A HIGH PERFORMANCE SOFTWARE INTENSIVE TESTBED FOR RAPID

PROTOTYPING AND CONTROLLED TESTING OF LTE AND

WI-FI RADIO FREQUENCY SIGNALS

MIRZA MOHAMMAD MAQBULE ELAHI, MS

Doctoral Program in Computational Science

APPROVED:

Virgilio Gonzalez, Ph.D., Chair

Rosa Fitzgerald, Ph.D.

Omar Badreddin, Ph.D.

Stephen L. Crites, Jr., Ph.D.
Dean of the Graduate School

Dedication

I would like to dedicate my dissertation paper to my loving wife Sharmila, parents Mr. and Mrs. Elahi, and my siblings for their constant motivation in pursuing my graduate studies.

A HIGH PERFORMANCE SOFTWARE INTENSIVE TESTBED FOR RAPID PROTOTYPING AND CONTROLLED TESTING OF LTE AND WI-FI RADIO FREQUENCY SIGNALS

by

MIRZA MOHAMMAD MAQBULE ELAHI, MS

DISSERTATION

Presented to the Faculty of the Graduate School of

The University of Texas at El Paso

in Partial Fulfillment

of the Requirements

for the Degree of

DOCTOR OF PHILOSOPHY

Computational Science Program

THE UNIVERSITY OF TEXAS AT EL PASO

August 2022

Acknowledgements

I would like to express my gratitude to Dr. Virgilio Gonzalez, Associate Chair of the Electrical and Computer Engineering (ECE) Department at the University of Texas at El Paso (UTEP) for his constant support and guidance towards my progress in graduate studies. Dr. Gonzalez is an amazing tutor in class and a wonderful person as a research advisor with plenty of technical knowledge. As a faculty member of the ECE Department he inspires me to pursue teaching as a profession.

I would like to thank my co-workers Jose Sandoval, Juan Gonzalez and Jose Castillo for their dedication and help with our research project. I have to mention Mr. Pabel Corral and Mr. Susumu "Duke" Yasuda from White Sands Missile Range for their full co-operation with the Spectrum Management Project. It has been my pleasure to work with these amazing people, or I would like to call them a friend. I look forward to crossing path with them in the future.

My appreciation goes to the Computational Science (CPS) Program and Electrical and Computer Engineering Department for their support. Also, my wife Sharmila and friends from the Bangladesh Student Association at UTEP have been a great inspiration.

Abstract

Long Term Evolution or LTE has gained interest for new applications that can benefit society including mobile broadband services like 802.11 or Wi-Fi. Both LTE and Wi-Fi uses similar modulation technique Orthogonal Frequency Division Multiplexing or OFDM. 6GHz sub carrier bands are crowded with LTE users. As wireless communications technology continues to develop, LTE technology in unlicensed bands (LTE-U) is a viable solution to the lack of spectrum resources. The competition between LTE-U and Wi-Fi will seriously impair their communication quality, so the friendly coexistence of both become an important research topic. This paper discusses the use of a software-defined radio (SDR) testbed at UTEP in order to rapidly prototype and classify radio frequency (RF) signals using deep learning (DL) techniques with validation accuracy as high as 96.67%. SDR testbed data is processed and fed into the Convolutional Neural Network (CNN), which performs feature extraction and trains the network to classify RF signals. The proposed method differentiates LTE-U and Wi-Fi signals effectively and allows them to coexist. The spectrum sensing function plays a key role in the coexistence. Several transfer learning algorithms are tested to increase the performance of the classification and to minimize the loss probability. The CNN extract features from the observations belonging to different class of RF signals for training, and finally validates the training set. The performance of the proposed transfer learnings were tested over the air using SDRs for variable signal-to-noise ratio with noise uncertainty. The UTEP SDR testbed is unique in several ways, including the extensive use of SDR technology, the use of industry-grade hardware and software-based systems, and the ability to design experiments in accordance with the user's preferences.

Table of Contents

Dedication iii

Acknowledgements v

Abstract vi

Table of Contents vii

List of Tables ix

List of Figures x

List of Illustrations xi

Chapter 1: Introduction 1

Chapter 2: Literature Review 6

- 2.1 Problem History 6
- 2.2 Technology Foundation 8
- 2.3 Related Work 10

Chapter 3: Background 15

- 3.1 LTE SDR Testbed 15
- 3.2 LTE-U 16
- 3.3 Application Framework 18
- 3.4 Neural Network 19

Chapter 4: Methodology 23

- 4.1 SDR Testbed 23
- 4.2 Power Spectral Density 24
- 4.3 Spectrogram Analysis 26
- 4.3 Convolutional Neural Network 26

Chapter 5: Results 28

- 5.1 Spectrum Sensing 28
- 5.2 Data Acquisition 29
- 5.3 Spectrogram 30
- 5.4 CNN Training 33

5.5 Classification Accuracy 35
5.5.1 GoogleNet 37
5.5.2 AlexNet 40
5.5.3 ResNet-18 44

Chapter 6: Conclusion..49

References..52

Glossary 58

Appendix..60

A1 60

A2 77

A3 84

A4 97

Vita 99

List of Tables

Table 1: List of testbed equipment.. 23
Table 2: Testbed Features and Support... 24
Table 3: Observations from the spectrum analyzer. 29
Table 4: Formation of class for CNN. 33
Table 5: CNN parameters. 34
Table 6: Performance comparison of pretrained CNN 36

List of Figures

Figure 1: LTE and Wi-Fi coexistence system in unlicensed spectrum band[24] 7
Figure 2: RF system with the transition of information from source to destination...................... 8
Figure 3: Sinusoidal waveforms with different time periods, sin(t) and sin(2t)........................... 9
Figure 4: Spectrum sweep from 1.35 GHz to 5.60 GHz in RF band.. 10
Figure 5: LTE-U waveform duty cycle.. 16
Figure 6: LAA LBT waveform.. 17
Figure 7: LabVIEW LTE Application Framework.. 18
Figure 8: LabVIEW 802.11 Application Framework.. 19
Figure 9: NN layers... 20
Figure 10: CNN steps.. 21
Figure 11:LTE/W-Fi coexistance experiment setup.. 23
Figure 12: PSDs where the horizontal axis represents frequency in GHz and vertical axis represents power in dB... 25
Figure 13: Superimposed PSD of LTE-U and Wi-Fi.. 25
Figure 14: Spectrograms of testbed data where horizontal axis is frequency in GHz, vertical axis is time in seconds and color code representing signal power in dB. 26
Figure 15: MATLAB Deep Learning Application. 27
Figure 16: PSD at center frequency 2.437 GHz and span of 80 MHz.. 28
Figure 17: Spectrogram at center frequency 2.437 GHz and span of 40 MHz........................... 29
Figure 18: LTE DL spectrogram observations. 30
Figure 19: Wi-Fi 20 MHz spectrograms.. 31
Figure 20: Wi-Fi 40 MHz spectrograms.. 31
Figure 21: Wi-Fi 80 MHz spectrograms.. 32
Figure 22: Null or no signal spectrograms... 32
Figure 23: Training data divided in class.. 34
Figure 24: Random observations for training. 35
Figure 25: GoogleNet network analysis. 37
Figure 26: GoogleNet validation accuracy and loss. 38
Figure 27: GoogleNet test image prediction accuracy... 40
Figure 28: AlexNet network analysis. 41
Figure 29: AlexNet validation accuracy and loss. 42
Figure 30: AlexNet test image prediction accuracy.. 44
Figure 31: ResNet-18 network analysis... 45
Figure 32: ResNet-18 validation accuracy and loss.. 46
Figure 33: ResNet-18 test image prediction accuracy. 48

List of Illustrations

Illustration 1: UTEP SDR Testbed. 15

Chapter 1: Introduction

A rapid development of wireless communication systems is being undertaken to meet the changing needs of individuals and businesses. Since wireless applications and services have grown to be more prevalent, it has become essential that the spectrum scarcity problem be addressed. In a study conducted by the Federal Communications Commission (FCC) of the United States telecommunications authority, it was found that licensed frequencies are not being used at a rate of as much as 90%. Results of the measurement have been reported in The FCC Spectrum Policy Task Force group report "The FCC Report of the Spectrum Efficiency Working Group" published by the FCC[1].

An essential step to enabling software defined radio-based cognitive radio and intelligent radio is the detection, classification, and characterization of wireless signals. The classification of signals in [2], [3] is based on machine learning algorithms in which features are defined by experts, before the model is trained. In recent years, deep learning (DL) has been explored as a method for classifying signals by learning features directly from data. Three main pretrained CNN DL algorithms are GoogleNet, AlexNet and ResNet-18 [4]–[6] CNNs are being used to solve a range of signal processing and classification problems with great success. A SDR system implementing a CNN has been proposed for use in classifying and coexistence of RF signals. The results of simulations provide a minimum classification accuracy of 90% [7].

The last few years have seen a lot of research done on the effectiveness of using these spectrum bands that are either unused or are not being used to their maximum potential. Mitola introduced the cognitive radio (CR) concept in 1999, which was considered an important concept in the research [8]. The software-based technology is able to detect the electromagnetic environment in which it operates, detect unused frequency bands, and adapt its radio working

parameters so that it broadcasts in those bands [9]. An opportunistic approach to using the limited and inefficiently used frequencies is the cornerstone of CR technology. Spectrum sensing plays an essential role in CR networks in maintaining communication performance and continuity.

Researchers, regulators, carriers, and manufacturers have been motivated by the limited spectrum available for cellular communications to investigate new spectrum and new ways to manage spectrum. A portion of 5 GHz unlicensed spectrum is currently being considered for LTE, which will have to coexist with Wi-Fi and different types of radar. In the US, the government has designated several bands for spectrum sharing, such as the new 3.5 GHz band and AWS-3. There are three tiers of spectrum access proposed by the Federal Communications Commission, among which incumbents have the highest priority to access the spectrum, followed by licensed secondary users, who will deploy LTE networks, and unlicensed opportunistic users [10].

SDR and CR technologies are driving the evolution of LTE due to frequency agility and extensive use of these technologies. Spectrum-aware LTE-U coexists with other systems in the 5 GHz band by regularly switching off its transmission. It has been proposed that different LTE-U variants accommodate the various regulations in different regions of the world [11]. Standards for this and other new LTE technologies need to be developed by combining theoretical and experimental research.

During the development of new technologies and systems, testbeds play a crucial role. By using these technologies in education, researchers can rapidly prototype and test their findings. In spite of the widespread availability of 4G/LTE services, LTE research and education has yet to reach saturation. On the path to 5G, this research propels the evolution of 4G cellular technology into new spectrum spaces and use cases.

Many methods have been explored to find a solution to the problem of a friendly coexistence between LTE and WiFi. In LTE, License Assisted Access (LAA) technology is an unlicensed band LTE technology that has Listen Before Talk (LBT) functions if the channel is not in use. In order to adapt to changes in the wireless environment, deep learning [12] has gradually been adapted to wireless communications [13], the Internet of things, and direction-of-arrival estimation [14] in the past few years.

It has been acknowledged that LTE operation in the unlicensed spectrum is a promising and effective solution that can assist in a more efficient exploitation of the wireless spectrum [15]. It has therefore drawn considerable attention from the wireless community, which has developed several approaches aimed at enabling harmonious coexistence between LTE and other well-established unlicensed technologies including Wi-Fi [16]. Depending on the regional regulations and the desired scenario, there are three predominant approaches for LTE operations in unlicensed spectrum. Listen Before Talk (LBT) is not required in regions where the regional regulations do not yet require it, such as in the United States or China, where it has been suggested that LTE could transmit in unlicensed frequencies through the use of duty-cycle techniques. Qualcomm has devised the carrier-sensing adaptive transmission (CSAT) [17], which is the most prominent technique of its kind. By leveraging duty-cycle periods to give other co-located networks transmission opportunities (TXOP), this technique builds upon elements of LTE Release 12 [18].

In contrast, the LTE Licensed Assisted Access (LTE LAA) standards were published by the 3GPP as part of its release 13 [19]. By implementing LTE LAA, the 3GPP hopes to create a coexistence technique that will comply with international regulations, including those in Europe and Japan that require an LBT procedure before transmitting in unlicensed spectrum. In order to transmit in the unlicensed spectrum, a LBT procedure, also known as a Clear Channel Assessment

(CCA) is required. Release 13 specifies that LTE LAA is to be used exclusively for downlink (DL) traffic in the unlicensed 5-GHz band at first. With Release 14, LTE LAA is supported both for downlink (DL) and uplink (UL) traffic [20]. Under LTE LAA, the evolved NodeB (eNB) is capable of activating and deactivating secondary cells adjacent to the primary cell in the licensed band owned by the operator as needed. Therefore, in accordance with Release 13, an operator can offload the LTE network by transferring DL data traffic over the Physical DL Shared Channel (PDSCH), while the LTE control signals and the UL traffic will be transmitted via the licensed anchor, ensuring timely, interference-free transmission.

Nevertheless, the wireless environment is inherently non-deterministic, since it is dynamic and constantly changing. There is always a possibility that users of networks will change frequently, that new networks may be launched, and that existing networks may be shut down. In addition, each node has a different amount of data to transmit and the load on the network is dynamic. A technique aimed at enabling coexistence of different wireless technologies in unlicensed spectrum must incorporate potential changes to the wireless environment. This article introduces a Convolutional Neural Network (CNN) [21] that is capable of enabling the transmission identification of both LTE and Wi-Fi networks. Spectrogram samples and frequency domain representation of the LTE and Wi-Fi signals from the testbed have been used to train and validate the designed CNN. A series of experiments is presented in this paper to achieve effective coexistence between LTE and Wi-Fi. A variation in the Signal to Noise Ratio (SNR) is used to test classification accuracy. The excellent feature extraction performance of CNNs makes these experiments feasible. CNN has demonstrated high accuracy in classification of LTE and Wi-Fi signals, thus ensuring a friendly coexistence of the two technologies.

A CNN-based SDR system implemented on two NI USRPs 2944 and N2954 radios programmed in LabVIEW is used to classify over-the-air signals in this paper using the MATLAB deep learning toolbox and a CNN-based SDR system. This demonstration highlights the feasibility of an accurate and reliable classification system for LTE and Wi-Fi signals. In this study, CNN has proven to be an effective candidate for detecting and classifying signals. The research provides a strong foundation for developing real-time signal classification systems using SDRs. The rest of this paper is organized as follows: In Chapter 2, we examine the literature related to coexistence of LTE and Wi-Fi. In addition, it describes several applications of deep learning in wireless networks. Chapter 3 introduces UTEP's SDR Testbed, LTE-U, the NI Application Frameworks and CNN, with references to their constituent elements and terms. In Chapter 4, the hardware setup and simulation software used to train and validate the CNN are discussed, as well as details of the application of the CNN. The simulation results are presented and discussed in Chapter 5, followed by a conclusion and future work in Chapter 6.

Chapter 2: Literature Review

2.1 Problem History

The Manual of Regulations and Procedures for Federal Radio Frequency Management describes the radio frequency standards for Aeronautical Mobile Telemetry (AMT) [22]. Radio frequency (RF) spectrum is used for a variety of applications, such as broadcasting, communication, and navigation. Standards define the equipment and frequencies to ensure interference-free use of the RF spectrum. These standards provide a general framework for data transfer and support between ranges, allowing for smooth test operations.

The reallocation of the Telemetry (TM) bands reduced the spectrum available for military use. Spectrum allocated for military use, such as 1695 - 1710 MHz, 1755 - 1780 MHz, and 2155 - 2180 MHz, was made available for commercial use. These bands were also known as AWS-3 bands and they were allocated during Auction 97 [23]. n total, 65 MHz of spectrum were specifically dedicated to meet the growing demand for wireless communications, ensuring high speeds and greater capacity.

Telemetry users experienced increased interference from adjacent spectrum users because of the spectrum loss. State-of-the-art radio devices can be used to measure the interference levels using the replicated real-time signal. Several methods can be employed to mitigate the interference, including guard bands and digital filtering techniques [24].

Smart wireless devices have shown an explosive growth trend recently due to the development and emergence of internet of things and big data technologies [25]. There is, however, a shortage of wireless spectrum resources, and they are slowly unable to meet the growing demand for bandwidth [26]. Mobile operators all face the same problem, which involves a limited spectrum resource and exponentially growing customer service demands [27].

Researchers are focusing their attention on fully utilizing unlicensed spectrum resources in an environment where the availability of licensed spectrum is limited [16] [17]. A key ingredient to solving the spectrum scarcity problem in next-generation wireless communications is LTE-U [30].

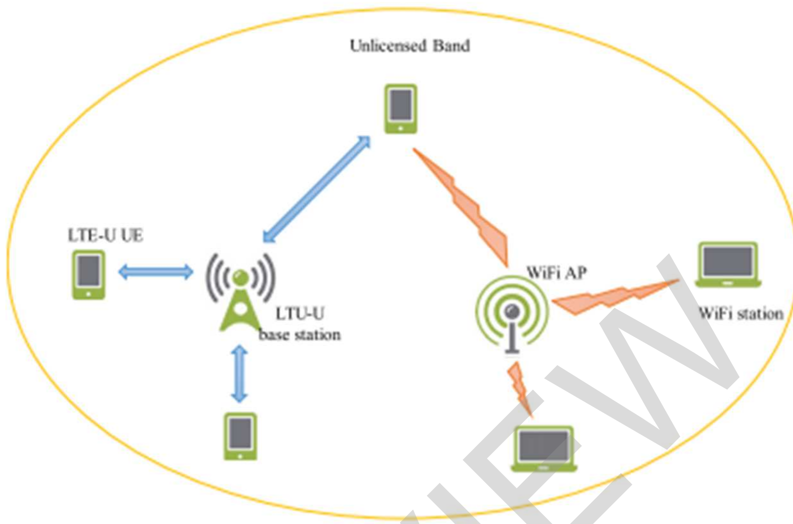

Figure 1: LTE and Wi-Fi coexistence system in unlicensed spectrum band[30].

Wi-Fi, however, is an important wireless technology in the unlicensed frequency band that is extensively used everyday [31]. It is readily available and has a large user base. In Figure 1, LTE-U shares channel resources with Wi-Fi as a result of LTE-U's implementation in unlicensed bands. The collision avoidance channel access method used in Wi-Fi is CSMA/CA [32]. With the existing LTE-U signal, its backoff mechanism will significantly adversely affect the performance of the Wi-Fi network, causing a decrease in Wi-Fi throughput as a result [33]. Over time, LTE-U can preempt channels, thereby consuming Wi-Fi channel resources in unlicensed bands [34], and causing non-negligible interference with Wi-Fi. LTE technology's biggest challenge in unlicensed bands is converging with Wi-Fi networks [35].

In this paper, a deep learning based CNN method is proposed to achieve friendly coexistence of LTE and Wi-Fi. Due to the outstanding performance of convolutional neural

networks (CNNs) in feature extraction. The proposed method can accurately classify the signals coexisting with LTE and Wi-Fi using spectrogram images, thereby achieving friendly coexistence of LTE-U/Wi-Fi signals.

2.2 Technology Foundation

The traditional radio devices have a simplified Communication System [36], which includes a message source, processing unit, transmitter, medium of transmission, a receiver, another processing unit, finally message destination as shown Figure 2. The message processing is the process of taking the source information and putting it into a format that can be transmitted over whichever medium is required. In a wireless or RF system, typical communication happens through free space or air, as opposed to through a cable/wire or a fiber network.

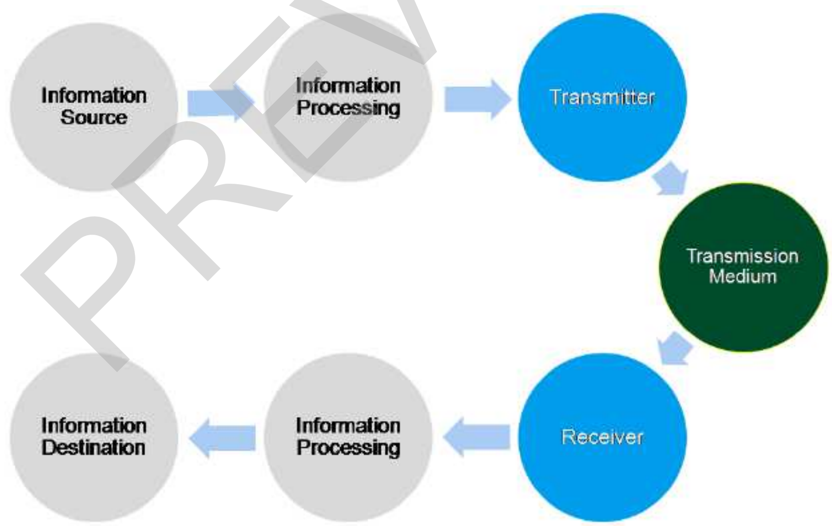

Figure 2: RF system with the transition of information from source to destination.

In early applications, it was more common to have a one-way path for the RF signals in RF design. Radio and television are good examples of the one-way path as large antennas transmitted signals one way to the radios and televisions. Today data is the major part of the communicated

information where there is a two-way path for the RF signals. Mobile smart phones are a great example of a device, which can both transmit and receive data.

In the early days of wireless communications, most signals were sine waves. A sine wave can be represented with a frequency, an amplitude, and a phase.

$$V = A\sin(\omega t + \varphi)$$

where A is the amplitude of the sine wave, $\omega = 2\pi f$ is the angular frequency, f is frequency and φ is the initial phase of the signal.

Figure 3 demonstrates two signals represented in the time domain. In terms of our communications system, the goal is to send message or information from a source to a destination by manipulating these sine waves. It is more often to have more complex digital signals nowadays.

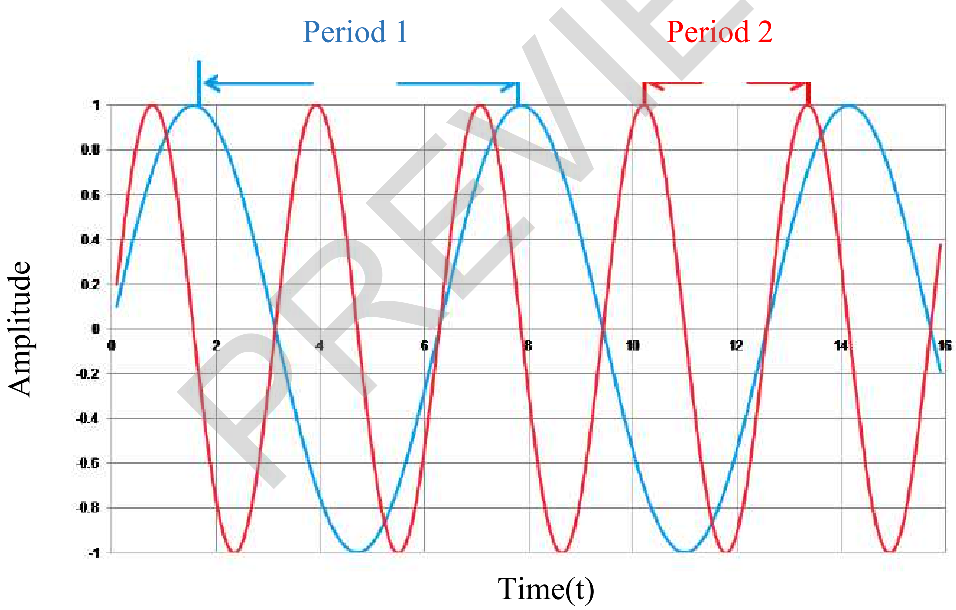

Figure 3: Sinusoidal waveforms with different time periods, sin(t) and sin(2t).

Typically, RF frequency domain is much preferred than the time domain. Figure 4 shows a spectrum sweep on a spectrum analyzer display. With the transmitted signals becoming more complex, modulated signals or signals with more information put on them, spectrum analyzer displays are better for understanding the multiple frequencies and modulation techniques. The

output of the spectrum analyzer gives the peak of the signal in dB, bandwidth of the signal occupied in the spectral band and the spacing between the signals.

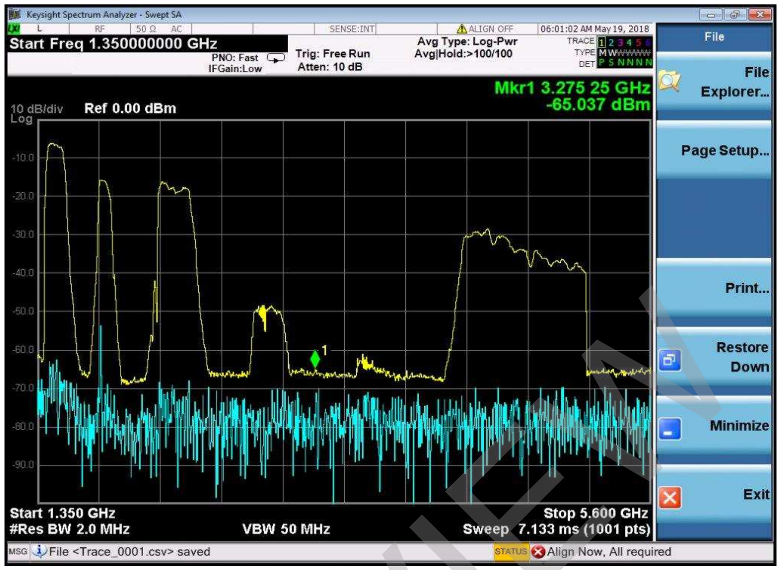

Figure 4: Spectrum sweep from 1.35 GHz to 5.60 GHz in RF band.

2.3 Related Work

The process of spectrum allocation and how the results are going to be obtained through a testbed is explained in this Journal [26]. The impacts of 4G LTE signal on Telemetry (TM) signal was analyzed and the results of how the TM system affected the LTE system, their rules of interaction in order to keep the LTE system at an acceptable performance, and a brief introduction into how these results will aid in the 5G technologies by implementing a similar testbed were explained in this ITC 2018 Paper [37]. For the interference mitigation of the LTE system on the TM system, different rules must be followed to protect the TM system. In the LTE system, interference from the TM system was felt instantaneously and the performance of the link suffered greatly, the spectrum graph of the LTE Rx displayed both TM and LTE signals simultaneously, and its effects were seen clearly. For the TM system, the LTE signal remains masked as noise to

the TM Rx, meaning that any LTE signal that gets closer and closer to the TM signal, will only be raising the noise level of the TM Rx, affecting its performance by increasing the FSER, reducing the channel capacity, and affecting the visual parameters such as the constellation and eye diagrams. Interference mitigation using digital filtering techniques were also explored in this Masters Theses and ITC 2019 Paper [38] [39].

Initially, when LTE was proposed to operate in unlicensed spectrum, serious concerns arose about unfair coexistence between LTE and other well-established technologies in the unlicensed spectrum such as Wi-Fi. The problems arise from the fact that LTE is a scheduled technology that operates in a licensed band, which means that no estimate of the availability of wireless channels can be made before transmission. Hence, arbitrary transmissions could force the nearby networks to continuously back off. An analysis of the impact of deploying a traditional LTE network using unlicensed spectrum is presented in [40]. An example is Commercial Off-The-Shelf (COTS) hardware used in LTE testbeds [41]. Three different levels of LTE signal power are examined in the study in order to find out whether LTE affects Wi-Fi to varying degrees. LTE appears to significantly interfere with the performance of Wi-Fi. The impact of LTE on Wi-Fi has also been demonstrated by a number of other studies [42]–[44] that evaluated the impact through experiments, mathematical analysis and simulations. In light of the results, it is clear that coexistence mechanisms are essential to enable spectral sharing between LTE and co-located technologies such as Wi-Fi in a fair and harmonious way.

The last few years have seen a number of coexistence mechanisms proposed with the goal of enabling LTE and Wi-Fi coexistence. The article [35] provides a detailed analysis of the coexistence between LTE and Wi-Fi on 5 GHz, as well as the related deployment scenarios. In the survey, key considerations regarding coexistence of LTE and Wi-Fi are detailed, including the

challenges, performance differences, and interference caused by cochannel. These authors cover in detail the various coexistence techniques that are discussed in the literature, and they analyze the concept of scenario-oriented coexistence. Based on this concept, different deployment scenarios can be used to solve coexistence problems.

The operation of LTE over unlicensed spectrum has been extensively investigated in [45]. In this article, the authors assess the current state of the art of coexistence between LTE and Wi-Fi. Furthermore, the article introduces a classification of techniques that can be used where Wi-Fi and LTE networks are overlapping. The literature review, coupled with a classification of the literature, revealed the lack of cooperation schemes between LTE and Wi-Fi that may help enable more effective use of wireless resources. To bridge this gap, several models of co-located LTE and Wi-Fi networks were proposed that can improve their spectral efficiency. Comparing the complexity and performance of each of the proposed methods, they are compared against each other.

The efforts to exploit unlicensed spectrum to optimize cellular networks is described in [46]. The 2.4 GHz band is an unlicensed spectrum that can be tapped by existing technologies (Wi-Fi) or by modification of existing cellular networks directly at the PHY and MAC layers. In the wake of this latter approach, cellular and Wi-Fi ecosystems differ about how it will impact existing and future Wi-Fi networks. The paper describes such a testbed platform utilizing National Instruments (NI) SDR hardware and NI LabVIEW Communications System Design Suite at the University of Texas at El Paso (UTEP), El Paso, Texas.

Almeida et al. [47] describe a coexistence mechanism that takes advantage of periodically blank subframes within an LTE frame to operate similarly to the CSAT mechanism. W i-Fi can

access the medium through these frames. Based on simulation results, the order and number of black subframes contribute to the performance of coexistence.

In several papers, the concept of channel estimation by LTE has been shown to enable coexistence. Kim et al. [48]suggest a LBT scheme for LTE that includes two components, on-off adjustment for channel utilization time and short-long adjustment for inactivity time. A LBT Category 4 (Cat 4) channel access scheme for LTE is proposed by Hao et al. [49]. Based on simulation results, the proposed LBT scheme for LTE LAA achieves better performance than fixing the Contention Window (CW) size.

In the last decade, deep learning has been widely applied in areas such as computer vision [50] and language processing [51], [52]. Furthermore, to date, deep learning algorithms have achieved or even exceeded human accuracy levels for these applications [53]. Due to that, wireless communication engineers are adopting neural networks to enhance their use of wireless networks for functions such as channel prediction, decoding, quantization, modulation recognition, and technology recognition [54].

One of the first approaches in this domain was presented in [55]. For radio modulation classification, the authors propose a CNN trained from I/Q data. The authors demonstrate how the proposed solution is superior to traditional methods, notably at low SNR. A CNN system developed by Zhang et al. [56] identifies eight types of signals. The proposed architecture enables the CNN classifier to achieve an overall recognition ratio of 93.7% when the SNR is 2 dB or higher. Kulina et al. [57] present an end-to-end learning framework for identifying wireless signals based on spectrum data, which enables various identification tasks. The article explains how machine learning, deep learning, and CNNs work and proposes a model of how they may be applied to spectrum monitoring.