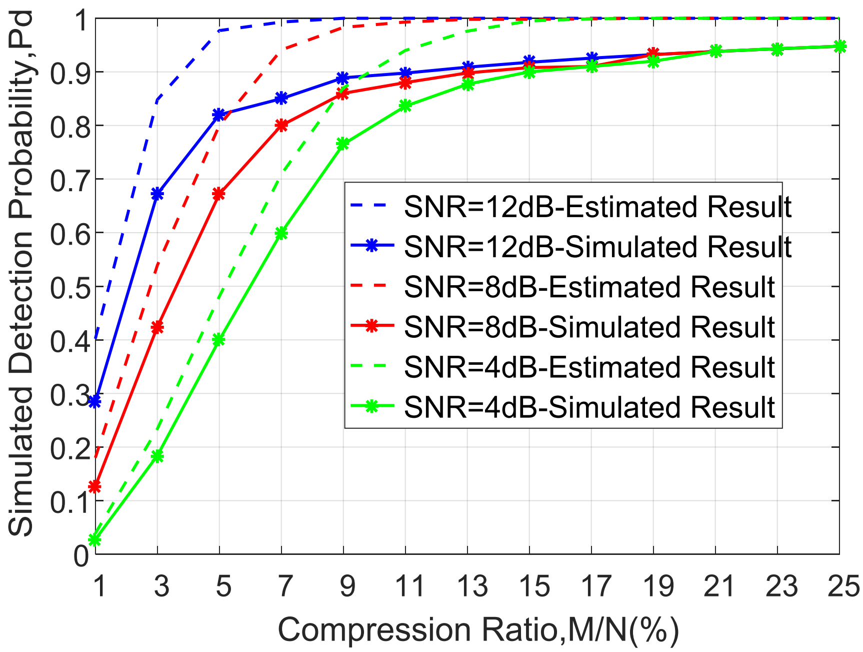

Fig. 4.7: Comparison of ROC curve between Estimated & Simulated Result for M/N (%) vs. P_d with different SNR values in the Wideband Frequency under AWGN channel.

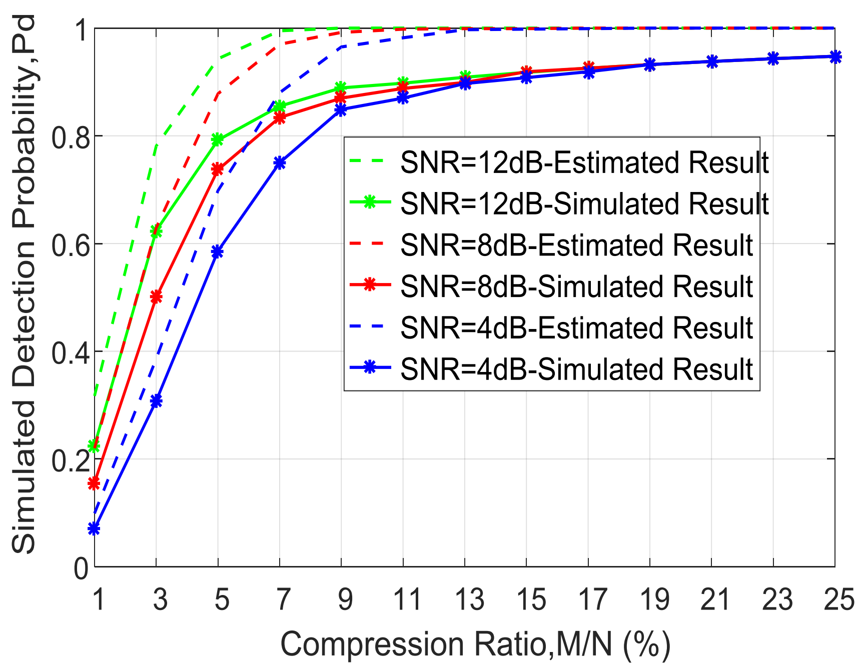

Fig. 4.8: Comparison of ROC curve between Estimated & Simulated Results for M/N (%) vs. P_d with different SNR values in the Wideband Frequency under Rayleigh channel.

4.2.6 $\boldsymbol{P_d}$ vs. SNR curve for a fixed Compression Ratio, M/N (%)

In the context of previous consequence of analysis, detection probability, P_d has been analyzed with respect to the increment of SNR for a fixed point compression ratio, M/N (%). It is found from this analysis that with the increment of the value of SNR the P_d is also increased for a fixed point M/N (%). This outcome is shown in Fig. 4.9. The numerical values are also presented which is given in Table 4.2.

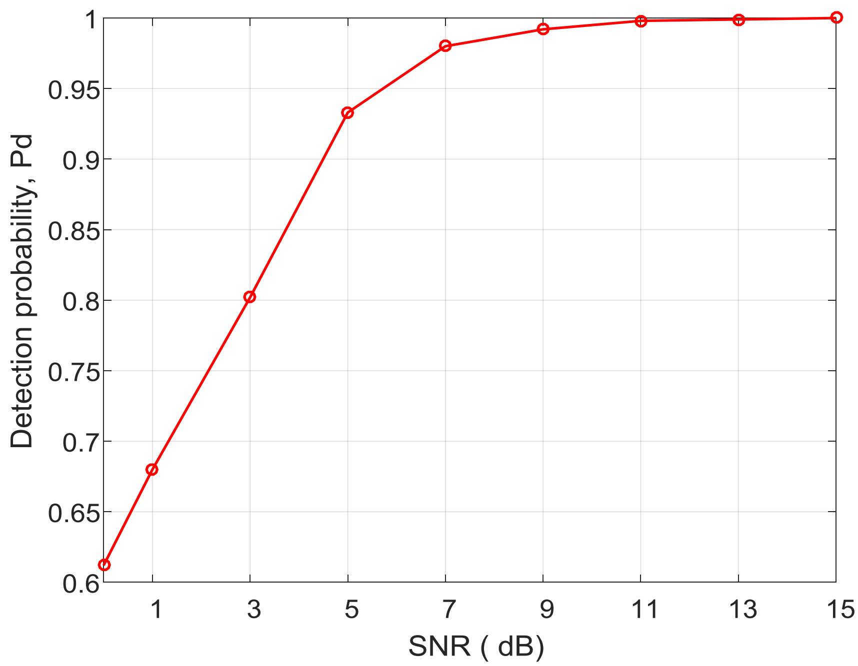

Fig. 4.9: P_d vs. SNR curve for a fixed compression ratio, M/N (%)

Table 4.2 Different SNR and their corresponding detection probability, P_d

SNR (dB)	Detection Probability, P_d
0 dB	0.61%
1 dB	0.68%
3 dB	0.80%
5 dB	0.93%
7 dB	0.98%
9 dB	0.99%
11 dB	0.998%
13 dB	0.999%
15 dB	100%

4.3 Analysis of Achievable Throughput of a Stand-Alone CR Terminal

Fig. 4.10 shows the simulated result of throughput vs. sensing time where x axis denotes sensing time and y axis denotes achievable throughput. This simulation is done using four BPFs. Later, to testify the achievable rate of the proposed CR system, the throughput performance is investigated. To make easily understandable, we choose low regime SNR value of the PU system, e.g., SNR= -8dB, probability of detection $P_d = 0.90$ and probability of PU transmission is absent, $P\ (H_0) = 0.90$ when a CR node wishes to transmit. Intuitively, the sensing time, τ occupied for the proposed approach and the full spectrum estimation with a single RF chain followed by promising CS method is considered during simulation operation. Meanwhile, this sensing time, τ is applied in equation (3.22) to find the optimum throughput for a fixed frame length of 100 ms and different SNR values.

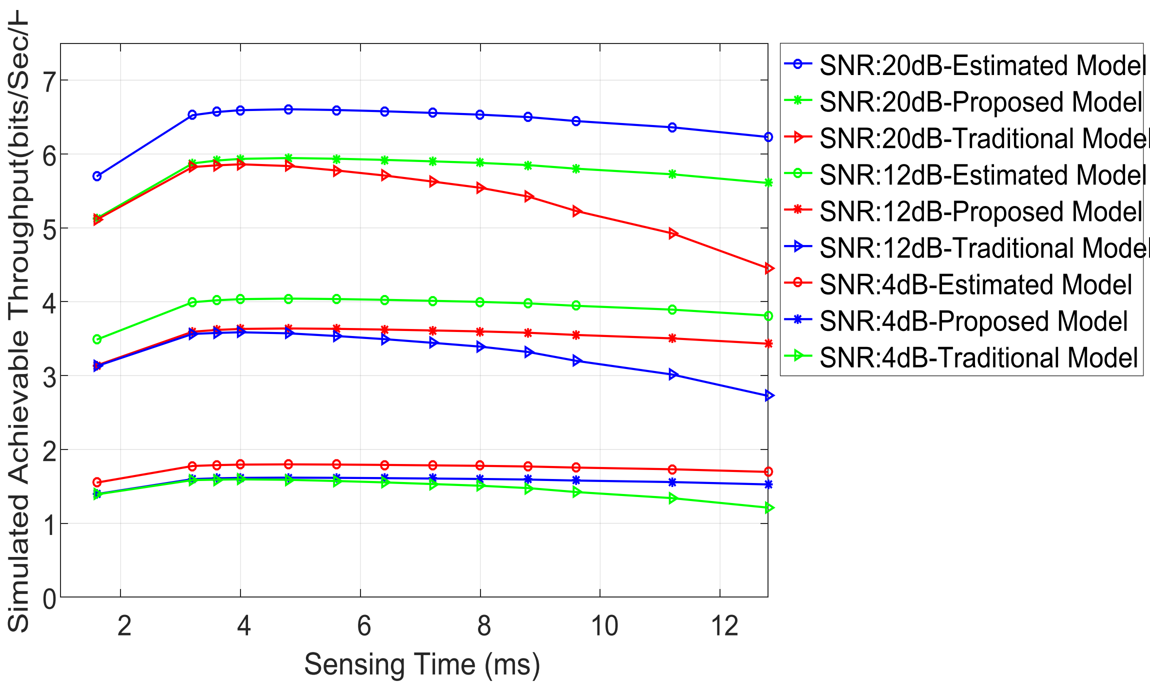

Fig. 4.10: Simulation of achievable Throughput against sensing time for a fixed frame length of 100 ms

From this figure, it is found that for 20dB the throughput is at the highest level from the initial sensing time. The throughput was almost same for sensing time 0 to 3.5ms for both proposed and traditional model. After 3.5ms the throughput is decreasing slowly. But we can see that throughput for traditional model was decreasing more rapidly than our proposed model because CR receiver is accommodated with four BPFs. When we consider comparatively low SNR i.e., for 4dBand 12dB the throughput is decreasing very slowly for the proposed method. For low SNR, traditional throughput is decreased more rapidly than that of the proposed approach. Therefore, we have found that the performance of the proposed model is better than traditional model.

In additional, Fig. 4.11 shows the simulated result of throughput vs. frame length. Where x axis denotes frame length and y axis denotes achievable throughput. This simulation is done using four BPFs. we again investigate the optimum throughput of the same arrangement but this time a variation of the frame length is used with a fixed sensing time, = 4.3ms.

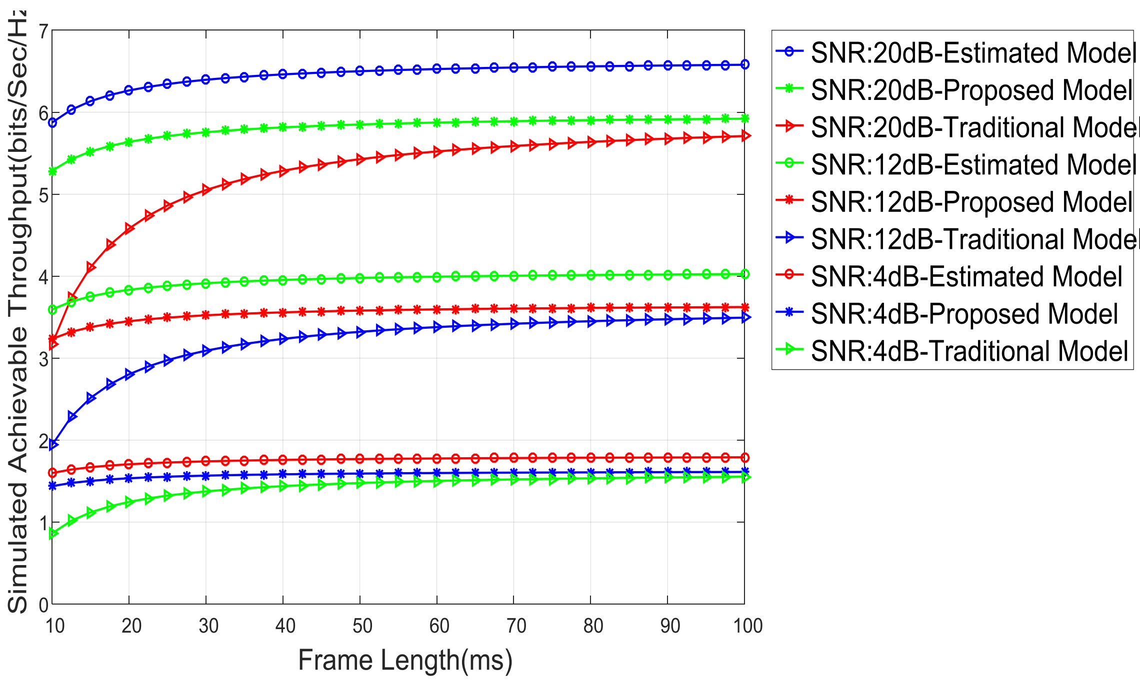

Fig. 4.11: Simulation of achievable Throughput against frame length for a fixed sensing time of 4.3 ms

This figure illustrates the comparisons of achievable throughput among the estimated, traditional, and proposed approaches with respect to different SNR's. From the figure it noticeable that for the throughput of the proposed model is higher than the traditional model and increasing with the value of the frame length. It is mentionable that the performance of the proposed model is slightly lower than the estimated model although the performance of the estimated model is questionable because of its impracticability. From the result given in Fig. 4.11, it can be concluded that in real-world concept the proposed model provides high throughput with real-world practicability.

4.4 Analysis of Computational Complexity and Memory space required

In Fig. 4.12, it is methodically computed the order of computational burden by using equation (3.28) which enables to perform Wideband Spectrum Sensing with fewer Computational Complexity. Here, the number of samples is decreased by the influence of the number of BPFs, K. Therefore, in the proposed system saves arithmetic computations in the order of $\mathcal{O}(K \log K)$. As a rough estimate, the proposed approach saves computational burden of 45% while using K =4.

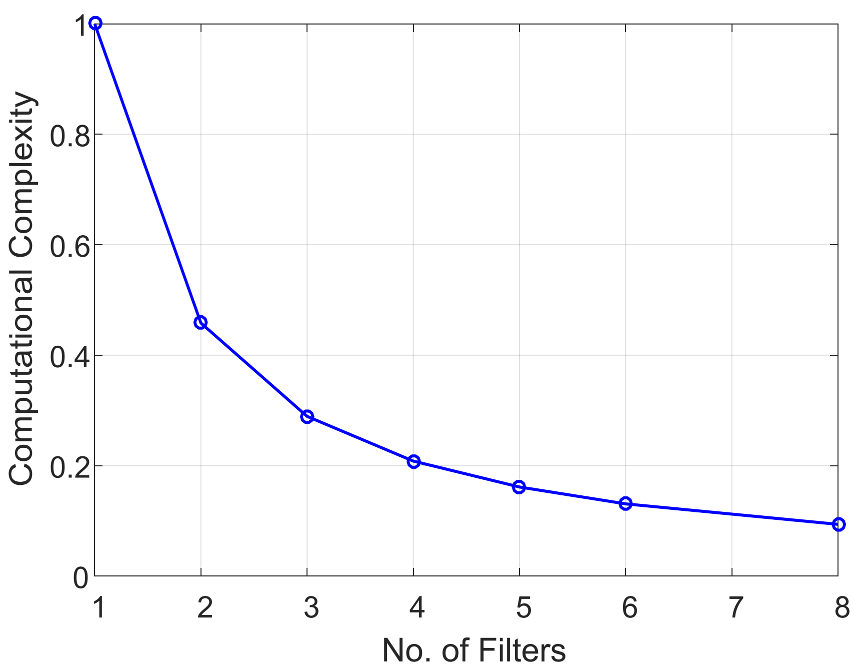

Fig. 4.12: Computational Complexity with the influence of the number of Filters

In addition, this approach of wideband sensing saves the memory storage of bits in the order of $\mathcal{O}(K)$ according to equation (3.29). The consequence of number of BPFs on the memory space requisite is plotted in Fig. 4.13. It displays the proposed technique of wide band sensing involves only 25 % of physical memory spaces than that followed by a single RF chain.

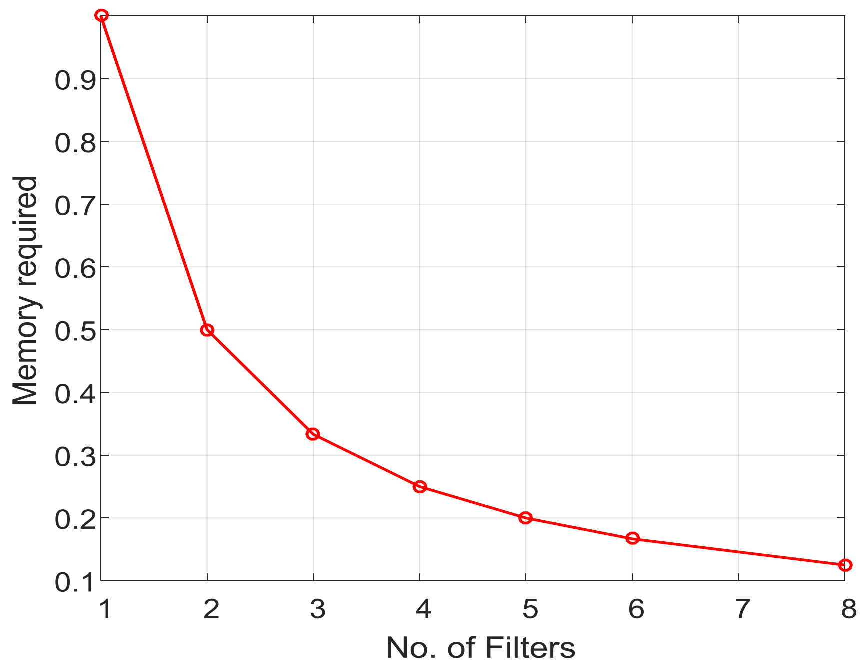

Fig. 4.13: Memory space requirement with the influence of the number of Filters

Chapter 5

Discussion and Conclusion

5.1 Discussion

This paper purposes to determine the HSFB by comparing the average energy of each FB. By taking the random sub-Nyquist rate samples of the AIC, the energy estimation of every FB has been performed. This HSFB determination indicates several hints; first, it ensures of having minimum number of PUs active which substantially exploit maximum opportunistic accessibility for a CR user. Second, the more the sparsity, the better would be the spectral estimation which contributes better detection performance. Third, spectral estimation of a single HSFB rather than entire wideband requires minor computational complexity. In this paper, we have given emphasis on spectral estimation of the HSFB through a convex optimization approach called l_1-norm minimization. After that, we have drawn our attention to check the spectrum occupancy status of a PU by using the ED. All the proposed hypothesis and corresponding modeling of the CR network have been widely examined and discussed in chapter 3. The proposed design consideration aims to provide outperforming results compared to the existing wideband spectrum sensing methods, in terms of lower computational complexity, lower memory requirements as well as high achievable throughputs for CR networks.

5.2 Conclusions

We successfully estimated the signal using CS technique and then we simulated the output signals to distinguish whether there is PUs presented or not. From the simulated analysis, we have got that how the SNR influences the probability of detections. So we can claim that the final outcomes have been achieved for CR based on the proposed CS as our expectation. According to this proposal, the relation of detection probability for different compression ratio, M/N with respect to different PUs has been explored which helps to find the required minimum energy. In addition, the impact of SNR on the detection probability has also been evaluated by this work. Since this work used higher number of BPFs, the arithmetic computational complexity has been reduced in satisfactory level. Eventually, we estimated that the proposed method provided better throughput performance for fixed frame length as well as fixed sensing period in the field of CR network. The achievable rate of a CR node varies with the sensing slot duration as well as frame duration the throughput is greater for shorter sensing time period. By calculating the energy estimator performances with respect to the compression ratio, M/N we observed that the accuracy of energy estimator increases with the increment of the value of compression ratio, M/N. The probability detection, P_d of estimated results with respect to the incremental compression ratio, M/N was analyzed under the different fixed value SNR environment. Similar performances were also calculated in simulated conditions. In practice, we found from our investigation that there exists slightly reduced performance of the simulated environment than the estimated performance. Therefore, in brief, we can conclude that the proposed method proves its significance in CR system.

5.3 Future Work

A future work can be carried out applying CS technique under Rician and Nakagami-m fading channel, as well. CS scheme has lot of prospers and applications, hence in future, the possible research including cooperative wideband sensing method could extend the contents of this research work. On the consideration of a dynamic spectrum management, the received signal of a PU at a single CR terminal may be severely despoiled due to hidden terminal problems, multipath fading or shadowing problems. This is a serious case that can be a challenge for satisfactory sensing performances. Such a problem can be solved by cooperative sensing strategies hybridizing with the proposed scheme to obtain highly reliable detection performance. Additionally, this proposition could be challenging for the computational complexity and hardware constraints. Cooperative spectrum sensing is considered as a solution to some common problems. Usually, control channels can be employed using suitable methodologies schemes to share common spectrum sensing outcomes. When the CR nodes perceive fading or shadowing independently,in such a scenario cooperative sensing performs better. Therefore, a wide investigation can be performed in future to analyze the flexible radio employment for wireless network; which will be increasingly complex and certainly heterogeneous in nature and the idea of flexible radio may be a concern playing a vital role in the future wireless communications. Eventually, that must satisfy the scalability,adaptability, re-configurability, modularity, and many more properties for advanced CR network, in future.

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List of Publications

1. S. S. Alam, S.M. B. Ahammed, A. Hossain, S. Anjuman, “Compressive Sensing of Wideband Cognitive Radio Networks for Different Fading Channels,” *International Conference on Computer, Communication, Chemical, Material and Electronic Engineering (IC^{4}ME^2-2017), January 26-27, 2017.*
2. S. S. Alam, A. Hossain, S.M. B. Ahammed, S. Anjuman,“ Blind Spectrum Sensing of Narrow-Band Signals under Different Fading Channels in Cognitive Radio Networks,’’ *International Conference on Computer, Communication, Chemical, Material and Electronic Engineering (IC^{4}ME^2-2017), January 26-27, 2017.*