SPECTRUM OCCUPANCY MEASUREMENTS
AND COGNITIVE RADIO SYSTEM
IMPLEMENTATION

by

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**Approval Signatures**

We, the undersigned, approve the Master’s Thesis of Firas Ahmed Kiftaro.

Thesis Title: Spectrum Occupancy Measurements and Cognitive Radio System Implementation

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To my beloved parents ...
Abstract

Nowadays, radio spectrum is mostly crowded and occupied by many fixed wireless services. Therefore, there is less opportunity of finding a vacant band (spatially or temporally) for deploying new wireless communication services or enhancing already existing ones. The Telecommunications Regulatory Authority (TRA) allocation chart in UAE shows some overlapping allocation for services given the same band which reinforces the spectrum scarcity concept. Insufficient frequency spectrum allocation and the problem of spectrum scarcity are standing against the will of introducing more services to the wireless communication community. As a result, many measurement campaigns around the world have been conducted in order to investigate more about the spectrum utilization and characterization. Dynamic Spectrum Access (DSA) technologies have been introduced and promised to use the idle spectrum bands and utilize them efficiently. One form of DSA technologies is Cognitive Radio (CR) which is based on allowing an unlicensed (secondary) user to access an unoccupied portion of licensed spectrum and use it without causing interference with the licensed (primary) user in an opportunistic way. This thesis is mainly divided into two parts; in the first part, the occupancy of the frequency spectrum is studied through multiple measurement campaigns. These campaigns lasted for twenty days and conducted at the American University of Sharjah. These measurements were done over the ultra-high frequency (UHF) due its potential to be utilized by cognitive radio systems. The measurements indicated that large portions of the UHF band are not utilized efficiently. A Gaussian mixture model (GMM) analysis was carried out to obtain quantitative observations about the UHF occupancy levels. The second part of this thesis is about implementing a cognitive radio system based on real data collected using a prepared experimental setup consists of Universal Software Radio Peripheral (USRP) devices. An energy detector and polynomial classifier were implemented for spectrum sensing. A comparison between the two approaches shows that polynomial classifier has better performance over the energy detector in terms of the misclassification rate.

Search Terms: cognitive radio, spectrum occupancy, spectrum sensing, energy detector, machine learning, polynomial classifier, Universal Software Radio Peripheral (USRP)
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<td>ASCII</td>
<td>American Standard Code for Information Interchange</td>
</tr>
<tr>
<td>AWGN</td>
<td>Additive White Gaussian Noise</td>
</tr>
<tr>
<td>BPSK</td>
<td>Binary Phase-Shift Keying</td>
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<tr>
<td>CR</td>
<td>Cognitive Radio</td>
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<tr>
<td>DC</td>
<td>Duty Cycle</td>
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<tr>
<td>FPGA</td>
<td>Field-Programmable Gate Array</td>
</tr>
<tr>
<td>GSM</td>
<td>Global System for Mobile communication</td>
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<tr>
<td>GMM</td>
<td>Gaussian Mixture Model</td>
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<tr>
<td>GPIB</td>
<td>General Purpose Interface Bus</td>
</tr>
<tr>
<td>GbitE</td>
<td>Gigabit Ethernet</td>
</tr>
<tr>
<td>GNSS</td>
<td>Global Navigation Satellite System</td>
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<tr>
<td>ITU</td>
<td>International Telecommunication Union</td>
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<tr>
<td>IEEE</td>
<td>The Institute of Electrical and Electronics Engineers</td>
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<tr>
<td>LNA</td>
<td>Low Noise Amplifier</td>
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<tr>
<td>PU</td>
<td>Primary User</td>
</tr>
<tr>
<td>RBW</td>
<td>Resolution Bandwidth</td>
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<tr>
<td>SA</td>
<td>Spectrum Analyzer</td>
</tr>
<tr>
<td>SDR</td>
<td>Software Defined Radio</td>
</tr>
<tr>
<td>SU</td>
<td>Secondary User</td>
</tr>
<tr>
<td>SCPI</td>
<td>Standard Commands for Programmable Instruments</td>
</tr>
<tr>
<td>SNR</td>
<td>Signal to Noise Ratio</td>
</tr>
<tr>
<td>TRA</td>
<td>Telecommunications Regulatory Authority</td>
</tr>
<tr>
<td>UHF</td>
<td>Ultra-High Frequency band</td>
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<tr>
<td>USB</td>
<td>Universal Serial Bus</td>
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<tr>
<td>USRP</td>
<td>Universal Software Radio Peripheral</td>
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<td>VBW</td>
<td>Video Bandwidth</td>
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Chapter 1: Introduction

Data communication has become an integral part of modern society. It facilitates human interaction over long distances and allows the rapid transfer of information, thus improving productivity in all aspects of human civilization.

Communication technology started out over wired channels. One of the most popular wired networks is the telephone cables system that involved the extension of cables for hundreds of kilometers to connect end users to a base operator office that works as an intermediate connection between users. This wired infrastructure required a huge financial investment, large land allocations as well as extensive physical work to be implemented, but as the coverage area of the channel increased, the arrangement became less cost effective and the use of wireless communication was explored. Since air was the medium, construction and set up only need to take place at the transmitting and receiving ends, thus reducing implementation costs and allowing the communication system to extend over longer distances. However, as the wireless channel started to be used for a wider variety of applications, the need to partition the spectrum and organize the allocation of frequency bands by governments arose to ensure services remain operational. For example, the old GSM 900 mobile network used as the basis for the 2G mobile technology was given the frequency band centered at 900 MHz; hence, a mobile phone had to be fitted with a receiver that can communicate with the GSM band and no other type of communication, such as that for military means, can occur over that band. Unlicensed communication over it can result in legal prosecution.

Traditionally, the user buys a channel wide enough to provide a certain data rate and deliver a service such as broadcast radio or mobile communications to its customers. The user only utilizes the band when there is a need to do so and hence some bands are never always occupied. There is usually sometime every day where a certain radio channel is idle, however, nobody can use it except the allocated user. This decreases the supply of wireless spectrum, driving up its price and shuts users with smaller capital out of the spectrum. In the UAE for example, the annual price per MHz for Public Land Mobile (Cellular) Service would cost more than 1 million AED [1]. Furthermore, the demand for spectrum access has increased over the years, driven by the increase in services utilizing the wireless channel - such as broadcast satellite, the rising demand for internet and Wi-Fi data as well as the push for network coverage in
rural areas [2] [3] [4]. This has resulted in the saturation of the wireless channels and motivated research into more efficient utilization of the spectrum.

In 1998, Joseph Mitola introduced the concept of cognitive radio as a solution to the inefficient utilization of the radio spectrum. It is a form of Dynamic Spectrum Access (DSA) whereby an unlicensed user (secondary) can access an unutilized portion of a licensed spectrum belonging to a primary user and transmit over it without hampering the primary user’s ability to access it when needed [5]. Therefore, the idea behind cognitive radio is the development of wireless transceivers that are aware of their channel and capable of sensing parameters such as the noise level and fading status of all the frequency bands in the radio spectrum to autonomously decide which bands are free and which aren’t. The transceivers should also be able to adapt their signals to the channel the secondary user is being migrated to, since parameters such as bandwidth, data rate, modulation type, fading type, and noise level vary from one band to another [6]. In this manner, any channel can be adapted for any service and the underutilized bands can be used more efficiently.

1.1. Problem Statement

Before implementing a cognitive radio system, a feasibility study where spectrum measurements are taken to monitor the behavior of the frequency spectrum users and usage cycles needs to be conducted. These measurements are needed to quantify the wireless channels utilization. The focus should be on the wireless channels that are inefficiently utilized, hence these are the ones potentially used by cognitive radio systems.

Secondary users in any cognitive radio system do not have the privilege to freely access the parts of the spectrum that are already licensed by the government to primary users. However, sometimes these parts of the spectrum are not utilized efficiently, hence spectrum sensing must be implemented to help secondary users accessing the unoccupied channels in such a way not causing a harm to the spectrum owners (primary users).

Given the Ultra-High Frequency (UHF) band (300 MHz – 3 GHz), it is required to build a measurement setup in order to study the spectrum occupancy within the American University of Sharjah campus, in addition to utilize the software defined
radio technologies and the different spectrum sensing techniques in implementing a cognitive radio system.

1.2. Motivation and Thesis Contributions

The efficient spectrum utilization promised by cognitive radio systems will help in solving the spectrum scarcity problem and provide better solutions for secondary users while accessing the unlicensed parts of the frequency spectrum. Building a system to statistically describe the utilization of the frequency spectrum will help other researchers and scientists in the field to apply their knowledge and be able to build actual fully functional cognitive radio systems. Since spectrum sensing is one of the major elements of cognitive radio system design, it is important to test the different spectrum sensing on real collected signals from the air.

To the author’s knowledge, there is no official spectral occupancy measurements that have been conducted and published in the UAE for the sake of assessing the feasibility of a cognitive radio system. Furthermore, vast majority of previously published work on cognitive radio was based on simulations and assumptions about the nature of the wireless channels, as opposed to actual measurements.

This thesis provides a proposed setup for measuring the spectrum occupancy rates by collecting the signals’ power over the UHF band. Moreover, this thesis proposes a statistical and analytical representation of the collected signals utilizing GMM (Gaussian Mixture Model) and probability of false alarm thresholding. Finally, this thesis covers the utilization of the available SDR (Software Defined Radio) technologies for the application of spectrum sensing on measurement-based (non-simulated) environments.

1.3. Thesis Outline

This thesis is organized as follows: Chapter 2 discusses the spectrum occupancy measurement hardware setup. It also specifies the measurement campaign time, location and plan. Chapter 3, describes the different analysis tools utilized in describing the data collected from the frequency spectrum. Chapter 4 describe the setup used for the implementation of the cognitive radio system followed by analysis and comparison between the different spectrum sensing schemes utilized in Chapter 5. Finally, Chapter 6 provides the thesis conclusions and discusses related future work.
Chapter 2: Spectrum Occupancy Measurements

This chapter discusses the spectrum scarcity problem. Moreover, it gives a detailed description about the overall hardware setup used in the spectrum measurement campaign along with the major steps followed in the spectral data collection process. In addition, this chapter provides information about the spectrum occupancy measurements time and location.

2.1. Spectrum Management

Electromagnetic frequency spectrum main application is to provide a wireless channel that can establish a connection or a path between two nodes or more, mainly these nodes are the transmitter and the receiver. Frequency spectrum is a natural resource that can be accessed by any person capable of transmitting or receiving a wireless signal. Therefore, the governments set some spectrum management regulations in order to control the frequency spectrum accessibility and to preserve the privacy and the security of the band owners (primary user).

The frequency spectrum is divided into regions or bands each is allocated for a user or a service as shown in the Telecommunications Regulatory Authority (TRA) allocation chart in UAE in Figure 1 [1]. Some overlapping allocation for services is given in the same band, which reinforces the spectrum scarcity concept. Insufficient frequency spectrum allocation and the problem of spectrum scarcity are standing against the will of introducing more services to the wireless communication community. As a result, many measurement campaigns around the world have been conducted in order to investigate more about the spectrum utilization and characterization [7] - [12].

2.2. Data Collection Equipment Description and Setup

The proposed system for spectrum occupancy measurements is shown in Figure 2. The system consists of a spectrum analyzer, a wideband discone omnidirectional antenna, a low noise amplifier (LNA), a laptop, and a weatherproof container. The equipment specifications are described in detail in Table 1. These specifications are obtained from the datasheet provided by the manufacturer.
Figure 1: Spectrum allocation chart of UAE [1]
Table 1: Measurement setup specifications

<table>
<thead>
<tr>
<th>Item</th>
<th>Details</th>
<th>Factory</th>
<th>Model</th>
<th>Frequency range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spectrum Analyzer</td>
<td></td>
<td>Rohde &amp; Schwarz</td>
<td>FSP13</td>
<td>9 KHz – 16 GHz</td>
</tr>
<tr>
<td>Wideband Omnidirectional Discone Antenna</td>
<td></td>
<td>A-INFO</td>
<td>JXTXPZ-112/P</td>
<td>1 GHz – 12 GHz</td>
</tr>
<tr>
<td>Low Noise Amplifier</td>
<td></td>
<td>HD Communications</td>
<td>HD27067</td>
<td>20 MHz – 4 GHz</td>
</tr>
</tbody>
</table>

Figure 2: Spectral measurements equipment

At first, the antenna is connected to the LNA through a coaxial cable and a DC power supply is used to bias the LNA circuitry. Then, the output from the LNA is connected directly to the spectrum analyzer for spectral power measurements. According to the datasheet provided by the spectrum analyzer manufacture, a DC block connector is needed at the spectrum analyzer input to avoid damaging the equipment. Finally, the power measured at each frequency point by the spectrum analyzer is sent from the spectrum analyzer memory buffer to the laptop through a GPIB-to-USB connector.

Since the data collection setup consists of sensitive devices that are prone to be damaged by the surrounding temperature, humidity and dust, a weatherproof container was designed to keep the equipment inside while running the measurements as shown in Figure 3.
2.3. **Data Collection**

According to the frequency spectrum allocation chart presented in Figure 1, the UHF band starts at 300 MHz and ends at 3 GHz (2700 MHz total bandwidth). To get a better understanding of the frequency spectrum utilization within the UHF band, the band was divided into ten equal sub-bands each of 270 MHz bandwidth. The detailed experimental work to control the spectrum analyzer and to collect the data is as follows:

1. The spectrum analyzer, the antenna, the LNA, and the laptop are all connected as shown in Figure 2.
2. After powering the spectrum analyzer, the device is then controlled remotely through Matlab by selecting the GPIB port address via SCPI commands (see Appendix A).
3. A device reset using the SCPI command “*RST;*WAI” is required to make sure all the spectrum analyzer parameters are set to the default values.
4. For each sub-band, the spectrum analyzer parameters are set remotely to the values presented in Table 2. Moreover, continuous frequency sweep turned off through the SCPI command “INIT:CONT OFF” so each sweep can be recorded individually.
5. For each triggered frequency sweep, the data stored in the device memory buffer will be transferred directly to the laptop in ASCII format. The command “TRACE? TRACE1” will do the job of reading the buffer memory and transferring the data.
6. Data are stored in sets each of 100 frequency sweeps to reduce the number of files stored on the computer and to make fetching data much reliable and practical.
Table 2: Spectrum analyzer configuration

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Band number</td>
<td>Center Frequency (MHz)</td>
</tr>
<tr>
<td>1</td>
<td>435</td>
</tr>
<tr>
<td>2</td>
<td>705</td>
</tr>
<tr>
<td>3</td>
<td>975</td>
</tr>
<tr>
<td>4</td>
<td>1245</td>
</tr>
<tr>
<td>5</td>
<td>1515</td>
</tr>
<tr>
<td>6</td>
<td>1785</td>
</tr>
<tr>
<td>7</td>
<td>2055</td>
</tr>
<tr>
<td>8</td>
<td>2325</td>
</tr>
<tr>
<td>9</td>
<td>2595</td>
</tr>
<tr>
<td>10</td>
<td>2865</td>
</tr>
<tr>
<td>Frequency span</td>
<td>270 MHz</td>
</tr>
<tr>
<td>Sweep points</td>
<td>8001</td>
</tr>
<tr>
<td>Sweep time</td>
<td>0.5 sec</td>
</tr>
<tr>
<td>Resolution Bandwidth</td>
<td>300 KHz</td>
</tr>
<tr>
<td>Video Bandwidth</td>
<td>10 KHz</td>
</tr>
<tr>
<td>Detector type</td>
<td>RMS detector</td>
</tr>
</tbody>
</table>

Figure 4, shows the data sampling algorithm developed in MATLAB in order to save the collected data directly after each sweep from the spectrum analyzer to the computer.

**Data Sampling Algorithm for a single band measurement**

1: **initialize** spectrum analyzer
2: \textit{time} \leftarrow \text{timer current value (in seconds)}
3: \textit{ts} \leftarrow \text{time to stop}
4: \textit{sweep} \leftarrow \text{trace vector of a single sweep}
5: \textit{data} \leftarrow \text{stored data}
6: \textit{i} \leftarrow \text{sweep number}
7: **trigger** (timer)
8: \textbf{for} (\textit{i} = 1, \textit{time} \leq \textit{ts}, \textit{i} \leftarrow \textit{i} + 1) \textbf{do}
9: \textbf{Trigger} (single frequency sweep)
10: \textit{data}_i \leftarrow \textit{sweep}
11: \textbf{end for}

Figure 4: Data sampling algorithm
2.4. Measurement Campaign

To form reliable conclusions about the measured spectrum, collecting the data should be scheduled carefully as shown in Figure 5. The spectrum is measured in two time intervals each of six hours. First interval is from 8:30 am to 2:30 pm and the second interval is from 2:30 pm to 8:30 pm. The data collection campaign is carried for 20 days starting from March 24, 2015 through April 12, 2015.

<table>
<thead>
<tr>
<th>Day NO.</th>
<th>Date</th>
<th>Band</th>
<th>Frequency (MHz)</th>
<th>Time from to</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>24-Mar</td>
<td>B1</td>
<td>300 - 570</td>
<td>8:30 - 14:30</td>
</tr>
<tr>
<td>2</td>
<td>25-Mar</td>
<td>B2</td>
<td>570 - 840</td>
<td>8:30 - 14:30</td>
</tr>
<tr>
<td>3</td>
<td>26-Mar</td>
<td>B3</td>
<td>840 - 1110</td>
<td>8:30 - 14:30</td>
</tr>
<tr>
<td>4</td>
<td>27-Mar</td>
<td>B4</td>
<td>1110 - 1380</td>
<td>8:30 - 14:30</td>
</tr>
<tr>
<td>5</td>
<td>28-Mar</td>
<td>B5</td>
<td>1380 - 1650</td>
<td>8:30 - 14:30</td>
</tr>
<tr>
<td>6</td>
<td>29-Mar</td>
<td>B6</td>
<td>1650 - 1920</td>
<td>8:30 - 14:30</td>
</tr>
<tr>
<td>7</td>
<td>30-Mar</td>
<td>B7</td>
<td>1920 - 2190</td>
<td>8:30 - 14:30</td>
</tr>
<tr>
<td>8</td>
<td>31-Mar</td>
<td>B8</td>
<td>2190 - 2460</td>
<td>8:30 - 14:30</td>
</tr>
<tr>
<td>9</td>
<td>1-Apr</td>
<td>B9</td>
<td>2460 - 2730</td>
<td>8:30 - 14:30</td>
</tr>
<tr>
<td>10</td>
<td>2-Apr</td>
<td>B10</td>
<td>2730 - 3000</td>
<td>8:30 - 14:30</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Day NO.</th>
<th>Date</th>
<th>Band</th>
<th>Frequency (MHz)</th>
<th>Time from to</th>
</tr>
</thead>
<tbody>
<tr>
<td>11</td>
<td>3-Apr</td>
<td>B1</td>
<td>300-570</td>
<td>14:30 - 20:30</td>
</tr>
<tr>
<td>12</td>
<td>4-Apr</td>
<td>B2</td>
<td>570-840</td>
<td>14:30 - 20:30</td>
</tr>
<tr>
<td>13</td>
<td>5-Apr</td>
<td>B3</td>
<td>840-1110</td>
<td>14:30 - 20:30</td>
</tr>
<tr>
<td>14</td>
<td>6-Apr</td>
<td>B4</td>
<td>1110-1380</td>
<td>14:30 - 20:30</td>
</tr>
<tr>
<td>15</td>
<td>7-Apr</td>
<td>B5</td>
<td>1380-1650</td>
<td>14:30 - 20:30</td>
</tr>
<tr>
<td>16</td>
<td>8-Apr</td>
<td>B6</td>
<td>1650-1920</td>
<td>14:30 - 20:30</td>
</tr>
<tr>
<td>17</td>
<td>9-Apr</td>
<td>B7</td>
<td>1920-2190</td>
<td>14:30 - 20:30</td>
</tr>
<tr>
<td>18</td>
<td>10-Apr</td>
<td>B8</td>
<td>2190-2460</td>
<td>14:30 - 20:30</td>
</tr>
<tr>
<td>19</td>
<td>11-Apr</td>
<td>B9</td>
<td>2460-2730</td>
<td>14:30 - 20:30</td>
</tr>
<tr>
<td>20</td>
<td>12-Apr</td>
<td>B10</td>
<td>2730-3000</td>
<td>14:30 - 20:30</td>
</tr>
</tbody>
</table>

Figure 5: Data collection time plan

As for the location, the spectrum occupancy measurement campaign took place at the American University of Sharjah. The measurement setup is placed in an open area within the campus to ensure minimization of attenuation and blockage due to the surrounding buildings. Hence, the position chosen is as shown in the satellite image in Figure 6 with coordinates of 25.3093570 latitude and 55.4907140 longitude.

Figure 6: Measurement campaign location
Chapter 3: Measurement Campaign Data Analysis and Results

This chapter describes the next stage in the spectrum occupancy process. The different approaches followed to analyze the data collected in Chapter 2 will be described in detail in this chapter. Since we have a large number of data points collected from the frequency spectrum, this chapter presents the Gaussian mixture model (GMM) as a powerful algorithm for estimating the data statistical parameters and showing how it can be utilized along with a predefined probability of false alarm to determine the occupancy state of a given band or channel.

3.1. Gaussian Mixture Model

In order to analyze the channels in terms of the occupancy state, data thresholding is required to set a baseline for the measured power value at each frequency point. Statistical information need to be extracted from the data before performing the thresholding. The main important statistical parameters for the noise presented in the collected data are the mean and the variance. The work done in this thesis utilizes the Gaussian Mixture Model (GMM) in order to estimate the parameter set \( \mathbf{\theta} = \{\alpha_m, \mu_m, \sigma^2_m\} \) for \( m \) mixed distributions, where \( \alpha \) is the mixture weight, \( \mu \) and \( \sigma^2 \) are the mean and the variance for the \( m^{th} \) distribution, respectively.

The power values presented in the collected data are assumed to have a distribution that is made of a mix between two Gaussian distributions. One distribution is relatively narrow and centered at lower power mean value, this distribution resamples the random noise collected by the setup. However, the other distribution is relatively wider and centered at a higher power mean value and this distribution resamples the power values from the transmitters surrounding the measurement setup. The model for the received power values distribution is as follows:

\[
Y = \alpha_1 N_n(x; \mu_1, \sigma_1^2) + \alpha_2 N_T(x; \mu_2, \sigma_2^2)
\]

where \( N_n \) and \( N_T \) are the noise and the surrounding transmitters probability distribution functions, respectively.

The assumption here is that both the noise and the surrounding transmitters’ distributions are Gaussian with means \( [\mu_1, \mu_2] \) and variances \( [\sigma_1^2, \sigma_2^2] \), respectively. Considering maximum likelihood for expectation maximization and Gaussian mixture
distribution, the following set of closed-form expressions from the maximization step can be used in an iterative manner to estimate the parameter set $\emptyset$ [13]:

\[
\alpha_m^{(i+1)} = \frac{1}{N} \sum_{k=1}^{N} h_m^{(i)}(k) \tag{2}
\]

\[
\mu_m^{(i+1)} = \frac{\sum_{k=1}^{N} h_m^{(i)}(k) x^{(k)}}{\sum_{k=1}^{N} h_m^{(i)}(k)} \tag{3}
\]

\[
\sigma_m^{(i+1)} = \frac{\sum_{k=1}^{N} h_m^{(i)}(k) [X^{(t)} - \mu_m^{(i)}] [X^{(t)} - \mu_m^{(i)}]^T}{\sum_{k=1}^{N} h_m^{(i)}(k)} \tag{4}
\]

where the posterior probabilities $h_m$ for the $i^{th}$ current estimate can be computed from the expectation step and given by [13]:

\[
h_m^{(i)}(k) = \frac{\alpha_m^{(i)} \mathcal{N}(X^{(t)}; \mu_m^{(i)}, \sigma_m^{(i)})}{\sum_{j=1}^{n} \alpha_j^{(i)} \mathcal{N}(X^{(t)}; \mu_j^{(i)}, \sigma_j^{(i)})} \tag{5}
\]

For a given observation $X^{(t)}$ generated from the $m^{th}$ component out of $n$ components, the conditional probability is calculated based on the $j^{th}$ parameter estimate for each data sample point $k = 1, ..., N$, where $N$ is the sample size. The parameters are then updated so that the average conditional probability is the new component weights $\alpha_m$, and the weighted average of the entire sample mean and covariance is the $m^{th}$ mean and covariance.

Figure 7 shows the different distributions obtained for a set of data measurements collected by the spectrum analyzer over the frequency range from 1.65 GHz to 1.92 GHz on March 29, 2015 from 12:30 pm to 2:30 pm. The solid line represents the original mixed distribution for the collected data, however, the dotted lines are the two estimated distributions extracted from the original mixed distribution using GMM algorithm. As noticed from the figure, one distribution is narrow (with relatively small variance value) and small mean value while the other distribution is flatter with relatively larger mean value. The narrower distribution (black dotted line) represents the noise distribution for the noise data point in the data collected. Knowing the noise parameters is important since they can be used in classifying the power values measured by the spectrum analyzer.
3.2. Data Thresholding

After obtaining the noise parameters (mean and variance), thresholding can be done on the data collected to study the occupancy state of each band. In this section, we discuss three types of thresholding approaches: \( m_{dB} \) above the noise mean value, the outlier value, and the fixed probability of false alarm threshold value.

The \( m_{dB} \) above the noise mean value approach assigns a fixed value so that the threshold level is \( m_{dB} \) above the noise mean value. For a given noise mean, \( \mu \), the threshold value is given by:

\[
\gamma_{m_{dB}} = \mu + m_{dB}
\]  

(6)

From the literature, usually a value between 3-dB to 10-dB is used [14] [15], however this approach is not reliable since noise statistical characteristics may vary with frequency bands. Therefore, there is uncertainty about the best value “\( m_{dB} \)” that achieves the most satisfying results.

On the other hand, the outlier value approach assigns a fixed threshold \( \gamma_{outlier} \) value given as follows:
\[ \gamma_{\text{outlier}} = \mu + 3\sigma \]  

(7)

where \( \mu \) and \( \sigma \) are the mean and the standard deviation of the noise distribution, respectively. The threshold obtained by this approach is mainly depending on the setup sensitivity and the calculated threshold value might be large that some weak transmissions would not be detected by the setup and would be classified incorrectly.

Finally, the fixed probability of false alarm threshold value assigns a threshold value depending on a specific probability of false alarm \( P_{fa} \) (the probability of deciding a channel to be occupied while the true state is not) and is defined as:

\[
P_{fa} = P_N(n > \gamma_{fa}) = 1 - P_N(n \leq \gamma_{fa}) = 1 - F_N(\gamma_{fa})
\]

(8)

where \( P_N \) is the noise probability density function, \( F_N \) is the noise cumulative distribution function and \( \gamma_{fa} \) is the threshold level. For a given channel with Additive white Gaussian noise (AWGN) of mean \( \mu \) and variance \( \sigma^2 \) and with a given probability of false alarm \( P_{fa} = p \), the threshold value associated is:

\[
\gamma_{fa} = F_N^{-1}(1 - p; \mu, \sigma^2)
\]

(9)

Where \( \gamma_{fa} \) is the threshold value calculated based on a predefined probability of false alarm value and \( F_N(x) \) is the Gaussian cumulative distribution function and given by:

\[
F_N(x; \mu, \sigma^2) = \frac{1}{\sigma \sqrt{2\pi}} \int_{-\infty}^{x} e^{-\frac{(t-\mu)^2}{2\sigma^2}} dt
\]

(10)

### 3.3. Duty Cycle and Average Occupancy

Duty cycle is defined as the fraction of the total time for a specific frequency point or channel being classified as occupied (power level measured exceeds the threshold value). Duty cycle analysis helps in analyzing the usage of a channel over time. For a given set of power measurements \( x_{ij} \),

\[
x_{ij} = \begin{bmatrix} x_{11} & \ldots & x_{1K} \\ \vdots & \ddots & \vdots \\ x_{M1} & \ldots & x_{MK} \end{bmatrix}
\]

(11)

where \( x_{ij} \) is the power value measured at \( i^{th} \) measurement time of the \( j^{th} \) frequency point. \( M \) is the total number of measurements and \( K \) is the total number of frequency points within a measurement session. The occupancy state of the channel is determined by:
for $i = 1, 2, ..., M$ and $j = 1, 2, ..., K$. The duty cycle at the $j^{th}$ frequency point is given by:

$$C_j = \frac{1}{M} \sum_{i=1}^{M} A_{ij}$$

The average occupancy measures the utilization fraction of the band of interest within the time of measurement session. The average occupancy $\beta_{avg}$ is given by:

$$\beta_{avg} = \frac{1}{K} \sum_{j=1}^{K} C_j$$

3.4. Results and Conclusions

The spectrum occupancy measurements stated in this thesis are analyzed graphically through four types of plots as the examples shown in Figure 8 and Figure 9. The first plot represents the power level measured for a randomly selected sweep of 270 MHz bandwidth. This plot is showing the power level measured by the spectrum analyzer versus the frequency for the band of interest. This plot also indicates the threshold level assigned for that particular band (dotted line). The threshold value indicated in the plot is obtained based on the estimated noise parameters and a 10% false alarm.

The second plot is the waterfall plot presenting the occupancy state of a channel at a specified time and frequency. The color level of each point on the waterfall plot indicates the power level measured by the spectrum analyzer, while the white space indicates that the channel measured power is less than the threshold value assigned for the band and therefore a point in the white area indicates a non-occupied channel spatially or temporally. The third plot is the duty cycle plot indicating the fraction of time that a specific channel has a power level exceeding the threshold power level and is classified as occupied by a primary user. The fourth plot in Figure 9 is the average occupancy chart showing the average occupancy per band per each two hour measurement over the time period from 8:30 AM to 8:30 PM. The average occupancy chart is important in demonstrating the variation in the spectrum utilization with time and helps in predicting the occupancy for related cognitive radio applications.
Figure 8: Power Level-Waterfall-Duty Cycle plot - Band 6 (1650 – 1920) MHz

Figure 9: Average Occupancy - Band 6 (1650 – 1920) MHz
Figure 10 shows the data analysis process. The raw data measured by the spectrum are first analyzed statistically via GMM algorithm to extract the noise distribution parameters. Then thresholding the data is done based on a fixed probability of false alarm. The figures in Appendix B represent the overall results for each sub-band considered in the UHF band.

\[
x_{ij} = \begin{bmatrix} x_{i1} & \cdots & x_{iK} \\ \vdots & \ddots & \vdots \\ x_{NI} & \cdots & x_{NK} \end{bmatrix}
\]

Power measurements raw data – From spectrum analyzer

\[ \phi = (\alpha_m, \mu_m, \sigma_m^2) \]
Noise parameter estimation via GMM

Data thresholding based on a fixed \( P_{fa} \)

Data analysis

**Figure 10: Spectral data analysis**

Figure 15 provides a general conclusion about the UHF band utilization at the American University of Sharjah in the United Arab Emirates for 12 hours of measurement for a 10% false alarm probability. The results reported in this figure are important since they show the channel utilization by the primary user, in addition, they show the channel potential to be utilized by cognitive radio system applications. It is noticed from the figure that the bands B6 (1650 MHz – 1920 MHz) and B3 (840 MHz – 1110 MHz) are the most active over the measurement period with occupancy rates of 30% and 34%, respectively. This main observation is due to the fact that bands B6 and B3 have a large portion of their spectrum busy with a 100% duty cycle. According to the United Arab Emirates Allocation Chart, these bands are mainly allocated for fixed wireless mobile applications (1800 MHz - 1785 MHz uplink, 1805 MHz – 1880 MHz downlink).

On the other hand, Figure 15 shows that the least active bands are bands B5 (1380 MHz – 1650 MHz) and B4 (1110 MHz – 1380 MHz) with occupancy of 10% and 11%, respectively. The United Arab Emirates Allocation Chart states that these bands are mostly allocated for aeronautical and satellite (earth-to-space) communications, hence the power received by the measuring equipment for these bands is weak at the ground level. Considering bands B5 and B4, the results in Figures 11, 12, 13, and 14 support the idea that these bands are underutilized and hence opening the door for cognitive radio technologies to handle the spectrum scarcity problem.

The different sub-bands illustrated in this thesis are assigned to different services licensed by the United Arab Emirates government. The work demonstrated in
this thesis is focusing on providing a clear picture about the spectrum utilization on the America University of Sharjah campus and suggest different ways to analyze and describe the frequency spectrum analytically and graphically.

Figure 11: Band B5 (1380 – 1650) MHz (8:30 to 10:30)
Figure 12: Band B4 (1110 – 1380) MHz (12:30 to 14:30)
Figure 13: Average occupancy for Band B5 (1380 – 1650) MHz

Figure 14: Average occupancy for Band B4 (1110 – 1380) MHz
Figure 15: Average occupancy per band over 120 hours (from 300 MHz to 3 GHz)
Chapter 4: Experimental Setup for Cognitive Radio System

This chapter discusses the cognitive radio implementation experimental setup. As illustrated in Chapter 3, a large portion of the frequency spectrum licensed by the government is not utilized efficiently by the spectrum owners. Moreover, there is less opportunity of finding a vacant band (spatially or temporally) for deploying new wireless communication services or enhancing already existing ones. A solution for spectrum scarcity would be cognitive radio.

4.1. Cognitive Radio (CR)

One form of Dynamic Spectrum Access (DSA) technologies is the Cognitive Radio (CR), which is based on allowing an unlicensed secondary user to access an unoccupied portion of the licensed spectrum and use it without causing interference with the licensed primary user in an opportunistic way as demonstrated in Figure 16.

![Figure 16: Cognitive radio principle](image)

Basically, Cognitive Radio systems have dynamic spectrum access capabilities that provide the ability to share the frequency spectrum in an opportunistic manner. A cognitive radio system tries to seek for the best available channel (spatially and temporally). The main important functionalities in a cognitive radio systems are
categorized into: spectrum sensing, spectrum management, spectrum sharing, and spectrum mobility [16]. Cognitive radio users will be able to:

1. Detect the presence of a primary user within a given frequency spectrum portion through spectrum sensing functionality.
2. Select the best available channel that meets the required communication resources (bandwidth, power, frequency, etc.) through spectrum management functionality.
3. Gain an access to the licensed spectrum by a scheduling mechanism for coexisting cognitive radio users through spectrum sharing functionality.
4. Maintain seamless communication requirements during the transition to a better available channel (spectrum hole) through spectrum mobility functionality.

Cognitive radio systems have the capabilities of real time interaction with the outside environment to determine the best communication parameters and adapt to the RF environment dynamically. For adaptive operation, the cognitive cycle shown in Figure 17 [17] summarizes the steps need to be followed by cognitive radio systems. These steps are spectrum sensing, spectrum analysis, and spectrum decision. In spectrum sensing, the cognitive radio monitors the frequency spectrum to capture the frequency bands’ information and detect the frequency spectrum holes. While in spectrum analysis, the cognitive radio estimates the characteristics of the detected frequency holes. In spectrum decision, the cognitive radio system will determine the appropriate frequency band based on the required transmission bandwidth, transmission mode, and transmission rate.

4.2. Universal Software Radio Peripheral (USRP)

Universal Software Radio Peripheral (USRP) by National Instruments (NI) is considered as one direct implementation of the Software Defined Radio (SDR) systems. The International Telecommunication Union (ITU) has defined the SDR as a radio transmitter/receiver or both (transceiver) that has the capabilities of altering the RF operating parameters (such as: center frequency, frequency range, modulation scheme, etc.) by software [18]. Basically, the USRP serves as a hybrid transceiver where hardware problems related to the radio signals can be turned into software problems [19]. Figure 18 shows a block diagram of the basic structure of an SDR system.
The SDR structure is divided into three main blocks: the RF front panel, USRP motherboard and software interfacing environment. The RF front panel connected directly to the antenna from one end and to the USRP motherboard from the other end. This block mainly serves as the interface between the transmitted/received RF signals and the USRP device in the analog RF domain. The USRP motherboard establishes the connection between the analog signals and the digital data. The Field-programmable gate array (FPGA) performs two main tasks: data rate conversion and up/down sampling of the digital data samples. Digital data sampled can be transferred to the host.
PC via USB or Gigabit Ethernet interface for further processing. A software interface like Labview® is required to apply signal processing algorithms such as: modulation, demodulation, graphical analysis, spectral measurements, etc.

4.3. USRP Instrument Control

The work done in this thesis is utilizing the NI USRP-2922 software defined radio shown in Figure 19. The NI USRP-2922 device is manufactured by National Instruments and desired in applications related to wireless communication prototyping. This SDR continuously covers frequency range from 400 MHz to 4.4 GHz that includes many commonly used bands in research such as Global Navigation Satellite System (GNSS), cellular, and 2.4 GHz WiFi band. The data and the instructions can be transferred from or to the USRP through the Gigabit Ethernet interface located in the device front panel. The NI USRP-2922 can be remotely controlled through LabVIEW programming environment and fully supported by National Instruments.

![NI USRP-2922 software defined radio](image)

Figure 19: NI USRP-2922 software defined radio

A link between the USRP device and the hosting computer must be established after powering up the USRP device and directly connecting it to the PC via Ethernet cable. As shown in Figure 20, there are four main steps that should be followed in order to control the USRP in LabVIEW:

1. Opening instrument session: where the device IP address is specified within LabVIEW front panel as shown in Figure 20 so a link between the USRP and the hosting PC will be established.
2. Specifying Communication parameters: where parameters like sampling rate, carrier frequency, and gain are specified before initiating the transmission/reception process.

3. Algorithm implementation for data processing

4. Closing instrument session between the USRP and the hosting PC.

![USRP software control in LabVIEW](image)

Figure 20: USRP software control in LabVIEW

Figure 21 shows the LabVIEW time-controlled transmitter design. The four main controlling steps were followed in the design. Two time controlling blocks are added in order to control the transmission period and generate an ON/OFF pattern. Moreover, BPSK modulator is added to the design and transmission parameters can be controlled directly from LabVIEW front panel as shown in Figure 22. The transmitter is designed to transmit a baseband complex BPSK signal. At first a pseudo random (PN) binary sequence is randomly generated and then sent to a BPSK modulator to generate both the in-phase and the quadrature components.

The receiver designed through LabVIEW is meant to receive the baseband complex signal transmitted over a specific channel frequency as shown in the LabVIEW receiver in Figure 23. Similar to the transmitter parameters control, the receiver communication parameters can be also controlled from the LabVIEW front panel.
Figure 21: Transmitter LabVIEW block diagram
Figure 23: Receiver block diagram in LabVIEW
4.4. Experimental Setup and Data Collection

The overall cognitive radio experimental setup is shown in Figure 24. Both the transmitter (Tx) and the receiver (Rx) are controlled separately by two hosting computers. The USRP devices interface with the computers through Ethernet cables and powered by DC power supplies. The transmitter is positioned at a fixed location during the experiment, while the receiver is moved to different locations to collect different signals with different power levels.

![Cognitive radio experimental setup block diagram](image)

Table 3 defines the main USRP parameters that defines the USRP testbed. The parameters are set in a way to meet the USRP performance limitation and to avoid overflows and underflows. Some of these parameters have been defined by default and there is no need to alter them. Without loss of generality, the USRP carrier frequency is selected to be 2.8 GHz since this carrier frequency is within the middle of the USRP frequency range. Moreover, the spectral measurements done in Chapter 3 have shown that this frequency has no activities relative to the other frequency bands. The transmitter and the receiver gains are set to zero dB gain due to the need to vary the power of the received signal and be able to implement the sensing algorithms at lower Signal to Noise Ratio (SNR). The receiver IQ sampling rate is set to 200k samples/second in order to avoid memory overflow while storing the received data in the computer.

SNR is the most common measure of performance for any communication systems. The SNR indicates the overall quality of the communication by comparing the power level of the useful signal to the power level of the background noise. Mathematically, the SNR is given by:
\[ SNR = 10 \log_{10} \left( \frac{\text{Average signal power}}{\text{Average noise power}} \right) \text{(dB)} \]  

(15)

For a given sampled received signal \( x(n) = x_r(n) + jx_i(n) \), and sampled received noise at the receiver output \( w(n) = w_r(n) + jw_i(n) \), the SNR can be calculated by:

\[ SNR = \frac{|x(n)|^2}{|w(n)|^2} \]  

(16)

where

\[ |x(n)|^2 = \frac{1}{N} \sum_{n=1}^{N} |x(n)|^2 \]  

(17)

and

\[ |w(n)|^2 = \frac{1}{N} \sum_{n=1}^{N} |w(n)|^2 \]  

(18)

where \( x_r(n) \) and \( w_r(n) \) are the real components of the signal and the noise respectively, \( x_i(n) \) and \( w_i(n) \) are the imaginary components of the signal and the noise respectively. \( N \) is the number of the total samples in a sampled frame.

Table 3: NI USRP-2922 device configuration for Tx and Rx

<table>
<thead>
<tr>
<th>Parameters</th>
<th>USRP Tx Value</th>
<th>USRP Rx Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>IQ Sampling Rate (kS/sec)</td>
<td>500</td>
<td>200</td>
</tr>
<tr>
<td>Gain (dB)</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Active Antenna</td>
<td>TX1</td>
<td>RX1</td>
</tr>
<tr>
<td>Carrier Frequency (GHz)</td>
<td>2.8</td>
<td>2.8</td>
</tr>
</tbody>
</table>

The location used for spectral measurements in Chapter 2 was revisited again for data collection using the experimental setup explained in Figure 24. After preparing the experimental setup and configuring the USRP devices for the desired communication parameters, the transmitter is kept at a fixed location and the receiver is placed at different locations around the transmitter. Figure 25 shows the SNR levels calculated using equation (16) and that is done for 65 locations (denoted in dots) within an area of 55×50 m². The distance between the measurement area and the transmitter location is 25 meters away. This distance is specified based on the SNR levels desired.
for the experiment. The transmitter is placed at the origin of the x-y axes, while the receiver is placed at different locations within the measurement area as shown in the figure. This way will guarantee sensing the transmitted signals at different SNR levels. As expected, the SNR levels are decreasing at far locations away from the transmitter and that serves the need for lower SNR levels needed to test the performance of the sensing schemes implemented in next chapter.

Figure 25: Measured signal-to-noise ratio for different receiver locations
Chapter 5: Data Analysis and Results for Cognitive Radio System

Implementation

This chapter utilizes the experimental setup discussed in Chapter 4 to implement a cognitive radio system. In order to implement a cognitive radio system, a spectrum sensing approach need to be considered. Spectrum sensing focuses on the primary user activities trying to decide the presence state. The work done in this thesis is focusing on describing the implementation of the energy detector and the polynomial classifier for spectrum sensing. We would like to remark that the use of a polynomial classifier for cognitive radio applications has been introduced by [20] [21], and [22]. However, these investigations were based on computer simulation only. In this thesis, we present a real-world hardware implementation of a cognitive radio system while deploying both polynomial and energy classifiers for spectrum sensing.

5.1. Energy Detection Sensing for a Fixed Probability of False Alarm

Figure 26 is showing the scheme for a conventional energy detector [23]. This block diagram consists of a low pass filter to remove the adjacent signals and to limit the noise captured by the sensing devices, an analog-to-digital converter to convert the continuous time signal $s(t)$ to discrete time signal samples $s[n]$, a squaring law device and integrator. Basically, the energy detector measures the energy associated with the sensed signal over a defined time period and frequency band. The measured energy value is then compared to a threshold value selected properly to determine the presence state of the primary user.

![Figure 26: Conventional energy detector](image)

Depending on the presence state of the primary user and the decision statistic calculated by the energy detector, the signal received can be modeled as a binary hypothesis testing problem and given as:

$H_0 : \text{The primary user is absent}$

$H_1 : \text{The primary user in present}$
where hypothesis 0 ($\mathcal{H}_0$) represents the absence of the primary user at a given time interval and only noise is sensed at the receiver input, however, hypothesis 1 ($\mathcal{H}_1$) represents the presence of the primary user and the receiver is sensing both the transmitted signal $x(t)$ and the background noise $w(t)$. The continuous time signal $S(t)$ received at the receiver end is given by:

$$
s(t) = \begin{cases} 
  w(t) & \text{Under } \mathcal{H}_0 \\
  x(t) + w(t) & \text{Under } \mathcal{H}_1 
\end{cases} \quad (19)
$$

For the discrete time signal $S[n]$, The decision statistic $T$ is given by:

$$
T = \sum_{n=1}^{N} |x[n]|^2 \quad (20)
$$

where $N$ in the number of samples. To characterize the performance of the energy detector or any detector, the following metrics can be exploited:

- Probability of false alarm ($P_{fa}$): is the probability of classifying a signal frame as present while the true state is absent ($\mathcal{H}_0$). For a given threshold level $\lambda$ and decision statistic $T$, the probability of false alarm is given by:

$$
P_{fa} = P(T > \lambda | \mathcal{H}_0) \quad (20)
$$

- Probability of missed detection ($P_{md}$): is the probability of classifying a signal frame as absent while the true state is present ($\mathcal{H}_1$). The probability of missed detection is given by:

$$
P_{md} = P(T < \lambda | \mathcal{H}_1) \quad (21)
$$

In cognitive radio concept, the lower the probability of false alarm contributes to higher spectrum usage by the secondary user. However, the large value of probability of missed detection reflects undetermined interference to the primary user. Figure 27 demonstrates graphically the tradeoff between the probability of false alarm and the probability of missed detection for $\mathcal{H}_0$ and $\mathcal{H}_1$. Considering a scenario where the threshold level is decreased, the probability of false alarm will increase but the probability of missed detection will decrease making the spectrum not efficiently utilized by the secondary user. On the other hand, increasing the threshold level will increase the probability of missed detection but decrease the probability of false alarm so that more interference will be introduced to the primary user.
The energy classifier in Figure 28 is implemented in this thesis. The data signal samples are divided into frames each of $N$ samples frame size. Each frame is processed through the energy detector so the energy is calculated and compared to a threshold level based on a given probability of false alarm. The energy classifier takes two inputs, the probability of false alarm $P_{fa}$ and the frame $h[n]$ then returns a Boolean (1 or 0) value representing the occupancy state where 1 indicates that the primary user is present and 0 indicates that the primary user is absent (a noise frame).

In order to set a proper threshold value corresponding to a specific $P_{fa}$, the energy values of noise signal frames (transmitter is off) are calculated and sorted in ascending order. Next, the probability of false alarm indicates the percentage of noise frames with energy levels above the threshold value. The example shown in Figure 29 is showing the probability of false alarm as a function of the threshold value that will achieve that specific false alarm probability for a frame size of $N = 100$ samples.
Table 4 summarizes the threshold values obtained in order to achieve probabilities of false alarm equivalent to 0.05, 0.1, and 0.15. We notice that as the probability of false alarm increases the threshold value decreases. Moreover, as the number of samples per frame increases the threshold value also increases, hence the threshold value is directly affected by the frame size and the probability of false alarm.

Another important metric to evaluate the performance of the classifier is the misclassification rate ($\varepsilon$) and given by:

$$\varepsilon = \frac{n_{1,0} + n_{0,1}}{n} \times 100$$

where $n_{1,0}$ is the total number of frames that are assigned with a frame state of 1 while the true frame state is 0, $n_{0,1}$ is the total number of frames that are assigned with a frame state of 0 while the true frame state is 1 and $n$ is the total number of frames processed through the classifier.

Misclassification rate calculates the overall error associated with the results obtained from the classifier in predicting the state of each frame. To get a reasonably accurate estimate to the misclassification rate, the number of frames processed ($n$) should be large enough.
Table 4: Threshold values for energy classifier

<table>
<thead>
<tr>
<th>$P_{fa}$</th>
<th>$N = 10$</th>
<th>$N = 100$</th>
<th>$N = 1000$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.05</td>
<td>$6.3625e-8$</td>
<td>$5.009e-7$</td>
<td>$4.019e-6$</td>
</tr>
<tr>
<td>0.10</td>
<td>$5.3362e-8$</td>
<td>$4.374e-7$</td>
<td>$3.866e-6$</td>
</tr>
<tr>
<td>0.15</td>
<td>$4.7719e-8$</td>
<td>$4.083e-7$</td>
<td>$3.558e-6$</td>
</tr>
</tbody>
</table>

Figure 30 presents the results obtained from the energy classifier from a set of data collected by the USRP receiver. The SNR value calculated is 14.5 dB which is relatively high resulting in lower misdetection rate. However, Figure 31 is for a set of data collected at an SNR value equal to 2.54 dB resulting in a higher misdetection rate due to the lower SNR value. For both cases the probability of false alarm is chosen to be 0.15 and the frame size is 1000 samples per frame. Both figures provide the
calculated values for probability of false alarm, probability of misdetection and the misclassification rate for each scenario.

![Graphs showing energy classifier performance at high SNR](image)

<table>
<thead>
<tr>
<th>$N$</th>
<th>SNR (dB)</th>
<th>$P_{fa}$</th>
<th>$P_{md}$</th>
<th>$\varepsilon$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1000</td>
<td>14.5</td>
<td>0.142</td>
<td>0</td>
<td>6.5%</td>
</tr>
</tbody>
</table>

Figure 30: Energy classifier performance at high SNR
<table>
<thead>
<tr>
<th>$N$</th>
<th>SNR (dB)</th>
<th>$P_{fa}$</th>
<th>$P_{md}$</th>
<th>$\varepsilon$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1000</td>
<td>2.54</td>
<td>0.15</td>
<td>0.4</td>
<td>7.3%</td>
</tr>
</tbody>
</table>

Figure 31: Energy classifier performance at low SNR
5.2. Polynomial Classifier

Polynomial classifiers are considered as a special case of neural networks forming a single-hidden layer neural network that uses the input patterns and the input polynomial patterns [24]. Polynomial classifiers have been utilized in many applications and they have shown advantages like better recognition performance and high identification efficiency [25] [26]. Moreover, polynomial classifier models mainly relay on simple mathematical operations like addition and multiplication and therefore modern digital signal processing circuits can handle the polynomial classifiers and simplify the process of implementation.

The main functionality of a polynomial classifier is that it expands an input vectors sequence to a higher dimension then maps the results to a desired sequence of output vectors [27]. The features extracted from a sequence are not always linearly separable, however, projecting the feature vectors into higher dimensional space will help make these features linearly separable according to their class labels [26]. Figure 32 demonstrates the basic blocks forming the polynomial classifier.

![Polynomial classifier block diagram](image)

Figure 32: Polynomial classifier block diagram

Considering the binary hypothesis problem mentioned in Section 5.1, a polynomial classifier can be designed to classify the two classes, \( \mathcal{H}_i \) for \( i \in \{0,1\} \). The design of the polynomial classifier involves two stages: training stage and testing stage as illustrated in Figure 33 [27]. Given the input training sequence arranged as the \( M \times N \) matrix \( D_{\text{train}} \), the input feature vectors are expanded into polynomial terms to form the \( M \times L \) matrix \( Y_{\text{train}} \), where \( M \) is the number of feature vectors, \( N \) is the dimensionality of the feature vectors and \( L \) is the dimensionality of the expanded feature vectors (the number of expansion terms). As a result, the 2\(^{nd}\) order expansion for the feature vectors in \( D_{\text{train}} \) can be expressed as [27]:
\[ Y_{\text{train}} = \begin{bmatrix} 1 & x_1 & x_2 & x_3 & \ldots & x_N & x_1^2 & x_1x_2 & x_1x_3 & \ldots & x_N^2 & x_1x_N & x_2x_N & \ldots \end{bmatrix}^T \]  \tag{23} 

where \((.)^T\) is the transpose operator and \(N\) is the dimensionality of the feature vectors in \(D_{\text{train}}\).

The polynomial classifier can be trained to obtain the class weights given the target vector 
\[ t_{\text{train}_i} = \begin{bmatrix} t_{i_1} & t_{i_2} & \ldots & t_{i_M} \end{bmatrix}^T, \]  where

\[ t_{i_k} = \begin{cases} 1, & \text{if feature vector } k \in \text{class } i \\ 0, & \text{if feature vector } k \notin \text{class } i \end{cases} \]  \tag{24} 

In order to train the classifier, the weights vector can be obtained by minimizing the sum of squared error (MSE) function \(J(W)\) that is given by [27] [28]:

\[ w_i^{\text{opt}} = \arg min_{w_i} \| Y_{\text{train}}W - t_{\text{train}_i} \|_2 \]  \tag{25} 

where \(Y_{\text{train}}\) is the expanded feature vector whose rows are the training features and \(t_{\text{train}_i}\) is the training target vector corresponding to the \(i^{th}\) class. The solution to (25) is given by [27]:

\[ w_i^{\text{opt}} = Y^+t_{\text{train}_i} \]  \tag{26} 

where \(Y^+\) is the pseudoinverse function of \(Y\) and given by:

\[ Y^+ = (Y_{\text{train}}^TY_{\text{train}})^{-1}Y_{\text{train}}^T \]  \tag{27} 

Finally, in the testing stage we are given a testing input sequence \(D_{\text{test}}\) to determine its class. At first, this input sequence will be expanded similar to (23) generating the sequence \(Y_{\text{test}}\). Then, the output score from the polynomial classifier can be obtained using \(Y_{\text{test}}\) along with the trained models \(w_i^{\text{opt}}\), the output score \(s_i\) is given by:

\[ s_i = Y_{\text{test}}w_i^{\text{opt}} \]  \tag{28} 

The polynomial classifier implemented throughout this thesis is shown in Figure 34. The complex baseband signals are measured by the USRP devices and then stored in the computer. The data is then divided into two sets: training data set and testing data set. At first, the training set is divided into frames each of size \(N\) and the states of each frame are used to define the frame state vector \(t_{\text{train}}\). A frame state of 1 indicates the presence of the primary user and a frame state of 0 indicates the absence of the primary user.
user. For each frame, the frame energy, given in equation (20), variance (2nd moment), skewness (3rd moment) and kurtosis (4th moment) were calculated in order to define the feature vector $D_{train}$.

**Training stage**

Input feature vectors $D_{train} = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,N} \\ \vdots & \ddots & \vdots \\ x_{M,1} & x_{M,2} & \cdots & x_{M,N} \end{bmatrix}$

Class weights $w_1, w_2, \ldots, w_L$

Polynomial expansion and model estimation

**Testing stage**

Test feature vectors $D_{test} = [d_1, d_2, \ldots, d_N]$

Output score $s_i$

Polynomial expansion and score calculation

Figure 33: Overall operation of polynomial classifier [27]

---

Figure 34: Polynomial classifier for fixed $P_{fa}$
Next, the feature vector $D_{\text{train}}$ is expanded through a second order polynomial expansion block to obtain $Y_{\text{train}}$. Using equation (26), the weight vector $W$ can be obtained from the expanded feature vector $Y_{\text{train}}$ and the frame state vector of the training data $t_{\text{train}}$. The testing data set is also divided into frames and the features for each frame are extracted forming the feature vector $D_{\text{test}}$ which then expanded through the second order expansion block to obtain the feature vector $Y_{\text{test}}$. Finally, using the weight vector $W$ obtained from the training step and the new expanded feature vector $Y_{\text{test}}$, equation (28) can be used to estimate the testing data set frame states vector $t_c$. The estimated state vector values obtained directly from the training data set are not whole numbers and hence not directly representative of the frame. Therefore, there is a need to clean the classifier output by thresholding.

One way to perform thresholding is by setting a fixed probability of false alarm the same approach explained in Section 5.1 for energy classifier. The polynomial classifier output for noise frames can be sorted in ascending order so that the desired probability of false can be plotted against the corresponding threshold value. As an example, Figure 35 is showing the sorted noise state values for noise frames of size $N = 100$ samples and corresponding threshold level at different probability of false alarms values. Table 5 shows the threshold values corresponding to specific probability of false alarm values and frame length $N$.

![Figure 35: Threshold value for polynomial classifier](image-url)
Table 5: Threshold values for polynomial classifier

<table>
<thead>
<tr>
<th>$P_{fa}$</th>
<th>Threshold value ($\lambda$)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$N = 10$</td>
</tr>
<tr>
<td>0.05</td>
<td>0.0922</td>
</tr>
<tr>
<td>0.10</td>
<td>0.0794</td>
</tr>
<tr>
<td>0.15</td>
<td>0.0725</td>
</tr>
</tbody>
</table>

Figure 36: Polynomial classifier performance at high SNR
5.3. Discussion of Results

In this chapter, the implementation of cognitive radio based on spectrum sensing has been tackled. The performance of both energy detector and polynomial classifier is analyzed and the different stages of implementation are described.

<table>
<thead>
<tr>
<th>$N$</th>
<th>SNR (dB)</th>
<th>$P_{fa}$</th>
<th>$P_{md}$</th>
<th>$\epsilon$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1000</td>
<td>2.4</td>
<td>0.11</td>
<td>0</td>
<td>4.8%</td>
</tr>
</tbody>
</table>

Figure 37: Polynomial classifier performance at low SNR
Both spectrum sensing approaches described in this thesis are simple to implement, in terms of calculation complexity, however putting them side by side, the polynomial classifier shows better performance than the energy detector. Figures 38, 39, and 40 show the misclassification rate $\varepsilon$ as a function of the SNR level for different frame size $N$ values and different probabilities of false alarm $P_{fa}$. For both classifiers, the misclassification rates at low SNR values are demonstrated in Table 6. It is noticed that both classification approaches have better performance at higher SNR levels since higher SNR means the presence of the signal within a sampled frame is overshadowing the noise presence. However, it is noticed that at lower SNR levels the polynomial classifier has better performance in terms of the misclassification rate.

Since data was collected at different locations around the transmitter, it is necessary to observe the relationship between each classifier performance and the area covered during the experiment. Figures 41 and 42 show the percentage of area ($A\%$) around the transmitter with a misclassification rate less than a target misclassification rate $\varepsilon_t$ for each spectrum sensing approach implemented.

For both energy detector and polynomial classifier, at a given misclassification target percentage $\varepsilon_t$ it is always desired that $A\%$ to be low. A lower $A\%$ percentage indicates a larger portion of the signals in the area are classified correctly. At a given $\varepsilon_t$, the relationship between the frame size $N$ and the $A\%$ is inversely propositional as observed in the figures.
Figure 38: Misclassification rate at frame size $N = 1000$ samples
Figure 39: Misclassification rate at frame size N = 100 samples
Figure 40: Misclassification rate at frame size $N = 10$ samples
| Frame size $N$ | $SNR_{db}$ | Energy Detector | Polynomia l Classifier | $p_{fa} = 0.05$ | Energy Detector | Polynomia l Classifier | $p_{fa} = 0.10$ | Energy Detector | Polynomia l Classifier | $p_{fa} = 0.15$ |
|----------------|----------------|----------------|-------------------------|----------------|----------------|-------------------------|----------------|----------------|----------------|----------------|----------------|
| 10             | 1.00           | 46.3           | 43.8                    | 44.6           | 40.5           | 42.4                    | 41.3           |                 |                 |                 |                 |
|                | 1.45           | 46.8           | 43.0                    | 42.1           | 33.1           | 41.4                    | 40.0           |                 |                 |                 |                 |
|                | 1.67           | 45.4           | 40.2                    | 39.7           | 36.1           | 36.2                    | 36.3           |                 |                 |                 |                 |
|                | 2.20           | 39.2           | 38.6                    | 33.1           | 34.5           | 30.2                    | 30.9           |                 |                 |                 |                 |
|                | 2.28           | 35.9           | 35.5                    | 33.5           | 32.9           | 29.5                    | 30.5           |                 |                 |                 |                 |
|                | 2.63           | 34.4           | 31.1                    | 30.5           | 27.7           | 25.5                    | 23.4           |                 |                 |                 |                 |
|                | 2.90           | 30.9           | 28.3                    | 27.9           | 25.3           | 23.5                    | 24.1           |                 |                 |                 |                 |
|                | 2.95           | 32.2           | 33.3                    | 24.6           | 23.8           | 22.2                    | 21.3           |                 |                 |                 |                 |
|                | 3.00           | 31.5           | 30.4                    | 24.3           | 22.7           | 20.8                    | 21.4           |                 |                 |                 |                 |
|                | 3.02           | 30.4           | 30.2                    | 24.4           | 22.7           | 20.6                    | 21.1           |                 |                 |                 |                 |
| 100            | 0.38           | 49.7           | 46.1                    | 45.6           | 43.7           | 46.4                    | 41.9           |                 |                 |                 |                 |
|                | 0.70           | 48.2           | 45.1                    | 44.8           | 41.7           | 42.8                    | 36.4           |                 |                 |                 |                 |
|                | 0.76           | 46.3           | 44.0                    | 43.2           | 41.6           | 42.3                    | 35.7           |                 |                 |                 |                 |
|                | 0.99           | 43.9           | 41.4                    | 38.5           | 38.4           | 37.6                    | 31.9           |                 |                 |                 |                 |
|                | 1.19           | 43.0           | 40.9                    | 35.9           | 36.8           | 34.0                    | 31.0           |                 |                 |                 |                 |
|                | 1.30           | 43.2           | 40.4                    | 35.8           | 34.7           | 31.4                    | 29.3           |                 |                 |                 |                 |
|                | 1.46           | 39.3           | 39.0                    | 30.6           | 31.9           | 26.9                    | 25.4           |                 |                 |                 |                 |
|                | 1.58           | 37.7           | 34.4                    | 26.6           | 26.7           | 23.4                    | 20.9           |                 |                 |                 |                 |
|                | 1.65           | 39.2           | 34.2                    | 26.7           | 26.0           | 20.9                    | 19.4           |                 |                 |                 |                 |
|                | 1.79           | 35.0           | 31.0                    | 25.6           | 23.4           | 20.0                    | 20.0           |                 |                 |                 |                 |
| 1000           | 0.41           | 50.1           | 40.7                    | 49.9           | 34.9           | 38.2                    | 31.2           |                 |                 |                 |                 |
|                | 0.74           | 38.7           | 30.3                    | 31.9           | 24.1           | 22.1                    | 21.5           |                 |                 |                 |                 |
|                | 1.00           | 32.3           | 20.2                    | 27.5           | 17.4           | 18.9                    | 17.0           |                 |                 |                 |                 |
|                | 1.19           | 20.1           | 15.2                    | 15.2           | 10.8           | 9.9                     | 11.0           |                 |                 |                 |                 |
|                | 1.23           | 16.8           | 12.5                    | 11.0           | 9.8            | 8.8                     | 8.2            |                 |                 |                 |                 |
|                | 1.27           | 13.8           | 8.1                     | 7.9            | 7.0            | 7.9                     | 8.0            |                 |                 |                 |                 |
|                | 1.47           | 5.7            | 6.3                     | 6.9            | 6.8            | 7.9                     | 7.3            |                 |                 |                 |                 |
|                | 1.60           | 5.0            | 2.8                     | 5.9            | 4.9            | 7.9                     | 6.8            |                 |                 |                 |                 |
|                | 1.65           | 4.0            | 2.0                     | 4.8            | 4.8            | 7.9                     | 7.2            |                 |                 |                 |                 |
|                | 2.06           | 2.8            | 1.8                     | 5.2            | 4.1            | 7.6                     | 6.7            |                 |                 |                 |                 |
Figure 41: The percentage of area ($A_{\%}$) for a misclassification rate less than a target misclassification rate $\varepsilon_t$ for energy classifier.
Figure 42: The percentage of area ($A_{\%}$) for a misclassification rate less than a target misclassification rate $\varepsilon_t$ for polynomial classifier.
Chapter 6: Conclusion and Future Work

6.1. Conclusion

A quantitative analysis for the spectrum occupancy of the UHF band was conducted using a spectral measurement setup that mainly consists of a wide band omnidirectional discone antenna, a spectrum analyzer, and a computer. The spectrum analyzer served as a spectral sensing instrument throughout the data collection sessions. Moreover, the spectrum analyzer was controlled remotely via MATLAB with the aid of the SCPI command lines provided by the device operating manual.

The UHF band was divided into ten equal bands, and the spectral measurements were carried out for a given predefined time plan. The channel occupancy within each band is decided based on the noise statistical parameters extracted by the Gaussian Mixture Model analysis and the predefined probability of false alarm. In this thesis, the duty cycle analysis and the average occupancy calculations helped in visualizing the spectrum utilization on the American University of Sharjah campus. As per the spectral measurements carried out, the results reported in this thesis show that the UHF band occupancy ranges between 10 to 34% and hence some portions of the spectrum are underutilized. As a result, a strong motivation exists to deploy cognitive radio technologies in solving the spectrum scarcity problem and the inefficient utilization of the frequency spectrum.

A cognitive radio system was deployed using a USRP software defined radio hardware. Both an energy detector based scheme and a polynomial classifier based scheme were implemented. This study is believed to be the first time where a real-world implementation of the polynomial classifier cognitive radio system is reported. It has been shown that the polynomial classifier based scheme has a lower misdetection rate of about 15% than the energy detector based scheme. The improvement in performance increase as the sensing time is increased from 0.5 ms to 5 ms by using a longer frame size.

6.2. Future work

For future work, extended more extensive spectrum measurement campaign could be carried out for different frequency bands and different locations around the United Arab Emirates to get better understanding about the spectrum utilization in the area. Moreover, the data collected from the spectrum could be used to develop statistical
models that help in predicting the spectrum utilization and serve the cognitive radio efficiently.

Another future work may include the implementation of other spectrum sensing schemes using the USRP devices presented in this thesis. In addition, multiple receivers could be added to the cognitive radio system implemented in the thesis to test the performance of cooperative spectrum sensing algorithms.
References


Appendix A: Spectrum Analyzers and FSP 13 Spectrum Analyzer Control

This appendix is intended to provide a brief introduction about the basic functionalities of spectrum analyzers in A.1. In addition, A.2 provides the FSP 13 spectrum analyzer control through SCPI commands through MATLAB.

A.1 Introduction to Spectrum Analyzers

The spectrum analyzer is used to collect data from the frequency spectrum by sampling the power received at each frequency value. The spectrum analyzer is a passive receiver, meaning it does not change the received signal but it demonstrates it in a way better to understand and analyze. Spectrum analyzers usually display raw data that are not processed yet. Those raw data are frequency, period, voltage, power, bandwidth, wave shape, and sidebands.

Spectrum analyzers help in understanding the performance of a system at a certain frequency (frequency response). Moreover, spectrum analyzers help in studying the behavior of the noise introduced in a channel (noise characterizing). In addition, studying the behavior of nonlinear devices like amplifiers, and measuring the distortion level introduced while in operation (amplifier testing). Understanding the basic aspects of the spectrum analyzer will help in obtaining accurate achievable results.

Figure 43: Frequency domain versus time domain sensed by spectrum analyzer

Figure 43 [30] shows the basic function of a spectrum analyzer. Usually spectrum analyzers build up analysis in frequency at a particular instant whereas
oscilloscopes (also spectrum analyzer under some conditions) analyze the signals in time domain at a particular frequency. Frequency domain measurements indicate the level and the frequency of a set of signals. Frequency of a signal is a measure of how many times a signal value come across specific value repeatedly (consecutive peaks or bottoms) within a fixed time interval. For a given center frequency and frequency span, each scan by the spectrum analyzer is called a “sweep”.

One important parameter in any spectrum analyzer is the Resolution bandwidth (RBW). RBW is the bandwidth of a bandpass filter centered at a defined intermediate frequency. Within a single frequency sweep, this filter acts as a moving window capturing the power received by the sensing device over a defined RBW bandwidth. RBW can be changed at any time from the spectrum analyzer configuration menu. The RBW plays a big rule in controlling the sweep time. Reducing the RBW will increase the sweep time and that is not desired for some applications where measurement speed is important. Therefore, there is a tradeoff between frequency selectivity and measurement speed. Moreover, the Signal to Noise Ratio (SNR) might be affected by changing the RBW value. As the RBW value increases, the SNR of the received signal decreases since more noise samples will be captured by the filter.

Parameters like center frequency, frequency span, resolution bandwidth (RBW), video bandwidth (VBW), start frequency and end frequency, etc., are important in controlling the spectrum analyzer display of the radio spectrum. These parameters also control the frequency resolution of the displayed spectrum and how quickly the display being updated.

A.2 Spectrum Analyzer Control

The spectrum analyzer (FSP 13) used as a sensing device is manufactured by Rohde & Schwarz. This device is capable of sensing radio frequencies ranging from 9 KHz to 16 GHz. Moreover, the maximum number of data points this device can store per sweep is 8001. This spectrum analyzer can be controlled manually or remotely. Manual control is useful when observing or studying the channel activities or characteristics such as bandwidth, received power levels, noise floor, etc. Manual control can be done only from the device front panel. In long spectral measurement sessions, remote control over the spectrum analyzer is much more efficient.
With the aid of Matlab programming environment and the controlling command lines provided in the spectrum analyzer operating manual, remote control can be achieved. When switching from manual control to remote control, an asterix symbol (*) appears on the spectrum analyzer display screen. Device remote control can be disabled by pressing the reset button manually from the device front panel. A GPIB interface enables the spectrum analyzer to be controlled remotely through Matlab. To enable the remote control, a GPIB-USB interface can be used between the connectors located at the rear of the spectrum analyzer and the USB port of mobile laptop.

The spectrum analyzer supports the Standard Commands for Programmable Instruments (SCPI) version 1997.0 that is based on standard IEEE 488.2. SCPI aims to impose a standardization of device command, error handling and status registers [30]. Irrespective of the type of the instrument remotely controlled, the SCPI sets a standard command set for programming instruments as described in the instrument manual [30]. The SCPI command line consists of a header followed by a space like resetting the device using the command header “*RST”. Table 7 presents the main SCPI command lines used to control the spectrum analyzer through Matlab.

Table 7: SCPI command lines

<table>
<thead>
<tr>
<th>SCPI Command</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>FREQ:CENT;SPAN</td>
<td>Frequency center and span settings</td>
</tr>
<tr>
<td>*RST</td>
<td>Reset instrument</td>
</tr>
<tr>
<td>INIT:CONT</td>
<td>Controlling sweep mode</td>
</tr>
<tr>
<td>SYST:DISP:UPD</td>
<td>Switch display on/off</td>
</tr>
<tr>
<td>SWE:POIN</td>
<td>Number of samples per sweep</td>
</tr>
<tr>
<td>DET</td>
<td>Selecting detector type</td>
</tr>
<tr>
<td>FORM:DATA ASCII</td>
<td>Storing data in ASCII format</td>
</tr>
<tr>
<td>BAND:RES;VID</td>
<td>RBW and VBW settings</td>
</tr>
<tr>
<td>TRACE? TRACE1</td>
<td>Copy trace to the device buffer</td>
</tr>
</tbody>
</table>
Appendix B: Spectrum Occupancy Measurements Campaign Results

This appendix is intended to provide the graphical representations of the results obtained from the spectral measurements campaign. Figures, similar to Figure 5, showing the spectrum occupancy campaign results for ten bands within the UHF band (300 MHz to 3 GHz) as presented. The band activities are represented by six plots each for a time frame of two hours. The white regions in the waterfall plot represent the times at which a specific channel is idle. The bar chart provides an indication about the band average occupancy for each two hours measurement.

B.1 Band B1 (300 MHz to 570 MHz)

Figure 44: B1 (300 – 570) MHz (8:30 to 10:30)
Figure 45: B1 (300 – 570) MHz (10:30 to 12:30)
Figure 46: B1 (300 – 570) MHz (12:30 to 14:30)
Figure 47: B1 (300 – 570) MHz (14:30 to 16:30)
Figure 48: B1 (300 – 570) MHz (16:30 to 18:30)
Figure 49: B1 (300 – 570) MHz (18:30 to 20:30)
Figure 50: Average Occupancy for B1 (500 – 570) MHz
B.2 Band B2 (570 MHz to 840 MHz)

Figure 51: B2 (570 – 840) MHz (8:30 to 10:30)
Figure 52: B9 (570 – 840) MHz (10:30 to 12:30)
Figure 53: B2 (570 – 840) MHz (12:30 to 14:30)
Figure 54: B2 (570 – 840) MHz (14:30 to 16:30)
Figure 55: B2 (570 – 840) MHz (16:30 to 18:30)
Figure 56: B2 (570 – 840) MHz (18:30 to 20:30)
Figure 57: Average Occupancy for B2 (570 – 840) MHz
B.3 Band B3 (840 MHz to 1.11 GHz)

Figure 58: B3 (840 – 1110) MHz (8:30 to 10:30)
Figure 59: B3 (840 – 1110) MHz (10:30 to 12:30)
Figure 60: B3 (840 – 1110) MHz (12:30 to 14:30)
Figure 61: B3 (840 – 1110) MHz (14:30 to 16:30)
Figure 62: B3 (840 – 1110) MHz (16:30 to 18:30)
Figure 63: B3 (840 – 1110) MHz (18:30 to 20:30)
Figure 64: Average Occupancy for B3 (840 – 1110) MHz
B.4 Band B4 (1.11 GHz to 1.38 GHz)

Figure 65: B4 (1110 – 1380) MHz (8:30 to 10:30)
Figure 66: B4 (1110 – 1380) MHz (10:30 to 12:30)
Figure 67: B4 (1110 – 1380) MHz (12:30 to 14:30)
Figure 68: B4 (1110 – 1380) MHz (14:30 to 16:30)
Figure 69: B4 (1110 – 1380) MHz (16:30 to 18:30)
Figure 70: B4 (1110 – 1380) MHz (18:30 to 20:30)
Figure 71: Average Occupancy for B4 (1110 – 1380) MHz
B.5  Band B5 (1.38 GHz to 1.65 GHz)

Figure 72: B5 (1380 – 1650) MHz (8:30 to 10:30)
Figure 73: B5 (1380 – 1650) MHz (10:30 to 12:30)
Figure 74: B5 (1380 – 1650) MHz (12:30 to 14:30)
Figure 75: B5 (1380 – 1650) MHz (14:30 to 16:30)
Figure 76: B5 (1380 – 1650) MHz (16:30 to 18:30)
Figure 77: B5 (1380 – 1650) MHz (18:30 to 20:30)
Figure 78: Average Occupancy for B5 (1380 – 1650) MHz
B.6  Band B6 (1.65 GHz to 1.92 GHz)

Figure 79: B6 (1650 – 1920) MHz (8:30 to 10:30)
Figure 80: B6 (1650 – 1920) MHz (10:30 to 12:30)
Figure 81: B6 (1650 – 1920) MHz (12:30 to 14:30)
Figure 82: B6 (1650 – 1920) MHz (14:30 to 16:30)
Figure 83: B6 (1650 – 1920) MHz (16:30 to 18:30)
Figure 84: B6 (1650 – 1920) MHz (18:30 to 20:30)
Figure 85: Average Occupancy for B6 (1650 – 1920) MHz
Figure 86: B7 (1920 – 2190) MHz (8:30 to 10:30)
Figure 87: B7 (1920 – 2190) MHz (10:30 to 12:30)
Figure 88: B7 (1920 – 2190) MHz (12:30 to 14:30)
Figure 89: B7 (1920 – 2190) MHz (14:30 to 16:30)
Figure 90: B7 (1920 – 2190) MHz (16:30 to 18:30)
Figure 91: B7 (1920 – 2190) MHz (18:30 to 20:30)
Figure 92: Average Occupancy for B7 (1920 – 2190) MHz
B.8 Band B8 (2.19 GHz to 2.46 GHz)

Figure 93: B8 (2190 – 2460) MHz (8:30 to 10:30)
Figure 94: B8 (2190 – 2460) MHz (10:30 to 12:30)
Figure 95: B8 (2190 – 2460) MHz (12:30 to 14:30)
Figure 96: B8 (2190 – 2460) MHz (14:30 to 16:30)
Figure 97: B8 (2190 – 2460) MHz (16:30 to 18:30)
Figure 98: B8 (2190 – 2460) MHz (18:30 to 20:30)
Figure 99: Average Occupancy for B8 (2190 – 2460) MHz
**B.9  Band B9 (2.46 GHz to 2.73 GHz)**

![Power Level Vs Frequency](image1.png)

![Water Fall Plot](image2.png)

![Duty Cycle (@ threshold power level = -87.79)](image3.png)

Figure 100: B9 (2460 – 2730) MHz (8:30 to 10:30)
Figure 101: B9 (2460 – 2730) MHz (10:30 to 12:30)
Figure 102: B9 (2460 – 2730) MHz (12:30 to 14:30)
Figure 103: B9 (2460 – 2730) MHz (14:30 to 16:30)
Figure 104: B9 (2460 – 2730) MHz (16:30 to 18:30)
Figure 105: B9 (2460 – 2730) MHz (18:30 to 20:30)
Figure 106: Average Occupancy for B9 (2460 – 2730) MHz
B.10  Band B10 (2.73 GHz to 3.00 GHz)

Figure 107: B10 (2730 – 3000) MHz (8:30 to 10:30)
Figure 108: B10 (2730 – 3000) MHz (10:30 to 12:30)
Figure 109: B10 (2730 – 3000) MHz (12:30 to 14:30)
Figure 110: B10 (2730 – 3000) MHz (14:30 to 16:30)
Figure 111: B10 (2730 – 3000) MHz (16:30 to 18:30)
Figure 112: B10 (2730 – 3000) MHz (18:30 to 20:30)
Figure 113: Average Occupancy for B10 (2730 – 3000) MHz
Vita

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