Performance Analysis of Spectrum Sensing Techniques for Cognitive Radio over Wireless Fading Channels

A Thesis submitted in the partial fulfilment of requirements for the award of degree of

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CERTIFICATE

I, Komal Arora hereby certify that the work which being is presented in this thesis entitled **"Performance Analysis of Spectrum Sensing Techniques for Cognitive Radio over Wireless Fading Channels"** by me in Partial fulfillment of the requirements for the award of degree of Master of Engineering in Electronics and Communication from Thapar University, Patiala is an authentic record of my own work carried under supervision of Dr. Kulbir Singh and Mr. Ankush Kansal and referred other researcher's work which are duly listed in the reference section.

The matter presented in this thesis has not been submitted in any University/Institution for the award of Master of Engineering.

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ABSTRACT

With the advance of wireless communications, the problem of bandwidth scarcity has become more prominent. On the other hand, the studies made by FCC (Federal Communications Commission) showed that large portion of the spectrum lies vacant most of the time and that portion is the licensed spectrum band; which is utilized by licensed users only. So, to solve this problem of spectrum under-utilization, FCC (Federal Communications Commission) allowed secondary users to utilize the licensed band when it is not in use and named it as Cognitive Radio.

To sense the existence of licensed users, spectrum sensing techniques are used. Energy detection, Matched filter detection and Cyclo-stationary feature detection are the three conventional methods used for spectrum sensing. However there are some drawbacks of these techniques. The performance of energy detector is susceptible to uncertainty in noise power. Matched filter spectrum sensing technique need a dedicated receiver for every primary user. Cyclostationary feature Detection requires lot of computation effort and long observation time. This thesis discusses the conventional energy detection method and proposed improved energy detection method using cubing operation. Also, cyclic prefix based spectrum sensing is discussed in this thesis. Mathematical Description of energy detection and cyclic prefix based spectrum sensing techniques is also illustrated for fading channels.

According to the simulations presented in the thesis, an improvement of up to 0.6 times for AWGN Channel and up to 0.4 times for Rayleigh channel; has been achieved as the squaring operation is replaced by cubing operation in an energy detector. Cooperation among the users is a valuable tool in the implementation of the spectrum sensing and it has been found that it improves the performance of energy detection and cyclic prefix based spectrum sensing techniques. By analyzing the plots of Probability of Detection versus Signal–to-Noise Ratio, it has been shown that Cooperative detection improves the performance of conventional energy detection method up to 2.7 times for AWGN Channel and 2.2 times for Rayleigh Channel as compared to single user detection. It has also been observed that the application of Cooperative

Detection in improved Energy detection method (using cubing operation) improves the performance up to 1.3 times for AWGN Channel and 2.3 times for Rayleigh Channel as compared to single user detection. An improvement of up to 3.9 times is achieved using cooperative detection in cyclic prefix based spectrum sensing.

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List of Abbreviations

A:

ADC:	Analag to Digital Converter
AOC:	Area under the Receiver Operating Characteristics Curve
AWGN:	Additive White Gaussian Noise
AGC:	Automatic Gain Control
ARQ:	Automatic Repeat Request

B:

BER:	Bit Error Rate

C:

CDF:	Cumulative Distribution Function
CDMA:	Code Division Multiple Access
CFO:	Carrier Frequency Offset
CP:	Cyclic Prefix
CR:	Cognitive Radio
CRN:	Cognitive Radio Network

D:

DECT:	Digital Enhanced Cordless Telecommunications
DSA:	Dynamic Spectrum Access

E:

ED:	Energy Detector

F:

FCC:	Federal Communications Commission
FEC:	Forward Error Correction
FFT:	Fast Fourier Transform

G:

GLRT:	Generalized Likelihood Ratio Test
GSM:	Global System for Mobile

L:

LNA:	Low Noise Amplifier
LRT:	Likelihood Ratio Test

M:

MAC:	Medium Access Control

O:

OFDM:	Orthogonal Frequency Division Multiplexing

P:

PAPR:	Peak to average Power Ratio
PLL:	Phase Locked Loop
PSD:	Power Spectral Density
PU:	Primary User

Q:

QOS:	Quality of Service

R:

RF:	Radio Frequency
ROC:	Receiver Operating Characteristics

S:

SNR:	Signal to Noise Ratio
SU:	Secondary User

T:

TDCS:	Transform domain Communication System

U:

UMTS:	Universal Mobile Telecommunications System

UTRA-FDD:	Evolved Universal Terrestrial Radio Access Frequency Division Duplexing
UTRA-TDD:	Evolved Universal Terrestrial Radio Access Time Division Duplexing

V:

VCO:	Voltage Controlled Oscillator

W:

WLAN:	Wireless Local Area Network
WMAN:	Wireless Metropolitan Access Network
WSS:	Wide Sense Stationary

CHAPTER 1

INTRODUCTION

1.1 Preamble

Cognitive radio is an intelligent wireless communication system that is aware of its surrounding environment (i.e., outside world), and uses the methodology of understanding-by-building to learn from the environment and adapt its internal states to statistical variations in the incoming RF stimuli by making corresponding changes in certain operating parameters (e.g., transmit-power, carrier-frequency, and modulation strategy) in real-time, with two primary objectives in mind : highly reliable communications whenever and wherever needed and efficient utilization of the radio spectrum [1].

According to its operational area, Cognitive Radio can be classified into following sub-systems:

- **A Multiband System**: A multiband system which is supporting more than one frequency band used by a wireless standard (e.g., GSM 900, GSM 1800, GSM 1900),
- **A Multi-standard system:** A multi-standard system that is supporting more than one standard. Multi-standard systems can work within one standard family (e.g., UTRA-FDD, UTRA-TDD for UMTS) or across different networks (e.g., DECT, GSM, UMTS, WLAN).
- **A Multi-service system:** A multi-service system which provides different services (e.g., telephony, data, video streaming),
- **A Multi-channel system:** A multi-channel system that supports two or more independent transmission and reception channels at the same time [2].

1.2 Cognitive Radio Characteristics : Cognitive Radio operation is based on three main principles:

Reconfigurability: This property of cognitive radios refers to their ability to dynamically modify their configuration. Reconfigurability can efficiently be realized through the use of network elements that can dynamically alter the parameters of their operation to improve the offered Quality of Services. Reconfigurations are software-defined, that is, they are accomplished by activating the appropriate software at the transceiver [3]. Reconfiguratability includes following capabilities:

- Frequency Agility: It is the ability of a radio to change its operating frequency. This ability usually combines with a method to dynamically select the appropriate operating frequency based on the sensing of signals from other transmitters or on some other method.
- Dynamic Frequency Selection: It is defined in the rules as a mechanism that dynamically detects signals from other radio frequency systems and avoids co-channel operation with those systems.
- Adaptive Modulation/Coding: A cognitive radio could select the appropriate modulation type for use with a particular transmission system to permit interoperability between systems.
- Transmit Power Control: Transmit power control is a feature that enables cognitive radio to dynamically switch between several transmissions power levels in the data transmission process [4].

Cognition: The stochastic nature of the environment conditions raises the need for the existence of the second main attribute of cognitive radio systems, namely, cognition. [3]. "Cognition" refers to the process of knowing through perception, reasoning, knowledge and intuition with a focus on information available from the environment [5]. Thus, Cognitive capability includes the features of spectrum sensing, spectrum sharing, location identification, network and service discovery [4].

Self-management: Each transceiver should be capable of self-adapting to its environment without the need to be instructed by a central management entity with higher rationality. This concept, which is aligned to the autonomic computing paradigm, provides significant reduction of system complexity because it does not call for a centralized management entity [3]. It includes the following features:

- Spectrum/Radio Resource Management: To efficiently manage and organize spectrum holes information among cognitive radios, good spectrum management scheme is necessary.
- Mobility and Connection Management: Due to the heterogeneity of CRNs, routing and topology information is more and more complex. Good mobility and connection

management can help neighbourhood discovery, detect available Internet access and support vertical handoffs, which help cognitive radios to select route and networks.

- Trust/Security Management: Since CRNs are heterogeneous networks in nature, various heterogeneities (e.g. wireless access technologies, system/network operators) introduce lots of security issues. Trust is thus a prerequisite for securing operations in CRNs [4].

1.3 Cognitive Radio Functions

Duty cycle of cognitive Radio includes detecting spectrum white space, selecting the best frequency bands, coordinating spectrum access with other users and vacating the frequency when a primary user appears. Figure 1 shows the duty cycle for Cognitive Radio.

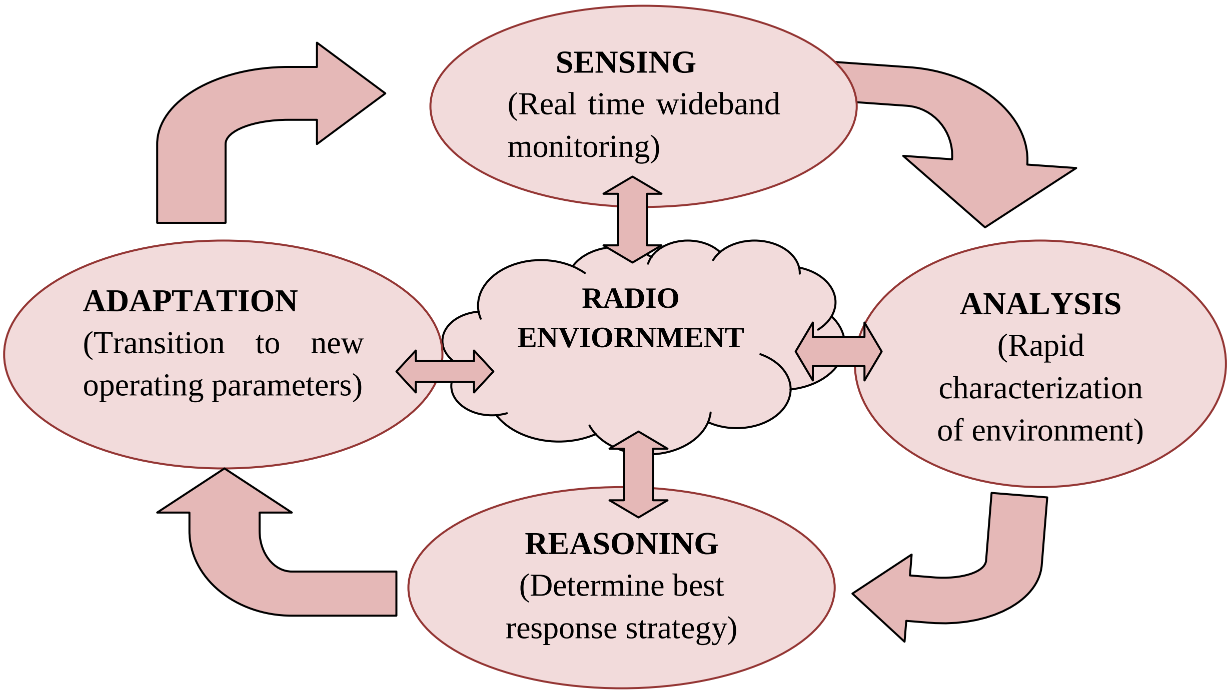

Figure 1: Cognitive Cycle.

Such a cognitive cycle is supported by the following functions:

• Spectrum sensing and analysis.

• Spectrum management and handoff.

• Spectrum allocation and sharing.

Spectrum sensing and analysis: Through spectrum sensing and analysis, CR can detect the spectrum white space as illustrated in Figure 2 i.e., a portion of frequency band that is not being used by the primary users, and utilize the spectrum. On the other hand, when primary users start using the licensed spectrum again, CR can detect their activity through sensing, so that no harmful interference is generated due to secondary users' transmission.

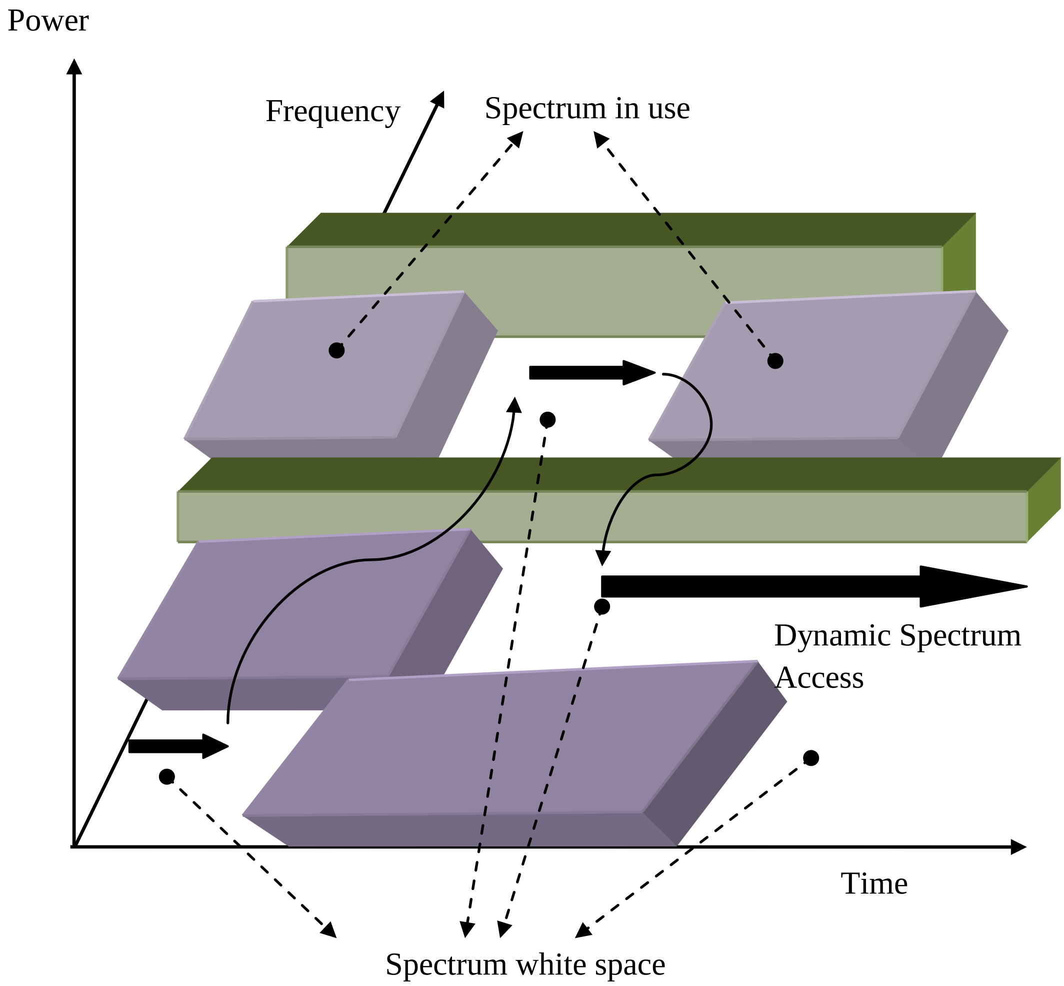

Figure 2: Spectrum holes and spectrum in use.

Spectrum management and handoff: After recognizing the spectrum white space by sensing, spectrum management and handoff function of CR enables secondary users to choose the best frequency band and hop among multiple bands according to the time varying channel characteristics to meet various Quality of Service (QoS) requirements. For instance, when a primary user reclaims his/her frequency band, the secondary user that is using the licensed band can direct his/her transmission to other available frequencies, according to the channel capacity determined by the noise and interference levels, path loss, channel error rate, holding time, and etc.

Spectrum allocation and sharing: In dynamic spectrum access, a secondary user may share the spectrum resources with primary users, other secondary users, or both. Hence, a good spectrum allocation and sharing mechanism is critical to achieve high spectrum efficiency. Since primary users own the spectrum rights, when secondary users co-exist in a licensed band with primary users, the interference level due to secondary spectrum usage should be limited by a certain threshold. When multiple secondary users share a frequency band, their access should be coordinated to alleviate collisions and interference [6].

1.4 Need of Cognitive Radio Technology

The progressive growth of the wireless communications, has led to under-utilization of the spectrum. The usage of radio spectrum resources and the regulation of radio emissions are coordinated by national regulatory bodies like the Federal Communications Commission (FCC). The FCC assigns spectrum to licensed holders, also known as primary users, on a long-term basis for large geographical regions [6]. It has been observed by Federal Communications Commission (FCC) that major portion of the spectrum remain unutilized most of the time; as it is reserved only for the licensed (primary) users while other is heavily used [7]. Figure 3 shows the underutilized spectrum.

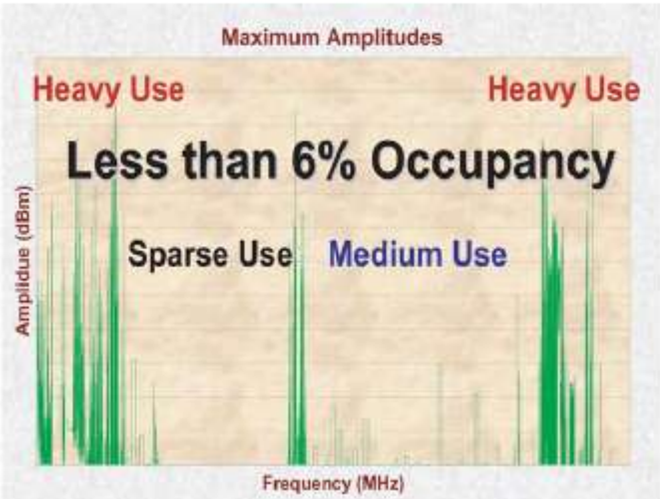

Figure 3: Spectrum usage [6].

The relatively low utilization of the licensed spectrum suggests that spectrum scarcity is largely due to inefficient fixed frequency allocations rather than any physical shortage of spectrum. This observation has prompted the regulatory bodies to investigate a radically different access paradigm [8]. Cognitive Radio (CR) has come out as a prominent solution to this problem which allows the secondary users to use the licensed band when it is not in use [7]. This new communication paradigm named as Cognitive Radio; can dramatically enhance spectrum efficiency, and is also referred to as the Next Generation (XG) or Dynamic Spectrum Access (DSA) network [9].

1.5 Physical Architecture of Cognitive Radio: The cognitive radio architecture is comprised of three sub-systems, as shown in Figure 4[10]:

- Digital Transceiver.
- Channel monitoring and spectrum sensing module.
- Communication management and control.

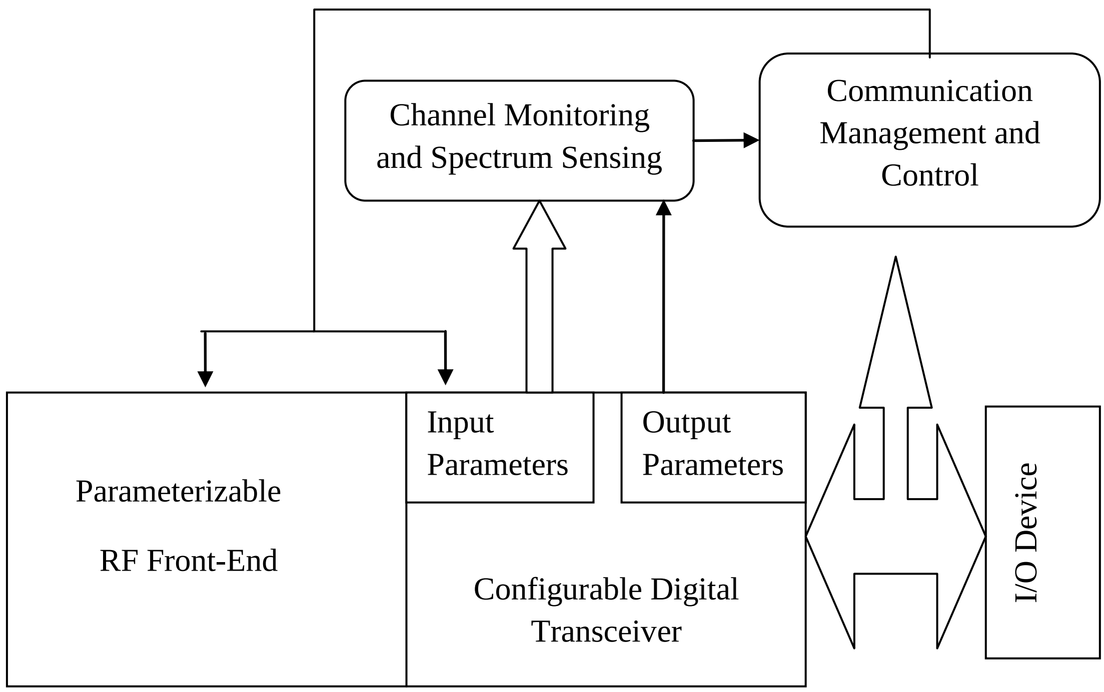

Figure 4: Cognitive Radio Architecture.

Digital Transceiver: The main components of a cognitive radio transceiver are: RF front-end and Baseband processing unit as shown in Figure 5. In the RF front-end, the received signal is amplified, mixed and A/D converted. In the baseband processing unit, the signal is modulated/demodulated and encoded/decoded. The baseband processing unit of a cognitive radio is essentially similar to existing transceivers. However, the novelty of the cognitive radio is the RF front-end. The novel characteristic of cognitive radio transceiver is a wideband sensing capability of the RF front-end. This function is mainly related to RF hardware technologies such as wideband antenna, power amplifier, and adaptive filter. RF hardware for the cognitive radio should be capable of tuning to any part of a large range of frequency spectrum. Also such spectrum sensing enables real-time measurements of spectrum information from radio environment [11].

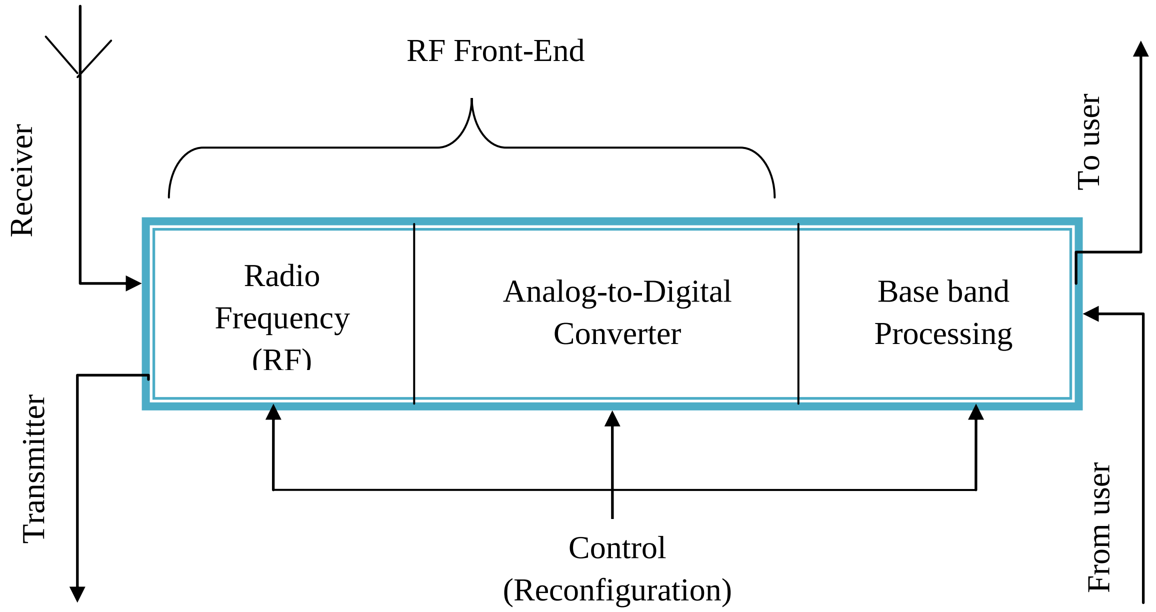

Figure 5: Cognitive Radio Transceiver.

RF Front-End: Generally, a wideband front-end architecture for the cognitive radio has the following structure as shown in Figure 6

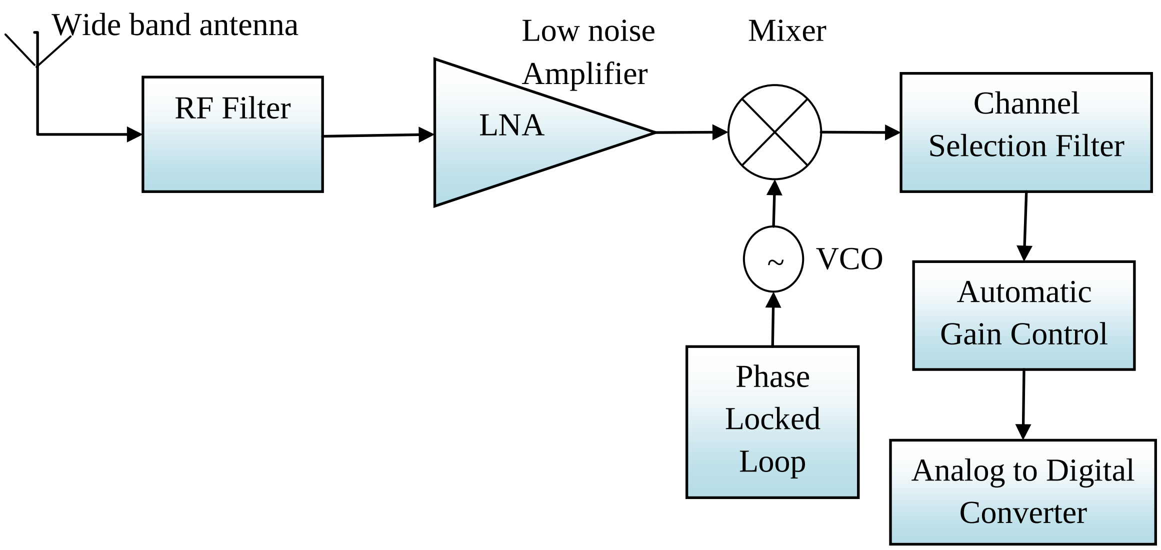

Figure 6: RF front-end architecture of Cognitive Radio.

The RF front-end has input parameters, including amplifier gains, operation frequency, and channel filters' bandwidth. The output parameters of the configurable transceiver are the performance metrics maintained by cognitive radio, e.g. BER and the power level [10].

The components of a cognitive radio RF front-end are as follows:

RF filter: The RF filter selects the desired band by band-pass filtering the received RF signal.

Low noise amplifier (LNA): The LNA amplifies the desired signal while simultaneously minimizing noise component.

Mixer: In the mixer, the received signal is mixed with locally generated RF frequency and converted to the baseband or the intermediate frequency (IF).

Voltage-controlled oscillator (VCO): The VCO generates a signal at a specific frequency for a given voltage to mix with the incoming signal. This procedure converts the incoming signal to baseband or an intermediate frequency.

Phase locked loop (PLL): The PLL ensures that a signal is locked on a specific frequency and can also be used to generate precise frequencies with fine resolution.

Channel selection filter: The channel selection filter is used to select the desired channel and to reject the adjacent channels. There are two types of channel selection filters. The direct conversion receiver uses a low-pass filter for the channel selection. On the other hand, the super heterodyne receiver adopts a band pass filter.

Automatic gain control (AGC): The AGC maintains the gain or output power level of an amplifier [11].

Channel monitoring and spectrum sensing module: This module senses the channel and sends its feedback to the communication management sub-system so as to adjust the operation parameters in the RF front end and digital transceiver. The configurability of cognitive radio is solely governed by the design of the configurable digital transceiver and adaptability is maintained by the second and third subsystems [10].

Communication Management and Control Sub-system: The communication management and control sub-system performs several key tasks in the cognitive radio [11]:

- Accomplish mode switching decision based on the values provided by the performance metrics.

- Controls the spectrum sensing scanning.
- Manages the mode switching mechanism.

1.6 Cognitive Radio Network Architecture: The network architecture of Cognitive Radio is shown in Figure 7.

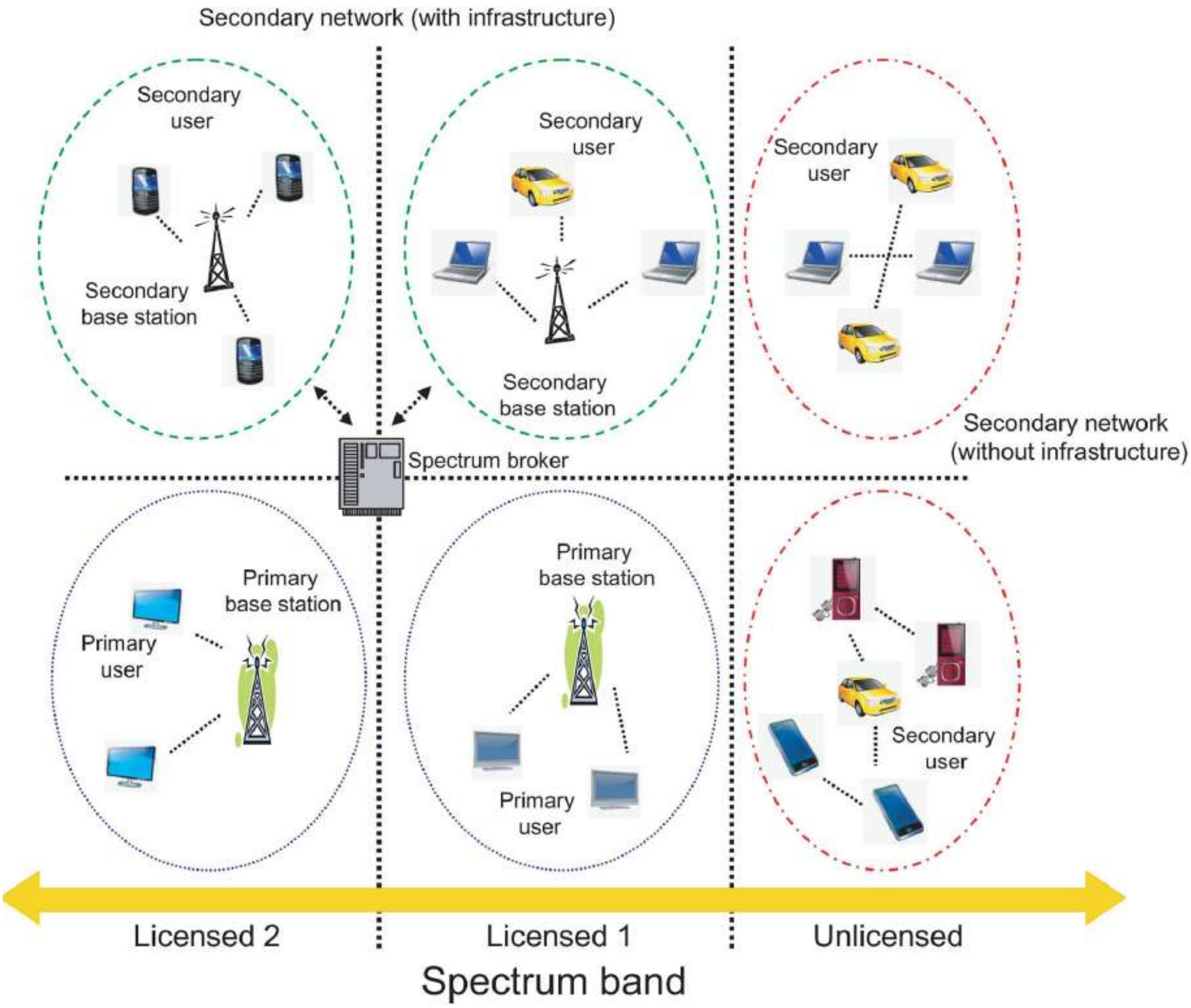

Figure 7: Cognitive Radio Network Architecture [6].

Components of Cognitive Radio Network: With the development of CR technologies, secondary users who are not authorized with spectrum usage rights can utilize the temporally unused licensed bands owned by the primary users [6]. Therefore, in a CR network architecture, the components include both a primary network and a secondary network, as shown in Figure 7.

- **Primary Network:** The primary network (or licensed network) is referred to as an existing network, where the primary users have a license to operate in a certain spectrum band. If primary networks have an infrastructure, primary user activities are controlled through primary base stations Due to their priority in spectrum access, the operations of primary users should not be affected by secondary users [12].
- **Secondary Network:** The CR network (also called the dynamic spectrum access network, secondary network, or secondary network) does not have a license to operate in a desired band. Hence, additional functionality is required for CR users to share the licensed spectrum band. CR networks also can be equipped with CR base stations that provide single-hop connection to CR users. Finally, CR networks may include spectrum brokers that play a role in distributing the spectrum resources among different CR networks [12].
- **Spectrum Broker:** If several secondary networks share one common spectrum band, their spectrum usage may be coordinated by a central network entity, called spectrum broker. The spectrum broker collects operation information from each secondary network, and allocates the network resources to achieve efficient and fair spectrum sharing [6].

Spectrum Management Framework for Cognitive Radio Network: The spectrum management process consists of four major steps and is depicted in Figure 8:

- **Spectrum Sensing:** A CR user can allocate only an unused portion of the spectrum. Therefore, a CR user should monitor the available spectrum bands, capture their information, and then detect spectrum holes [12].
- **Spectrum Decision:** Once available spectrum bands are identified through spectrum sensing, CR networks need to select the proper spectrum bands according to the application requirements [13].
- **Spectrum Sharing:** Two major steps in spectrum sharing are: spectrum exploration and spectrum exploitation. The objectives of spectrum exploration are to discover and maintain the statistics of spectrum usage, and identify the spectrum opportunities. In this step a cognitive radio transceiver needs to measure and observe the transmissions in the ambient environment. In the spectrum exploitation step a cognitive radio

transceiver makes a decision on whether and how to exploit the spectrum opportunities [14].

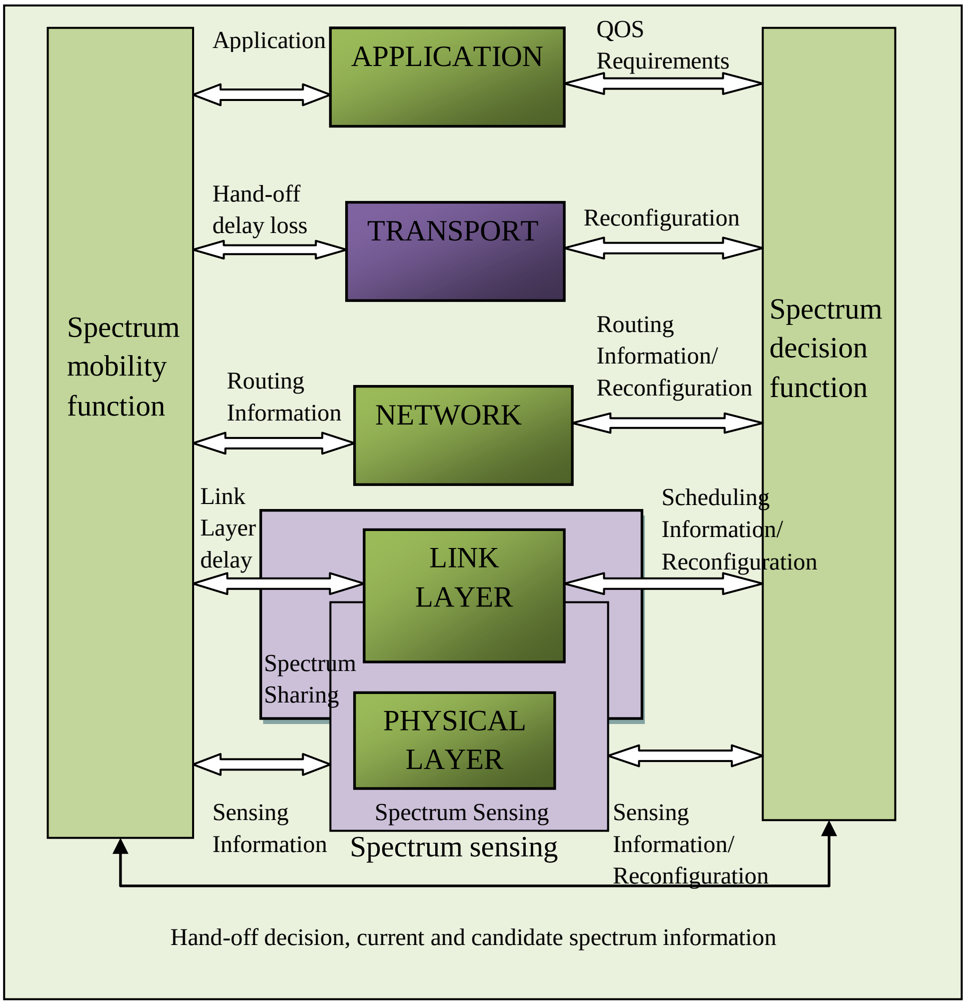

Figure 8: Spectrum Management Framework.

- **Spectrum Mobility:** CR users are regarded as visitors to the spectrum. Hence, if the specific portion of the spectrum in use is required by a primary user, the communication must be continued in another vacant portion of the spectrum [12].

Communication Layers in Cognitive Radio Network Architecture

- **Physical Layer**: The physical layer of a Cognitive Radio node should provide the capability of reconfiguring its operating frequency, modulation, channel coding, and output power without hardware replacement [15].

- **Data Link Layer:** Data link layer provides the ability to control the errors. The main error control schemes are forward error correction (FEC) and automatic repeat request (ARQ). The MAC (Medium Access Control) layer of a Cognitive Radio node must handle additional challenges such as silent spectrum sensing periods temporarily inhibiting transmission, the impracticality of broadcast over a network-wide common channel, and the need for high-priority access mechanism for the distribution of spectrum sensing and decision results.
- **Network Layer:** Due to spectrum mobility in Cognitive Radio Networks, hop-based channel characteristics like channel access delay, interference, operating frequency, and bandwidth are new metrics to consider in the design of new routing techniques. Rerouting algorithms should also be highly energy-efficient in Cognitive Radio Networks.
- **Transport Layer:** In Cognitive Layer networks the transport layer is mainly responsible for end-to-end reliable delivery of event readings and congestion control to preserve scarce network resources while considering application-based QoS requirements.
- **Application Layer:** Application layer algorithms in Cognitive Radio networks mainly deal with the generation of information and extracting the features of event signals being monitored to communicate to the sink. Other services provided by the application layer include methods to query sensors, interest and data dissemination, data aggregation, and fusion [15].

1.7 Physical Layer for Cognitive Radio

Physical Layer Requirements for Cognitive Radio

Cognitive Radio should use transmission schemes that provide the best spectrum utilization and capacity. There are several unique requirements that a modulation scheme should provide which are illustrated below [16]:

- First, spectrum bands available for transmission could be spread over a wide frequency range, with variable bandwidths and band separations. The unoccupied spectrum distribution is a function of geographic location and time of usage, and it is updated after every spectrum sensing period.

- Secondly, for optimal spectrum and power efficiency every cognitive radio estimates the quality of unoccupied frequencies in order to provide higher layers with signal-to-noise measurements to be used for power and bit allocation.
- Lastly, different applications might require selection of frequency bands based on propagation characteristics or interference measurements. Therefore, the transmission scheme should allow assignments of any frequency band to any cognitive user, and should be scalable with the number of users and bands. In order to keep the cognitive receiver demodulator fairly simple, it is desirable to restrict a single user transmission in a single frequency band. This constraint could be further justified by reduced transmission power of a single user rather than additive transmission power of many users, which would potentially cause interference to the active primary user in the vicinity [16].

OFDM as Physical Layer for Cognitive Radio

The modulation scheme based on orthogonal frequency division multiplexing (OFDM) is a natural approach that might satisfy desired properties. OFDM has become the modulation of choice in many broadband systems due to its inherent multiple access mechanism and simplicity in channel equalization, plus benefits of frequency diversity and coding [16].

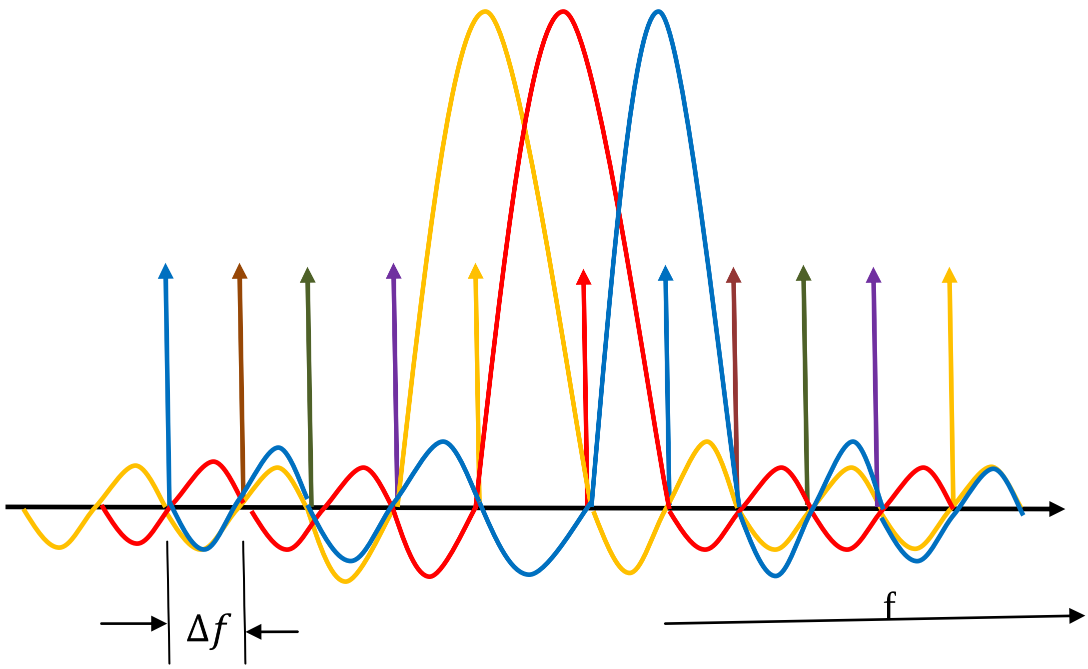

Figure 9: Orthogonality of sub-carriers in OFDM System.

OFDM is a multi-carrier modulation technique that can overcome many problems that arise with high bit-rate communications, the most serious of which is time dispersion. The data-bearing symbol stream is split into several lower-rate streams, and these streams are transmitted on different carriers. Because this splitting increases the symbol duration by the number of orthogonally overlapping carriers (subcarriers), multipath echoes affect only a small portion of the neighbouring symbols [17]. The orthogonality as illustrated in Figure 9, of all modulated subcarriers is maintained if the subcarrier spacing equals the reciprocal value of the OFDM symbol duration and rectangular pulse shaping is assumed [18].

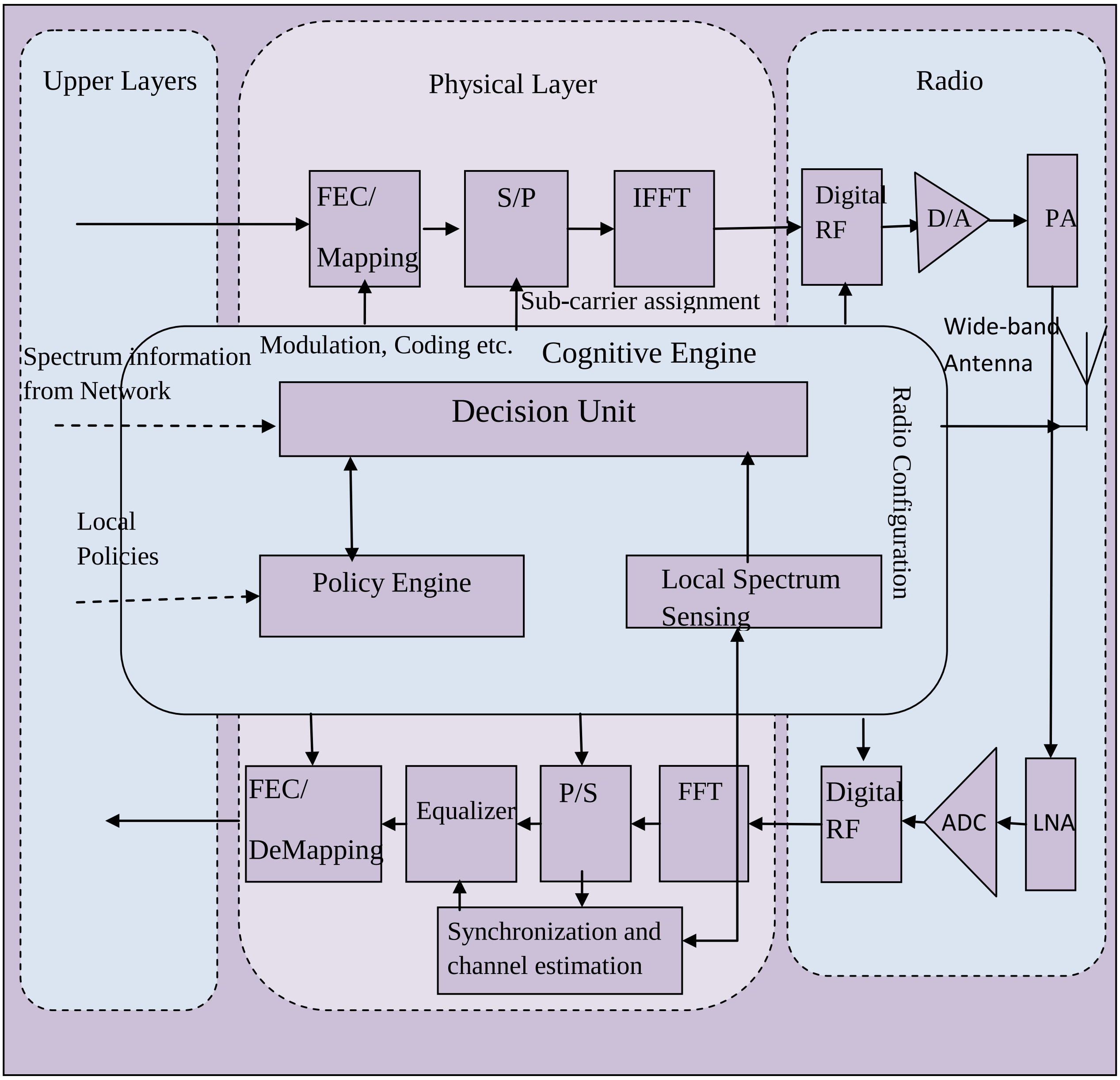

Figure 10: Block Diagram of OFDM Based Cognitive Radio System.

The block diagram of OFDM based cognitive radio is shown in Figure 10. The cognitive engine is responsible for making intelligent decisions and configuring the radio and PHY parameters. The transmission opportunities are identified by the decision unit based on the information from the policy engine, as well as local and network spectrum sensing data. As far as the PHY layer is concerned, CR can communicate with various radio-access technologies in the environment, or it can improve the quality of communication depending on the environmental characteristics, by simply changing the configuration parameters of the OFDM system and the radio frequency (RF) interface. Coding type, coding rate, interleaver pattern, and other medium access control (MAC) and higher layer functionalities, and so on, should also be changed accordingly [17]. OFDM's Strengths which make it best transmission technology for Cognitive Radio are listed in Table 1.

Table 1: OFDM's strengths for Cognitive Radio.

CR Requirements	OFDM's Strengths
Spectrum Sensing	Inherent FFT Operation of OFDM in frequency domain eases spectrum sensing.
Efficient Spectrum utilization.	Waveforms can easily be shaped by turning off some sub-carriers where primary users exist.
Adaptation/Scalability	OFDM Systems can be adapted to different transmission environments and available resources. Some adaptable parameters are FFT size, subcarrier spacing, CP size, modulation, coding, sub-carrier powers.
Advanced Antenna Techniques	Techniques such as Multiple Input Multiple Output (MIMO) are commonly used with OFDM mainly because of reduced equalizer complexity. OFDM also supports smart antennas.
Interoperability	With WAN (IEEE 802.11), WMAN (IEEE 802.16), WPAN (IEEE 802.15.3a) all using OFDM as their physical layer techniques, Interoperability becomes easier to other technologies.
Multiple accessing and	Support for multiple- access is already inherited in the system

Spectral Allocation	design by assigning groups of sub-carriers to different users (i.e. OFDMA).
NBI Immunity	NBI affects only subcarriers in OFDM Systems. These sub-carriers can simply be turned off.

1.8 Spectrum Sensing: Most Essential Task of Cognitive Radio.

Spectrum sensing, defined as the task of finding spectrum holes by sensing the radio spectrum in the local neighbourhood of the cognitive radio receiver in an unsupervised manner [19]. The sensing function is considered to be an essential part of cognitive radio for a number of reasons. One of them is identifying spectrum not used by primary users (‘spectrum white spaces’). It can then transmit in these white spaces with power levels such as not to cause any interference to these primary users. Another reason for cognitive radios to sense the wireless medium is to detect the transmission of other secondary devices. In this case, the cognitive radio needs to share some or all of the channels occupied by other secondaries thus reducing its own blocking probability [20].

The sensing function in cognitive radios is different from conventional radios as the later are designed to share the medium with like devices only. As an example, consider the IEEE 802.11 wireless LAN technology. Here, all devices use the same sensing thresholds to determine if the channel is idle before a transmission. On the other hand, cognitive radios have to detect the presence of the primary signal at thresholds that are under signal levels (for decoding) of primary devices. In general, the detection sensitivity of the cognitive radio should outperform primary radio system by a large margin (say, 20-30 dB) in order to prevent what is essentially called as hidden terminal problem. This is one of the key issues that makes spectrum sensing a very challenging research problem. Meeting the sensing requirement in each band, which has different primary users with different characteristics, would be very difficult. This is done so that the cognitive radio can determine the transmit power, and the transmission and interference radius opportunistically [20].

1.9 Spectrum Sensing Techniques: Three conventional methods for spectrum sensing are: matched filter, energy detector and cyclostationary feature detector.

Matched Filter Technique:

The optimal way for any signal detection is a matched filter since it maximizes received signal-to-noise ratio. However, a matched filter effectively requires demodulation of a primary user signal. This means that cognitive radio has a priori knowledge of primary user signal at both PHY and MAC layers, e.g. modulation type and order, pulse shaping, packet format. Such information might be pre-stored in CR memory, but the cumbersome part is that for demodulation it has to achieve coherency with primary user signal by performing timing and carrier synchronization, even channel equalization. This is still possible since most primary users have pilots, preambles, synchronization words or spreading codes that can be used for coherent detection. For examples: TV signal has narrowband pilot for audio and video carriers; CDMA systems have dedicated spreading codes for pilot and synchronization channels; OFDM packets have preambles for packet acquisition. The main advantage of matched filter is that due to coherency it requires less time to achieve high processing gain since only O(1/SNR) samples are needed to meet a given probability of detection constraint. However, a significant drawback of a matched filter is that a cognitive radio would need a dedicated receiver for every primary user [21].

Block Diagram of Matched filter technique:

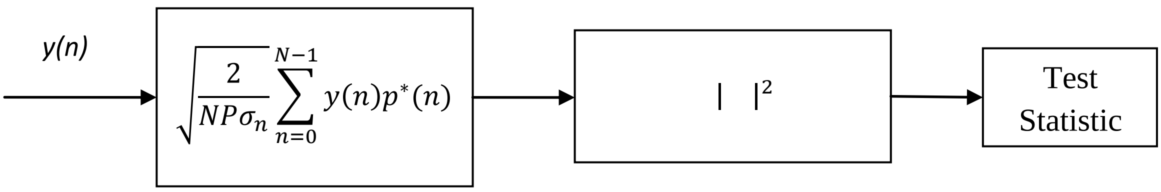

Figure 11: Block Diagram of Matched filter technique.

Received signal at the Cognitive Radio user:

$$y(n) = \theta h p(n) + w(n), \qquad 0 \le n \le N-1 \tag{1.1}$$

where $p(n)$ is the pilot sequence and $w(n)$ denote the white noise, h denotes the fading channel ,and $\theta = 0$ and $\theta = 1$ denote the absence and presence of the primary signal respectively. Let P denotes the average Signal to Noise Ratio for pilot signal:

$$P = \frac{1}{N}\sum_{n=0}^{N-1}|p(n)|^2 \tag{1.2}$$

The instantaneous Signal to Noise Ratio within the detection period:

$$\gamma = \frac{|h|^2 P}{\sigma_n^2} \tag{1.3}$$

where σ_n^2 is the noise variance.

Test statistics for Matched Filter Technique:

$$Y = \sqrt{\frac{2}{NP\sigma_n}}\sum_{n=0}^{N-1} y(n)p^*(n) \tag{1.4}$$

$$Y = \begin{cases} \left|\sqrt{\frac{2}{NP\sigma_n}}\sum_{n=0}^{N-1} w(n)p^*(n)\right|^2, & H_0 \\ \left|\sqrt{\frac{2NP}{\sigma_n{}^2}}h + \sqrt{\frac{2}{NP\sigma_n}}\sum_{n=0}^{N-1} w(n)p^*(n)\right|^2, & H_1 \end{cases} \tag{1.5}$$

And makes decision accordingly:

$$\theta = \begin{cases} H_1, & if\ Y < T \\ H_0, & ifY > T \end{cases} \tag{1.6}$$

Under AWGN, test statistics of Matched Filter Detection follows a central chi-square distribution with two degrees of freedom under H_0 and a non-central chi-square distribution with two degrees of freedom and a non-centrality parameter $\mu = 2N\gamma$ under H_1 i.e.

$$f_Y(Y) \sim \begin{cases} \chi_2{}^2, & H_1 \\ \chi_2{}^2(\mu), & H_0 \end{cases} \tag{1.7}$$

Since the Cognitive Radio user does not know whether the primary signal exists , the perfect timing assumption may not be true in practice [7].

Energy Detection Technique:

Energy detector based approach, also known as radiometry or periodogram, is the most common way of spectrum sensing because of its low computational and implementation complexities [22]. If the receiver cannot gather sufficient information about the primary user signal, (which was one of the limitation of the matched filter technique) then we use energy detection technique, the optimal detector is an energy detector. In order to measure the energy of the received signal, the output signal of band-pass filter with bandwidth W is squared and integrated over the observation interval T. Finally, the output of the integrator, Y, is compared with a threshold λ to decide whether a licensed user is present or not [23]. The disadvantage of the energy detector is the increased sensing time [24]. Some of the challenges with energy detector based sensing include selection of the threshold for detecting primary users, inability to differentiate interference from primary users and noise, and poor performance under low signal-to-noise ratio (SNR) values. Moreover, energy detectors do not work efficiently for detecting spread spectrum signals [22]. Figure 12 shows the block diagram of Energy Detection Based Spectrum Sensing.

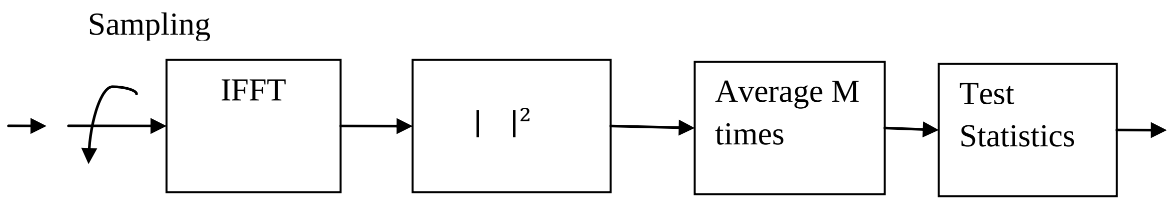

Figure 12: Block Diagram of Energy Detection Based Spectrum Sensing.

The spectral component on each spectrum sub-band of interest is obtained from the fast fourier transform (FFT) of the received signal. Then the test statistics of the energy detector is obtained as the energy summation with M consecutive segments:

$$Y = \begin{cases} \sum_{m=1}^{M} |W(m)|^2, & H_0 \\ \sum_{m=1}^{M} |S(m) + W(m)|^2, & H_1 \end{cases} \tag{1.8}$$

where $S(m)$ and $W(m)$ denote the spectral components of the received primary signal and white noise on the subband of interest. The decision of energy detector is given by:

$$\theta = \begin{cases} H_1, & if\ Y < T \\ H_0, & ifY > T \end{cases} \tag{1.9}$$

where T is the threshold. $W(m)$ is complex Gaussian with zero mean and variance two. Due to instantaneous Signal to noise Ratio of the received primary signal within the current M segments:

$$\gamma = \frac{1}{2M} \sum_{m=1}^{M} |S(m)|^2 \tag{1.10}$$

Test statistics of Energy Detection follows a central chi-square distribution with $2M$ degrees of freedom under H_0 and a non-central chi-square distribution with $2M$ degrees of freedom and a non-centrality parameter $\mu = 2M\gamma$ under H_1 i.e.

$$f_Y(Y) \sim \begin{cases} {\chi_{2M}}^2, & H_1 \\ {\chi_{2M}}^2(\mu), & H_0 \end{cases} \tag{1.11}$$

where $f_Y(Y)$ denotes the probability density function of Y and $\chi_M{}^2$ and $\chi_M{}^2(\mu)$ denote a central and non-central distribution respectively [7].

Cyclostationarity feature detection

Cyclostationary feature detection is a method for detecting primary user transmissions by exploiting the cyclostationarity features of the received signals. Cyclostationary features are caused by the periodicity in the signal or in its statistics like mean and autocorrelation or they can be intentionally induced to assist spectrum sensing. Instead of power spectral density (PSD), cyclic correlation function is used for detecting signals present in a given spectrum. The cyclostationarity based detection algorithms can differentiate noise from primary users' signals. This is a result of the fact that noise is wide-sense stationary (WSS) with no correlation while modulated signals are cyclostationary with spectral correlation due to the redundancy of signal periodicities. Furthermore, cyclostationarity can be used for distinguishing among different types of transmissions and primary users [23].

Consider a typical digitally modulated signal of the form:

$$s(t) = \sum_n a(n) g(t - nT_0 - t_0) \tag{1.12}$$

where T_0 is the symbol period, t_0 is unknown timing offset, and $g(t)$ is the shaping pulse. $a(n)$ is assumed to be stationary with zero mean and variance σ_a^2 . Time-varying auto-correlation of $s(t)$ is defined as:

$$R_s(t,\tau) = E\{s(t+\tau)s^*(t)\} \tag{1.13}$$

$$= \sum_n \sigma_a^2 g(t+\tau-nT_0-t_0) g^*(t-nT_0-t_0) \quad = \sum_{\alpha=k/T_0} R^\alpha(\tau) e^{j2\pi at} \tag{1.14}$$

where

$$R^\alpha(\tau) = \begin{cases} \dfrac{\sigma_a^2 e^{j2\pi\alpha t_0}}{T_0} \displaystyle\int G^*(f+\alpha) G(f) e^{j2\pi f\tau} df \ , & \alpha = \dfrac{k}{T_0} \\ 0 \ , & otherwise \end{cases} \tag{1.15}$$

and $G(f)$ is the fourier transform of $g(t)$. The function $R^\alpha(\tau)$ denotes the cyclic auto-correlation function and α is called cyclic frequency. The Cyclic Auto-correlation function at a given cyclic frequency α determines the correlation between the spectral components of the signal separated in frequency by an amount of α. The Cyclic Auto-correlation function is non-zero only for the integral multiples of a fundamental frequency, $\alpha_0 = 1/T_0$. Thus, given T_0, the cyclic Auto-correlation function can be utilized to determine the presence or absence of the primary signal by evaluating the values of $R^{\alpha}(\tau)$ at corresponding cyclic frequencies[7].

Cooperation Detection

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 mis-detection and false alarm considerably. Cooperation can be implemented in two fashions: centralized or distributed. In centralized sensing, a central unit collects sensing information from cognitive devices, identifies the available spectrum, and broadcasts this information to other cognitive radios or directly controls the cognitive radio traffic. In the case of distributed sensing, cognitive nodes share information among each other but they make their own decisions as to which part of the spectrum they can use. Distributed sensing is more advantageous than centralized sensing in the sense that there is no need for a backbone infrastructure and it has reduced cost [22].

1.10 Wireless Channels: The channel provides the physical means for transporting the signal produced by the transmitter and delivering it to the receiver.

Channel impairments in Wireless Systems

- **Channel Distortion:** It may take the form of multipath- the constructive and destructive interference between many copies of the same signal received.
- **Time-varying nature:** It may be due to either the terminal mobility or a change in conditions along the propagation path.
- **Interference:** It is produced by other sources whose output signals occupy the same frequency band as the transmitted signal.
- **Receiver Noise:** It is produced by electronic devices at the front end of the receiver. The effect of receiver noise will depend on the received signal strength, which in turn will depend on the propagation path between the transmitter and receiver.

Simplest Channel Model

The additive white Gaussian Noise (AWGN) channel is the channel model most often used in the communications theory. With this model, zero-mean noise having a Gaussian distribution is added to the signal. The noise is usually assumed to be white over the bandwidth of interest, i.e. the samples of the noise process are un-correlated with each other. Noise has an auto-correlation function given by $\frac{N_0}{2}\delta(t)$, where $\delta(t)$ is the Dirac-delta function or, equivalently, it has a flat two-sided power spectral density $\frac{N_0}{2}$. For fixed satellite communication, in which there is a direct line-of-sight path between the transmitter and satellite [25]. The AWGN Channel Model is shown in the Figure 13.

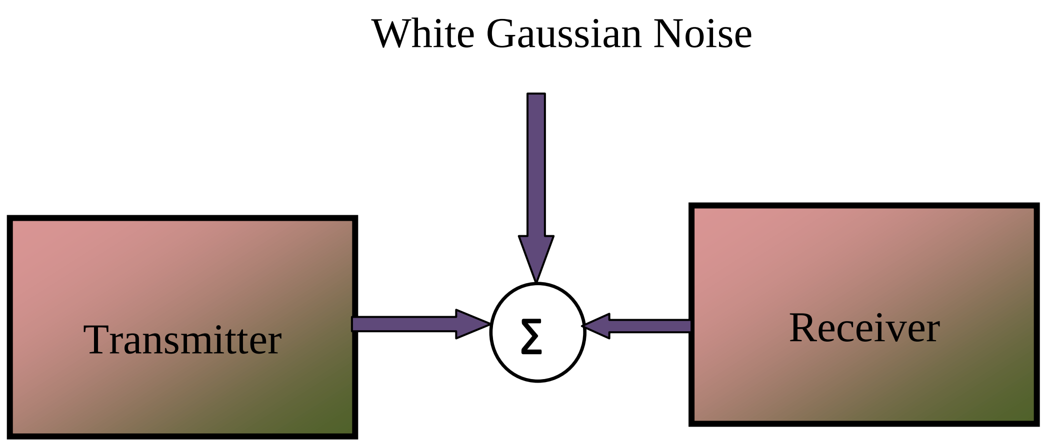

Figure 13: AWGN Channel Model.-

Channel Classification based on large-scale and small-scale effects

- **Large-scale effects :** These effects are due to the terrian and density and height of buiildings and vegetation. Large-scale effects are important for predicting the coverage and availabilty of a particular service. These effects are characterized statistically by mean path loss and log normal shadowing. Both of these phenomena have a behavior that varies relatively slowly with time [25].
    - **Path Loss:** The **path loss,** which represents signal attenuation as a positive quantity measured in dB, is defined as the difference (in dB) between the effective transmitted power and the received power, and may or may not include the effect of the antenna gains.
    - **Shadowing**; When shadowing is caused by a single object such as a hill or mountain, the attenuation caused by diffraction can be estimated by treating the obstruction as a diffracting knife edge. This is the simplest of diffraction models, and the diffraction loss in this case can be readily estimated using the

classical Fresnel solution for the field behind a knife edge (also called a half-plane) [26].

- **Small-scale effects:** These effects are due to the local environment, near-by trees, buildings and movement of the radio terminal through that environment. These effects have a much shorter time scale. They have been characterized statistically as fast Rayleigh fading. A consideration of small-scale effects is important for design of the modulation format and for general transmitter and receiver design [25].In Stochastic models take into account fading over short time interval over short distances i.e. Small-scale fading .**Small scale fading** manifests itself in two mechanisms:
    - **Time-variance of the channel** due to motion of the receiver (or occasionally a transmitter). Based on the time-variance of the channel, the fading can be classified into : slow and fast fading.
        - Slow-fading: If Symbol period is greater than the coherence-time of a channel, the fading is called as slow-fading.Coherence time is the measure of the expected time duration over which channel's response is essentially invariant [26].
        - Fast-fading: If Symbol period is less than the coherence-time of a channel, the fading is called as fast-fading.
    - **Time-spreading** of the underlying pulses within the signal and based on time-spreading of the pulses, fading can be classified into: frequency-selective fading and flat fading.
        - Frequency-selectivefading: If maximum excess delay is greater than the time period of pulse, type of fading is called as frequency-selective fading. Maximum excess delay is defined as the time between the first and last received component of a transmitted pulse.
        - Flat fading: If maximum excess delay is greater than the time period of pulse, type of fading is called as flat fading[25].

Amplitude distributions of fading Channels :

- **Rayleigh Distribution**: In mobile radio channels, the Rayleigh distribution is commonly used to describe the statistical time varying nature of the received envelope ofa flat fading signal, or the envelope of an individual multipath component. It is well known that the envelope of the sum of two quadrature Gaussian noise signals obeys a Rayleigh distribution. Figure shows a Rayleigh distributed signal envelope as a function of time. The Rayleigh distribution has a probability density function (pdf) given by:

$$p(r) = \begin{cases} \frac{r}{\sigma^2} \exp\left(\frac{-r^2}{2\sigma^2}\right) & (0 \leq r \leq \infty) \\ 0 & (r < 0) \end{cases}$$

  where σ is the rms value of the received signal and σ^2 is the time-average power of the received signal [25].

- **Ricean Fading Distribution:** When there is a dominant stationary (nonfading) signal component present, such as a line-of-sight propagation path, the small-scale fading envelope distribution is Ricean. In such a situation, random multipath components arriving at different angles are superimposed on a stationary dominant signal. At the output of an envelope detector, this has the effect of adding a dc component to the random multipath. Just as for the case of detection of,a sine wave in thermal noise, the effect of a dominant signal arriving with many weaker multipath signals gives rise to the Ricean distribution.

  As the dominant signal becomes weaker, the composite signal resembles a noise signal which has an envelope that is Rayleigh. Thus, the Ricean distribution degenerates to a Rayleigh distribution when the dominant component fades away [27]. The Ricean distribution is given by

$$p(r) = \begin{cases} \frac{r}{\sigma^2} e^{-\frac{(r^2+A^2)}{2\sigma^2}} I_0\left(\frac{Ar}{\sigma^2}\right) & (A \geq 0, r \geq 0) \\ 0 & (r < 0) \end{cases}$$

  The parameter A denotes the peak amplitude of the dominant signal and $I_0(.)$ represents the modified Bessel function of the first kind and zero-order. The ricean distribution is often described in terms of a parameter K which is defined as the ratio between the deterministic signal power and the variance of the multipath. It is given by

$$K(dB) = 10log\frac{A^2}{2\sigma^2}\ dB$$

The paramter K is known as Ricean Factor and completly satisfies the Ricean distribution. As $A \to 0, K \to \infty\ dB,$ and as the dominant path decreases in amplitude, the Ricean distrubution degrades to a Rayleigh distribution [25].

- **Nakagami Fading Distribution**: In contrast to the Rayleigh distribution, which has a single parameter that can be used to match the fading-channel statistics, the Nakagami- is a two-parameter distribution, with the parameters .As a consequence, this distribution provides more flexibility and accuracy in matching the observed signal statistics. The Nakagami- distribution can be used to model fading-channel conditions that are either more or less severe than the Rayleigh distribution, and it includes the Rayleigh distribution as a special case [27].

$$p_R(r) = \frac{2}{\Gamma(m)}\left(\frac{m}{\Omega}\right)^m r^{2m-1}e^{-\frac{mr^2}{\Omega}}, \qquad r \geq 0$$

Parameter m is defined as called the fading parameter and its value lies between 0.5 to ∞. [28].

1.11 Advantages of Cognitive Radio Technology:

Cognitive Radio capabilities of frequency agility, dynamic frequency selection, adaptive modulation, transmit power control, location awareness and negotiated use; make it very suitable to use the wirless spectrum oppurtunistically [29]. Some of the benfits of Cognitive Radio are as follows:

• **Dynamic spectrum access:** The existing Wireless Network deployments assume fixed spectrum allocation over very crowded secondary bands also used by other devices. Nevertheless, a spectrum lease for a licensed band amplifies the overall deployment cost. Hence, to be able to cooperate efficiently with other types of users, opportunistic spectrum access may be utilized in Wireless Networks.

• **Opportunistic channel usage for bursty traffic:** A large number of sensor nodes detecting an event generate bursty traffic and try to acquire the channel to send their readings. This increases the probability of collisions and packet losses, which decreases the overall communication reliability with excessive power consumption. Opportunistic access to multiple alternative channels may alleviate these potential challenges.

• Adaptability for reducing power consumption: The dynamic nature of the wireless channel causes energy consumption due to packet losses and retransmissions. Cognitive radio capable sensor nodes may be able to adapt to varying channel conditions, which would increase transmission efficiency, and hence help reduce power used for transmission and reception.

• **Overlaid deployment of multiple concurrent wireless Networks**: Dynamic spectrum management may significantly contribute to th efficient coexistence of spatially overlapping sensor networks in terms of communication performance and resource utilization.

• **Communication under different spectrum regulations**: A certain band available in one specific region or country may not be available in another due to varying spectrum regulations. Sensor nodes equipped with cognitive radio capability may overcome this potential problem [15].

CHAPTER 2
LITERATURE REVIEW

2.1 Literature Review:

Software radios were considered to be the platforms for personal communication systems but the contemporary process of modifying radio etiquettes was quite cumbersome as there was no way to represent the information about the radio environment and this limited the flexibility and responsiveness of the radio to the network and user. J. Mitola et al. [30] elaborated the need for cognitive radios by considering the example of an equalizer. Global System for Mobile Communications (GSM) radio's equalizer taps reflect the channel multipath structure. A network might want to ask a handset, "How many distinguishable multipath components are you seeing?" Knowledge of the internal states of the equalizer could be useful because in some reception areas, there may be little or no multipath and 20 dB of extra signal-to-noise ratio (SNR). Software radio processing capacity is wasted running a computationally intensive equalizer algorithm when no equalizer is necessary. That processing capacity could be diverted to better use, or part of the processor might be put to sleep, saving battery life. In addition, the radio and network could agree to put data bits in the superfluous embedded training sequence, enhancing the payload data rate accordingly.

In 1999, J. Mitola et al. [30] coined a term named Cognitive radio that extends the concept of software radio by enhancing the flexibility of personal services through a Radio Knowledge Representation Language. This language represents knowledge of radio etiquette, devices, software modules, propagation, networks, user needs, and application scenarios in a way that supports automated reasoning about the needs of the user. Using this ontology, the radio can track the user's environment over time and space. Cognitive radio, then, matches its internal models to external observations to understand the requirements of the system. Significant memory, computational resources, and communications bandwidth are also needed for cognitive radio.

In addition to it, recent rapid growth of wireless communications has made the problem of spectrum utilization ever more critical. On one hand, the increasing diversity (voice, short message, Web, and multimedia) and demand of high quality-of-service (QoS) applications have resulted in overcrowding of the allocated (officially sanctioned) spectrum bands, leading to significantly reduced levels of user satisfaction. The problem is particularly serious in communication-intensive situations such as after a ballgame or in a massive emergency (e.g., the 9/11 attacks). On the other hand, major licensed bands, such as those allocated for television broadcasting, amateur radio and paging, have been found to be grossly underutilized, resulting in spectrum wastage. J. Ma et al. [7] described that according to measurements made by Federal Communications Commission (FCC); the spectrum utilization in the 0–6 GHz band varies from 15% to 85%. Depending on the location, time of the day, and frequency bands, the spectrum actually is underutilized. However, those unused portions of the spectrum are licensed and thus cannot be used by systems other than the license owners. This has prompted the FCC to propose the opening of licensed bands to secondary users and given birth to cognitive radio. Cognitive radio allows for usage of licensed frequency bands by secondary users. However, these secondary (cognitive) users need to monitor the spectrum continuously to avoid possible interference with the licensed (primary) users. Apart from this, cognitive radio is expected to learn from its surroundings and perform functions that best serve its users. The IEEE has formed a working group (IEEE 802.22) to develop an air interface for opportunistic secondary access to the TV spectrum via the cognitive radio technology.

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I. Budiarjo et al.[31] et al. proposed the use of TDCS as transmission technology for Cognitive Radio. Transform domain communication system **(**TDCS) is a single carrier transmission where its bandwidth can be divided into smaller sub-bands. In this way it is easier to locate the part of the band occupied by the licensed users and then not to put energy on that region. Information regarding the spectrum occupancy of the licensed users is distributed to each Cognitive Radio device. Upon receiving the information about the region of the LU's band, a vector map is produced by Spectrum Magnitude. Guard interval (GI) is added to combat the multipath fading channel effect. Windowing can be added in order to reduce the side-lobes of the transmitted signal on the LU's band. Although TDCS gives larger degree of freedom in shaping its pulse without reducing its bit rate, still in SISO and MIMO with balanced number of antenna, multi carrier OFDM with interference avoidance capability is the preferred method in terms of higher bit rate, more than 5–6 dB SNR gain, and less complexity comparing to TDCS.

An important issue about CR (Cognitive Radio) is to design the transmitting waveform adapting to practical spectrum resources. OFDM seems to be the best choice for CR spectrum technology due to its inherent advantages of flexibility and versatility. However, OFDM itself also has some intrinsic demerits of high peak-to-average power ratio (PAPR), which will further deteriorate in CR (Cognitive Radio) systems because of turning off certain spectrum tones. C. Han et al. [32] suggested a new implementation of TDCS, i.e. OFDM-based TDCS in which the complex RAKE receiver is avoided. However, one disadvantage of this OFDM-based TDCS is that the overhead may be relatively large, when the channel multipath delay is very large.

Cognitive radio technology will enable the users to perform the following functions and these are illustrated by K. B. Letaief et al.[33]:

- ❖ Spectrum Sensing: to determine which portions of the spectrum are available and detect the presence of licensed users when a user operates in a licensed band.
- ❖ Spectrum Management: to select the best available channel.
- ❖ Spectrum Sharing: to coordinate access to this channel with other users.
- ❖ Spectrum Mobility: to vacate the channel when a licensed user is detected.

One of the most important components of CR is the ability to measure, sense, learn, and be aware of the parameters related to the radio channel characteristics, availability of spectrum and power, interference and noise temperature, radio's operating environment, user requirements, and applications. In CR, the PUs are referred to those users who have higher priority or legacy rights on the usage of a part of the spectrum. K. B. Letaief et al.[33] illustrated Spectrum sensing as a key element in CR communications, as it enables the CR to adapt to its environment by detecting spectrum holes. The most effective way to detect the availability of some portions of the spectrum is to detect the PUs that are receiving data within the range of a CR. However, it is difficult for the CR to have a direct measurement of a channel between a primary transmitter and receiver. Therefore, most existing spectrum sensing algorithms focus on the detection of the primary transmitted signal based on the local observations of the CR.

As illustrated by F.F. Digham et al. [34] and V. I. Kostylev et al. [35], in energy detector, the received signal is first filtered with a band pass filter in bandwidth to normalize the noise variance and to limit the noise power. The output signal is then squared and integrated as follows: for each in-phase or quadrature component, a number of samples over a time interval are squared and summed.

The conventional energy detection method assumes that the primary user signal is either absent or present and the performance degrades when the primary user is absent and then suddenly appears during the sensing time. An adaptive method to improve the performance of Energy detection based spectrum sensing method is proposed by T.S. Shehata et al [36]. In this proposal, a side detector is used which continuously monitor the spectrum so as to improve the probability of detection. The Primary user uses a QPSK signal with a 200 kHz band-pass bandwidth (BW). The sampling frequency is 8 times the signal BW. A 1024-point FFT is used to calculate the received signal energy. Simulation results showed that when primary users appear during the sensing time, the conventional energy detector has lower probability of detection as compared to the proposed detector.

N. Reisi et al. [37] analyzed the performance of energy detector based spectrum sensing method over fading channels. In his paper, he also presented the relation between the number of samples and Signal to noise ratio. Simulation results showed that for a 5dB decrease in the SNR, the required number of samples will be multiplied by ten.

The performance of energy detector is characterized by Receiver Operating curves usually. S. Atapattu et al. [38] used AOC (Area under the Receiver Operating curves) to analyze the performance of the energy detector method over Nakagami fading channels. Results showed that a higher value of fading parameter leads to larger average AUC, and thus, higher overall detection capability. This is because the average AUC converges to unity faster when the average SNR and the fading index increase Also, amongst the average SNR and the fading parameter, the average SNR is shown to be the dominant factor in determining the detection capability, particularly in the low-SNR region.

R. Tundra et al. [39] proposed a coherent detection method using matched filter. The comparison of capacity- robustness trade-off curves is made for radiometer and coherent detection with and without noise collaboration. The Bandwidth is assumed to be 1 MHz, Signal to noise ratio= -10 dB and the results showed that coherent detection is much better than the radiometer, i.e., for a given loss in primary data rate, it gives better robustness gains for the secondary system. Essentially, the primary system is not power limited. So, sacrificing some power to the pilot tone is not a significant cost, but it gives significant robustness gains. However, shrinking the bandwidth and using fewer degrees of freedom to improve radiometer robustness is painful since it is degrees of freedom that are the critical resource for high SNR primary users.

A cyclostationary signature is a feature, intentionally embedded in the physical properties of a digital communications signal, which may be easily generated, manipulated, detected and analyzed using low complexity transceiver architectures. P. D. Sutton et al. [40] suggested a spectrum sensing method which utilizes this feature of the transmitted signal. This method offers advantages of little signalling overhead and short signal observation times. A limitation of cyclostationary signatures generated using single OFDM subcarrier set mapping is the sensitivity exhibited to frequency-selective fading. The effects of frequency selective fading are overcome by increasing the frequency diversity of the cyclostationary signature. This is achieved through use of multiple mapped subcarrier sets in order to generate features at a number of discrete spectral frequencies but this increases the overhead. Results showed that with an observation time of just 10 transmitted symbol durations, signatures may be reliably detected in signals received with SNR of greater than 2 dB. Also, it is observed that though Signal to Noise Ratio varies little with increased signal observation time, the threshold required for a low probability of false alarm falls considerably. Thus reliable signal detection may be performed at lower levels of SNR using increased observation times.

T. Ikuma et al. [41] analyzed and compared the performance of three different types of spectrum sensing algorithms: the energy detector, autocorrelation detector and the cyclic autocorrelation detector. Energy detector is the simplest algorithm and is the optimal detector if the noise power is perfectly known. However, in the presence of noise power uncertainty, the performance of this algorithm degrades significantly. The autocorrelation detector does not require exact knowledge of the noise power. In addition to it, the computational complexity of this algorithm is reasonably low. The cyclic autocorrelation detector has an added computational complexity over the autocorrelation detector.

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Previous cooperation spectrum sensing methods described by S. M. Mishra et al.[42] and E. Visotsky et al. [43] used two rules. One used some kind of joint detection and other is based on making hard decisions to mitigate the sensitivity requirements on individual radios**.** Gathering the entire received data at one place may be very difficult under practical communication constraints. Moreover, in practice, cooperation between the cognitive radio users cannot be guaranteed always, since a user can cooperate with others only when there are other users in its vicinity monitoring the same frequency band as itself.

J. Unnikrishnan et al. [44] proposed a fusion rule in which linear quadratic detector is used for cooperative detection. Linear quadratic detector is a detector that compares a linear-quadratic function of the local decisions with a threshold. Simulation results showed that the LQ detector is seen to give around 2-3 times the detection probability as that of the single sensor detector for the interference probability values considered even though the observations are highly correlated.

In sequential detection scheme, many secondary users cooperate to detect the same primary user. It helps to reduce the delay and the amount of data needed in identification of the underutilized spectrum. A simple and computationally efficient spectrum sensing scheme for Orthogonal Frequency Division Multiplexing (OFDM) based primary user signal using its autocorrelation coefficient is proposed by S. Chaudhari et al. [45] and a decentralized sequential detection scheme is used to combine the soft decisions (autocorrelation-based LLRs) from the cooperating secondary users at the FC (Fusion Centre). The performance of Sequential detection is improved in comparison to the FSS (fixed sample size) detection. Relative efficiencies of approximately 2.0 for AWGN and 1.8 for shadowing scenarios can be obtained when there are large numbers of secondary user statistics.

A robust spectrum sensing algorithm for OFDM modulated signals at low SNR is given by H.W. Chen et al. [46]. The proposed technique is based on the unique feature provided by the in-pilot, correlating the received signal with a local pilot reference and making a decision based on the correlation outcome. In this work, effects of multiple channels and CFO (Carrier Frequency Offset) have also been taken into account. By using this technique, a shorter sensing time by 1/3 is achieved as compared to the original system in the same performance of -20dB.

Z. Quan et al. [47] proposed a spectrum sensing method which work reliably at low SNR. The basic strategy is to correlate the periodogram of the received signal with the a priori known spectral features of the primary signal. This sensing technique is asymptotically equivalent to the likelihood ratio test (LRT) at very low SNR, but with less computational complexity. That is, the spectral correlation-based detector is asymptotically optimal according to the Neyman- Pearson criterion. Simulation results show that the proposed sensing technique can reliably detect analog and digital TV signals at SNR levels as low as −20 dB.

A GLRT (Generalized Likelihood Ratio Test) based spectrum sensing method by exploiting the statistics of the received signal and the prior knowledge on the channel, noise and data signal; is suggested by J. F. Segura et al. [48]. The proposed method is used when the secondary users have only a small number of signal samples. Results showed that the simple non-iterative GLRT sensing algorithm, offers the best performance in all systems under considerations, including slow-fading channels, fast-fading channels and OFDMA systems whereas iterative sensing algorithms offer high complexities.

A novel spectrum-sensing method for cognitive radio (CR) based on stochastic resonance (SR) has been suggested by D. He et al. [49]. The spectral power of primary users (PUs) can be amplified, and the signal-to-noise ratio (SNR) of a received signal can be increased using SR. This ensures that the detection probability of the proposed approach is higher than that of the traditional energy detector and about 5dB SNR improvement is obtained. Simulation results show that the effectiveness of the proposed SR-based spectrum-sensing approach, particularly under low SNR circumstances (SNR <-10 dB) is better than that of the traditional energy-detection method. The computational complexity of the proposed approach can also be guaranteed to be comparable with the traditional spectrum-sensing methods as 5 multiplications per sample are required**.**

One requirement of spectrum sensing method is the fast and effective detection of idle primary channels by secondary users. A two-stage method has been proposed by L. Luo et al. [50] that comprises preliminary coarse resolution sensing followed by fine resolution sensing thus providing significantly faster idle channel detection than conventional single-stage random searching. The results showed that the two-stage sensing is generally preferable, especially when L/N (Ratio of idle channels to the total number of channels) is small. However, the mean number of detection steps required for one stage sensing decreases dramatically as *L/N* increases, and eventually becomes slightly smaller than that of the two-stage scheme due to the increased mean number of steps required in the CRS stage.

The conventional periodic sensing scheme may work well in a favourable environment; however, its performance significantly degrades under certain adverse conditions. These schemes require a long sensing time to detect a weak signal from the primary user with fast-channel usage variation. One possible solution to sense very weak PU signals is to prolong the sensing time. However, this leads to low spectrum utilization. An adaptive scheme given by K.W.Choi et al. [51] adaptively decides whether to sense the channel or to transmit the user data based on previous sensing results thereby improving the spectrum utilization. Two thresholds are used and channel utilization of 0.75 and a collision probability of 0.01 by choosing 0.015 as the value of lower threshold, is obtained.

In cognitive radio (CR) networks, there is a trade-off between two conflicting goals at the same time: one is to maximize its own transmit throughput; and the other is to minimize the amount of interference it produces at each primary receiver. R. Zhang et al.[52] in his work, made use of multiple antennas to effectively balance between spatial multiplexing for the secondary transmission and interference avoidance at the primary receivers. Results showed that even under stringent interference-power constraints, substantial capacity gains are achievable for the secondary transmission by employing multi-antennas at the secondary transmitter.

Two major challenges exist in the development and deployment of cognitive radio networks: spectrum sensing and hidden terminal problem. Z. Han et al. [47] suggested a network structure in which the spectrum sensing task is separated from the secondary users (secondary users). The sensing devices for the secondary users are placed within the networks of licensed users (primary users). These sensing devices sense the primary users' activity and also decide whether to permit a secondary user's transmission. The proposed protocol is analyzed using the theory of Lame curve. The other advantage of the proposed scheme is from the business model point of view: the expensive sensing devices will be implemented by the cognitive radio service provider, instead of being built in the secondary user devices which are usually consumer products demanding low cost.

2.2 Gaps in Studies:

I. Budiarjo et al. [36] et al. proposed the use of TDCS as transmission technology for Cognitive Radio. Although TDCS gives larger degree of freedom in shaping its pulse without reducing its bit rate, but complexity of TDCS is very high as compared to OFDM. C. Han et al. [32] suggested a new implementation of TDCS, i.e. OFDM-based TDCS in which the complex RAKE receiver is avoided. But, drawback of this OFDM-based TDCS is that the overhead may be relatively large, when the channel multipath delay is very large.

Energy detection based spectrum sensing method is discussed by F.F. Digham et al. [34] and V. I. Kostylev et al. [35]. Although it is the simplest method and doesnot require any prior knowledge of the signal. However its performance is susceptible to uncertainty in noise power.

R. Tundra et al. [39] suggested a coherent detection method using matched filter which performs much better than the conventional energy detector. But there was a drawback of it is that it uses fewer degrees of freedom which is a critical resource for high SNR Primary users.

A two-stage spectrum sensing method that comprises preliminary coarse resolution sensing followed by fine resolution sensing thus providing significantly faster idle channel detection than conventional single-stage random searching has been given by L. Luo et al. [50]. However, the mean number of detection steps required for one stage sensing decreases dramatically as *L/N* increases, and eventually becomes slightly smaller than that of the two-stage scheme due to the increased mean number of steps required in the CRS stage.

J. F. Segura et al. [48] proposed a GLRT (Generalized Likelihood Ratio Test) based spectrum sensing method by exploiting the statistics of the received signal and the prior knowledge on the channel, noise and data signal. In his paper, GLRT offers the best performance in all systems under considerations, including slow-fading channels, fast-fading channels and OFDMA systems. S. Chaudhari et al. [45] in his paper illustrated that the cooperative detection improves the system performance. In this thesis also, GLRT is used in the cyclic-prefix based spectrum sensing method and cooperative detection is used to improve the probability of detection of spectrum sensing method.

2.3 Objectives:

Primary objectives of this thesis are:

- ❖ To study and simulate the OFDM based cognitive radio transmitter.
- ❖ To study and analyze the performance of energy detection based spectrum sensing technique and cyclic -prefix based spectrum sensing technique using ROC (Receiver Operating characteristics) curves.
- ❖ To show that the cooperative detection improves the performance of spectrum sensing techniques.
- ❖ To study and analyze the impact of fading channels on the spectrum sensing techniques.

2.4 Methodology:

In this thesis, two spectrum sensing sensing techniques (Energy detection based spectrum sensing and Cyclic prefix Based Spectrum Sensing) have been discussed. Mathematical description of both these techniques is illustrated and the closed form expressions of probability of detection for AWGN and Rayleigh Channels are described. Experimental results for Energy detection based spectrum sensing using squaring and cubing operation; and for Cyclic-Prefix based Spectrum Sensing over AWGN and Rayleigh channels are presented using ROC curves.

Cooperative detection is a very valuable tool in improving the performance of spectrum sensing techniques. The impact of cooperative detection over energy detection and cyclic-prefix based spectrum sensing has also been illustrated.

CHAPTER 3

ENERGY DETECTION BASED SPECTRUM SENSING

Energy detection is the most popular spectrum sensing method since it is simple to implement and does not require any prior information about the primary signal [37]. An energy detector (ED) simply treats the primary signal as noise and decides on the presence or absence of the primary signal based on the energy of the observed signal. Since it does not need any a priori knowledge of the primary signal, the ED is robust to the variation of the primary signal. Moreover, the ED does not involve complicated signal processing and has low complexity. In practice, energy detection is especially suitable for wide-band spectrum sensing [7]. Energy detector is composed of four main blocks [48]:

1) Pre-filter.

2) A/D Converter (Analog to Digital Converter).

3) Squaring Device.

4) Integrator.

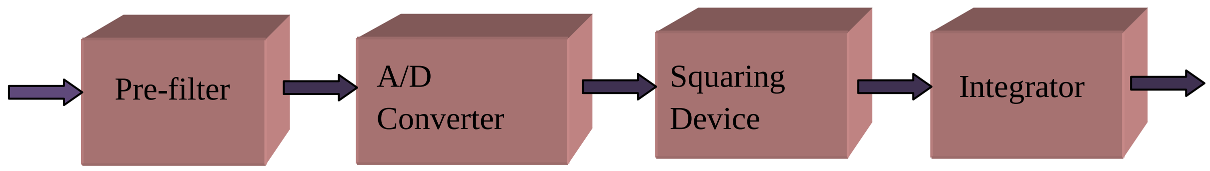

Figure 14: Block Diagram of Energy Detection Based Spectrum Sensing Using Squaring Operation.

The output that comes out of the integrator is energy of the filtered received signal over the time interval T and this output is considered as the test statistic to test the two hypotheses H_0 and H_1 [55].

H_0 : corresponds to the absence of the signal and presence of only noise.

H_1 : corresponds to the presence of both signal and noise.

3.1 Test Statistics

Considering the following notations:

$x(t)$ is the transmitted signal waveform, $y(t)$ is the received signal waveform, $w_i(t)$ is in-phase noise component, $w_q(t)$ is quadrature phase component, B_N is noise bandwidth, N_0 is power-spectral density (two-sided), N is power spectral density (one-sided), T is the sampling interval, E_s is the signal energy, Λ is decision threshold. The received signal $y(t)$ is filtered by a pre-filter which is a band-pass filter. The filtered signal is then passed through A/D converter i.e. converted to samples. Now, if noise $w(t)$ is a band-pass random process, its sample function can be written as [56, Eq. (5.4)]:

$$w(t) = w_i(t)cosw_ct - w_q(t)sinw_ct \tag{3.1}$$

where w_c is angular frequency. If $w(t)$ is confined to a bandwidth of B_N and has a power-spectral density N_0, then $w_i(t)$ and $w_q(t)$ can be considered as two low-pass processes with bandwidth less than $B_N/2$ and power spectral density of each equal to $2N_0$. Now, if a sample function has Bandwidth B and duration T, then it can be described approximately by a set of sample values $2BT$ or degrees of freedom will be $2BT$. Thus, $w_i(t)$ and $w_q(t)$ each will have degrees of freedom, d equal to B_NT [49]. Also, using approximation as in [57, Eq. (2.1-21)]:

$$\int_0^T w^2(t)dt = \frac{1}{2}\int_0^T [w_i{}^2(t) + w_q{}^2(t)]dt \tag{3.2}$$

As $w_i(t)$ and $w_q(t)$ are considered as low-pass processes, therefore according to sampling theorem, $w_i(t)$ can be written as [58]:

$$w_i(t) = \sum_{k=-\infty}^{+\infty} c_{ik}sinc(B_Nt - k) \tag{3.3}$$

where $sincx = \frac{sin\pi x}{\pi x}$ and $c_{ik} = w_i(\frac{k}{B_N})$ is a Gaussian random variable with zero mean and variance $\sigma_k{}^2 = 2N_0B_N, \forall\, k$.

Now, using the fact as in [55],

$$\int_{-\infty}^{\infty} sinc(B_N t - k) sinc(B_N t - m) dt = \begin{cases} \frac{1}{B_N}, & k = m \\ 0, & k \neq m \end{cases} \quad (3.4)$$

Therefore using (3) and (4), we obtain:

$$\int_{-\infty}^{\infty} \mathrm{w_i}^2(\mathrm{t})\mathrm{dt} = \frac{1}{\mathrm{B_N}} \sum_{\mathrm{k}=-\infty}^{+\infty} \mathrm{c_{ik}}^2 \quad (3.5)$$

As $w_i(t)$ has $B_N T$ degrees of freedom over the interval $(0, T)$ [55], therefore

$$w_i(t) = \sum_{k=1}^{B_N T} c_{ik} sinc(B_N t - k), \qquad 0 < t < T \quad (3.6)$$

And the integral $\int_{-\infty}^{\infty} w_i{}^2(t)dt$ over the interval $(0, T)$ can be written as

$$\int_0^T w_{\mathrm{i}}{}^2(t)dt = \frac{1}{B_N} \sum_{k=1}^{B_N T} c_{ik}{}^2 \quad (3.7)$$

Similarly,

$$\int_0^T w_q{}^2(t)dt = \frac{1}{B_N} \sum_{k=1}^{B_N T} c_{qk}{}^2 \quad (3.8)$$

Substituting $\frac{c_{ik}}{\sqrt{2B_N N_0}} = d_{ik}$ and $\frac{c_{qk}}{\sqrt{2B_N N_0}} = d_{qk}$ in (3.7) and (3.8), and using (2), we arrive at [55]:

$$\int_0^T w^2(t)dt = \left[\sum_{k=1}^{B_N T} d_{ik}{}^2 + \sum_{k=1}^{B_N T} d_{qk}{}^2\right].\ N_0 \quad (3.9)$$

Similarly, considering transmitted signal $x(t)$ as a band-pass process [56], we have

$$\int_0^T x^2(t)dt = \left[\sum_{k=1}^{B_N T} b_{ik}{}^2 + \sum_{k=1}^{B_N T} b_{qk}{}^2\right].\ N_0 \quad (3.10)$$

or,

$$\sum_{k=1}^{B_N T} (b_{ik}{}^2 + b_{qk}{}^2) = \frac{E_s}{N_0} \quad (3.11)$$

where $b_{ik} = \frac{x_i\left(\frac{k}{B_N}\right)}{\sqrt{2B_N N_0}}$, $b_{qk} = \frac{x_q\left(\frac{k}{B_N}\right)}{\sqrt{2B_N N_0}}$ and $E_s = \int_0^T x^2(t)dt$ is the signal energy. The output of the integrator is $Y = \frac{1}{T}\int_0^T y^2(t)\, dt$.Test statistic can be Y or any quantity monotonic with Y. Taking Y' as the test statistic [55]:

$$Y' = \frac{1}{N_0}\int_0^T y^2(t)\, dt \tag{3.12}$$

Now, Under Hypothesis H_0, the received signal is only noise i.e. $y(t) = w(t)$, therefore using (3.9) test statistic Y' can be written as:

$$Y' = \sum_{k=1}^{B_N T} ({d_{ik}}^2 + {d_{qk}}^2) \tag{3.13}$$

Thus, Test statistic Y'under H_0 is chi-square distributed [57] with $2B_N T$ degrees of freedom or $Y' \sim \chi^2_{2d}$ [34]. Under Hypothesis H_1, received signal is the sum of signal and noise i.e. $y(t) = w(t) + x(t)$. Again considering $y(t)$ as a band-limited process [56], using equations (3.2- 3.10), we arrive at [55]:

$$\int_0^T y^2(t)dt = \left[\sum_{k=1}^{B_N T}(d_{ik} + b_{ik})^2 + \sum_{k=1}^{B_N T}(d_{qk} + b_{qk})^2\right].\, N_0 \tag{3.14}$$

Then, using (3.12) and (3.14), test statistic Y' can be written as:

$$Y' = \left[\sum_{k=1}^{B_N T}(d_{ik} + b_{ik})^2 + \sum_{k=1}^{B_N T}(d_{qk} + b_{qk})^2\right] \tag{3.15}$$

Thus, test statistic Y'under H_1 has a non-central chi-square distribution [57] with $2B_N T$ degrees of freedom and a non-centrality parameter λ given by $\frac{E_s}{N_0}$ [55]. Now, Defining Signal to Noise Ratio, γ in terms of non-centrality parameter as in [34]:

$$\gamma = \frac{E_s}{N} = \frac{E_s}{2N_0} = \frac{\lambda}{2} \tag{3.16}$$

Thus, test statistic Y' under H_1: $Y' \sim \chi^2_{2d}(\lambda)$ [34]. Also, probability density function of Y' can be expressed as [57, Eq. (2.3-21) & Eq. (2.3-29)]:

$$f_{Y'}(y) = \begin{cases} \dfrac{1}{2^d \Gamma(u)} y^{d-1} e^{-(\frac{y}{2})}, & H_0 \\ \dfrac{1}{2}\left(\dfrac{y}{\lambda}\right)^{\frac{d-1}{2}} e^{-(\frac{\lambda+y}{2})} I_{d-1(\sqrt{\lambda})}, & H_1 \end{cases} \tag{3.17}$$

3.2 Probability of Detection for AWGN Channel

Probability of detection P_d and false alarm P_f can be evaluated respectively by [34]:

$$P_d = P(Y' > \Lambda | H_1) \tag{3.18}$$

$$P_f = P(Y' > \Lambda | H_0) \tag{3.19}$$

where Λ is the decision threshold. Also, P_f can be written in terms of probability density function as:[59, Eq. (4-16) & Eq. (4-22)]

$$P_f = \int_{\Lambda}^{\infty} f_{Y'}(y)\, dy \tag{3.20}$$

Using (3.19),

$$P_f = \frac{1}{2^d \Gamma(d)} \int_{\Lambda}^{\infty} y^{d-1} e^{-(\frac{y}{2})}\, dy \tag{3.21}$$

Dividing and multiplying the R.H.S. of above equation by 2^{d-1}, we get

$$P_f = \frac{1}{2\Gamma(d)} \int_{\Lambda}^{\infty} \left(\frac{y}{2}\right)^{d-1} e^{-(\frac{y}{2})}\, dy \tag{3.22}$$

Substituting $\frac{y}{2} = t, \frac{dy}{2} = dt$ and changing the limits of integration to $(\frac{\Lambda}{2}, \infty)$, we get

$$P_f = \frac{1}{\Gamma(d)} \int_{\Lambda/2}^{\infty} (t)^{d-1} e^{-(t)}\, dt \tag{3.23}$$

or,

$$P_f = \frac{\Gamma(d, \Lambda/2)}{\Gamma(d)} \tag{3.24}$$

where $\Gamma(.)$ is the incomplete gamma function [60]. Now, Probability of detection can be written by making use of the cumulative distribution function [59, Eq. (4.22)].

$$P_d = 1 - F_{Y'}(\Lambda) \tag{3.25}$$

The cumulative distribution function (CDF) of Y' can be obtained (for an even number of degrees of freedom which is $2d$ in our case) as [57, Eq. (2.1-124)]:

$$F_{Y'}(y) = 1 - Q_d\left(\sqrt{\lambda}, \sqrt{y}\right) \tag{3.26}$$

Therefore, using (3.25) and (3.26), probability of detection P_d for AWGN channel is [34]:

$$P_d = Q_d\left(\sqrt{\lambda}, \sqrt{\Lambda}\right) \tag{3.27}$$

Using (16),

$$P_d = Q_d\left(\sqrt{2\gamma}, \sqrt{\Lambda}\right) \tag{3.28}$$

where, $Q_u(.,.)$ is the generalized Marcum-Q function and thus, probability of detection for AWGN Channel can be evaluated using above expression.

3.3 Probability of Detection for Rayleigh Channel

Probability density function for Rayleigh channel is [53, Eq. (4-44)]:

$$f(\gamma) = \frac{1}{\bar{\gamma}} ex\,p\left(\frac{-\gamma}{\bar{\gamma}}\right) \qquad\qquad \gamma \geq 0 \tag{3.29}$$

The Probability of detection for Rayleigh Channels is obtained by averaging their probability density function over probability of detection for AWGN Channel [34]:

$$P_{d,R} = \int_0^\infty P_d\, f(\gamma) d\gamma \tag{3.30}$$

where $P_{d,R}$ is the probability of detection for Rayleigh channel.

With (3.28) and (3.29), (3.30) becomes:

$$P_{d,R=}\frac{1}{\bar{\gamma}} \int_0^\infty Q_d\left(\sqrt{2\gamma}, \sqrt{\Lambda}\right) exp\left(\frac{-\gamma}{\bar{\gamma}}\right) d\gamma \tag{3.31}$$

Now, substituting $\sqrt{\gamma} = x\ , \gamma = x^2, d\gamma = 2xdx$ in (3.31), we get

$$P_{d,R} = \frac{2}{\bar{\gamma}} \int_0^\infty x.\, Q_d\left(\sqrt{2}x, \sqrt{\Lambda}\right) exp\left(\frac{-x^2}{\bar{\gamma}}\right) dx \tag{3.32}$$

Considering the result [61]

$$\int_0^{\infty} dx.x.exp\left(\frac{-p^2x^2}{2}\right)Q_M(ax,b) = \frac{1}{p^2}.exp\left(-\frac{b^2}{2}\right).\left\{\left(\frac{p^2+a^2}{a^2}\right)^{M-1}\left[exp\left(\frac{b^2}{2}.\frac{a^2}{p^2+a^2}\right) - \sum_{n=0}^{M-2}\frac{1}{n!}\left(\frac{b^2}{2}.\frac{a^2}{p^2+a^2}\right)^n\right] + \sum_{n=0}^{M-2}\frac{1}{n!}\left(\frac{b^2}{2}\right)^n\right\} \quad (3.33)$$

Comparing (3.32) and (3.33), $p^2 = \frac{2}{\bar{\gamma}}, a = \sqrt{2}\, b = \sqrt{\Lambda}, M = d$.Thus, using (3.33), Probability of detection for Rayleigh channel can be expressed as [34]:

$$P_{d,R} = e^{(-\Lambda/2)} \sum_{n=0}^{d-2}\frac{1}{n!}\left(\frac{\Lambda}{2}\right)^n + \left(\frac{1+\bar{\gamma}}{\bar{\gamma}}\right)^{d-1}\left[\exp\left(-\frac{\Lambda}{2(1+\bar{\gamma})}\right) - \exp\left(-\frac{\Lambda}{2}\right)\sum_{n=0}^{d-2}\frac{1}{n!}\left(\frac{\Lambda\bar{\gamma}}{2(1+\bar{\gamma})}\right)^n\right] \quad (3.34)$$

The above expression gives the probability of detection for Energy detection based spectrum sensing over Rayleigh Channel.

3.4 Comparative Study

Energy detector based approach, also known as radiometry or periodogram, is the most common way of spectrum sensing because of its low computational and implementation complexities. The signal is detected by comparing the output of the energy detector with a threshold which depends on the noise floor. In addition, it is more generic as compared to other methods, as receivers do not need any knowledge on the primary users' signal [22]. While compared to matched filtering energy detection requires a longer sensing time to achieve a desired performance level. However, its low cost and implementation simplicity render it a favourable candidate for spectrum sensing in cognitive radio systems [8].

The main drawback of the energy detector is its inability to discriminate between sources of received energy (the primary signal and noise), making it susceptible to uncertainties in background noise power, especially at low signal-to-noise ratio (SNR). If some features of the primary signal such as its carrier frequency or modulation type are known, more sophisticated feature detectors may be employed to address this issue at the cost of increased complexity. These detectors rely on the fact that, unlike stationary noise, most communication signals exhibit spectral correlation due to their built-in periodicities (features) such as carrier frequency, bit rate, and cyclic prefixes. Since the spectral correlation properties of different signals are usually unique, feature detection allows a cognitive radio to detect a specific primary signal buried in noise and interference. However, Energy detection is considered to be optimal if the cognitive devices have no prior information about the features of the primary signals except local noise statistics [62].

Thus, challenges with energy detector based sensing include selection of the threshold for detecting primary users, inability to differentiate interference from primary users and noise and poor performance under low signal-to-noise ratio (SNR) values. Moreover, energy detectors do not work efficiently for detecting spread spectrum signals [8].

CHAPTER 4

CYCLIC PREFIX BASED SPECTRUM SENSING

This method uses a special feature of OFDM signals i.e. Cyclic prefix to detect the presence of the primary user's signal.

4.1 Test Statistics

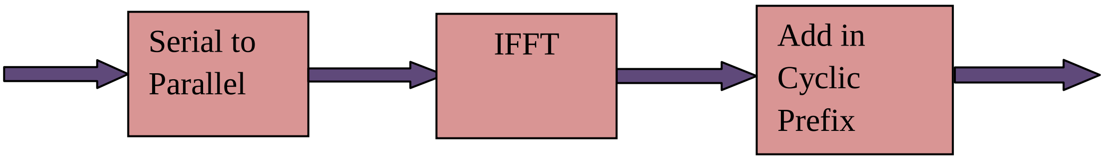

Figure 15: Simplified block diagram of OFDM transmitter.

An OFDM System with T_d subcarriers is considered:

$$\{a(0), a(1), \ \ldots\ldots, a(T_d - 1)\}$$

The block of data in frequency is converted into time-domain signals by the inverse fast fourier transform (IFFT) function block. The IFFT block size is assumed to be equal to T_d. To guarantee the continuity of the signal and orthogonality between subcarriers, the OFDM transmitter copies the last T_c samples in the OFDM symbol and attaches them to the front of the OFDM symbol as Cyclic prefix. i.e. after IFFT operation, each block of time-domain signal is appended with a sequence of $T_c < T_d$ symbols to the beginning of each block [63].

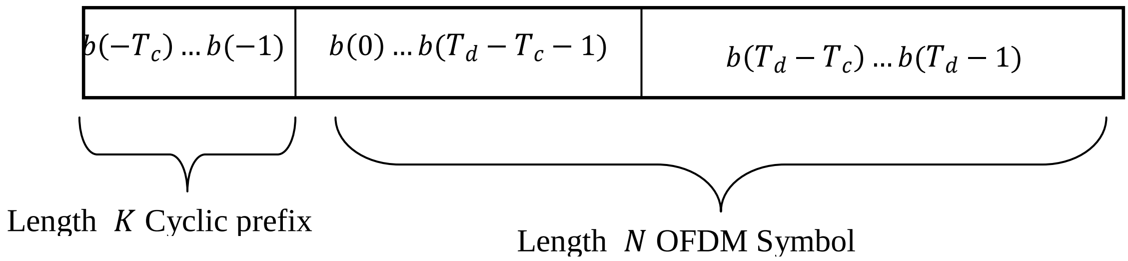

Figure 16 : OFDM Frame.

The structure of the resulting time-domain signal is represented in Figure 16. The signal $a(-T_c), \ldots, a(-1)$ is an exact copy of $a(T_d - T_c), \ldots., a(T_d - 1), i.e. a(t) =$

$a(T_d + t)$, where index $t \in [-T_c, -1]$ in Figure 4.3. The relationship between the signals between the signals before and after the IFFT block is [45]:

$$a(t) = \frac{1}{\sqrt{T_d}} \sum_{k=0}^{T_d-1} b(k) e^{j2\pi(t-T_c)k/T_d} \tag{4.1}$$

The time-domain signal $b(t)$ is pulse shaped before transmission.

A transmitted OFDM frame may contain several such blocks. Let $\{y(t)\}$ denote the symbols of the transmitted OFDM frame. Detection is based on two hypotheses :

$$H_0: \qquad r(t) = n(t) \tag{4.2}$$

and

$$H_1: \qquad r(t) = y(t) + n(t) \tag{4.3}$$

where $r(t)$ is the received signal, $n(t)$ is the additive white Gaussian noise with zer mean and variance σ_n^2. H_0 represents the hypothesis when the signal is absent and only noise is present. H_1 represents the hypothesis when both signal and noise are present. Let χ is a measure of correlation between two samples distance T_d apart [64].

$$\chi = \sum_{t=1}^{W} \frac{r(t) r^*(t + T_d)}{E[|r(t)|^2]} \tag{4.4}$$

For CP (Cyclic prefix) OFDM signal, the statistic χ under the above two hypothesis can be expressed as [45]:

$$H_0: \qquad \chi = \sum_{t=1}^{W} \frac{n(t) n^*(t + T_d)}{E[|n(t)|^2]} \tag{4.5}$$

and

$$H_1: \qquad \chi = \sum_{t=1}^{W} \frac{\big(y(t) + n(t)\big)(y^*(t + T_d) + n^*(t + T_d))}{E[|y(t) + n(t)|^2]} \tag{4.6}$$

4.2 Probability of detection for AWGN Channel

The correlation will be at its peak when an OFDM signal is present due to the CP. On the other hand, noise or a signal without this property is uncorrelated, and there will be minor, if any, correlation between samples from noise or other signals. Therefore, based on the statistic χ, we could distinguish an OFDM signal from noise or other signals. First, we will need to obtain the pdf of χ under each hypothesis [45].

The detection time required for signal detection in OFDM systems in Cognitive Radio and is usually at the level of hundreds of milliseconds. This corresponds to an observation window with thousands to hundreds of thousands of samples.

Under hypothesis H_0, χ can be assumed to be a Gaussian distributed random process based on the central limit theory [59]. The mean of χ can be calculated as:

$$\mu_0 = E[\ \chi|H_0] \tag{4.7}$$

$$= E\left[\sum_{t=1}^{W} \frac{\left(n(t)n^*(t+T_d)\right)}{E[|n(t)|^2]}\right] \tag{4.8}$$

$$= \sum_{t=1}^{W} \frac{E[(n(t)\left(n^*(t+T_d)\right)]}{|\sigma_n|^2} \tag{4.9}$$

As noise samples are uncorrelated, the above term reduces to zero i.e.

$$\mu_0 = 0 \tag{4.10}$$

Variance of χ under Hypothesis H_0 can be written as [45] :

$$\chi = \sum_{t=1}^{W} \frac{E[\left(y(t)+n(t)\right)(y^*(t+T_d)+n^*(t+T_d))}{E[|y(t)+n(t)|^2]} \tag{4.11}$$

$$\sigma_0^2 = E[|\chi|^2|H_0] \tag{4.12}$$

$$= \sum_{\tau_1} \sum_{\tau_2} \frac{E[(n(\tau_1)n^*(T_d + \tau_1))(n(\tau_2)n^*(T_d + \tau_2)]}{\sigma_n^4} \tag{4.13}$$

When $\tau_1 = \tau_2 = \tau$ and using the assumption that noise samples are uncorrelated, equation(4.13) can be written as:

$$\sigma_0^2 = \sum_{\tau} \frac{E\left[\left(n(\tau)n^*(T_d + \tau)\right)\right]E[(n(\tau)n^*(T_d + \tau)]}{\sigma_n^4} \tag{4.14}$$

$$\sigma_0^2 = \sum_{\tau=1}^{W} \frac{\sigma_n^2 . \sigma_n^2}{\sigma_n^4} = W \tag{4.15}$$

Mean under Hypothesis H_1 can be expressed as:

$$\mu_1 = E[\ \chi | H_1] \tag{4.16}$$

$$= E\left[\sum_{t=1}^{W} \frac{\left(y(t) + n(t)\right)\left(y^*(t + T_d) + n^*(t + T_d)\right)}{E[|y(t) + n(t)|^2]}\right] \tag{4.17}$$

$$= \sum_{t=1}^{W} \frac{E[(y(t)\left(y^*(t + T_d)\right)]}{E[|y(t) + n(t)|^2]} \tag{4.18}$$

Since $y(t) = \left(y^*(t + T_d)\right)$ only when $y(t)$ falls into the cyclic prefix period, equation (4.18) can be expressed as [65]:

$$\mu_1 = \sum_{t=1}^{W} \frac{P(y(t) \in CP)E[|y(t)|^2]}{\sigma_y^2 + \sigma_n^2} \tag{4.19}$$

$$= \sum_{t=1}^{W} \frac{T_c}{T_d + T_c} \frac{\sigma_y^2}{\sigma_y^2 + \sigma_n^2} \tag{4.20}$$

$$= \sum_{t=1}^{W} K \frac{\sigma_y^2}{\sigma_y^2 + \sigma_n^2} \tag{4.21}$$

$$= \frac{KW\gamma}{1+\gamma} \tag{4.22}$$

where $K = \frac{T_c}{T_d+T_c}$ and $\gamma = \frac{\sigma_y^2}{\sigma_n^2}$ is the signal to noise ratio.

Variance under Hypothesis H_1 can be expressed as [59]:

$$\sigma_1^2 = E[|\chi|^2|H_1] - {\mu_1}^2 \tag{4.23}$$

According to definition of χ in (4.16) , the first term in equation (4.23) can be written as:

$$E[|\chi|^2] = \sum_{t=1}^{W} \frac{\left|E\left[\left(y(t)+n(t)\right)\left(y^*(t+T_d)+n^*(t+T_d)\right)\right]\right|^2}{E[|y(t)+n(t)|^2]} \tag{4.24}$$

$$= \sum_{t=1}^{W} \frac{E\left[\left(y(\tau_1)+n(\tau_1)\right)\left(y^*(\tau_1+T_d)+\ n^*(\tau_1+T_d)\right)\,\left(y(\tau_2)+n(\tau_2)\right)\left(y^*(\tau_2+T_d)+n^*(\tau_2+T_d)\right)\right]}{E[|y(t)+n(t)|^2]}$$

(4.25)

After removing terms due to uncorrelated noise samples [65]:

$$= \frac{1}{W^2}\sum_{\tau_1}\sum_{\tau_2(\tau_1 \neq \tau_2)} E[y(\tau_1)y^*(T_d+\tau_1)y^*(\tau_2)y(T_d+\tau_2)] + \frac{1}{W}E[|z(t)|^2] \tag{4.26}$$

where $z(t) = (\left(y(t)+n(t)\right)\,(y^*(t+T_d)+\ (n^*(t+T_d)\right))$

Now, Considering some expectations as the received signal and noise are Gaussian Distributed :

$$E[y(t)] = E[y(t+T_d)] = E[y^*(t)] = E[y^*(t+T_d)] = 0 \tag{4.27}$$

$$E[|y(t)|^2] = \sigma_y^2 \tag{4.28}$$

$$E[y(t)y^*(t+T_d)] = \mu_1^* = K\sigma_y^2 \tag{4.29}$$

$$E[y(t)y(t+T_d)] = 0 \tag{4.30}$$

Considering the Second moment of $z(t) = (y(t)+n(t))\ (y^*(t+T_d)+\ (n^*(t+T_d))$

After removing zeros,

$$E[|z(t)|^2] = E[|y(t)|^2|y(t+T_d)|^2] + E[|y(t)|^2|n(t+T_d)|^2] + E[|n(t)|^2|y(t+T_d)|^2] + E[|n(t)|^2|n(t+T_d)|^2] \quad (4.31)$$

Since $y(t)$ and $n(t)$ are complex Gaussian distributed, according to formula [66] ,to compute fourth moments:

$$E[d_1d_2d_3d_4] = E[d_1d_2]E[d_3d_4] + E[d_1d_3]E[d_2d_4] + E[d_1d_4]E[d_2d_3] - 2E[d_1]E[d_2]E[d_3]E[d_4] \quad (4.32)$$

Using (4.32) and considering first term of equation(4.31):

$$E[|y(t)|^2|y(t+T_d)|^2] = E[|y(t)|^2]E[|y(t+T_d)|^2] + E[y(t)y(t+T_d)]E[y^*(t)y^*(t+T_d)] + E[y(t)y^*(t+T_d)]E[y^*(t)y(t+T_d)] \quad (4.33)$$

Using (4.28) and (4.29), equation (4.33) becomes:

$$E[|y(t)|^2|y(t+T_d)|^2] = (1+K^2)\sigma_y^4 \quad (4.34)$$

Using (4.28), second and third term of equation(4.31) can be written as:

$$E[|y(t)|^2|n(t+T_d)|^2] = E[|y(t)|^2]E[|n(t+T_d)|^2] = \sigma_y^2\sigma_n^2 \quad (4.35)$$

$$E[|n(t)|^2|y(t+T_d)|^2] = E[|y(t+T_d)|^2]E[|n(t)|^2] = \sigma_y^2\sigma_n^2 \quad (4.36)$$

Considering σ_n^2 as noise variance, fourth term of equation (4.31) is given by:

$$E[|n(t)|^2|n(t+T_d)|^2] = E[|n(t)|^2]E[|n(t+T_d)|^2] = \sigma_n^4 \quad (4.37)$$

Using (4.34), (4.35), (4.36) and (4.37) , Equation (4.31) can be written as [66]:

$$E[|z(t)|^2] = (1+K^2)\sigma_y^4 + 2\sigma_y^2\sigma_n^2 + \sigma_n^4$$

Considering the first term of equation(4.26):

$$= \frac{1}{W^2}\sum_{\tau_1}\sum_{\tau_2(\tau_1\neq\tau_2)} E[y(\tau_1)y^*(T_d+\tau_1)y^*(\tau_2)y(T_d+\tau_2)] \quad (4.38)$$

$$= \frac{1}{W^2}\sum_{\tau_1}\sum_{\tau_2(\tau_1\neq\tau_2)}\{E[y(\tau_1)y^*(T_d+\tau_1)]E[y^*(\tau_2)y(T_d+\tau_2)] + E[y(\tau_1)y^*(\tau_2)]E[y^*(T_d+\tau_1)y(T_d+\tau_2)] + E[y(\tau_1)y(T_d + \tau_2)]E[y^*(T_d+\tau_1)y^*(\tau_2)]\} \quad (4.39)$$

The second term with in the brace is non-zero only when $\tau_1 = M + \tau_2$ or, $\tau_2 = M + \tau_1$. The third term is zero since $E[y(t)] = 0$.

$$E[|\chi|^2] = \left(1+\frac{2}{W}\right){\mu_1}^2 + \frac{1}{W}\left(\sigma_y^2+\sigma_n^2\right)^2 \quad (4.40)$$

Using equation (4.22) and (4.40), equation (4.23) can be written as:

$$\sigma_1^2 = W\left[1+\frac{2K^2\gamma^2}{(1+\gamma)^2}\right] \quad (4.41)$$

Likelihood Ratio test of the statistic χ in logarithmic scale can be written as [48]:

$$\Lambda = ln\frac{p_{\chi|H_1}(\chi|H_1)}{p_{\chi|H_0}(\chi|H_0)} \quad (4.42)$$

As signal and noise are Gaussian distributed, therefore the pdf's of χ under H_1 and H_0 can be expressed as [59]:

$$p_{\chi|H_1}(\chi|H_1) = \frac{1}{\sqrt{2\pi\sigma_1^2}}\exp\left(-\frac{(\chi-\mu_1)^2}{2\sigma_1^2}\right) \quad (4.43)$$

$$p_{\chi|H_0}(\chi|H_1) = \frac{1}{\sqrt{2\pi\sigma_0^2}}\exp\left(-\frac{(\chi-\mu_0)^2}{2\sigma_0^2}\right) \quad (4.44)$$

Using Equation(4.43) and (4.44), equation (4.42) can be written as:

$$\Lambda = ln\frac{\sigma_0}{\sigma_1} + \frac{|\chi|^2}{2\sigma_0^2} - \frac{|\chi-\mu_1|^2}{2\sigma_1^2} \quad (4.45)$$

Therfore the Generalized LRT is[48] :

$$H_0: \qquad \Lambda < lnT_0 \quad (4.46)$$

$$H_1: \qquad \Lambda > lnT_0 \quad (4.47)$$

where (T_0) is the likelihood test ratio. Using (4.45), (4.46) and (4.47), The likelihood test can be written as [45] :

$$ln\frac{\sigma_0}{\sigma_1}+\frac{|\chi|^2}{2\sigma_0^2}-\frac{|\chi-\mu_1|^2}{2\sigma_1^2}=ln(T_0) \tag{4.48}$$

or,

$$\frac{|\chi|^2}{2\sigma_0^2}-\frac{|\chi-\mu_1|^2}{2\sigma_1^2}=ln(T_0)-ln\frac{\sigma_0}{\sigma_1} \tag{4.49}$$

or,

$$\frac{|\chi|^2}{2\sigma_0^2}-\frac{|\chi-\mu_1|^2}{2\sigma_1^2}=ln(T_0\frac{\sigma_1}{\sigma_0}) \tag{4.50}$$

or,

$$\frac{|\chi|^2}{2\sigma_0^2}-\frac{|\chi|^2}{2\sigma_1^2}-\frac{|\mu_1|^2}{2\sigma_1^2}+\frac{2\chi\mu_1}{2\sigma_1^2}=ln(T_0\frac{\sigma_1}{\sigma_0}) \tag{4.51}$$

or,

$$\frac{|\chi|^2}{2}\left(\frac{1}{\sigma_0^2}-\frac{1}{\sigma_1^2}\right)-\frac{|\mu_1|^2}{2\sigma_1^2}+\frac{\chi\mu_1}{\sigma_1^2}=ln(T_0\frac{\sigma_1}{\sigma_0}) \tag{4.52}$$

or,

$$\frac{|\chi|^2}{2\sigma_1^2}\left(\frac{\sigma_1^2}{\sigma_0^2}-1\right)-\frac{|\mu_1|^2}{2\sigma_1^2}+\frac{\chi\mu_1}{\sigma_1^2}=ln(T_0\frac{\sigma_1}{\sigma_0}) \tag{4.53}$$

or,

$$\frac{|\chi|^2}{2\sigma_1^2}\left(\frac{\sigma_1^2}{\sigma_0^2}-1\right)-\frac{|\mu_1|^2}{2\sigma_1^2}+\frac{\chi\mu_1}{\sigma_1^2}=ln(T_0\frac{\sigma_1}{\sigma_0}) \tag{4.54}$$

Dividing (4.88) by $\frac{1}{2\sigma_1^2}\left(\frac{\sigma_1^2}{\sigma_0^2}-1\right)$, we get

$$|\chi|^2-\frac{|\mu_1|^2 2\sigma_1^2}{2\sigma_1^2\left(\frac{\sigma_1^2}{\sigma_0^2}-1\right)}+\frac{\chi\mu_1 2\sigma_1^2}{\sigma_1^2\left(\frac{\sigma_1^2}{\sigma_0^2}-1\right)}=ln(T_0\frac{\sigma_1}{\sigma_0})\frac{2\sigma_1^2}{\left(\frac{\sigma_1^2}{\sigma_0^2}-1\right)} \tag{4.55}$$

$$|\chi|^2 - \frac{|\mu_1|^2}{\left(\frac{\sigma_1^2}{\sigma_0^2} - 1\right)} + \frac{\chi\mu_1 2}{\left(\frac{\sigma_1^2}{\sigma_0^2} - 1\right)} = ln(T_0 \frac{\sigma_1}{\sigma_0}) \frac{2\sigma_1^2}{\left(\frac{\sigma_1^2}{\sigma_0^2} - 1\right)} \tag{4.56}$$

Substituting $\frac{\mu_1}{\left(\frac{\sigma_1^2}{\sigma_0^2} - 1\right)} = t$ in equation (4.56), we get

$$|\chi|^2 - \mu_1 t + \frac{\chi\mu_1 2}{\left(\frac{\sigma_1^2}{\sigma_0^2} - 1\right)} = ln(T_0 \frac{\sigma_1}{\sigma_0}) \frac{2\sigma_1^2}{\mu_1} t \tag{4.57}$$

$$|\chi|^2 - \mu_1 t + 2\chi t = ln(T_0 \frac{\sigma_1}{\sigma_0}) \frac{2\sigma_1^2}{\mu_1} t \tag{4.58}$$

Adding and subtracting t^2, in above equation, we get:

$$|\chi|^2 - \mu_1 t + 2\chi t + t^2 - t^2 = 2ln(T_0 \frac{\sigma_1}{\sigma_0}) \frac{\sigma_1^2}{\mu_1} t \tag{4.59}$$

$$|\chi + t|^2 - \mu_1 t - t^2 = 2ln(T_0 \frac{\sigma_1}{\sigma_0}) \frac{\sigma_1^2}{\mu_1} t \tag{4.60}$$

$$|\chi + t|^2 = 2ln(T_0 \frac{\sigma_1}{\sigma_0}) \frac{\sigma_1^2}{\mu_1} t + \mu_1 t + t^2 \tag{4.61}$$

$$|\chi + t|^2 = t\left(ln\left(\frac{T_0\sigma_1}{\sigma_0}\right)^2 \frac{\sigma_1^2}{\mu_1} + \mu_1\right) + t^2 = f(\Lambda) \tag{4.62}$$

Substituting $t\left(ln\left(\frac{T_0\sigma_1}{\sigma_0}\right)^2 \frac{\sigma_1^2}{\mu_1} + \mu_1\right) + t^2 = T$, Equation(4.62) can be expressed as:

$$\mathrm{f}(\Lambda) = \begin{cases} |\chi + t|^2 > T & ; H_1 \\ |\chi + t|^2 < T & ; H_0 \end{cases} \tag{4.63}$$

$f(\Lambda)$ is computed using the samples observed in the observation window with length *W*. Then, $f(\Lambda)$ is compared with a predetermined threshold value T. If $f(\Lambda)$ is larger than T, we declare the presence of an OFDM signal. Otherwise, we declare that there is no OFDM signal present. The threshold value T is set according to the required *FAR* following the Neyman–Pearson criterion.

To derive the theoretical Probability of Detection and Probability of false alarm for the LRT, we need to obtain the distribution of the test statistics $f(\Lambda)$ under hypotheses $H_0$and H_1. It is known that the square of a sum of a real Gaussian variable and a real scalar follows a noncentral chi-square distribution [59]. However, it is not clear whether this is the case for a complex Gaussian variable, so firstly considering the distribution of $f(\Lambda)$ as follows: The complex random variable χ is defined as the sum of two independent real random variables $a$and b, i.e., $\chi = a + j.b$, then, we have [65] :

$$f(\Lambda) = |a + j.b + t|^2 = (a + t)^2 + b^2 \tag{4.64}$$

where $a + t \sim N(\mu_a + t, {}^{\sigma_\chi^2}/_2)$ and $b \sim N(\mu_b, {}^{\sigma_\chi^2}/_2)$, σ_χ^2 is the variance of χ and μ_a and μ_b are the means of a and b respectively.Also, $\frac{(a+t)^2}{\sigma_\chi^2/2}$ and $\frac{b}{\sigma_\chi^2/2}$ are non-central chi-square distribued with one-degree of freedom and the following Non-centrality parameters [59]:

$$\lambda_a = \frac{(\mu_a + t\,)^2}{\sigma_\chi^2/2} \tag{4.65}$$

$$\lambda_b = \frac{{\mu_b}^2}{\sigma_\chi^2/2} \tag{4.66}$$

Now using the proposition :The sum of independent random variables $\{r_1, r_2, \dots . r_N\}$ with a noncentral chi-square distribution is still a noncentral-chi-square-distributed variable with $\sum_{i=1}^{N} k_i$ degrees of freedom and noncentrality parameter $\sum_{i=1}^{N} \lambda_i$, where k_i and λ_i are the degrees of freedom and non-centrality parameter for $r_i, i = 1,2, \dots, N$ [59]:

Therefore,

$$\frac{\mathrm{f}(\Lambda)}{\sigma_\chi^2/2} = \frac{(a + t\,)^2 + b^2}{\sigma_\chi^2/2} \tag{4.67}$$

is non-central chi-square distributed [59] with degrees of freedom $k = 2$ and noncentrality parameter:

$$\lambda = \lambda_a + \lambda_b = \frac{2((\mu_a + t\,)^2 + {\mu_b}^2)}{\sigma_\chi^2} \tag{4.68}$$

Now under hypothesis H_0, χ has zero mean and variance σ_0^2 i.e. $\mu_a = \mu_b = 0$ and $\sigma_\chi^2 = \sigma_0^2 = W$.

Under Hypothesis H_1, mean is μ_1 or $\mu_a = \frac{KW\gamma}{1+\gamma}$ and $\mu_b = 0$, variance $\sigma_\chi^2 = \sigma_1^2 = W[1 + \frac{2K^2\gamma^2}{(1+\gamma)^2}]$

Non-centrality parameter, Under hypothesis H_0 using (4.68)[65]:

$$\lambda_0 = \lambda_a + \lambda_b = \frac{2(t^2)}{\sigma_0^2} = \frac{W}{2K^2} \ (1 + 1/\gamma)^2 \tag{4.69}$$

As $t = \frac{\mu_1}{\left(\frac{\sigma_1^2}{\sigma_0^2} - 1\right)}$ using (4.15), (4.22) and (4.41) , t can be written in terms of γ as:

$$t = \frac{W}{2K}\left(1 + \frac{1}{\gamma}\right) \tag{4.70}$$

Thus, equation (4.69) can be written as:

$$\lambda_0 = \frac{W}{2K^2} \ (1 + 1/\gamma)^2 \tag{4.71}$$

Similarly, non-centrality parameter under hypothesis H_1 can be written as:

$$\lambda_1 = W + \lambda_0 \tag{4.72}$$

Therefore, the cummutative distribution function of $\frac{\mathrm{f}(\Lambda)}{\sigma_\chi^2/2}$under Hypothesis H_0 and H_1 are expressed as[59]:

$$P(x; 2, \lambda_0 | H_0) = \sum_{i=0}^{\infty} e^{-\left(\frac{W}{4K^2}\right)\left(1+\frac{1}{\gamma}\right)^2} \frac{[(W/4K^2)^i \left(1 + \frac{1}{\gamma}\right)^2]^i}{i!} Q(x; 2 + 2i) \tag{4.73}$$

$$P(x; 2, \lambda_1 | H_1) = \sum_{i=0}^{\infty} e^{-\frac{W}{2}} e^{-\left(\frac{W}{4K^2}\right)\left(1+\frac{1}{\gamma}\right)^2} \frac{[\frac{W}{2} + (W/4K^2)^i \left(1 + \frac{1}{\gamma}\right)^2]^i}{i!} Q(x; 2 + 2i) \tag{4.74}$$

where $x = \frac{\mathrm{T}}{\sigma_\chi^2/2}$, the probabiltiy of false alarm P_f can be expressed as:

$$P_f = 1 - P\left(\frac{T}{\sigma_0^2/2}; 2, \lambda_0 \middle| H_0\right) \tag{4.75}$$

$$P_d = 1 - P\left(\frac{T}{\sigma_1^2/2}; 2, \lambda_1 \middle| H_1\right) \tag{4.76}$$

Under Neymann-Pearson criterion is used to compute the theoretical T of the LRT for a given P_f and can be computed as [45]:

$$\mathrm{T} = \frac{W}{2} P^{-1}_{k=2,\lambda_0=\frac{2(t^2)}{\sigma_0^2}}\left(1 - P_f\right) \tag{4.77}$$

where $P^{-1}_{k=2,\lambda_0}(y)$ represents the inverse of the non-central chi-square cdf [59] with k degrees of freedom and non-centrality paramter λ_0 at a particular probability in P.

Using (4.10) and(4.15), it can be observed that the mean and variance of χ under hypotheses are independent of the SNR as it is a signalfree case .Also (4.22) and (4.41) shows that under hypotheses H_1, the mean and variance are functions of the SNR. They are, in fact, monotone functions and increase with the SNR. With simple manipulations, two limits of the means and variances are defined:

$$\mu_1 = \begin{cases} 0 & ,\gamma \to 0 \\ KW & ,\gamma \to +\infty \end{cases} \tag{4.78}$$

$$\sigma_1^2 = \begin{cases} W & ,\gamma \to 0 \\ W(1+2K^2) & ,\gamma \to +\infty \end{cases} \tag{4.79}$$

Thus, $0 \le \mu_1 \le KW$ and $W \le \sigma_1^2 \le W(1+2K^2)$. K is usually less than 0.2. i.e. $W \le \sigma_1^2 \le 1.08W$ and $0 \le \mu_1 \le 0.2W$. Based on this, the variance $\sigma_1^2 \approx W = \sigma_0^2$. Log-likelihood ratio expressed in equation (4.45) can be approximated by[45] :

$$\Lambda' = \frac{\chi\chi^H - (\chi - \mu_1)(\chi - \mu_1)^H}{2\sigma_0^2} \tag{4.80}$$

Using (4.46) and (4.47), Equation (4.80) can be rewritten as:

$$Re(\chi) > \mu_1 + \frac{\sigma_0^2}{\mu_1}\ln(T_0); \qquad H_1 \tag{4.81}$$

$$Re(\chi) < \mu_1 + \frac{\sigma_0^2}{\mu_1}\ln(T_0); \qquad H_0 \tag{4.82}$$

Since the distribution of χ is Gaussian under either hypothesis H_0 or H_1, therefore distribution of $Re(\chi)$ is also Gaussian[65]. Thus, Probability of false alarm :

$$P_f{}' = P(Re(\chi) > T'|H_0) \tag{4.83}$$

Therefore equation(4.83) can be written as [59]:

$$= \int_{T'}^{\infty} \frac{1}{\sqrt{\pi}\sigma_0} e^{-(x-\mu_0^2)/\sigma_0^2} \quad dx \tag{4.84}$$

Thus, using(4.10) and (4.15), and using the definition of complementary error function (4.84) becomes:

$$= \frac{1}{2} erfc\left(\frac{\sqrt{2}T'}{\sqrt{W}}\right) \tag{4.85}$$

where $erfc(y) = 2/\sqrt{\pi} \int_y^{\infty} e^{-x^2} dx$. Threshold T' can be written as [45]:

$$T' = \sqrt{\frac{W}{2} erfc^{-1}(2P_f')} \tag{4.86}$$

Similarly, Probability of detection :

$$P_d{}' = P(Re(\chi) > T'|H_1) \tag{4.87}$$

Therefore equation(4.87) can be written as [59]:

$$= \int_{T'}^{\infty} \frac{1}{\sqrt{\pi}\sigma_0} e^{-(x-\mu_1^2)/\sigma_0^2} \quad dx \tag{4.88}$$

$$= \frac{1}{2} erfc\left(\frac{T' - \mu_1}{\sqrt{W}}\right) \tag{4.89}$$

4.3 Probability of detection for Rayleigh Channel:

Probability of Detection for cyclic prefix based spectrum sensing method over Rayleigh channel can be expressed as [34]:

$$P_{d,Ray=} \int_0^{\infty} P_d{}' f(\gamma) d\gamma \tag{4.90}$$

where $P_d{}'$ is the probability of detection for AWGN channel and $f(\gamma)$ is the probability density function for Rayleigh channel [59, Eq.(4-44)].

$$f(\gamma) = \frac{1}{\bar{\gamma}} \exp\left(\frac{-\gamma}{\bar{\gamma}}\right) \tag{4.91}$$

Using (4.89), (4.22) and (4.91), equation (4.90) can be rewritten as:

$$P_{d,Ray} = \frac{1}{2\bar{\gamma}} \int_0^\infty erfc\left(\frac{T' - \frac{KW\gamma}{1+\gamma}}{\sqrt{W}}\right) \exp\left(\frac{-\gamma}{\bar{\gamma}}\right) d\gamma \tag{4.92}$$

Now considering the notations: $\gamma = \frac{t}{1-t}$, $d\gamma = \frac{dt}{(1-t)^2}$, $\frac{T'}{\sqrt{W}} = a$, $K\sqrt{W} = b$

Using these notations, equation (4.92) can be rewritten as:

$$P_{d,Ray} = \frac{1}{2\bar{\gamma}} \int_0^1 erfc(-bt) \exp\left(\frac{-t}{\bar{\gamma}(1-t)}\right) \frac{dt}{(1-t)^2} \tag{4.93}$$

Taking the assumption $t \ll 1$ and applying Binomial approximation, we have:

$$P_{d,Ray} = \frac{1}{2\bar{\gamma}} \int_0^1 erfc(a-bt) \exp\left(\frac{-t}{\bar{\gamma}(1-t)}\right) (1+2t)\, dt \tag{4.94}$$

or,

$$P_{d,Ray} = \frac{1}{2\bar{\gamma}} \int_0^1 erfc(a-bt) \exp\left(\frac{1}{\bar{\gamma}} - \frac{1}{\bar{\gamma}(1-t)}\right) (1+2t)\, dt \tag{4.95}$$

or,

$$P_{d,Ray} = \frac{1}{2\bar{\gamma}} \int_0^1 erfc(a-bt) \exp\left(\frac{1}{\bar{\gamma}} - \frac{1}{\bar{\gamma}}(1+t)\right) (1+2t)\, dt \tag{4.96}$$

or,

$$P_{d,Ray} = \frac{1}{2\bar{\gamma}} \int_0^1 erfc(a-bt) \exp\left(\frac{-t}{\bar{\gamma}}\right) (1+2t)\, dt \tag{4.97}$$

Solving , we get the approximated expression for probability of detection for Rayleigh channel as:

$$P_{D,Ray} \cong \frac{1}{2\bar{\gamma}b^2}\left[e^{-\frac{a}{b\bar{\gamma}}}\left[\left(-1+2ab\bar{\gamma}+b^2\bar{\gamma}(1+2\bar{\gamma})\right)e^{\frac{1}{4b^2\bar{\gamma}^2}}erf\left(a-\frac{1}{2b\bar{\gamma}}\right)\right.\right.$$

$$+\frac{1}{\sqrt{\pi}}\left[e^{-\frac{1+a^2\bar{\gamma}+b^2\bar{\gamma}}{\bar{\gamma}}}\left[-\left(-1+2ab\bar{\gamma}\right.\right.\right.$$

$$\left.+b^2\bar{\gamma}(1+2\bar{\gamma})\right)e^{a^2+b^2+\frac{1}{4b^2\bar{\gamma}^2}+\frac{1}{\bar{\gamma}}}\sqrt{\pi}erf\left(a-b-\frac{1}{2b\bar{\gamma}}\right)$$

$$+b\bar{\gamma}e^{\frac{a}{b\bar{\gamma}}}\left[-2e^{2ab}+2e^{b^2+\frac{1}{\bar{\gamma}}}+b(1+2\bar{\gamma})e^{a^2+b^2+\frac{1}{\bar{\gamma}}}\sqrt{\pi}erfc(a)\right.$$

$$\left.\left.\left.\left.\left.-b(3+2\bar{\gamma})e^{a^2+b^2}\sqrt{\pi}erfc(a-b)\right]\right]\right]\right]\right] \quad (4.98)$$

Thus, Probability of detection for cyclic-prefix based spectrum sensing over Rayleigh Channel can be calculated using the above expression.

4.4 Comparative Study

Energy detection is easy to implement and doesn't need the signal's prior knowledge, but its performance will be deteriorated under low SNR or with noise uncertainty. Pilot detection performs well, it can detect signals quickly under low SNR, but it needs prior knowledge of signal and perfect synchronization, it also needs different types of receivers for different types of signal, which is hard to realize in real situation[67].

The insertion of Cyclic prefix helps to avoid the Inter Symbol Interfernce. The Cyclic prefix method doesn't need OFDM to transmit the signals and can adapt to most of modulation types. Comparing with pilot detection, this method doesn't need receiver synchronization and different types of receivers to different signal types. It can also overcome the problem of noise uncertainty in energy detection. Also, it works well under low SNR Conditions. The main weakness of this method is the need for knowledge of some parameters of the signal. Second drawback is the high of computational demands [68].

CHAPTER 5:

RESULTS AND DISCUSSIONS

Detection probability (P_d), False alarm probability (P_f) and missed detection probability ($P_m = 1 - P_d$) are the key measurement metrics that are used to analyze the performance of spectrum sensing techniques. The performance of an spectrum sensing technique is illustrated by the receiver operating characteristics (ROC) curve which is a plot of P_d versus P_f or P_m versus P_f.

5.1 Implementation of Squaring Operation in Energy Detection based Spectrum Sensing:

Figure 17 shows the block diagram of energy detection based spectrum sensing using squaring operation [49].

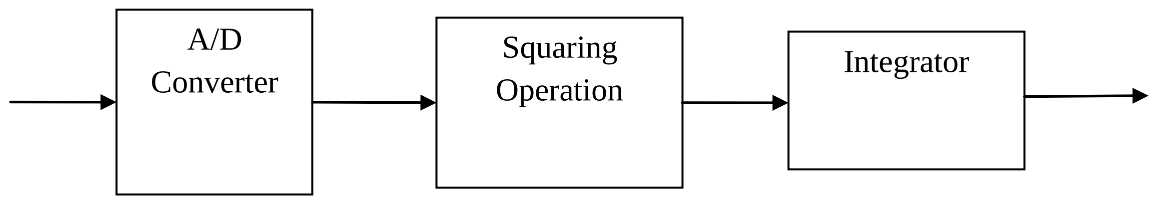

Figure 17: Energy detector using squaring operation.

The performance of energy detector is analysed using ROC (Receiver operating characteristics) curves. Monte-Carlo method is used for simulation. The plot of Signal to noise ratio versus Probability of detection for different values of probability of false alarm is illustrated in Figure 19 and it can be interpreted from Figure 16 and Figure 17 that the performance of energy detector improves with increase in SNR and increase in probability of false alarm respectively. Figure 18 and 19 depicts the degradation in performance of energy detector in Rayleigh fading channel.

AWGN Channel

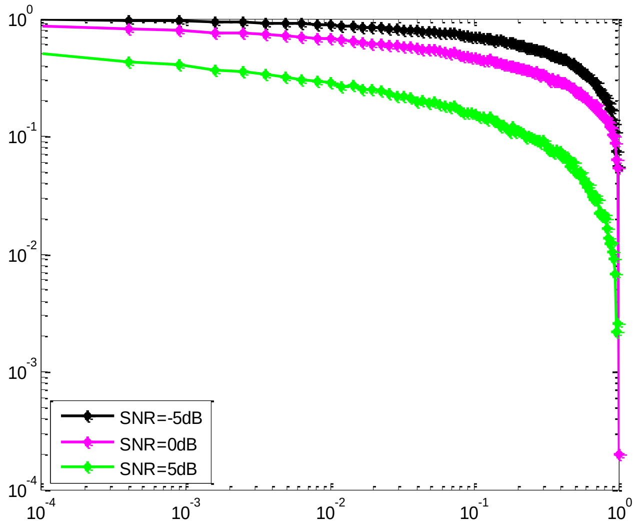

Figure 18: ROC Curve for squaring operation over AWGN Channel.

Figure 18 illustrates the ROC (Receiver Operating Characteristics) curves i.e. P_m versus P_f using Energy detection method for spectrum sensing. This conventional method uses squaring operation. The graph is plotted for different SNR values over AWGN channel and it shows that with increase in SNR (Signal to Noise Ratio), the probability of detection increases and is quantified in Table 2.

Table 2: Improvement in Probability of detection with increase in Signal to Noise Ratio in Energy Detection Method using Squaring operation for AWGN Channel.

Probability of False Alarm	**Probability of Detection (SNR=0 dB)**	**Probability of Detection (SNR=5 dB)**	**Improvement (in times)**
0.0100	0.1294	0.5004	0.4261
0.2100	0.4576	0.8044	0.6394
0.4100	0.5946	0.8840	0.7139
0.6100	0.7074	0.9256	0.7457
0.8100	0.8006	0.9638	0.8185

Table 2 shows that 5 dB increase in Signal to Noise Ratio; increases the probability of detection (at SNR=5 dB) up to 0.8 times as compared to probability of detection (at SNR=0 dB) for AWGN Channel.

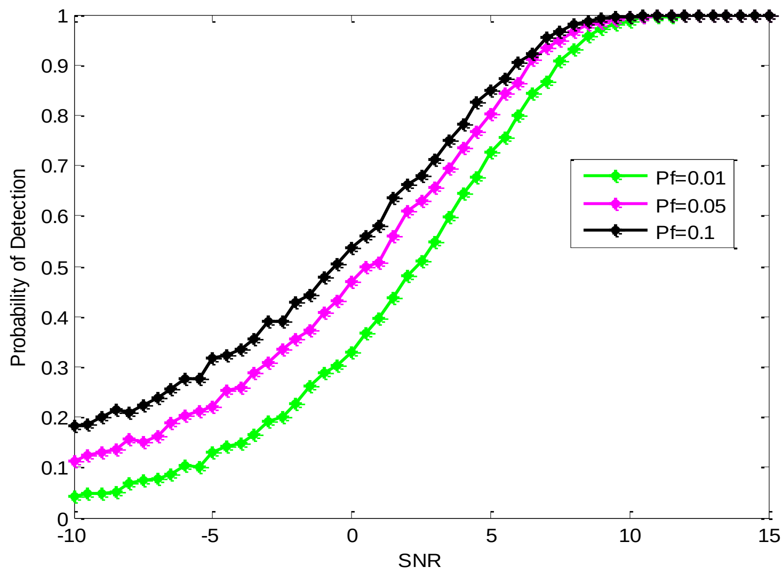

Figure 19: Probability of detection versus SNR Curve for squaring operation over AWGN Channel.

Figure 19 shows the plot for probability of detection versus Signal-to-Noise Ratio over AWGN Channel .Squaring operation is used in Energy detection to detect the signal. The graph is plotted for different values of Probability of False alarm and it shows that increasing the probability of false alarm improves the probability of detection. Table 3 illustrates this improvement in performance.

Table 3: Improvement in Probability of detection with increase in Probability of False Alarm in Energy Detection Method using Squaring operation for AWGN Channel.

Signal to Noise Ratio (in dB)	Probability of Detection (P_f=0.01)	Probability of Detection (P_f=0.05)	Improvement (in times)
-10	0.0402	0.1142	1.8408
-5	0.1138	0.2184	0.9192
0	0.3318	0.4622	0.3930
5	0.7128	0.8000	0.1223
10	0.9882	0.9958	0.0077

Table 3 shows that 5 % increase in probability of false alarm; increases the probability of detection (for P_f=0.05) up to 1.8 times as compared to probability of detection (for P_f=0.01) over AWGN Channel.

Rayleigh Channel

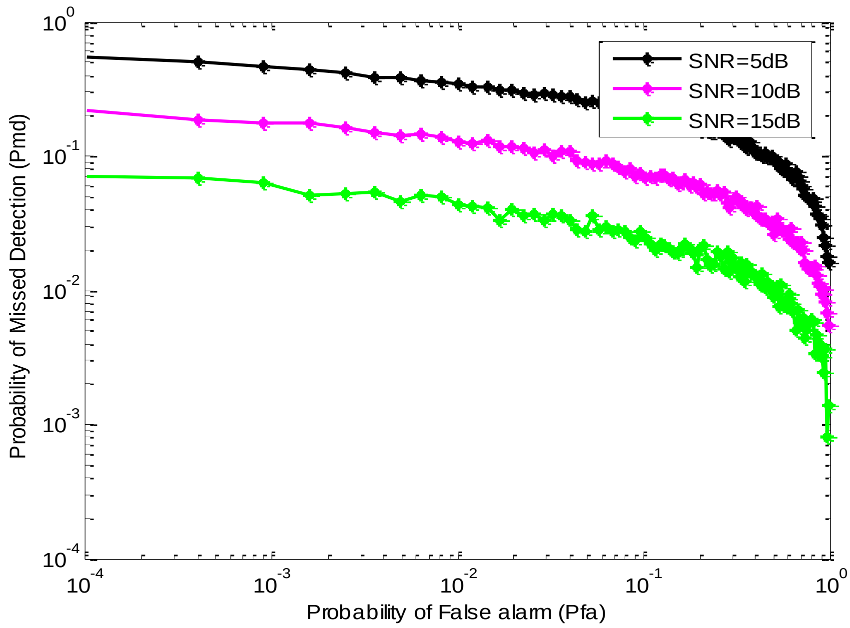

Figure 20: ROC Curves for squaring operation over Rayleigh Channel.

Figure 20 illustrates the ROC (Receiver Operating Characteristics) curves i.e. P_m versus P_f using Energy detection method for spectrum sensing. This conventional method uses squaring operation. The graph is plotted for different SNR values over Rayleigh channel and it shows that with increase in SNR (Signal to Noise Ratio), the probability of detection increases and is quantified in Table 4.

Table 4: Improvement in Probability of detection with increase in Probability of False Alarm in Energy Detection Method using Squaring operation for Rayleigh Channel.

Probability of False Alarm	Probability of Detection (SNR=5 dB)	Probability of Detection (SNR=10 dB)	Improvement (in times)
0.0100	0.4480	0.7690	0.7165
0.2100	0.7462	0.9076	0.2163
0.4100	0.8250	0.9386	0.1377
0.6100	0.8804	0.9604	0.0909
0.8100	0.9332	0.9798	0.0409

Table 4 shows that 5 dB increase in Signal to Noise Ratio; increases the probability of detection (at SNR=10 dB) up to 0.7 times as compared to probability of detection (at SNR=5 dB) for Rayleigh Channel.

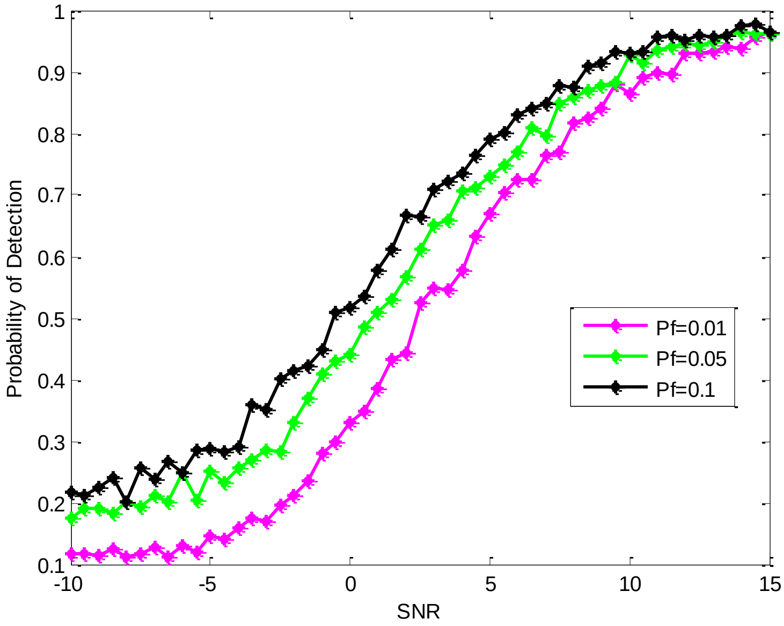

Figure 21: Probability of detection versus SNR Curves for squaring operation over Rayleigh Channel.

Figure 21 shows the plot of probability of detection versus Signal-to-Noise Ratio over Rayleigh Channel. Squaring operation is used in Energy detection to detect the signal. The graph is plotted for different values of Probability of False alarm and it shows that increasing the probability of false alarm improves the probability of detection. Table 5 illustrates this improvement in performance.

Table 5: Improvement in Probability of detection with increase in Probability of False Alarm in Energy Detection Method using Squaring operation for Rayleigh Channel.

Signal to Noise Ratio (in dB)	**Probability of Detection (P_f=0.01)**	**Probability of Detection (P_f=0.05)**	**Improvement (in times)**
-10	0.0880	0.1590	0.8068
-5	0.1050	0.1890	0.8000
0	0.3130	0.4470	0.4281
5	0.6500	0.7410	0.1400
10	0.8590	0.8960	0.0431

Table 5 shows that 5 % increase in probability of false alarm; increases the probability of detection (for P_f=0.05) up to 0.8 times as compared to probability of detection (for P_f=0.01) over Rayleigh Channel.

5.2 Implementation of Cubing Operation in Energy Detection:

Figure 22 shows the block diagram of energy detection based spectrum sensing using squaring operation [50]. Figures 21-24 depicts the improvement in performance of energy detector using cubing operation.

Figure 22: Block diagram of Energy detector using cubing operation.

AWGN Channel

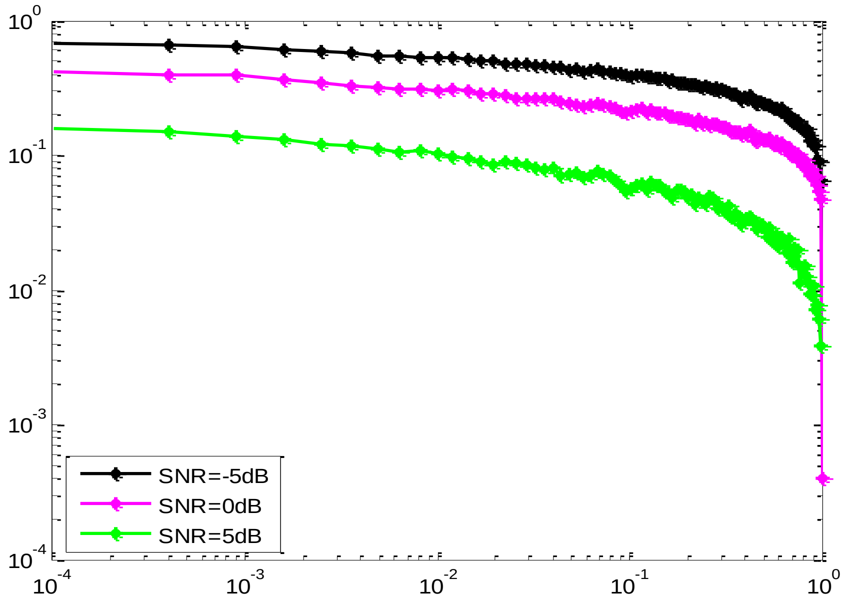

Figure 23: ROC Curve for cubing operation over AWGN Channel.

Figure 23 illustrates the ROC (Receiver Operating Characteristics) curves i.e. P_m versus P_f using Energy detection method for spectrum sensing. This improved method uses cubing operation. The graph is plotted for different SNR values over AWGN channel and it shows that with increase in SNR (Signal to Noise Ratio), the probability of detection increases and is quantified in Table 6.

Table 6: Improvement in Probability of detection with increase in Signal to Noise Ratio in Energy Detection Method using Cubing operation for AWGN Channel.

Probability of False Alarm	**Probability of Detection (SNR=0 dB)**	**Probability of Detection (SNR=5 dB)**	**Improvement (in times)**
0.0100	0.5708	0.8366	0.4657
0.2100	0.7372	0.9176	0.2447
0.4100	0.8022	0.9440	0.1768
0.6100	0.8578	0.9660	0.1261
0.8100	0.8902	0.9820	0.1031

Table 6 shows that 5 dB increase in Signal to Noise Ratio; increases the probability of detection (at SNR=5 dB) up to 0.4 times as compared to probability of detection (at SNR=0 dB) for AWGN Channel.

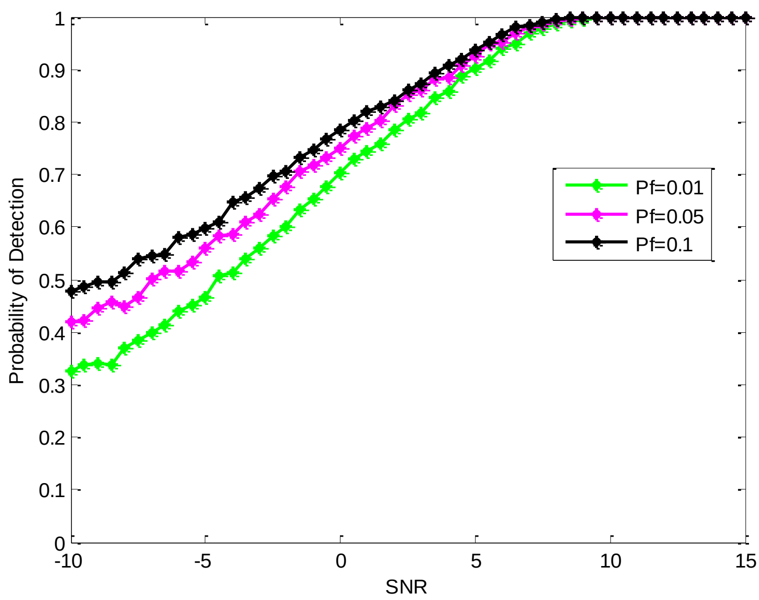

Figure 24: Probability of detection versus SNR Curves for cubing operation over AWGN Channel.

Figure 24 shows the plot for probability of detection versus Signal-to-Noise Ratio over AWGN Channel using cubing operation in Energy detection. The graph is plotted for different values of Probability of False alarm and it shows that increasing the probability of false alarm, improves the probability of detection. Table 7 illustrates this improvement in performance.

Table 7: Improvement in Probability of detection with increase in Probability of False Alarm in Energy Detection Method using Cubing operation for AWGN Channel.

Signal to Noise Ratio (in dB)	Probability of Detection (P_f=0.01)	Probability of Detection (P_f=0.05)	Improvement (in times)
-10	0.3074	0.4070	0.3240
-5	0.4734	0.5588	0.1804
0	0.7054	0.7578	0.0743
5	0.9064	0.9326	0.0289
10	0.9988	0.9990	0.0002

Table 7 shows that 5 % increase in probability of false alarm; increases the probability of detection (for P_f=0.05) up to 0.3 times as compared to probability of detection (for P_f=0.01) over AWGN Channel.

Rayleigh Channel

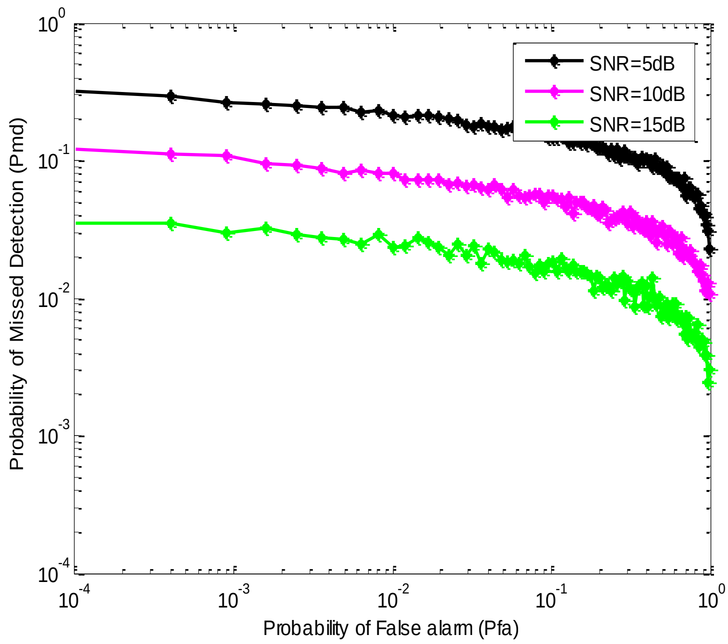

Figure 25: ROC Curve for cubing operation over Rayleigh Channel.

Figure 25 illustrates the ROC (Receiver Operating Characteristics) curves i.e. P_m versus P_f using Energy detection method for spectrum sensing. This improved method uses cubing operation. The graph is plotted for different SNR values over Rayleigh channel and it shows that with increase in SNR (Signal to Noise Ratio), the probability of detection increases and is quantified in Table 8.

Table 8: Improvement in Probability of detection with increase in Signal to Noise Ratio in Energy Detection Method using Cubing operation for Rayleigh Channel.

Probability of False Alarm	Probability of Detection (SNR=5 dB)	Probability of Detection (SNR=10 dB)	Improvement (in times)
0.0100	0.2060	0.2680	0.3010
0.2100	0.2830	0.3430	0.2120
0.4100	0.4920	0.5690	0.1565
0.6100	0.7920	0.8340	0.0530
0.8100	0.9340	0.9460	0.0128

Table 8 shows that 5 dB increase in Signal to Noise Ratio; increases the probability of detection (at SNR=10 dB) up to 0.3 times as compared to probability of detection (at SNR=5dB) for Rayleigh Channel.

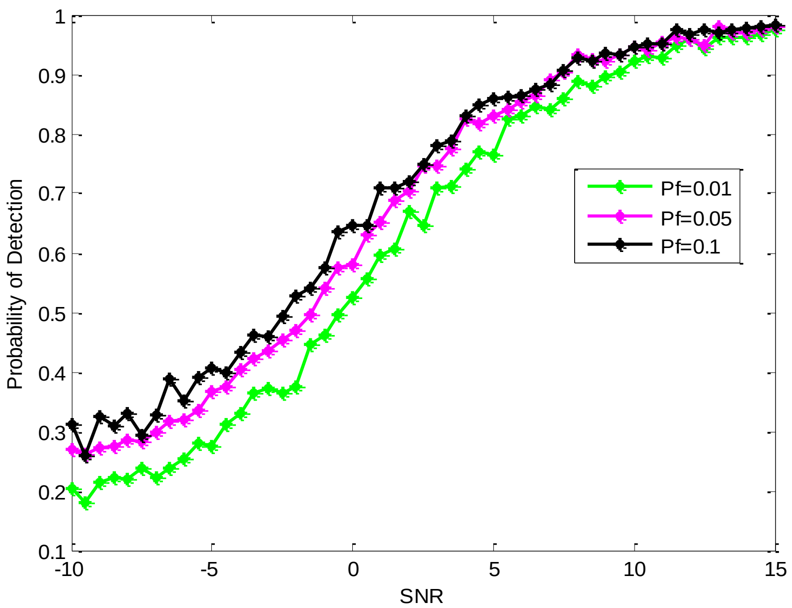

Figure 26: Probability of detection versus SNR Curves for cubing operation over Rayleigh Channel.

Figure 26 shows the plot for probability of detection versus Signal-to-Noise Ratio over Rayleigh Channel using cubing operation in Energy detection. The graph is plotted for different values of Probability of False alarm and it shows that increasing the probability of false alarm improves the probability of detection. Table 9 illustrates this improvement in performance.

Table 9: Improvement in Probability of detection with increase in Probability of False Alarm in Energy Detection Method using Cubing operation for Rayleigh Channel.

Signal to Noise Ratio (in dB)	Probability of Detection (P_f=0.01)	Probability of Detection (P_f=0.05)	Improvement (in times)
-10	0.6894	0.8788	0.2747
-5	0.8246	0.9376	0.1370
0	0.8696	0.9528	0.0957
5	0.8920	0.9648	0.0816
10	0.9380	0.9788	0.0435

Table 9 shows that 5 % increase in probability of false alarm; increases the probability of detection (for P_f=0.05) up to 0.27 times as compared to probability of detection (for P_f=0.01) over Rayleigh Channel.

5.3 Improvement using Cubing Operation in Energy Detection:

AWGN Channel

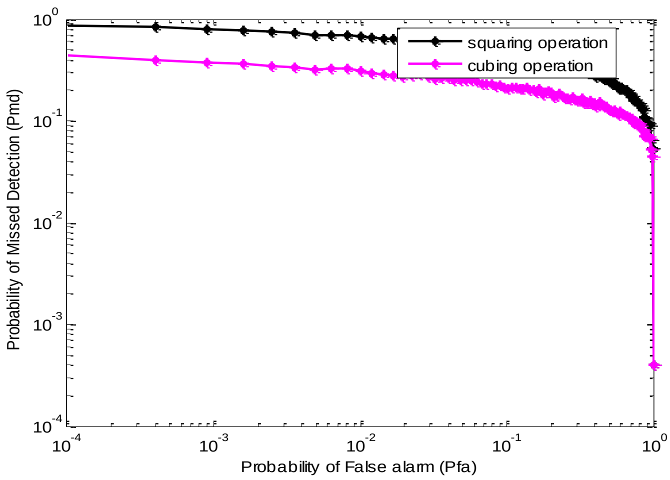

Figure 27: Comparison of plots of ROC Curve using Squaring and Cubing operation for AWGN Channel.

Figure 27 illustrates the comparison of ROC Curves for squaring and cubing operations over AWGN Channel. The graph is plotted at SNR=0dB. The cubing operation improves the performance of energy detection based spectrum sensing method and this improvement is illustrated in Table 10.

Table 10: Improvement using cubing operation in Energy Detection over AWGN Channel

Probability of False Alarm	Probability of detection (Squaring)	Probability of detection(Cubing)	Improvement (in times)
0.0001	0.5372	0.8656	0.6113
0.0441	0.8792	0.9594	0.0912
0.1681	0.9390	0.9758	0.0392
0.3721	0.9748	0.9862	0.0117
0.6561	0.9938	0.9952	0.0014

Table 10 shows that using cubing operation in energy detection improves the performance up to 0.6 times as compared to the squaring operation for AWGN Channel.

Rayleigh Channel

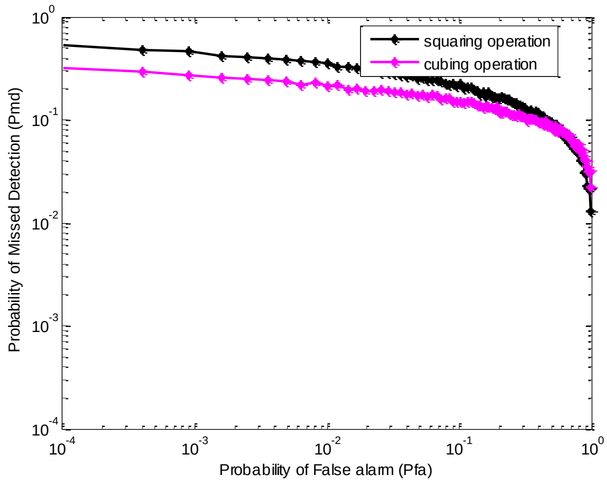

Figure 28: Comparison of plots for ROC Curves using Squaring and Cubing operation for Rayleigh Channel.

Figure 28 illustrates the comparison of ROC (Receiver Operating Curves) for squaring and cubing operations over Rayleigh Channel. The graph is plotted for probability of false alarm SNR= 5 dB. The improvement obtained using cubing operation is illustrated in Table 11.

Table 11: Improvement using cubing operation in Energy Detection over Rayleigh Channel.

Probability of False Alarm	**Probability of detection (Squaring Operation)**	**Probability of detection (Cubing Operation)**	**Improvement (times)**
0.0001	0.6516	0.9746	0.4957
0.0441	0.4096	0.9982	0.0146
0.1681	0.9976	0.9996	0.0020
0.3721	0.9998	1.000	0.0002
0.6561	1.000	1.000	0

Table 11 shows that using cubing operation in energy detection improves the performance up to 0.4 times as compared to the squaring operation for Rayleigh Channel.

5.4 Effect of Cooperative Detection on Energy detection Based Spectrum Sensing with squaring operation:

AWGN Channel

Cooperative Detection helps to mitigate the fading effects and thus, helps to improve the system's performance. Here number of cognitive users=4.

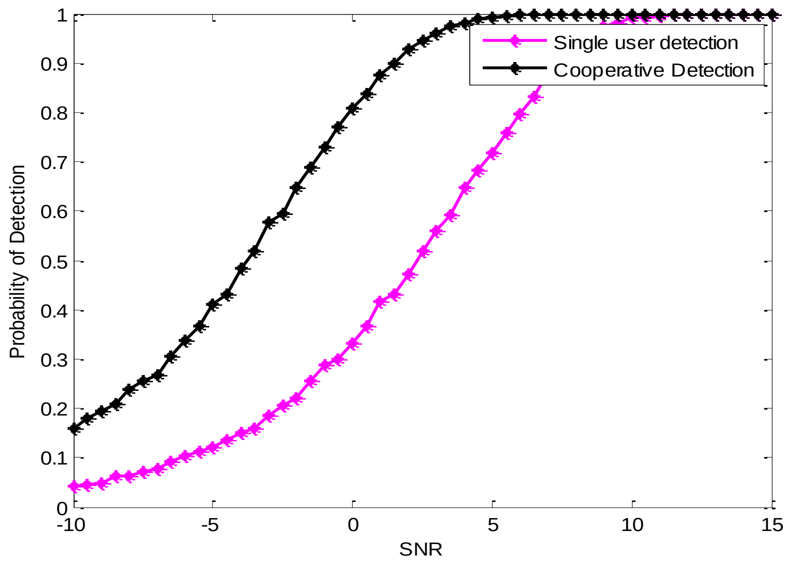

Figure 29: Probability of detection versus Signal to Noise Ratio using cooperative detection (N=4) and single-user detection for conventional energy detection method over AWGN Channel

Figure 29 shows the plot for probability of detection versus Signal to Noise Ratio for cooperative detection (N=4) and single-user detection over AWGN Channel. Probability of false alarm is assumed to be 0.01. Squaring operation is used in energy detection. The improvement obtained using Cooperative Detection is quantified in Table 12.

Table 12: Improvement using Cooperative Detection in squaring operation based Energy Detection over AWGN Channel.

Signal to Noise Ratio (in dB)	Probability of Detection (squaring operation)	Probability of Detection (squaring operation) with Cooperative detection; Number of users=4.	Improvement (in times)
-10	0.0440	0.1666	2.7874
-5	0.1330	0.4041	2.0385
0	0.3376	0.8011	1.3728
5	0.7192	0.9938	0.3818
10	0.9892	1.0000	0.0109
15	1.000	1.0000	0.0000

Table 12 shows that Cooperative detection improves the probability of detection 2.7 times as compared with single user detection in energy detection based spectrum sensing method using squaring operation for AWGN Channel.

Rayleigh Channel

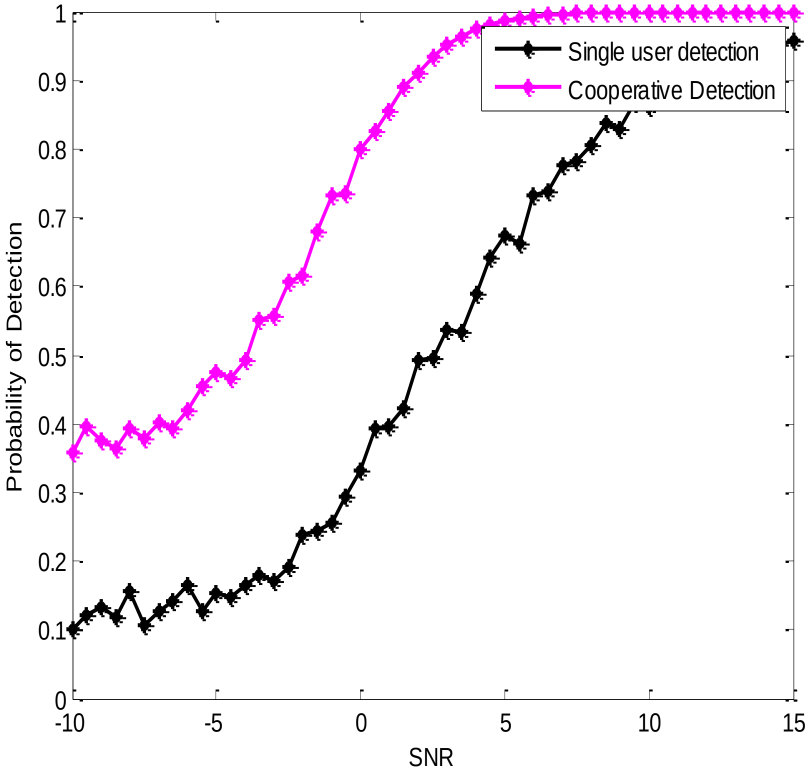

Figure 30: Probability of detection versus Signal to Noise Ratio for cooperative detection (N=4) and single-user detection for squaring operation over Rayleigh Channel.

Figure 30 shows the plot for probability of detection versus Signal to Noise Ratio for cooperative detection (N=4) and single-user detection over Rayleigh Channel. Probability of false alarm is assumed to be 0.01. Squaring operation is used in energy detection. The improvement obtained using Cooperative Detection is quantified in Table 13.

Table 13: Improvement using Cooperation detection in Energy Detection Based Spectrum Sensing(using squaring operation) over Rayleigh Channel

Signal to Noise Ratio (in dB)	Probability of Detection (squaring operation)	Probability of Detection (squaring operation) with Cooperative detection	Improvement (in times)
-10	0.1180	0.3777	2.2005
-5	0.1490	0.4696	2.1518
0	0.3450	0.7919	1.2952
5	0.6660	0.9850	0.4790
10	0.8710	0.9997	0.1477
15	0.9500	1.0000	0.0526

Table 13 shows that Cooperative detection improves the probability of detection 2.2 times as compared with single user detection in energy detection based spectrum sensing method using squaring operation for Rayleigh Channel.

5.5 Effect of Cooperative Detection on Energy detection Based Spectrum Sensing with cubing operation:

AWGN Channel:

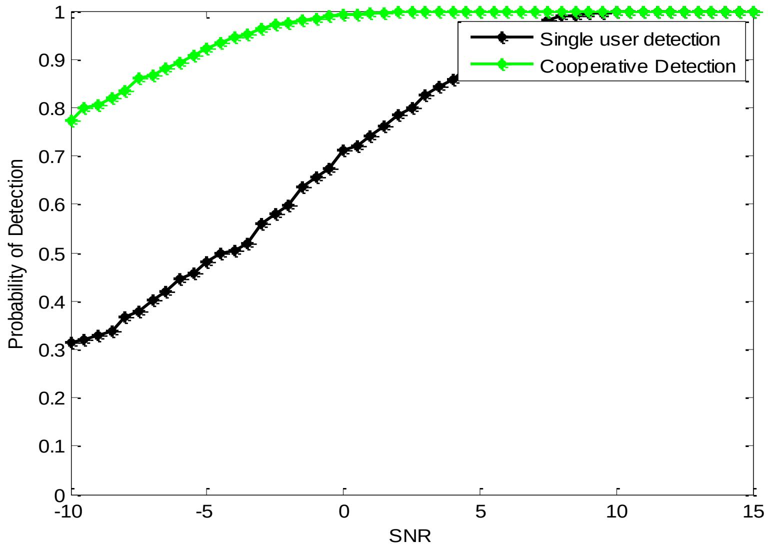

Figure 31: Probability of detection versus Signal to Noise Ratio for cooperative detection (N=4) and single-user detection for improved energy detection method over AWGN Channel.

Figure 31 shows the plot for probability of detection versus Signal to Noise Ratio for cooperative detection (N=4) and single-user detection over AWGN Channel. Probability of false alarm is assumed to be 0.01. Cubing operation is used in energy detection. The improvement obtained using Cooperative Detection is quantified in Table 14.

Table 14: Improvement using Cooperation detection in Energy Detection Based Spectrum Sensing(using cubing operation) over AWGN Channel

Signal to Noise Ratio (in dB)	Probability of Detection (cubing operation)	Probability of Detection (cubing operation) with Cooperative detection	Improvement (in times)
-10	0.3252	0.7745	1.3815
-5	0.4666	0.9218	0.9755
0	0.7026	0.9910	0.4105
5	0.9042	0.9999	0.1058
10	0.99984	1.0000	0.0016
15	1.0000	1.0000	0

Table 14 shows that using cooperative detection in Energy detection based Spectrum Sensing improves the performance up to 1.3 times as compared to single user detection over AWGN Channel.

Rayleigh Channel:

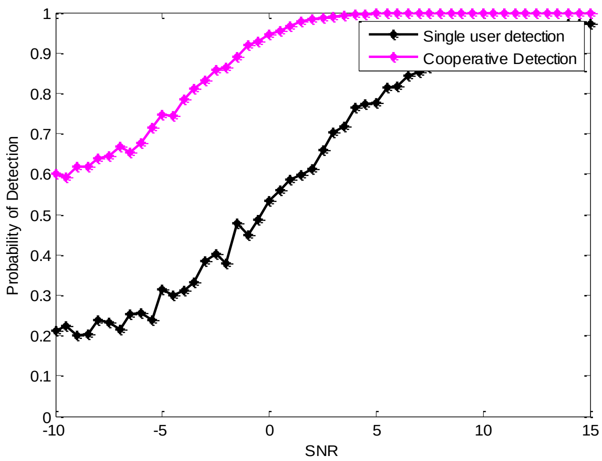

Figure 32: Probability of detection versus Signal to Noise Ratio for cooperative detection (N=4) and single-user detection for improved energy detection method over Rayleigh Channel.

Figure 32 shows improvement in probability of detection using cooperative detection over Rayleigh Channel. Cubing operation is used in the energy detection. The probability of false alarm is assumed to be equal to 0.01. The improvement obtained is quantified in Table 15.

Table 15: Improvement using Cooperation detection in Energy Detection Based Spectrum Sensing over Rayleigh Channel for Probability of False Alarm=0.01.

Signal to Noise Ratio (in dB)	Probability of Detection (cubing operation)	Probability of Detection (cubing operation) with Cooperative detection	Improvement (in times)
-10	0.1850	0.6169	2.3346
-5	0.2790	0.7398	1.6517
0	0.5360	0.9521	0.7763
5	0.7990	0.9979	0.2489
10	0.9180	1.0000	0.0893
15	0.9760	1.0000	0.0246

5.6 Cyclic Prefix Based Spectrum Sensing

AWGN Channel

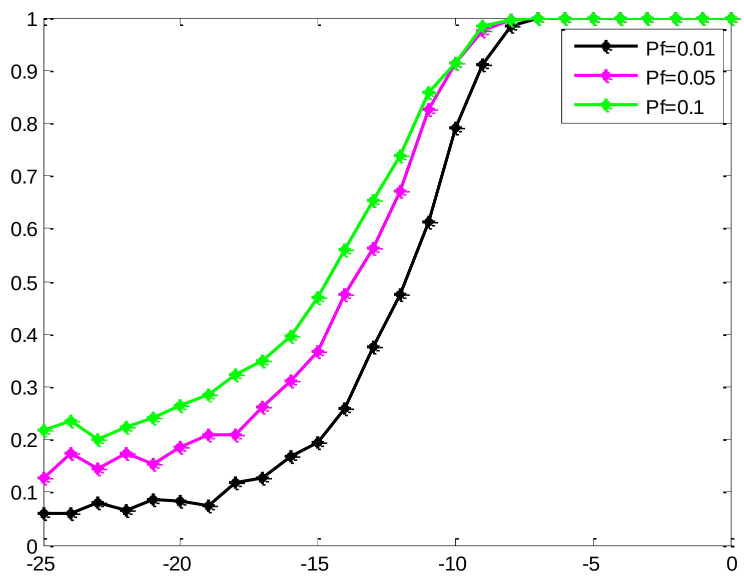

Figure 33: Probability of Detection versus SNR (Signal to Noise Ratio) for Cyclic Prefix Based Spectrum Sensing over AWGN Channel.

The detection period is assumed to be 100 OFDM blocks for each secondary user. Complex symbols, input to the IFFT at the transmitter, are chosen from a 16 QAM constellation. Size of FFT is kept equal to 64, i.e. $T_d = 64$ and the cyclic prefix size is chosen to be $\frac{64}{4} = 16$. Therefore the number of samples is equal to $100(T_d + T_c) = 100(64 + 16) = 8000$. The results have been averaged over 1000 realizations.

Figure 33 shows the plot for Probability of Detection versus SNR for different values of Probability of false alarm and it is observed that with increase in probability of false alarm, system performance improves and this improvement is quantified in Table 16.

Table 16: Improvement in Probability of detection with increase in Probability of False Alarm in Cyclic Prefix Specrum Sensing Method for AWGN Channel.

Signal to Noise Ratio (in dB)	**Probability of Detection (P_f=0.01)**	**Probability of Detection (P_f=0.05)**	**Improvement (in times)**
-25	0.0560	0.1390	1.482
-20	0.0730	0.1750	1.397
-15	0.2030	0.3690	0.8177
-10	0.7990	0.9380	0.173
-5	1.0000	1.0000	0.0000

Table 16 shows that 5 % increase in probability of false alarm; increases the probability of detection (for P_f=0.05) up to 1.48 times as compared to probability of detection (for P_f=0.01) over AWGN Channel.

Rayleigh Channel

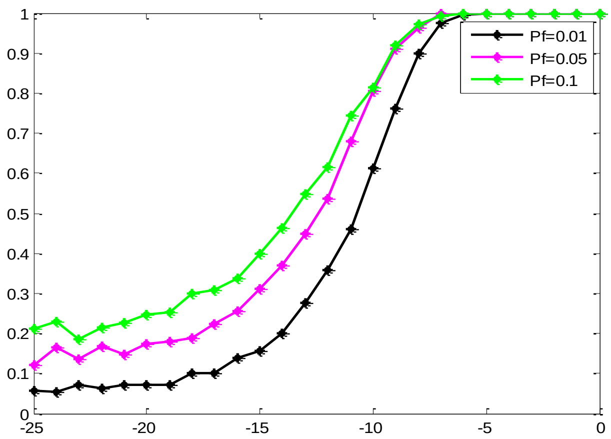

Figure 34: Probability of Detection versus SNR (Signal to Noise Ratio) for Cyclic Prefix Based Spectrum Sensing over Rayleigh Channel.

Figure 34 shows the plot for Probability of Detection versus SNR (Signal to Noise Ratio) using Cyclic Prefix Feature of OFDM Signals. It is observed that this sensing method performs well even in the fading channel. The increase in Signal to Noise Ratio improves the performance and is depicted in Table 17.

Table 17: Improvement in Probability of detection with increase in Probability of False Alarm in Cyclic Prefix Spectrum Sensing Method for Rayleigh Channel.

Signal to Noise Ratio (in dB)	Probability of Detection (P_f=0.01)	Probability of Detection (P_f=0.05)	Improvement (in times)
-25	0.0680	0.1170	0.7205
-20	0.0720	0.1700	1.36
-15	0.1600	0.3250	1.0312
-10	0.6360	0.8020	0.2610
-5	1.0000	1.0000	0

Table 17 shows that 5 % increase in probability of false alarm; increases the probability of detection (for P_f=0.05) up to 1.36 times as compared to probability of detection (for P_f=0.01) over Rayleigh Channel.

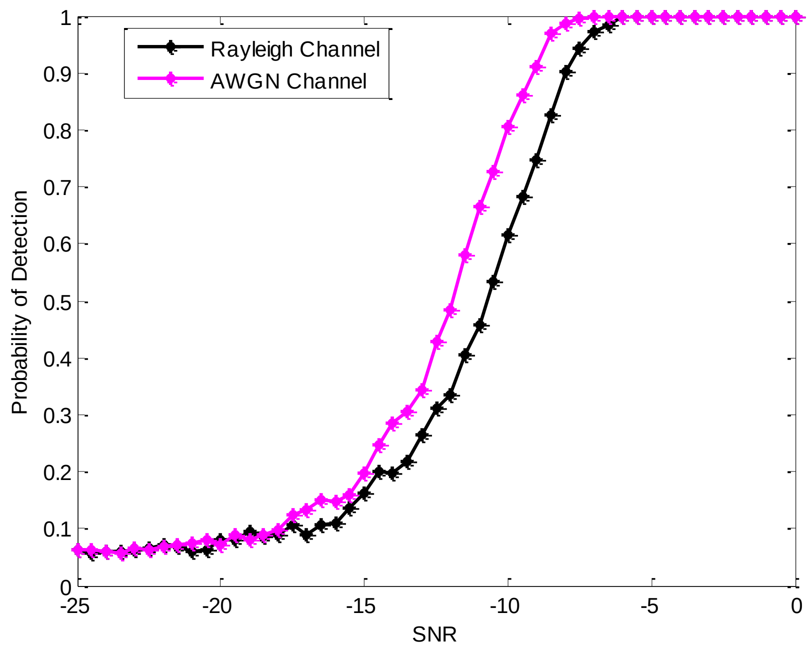

Figure 35: Comparison of plots for Probability of detection versus SNR for AWGN and Rayleigh Channel.

Figure 35 shows that the Rayleigh channel performs almost equally well as AWGN Channel in Cyclic-Prefix Based Spectrum Sensing Method. And the difference in the channel's performances is depicted in Table 18.

Table 18: Comparison of plots for Probability of detection versus SNR for AWGN and Rayleigh Channel.

Signal to Noise Ratio (in dB)	Probability of Detection for Rayleigh (P_f=0.01)	Probability of Detection for AWGN (P_f=0.01)	Degradation in Rayleigh Channel
-25	0.0680	0.0560	-0.012
-20	0.0720	0.0730	0.001
-15	0.1600	0.2030	0.043
-10	0.6360	0.7990	0.163
-5	1.0000	1.0000	0

5.7 Effect of Cooperative Detection in cyclic-prefix based spectrum sensing

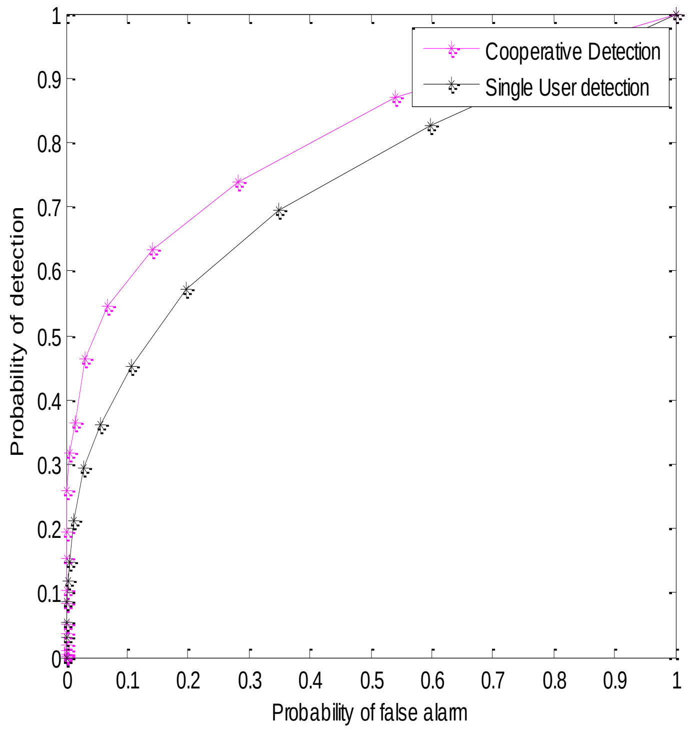

Figure 36: Comparison of ROC plots using single-user detection and Cooperative Detection for AWGN Channel.

Figure 36 shows that Cooperative detection (with 10 secondary users) improves the performance of spectrum sensing up to 3.99 times as compared to detection made by single user and this improvement is quantified in Table19.

Table19: Improvement using Co-operative Detection in Cyclic Prefix Based Spectrum Sensing

Probability of False Alarm	**Probability of Detection (Single user)**	**Probability of Detection(Cooperative Detection)**	**Improvement(times)**
0.0003	0.1870	0.05	2.74
0.0010	0.1997	0.04	3.99
0.0025	0.2808	0.15	0.87
0.0060	0.2919	0.23	0.26
0.0135	0.4286	0.24	0.78
0.0282	0.4239	0.35	0.21

5.8 Comparison of three spectrum sensing methods under Low Signal-to-Noise Ratio (SNR) Conditions:

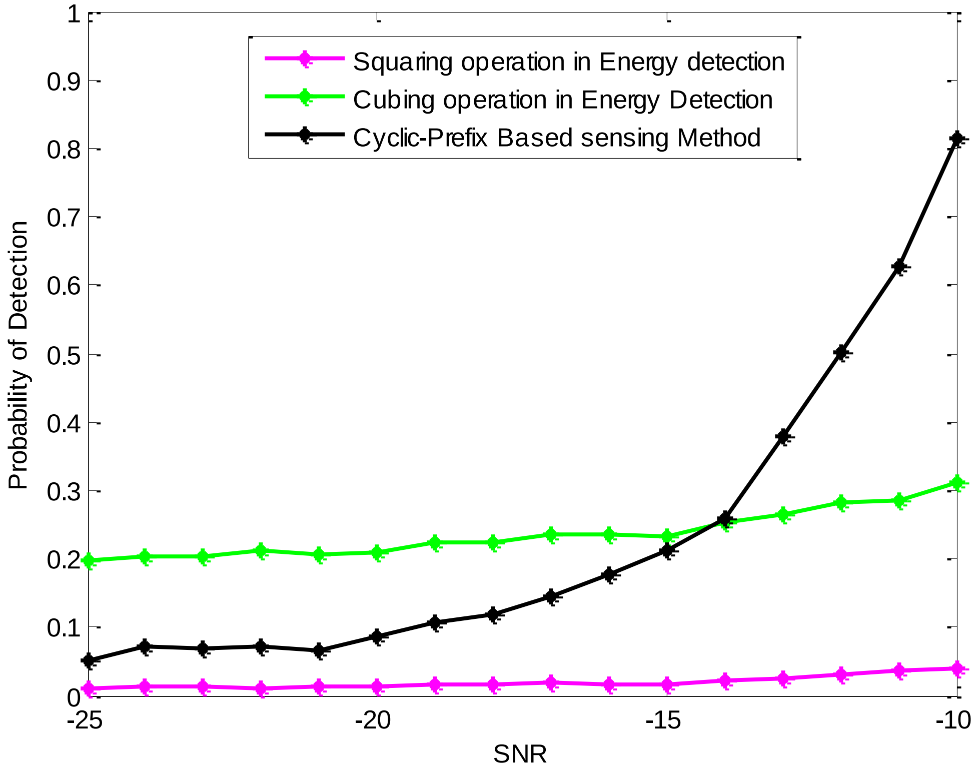

Figure 37: Comparison of Squaring, cubing operations and cyclic-Prefix based Sensing Methods

Plot for Probability of Detection versus Signal to Noise Ratio for three different spectrum sensing methods (squaring operation, cubing operation and Cyclic-Prefix Based) is illustrated in Figure 3. It can be observed that under low Signal-to-Noise Conditions, energy detector (using squaring and cubing operation) does not perform well while Cyclic-Prefix Based Spectrum Sensing method works well under these conditions.

CHAPTER 6:
CONCLUSIONS

In this thesis, two spectrum sensing techniques (Cyclic-Prefix Based Spectrum Sensing and Energy detection Based Spectrum Sensing) have been discussed. Two operations (cubing and squaring) have been used to implement Energy Detection method. The Performance of Spectrum Sensing techniques has been evaluated using ROC (Receiver Operating Characteristics) curves and Probability of detection versus SNR plots. The cyclic-prefix based spectrum sensing method has been shown to be the best method for spectrum sensing as it performs well in the fading channels and under low SNR conditions.

The proposed cubing operation helps to improve the performance of conventional energy detector. An improvement of up to 0.6 times for AWGN Channel and up to 0.4 times for Rayleigh channel has been achieved, as the operation is changed from squaring operation to cubing operation in an energy detector.

With increase in SNR, the performance of spectrum sensing method improves. It has been found that with 5 dB increase in SNR, the probability of detection increases up to 0.8 times for AWGN Channel; and up to 0.7 times for Rayleigh Channel, in case of squaring operation based energy detection method. While this improvement is up to 0.4 times for AWGN Channel and up to 0.3 times for Rayleigh Channel; if squaring operation is replaced by cubing operation in energy detector.

It has also been observed that increase in probability of false alarm, improves the probability of detection of a particular spectrum sensing method. 5% increase in probability of false alarm; increases the probability of detection up to 1.8 times for AWGN Channel and 0.8 times for Rayleigh Channel in case of conventional energy detection method (i.e. using squaring operation). While in case of cubing operation, this improvement is up to 0.3 times for AWGN Channel and 0.27 times for Rayleigh Channel. The cyclic prefix based spectrum sensing method provides an improvement of up to 1.48 times for AWGN Channel and 1.36 times for Rayleigh Channel with 5% increase in probability of false alarm.

Cooperation among the users helps to mitigate the effects of fading and thus improves the performance of spectrum sensing method. It has been shown that Cooperative detection improves the performance of conventional energy detection method up to 2.7 times for AWGN Channel and 2.2 times for Rayleigh Channel. Cooperative Detection in improved Energy detection method (using cubing operation), improves the performance up to 1.3 times for AWGN Channel and 2.3 times for Rayleigh Channel. An improvement of up to 3.9 times has been achieved by using Cooperative Detection in cyclic prefix based spectrum sensing.

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LIST OF PUBLICATIONS

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