APPLICATION OF SPECTRUM OBSERVATORY MEASUREMENTS TO SUPPORT
TRAFFIC MODEL-BASED DYNAMIC SPECTRUM ACCESS

BY

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<td>Abbreviation</td>
<td>Term</td>
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</tr>
<tr>
<td>ADC</td>
<td>Analog to Digital Converter</td>
<td></td>
</tr>
<tr>
<td>AM</td>
<td>Amplitude Modulation</td>
<td></td>
</tr>
<tr>
<td>AP</td>
<td>Access Point</td>
<td></td>
</tr>
<tr>
<td>AWGN</td>
<td>Additive White Gaussian Noise</td>
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</tr>
<tr>
<td>BER</td>
<td>Bit Error Rate</td>
<td></td>
</tr>
<tr>
<td>CA</td>
<td>Collision Avoidance</td>
<td></td>
</tr>
<tr>
<td>CBM</td>
<td>Comprehensive Band Modeling</td>
<td></td>
</tr>
<tr>
<td>CPD</td>
<td>Chicago Police Department</td>
<td></td>
</tr>
<tr>
<td>CSMA</td>
<td>Carrier Sense Multiple Access</td>
<td></td>
</tr>
<tr>
<td>CSMAC</td>
<td>Commerce Spectrum Management Advisory Committee</td>
<td></td>
</tr>
<tr>
<td>DAC</td>
<td>Digital to Analog Converter</td>
<td></td>
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<tr>
<td>DARPA</td>
<td>Defense Advanced Research Projects Agency</td>
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<tr>
<td>DSA</td>
<td>Dynamic Spectrum Access</td>
<td></td>
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<tr>
<td>FCC</td>
<td>Federal Communications Commission</td>
<td></td>
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<tr>
<td>FEMA</td>
<td>Federal Emergency Management Agency</td>
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</tr>
<tr>
<td>FM</td>
<td>Frequency Modulation</td>
<td></td>
</tr>
<tr>
<td>FoC</td>
<td>Fraction of Collisions</td>
<td></td>
</tr>
<tr>
<td>HDO</td>
<td>Hole Descriptor Object</td>
<td></td>
</tr>
<tr>
<td>IEEE</td>
<td>Institute of Electrical and Electronics Engineers</td>
<td></td>
</tr>
<tr>
<td>iid</td>
<td>independent and identically distributed</td>
<td></td>
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<tr>
<td>IIT</td>
<td>Illinois Institute of Technology</td>
<td></td>
</tr>
<tr>
<td>Abbreviation</td>
<td>Definition</td>
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<tr>
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<tr>
<td>ISI</td>
<td>Inter-Symbol Interference</td>
<td></td>
</tr>
<tr>
<td>ISM</td>
<td>Industrial, Scientific and Medical</td>
<td></td>
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<tr>
<td>KS</td>
<td>Kolmogorov Smirnov</td>
<td></td>
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<tr>
<td>KPSS</td>
<td>Kwiatkowski–Phillips–Schmidt–Shin test</td>
<td></td>
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<tr>
<td>LBT</td>
<td>Listen Before Talk</td>
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<tr>
<td>LMR</td>
<td>Land Mobile Radio</td>
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<tr>
<td>LTE</td>
<td>Long Term Evolution cellular</td>
<td></td>
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<tr>
<td>Mbps</td>
<td>Mega Bits Per Second</td>
<td></td>
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<tr>
<td>mse</td>
<td>mean squared error</td>
<td></td>
</tr>
<tr>
<td>NSF</td>
<td>National Science Foundation</td>
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<tr>
<td>NTIA</td>
<td>National Telecommunication and Information Agency</td>
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<tr>
<td>OFDM</td>
<td>Orthogonal Frequency Division Multiplexing</td>
<td></td>
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<tr>
<td>PCAST</td>
<td>President’s Council of Advisors on Science and Technology</td>
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<tr>
<td>PSD</td>
<td>Power Spectral Density</td>
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<tr>
<td>PSR</td>
<td>Public Safety Radio</td>
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<tr>
<td>PTT</td>
<td>Push-to-talk</td>
<td></td>
</tr>
<tr>
<td>PU</td>
<td>Primary User</td>
<td></td>
</tr>
<tr>
<td>RF</td>
<td>Radio frequency</td>
<td></td>
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<tr>
<td>SDO</td>
<td>Signal Descriptor Object</td>
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<tr>
<td>SDR</td>
<td>Software Defined Radio</td>
<td></td>
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<tr>
<td>SIR</td>
<td>Signal-to-Interference Ratio</td>
<td></td>
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<tr>
<td>SNR</td>
<td>Signal to Noise Ratio</td>
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<tr>
<td>SO</td>
<td>Spectrum Observatory</td>
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<tr>
<td>Abbreviation</td>
<td>Full Form</td>
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<td>--------------</td>
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</tr>
<tr>
<td>SOA</td>
<td>Spectrum Opportunity Accessed</td>
<td></td>
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<tr>
<td>SOF</td>
<td>Spectrum Opportunity Fraction</td>
<td></td>
</tr>
<tr>
<td>SU</td>
<td>Secondary User</td>
<td></td>
</tr>
<tr>
<td>USRP</td>
<td>Universal Software Radio Peripheral</td>
<td></td>
</tr>
<tr>
<td>Wi-Fi</td>
<td>Wireless-Fidelity</td>
<td></td>
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<tr>
<td>WiFiUS</td>
<td>Wireless Finland USA</td>
<td></td>
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<tr>
<td>WIL</td>
<td>Wireless Interference Laboratory</td>
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<tr>
<td>WiNCom</td>
<td>Wireless Networking and Interference Research Center</td>
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**LIST OF SYMBOLS**

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
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<tbody>
<tr>
<td>$T_{C_{max}}$</td>
<td>maximum value of sensing countdown timer</td>
</tr>
<tr>
<td>$T_{X_{max}}$</td>
<td>maximum value of transmit duration</td>
</tr>
<tr>
<td>$T_{slot}$</td>
<td>slot duration in DSA algorithm</td>
</tr>
<tr>
<td>$T_e$</td>
<td>sensing countdown duration in one cycle</td>
</tr>
<tr>
<td>$T_x$</td>
<td>transmit duration in one slot</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>variance parameter for lognormal model of channel</td>
</tr>
<tr>
<td>$\mu$</td>
<td>mean parameter for lognormal model of channel</td>
</tr>
<tr>
<td>$f_I(\tau)$</td>
<td>probability distribution function for idle times</td>
</tr>
<tr>
<td>$C(T_e, T_x)$</td>
<td>Collision probability as a function of 2 parameters</td>
</tr>
<tr>
<td>$SOA(T_e, T_x)$</td>
<td>Spectrum Opportunity accessed as function of 2 parameters</td>
</tr>
<tr>
<td>$SOF$</td>
<td>Spectrum Opportunity Fraction</td>
</tr>
<tr>
<td>$K$</td>
<td>A constant used during integration defined by equation (4.11)</td>
</tr>
<tr>
<td>$F_I(T)$</td>
<td>Cumulative distribution function of idle times from 0 to $T$ s.</td>
</tr>
<tr>
<td>$t$</td>
<td>time variable</td>
</tr>
<tr>
<td>$f_{SU}$</td>
<td>Center frequency of a sub-channel within a hole for SU use</td>
</tr>
<tr>
<td>$W_{SU}$</td>
<td>Secondary user bandwidth</td>
</tr>
<tr>
<td>$B_{hole}$</td>
<td>Bandwidth of Hole</td>
</tr>
<tr>
<td>$B_{free}$</td>
<td>Bandwidth within hole that is available at a time instant</td>
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</table>
ABSTRACT

In a 2012 report, the President’s Council of Advisors in Science and Technology (PCAST) published a memorandum that calls for the identification of 1000 MHz of Federal Spectrum to be shared with private (commercial) users. This dissertation proposes a system that employs RF measurements for spectrum usage modeling and Dynamic Spectrum Access (DSA) methodologies that utilize the modeling information to permit sharing of wireless resources. A procedure called the Comprehensive Band Modeling (CBM) procedure is developed that automatically models measured RF data from any band of interest and identifies the locations of signals and holes present in the band. The output of the CBM procedure is summarized in a compact versatile format that makes DSA applications feasible.

The research primarily focuses on the 450-474 MHz land mobile radio (LMR) band, and several additional bands like the TV band and the 2.5-2.7 GHz band. However, the research methodology and techniques are broadly applicable to many more frequency ranges. The research has four main areas: (a) spectrum sensor design and measurements, (b) occupancy modeling, (c) communicating the modeling information in a compact form to secondary users to support DSA algorithms and protocols, and (d) tools and metrics for spectrum sharing favorability analysis.

Three spectrum sensor platforms were employed in measurements – (1) a spectrum analyzer based Spectrum Observatory (SO) that was developed earlier, (2) a specially purposed software-defined radio (SDR) for measuring LMR channels, (3) and a high-speed and portable SO system based on a sensor called the RFeye.
An SO continually measures RF data in a band at a high temporal resolution such that the channel switching activity is seen – like, transmitters turning on and off. Spectrum measurements of the individual RF channels in the 450-474 MHz LMR band and the two commercial bands are used to generate statistical traffic and occupancy models. Long-term measurement data is used to assess how stationary the channel is, and how often the model parameters need to be updated. The spectrum observatory supports a network of Secondary Users (SU) by communicating the traffic model parameters in a compact format to the SUs. The SUs share Primary User (PU) channels via DSA techniques. The DSA algorithms take advantage of the model parameters provided by the SO to maximize SU throughput with limited interference on the PU. The DSA coexistence techniques are evaluated via simulation. The simulation results including Spectrum Opportunity Accessed (SOA), SU throughput, and collision rates are then analyzed to provide an assessment of DSA-based spectrum sharing in that band.

The main contribution of this dissertation is the aforementioned CBM procedure. The white spaces in the frequency and time domains, that is, the underutilized spectrum opportunities available for possible secondary use via DSA are automatically identified, as well as the frequency locations that are not conducive to DSA due to the presence of frequent primary licensee transmissions. In CBM, white spaces are referred to as ‘Holes’, and the licensed primary transmission frequencies as ‘Signals’. Useful information about the duty cycles and traffic patterns of incumbent users’ activity within possible secondary use channels is extracted and modeled. The model enables prospective secondary users of white
spaces to predict the expected level of interference in any channel, which allows for channel ranking and optimal selection of DSA transmission parameters. The CBM model is describable by a tiered structure, where the first tier identifies the holes and signals; the second tier ranks the holes in terms of available bandwidth and incumbent duty cycle; and the third tier models the infrequent incumbent transmissions. With the three tiers of information, an SU can readily identify all the suitable DSA channels within the entire spectrum band. This essential summary information is retrieved as a “Hole Descriptor Object” (HDO) that is both compact and tractable. Empirical spectrum measurement data obtained from the three different SO platforms is used to test the performance of the CBM procedure in the 2500-2700 MHz frequency range that currently has WiMAX deployments, the TV white space band, and the 450-474 MHz LMR band in Chicago.

Spectrum measurement data runs into hundreds of megabytes or gigabytes. As such, the raw information is not very applicable in practical wireless networks. The HDO objects on the other hand are compact and only kilobytes in size. The HDO objects contain all the useful and applicable information necessary for any smart radio (primary or secondary) to select transmission parameters like frequency of operation and bandwidth, so that it can efficiently operate. Thus, the advantage of the CBM procedure is that it summarizes gigabytes of raw spectrum measurements in a usable compact format that can be directly used by practical smart radios to operate using DSA paradigms. Another advantage of CBM is that it is comprehensive and automatically identifies all holes and signals.
The research findings are of interest and value to a variety of Federal and Commercial entities. The models and relevant model parameters for public safety radio in the LMR band have been provided on request to the Public Safety and Homeland Security Bureau of the Federal Communications Commission (FCC). The DSA feasibility analysis methodology is of great national economic interest based on the contents of the PCAST report. The PCAST report recommends finding 1000 MHz of federal frequencies to be allocated for shared commercial and federal use. However, the technology for doing so and identifying the suitable bands requires measurements of actual spectrum usage, modeling the occupancy and existing traffic activity, and assessing DSA feasibility – these are important research aspects, and all of which are addressed in this dissertation. The results are of crucial importance to policy makers like the FCC and NTIA who will ultimately make the spectrum allocations decisions.

A future network of commercial DSA SU radios operating in a shared band is likely to need access to a system to obtain live information about PU activity to optimally operate in the band with high throughput and low interference. The overall system, based on the CBM procedure and HDO objects, proposed in this thesis describes a framework for providing this information as a service to DSA networks, and hence the work is also of practical relevance to radio system designers.
CHAPTER 1
INTRODUCTION

1.1 Background

The development and deployment of wireless technologies have experienced rapid growth since the mid-90s. Majority of the world's population are now connected on-the-go and at all times, due to the proliferation of highly capable, yet affordable wireless portable devices. National and global economies have become highly dependent on wireless technologies like broadcast radio and TV, public safety radio, cell phone systems, GPS, Wi-Fi and Bluetooth [PRO94]. All these technologies rely on a finite natural resource—the radio spectrum. Decades ago, demand for radio services was much less, most of the spectrum was divided into application-specific bands such as the radio bands (AM and FM) and the various television bands, explicitly allocating the bands to specific users or groups of users [KOB01]. This waveform allocation was established either through the development of rules by the regulatory agencies to serve a particular policy objective, or by providing licenses to different users or user groups. This framework for static allocations was intended to prevent the various radio licensees from harmfully interfering with each other. Since then, the intensity of radio usage has grown by orders of magnitude in certain frequencies, like the cellular bands, to the extent that high utilization is evident; in other bands, observations indicate a much lower usage level [BAC08].

The availability of sufficient RF spectrum for technologies like mobile and fixed wireless internet access and the innovative services and applications these support is a
driver for economic growth [FCC10, SUM10]. Government and industry sources agree that significant additional RF spectrum for both licensed and unlicensed uses is required to meet the RF spectrum demand. [FCC10a] Since the RF spectrum usable for wireless services has already been allocated to specific uses and service categories, the only options available to secure this spectrum are to a) increase the efficiency of current spectrum use via new technology; b) re-purpose spectrum from one use to another; and c) institute spectrum sharing in bands that are currently assigned exclusively to a single user or usage category.

In 2008 the FCC voted unanimously to open up the TV “white spaces” for unlicensed radio usage. TV white space refers to the spectrum in a certain geographical location that is not being used for either TV broadcast or licensed wireless microphone transmissions [WYG09]. The (new) unlicensed “white space” transmitters should not interfere with any of the active TV broadcast channels, and the devices must consult geographic databases to determine which TV channels can be safely used without interference in a particular region. Although the initial FCC rules required that white space devices perform local spectrum sensing in addition to database look up, in September 2010 the FCC removed this requirement [GRE10]. Since spectrum sensing adds significant hardware and software complexity to a radio device, the new FCC regulation stimulated a more affordable and faster path of adoption for unlicensed TV white space use. Currently, several manufacturers [ADA12][NIC13] are demonstrating TV white space wireless Internet access devices/base stations, where the maturing TV white space technology has taken advantage of the standardization activities through the IEEE 802.22 standard [STE09] as well as the establishment of geographical support
databases that list which channels are available for use in a locale. It is envisioned that more IEEE 802.22 wireless regional area network (WRAN) devices or proprietary devices will begin to use the TV white space spectrum, in view of the large unoccupied bandwidths that are now available in many areas.

Advances in communication technology such as the 3GPP Long Term Evolution (LTE) protocol have led to significant improvements in spectrum efficiency [RYS10], but these gains have been overtaken by the bandwidth demands of highly capable handheld devices (smartphones and tablet computers), which consume 50-200 times the data per month of a regular cellphone [CIS12]. Smartphones today represent the largest segment in cell phone sales due to their convenient and compelling user interface to video, multimedia internet browsing, and enterprise (business) applications. The demand for smartphones and their bandwidth intensive applications is evident in the consumer, business, and government domains, including federal, state and local public safety operations.

The identification of RF spectrum that can be repurposed to broadband wireless use, exemplified by the re-allocation and re-assignment of broadcast TV channels in the 700 MHz band to mobile “4G” LTE wireless service has emerged as a major initiative. Similarly, the identification of RF spectrum that can be utilized more efficiently by instituting sharing between an incumbent, primary user, and new secondary users, without impacting primary user operation, has also become a goal of policymakers and policy advisors. This type of operation is demonstrated by the recently developed co-existence regulations and technical standards that allow the sharing of the U.S. Federal radar band with wireless internet access [SAN10].
Groups such as the Commerce Spectrum Management Advisory Committee (CSMAC) [COM04] and the President’s Council of Advisors on Science and Technology (PCAST), in addition to the FCC and NTIA, have ongoing, active initiatives to identify spectrum that can be repurposed or shared [NAT12]. Critical to this work and the value of their recommendations is up-to-date information on the actual utilization of the RF spectrum, and new analysis methods to create insights into spectrum sharing approaches.

While the FCC maintains databases of the authorized, licensed users of the RF spectrum by frequency and location via such tools as the Spectrum Dashboard [SUM10] and License View [FCC11], these databases do not contain information on actual RF spectrum utilization in time, frequency, and space.

In order to accurately assess actual spectrum utilization to identify spectrum that can be repurposed or shared, long-term observation of RF usage is essential. It is also necessary to analyze and model the activity of incumbent users in a frequency band to determine if it is feasible for secondary users to share this band without adversely affecting the incumbents. At the simplest level, a spectrum audit can reveal how efficiently the allocated spectrum is being utilized, and if there are any spectrum holes – that is allocated frequencies that are not being used at a specific location, and hence can be easily shared or re-assigned to others.

In a 2012 report, PCAST published a memorandum that calls for the identification of 1000 MHz of Federal Spectrum to be shared with private (commercial) users. The PCAST report recommends finding this 1000 MHz spectrum; but the technology for doing so and identifying the suitable bands requires measurements of actual spectrum
usage, modeling the occupancy and existing traffic activity, and determining Dynamic Spectrum Access (DSA) feasibility – important research aspects that need investigation.

In 2011, the NTIA published a report [COM11] where they selected and ranked six blocks of currently Federal-owned spectrum for priority repurposing to non-Federal use. These include the 1755-1850 MHz, 1695-1710 MHz, 406.1-420 MHz, and 1370-1390 MHz, 4200-4400 MHz and 3500-3650 MHz blocks. This priority or fast-track evaluation has recently opened up research opportunities of national importance – particularly, the analysis of spectrum usage, wireless traffic modeling and spectrum repurposing or sharing feasibility studies in these bands are of interest and practical relevance.

1.2 Literature Review

Dynamic spectrum access technology and cognitive radios are currently a hot research area. DSA technologies aim to increase efficient use of finite radio spectrum resources as well as attempting to satisfy the increasing demand for wireless resources. [JAB10] gives a very good overview of current and past research in that area. DSA is a wide field, and [JAB10] covers several areas including spectrum occupancy measurements, dynamic frequency selection, DSA testbeds, coexistence techniques, spectrum access techniques, interference avoidance methods, dynamic sensing, and more. In the area if spectrum measurements, [JAB10] identified that more research needs to be done to understand spectrum utilization, hence the need for more analysis. This dissertation aims to analyze spectrum measurements to explore and model utilization characteristics in several frequency bands.
Many studies have looked at short term monitoring of RF spectrum [ROB06, MCH05, ISL08]. However, short term monitoring provides inadequate data for modeling wireless traffic characteristics. To properly model traffic in any band, high resolution data spanning a relatively long period of time (>1 week) would be necessary [WEL09]. On the other hand, the models developed in this dissertation were based on years’ worth of measurements. Previous spectrum measurement and analysis work has primarily focused on simple occupancy studies [TAH11b, MCH05, ISL08], which though useful, only provide a narrow lens towards understanding the true dynamics, patterns and intricacies of radio usage. Primarily, analysis of spectrum measurement data in prior work has produced simple average occupancy values for bands of interest [MCH05, ISL08]. Detailed analysis of a band to identify the holes and signals present in the band, and modeling these for the entire band has not been done before. Part of the reason is that only few researchers have access to the necessary long-term high-resolution spectrum data of the kind available at the Wireless Networks and Communications (WiNCom) research center at the Illinois Institute of Technology (IIT). In this dissertation, methods to characterize and extract complete models of entire bands are presented using high fidelity RF spectrum measurements.

Public safety voice traffic has been modeled before using empirical data [JOR97, BAR97, ASC06, ASC07, ASC09]. Modeling of public safety traffic is useful for planning and designing new or upgraded first-responder networks. The problems with the models above are that they are based upon “busy-period” traffic data and do not work well at other times. A stationary approximation is made to the above models, so one drawback is that the models do not track the channel activity for long periods of time.
greater than a few hours. Also, none of these studies have quantified the non-stationarity inherent in public safety traffic.

In the above papers, the hold times during a call are commonly modeled by exponential lognormal distributions. Lognormal distribution is a closer fit. Cell phone call durations have been modeled by a log-logistic distribution function in [PED10]. The log-logistic distribution is commonly used in survival analysis modeling [BEN83]. The authors of [PED10] give an intuitive explanation about why cellular call durations follow the log-logistic distribution closely. Lognormal distribution is very similar in shape to a log-logistic distribution, although log-logistic is a closer fit to cellular call durations. Though somewhat different from cellular call durations, it is also likely that for Land Mobile Radios (LMR), similar call generation and hold process gives rise to a histogram of call durations where the histogram is closely related to both the lognormal and log-logistic distribution shapes. Hence, the results of the previous studies and this dissertation show that LMR traffic can be closely fitted by the lognormal distribution function.

Understanding the behavior of first responder networks is of great importance for national security, and has been studied extensively by government agencies including the FCC. [FCC08b] documents the affect that the Minneapolis bridge collapse had on public safety networks in the region, and how the networks reached near saturation. [FCC09] does a similar study of public safety traffic during Hurricane Ike that hit several states including Texas. The results show that research is needed to examine how to expand or provide backup capacity to first responders during an emergency. One of the objectives of the dissertation is to see how DSA can be applied to improve public safety capacity in
the LMR bands, which would be particularly beneficial during natural or man-made disaster scenarios.

Dynamic spectrum sharing algorithms have been the focus of many studies. A DSA testbed was designed and field tested [MCH07, MCH08] as part of the funding agency DARPA’s XG radio program. The XG radios used a simple listen-before-talk algorithm to communicate. The results show that DSA is a promising technology for the future, but more research is needed before the technology matures. Authors in [HUA08, HUA09] present a secondary spectrum access methodology that is optimal based on a collision constraint on the primary user. This algorithm performs optimally when the distribution of primary user idle times’ is known. This dissertation extensively studies and models the idle time distributions in multiple bands, which would support the application of DSA algorithms that employ this knowledge for opportunistic spectrum access.

The use of object abstraction in the field of spectrum measurements and analysis is a relatively new concept. In [STI11], the concept of how abstraction layers would aid research in the spectrum management field is presented. This dissertation expands greatly on this idea and uses three tiers of abstraction to represent spectral model data in a band. Beyond [STI11], the dissertation borrows information from the Computer Science (CS) field – particularly, the idea of computer programming objects. Analogous to CS programming objects, spectrum descriptor objects are presented that add a great deal of versatility to research in this domain.
1.3 Overview of Dissertation

This dissertation proposes a system to use RF measurements for spectrum usage modeling. The system supports a dynamic spectrum access methodology that utilizes the modeling information to permit spectrum sharing between incumbent and opportunistic users. The research specifically focuses on the 450-474 MHz land mobile radio band, and two commercial bands; but the research methodology and techniques are broadly applicable to more frequency ranges. The research has four main areas: (a) spectrum sensor design and measurements, (b) occupancy and spectrum band modeling, (c) communicating the modeling information in a compact form to secondary users to support DSA algorithms and protocols, and (d) tools and metrics like the number of spectrum white spaces and their associated properties to assist the researcher in conducting spectrum sharing favorability analysis.

Of the four main research areas listed above, specialized spectrum sensors are implemented to capture the switching activity of wireless traffic with high time and frequency resolutions. This permits band modeling, which is the second area of research. Dynamic spectrum access algorithms that use these models to their advantage for opportunistic spectrum sharing are the focus of the third area. Finally, the fourth area combines all the areas to help the researcher determine if spectrum sharing is feasible in each of the bands, and if so, how this can be achieved for maximum spectrum efficiency with minimum impact on legacy non-cognitive radio systems.

Three spectrum sensor platforms were employed in measurements – (1) a spectrum analyzer based Spectrum Observatory (SO) that was developed earlier at WiNCom, (2) a specially purposed software-defined radio (SDR) based on the Ettus
Universal Software Radio Peripheral (USRP) for measuring LMR channels [ETT13], (3) and a high-speed, compact and portable SO system based on a sensor called the RFeye manufactured by CRFS [CRF14]. An SO continually measures RF data in a band at a high temporal resolution such that the channel switching activity is seen – like, transmitters turning on and off. Spectrum measurements of the individual RF channels in the 450-474 MHz LMR band and the two commercial bands are used to generate statistical traffic and occupancy models. Long-term measurement data is used to assess how stationary the channel is, and how often the model parameters need to be updated. The spectrum observatory supports a network of Secondary Users (SU) by communicating the traffic model parameters in a compact format to the SUs. The SUs share Primary User (PU) channels via DSA techniques. The DSA algorithms take advantage of the model parameters provided by the SO to maximize SU throughput with limited interference on the PU. The DSA coexistence techniques are evaluated via simulation. The overall system setup is illustrated in Figure 1.1.

The DSA coexistence scenario in Figure 1.1 is evaluated via simulation. The simulation results including Spectrum Opportunity Accessed (SOA), SU throughput, and collision rates are then analyzed to provide an assessment of DSA-based spectrum sharing in that band of interest.
1.3.1 Additional Findings. Chapter 2 of this thesis also presents additional findings about spectral usage in the wideband frequency range between 30 MHz to 3 GHz (or higher) which are of use to researchers in the field as well as spectrum policy makers and experts. Chapter 2 also presents results about the characteristics of radio use in the public safety bands which is of interest to the public safety community, including the FCC’s public safety and homeland security bureau.

1.3.2 CBM Procedure. At a more detailed level, The main contribution of this dissertation is the Comprehensive Band Modeling (CBM) procedure. The white spaces in the frequency and time domains, that is, the underutilized spectrum opportunities available for possible secondary use via DSA are automatically identified, as well as the frequency locations that are not conducive to DSA due to the presence of frequent primary licensee transmissions. In CBM, white spaces are referred to as ‘Holes’, and the
licensed primary transmission frequencies as ‘Signals’. Useful information about the duty cycles and traffic patterns of incumbent users’ activity within possible secondary use channels is extracted and modeled. The model enables prospective secondary users of white spaces to predict the expected level of interference in any channel, which allows for channel ranking and optimal selection of DSA transmission parameters.

The CBM model is describable by a tiered structure, where the first tier identifies the holes and signals; the second tier ranks the holes in terms of available bandwidth and incumbent duty cycle; and the third tier models the infrequent incumbent transmissions. With the three tiers of information, an SU can readily identify all the suitable DSA channels within the entire spectrum band. This essential summary information is retrieved as a “Hole Descriptor Object” (HDO) that is both compact and tractable.

Empirical spectrum measurement data obtained from the three different SO platforms is used to test the performance of the CBM procedure in the 2500-2700 MHz frequency range that currently has WiMAX deployments, the TV white space band, and the 450-474 MHz LMR band in Chicago.

Spectrum measurement data runs into hundreds of megabytes or gigabytes. As such, the raw information is not very applicable in practical wireless networks. The HDO objects on the other hand are compact and only kilobytes in size. The HDO objects contain all the useful and applicable information necessary for any smart radio (primary or secondary) to select transmission parameters like frequency of operation and bandwidth, so that it can efficiently operate. Thus, the advantage of the CBM procedure is that it summarizes gigabytes of raw spectrum measurements in a usable compact format that can be directly used by practical smart radios to operate using DSA
paradigms. Another advantage of CBM is that it is comprehensive and automatically identifies all holes and signals.

1.4 Relevance

As stated in Section 1.1 that in light of recent policy developments, there is great interest in research that uses spectrum measurement data to analyze wireless usage, model it and to examine how spectrum efficiency can be improved – particularly through spectrum sharing. Therefore, the work to analyze and model wireless usage activities in the Federal and commercial bands is very relevant today.

The models of Public Safety Radio (PSR) are of use to Federal agencies for disaster management planning. At their request, the PSR models have been shared with FCC’s department of public safety and homeland security bureau. The models thus should help improve the specifications for future public safety radio networks and improve disaster management.

Wireless occupancy studies that map how radio spectrum is utilized in different bands are useful for planning purposes and developing new regulations to support and sustain the growth and value of radio related technologies and applications. Spectrum also has a high economic value. The results of spectral occupancy studies are useful for making decisions on the reallocation of spectrum and/or valuation estimation. Thus, some of the broader spectrum findings (Chapter 2 of dissertation) are relevant to spectral policy drafting efforts.

Due to the PCAST report’s recommendations to explore spectrum sharing in Federal bands, the National Science Foundation (NSF) is strongly supporting such research. In fact, similar research efforts are being replicated in other universities in the
US and around the world. Recently, the WiNCom research center entered into a partnership with Virginia Tech, Maryland, and three top universities/institutions in Finland to replicate the spectrum measurement and modeling research work in five locations – three in the US and two in Finland. This cross-Atlantic research is being supported by the NSF and the Tekes Academy of Finland, with the goal of understanding wireless usage through empirical measurements and exploring DSA technologies towards the goal of improving spectrum efficiency.

The proposed CBM has obvious applications in upcoming cognitive radio (CR) networks employing DSA technologies. By regulation, IEEE 802.22 CRs operating in TV white spaces [FCC10b] have to consult a database to identify the white space TV channels where they can operate [GOO14] at a particular geographical location. Although TV broadcast channel locations are reliably recorded in the geographic database, often the locations of wireless microphones in the TV bands are not. The microphones are classified as devices protected from IEEE 802.22 interference. The CBM procedure can be implemented on TV white space measurements obtained by a spectrum observatory that senses the RF environment at the network location. In this application, the SO communicates the CBM outputs (the HDOs) to IEEE 802.22 radios, where the HDOs identify spectrum holes ideal for CR operation and free from interference with any measured wireless microphone transmissions.

Apart from IEEE 802.22, next generation CRs would likely have the need to rapidly scan wide bandwidths and quickly identify operating frequencies that are free from PU interference. Commercial radios should be inexpensive in order to be economically viable in the mass market, but wideband sensing hardware adds cost to CR
systems. The CR’s spectrum sensor may suffer from the hidden node problem [RAP02], shadowing, and other effects in the radio path like absorption that limit its sensitivity. An alternative would be to outsource the sensing function of the CR network to a spectrum observatory. A single well-designed SO has high sensitivity and can provide the service of identifying good secondary usage channels to a large number of CRs operating in the area. The SO would implement the CBM procedure to obtain a set of HDOs in the frequency bands of interest and communicate this set as a service to the next generation CR networks. Thus, CBM expands the scope of spectrum observatory systems beyond the current application of simply monitoring and auditing radio use to one of practical utility, where the SO facilitates operation of DSA networks.

One of the long-term goals at WiNCom is to deploy a CBM-based analysis library that processes incoming and historic RF measurements to support DSA networks throughout the cities. The expansive nature of this goal also includes processing spectral data from multiple bands where DSA sharing is feasible based on the CBM procedure or its future derivatives. The vision is to setup a spectrum observatory network to facilitate deployment and operation of cognitive radio systems in multiple bands where DSA is feasible.

One of the objectives of this dissertation is to demonstrate an application for a continuous spectrum monitoring system. The spectrum observatory plays an integral part of the DSA sharing framework presented in Figure 1.1 by measuring the RF powers in the band to be shared. Then the CBM procedure identifies the holes, models the PU traffic, and then reports the parameters to the SU via hole-descriptor objects. Without the
spectrum observatory measuring RF power and then running the CBM procedure, the spectrum efficiency gains of DSA may not be feasible.

The final relevance is in the design of practical DSA radios. Future radio systems that aim to share spectrum in the radio bands will benefit from the overall system design presented in this dissertation. The employment of a spectrum observatory to sense wireless traffic, model it, then share the channel info with a DSA network to facilitate spectrum sharing can serve as a framework for future practical DSA radio networks. Furthermore, the large volume of data collected at spectrum observatories has limited the scope of measurements-based research to academic circles, and it is necessary to compactly summarize the data prior to doing R&D work on practical radios. This dissertation presents a novel effective method to summarize measured data by orders of magnitude, thus permitting further research into practical DSA systems. This is done through the generation of HDO summary objects.

1.5 Novelty

The dissertation is novel in the following areas that are directly related to the main goal of the research, which is to measure and model primary user spectrum usage and test DSA spectrum sharing with secondary users:

1. **LMR Models.** New time-varying models for LMR switching traffic were presented that are able to track the channel for arbitrarily long periods of time.

2. **New Application for Spectrum Observatory.** The framework where the SO models PU traffic and then provides useful PU channel information to the SU in real-time is novel and it makes spectrum sharing possible.
3. **Quantitative Method to assess channel stationarity.** The method to use long-term RF measurement data to assess the stationarity of wireless traffic activity is novel.

4. **Low-cost Measurement Systems.** The design of low cost high resolution spectrum sensors to monitor hundreds of wireless channels simultaneously is an important contribution to this field.

5. **DSA algorithms.** The DSA algorithms that utilize model information from the SO may be simple, but they are novel in that they make use of a unique data-set made possible by the SO spectrum measurements.

6. **Procedure to Model whole bands at a time.** The CBM method to automatically process gigabytes of spectrum data corresponding to a band and obtain a compact yet comprehensive model of the entire band is novel.

7. **DSA Assessment.** The CBM procedure outputs metrics like: (a) number of holes available in band, (b) sensitivity requirement for the SO and the SUs – how weak or strong are the PU signals, (c) bandwidth of holes, (d) occupancy statistics in the hole, (e) spectrum efficiency achieved through DSA, (f) and collision probabilities. Combined, they provide novel tools for the researcher to assess DSA feasibility.

8. **Hole/ Signal Descriptor Objects (HDO/ SDO).** The use of object abstraction in the field of spectrum measurements and analysis is a relatively new concept. The HDO/ SDO objects that layer different levels of details while modeling of channels (either hole or signal channels), and then compactly represent this information in a flexible object format are novel and very useful.
contributions to the field. The HDO/ SDO concept is in the process of being patented.

Although not the main focus of the thesis, during the course of the PhD research, several new interesting findings were presented that represent new knowledge in the field of spectrum measurements and utilization. These are:

9. **New Analysis and Findings on spectrum usage.** Long term results about spectrum usage in the LMR and Federal bands were presented. This includes highlighting the differences between public safety and commercial LMR users, and the changes in public safety LMR usage during emergencies.

10. **Spectrum usage audit.** This was done for Chicago during the years 2008, 2009, 2010. Also, day-long snapshot spectrum audits were done at several locations in and around Chicago in 2013, and at Turku in 2013.

1.6 **Overview of Public Safety Communication Systems**

Public safety personnel use a variety of technologies for communications. Many services are provided over commercial networks; for example, many public safety agencies provide cell phones to their personnel or use cellular data networks for data communications. However, such commercial systems are not capable of meeting many mission-critical communications needs, and especially those that occur during various emergency situations. The cellular networks are infamously unreliable (dropped calls, etc.), and are often locally overloaded during emergencies, and usually lack the user based prioritization features necessary for public safety applications. In general, public safety systems require the following features [NAT03]:
- Dedicated channels with priority access
- One to many broadcast features
- Highly reliable networks with redundancies to ensure network coverage during disaster situations
- Good quality signal throughout the coverage area
- Near instantaneous Communications set-up time, e.g. push-to-talk (PTT)

Thus reliability, range, security, and robustness are all important. While many public safety radio (PSR) systems like digital video networks for broadcasting surveillance camera footage are secure, many of the older technologies are not. Analog FM LMR is not really secure as off-the-shelf radio scanners are available that allow anyone to monitor broadcasts. Due to the stringent performance requirements, PSR systems are very expensive to set up. Due to the limited budget of various city and state agencies, PSR infrastructure are infrequently upgraded, often after many years, and hence, another requirement for PSR systems is longevity. The FM LMR systems currently in place for Chicago’s police and fire departments has been there for more than two decades.

The FCC has assigned PSR users 10 MHz in the VHF bands at 25-50 and 150-174 MHz, 3.5 MHz in the UHF 450-470 MHz LMR band and 9.5 MHz in the 800-900 MHz region. These frequency allocations are mainly used by LMR systems; both for individual mobile transmissions and trunking. Recently, 24 MHz was made available to PSR by the switch from NTSC analog television to ATSC digital TV [PEH06]. For broadband digital communication, contiguous 50 MHz of spectrum between 4940 and
4990 MHz have been allocated for PSR. The contiguous nature is important as it allows high data rate communications at 4.9 GHz, while at the lower frequencies, discrete swaths of spectrum for PSR necessitates narrowband transmission. The focus of this paper is mainly on the mission-critical LMR bands as these are the channels most used by public safety personnel in the field. We will also look at occupancy in the 4.9 GHz band.

The LMR channels at VHF and UHF have been allocated to a wide number of users: business, public works, public safety, public and private maintenance service personnel, etc. In these frequencies, a total of about 13 MHz is available for PSR, but this spectrum is divided for all federal and non-federal agencies. Amongst the federal agencies are the FBI and FEMA. The non-federal agencies include state and city police, fire, and hospital and EMS services. There are also some interoperability channels set aside that allow inter-agency communication at both the federal and non-federal levels.

Each FM LMR channel is 25 kHz channel wide. A total of a few hundred channels are available for LMR, and once divided amongst the various contenders, only a few dozen channels at most are available to one particular agency for an entire city.

Due to the limited number of 25 kHz channels that can be accommodated within the LMR bands, FCC’s Part 90 Narrowbanding [NAT95] mandate requires that by January 2013 all LMR channels must be narrow-banded from existing 25 kHz to 12.5 kHz. This spells an end to the 25 kHz analog FM transmissions for LMR, and should theoretically double the available number of channels. A newer digital LMR standard called the Project 25 (P-25) [APC10] with bandwidths of either 12.5 or 6.25 kHz, is gradually replacing the analog FM channels. LMR operators including public safety agencies are currently investing on upgrading their systems to P-25 before 2013.
Since investments are already being made for system upgrades, this is also an opportunity to invest in newer technology like cognitive radio that promises even more optimal spectral utility in the highly desired LMR frequency bands.

The specific channel assignments for LMR are through various “Frequency Coordinators”. A frequency coordinator is a departmental entity within an organization (like a fire coordinator for fire department) or a private company that provides LMR licensing services to businesses. A frequency coordinator provides the services of planning and licensing of LMR channels to various users on a fee basis. While this has worked quite well, the problem with this approach is that channels are often assigned on a first-come-first-serve basis. Also, once assigned, a LMR channel is made available exclusively to one group of users; thus even if that particular channel is under-utilized, no other LMR user is allowed to use the channel when it is unoccupied.

The LMR radio network for PSR consists of mobile radios, base station repeaters, control circuitry, and backhaul infrastructure [JES07]. The large LMR networks for public safety often employ trunked systems with some central switching to manage trunking requirements. Most of the LMR radios are Push-to-talk (PTT) [BAT01]. A conventional PSR radio user manually monitors the channel and presses the PTT switch to transmit when the channel is clear. A trunked PSR user presses the PTT button and the radio is assigned a transmission channel from a pool of available frequencies. The switching central system combines the transmissions from individual mobiles and/or the dispatch center, and broadcasts the aggregate communications in one of the several one-to-many broadcast channels which the LMR receivers are tuned to in order to receive the information. Thus a PSR system needs several LMR channel allocations to allow mobile
units to transmit and at least one one-to-many channels broadcast channel in order to function.

1.6.1 Interoperability Issues. Currently, LMR channels for separate public safety agencies are allocated separately. Hence, one agency cannot communicate with another using its own channels. To facilitate some inter-agency communications, several shared interoperability channels have been allocated that allow different agencies to communicate with each other. However, this current system has proved inadequate during emergency situations like Hurricane Katrina when the federal agents from FEMA had difficulty communicating with local agencies in Louisiana. The main reasons why interoperability is an issue are [NAT03] – incompatible and old equipment, limited funding for interoperability channels and infrastructure, inadequate planning and coordination amongst agencies, and inadequate spectrum since (as mentioned before) there are only a few LMR channels for PSR and this pool is sub-divided amongst many contenders.

Broadband Communications: Agencies like the Chicago Police Department (CPD) utilize the 50 MHz public safety band at 4.9 GHz for broadband digital communications like live video. No technical standards have been mandated by FCC to date in this band, thus various proprietary technologies are used in different cities. Cameras in the city of Chicago are linked wirelessly using a wireless mesh network based on the IEEE 802.11n [PER08] technology implemented by Firetide corporation [FIR13]. Agencies in other cities or states have allocated 1, 5, and 10 MHz channels to specific users in this band.
Dynamic Spectrum Access for Public Safety

Dynamic spectrum access/cognitive radio technology can be employed in LMR systems for PSR to provide good performance in emergency scenarios when extra PSR capacity is needed. It is well known that cognitive radio paradigms enable more efficient spectrum utilization. In a channel, if the primary user has a low duty cycle, a secondary user may access the channel. By providing cognitive capabilities to selected public safety radios, under-utilized business or other non-public safety LMR channels can be utilized during a “disaster situation”. Such a system can be facilitated by spectrum monitoring stations like IIT’s SO with its occupancy database. In an emergency, a cognitive LMR system would select for PSR use, extra channels with low primary user duty cycles, from the SO database to minimize impact on business and other applications, and more importantly to minimize interference on PSR communications. The central control system in the LMR network can provide information about the newly offered emergency spectrum through a control channel. Even today, most PSR LMR radios in the field are tunable to any of the LMR channels in the VHF or UHF bands; thus the PSR mobile units should be easily able to tune to the optimal channels when necessary.

The second area where dynamic spectrum access technology would be useful for PSR is to enhance communications system interoperability. One of the main problems for interoperability is the lack of coordination between PSR systems from different departments and agencies. Local agencies, for example, city fire and police departments have pre-set frequencies which they use for communications. Communications problems may arise in disaster situations when personnel from federal or distant non-federal agencies converge in a locality. A cognitively equipped PSR radio is envisioned that
periodically senses the known inter-operability frequencies at specially assigned “disaster channels”. The radio would automatically alert the user to a sudden increased activity level in those channels and switch the radio to common interoperability transmission channels enabling the radios from different agencies to communicate. To avoid interference and overcrowding, optimal resource allocation algorithms for cognitive radio should be utilized for the mobile transmit channels. If and when the PSR user wishes, the radio can be switched from the interoperability channel back to the “home” department’s channel for inner agency communications, and vice versa.
CHAPTER 2

BROAD FINDINGS FROM SPECTRUM MEASUREMENTS

2.1 Spectrum-Analyzer based RF Measurement System Overview

The IIT Spectrum Observatory has been monitoring the 30 - 6000 MHz radio activity of the city of Chicago since July 2007 from its location at the top of the 22 story IIT Tower on IIT’s main campus on the south side of Chicago. This building is located 5.3 km south of the Willis (formerly Sears) Tower and has the advantage of an unobstructed view of downtown Chicago from its roof, where the antennas of the Spectrum Observatory are situated. The major components of the base Spectrum Observatory data acquisition system are shown in the diagram in Figure 2.1 and include: a Rohde & Schwarz FSP-38 spectrum analyzer, a pre-selector/RF frontend with independently selectable bands, three directional antennas (two log-periodic and a microwave horn), a desktop computer and various auxiliary sensors (e.g. a weather station and a GPS receiver).

Spectrum occupancy measurement efforts for broad spectral ranges always involve a fundamental trade-off between spectral resolution, time resolution and spectrum coverage. Therefore, the ~6 GHz frequency range of the IIT system is divided into smaller bands of varying spectral widths and frequency resolutions. Some of these band assignments are determined by the preselector ranges, while the other band ranges were chosen to match data collection and analysis needs. High frequency resolution requires long sweep times, hence resulting in low time resolution. Depending on the current research focus and related needs, the band assignments of the measurement
system have on occasion been modified, for example, to obtain a high frequency resolution scan of the land mobile radio (LMR) frequencies [BAC10].

A more detailed description of the system can be found in [BAC08] and [BAC10].

![Diagram of Spectrum Observatory System]

Figure 2.1. Overview of Spectrum Observatory System

### 2.2 Wideband Long-Term Spectrum Measurement Results

This section summarizes the results of wideband measurements and related analysis efforts at the IIT Spectrum Observatory in Chicago over the three years 2008, 2009 and 2010. The results are unique in the sense that the spectral occupancy estimates are based on multiple years of observations, whereas previous studies produced occupancy numbers based on short term snapshot measurements, often of a few hours duration or at most spanning a few days or weeks [ISL08][MCH05]. The results illustrate
occupancy trends and notable spectral events, such as the 2009 broadcast television transition and the related vacating of the 700 MHz band, which have created significant spectrum opportunities in the 30 - 1000 MHz region. The daily, weekly and yearly trends reported are applicable to long term spectrum modeling, spectrum planning, and regulatory decision-making efforts applicable to dynamic spectrum access networks.

Wireless occupancy studies that map how radio spectrum is utilized in different bands are useful for planning purposes and developing new regulations to support and sustain the growth and value of radio related technologies and applications. Spectrum also has a high economic value [KEL08]. The results of spectral occupancy studies are useful for making decisions on the reallocation of spectrum and/or valuation estimation. Several short duration studies [ROB06, MCH05, ISL08] have audited spectrum occupancy in the past, but long term studies are also valuable in tracking trends and in developing a comprehensive picture of radio usage over time as well developing empirical time and frequency domain models of spectrum use [WEL09]. IIT’s Spectrum Observatory has been the center of the longest running study of wide band terrestrial RF spectrum utilization ever performed. The observatory has been conducting its measurements during a particularly exciting period of time for the wireless industry: for example, major regulatory changes recently freed up significant spectrum in the TV bands; new wireless services such as WiMAX have been introduced in other bands; and we have witnessed a period of dramatic growth and expansion in the use of cellular and Wi-Fi technologies.

In order to free up spectrum in the 700-800 MHz region (formerly a part of the broadcast TV band in the U.S.) and in the TV bands in general, the FCC had mandated a
switchover of terrestrial broadcast television from analog NTSC transmission to digital ATSC. The switchover took place at midnight on June 12, 2009. Many TV stations in Chicago had already switched to digital prior to that date but were also broadcasting on separate analog channels; on June 12th these analog stations were switched off (a special exemption was made for low-power analog stations to continue transmission, however). Based on the need for coordinated spectrum transitions, other stations waited until the midnight, June 12th deadline to convert from analog to digital broadcasting. Since the ATSC standard allows multiple digital TV (DTV) signals to share the same 6 MHz television bandwidth, the switchover to ATSC freed up significant spectrum in the TV bands. More importantly, the transition opened up the 698-806 MHz region for other uses as TV broadcast was suspended in this frequency range and relocated to lower frequency channels freed up by transition. The Spectrum Observatory captured the moment of this important historical transition. Licenses to parts of the freed up 700-800 MHz spectrum were recently auctioned to wireless providers by the FCC for the impressive sum of nearly $20 billion dollars [FCC08a].

2.2.1 Data Processing Overview. For each sweep of a spectrum region by the analyzer, the spectral occupancy (unoccupied/occupied, or 0/100%) at each measured frequency point was estimated by comparing the measured power density to a threshold. From this, the overall average occupancy in a given frequency range of a sweep was calculated. Repeating this calculation for every sweep in the three years of data resulted in a time-series representation of the occupancy over this period by frequency band. The time-series is smoothed to uncover underlying trends (e.g. Figure 2.5).
A major challenge in the undertaking of long-term, wideband measurements, is handling the large dynamic range that such systems will encounter. High sensitivity is obviously an essential requirement, but equally important is the ability to accommodate the high-powered signals that may be present in certain bands, particularly those used by broadcast FM radio and television. The use of a preselector with digitally programmable attenuators prevents signals in these troublesome bands from overloading the frontend of the measurement system, but this also has an effect on the noise floor of the system: the result is that sensitivity varies from band to band.

During the course of the 3 years (2008-2010) the measurement parameters were occasionally changed which affected the sensitivity of the sensors and the noise floor of the measured data. This issue of varying sensitivity is problematic in occupancy estimation as the noise floor is not flat across bands. The thresholds used to determine occupancy are intended to be set at a fixed offset above the noise floor of the measurement system, but variations in the system’s response over frequency and over the three year period necessitated different thresholds for each measurement band and each year. Typically the value chosen was set between 5 and 10 dB above the noise floor, allowing for compensation due to equipment changes (such as an added low-noise amplifier), and parameter changes (different attenuator values). Care was exercised in choosing the occupancy threshold to avoid system induced inaccuracies in the occupancy calculations.

The spectral occupancy estimates in the 30 - 3000 MHz frequency range were grouped into 21 bands for analysis purposes. These are different from the bands that were used in the measurement system itself, and were roughly based on their FCC
designations, such as cellular, FM, LMR, ISM, and so forth. The start- and stop-frequency ranges of these bands are indicated in the bar charts of Section 2.2.2 (Figures 2.2, 2.3, 2.4). Time series plots of occupancy vs. time were generated for each band from which minimum, average and maximum values were obtained.

The occupancy data is presented in several different ways: bar-graphs showing the minimum, average and maximum occupancy by band for each year; and smoothed time-series plot that shows occupancy as a function of time in a TV band. A spectrogram is also presented, which shows power levels as a function of both frequency and time.

2.2.2 Occupancy Summaries (2008-2010). The bar charts in Figures 2.2 – 2.4 show the minimum, average and maximum occupancies in 21 different spectrum bands for the years 2008 - 2010. The results for 2010 (Figure 2.4) include measurements up to and including the month of October. The minimum occupancy (in percent) can be read from the boundaries of the green and yellow bars, the average occupancy is marked by the junction between yellow and red bars, and the maximum occupancy is indicated by the end of the red bar. In these charts, wide yellow bars indicate that the maximum and minimum occupancy values are widely separated; and a wide red bar means that the maximum occupancy observed is significantly higher than the average occupancy: thus a wide range variation in occupancy was in evidence, perhaps due to high-bandwidth signals vacating or coming into existence in that band during the course of the year. More information can be found in [TAH11b].
Figure 2.2. Estimated occupancy by band for 2008. Average overall occupancy is 18% for 30-3000 MHz.

Figure 2.3. Estimated occupancy by band for 2009. Average overall occupancy is 15% for 30-3000 MHz.
Figure 2.4. Estimated occupancy by band for Jan-Oct 2010. Average overall occupancy is 14% for 30-3000 MHz.

The three charts all show a similar distribution of occupancy levels, namely high occupancy at the lower frequencies (< 1 GHz) used for cellular transmissions, broadcast radio and television, and other high power, long range applications; and reduced occupancy at the higher frequencies (> 1 GHz) used mostly for lower-power, satellite and point-to-point communications. The 2.5 - 2.7 GHz band shows an increase in 2008, likely due to the roll-out of CLEAR™ (WiMAX) service in the Chicago area. The 2.4 GHz ISM band shows a large range of occupancies: 10 - 40 % in 2008 and 2009 and 15 - 44 % in 2010, while the well-established 800 MHz cellular bands have a fairly constant occupancy within all years.

The bands between 1000 - 1710 MHz, used by GPS, RADAR, etc., and the 2 - 2.4 GHz bands used for satellite TV and point-to-point communications, show particularly low occupancy. Since our measurement system uses directive antennas on the IIT campus pointed in the direction of downtown Chicago, the measurements most likely do not
accurately reflect the true minimum, maximum or average values in these bands. Signals in these bands would require different antenna configurations and perhaps more sensitive equipment to be accurately observed.

One noteworthy occurrence in 2009 is the dramatic change that occurred in the TV bands due to the transition from analog to digital transmission, along with the vacating of the 698-806 MHz band. The exact moment of this transition (June 12, 2009) was captured by the observatory (a spectrogram of this event can be seen in Figure 2.6). From the bar charts, the TV (475-698 MHz) band occupancy for 2008 is fairly constant, but the range is high in the 2009 year (wide red bar). This happens because a significant amount of TV spectrum was vacated in the middle of 2009 - thus occupancy was high in early 2009, and occupancy was low after mid 2009.

Computing the average occupancy of the data given in these charts over the 3 GHz span, gives values of 18%, 15% and 14% for the years 2008-2010, respectively. These are of the same order as reported in previous studies [BAC08, MCH05], though not directly comparable due to different thresholds and different measurement equipment, etc. Nonetheless, the opening of spectrum due to the changes in the TV bands, is clearly demonstrated.

2.2.3 Trends in the Occupancy. Figure 2.5 shows a time-series plot of the occupancy in the 475 - 698 MHz UHF television band for 2009. The occupancy levels for January to mid April are fairly constant, at around 55%. From the end of this period until early June, there are fluctuations in the occupancy while television stations conducted tests of their digital transmitters and some began switching completely from analog. On June 12th there is a 10% drop in occupancy as the transition deadline passes (Point A in Figure 2.5),
and all high-power analog transmissions cease. The moment of this transition can be seen near the middle of the spectrogram in Figure 2.6. The distant channels that seem to be fade in and out (Figure 2.6) are also responsible for some of the fluctuations in Figure 2.6. The sudden jump at the end of October (Point B in Figure 2.5) is caused by the introduction of another digital channel. The transitional period of 2009 ultimately leads to a slight (~5%) decrease in the overall occupancy of the UHF channels. However, a much greater reduction in occupancy happens in the 698-800 MHz range where all TV channel broadcasts ceased on June 2009 (with the exception of Qualcomm's MediaFLO™ channel [FIT09], as noted in Figure 2.6).

Figure 2.5. Occupancy vs. Time plot in the 475-698 MHz TV band
In summary, the Spectrum Observatory has provided enormous value to the wireless research community, in documenting spectral usage trends and capturing valuable data covering such a long-period of time in an important urban environment.

2.3 Findings from a Global Spectrum Observatory Network

This section presents the results of WiNCom’s participation in the Wireless Finland US (WiFiUS) forum. It provides an overview of a coordinated multi-national effort currently underway, where a three-pronged approach is being pursued to develop this RF understanding. This includes the: 1) deployment of geographically dispersed, temporally coordinated RF spectrum observatories in multiple locations in the US and Finland. The spectrum observatories are based on a common platform and the goal is to generate a single RF spectrum measurement dataset (database); 2) development of
empirically validated, statistical models of spectrum utilization for different wireless application types based on this dataset; 3) use of “big data” analytical techniques to further mine the RF dataset to discover temporal and spectral correlations and relationships not obvious using traditional approaches.

The partners in this multi-national project are based at the IIT, Chicago, USA; Virginia Tech (VT), Blacksburg, USA; Turku University of Applied Sciences (TUAS), Turku, Finland; University of Oulu, Oulu, Finland; and VTT Technical Research Centre, Finland. The funding for the two-year long project is provided by the National Science Foundation in the US and the Finnish Funding Agency for Technological Innovation (TEKES). Specialized spectrum observatories are currently deployed (or being deployed) at three locations (Chicago, Blacksburg and Turku), with the potential to add two more (a second Chicago location and at Helsinki or Turku). A centralized database and analytical processing system is being implemented at the WiNCom research center at IIT, which is taking the lead role for this project. Data collected at each measurement site is stored locally, as well as being aggregated over the Internet at WiNCom’s data center. All the partners in this project have remote access to the central data location for subsequent retrieval and analysis work.

2.3.1 RFeye System Overview. Each Spectrum Observatory consists of a CRFS RFeye receiving system, data storage, and data transfer equipment. The antenna is broadband [MP13], omni-directional and multi-polarized and covers the 85 – 6000 MHz frequency range (see Figure 2.7). The RFeye receiver (shown in Figure 2.8) is a dedicated FFT-based spectrum monitoring receiver analyzer manufactured by CRFS, UK [CRF14] that has the following technical specifications: frequency range 10-6000MHz, fast digital
sweep with instantaneous 20 MHz bandwidth, resolution bandwidth (RBW) selectable between .073-1200 kHz, four RF inputs, rugged compact outdoor environment construction, GPS support, and Power over Ethernet (PoE).

Figure 2.7. Multi-polarized broadband 85 – 6000 MHz antenna

Figure 2.8. CRFS RFeye receiving spectrum analyzer

The measurement parameters consisting of the frequency bands, resolution bandwidths and sweep times are given in Table 2.1. Spectrum data is constantly measured as time looped sweeps based on the band-plan provided. The goal is to collect spectrum data continuously from all locations and store it in the central database at WiNCom. For redundancy, local measurement data is also stored on-site at each observatory.
Table 2.1. Measurement Bandplan for the RFeye system

<table>
<thead>
<tr>
<th>Band</th>
<th>Freq. range (MHz)</th>
<th>Resolution bandwidth</th>
<th>Scan interval</th>
<th>RF Input Port</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>30-130</td>
<td>78.125 kHz</td>
<td>10 s</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>130-800</td>
<td>39.0625 kHz</td>
<td>3 s</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>650-1200</td>
<td>39.0625 kHz</td>
<td>3 s</td>
<td>2</td>
</tr>
<tr>
<td>4</td>
<td>1200-3000</td>
<td>39.0625 kHz</td>
<td>3 s</td>
<td>3</td>
</tr>
<tr>
<td>5</td>
<td>3000-6000</td>
<td>78.125 kHz</td>
<td>3 s</td>
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</tbody>
</table>

2.3.2 Measurement Locations. In Finland, the spectrum observatory is located near central Turku, installed on the roof of a four story building at TUAS Sepänkatu-campus. The antenna is mounted on a four meter mast. The power supply and intermediate data storage drives are co-located in the building. The spectrum observatory is designed to operate continuously and independently in case of power outages or network connectivity losses. The observatory system in Turku was procured and deployed during the first half of 2013 and became operational in July 2013. A photograph of the deployment at Turku is given in Figure 2.9.

![Figure 2.9. Deployment of RFeye spectrum observatory at Turku, Finland](image)
In Chicago, the selected location of the primary RFeye-based spectrum observatory is on the roof of the IIT Tower. A second RFeye spectrum observatory has been set up at a height of 168 meters on the roof of the 54 story Harbor Point building located at the eastern edge of downtown Chicago near Lake Michigan. The location for the observatory at Blacksburg, though not finalized, is likely to be at the suburban Virginia Tech campus.

The RFeye device for the static IIT spectrum observatory was temporarily reassigned for mobile measurements as part of a related WiNCom project. The RFeye and several antennas were mounted on the boom of a truck on loan from Motorola Solutions. This lab on wheels, complete with a generator, had an extendable 40 foot boom as shown in Figure 2.10, and permits mobile short-term measurements at multiple locations. The RFeye sits inside a box attached to the mast of the omni-directional 85-6000 MHz broadband antenna (Figure 2.7), with a PoE connection from the RFeye extending down to the lab inside the truck. Additional directional antennas are also attached to the mast, and lightning protection was been provisioned. In this section, the results from analyzing the truck-based spectral measurements in and around Chicago are presented for the wideband 100-6000 MHz scans. This data is supplemented by the data from the Harbor Point RFeye which does use the same band plan as that utilized in Turku affording very direct comparisons of the spectral data. Multiple locations have been scanned using the Motorola Laboratory truck which are listed below:

1. IIT Mies campus (5 km south of downtown)
2. Northerly Island, a manmade island just east of downtown
3. IIT Rice Campus at Wheaton (suburb ~30 km west of Chicago downtown)
4. University of Illinois at Chicago (UIC) campus just west of downtown
5. Midway airport (airport in Chicago’s south-west side)
6. Lincoln Park Zoo (4 km north of downtown)
7. Chicago State University (CSU) campus 16 km south of downtown Chicago

![Figure 2.10. Mobile platform for spectrum observatory](image)

**2.3.3 Data Aggregation Plan.** Operationally, the RFeye spectrum analyzer sweeps the desired bands and saves the gathered data in binary format on the observatory site via a Network Assisted Storage (NAS) drive. The data is then transferred to local storage servers using university intranet. The centralized server infrastructure is presented in Figure 2.11. The design calls for the data from each site to be automatically uploaded over the Internet to the database at IIT, for organized indexed storage and archival. The researchers from the five partner institutions will have remote access to all the data from IIT over a very fast Internet connection. Specifically, the server has a 10 Gbit/sec link
from the server to IIT’s connection to the Internet. This is in turn directly connected to one of the major global Internet hubs here in Chicago. This configuration should provide for a very high performance link between the partner sites and over time to the rest of the research community.

2.3.4 Occupancy Statistics. In this sub-section, occupancy statistics at several locations in Chicago and its suburbs are presented, as well as in the corresponding data from Turku, Finland. The measurements in Chicago and vicinity were obtained using RFeye based equipment nearly identical to that deployed in the permanent static observatory in Turku, Finland. The major difference is that it was mounted on a mobile truck platform on loan to WiNCom from Motorola Labs. The results here were obtained from the 100-6000 MHz band measurement with a frequency resolution of 312.5 kHz. Results from IIT’s long running spectrum observatory [BAC08] are also presented, but with different measurement parameters compared to the RFeye.
In order to determine the occupancy, it is first necessary to apply a threshold to determine if the measured power exceeds the noise floor and hence constitutes a valid signal that was detected. For such a wide range spanning from 100 to 6000 MHz, the measured noise floor fluctuates by several dB power levels. Hence, a fixed threshold cannot be used for the entire 6 GHz range and different thresholds must be used in each sub-band. Selecting the thresholds individually for such a broad frequency is a non-trivial task, and an automated method to rapidly and accurately select a threshold is desired.

Hence, an algorithm based on [REA97] was developed at IIT and used to automatically estimate the noise floor power at each measurement frequency. The threshold values at each frequency point are then easily calculated as several dBs above the estimated noise floor. The occupancy numbers were calculated from these threshold values. This algorithm is described in more detail in Section 5.3.1.

Figure 2.12 shows an average power spectrum that was obtained by averaging across time all the power measurements for September 8th, 2013 at the Rice campus location. Note the fluctuating noise floor that corresponds to different RF bands’ frontends in the RFeye device. The noise floor also changes due to automatic gain control and attenuation settings employed by the RFeye. It is difficult to manually select the noise threshold for each frequency point; however, as Figure 2.12 demonstrates, the algorithm readily and accurately identifies the noise floor throughout the 100-6000 MHz range. For the threshold, a value of 2 dB higher than the estimated noise floor is used to define occupancy, where the noise floor is estimated from a MaxHold power spectrum obtained from approximately a days’ worth of measurements. The high threshold is needed because the RFeye noise shows a high level of variability due to the automatic
gain/attenuation function. The noise floor variability is illustrated by the fact that the MaxHold noise power spectrum is 9-11 dB higher than the average spectrum in those frequency locations where signals are absent (Figure 2.12).

The average occupancy statistics for five measurement locations are shown in Figure 2.13. Approximately 24 hours’ worth of data was used to generate the bar charts. In Figure 2.13, the first set of bar charts (IIT-SO) is a special case. Data from the long-term spectrum observatory at IIT tower was used for IIT-SO, while RFeye measurements were used for the rest. The IIT-SO system is more sensitive to weaker signals and has a higher dynamic range than the RFeye, but performs a full band sweep at a slower rate of once every 45 seconds compared to 10 seconds for the RFeye. The five locations and the measurement dates corresponding to the data are listed in Table 2 below. In [TAH11b], occupancy bar charts were presented based on IIT-SO data for the years 2008, 09 and 10; the difference in this paper is that the occupancy numbers were calculated over a one day period at multiple locations.

![Figure 2.12. Average power spectrum in Chicago suburb (Wheaton, IL) for Sept 8, 2013 and the estimated noise floor](image-url)
Figure 2.13. Average occupancies at five locations

In Figure 2.13, the rotated labels at the bottom of the bars indicate the start and stop frequency of each sub-band. The labels also list some of the wireless services that are deployed in the US at those sub-bands, as well as some ITU-R regulatory notes corresponding to alternate spectrum allocations in the Turku, Finland location.

Table 2.2. Measurement Locations for Occupancy Bar Charts (Figure 2.13)

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Location</th>
<th>System Used</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>IIT-SO</td>
<td>IIT tower, Chicago, IL, USA</td>
<td>Spectrum Analyzer</td>
<td>August 23, 2013</td>
</tr>
<tr>
<td>IIT-RFeye truck</td>
<td>IIT campus, Chicago</td>
<td>RFeye on truck</td>
<td>August 23, 2013</td>
</tr>
<tr>
<td>Chicago UIC</td>
<td>UIC university, Chicago</td>
<td>RFeye on truck</td>
<td>September 11, 2013</td>
</tr>
<tr>
<td>Rice Campus</td>
<td>Wheaton, IL, USA</td>
<td>RFeye on truck</td>
<td>September 8, 2013</td>
</tr>
<tr>
<td>Turku</td>
<td>Turku university campus, Turku, Finland</td>
<td>RFeye at fixed location</td>
<td>August 23, 2013</td>
</tr>
</tbody>
</table>
Several factors affect the accuracy of these occupancy estimates:

1. Due to the presence of some very high-powered transmitters, the RF front-end uses a high attenuation setting in some of the RFeye’s sub-bands. This raises the overall noise floor, which leads to a high noise threshold for those bands. This means that several low-powered signals are missed that are buried below the threshold. An ongoing process to remedy this is through the installation of notch filters tuned to the frequencies where the high-powered transmitters are detected.

2. The primary advantage of the energy detection approach used to estimate occupancy is its simplicity; however, its accuracy is poor when the signal-to-noise ratio of the received signals is low, in which case missed detections or false alarms may occur.

3. The time resolution of 10 seconds for the measurements may not be high enough to capture shorter duration events such as modern radar signals.

4. Directional signals (like satellite communications, point-to-point links, higher frequency directional links) may not be detected by the omni-directional antenna used. For the frequency bands where these signals exist, specialized directional antennas and pre-amplifiers may be necessary to obtain more accurate occupancy numbers.

The occupancy values presented are nevertheless useful for illustrative purposes, and given our multi-site context, for comparative purposes – to compare the usage over time and across different locations. The occupancy numbers are also useful to rapidly identify under-utilized areas of the spectrum, and also to compare the occupancy across different bands of the spectrum.
Comparing the occupancy numbers obtained from the three Chicago locations (IIT-SO, IIT RFeye truck, Chicago UIC), the spectrum usage seems very similar from the IIT-RFeye and UIC data. This is expected as the measurement locations are only about 5 km apart and both are near downtown Chicago. The IIT-SO data for Chicago occupancy, however, shows somewhat higher values in most sub-bands, particularly in the higher frequencies above 2.5 GHz. This is due to the fact that the IIT-SO system is more sensitive than the RFeye, its antennas are located 160 feet higher than the RFeye-truck deployment, and the system has a much lower 3 dB variability in the noise floor that allows a lower signal-power threshold to be used. Also, higher frequency signals are more directional, and so the IIT-SO’s higher altitude is more conducive to their observation. In several high utility bands though, like cellular (700, 800 MHz bands), the IIT-SO occupancy numbers are comparable to the IIT-RFeye and UIC measurements.

2.3.5 Measured Differences in Occupancy. Comparing the occupancy bar charts in Figure 2.13, we notice that the usage in the lower broadcast frequencies (TV bands) is higher in Chicago than in Turku. This is expected since there are more TV channels in Chicago in line with its larger population. The 840-902 MHz band shows high occupancy in Chicago and very low occupancy in Turku. This is because the GSM-850 band is used for cellular services in the US but not in Finland. In contrast, Turku has higher occupancy in the 900-1000 MHz range compared to Chicago due to cellular deployments in the GSM-900 band in Europe. The Chicago location shows significant usage in the 698-798 MHz range, commensurate with the rising popularity of LTE in recent years. In Finland, LTE only recently became operational in the 791-862 MHz region.
In the United States the 1755-1850 MHz band is currently used for military and Federal government services. The US Congress is considering legislation to reallocate the 1755-1780 MHz block for commercial use [HR4817]. The entire 1755-1850 MHz band has also been considered for relocation from military to commercial use, and the Department of Defense (DoD) has estimated that the cost to do so would cost $12.6 billion over 10 years [GAO13]. Commercial wireless service providers have expressed interest in deploying broadband data services in this band, as it is just adjacent to the PCS bands where such services are well established.

In contrast, in Finland, broadband LTE services are already deployed in part of the 1755-1850 MHz region. In particular, the 1805-1880 MHz Digital Cellular System (DCS) band is widely used in parts of Europe including Finland for cellular voice and broadband services.

![Power spectrum in the 1755-1850 MHz band at Turku and Chicago](image)

**Figure 2.14.** Power spectrum in the 1755-1850 MHz band at Turku and Chicago

Figure 2.14 is an interesting example that contrasts the different ways in which the 1755-1850 MHz band is utilized in Chicago and Turku. Figure 2.14 shows the
average and MaxHold power spectrum at Chicago (IIT-RFeye truck) and at Turku, as observed on August 23rd, 2013 in the 1755-1850 MHz band. The low-power wideband signal observed in Chicago is possibly a spread-spectrum radar transmission. The two Turku wideband signals are coming from two cellular base stations operating in the DCS band.

Such comparative spectrum utility and analysis studies are useful to researchers and policy makers who are designing systems or policies intended for worldwide adoption. This example illustrates real differences observed in the empirical data that would aid researchers to mold spectrum solutions that accommodate a range of radio environments across the world.

Simple spectrum occupancy audit results at Chicago, Wheaton (a Chicago suburb) and at Turku were presented, and comparisons were made. Chicago is a major city, Turku is a town, and the suburban locations are Wheaton and Blacksburg. The different measurement locations will allow comparisons between radio environments that are differentiated by geography and population densities. As data collection continues, it will be of interest to examine how the occupancy changes over time and to identify any daily, weekly, monthly trends in the radio environment usage. Much of this information is of interest to radio policy planners, wireless service providers, and to researchers in the area of cognitive radio and dynamic spectrum access (example in [BAC10, TAH11a]). At present, spectrum sharing approaches are receiving a lot of attention from regulators and researchers alike, and [MAT14] discusses recent developments in these areas in detail, both in European and American contexts.
2.4 Occupancy Findings across multiple Public Safety bands

Radios for public safety communication have some of the most stringent requirements for access, reliability and robustness. While wireless technology has seen tremendous strides in the past decade, large parts of the public safety infrastructure have unfortunately lagged behind. Today a large number of the Land Mobile Radios (LMR) used by police and fire departments, among others, utilize bandwidth inefficient analog FM radio systems, despite the limited available radio spectrum allocated for these applications. Additionally, numerous interoperability issues continue to exist between the various agencies, jurisdictions and disciplines; for example, radios from the state law enforcement authorities may not be able to communicate with Federal ones.

This section presents data from spectral measurements carried out over several public safety bands in the city of Chicago. Occupancy estimates over a period of several months are given and analyzed, and seasonal/event-driven variation and trends are discussed. The results demonstrate an imbalance in occupancy between public safety channels, which show high peak occupancy during normal day to day operations, and adjacent commercial LMR channels, which have much lower usage. This indicates potential opportunities for the application of dynamic spectrum access techniques to increase the capacity of public safety channels during emergencies. Furthermore, the spectrum utilization data may be useful for planning for the expansion or optimization of present-day systems.

This section presents and discusses spectral usage measurements for the LMR bands, and some other public safety bands. The spectral measurements were taken at the spectral observatory at the WiNCom research center at IIT. The information gleaned can
be used to assess the adequacy of the available spectral capacity. The SO data is analyzed to identify trends in the usage and to infer how efficiently the LMR spectrum is utilized.

2.4.1 Spectrum Measurement Parameters. Three different sets of measurements are discussed in this section: "coarse" data obtained from the broadband IIT spectrum observatory, higher spectral resolution data collected via a snapshot study specifically focused on the public safety bands, and data collected by monitoring a public safety channel with a commercial radio scanner.

In the case of the public safety bands where channel bandwidths are narrow (< 30 kHz) and signals tend to be of a short duration (< 10s), the parameters of the wideband observations setup (see Table 2.3) are not optimally suited for the measurements of interest; specifically, the resolution bandwidth is not narrow enough to discern individual channels and the high sweep time cannot detect short transmissions. To address these issues, the wideband observations were temporarily suspended in order to obtain higher time and frequency resolution data only from the public safety bands. The equipment was re-tuned to scan only the LMR band (including the public safety bands - see Table 2.4) for a period of 5 days, at the end of which normal, wideband operation was resumed.

The measurement parameters of this snapshot study are also shown in Table 2.3.

Table 2.3. Measurement parameters for SO and snapshot study

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Long-term</th>
<th>Snapshot study</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency span</td>
<td>6 GHz</td>
<td>159 MHz (^a)</td>
</tr>
<tr>
<td>Resolution bandwidth</td>
<td>10 kHz, 30 kHz (^b)</td>
<td>3 kHz, 10 kHz (^c)</td>
</tr>
<tr>
<td>Sweep time</td>
<td>39 s</td>
<td>9.7 s</td>
</tr>
</tbody>
</table>

\(^a\) not continuous \(^b\) varies by band \(^c\) 10 kHz for 4990 MHz
<table>
<thead>
<tr>
<th>Start frequency</th>
<th>End frequency</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>150 MHz</td>
<td>174 MHz</td>
<td>LMR (VHF)</td>
</tr>
<tr>
<td>406 MHz</td>
<td>421 MHz</td>
<td>LMR (UHF)</td>
</tr>
<tr>
<td>450 MHz</td>
<td>471 MHz</td>
<td>LMR (UHF)</td>
</tr>
<tr>
<td>820 MHz</td>
<td>869 MHz</td>
<td>NPSPAC 11 [3]</td>
</tr>
<tr>
<td>4940 MHz</td>
<td>4990 MHz</td>
<td>Public Safety</td>
</tr>
</tbody>
</table>

The data obtained from the snapshot study still does not possess the time granularity necessary to capture all the short transmissions (< 9 s) that may occur on a typical public safety channel; but is an improvement over the observatory measurements as it allows individual public safety channels to be analyzed. To address the issue of previously unmeasured, short duration transmissions, an additional experiment was performed with the goal of obtaining typical signals usage statistics. The 460.400 MHz LMR channel, used by the Chicago Police Department (CPD) for dispatch communication, was selected and measurements were carried out using a Regency model HX1500 radio scanner. Several hours of audio communication were recorded by connecting the output of the unit to a computer, which was used to digitize and store the usage data. Subsequent processing was then performed to analyze the distributions of the transmission time.

2.4.2 Observations in the 450-474 MHz LMR Band. The 450-474 MHz frequency range includes hundreds of business and commercially used LMR channels, along with multiple public safety radio (PSR) channels. To compare the occupancy due to PSR and non-PSR systems, the high resolution LMR band data collected in the snapshot study with measurements parameters from Table 2.4 was examined. Figures 2.15 – 2.17 compare five day occupancy estimates for all 21 CPD dispatch channels, four Chicago
Fire Department EMS channels, and for 21 LMR channels allocated to business and commercial entities [RAD09].

In Figures 2.15 – 2.17, the plots in green show the estimated instantaneous occupancy of the LMR channels under consideration. These estimates were calculated by first finding the total power for each LMR channel. For each 9.7 s long sweep, the instantaneous occupancy of each channel was determined by applying a threshold to the total power. The green instantaneous occupancy plot was obtained by calculating the average usage across the total number of channels. The red plot shows the result of applying a 10 minute long moving average filter to the previous result. Finally, the blue "spectrum efficiency" plot shows the resulting estimate obtained using the approach of calculating the occupancies at each of the measured frequency points as opposed to the specific LMR channel occupancies. The occupancy numbers obtained by this method (blue plot) are low (<20%) suggesting that the police LMR channels have a low usage rate; however, the channel-centric occupancy estimate that determines the capacity of the PSR network returns a much higher value (see green plot, Figure 2.15).

From the CPD dispatch usage data in Figure 2.15, the instantaneous channel occupancy (green plot) can be seen to peak as high as 91%. This is potentially a very important observation, as at peak times during day-to-day operations, the police LMR radio occupancy appears to be close to its limit. In the event of higher than usual demand, such as during disasters, the capacity may easily become saturated leading to call-blocking – a highly undesirable scenario. The average occupancy (red plot) is periodic, peaking around the middle of the day, and decreasing at night. Additionally, the variance appears to be cyclic, also with a daily period. The major difference between the
commercial LMR channels is that CPD dispatch occupancy on Saturdays is more similar to weekday observations, compared to the wider LMR band occupancy.

Figure 2.18 shows a spectrogram for the police frequencies between 460.025-460.575 MHz over one day and Figure 2.19 shows a plot of occupancies versus time for the 21 police channels over 5 days. Figures 2.18 and 2.19 illustrate the difference between the two approaches used to obtain the blue and red plots in Figure 2.15. The blue spectral efficiency estimate was computed from data where each frequency axis point (Figure 2.18) including the guard band frequencies are factored in the occupancy calculation. The red channel-dependent occupancy estimate was obtained by looking at each LMR channel as a whole frequency unit for the purpose of occupancy calculation. Both the plots in Figures 2.18 and 2.19 show that the measured police radio utilization declines during the night.

Figure 2.15. Occupancy for police LMR channels at 460-460.5 MHz over 5 days (high resolution data, Oct. 13-17, 09)
Figure 2.16. Occupancy for 4 fire dispatch channels over 5 days (Oct. 13-17, 2009)

Figure 2.17. Occupancy across multiple business LMR channels (Oct. 13-17, 2009)
The radio usage by the Chicago Fire Department (Figure 2.16) also shows the daily trend of higher usage during the day time compared to night time. However, what is unique about this average occupancy estimate (red plot) is that there are three high peaks that appear distinctly above the daily pattern. These may indicate periods of increased activity by the fire department. Also, the occupancy on Saturday was measured to be somewhat lower than the weekdays. The 21 business LMR channels (Figure 2.17) show much lower usage compared to the 21 police channels. The business channels’ usage max out at 40%. Also, there is significantly lower activity on Saturday than during the weekdays which is markedly different from the public safety services’ radio activity (Figures 2.15 and 2.16).

In summary, the high resolution spectrum occupancy plots of the wider 450-465 MHz shows that most of the business LMR bands (Figure 2.17) are underutilized, while the police PSR channels are highly occupied during normal day to day operations (Figure 2.15). During emergency situations, the occupancy for the police channels is likely to be higher than in Figure 2.15, which may cause call blocking. This is highly undesirable and even dangerous indicating that the existing PSR systems need additional capacity to adequately prepare for disaster situations. Dynamic spectrum access/cognitive radio technology can be employed in LMR systems for PSR to provide good performance in such scenarios.
Figure 2.18. Spectrogram of Chicago police frequencies

Figure 2.19. Occupancies (%) at 21 discrete police channels over 5 day period (high resolution snapshot study). A smoothing filter was applied in order to reveal daily trends. (Oct. 13-17, 2009)

Push-To-Talk transmissions are generally kept as brief as possible to allow other parties use of the channel. In order to better understand PSR usage or for PSR system
planning, it is important to estimate the characteristics of such transmissions. Using a Regency HX1500 radio scanner, audio conversations on the CPD channel at 460.400 MHz, were recorded over a one hour period beginning at noon on Wednesday, October 28th, 2009. This time and day was deliberately chosen as a period of high usage, as suggested by Figures 2.15. The data obtained was then analyzed to obtain the estimate of transmission durations by applying a threshold to the envelope of the audio signals and then measuring the width of the “On” durations. A histogram of the measured “On” durations is shown in Figure 2.20. These durations range from 0.2s to 49.5s, with only 4% lasting for more than 10s. The highest peak at 0.2 s corresponds to non-conversational transmissions, perhaps due to channel switching at the repeater. The mean “On” time is measured to be 2.84 s and the mean “off” time is 0.9 s.

Any cognitive radio technology for PSR needs a very fast call set up and response time. Our measurements have indicated that a large number of the inter-transmission gaps are less than 0.2 s (the peak of the histogram in Figure 2.20). Thus the cognitive
radio for PSR applications must respond rapidly to changes in the radio environment, such that the entire process of channel selection and broadcast occurs faster than 0.2 s; the faster the better, preferably within tens of milliseconds.

2.4.3 Observations in other Public Safety Bands. Beyond the 450-465 MHz LMR band, spectrum observatory data was also analyzed to study several of the other public safety bands: the LMR band between 150-174 MHz, the 800 MHz public safety frequencies used mainly for trunking, and the high bandwidth 4940-4990 MHz PSR data channels. Figure 2.21 shows the average occupancy over a 24 hour period across the 150-170 MHz LMR band. The overall occupancy is 1.6% across the band, with a wide range of occupancy readings across the LMR channels. Figure 2.22 displays occupancy versus time plot for the VHF LMR band where a daily periodic trend is clearly seen. It is important to note that the VHF LMR band also has business and commercial radios in addition to PSR as stated before. Figures 2.21 and 2.22 were obtained by calculating the occupancies at each of the measured frequency points as opposed to the specific LMR channel utilizations; hence the channel based occupancy definition is likely to return comparatively higher numbers.
Figure 2.21. Average occupancy of 150-170 MHz LMR channels

Figure 2.22. Spectrum efficiency/Occupancy versus time plot for 150-174 MHz VHF channels (Oct 13-15th, 2009)

Figure 2.23 shows the average occupancy across the 866-869 MHz public safety band over a 2.5 day period using data from the high resolution snapshot study. A daily periodic trend is readily observed with lower nightly usage than daytime. However, the
occupancy varies by only 3% throughout the day in this band. Figure 2.23 was plotted by computing the occupancy numbers at each measured frequency point.

![Figure 2.23](image.png)

Figure 2.23. Occupancy of public safety frequencies 866-869 MHz over 2.5 day period (high resolution data)

Figure 2.24 shows the channel occupancies versus time plot for the 4940-4990 MHz public safety band where the 50 MHz bandwidth is occupied by three 10 MHz wide channels (centered at 4945 MHz, 4960 MHz, and 4972.5 MHz) and about 20 MHz of unused space. The channel assignments in Figure 2.24 were determined by examining a power spectral density plot (refer to Figure 2.17) averaged over a 24 hour period for this band. The channels centered at 4945 and 4960 MHz are separated by a 5 MHz space, while the 4960 MHz and 4972.5 MHz channels have a 2.5 MHz guard band. Based on these two guard band spacing numbers, one more 10 MHz channel centered at 4985 should be able to operate in Chicago; this means that at any instant, a maximum of 3 out of 4 or 75% of the allowable video channels are being utilized. The powers measured in this band were very low (2-8 dB above noise floor) due to greater path loss at such high frequencies [RAP02] [GOL05]. Figure 2.26 shows the overall occupancy in this band, where the estimates were computed in three different ways: the green, red, and blue plots were computed in the same manner as described before for Figure 2.15. The
blue spectrum efficiency plot is significantly lower than the red average channel occupancy plot since the 3 channels present have large guard bands. Compared to the LMR bands and the 800 MHz public safety frequencies, no daily trends are observed in the utilization at 4.9 GHz. The blue and red plots are mostly flat, indicating that the police cameras are continually broadcasting in the occupied channels while no transmissions are detected in the unoccupied channel. The results match with the rationale that surveillance cameras are “On” at all times.

Figure 2.24. Channel occupancies versus time at discrete police video channels at 4940-4990 public safety band over 2 day period, October 16-17, 2009.

Figure 2.25. 24 hour average power spectral density for 4940-4990 public safety band
2.5 Dynamic Spectrum Sharing Opportunities in the 450-474 MHz LMR band

In this section, the results of a preliminary assessment of the potential for applying Dynamic Spectrum Access methods to improve radio frequency spectrum utilization in the land mobile radio band are presented. This band includes both public safety and commercial user frequency assignments. Occupancy statistics in the widely used 450 - 470 MHz band are presented for several days during 2009 and 2011. The results show an increase in the average occupancy, and also in the total number of active channels detected. Between 2009 and 2011, the detected number of active LMR channels has increased by 15% in just 15 months. However, overall occupancy remains rather low, suggesting good opportunity for DSA systems. This section also illustrates the effect of a major weather event (the Chicago Blizzard of 2011) on the utilization of the spectrum in the LMR band. The event reveals that while overall LMR utilization decreased during
this weather event, public safety utilization increased, indicating that DSA could provide additional capacity for public safety during similar events.

In aggregate, spectrum allocated for public safety voice and “narrowband data” communications in the U.S. totals about 39.7 MHz [TMO10]. Of this total, 3.7 MHz falls within the 450-470 MHz LMR band, and another 12 MHz falls in the 700 MHz region vacated in June, 2009, as a result of the digital TV transition and broadcast TV channel re-assignments. In the 700 MHz band, 6.25 kHz voice equivalent bandwidth has been mandated for all deployments.

In 2004, the FCC issued a narrowbanding mandate [FCC04] which requires all LMR devices to switch from 25 kHz wide channels to more spectrally efficient 12.5 kHz bandwidth ones by January 2013. The main reason for this is that in many urban areas, the limited number of LMR channels available in the VHF (148-174 MHz) and UHF (450-512 MHz) bands are for the most part already allocated to specific users. By reducing channel bandwidth from 25 kHz to 12.5 kHz, the FCC effectively doubled the number of available LMR channels and therefore boost the voice capacity for LMR applications. This transition has been enabled by the advances in wireless technology, which provide comparable voice quality while utilizing half (or even a quarter) of the original channel bandwidth. In this section, results are presented to show that between 2009 and 2011, only 10% of the 25 kHz channels in Chicago had narrow-banded to 12.5 kHz and the number of active 12.5 kHz channels showed a 40% increase!

For the purposes of this study, the wideband (30-6000 MHz) measurements by the spectrum analyzer based spectrum observatory were temporarily suspended in order to obtain high resolution time and frequency measurements of the LMR band between 450-
470 MHz. A small 3 kHz resolution bandwidth was used and the average sweep time across the band was 10.9 seconds. This replicated another short term (5 day) study of the LMR bands conducted 15 months prior in October 2009 [BAC10].

2.5.1 Occupancy and Count of Active Users. Figure 2.27 shows the spectrum occupancy versus time plots for the 450 - 470 MHz UHF LMR band over a fifteen day period from January 26th to February 9th, 2011. The occupancy was calculated for three different sensing bandwidths: 3 kHz, the minimum resolution of the Observatory measurements; 12.5 kHz, the narrowbanding target channel bandwidth; and 25 kHz, the historic standard bandwidth for LMR. A 90 minute moving average filter was applied to smooth the results.

![Figure 2.27. Occupancy vs. time in 450 - 470 MHz in early 2011](image)

In Figure 2.27, the daily periodicity in the occupancy is readily seen over the two week period, as are the weekly cycles. The weekday activity is typically 35% higher than weekend activity, and has local minima around midday (during the lunch hour). Nighttime spectrum usage is also about 40% lower than the daytime value.
The 15 day span shown in Figure 2.27 included measurements taken during the Chicago blizzard of 2011 [REU11], with roughly 0.5 m. of snow falling in less than 24 hours between mid-afternoon of Tuesday, 1 February and approximately noon Wednesday, 2 February 2011. For reference, this was the highest snowfall in decades, and the third highest snowfall recorded in Chicago after the blizzards of 1967 and 1999. The significant reduction in spectrum occupancy is readily visible in the plot, transforming the Wednesday utilization to roughly the level of a normal weekend. This observation seems very reasonable since all commercial activity virtually ceased on that day as the city was virtually paralyzed. Public safety utilization, however, increased, presumably due to an increase in the need for emergency responses.

A comparison of the average occupancy levels calculated from high resolution measurement data in the 450 - 470 MHz UHF LMR band for October 2009 and February 2011 is shown in Table 2.5. These values were obtained by computing the percentage of the spectrum exceeding a threshold of -128 dBm/Hz (corresponding to a false alarm rate of 5% [HIP01]). The occupancy was calculated for the three bandwidths mentioned earlier and averaged over three day periods for each of the two years. As the occupancy is known to possess a weekly periodicity (see Figure 2.27), both years’ data-sets were obtained over three typical weekdays (excluding storm days).

Table 2.5. Spectrum occupancy comparison for years 2009 and 2011 with 3 bandwidths

<table>
<thead>
<tr>
<th>Year</th>
<th>Occupancy (3 kHz)</th>
<th>Occupancy (12.5 kHz)</th>
<th>Occupancy (25 kHz)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2009</td>
<td>3.8 %</td>
<td>5.7 %</td>
<td>8.7 %</td>
</tr>
<tr>
<td>2011</td>
<td>4.8 %</td>
<td>6.7 %</td>
<td>10.9 %</td>
</tr>
<tr>
<td>Change</td>
<td>+26%</td>
<td>+18%</td>
<td>+25%</td>
</tr>
</tbody>
</table>
Though the absolute changes in Table 2.5 are relatively small, they represent a significant (~20%) increase in utilization over the 15 month period. Clearly the level of occupancy is affected by the sensing bandwidth; however an increase is apparent in all three bandwidths examined. A decrease in view of the effective doubling of the voice channels available due to the transition to a narrower transmission bandwidth may have been expected. To examine why the occupancy in fact increased, the data was analyzed further to estimate the total number of 12.5 kHz and 25 kHz LMR channels actively in use at our measurement location during October 2009, and how that changed in January 2011. The results are shown in the bar graph in Figure 2.28. An algorithm was used to classify 12.5 kHz and 25 kHz channels during 2009 and 2011, based on the location of peaks in the average power spectrum and channel center frequencies.

![Number of 12.5 kHz and 25 kHz transmissions detected in 2009 and 2011.](image)

Figure 2.28. Number of 12.5 kHz and 25 kHz transmissions detected in 2009 and 2011.

The likely source of the increased occupancy in Table 2.5 appears to be a rather large 40% rise in the number of 12.5 kHz transmission channels detected in 2011 vs. 2009. This is expected and demonstrates that some LMR users are shifting to narrowband
equipment, or that new users are purchasing 12.5 kHz equipment (a mandatory requirement for devices sold after January 1st, 2011). The number of 25 kHz transmissions shows only a slight decrease of 10% between October 2009 and January 2011, suggesting that other users may be slow to upgrade. This observation is not entirely surprising. A recent survey of LMR users revealed that only 25% of the respondents were both aware of, and currently meeting the narrowbanding mandate, and 31% were either unaware, or did not have any plans to meet it [JAC11]. An examination of the public safety channels used by the Chicago Police Department (CPD) in the 460 MHz region showed only two 12.5 kHz channels operating in 2011, compared to none in 2009, while the twenty one 25 kHz channels are still being utilized.

The total number of LMR users detected, including both 12.5 kHz and 25 kHz channels, increased by 15% in 15 months indicating robust growth in LMR spectral demand. Narrowbanding should help by increasing the number of available LMR channels to satisfy this growth for several more years; but ultimately, if high LMR growth continues, then the new channels opened up by narrowbanding may soon (10 - 15 years) reach capacity. As such, fixed frequency allocation strategies including narrowbanding may be inadequate to meet the future requirements of public safety and commercial LMR users, and new paradigms for increasing the number of available channels need to be investigated.

2.5.2 Dynamic Spectrum Access Opportunities. The disparity between the high number of LMR users and low spectrum utilization is largely a consequence of the traditional, but outdated, paradigm of fixed frequency allocations, whereby each user (or user group) is assigned their own physical channel, and relatively low spectral efficiency
communication standards are employed. Furthermore, the voice transmissions on each channel typically have very low duty cycles [BAC10], meaning that most channels are unused for the majority of the time (as evidenced by the low occupancy numbers in Table 2.5). Many commercial LMR channels may only be used during the day and/or during weekdays, with lower average occupancy over weekends. Public safety channels typically have higher usage rates, and also show daily periodic trends with peaks during the day (or during emergencies) and lower usage at night [BAC10].

These observations indicate that there is considerable potential for dynamic spectrum access techniques to improve the overall spectrum use. This can be further quantified by examining a number of channel utilization metrics. The histograms in Figure 2.29 show the distribution of individual channels’ occupancies for bandwidths of 12.5 kHz and 25 kHz for the year 2011. As shown, only a small fraction of the channels have mean occupancies that exceed 5 or 10%.

To further understand this distribution, the cumulative histogram of 12.5 kHz channel occupancies obtained from this data is shown in Figure 2.30 for the 2009 and 2011 measurements. Note that the curve for 2011 is slightly lower than for 2009, which again indicates an overall occupancy increase from 2009 to 2011. Nevertheless, both for 2009 and 2011, the plots show that a large percentage (about 60%) of the LMR channels are hardly used at all. More specifically, Figure 2.30 suggest that 80% of the channels have occupancy less than 10%; or in other words, 90% of the time 80% of all the LMR channels are unused. A future DSA enabled radio approach, including the smart Secondary Usage (SU) radios presented in this dissertation can take advantage of the spectral opportunity provided by the underutilized channels.
Figure 2.29. Histogram of occupancy levels for 2011 measurements

Figure 2.30. Cumulative histogram of occupancy levels for 2009 and 2011 measurements with 12.5 kHz bandwidth

2.5.3 Public Safety Radio Usage during a weather related Emergency. The occupancy-versus-time plot in Figure 2.31 shows the average occupancy across the 21
Chicago Police Department (CPD) dispatch channels between January 26th and February 9th, 2011. The 21 CPD channels are all 25 kHz in bandwidth and have center frequencies ranging from 460.000 to 460.500 MHz. The Governor of the State of Illinois issued a disaster declaration [ILL11] during the blizzard (February 1 - 2, 2011). During the two blizzard days, the CPD radio usage is seen to be higher than typical, and the nighttime activity is also significantly higher than the norm. This is in contrast to the average occupancy across all LMR channels in the 450-470 MHz band where the Wednesday (February 2nd) activity was much lower than normal. For comparative purposes, the occupancy-vs-time plot from Figure 2.27 for the 25 kHz bandwidth has been reproduced in Figure 2.31 with a separate Y-axis.

The plots in Figure 2.31 have been smoothed with a 90 minute moving average filter, and the average occupancy for the CPD radios is found to range between 7 to 32%. However, due to the smoothing, the transient behavior of CPD radio usage, particularly, peak occupancy levels between 90-100% cannot be seen as was seen before in Figure 2.15. The transient behavior was observed in the unfiltered CPD occupancy data. On multiple occasions, particularly during the blizzard and for two days afterwards, the CPD occupancy spiked to very high values (90-100%). The transient behavior indicates that during emergencies, CPD radio usage approaches full capacity, and for future emergencies, more LMR channels may be needed.

During such emergencies as in the Chicago 2011 blizzard, it is conceivable that the demand for the number of LMR channels by state and city public safety officials will go up. This is suggested in Figure 2.31 by the rise in CPD activity during the storm. At the same time, the overall occupancy in the LMR band could drop due to the emergency
situation, as it did on February 2nd, 2011. The drop in average overall LMR occupancy corresponds to an increase in the spectral opportunity for future DSA enabled radios. If DSA enabled public safety LMR radios were deployed in the future, first responders could have additional channels available to them during emergencies caused by natural disasters such as snowstorms, exactly when additional channel capacity is needed. While the one event observed above does not prove the value of DSA in the LMR bands, the measurement data strongly suggests that a significant increase in capacity for public safety users could be achieved if DSA were deployed, and that further investigation is warranted.

Figure 2.31. Occupancy vs. time plot for Chicago Police Department channels (blue) and aggregate LMR channels (green)

Figure 2.32 repeats the results of Figure 2.31, but in this case, the activity in the LMR band minus the CPD channels is shown via the green plot. This plot properly compares the difference in occupancy behavior between public safety CPD channels and all other users in the LMR band. The green plot’s occupancy peak during Wednesday in
Figure 2.31 was 9.5%, but this value fell to 8% in Figure 2.32. This suggests that the overall LMR band occupancy in Figure 2.23 during the blizzard was somewhat higher due to the contribution of the highly active CPD channels. In Figure 2.32, the LMR band occupancy minus the CPD channels shows a noticeable drop of 1.5%. This further bolsters the argument that during emergencies, the public safety channels need access to more radio resources – which may be obtainable from commercial sources.

In summary, in this Section 2.5, the occupancy variations across different LMR channels were investigated and it was found that most LMR channels are not in use the majority of the time. The spectral opportunity for improving utilization in the 450-470 MHz LMR band was quantified. Our research shows that public safety users may have the most to gain from DSA applications in the voice LMR bands, especially during an emergency. The results also motivate a more comprehensive measurement and analysis.
program to determine specifically how DSA approaches might result in higher spectrum efficiency.

Improving spectrum efficiency is of particular importance for public safety systems, not only in the 450-470 MHz band, but also in the 700 MHz band, where systems are just beginning to be deployed, and where there is necessity to optimize the overall use of the public safety spectrum to provide for both conventional voice systems as well as broadband data networks. The dynamic spectral opportunities discussed this section are potentially useful for public safety policymakers who are exploring technologies and means to increase capacity for LMR voice communications such that the growing needs of the public safety community can be met years into the future.
CHAPTER 3
EMPIRICAL MODELING OF LAND MOBILE RADIO TRAFFIC

In urban areas, most of the limited number of LMR channels available in the VHF (148-174 MHz) and UHF (450-512 MHz) bands are already allocated to specific users. At the same time it has been observed that most of the time this allocated spectrum is not fully utilized [BAC10]. Hence, the LMR bands are candidates for studying the feasibility of Dynamic Spectrum Access (DSA) technology to improve the capacity utilization in these highly sought after frequencies. Particularly, during emergency situations when federal, state and city agencies may converge in a geographic locale [FCC08b, FCC09], DSA could be applied to increase the pool of voice channels available for public safety use [TAH11a].

The characterization of radio activity is an important step in the design of a communication system [ASC09], particularly for cognitive radios that must transparently coexist alongside legacy implementations and make optimal use of limited spectrum. This activity is often random, and effective characterization requires the use of statistical models that may be derived from some fundamental knowledge of the nature of the activity, or from empirical data. For traffic characterization purposes, empirical data of radio usage in the 450 MHz LMR band was extracted from RF measurements conducted at the WiNCom research center in IIT; particularly, Public Safety Radio (PSR) traffic was analyzed. This empirical data was then used to create first-order and second-order models for LMR traffic that can track the activity in a channel for long periods of time (~multiple weeks). This has generated interest in the research community that studies public safety radios. In fact, the models and the parameter values corresponding to multiple PSR
75

channels have been shared with FCC’s department of Public Safety and Homeland Security Bureau at their request.

3.1 Background of RF Measurement System in the LMR band

A low-cost high speed RF data acquisition and storage system was implemented to measure voice channels in the 450 MHz LMR band, as shown in Figure 3.1. The system utilizes a USRP N200 software radio platform and a WBX frontend [ETT13] (tunable between 50 MHz and 2.2 GHz) to obtain time-domain samples. These are then used to estimate the Power Spectrum via Fast Fourier Transform (FFT) [PRO96], from which the power within every 12.5 kHz channel span is found by integration. These power values are then stored in a database for later analysis or for real-time web-streaming. Considerable effort went into the robust design and optimization of this database system, both in terms of hardware and software; especially, since about 1 gigabyte of data is collected daily. More details of the storage back-end can be found in [NOO12].

Figure 3.1. LMR RF Measurement System - Block diagram

The system was installed on the roof of the 22 story IIT Tower approximately 5 km south of the central Chicago business district, and conveniently across the street from the Headquarters of the Chicago Police Department (CPD). The system includes an
omni-directional 50 MHz - 1.3 GHz discone antenna. A 450-474 MHz bandpass filter and a fixed 10 dB attenuator were added to reduce out of band interference and distortion of the WBX frontend. The measurement parameters were also adjusted to reduce spurious artifacts in the received signal. A more elaborate system diagram is shown in Figure 3.2.

![Diagram](image)

**Figure 3.2.** Process diagram for LMR measurement system

The system is capable of measuring the power in each 12.5 kHz channel with a time resolution of 250 ms, sufficient enough to allow the observation of public safety and commercial voice traffic. Lab testing of a commercially available LMR radio (Motorola
Radius CP200 [MOT12]) indicated a minimum transmission duration of 500 ms. Hence, a sampling time of 250 ms is adequately small to capture most, if not all events in these channels. Every 10 minutes, the measurement system also stores the high frequency resolution (~50 Hz) FFT based plots of the max-hold and average power spectrum within that 10 minute window. Figure 3.3 illustrates a sample max-hold plot, which is useful in post-processing for classifying the signals; for example, an analog FM has a very different spectrum signature from digital P25 LMR [APC10].

![Figure 3.3 Max-hold high-res spectral plot showing multiple LMR channels](image)

In this chapter, this USRP based RF measurement system will be referred to as a “spectrum observatory” as it continually monitors the spectrum and channel usage in the 450 MHz LMR band on which this research is based. Although not the focus of this thesis, parallel systems for measuring public safety narrowband traffic in the 700 MHz Block D spectrum, and the 851-854 MHz NPSPAC frequencies have also been implemented at IIT.
3.2 First-order model of public safety voice traffic

In this section, the applicability of simple statistical models to the observed data is investigated, as well as their validity over short and long periods of time. The results show that the statistics of the idle and holding times of communication on these channels vary significantly over time and demonstrate daily periodicity, requiring non-stationary models to accurately represent them. Over short durations of time however, conventional distributions such as the exponential and lognormal may adequately characterize the properties of these quantities, allowing convenient and compact representations of the data. Results based on empirical data are presented to quantify the probability of stationarity for voice traffic within a time span of given length.

For the first-order model, the researcher analyzed data collected over a five week period starting from September 15th, 2011 in the 453-465 MHz frequency range. The date range was selected as there were no maintenance related periods of interruption in the measurement system and the data is continuous over the five weeks.

3.2.1 Long-term Channel Statistics. The Chicago Police Department (CPD) uses 21, 25 kHz bandwidth analog FM broadcast channels with center frequencies uniformly spaced at 25 kHz intervals starting from 460.025 to 460.525 MHz. The measurement system has a frequency resolution of 12.5 kHz and so measures two frequency points per channel every 250 ms. Statistics for the “idle” durations, “hold”, and “inter-arrival” times were developed from this data.

Idle time is defined as the time period between transmissions, when there is no measurable RF power in the LMR channel. No attempt is made to group a series of calls
in to conversations. Hence, all the longer idle times separating conversations and all the shorter gaps between the calls within a conversation are treated together for analysis in this paper.

Hold time is the duration of transmissions, that is, the time when the channel has power that exceeds a threshold. Finally, inter-arrival time [BAR99] is the time duration between the start of one transmission and the next, and is equivalent to the sum of two, consecutive hold and idle times. The thresholds to determine activity were determined experimentally for each LMR channel by examining histograms of the channel powers. In most cases the transmit power was high enough to create a clear distinction between activity and non-activity; hence the error in classifying the two should be low. The definition of the times are illustrated in Figure 3.4. Figure 3.4 also demonstrates the goal of this dissertation – which is to support secondary users to operate in the idle durations.

Figure 3.4. Definition of Idle, Hold and Inter-arrival times
**Idle Times.** Figure 3.5 shows a histogram of the idle time durations for the CPD channel centered at 460.125 MHz, measured between 12.01 am, September 15th to 11.59 pm, September 21st, 2011 (seven days). Also shown are several model distributions that were used for curve-fitting this histogram.

The general shape of the histogram is reminiscent of the exponential distribution - which is commonly used to model idle times [SHA04]. However, the histogram is heavy-tailed and does not decay very fast. Consequently the arrival rate for a standard exponential model to fit the data gives a skewed result that does not match the idle time distribution very closely. An alternative “clipped” exponential model was tried, where only the idle time durations between 0 and 30 seconds were used to estimate the arrival rate parameter. This model performed better, but of course fails to take account of the heavy tail idle times greater than 30 seconds. For this CPD channel, 82% of the idle durations fell within the 30 second clipping time, and 18% were heavy tail data.

![Figure 3.5. Idle times’ histogram and model fits (week long data)](image-url)
The generalized Pareto distribution performed reasonably for shorter idle time durations. However, this distribution decays slowly and the fit gives a higher probability for long idle times than what was actually observed. The best fit for the long term idle time data collected over the one week was obtained with a lognormal distribution.

To quantify the fit, the mean squared error (MSE) between the histogram and the estimated distribution for each type of model was calculated. The average MSE across the 21 channels for each model was calculated and normalized with the largest value of the error. This is shown in Table 3.1.

<table>
<thead>
<tr>
<th>Model Distribution</th>
<th>Long term (1 week) MSE</th>
<th>Short term (2 hours) MSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exponential</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Generalized Pareto</td>
<td>0.917</td>
<td>0.96</td>
</tr>
<tr>
<td>Lognormal</td>
<td>0.409</td>
<td>0.555</td>
</tr>
<tr>
<td>Clipped Exponential</td>
<td>0.611</td>
<td>0.524</td>
</tr>
</tbody>
</table>

Of the simple distributions considered, the lognormal distribution most closely fits the measurements, followed by the clipped exponential model. The standard exponential model fits poorly with the histogram and has a MSE two and a half times higher than the lognormal distribution. Interestingly, previous papers have discussed the modeling of the idle time as a memory-less exponentially distributed random variable [HES81, HOW10]. Graphically, the generalized Pareto distribution seems to follow the histogram well, but the MSE is quite high.

**Hold Times.** A histogram showing the distribution of the channel hold times is shown in Figure 3.6, along with several candidate distributions (exponential, generalized
Pareto, lognormal and gamma). The clipped exponential model was not considered as the hold time data is not heavy-tailed. The data shown in this plot is taken from the same one week time period as the idle times data.

Unlike the idle time, the holding time distribution possesses a distinctly non-zero peak at approximately 2.25 seconds – a reasonable value for typical push to talk voice communications. The exponential and Pareto distributions show poor fits; however, the lognormal and gamma distributions show a good representation. The MSE across the 21 CPD channels normalized to the worse case fit (Pareto in this case) is shown in Table 3.2.

![Graph showing hold times' histogram and model fits (week long data)](image)

**Figure 3.6.** Hold times’ histogram and model fits (week long data)

**Table 3.2.** Normalized MSE between Hold times’ histogram and model fits

<table>
<thead>
<tr>
<th>Model Distribution</th>
<th>Long term (1 week) MSE</th>
<th>Short term (2 hours) MSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exponential</td>
<td>0.855</td>
<td>0.951</td>
</tr>
<tr>
<td>Generalized Pareto</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Lognormal</td>
<td>0.180</td>
<td>0.324</td>
</tr>
<tr>
<td>Gamma</td>
<td>0.274</td>
<td>0.441</td>
</tr>
</tbody>
</table>
The models discussed are valid for the majority of channels observed which possess unimodal distributions; however several cases were observed where the holding time was substantially different. Figure 3.7 shows the distribution of the holding times taken from several different channels in the same LMR band over a one day period.

![Histograms of hold times for different channels to illustrate the anomalies](image)

Figure 3.7. Histograms of hold times for different channels to illustrate the anomalies

Most channels follow the typical lognormal shape (e.g. channels 2, 4, 18), but others (11 and 21) are more exponentially distributed, or possess peaks at multiple locations. The channels demonstrating such behavior may be used for non-voice applications or just have atypical usage. Network simulation studies of public safety [ASC07] LMR would require special models for treatment of such less common channels; alternatively, the actual traffic data measured and stored in the database (see Section II) is usable to source traffic information in the simulations.
**Inter-Arrival Times.** A histogram of the inter-arrival times along with various candidate distributions is shown in Figure 3.8, for the same dataset as previously discussed.

The inter-arrival time is generated from the sum of the holding and idle times. In this case, the shape of the histogram is dominated by that of the holding time, possessing a peak at around 3.75 s. However, the distribution is not as well approximated by the lognormal distribution, as demonstrated by the MSE values in Table 3.3 Some more accurate models consist of a mixture of lognormal distributions [SAN98].

![Interarrival times’ histogram and model fits (week long data)](image)

**Figure 3.8.** Interarrival times’ histogram and model fits (week long data)

<table>
<thead>
<tr>
<th>Model Distribution</th>
<th>Long term (1 week) MSE</th>
<th>Short term (2 hours) MSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exponential</td>
<td>0.990</td>
<td>0.988</td>
</tr>
<tr>
<td>Generalized Pareto</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Lognormal</td>
<td>0.728</td>
<td>0.830</td>
</tr>
</tbody>
</table>
3.2.2 Time Series of Parameters for Modeling non-stationary activity. The histograms and models previously discussed were based on data collected over a period of days. It is likely that statistics such as the holding, idle and inter-arrival times will be non-stationary and possess periodicity and other trends. The histograms for the idle times, hold times, and inter-arrival times were recalculated for a two hour duration at lunch hour on a weekday. The standard distributions introduced in Section 3.2.1 were again used to model the histograms. As an example, Figure 3.9 shows the histogram of idle times and the model fits for one CPD channel. There are gaps in the histogram as the total number of calls within the two hours is lower compared to the seven day period in Section 3.2.1. Due to these gaps (zero values), the cumulative errors between the histogram and the model distributions are higher for the short term study (higher MSE).

![Figure 3.9](attachment:image.png)

Figure 3.9. Short term modeling of idle times (2 hours)

The MSE values for each of the three traffic characteristics were calculated for all 21 CPD channels, and the mean MSE values for the idle, hold and interarrival times across the 21 channels were normalized. The results are presented in Tables 3.1, 3.2 and 3.3 in the third columns labeled as “Short-term (2 hours) MSE”. For the short term idle
time durations, the clipped exponential has the least MSE. It is observed that for modeling long term idle time data a lognormal distribution performs best, but over shorter periods, the clipped exponential fits slightly better than the lognormal. For the hold and inter-arrival times, the lognormal distribution was found to have the closest fit both for short and long terms. The major difference observed between the long term and short term modeling was related to the estimated values of the parameters for the models, indicating that these parameters are not stationary over longer periods of time.

The plot in Figure 3.10 shows a time-series plot of the mean idle and holding times within 30 minute windows. The data was collected over a 7 day period beginning on 15/9/2011 (a Thursday) and was smoothed with a three hour moving average filter. Daily weekday and weekend trends are evident in both the idle and holding times; the hold times showing peaks during the daytime, and lower levels during the weekend. Similar periodicity was seen in time series of statistical parameters for inter-arrival times.

This non-stationary behavior implies that the previous models in Section 3.2.1 are not appropriate over shorter periods of time as the activity is modulated by the date and time of day. One option to extend the applicability of these results is to model the relevant distribution parameters as a time series, creating a dynamic model which can be updated at periodic intervals. For example, the reciprocal of the mean idle times plotted in Figure 3.10 are estimates of the rate parameter if a simple, but less accurate, exponential distribution is used to model the inter-call gaps.

As another example, Figure 3.11 shows the variation of the two parameters for the lognormal distribution model of idle times. The parameters were calculated for every 30 minute window during a one week period, and each time series was smoothed with a 3
hour moving average filter. The two time series’ are again periodic, and show significant differences from the log-normal distribution’s parameter values estimated from the long-term data (represented by the two horizontal lines in Figure 3.11).

![Figure 3.10](image1.png)

Figure 3.10. Time series of hold and idle time statistics for a CPD channel

![Figure 3.11](image2.png)

Figure 3.11 Time series of lognormal parameters for modeling idle time characteristics
For simulation studies, a simple model that captures the variation of the statistical parameters is useful to dynamically track the statistics of the voice traffic data. Dynamic spectrum access technologies may make it possible for multiple voice traffic sources to share the same RF channel. As part of this dissertation, we investigate the feasibility of channel sharing and collision probabilities if two or more public safety channels shared the same RF frequency, or if a public safety user opportunistically shares the frequency with a low duty cycle commercial user (see Chapter 4). In such simulations, the statistical parameters for the traffic sources have to be periodically updated, where the update period should be short enough such that the model parameters remain stationary.

3.2.3 Quantitative Method to Estimate the Likelihood of Parameter Stationarity. A method was devised to investigate the limitations of simple stationary models of idle and holding time statistics over long periods of time, utilizing the Kolmogorov-Smirnov (KS) 2-sample test, which tests the hypothesis that two independent non-overlapping sets of data are derived from the same stochastic distribution [HAZ01]. For each of the 21 CPD channels and 1 IIT channel, the voice activity over 35 days was divided into bins of a fixed time length. The 2-sample KS test was then applied to each pair of non-overlapping consecutive windows, i.e., the KS test was ran hundreds of times in each channel representing the hundreds of pairs of consecutive windows spanning the 35 day period. If the traffic generation process is non-stationary, then the 2-sample KS test is expected to reject the hypothesis that the data samples in 2 consecutive windows are derived from the same stochastic process. This is because, if a process is non-stationary, then the statistics of the data samples will change over time. The further the windows are separated in time, the more likely the distributions are to be different, and the KS test is more likely to fail –
meaning the fraction of times the KS test passes is an indication of the stationarity of the underlying stochastic process. This method will be called the “likelihood of stationarity test”, and it is a quantitative method to determine how stationary a channel model is depending on the model parameter update interval.

For each channel, the 2-sample KS test with a 5% significance level was applied to the data in each pair of consecutive bins over the 35 day period. The percentage of bins that passed the test was recorded. This analysis was then repeated for bin sizes starting from 10 minutes to 600 minutes. The likelihood results are plotted in Figure 3.12 for the hold times in each of the individual 22 channels, and also the average result across all the channels. The plot shows how the likelihood of channel stationarity changes as the modeling window duration is increased – the longer the time before the model parameters are updated, the less likely the channel is to be stationary. Figure 3.13 shows the likelihood of stationarity of idle times for the 22 channels, and also the average result. Figure 3.14 only plots the average “likelihood of stationarity results” across the 22 channels for both hold and idle times.

The results of Figure 3.14 show that a 20 minute window for the hold/ idle time is 90% likely to be stationary, and 75% for a 2 hour window. For modeling work (Section 3.3), simulation studies (Section 3.4), DSA coexistence scenarios (Chapter 4); the results from the stationarity study suggest that the traffic-model parameter updates should be done at frequent intervals (between 20 to 30 minutes) to ensure the model is able to closely track the variations in the channel over time.
Figure 3.12. Fraction of bins passing the 2-sample KS test versus window length for 21 CPD and 1 IIT channels (5 weeks of data) for Hold times. The thick blue line in the middle is the average result.

Figure 3.13. Fraction of bins passing the 2-sample KS test versus window length for 21 CPD and 1 IIT channels (5 weeks of data) for Idle times. The thick red line in the middle is the average result.
Figure 3.14. Fraction of bins passing the 2-sample KS test versus window length for 21 CPD and 1 IIT channels (5 weeks of data). This is the summarized result of the “likelihood of stationarity test” for hold and idle times.

3.2.4 Relevance and summary. The results of this Section 3.2 show that the commonly used lognormal distribution is a good model for characterizing both channel holding and idle times in public safety LMR radio channels, over various time periods. The inter-arrival time statistics are more difficult to quantify with simple distributions. As may be expected, the probability of the traffic statistics within a window being stationary decreases with the time length of the window. This was demonstrated quantitatively using a large set of 22 channels and empirical data obtained over five weeks.

A major goal of this dissertation is to study the feasibility of a cognitive radio that can opportunistically use the LMR channels in emergencies. Such a cognitive radio needs channel characteristics to rank the channels that it can opportunistically use. Once an
unoccupied channel has been selected for secondary transmission, the primary user’s idle
time statistics become important to predict how long the secondary user can continue to
stay in the channel with minimal interference probability. The plot showing the
*probability of stationarity versus window length* is useful as it gives *quantitative*
guidelines on how often the channels’ statistics must be updated for the cognitive radio to
perform optimally.

### 3.3 Time-Varying Second-order model of LMR voice Traffic

In this Section, a statistical model of land mobile radio voice traffic is developed
from empirical RF Spectrum measurement data. This model builds upon previous work,
and is used to generate synthetic voice traffic that closely follows the daily and weekly
patterns of the measured traffic. The RF measurement system in 3.1 was used to collect
the traffic data. The researcher analyzed data collected over a five week period starting
from September 15th, 2011 in the 453-465 MHz frequency range. The channels studied
included 21 Chicago Police Department public safety city-wide dispatch channels and
one business related voice channel used by IIT. These channels and the date range
 correspond to the same data used for modeling work in Section 3.2 and [TAH12]. This
permits direct comparison with the newer channel model presented here.

Statistical models for LMR traffic are applicable in network studies for simulating
traffic [ASC09] – which, for example, could help in the understanding the dynamics of a
public safety network. The model presented here is used to generate synthetic public
safety traffic data which is then compared with the empirically measured traffic.
3.3.1 The Second-Order Model. In [TAH12] and Section 3.2, statistical models for the “idle time” durations, “hold times”, and “inter-arrival times” were provided. Idle time is defined as the time period between transmissions, when there is no measurable RF power in the LMR channel. Hold time is the duration of transmissions, that is, the time when the channel has power that exceeds a threshold. Inter-arrival time [BAR97] is the time duration between the start of one transmission and the next, and is equivalent to the sum of two, consecutive hold and idle times.

In this Section 3.3, the term “conversation duration” is introduced which is the combined time duration of a group of calls that are spaced with very short gaps – so the series of calls are likely to be part of one relatively long conversation. An “idle period threshold time” of 10 s is chosen, which is used to group a series of calls into conversations – that is, if the idle period is lesser than 10 s between two consecutive calls (On-times), then the calls are part of the same conversation. Ten seconds was chosen since in voice communications, a pause longer than that generally indicates that the previous conversation has ended. However, for modeling purposes, it is possible to choose a different value for “idle period threshold time”.

Figure 3.13 illustrates the states in the new model. “Quiet state” refers to idle times longer than “idle period threshold time”. Within the “busy state”, several calls, with On-periods described as “hold times” and Off-periods between them labeled as “short gaps”, occur. “Short gaps” correspond to idle times less than 10 s. The model distribution for “busy state” is obtained from the histogram of “conversation durations”; a histogram of “quiet periods” (idle times > 10 s) corresponds to the distribution of the “quiet state”;
and one histogram for “hold times” and another for “short gaps” describe the behavior of the measured traffic within the “busy state” conversations.

Figure 3.15. State Diagram for LMR channel model

3.3.2 Histograms and Distributions for Second-order Model. The channel can be modeled with four histograms to be mapped and curve-fitted with common probabilistic distributions. The histograms being: (a) histogram of quiet periods; (b) histogram of conversation durations; (c) histogram of hold times; (d) and histogram of short gaps. Figure 3.16 shows the four histograms for a CPD LMR channel as measured empirically over a 24 hour time window. Notice that the quiet periods are all greater than 10 s, while the short gaps are all less than that due to the state assignments defined by Figure 3.15. Subsequently, it was determined (via the method in Section 3.5) that an Idle period threshold of 30 seconds gave the best results; that is, the model closely matched empirical data when the modeling parameters were set such that quiet periods > 30 s, and idle times ≤ 30 s.
Each of the four histograms was curve-fitted with exponential, generalized Pareto, lognormal, and Gamma distributions and maximum likelihood estimation was used to calculate the parameters of the probability density function (pdf) each time. For the histogram of “quiet periods”, the time axis is first offset back to the origin before estimation is performed. For each of the four sets of quantities, the mean squared error (MSE) between the histogram and the estimated pdf for each type of distribution (e.g. lognormal, Gamma, etc) was calculated. The MSE was used to identify the closest matching distribution function for each of the four histograms described in the new model. Similar MSE analysis was done in [TAH12] and more details can be found there.

For the 22 LMR channels tested, lognormal distribution closely matched the histograms for both the “hold times” and “short gaps”, that is, the MSE was found to be low. The lognormal distribution gave higher MSE values for the histogram of “quiet periods”; and significantly higher values for the histogram of “conversation lengths”
since conversation lengths tend to have a high variance. Nevertheless, compared to the exponential, Gamma and generalized Pareto, the lognormal distribution was still a better fit for both the histograms of “quiet periods” and “conversation lengths”. Ideally, other than the ones mentioned in the paper, some other pdf function should be tested for “quiet period” and “conversation length” histograms for better correspondence, but that is outside the scope of this short paper. Thus, in this paper, for the 22 LMR channels measured, lognormal distribution is used to model the statistics for each of the four sets of random quantities.

In [TAH12] and Section 3.2.3, it was shown that the traffic in a channel is non-stationary. Also, a novel method was described for quantitatively predicting how likely the traffic data is to be stationary within a time interval window of specific size. It was shown that the probability of the channel being stationary within the interval declines in an approximate linear fashion as the length of the time window increases. Thus, the parameters of the pdf distributions of the model presented above should be frequently updated to properly track the changes in traffic patterns within the LMR channel.

From Figure 3.14, it is seen that as the time interval window length is increased from 30 minutes to 120 minutes, the probability of the hold time being stationary drops from 90% to 75%; for larger window lengths, the probability is even lower. Thus, to track a channel over a long period of time, the 8 parameters corresponding to the 4 lognormal distributions of the model need to be updated at a frequency of anywhere between 30 minutes to 120 minutes. Figure 3.17a shows the channel activity over 3 days beginning September 15th, 2011 for the same CPD channel as in Figure 3.16. A smoothing filter was used for plotting purposes only, to reveal daily trends and dynamics. The model
developed in this section was then applied to the channel activity data from the spectrum observatory, and every 120 minutes, the 8 parameters were re-estimated and 8 time series’ of parameters were obtained. From these, four selected time series’ of parameters are plotted in Figure 3.17b, to illustrate that the model is able to track a channel for long periods of time, even as the channels statistics keep changing over time. The fifth graph (green) in 3.17b is the plot of the ratio between the number of “quiet periods” observed and the number of “short gaps” within each 120 minute time window. This ratio, although not required for generating synthetic data (Section 3.4) and hence not part of the model, gives useful information that allows a SU in a DSA scenario to track how many “quiet periods” it is likely to find while attempting to share the channel with the PU.

Figure 3.17. (a) Occupancy vs time in the CPD channel over 3 days. (b) Variation of model parameters in 120 minute intervals over the 3 days
3.4 Synthetic Traffic Generated from Model

In this section, the model developed in Section 3.3 is used to generate synthetic traffic data for a CPD channel. The traffic generated is then compared with the empirical data in order to validate the model. The 8 time-series of parameters estimated from the LMR spectrum observatory measurements for the CPD channel over a 3 day period are applied to a simulation algorithm to generate 3 days worth of synthetic voice traffic data that mimics the activity in the CPD channel. The algorithm runs as given below and is also illustrated by the flowchart of Figure 3.18:

1) Update the 8 statistical parameters for the model’s four lognormal distributions in the current time window with data from LMR spectrum observatory.

2) Generate a random number from the pdf of “conversation durations”. This will be the duration of one conversation.

3) Generate calls within this conversation:
   a. Generate a random number for call hold duration from the pdf of “hold times”.
   b. Generate a random number for the short idle time before the next call from the pdf of “short gaps”.
   c. If the series of On-Off calls fill up the conversation duration from step 2, advance to step 4; otherwise iterate to 3a.

4) Generate a random number to be used as the long quiet state after the conversation ends from the pdf of “quiet periods”.

5) Simulation time-limit reached? If No, advance to step 6. If Yes, then End simulation.
6) Check if the simulation time has reached the end of the current time window. If Yes, advance to the next time window and iterate to step 1; if No, iterate to step 2.

Figure 3.18. Flowchart for Synthetic LMR traffic generation from the second order model

Figure 3.19. Comparison of Computer-generated traffic with Empirically-measured activity for a CPD channel
The same scheme is easily extendable to any of the 22 LMR channels and also for any time period spanning weeks and even months. However, for illustration purposes, only 3 days of synthetic traffic data is plotted in Figure 3.19. Figure 3.19 plots the empirically measured traffic activity in the CPD channel alongside the computer-generated traffic where the model parameters were updated (algorithm step 1) every 30 minutes. Both the plots are smoothed with a 20 minute moving average filter to reveal daily features and traffic dynamics. The synthetic traffic is seen to follow the empirical traffic very closely in Figure 3.19, thus validating the modeling procedure developed here.

Further model validation is demonstrated by the plots in Figure 3.20. In this case, 5 days’ worth of synthetic data was generated using a time window length of 45 minutes for the same CPD channel. Figure 3.20a counts the total number of calls within each 45 minute time window and compares the values obtained for synthetic and empirical traffic data. Close match is again observed, despite the random nature of the statistical model used to generate the synthetic traffic. The count of calls within a time window is a good metric for model validation as it does not follow directly from the statistical state distributions, but rather is a consequence of the model’s dynamics. Similarly, 3.20b uses another high-level metric – that is the count of separate conversations within each time window. Again, good correspondence in the number of conversations counted is seen between the synthetic and empirical traffic datasets. Thus, the model has been demonstrated to closely track the LMR channel for arbitrarily long periods of time, given that good statistical estimates for the model parameters are available from a spectrum observatory.
Figure 3.20. Model validation by comparing call statistics of Computer-generated traffic with that of traffic measured by the spectrum observatory in a CPD channel. (a) Total number of calls in each 45 minute time window. (b) Total number of separate conversations in each 45 minute time window.

3.5 Verification of Synthetic Traffic with 2-Sample KS test

A quantitative way to test how well the synthetic traffic generated in Section 3.4 compares to the measured empirical traffic is again by making use of the 2-sample KS test [HAZ01]. In this method, for each of the 21 CPD and 1 IIT channels, 30 days worth of measured data is split into 20 minute modeling windows. The model parameters obtained for each 20 minute bin are used to generate synthetic traffic for that 20 minute window, and this is repeated for all bins over the 30 day stretch using the algorithm outlined in Section 3.4. The synthetic traffic within each 20 minute bin is then compared with the corresponding 20 minute window of empirical data using the 2-sample KS test.
The KS metric is used to test the hypothesis that the two sets of data come from identical stochastic distributions. If the hypothesis passes, then it means that the synthetic traffic closely matches empirical traffic. Over the 30 day period, the fraction of pairs of windows containing empirical and synthetic traffic datasets that pass the 2-sample KS test is thus a good quantitative indicator of how well the synthetic traffic tracks empirical traffic over the long simulation run.

This is illustrated by Figure 3.21 that shows empirical and synthetic traffic patterns in a CPD channel over a 7 day period. A model update window of 20 minute duration was used to generate synthetic traffic data from empirical. The fraction of the total 504 twenty minute bins over the 7 days that pass the 2-sample KS test for hold, idle and inter-arrival times are printed on the Figure 3.21 caption. The 80%+ numbers give a quantitative verification and validation that the synthetic traffic closely matches empirical data.

Figure 3.21. Synthetic and empirical traffic compared over a 7 day period with 2-sample KS test. The KS test results are in the caption for Hold, Idle and Inter-Arrival (IA) time quantities.
Initially, when the above method was first applied to compare synthetic and empirical data, the hold times showed a good 90%+ pass percentage. However, the interarrival times only showed a pass rate of ~70%, while the idle times had an abysmal figure of ~50%. This meant that the synthetic traffic had significantly different characteristics compared to empirical. To investigate the reason behind this, the researcher took a step back to the second-order model where the “Idle period threshold” of the model was initially set to 10 seconds. In an attempt to obtain better correspondence between empirical and synthetic traffic, “the idle period threshold” was increased in steps, until at 30 seconds a good match was obtained between empirical and artificial traffic as indicated by the caption of Figure 3.21. This example demonstrated the utility of this method of comparing real and artificial data for the purpose of refining models of spectral traffic.

![Figure 3.22. Synthetic and empirical traffic compared over a 30 day period with 2-sample KS test. The overall average 2-sample KS test results across the 22 channels are in the caption for Hold, Inter-Arrival (IA) and Idle time quantities](image)

The method outlined above was repeated for each of the 21 CPD channels and 1 IIT channel. Each time, 30 days worth of empirical and synthetic traffics were compared...
with a model update period of once every 20 minutes. The fraction of bins that passed the 2-sample KS test for hold, interarrival and idle times for each channel are plotted in the bar chart of Figure 3.22. The caption of the bar chart also shows the average pass percentages across all the 22 channels. Again, the high 80-95% numbers in the caption give a quantitative verification and validation that the synthetic traffic closely matches empirical data for each of the 22 channels.

**Summary.** An improved model for the voice traffic in public safety channels in the LMR band was presented. This model consists of busy and quiet states; the busy state in turn is subdivided into two sub-states, namely holds and gaps. The histograms of the dwell time in each state were compared to common distributions, and lognormal distribution was selected to model each state. Time-series’ of parameters for the four distributions allow the model to track the traffic in any channel for long time periods. The model was validated by employing it to generate synthetic traffic whose characteristics and dynamics matched closely with empirical traffic measurements.
CHAPTER 4
MODEL-BASED DYNAMIC SPECTRUM ACCESS IN THE 450-474 MHZ LAND MOBILE RADIO BAND

In Chapter 2, it has been shown that the allocated LMR spectrum is sparsely utilized by some commercial user groups, while users like public safety commonly reach near full capacity – especially during emergencies. Hence, the LMR bands are candidates for studying the feasibility of Dynamic Spectrum Access technology such that users in a high activity channel (like public safety) can gain extra capacity when needed by sharing spectrum with low activity channels [LEE10]. For example, DSA technology can be applied to increase the pool of public safety channels during an emergency situation when federal, state and city agencies may converge in a geographic locale [FCC08b][FCC09].

In order to permit channel sharing, knowledge of the Primary User (PU) activity is essential towards the goal of limiting the likelihood of collisions between the PU and Secondary User (SU) [HUA09]. Additionally, the SU is able to use information about the PU to assess the level of spectrum opportunity available in that channel so it can decide whether to use it or to search for a more favorable channel. Knowledge of the PU has to be obtained from RF spectrum measurements – to this end, the spectrum measurements and modeling results presented in Chapter 3 are employed to examine DSA feasibility in the LMR band. The models are used to develop algorithms for PU and SU coexistence.

In [MCH07][MCH08], a DSA algorithm was designed and field-tested that used the Listen-before-talk (LBT) algorithm. This achieved good results, but did not use any statistical knowledge of the PU channels. In [HUA08], the authors describe a system
where the SU is able to use statistical knowledge of the PU’s idle times in order to achieve optimal SU throughput subject to a collision limit constraint; the advantage of knowing the PU’s traffic characteristics was thus demonstrated. In the chapter, a DSA framework is presented where a spectrum monitoring and analysis system continually measures LMR PU channels and then calculates the statistical parameters corresponding to the models from Chapter 3. The model parameters are provided to an SU which is able to opportunistically access the temporal vacancies of the PU with minimal collisions. This DSA framework is compared to the basic LBT algorithm.

The model is applied to a Dynamic Spectrum Access (DSA) simulation. A coexistence algorithm that takes advantage of the modeled channel statistics is presented that allows an opportunistic secondary user (SU) to share a channel with a primary user (PU). The algorithm shows a clear improvement compared to the basic Listen-before-talk scheme that has no knowledge of a PU’s statistical traffic characteristics. Spectrum Opportunity Accessed and collision rate are used as metrics to compare the DSA coexistence techniques. We demonstrate the utility of a spectrum observatory system as being the integral part of this DSA framework, where the observatory continually monitors and models PU channel activity in order to provide the SU with useful statistical information about the PU’s traffic characteristics.

4.1 A Framework for PU & SU Coexistence and Simulation Results

A simulation environment for spectrum sharing was created consisting of PU traffic (either empirical or synthetic) in a channel. A LMR spectrum observatory constantly monitors the PU traffic and obtains model parameters to describe the channel-
traffic’s statistics once every 30 minutes. This observatory is an integral part of the DSA framework. An SU attempts to make use of the Spectrum Opportunity available – that is, the fraction of time that the PU is vacant from the channel. Two test cases are studied – in case 1, the SU has no knowledge of the PU and receives no information from the spectrum observatory; in case 2, the observatory provides the SU with channel model parameters once every 30 minutes, and the SU assumes that these parameters describe the channel condition sufficiently well for the following 30 minutes.

In case 1, the SU uses a simple LBT algorithm to access the channel. The SU senses the channel first; if the PU is absent or if the channel is observed to transition from busy to vacant, then a countdown timer of random duration $T_c$ is started. If the PU does not return during this countdown interval, the SU transmits for a random duration $T_x$. During the transmission state, the SU cannot do channel sensing, and hence collisions can occur if the PU returns. $T_c$ is a uniform random variable between $[T_{slot}, T_{C_{max}}]$ and $T_x$ is uniform between $[T_{slot}, T_{X_{max}}]$, where $T_{slot}$ is the time-slot used in the simulation and $T_{C_{max}}$ and $T_{X_{max}}$ are, respectively, the maximum countdown timer and the maximum transmit duration. The $T_{C_{max}}, T_{X_{max}}$ are constant during every time window throughout the simulation duration, and are not functions of the PU traffic’s model. For the simulation $T_{slot}=0.25$ s, $T_{C_{max}}=4$ s and $T_{X_{max}}=2$ s. The latter two parameters were chosen rather arbitrarily. The only design consideration was that $T_{C_{max}} > T_{X_{max}}$, to minimize the likelihood of interference that occurs when the SU collides with the PU; since the maximum sensing duration was selected to be larger than the maximum transmit duration.
The secondary opportunistic spectrum access user in simulation case 2 employs a smart LBT algorithm. Here the maximum sensor countdown timer, $T_{Cmax}$, and the maximum transmission duration, $T_{Xmax}$, are recalculated during every 30 minute interval using the PU traffic model parameters provided to the SU by the LMR spectrum observatory. Many different functions with varying levels of sophistication can be used to obtain the two SU parameters, $T_{Cmax}$ and $T_{Xmax}$. However, the goal of this section is to demonstrate the utility of modeling PU traffic and the advantages of incorporating, within the DSA framework, a spectrum observatory that measures empirical PU traffic and calculates the model parameters. Hence, for simplicity, non-complex equations are used to calculate $T_{Cmax}$ and $T_{Xmax}$ from the PU model parameters. Equations (4.1) and (4.2) are used to calculate $T_{Cmax}$ and $T_{Xmax}$. Equation (4.2) is the lognormal cdf function where $\mu$ and $\sigma$ correspond to the channel model parameters for the distribution of “short gaps” in the PU traffic. For both $T_{Cmax}$ and $T_{Xmax}$ $p=0.6$ was used as inputs to (4.1) and (4.2). As stated above, both these LBT control parameters are recalculated at the start of each new window.

$$T = F^{-1}(p|\mu, \sigma), \quad (4.1)$$

$$p = F(T|\mu, \sigma) = \frac{1}{\sigma \sqrt{2\pi}} \int_{0}^{T} e^{-\frac{(\ln(\tau) - \mu)^2}{2\sigma^2}} d\tau, \quad (4.2)$$

Two metrics are used to test the performance of the coexistence techniques employed by the SU – Spectrum Opportunity Accessed (SOA) and Fraction of Collisions (FoC) affecting the PU. These metrics are obtained by (4.3) and (4.4), respectively. For both case 1 and case 2 DSA scenarios, SOA and FoC are calculated and plotted.
Figure 4.1 displays the results of the DSA coexistence simulation for cases 1 and 2. The smart SU (case 2) which utilizes the PU traffic’s model parameters achieves higher throughput than the simple LBT (case 1) that has no knowledge about the PU’s statistics. Figure 4.2 shows how the SOA and FoC values change over the two day period when the smart case 2 SU operates in the channel. Overall, the case 2 smart SU is able to achieve an SOA of 53.3% while the PU experiences a FoC of only 3.6%. In contrast, the simple LBT (case 1) SU algorithm attains a lower SOA of 43.6% but causes higher interference to the PU (FoC is 6.2%). Hence, for this particular channel, the smart SU easily outperforms the simple LBT coexistence technique. This shows the advantage of having a spectrum observatory within the DSA framework to measure and model the PU channel statistics for appropriate use by intelligent SUs.

\[
SOA = \frac{(SU\text{ Transmit Duration} - \text{Collision Duration})/\text{total time}}{1 - \frac{PU\text{ Transmit Duration}}{\text{total time}}},
\]

(4.3)

\[
FoC = \frac{\text{Collision Duration}}{PU\text{ Transmit Duration}}
\]

(4.4)
Figure 4.1. Throughput achieved in case 1 with simple LBT (green) compared to throughput when case 2 smart SU (red) is used. The available spectrum opportunity in the channel as it varies over the 2 days is indicated in blue. This is the same CPD channel analyzed in Figures 3.13 through 3.16.

Figure 4.2. Blue plot shows Spectrum Opportunity Accessed (SOA) by the smart SU in case 2, and red plot shows the Fraction of Collisions (FoC) experienced by the PU during the case 2 channel sharing simulation.
The set of simulations was repeated for each of the 22 LMR channels, over a longer 14 day time-span. This was done with both real empirically measured traffic (Table 4.1) and synthetic computer-generated traffic (Table 4.2). Tables 4.1 and 4.2 present the minimum, average and maximum SOAs achieved by the simple LBT and the smart SU during the 22 channel simulation run. A higher SOA value means higher SU throughput. Tables 4.1 and 4.2 also show the min, mean, and max FoC values obtained across the 22 channels. A higher FoC value indicates higher interference experienced by the PU.

Both with real and synthetic data, it is seen every time that the smart SU with PU traffic model information outperforms the simple LBT algorithm and attains a higher SOA. The mean FoC is approximately the same for both algorithms. So for the same interference level, the smart SU achieves higher throughput and higher spectrum opportunity utilization for each of the 22 LMR channels. This validates the performance of the smart SU algorithm, and demonstrates the advantages of the SU possessing statistical knowledge of PU traffic. However, the max values for the collisions are higher for the smart SU than the simple LBT-enabled SU (0.165 compared to 0.132). This is because 1 of the 22 LMR channels tested is really unsuited for dynamic secondary access. Both algorithms perform poorly in that channel – thus raising the max collision values.
Table 4.1. Performance of DSA coexistence techniques where real empirical data is used for PU Traffic; all 22 LMR channels tested in simulation

<table>
<thead>
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<th></th>
<th>Min</th>
<th>Mean</th>
<th>Max</th>
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<tbody>
<tr>
<td>Spectrum Opportunity Accessed (simple LBT)</td>
<td>0.417</td>
<td>0.460</td>
<td>0.482</td>
</tr>
<tr>
<td>Spectrum Opportunity Accessed (smart SU)</td>
<td>0.446</td>
<td>0.572</td>
<td>0.705</td>
</tr>
<tr>
<td>Collisions experienced by PU (simple LBT)</td>
<td>0.039</td>
<td>0.072</td>
<td>0.132</td>
</tr>
<tr>
<td>Collisions experienced by PU (smart SU)</td>
<td>0.035</td>
<td>0.071</td>
<td>0.165</td>
</tr>
</tbody>
</table>

Table 4.2. Performance of DSA coexistence techniques where Computer-generated data is used for PU Traffic; all 22 LMR channels tested

<table>
<thead>
<tr>
<th></th>
<th>Min</th>
<th>Mean</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spectrum Opportunity Accessed (simple LBT)</td>
<td>0.391</td>
<td>0.448</td>
<td>0.479</td>
</tr>
<tr>
<td>Spectrum Opportunity Accessed (smart SU)</td>
<td>0.442</td>
<td>0.564</td>
<td>0.690</td>
</tr>
<tr>
<td>Collisions experienced by PU (simple LBT)</td>
<td>0.019</td>
<td>0.073</td>
<td>0.126</td>
</tr>
<tr>
<td>Collisions experienced by PU (smart SU)</td>
<td>0.028</td>
<td>0.072</td>
<td>0.169</td>
</tr>
</tbody>
</table>

**Summary.** The model in Section 3.3 was applied in a dynamic spectrum sharing scenario where a secondary user with knowledge of the PU traffic’s model parameters was able to coexist with minimal interference and at the same time make high utilization of the available spectrum opportunity. This smart SU was shown to attain a higher performance level than the simple LBT coexistence technique that employs no knowledge of the PU’s traffic characteristics. The key point in this work was to demonstrate an application for continuous spectrum monitoring systems. The spectrum monitor played an integral part of the spectrum sharing framework by measuring the
PU’s traffic characteristics, modeling them and then reporting the parameters to the SU. Without the spectrum observatory, the smart SU would not have performed any differently than the simple LBT SU. The results are also published in [TAH13].

4.2 Optimizing the Parameters for the DSA algorithm

The $T_{C_{max}}$ and $T_{X_{max}}$ parameters for the LBT DSA algorithm were not optimized for the results in Section 4.1. Analytical and numeric studies were undertaken to optimize the DSA sensing and transmission parameters such that maximum secondary user throughput is achieved subject to a collision constraint. Figure 4.3 illustrates the LBT algorithm when there is no collision, and Figure 4.4 shows how collisions may occur between primary and secondary user transmissions. The goal of the secondary user is to spend maximum available PU idle time transmitting; but on the other hand, if the SU transmits too long, the PU may return at the end of the idle duration and a collision occurs. To avoid collisions, the SU must spend part of the idle time sensing prior to transmitting. However, the more time the SU spends sensing, the lesser the SU throughput. So the sensing and transmission parameters need to be selected carefully.
Figure 4.3. Listen Before Talk scheme when no collision occurs

To recap, in Figure 4.3, $T_C$ is a random back-off timer in the LBT algorithm that is activated when the SU detects a falling PU edge. From $T_C$ is uniformly distributed in the interval $[T_{\text{slot}}, T_{\text{Cmax}}]$. The SU transmit duration is given by the random variable $T_x$ where $T_x$ is uniform between $[T_{\text{slot}}, T_{\text{Xmax}}]$. $T_{\text{slot}}$ is the time-slot used in the simulation and $T_{\text{Cmax}}$ and $T_{\text{Xmax}}$ are, respectively, the maximum countdown timer and the maximum transmit duration. The $T_{\text{Cmax}}$, $T_{\text{Xmax}}$ are calculated at the beginning of each modeling window, that is the time window, when the PU traffic model parameters are constant.

The SU senses at $T_{\text{slot}}$ intervals as long as it is not transmitting. Since the SU has only one transceiver, it is unable to sense when it is transmitting. The PU idle time duration is a random variable $I$ that is modeled by the probability distributions in Sections 3.2.2 and 3.3.2. The probability distribution function (pdf) of the idle time is given by $f(I)$ where the probability of $I=\tau$ is given by the pdf. The pdf for a lognormal distribution of idle PU times are given by (4.5).
where the lognormal parameters $\mu$ and $\sigma$ describe the PU channel’s traffic characteristics and these values are obtained by the Spectrum Observatory and PU modeling framework described above (Chapter 3 and Section 4.1).

Figure 4.4 illustrates that collision occurs between the PU and SU if the PU idle time duration $I$ is short and the PU returns while the SU is transmitting. During this collision time, the SU is not sensing, and is unable to detect the collision until it completes its transmission duration $T_X$ and senses the channel after that time. So clearly, the probability of collisions can be reduced if the SU is aware of the PU’s idle time distribution $f_I(\tau)$, and uses that knowledge to limit the combined SU sensing and transmit time ($T_C + T_X$).
4.2.1 **Assumptions in the analytical framework.** If the PU traffic rapidly turns on and off, a single SU transmission can experience collisions with more than one PU transmission. On the other hand, if the PU traffic has long idle times, then the SU can transmit multiple times during a single PU idle duration. For complete analytical work, both those scenarios and their sub-cases (e.g. two, three, etc, SU transmissions during a single PU idle time) require investigation, but the analytical problem then rapidly becomes cumbersome. To simplify the analytics, the following assumptions are made:

1. A PU transmission can collide only once with an SU transmission.
2. We only consider the one sub-case where only one SU transmission occurs during a PU idle duration.
3. We assume that the parameter values that give the highest expected value of the throughput with an expected value of collisions below the collision constraint will give good results for the LBT algorithm.

The $T_{C_{\text{max}}}$ and $T_{X_{\text{max}}}$ parameters are optimized with these assumptions. It is expected that the parameters that give the best performance for the most common practical cases (as listed by assumptions 1 and 2) are likely to provide the best overall dynamic spectrum sharing performance, especially since the sub-cases (two or more SU transmissions during one PU idle time) are less common events in practice. This simplifies the problem and the analytics become tractable. Assumption three makes logical sense since a high expected throughput with expected collision rate below the constraint is likely to give good performance.

4.2.2 **Optimizing the DSA parameters for the SU.** During each cycle of sense-then-transmit for the SU, the back-off time $T_C$ and the transmit time $T_X$ determine the collision
probability. Equations (4.6) gives the probability that the idle duration, $I$ is greater than the back-off sensing time; that is, the PU does not return before the SU stops sensing and starts to transmit. The probability that the collision occurs during the SU transmit time, given that the PU did not return during the back-off time $T_C$ is given by (4.7). The Spectrum Opportunity Accessed is used as a metric for the throughput, where the SOA was introduced in Section 4.1. During a given sense-then-transmit cycle, the SOA is given by (4.8).

$$P(\tau > T_C) = 1 - P(\tau \leq T_C) = 1 - \int_0^{T_C} f_I(t)dt,$$

(Collision Probability), $C(T_C, T_X) = P(T_C < \tau \leq T_C + T_X | \tau > T_C)$

$$= \frac{\int_{T_C}^{T_C+T_X} f_I(t)dt}{1 - \int_0^{T_C} f_I(t)dt}, \quad (4.7)$$

$$SOA(T_C, T_X) = (1 - Collision \ Probability). (Transmit \ duty \ cycle)$$

$$= \left(1 - \frac{\int_{T_C}^{T_C+T_X} f_I(t)dt}{1 - \int_0^{T_C} f_I(t)dt}\right) \cdot \left(\frac{T_X}{T_C+T_X}\right)$$

$$= \left(1 - \frac{\int_0^{T_C+T_X} f_I(t)dt}{1 - \int_0^{T_C} f_I(t)dt}\right) \cdot \left(\frac{T_X}{T_C+T_X}\right), \quad (4.8)$$

Since $T_X$ and $T_C$ are uniformly distributed, the expected values of the functions in (4.7) and (4.8) are given by (4.9) and (4.10) respectively, where $K$ is given by (4.11) and $F_I(\tau)$ is the cumulative distribution function (cdf) of idle times.

$$E[collision] = \int_{T_{slot}}^{T_{cmax}} \int_{T_{slot}}^{T_{xmax}} C(T_C, T_X)f_{Tx}(T_X)f_{Tc}(T_C)dT_XdT_c$$

$$= K \int_{T_{slot}}^{T_{cmax}} \int_{T_{slot}}^{T_{xmax}} C(T_C, T_X)dT_XdT_c$$
\[ E[SOA] = \int_{T_{slot}}^{T_{cmax}} \int_{T_{slot}}^{T_{x}} SOA(T_C, T_X) f_{T_X}(T_X) f_{T_c}(T_c) dT_X dT_c \]

\[ = K \int_{T_{slot}}^{T_{cmax}} \int_{T_{slot}}^{T_{x}} SOA(T_C, T_X) dT_X dT_c \]

\[ = K \int_{T_{slot}}^{T_{cmax}} \int_{T_{slot}}^{T_{x}} \left( 1 - \int_{0}^{T_C+T_X} f_I(t) dt \right) \frac{dT_X}{1 - \int_{0}^{T_C} f_I(t) dt} \cdot \frac{T_X}{T_C + T_X} dT_X dT_c \]

\[ = K \left( \frac{T_X}{T_C + T_X} \right) \int_{T_{slot}}^{T_{cmax}} \int_{T_{slot}}^{T_{x}} \frac{[1-F_I(T_C+T_X)]}{1-F_I(T_C)} \frac{dT_X}{dT_c} dT_c, \quad (4.10) \]

\[ K = f_{T_X}(T_X) f_{T_c}(T_c) = \frac{1}{(T_{x_{max}} - T_{slot})} \cdot \frac{1}{(T_{c_{max}} - T_{slot})}, \quad (4.11) \]

Equations (4.9) and (4.10) may have a closed form for some idle time cumulative distribution functions \( F_I \). However, for the lognormal distribution of (4.5), there is no closed form. Hence, numeric partial integration methods need to be employed. The numeric method equations for the expected value of collisions and expected value of SOA are given by (4.12) and (4.13).

\[ E[\text{collision}] = K \sum_{T_{Cn}=T_{slot}}^{T_{C_{max}}} \sum_{T_{Xn}=T_{slot}}^{T_{X_{max}}} \frac{[F_I(T_{Cn}+T_{Xn})-F_I(T_{Cn})]}{1-F_I(T_{Cn})} \Delta T_X \Delta T_c, \quad (4.12) \]

\[ E[SOA] = K \left( \frac{T_X}{T_C + T_X} \right) \sum_{T_{Cn}=T_{slot}}^{T_{C_{max}}} \sum_{T_{Xn}=T_{slot}}^{T_{X_{max}}} \frac{1-F_I(T_{Cn}+T_{Xn})}{1-F_I(T_{Cn})} \Delta T_X \Delta T_c, \quad (4.13) \]

where, \( \Delta T_X \) and \( \Delta T_c \) are the numerical integration step sizes for the outer and inner summations, respectively.
For a given duplet of $T_{C_{max}}$ and $T_{X_{max}}$ values, (4.12) and (4.13) give the expected value of the probability of collisions and the expected SOA. However, to find the optimized values of the $(T_{C_{max}}, T_{X_{max}})$ duplet, a range of values must be tried and the $E[collision]$ and $E[SOA]$ calculated each time. As an example, Figure 4.5 shows how the $E[collision]$ and $E[SOA]$ values change as a 2-dimensional range of $(T_{C_{max}}, T_{X_{max}})$ duplet values are tried. This was done for a lognormal idle time distribution where the parameters $\mu$ and $\sigma$ were chosen to mimic typical voice traffic. For a given collision constraint, a sub-set of $(T_{C_{max}}, T_{X_{max}})$ values are obtained from the entire 2-dimensional range of $(T_{C_{max}}, T_{X_{max}})$ provided the $E[collision] < \text{constraint}$. From this, the duplet $(T_{C_{max}}, T_{X_{max}})_{\text{opt}}$ with the highest $E[SOA]$ gives the best value that the secondary user radio can use in the LBT algorithm to access the spectrum.

With this analytical and numeric framework in place for optimizing the parameters of the smart LBT algorithm presented in Section 4.1, a DSA simulation was done where the PU was a CPD channel and where the SU attempts to access the PU idle periods opportunistically. As before, the spectrum observatory models the PU traffic data in every 30 minute interval and sends the model parameters of the last 30 minutes to the SU. During each 30 minute window, the SU then uses (4.12) and (4.13) as well as a range of $(T_{C_{max}}, T_{X_{max}})$ values to adjust its LBT parameters so that maximum expected SOA is achieved at a low collision constraint of 5%. The results are shown in Figure 4.6, where the SOA accessed by the SU over a two and half day period is shown as well as the fraction of collisions (FoC) experienced by the PU. Over 2.5 days, the average SOA was 74.2% and the FoC seen by the PU was 6.75%. This is compared by the unmodified LBT
algorithm from Section 4.1 with un-optimized \((T_{c_{\text{max}}}, T_{x_{\text{max}}})\) duplet values, and the results in Figure 4.7 show that the mean SOA was only 52.8\% and the FoC 3.63\%.

![Figure 4.5. E[Collision] and E[SOA] charts for a range of \((T_{c_{\text{max}}}, T_{x_{\text{max}}})\) values](image)
Figure 4.6. With good DSA parameters, the smart LBT algorithm performs better compared to Figure 4.7. Over 2.5 days, average SOA = 74.2% and FoC = 6.75%

Figure 4.7. The unmodified smart LBT algorithm from Section 4.1 performs worse than Figure 4.6. Over 2.5 days, average SOA = 52.8% and FoC = 3.63%
Summary. An analytical and numeric framework for maximizing the performance of the smart LBT algorithm was described that finds good \((T_{C_{\text{max}}}, T_{X_{\text{max}}})\) duplet parameters for the DSA setup. The drawback of the approach is that the method is computationally intensive as the numeric integrations of (4.12) and (4.13) has to be repeated for each of the hundreds of possible trial values of the \((T_{C_{\text{max}}}, T_{X_{\text{max}}})\) duplets. To limit the computation time, the maximum range of the trial values is limited to 7 seconds. Another drawback is that assumption 2 used in the derivation does not always hold during long PU idle times. Hence, there is some discrepancy between the predicted SOA, collision rate and the two and half day average SOA and FoC values observed from the simulation results of Figure 4.6. Overall, though, there is marked improved in the DSA algorithm performance by employing the analytical and numeric framework as shown by Figure 4.6, compared to not employing this methodology as in Figure 4.7.
CHAPTER 5
COMPREHENSIVE BAND MODELING PROCEDURE

5.1 Introduction

The need for increased RF spectrum access for wireless broadband applications continues within the commercial and government user domains. Since the usable RF spectrum is fully allocated, the only options available are to: a) increase the efficiency of current spectrum uses; b) re-purpose spectrum to higher value uses; or c) institute spectrum sharing. While the FCC has a database of authorized, licensed spectrum users, the ultimate success of any of these options depends on knowledge of actual RF spectrum utilization in time, frequency, and space. Studies [TAH11b, BAC08, MCH05, ISL08] have shown that although the spectrum is fully allocated, the actual occupancy at a given time and place may be low, which is indicative of low spectral efficiency. To improve the efficiency and at the same time support additional wireless applications, Dynamic Spectrum Access paradigms are promising in the bands with low measured occupancy numbers [JAB10]. In the United States, on June 2013, the President’s office published a memorandum [PRE13], based on an earlier report [PCA12] by the President’s Council of Advisors on Science and Technology, stating that the US government must make more spectrum available for wireless innovation. One principal stated way of realizing this will be to allow and encourage shared access to spectrum that is currently allocated exclusively for Federal use. In Europe and America, [MAT14] provides a good overview of recent developments in regulation and research related to spectrum sharing approaches.
Given the need to obtain mappings and models of the temporal and spatial variations of the RF environment with sufficiently high fidelity to estimate, characterize, and model spectrum utilization, actual multi-site RF measurements are necessary. To this end, back in 2007, the Wireless Networks and Communications research center at the Illinois Institute of Technology, with support from the National Science Foundation, setup the world’s first and longest running continuous wideband spectrum observatory [BAC08] based on a dedicated spectrum analyzer. Over the years, additional FFT-based spectrum sensors were deployed – some of these are wideband, while others monitor select frequency bands. WiNCom is currently in the process of deploying a multi-site spectrum sensor network in Chicago to study the RF activity in several Federal bands – the selected bands are mentioned in the PCAST report [PCA12] as candidates for sharing with non-Federal users.

At an international level, IIT in partnership with Virginia Tech, VTT Technical Institute of Finland, Turku University of Applied Sciences, and University of Oulu, has deployed a network of Spectrum Observatories in Chicago and Blacksburg, VA in the USA, and at Turku in Finland. In this ongoing Wireless-Finland-US Global Spectrum Observatory Network project [TAH14], RF spectrum measurements are currently being collected and aggregated at the central storage database at IIT. IIT also is the repository of long-term spectrum observation data dating back to 2007 [NOO12] measured by the continually running IIT Spectrum Observatory (IITSO) [BAC08].

With the infrastructure to collect and access spectrum data in place, it is necessary to 1) provide new methods for analyzing, modeling, and visualizing the resulting large, multi-dimensional information base; and 2) model spectrum activity to test the feasibility
of spectrum sharing in candidate bands in order to facilitate decision-making and innovation in spectrum repurposing and sharing. To facilitate both of these analysis goals in any specific band, the entire list of signals and holes needs to be extracted and modeled. The frequency allocations of some of the signals are sometimes stored in a repository, such as the TV white space spectrum database [GOO14]. For such signals, the analysis of measured spectrum data is easier. However, this is frequently not the case, especially when it comes to analyzing wideband measurements that can span multiple frequency bands. In a majority of cases, the positions of the signals are not known by the spectrum sensor and the frequency locations of the signals and holes themselves need to be extracted first.

If a secondary cognitive radio user aims to make share-use of the spectrum, its spectrum sensor needs adequate knowledge of the Primary User signal frequencies that it must avoid, and also the spectrum holes which it can use. The duty cycle of a PU signal can vary – hence the signal may not be identified from short time measurements, especially if its duty cycle is low. This makes the functioning of a secondary spectrum user difficult. First, it may not have a-priori knowledge of the primary user frequencies and the spectrum holes. Second, even if it attempts to estimate the PU frequency locations, it may not be able to detect low duty cycle primaries during its short sensing phase. A continuously running Spectrum Observatory (SO), however, can detect and build up a list of all the primary user transmissions in a band over time. It can also extract a list of opportune spectrum holes. Thus a spectrum observatory can serve as a facilitator for a network of Secondary Users (SUs) thus driving the paradigms of dynamic spectrum sharing. In such an application, the long-term data collected by the SO needs to be
continually analyzed to extract the list of frequencies that correspond to signals or holes in a band of interest. An efficient automated algorithm for this list extraction is necessary, especially since the signal frequencies may not be known initially, as mentioned above.

This chapter presents the Comprehensive Band Modeling (CBM) procedure that automatically extracts all the signals and holes in a band from SO data without a-priori information. Statistics of wireless traffic activity in each signal/hole frequency in the list is extracted. For the band’s frequencies classified as holes, CBM ranks the holes by quantifying the DSA opportunity, and also models the infrequent PU traffic within a hole. The extracted information is compact and tractable compared to the many gigabytes of raw SO data. The CBM procedure is readily implementable in a DSA architecture, where an SO supports a network of SU cognitive radios by relaying information about PU signals and spectrum holes in the band of operation by the use of “data objects”. The SU radios would be able to efficiently utilize the frequency band with minimal interference from PUs.

The remainder of the chapter is organized as follows. Section 5.2 provides overviews of the spectrum measurement systems used to obtain RF utilization data. Section 5.3 presents the CBM procedure and details the algorithms used in each step. The steps are illustrated using data from the 2.5-2.7 GHz band in Chicago. Section 5.4 presents the results when CBM is applied to the television white space (TVWS) and 450-474 MHz Land Mobile Radio (LMR) band measurements. Possible applications of the CBM to support secondary spectrum sharing are described in Section 5.5.
5.2 Recap of Spectrum Measurement Systems

A spectrum observatory is defined as one or more spectrum power sensors that are connected to one or more antennas, amplifiers, RF pre-selectors, and additional sensors like GPS. At regular intervals (in the order of seconds or minutes), the spectrum sensor measures and stores the RF powers in a computerized database or file format. The WiNCom research center at IIT has implemented several separate kinds of SOs each consisting of a different spectrum sensor. This section gives overviews of three most prominent SO systems at IIT. The data from these 3 systems are analyzed via CBM and the results are presented in Sections 5.3 and 5.4.

5.2.1 Spectrum Analyzer based IITSO. The IIT Spectrum Observatory has been monitoring the 30 - 6000 MHz radio activity of the city of Chicago since July 2007 from its location at the top of the 21 story IIT Tower on IIT’s main campus on the south side of Chicago. This building is located 5.3 km south of the Willis (formerly Sears) Tower and has the advantage of an unobstructed view of downtown Chicago from its roof, where the Spectrum Observatory antennas are situated. Figure 5.1(a) displays a photograph of the largest log-periodic antenna facing downtown Chicago. The major components of the base Spectrum Observatory data acquisition system are shown in in Figure 5.1(b) and include: a Rohde & Schwarz FSP-38 spectrum analyzer, a custom pre-selector/RF frontend with independently selectable bands, three directional antennas (two log-periodic and a microwave horn), a desktop computer and various auxiliary sensors (e.g. a weather station and a GPS receiver). This is WiNCom’s first and longest running spectrum observatory, and is referred to as the IITSO. More details of the setup can be found in [BAC08].
5.2.2 Land Mobile Radio monitor system. A RF data acquisition and storage system was implemented to measure voice channels in the 450 MHz LMR band, as shown in Figure 5.2. The system consists of an omni-directional discone antenna set up on the roof of the IIT tower. The antenna is connected to a 450-474 MHz bandpass filter, and then to a USRP N200 software radio platform [ETT13] with a wideband frontend. During each measurement sweep, the USRP captures time-domain samples which are then used to estimate the Power Spectrum via Fast Fourier Transform (FFT). From the power spectrum, the power within every 12.5 kHz LMR channel span is found by integration. These power values are then stored in a database and also web-streamed live in real-time. A more detailed description of the system is found in [TAH12]. The LMR band monitor was operational between April 2011 and summer 2012.
5.2.3. **CRFS RFeye for the global SO network.** For the WiFiUS project, the spectrum occupancy measurement setup consists of a CRFS RFeye receiving system [CRF14], data storage, and data transfer equipment. The RFeye receiver (shown in Figure 5.3) is a dedicated FFT-based spectrum analyzer that has the following technical specifications: frequency range 10 MHz to 6 GHz, fast digital sweep with maximum of 20 MHz bandwidth (BW), resolution bandwidth (RBW) selectable between .073-1200 kHz, four RF inputs, rugged compact outdoor environment construction and Global Positioning System (GPS) support. It is able to send the measured data via Ethernet to a centralized database. We use a broadband omni-directional and multi-polarized antenna covering the 85 – 6000 MHz frequency range. The whole band is divided into multiple sub-bands and is continuously monitored with a selected set of parameters. More details of this setup are available in [TAH14].

In Chicago, the selected location of the primary RFeye-based spectrum observatory is on the top of the same 21 story building on the IIT campus. A second RFeye spectrum observation system has been set up at a height of 168 meters on the roof of the 54 story Harbor Point building located at the eastern edge of downtown Chicago near Lake Michigan. The photograph in Figure 5.4 shows the antenna and RFeye deployment at Harbor Point.
5.3 **Comprehensive Band Modeling Procedure**

Spectrum data collected by an SO is retrieved from the measurement database in a 2 dimensional matrix format, where one axis corresponds to the frequency and the other to the timestamps of sensing instants, and each value within the matrix is a power measurement. The matrix is conveniently plotted via a spectrogram, as shown in Figure 5. The overall objective of the CBM is to extract the frequency locations of the signals and holes from this matrix, and to model the on-off traffic activity.
In this Section 5.3, data from the RFeye spectrum sensor in Chicago as obtained on August 23rd, 2013 is used to illustrate the steps of the CBM procedure. On that particular date, the RFeye sensor was mounted on top of a 40 foot mast on a measurement truck on loan to WiNCom from Motorola Solutions, and 10 hours of data was captured while the truck was located at the IIT campus. The CBM analysis is done on data from the 2.5-2.7 GHz band that currently has WiMAX deployments.

Figure 5.5. Sample Spectrogram for the 2.5-2.7 GHz band in Chicago (August 23, 2013)

5.3.1 Threshold for Energy Detection. The first step is to estimate the noise floor so that a simple energy detection algorithm can be used to threshold the matrix of powers into a binary matrix. A simple option is to manually select a fixed threshold for all frequency bands, but the problem is that the noise floor in SO data varies from band to band. This is due to a number of factors. In some bands, large attenuation may be necessary at the SO’s RF frontend due to the presence of strong signals (e.g. FM radio,
TV) and this raises the noise floor. In other bands there may be no attenuation needed. The resolution bandwidth for measurements can vary from one band to the next depending on the band’s spectral use characteristics and measurement parameters. Finally, leakage from strong signals raises the noise floor on adjacent channel frequencies. Thus, the noise floor needs to be adaptively and automatically estimated band by band across the wideband frequencies measured. The noise floor can be estimated from the average or max-hold power spectrum plots.

The automatic noise floor estimation algorithm applied in the CBM procedure is based on [REA97], and uses morphological image processing techniques to iteratively estimate the noise floor starting from a power spectrum plot. The procedure was chosen as it gives good results across very wide bandwidths of signal measurements (tested from 30-6000 MHz), even when the spectrum sensor has non-flat frequency response and noise. At start, the power spectrum plot is converted to a binary 2-D image where the x-axis is the same frequency axis as in the original plot, but the y-axis represents a dBm power scale. The y-axis is spaced discretely in steps of 0.25 dB, and ranges from the minimum measured power level of the power spectrum plot to a maximum allowed noise estimate level (-80 dBm used here). At a specific x-axis column, that is, at a specific frequency value, the binary image pixels have value ‘1’ at the y-axis power levels that are lesser than the power spectrum value at that frequency, and ‘0’ otherwise. This binary image (shown in Figure 5.6) is then processed by a rectangular kernel of size $k$, first with the erosion operator and then a dilation operator. In image processing terminology, the erosion and dilation operations combined constitute an image “opening” function [REA97]. The opening operation is iteratively repeated, where the kernel size $k$ is
incremented by 1 each time. Convergence is achieved when the mean squared error between two consecutive binary image iterations is less than a pre-defined value. After convergence, the final 2-D binary image is converted back to a spectrum plot in a manner complementary to the procedure mentioned above. This plot is the noise floor estimate. Once the noise floor has been estimated, a threshold value several dBs above the noise estimate is applied to the spectrum data matrix.

Figure 5.6 illustrates the results of the application of this algorithm, where the spectrum data in the 2.5-2.7 GHz band was used. There are WiMAX deployments in that band by Clearwire Corporation [CLE14]. The RFeye spectrum sensor was used for the measurements. In Figure 5.6, the starting binary image, colored yellow (0) and brown (1), that was input to the noise floor estimation algorithm is super-imposed behind the max-hold and average power spectrum plots, and the noise floor estimate and threshold plots. Notice, the estimated noise floor tracks the lowest points of the average power spectrum plot closely. A threshold setting of 8 dBs is used above the estimated noise floor. This is
because the measured noise is sometimes found to be higher than the average; for example, during some measurement instances when the RFeye’s automatic gain control (AGC) block selects high attenuation due to the presence of high powered signals. Custom band-reject filters to attenuate the specific frequency locations of the high powered signals help alleviate the AGC issue, but were not in place for measurements shown in this paper.

5.3.2 Extract data points’ clusters representing signals and holes. The goal of the second step in CBM is to extract the cluster of all detected transmissions, and also extract the cluster of spectrum holes within the two-dimensional spectrum data matrix. A simple method to do this is to threshold the average or MaxHold power spectrum chart, find the frequency points where the power spectrum is above the threshold and label them as signals, and label the regions below the threshold as holes. While this may work in some bands, it will not work in others where signals are situated very close together and cannot be resolved; where the holes and signals overlap, for example, if the PU has a very low duty cycle; and in multi-use bands where multiple signals could overlap with each other. Hence, it is necessary to use the power variations within both the time and frequency domains to properly resolve all the signals and holes.

Starting with the 2-D SO data matrix, each sweep of measurements is sequentially extracted as a vector, and then analyzed as follows. First, the vector of power values is thresholded with the several dB offset above the noise floor estimate. The zero crossings of the resulting binary vector are extracted using the first derivative of this binary vector. For that single sweep, the signal starts are the frequency points where the first derivative of the binary power spectrum vector is positive, and the signal stops are the frequency
points where the derivative is negative. In between the signal gaps are the hole locations, where the hole start and stop frequency points are found in similar fashion. For each signal/ hole, the integrated power, the center frequency, and the bandwidth values are recorded as a data point. Additional information can also be recorded, for example, the time information.

After analyzing all the sweeps in the data matrix, a set of data points of signals and an alternate set of hole data points are obtained. If the set of data points of signals are plotted in 3-dimensional (center frequency, power, and bandwidth) space, the points appear clustered in several regions in the frequency domain – this corresponds to the frequency centers of the signals. Similar clustering is seen in the sets of hole data. From these clusters, all the signals/ holes can be resolved and classified after extraction.

Figure 5.7 includes a 3D plot of the clusters of data points representing holes and signals extracted from the 2.5-2.7 GHz band. The holes are color coded as yellow points, signals with bandwidth below 5 MHz as green, and signals above 5 MHz bandwidth are colored magenta. Note, that in the average power axis, the yellow holes lie in a low power plane below the signals. A researcher has the flexibility to rotate/ zoom/ analyze the 3D plot to reveal useful information about the signals and holes in the band.
5.3.3 Extract frequency information of the Signals and Holes. The next step is to identify all the signals and holes in the band by extracting their start and stop frequencies, and bandwidths. There are two ways of doing this. The first method involves clustering the data points of signals and clusters extracted in Section 5.3.2, and then using an association algorithm twice – first to extract the signal frequency locations, and then to repeat this process for the holes. The second method starts off exactly in the same way, but once the association algorithm has identified the signal frequencies, the holes’ locations are simply identified as the frequency points complementary to those of the signals.

Method A, Identify Signal and Hole frequencies in an analogous manner. This method is generally preferred for most bands, unless the signals in the band exhibit rapid on-off switching characteristics. The first step is to associate the data points in the cluster and identify the start and stop frequencies of the signals/holes. This is done by
obtaining a histogram of start frequencies of the clustered points for signals/holes. For each of the data points, the start frequency is noted, and the start frequencies of all of the points are used to construct a probability distribution of signals'/holes’ start frequencies, i.e., a histogram. For the frequency value where a signal/ hole begins, there will be a localized peak in the histogram of start frequencies. Similarly, a histogram of stop frequencies is obtained from the data points extracted in 5.3.2, and localized peaks are seen in those frequency values where signals/ holes end. A standard peak detection algorithm is applied to the histograms to obtain the frequency values of all the start/ stop peaks of the signals/ holes.

Once the histogram peaks for start and stop frequency values of signals/holes are obtained, the next step is to associate each start frequency peak with the corresponding stop frequency peak for the signal/hole. When the association is complete, all the signal and hole locations would be extracted, and then the data points of 5.3.2 can be classified as belonging to a particular signal/hole. Also, the full list of all signals/holes in the frequency band being studied would be obtained. The association between histogram start and stop frequency peaks is done as described below.

First, out of all the start peaks of the signals/holes, $n$ number of the peaks with the highest histogram values are selected and sorted in order of decreasing height. This insures that only the clearly discernable peaks are used for further analysis. The selection of $n_s$ (number of signals)/ $n_h$ (number of holes) is one of the few manual processes in the entire CBM procedure. The researcher needs to apply background knowledge about the band being studied to select $n_s$ and $n_h$. For example, if the band is expected to have 10 signals and 7 holes, then the researcher can manually set $n_s=10$ and $n_h=7$. It is also
possible to automate this process by setting $n_s/n_h$ equal to the total number of prominent start peaks for signals/holes. However, better results were obtained by manually setting $n_s$ and $n_h$.

The simplest way of association is to connect each start frequencies’ histogram peak with the closest higher frequency value stop histogram peak. In practice, this did not work well with the spectrum data. Part of the reason for this is that for OFDM wideband signals, some of the OFDM sub-carriers or pilots may be low power some of the time and below the detection threshold; this leads to two or more peaks in the histograms of stop frequencies for the same signal where the peaks are of different heights. If the simplistic peak association approach was used, the single OFDM signal would be erroneously classified as two or more separate signals by the algorithm. Thus it is necessary to go back to the data points’ clusters obtained in 5.3.2 and use additional information to robustly associate the start and stop peaks.

For each start peak, the subset of data points from 5.3.2 where the signal/hole begin at that particular peak are analyzed. For each point in this cluster, the stop frequency is found and if it is found to match with one of the stop frequencies’ histogram peaks, then a score of $+1$ is given to the stop peak. At the end, the stop peak with the highest score is associated with that particular start peak. Even if an OFDM signal beginning at a start peak produces multiple stop peaks due to the lower powered sub-carriers, the true stop frequency of the wideband signal is likely to have the highest score. Hence the correct start and stop frequencies of the particular signal are more likely to be extracted. This is because, even if some of the sub-carriers are off during individual measurement sweeps, the OFDM signal always stops at that stop peak frequency that also
corresponds to the highest OFDM sub-carrier. A similar analogous approach is used to obtain the start and stop frequencies of the holes. At the end of this algorithm step, the list of \( n_s \) signals and \( n_h \) holes within the entire band are obtained. Each signal/hole is identified with its start, stop, and center frequencies and its bandwidth.

Figure 5.7 shows the histogram of start and stop frequencies for the spectrum holes in the 2.5-2.7 GHz band from the Chicago data. To extract the holes’ frequency information, the start and stop histogram peaks are associated by the algorithm described above. The center locations and the bandwidths of the main holes are shown via the yellow rectangles in Figure 5.8. Table 5.1 lists the top four holes extracted from this band, where the ranking is done based on the peak heights observed in the histogram of hole start frequencies. Comparing the results of Table 5.1 with the power spectrum plot of Figure 5.6, it is seen that the CBM procedure correctly identified the holes as situated within the distinct low power regions of the spectrum.

Figure 5.8. Holes extracted from the 2.5-2.7 GHz band. The center frequency and bandwidth tuple characterize each hole shown by the yellow rectangles in the plot.
### Table 5.1. List of Extracted Holes in 2.5-2.7 GHz band

<table>
<thead>
<tr>
<th>Hole ID</th>
<th>Frequency Information about the Hole</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Start (MHz)</td>
</tr>
<tr>
<td>1</td>
<td>2583.1</td>
</tr>
<tr>
<td>2</td>
<td>2652.2</td>
</tr>
<tr>
<td>3</td>
<td>2545.9</td>
</tr>
<tr>
<td>4</td>
<td>2671.6</td>
</tr>
</tbody>
</table>

Method B, **Identify the Signal locations first – the holes lie at the complementary frequencies.** Method B is used when good results are not obtained by Method A, particularly, in bands where the signals switch on and off rapidly – for example, in the LMR 450-474 MHz band. Method B is exactly the same as Method A when it comes to extracting the list of signals’ frequency and bandwidth information. However, processing to begin extraction of holes does not begin until all the signals in the band have been extracted. Once all the signals are known, the discrete continuous stretches in the band’s frequency axis that are not spanned by any of the signals are then identified as the individual holes. Thus, the list of frequency-spans, which are complementary to the signal locations, constitutes the list of holes. The holes’ start, stop frequencies, and bandwidths are noted and output by Method B. Section 5.4.2 shows how Method B is applied in the LMR band to extract the holes.

This *completes* the first tier of the CBM procedure. The signal and hole frequencies within the band are now extracted and describable with five (5) sets of information: spectrum type (hole or signal), start frequency, stop frequency, center frequency, and bandwidth. It is now possible to classify all the data points from Section 5.3.2 as belonging to a particular signal/ hole included in the extracted list. The next two
tiers of the CBM only deal with those spectrum frequencies that have been classified as holes.

5.3.4 Analyze the Spectrum Opportunity in the Holes. For DSA, the secondary access channel or hole should ideally have large enough bandwidth and have a low probability of interference from the primary user. In other words, the PU should have a low duty cycle. Conversely when this condition is met, the use of the channel by the secondary user would cause little interference to the PU. In this step, the holes are first ranked in order of decreasing bandwidth, and then further analyzed to calculate the expected PU interference on secondary operation. It is important to note that a hole identified by CBM in 5.3.3 is not completely free of PU transmissions; rather, the hole identification is done because in the time domain, PU activity within the start and stop frequencies of the hole is low. That is, the spectrum opportunity of the hole exists only in those time slots when the PU is not transmitting.

Since a spectrum observatory collects measurements continuously for long periods of time, it is possible to retrieve the time series of radio activity within a frequency range of interest and then examine its suitability for DSA. Given the start and stop frequencies of a hole, the RF power measurements in each time sweep are integrated to obtain a time series of integrated power over time. The power values are thresholded to obtain a second binary time series of channel occupancy versus time. The threshold is calculated by integrating the same estimated noise threshold vector from 5.3.1 across the frequency values spanned by the hole. The average PU occupancy percentage in the hole is simply calculated as the mean of the binary time series.
The time series of integrated powers within the hole is further analyzed as follows. First, the integrated power is divided by the total hole-bandwidth to obtain a vector of instantaneous average power spectrum density (PSD) values in dBm/Hz as expected at any frequency point within the hole. Histograms of the PSD vectors for all the holes are then calculated and plotted to compare the power profiles of the holes. The histograms are shown in Figure 5.9 for the 2.5-2.7 GHz band, and in Section 5.4 for the TV white space band. A hole with good spectrum opportunity would have only one narrow peak in the PSD histogram at a low power level, whereas a hole with more than one peak or a wide single peak is indicative of PU activity within the hole.

![Figure 5.9. Histogram of PSD values observed in the holes of the 2.5-2.7 GHz band](image)

The next step is to calculate the Spectrum Opportunity Fraction (SOF) that a SU with bandwidth, $W_{SU}$, will expect if it operated in a particular hole of bandwidth, $B_{hole}$. It is assumed that the SU is a smart cognitive radio that uses techniques like discontinuous orthogonal frequency division multiplexing (DOFDM) [CHE12] to permit it to operate with an aggregated $W_{SU}$ bandwidth even if the sub-carriers are not all in one block of
continuous spectrum. To calculate the SOF, a sub-matrix is extracted from the SO data matrix, where the frequency dimension only spans the data points between the start and stop frequencies of the hole, but the time dimension spans all the time sweeps of the SO data matrix. Then using the sub-matrix’s data for the \(i^{th}\) sweep at time \(t_i\), the frequency points spanning \(B_{\text{hole}}\) are thresholded with the noise estimate of 5.3.1, and the bandwidth \(B_{\text{free}}\) is calculated by summing the frequency point widths below the threshold. The fraction of available spectrum at time \(t_i\) is simply calculated as \(B_{\text{free}} / B_{\text{hole}}\).

Assuming \(W_{SU} < B_{\text{hole}}\), for the \(i^{th}\) time sweep, a total of \((B_{\text{hole}} / W_{SU})\) instances of the SU could have simultaneously transmitted at \(t_i\) if all the RF measurements were found to be below the threshold. In reality, we are only able to accommodate \((B_{\text{free}} / W_{SU})\) simultaneous SU transmissions of \(W_{SU}\) bandwidth at time \(t_i\). The SOF\(_i\) at time instant \(t_i\) is simply the ratio of these two fractions, and is calculated as:

\[
\text{SOF}_i = \begin{cases} 
0, & \text{when } B_{\text{free},i} < W_{SU} \text{ during } t_i \\
\frac{B_{\text{free},i}}{B_{\text{hole}}} W_{SU}, & \text{when } B_{\text{free},i} \geq W_{SU} \text{ during } t_i
\end{cases}
\]

\[
= \begin{cases} 
0, & \text{when } B_{\text{free},i} < W_{SU} \\
\frac{B_{\text{free},i}}{B_{\text{hole}}} W_{SU}, & \text{when } B_{\text{free},i} \geq W_{SU},
\end{cases}
\)

(5.1)

The \(\text{SOF}_i\) is zero if the unoccupied bandwidth \((B_{\text{free},i})\) at time \(t_i\) is less than the minimum required SU bandwidth \((W_{SU})\). The overall SOF is found by averaging \(\text{SOF}_i\) over all \(n\) time sweeps using (5.2):

\[
\text{SOF} = \frac{1}{n} \sum_{i=1}^{n} \text{SOF}_i,
\]

(5.2)

The \(W_{SU}\) parameter is then swept for a range of possible values representing SU’s of different operational bandwidths, and a plot of SOF versus SU bandwidth is obtained.
The SOF as a function of SU bandwidth calculated this way can be a more practical expression of the prospect of improving spectrum utilization in a band compared to the occupancy measure calculated from the binary time series as mentioned above, since it incorporates the bandwidth of the potential application as a parameter. Result plots are included in Figure 5.10 for the 2.5-2.7 GHz band and in Section 4 for the 500-698 MHz band. The chart of SOF versus the SU bandwidth ($W_{SU}$) is a useful result as the SU can use it to decide what transmission bandwidth to use, and to get the probability of interference free operation for the chosen $W_{SU}$. Furthermore, the SU can readily compare SOF vs bandwidth charts for each of the extracted holes in the band, and select the hole that gives the highest SOF for the highest possible SU bandwidth of operation.

![Spectrum Opportunity Fractions for the three widest bandwidth holes in the 2.5-2.7 GHz band](image)

Figure 5.10. Spectrum Opportunity Fractions for the three widest bandwidth holes in the 2.5-2.7 GHz band
5.3.5 **Subdividing a Hole into SU channels.** In this step of the CBM, it is assumed that the SU operates in a contiguous block of spectrum unlike the DOFDM assumption used in 5.3.4. When the hole’s bandwidth $B_{hole}$ is greater than the bandwidth $W_{SU}$ for the desired SU operation, the center frequency of transmission for the SU can take a range of values within the spectrum hole. There is a need to determine the optimal center frequency that gives the least level of predicted interference to the SU. This is done as follows.

The 2D sub-matrix of spectrum data with frequency span corresponding to the specific hole is averaged along the time axis over all measurement sweeps to obtain a vector of average power spectrum density. Then, an integration window with bandwidth $W_{SU}$ is swept across the hole, where at each integration point, the center of the window is sequentially incremented along the frequency span of the hole. For a hole with center frequency, $f_c$ and bandwidth, $B_{hole}$, the center frequency of the integration window, $f_{SU}$, is swept incrementally from $(f_c - \frac{B_{hole}}{2} + \frac{W_{SU}}{2})$ to $(f_c + \frac{B_{hole}}{2} - \frac{W_{SU}}{2})$. The boundary condition $(\pm \frac{W_{SU}}{2})$ ensures that the edges of the SU transmission do not go beyond the frequency boundaries of the hole.

At the conclusion of this step, a vector of integration powers is obtained where the noise/ interference power expected by the SU at any center frequency of operation, $f_{SU}$, within the hole is recorded. The optimal center frequency of SU operation is simply the frequency $f_{SU,\text{optimal}}$, where the integrated window power value is minimum. If the SU utilizes the channel with this center frequency $f_{SU,\text{optimal}}$ and with bandwidth $W_{SU}$, it is expected to receive minimal interference from PUs and other noise/ signal sources. This is illustrated by Figure 5.11 (2.5-2.7 GHz band) and in Section 5.4.
Figure 5.11. Plot of expected average interference power by SU with $W_{SU}=5$ MHz and with varying $f_{SU}$, where the $f_{SU,\text{optimal}}=2599$ MHz is indicated in green.

The SU, however, is not restricted to operation only at center $f_{SU,\text{optimal}}$ within the same hole. Especially if contending SUs attempt to share the same hole, their channel centers should ideally be different. The expected average interference power at each possible center frequency for the SU is obtained from the vector of windowed integration powers calculated above. Beyond the average expected interference power, a time series of instantaneous interference powers reveals more information about the level of noise the SU would expect at different times of day.

It is straightforward to extract a time series plot of measured RF powers at any possible SU channel with center frequency $f_{SU}$, by integrating the SO power data during each sweep time between frequency values $(f_{SU}-\frac{W_{SU}}{2})$ to $(f_{SU}+\frac{W_{SU}}{2})$. Since $f_{SU}$ can vary

![Graph](image-url)
between the large range \((f_c - \frac{B_{hole}}{2} + \frac{W_{SU}}{2})\) to \((f_c + \frac{B_{hole}}{2} - \frac{W_{SU}}{2})\) where \(f_c\) is the hole’s center frequency, this would result in a large number of time series plots, and the analysis would become intractable. Thus a finite set of time series plots is obtained by varying \(f_{SU}\) from the range \((f_c - \frac{B_{hole}}{2} + \frac{W_{SU}}{2})\) to \((f_c + \frac{B_{hole}}{2} - \frac{W_{SU}}{2})\) in steps of \(W_{SU}/2\), and then calculating the time series at each of this finite set of \(f_{SU}\) values.

The results in Figure 5.12 include a 2-dimensional compact plot for the set of time series graphs obtained from one hole, where the horizontal axis represents the possible SU channel centers, the vertical axis represents time and the values of integrated powers are indicated by color intensity. Alongside the integrated powers’ time series, an equal number of binary time series representations are interspersed in Figure 5.12, where “red” means “On” and “cyan” means “off”.

![Figure 5.12. Binary and integrated time series plots for integration bandwidth, \(W_{SU}=5\text{MHz}\) at various \(f_{SU}\)](image)

Although the SU channels lie within the spectrum hole, the primary user(s) could appear from time to time anywhere in the hole. PU arrivals in a channel with center \(f_{SU}\)
are observable as power spikes within the time series corresponding to that channel. Hence, a time series which tracks the variation in the channel’s power levels is useful for developing models of PU activity, and to obtain statistics about the interarrival times and gaps between PU transmissions. The SU can then use the PU’s traffic model and statistics to efficiently control its transmission times in the channel, and operate with low interference to itself and with minimal disruption to the incumbents’ service. The extraction of the set of time series plots completes tier 2 of the CBM procedure. Tier 3 is concerned with further analyzing the time series plots of PUs’ activities within the channels in an effort to statistically model PU traffic.

5.3.6 Models for Primary User activity. So far, it has been demonstrated how to automatically extract all the signals and holes (5.3.1 – 5.3.3) from spectrum measurement data; then it was shown how to quantify the spectrum opportunity in any hole (5.3.4); next it was shown how to optimally select the center frequency for secondary user operation within the hole, what the expected average interference power will be, and finally how to extract the time series of integrated powers observed due to incumbent transmissions (5.3.5). All these steps facilitate DSA-based resource sharing between secondary and incumbent users. Tier 3 of the CBM procedure provides a time-varying model of the incumbent user’s activity. The model is compact and tractable, and is capable of greatly assisting coexistence between legacy incumbent radios and smart secondaries.

In [TAH12], a time varying model for the time series of wireless voice activity in LMR channels was presented, and this was further enhanced in [TAH13]. The model tracked the PU activity quite well and enabled efficient coexistence with secondaries.
subject to a maximum interference constraint. In the Tier 3 part of the comprehensive band modeling procedure, similar PU modeling methods are presented to achieve similar objectives. That is to track PU behavior and construct an artificial PU traffic generator, and facilitate SU network access in that channel by taking advantage of knowledge about the PU’s traffic characteristics.

The modeling procedure first involves thresholding the time series of integrated powers extracted in 5.3.5, where the threshold value is calculated by integrating the noise floor estimate (from Section 5.3.1) across a frequency domain window of width \( W_{SU} \) and center \( f_{SU} \), and then adding an offset of several dBs. This gives a binary time series of On-Off activity within the sub-channel inside the broader spectrum hole. It is assumed, that all the On activity comes from PU signals, and that the PU is absent during the Off durations.

The total number of “calls” (separate instances of PU transmissions) that are measured during the entire duration is obtained from the time series. Depending on this total and on the rate of calls, the specific model is selected. This part needs researcher input. With a good background and understanding of the radio environment in that band, the researcher selects a statistical model that fits well with the PU transmissions in the band. In this section, three such models are presented.

**Model 1, Two-state model (when many calls observed).** If the number of calls is reasonably high, the first model is selected which is a simple time varying statistical model of the PU activity. First, the whole binary time series data is divided into windows of duration \( T_{Win} \). Next, within each window, three sets for all the “hold” times (durations of On periods), “idle” times (durations of Off periods), and “interarrival” times (durations
between the starts of consecutive calls) are extracted from the On-Off binary time series. The set of hold/ idle/ interarrival times is used to construct a histogram of hold/ idle/ interarrival durations. Then common probability distribution functions (pdf) like the lognormal, exponential, beta, gamma, etc. are curve fitted to each histogram, where the parameters of the fitting pdf function are estimated by using the maximum likelihood (ML) approach. Each fitted distribution is definable by a set of parameters – one parameter for the exponential, and a pair of parameters for the lognormal/ beta/ or gamma distributions. Thus in this first model, within the \( j \)'th time window of length \( T_{\text{Win}} \), the PU traffic in the sub-channel can be described by 3 pdf distribution choices and 3 sets of parameters for each of the selected distributions of hold, idle and interarrival times.

Over a long period of time, the PU activity in the sub-channel of the hole can be tracked by updating the three sets of pdf distribution parameters within the \( j+1, j+2, \ldots j+n \)'th time windows. As the SO measures the spectrum continually, the model parameters are updated continually after every \( T_{\text{Win}} \) intervals, which permits continuous tracking of the traffic patterns of the PU. Such a model was presented in [TAH12].

**Model 2, Model as Poisson process (when few calls observed).** The second model is used when only a few calls are observed in the sub-channel. The small number of calls means that there are only small sets for the hold, idle and interarrival durations. This makes it difficult to estimate the ML parameters when attempting to fit standard probability distributions to measured histograms. Over long durations of time, our analysis has showed that the hold times tend to be steady; that is, hold times across well separated call intervals are statistically similar. Thus, over a long observation window, it is possible to assemble enough instances of hold durations, such that a histogram of hold
times can be obtained and modeled with a common pdf function. This is not the case, however, for idle and interarrival times as they vary significantly across time. In model 2, the lognormal pdf is used to curve fit only the histogram of hold times obtained from the full binary time series, where the lognormal distribution parameters are estimated by ML.

The time varying nature of the call rate in the channel is modeled with Poisson processes. The binary time series is divided into windows of duration $T_{\text{Win}}$. Within the $j$'th window, the number of separate calls, $n_{\text{calls},j}$, is counted, and the call rate, $\lambda_j$, is calculated as (3):

$$\lambda_j = \frac{n_{\text{calls},j}}{T_{\text{Win}}}$$

(5.3)

When model 2 is applied to a synthetic traffic generator, the interarrival times between consecutive calls within the $j$'th window are generated by a Poisson process with call rate parameter $\lambda_j$. Once a call is generated, the hold time for it is selected by a lognormal random process that uses the ML parameters estimated earlier.

Figure 5.13. Measured PU activity (above plot), simulated PU activity (lower plot), in the hole with BW=10 MHz and $f_c=2657$ MHz
For the 2.5-2.7 GHz band, the measured PU activity in the holes is low. Hence model 2 is applicable to track the PU activity within the sub-channels of the holes. Figure 5.13 shows the results when model 2 is applied to track PU activity over 10 hours in a sub-channel within the Hole ID 2 (referenced in Table 5.1). The model of the PU is then applied to a traffic generator to make synthetic traffic that mimics the PU behaviour within the sub-channel. Note, the simulated call generation activity is random and is not likely to match up with the time instances of the actual calls. However, the average occupancy fraction is expected to match closely between the real and simulated time series plots. A qualitative visual comparison of the two sets of plots in Figure 5.13 shows that the average occupancy of the simulated traffic tracks that of the real traffic, but since there are so few calls generated (a handful of calls per hour), a complete match is not observed.

**Model 3, Special 4 state model for Land Mobile Radio traffic.** Model 3 is a specific model that was developed in [TAH13] for modeling voice traffic in the LMR band. This model consists of busy and quiet states; the busy state in turn is subdivided into two sub-states, namely holds and gaps. The four states of this model are shown in Figure 5.14. Figure 5.14 also shows the allowed transition paths from one state to another. The histograms of the dwell time in each state are compared to common distributions – the lognormal distribution is used to model the holds and gaps; the gamma distribution models the busy and quiet states. Time-series’ of parameters for the four distributions allow the model to track the traffic in any channel for long time periods. This model is specifically used for analyzing the LMR band holes in Section 5.4.
This completes the third and final tier of the CBM procedure. Section 5.3.7 presents how all the information extracted in Tiers 1, 2, and 3 can be conveniently represented in a form that is useful to researchers, software defined radios, frequency managers, etc.

5.3.7 **Hole-Descriptor Object (HDO).** All the information extracted from the CBM is assembled into a representation format that is tractable, compact and machine-readable. This section borrows ideas from the well-known abstraction tool used in computer programming, that is, an “Object” [GRA07]. In software code, objects are passed from one module to another, where within the abstract object, all the necessary fields that a module needs are stored. The fields are called “properties”. This greatly simplifies the task of coding and broadens the scope for rapid development of complex software applications. Apart from information storage properties, software programming objects also incorporate built-in methods – that is modules closely related with the object that performs frequently needed computations and programmed tasks.

Similarly, the motivation for using the Hole-Descriptor Object (HDO) is to conveniently store all the location and modeling information about a hole in a compact...
format, which can then be communicated (passed on) to secondary users attempting to
dynamically share the spectrum with primaries. Just like a programming object’s
methods, the HDO design includes computational functions that can calculate the SOF,
estimate the hole’s occupancy percentage from the PU model, and generate synthetic PU
traffic – all of which an SU radio can commonly utilize to select its operational frequency
and DSA transmission parameters. In fact, the HDO output of the CBM is stored and
manipulated in practice as a computer programming object – specifically a MATLAB
programming object for the purposes of this paper. In principle, any language like
Python, Java, C++, etc. that supports object-oriented programming can be used to
represent and manipulate HDOs.

The HDO stores the following \textit{properties} related to Tier 2 information about the
full spectrum hole:

(i) Hole center frequency

(ii) Hole bandwidth

(iii) A vector of average power spectrum densities across the frequency points
in the hole

(iv) A vector containing the \textit{histogram} of average PSD observed in the hole
over time

(v) A vector storing the SOF versus SU bandwidth for the hole.

The properties i-v are applicable for the entire hole bandwidth $W_{\text{hole}}$. Recalling
from Section 5.3.5, the hole is sub-divided into multiple sub-channels where SUs with a
lower bandwidth $W_{\text{SU}}$ can operate. The next set of \textit{properties} applies only to a single sub-
channel with center $f_{\text{SU}}$:
(vi) The sub-channel frequency within the hole that the SU can utilize referenced by $f_{SU}$

(vii) The sub-channel BW, $W_{SU}$

(viii) Average PU occupancy observed from the extracted time series (from Section 5.3.5)

(ix) Window length $T_{Win}$ used in modeling the time series of PU activity

(x) Model type 1, 2 or 3 used (from Section 5.3.6)

(xi) Pdf distribution types used for each of the states of the corresponding model (lognormal/ exponential/ gamma/ etc.)

(xii) Vectors for each of the time-varying parameters related to each of the state distributions

A numerical example demonstrates why HDO objects are so useful. Let us assume that there are 3 holes, within a spectral band. The next assumption is that each of the holes on average supports 5 sub-channels. The total number of HDOs required to describe the band is $3 \times 5 = 15$.

Properties i and ii are 1 unit in length, and assume that the vectors for properties iii-v are of length 30 units each. Next we assume that the modeling window has duration, $T_{Win} = 2$ hours; and that we need to track each sub-channel for a day (24) hours. Properties vi-x are 1 each unit long. Assume model type 1 is used for the time series in each sub-channel, that lognormal pdf is used for the hold times’ distribution, and that gamma pdf describes the idle times’ distribution. Each of these distributions have 2 parameters each, and modeling 24 hours with a 2 hour window duration gives 12 instances of each parameter pair. This means that for tracking PU activity within a single sub-channel, the
total unit length is calculated as \(2 \times 2 \times 12 = 48\) units. The size of each HDO is thus: 
\[1 + 1 + (3 \times 30) + 1 + 1 + 1 + 1 + 48 = 145\] units.

Thus for the 15 HDOs that summarize all necessary information in the band that would permit dynamic spectrum access, the total length is \(15 \times 145 = 2175\) units. Assuming 2 bytes per unit, the required memory space to store this is only 4.35 kB. Compare this to the total size of the spectrum data matrix – for example, to store 24 hours of measurements in the 2.5-2.7 GHz band over 24 hours takes 22.2 MB, and yet the HDO summary is only in the order of a few kilobytes, that is, a reduction in size of nearly 4 orders of magnitude! Thus HDO simplifies, compacts, and summarizes the usable findings from spectrum measurement data in a highly tractable format that facilitates DSA usage.

The HDO also provides methods that can be executed by the SU to output relevant information. The following methods have been provisioned so far:

(i) From the average PSD vector, the method calculates the expected PU interference on the sub-channel used by SU.

(ii) From the PU model parameters, the method estimates the average PU occupancy.

(iii) Synthetic PU traffic generator methods (one for each model) – this is currently used by the author to validate the models of PU activity, and in simulations of PU and SU coexistence.

The HDO structure is flexible, and additional properties and methods can be easily added as deemed necessary by the researcher. Particularly, if alternate PU traffic models are developed in various spectrum bands, the HDO can incorporate the newer
models. The HDO object can also be inherited when working with more complex derived classes. In all, the HDO design of the CBM provides a powerful tool to researchers and engineers building DSA radios.

5.3.8 Verification of Extracted Hole Locations. A quantitative statistical method is needed to verify that the holes extracted by the CBM procedure are indeed valid. From Section 5.3.4, the histogram of PSD for a hole is a good indicator that an extracted hole is situated within the frequency boundaries of a spectral white space. If the histogram has one narrow peak at a lower PSD level, then it means that there is very little if any PU activity, and the hole is ideal for SU access.

The plot of Spectrum Opportunity Fraction derived also in Section 5.3.4 also gives a validity assessment for an extracted hole. If the SOF is close to 1 for most $f_{SU}$ values at or below the hole bandwidth, then it again means that there is very little PU activity. This means that the frequency span identified by the CBM is a valid white space location, i.e., a hole.

Beyond the two methods introduced in Section 5.3.4, two additional statistical methods are presented in this subsection to provide validation of the results produced by the CBM procedure. The first method is shown in Figure 5.15 and it expands on the histogram of PSDs for the 2.5-2.7 GHz band. In the same chart, PSD histograms for each individual hole and each signal are plotted. The holes and signals were automatically extracted by the CBM procedure, and the goal here is to verify that CBM identified the hole and signal locations correctly. Towards this goal, the mean PSD in each hole, and in each signal along with the standard deviation of PSD values are calculated. The standard deviation magnitudes are also plotted in Figure 5.15. The legend in Figure 5.15 clearly
identifies the histogram for the holes and the signals; and also displays the mean PSD and standard deviation. Note that the holes have mean PSD values lesser than that for the whole band, and much lesser PSD means compared to signals. Also, holes have low standard deviation values for PSD compared to signals. Thus, holes and signals extracted by the CBM are clearly distinguished, and the results of the CBM are verified and validated. A hole is definable as the band region where the average PSD is below 150 dBm/Hz, and the average PSD is above 150 at a signal location. If a Gaussian distributed random variable (r.v.) is created with the same mean and standard deviation parameters as in any of the holes listed, the probability of the r.v. of exceeding 150 dBm/Hz is exceedingly small as calculated by the Q-function and indicated in Figure 5.15. A Gaussian r.v. with mean and standard deviation values as in a signal location has high probability of exceeding 150 dBm/Hz.

![Figure 5.15. Validation of the Hole and Signal Locations extracted by the CBM procedure by using histograms, means and standard deviations of measured PSD values at those frequency locations (calculated with a day’s data in 2.5-2.7 GHz band)](image-url)
In the next method (second method in this Section 5.3.4 and the fourth method of validation) to verify and validate the performance of the CBM algorithm, histograms of occupancy over time are used. For a given hole at each SO sweep instance, the number of measured data points that exceed the noise threshold are used to calculate the occupancy percentage at that time. This is repeated for each sweep instance, and the occupancy values are recorded in an array, from which the histogram of instantaneous occupancies are obtained for that hole. The mean instantaneous occupancy and standard deviation are also calculated – a small mean and low standard deviation value means that PU signals are mostly absent. This would validate the holes extracted by CBM.

Figure 5.16. Validation of the Hole Locations extracted by the CBM procedure by using histograms, means and standard deviations of measured instantaneous occupancy values at those frequency locations. This was calculated using data over a 24 hour period for the 2500-2700 MHz band.

Figure 5.16 shows the histograms of instantaneous occupancies for the 2.5-2.7 GHz band that currently has WiMAX deployments in Chicago. The histogram for the entire band is also shown. The legend in Figure 5.16 prints the mean instantaneous
occupancy for the whole band and for each hole. It also includes the standard deviation for the instantaneous occupancy. The hole histogram peaks are all located to the left of the figure on or very close to 0% instantaneous occupancy. This means that the frequency locations identified as holes by the CBM procedure have very little if any PU activity, and thus are valid spectral white spaces. Thus, for a fourth time, the extracted hole results of the CBM procedure are validated.

5.4 Results of CBM procedure applied to the TV and LMR bands

In this section, the CBM procedure is applied to the 500-698 MHz region that includes TV channels and TV white spaces, and to LMR (450-474 MHz) band data. The TVWS spectrum measurements were obtained by the IITSO (Section 5.2.1), and the LMR measurements were made by the USRP sensor (Section 5.2.2). The results in Section 5.3 were based on data captured by the RFeye sensor (Section 5.2.3) in the 2.5-2.7 GHz band. The goal here is to show that the CBM procedure is versatile and platform independent that is applicable on spectrum measurements made by a variety of sensors and in different frequency bands. Before presenting the results of this section, a summary of the steps are listed below to serve as a refresher:

i. Noise floor estimation

ii. Extract clusters of signal and hole data points by analyzing spectrum matrix data sweep by sweep. Each data point contains 4 fields of information.

iii. Extraction of Signals and Holes: from the cluster of signal/hole data points, generate histograms of start and stop frequencies for the signal/
hole. Then associate the start and stop frequency peaks to determine information about the signals’/holes’ center frequency and bandwidth.

iv. Analysis of the spectrum holes to determine Spectrum Opportunity Fraction versus SU bandwidth, and expected interference power at each possible \( f_{SU} \).

v. Optimal selection of the secondary user center frequency.

vi. Extraction of sets of time series of PU data for varying \( f_{SU} \).

vii. Modeling the time series data in each sub-channel.

viii. Creation of the HDO object with all information about a hole in tractable form.

![Spectrogram of 500-698 MHz TVWS band, Chicago (March 1, 2014)](image)

Figure 5.17. Spectrogram of 500-698 MHz TVWS band, Chicago (March 1\(^{st}\), 2014). The measurements were made by IIT WiNCom’s long running spectrum analyzer based observatory – the IITSO

5.4.1 Results on TV White Space. In the US, TV white spaces refer to 6 MHz wide channels within the VHF and UHF TV bands that do not have a TV signal at a particular
location. The TV White Space approach for DSA focuses on enabling geographically based two-tier sharing between existing TV stations, the primaries, and secondary users who are allowed to use the spectrum only in specified areas where TV coverage does not exist in the TV channel of interest. Currently, TVWS devices like the IEEE 802.22 [STE09] must consult a geographic database like [GOO14] to identify the empty TV channels to use. Due to the intense focus TVWS has received in relation to DSA, the TV band is an obvious choice to test CBM performance.

We start off with a 2-D matrix of measured spectrum powers spanning 24 hours that is plotted as a spectrogram in Figure 5.17. The selected date is March 1st, 2014 and the frequency band is 500-698 MHz. The measurements were made by the IITSO with a 54 second time resolution. The spectrogram shows that most TV channels are “on” throughout the 24 hours, but four channels switch off around 2200 hours for some time before switching back on. Over the next several days, all the channels were found to be “on” all the time. This example demonstrates the advantage of continuous long-term spectrum monitoring – anomalous events like the 4 TV channels turning off briefly are observable. Two hours after 11.59pm March 1st marked the “spring forward” daylight savings time change. The TV channels were possibly down due to maintenance work prior to the daylight savings time change.

The average and maxhold power spectrums are calculated from the Figure 5.17 2-D matrix. The noise floor is found using the automated noise estimation algorithm, and a threshold 4 dB is selected above the noise estimate. Figure 5.18 shows the power spectrum plots and the noise floor. The cluster of signals and holes are extracted as described in Section 5.3.2, and this is plotted in Figure 5.19. Notice that the signals are
clearly distinct from the holes and lie in a higher power plane. The high power of the TV channels makes CBM procedure accurate. Next, the frequency locations of the holes are found as described in Section 5.3.3, Method A. Table 5.2 lists the 8 holes identified. Comparing with Figure 5.19, it is obvious that there are 8 TVWS channels in the 500-698 MHz region. Thus the results of Table 5.2 are verified.

![Power spectrum plots and automated noise floor estimation for the 500-698 MHz TVWS band](image)

Figure 5.18. Power spectrum plots and automated noise floor estimation for the 500-698 MHz TVWS band

<table>
<thead>
<tr>
<th>Hole ID</th>
<th>Start (MHz)</th>
<th>Stop (MHz)</th>
<th>Bandwidth (MHz)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>518.07</td>
<td>530.97</td>
<td>12.37</td>
</tr>
<tr>
<td>2</td>
<td>542.35</td>
<td>546.63</td>
<td>4.76</td>
</tr>
<tr>
<td>3</td>
<td>555.20</td>
<td>559.01</td>
<td>4.28</td>
</tr>
<tr>
<td>4</td>
<td>595.66</td>
<td>601.85</td>
<td>6.66</td>
</tr>
<tr>
<td>5</td>
<td>608.51</td>
<td>613.27</td>
<td>5.24</td>
</tr>
<tr>
<td>6</td>
<td>632.31</td>
<td>643.74</td>
<td>11.9</td>
</tr>
<tr>
<td>7</td>
<td>662.30</td>
<td>667.54</td>
<td>5.71</td>
</tr>
<tr>
<td>8</td>
<td>674.68</td>
<td>679.91</td>
<td>5.71</td>
</tr>
</tbody>
</table>
Figure 5.19. Cluster of extracted signals and holes in the 500-698 MHz TVWS (Chicago)

The spectrum holes are then further analyzed to obtain the histogram of PSD values. The PSD histograms are plotted for four selected holes in Figure 5.20. This shows that the holes with IDs 1, 4, and 6 (from Table 5.2) have lowest background noise, but Hole ID #7 suffers from higher interference. This means that Hole ID #7 is less suitable as a secondary use channel. Next, the SOF versus SU bandwidth plot is obtained and shown in Figure 5.21. The results show that the holes can support secondary users with a wide range of bandwidths, and that the SOF value holds close to 1 for bandwidths nearly as high as the hole’s bandwidth, Bhole. The optimal center frequency of operation for a SU of bandwidth 5 MHz is shown in Figure 5.22 for Hole ID #1. To properly examine the suitability of DSA in a hole, the set of time series are extracted for each hole. Figure 5.23 shows three time series plots for Hole ID #6. All the time series show zero occupancy. This means there is no PU activity in the sub-channels and that they are highly suitable for DSA.
Figure 5.20. Histogram of average PSD seen in 4 holes

Figure 21. Spectrum Opportunity Fraction versus SU bandwidth for 4 holes in the TVWS band
Figure 5.22. Identification of optimal center frequency for operation of SU with 5 MHz bandwidth in Hole ID #1

Figure 5.23. Integrated power and thresholded binary time series plots seen with a 5 MHz integrating window positioned at 3 locations within Hole ID #6.
The time series’ are modeled by Model 2 (Poisson process), due to the low number of PU arrivals in the measured data. The model was used to generate synthetic traffic data representing PU activities in several sub-channels. The synthetic traffic also showed zero occupancy, just like the empirically measured traffic. Due to zero occupancy, the plots of empirical and synthetic traffic are uninteresting and similar to the zero activity plot of Figure 5.27 obtained correspondingly from LMR data. Finally, HDO objects are created that summarize all the information in each of the holes in the 500-698 MHz band.

5.4.2 Results from the LMR band. The land mobile radio channels have been allocated by the FCC primarily for voice communications by state and local government agencies, and commercial entities [KOB01]. Public safety agencies like police and fire departments use LMR systems for communication between dispatch centers and mobile field agents, or for direct mobile-to-mobile communications. Similarly, commercial users often employ LMR for “walkie-talkie” mode two-way communications. In urban areas, most of the limited number of LMR channels available in the VHF (148-174 MHz) and UHF (450-512 MHz) bands are already allocated to specific users. During emergency situations when federal, state and city agencies may converge in a geographic locale [FCC08, FCC09], DSA could be applied to increase the pool of voice channels available for public safety use [TAH11a]. Hence, the LMR 450-474 MHz band was selected as a candidate test band for the CBM procedure. The measurements were obtained by the USRP software defined radio sensor specially purposed to conduct LMR channel measurements with a 12.5 kHz resolution and a 250 ms time sweep (see Section 5.2.2).
Figure 5.24 shows a binary 2-D matrix for measurements of LMR channels made on September 15th, 2011. The spectrum data file used in this analysis only stored binary spectrum data and not the actual power measurements. Originally when the data-file was created, the binary matrix was obtained by pre-processing the 2-D matrix of measured LMR power values and comparing them to a fixed threshold value. Hence, the automatic noise floor estimation algorithm of Section 5.3.1 was supplanted by the use of a fixed noise floor. The channels shown span the frequencies 460.000 to 460.625 MHz. The channels were in use by the Chicago Police Department (CPD) and this was before the “narrowbanding” [FCC04] deadline of January 1st, 2013. Hence, most of the channels shown in Figure 5.24 are 25 kHz wide.

Figure 5.24. Binary spectrogram of LMR channels at 460-460.625 MHz band in Chicago (Sept 15th, 2011) measured by the LMR monitor system (Section 5.2.2)
Since the measurement interval is 250 ms, the data plotted over 24 hours in Figure 5.24 represents 345,600 sweeps! Computationally, it would take a long time to process so many measurements. Hence, a subset of the measurements representing 86,400 sweeps or the six hour stretch between 10 am and 4 pm on Thursday, September 15th, 2011 was analyzed, and the results are presented here. The time period 10 am to 4 pm was deliberately selected for analysis, since late morning to late afternoon usually has the highest number of LMR call activity during a typical weekday.

Figure 5.25. Percentage Duty Cycle at each measured frequency point in the 460-460.625 MHz LMR region

The bar chart in Figure 5.25 shows the percentage duty cycle at each measured frequency point during the 6 hour analysis period. From Figure 5.25, it is possible to see that the frequency points with high duty cycle values are probable signal locations, while the low duty cycle regions are holes. A close examination of Figure 5.25 shows that most pairs of adjacent duty cycle bars have identical occupancy values. This is expected since
the measured CPD channels were 25 kHz wide, and with a measurement resolution bandwidth of 12.5 kHz, each LMR channel spans two adjacent frequency points in the measured data. However, there are a few narrowband 12.5 kHz channels in evidence, and their frequency locations are indicated by the individual “unpaired” duty cycle bars. Figure 5.25 also indicates the locations of the LMR channels that are subsequently analyzed in Figures 5.27 and 5.28.

From the 2-D matrix, the clusters of data points for signals were extracted using the method described in Section 5.3.2. Method B described in Section 5.3.3 was then used to identify the start and stop frequencies, and bandwidths of all the signals. Method B identified and extracted a total of 16 signal locations – 13 signals were 25 kHz LMR channels and 3 were 12.5 kHz wide. However, the holes’ locations are of greater interest due to this paper’s focus in DSA. Using Method B, the locations of all the holes were simply identified as the frequency regions not spanned by any of the identified signals. That is, the hole locations are complementary to the signal locations. Table 5.3 lists the 7 holes identified. Comparing with Figure 5.25, it is obvious that there are 7 distinct regions within the 460-460.625 MHz LMR channels that have very low duty cycles (below 0.5%). Thus the results of Table 5.3 and Method B of Tier 1 of the CBM procedure are verified. Method A was also tried in this LMR band, but poor results were obtained. As mentioned before in Section 5.3.3, Method B is better suited for spectral bands where the signals switch rapidly, such as with LMR.

After the 7 holes were identified, plots of the spectrum opportunity fraction versus secondary user bandwidth were obtained as shown in Figure 5.26 using the method described in Section 5.3.4. For Hole IDs 1 to 6, the SOF stays close to 1 for SU
bandwidths equal or lesser than the hole’s bandwidth. This means there will be low interference experienced by secondaries operating in those holes. Hole 7 has a lesser SOF value. Thus, an SU operating in Hole ID# 7 would experience some interference from the PU.

Table 5.3. List of Extracted Holes in 460-460.625 MHz LMR band, Chicago (September 15th, 2011)

<table>
<thead>
<tr>
<th>Hole ID</th>
<th>Start (MHz)</th>
<th>Stop (MHz)</th>
<th>Bandwidth (kHz)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>459.9937</td>
<td>460.0063</td>
<td>12.5</td>
</tr>
<tr>
<td>2</td>
<td>460.1437</td>
<td>460.1812</td>
<td>37.5</td>
</tr>
<tr>
<td>3</td>
<td>460.2188</td>
<td>460.2313</td>
<td>12.5</td>
</tr>
<tr>
<td>4</td>
<td>460.2687</td>
<td>460.2813</td>
<td>12.5</td>
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<td>5</td>
<td>460.3312</td>
<td>460.3813</td>
<td>50.0</td>
</tr>
<tr>
<td>6</td>
<td>460.4063</td>
<td>460.4312</td>
<td>25.0</td>
</tr>
<tr>
<td>7</td>
<td>460.5063</td>
<td>460.6313</td>
<td>125.0</td>
</tr>
</tbody>
</table>

Figure 5.26. Spectrum Opportunity Fraction versus SU bandwidth in the LMR 460-460.625 MHz band
After the frequency information about the holes was obtained, the set binary time series’ of PU activities for all the holes was extracted. The 4-state Model #3 mentioned in Section 5.3.6 was then applied. For each hole, the PU activity within every 20 minute window was modelled, and the 6 hour time span was divided into 18 separate modeling windows. Within each 20 minute window, the 4-state model uses 4 pdf distributions giving a total of 8 parameters. This means that $8 \times 18 = 144$ parameter values need to be stored and handled to properly track PU traffic. A hole-descriptor object is generated to model the time series in each hole, and the HDO conveniently stores all these numbers with 8 vectors. Each vector represents one of the 8 parameters of the 4-state model and is of length 18 to track the parameter variations over the full 6 hour time span. In Section 5.3.7, it was mentioned that the HDO is provisioned with methods for generating artificial traffic. The 4-state LMR traffic model was used by the HDO Method (iii) to generate synthetic PU traffic as shown in Figure 5.27. Figure 5.27 also shows the empirically measured PU traffic over the 6 hour period. Figure 5.27 is quite unexciting as both the measured and synthetic plots show zero occupancy. This is expected as the CBM algorithm correctly identified the holes where the PU activity should be as low as is seen in Figure 5.27.

To properly test how well the 4-state model for LMR traffic fits with measured data in a high activity LMR channel, it is necessary to apply it to a channel identified as a “signal location” by the CBM procedure. This was done for the LMR channel centered at 460.2 MHz which was classified as a signal by CBM. Analogous to HDO, a Signal-Descriptor Object (SDO) was generated with frequency and bandwidth information about the signal in the 460.2 MHz LMR channel. Also, to track the PU traffic over the 6 hour
period, the SDO stores a set of 8 vectors of parameter values for the 4-state model. Figure 5.28 plots the empirically measured PU traffic and compares it with PU activity synthetically generated by the 4-state model contained in the SDO. Both the plots were smoothed with a 15 minute moving average filter to reveal peaks and trends in the LMR activity. The results show that the synthetic traffic follows the general trends of the empirical PU traffic. Exact match is not seen, since the synthetic traffic is generated by a random call initiation process and the calls are of random duration.

![Figure 5.27. Measured PU activity (above plot), simulated PU activity (lower plot), in the “hole” with BW=50 kHz and $f_c=460.3562$ MHz](image)

The results of this section demonstrate the versatility and accuracy of the CBM procedure. Particularly, the utility of Method B for extraction of holes has been demonstrated by its application on LMR measurement data. The 2.5-2.7 GHz and 500-698 MHz TVWS examples have already demonstrated the utility of “hole extraction Method A”. The usefulness of HDO/SDO to compactly represent hours of information about the radio environment and PU traffic in a white space/signal is also seen. Since the
starting spectrum data file only contained binary values, the plots of histogram of average PSDs was not computed for the holes. Finally, the 4-state LMR traffic model that was first presented in [TAH13] received further validation by the synthetic traffic generation results and the comparison with empirical traffic in Figures 5.27 and 5.28. The quantitative method to compare empirical and synthetic traffic introduced in Section 5.3.5 is also applicable here to show good correspondence.

![Empirical PU traffic (smoothed), LMR Center=460.2 MHz](image1)

**Figure 5.28.** Measured PU (above plot) traffic and simulated PU activity (lower plot) at a “signal location”; LMR center at 460.200 MHz and channel width 25 kHz

5.5 Applications of CBM Procedure

The proposed CBM has obvious applications in upcoming cognitive radio (CR) networks employing DSA technologies. By regulation, IEEE 802.22 CRs operating in TV white spaces [FCC10b] have to consult a database to identify the white space TV
channels where they can operate [GOO14] at a particular geographical location. Although TV broadcast channel locations are reliably recorded in the geographic database, often the locations of wireless microphones in the TV bands are not. The microphones are classified as devices protected from IEEE 802.22 interference. The CBM procedure can be implemented on TV white space measurements obtained by a spectrum observatory that senses the RF environment at the network location. In this application, the SO communicates the CBM outputs (the HDOs) to IEEE 802.22 radios, where the HDOs identify spectrum holes ideal for CR operation and free from interference with any measured wireless microphone transmissions.

Apart from IEEE 802.22, next generation CRs would likely have the need to rapidly scan wide bandwidths and quickly identify operating frequencies that are free from PU interference. Commercial radios should be inexpensive in order to be economically viable in the mass market, but wideband sensing hardware adds cost to CR systems. The CR’s spectrum sensor may suffer from the hidden node problem [RAP02], shadowing, and other effects in the radio path like absorption that limit its sensitivity. An alternative would be to outsource the sensing function of the CR network to a spectrum observatory. A single well-designed SO has high sensitivity and can provide the service of identifying good secondary usage channels to a large number of CRs operating in the area. The SO would implement the CBM procedure to obtain a set of HDOs in the frequency bands of interest and communicate this set as a service to the next generation CR networks. Thus, CBM expands the scope of spectrum observatory systems beyond the current application of simply monitoring and auditing radio use to one of practical utility, where the SO facilitates operation of DSA networks.
At IIT’s WiNCom research center, we are currently deploying a network of spectrum monitoring sensors in and around Chicago, and in Turku, Finland. One of the long-term goals of the spectrum sensor network is to deploy a CBM-based analysis library that processes incoming and historic RF measurements to support DSA networks throughout the cities. The expansive nature of this goal also includes processing spectral data from multiple bands where DSA sharing is feasible based on the CBM procedure or its future derivatives. In summary, the vision is to setup a spectrum observatory network to facilitate deployment and operation of cognitive radio networks in multiple bands where DSA is feasible.

5.5.1 Monte-Carlo Coexistence Simulations. To demonstrate the utility of the CBM procedure in practical DSA coexistence systems between PU and SU radios, the common Listen-Before-Talk medium access control (MAC) technique was applied in three sets of Monte-Carlo (MC) simulations [FIS95]. A simulation environment was developed that uses empirically measured PU traffic from the binary time series of PU activity. For each MC run, the binary PU time series is extracted from the spectrum powers matrix as described in Section 5.3.5. The SU uses a simple LBT algorithm to share the channel with the PU. Figure 5.29 illustrates how the LBT technique works.

The SU senses the channel first; if the PU is absent or if the channel is observed to transition from busy to vacant, then a countdown timer of random duration $T_c$ is started. If the PU does not return during this countdown interval, the SU transmits for a random duration $T_x$. During the transmission state, the SU cannot do channel sensing, and hence collisions can occur if the PU returns. $T_c$ is a uniform random variable between $[T_{\text{slot}}, T_{C\text{max}}]$ and $T_x$ is uniform between $[T_{\text{slot}}, T_{X\text{max}}]$, where $T_{\text{slot}}$ is the time-slot used in
the simulation and $T_{C\text{max}}$ and $T_{X\text{max}}$ are, respectively, the maximum countdown timer and the maximum transmit duration. The $T_{C\text{max}}$, $T_{X\text{max}}$ are constant for all the MC simulations. The 2.5-2.7 GHz band was used in this MC study where the SO measured PU activity every 10 seconds. Hence, $T_{\text{slot}}=10$ s, and the LBT parameters were set to $T_{C\text{max}}=2 \cdot T_{\text{slot}} = 20$ s and $T_{X\text{max}}=4 \cdot T_{\text{slot}} = 40$ s. Each MC run simulates 10 hours of PU and SU coexistence, where the channel center is $f_{SU}$ and the channel bandwidth, $W_{SU}=5$ MHz.

![Figure 5.29. Illustration of LBT MAC scheme](image)

As mentioned above, three sets of MC simulations were performed that correspond to the following three scenarios:

(i) The SU selects any channel within the 2.5-2.7 GHz band with center frequency $f_{SU}$ and bandwidth $W_{SU}$. This represents the practical scenario where a DSA radio does not have access to a geographic spectrum allocation database, and hence randomly selects an operation channel and attempts to share it with LBT.

(ii) In the second scenario, the SU selects any channel randomly, but within the identified “holes” or white spaces. This is analogous to the case where the DSA
radio has access to a geographic spectrum database, or has access to partial results of the CBM procedure; but it has no information about the ideal channel to use within the hole. The center frequency $f_{SU}$ and bandwidth $W_{SU}$ lie within the hole.

(iii) In the final scenario, the SU has full access to the results of the CBM procedure, and operates on the optimal channel of the hole with $f_{SU,\text{optimal}} = 2599$ MHz.

During each simulation run, the fraction of SU packets that collide, i.e. “the Collision Fraction” (CF); the fraction of time there is any PU or SU transmission, i.e. “the Spectrum Efficiency” (SE); and the fraction of the PU’s off-time utilized by the SU, i.e. “the Spectrum Opportunity Utility” (SOU) are noted at every 15 minute interval. SOU differs from SOF in the sense that the SOF indicates the total spectrum opportunity available in a channel, while the SOU refers to the actual opportunity utilized by the SU radio. Figure 5.30 plots these values for a 10 hour simulation run corresponding to the first DSA scenario, where a SU radio with 5 MHz bandwidth randomly selected $f_{SU} = 2587.5$ MHz as its operating frequency. The PU and SU activities are also plotted. Notice that when PU activity increases, the number of collisions and CF increase, and the SU throughput is throttled down by the LBT MAC. The SE and SOU are very similar in this case as PU activity is rare – meaning that the spectrum efficiency is dominated by the SU, and hence SE≈SOU.

At the end of the simulation run, the average values for the SE, SOU, and CF are calculated. For each of the three scenarios, the Monte Carlo simulations are run a thousand times. Each time, the channel centers for scenarios i and ii change randomly, but the channel is fixed for scenario iii. Across the 1,000 simulation runs, the overall average SE, SOU and CF are shown in Table 5.4.
Table 5.4. Average results for 1,000 MC simulations where SU uses LBT MAC to coexist with PU. $\mu$ is mean, $\sigma$ is standard deviation.

<table>
<thead>
<tr>
<th>Results</th>
<th>Scenarios</th>
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<th>ii</th>
<th>iii</th>
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<tr>
<td></td>
<td></td>
<td>$\mu_i$</td>
<td>$\sigma_i$</td>
<td>$\mu_{ii}$</td>
</tr>
<tr>
<td>Spectrum Efficiency SE</td>
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<td>2.12</td>
<td>72.6%</td>
</tr>
<tr>
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<td></td>
<td>58.2%</td>
<td>18.9</td>
<td>74.0%</td>
</tr>
<tr>
<td>Collision Fraction, CF</td>
<td></td>
<td>18.4%</td>
<td>19.2</td>
<td>0.485%</td>
</tr>
</tbody>
</table>

Figure 5.30. Top plot shows measured PU and simulated SU activity. The lower one shows the performance of LBT MAC with SE, SOU and CF plots. The SU has 5 MHz bandwidth and $f_c=2587.5$ MHz, and corresponds to scenario i.

5.5.2 Application of PU Channel Models. The models of primary user activity generated by the CBM are usable to further enhance DSA to improve spectrum utilization. In [HUA08, HUA09], the authors describe a system where the SU is able to use statistical knowledge of the PU’s idle times in order to achieve optimal SU throughput subject to a collision limit constraint. The advantage of knowing the PU’s traffic characteristics was thus demonstrated. In [HUA08, HUA09], the mathematically
modelled probability and cumulative distribution functions of PU idle time are used by the SU’s spectrum access policy decision block to achieve throughput maximization. Thus, the CBM procedure can be used to support elaborate DSA systems that incorporate the optimal scheme [HUA08, HUA09].

In [TAH13], two separate LBT algorithms were presented. The simple LBT algorithm used no information about the PU’s idle times. The smart LBT algorithm in [TAH13] used the cumulative distribution function of the PU’s idle times to optimize the parameters governing the LBT MAC behaviour. The smart LBT algorithm easily outperformed the simple case. This further demonstrates that the PU traffic models generated by CBM can assist highly efficient DSA techniques and improve spectrum efficiency.

Figure 5.31 illustrates how a spectrum observatory and a CBM analysis block can be incorporated in a DSA setup to support a network of SU radios. This general setup will work for both of the two DSA systems ([HUA08, HUA09] and [TAH13]) mentioned here in Section 5.5.2. The SO measures incumbent user activity. The measurements are continually analyzed by the CBM block. The CBM outputs, i.e. the hole-descriptor objects characterizing the spectrum opportunities in the radio environment, are communicated to SU radios using a control channel. The SU radios thus are able to select their channel centers and transmission parameters, and dynamically share the spectrum with the PUs using any efficient DSA paradigm such as presented in [HUA08, HUA09] or [TAH13]. In addition, this DSA network setup presents a practical application for spectrum observatory systems. It also demonstrates how CBM can enhance dynamic spectrum sharing and make DSA practically feasible.
Summary of the CBM Procedure, its Applications and DSA Assessment

A comprehensive set of algorithms was introduced that analyzes spectrum measurement data for an entire band, identifies the signals and white spaces within the band, selects the ideal channels for SU operation, models the primary’s activities within a channel, and finally wraps all this information in a compact object format. The CBM procedure has fast execution times – a standard desktop computer is able to process all the data in an entire band over 24 hours within a few minutes (<10 mins).

Previous spectrum measurement and analysis work has primarily focused on simple occupancy studies [TAH11b, MCH05, ISL08], which though useful, only provide a narrow lens towards understanding the true dynamics, patterns and intricacies of radio usage. A statistical model of radio activity, however, provides a deep insight into spectrum utilization behavior. Particularly, the compact HDO models generated by the CBM procedure permit simulation of PU traffic and allows for a more complete understanding of the dynamics of traffic behavior. Also, the HDOs permit data-driven detailed research into PU and SU coexistence, thus helping DSA feasibility studies. As
demonstrated, the HDOs compact and summarize spectrum measurement data by up to four (4) orders of magnitude. This makes it technically feasible for a spectrum observatory to operate in a supportive capacity and service future CR SU networks.

The “applications” Section 5.5 demonstrated the benefits of using the CBM procedure in a simulated DSA network. The smart SU was shown to attain a higher performance level than an SU coexistence technique that does not employ the CBM procedure. One of the objectives of this simulation was to demonstrate an application for a continuous spectrum monitoring system. The spectrum observatory played an integral part of the DSA sharing framework by measuring the RF powers in the 2.5-2.7 GHz band. Then the CBM procedure identified the holes, modeled the PU traffic, and then reported the parameters to the SU via hole-descriptor objects. Without the spectrum observatory or the CBM procedure, the spectrum efficiency gains would not have been realized.

5.6.1 **DSA Assessment for an entire band.** DSA feasibility study is an important research area where the CBM procedure is applicable. Due to the expected influence on policy due to the PCAST report [PCA12] and President’s memorandum about “Expanding America’s Leadership in Wireless Innovation” [PRE13], it is clear that dynamic spectrum sharing paradigms will lead the way for future technological advances in the wireless domain. Thus the importance and applications of such research will continue to increase.

The CBM procedure extracts a complete list of spectral white spaces in the entire band. The total number and bandwidths of the holes are important in assessing if DSA is feasible – this determines how many secondary use channels could be provisioned in the
band. The level of interference expected in each hole is indicated by the histogram of PSD values, and also the histogram of instantaneous occupancies. The bandwidths that SU radios can optimally operate within a hole are indicated by the Spectrum Opportunity Fraction versus SU bandwidth plot. All these tools are made available to the researcher via CBM, and by combining all these metrics, a good assessment of DSA feasibility can be made.

The application of CBM HDO objects in a DSA coexistence study as presented in Section 5.5.1 gives a direct methodology to quantitatively assess the spectrum efficiency gains achievable through spectrum sharing protocols like LBT. The quantitative results of DSA coexistence provide a direct and easy method for the researcher to assess DSA feasibility in the entire band. For example, the results of Table 5.4 show that up to 74.3% of the available spectrum opportunity in the 2.5-2.7 GHz band of Chicago can be safely utilized by secondary CRs via DSA techniques like simple LBT, with minimum interference (shown by very low collision fraction for scenario iii) to incumbent legacy PU radios. Hence, Table 5.4 indicates that DSA is indeed feasible in the 2.5-2.7 GHz band of Chicago.

In summary, the CBM procedure and its application produces metrics like: (a) number of holes available in band, (b) average PSD in the hole, (c) bandwidth of holes, (d) occupancy statistics in the hole, (e) spectrum efficiency achieved through DSA, (f) collision probabilities, (g) spectrum opportunity fraction utilized, (h) optimal SU channel locations for operation, etc. Combined, they provide novel tools for the researcher to assess DSA feasibility in the entire band.
CHAPTER 6
CONCLUSION

6.1 Executive Summary

Three spectrum observatory systems are implemented with which RF Spectrum use is measured and analyzed across multiple bands over both short and long time periods. Broad findings on occupancy, trends in spectrum usage, statistical analysis results are presented for a wide range of bands stretching from 30-6000 MHz at Chicago, US and at Turku, Finland. Particularly, detailed results of radio use by public safety agencies in Chicago are presented. These findings are of use to radio policy planners, public safety agencies, and to commercial or government entities looking for ways to improve spectrum efficiency. At a deeper level of detail, land mobile radio (LMR) channel use by public safety agencies like the Chicago Police Department are extensively studied and models of wireless traffic activity obtained. The models provide a deep understanding of the wireless environment, and were shared with government agencies in charge of public safety radio policy. The models are used to generate synthetic traffic that closely match measured activity, and also to support Dynamic Spectrum Access (DSA) sharing in the LMR band for a simulated wireless environment. The modeling work is expanded from individual RF channel analysis to modeling entire spectral bands through the development of the Comprehensive Band Modeling (CBM) procedure. The CBM procedure is a set of automated algorithms that analyze measured spectrum data in a band to identify all holes (white spaces) and signals, identify the spectrum sharing opportunities in the holes, calculate optimal operation parameters for secondary spectrum users, model activities of the incumbent users, and summarize all hole information in the
form of highly versatile Hole Descriptor Objects (HDO). The metrics and results of the CBM procedure allow researchers to obtain an effective assessment of DSA feasibility. CBM was applied and validated with measured RF data in three bands. Crucially, the results demonstrate the suitability of DSA applications to boost the efficiency of spectrum use. The research findings in this dissertation are of practical relevance due to recent policy developments by the Federal Government that have prioritized the need for dynamic spectrum sharing to foster continued growth and innovation in the wireless field.

6.2 Recap of Dissertation

Section 2.1 provided an overview of the long running IITSO. The spectrum measurements conducted at the WiNCom research center at IIT represent the longest-running and most comprehensive RF usage dataset in the world. Due to the unique nature of the dataset, the insights about wideband spectral activity presented in Section 2.2 represent new knowledge that is of practical relevance to spectrum managers, policy makers, and wireless companies. Expanding from our experience with the Chicago spectrum observatories, a global spectrum observatory was deployed in partnership with Virginia Tech, and with research labs and universities at Finland. This global spectrum monitoring network and findings on occupancy statistics at Chicago and Finland were presented in Section 2.3. Also, the measurements in the 450-474 MHz band constitute the longest and most detailed empirical dataset on LMR channel usage that covers many public safety and commercial users. The data presented in Section 2.4 is of interest to public safety agencies and network planners.

The modeling work of public safety activity presented in Chapter 3 is of practical importance to companies like Motorola Solutions that manufacture network PSR
equipment. The results have been shared with Motorola Solutions. FCC’s department of public safety and homeland security is greatly interested in modeling public safety channels as they work towards making first responder networks more robust and to ensure that there is adequate capacity during emergencies. The CPD traffic models, the parameter values to track the CPD channels have been provided to this FCC department at their request. The models developed have thus proved to be practically relevant and useful to commercial and government researchers. An overview of the specialized spectrum sensor developed for LMR measurements was presented in Section 3.1. A first-order 2-state time-varying model for LMR channel traffic was presented in Section 3.2. Section 3.2.3 presented a novel quantitative method to estimate the likelihood of parameter stationarity for stochastic quantities of interest, like hold and idle times. Section 3.3 provided an enhanced and improved 4-state model of LMR RF traffic which was used to generate synthetic traffic in Section 3.4. Section 3.5 provided a quantitative method to compare synthetic and empirical traffic data, and it was applied to provide validation to the developed 4-state LMR model.

Section 4.1 presented a framework for DSA sharing in the 450-474 MHz LMR band that takes advantage of the 4-state LMR model. The results of applying an enhanced form of the listen-before-talk MAC protocol that takes advantage of LMR modeling information was demonstrated by the DSA simulation results of Tables 4.1 and 4.2. Section 4.2 provided optimization of the DSA sharing protocol presented earlier, and better performance was obtained.

Chapter 5 presented the main contribution of this dissertation, that is the Comprehensive Band Modeling procedure. The need for a system like the CBM was
described in Section 5.1. Section 5.2 provided a brief recap of the three spectrum sensors. Section 5.3 provided a detailed description of all the CBM procedure steps – Section 5.3.1 described the automated noise threshold estimation algorithm; Section 5.3.2 outlined the algorithm to extract clusters of data points representing signals and holes; Section 5.3.3 applied the data clusters to identify the signal and hole locations in the entire band; Section 5.3.4 provided methods to analyze the spectrum opportunity present in the holes; Section 5.3.5 presented procedures to divide the band into sub-channels for SU use and how to rank and select the best sub-channel for secondary operation; Section 5.3.6 provided three separate models that are usable to describe incumbent user activity in any sub-channel in any hole within the band; Section 5.3.7 introduced the concept of abstraction layers and use of hole and signal descriptor objects (HDO/SDO) to compact intractable gigabytes worth of spectrum measurement data into tractable and highly useful blocks of key summary information; and finally Section 5.3.8 provided 2 additional methods to validate the hole identification results of CBM. The entire CBM procedure was illustrated in Section 5.3 by its application in the 2.5-2.7 GHz band in Chicago that currently has WiMAX deployments.

Section 5.4.1 presented the results of applying CBM to the TV band frequencies between 500 and 698 MHz. Section 5.4.2 applied CBM to the LMR band at 460 MHz that had CPD dispatch channels deployed. The results of Section 5.4 proved that the CBM is versatile across multiple spectral bands and that it works with multiple different spectrum sensors. Section 5.5 presented practical applications of CBM. Section 5.5.1 used Monte-Carlo DSA simulations to demonstrate the gains in DSA performance when just the first two tiers of CBM model are used. Section 5.5.2 recapped how a spectrum
observatory running the CBM procedure can support a practical DSA network. Finally, Section 5.6.1 described how the metrics and outputs of the CBM procedure can be interpreted to obtain a feasibility assessment for dynamic spectrum sharing within the band.

In view of the recommendations contained in the PCAST 2012 report, identifying spectrum for sharing and examining the feasibility of coexistence with incumbent users is now an issue of national economic importance and government supported policy. This dissertation conducted spectrum sharing and feasibility assessments on the 450-474 MHz LMR band, the TV band and the 2.5-2.7 GHz band. The dissertation thus met a real research need that is of interest to the Federal government. The research findings can also pave the way to future spectrum sharing in the studied bands with commercial users, and thus promote innovation in the wireless field.

Similar research efforts are being replicated in other universities in the US and around the world. As mentioned, the WiNCom research center entered into a partnership with Virginia Tech, Maryland, and three top universities in Finland to replicate the spectrum measurement and modeling research work in three locations – three in the US and two in Finland. This cross-Atlantic research is being supported by the NSF and the Tekes Academy of Finland, with the goal of understanding wireless usage through empirical measurements and exploring DSA technologies towards the goal of improving spectrum efficiency.

Finally, the overall system described in the dissertation – the SO based RF measurement system, the traffic analysis and modeling system, model information sharing with secondary users, and DSA access by SU networks – lays the foundation for
a practical cognitive radio network. Such networks can make it practically possible for commercial radios to share spectrum with incumbent users and smart CRs. Thus, the overall system is practically relevant in the design of dynamic access based spectrum sharing network technology.

6.3 Contributions and Relevance

The novel contributions in this dissertation were listed previously in Section 1.5. They are reviewed in this section. The dissertation is novel in the following areas that are directly related to the main goal of the research, which is to measure and model primary user spectrum usage and test DSA spectrum sharing with secondary users:

1. **LMR Models.** New time-varying models for LMR switching traffic were presented that are able to track the channel for arbitrarily long periods of time. The models are of use to the public safety community, and have been shared with government PSR planners.

2. **New Application for Spectrum Observatory.** The framework is novel, where the SO models PU traffic and then provides useful PU channel information to the SU in real-time is novel and it makes spectrum sharing possible. The Federal government recently mentioned the need to test dynamic spectrum sharing in test cities that would require spectrum sensors at multiple locations. The framework presented in the dissertation is relevant to this application.

3. **Quantitative Method to assess channel stationarity.** The method to use long-term RF measurement data to assess the stationarity of wireless traffic
activity is novel. This method was useful to quantitatively find the model parameter update times.

4. **Low-cost Measurement Systems.** The design of low cost high resolution spectrum sensors to monitor hundreds of wireless channels simultaneously is an important contribution to this field. This design experience is helpful in designing low-cost spectrum sensors for other projects that WiNCom was recently funded to perform.

5. **DSA algorithms.** The DSA algorithms that utilize model information from the SO may be simple, but they are novel in that they make use of a unique data-set made possible by the SO spectrum measurements.

6. **Procedure to Model whole bands at a time.** The CBM method to automatically process gigabytes of spectrum data corresponding to a band and obtain a compact yet comprehensive model of the *entire* band is novel. This is highly relevant as it is very important to identify the holes and spectrum opportunities present in any band.

7. **DSA Assessment.** The CBM procedure outputs metrics like: (a) number of holes available in band, (b) sensitivity requirement for the SO and the SUs – how weak or strong are the PU signals, (c) bandwidth of holes, (d) occupancy statistics in the hole, (e) spectrum efficiency achieved through DSA, (f) and collision probabilities. Combined, they provide novel tools for the researcher to assess DSA feasibility. Federal agencies like the FCC may find such tools for DSA assessment highly relevant as they work to identify which Federal bands would support sharing with commercial entities.
8. **Hole/ Signal Descriptor Objects (HDO/ SDO).** The use of object abstraction in the field of spectrum measurements and analysis is a relatively new concept. The HDO/ SDO objects that layer different levels of details while modeling of channels (either hole or signal channels), and then compactly represent this information in a flexible object format are novel and very useful contributions to the field. The HDO/ SDO concept is in the process of being patented – there are many possible applications for this.

Although not the main focus of the thesis, during the course of the PhD research, several new interesting findings were presented that represent new knowledge in the field of spectrum measurements and utilization. These are:

9. **New Analysis and Findings on spectrum usage.** Long term results about spectrum usage in the LMR bands were presented. This includes highlighting the differences between public safety and commercial LMR users, and the changes in public safety LMR usage during emergencies. This has practical relevance in the design of more resilient public safety radio systems.

10. **Spectrum usage audit.** This was done for Chicago during the years 2008, 2009, 2010. Also, day-long snapshot spectrum audits were done at several locations in and around Chicago in 2013, and at Turku in 2013. Policy makers and planners usually are interested in spectrum audits to understand the trends in spectrum usage for better planning purposes.

6.4 **Research Support**

The research was supported by the following NSF grants:

1. **Spectrum Observatory System.** NSF NeTS CNS 0722003 (Aug 07-July 09).


### 6.5 Publications

The following IEEE conference papers were published during the course of the PhD dissertation:


7) T. Taher, *et al.*, “Global spectrum observatory network setup and initial findings,” accepted for publication at *Crowncom 2014* conference to be held at Oulu, Finland.

8) M. Hoyhta, M. Matinmikko, X. Chen, J. Hallio, J. Roning, A. Riaz, A. T. Taher, D. Roberson, and J. Kalliovaara, “Measurements and Analysis of Spectrum Occupancy in the 2.3-2.4 GHz band in Finland and Chicago”, accepted for publication at *Crowncom 2014* conference to be held at Oulu, Finland.

There were two other IEEE conference papers that I published during my PhD coursework. However, at that time, the focus of my research was in the somewhat different area of wireless interference identification and mitigation. Hence, the contents of those two papers are not included in this dissertation document.

In addition, two articles for IEEE Journals and one article for an IEEE Magazine are to be submitted soon. The first IEEE journal article will present parts of the CBM procedure mentioned in Sections 5.3.1 to 5.3.6. The second journal article will expand on this, but primarily focus on the use of HDO objects in dynamic spectrum sharing scenarios. The IEEE magazine article will be a higher level treatise on spectrum measurements and on how to extract useful information about whole bands from the data, and how DSA can be applied in bands of interest to improve spectrum sharing.
BIBLIOGRAPHY


