**MINT 709 Capstone Project Report**

# Dynamic Spectrum Access in Random Interference-Prone LTE Networks


Kaushik Vinjamoor Murali
kaushikv@ualberta.ca


**Supervisor**
Vesh Raj Sharma Banjade

**Submitted to**
Mike MacGregor
Professor and Director of MINT
Department of Computing Science
University of Alberta

January 23, 2015

**Abstract**

The widespread adoption of wireless technologies is leading to an ever increasing demand for the Radio Frequency (RF) spectrum that supports mobile communication. A Cognitive Radio (CR) can increase the amount of a radio frequency spectrum that is usefully employed by authorizing unlicensed users to connect to licensed spectrum spaces when they are idle. Long Term Evolution (LTE) is a technology that has developed to support next generation multimedia applications coupled with high data rates. To overcome the spectrum scarcity issue and to multiply capacity, dynamic spectrum access is deployed in LTE. Dynamic Spectrum Access (DSA) identifies the possibilities of utilizing the spectrum wisely. The Energy Detector (ED), a popular device helps in sensing spectrum holes (idle licensed spectrum) but its performance degrades in an interference-prone LTE network comprising a large number of nodes (hot spots, relays, base stations) whose locations and distances are random. Thus, we explored energy detection using an Improved Energy Detector (IED) which has the flexibility of adapting its parameter $p$ (the traditional ED has a fixed value of $p$ equal to 2). We extended the investigation to a cooperative spectrum sensing network where multiple CRs cooperated with a fusion center (eNB). We found that multiple cooperating CRs yield an additional performance gain compared to a single CR unit.

$\sim$

# Contents

# List of Figures

# List of Tables

# List of Acronyms

**ADC** Analog-to-Digital Converter

**AWGN** Additive White Gaussian Noise

**CDMA** Code Division Multiple Access

**CR** Cognitive Radio

**DSA** Dynamic Spectrum Access

**ED** Energy Detector

**EPS** Evolved Packet System

**EPC** Evolved Packet Core

**FC** Fusion Center

**GSM** Global System for Mobile communication

**HeNB** Home Evolved Node B

**IED** Improved Energy Detector

**LTE** Long Term Evolution

**M2M** Mobile to Mobile

**E-UTRAN** Evolved UMTS Terrestrial Radio Access Network

**EPC** Evolved Packet Core

**MIMO** Multiple-Input Multiple-Output

**MME** Mobility Management Equipment

**OFDM** Orthogonal Frequency Division Multiplexing

**PDN-GW** Packet Data Network Gateway

**PU** Primary User

**RF** Radio Frequency

**SGW** Serving Gateway

**SU** Secondary User

**UMTS** Universal Mobile Telecommunication System

**UE** User Equipemnt

**UWB** Ultra-Wideband

**WLAN** Wireless Local Area Network

# List of Symbols

Listed below are the notations used throughout the report.

| | |
|---|---|
| $P_k$ | Transmission power of PU |
| $\beta$ | Interferer Density |
| $\lambda$ | Detection threshold |
| $\alpha$ | Path loss Exponent |
| $H_0$ | Hypothesis $0$ |
| $H_1$ | Hypothesis $1$ |
| $K$ | Number of Interferer |
| $N$ | Total number of signal samples |
| $n(t)$ | Additive white Gaussian noise |
| $P_d$ | Probability of detection |
| $P_f$ | Probability of false alarm |
| $P_e$ | Probability of error |
| $P_{md}$ | Probability of missed detection |
| $P_i$ | Power of Interference |
| $p$ | $p$-norm detection parameter |
| $r$ | Distance of interfeence from sensing CR |
| $s(t)$ | Signal transmitted by PU |
| $Y$ | Detector decision variable |
| $x(t)$ | Signal observed by CR |
| $i_k$ | Energy from $k$th interfering signal |
| $\mathbb{M}$ | CRs inferring the existence of PU |

# Chapter 1

# Introduction

The considerable growth of wireless devices such as smart phones has resulted in a scarcity in Radio Frequency (RF) spectrum resources due to a large increment in users. Some of the RF spectrum that is licensed to users is underutilized temporally and geographically and, therefore, theoretically available. To address this issue, the RF spectrum licensed to Primary User (PU) is leased to Secondary User (SU) to efficiently utilize the spectrum. SU's access the RF spectrum with the help of a new technology (Cognitive Radio (CR), described below), which was introduced to reduce the wastage of bandwidth [1].

Table 1.1 predicts the collation of global devices and the growth in data traffic of mobile devices during a 5 year period (2013 to 2018). Table 1.1 shows that the Mobile to Mobile (M2M) module leads the group with a 43% increase in device use during the five year period, followed by tablet and smart phone with 41% and 18% increases in use, respectively. This tremendous growth has in turn increased the growth in mobile data traffic led by M2M (113%). The tablet will contribute 87%, the smart phone 63%, and the laptop 30% to the blooming mobile data traffic in the five years considered. Such an increase in the growth of mobile devices is bound to result in an intense competition for the use of available RF spectrum leading to a scarcity in this resource.

To deal with efficient spectrum utilization and to increase user capacity, a new technology called CR has surfaced. CR's are intelligent sensors used for spectrum sensing over a wireless channel. PU's have priority in spectrum use and CR devices help in sharing the allocated spectrum with secondary users (unlicensed users) when the channel is idle [2].

A CR senses unused spectrum holes (white spaces) and provides service to the SU without hindering the licensed user [1]. The CR backs off when it identifies a PU [4]. This becomes a

| Device Type | Global Mobile Devices, 2013 to 2018 | Global Mobile Data Traffic, 2013 to 2018 |
|---|---|---|
| Smart Phone | 18% | 63% |
| Tablet | 41% | 87% |
| Laptop | 13% | 30% |
| Mobile to Mobile | 43% | 113% |

**Table 1.1:** Growth of Global Device versus Global Mobile Data Traffic[3]

tedious task, as various PUs employ a transmission power, modulation scheme in the environment where SUs interfere and the environment keeps changing [1].

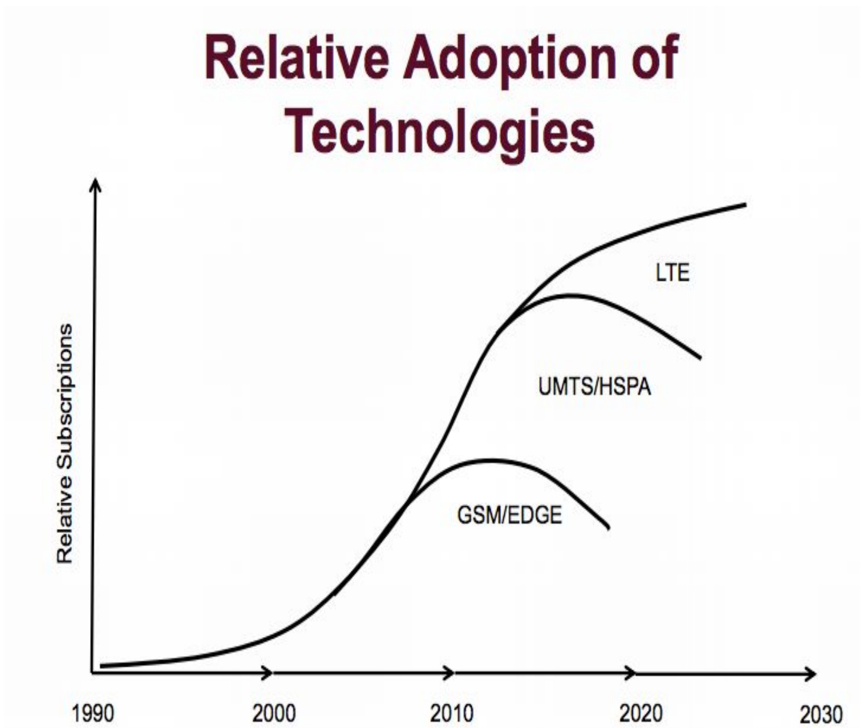


**Figure 1.1:** Adoption of Mobile network standards [5]

Figure 1.1 describes the predicted adoption of technologies over a span of 40 years (1990 to 2030). The diagram shows that Global System for Mobile communication (GSM) was dominant till 2008 and is becoming an outdated technology in recent years. The Universal Mobile Telecommunication System (UMTS) since its origin in 2002, has played a major role in mobile network technology, after which Long Term Evolution (LTE) will be the key technology adopted in telecommunication systems. LTE is predicted to have a long run till 2025 because of the features (user capacity, faster data rate).

In early 2014, mobile network operator's spectral capacity has been limited because of the introduction of new mobile applications. To meet future demands and to increase capacity, operators may choose to install Dynamic Spectrum Access (DSA) capability which integrates efficient protocol interfaces and signaling flow into LTE architectures. By proper lease management the capacity of the network can be increased. Networks can then opportunistically use TV and GSM spectra [6].

CRs help to improve the efficiency of detection probability by DSA. Because an important CR function is spectrum sensing, a CR must be capable of learning and sensing parameters such as channel characteristics, interference, and spectrum availability, and must adapt wisely to the environment by utilizing unused spectrum holes. Thus, the goals of CR in real time are to provide reliable communication whenever required and to use the RF spectrum effectively and efficiently [1].

To improve the performance of CR, new detection techniques are being tested. For example, easy implementation and lesser complexity has led to the use of energy detection in majority. During energy detection, the channel energy is monitored and calculated to decide if the channel is being used [1]. Energy Detector (ED) identifies the presence of a signal by collating the measured energy with a predetermined threshold value. Though implementing an energy detection scheme is not tedious, EDs have drawbacks in the presence of low signal to noise ratio and when they are unable to differentiate SUs from PUs in a single channel. The performance of an ED is affected when they are subjected to multiple interferences. Therefore, when there are numerous interferences in the given environment, an option to improve CR sensing performance is needed. In this research project, simulation and investigations are performed to analyze the energy detection performance in the following contexts.

## 1.1 Problems

**P1.** Effective DSA could be achieved with the help of reliable spectrum sensing. In a network consisting of a large number of randomly interfering nodes, spectrum sensing performance of an ED degrades significantly. This degradation of spectrum sensing may be rectified by the use of an Improved Energy Detector (IED). As the traditional ED has a fixed value of the detection parameter $p$ ($p = 2$), an IED which has flexibility in the parameter $p$ may possibly be able to attain better sensing performance than ED in the presence of interference.

**P2.** With the goal of investigating further improvement of sensing performance considered in Problem **P1**, a cooperative network of $p-$norm detector based CRs may be considered. In this technique a Fusion Center (FC) (eNB) combines all the local decision made by the CRs and decides on the existence of PU in the band of interest. As this may yield additional performance gains with respect to a single CR based sensing, we seek to explore the possible gains from cooperative sensing network.

These objectives are further elaborated as problems stated below.

## 1.2 Objectives

The key objectives of this project are stated as follows.

1. Determine the value of the detection parameter $p$ ($p-$norm) in an IED and study the effect of the value $p$ on spectrum sensing. Explore the possible gain in sensing performance through the use of an IED in random network interference.

2. Extend the scenario 1 to cooperative spectrum sensing and explore further possible gains.

## 1.3 Potential impact and significance of the research

Spectrum scarcity has led to a need for DSA, which utilizes the spectrum in an efficient and opportunistic manner with the aid of CR networks. But the challenge lies in sensing the spectrum in heterogeneous networks [7]. Energy detection is the first choice technology in spectrum sensing schemes due to its simplicity and implementation feature.

Signal interference impose significant drawback for ED. Performance of EDs have been upgraded to mitigate these drawbacks in IED [8] (see section 2.5). Using the available RF spectrum efficiently is another way of promoting the development of the wireless industry.

This research contributes to the idea of having ubiquitous information access for all because an increase in RF spectral efficiency will (i) lead to satisfaction of the demand for mobile services, (ii) help in accommodating several network operators wisely, (iii) lead to the convergence of mobile communications and other industries, and (iv) lead to the creation of new mobile devices and applications (i.e., Net books, smart devices, etc.)

$\sim$

# Chapter 2

# Literature Review

## 2.1 Cognitive Radio

In wireless communication, there is always a huge demand for both licensed and unlicensed frequency spectrum. The way licensed spectrum is utilized is a major concern because PUs who have been licensed to use a portion of the RF spectrum do not utilize it all the time, leaving spectrum holes or white spaces, where the spectrum is not being used. To counter this problem, CR networks have evolved to help in accessing discontinuous periods of the unused frequency spectrum [9]. The major functions of CRs are to (1) detect the availability of the spectrum, (2) select the best available spectrum among all the available spectrum, (3) assist SUs to access the unused channel, and (4) back out when a PU uses the spectrum band.

### 2.1.1 Architecture

Figure 2.1 shows that a CR consists of a transceiver, RF unit, an analog-to-digital converter, and a base band processing unit. The transceiver enables the transmission and reception of signals. The RF unit amplifies the signal and passes it to the Analog-to-Digital Converter (ADC). The final stage in signal transmission involves modulation and demodulation. The factors and parameters that play important roles in the function of CR networks are described in sections 2.1.2 and 2.1.3.

### 2.1.2 RF Spectrum

RF, an oscillation rate ranges between 300 KHz and 300 GHz. RF energy in the form of radio waves has been used in radio, mobile, satellite communications and in the fields of medicine.

The radio spectrum is separated into frequency bands for single or range of compatible uses [11]. The band characteristics vary in the RF spectrum. Low frequencies penetrate any obstacle whereas high frequencies have more capacity than low frequencies but cannot pass through

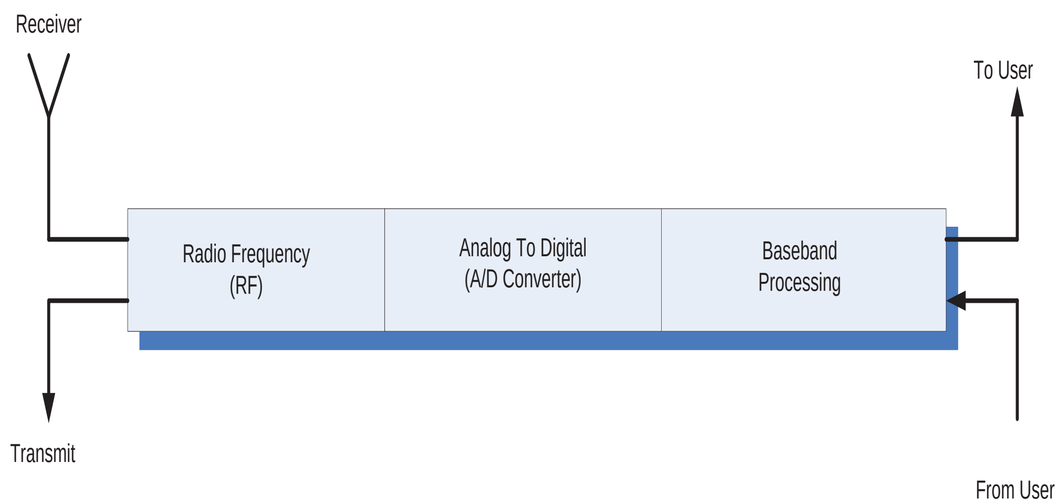


**Figure 2.1:** Anatomy of CR [10]

buildings and have less coverage. Recent research has found that there is more demand for the spectrum between 400 MHz and 40 GHz as most of the wireless application are dependent on these above factors [11].

### 2.1.3 Spectrum Holes

A spectrum hole represents an opportunity for non interfering use of a spectrum [12]. Hence, a band of spectrum can be considered utilized if secondary transmissions are assisted without hindering primary transmissions. A spectrum hole defines a frequency band that is allocated exclusively to a PU but is currently unused by the PU [13]. The regions available to SUs for signal transmission are called spectrum holes [12]. Spectrum sensing schemes opted by CR aid in identifying these spectrum holes by monitoring the channel.

## 2.2 Spectrum Sensing

Key functions of CR networks are the capability in acquiring, measuring, sensing and being aware of the environment to identify the spectrum opportunities and use them efficiently for transmission [14]. To provide better communication with less intervention to the PU, the CR should sense the white spaces accurately and effectively. Several traditional techniques for detecting spectrum holes are described below.

1. **Energy Detection:** The conventional way of detecting the primary transmission because the method is simple and easy to implement. Energy detection compares the received energy signal with energy of threshold. Though energy detection scheme is widely used, the

method has certain drawbacks: (i) it finds it difficult to distinguish the PU from the signal from another CR when both use the same channel, and (ii) its performance is degraded under interference. However, it is still preferred over other sensing techniques [14].

2. **Matched Filter Detection:** Matched filter detection is a reliable method of PU detection. One major supremacy of this method is the time and few samples it takes to achieve required level of false alarm or missed signal [14]. Unlike energy detection, matched filter detection requires awareness of the primary signal. However, this entails large power consumption and loss of synchronization which prevents a wider implementation.

3. **Cyclostationary Detection:** Cyclostationary spectrum sensing performs well in areas where the SNR is low because of its limited noise rejection capability. This detection scheme uses the cyclic spectral correlation function (SCF) parameter to determine the existence of the PU signal. However, nonlinearity and spectral leakage are disadvantages of this detection system. Furthermore, because of the computational complexity they require longer observation time and are expensive to implement [15].

4. **Wavelet Detection:** Wavelet detection divides the signal into components of different frequencies. The spectrum is divided into smaller bands to detect edges in the power spectral density. This allows the power spectral density to distinguish the occupied bands and spectrum holes [16]. Based on this information, SUs can identify the spectrum holes. Practicing high sample rates remains to be a major drawback of wavelet approach.

## 2.3 Hypothesis Testing

Spectrum sensing is accomplished with the aid of binary hypothesis testing. The two possibilities in determining the presence of a PU. $H_0$ denotes a PUs absence and $H_1$ denotes a PUs presence. The major spectrum sensing metrics are detection probability, false alarm, and missed detection probability. There are two classical hypotheses ($H_0$ and $H_1$) for spectrum sensing [1]

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

where $y(t)$ is the CR received signal, $s(t)$ is PU's signal transmission, $n(t)$ is the Additive White Gaussian Noise (AWGN)

## 2.4 Energy Detector

The outcome of ED is a test statistic which compares the received primary signal with that of the threshold to adjudicate the existence of a PU [17]. The ED's decision variable $Y$ is given as

$$Y = \sum_{i=1}^{N} |y_i|^2 \tag{2.2}$$

Where $N$ denotes the number of samples received while sensing and $y_i$ denotes the input signal to the ED.

### 2.4.1 Performance Metrics

The ED senses the primary signal by collating the received signal with threshold value $\lambda$. The key parameters that define the measurement are the probability of detection ($P_d$), probability of false alarm ($P_f$), and probability of error ($P_e$). These key parameters are defined below [17]

$$\begin{aligned} P_d &= \mathbb{P}(Y > \lambda | H_1) \\ P_f &= \mathbb{P}(Y > \lambda | H_0) \\ P_e &= P_f . \mathbb{P}(H_0) + P_m . \mathbb{P}(H_1) \end{aligned} \tag{2.3}$$

where $P_m$ is the probability of missed detection, given by $P_m = (1 - P_d)$

## 2.5 Improved Energy detector

To refine the detection performance of a traditional energy detector, an enhanced version of the ED was proposed and is known as the IED [8]. Figure 2.2 shows the working of an IED, which deduces the appearance or nonappearance of a PU by comparing the received signal with threshold. The decision statistic for IED is given as [8]

$$Y = \frac{1}{N} \sum_{i=1}^{N} \left( \frac{|y_i|}{\sigma_w} \right)^p = \frac{1}{N} \sum_{i=1}^{N} Y_i^p \quad \underset{H_0}{\overset{H_1}{\gtrless}} \quad \lambda, \tag{2.4}$$

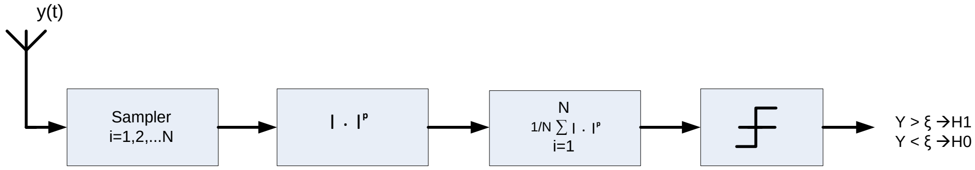


**Figure 2.2:** Improved Energy Detector Block Diagram [8]

where $p > 0$ is an arbitrary constant. A conventional ED can be differentiated from an IED by the $p$ value [8]. The detection parameter $p$ is fixed at 2 for a conventional ED, whereas it is an arbitrary positive value for the IED.

## 2.6 Dynamic Spectrum Access

DSA, one of the counter measures for spectrum scarcity challenges [18], establishes communication via spectrum holes or white spaces [19]. A frequency band consists of two systems primary and secondary as shown in the Figure2.3. Primary users are licensed users who are allocated a portion of the radio frequency spectrum and SUs are the ones that access the spectrum holes when the primary system is silent [18].

DSA is the most frequent application of CR networks. In DSA, the PU bands are used in such a way that the interference to the SU is negligible. In dynamic spectrum access the system adapts itself with the spectrum holes dynamically. The key functions of DSA are spectrum awareness, cognitive processing, and spectrum access [6]. DSA can be applied by a CR which has a structure that includes licensed and unlicensed users.

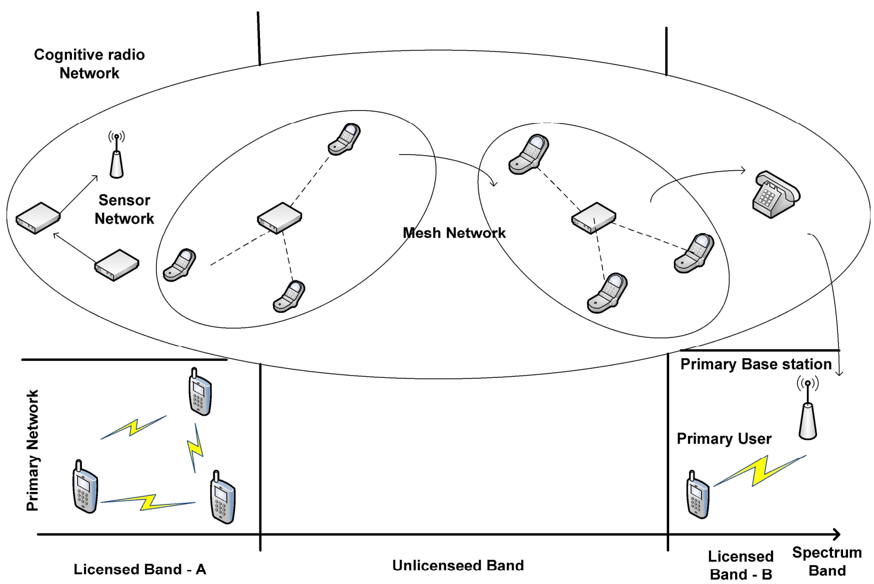


**Figure 2.3:** Cognitive network architecture [20]

The key functions of DSA are given below

1. Spectrum awareness of the RF environment so the available spectrum can be used efficiently [19].

2. Cognitive sensing in the radio frequency environment to detect interference when PUs and SUs coexist [19].

## 2.7 Cooperative spectrum sensing

Co-operative spectrum sensing involves the sensing performance of several CRs. Shared sensing information among several CRs have high accuracy than that of the information shared by CR. The combined sensing information is sent to the FC, which deduces the existence of a signal. Thereby, cooperative spectrum sensing improves signal detection.

Signal detection can be a tedious process because of shadowing (barrier in the propagation path between the end points during transmission) and multi-path fading [1]. These factors cause impact on the strength of the signal, which eventually makes it difficult for the receiver to sense signal without any error. As receiver sensitivity determines the potential of detection, the receiver is subject to sensitivity requirements that lead to higher costs of implementation and hardware. Co-operative spectrum sensing improves signal detection and thus lessens the sensitivity requirements of the receiver [1].

### 2.7.1 Classification

Co-operative spectrum sensing in the network can be classified as centralized, distributed, and relay-assisted.

1. **Centralized cooperative spectrum sensing** is assisted by the FC. Three processes are involved in the centralized cooperative spectrum sensing: (1) The FC identifies the spectrum band for sensing and controls all other cooperating CR users to carry out local sensing. (2) The control channel aids the transit of cooperating CR reports. (3) The FC combines all the sensing reports to determine the existence of PUs [21] .

2. **Distributed cooperative spectrum sensing** unlike centralized cooperative sensing, does not depend on the FC to build a cooperative decision. In this case, all the local CRs report to each other and proceed to a conclusion by iterations regarding the existence/nonexistence of a PU [21].

   After sensing the signal, the CR users share their sensing reports with other local CR users that are within visible range. This type of cooperative sensing scheme uses a distributed algorithm in sending the sensing reports to other CR users. Each CR determines the existence of a PU by combining the received data with its own data and compares the combined data with a standard or rule. In case of unsatisfied criterion, the CR repeats the process of sending the combined results to other CR users until the criterion is satisfied. Several iterations are carried out to make a cooperative decision [21].

3. **Relay assisted cooperative spectrum sensing** In this scheme, CRs complement each other in improving the performance of cooperative spectrum sensing. Briefly, a CR near the PU can sense the signal effectively and efficiently, but the report channel may be weaker, whereas in the same network, there would be other CR users who have a strong report channel but a weaker sensing channel [21]. In this case the former CR user relay-assists the others with sending the sensing results to the FC. Relay-assisted cooperative sensing can be used in a distributed scheme. It is used when multiple hops are required in sending the sensed results and these multiple hops are achieved via relays. Centralized and distributed spectrum sensing is considered to be one hop cooperative spectrum sensing, whereas relay-assisted spectrum sensing is considered to be multi-hop cooperative spectrum sensing [21].

## 2.8 Long Term Evolution

LTE has developed a fourth generation (4G) mobile telecommunications technology that can support multimedia applications with high capacity and high mobility needs [22]. This defines the next generation of technology for GSM and Code Division Multiple Access (CDMA) cellular carriers. LTE also provides high data rates combined with low latency with the help of two techniques, namely Multiple-Input Multiple-Output (MIMO) and Orthogonal Frequency Division Multiplexing (OFDM). The increase in the number of users has led to the requirement of using mobile data access (i.e., Internet access) everywhere. The primary goal of LTE is to provide high capacity along with better spectrum usage.

The Internet causes a great demand for wireless connectivity all over the world. Therefore, cooperation is necessary among multiple agents of network allocation, i.e., operators and users belonging to different networks and systems. Spectrum sharing is a result of cooperation among multiple operators that normally operate on frequency bands [23].

Spectrum sharing may be orthogonal (only one operator at a time has access to the shared resources, the rest being automatically excluded when a single operator is active) or nonorthogonal (operators are allowed to use the same transmission frequency resource simultaneously). The goal of spectrum sharing is to provide better performance by efficiently using available bandwidth through increased spatial and frequency diversity. Nonorthogonal sharing can be opted only if the interference is below a predetermined threshold. When users are allocated simultaneously on the same frequency, the intercell interference must be coordinated [23].

The spectrum sharing concept implies dynamic access to the licensed frequency by a secondary system without any modifications in the terminals, system, network, and architecture. When a secondary system attempts to acquire control of a frequency band, it scans the radio frequency spectrum, senses the PUs, and transfers its connection to a spectrum band where the PU is idle [18]. This is also referred as a spectrum hand off procedure. Three models through which the spectrum band is dynamically accessed are described below.

### 2.8.1 Spectrum access models

The three models through which the spectrum band is dynamically accessed are given below

**Dynamic Exclusive Model**

This model uses two approaches to improve spectrum efficiency: spectrum property rights and dynamic spectrum allocation [24].

*Spectrum property rights,* Licensed spectrum bands can be traded or sold, but such activity is not regulated. The three parameters that specify spectrum property rights are area, time, and spectrum band. The major concern in implementing a spectrum property right is the radio wave propagation, because radio wave propagation is unpredictable and depends on the transmitter and receiver [24].

*Dynamic spectrum allocation,* Spectrum efficiency can also be improved by dynamic spectrum assignment, in which spectrum is allocated exclusively at a given time for a service.

**Open sharing model**

The open sharing model also coined as spectrum commons, aids in sharing with peers that are limited to a spectral region [24]. This model is used in industrial or scientific areas which are operated by wireless services.

**Hierarchical access model**

The hierarchical access model is a hybrid of the dynamic exclusive model and the open sharing model. The idea behind this model is to use the allocated spectrum without creating hindrance to the PU [24]. The policies of spectrum management are better served by the hierarchical access

model than the dynamic exclusive and open sharing models.
The PUs and SUs share spectrum via the two approaches discussed below.
*Spectrum underlay,* The underlay approach can reduce the secondary transmission power as they function below the noise floors of PUs. But SUs can attain high data rates at low power transmission if transmitted signals are scattered over a wide frequency band. However, in the worst case scenario where PUs are transmitting all the time, this approach doesn't work well in exploiting the white spaces [24].
*Spectrum overlay,* Spectrum overlay is different from the underlay technique in that it doesn't impose any complications or restrictions on transmission power [24]. In spectrum underlay, SUs try to exploit the spectrum holes within a traffic of PUs whereas in spectrum overlay SUs take advantage of the resource where PUs are absent.

### 2.8.2 Architecture

The LTE architecture is incorporates three major components described below.

#### User Equipment

The User Equipemnt (UE) consists of modules such as mobile termination, terminal equipment, and a Universal Integrated Circuit Card.
Mobile termination manages communication. A terminal Equipment aborts the data streams and the universal subscriber identity module embedded in the Universal integrated circuit card carry phone number and network identity. It serves as SIM card for all LTE equipments [25].

#### E-UTRAN

The Evolved UMTS Terrestrial Radio Access Network (E-UTRAN) is categorized as third generation mobile cellular system for networks based on the GSM standard [25]. The E-UTRAN manages communication involving mobile and the evolved packet core. It incorporates evolved base stations called eNodeBs or eNBs (E-UTRAN NodeBs). An E-UTRAN Node B (eNB) is a base station manages mobile within the cells and these eNB's are referred as serving eNB [25].
A Home Evolved Node B (HeNB) is a base station that provides coverage in a closed subscriber group (CSG) and it's access is limited to the mobiles with USIM [25].

#### Evolved packet core

An Evolved Packet System (EPS) represents the whole IP network and contains both the Evolved Packet Core (EPC) and LTE. The evolved packet core is comprised of two domains, the packet core domain and the user domain.

The packet domain includes three components:

1. **Mobility Management Equipment (MME)**
2. **Serving Gateway (SGW)**
3. **Packet Data Network Gateway (PDN-GW)**

*Mobility management equipment* is the node that manages signal trade off between base stations, core networks, and subscribers. The functionalities of MME are authentication, support for voice and messages, handover, and establishing bearers [26].

*Serving Gateways* manages the user IP tunnels between eNBs and the packet data network gateway [26].

*Packet data network gateway* assigns an IP address to a mobile device when a user switches it ON. The mobile device dispatches a request to the eNB and it is further forwarded to the MME. The MME's responsibility is to authenticate the user. The MME authorizes the request, and asks the PDN-GW for an IP address. When the PDN gateway approves the request the IP address is sent to the MME. Multiple IP addresses are allocated to a single mobile device when a user uses multiple services provided by the network operator [26].

## 2.9 Heterogeneous and Homogeneous Networks

According to node diversity criteria, CR networks are classified as cognitive, non cognitive, and mixed cognitive wireless networks [27].

Cognitive wireless network consists of same cognitive devices and mixed network comprises of non cognitive nodes and cognitive nodes [27]. Cognitive wireless networks are further classified into homogeneous and heterogeneous networks.

In a homogeneous network, CR nodes are identical in a given area (i.e., they use the same waveform) . For example, the network shown in Figure 2.4 has similar WiMax nodes and forms a homogeneous network [27]

If a network comprise of mixture of several CR nodes they are called as heterogeneous networks. For example, the heterogeneous network shown in Figure 2.5 is comprised of nodes such as CDMA, Blue-tooth, Wireless Local Area Network (WLAN) device, GSM, Ultra-Wideband

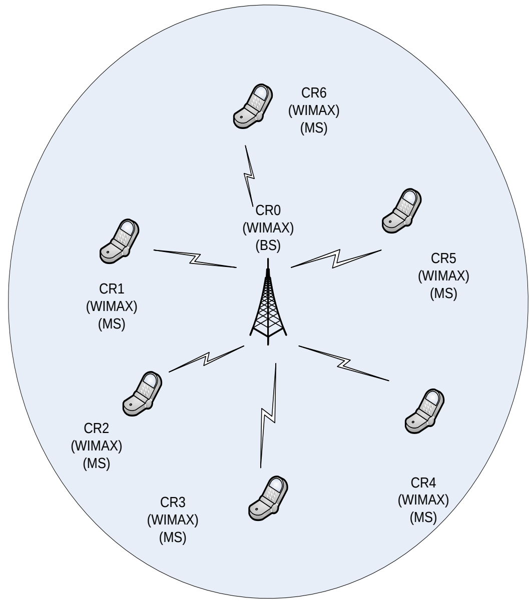


**Figure 2.4:** Homogeneous Network [27].

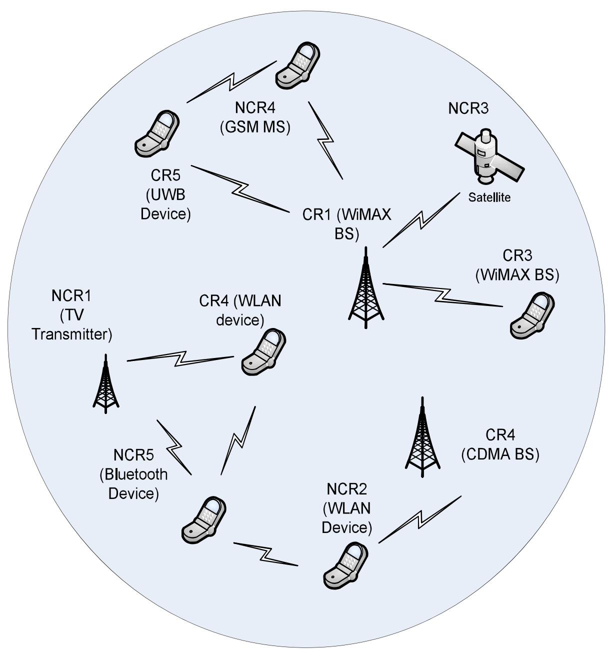


**Figure 2.5:** Heterogeneous Network [27]

(UWB) device and TV transmitter forms the heterogeneous networks. In non CRs location information defines the uninterrupted connectivity. Non CRs can adapt dynamically when in heterogeneous networks with CRs [27]. Hence, a heterogeneous network in a geographical region has a blend of different nodes (e.g., WiMAX base stations, ultra-wide band nodes) [27]. A heterogeneous network is illustrated in Figure 2.5.

## 2.10 Interference Assessment

In a wireless network consisting for nodes scattered, there are several impairments that restrain communication. They are thermal noise, network interference and wireless propagation effects. The three factors namely path loss, shadowing and multi path fading lead to wireless propagation effects. Secondly, radiation of signals from other transmitters causes network interference which is a hindrance to the receiving nodes. Thirdly, thermal noise occurs due to the receiver electronics [28].

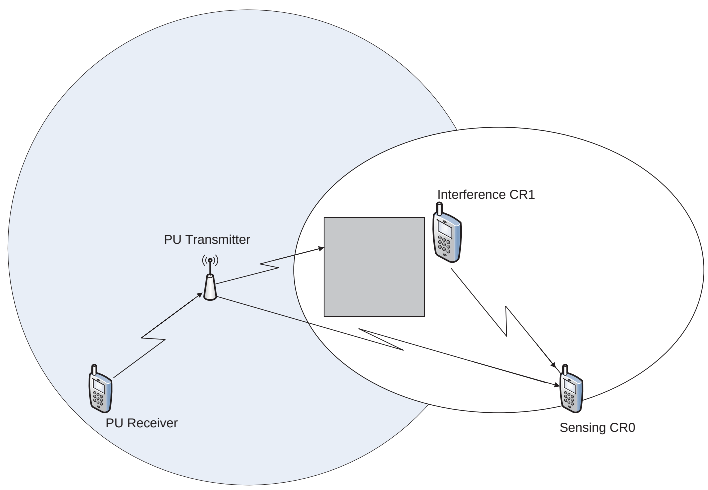


**Figure 2.6:** Shadowing effect [10].

### Factors affecting wireless propagation

*Shadowing* the propagation path between transmitter and receiver is obstructed during spectrum sensing. Figure 2.6 shows that CR is subjected to shadowing effect, i.e., Obstacle in the medium. Thus the CR is unable to determine the PUs existence and hence is prohibited from accessing the medium when the PU is idle [1].

Figure 2.6 depicts a scenario in which $CR_1$ has a line of sight to $CR_0$, but because of the shadowing effect, $CR_1$ is prohibited from identifying the PUs existence though it is in the range of $CR_1$. This occurs as a result of an obstacle in the communication link. When $CR_1$ starts transmission, assuming the PU to be absent, $CR_0$ experiences interference as it tries to sense the existence of a PU.

To effectively use the radio spectrum, a CR should possess good sensing measures. To counter the attack of interference in CR, EDs that are robust to interference could be used, thereby attaining high sensing reliability.

The modeling of network interference with several application to design, analyse, develop mitigation technique has always been a tedious task. The Gaussian random process which helps in modeling the interference, is discussed in the third chapter.

*Path Loss* the phenomenon of reducing the power intensity of an electromagnetic wave as it promulgates through space is known as Path loss and in the link budget of a telecommunication system, path loss is the preeminent component. When there is natural expansion of the radio wave front in free space it leads to propagation loss which is one of the main factor for path loss [29].

*Multipath fading* The radio waves travels via a number of paths between transmitter and receiver, this is simply termed as multi path. Hence there would be an occurrence of multi path interference causing multi path fading. Fading occurs due to the small shift in phase or amplitude over a period of time, which in turn caused by the effect of the movement of transmitter or receiver [30].

**Interference in a random network and mitigation process**

With an increase in the need of data rates, there has been a scarcity in the electromagnetic spectrum. The other reason for this scarcity is the policy allocation and allocation of spectral bands in a given area [28].

In CR networks, effective spectrum sensing involves ample spectrum utilization without disturbance of PUs. But in a multiuser environment, CRs are subjected to interference which in turn affects sensing performance [4]. Interference in a CR can be classified into two types: Inter-network interference and Intra-network interference.

*Intra-network interference* also coined as self-interference, is most common among various wireless communication systems. They can be effectively mitigated by several techniques [31].

*Inter-network interference* is an interference between the primary network and CR network i.e., It could be an interference from CR to primary networks and from primary to CR networks. They can be mitigated by the following techniques: interference mitigation and interference avoidance [31].

*Interference mitigation* aids in reducing interference impact during transmission and reception of signal. Interference mitigation follows methods such as (1) interference randomization where interleaving or frequency hopping could be used to mitigate interference, (2) interference cancellation: where interference signals are subtracted from the desired received signal or by employing multiple antennas, so as to receive the best signal among various received signals, (3) dynamically changing radiation pattern depending on interference [32].

*Interference avoidance* aims at better SINR by allocation of time/frequency/power and it also ensure the inter-cell interference in within limits [32].

$\sim$

# Chapter 3

# Improved Energy Detection performance in the Presence of Interference

## 3.1 Introduction

In this chapter, the role of an IED in improving the spectrum sensing performance (compared to a traditional ED) is explored. Particularly, the effect of adapting the parameter $p$ is studied. When a multiuser environment is considered, say, an LTE network with relays and hot spots, the interferers in a geographical region are positioned randomly (re location and distance) and the number of interferers is unknown. Performance improvements are explored by the cooperative sensing technique (section 2.7). The performance is analyzed using Monte-Carlo simulations.

## 3.2 System Model

We assume a network $K$ with interfering users $U_1$,$U_2$,$U_3$,...$U_K$ with a PU and sensing CR in a given geographical region as shown in Figure 3.1. $U_1$,$U_2$,$U_3$,...$U_K$ in Figure 3.1 could be a PU or the CRs that may be transmitting or receiving in the same frequency and thus, cause interference to the sensing CR. We presume a reference CR sensing node $CR_0$ at a spherical region of radius $D$ surrounded by $K$ other interfering nodes. When non cooperating CR network is considered, the status of SUs is unknown. The PU transmitter is randomly located at distances $d_0$ from $CR_0$ and $d_k$ from the $k$-th interfering node at a distance $r_k$ from the sensing node. The signal at ED is given as

$$y(t) = \begin{cases} w(t) + \sum_{k=1}^{K} i_k(t), & : H_0 \\ s(t) + w(t) + \sum_{k=1}^{K} i_k(t), & : H_1 \end{cases} \tag{3.1}$$

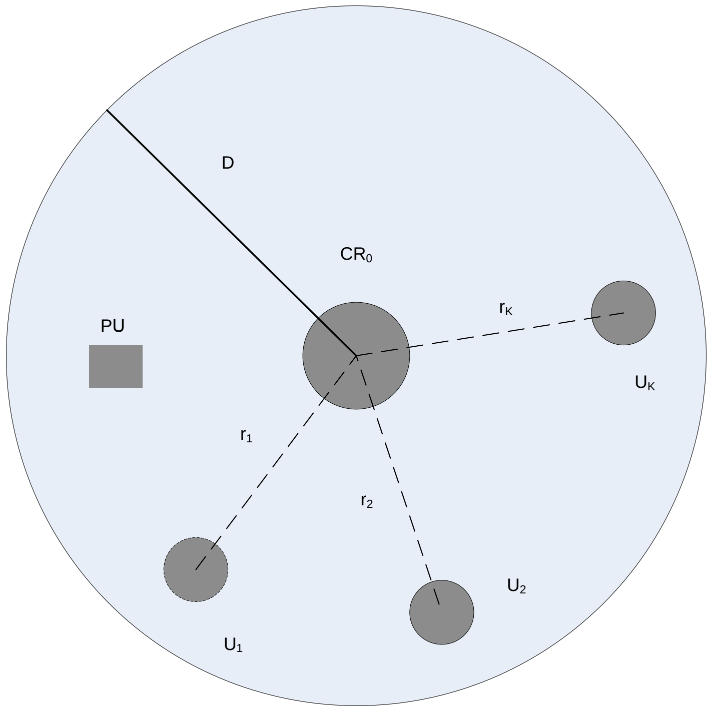


**Figure 3.1:** Spectrum Sensing in random Interference network

where $H_0$ and $H_1$ represent the non existence and existence of PU signal, respectively; $s(t)$ and $w(t)$ represent the PUs signal and AWGN, respectively; $i_k(t)$ is the $k$-th interfering signal which is given by

$$i_k(t) = \sqrt{P_k r_k^{-\alpha} s_k(t)} \tag{3.2}$$

where $P_K$ is the transmission power of the PU. $\alpha$ denotes path loss exponent. This received signal $y(t)$ is sampled and fed into the IED to deduce the presence or absence of PU.

## 3.3 Description of simulation model

For our purpose of evaluating the sensing performance, we deploy the Monte Carlo simulation method. This method is an iterative technique for performing computations based on random sampling of unknown probabilistic entities. For our purpose, Monte Carlo technique is important for obtaining an overall (average) performance over a region of random variables that include noise, random interfering signals. The interfering signals $i_k(t)$, are modeled as Gaussian signals conditioned on the random variables $k$ and random locations $r = r_1, r_2, ...r_k$. Considering Poisson distributed interfering nodes, the probability of $k$ interfering nodes in the given geographical region of $\pi D^2$ with an average density $\lambda$ is given as [4]

$$\mathbb{P}(K = k) = \frac{e^{-\lambda \pi D^2} (\lambda \pi D^2)^k}{k!} \tag{3.3}$$

whereas the location $r = r_1, r_2, ...r_k$ within the disc of radius $D$ are uniformly distributed as

$$f_{r_k}(x) = \begin{cases} \frac{2x}{D^2}, & 0 < r < D \\ 0, & otherwise \end{cases} \tag{3.4}$$

Then, the use of (2.4) followed by that of (2.3) yields the desired $P_d$ and $P_f$.

### 3.3.1 Cooperative spectrum sensing scheme

In cooperative spectrum sensing, multiple CRs are involved in performing spectrum sensing. Probability of detection is improved by cooperative spectrum sensing [33]. In the cooperative spectrum sensing algorithm, each CR makes an unified conclusive decision depending on the local sensing scheme and feeds this result to a FC.

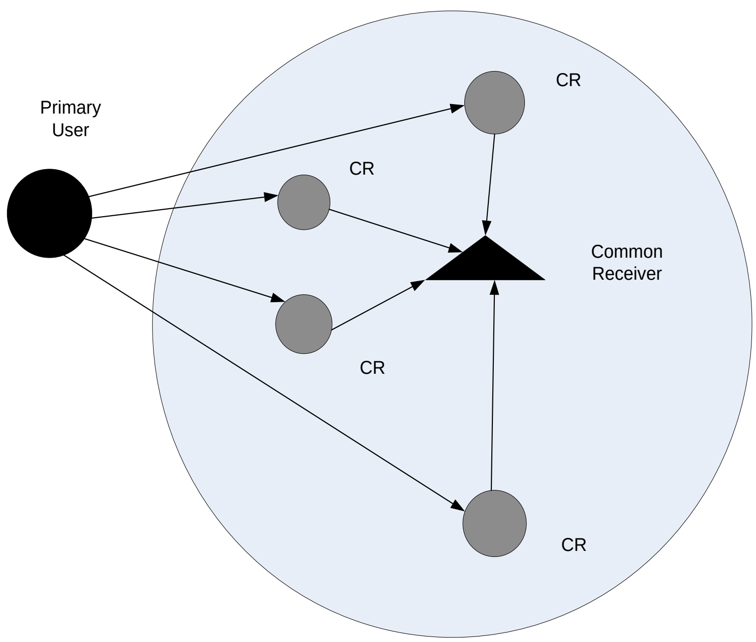


**Figure 3.2:** Spectrum sensing in CR network [10]

The decisions made are fused together at the FC by using the MAJORITY fusion rule [33]. According to this rule, the decisions from each individual CR, $D_i$ are combined and used for the overall decision making as [33]

$$Z = \sum_{i=1}^{K} D_i \begin{cases} \geq n & H_1 \\ < n & H_0 \end{cases} \tag{3.5}$$

where n is obtained by

$$n = \begin{cases} C/2 & for\ even\ '\mathcal{M}' \\ (C+1)/2 & for\ odd\ '\mathcal{M}' \end{cases} \tag{3.6}$$

Equation 3.5 demonstrates the FC's decision regarding the presence of the PU. $H_1$ infers the existence of a PU when $\mathcal{M}$ out of $C$ CRs infer $H_1$. Otherwise the FC decides that the PU is absent. The false alarm probability of cooperative spectrum sensing is given as

$$Q_f = \sum_{l=\mathcal{M}}^{C} \binom{C}{l} P_f^l (1 - P_f)^{C-l} \tag{3.7}$$

And missed detection probability of cooperative spectrum sensing by majority rule is given as [33]

$$Q_d = \sum_{l=\mathcal{M}}^{C} \binom{C}{l} P_f^l (1 - P_d)^{C-l} \tag{3.8}$$

### 3.3.2 Performance metrics

In the following, performance parameters are used to quantify the detection performance:

1. Detector parameters include a fundamental parameter $p$ which decides the version of IED, a detection threshold to infer the occurrence of a PU or SU, and the number of samples $N$.

2. Wireless network parameters include the area of the geographical region $R$, the interferer density $\beta$, the path loss exponent $\alpha$, the signal power $P_s$, and interference power $P_i$.

## 3.4 Numerical Results: IED Performance in the Presence of Interference

The numerical results described in the below sections defines the effect of parameter $p$ and its effect with respect to cooperative spectrum sensing. This section focuses on the study of the performance of $p$-norm detector with the effects of samples, SINR, interference density and path loss. The results define the value of $p$ at which the probability of error is minimum without cooperative sensing.

### 3.4.1 Effect of $N$ on IED performance

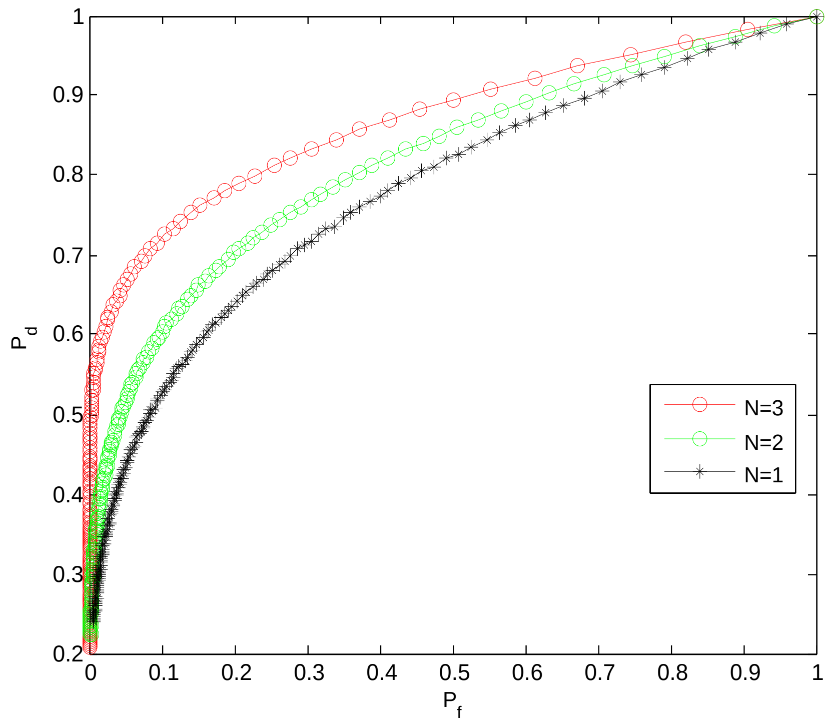


**Figure 3.3:** ROC for varying samples, $u$ = 2, SINR = 5 dB, $\beta$ = 0.001, $R$ = 150, $\alpha$ = 2.5

Figure 3.3 describes the IED performance as samples increase. When the number of samples increases, the performance of energy detection increases. When the number of samples is reduced from 2 to 1, there is a decrease in detection performance of 14%. When the number of samples decreases from 3 to 2, there is a decrease in energy detection performance of 11%. These results indicate that the higher the number of samples, the better is the ED performance.

### 3.4.2 Effect of SINR over $P_e$ for varying $p$

Figure 3.4 is a plot of probability of error $P_e$ versus $p$ (energy detection performance) for various SINR values. As expected, the probability of error was reduced as the SINR was increased for varying values of $p$. As SINR is increased from -10 to -5 dB at $p = 2$, the probability of error is decreased by 40%, a good margin. Also, at the value of $p = 4$, $P_e$ is decreased by 15% as the SINR changes from -10 to -5 dB. Thus, we can conclude that the error probability is minimum at an optimal $p$, when SINR is increased.

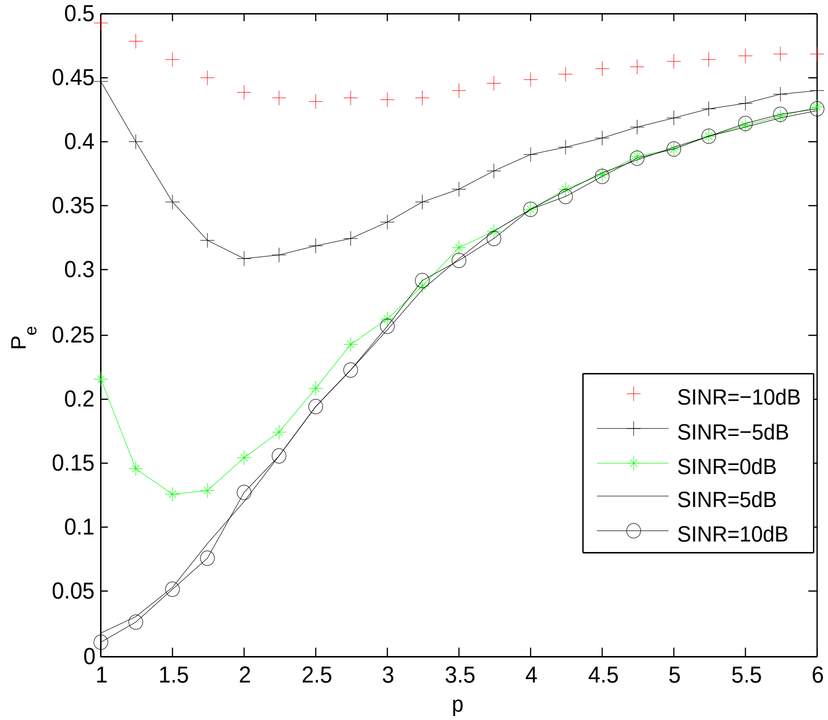


**Figure 3.4:** $P_e$ vs. $p$ for varying SINR, $u = 5$, $\lambda = 1.3$, $\beta = 0.001$, $R = 150$, $\alpha = 2.5$

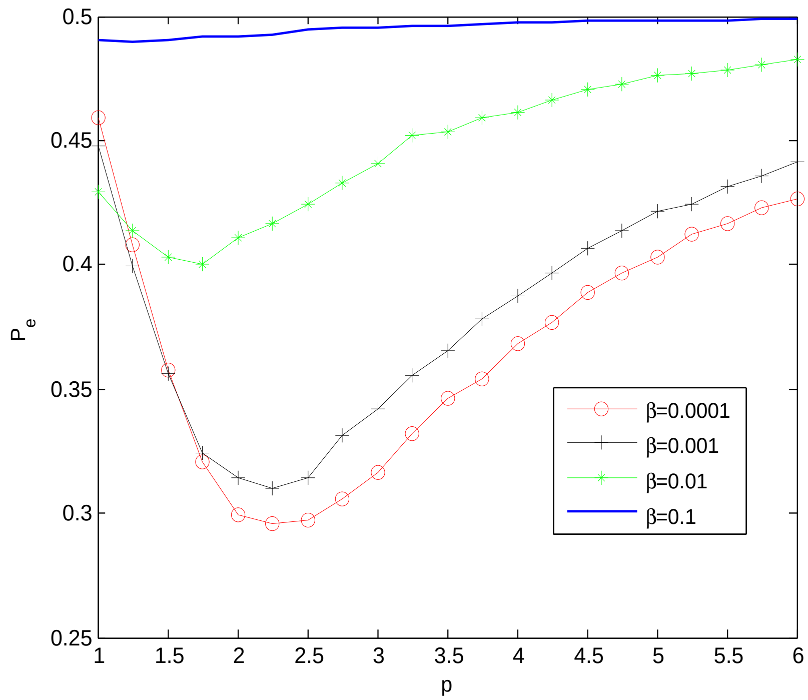


**Figure 3.5:** $P_e$ vs. $p$ for varying $\beta$, $u = 5$, SINR $= -5$ dB, $R = 150$, $\alpha = 2.5$

### 3.4.3 Effect of $\beta$ over $P_e$ for varying $p$

Figure 3.5 describes the effect of interferer density $\beta$ on the probability of error for various $p$. Results conclude that probability of error $P_e$ is lower at a lower interferer density $\beta$ values.

Similarly, at $p$ of 2.25, the probability of error is low as $\beta$ decreases from 0.1 to 0.01 and the probability of error is decreased by 16%. Considering the decrease in $\beta$ from 0.01 to 0.001, the probability of error decreases by 35%. At the same $p$ value, when $\beta$ decreases from 0.001 to 0.0001 the $P_e$ is reduced by 5%. This clearly shows the effect of $\beta$ on the error probability, i.e., when $\beta$ decreases, $P_e$ decreases for a particular value of $p$.

### 3.4.4 Effect of $\alpha$ over $P_e$ for varying $p$

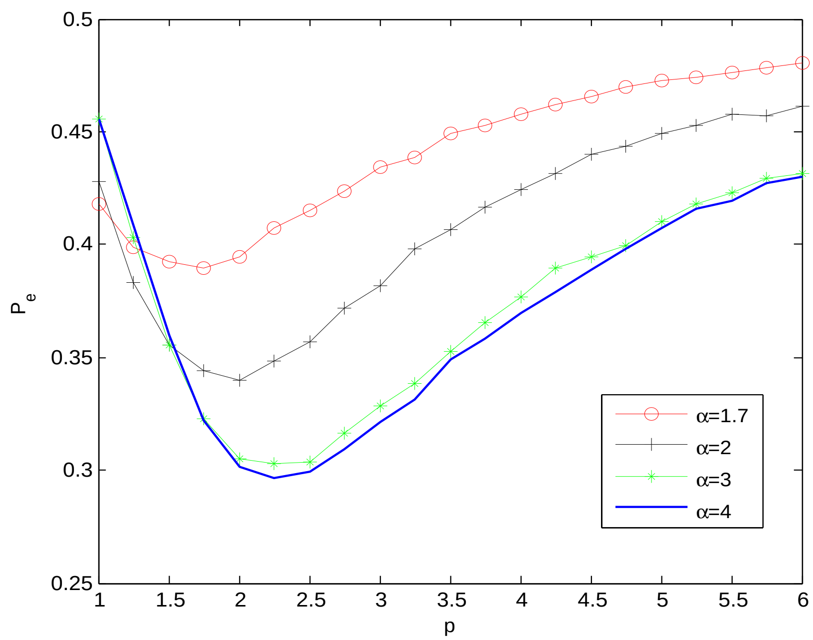


**Figure 3.6:** $P_e$ vs. $p$ for varying $\alpha$, $u = 5$, SINR $= -5$ dB, $\lambda = 1.3$, $R = 150$

Figure 3.6 shows the effect of path loss factor $\alpha$ on the energy detection performance $p$. The results shows increase in $\alpha$ increases the detection probability for any value of $p$. In this case, when $p$ is 2.2 the probability of error is reduced by 16% as the path loss factor is increased from 1.7 to 2. Similarly at the same value of $p$, when $\alpha$ is increased from 2 to 4, $P_e$ decreases by just 17%. Hence we conclude that larger value of $\alpha$ reduces the probability of error.

## 3.5 Numerical Results: Performance of IED in Cooperation Spectrum Sensing

The following section illustrates the effect of cooperation spectrum sensing on the energy detection performance. The sections below illustrates the effects such as SINR, interference density, path loss exponent, interference power and threshold on the energy detection performance of IED.

### 3.5.1 Effect of SINR over $Q_d$ for varying $Q_f$

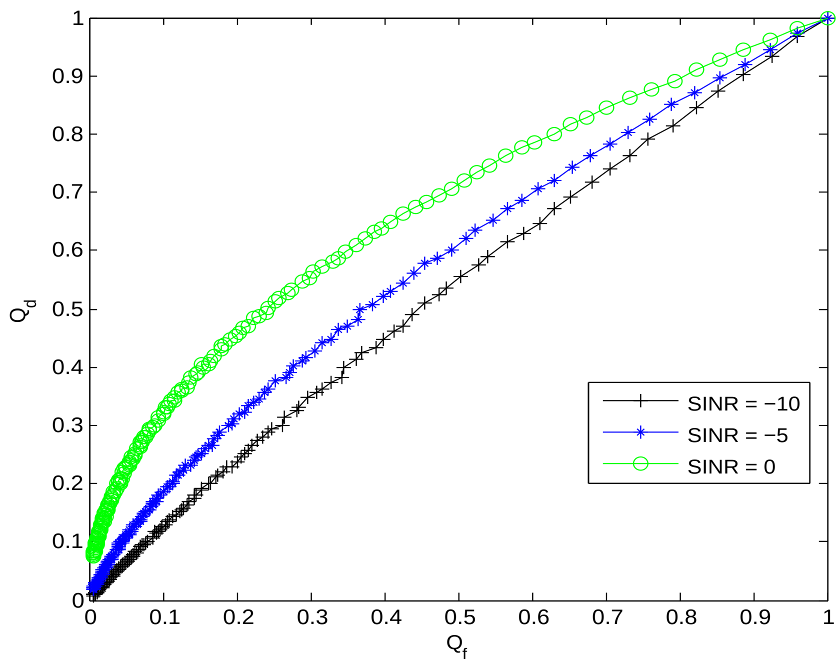


**Figure 3.7:** $Q_d$ vs. $Q_f$ for varying SINR, $\beta = 0.0001$, $P_i = 5\,\text{dB}$, $R = 150$, $\alpha = 2$

Figure 3.7 illustrates the effect of SINR on energy detection performance $p$ in cooperation spectrum sensing. When the SINR increases, $Q_d$ increases. When the SINR increases from -10 to -5, the detection performance increases by 26%. Similarly, when the SINR further increases from -5 to 0, the detection performance increases further by 37%. Thus we conclude higher the SINR, better the detection probability.

### 3.5.2 Effect of $\beta$ over $Q_e$ for varying $\mathcal{M}$

Figure 3.8 shows the impact of interferer density $\beta$ on the probability of error $P_e$ in a cooperative spectrum sensing scheme. The graphs clearly defines lesser the interference density, lesser the probability of error. Now, When the interferer density is 0.001 and 0.0001, at a constant value of $\mathcal{M}$, the probability of error $P_e$ decreases. When $\beta$ is 0.001 $P_e$ gradually drops as the number of CRs increases. In the presence of 5 CRs, $P_e$ falls to 0.1129. Similarly, when $\beta$ is 0.0001, $P_e$ gradually reduces and when $\mathcal{M}$ is 4, $P_e$ reaches a minimum value of 0.07997. This indicates that when the interferer density is high, a large number of CRs are required to get a minimal value of $P_e$.

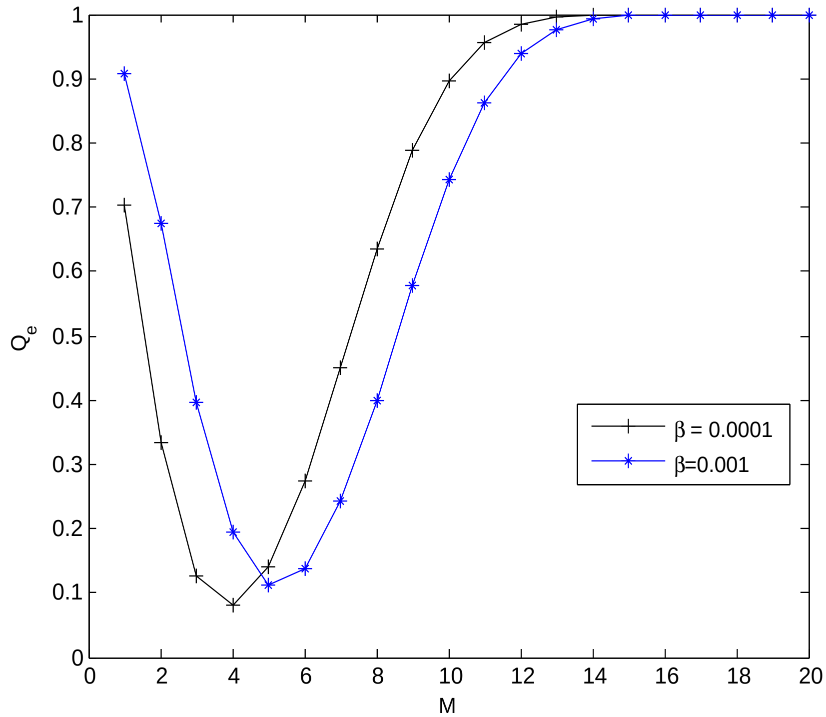


**Figure 3.8:** $Q_e$ vs. $\mathcal{M}$ for varying $\beta$, $u = 5$, $P_i = 0$

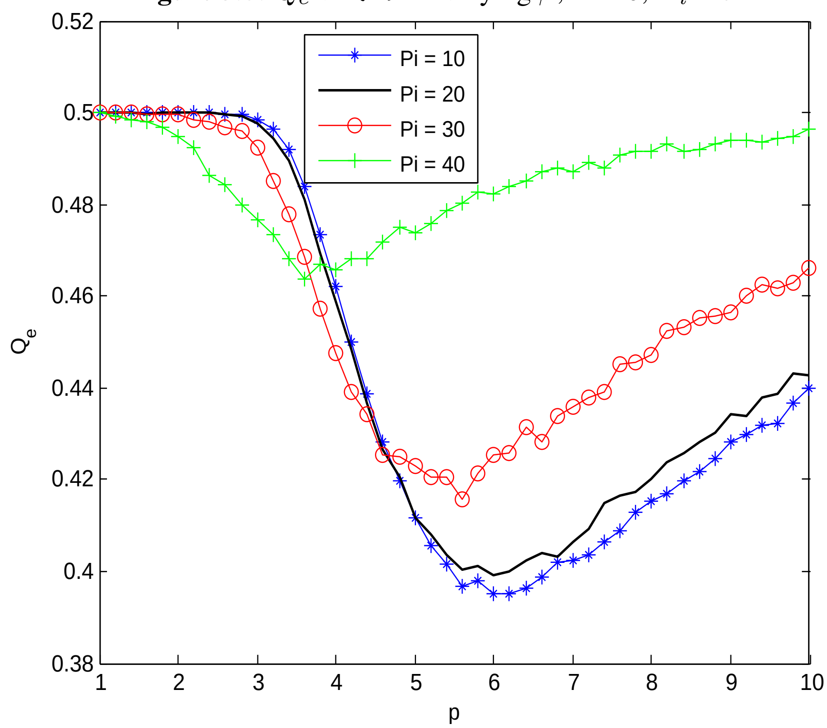


**Figure 3.9:** $Q_e$ vs. $p$ for varying $P_i$, $u = 5$, $P_s = -5\,\text{dB}$, $\lambda = 5.5$, $R = 150$, $\alpha = 2.5$

### 3.5.3 Effect of interference power $P_i$ over $Q_e$ for varying $p$

Figure 3.9 depicts the behavior of $P_e$ with respect to $P_i$ for different values of $p$. In this case we observe that for a particular value of $P_i$, $P_e$ decreases only up to a certain value of $p$ and then gradually increases after that. For an instance when interference power $p_i$ is 40 dB, minimal $P_e$ is obtained when $p$ is 3.6. As $P_i$ decreases to 30, 20 and 10 we can notice the value of $p$ at which the probability of error is minimum changes to 5.6, 6 and 6.2 respectively. This provides a clear picture on effect of interference power on the error probability, (i.e) at any interference power $P_i$, the probability of error $P_e$ decreases for a particular value of $p$.

### 3.5.4 Effect of $\mathcal{M}$ over $Q_e$ for varying $\lambda$

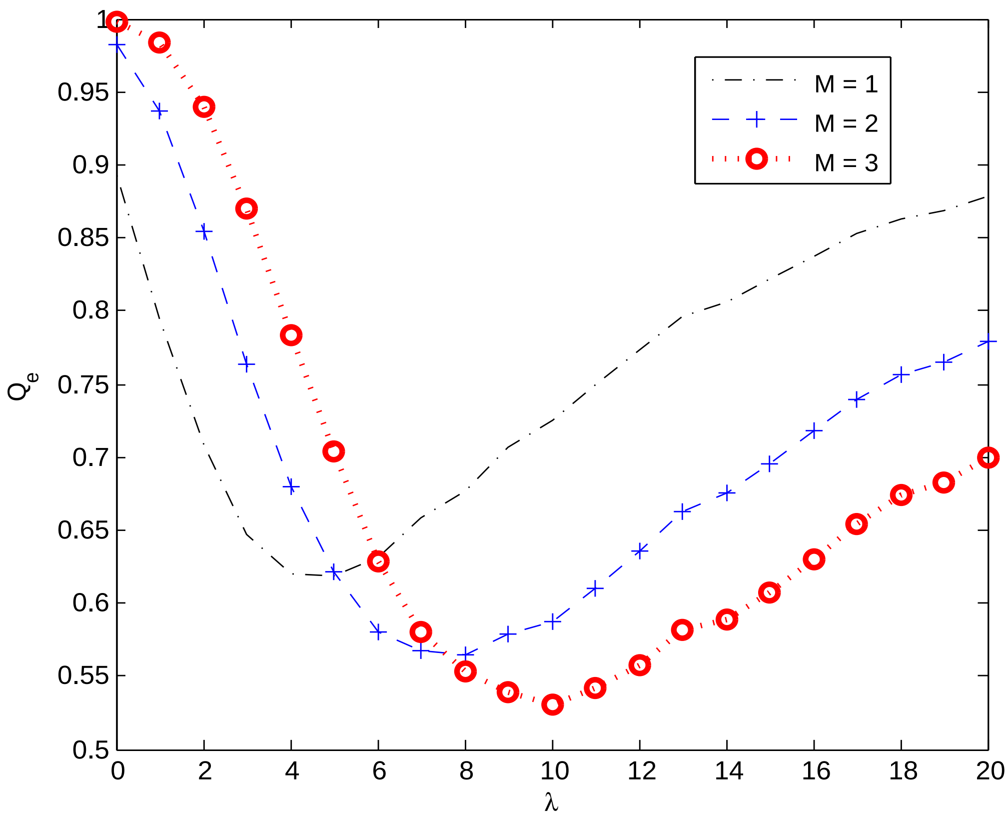


**Figure 3.10:** $Q_e$ vs. $\lambda$ for varying $\mathcal{M}$, $u = 5$ , $P_s = -5$ dB , $\lambda = 5.5$ , $R = 150$, $\beta = 0.001$

Figure 3.10 shows the influence of $p$ over $P_e$ in the presence of several CRs. As the value of $\mathcal{M}$ increases, $P_e$ decreases to an optimal threshold value. For instance, when $\mathcal{M}$ is 1, the minimum value of $\lambda$ is 5, when $\mathcal{M}$ increases to 2, $\lambda$ becomes 8, and when $\mathcal{M}$ increases to 3, $\lambda$ becomes 10. From these results we infer that $P_e$ decreases when the number of CRs increased.

## 3.6 Conclusion

In this chapter, the performance of IED in a random interference environment is characterized with the aid of simulations performed in MATLAB. In a geographical region with interferer's are positioned random, the performance of Energy Detector (ED) degrades and to mitigate the interference in such network of random interferer's an IED is used and simulations are performed to obtain the optimal value of parameter $p$ at which the probability of detection error is minimum. Further introducing cooperative spectrum sensing scheme to the IED has shown significant decrease in the error detection by alleviating the interference problem thereby helping to achieve the desired goal of robust spectrum sensing of CR networks in the presence of interference.

$\sim$

# Chapter 4

# Conclusion

This project is dealt with ED for addressing spectrum sensing drawbacks in CR networks. Also it depicted the effect of interference on the ED. With an aim of alleviating such degradation in detector performance $p$, we investigated the effect of parameter $p$ and extended it over a cooperative spectrum sensing scheme to achieve additional performance gain compared to a single CR based sensing.

The spectrum sensing performance of improved energy detection was examined in a random network of interferers with respect to non cooperative and cooperative environments. Semi-analytical Monte Carlo simulations were performed in MATLAB to characterize the effects of parameters such as detection threshold, signal to interference noise ratio, improved energy detection parameter $p$ and a cooperation spectrum sensing scheme. The energy detection performance degrades in the presence of interference. Also the reception of unwanted signals at the ED degrades its sensing performance. With the goal of alleviating such degradation we have studied the effect of $p$ on spectrum sensing by tuning the parameter $p$. Further we extended the scenario to a cooperative spectrum sensing network where multiple CRs cooperate with a FC (eNB). This indeed enhanced performance detection is expected to improvise the spectrum sensing performance of CR networks in the presence of interference

$\sim$

# References


[1] K. Letaief and W. Zhang, "Cooperative communications for cognitive radio networks," *Proceedings of the IEEE*, vol. 97, no. 5, pp. 878–893, May 2009.

[2] J. Deaton, R. Irwin, and L. DaSilva, "The effects of a dynamic spectrum access overlay in LTE-advanced networks," in *Proceedings of IEEE Symposium on New Frontiers in Dynamic Spectrum Access Networks (DySPAN)*, May 2011, pp. 488–497.

[3] http://www.cisco.com/c/en/us/solutions/collateral/service-provider/visual-networking-index-vni/white_paper_c11-520862.html.

[4] A. Makarfi and K. Hamdi, "Efficiency of energy detection for spectrum sensing in the presence of non-cooperating secondary users," in *Proceedings of IEEE Global Communications Conference (GLOBECOM)*, December 2012, pp. 4939–4944.

[5] http://cdn.arstechnica.net/wp-content/uploads/2012/05/Screen-Shot-2012-05-09-at-8.57.25-PM.png.

[6] J. D. Deaton, R. E. Irwin, and L. A. DaSilva, "Dynamic spectrum access in LTE-advanced networks," *Physical Communication*, vol. 10, pp. 127–143, 2014.

[7] http://www.researchgate.net/publication/228875706_Spectrum_Sensing_Methods_and_Dynamic_Spectrum_Sharing_in_Cognitive_Radio_Networks_A_Survey.

[8] Y. Chen, "Improved energy detector for random signals in gaussian noise," *IEEE Transactions on Wireless Communications*, vol. 9, no. 2, pp. 558–563, February 2010.

[9] Ian, "cooperative spectrum sensing," Tech. Rep., December 2010.

[10] I. Akyildiz, W.-Y. Lee, M. C. Vuran, and S. Mohanty, "A survey on spectrum management in cognitive radio networks," *IEEE Communications Magazine*, vol. 46, no. 4, pp. 40–48, April 2008.

[11] http://www.gsma.com/spectrum/what-is-spectrum/.

[12] A. S. Rahul Tandra and S. Mishra, "What is a spectrum hole and what does it take to recognize one?" Tech. Rep., 2009.

[13] T. Renk, C. Kloeck, and F. Jondral, "A cognitive approach to the detection of spectrum holes in wireless networks," in *Proceedings of IEEE Consumer Communications and Networking Conference*, Jan 2007, pp. 1118–1122.

[14] http://www.fer.unizg.hr/_download/repository/KDI_Tabakovic_Zeljko.pdf.

[15] P. Aparna and M. Jayasheela, "Cyclostationary feature detection in cognitive radio using different modulation schemes," *International Journal of Computer Applications*, vol. 47, no. 21, pp. 12–16, 2012.

[16] http://www.jatit.org/volumes/Vol41No1/3Vol41No1.pdf.

[17] A. Makarfi and K. Hamdi, "Interference analysis of energy detection for spectrum sensing," *IEEE Transactions on Vehicular Technology*, vol. 62, no. 6, pp. 2570–2578, July 2013.

[18] Y. Zhang, "Dynamic spectrum access in cognitive radio wireless networks," in *Proceedings of IEEE International Conference on Communications*, May 2008, pp. 4927–4932.

[19] G. Ghosh, P. Das, and S. Chatterjee, "Cognitive radio and dynamic spectrum access–a study," *International Journal of Next-Generation Networks*, vol. 6, no. 1, 2014.

[20] S. Atapattu, C. Tellambura, and H. Jiang, *Energy Detection for Spectrum Sensing in Cognitive Radio*. Springer, 2014.

[21] I. F. Akyildiz, B. F. Lo, and R. Balakrishnan, "Cooperative spectrum sensing in cognitive radio networks: A survey," *Physical Communication*, vol. 4, no. 1, pp. 40–62, 2011.

[22] J. Xiao, R. Hu, Y. Qian, L. Gong, and B. Wang, “Expanding LTE network spectrum with cognitive radios: From concept to implementation,” *IEEE Wireless Communications*, vol. 20, no. 2, pp. 12–19, April 2013.

[23] L. Badia, R. Del Re, F. Guidolin, A. Orsino, and M. Zorzi, “A tunable framework for performance evaluation of spectrum sharing in LTE networks,” in *World of Wireless, Mobile and Multimedia Networks (WoWMoM), 2013 IEEE 14th International Symposium and Workshops on a*, June 2013, pp. 1–3.

[24] Q. Zhao and A. Swami, “A survey of dynamic spectrum access: Signal processing and networking perspectives,” in *IEEE International Conference on Acoustics, Speech and Signal Processing*, vol. 4, April 2007, pp. IV–1349–IV–1352.

[25] http://www.tutorialspoint.com/lte/lte_network_architecture.htm.

[26] http://ece.engineering.ualberta.ca/en/Graduate/~/media/ece/Graduate/Documents/GradDocs/Intro_to__Evolved_packet_core_network.pdf.

[27] H. Arslan, *Cognitive Radio, Software Defined Radio, and Adaptive Wireless Systems page=305-306*.

[28] M. Win, P. Pinto, and L. Shepp, “A mathematical theory of network interference and its applications,” *Proceedings of the IEEE*, vol. 97, no. 2, pp. 205–230, Feb 2009.

[29] http://en.wikipedia.org/wiki/Path_loss.

[30] http://www.iitg.ernet.in/scifac/qip/public_html/cd_cell/chapters/a_mitra_mobile_communication/chapter5.pdf,.

[31] http://home.eps.hw.ac.uk/~cw46/2009_Wang_VT%20Mag_09_04_76.pdf.

[32] http://4gpp-project.net/attachments/section/4/WP4_ICIC_v3.pdf.

[33] W. Zhang, R. Mallik, and K. Letaief, “Cooperative spectrum sensing optimization in cognitive radio networks,” pp. 3411–3415, May 2008.