

Assessing the Impact of Wi-Fi Radio Frequency Interference on Mobile Application  
Quality of Experience

by

Brennen Chow

B.Eng., University of Victoria, 2010

A Thesis Submitted in Partial Fulfillment of the  
Requirements for the Degree of

MASTER OF APPLIED SCIENCE

in the Department of Electrical and Computer Engineering

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Supervisory Committee

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Dr. Thomas E. Darcie, Co-Supervisor  
(Department of Electrical and Computer Engineering)

---

Dr. Stephen W. Neville, Co-Supervisor  
(Department of Electrical and Computer Engineering)

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Dr. Thomas E. Darcie, Co-Supervisor

(Department of Electrical and Computer Engineering)

---

Dr. Stephen W. Neville, Co-Supervisor

(Department of Electrical and Computer Engineering)

## ABSTRACT

This thesis assesses the impact of Wi-Fi radio frequency interference (RFI) on mobile application quality of experience (QoE). Wi-Fi is a wireless radio network for transferring data between two end points and is based on the IEEE 802.11 standards and operates in the unlicensed 2.4 GHz and 5 GHz radio frequency bands. This thesis explores the QoE of mobile applications when considering the impact of RFI caused by Wi-Fi access points (WAPs) within a campus Wi-Fi network. The research was conducted to assess the effect of RFI on mobile application network performance metrics. This is evaluated by collecting broadcasted WAPs within a campus network, assessing the experienced RFI, and evaluating the mobile application QoE at specific locations to assess the impact of the experienced interference.

# Contents

<b>Supervisory Committee</b>	<b>ii</b>
<b>Abstract</b>	<b>iii</b>
<b>Table of Contents</b>	<b>iv</b>
<b>List of Tables</b>	<b>viii</b>
<b>List of Figures</b>	<b>ix</b>
<b>Acknowledgements</b>	<b>xii</b>
<b>Dedication</b>	<b>xiii</b>
<b>1 Introduction</b>	<b>1</b>
1.1 Statement of Problem . . . . .	1
1.2 Goal . . . . .	2
1.3 Background . . . . .	3
1.3.1 Growth of Mobile Devices . . . . .	4
1.3.2 Growth of Mobile Data Traffic . . . . .	6
1.3.2.1 Increased Mobile Network Connection Speed . . . . .	6
1.3.2.2 Multi-Device Users . . . . .	7
1.3.2.3 Increased Mobile Dependency . . . . .	7
1.3.2.4 Growth of Mobile Video Data Traffic . . . . .	8

1.3.3	Roll of Data Offload to Wi-Fi . . . . .	9
1.4	Problem Space . . . . .	10
1.4.1	Wi-Fi . . . . .	11
1.4.2	Wi-Fi Offload . . . . .	13
1.4.3	Radio Frequency Interference (RFI) . . . . .	14
1.4.4	Mobile Application Quality of Experience (QoE) . . . . .	15
1.4.5	Quality of Experience (QoE) versus Quality of Service (QoS) . . . . .	17
1.5	Summary of Thesis . . . . .	18
1.6	Thesis Outline . . . . .	19
<b>2</b>	<b>Literature Review</b>	<b>20</b>
2.1	Mobile Crowd Sensing . . . . .	20
2.2	Client-Based Data Collection . . . . .	21
2.3	Wireless Performance Monitoring . . . . .	22
2.4	Crowdsourcing Cellular Performance Monitoring . . . . .	23
2.5	Crowdsourcing Wi-Fi Performance Monitoring . . . . .	24
2.6	Mobile User Experience Measurement . . . . .	25
2.7	Chapter Summary . . . . .	26
<b>3</b>	<b>Methodology</b>	<b>28</b>
3.1	Approach Outline . . . . .	28
3.2	Experimental Setup . . . . .	29
3.2.1	Equipment Used . . . . .	30
3.2.2	Software Used . . . . .	32
3.2.2.1	Mobile Wi-Fi Scan Measurement Application . . . . .	32
3.2.2.2	Mobile QoE Measurement Application . . . . .	33
3.2.2.3	Post-Processing Software . . . . .	34

3.3	Analysis Procedure . . . . .	35
3.3.1	Wi-Fi Radio Frequency Conflicts . . . . .	35
3.3.2	Application QoE . . . . .	37
3.4	Chapter Summary . . . . .	38
<b>4</b>	<b>Results</b>	<b>39</b>
4.1	RFI Location Evaluation . . . . .	39
4.1.1	Wi-Fi Scan Locations . . . . .	39
4.1.2	QoE Test Locations . . . . .	47
4.1.3	RFC Locations of Interest . . . . .	49
4.2	Low Interference Location . . . . .	55
4.2.1	WAP Distribution . . . . .	55
4.2.2	QoE Distribution . . . . .	56
4.3	Medium Interference Location . . . . .	59
4.3.1	WAP Distribution . . . . .	59
4.3.2	QoE Distribution . . . . .	60
4.4	High Interference Location . . . . .	63
4.4.1	WAP Distribution . . . . .	64
4.4.2	QoE Distribution . . . . .	65
4.5	Analysis of Results . . . . .	68
4.5.1	Download Throughput . . . . .	70
4.5.2	Upload Throughput . . . . .	71
4.5.3	Latency . . . . .	73
4.6	Chapter Summary . . . . .	75
<b>5</b>	<b>Epilogue</b>	<b>78</b>
5.1	Evaluation of the Results . . . . .	78

5.2	Limitations . . . . .	79
5.3	Conclusions . . . . .	80
5.4	Future Work . . . . .	81
	<b>Bibliography</b>	<b>83</b>

# List of Tables

Table 1.1	Forecasted Smart Connected Device Market by Product Category, Unit Shipments, and Market Share 2013 to 2017 [1]	5
Table 1.2	Wi-Fi Generations . . . . .	12
Table 3.1	Mobile Devices Used for Data Collection . . . . .	31
Table 4.1	WAP Location Summary from December 10-21, 2012 and January 7-May 31, 2013 . . . . .	42
Table 4.2	QoE Test Location Summary from December 10-21, 2012 and January 7-May 31, 2013 . . . . .	49
Table 4.3	RFI Locations of Interest . . . . .	53
Table 4.4	Low Interference QoE Summary . . . . .	59
Table 4.5	Medium Interference QoE Summary . . . . .	63
Table 4.6	High Interference QoE Summary . . . . .	68
Table 4.7	Summary of RFI Study Location Measurements . . . . .	69

# List of Figures

Figure 1.1	Forecasted Market Share by Product Category 2012 to 2017[1]	5
Figure 1.2	Global Mobile Data Traffic Growth [2]	6
Figure 1.3	Mobile Application Usage Growth [3]	8
Figure 1.4	Video Mobile Data Traffic Growth [2]	9
Figure 1.5	Mobile Data Offload Growth [2]	10
Figure 1.6	IEEE 802.11 b/g Channels [4]	12
Figure 3.1	Data Collection Route	30
Figure 3.2	Nexus S	31
Figure 3.3	Nexus 4	31
Figure 3.4	Ookla Speed Test Android Mobile Application [5]	33
Figure 4.1	Wi-Fi Scan Test Locations	41
Figure 4.2	WAPs Profile at 48.4615, -123.3110	43
Figure 4.3	WAPs Profile at 48.4615, -123.3115	43
Figure 4.4	WAPs Profile at 48.4633, -123.3105	43
Figure 4.5	WAPs Profile at 48.4635, -123.3105	43
Figure 4.6	WAPs Profile at 48.4640, -123.3100	44
Figure 4.7	WAPs Profile at 48.4640, -123.3115	44
Figure 4.8	WAPs Profile at 48.4645, -123.3115	44
Figure 4.9	WAPs Profile at 48.4645, -123.3120	44
Figure 4.10	WAPs Profile at 48.4650, -123.3115	45

Figure 4.11	WAPs Profile at 48.4658, -123.3075 . . . . .	45
Figure 4.12	WAPs Profile at 48.4660, -123.3080 . . . . .	45
Figure 4.13	WAP Location Summary Plot . . . . .	46
Figure 4.14	QoE Test Locations . . . . .	48
Figure 4.15	QoE Distribution at 48.4615, -123.3110 . . . . .	50
Figure 4.16	QoE Profile at 48.4615, -123.3115 . . . . .	50
Figure 4.17	QoE Profile at 48.4633, -123.3105 . . . . .	50
Figure 4.18	QoE Profile at 48.4635, -123.3105 . . . . .	50
Figure 4.19	QoE Profile at 48.4640, -123.3100 . . . . .	51
Figure 4.20	QoE Profile at 48.4640, -123.3115 . . . . .	51
Figure 4.21	QoE Profile at 48.4645, -123.3115 . . . . .	51
Figure 4.22	QoE Profile at 48.4645, -123.3120 . . . . .	51
Figure 4.23	QoE Profile at 48.4650, -123.3115 . . . . .	52
Figure 4.24	QoE Profile at 48.4658, -123.3075 . . . . .	52
Figure 4.25	QoE Profile at 48.4660, -123.3080 . . . . .	52
Figure 4.26	WAP Histogram for Three Locations of Interest . . . . .	53
Figure 4.27	RFI Locations at the University of Victoria . . . . .	54
Figure 4.28	Low Interference WAP Profile . . . . .	56
Figure 4.29	Low Interference QoE Scatter Plot . . . . .	57
Figure 4.30	Low Interference QoE Histogram . . . . .	58
Figure 4.31	Medium Interference WAP Profile . . . . .	60
Figure 4.32	Medium Interference QoE Scatter Plot . . . . .	61
Figure 4.33	Medium Interference QoE Histogram . . . . .	62
Figure 4.34	High Interference WAP Profile . . . . .	64
Figure 4.35	High Interference QoE Scatter Plot . . . . .	66
Figure 4.36	High Interference QoE Histogram . . . . .	67

Figure 4.37 Download Throughput Distribution versus Number of WAPs .	71
Figure 4.38 Upload Throughput Distribution versus Number of WAPs . .	73
Figure 4.39 Latency Distribution versus Number of WAPs . . . . .	75

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## DEDICATION

I dedicate this thesis to my Mom, Dad, and Sister for all the love and support they have provided me throughout my education, career, and life. I would not be able to accomplish so much without you all.

# Chapter 1

## Introduction

This chapter introduces the main goal of the thesis and explores the details of the problem to be solved. The background technology and state of the art industry space of mobile device growth, data usage growth, and data offload is also described. Finally the problem space is presented and placed in context of the industry background and current research and technologies.

### 1.1 Statement of Problem

The goal of this thesis is to assess the impact of Wi-Fi radio frequency interference (RFI) on mobile application quality of experience (QoE). Wi-Fi is a wireless radio network for transferring data between two end points and is based on the Institute of Electrical and Electronics Engineers' (IEEE) 802.11 standards. Wi-Fi networks operate in the unlicensed 2.4 GHz and 5 GHz radio frequency bands. Many other devices also operate in the 2.4 GHz band such as microwave ovens, ISM band devices, security cameras, ZigBee devices, Bluetooth devices, cordless phones and baby monitors. These devices along with the Wi-Fi wireless access points (WAPs), electromagnetic interference, or RFI, impact the QoE experienced by Wi-Fi devices

on the Wi-Fi network. More generally, such networks tend to give rise to interference-limited, as opposed to noise-limited communication systems [6].

This thesis explores the QoE of mobile applications when considering the impacts of RFI caused by WAPs within a campus Wi-Fi network. The research was conducted to assess the effect of RFI on mobile application network performance measures. This is evaluated by collecting broadcasted WAPs within a campus network, plotting the experienced RFI, and evaluating the network performance at specific locations to test the impact of the interference.

## 1.2 Goal

The goal of this thesis is to assess the impact of Wi-Fi RFI on mobile application QoE. This thesis proposes that information regarding the RFI between WAPs is necessary in order to maintain mobile application QoE within a Wi-Fi network for Wi-Fi offload policy. The mobile application QoE is defined for the purpose of this thesis as the upload throughput, download throughput, and latency experienced by the mobile device on the application layer of the operating system.

The approach outlined in this thesis uses information regarding WAP properties such as BSSID, SSID, and frequency to establish an RFI plot of a campus Wi-Fi network. This WAP information is collected using an Android mobile device application for analysis. An algorithm was developed to plot WAP interferences to evaluate mobile device QoE at locations of interest. These locations are of interest because of their potential that RFI may cause network performance problems.

## 1.3 Background

Wireless service providers are experiencing an exponential growth in mobile data usage. This has left wireless service providers with the sizeable task of coping with unprecedented levels of infrastructure strain while simultaneously facing an ever increasing gap between data usage and generated revenue [7]. This ongoing congestion concern has been exacerbated by the growing use of devices (such as smartphones, tablets, data heavy applications, USB dongles, etc), all of which ultimately impacts customer quality of service. As a result, service providers are now turning to new and innovative solutions for maintaining client service quality while minimizing incurred costs.

One such wireless service provider solution involves bypassing congested and expensive cellular networks by connecting to and streaming data over the growing number of non-cellular access points, such as WiMAX and WLAN. This process of transferring cellular network connections and data flows to other networks to reduce congestion is known as data offload. Ultimately, this requires a connection manager on a device, governed by an offloading policy, to facilitate the transfer of data traffic and network connections between cellular and non-cellular networks.

The goal of a mobile device connection manager is to maintain or increase the level of QoE delivered to the user. This can be accomplished by directing all or part of the device data traffic over specific network connections. Having an understanding of QoE as experienced by the end user of the device is essential to the operation and functionality of the connection manager. The last thing a user wants is to be switched to a less adequate network for their particular location, applications, or user behaviour.

### 1.3.1 Growth of Mobile Devices

Mobile devices have transformed from the days of pure cordless phones. A mobile device is much harder to define in today's commercial marketplace. Mobile devices have become the primary mechanism for content consumption, data storage, and delivery of all kinds of music, games, Internet browsing, file sharing, productivity applications, etc. Manufacturers continue to push the limit of new features year after year as they deliver new, ground-breaking products to a population of eager early adopters. These devices introduce different form factors and increased capabilities and intelligence into the marketplace.

The smart devices span PCs, tablets, and smartphones, as well as other forms of emerging devices. In 2013, 1.6 billion of these devices were shipped with smartphones make up 65.1% share and tablets 14.6% [1], while desktop PCs and portable PCs make up 8.6% and 11.6% [1]. IDC forecasts that shipments of PCs will be exceeded by tablet shipments by the end of 2015 on an annual basis, whilst smartphones will exceed 1.4 billion units [1]. Looking forward to 2017, tablets and smartphone shipments will account for 16.5% and 70.5% of the 2,460 million devices shipped [1]. From 2013 to 2017, the growth in tablet shipments is expected to be 78% while smartphone shipment growth is equal to 71%.

The growth in market share of smart connected devices year-over-year is summarized in Figure 1.1 and in Table 1.1. It is safe to say that one of the primary contributors to data traffic growth is the increasing number of wireless devices accessing mobile networks [2].

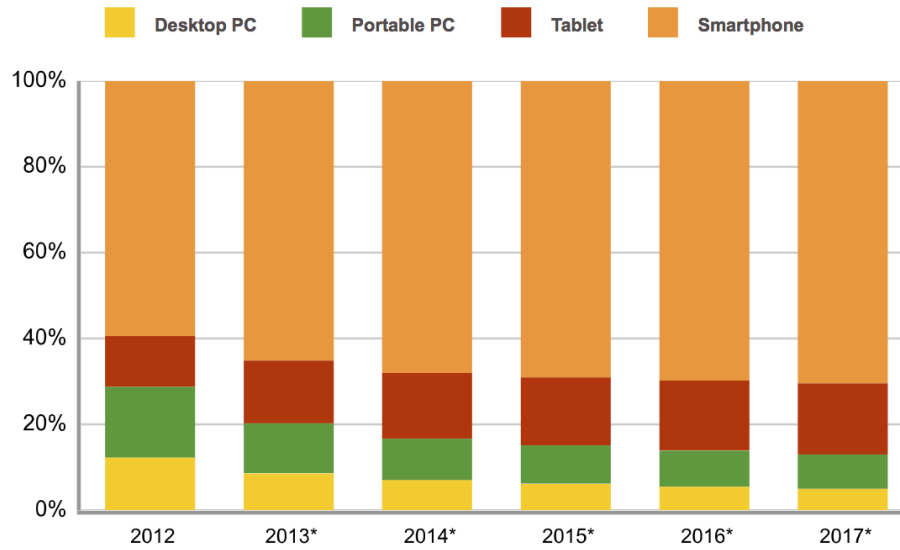


Figure 1.1: Forecasted Market Share by Product Category 2012 to 2017[1]

Product Category	2013 Unit Shipments	2013 Market Share	2017 Unit Shipments	2017 Market Share	2013 to 2017 Growth
Desktop PC	134.4M	8.6%	123.11 M	5%	-8%
Portable PC	180.9M	11.6%	196.6 M	8%	8%
Tablet	227.3M	14.6%	406.8 M	16.5%	78%
Smartphone	1,013.2 M	65.1%	1,733.9 M	70.5%	71%
<b>Total</b>	<b>1,556</b>	<b>100%</b>	<b>2,460.5</b>	<b>100%</b>	<b>58%</b>

Table 1.1: Forecasted Smart Connected Device Market by Product Category, Unit Shipments, and Market Share 2013 to 2017 [1]

### 1.3.2 Growth of Mobile Data Traffic

It is not surprising then that total data transmission demands from mobile phones roughly doubles each year. Latest estimates indicate that data demands may increase 20x over the next five years [2]. A recent report by Cisco estimates that in 2019 the overall mobile data traffic growth will be a 10-fold increase from 2014. This amounts to 24.3 exabytes per month as in Figure 1.2 [2]. From 2014 to 2019, the growth in mobile data traffic will be at a compound annual growth rate of 57 percent. There are notable trends that are associated with the growth in mobile data usage as discussed below.

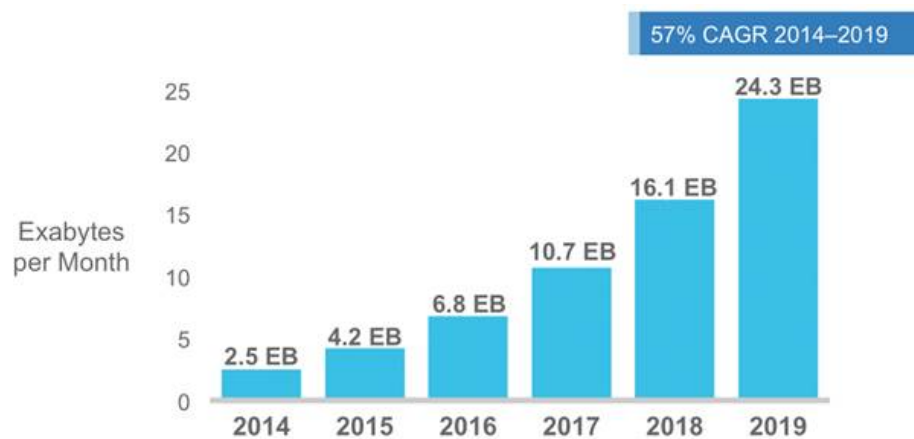


Figure 1.2: Global Mobile Data Traffic Growth [2]

#### 1.3.2.1 Increased Mobile Network Connection Speed

As technology advances and mobile network connection speeds increase, a proportional increase in content bit rate is expected [2]. With the increase in speed and bit rate, the demand for high-definition video and streamed video increases in concert. This shift towards on-demand video expands the proportion of streamed content compared to sideloaded content or transferred from a computer to the

mobile device. This is a result of climbing average mobile network connection speeds to transfer content.

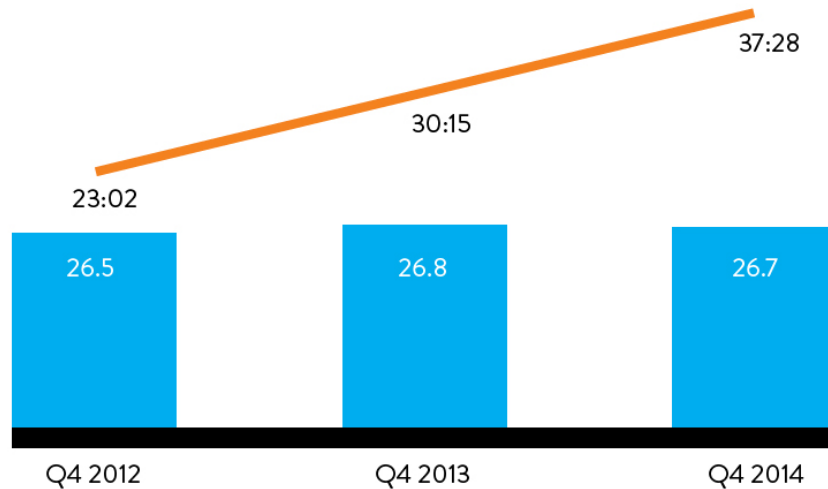
### **1.3.2.2 Multi-Device Users**

The decrease in mobile technology costs and the growth in the number of multiple-device users has also contributed to the increase in mobile data usage [2]. This trend has led operators to offer mobile broadband packages with comparable price and speed to fixed broadband. Making mobile data more accessible and allowing it to act as a substitute for fixed broadband.

### **1.3.2.3 Increased Mobile Dependency**

The growth in multi-device users also increases a user's contact time with the network. This increased contact time leads to an escalation in time of use per user and, therefore, an escalation in the amount of mobile data traffic [2]. In parallel, data hungry applications are taking over mobile devices and user contact time [3]. These applications include location-based services, mobile-only games, social services, and mobile commerce applications. This is fostering an ever increasing dependency on mobile devices and mobile data. As found in Nielsen's recent report on mobile app usage, smartphone users have spent on average of 37 hours and 28 minutes per month using an average of 26.7 apps per month as illustrated in Figure 1.3 in Q4 2014 [3]. This is an increase from 23 hours and 2 minutes in Q4 2012 two years later.

## AVERAGE NUMBER OF APPS USED AND TIME PER PERSON PER MONTH



Read As: In Q4 2014, smartphone users accessed 26.7 apps per month on average, and spent 37 hours and 28 minutes per month on apps.

Source: Nielsen

Copyright © 2015 The Nielsen Company

Figure 1.3: Mobile Application Usage Growth [3]

### 1.3.2.4 Growth of Mobile Video Data Traffic

As previously mentioned, the increased mobile network connection speeds are shifting demand for high-definition on-demand video content. In addition, mobile video content is transmitted at much higher bit rates than other mobile data types. As a result of these trends, it is not surprising that mobile video traffic is expected to generate a larger portion of the overall data traffic. In 2019, it is estimated that over two-thirds (72%) of the mobile data traffic will be associated with video as

illustrated in Figure 1.4. This is estimated to equal 17.4 exabytes of mobile video traffic per month compared to a overall total of 24.3 exabytes of mobile data traffic per month [2].

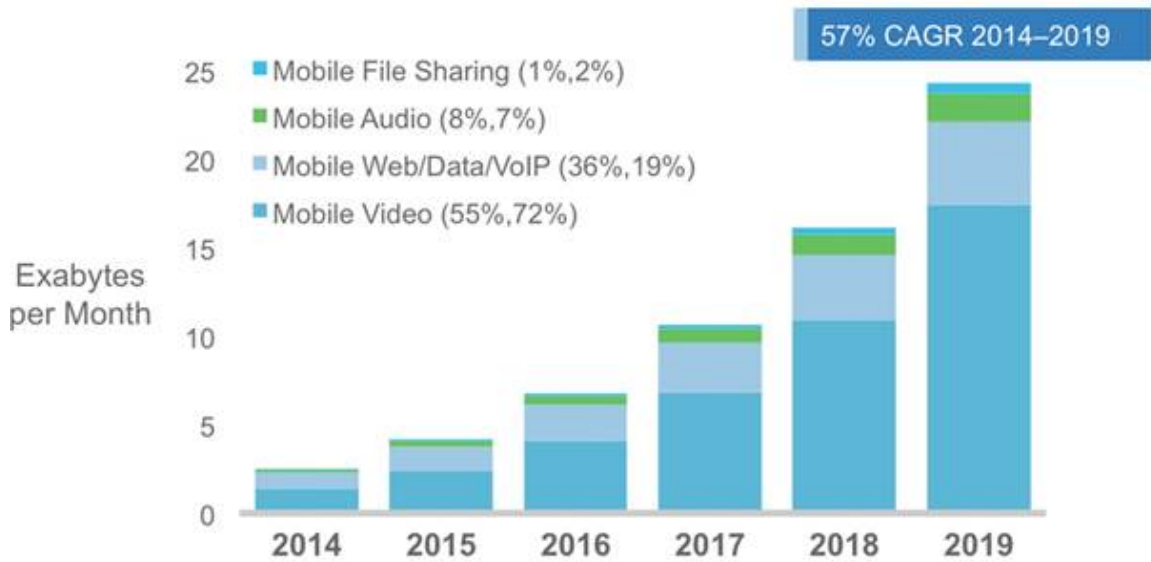


Figure 1.4: Video Mobile Data Traffic Growth [2]

### 1.3.3 Roll of Data Offload to Wi-Fi

It is estimated 54% of the total overall mobile data traffic will be offloaded to Wi-Fi access points or fixed broadband networks by 2019 as illustrated in Figure 1.5. This progression can be linked to users using and connecting with fixed networks or Wi-Fi access points at home where generally much more mobile data activity takes place. It can also be linked to the increased deployment of service provider-owned femtocells, picocells, and Wi-Fi access points to combat the escalating mobile data traffic.

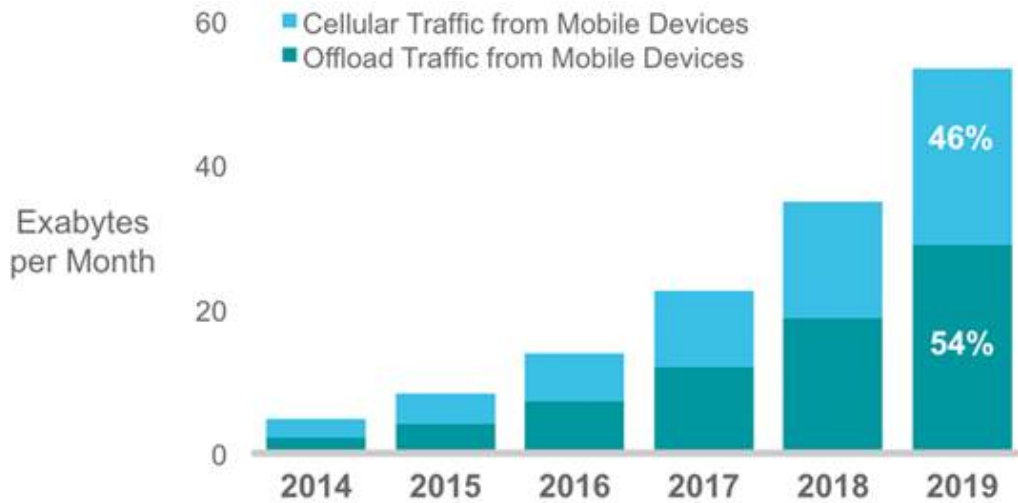


Figure 1.5: Mobile Data Offload Growth [2]

## 1.4 Problem Space

The increasing amount of data being transmitted over the cellular infrastructure is a major problem for mobile service providers. When the majority of global cellular networks were engineered and installed the smartphone did not exist. Legacy cellular infrastructure does not have the bandwidth to support smartphones and the data traffic that is generated. Consequently, network upgrades to newer generations (such as the Long Term Evolution (LTE) or 4G standards) or alternative networks (such as Worldwide Interoperability for Microwave Access (WiMAX) or Wi-Fi standards) are required. These upgrades are expensive and the majority of profits generated from these new bandwidth hungry features do not go to the mobile service providers. Instead, profits go to the mobile device manufactures and a newly developed community of mobile application developers. The result for mobile service providers is a growing gap between additional data to support and additional

revenue received. In many cases it is difficult to afford the necessary cellular network upgrades needed to keep up with modern bandwidth data demands.

The increasing gap between profits and costs are magnified by the costs of upgrading legacy cellular infrastructure, expensive cell site leasing, and the not in my backyard mentality. These factors have led mobile service providers to begin turning to smaller, more cost effective technologies to alleviate their bandwidth crunch. Femtocells, picocells, WiMax and Wi-Fi, which are all less expensive than traditional cellular radio towers and cells, may provide the answer. However, despite the lower cost for bandwidth, it is not yet clear how to make these technologies behave as seamless extensions to normal cellular networks. True seamlessness requires that users are able to move between network types and access points smoothly without risk of service interruptions or delays.

### **1.4.1 Wi-Fi**

Wi-Fi is a wireless radio network for transferring data between two end points and is based on the Institute of Electrical and Electronics Engineers' (IEEE) 802.11 standards. Wi-Fi networks operate in the unlicensed 2.4 GHz and 5 GHz radio frequency bands. Wi-Fi technology has followed four generations. Each generation, as illustrated in Table 1.2, is defined by enhanced performance, frequency, bandwidth, and security. This thesis focuses on the commonly used IEEE 802.11 b/g standards.

The IEEE 802.11 b/g spectrum is divided into 14 partial overlapping channels as illustrated in Figure 1.6. Each channel is spaced 5 MHz apart from the next, with a total width of 22 MHz. As a result, only three channels do not overlap, channels 1, 6, and 11. General WAPs are deployed on one of these three channels to avoid RFI within a Wi-Fi network. Overlapping channels can cause degradation in signal

quality, throughput, and over all QoE delivered to the end user devices [4]. This is otherwise known as the 2.4 GHz Wi-Fi band.

IEEE Standard	Frequency Band	Bandwidth or maximum data rate	Year Introduced
802.11a	5 GHz	54 Mbps	1999
802.11b	2.4 GHz	11 Mbps	1999
802.11g	2.4 GHz	54 Mbps	2003
802.11n	2.4 GHz, 5 GHz, 2.4 or 5 GHz (selectable), or 2.4 and 5 GHz (concurrent)	450 Mbps	2009

Table 1.2: Wi-Fi Generations

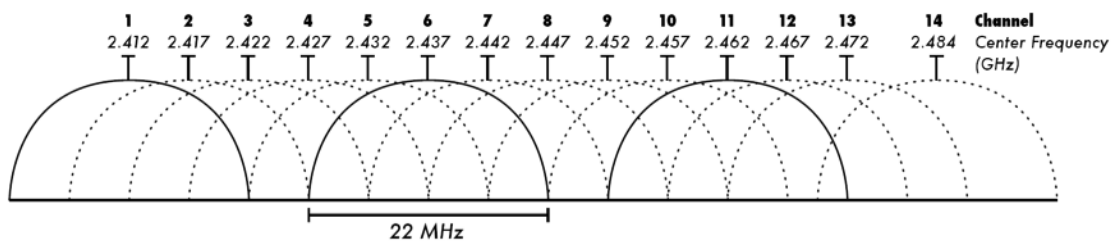


Figure 1.6: IEEE 802.11 b/g Channels [4]

### 1.4.2 Wi-Fi Offload

Systems designed to manage the network connections of wireless devices, or data offload, operate based on connection policies. These policies outline the actions to be taken when certain conditions are met. Many of these systems make use of a policy type that sets a prioritized list of networks for connections. This lets service providers ensure that their access points are always preferred by their clients. It also allows them to set preferred roaming partners. For users, it provides a mechanism for prioritizing the use of known home or work access points [8].

Connection policy can be appropriately enforced by connection managers to ensure that data offload does not interrupt the user's experience, and that their expected quality of service is provided on the new access network. Current technology in offloading presupposes relatively static policies that are structured to manage issues within the context of a specific communications network [8]. These offload policies specify the access points to which wireless devices should connect to and are limited to one aspect of this network.

The current offload policy technologies do not comprise the development of advanced connection policies based on a composite of information:

- Collected from multiple networks and network access points.
- Available from 3rd party sources (i.e., non-network and non-wireless device based information sourced).
- Available from multiple mobile devices in a network, whether or not they are receiving wireless network services.

Many data offload and policy enforcement processes rely heavily on knowing the devices' locations. It is one of the most common measures for determining whether or not a particular policy should be enforced. However, existing methods for determining

device location have some inherent issues. GPS radios used in devices drain batteries quickly and GPS locations are often inaccurate [9], especially in dense urban areas. Finding device location based on a triangulation process with nearby cellular towers or Wi-Fi access point signals are likewise often inaccurate [9]. Inaccuracies in device location are problematic for data offloading solutions that attempt to make very precise decisions about when and how mobile devices should transition over to Wi-Fi networks. Therefore connection polices must leverage the relative location of the wireless environment as experienced by the mobile device.

To date, offload policy servers have been limited in scope and have not fully leveraged the improvements to policy enforcement processes that are achievable through the dynamic analysis of operations data from all related devices and systems to incorporate the complexity of real world radio propagation.

### **1.4.3 Radio Frequency Interference (RFI)**

Radio frequency interference (RFI) is also know as electromagnetic interference (EMI). RFI is any electromagnetic disturbance that interrupts, obstructs, or otherwise degrades or limits the effective performance of electronics and electrical equipment. It can be induced intentionally, as in some forms of electronic warfare, or unintentionally, as a result of spurious emissions and responses, and intermodulation products. In the case of the 2.4 GHz Wi-Fi band, RFI is generally caused unintentionally by Wi-Fi wireless access points (WAPs) on the same channel.

The QoE of a Wi-Fi connection can decreased or be disrupted in the presence of other 2.4 GHz devices in the same area. Many 2.4 GHz Wi-Fi band 802.11b and 802.11g WAPs default to the same channel on initial startup, particularly channels 1, 6 and 11. This further contributes to congestion on these popular channels. An excessive number of WAPs in the area, especially on a neighbouring channel, known

as "Wi-Fi pollution," can prevent access and interfere with other devices' use of other WAPs. This is caused by overlapping channels in the 802.11b/g spectrum, as well as with decreased signal-to-noise ratio (SNR) between WAPs. Each issue can contribute to decreased QoE for users of the Wi-Fi network. This can become a problem in high-density areas, such as large apartment complexes, office buildings, or university campuses with many Wi-Fi WAPs.

Many other devices also operate in the 2.4 GHz Wi-Fi band such as microwave ovens, ISM band devices, security cameras, ZigBee devices, Bluetooth devices, cordless phones and baby monitors. These devices along with the Wi-Fi WAPs can cause electromagnetic interference, or RFI, thus negatively impact the QoE of Wi-Fi devices on the Wi-Fi network on the same frequency.

#### **1.4.4 Mobile Application Quality of Experience (QoE)**

Small cell networks are composed of distributed femtocells, picocells, WiMax or Wi-Fi, etc with a centralized base controlled and managed by the mobile service provider. Small cell networks have grown in popularity because mobile service providers are using them to extend service coverage and/or increase network capacity. Nonetheless, small cell networks have not achieved their full potential as better priced alternatives to cellular networks. Mobile service providers seeking to use small cell networks collaboratively with their cellular networks using data offload solutions are faced with a few major challenges.

The first challenge is that small cells have much smaller and less predictable signal radius than full scale cellular towers. As a result, the average duration of a connection to a small cell is much shorter. When using a small cell network, mobile devices must regularly bounce between wireless access points and network access technologies. This is known as network ping-pong, causing complications with the user experience if the

switches between available networks are not seamless [10]. For this reason, mobile service providers must find new and innovative processes for managing users travelling through small cell networks to preserve quality of user experience. Service providers must also strive to pro-actively design small cell networks for this type of activity and understand when offloading from 3G/4G is appropriate.

The second challenge for small cell networks is that devices users will not accept having poor network service only to then be offloaded to a new network with even worse performance. As a result, new levels of user QoE understanding is required for these offloading solutions to be used and deployed successfully with a means of measuring user-perceived QoE on connected networks. Unfortunately, such QoE measures are difficult to obtain. The service quality that a network service provider observes from the network access points is often not reflective of what is actually being experienced on the mobile device. This is because the access point perspective is only limited to what is connected to the access point and in range of WAP signal. For this reason it is important for network service providers to fully understand what gives rise to these differences between user-viewed and network-viewed QoE so that operators can correctly influence their client's network connection decisions.

Service providers currently rely on network analytics for activities spanning from engineering operations planning to designing targeted marketing campaigns. It is important to note that current network analytics mainly rely on network-side measures for analysis because they do not capture information from the mobile device itself. Performance readings measured directly on the device are more representative of what the user is actually experiencing than readings taken anywhere else. Many issues give rise to the differences between network-side and device-side readings, one of which is wireless signal interference. It is important to

note that current network analytics are not designed specifically for the needs of offloading solutions or the users of offloading solutions.

Device-side QoE measurement has been limited to date. This is mainly due to the lack of devices capable of performing such measurements. Device improvements and increased capable of measuring, storing, and transferring data in a meaningful way without negatively impacting battery performance or memory usage of the device have made new applications possible. Technology advantages have made it possible for newer devices to be used as measurement devices. In addition, the mobile device, specifically the applications running on the mobile device, influence the user's perceived QoE of the operators network. Maintaining a level of satisfactory QoE from this perspective is best accomplished by understanding what exactly is happening and being experienced on the mobile device.

#### **1.4.5 Quality of Experience (QoE) versus Quality of Service (QoS)**

The current definitions and differences of quality of service (QoS) versus quality of experience (QoE) can vary between industries. QoS in the telecommunications industry refers to the performance of a mobile or Wi-Fi network as measured quantitatively. Examples of these measurements are download throughput, upload throughput, latency, jitter, packet loss, signal strength, etc. QoS measurements are usually taken from a networks perspective at router, WAP, or network end point. In comparison, QoE is the measure of a user's experience with a service such as web browsing, video streaming, or game play. QoE measurements focus on the subjective measurement of a user's perceived value of a service.

For this thesis, the focus is on quantitatively measuring download throughput, upload throughput, and latency on the application layer of a mobile device and is

defined as the mobile application QoE. The mobile application QoE measurements focuses on the incorporating network performance factors from the Wi-Fi wireless environment to the user mobile device. Measuring the subjective experience of a user can be challenging and is beyond the scope of this thesis. Measuring the download throughput, upload throughput, and latency from the application layer of a mobile device provides a representative measure of the QoE that can be compared quantitatively. The remainder of this thesis focuses on measuring these metrics.

## 1.5 Summary of Thesis

This thesis provides a case study of the experienced RFI within a campus Wi-Fi network. This is accomplished by collecting broadcasted WAP information through an Android mobile device application. This data is used in combination of location and WAP properties (BSSID, SSID, frequency) to determine a mapping for potential RFI locations.

This thesis then assess the RFI locations using network performance metrics to evaluate the QoE. The network performance metrics being measured include upload throughput, download throughput, and latency. This provides the experienced mobile application QoE at a particular location. QoE is then compared between RFI locations and non-RFI locations to evaluate the impact of RFI on mobile application QoE.

## 1.6 Thesis Outline

The following are covered in this thesis:

**Chapter 1** introduces the main goal of the thesis and explores the details of the problem to be solved.

**Chapter 2** evaluates the past research which this thesis builds upon, and then explains the overall motivation for the research.

**Chapter 3** provides the research methodology used to obtain the results and conduct the analysis.

**Chapter 4** presents the main results in detail through tables, and summarizes them with graphs. An evaluation follows each data set to highlight the key aspects of the results.

**Chapter 5** summarizes the main points made in the analysis. It concludes by discussing several areas of future work and applications.

## Chapter 2

# Literature Review

This chapter evaluates the past research upon which this thesis builds. In particular, two papers are presented in detail and analyzed for completeness and future work. The review is broken into evaluating WAP performance and understanding mobile application QoE.

### 2.1 Mobile Crowd Sensing

The model of Mobile Crowd Sensing (MCS) is explored in the work by Guo et al. [11]. This paper presents the issues with and the history of MCS. Guo et al. describe the two unique characteristics of MCS: first, it can involve both implicit and explicit participation by a user; and second, data is collected from two user-participant data sources approaches, namely: mobile social networks and mobile sensing. The three unique issues of MCS are also described in the work: styles of data collection (implicit versus explicit), proper incentive mechanisms for data collection, quality of user contributed data and cross-space data fusion.

The work by Lane et al. provides a survey of existing mobile phone sensing algorithms, applications, and systems [12]. The paper suggests that the emerging

power and ability to program today’s smartphones with an increasingly powerful set of embedded sensors, such as a camera, microphone, GPS, accelerometer, light sensor, digital compass, gyroscope, barometer, and fingerprint scanner, will enable the growth and emergence of new personal, group, and crowd sensing applications. The paper presents a framework in which sensor-equipped mobile devices will revolutionize many sectors of our economy including business, health care, social networks, environmental monitoring, and transportation [12]. All of this supports the notion that data collected from a powerful mobile device can revolutionize the way in which systems perform and applications are used.

## 2.2 Client-Based Data Collection

Using resource-constrained mobile phones across a limited area can introduce a different set of measurement and systems challenges [13]. Livelab [14] and JamLogger [15] both explore client-based measurements and the impacts on mobile devices.

Livelab’s work presents a platform to measure real-world smartphone usage and wireless networks with a reprogrammable in-device logger designed for long-term user studies [14]. This work touches on two challenges associated with client-side monitoring: privacy and power. In relation to privacy, the study conducted individual participant interviews to determine that protecting one’s identity (e.g. phone numbers and emails) was the number one priority. The study was able to apply a one-way hash to identifiers, such as phone numbers, and extract only emoticons from emails and text messages without revealing the raw content. To address concerns over power overhead and reduced battery lifetime, the study carefully mitigated the power impact of the data collection by: event-driven logging;

piggy-backing on existing logs; optimizing the logging interval for periodically logged items; and finally, hitch-hiking on exiting system wakeup calls. The Livelabs project was able to successfully develop and deploy a tool to collect data on an Apple iPhone<sup>TM</sup>. The tool was used to provide insights into both iPhone application usage and web access, as well as categorize both cellular and enterprise Wi-Fi networks.

The challenges of monitoring on resource-constrained mobile devices has also been explored in other contexts of measuring user activity with JamLogger [15]. A logger application was developed for Android to collect traces of real user activity and classify power consumption. This data was used to influence the development of power optimizations. The work was successful in showing that energy consumption varies widely based on the user. The results showed that the screen and CPU were the two largest power consuming components. Two methods of power reduction are presented: slowly reducing screen brightness over time; and slowing reducing the CPU frequency over time.

## 2.3 Wireless Performance Monitoring

Generally, wireless network performance is measured from the WAP's radio and sensors using commercial tools such as those from AirTight and Hewlett-Packard [16] [17]. These commercial tools use methods such as time-slicing, or in multi-radio WAPs, a dedicated radio for monitoring is used. Both of these methods add cost and overhead to the network. Passive interference estimation has been explored in research work such as PIE in the sky [18]. PIE dynamically generate fine-grained interference estimates across an entire WLAN. PIE introduces no measurement traffic, and yet provides an accurate estimate of WLAN interference tracking

changes caused by client mobility, dynamic traffic loads, and varying channel conditions. This work has been successful in helping performance diagnosis and real-time WLAN optimization with channel assignment, transmit power control, and data scheduling. Other projects such as DAIR [19] and Jigsaw [20] explore measuring Wi-Fi performance from fixed vantage points. Both of these works point out that a dense deployment of sensors is necessary to effectively monitor Wi-Fi networks for certain types of threats and performance, and one can not accomplish this using access points alone.

## 2.4 Crowdsourcing Cellular Performance Monitoring

Client-based crowdsourcing has been used to monitor networks for other circumstances for cellular wireless networks as presented with WiScape [21]. The objective of WiScape was to provide a coarse-grained view of a wide-area wireless landscape to operators and users in order to better understand broad performance characteristics. This approach uses a centralized controller to instruct clients both in fixed locations and in vehicles to collect samples over time and space. WiScape is designed to be cautious of energy overheads and limited bandwidth used by the measurement clients. WiScape demonstrate that it can provide an accurate performance characterization of cellular networks over a wide area with low overhead to the clients.

## 2.5 Crowdsourcing Wi-Fi Performance Monitoring

The work related to MCNet looks to prove that measuring Wi-Fi performance of an enterprise through crowdsourcing data with a uniform consumer mobile device is an effective solution [13]. This work provides a tool that uses a smartphone to intelligently schedule periodic sample collections of a representative set of performance data while keeping battery consumption low by using mobile sensor information.

The article validates that good wireless and Wi-Fi performance is hard to model because of interference issues, building layouts, and building construction materials [13]. Existing approaches include monitoring from the wireless access point (WAP) perspective, manual site surveys, or deploying custom-built sensors in key locations. The article goes on to state that these existing methods are not comprehensive and are potentially expensive [13].

The paper presents a Mobile Crowdsourcing Network for Wireless Network Management (MCNet) tool to capture Wi-Fi performance measurements from mobile devices. The tool intermittently samples different performance measures both actively and passively. Active measurements include latency and throughput while passive measurements include connection RSSI, connection change events, and Wi-Fi scans. The tool uses the device power state and accelerometer to intelligently schedule measurements to keep power consumption low.

The tool was deployed in a large corporation over one floor as well as in a four-story university building. Data was collected from volunteer user devices over several months. The MCNet tool was used to successfully detect performance problems that went unnoticed by existing WLAN management tools. The MCNet tool and the approach described in this article was able to present a solution that

provided to be an effective, practical system for enabling mobile clients to crowdsource Wi-Fi performance measurements.

## 2.6 Mobile User Experience Measurement

As the interaction with mobile devices steadily increases so does the dependability on mobile applications to deliver a quality user experience [22]. The article by Ickin et al. [22] breaks out the factors that influence the quality of experience of commonly used mobile applications. A 4-week long user study was conducted on 29-Android phones to collect both the users quality of experience (QoE) and the underlying network quality of service (QoS). The users were to use the mobile devices as they normally would in order to measure data in natural environments and different daily contexts. The approach was to combine the measurements of QoE and QoS with the goal of improving the understanding of factors influencing QoE so that more developers could design and build better mobile applications.

This paper reinforces that it is common practice for mobile application designers to use their own judgement to evaluate a users QoE. In the case where the users QoE is unsatisfactory, the application can be given up, switched to another app provider, or deleted from the device. The QoS can also be important to the mobile application QoE for applications often rely on the connected network performance and infrastructure to provide content to the user. The four-week study used both qualitative and quantitative methods: a continuous, automatic, unobtrusive context data collection application on the users mobile phone; a short mobile-device-based survey that was completed multiple times a day; and a weekly interview to review usage patterns and user context. The results were presented in an attempt to influence the design of mobile applications.

There have been several other studies that conclude that mobile user experience is a factor of many different influences. The work by Jaroucheh et al. [23] suggests that both historical and current user context should be considered in addition to the flexibility of user behaviour in relation to the historical and current user context. Moreover the work by Hassenzahl proposes that a user's internal state, the characteristics of the system design, the interaction context, and the meaningfulness of the activity influences user experience [24]. Furthermore a survey by Korhonen et al. of twenty-one participants supported this and added that the physical mobile device, the actual task at hand, and the social context of the user effected a user's perceived QoE [25]. This was also backed by the work from Park et al., which provided insights that the usability, usefulness, and affect of the experience are factors in mobile quality of user experience [26].

## 2.7 Chapter Summary

Previous literary works in this field of study have been very detailed in the outlining the areas of mobile crowd sensing and client-based data collection. These works have presented the advantages and difficulties of monitoring user quality of experience from a mobile device. These findings support the theory and motivation of this thesis for attempting to gain insight into the user's quality of experience from the device's perspective.

The main difference between the crowdsourcing network performance monitoring tools, such as the MCNet tool, and the tools presented in this thesis study is the explicit collection of data from selected locations with different numbers of visible WAPs. The thesis study explores QoE of the Wi-Fi network while looking at the

density of WAPs and potential interference from these WAPs. This was not studied in these prior works.

The primary contrast between these previous studies on user experience management and the current work is the focus on quantitative measurements from the mobile device. This is similar to the study by Shin et al. that suggested enjoyment as well as network access quality are influencers to user QoE [27]. However, this current study only focuses on connection active measurements of the wireless network used to identify user quality of experience issues. The quantitative approach in this study focuses on anonymous collecting quality of service data to infer the perceived user quality of experience.

# Chapter 3

## Methodology

This chapter provides the research methodology used to obtain the results and conduct the analysis of the Wi-Fi environment and QoE measurements. The process of collecting the WAP and QoE data is presented. Basic mathematical algorithms are presented as well.

### 3.1 Approach Outline

Two mobile Android applications were utilized to collect data on the Wi-Fi environment and to collect network performance tests on a university campus Wi-Fi network in order to study the impact of the Wi-Fi RFI.

1. **Wi-Fi Radio Frequency Conflicts** - The data collected regarding the Wi-Fi environment was used to map out the RFI for a given area. This plot provides a geographical representation of the RFI for a given frequency band. Areas of high RFI are identified for further study to evaluate the mobile application QoE.

2. **Application QoE** - Areas identified in the previous analysis are used to evaluate the network performance. These tests allow the assessment of the mobile application QoE as measured by a mobile device. The results from these tests are used to determine the influence of RFI on mobile application network QoE performance.

## 3.2 Experimental Setup

To assess the impact of Wi-Fi RFI, measurements from the broadcasting wireless access points (WAPs) were collected from a campus network. This data was used to evaluate the RFI for a given area. A radio frequency conflicts (RFC) algorithm was developed to estimate the RFI based on the WAPs seen by the collection devices during a Wi-Fi scan. In areas of high interference, upload throughput, download throughput, and latency tests were performed to determine the mobile application QoE.

The experimental setup is based on data collected from the University of Victoria campus in Victoria, B.C. The data was collected on mobile devices with Android operating systems. Data was collected over a period from December 10, 2012 to December 21, 2012 and January 7, 2013 to May 31, 2013 inclusive. The route by which data was collected is illustrated in Figure 3.1. This route was chosen to maximize the collection region around high foot traffic areas and common areas around the campus such as the library and cafeteria.

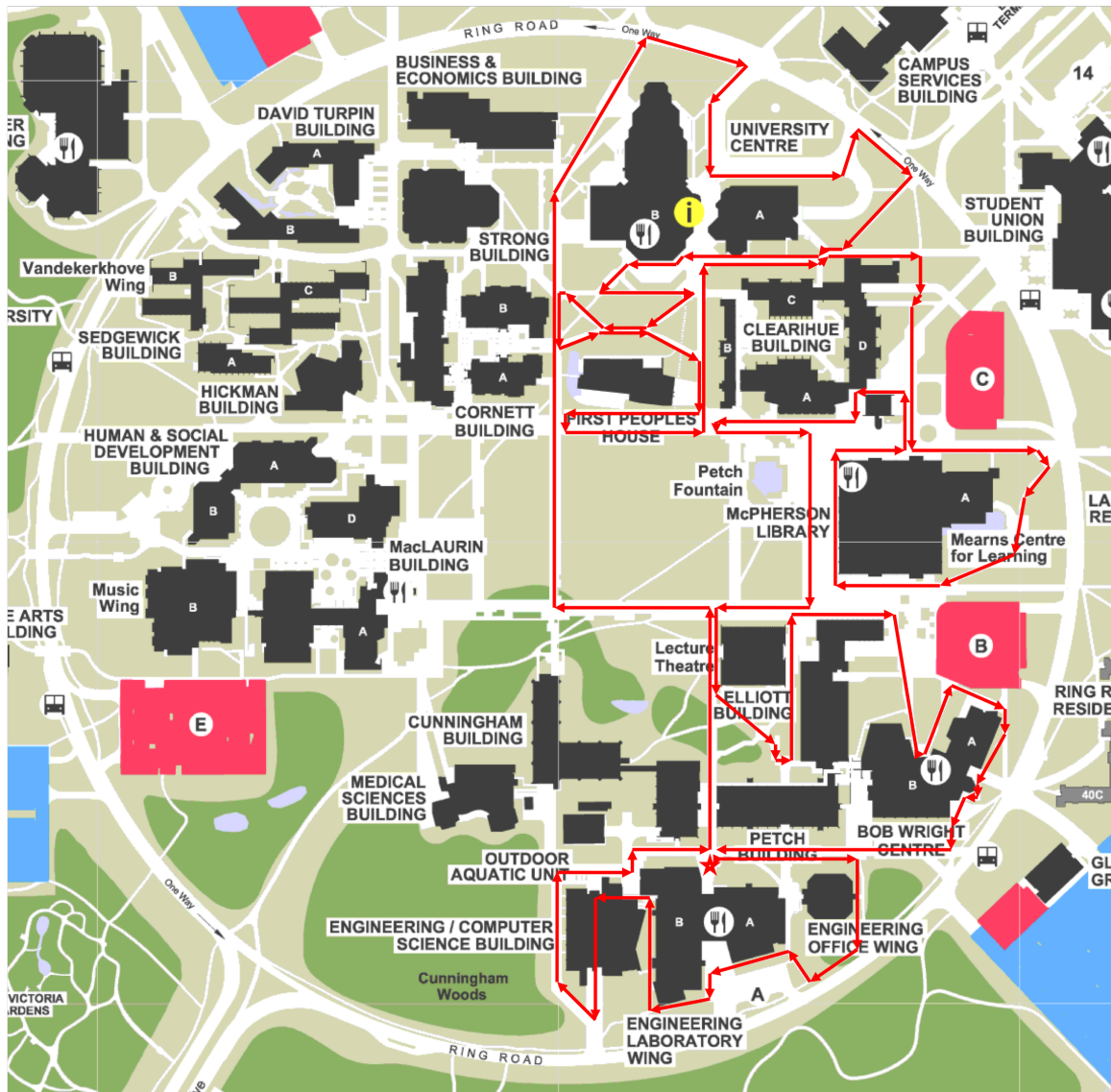


Figure 3.1: Data Collection Route

### 3.2.1 Equipment Used

The primary equipment used to collect data for this experiment was two Android smartphones. The two mobile devices used were the Samsung Nexus S with Android 2.3 (Gingerbread) operating system in Figure 3.2 and the LG Nexus 4 with

Android 4.2 (Jelly Bean) operating system in Figure 3.3. The devices' features and characteristics are summarized in Table 3.1



Figure 3.2: Nexus S



Figure 3.3: Nexus 4

Feature	Nexus S	Nexus 4
Manufacturer	Samsung	LG Electronics
Operating System	Android 2.3 Gingerbread	Android Jelly Bean 4.2
Chip	Samsung Exynos 3 Single	Qualcomm Snapdragon S4 Pro APQ8064
CPU	1 GHz single-core ARM Cortex-A8	1.5 GHz quad-core Krait
Memory	512 MB	2 GB
Storage	16 GB	8 GB
Connectivity	Wi-Fi 802.11 b/g/n	Wi-Fi 802.11 a/b/g/n (2.4/5 GHz)

Table 3.1: Mobile Devices Used for Data Collection

Each device was chosen because it is developed and manufactured in part with the Google Android platform. The devices used are representative of leading device hardware in the industry. The Nexus S was manufactured in December 2010 while

the Nexus 4 was manufactured almost two years later in November 2012. Wi-Fi scans and QoE measurements were taken from both and the results were aggregated for the analysis.

### **3.2.2 Software Used**

Several pieces of software were used to collect test data, analyze, and visualize the results. Two mobile applications were used to collect data from the mobile devices. Other more common software was used to post-process and visualize the data for this report.

#### **3.2.2.1 Mobile Wi-Fi Scan Measurement Application**

A mobile Android application was built to collect WAPs during a Wi-Fi scan. It was built using the Android SDK, primarily the Wi-Fi Manager public APIs. The application scans the Wi-Fi environment at five second intervals. The results are stored in a CSV file on the device to be exported after a test run for further processing.

A Wi-Fi scan is defined as a survey of the Wi-Fi frequency band for available WAPs within range of the scan device. The scan returns information describing the detected WAPs. For each experiment, the following data was collected for each of the broadcasting WAPs: the basic service set identification (BSSID); service set identification (SSID); received signal strength indicator (RSSI); WAP frequency; and the GPS latitude and longitude of the scan location. Each record was referred to as a Wi-Fi scan result. The Wi-Fi scan results were used to plot the WAP environment according to the broadcast channel, signal strength, and WAP BSSID.

### 3.2.2.2 Mobile QoE Measurement Application

One of the more critical software components was the mobile Android application used to evaluate the mobile application QoE. This application was used to perform upload throughput, download throughput, and latency network performance tests. The mobile application for testing the network performance was built by Ookla. Ookla operates Speedtest.net using a massive global infrastructure to minimize the impact of Internet congestion and latency. The Ookla Speed Test mobile application is distributed free through the Google Play Android Store [5]. A screen capture of the Ookla Speed Test Android mobile application can be found in Figure 3.4



Figure 3.4: Ookla Speed Test Android Mobile Application [5]

The Ookla Speed Test mobile application performs the tests over an HTTP connection for maximum compatibility. For upload throughput tests, a small amount of random data is generated in the application and sent to the web server to estimate the connection speed [28]. The upload tests are performed by sending small chunks of uniformly sized random data to the server-side script via an HTTP POST event. The chunks of data are sorted by the associated speed and the fastest half is averaged to eliminate anomalies. For download throughput tests, binary files are downloaded from the web server to the application to estimate the connection speed [28]. The application and web server are designed to download as much data as possible within ten seconds of establishing the HTTP connection. Random strings are used to prevent any caching of the downloaded data. The samples of downloaded data are aggregated into twenty slices and the fastest 10% and the slowest 30% are discarded. The remainder samples are averaged to eliminate anomalies. For latency tests, the application sends HTTP requests to the web server and measures the time to get back a response [28].

### **3.2.2.3 Post-Processing Software**

After a Wi-Fi scan is recorded, QoE measurements stored on the mobile devices were presented in comma-separated value (CSV) files for post-processing. Data from the two mobile applications was transferred to a Mongo DB for easier querying and compiling results. A web application was built using Google Web Tools 2.4.0 (GWT) and Google maps to visualize the RFC on a map of UVic. The Java Machine Learning library was used for a K-D tree space-partition algorithm [29]. GWT and Google maps are distributed under an Apache License, version 2.0. The Java Machine Learning library is distributed under a GNU General Public License (GPL). MATLAB R2010b

was used to assemble and assess the network performance data. Graphs were plotted based on this information for each specific RFC location.

### **3.3 Analysis Procedure**

For this thesis, the analysis was broken into two stages:

1. Determine the WAP locations from the collected data and map the radio frequency environment.
2. Map the QoE wireless performance measurements against the WAP locations

These two stages were necessary to first map the WAP radio frequency environment to determine the areas of high, medium, and low RFC. These locations became areas of interest to study in more detail. Then, QoE performance measurements needed to be plotted against the location of the WAPs. This provided the ability to compare and contrast various locations of RFC with the relative performance measures.

#### **3.3.1 Wi-Fi Radio Frequency Conflicts**

The data from the mobile Wi-Fi scan measurement application was structured such that Wi-Fi scans can be split by BSSID, SSID, or frequency and then plotted on a map using the GPS location. This way specific networks, WAPs, and frequencies can be compared for RFI. The radio frequency conflicts (RFC) algorithm was developed to evaluate the RFI for a given area. The RFC algorithm used a k-d tree space-partitioning data structure to organize the Wi-Fi scan locations using the Java Machine Learning Library [29]. The data structure was useful for searching for Wi-Fi scan locations within a range of locations. Given this, the RFC algorithm

divided the area of interest into smaller ranges of 5.6 meters North to South and by 7.4 meters East to West. These areas defined the location bins. The locations bins were used to classify the region in which a WAP effects the RFI environment. Within these ranges the k-d tree search was able to return the number of WAPs found with the nearest neighbour. These WAPs were compared based on the broadcasted WAP frequency. WAPs with the same broadcasted frequencies were classified as radio frequency conflicts for a given geographical area.

This data was used to create a plot of the number of WAPs per frequency per location bin. These location bins were plotted on a map to show the density of a particular WAP frequency or location bin. The process of splitting the W-Fi scan records by location provides a limited view of the wireless environment for this analysis. Wireless environments can vary with time, which is not accounted for in the above analysis. The WAPs are assumed to be static locations on a static channel between the tests runs and data collected.

Channels 1, 6, and 11 are of particular interest because the frequencies of these channels do not overlap and, hence are commonly chosen within a Wi-Fi network. These channels are more frequently used in larger scale commercial Wi-Fi deployments. The RFC algorithm was used to visually plot on a map the RFI for a given geographical area. Areas with high RFI were used in the second part of the study to evaluate the mobile application QoE by performing upload throughput, download throughput, and latency network performance tests. Five areas of significance were chosen for assessment based on their observed RFI variations as calculated from the RFC algorithm.

### 3.3.2 Application QoE

To collect the QoE performance measurements, the mobile devices were brought to each location. The mobile devices were connected to the Wi-Fi network and six sets of tests were performed from the same location using the Ookla application. Each test set included the instantaneous download throughput, upload throughput, latency, and the GPS latitude and longitude of the test location. The same network server located in Bellingham, Washington was used for all network performance tests. In addition, the same sets of tests were performed with the Wi-Fi radio off and data transferred over the mobile 3G cellular network for comparison. In total, six Wi-Fi and six mobile cellular network performance tests were done for each of the five chosen locations.

These test results were used to compare the impact of RFC on the mobile application QoE. The RFC algorithm described above was also implemented to sort and place the QoE performance measurements collected into assorted location bins. QoE performance measurements were classified into location bins similar to the Wi-Fi scan records and the average as well as the standard deviation and median were calculated. QoE measurements were plotted for each location bin to visualize the distribution of the results. The main factors in relating the measurements to the perceived QoE on the mobile device were the mean and standard deviation of the measurements. The mean provided a sense of the average performance of the network. As the mean increases for download throughput and upload throughput, the greater the perceived experience by the user because they could send and received data in larger volumes faster. The lower the latency, the faster response from a given server for an application, resulting in a better QoE for the user. However, the standard deviation provides a measure of the amount variation of the data. Standard deviation could be an indication of the fluctuation of the

performance of the WAP. A greater variation in the QoE measurements could result in a good experience at one instance and a poor experience at another. This discrepancy could result in a poor experienced QoE overall by the user of the mobile device. Both must be taken into consideration.

### **3.4 Chapter Summary**

The measurements for this study are collected via two Android mobile applications. All the measurements were focused on a university campus Wi-Fi network. The data was collected in order to map the Wi-Fi radio frequency environment of particular areas. These measurements were used to identify different areas to be used as case studies for further analysis. In parallel, quality of service measurements were taken. These measurements included download throughput, upload throughput, and latency. The quality of service measurements were compared against different location case studies to determine the influence of the Wi-Fi radio frequency environment. Because of the amount of data collected over the study period, map-reduce algorithms were implemented to aggregate and average the data into manageable divisions.

# Chapter 4

## Results

This chapter presents the main results of the conducted assessments in detail. An evaluation follows each data set to highlight the key aspects of the results. Three locations were chosen for examination: a low interference case, a medium interference case, and a high interference case. An analysis of the results in terms of the download throughput, upload throughput, and latency as a function of the total number of WAPs is included.

### 4.1 RFI Location Evaluation

The evaluation of the RFI locations was done in two stages. First locations with differing levels of WAPs present were identified. Second QoE test measurements were assessed at each location to determine RFI impacts on QoE.

#### 4.1.1 Wi-Fi Scan Locations

The data collected over the studied time period and the collection route is visualized in Figure 4.1. The plot illustrates the concentration of Wi-Fi scan results over the collection route. As expected, most of the scan results are near or adjacent

to buildings on the UVic campus. The campus has an extensive existing Wi-Fi network for both students and guests. There are also a few private and engineering department Wi-Fi networks around campus. Areas near open fields and tree-lined spaces are expected to have fewer Wi-Fi scan results.

In total there were 450,119 Wi-Fi scan results collected over the period of study. These Wi-Fi scan results were used to uniquely identify 6094 WAPs with 3734 unique SSIDs across the UVic campus network. The common SSIDs or network names are UVic, UVicOpen, and eduroam.

The scans were collected over a total of 1777 locations bins. These bins follow the collection route as described in Chapter 3.

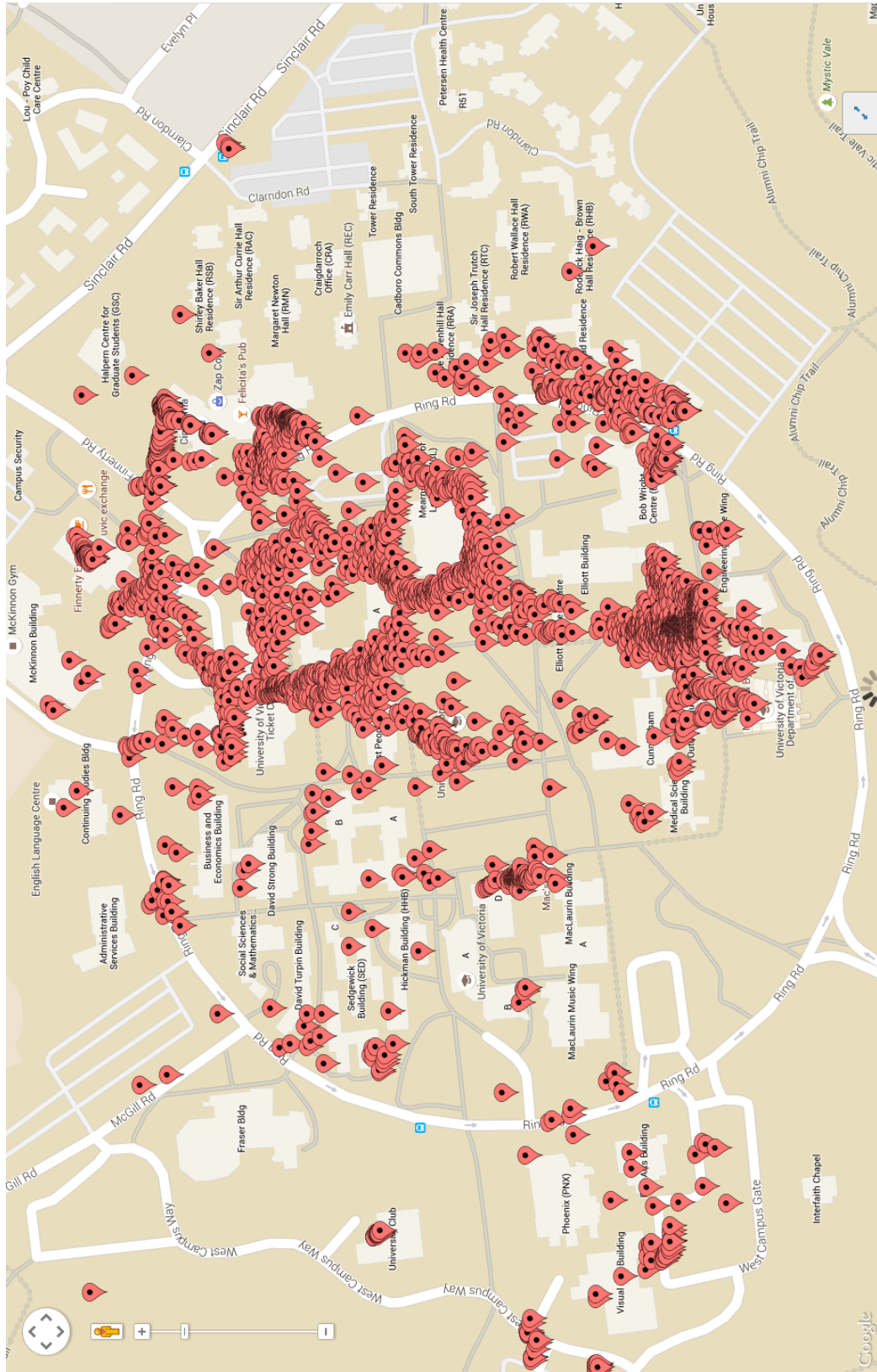


Figure 4.1: Wi-Fi Scan Test Locations

The WAP histogram for the eleven location points of interest for this study are summarized in Table 4.1 for most common frequencies 2412 MHz, 2437 MHz, and 2462 MHz. The list of figures containing the histogram of the WAP distribution can also be found in this table. These locations are also plotted in Figure 4.13 with low interference locations marked in green, medium interference locations marked in yellow, and high interference locations marked in red.

Latitude, Longitude	Number of WAPs on			Figure
	2412 MHz	2437 MHz	2462 MHz	
48.4615,-123.3110	81	75	69	4.2
48.4615,-123.3115	20	13	21	4.3
48.4633,-123.3105	142	128	109	4.4
48.4635,-123.3105	90	86	63	4.5
48.4640,-123.3100	62	61	65	4.6
48.4640,-123.3115	76	42	57	4.7
48.4645,-123.3115	73	58	58	4.8
48.4645,-123.3120	50	45	37	4.9
48.4650,-123.3115	39	36	33	4.10
48.4658,-123.3075	3	0	3	4.11
48.4660,-123.3080	19	7	10	4.12

Table 4.1: WAP Location Summary from December 10-21, 2012 and January 7-May 31, 2013

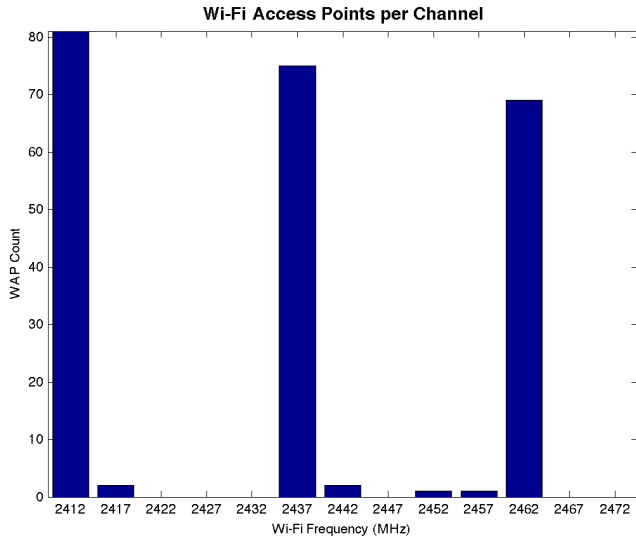


Figure 4.2: WAPs Profile at 48.4615, -123.3110

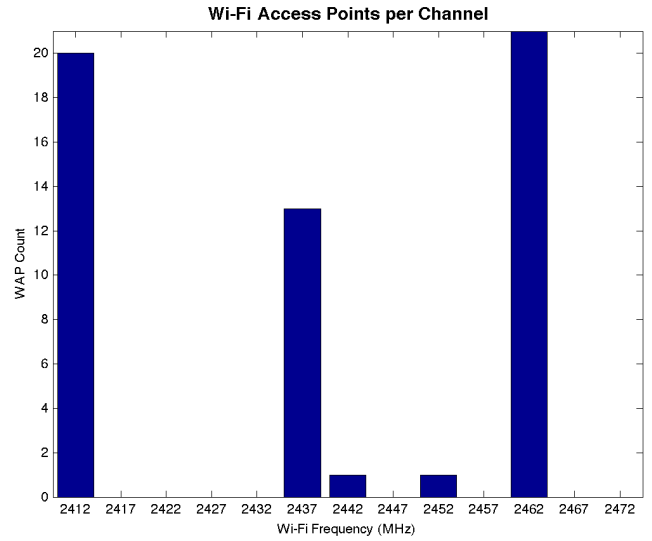


Figure 4.3: WAPs Profile at 48.4615, -123.3115

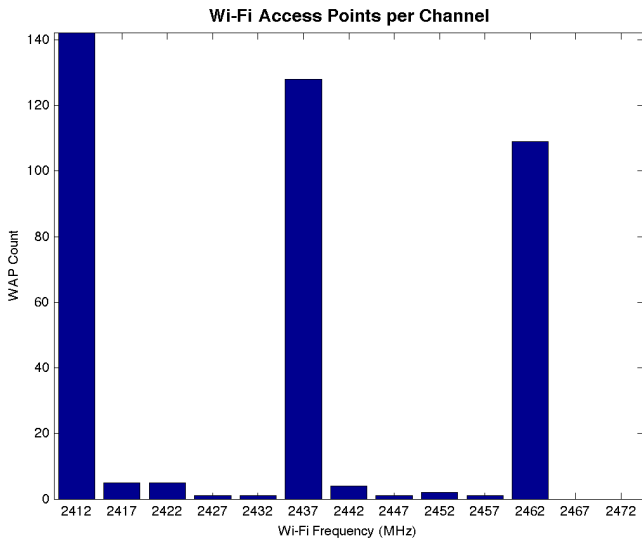


Figure 4.4: WAPs Profile at 48.4633, -123.3105

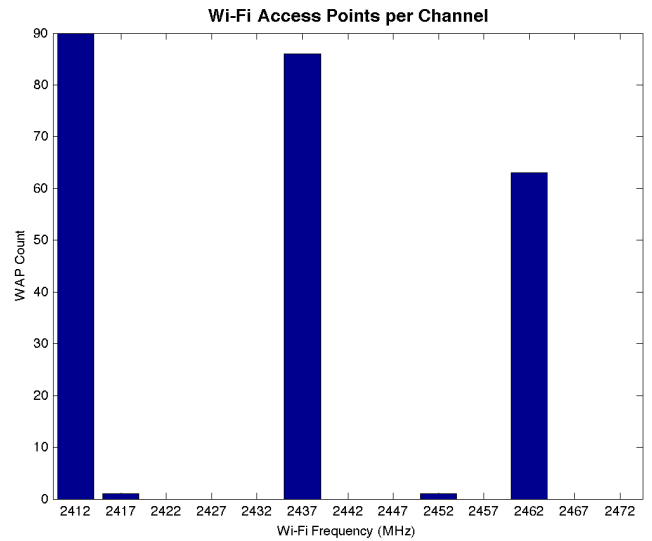


Figure 4.5: WAPs Profile at 48.4635, -123.3105

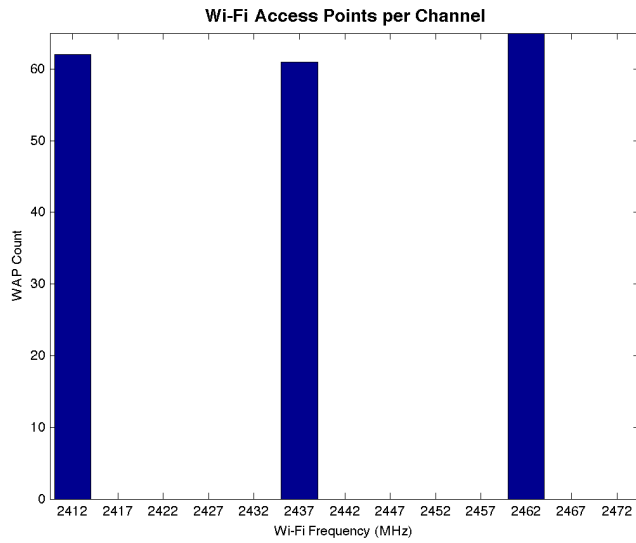


Figure 4.6: WAPs Profile at 48.4640, -123.3100

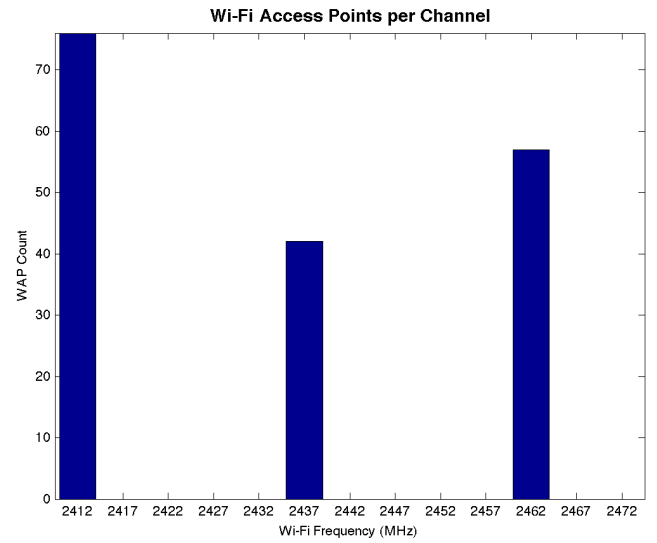


Figure 4.7: WAPs Profile at 48.4640, -123.3115

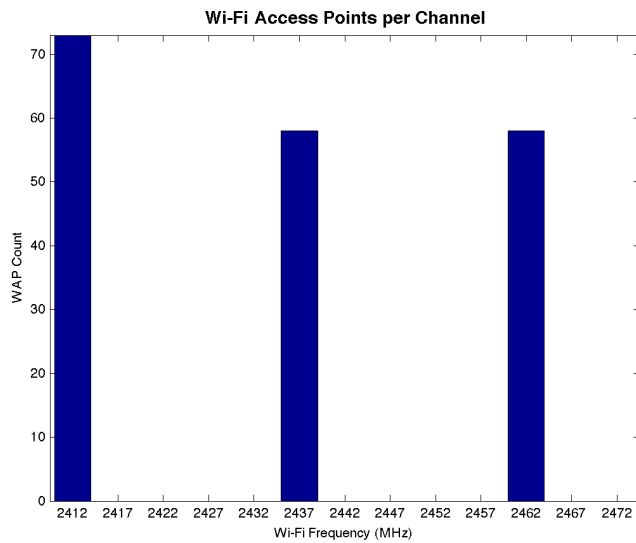


Figure 4.8: WAPs Profile at 48.4645, -123.3115

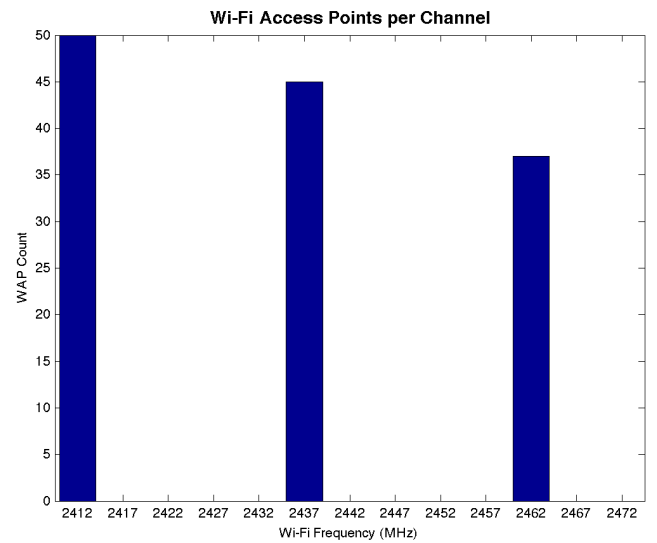


Figure 4.9: WAPs Profile at 48.4645, -123.3120

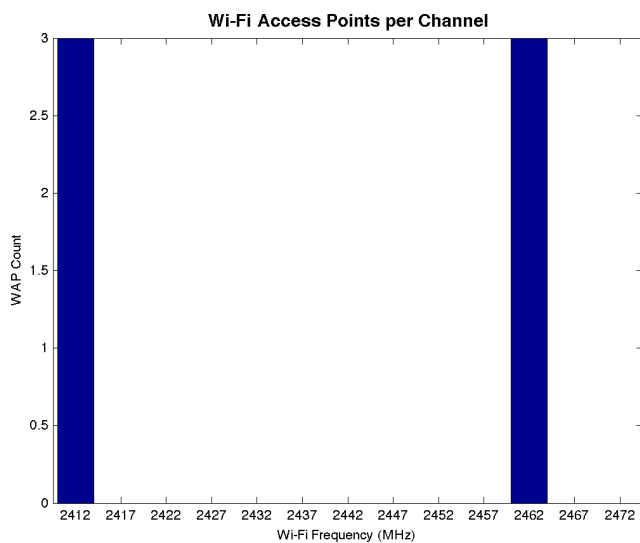
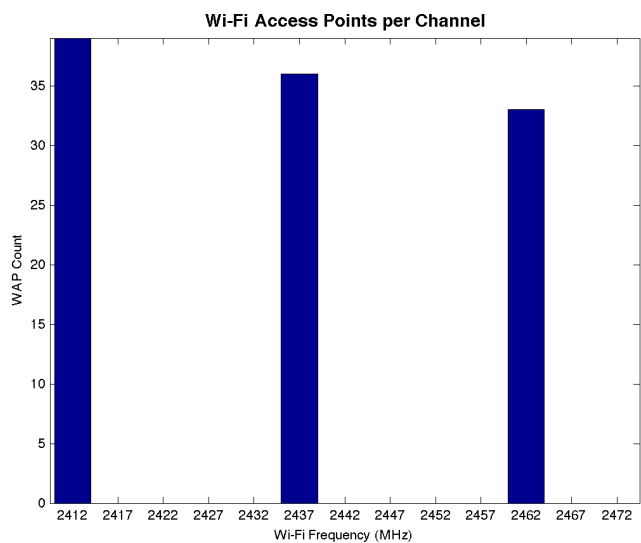


Figure 4.10: WAPs Profile at 48.4650, -123.3115

Figure 4.11: WAPs Profile at 48.4658, -123.3075

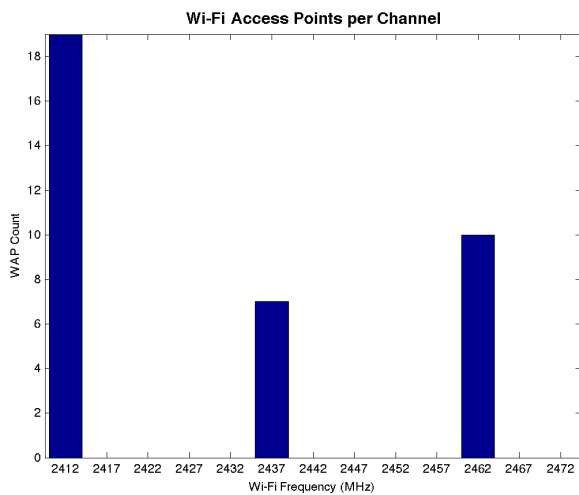


Figure 4.12: WAPs Profile at 48.4660, -123.3080



Figure 4.13: WAP Location Summary Plot

### 4.1.2 QoE Test Locations

There were 928 QoE tests taken over eleven overlapping location bins as the Wi-Fi scan results over the same time period as plotted in Figure 4.14. The majority of the tests were performed over the UVicOpen Wi-Fi network SSID. These tests consisted of download throughput, upload throughput, and latency collected from an Android mobile device. These tests allowed the assessment of the impact of Wi-Fi RFI on mobile application QoE. The QoE histogram for the eleven location points of interest can be found in Table 4.2 with a list of figures corresponding to the histograms.

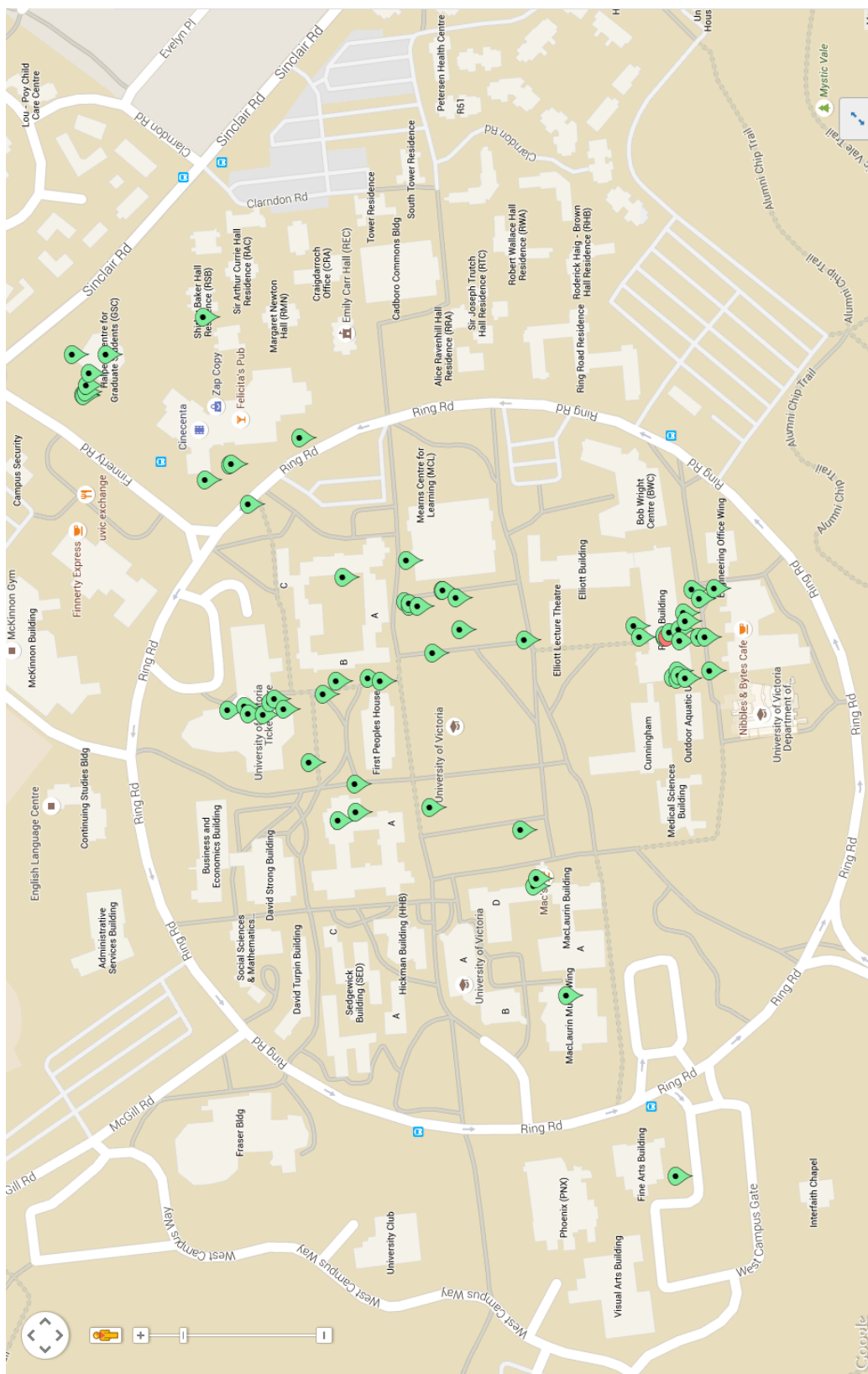


Figure 4.14: QoE Test Locations

<b>Latitude, Longitude</b>	<b>Figure</b>
48.4615, -123.3110	4.15
48.4615, -123.3115	4.16
48.4633, -123.3105	4.17
48.4635, -123.3105	4.18
48.4640, -123.3100	4.19
48.4640, -123.3115	4.20
48.4645, -123.3115	4.21
48.4645, -123.3120	4.22
48.4650, -123.3115	4.23
48.4658, -123.3075	4.24
48.4660, -123.3080	4.25

Table 4.2: QoE Test Location Summary from December 10-21, 2012 and January 7-May 31, 2013

### 4.1.3 RFC Locations of Interest

Three locations are of particular interest for evaluating the potential impact of application QoE from the dataset collected. These locations were chosen because of the relative low, medium, and high number of visible WAPs as shown in Figure 4.26. Table 4.3 summarizes the three RFC locations.

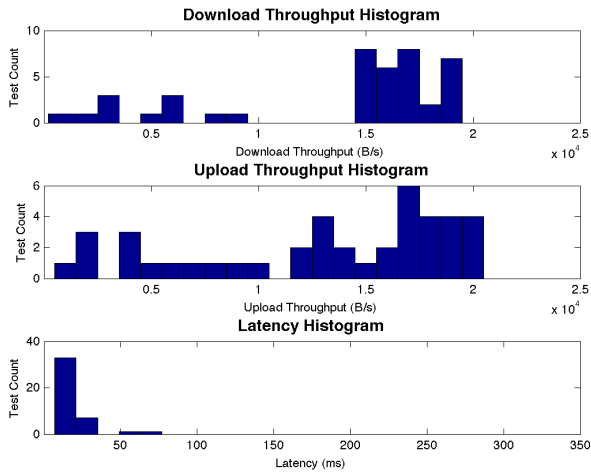


Figure 4.15: QoE Distribution at 48.4615, -123.3110

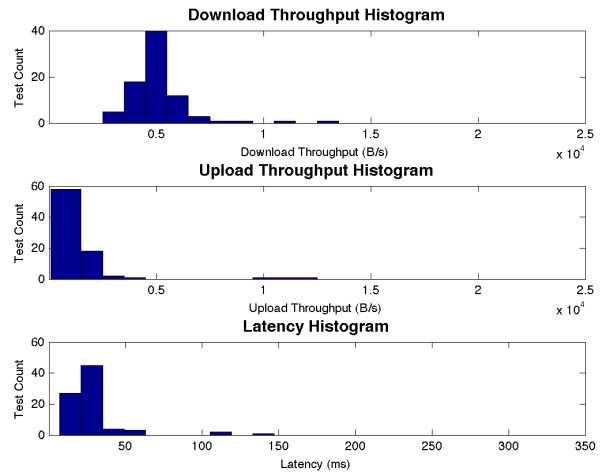


Figure 4.16: QoE Profile at 48.4615, -123.3115

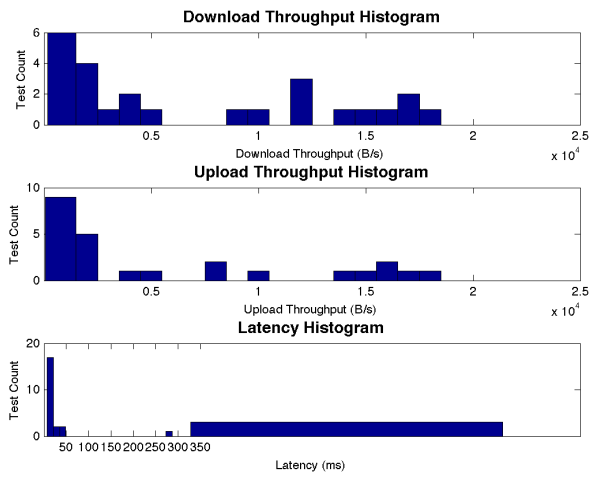


Figure 4.17: QoE Profile at 48.4633, -123.3105

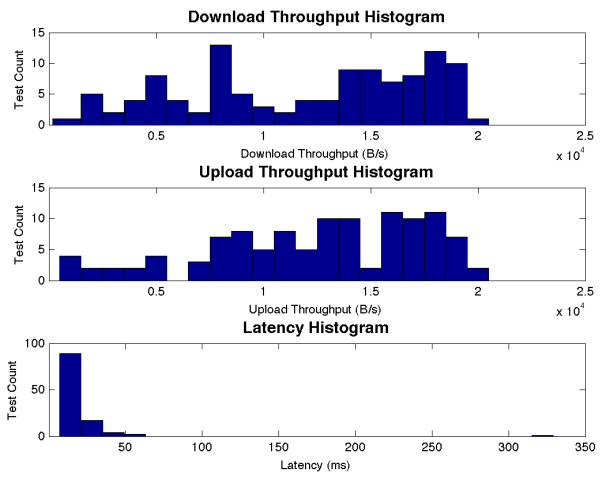


Figure 4.18: QoE Profile at 48.4635, -123.3105

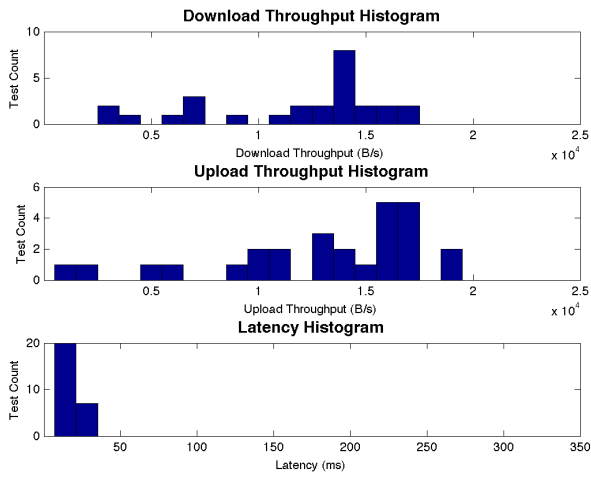


Figure 4.19: QoE Profile at 48.4640, -123.3100

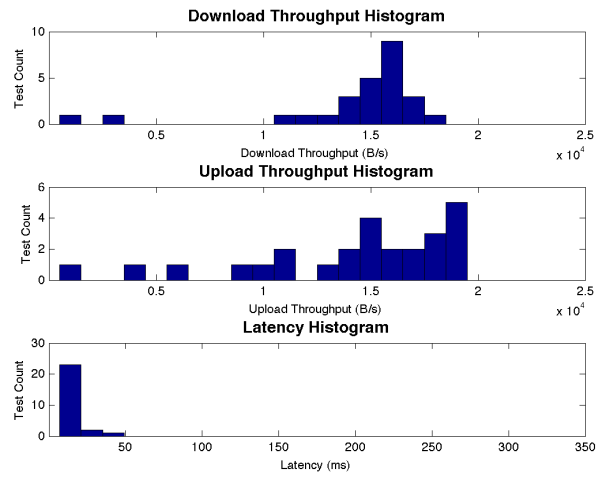


Figure 4.20: QoE Profile at 48.4640, -123.3115

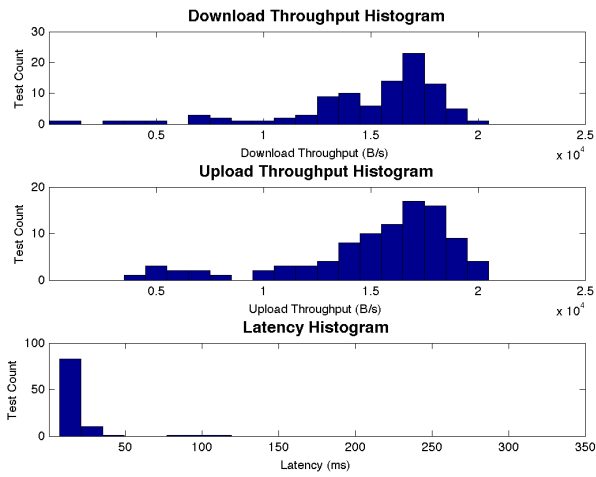


Figure 4.21: QoE Profile at 48.4645, -123.3115

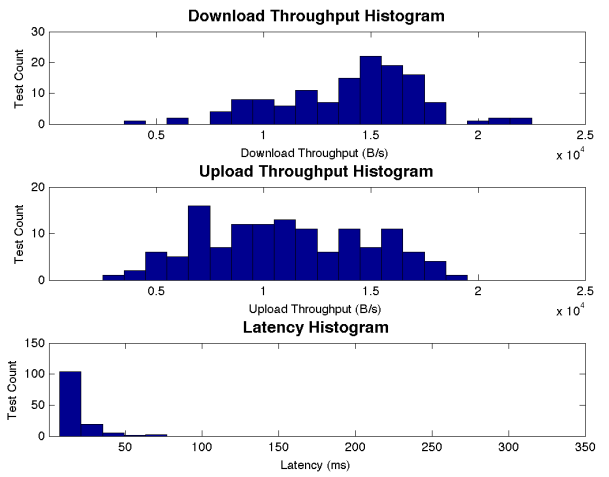


Figure 4.22: QoE Profile at 48.4645, -123.3120

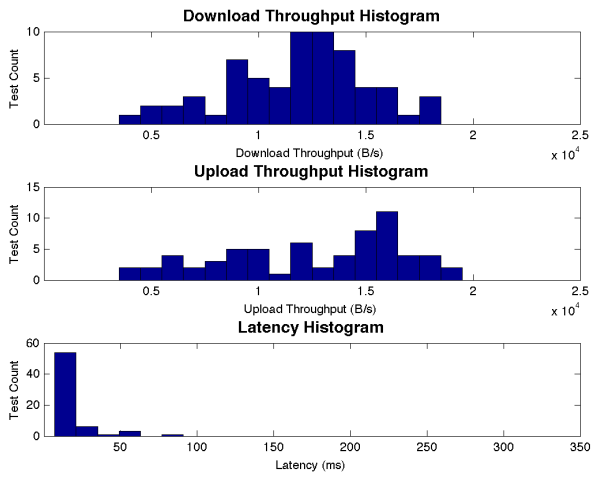


Figure 4.23: QoE Profile at 48.4650, -123.3115

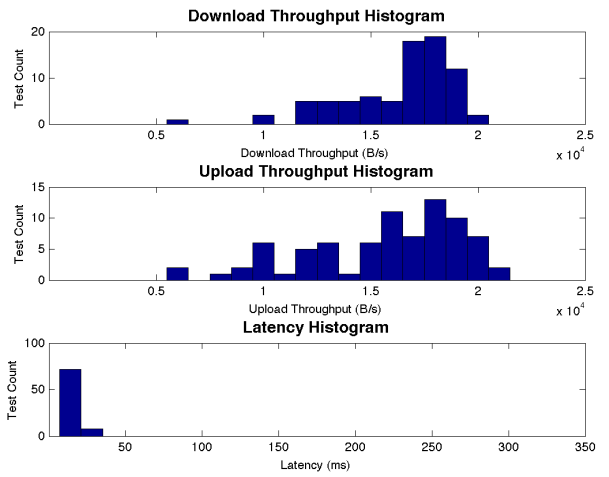


Figure 4.24: QoE Profile at 48.4658, -123.3075

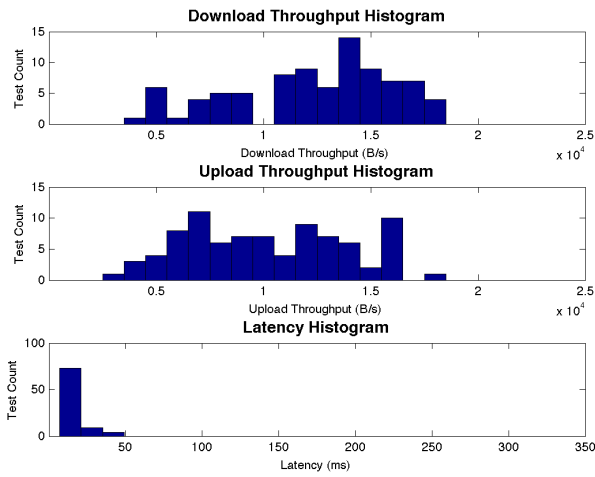


Figure 4.25: QoE Profile at 48.4660, -123.3080

Interference Classification	Number of WAPs on			Latitude, Longitude
	2412 MHz	2437 MHz	2462 MHz	
Low	20	13	21	48.4615, -123.3115
Medium	50	45	37	48.4645, -123.3120
High	90	86	63	48.4635, -123.3105

Table 4.3: RFI Locations of Interest

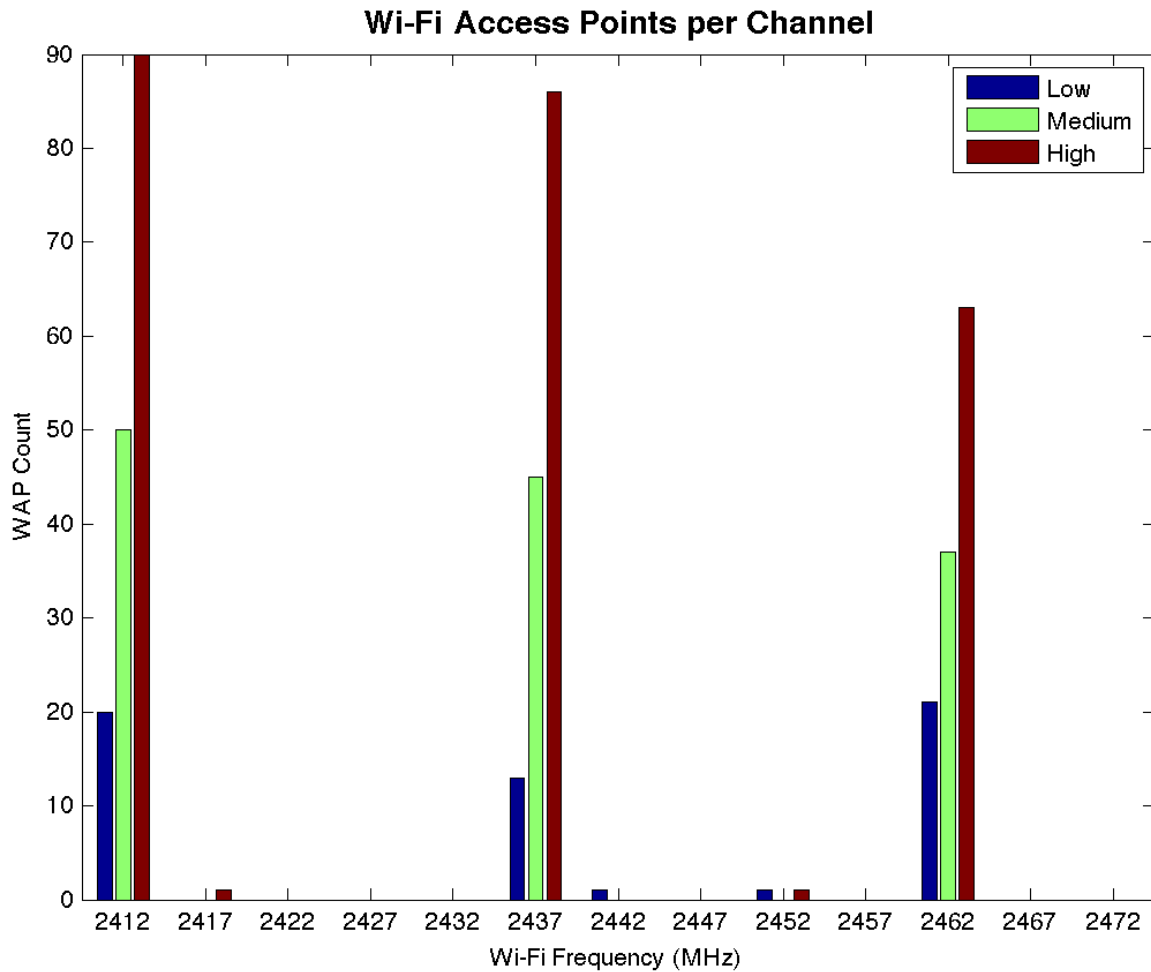


Figure 4.26: WAP Histogram for Three Locations of Interest

The low, medium, and high RFI locations are overlaid on a map of the University of Victoria in Figure 4.27. The green, yellow, red stars represent the low, medium, and high respectively.



Figure 4.27: RFI Locations at the University of Victoria

The figures illustrate the measured download throughput, upload throughput, and latency over the period of the study. Each figure contains a scatter plot, histogram, and time series plot of the QoE measurements.

## **4.2 Low Interference Location**

The low interference location is specifically chosen because of the relatively low number of WAPs on each channel compared to other locations in the study area. The following presents the WAP distribution and the measured QoE for this particular location.

### **4.2.1 WAP Distribution**

The WAPs at this location are presented in Figure 4.28. The WAPs are mainly on the primary channels 1, 6, and 11. As expected, the WAP frequencies are generally distributed over these channels.

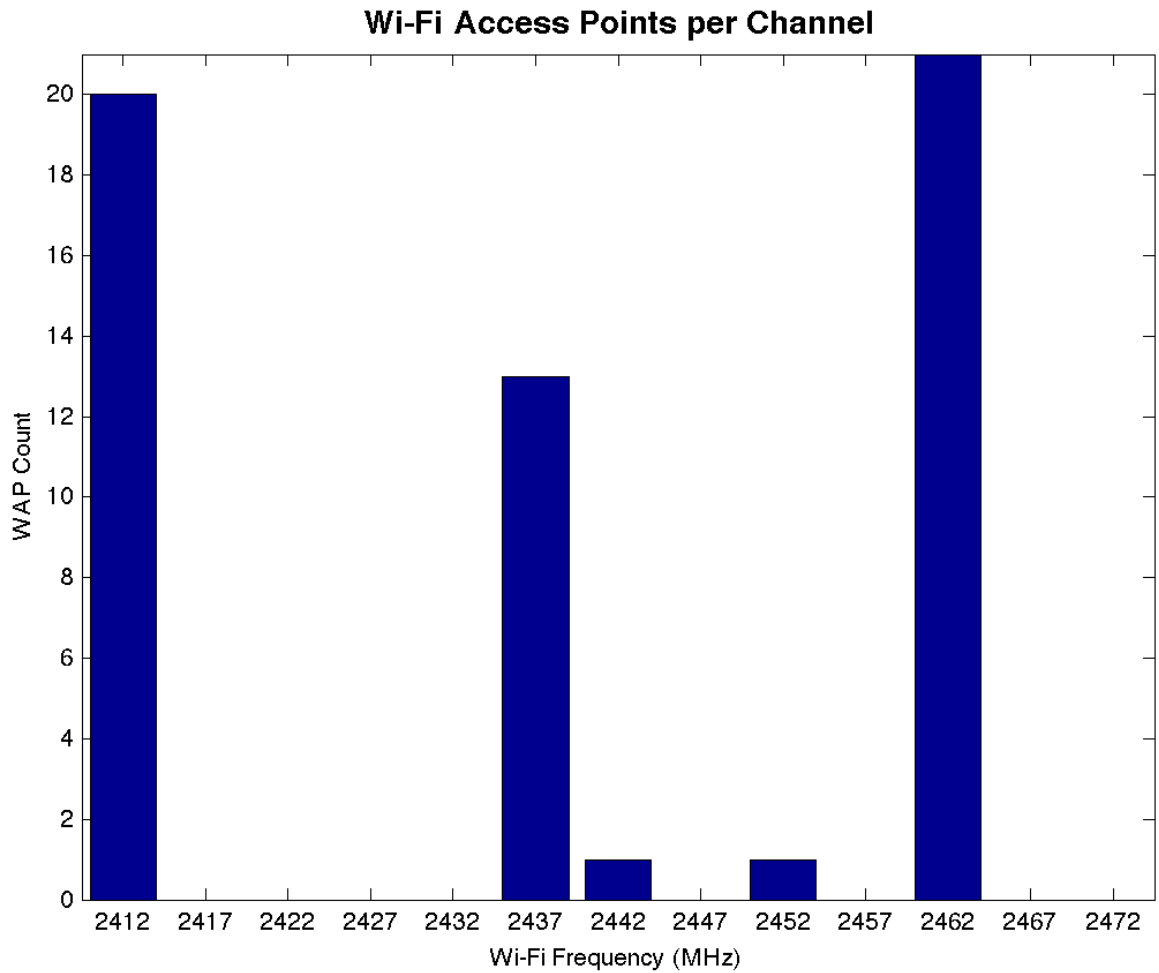


Figure 4.28: Low Interference WAP Profile

## 4.2.2 QoE Distribution

Figure 4.29 illustrates the download throughput, upload throughput, and latency scatter plots versus time for a low RFI location. The download throughput has a small standard deviation focused around the mean of 5,095.7 B/s. The measurements have standard deviation of 1,491.9 B/s and median of 4,829.5 B/s. The upload throughput has a larger range than the download throughput. The mean of the upload throughput

is 1,595.6 B/s with a standard deviation of 1,970.9 B/s and median of 1,143.5 B/s. The average latency is 28.6 ms with a standard deviation of 19.8 ms and median of 23.0 ms. A histogram of the measurements is shown in Figure 4.30.

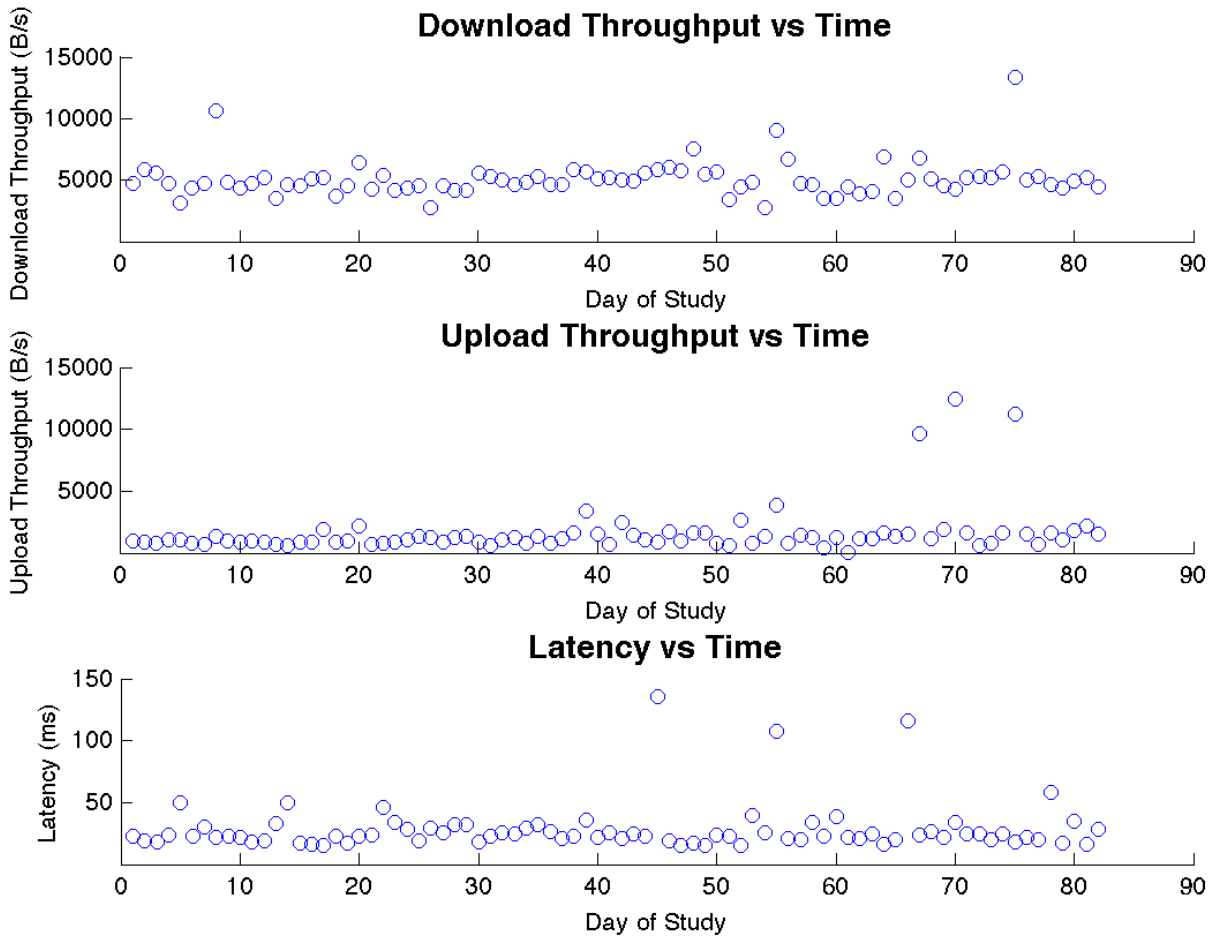


Figure 4.29: Low Interference QoE Scatter Plot

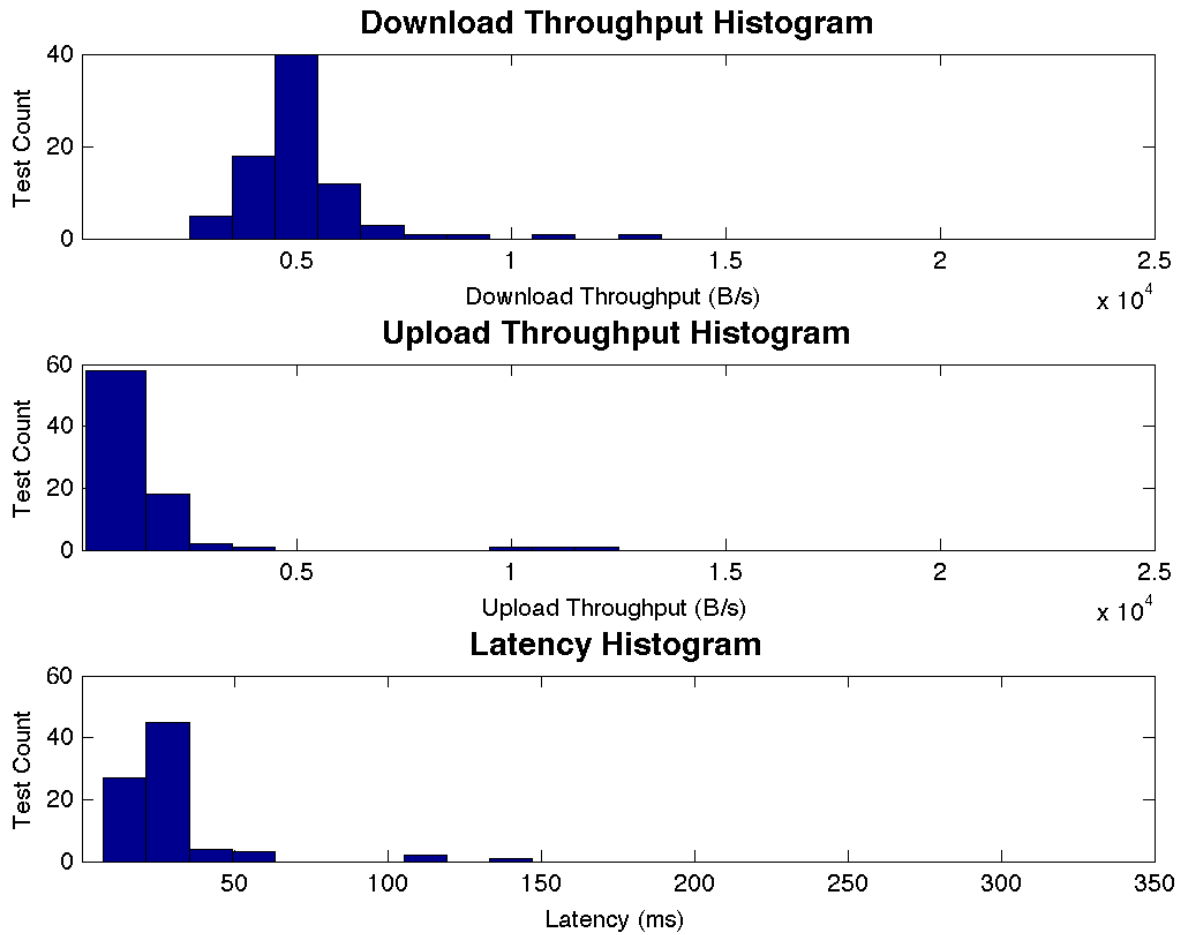


Figure 4.30: Low Interference QoE Histogram

As expected, there was a smaller standard deviation of measurements in locations with less RFI. This suggests that there is less fluctuation in the wireless performance in these areas. The results are summarized in Table 4.4.

QoS Measurement	Mean	Standard Deviation	Median
Download Throughput (B/s)	5,095.7	1,491.9	4,829.5
Upload Throughput (B/s)	1,595.6	1,970.9	1,143.5
Latency (ms)	28.6	19.8	23.0

Table 4.4: Low Interference QoE Summary

### 4.3 Medium Interference Location

The medium interference location is specifically chosen because of the number of WAPs on each channel is in the average of WAPs when compared to other locations in the study area. The following presents the WAP distribution and the measured QoE for this particular location.

#### 4.3.1 WAP Distribution

The WAPs at this location are presented in Figure 4.31. The WAPs are mainly on the primary channels 1, 6, and 11 as before. As expected the WAP frequencies are generally distributed over these channels.

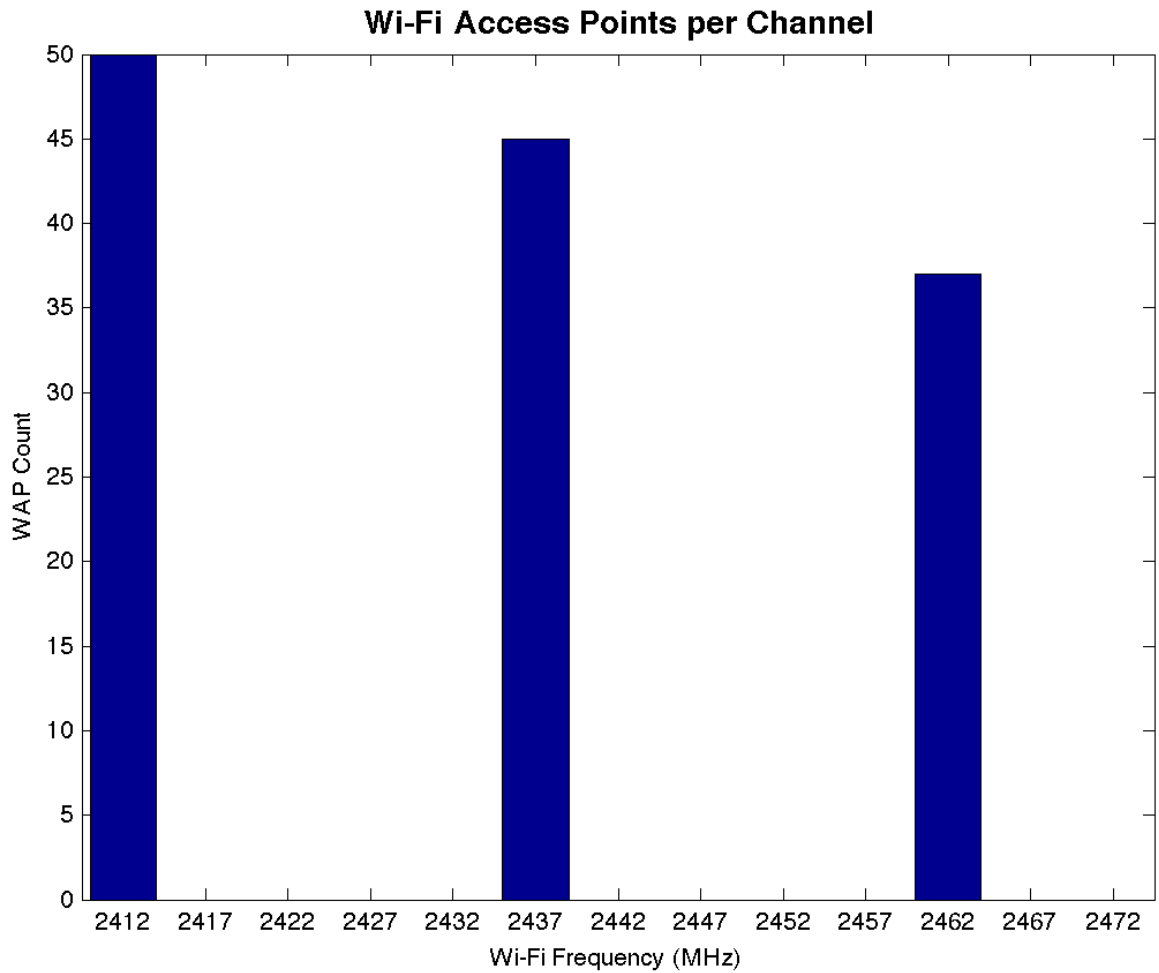


Figure 4.31: Medium Interference WAP Profile

### 4.3.2 QoE Distribution

Figure 4.32 illustrates the QoE profile for a medium RFI location. The download throughput has a mean of 14,055.3 B/s. The download throughput measurements have a standard deviation of 3,335.9 B/s and a median of 14,916.0 B/s. The upload throughput has a larger standard deviation than the download throughput. The mean of the upload throughput is 11,024.1 B/s with a standard deviation of 3,818.6 B/s and

median of 10,732.0 B/s. The average latency is 19.3 ms and has a standard deviation of 9.8 ms and median of 16.0 ms. A histogram of the measurements is shown in Figure 4.33.

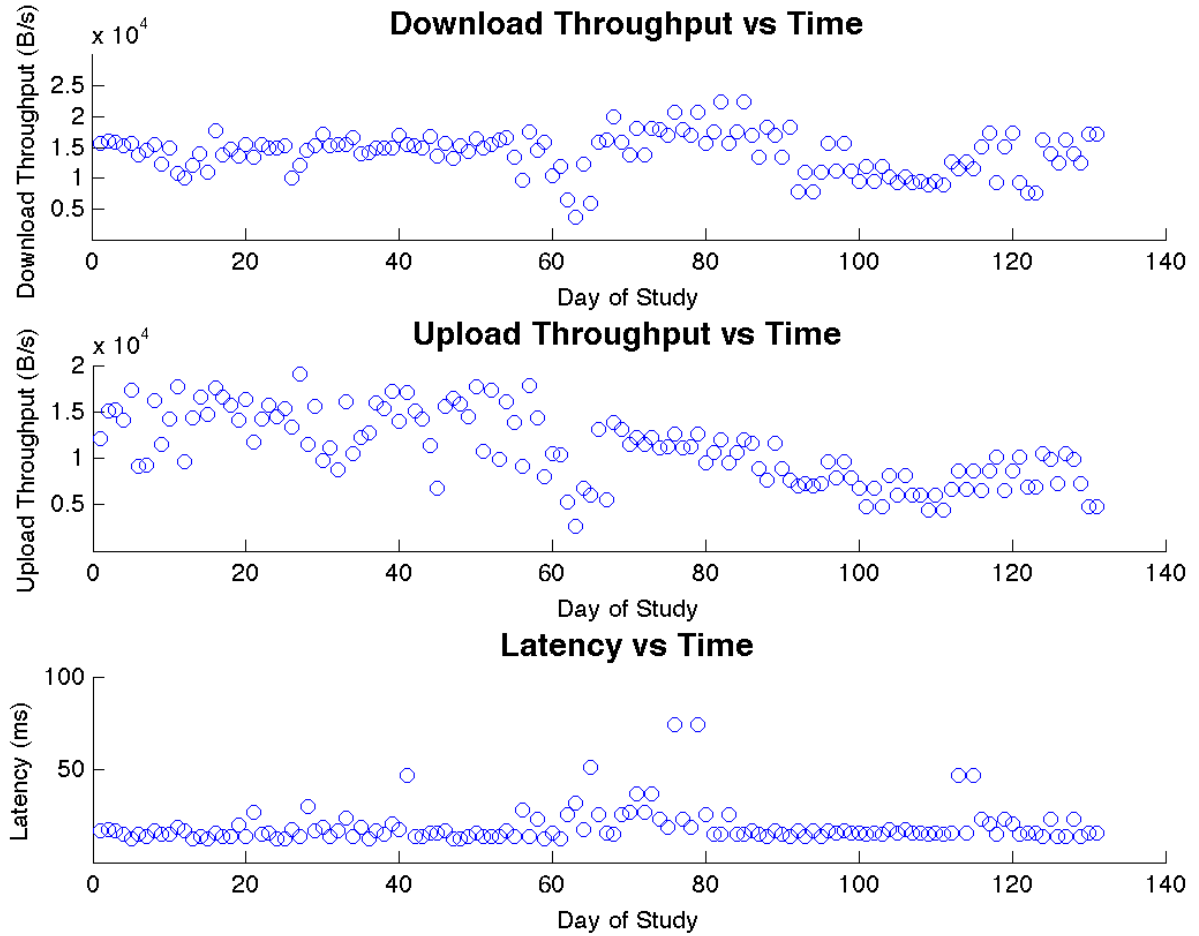


Figure 4.32: Medium Interference QoE Scatter Plot

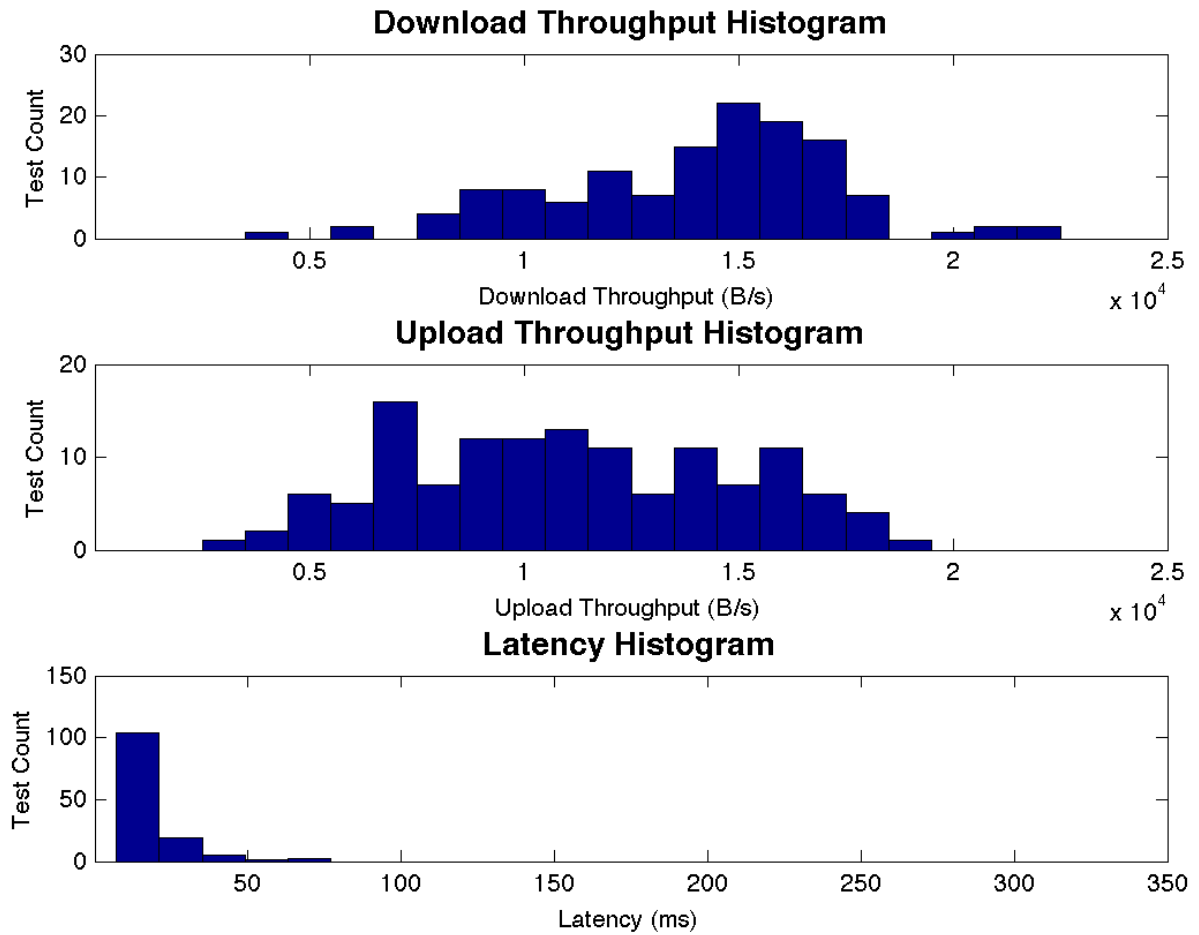


Figure 4.33: Medium Interference QoE Histogram

A larger standard deviation of the download throughput and upload throughput measurements was observed compared to the case with fewer WAPs in the particular location. However, there was a significantly higher average download throughput and upload throughput experience in the medium interference case than in the low interference case. This suggests that there is more fluctuation in the wireless download and upload throughput performance but a higher average performance in this area with an average number of WAPs. This may be because the device has more WAPs

to connect to in order to establish a connection. However when that connection is established, the interference from other WAPs causes the throughput to drift or fluctuate from connection to connection.

The average latency in the medium interference case was less than that of the low interference case. The standard deviation was also less in the medium case than the low interference case. This suggests that the wireless latency performance in the medium interference case has less fluctuation and a smaller average in this area of average WAPs per channel. This may be because of the increased number of WAPs in the location of interest may allow the device to establish a low latency connection that is not effected by the imposed interference. The results are summarized in Table 4.5.

<b>QoS Measurement</b>	<b>Mean</b>	<b>Standard Deviation</b>	<b>Median</b>
Download Throughput (B/s)	14,055.3	3,335.9	14,916.0
Upload Throughput (B/s)	11,024.1	3,818.6	10,732.0
Latency (ms)	19.3	16.0	9.8

Table 4.5: Medium Interference QoE Summary

## 4.4 High Interference Location

The high interference location is specifically chosen because of the relatively high number of WAPs on each channel compared to other locations in the study area. The following presents the WAP distribution and the measured QoE for this particular location.

### 4.4.1 WAP Distribution

Figure 4.34 displays the WAPs for this location. As expected the WAP frequencies are generally distributed over channels 1, 6, and 11 as with the other locations in consideration.

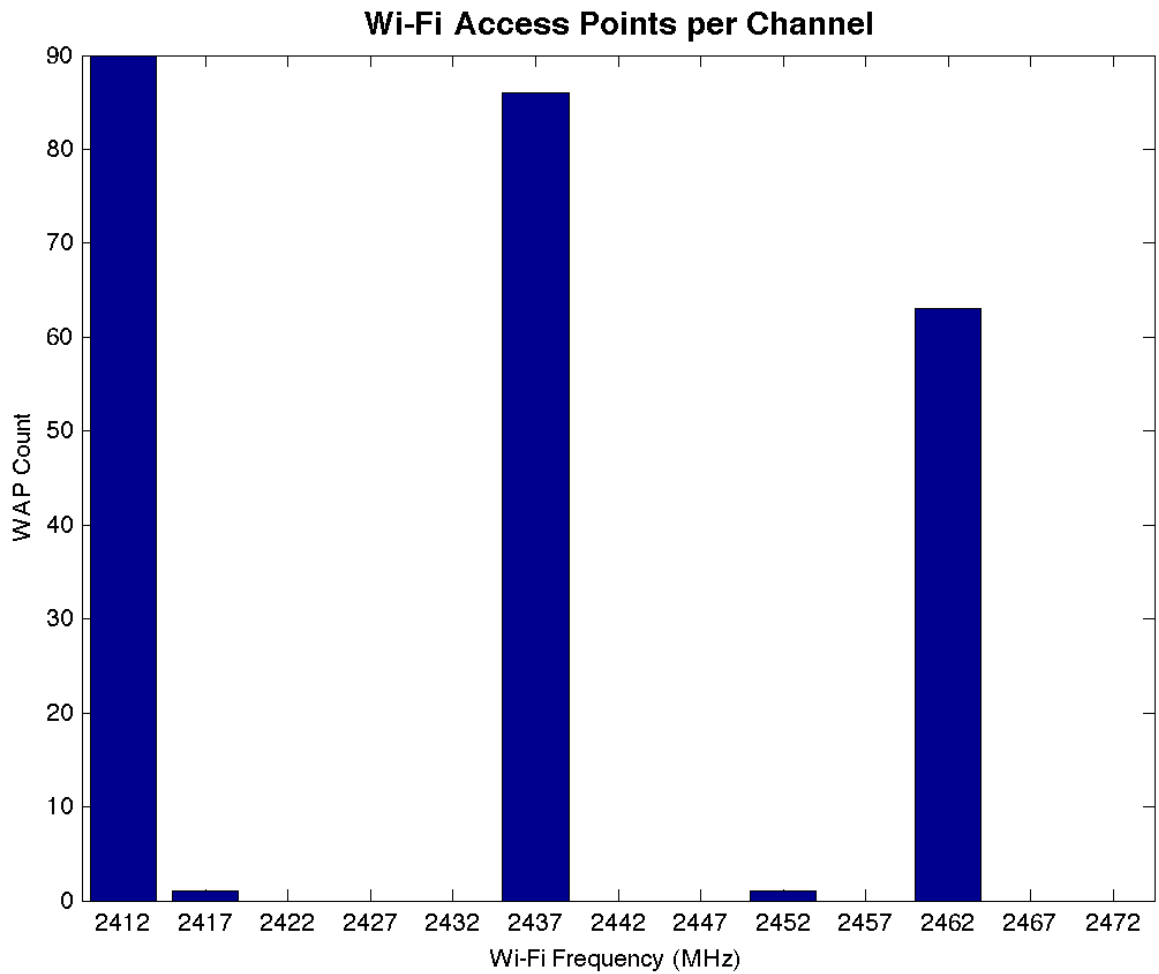


Figure 4.34: High Interference WAP Profile

### 4.4.2 QoE Distribution

Figure 4.35 illustrates the QoE profile for a high RFI location. The download throughput has a larger standard deviation of 5,509.0 B/s focused around the mean of 11,932.3 B/s and a median of 13,000.0 B/s. The upload throughput has a slightly smaller standard deviation than the download throughput. The mean of the upload throughput is approximately 12,395.2 B/s with a standard deviation of 4,993.4 B/s and a median of 13,022.0 B/s. The average latency is 21.3 ms and has a large standard deviation of 29.8 ms and median of 16.0 ms. A histogram of the measurements is shown in Figure 4.36.

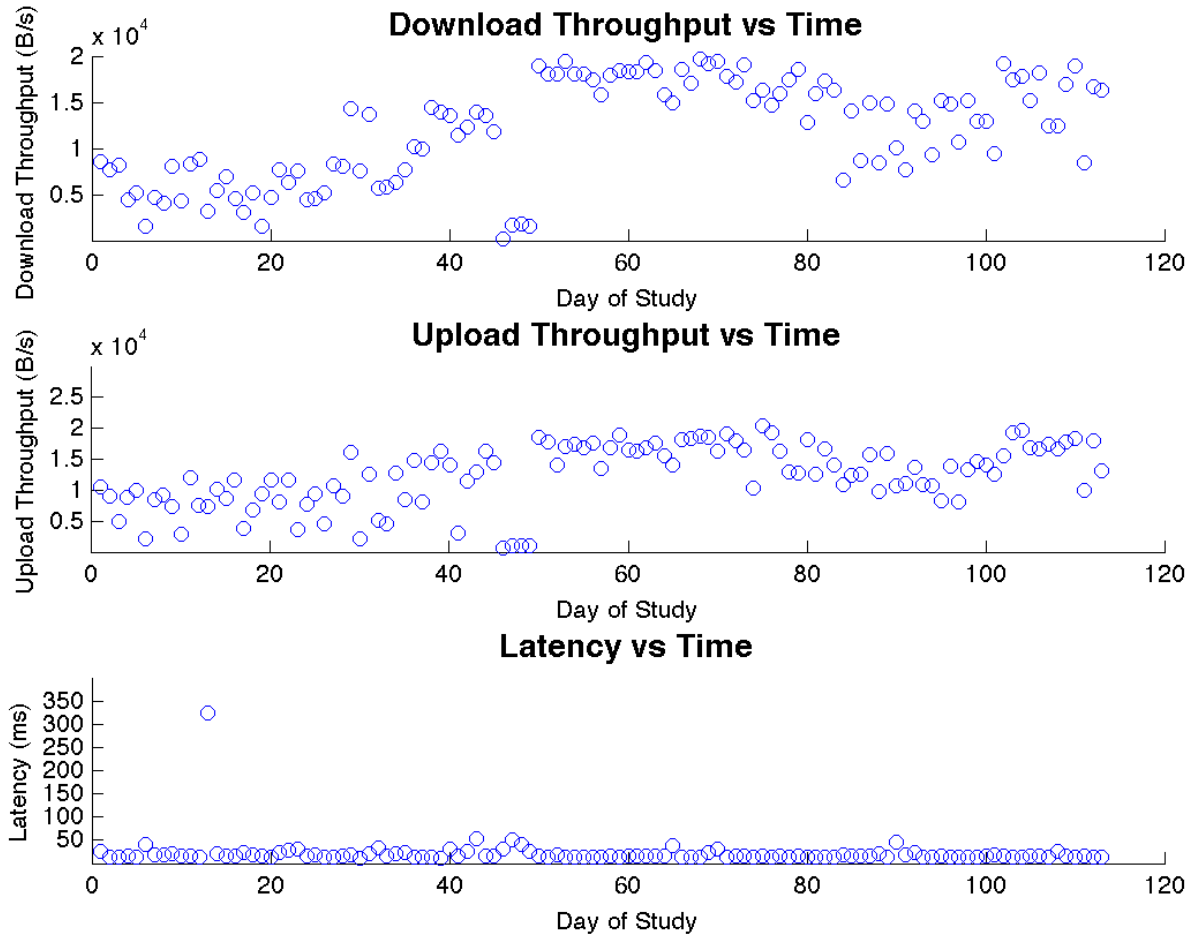


Figure 4.35: High Interference QoE Scatter Plot

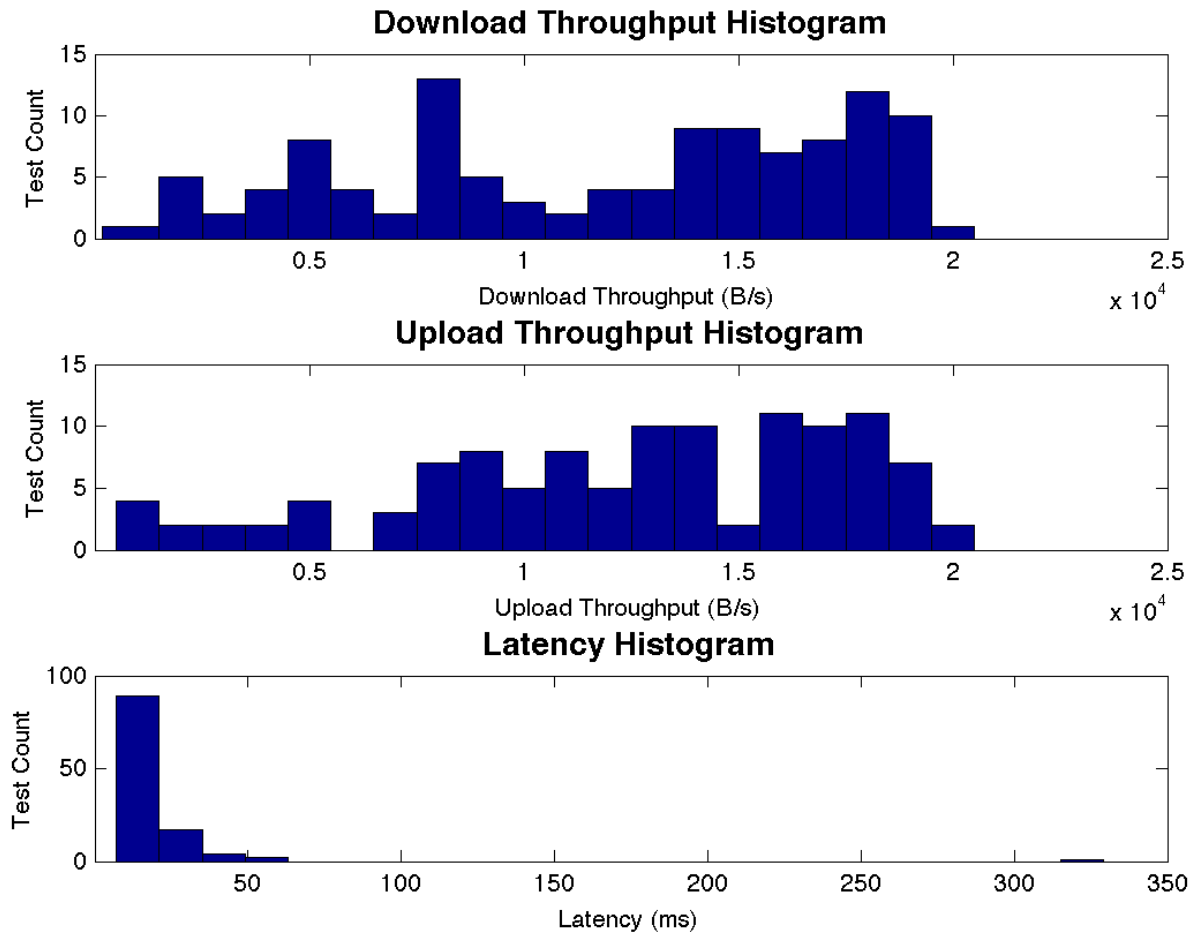


Figure 4.36: High Interference QoE Histogram

When compared to the medium interference case, the high interference case has a lower average download throughput and a much larger standard deviation. This suggests that average download performance is lower and has a greater fluctuation. However in the high interference case, the average upload throughput is slight higher and has a larger standard deviation than in the case with medium interference. In this situation, the high interference case had better performing upload throughput but also had a larger range. Again this could be the result of the device has more opportunity

to connect to a WAP with a high throughput when establishing the connection. But when the connection is established, the interference from other WAPs causes the throughput to fluctuate from connection to connection across the WAPs.

The average latency in the high interference case was greater than that of the medium interference case. The standard deviation was also much higher in the high case than in the medium interference case. This suggests that the wireless latency performance in the high interference has more fluctuation and a higher average in this area of high WAPs per channel. In a similar sense, the decreased latency measurements could be due to increase in the number of WAPs with the same broadcasting channel. The results are summarized in Table 4.6.

<b>QoS Measurement</b>	<b>Mean</b>	<b>Standard Deviation</b>	<b>Median</b>
Download Throughput (B/s)	11,932.3	5,509.0	13,000.0
Upload Throughput (B/s)	12,395.2	4,993.4	13,022.0
Latency (ms)	21.3	29.8	16.0

Table 4.6: High Interference QoE Summary

## 4.5 Analysis of Results

Table 4.7 summarizes the test results for the low, medium, and high RFI locations identified for this study. Within the table the three locations of interest can be found with the average, standard deviation, and median for the download throughput, upload throughput, and latency. In order to evaluate the impact of increased RFI in a particular area on the wireless network performance, each QoE measure is evaluated individually in the below analysis.

<b>Location Characteristic</b>	<b>Low RFI</b>	<b>Medium RFI</b>	<b>High RFI</b>
Latitude, Longitude	48.4615, -123.3115	48.4645, -123.3120	48.4635, -123.3105
Number of WAPs on 2412 MHz	20	50	90
Number of WAPs on 2437 MHz	13	45	86
Number of WAPs on 2462 MHz	21	37	63
Average Download Throughput (B/s)	5095.7	14055.3	11932.3
Download Throughput Standard Deviation (B/s)	1491.9	3335.9	5509.0
Download Throughput Median (B/s)	4829.5	14916.0	13000.0
Average Upload Throughput (B/s)	1595.6	11024.1	12395.2
Upload Throughput Standard Deviation (B/s)	1970.9	3818.6	4993.4
Upload Throughput Median (B/s)	1143.5	10732.0	13022.0
Average Latency (ms)	28.6	19.3	21.3
Latency Standard Deviation (ms)	19.8	9.8	29.8
Latency Median (ms)	23.0	16.0	16.0

Table 4.7: Summary of RFI Study Location Measurements

### 4.5.1 Download Throughput

Figure 4.37 shows the average download throughput as a function of the total number of seen WAPs at each particular study location. Generally, the measurements are all within one standard deviation of the mean. There appears to be no strong correlation between the average download throughput and the number of WAPs for these test locations.

Figure 4.37 also shows the standard deviation of the download throughput as a function of the total number of seen WAPs. From the limited data, there appears to be a relationship between the standard deviation of the download throughput measurements as the number of WAPs changes. This would suggest as the number of WAPs increases, the variation in the download throughput also increases. This could cause fluctuating QoE.

Finally, the median of the download throughput as a function of the total WAPs is plotted in Figure 4.37. Again, as with the mean, the download throughput measurements are generally within one standard deviation. There does not appear to be a strong relationship between the two variables.

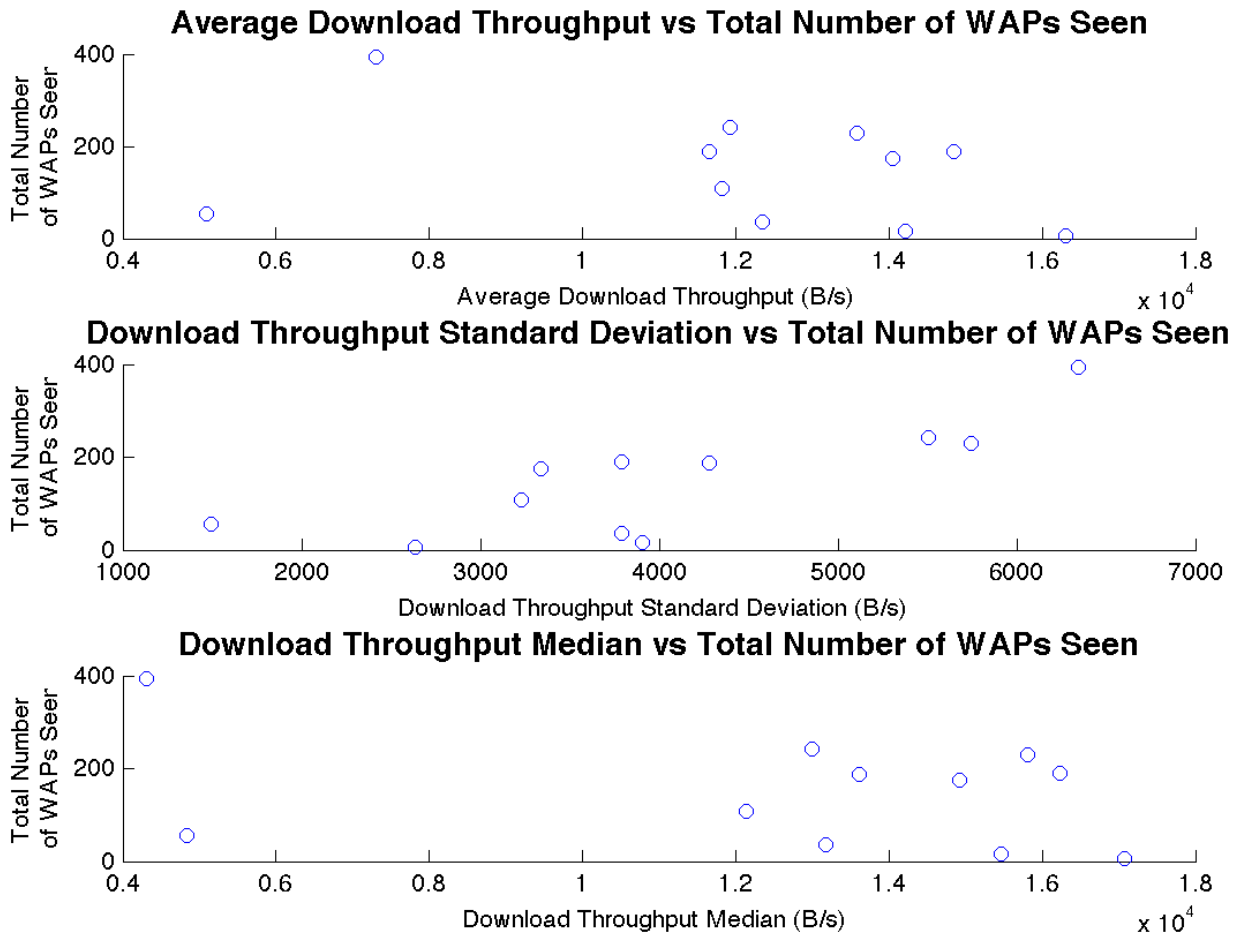


Figure 4.37: Download Throughput Distribution versus Number of WAPs

## 4.5.2 Upload Throughput

Figure 4.38 displays the average upload throughput as a function of the total number of WAPs in the study area. The upload throughput measurements were most often found within one standard deviation of the mean. Implying that there is not a strong correlation of the average throughput to the number of WAPs in an area.

The standard deviation of the average upload throughput as a function of the total number of seen WAPs is also shown in Figure 4.38. As with the download throughput, the upload throughput suggests that there is a relationship between the variation in the upload throughput and the number of WAPs in a location. As the number of WAPs increase in an area, increase in variation can be observed. Again, the fluctuation or variation on upload throughput could be perceived by a users as a degraded QoE while connected to the network.

Figure 4.38 also shows the upload medium throughput as a function of the number of total WAPs. Generally the measurements are within one standard deviation of the mean. This is similar to the behaviour observed with the download throughput.

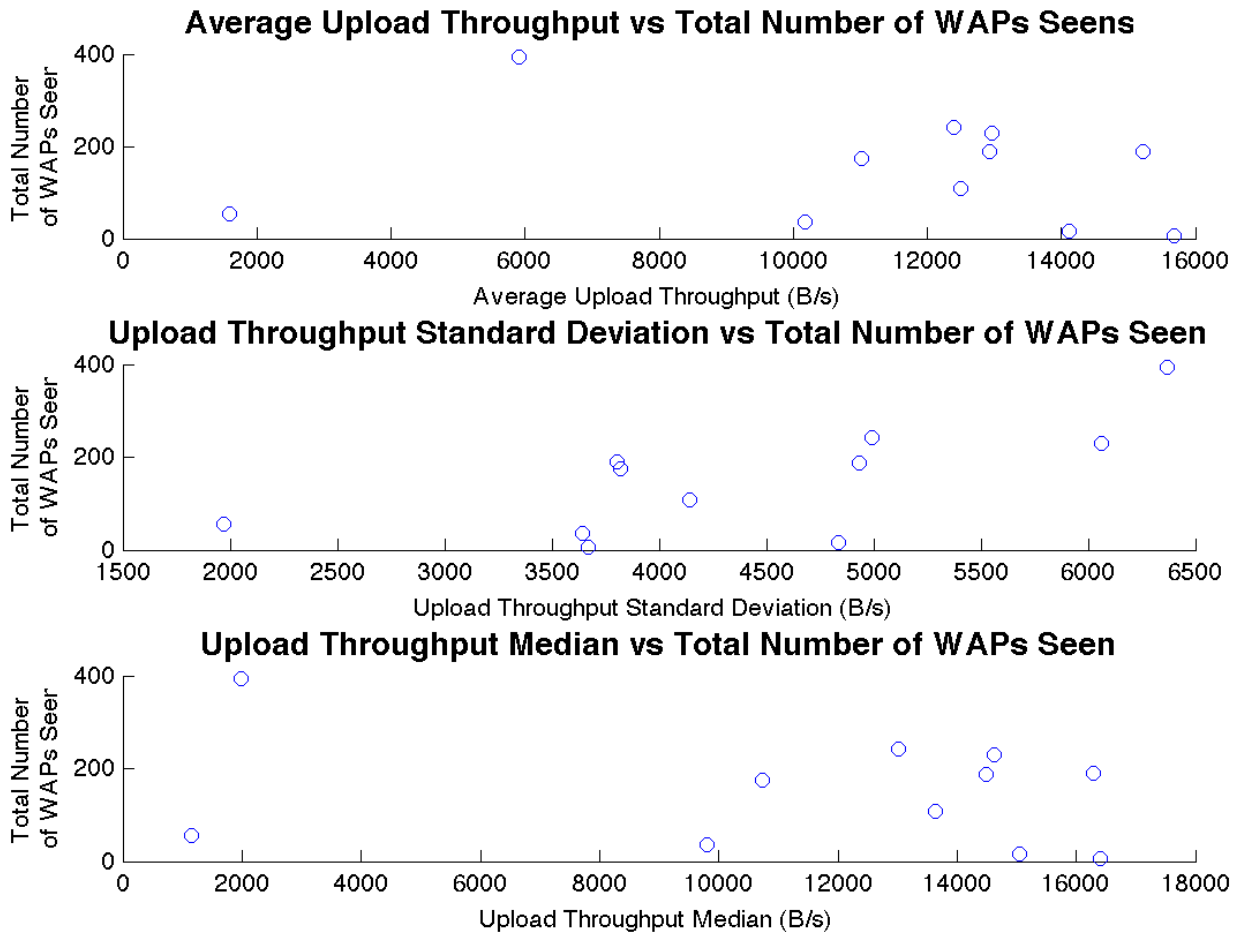


Figure 4.38: Upload Throughput Distribution versus Number of WAPs

### 4.5.3 Latency

Figure 4.39 shows the average latency measurement versus the number of total visible WAPs. From the limited data, there is a relationship between the two variables. As the number of WAPs increases, the latency also increases. This increase in latency would appear to the user as a delayed response from an application or web page, thus degrading the user's QoE.

The standard deviation of the latency measurements versus the number of total WAPs is also illustrated in Figure 4.39. There appears to be relationship between the two variables; when the number of total WAPs increases so does the variation in the latency measurements. This suggests that the user would experience a large fluctuation on latency or server response in areas with high WAPs, effecting the user QoE.

Lastly Figure 4.39 shows the median of the latency measurements versus the number of total WAPs. Again, there is a correlation between the number of WAPs and the median of the latency. As a result, the user QoE would be affected by the change in WAPs in this case.

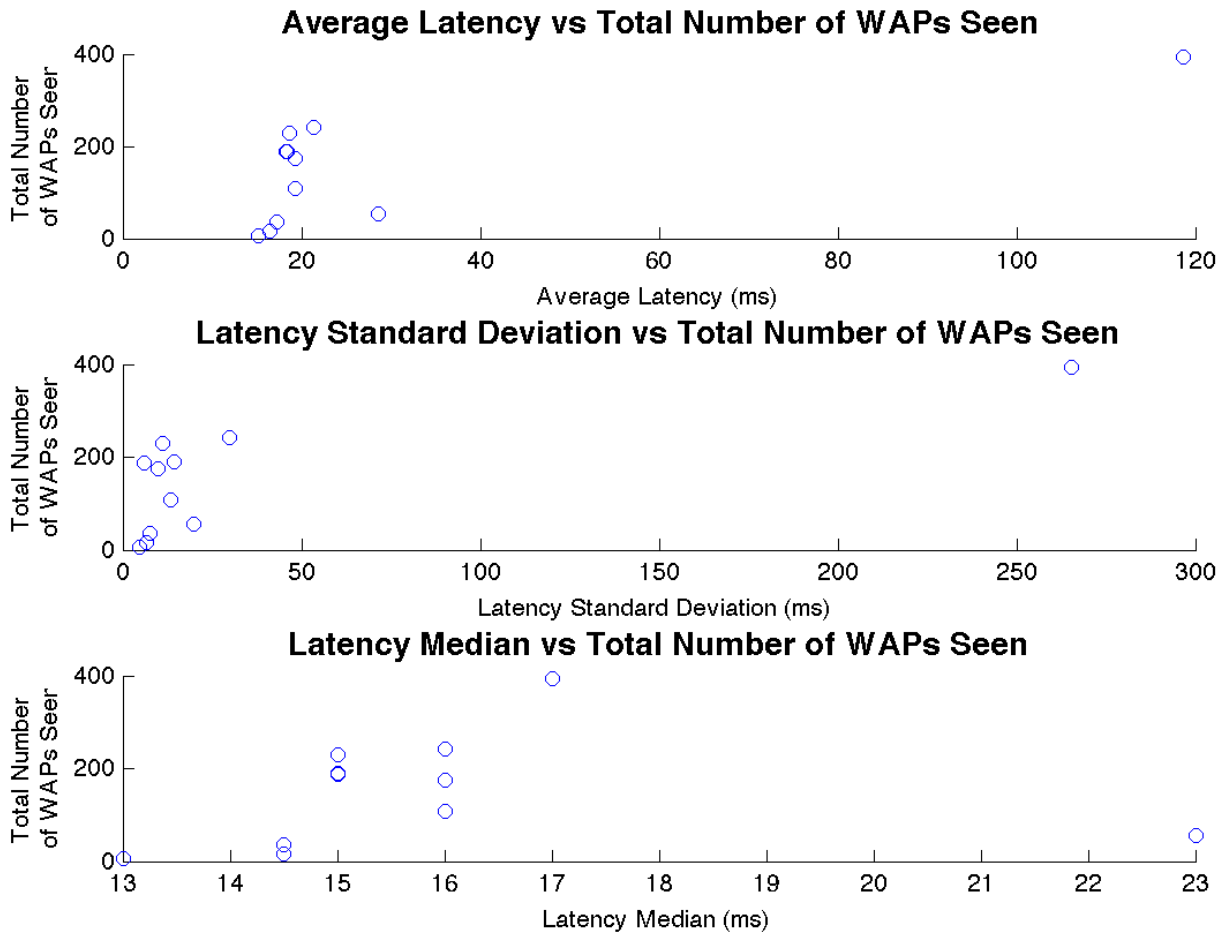


Figure 4.39: Latency Distribution versus Number of WAPs

## 4.6 Chapter Summary

In summary there is a relationship between the number of WAPs in a particular location and the experience application QoE of user on a mobile device. The limited data and measurements implied that there was a linear relationship between the variation of the download throughput and upload throughput as a function of the

number of WAPs. As the number of WAPs increased, the fluctuation in download throughout and upload throughput also increased. In addition, the data suggests that there is a relationship between the average experienced latency and variation in the latency measurements against the number of WAPs. As the number of visible WAPs increased, the average latency increased and the variation in the latency measurements also increased. All of these factors support the argument that the increasing number of WAPs will have an effect of the user QoE on a mobile device.

However, the trends in the test measurements do not point to a conclusive analysis of the QoE environment based on the number of WAPs in a particular location for data offloading. There are generally trends in the limited sample data that support the arguments but the results are not conclusive because the sample data size and location range is limited. This suggests that collecting data only from a single mobile device is not enough to build a picture of when or where to make an offload decision. To build a more comprehensive picture of the wireless environment, a crowdsourcing model of collecting the QoE measurements could be effective. In addition, including other data sources into the analysis such as user density, user applications, WAP load, network backhaul load, etc could be useful. It is also likely that a multitude of samples per WAP per frequency over time are needed as wireless environments can change over time and be affected by varying loads on the network.

The approach of collecting sample QoE data from a single device and comparing against WAP locations and frequencies seems to only provide a limited insight into the user's QoE on a mobile device. Moreover, this data was taken from only two makes, models, and device operating systems. Different mobile devices can behave differently on different wireless networks and in different environments. However, the idea of using the ability of hundreds to thousands of mobile devices to crowdsource mobile application QoE while connected to a WAP becomes much more attractive.

Crowdsource data from a large, concentrated user base becomes a much easier means of obtaining large quantities of data. The obtained data would also provide a much broader set of environmental variables and factors to consider in the case of data offloading.

# Chapter 5

## Epilogue

This chapter summarizes the main points made in the thesis. The limitations of the current level of study are discussed. It concludes by discussing several areas of future work and applications.

### 5.1 Evaluation of the Results

The objective of this thesis was to assess the impact of Wi-Fi radio frequency interference (RFI) on mobile application quality of experience (QoE). There are many variables that are involved in determining the impact of Wi-Fi access points and radio frequency in relationship to QoE. This thesis focused on understanding the effect of download throughput, upload throughput, and latency on the user's mobile device due to the number of WAPs in a particular location. The data suggests that there was a potential linear relationship between the standard deviation of the download throughput and upload throughput and the number of WAPs in a particular location. As the number of WAPs increased, the variation in the download throughput and upload throughput increased as well. Furthermore, the data showed that the average latency measurements and the standard deviation

of the latency measurements increased with the number of WAPs in a location. The fluctuation in the download throughput, upload throughput, and latency, in addition to the increase in average latency could cause a noticeable effect in the user QoE on a mobile device in such a location.

Nevertheless, the limited data set did not provided any conclusive analysis of the QoE environment based on the number of WAPs in a particular location for data offloading. The sample data shows trends that offer an indication that there is in fact an effect on the experienced QoE due to the number of WAPs, but the extent of the impact is unknown. The limited number of tests performed from two Android devices only provides a small point of reference. The trends found suggest that a larger data set from a multitude of crowdsourced devices is needed. Such data would provide a stronger indication of the general effect on QoE desirable for determining network or Wi-Fi offload events and policies.

## 5.2 Limitations

The limitation of this work is due to the dataset being restricted to only the mobile application layer side of the QoE. To gain a richer perspective of the QoE and the factors effecting QoE would require insight into the load on the WAP and the backhaul load in the network to the Internet. These can have varying effects on QoE. In addition, Wi-Fi network authentication duration, obtaining an IP address, and be granted access to the Internet needs to be considered for a more complete study.

Furthermore, the study does not examine the density of user devices and the applications running on these devices. Users could be classified as heavy, medium, or light Wi-Fi network consumers. This can have further repercussions to the QoE of consumers. For example, a heavy consumer may be more adverse to a degraded

QoE from a Wi-Fi environment with a high interference location because he or she is accustomed to a higher QoE experience. Alternatively, a light consumer may be more agreeable to a degraded QoE because there is little experienced difference between having access and no access. Moreover, the perceived user QoE on the device could be influenced by applications that are heavy network applications as opposed to light network applications. Other possible factors effecting QoE are the number of applications running on the device at one time that are also using network bandwidth, device radio, CPU, memory, and battery resources.

### **5.3 Conclusions**

Facing the explosive growth of mobile data traffic and user demand, Wi-Fi network operators and cable operators are investing significant amounts of time, effort and money in building new and upgrading existing infrastructure. Wi-Fi networks have now been deployed in many parts of North America and globally, and mobile technologies are increasing accessible. As the new generations of networks are getting more and more complex while network load rockets high, planning, configuration, management, optimization, operation and healing of a Wi-Fi network all become increasingly challenging. The efficient deployment, management and operation of a network are critical to the success of a network operator in a fiercely competitive market.

The objective of this thesis was to assess the impact of Wi-Fi radio frequency interference (RFI) on mobile application quality of experience (QoE). Two mobile Android applications were utilized to collect data on the Wi-Fi environment and to do network performance tests on a university campus Wi-Fi network in order to study

the impact of the Wi-Fi RFI. The Wi-Fi radio frequency conflicts and the user's QoE are both considered in the analysis engendered by data taken from the mobile devices.

This thesis proposed that information regarding the RFI between WAPs is necessary in order to maintain mobile application QoE within a Wi-Fi network. It was found that the average download throughput and upload throughput did not seem to be affected by the increase in the number of WAPs at a particular location. However, the standard deviation of the download throughput, upload throughput, and latency did have an effect, as did the average latency in particular locations as the number of WAPs increased. This indicates that there is a trend or relationship in the data that supports the hypothesis that the user QoE is affected by the increase in WAPs and RFI in a limited location. The trends do not point to a conclusive analysis of the QoE environment based on the number of WAPs in a particular location due to the limited data set. Other factors such as user density, network traffic, available bandwidth, mobile application usage, and user behaviour could all be possible additions to the analysis for developing Wi-Fi offload policies.

## 5.4 Future Work

It is likely that thousands of samples per WAP per frequency over time are needed to draw a conclusion. In practice, this is unattainable for such a small study with a limited scope. However, using the ability of millions of mobile devices to crowdsource mobile application QoE while connected to WAP becomes an attractive possible solution. Crowdsourced data from a large, concentrated user base becomes a much easier means of obtaining large quantities of data and aggregating the results. A more comprehensive mobile application or library could be developed to capture a greater set of variables. This application could be made available over a

mobile application store or integrated within other applications to be widely downloaded and distributed. This would provide a mechanism to collect a vast amount of data from a larger and more diverse set of users and devices. Such a collection instrument could provide a larger, crowdsourced data set over a greater collection time interval to perform a similar study.

In addition, combining the measured QoE data from mobile devices with information about the user density, the network traffic, and application usage could be useful. Having the point of view of both the mobile device and WAP could be powerful in understanding the complete picture of not only the wireless environment but also the wired network, and user device. Likewise, examining user behaviour and habits might help in designing Wi-Fi offload policies and events.

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