Wireless Channel Characterization based on Crowdsourced Data and Geographical Features

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WIRELESS CHANNEL CHARACTERIZATION BASED ON CROWDSOURCED DATA AND GEOGRAPHICAL FEATURES

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WIRELESS CHANNEL CHARACTERIZATION BASED ON CROWDSOURCED DATA AND GEOGRAPHICAL FEATURES

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in
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with a
Major in Electrical Engineering
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To design and plan wireless communication systems, an accurate propagation estimate is required of a deployment region. Propagation prediction models consist of two types of fading: large-scale and small-scale fading. With large-scale fading, the path loss information is crucial for cell planning, coverage estimation, and optimization. With small-scale fading, the statistical fluctuation on the local variations of the average signal level can have a dramatic effect on protocol decisions and resulting performance. To obtain accurate estimates of both types of fading, typically field measurements are needed that use drive testing, which is expensive in terms of time and cost. Recently, LTE release 10 in 3GPP TS 37.320 has developed a Minimization of Drive Test (MDT) specification to monitor the network Key Performance Indicators (KPIs) via crowdsourcing.

In this approach, each User Equipment (UE) will be used as a measurement tool to provide the required performance measurement for the operators. MDT is a crowdsourced approach that does not increase the processing load of a UE, and the UE does little more than its regular network monitoring already required for cellular operation. The additional step required by the UE is to share these measurements periodically with the base station and network infrastructure. MDT requests the location information of the UE along with the KPI information in case that the GPS receiver is enabled. Many use cases have been defined for MDT such as coverage optimization, mobility optimization, capacity optimiza-
tion, parametrization for common channels, and Quality of Service (QoS) verification. In this thesis, we study the capability of the MDT to infer wireless channel characteristics.

However, mobile phones are not designed to function as a measurement tool. Namely, there are various imperfections induced by user equipment when sampling signal quality. To confidently use the MDT approach, we first need to understand the role that mobile phone imperfections have on wireless characterizations when compared to drive testing equipment. In particular, our focuses in this work consists of three fundamental concepts. First, we evaluate the perceived channel quality in terms of the average loss from crowdsourced data using state of the art phones versus professional RF measurement tools. Specifically, we perform extensive experimentation across different mobile phone types, two pieces of software, and a channel scanner in three representative geographical regions: single-family, multi-family, and downtown areas. With these devices and in-field measurements, we evaluate the effects of averaging over multiple samples, uniform and non-uniform downsampling (in time and space), quantization, and crowdsourcing on the path loss exponent estimation.

Then, we design a model to use the crowdsourced data efficiently. We build a regional analysis framework to infer KPIs by establishing a relationship between geographical data and crowdsourced measurements. To do so, we use a neural network and crowdsourced data obtained by a UE to predict the KPIs in terms of the reference signal’s received power (RSRP) and path loss estimation. Since these KPIs are a function of terrain type, we provide a two-layer coverage map by overlaying a performance layer on a 3-dimensional geographical map. As a result, we can efficiently use crowdsourced data (to not overextend user bandwidth and battery) and infer KPIs in areas where measurements have not or can not be performed.

Finally we study the capability of the MDT approach to estimate the fast fluctuations of the wireless channel which has rarely been addressed in prior studies. Estimating the multipath and fading characterization would help in different real-life scenarios such as channel characterization, link budget calculations, adaptive modulation, and geolocation applications, to enhance the network performance for the end user. However, currently this information is only achievable in a lab environment, and under controlled conditions.
A UE in an LTE network can measure the rapid fluctuations of the wireless channel condition using reference signals. MDT enables the UE to periodically send additional information to the transmitter according to the base station and infrastructure requirements. There is, however, concerns over battery consumption if the MDT reporting becomes too frequent, memory concerns if the reporting becomes too infrequent (and yet the recording level stays high), and privacy concerns over providing location information.

Also, a mobile phone may average over multiple samples of received signal quality, which might affect the instantaneous observations of the channel variations. In this work, we study the capability of MDT measurements to estimate the channel fluctuation characteristics in the presence of phone measurements shortcomings include averaging over multiple samples, imprecise quantization, and non-uniform and/or less frequent channel sampling. We use outage probability as the performance metric, which is a function of the wireless channel variation. Outage probability defines as the point at which the receiver power value falls below a threshold. This threshold is the minimum signal-to-noise ratio within a channel to have a certain QoS.
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Chapter 1
Introduction

Cellular network providers collect and analyze radio signal measurements continuously to improve network performance and optimize the network configuration. Available methods to obtain the signal measurements consist of drive testing, network-side-only tools, dedicated testbeds, and crowdsourcing [47]. The former three methods are extremely resource intensive. For example, one common approach for capturing radio signal measurements is to outfit a backpack with six mobile phones running various applications and network protocols alongside an expensive mobile channel scanner (see Fig. 1.1) for network engineers to gather data on foot. Vehicles are often used for a greater number of and potentially higher-powered and more costly devices, allowing higher levels of mobility in a targeted region. In congested areas with various technologies (e.g., LTE, GSM, UMTS, and TETRA) the problem becomes worse: to get an acceptable quality of service, data collection should be repeated multiple times per roll out of each technology to appropriately configure the network [126]. Further complicating matters, physical changes to the environment such as construction of new buildings or highways can decrease the effectiveness of the obtained data. Estimation shows that the drive testing cost reached $961.2 million in 2016 and will touch $1.6 billion by the end of 2023.

An alternative and less-costly way to capture such Key Performance Indicators (KPIs) is crowdsourcing, as outlined in the Minimization of Drive Test (MDT) effort of LTE release 10 in 3GPP TS 37.320. MDT allows carriers to monitor the in-situ network performance of end users to detect variations of the provided Quality of Service (QoS) to perform such actions as handover, if the problem is confined to a single user, or self-organization, if the problem extends to one or more towers. The use case scenarios for MDT are determined as follows: coverage optimization, mobility optimization, capacity optimization, parametrization for
common channels, and QoS verification [53]. Coverage optimization contains some other use cases such as coverage mapping, detection of excessive interference, and overshoot coverage detection.

In MDT, the User Equipment (UE) is used as a measurement tool to log the signal quality measurements coupled with the location information of the user at the time of each measurement. Furthermore, a UE can log the signal measurements when either active or idle. Since the required signal measurements can be obtained from the regular Radio Resource Management Process (RMP), MDT does not put a burden on a network regarding computational complexity or excessive battery consumption.

However, the mobile phones are not calibrated measurement devices. Hence, a first step in using crowdsourced data requires understanding the viability of mobile phones to replace more advanced measurement equipment as channel modeling probes. A phone possesses a number of shortcomings when compared to a channel scanner in reporting channel quality, such as: (i) averaging over multiple samples, (ii) coarse quantization, which can impose a unit step for minuscule changes, (iii) sampling at non-uniform intervals when crowdsourcing information as opposed to long, consecutive testing periods recorded when drive testing, and (iv) clipping that results from less sensitive receivers with fringe network connectivity.

In this work, we study the capability of MDT to estimate the channel characteristics. The propagation characteristics of a wireless channel consist of large- and small-scale fading. Large-scale fading consists of two components: (i) path loss which is signal strength degradation as a function of distance and (ii) shadowing which happens due to large objects such as buildings and hills in the concerning region. We first study the accuracy of the perceived path loss characteristics by phone measurements in the presence of the aforementioned phone measurement shortcomings versus a piece of advanced equipment (e.g., channel scanner). To do so, we perform extensive in-field experimentation to quantify the impact of each of these four effects when evaluating the viability of mobile phones to characterize the path loss exponent, a metric commonly used by carriers for deployment planning, frequency allocation, and network adaptation.
Furthermore, we address how efficiently we can use the crowdsourced data (to not overex-
tend user bandwidth and battery) to infer the signal quality level in areas where measure-
ments have not or can not be performed. It is well known that channel characteristics depend
on the surrounding geographical features, though the relationship and correlation thereof has
not be formalized to a large extent. Thus, we establish the relationship required by MDT ef-
forts between geographical data and user-based data to improve the accuracy of the channel
propagation estimation. Using our framework, Regional Analysis to Infer KPIs (RAIK), we
predict the network coverage using neural networks alongside crowdsourced data collected by
UEs with an overlaid LiDAR dataset in that same region. The prediction model is based on
a feed-forward, back-propagation model, which employs multilayer perceptron (MLP) with
the geographical features of a region to provide a KPI-based coverage map. To evaluate
RAIK, we perform extensive in-field measurements from urban and suburban regions with
diverse geographical features such as type, density, and height of the buildings and trees.
RAIK forms a generalized framework that allows prediction of the KPIs in areas that have
yet to receive crowdsourced channel quality measurements from users, relying solely on the
terrain and clutter information of a given area.

Finally, we study the capability of phone measurements to estimate the fluctuations of a
wireless channel. Small-scale fading or fast fading is the rapid fluctuation of the amplitude of
received signal over a short period of time and distance. Fading is mainly caused by multiple
paths of propagation, where more than one copy of the transmitted signal arrive at the
receiver with random phases and various delays. The different copies are generated due to the
reflection and scattering from objects like trees and buildings surrounding the transmitter and
receiver. Fading estimation would help in different scenarios such as channel characterization,
link budget calculations, adaptive modulation, and geolocation applications, to enhance the
network performance for the end user. A UE in an LTE network can measure the rapid
fluctuations of the wireless channel condition using reference signals. In LTE networks, the
UE measures a reference signal every 0.5 milliseconds. With MDT, a UE can log these KPIs
of the network to report them to the MDT servers immediately or periodically. However,
there are some limitations on the UE side to measure, log, and report the KPIs of the network regarding the memory, bandwidth, and battery usage. Also, a mobile phone may average over multiple samples of received signal quality, which might affect the instantaneous observations of the channel variations. We study the impact of the averaging and the number of signal samples on the accuracy of the fast-fading estimation in terms of outage probability, which is a function of the wireless channel variation.

1.1. Summary of Thesis Contributions

Mobile Network Operators need to perform ongoing signal quality testing to improve the network coverage prediction accuracy. Knowledge of the wireless channel is essential to accurately estimate the network coverage. However, performing signal measurements using drive testing, which is the common approach, is expensive in time, manpower, and equipment. During the last decade, on-device measurement or crowdsourcing has become an alternative approach to drive testing. Crowdsourcing provides large-scale network testing using distributed mobile phones. Furthermore, LTE release 10 in 3GPP TS 37.320 has developed a Minimization of Drive Test (MDT) specification to monitor the network Key Performance Indicators (KPIs) via crowdsourcing to reduce the time and cost of the drive testing.

In this dissertation, we analyze the viability and the accuracy of crowdsourced data to estimate the propagation characteristics of a cellular network, considering the large-scale and small-scale fading. Then, we establish a platform to use the crowdsourced data along with the geographical features to improve the accuracy of the propagation prediction model and channel estimation. Later, we study the capability of MDT measurement to estimate the fast-fading parameters.

The contributions of this thesis are as follows: First, we study the impact of various effects induced by user equipment when sampling signal quality. These shortcomings include averaging over multiple samples, imprecise quantization, and non-uniform and/or less frequent channel sampling. We specifically investigate the accuracy of characterizing large-scale
fading using crowdsourced data in the presence of the aforementioned phone measurement shortcomings.

Secondly, we address how efficiently crowdsourced data may be used (to not overextend user bandwidth and battery) to infer the signal quality level (MDT or drive testing) in areas where measurements have not or can not be performed. To do so, we establish the relationship between geographical data of a region and corresponding channel characteristics. We improve the prediction accuracy of the model by considering the obstacles along the direct path from the base station to the mobile user that has a large effect on the propagation characteristics. Additionally, due to multipath, there is a width of this direct path that comes into question. The angle around this direct path might be larger or smaller depending on the degree to which the multipath delay spread exists in the environment and varies due to the region type. We optimize this angle using the delay spread information obtained from the concerning region.

Finally, we study the capability of MDT measurements to estimate the channel fluctuation characteristics in the presence of phone measurements shortcomings include averaging over multiple samples, imprecise quantization, and non-uniform and/or less frequent channel
sampling. We use outage probability as the performance metric, which is a function of the wireless channel variation. Outage probability defines as the point at which the receiver power value falls below a threshold. This threshold is the minimum signal-to-noise ratio within a channel to have a certain QoS.

1.2. Thesis Overview

The thesis is structured as follows. In Chapter 2, we present background information on the hardware and software platforms used for the experiments. In Chapter 3, we quantify the impact of various effects induced by mobile phones when interpreting signal quality such as averaging over multiple samples, imprecise quantization, and non-uniform and/or less frequent channel sampling. In Chapter 4, we use a neural network and crowdsourced data obtained by a UE to predict the KPIs in terms of the reference signal’s received power (RSRP) and path loss estimation. In Chapter 5, we study the viability of MDT measurement to measure fast-fading parameters under different circumstances such as averaging over different numbers of samples, quantization, and less frequent channel sampling in a different fashion (uniform and non-uniform). Finally, we conclude in Chapter 6 and discuss future possible directions for this line of work.
Chapter 2
Background

The purpose of this study is to compare the ability of mobile phone measurements to measure wireless channel characteristics, captured either at the API level or the firmware level, to an advanced measurement tool, the channel scanner. Before doing so, in this section, we compare and calibrate the raw measurements provided by diverse mobile phones at different levels of the software stack with data provided by a channel scanner. API-Level Phone Data. At the API level, we modify our Android application WiEye, which we designed to crowdsource measurements, to log signal quality measurements at the highest sampling rate that the operating system will allow (1 Hz). Since WiEye can be installed on any Android-based phone, we can compare API-level measurements across a wide array of devices. In our study, we use four different mobile phones: (i.) Samsung S5, (ii.) Nexus 5, (iii.) Google Pixel, and (iv.) Samsung S8. While the former two phones are not the latest models, they provide a comparison across multiple generations, and the Samsung S5 is the phone that allows a firmware-based tool that we will now discuss.

In this chapter, we describe the background of our research, including the basic technology related to this work, the hardware and software tools that we used to conduct and evaluate our proposed approaches in this work.

2.1. WiEye: Free Android Base Spectrum Analyzer

For our research purposes, our wireless and communication team developed a smartphone application called WiEye which works as a spectrum analyzer. This application allows users to scan and collect signal measurements form different cellular technologies such as GSM, LTE, CDMA, WCDMA, and WiFi networks. From WiFi perspective, the application facilitates setting the routers wireless channel or simply viewing the potential interference of
other networks to the user.

The application allows the users to opt into data collection for our research, covered by an Institutional Review Board (IRB). If the user opts into the research, the application on the users device will log RF measurements to our repository. The crowdsourced measurements are recorded periodically approximately ten times per day to be mindful of data usage and energy constraints of our participants’ phones. Each record includes the received signal level coupled with user’s coordinate in time of measurement. Table 2.1 contains the provided features by the application, such as the received signal level, the user’s coordinate, location accuracy, velocity, device ID, Mobile Network Operator’s name, and the base station identification.

This publicly-available Android application has recorded measurements from voluntary participants to form a crowdsourced data set. We have captured more than 250 million number of signal quality measurements from more than 60 thousands users worldwide. Fig. 2.1 shows the reported signal quality measurement for LTE technology. The dataset consists of the performance metrics from different technologies such as GSM, UMTS, WCDMA, and LTE.

To perform controllable measurement we developed a local version of WiEye to log the signal quality on the phone in a higher rate as 1Hz. Also we recorded the logs directly on the phone to avoid any confusion with our global data base.

Table 2.1: Measured Metrics with Android.

<table>
<thead>
<tr>
<th>Features</th>
<th>Content</th>
</tr>
</thead>
<tbody>
<tr>
<td>Country and network code</td>
<td>MCC &amp; MNC</td>
</tr>
<tr>
<td>Time stamp</td>
<td>Date and time</td>
</tr>
<tr>
<td>Location</td>
<td>Latitude and longitude</td>
</tr>
<tr>
<td>Received Signal Level</td>
<td>ASU</td>
</tr>
<tr>
<td>BTS identification</td>
<td>LAC and CID</td>
</tr>
<tr>
<td>Network operator type</td>
<td>AT&amp;T, T-mobile</td>
</tr>
<tr>
<td>Device ID</td>
<td>Unique ID of a UE device</td>
</tr>
<tr>
<td>Velocity</td>
<td>MPH</td>
</tr>
</tbody>
</table>
2.2. Acquiring Signal Measurements Using Advanced RF Measurement tools

Drive testing requires advanced RF measurement tools to carry out the measurements such as a channel scanner. In this work we evaluate the accuracy of the received signal reporting by mobile phones as compared to two advanced RF measurement tools include (i) a channel scanner (TSMW) and (ii) a smartphone-based RF optimization and service quality assessment application from Rohde & Schwarz company.

2.2.1. R&S TSMW Universal Radio Network Analyzer

The TSMW network analyzer depicted in Fig. 2.2 includes two antennas for any input frequency from 30 MHz to 6 GHz, and a global positioning system (GPS) receiver. We control the equipment by a laptop while performing the drive testing. The channel scanner architecture is different with a mobile phone. It has a broadband RF front-end and a based band processing system, which is independent from any mobile phone chipset. So it can be configured to collect signal measurements from different technologies, such as LTE, GSM, and WCDMA in a certain frequency range simultaneously. The collected data by the scanner is post processed by using Rohde & Schwarz ROMES software.
2.2.2. QualiPoc Android

QualiPoc Handheld release 15.3 has been designed for handheld radio network optimization and quality assessment. This application supports different technologies such as GSM, GPRS, EDGE, WCDMA, HSDPA, HSUPA and LTE. Also, it can be installed on a variety of devices. Using QualiPoc we can collect data and voice services statistics. Using Qualipoc we can collect the Key Performance Indicators (KPI)s of the network such as Received Signal Level, Received Signal Quality.
Chapter 3
Pre-Crowdsourcing: Predicting Wireless Propagation with Phone-Based Channel Quality Measurements

3.1. Introduction

For configuration and maintenance of a wireless network, a regular monitoring of the wireless network is required. A conventional approach to collect data from mobile networks is drive testing which consumes enormous time and is expensive in terms of manpower and equipment. Within the last decade crowdsourcing has emerged as a competitive approach to drive testing.

While there is less control of the factors leading to a recorded channel quality, there are many advantages to crowdsourcing this information in terms of lessening the need for costly equipment, reduced in-field man hours, rapid scalability of data sets, and penetration into restricted physical locations.

However, mobile phones possess a number of shortcomings when compared to a channel scanner in reporting channel quality, such as: (i) averaging over multiple samples, which can flatten channel fluctuations [114] with manufacturer-specific methodologies to estimate the received signal power [22], (ii) coarse quantization, which can impose a unit step for minuscule changes, (iii) sampling at non-uniform intervals when crowdsourcing information as opposed to long, consecutive testing periods recorded when drive testing, and (iv) clipping that results from less sensitive receivers with fringe network connectivity. The accuracy of the received signal reporting by mobile phones as compared to a channel scanner was evaluated in [71], but the effect of averaging, the impact on path loss calculation, and the resulting coverage estimation impact was not considered. Hence, while a crowdsourcing framework for characterizing wireless environments would have tremendous impact on drive testing costs,
we believe that a first step in doing so requires understanding the viability of mobile phones to replace more advanced measurement equipment as channel modeling probes.

In this chapter, we study the impact of various effects induced by user equipment when sampling signal quality. These shortcomings include averaging over multiple samples, imprecise quantization, and non-uniform and/or less frequent channel sampling. We specifically investigate the accuracy of characterizing large-scale fading using crowdsourced data in the presence of the aforementioned phone measurement shortcomings. To do so, we perform extensive in-field experimentation to quantify the impact of each of these four effects when evaluating the viability of mobile phones to characterize the path loss exponent, a metric commonly used by carriers for deployment planning, frequency allocation, and network adaptation. Our results indicate that the inferred propagation parameters by smartphone measurements in GSM and LTE networks is comparable to those obtained by the advanced equipment that are frequently used by drive testers (e.g., channel scanners). Finally, we analyze the impact of the path loss prediction error on a carrier’s misinterpretation of coverage area and predicted network throughput. In wireless networks, the percentage of coverage area is determined by a region over which the signal level exceeds the sensitivity level with a specified level of probability. This value is the likelihood of coverage at the cell boundary and a function of the received signal level. Therefore, an accurate network design will avoid possible gaps in the network (overestimating propagation) or interference in adjacent cells (underestimating propagation), which both affect the network throughput [64]. In particular, our work makes the following four contributions.

First, we set forth a framework to evaluate the impact of strictly using mobile phones (as opposed to a channel scanner) in propagation prediction. As depicted in Fig. 5.1, we consider how the averaging, uniform and non-uniform downsampling over time and space, and quantization of mobile phone channel quality samples at both the firmware and API levels affect the path loss characterization. At the API level, we have designed a freely-available Android application called WiEye, which can help users globally analyze spectrum in an economical manner. Additionally, WiEye functions as a crowdsourcing tool, which
has captured over 250 million signal quality measurements from over 60 thousand users worldwide (protected by an IRB). At the firmware level, we capture signal quality directly from the hardware via a Rohde & Schwarz tool called Qualipoc.

Figure 3.1: Pre-processing and post-processing of collected data by channel scanner and mobile phones.

Second, we compare the perceived channel quality across the channel scanner, multiple mobile phone models, and various levels of the software stack. To do so, we perform extensive local experiments across downtown, single-family residential, and multi-family residential regions and directly compare the received channel quality as reported by the channel scanner to mobile phone firmware-level and API-level data, where each mobile phone measurement considered has a corresponding channel scanner measurement for comparison. We initially observe that even over different sectors from the same base station in the same region type there can be a 0.4 difference in inferred path loss exponent and identify some of the geographical features that are responsible for this variation. More generally, as compared with the path loss exponent calculated for each region based on the channel scanner, we find
that the firmware level measurements had an average path loss exponent estimation error of 0.06, 0.06, and 0.1 and API-level measurements had an error of 0.12, 0.13, and 0.11 for the single-family, multi-family, and downtown regions, respectively. This result considers the same number of samples from each device for direct comparison. Each prediction error occurred in the positive direction, meaning the value of the predicted path loss exponent from the mobile phone was greater than that predicted by the channel scanner data, an observation that can be used for future MDT calibration. We also examine the range over which each user-side device and software is able to receive cellular base station transmissions \(i.e.,\) their sensitivities to understand where clipping of crowdsourced data might occur.

Third, we quantify the impact on inferring propagation characteristics from the various calculations and imperfections that mobile phones induce on received channel quality before reporting it to the user.

To do so, we consider numerous data sets from the channel scanner in the aforementioned environmental contexts and impose these imperfections to understand their role by evaluating against the root mean-squared error of path loss prediction from the original channel scanner data set in that region. Our results show that the path loss parameters obtained by mobile phone samples are sufficiently comparable to the advanced drive testing equipment, paving the way for crowdsourcing as a viable solution for in-field performance analysis.

Fourth, considering the fact that any error in path loss estimation will ultimately affect the coverage area estimation and Bit Error Rate (BER), we build intuition about the prediction errors reported throughout the previous sections of the chapter as they relate to network planners and operators by quantifying the impact on coverage estimation and user BERs. Since we observe path loss exponents ranging from 2 to 4 from our crowdsourcing platform, we consider a situation in which the actual path loss exponent is 3, but errors in prediction range from -1 to +1. In doing so, we allow a continuum of analysis about how much the network holes (overestimating propagation) or redundancy (underestimating propagation) might exist from the original targeted area. In particular, a modest propagation overestimation error of -0.4 (13% error) from an actual path loss exponent of 3 results in a
quarter (25%) of the targeted area having coverage holes in regions that were assumed to be covered. Conversely, the same modest propagation underestimation error of +0.4 from actual path loss exponent of 3 would result in a 40% overlap in the targeted coverage region. While the percentage of error is very small (-/+13%), the impact on coverage estimation is large. In terms of user BER, such a 0.4 prediction error frequently raises the BER by an order of magnitude for many situations (e.g., predicting 2.1 but an actual path loss exponent of 2.5, a relative error of only 16%, for an SNR of 15). In other words, at locations where there was assumed to be moderate to high SNR, the prediction errors can have a dramatic effect on user performance. For example, some services like video streaming require a specific throughput. Small variations in throughput will increase the latency of live streams, especially at the cell boundaries.

The remainder of the chapter is organized as follows. We discuss related work in Section 3.2. In Section 3.3, we experimentally quantify the channel quality reporting differences of mobile phones versus a channel scanner. In Section 3.4, we analyze the role of mobile phone imperfections in terms of path loss prediction. Section 3.5 relates path loss prediction error to coverage estimation for operational networks. Lastly, we conclude in Section 3.6.

3.2. Related Work

The Minimization of Drive Tests (MDT) initiative in the 3GPP standard has been created to exploit the ability of smartphones to collect radio measurements in a wide range of geographical areas to enhance coverage, mobility, capacity, and path loss prediction [2]. MDT is a crowdsourcing approach which enables a large-scale network testing using smartphone. Crowdsourced data has already been utilized in some studies to identify network topology [27], perform real-time network adaptation [111], characterize Internet traffic [110], detect network events [19], fingerprint and georeference physical locations [96], assess the quality of user experience [60], and study network neutrality [33]. The bandwidth, latency, and throughput have previously been used as crowdsourced KPIs [102,114] to evaluate wide-area wireless network performance [44] and in-context performance [127].
Also, a few measurement studies have used API-level measurements to estimate different KPIs of cellular networks [51, 86, 102, 114]. They each measured KPIs in terms of throughput, received signal power, and delay and involved regular users to provide measurements (i.e., crowdsourcing) across large geographical regions in some cases. In contrast, we focus on characterizing the wireless channel using diverse end-user devices at different levels of the software stack. Predicting the cellular network coverage by using the crowdsourced data has been studied in a few studies. For example, network coverage maps using crowdsourced data is studied in [74]. However, the authors provided the observed received signal level without a discussion of the differences across end-user devices. In addition, another work used a similar idea of using crowdsourced data along with interpolation techniques to predict the coverage area [78]. Although, the impact of location inaccuracy and data distribution of the interpolation techniques was investigated, the impact of the imperfections of end-user devices was not explored. In fact, [73] argued that [78] suffers from a lack of control and repeatability of capturing data and piggy-backing mobile broadband measurements onto public transport infrastructures.

Furthermore, others proposed the Bayesian Prediction method to improve the coverage estimation obtained by drive testing and MDT measurements, but the results were strictly based on advanced devices as opposed to mobile phone measurements [105]. The provided X-map accuracy from simulated data in [84] has been evaluated in terms of position inaccuracy, UE inaccuracy, and number of measurements. However, to analyze crowdsourced data, using in-field experimentation is important to distinguish between the performance of more advanced equipment versus a mobile phone in channels similar to those experienced by user devices. Furthermore, three major application scenarios for spatial big data obtained by performing MDT in a wireless network are depicted in [65]. Also, it has been shown that massive amounts of data needs a high-performance processing platform and solutions to obtain meaningful conclusions. Hence, [24, 65] have focused on providing a platform to deal with big data regarding different applications. To estimate the channel quality, we are using RSRP as our metric from the LTE standard. It was previously observed by [22] that the
reported value by a mobile phone in terms of RSRP is influenced by averaging but did not consider the compounding effects. Similarly, [71] depicts that the received signal power by commercial phones is comparable to an advanced tool. While this is close in nature, we also consider many of the spatial and temporal downsampling effects that would cause imprecise estimation of the path loss estimation for a given environment and develop a carrier-focused intuition of the network and user impact of these errors.

3.3. In-Field Calibration of Received Signal Power from Mobile Phones

The purpose of this study is to compare the ability of mobile phone measurements, captured either at the API level or the firmware level, to an advanced measurement tool in characterizing wireless channels in terms of path loss. Before doing so, in this section, we compare and calibrate the raw measurements provided by diverse mobile phones at different levels of the software stack with data provided by a channel scanner.

**API-Level Phone Data.** At the API level, we modify our Android application WiEye, which we designed to crowdsource measurements, to log signal quality measurements at the highest sampling rate that the operating system will allow (1 Hz). Since WiEye can be installed on any Android-based phone, we can compare API-level measurements across a wide array of devices. In our study, we use four different mobile phones: (i.) Samsung S5, (ii.) Nexus 5, (iii.) Google Pixel, and (iv.) Samsung S8. While the former two phones are not the latest models, they provide a comparison across multiple generations, and the Samsung S5 is the phone that allows a firmware-based tool that we will now discuss.

**Firmware-Level Phone Data.** At the firmware level, we have purchased a software tool called Qualipoc from Rohde & Schwarz, which allows signal strength measurements to be reported directly from the chipset. Qualipoc can receive the channel quality information from many diverse technologies, such as LTE, GSM, and WCDMA. The sampling rate of the Qualipoc is approximately 3 Hz. Unlike the channel scanner, the mobile phones continuously search for the best visible base station by measuring the signal power received from multiple base stations, affecting both the API-level and firmware-level measurements.
**Channel Scanner Data.** To replicate the measurement process typically performed by drive testers, we use a commonly-used Rohde & Schwarz TSMW Channel Scanner for obtaining detailed signal quality measurements. The TSMW can passively and continuously monitor numerous technologies in 30 MHz - 6 GHz frequency range, with a sampling rate of 500 Hz. The scanner is controlled by Romes software (version 4.89), which is installed on a laptop connected via an Ethernet cable to the TSMW.

**In-Field Measurement Setup and Calibration.** We conduct a measurement campaign across three diverse regions of Dallas, Texas with respect to terrain type: single-family residential, multi-family residential, and downtown. All five device types are connected to the same network operator for direct comparison and perform measurements in parallel on a co-located roof of a car. In each region, we observe cellular transmissions and record data from 11 total base stations.

We first quantify the signal quality sensitivities of each device for measurements taken at the same time and location. To do so, we applied a post-processing procedure on the entire collected data set. Since the sampling rate of the channel scanner is higher than that of Qualipoc (firmware) or WiEye (API), we extract the samples from the channel scanner data set, which are the closest in time to that of WiEye and Qualipoc. The matching process consists of two steps: (i.) grouping measurements based on the transmitting base station, and (ii.) downsampling channel scanner data to have the same number of samples as the Qualipoc and WiEye’s data set, where each mobile phone sample has a corresponding channel scanner measurement in time. If the channel scanner did not report a measurement within one second of the mobile phone measurement, we do not consider that data point in our comparison.

Table 3.1 shows the minimum, maximum, and range of the received signal power for all of these measurements across all cell towers in each region. As it is seen from the results, the widest range (77) and greatest sensitivity (-134 dBm) is captured by the channel scanner with the least range (71) and sensitivity (-128 dBm) captured by WiEye. The reduced range experienced by the mobile phone will cause some clipping on the extreme ends of the
connectivity ranges, especially with poor signal quality.

Table 3.1: Field-tested range of reported signal quality (dBm) from channel scanner (TSMW), Qualipoc, and WiEye.

<table>
<thead>
<tr>
<th>Device</th>
<th>Min</th>
<th>Max</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Channel Scanner</td>
<td>-134</td>
<td>-56</td>
<td>77</td>
</tr>
<tr>
<td>Qualipoc Phone</td>
<td>-129</td>
<td>-55</td>
<td>74</td>
</tr>
<tr>
<td>WiEye Phone</td>
<td>-128</td>
<td>-57</td>
<td>71</td>
</tr>
</tbody>
</table>

Next, we again consider this downsampled data set which matches the time stamps across devices to consider the difference in reported signal quality per signal quality sample across devices. Table 3.2 shows the difference of WiEye compared to the matched channel scanner measurement and Qualipoc compared to the matched channel scanner measurement across the three region types. This measurement shows the dBm offsets that mobile phones could induce on a crowdsourced data set as compared to more advanced equipment. We also report the mean reported signal strength per region for completeness.

Table 3.2: Average signal quality offsets (dBm) reported from Qualipoc and WiEye with matched channel scanner measurement.

<table>
<thead>
<tr>
<th>Location</th>
<th>Qualipoc dBm Diff. (Mean)</th>
<th>WiEye dBm Diff. (Mean)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Downtown</td>
<td>-1.5 (-75.6)</td>
<td>-4.4 (-78.5)</td>
</tr>
<tr>
<td>Single-Family</td>
<td>-1.3 (-82.5)</td>
<td>-3.8 (-85.0)</td>
</tr>
<tr>
<td>Multi-Family</td>
<td>-1.9 (-78.4)</td>
<td>-4.1 (-80.3)</td>
</tr>
</tbody>
</table>

We observe that the difference in reported received signal level is on average 1.57 dBm higher on the channel scanner versus Qualipoc across the three regions with a range of 1.3 to 1.9. In contrast, the difference in reported received signal level is on average 4.43 dBm higher on the channel scanner versus WiEye across the three regions with a range of 4.1 to 4.8. These dBm offsets could affect the path loss characterization as a higher reported
channel quality could lower the path loss exponent versus a lower reported channel quality which could raise the path loss exponent. In the following section, we will consider the role of these dBm offsets as well as multiple other mobile phone imperfections.

3.4. Leveraging Mobile Phone Based Measurements on Path Loss Prediction

One of the most common metrics which drive testers use to evaluate a given region is path loss. Since we ultimately want to use mobile phone measurements in a crowdsourcing manner to obtain this metric, we need to understand the role of mobile phone imperfections on evaluating the path loss of a given environment. In particular, reported signal quality from mobile phones will have the following effects: averaging, uniform and non-uniform downsampling, and different resolutions caused by quantization. In this section, we first provide some background on path loss modeling and then experimentally evaluate the role of these mobile phone imperfections on path loss estimation.

3.4.1. Modeling Large-Scale Fading: Path Loss

Large-scale fading refers to the average attenuation in a given environment for transmission through and around obstacles in an environment for a given distance [97]. Path loss prediction models are classified into three different categories: empirical, deterministic, and semi-deterministic. Empirical models such as [57] and [87] are based on measurements and use statistical properties. However, the accuracy of these models is not as high as deterministic models to estimate the channel characteristics. These models are still widely-used because of their low computational complexity and simplicity. Deterministic models or geometrical models consider the losses due to diffraction, and detailed knowledge of the terrain is needed to calculate the signal strength [62, 121]. These models are accurate. However, their computational complexity is high, and they need detailed information about the region of interest. Semi-deterministic models applied in [25] and [32] are based on empirical models and deterministic aspects.
In our study, we use empirical methods since it is the type of modeling that would be most appropriate to leverage crowdsourcing. The large-scale fading is a function of distance \((d)\) between the transmitter and the receiver, and \(\gamma\) is the path loss exponent, where the path loss exponent varies due to the environmental type from 2 in free space to 6 in indoor environments. Some typical values are 2.7-3.5 in typical urban scenarios and 3-5 in heavily shadowed urban environments [97]. In this work, we focus on the inferred path loss exponent from mobile phone measurements and use a linear regression model to calculate the path loss exponent.

3.4.2. In-Field Analysis of Inferred Path Loss Across Region and Device Types

As discussed in Section 3.3, our experimental analysis spans three region types (single-family residential, multi-family residential, and downtown) with multiple mobile phone types at the API-level (WiEye), with mobile phones at the firmware level (Qualipoc), and with a channel scanner (TSMW). All of these devices report which base station sector is transmitting the received signal. We performed the measurements while the car speed was maintained at approximately 20 mph. To avoid stopping at the traffic lights, we observed traffic light patterns, and we drove each route many times to record data regarding our requirements. In the future, we could consider predicting the future received signal strength concerning the UE speed and direction regarding the base station. To do so, we can record the compass data from the phone along with the signal strength, location information, and time stamp.

Since prior works have shown per region performance [97] and per sector performance can differ [44], we first analyze the variation of the path loss exponent from each region and each sector in three regions from the channel scanner to show some examples of the \(\gamma\) diversity. We consider the following three types of areas:

1. A downtown region containing tall buildings and trees, which are non-uniformly distributed over the region.

2. A single-family area that is covered by a high density of foliage and mostly two-story buildings.
3. A multi-family area that has a mixture of vegetation and buildings of two stories or more in height.

Since path loss is not only a function of distance but is also affected by obstacles between the transmitter and receiver and environment type, we consider the geographical features in different areas to explain the variation of the observed path loss exponents (even within the same region type). For a more thorough investigation on the relationship between the geographical features and the role they play on propagation effects please refer to our recent work [34, 112]. Here, we make the following observations:

i). *Path loss slope varies in different region types:* To study the path loss exponent’s variation in each region, we inferred all available $\gamma$s corresponding to different sectors in each region. We eliminated the sectors with a low number of measurements as defined by the results in Fig. 3.9. We performed linear regression on each sector’s signal strength measurements independently to find the path loss exponent for that sector. Then, in each region, we select the sectors containing the minimum and maximum $\gamma$.

A received signal is a combination of transmitted signals, composed of reflected or scattered transmissions that are obscured by buildings or trees. Thus, the propagation environment is profoundly influenced by the path loss and affects the network performance. The impact of the buildings would be more visible in an urban environment where a diversity in building height surrounds the UE. In this work, we considered three different area types to measure. Table 3.3 shows the minimum and maximum path loss exponent obtained using channel scanner measurements for a particular sector in each region. As we can see, there are differences between the path loss exponent readings from different regions. To enhance our understanding about these differences, we provide detailed information of the buildings and foliage corresponding to each region. To provide 3-dimensional geographical features of a region, we used a database of Light Detection and Ranging (LiDAR) information from that region. This dataset contains detailed information of buildings and trees as we discussed extensively in our recent work [34].

The height of surrounding objects plays an important role on the signal attenuation,
because the receiver height is typically lower than the clutter height. Therefore, we provide the average and standard deviation of object heights in that area. Here, $B_h$ and $T_h$ depict the average height of the buildings and trees and the standard deviation of these object heights for and $\gamma_{\text{max}}$ and $\gamma_{\text{min}}$ are depicted as $B_{h,a}$ and $T_{h,a}$, respectively. Furthermore, we consider the number of objects (scatterers and reflectors) and ground elevation information of an area. The ground elevation information of the receiver and the transmitter would ultimately influence the difference between the clutter height and transmitter height.

Table 3.3: Minimum and maximum observed path-loss exponent per region and corresponding geographical features.

<table>
<thead>
<tr>
<th>Region</th>
<th>$\gamma$</th>
<th>$B_h$</th>
<th>$B_{h,a}$</th>
<th>#B</th>
<th>$T_h$</th>
<th>$T_{h,a}$</th>
<th>#T</th>
<th>$R_{GE}$</th>
<th>$R_{GE,a}$</th>
<th>BTS$_{GE}$</th>
<th>$\Delta_\gamma$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single-Family</td>
<td>min</td>
<td>3.2</td>
<td>8.34</td>
<td>2.7</td>
<td>209</td>
<td>10</td>
<td>2.9</td>
<td>1846</td>
<td>176</td>
<td>2</td>
<td>180</td>
</tr>
<tr>
<td></td>
<td>max</td>
<td>3.7</td>
<td>8.6</td>
<td>2.6</td>
<td>470</td>
<td>11</td>
<td>3.5</td>
<td>2300</td>
<td>186</td>
<td>7</td>
<td>180</td>
</tr>
<tr>
<td>Multi-Family</td>
<td>min</td>
<td>2.9</td>
<td>10.4</td>
<td>15.3</td>
<td>21</td>
<td>8.7</td>
<td>3.1</td>
<td>230</td>
<td>184</td>
<td>1.9</td>
<td>186</td>
</tr>
<tr>
<td></td>
<td>max</td>
<td>3.9</td>
<td>11.8</td>
<td>11.5</td>
<td>98</td>
<td>12</td>
<td>14</td>
<td>500</td>
<td>184</td>
<td>3</td>
<td>176</td>
</tr>
<tr>
<td>Downtown</td>
<td>min</td>
<td>2.8</td>
<td>35</td>
<td>35</td>
<td>36</td>
<td>9.7</td>
<td>7.8</td>
<td>197</td>
<td>135</td>
<td>2</td>
<td>136</td>
</tr>
<tr>
<td></td>
<td>max</td>
<td>3.8</td>
<td>37</td>
<td>32</td>
<td>41</td>
<td>14</td>
<td>10</td>
<td>233</td>
<td>136</td>
<td>2.8</td>
<td>127</td>
</tr>
</tbody>
</table>

We observe that downtown and multi-family regions report the highest variation range of the path loss slope. In the single-family area, there is not as big of a difference in the average and standard deviation of the object heights for $\gamma_{\text{max}}$ and $\gamma_{\text{min}}$. However, the number of the trees (#$T$) and buildings (#$B$) located in the sector corresponding to $\gamma_{\text{max}}$ is much higher than the others. Furthermore, the ground elevation of the area is about 7 meters higher than the ground elevation of the base station in the $\gamma_{\text{max}}$ case. The range of the observed path loss exponent in each environment is depicted by $\Delta_\gamma$, and the results show that the variation in the path loss exponent of multi-family and downtown regions are higher than the single-family area.

ii. $\gamma$ varies in different sectors of a particular base station (even in the same region type). We consider a particular base station consisting of three sectors in each region and
the corresponding geographical characteristics of each sector. Fig. 3.2a depicts the spatial
distribution of signal strength measurements obtained from a channel scanner for a base
station located in a single-family residential region. The measurement locations across the
three sectors are represented by red dots. In Fig 3.2b, we see that the path loss exponent of
sector (a) to sector (c) ranges from 3.1 to 3.4, even from the same base station.

(a) Measurements from a base station in the single
family region. (b) Regression line fit to the measurements of each
sector.

Figure 3.2: Signal quality data from three sectors around a base station (left) related path
loss exponents of each (right).

To generalize this behavior over multiple region types, Table 3.4 depicts the path loss
exponent of three sectors of a particular base station in three different areas (downtown,
single-family, and multi-family residential areas). The $\gamma$ in the downtown area shows a
higher variation (0.7) than two other regions with the multi-family and single-family areas
having a value of 0.3 and 0.4, respectively. Furthermore, we can see that the small variations
in average height of the objects in each region account for small changes in estimated $\gamma$
because the taller objects around the receiver or in between the base station and the UE
are more likely to scatter or reflect the signal. Also, in single- and multi-family areas, the
number of objects located in a sector and near to the receiver has an impact on the path
loss slope [90].

The $\gamma$ in the downtown area shows a higher variation (0.7) than two other regions with
We can see that the small variations in average height of the objects in each region accounts for small changes in estimated $\gamma$. Also, in single- and multi-family areas, the number of buildings and trees located in a sector has an impact on the path loss slope.

Table 3.4: Field-tested path-loss exponent per cell from channel scanner (TSMW) and corresponding geographical features.

<table>
<thead>
<tr>
<th>Region</th>
<th>Sector</th>
<th>$\gamma$</th>
<th>$\bar{B}_h$</th>
<th>$B_{h_0}$</th>
<th>$#B$</th>
<th>$\bar{T}_h$</th>
<th>$T_{h_0}$</th>
<th>$#T$</th>
<th>$R_{GE}$</th>
<th>$R_{GE_0}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single-Family</td>
<td>Sector 1</td>
<td>3.2</td>
<td>8.34</td>
<td>2.7</td>
<td>190</td>
<td>10</td>
<td>2.9</td>
<td>1846</td>
<td>182</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>Sector 2</td>
<td>3.5</td>
<td>8.3</td>
<td>2.8</td>
<td>270</td>
<td>10</td>
<td>2.9</td>
<td>2572</td>
<td>186</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>Sector 3</td>
<td>3.6</td>
<td>8.6</td>
<td>2.7</td>
<td>330</td>
<td>10.7</td>
<td>3.2</td>
<td>2760</td>
<td>186</td>
<td>6</td>
</tr>
<tr>
<td>Multi-Family</td>
<td>Sector 1</td>
<td>3.7</td>
<td>10.3</td>
<td>2.7</td>
<td>130</td>
<td>8.8</td>
<td>3</td>
<td>1117</td>
<td>182</td>
<td>3.5</td>
</tr>
<tr>
<td></td>
<td>Sector 2</td>
<td>3.6</td>
<td>11</td>
<td>5</td>
<td>276</td>
<td>10.5</td>
<td>4.5</td>
<td>1400</td>
<td>180</td>
<td>2.5</td>
</tr>
<tr>
<td></td>
<td>Sector 3</td>
<td>3.4</td>
<td>9.7</td>
<td>3</td>
<td>230</td>
<td>9.7</td>
<td>4.6</td>
<td>1960</td>
<td>184</td>
<td>2.5</td>
</tr>
<tr>
<td>Downtown</td>
<td>Sector 1</td>
<td>3.5</td>
<td>60</td>
<td>53</td>
<td>38</td>
<td>16</td>
<td>10</td>
<td>305</td>
<td>134</td>
<td>2.6</td>
</tr>
<tr>
<td></td>
<td>Sector 2</td>
<td>3.2</td>
<td>43</td>
<td>30</td>
<td>56</td>
<td>12.5</td>
<td>9</td>
<td>300</td>
<td>133</td>
<td>3.6</td>
</tr>
<tr>
<td></td>
<td>Sector 3</td>
<td>2.8</td>
<td>35</td>
<td>35</td>
<td>36</td>
<td>9.7</td>
<td>7.8</td>
<td>147</td>
<td>135</td>
<td>2</td>
</tr>
</tbody>
</table>

iii. **RSRP samples form diverse statistical distributions based on device and region types.**

To depict the difference in received signal power between the channel scanner, firmware, and API level, we plot the distribution of the Reference Signal Received Power (RSRP) values obtained by each tool for a specific base station sector in Fig. 3.3a. We observe that the difference between the CDF’s median of the channel scanner (-77 dBm), Qualipoc (-78.8 dBm), and WiEye (-79.5 dBm) are about 1.8 dB and 2.5 dB, respectively. This difference is similar to that discussed in Table 3.1, especially for the firmware measurements but shows that the API level samples are subject to other effects such as averaging of samples, which will be explored in greater depth in Section 3.4.3.1.

To evaluate the viability of a measurement sample size for each region, we use the Kolmogorov-Smirnov test (KS test), which attempts to determine if the samples come from the same distribution. There are two metrics with the test, $h$ and $p$, which are the results
of the hypothesis test at the default 5% significance level. In particular, $h$ determines if the test is passed or failed, and $p$ is the estimated significance for the specific test evaluated. An $h$ flag will be reported as 0 (false) if the null hypothesis that the two distributions have a common distribution and cannot be rejected at the chosen significance level and concurrently does not have enough evidence to support the similarity.

In our application, if the number of measurements is too small to be representative of the region, the $p$ value will be above a threshold of 0.05. Conversely, if $p \leq 0.05$, it signifies that there are a sufficient number of measurements to be confident in the path loss exponent prediction. In Fig. 3.3b, we show the $p$ value of the KS test based on the measurement number per region type. In our case, when $p \leq 0.05$, then $h$ is always 1, which means the test passes for these values of $p$. When the threshold is crossed, the number is approximately 600 samples for each region. Furthermore, the figure shows that decreasing the number of measurements in a single-family area has a lower impact on the KS value as compared to multi-family and downtown areas. This effect can be credited to the relative homogeneity of the geographical features in the single-family area as opposed to the more heterogeneous multi-family or downtown regions. We will extend this investigation on measurement number
size in Section 3.4.3.2, where we focus on the role of downsampling in both time and space from a very large number of measurements taken by the channel scanner.

iv. **Matching the mobile phone samples in time to the channel scanner samples provides precise path loss exponent prediction.** We now focus on a single mobile phone (Samsung Galaxy S5) to directly compare the path loss exponent inferred from the received signal quality reported at the API and firmware levels to that reported by the channel scanner in the same environment. We consider the most densely-measured sector from each region type in our comparison and calculate three different path loss exponents. First, we consider the path loss exponent $\gamma_X$ as calculated from all measurements in the chosen sector for device $X$, where $X$ is $T$ for TSMW, $Q$ for Qualipoc, or $W$ for WiEye. Second, we downsample the TSMW measurements according to the matching process mentioned in Section 3.3, where the TSMW measurement with the closest time stamp to the mobile phone measurement is chosen for Qualipoc and then for WiEye. This second calculated path loss exponent is represented by $\gamma_Q'$ and $\gamma_W'$, respectively, and allows the path loss exponent to be considered for the same number of measurements as Qualipoc and WiEye but with the signal strength readings from the TSMW. This approach inherently controls for the number of samples, which we later evaluate extensively.

These two $\gamma$ values are shown in Table 3.5. By comparison across these path loss exponents, $\gamma_T$ with $\gamma_Q'$ and $\gamma_W'$, we observe that even when the same device is used (TSMW) to capture the signal strength measurements, downsampling the number to match the mobile phones raises the estimate of the path loss exponent in every environment. This effect could

<table>
<thead>
<tr>
<th>Region</th>
<th>TSMW Samples</th>
<th>$\gamma_T$</th>
<th>$\Delta Q&amp;T$ (dB)</th>
<th>Qualipoc Samples</th>
<th>$\gamma_Q$</th>
<th>$\gamma_Q'$</th>
<th>$\Delta W&amp;T$ (dB)</th>
<th>WiEye Samples</th>
<th>$\gamma_W$</th>
<th>$\gamma_W'$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single-Family</td>
<td>2063</td>
<td>3.1</td>
<td>1.4</td>
<td>620</td>
<td>3.23</td>
<td>3.17</td>
<td>3.8</td>
<td>293</td>
<td>3.31</td>
<td>3.19</td>
</tr>
<tr>
<td>Multi-Family</td>
<td>1961</td>
<td>3.41</td>
<td>0.9</td>
<td>970</td>
<td>3.48</td>
<td>3.42</td>
<td>3.1</td>
<td>350</td>
<td>3.51</td>
<td>3.38</td>
</tr>
<tr>
<td>Downtown</td>
<td>11634</td>
<td>3.85</td>
<td>1.2</td>
<td>512</td>
<td>3.97</td>
<td>3.87</td>
<td>3.5</td>
<td>225</td>
<td>4.00</td>
<td>3.89</td>
</tr>
</tbody>
</table>
be explained by the inclusion of lower quality measurements (*i.e.*, considering the measurements that were clipped from the mobile phone measurements), which in turn lowers slightly increases the value of the path loss exponent. Despite the consistently positive path loss exponent error in prediction, the matched $\gamma$ values of $\gamma_{Q'}$ and $\gamma_{W'}$ are within 0.06, 0.06, and 0.1 for the firmware level measurements and 0.12, 0.13, and 0.11 for the API-level measurements for the single-family, multi-family, and downtown regions, respectively. Therefore, matching the mobile phone measurements in time to the channel scanner measurements allowed highly-effective path loss exponent prediction, especially at the firmware level.

3.4.3. Mobile Phone and Crowdsourcing Impact on Path Loss Estimation

In this section we study the impact of different shortcomings with mobile phone measurements (averaging, temporal downsampling, and quantization) and imperfections that arise with crowdsourcing wireless signal strengths (non-uniform downsampling in both time and space) as opposed to drive testing in a known physical pattern with a known periodic sampling frequency in a particular region under test. In this subsection (3.4.3) and Section 3.4.4, we use signal strength samples from the channel scanner exclusively in our analysis and emulate each mobile phone imperfection in isolation to evaluate the impact of that effect.

3.4.3.1. Averaging of the Received Signal Power

Network interfaces often use some form of hysteresis to suppress sudden fluctuations in channel state that might lead to overcompensation in adaptive protocols. Many times this hysteresis is performed by averaging multiple received signal qualities before reporting it to the higher layers (*e.g.*, within the firmware) and/or the user (*e.g.*, within the operating system in support of API calls). Each device uses its own policy (often proprietary) to take a specific number of samples over a certain period of time. In particular, a mobile phone in an LTE network is required to measure the Reference Signal Received Power (RSRP) and Reference Signal Received Quality (RSRQ) level of a serving cell at least every Discontinuous
Reception (DRX) cycle to see if the cell selection criteria is satisfied [5]. To do so, a filter is applied on the RSRP and RSRQ of the serving cell to continually track the quality of the received signal. Within the set of measurements used for the filtering, two measurements shall be spaced by no longer half of DRX cycle [4]. On the other hand, a mobile phone receives multiple resource elements and measures the average power of resource elements. However, the number of resource elements in the considered measurement frequency and period over which measurements are taken to determine RSRP by the mobile phone depends on the manufacturer.

As a result, even if two devices are in the same environment in close proximity and experience virtually the same channel quality fluctuations, differences in averaging window sizes could be interpreted as diverse fading behaviors. More importantly, when crowdsourcing signal strengths, we are forced to accept the averaging behavior of a broad range of devices. Hence, there is a question as to the degree to which an MDT update should be filtered. Since we are focused on large-scale path loss in this paper, we assume that applying a filtering mechanism on the measurements to average out the effect of the fast fading avoids misinterpretation of extreme instantaneous behavior. In other words, the eNodeB does not want to misinterpret the channel condition due to uncharacteristic spurs in the measurement, which could lead to erroneous actions such as excessive handover.

Hence, we seek to empirically quantify the degree to which a range of averaging windows (i.e., the number of samples used in the average reported) affects the calculation of the path loss exponent parameter. We depict the variation of the $\gamma$ parameter in Fig. 3.4 when we vary the averaging window from 0.25 to 6 seconds on the collected measurements by the channel scanner, which corresponds to a window size of 0 to 200 samples. We averaged the Mean Squared Error (MSE) corresponded to each window size over multiple base stations in each region. As we see, by increasing the filter size, the maximum error in three regions is about 0.1. In other words, we show that decreasing the window size does not improve the results dramatically.

Also, we represent the average and standard deviation of the estimated errors in $\gamma$ es-
estimation caused by averaging for each region via a box plot in Fig. 3.5. The x-axis shows a period of 6 seconds with a step size of one second. We see that the average error for the averaging window size varies between 1 to 6 seconds and is approximately 0.01 MSE of the path loss exponent, on average, among the three regions. In addition, we observe that by increasing the averaging window size, the absolute error in all the three regions increases. However, the variation of the error decreases because of the fluctuations of the signal is flattened by applying a large averaging window size.

3.4.3.2. Non-Continuous Measurement Periods

When crowdsourcing information from willing participants, we must be sensitive to their data usage and battery consumption issues, precluding prolonged, continuous measurements of detailed signal strength values. One option may be to uniformly reduce the number of samples per unit time for a given user over an extended period. Another option could be to aggregate small numbers of samples at different time periods and space from one or more
users to compose an aggregate channel effect. We now study both the former (uniform downsampling) and latter (non-uniform downsampling).

**Uniform Downsampling Impact.** The channel scanner samples the channel quality at approximately 500 times per second as opposed to about 3 and 1 Hz with the Qualipoc and WiEye, respectively. In this scenario, as the mobile phone preserves energy and/or data usage the question becomes: how would the $\gamma$ parameters further diverge from the results shown in Table 3.5? In other words, the previous result showed the extreme cases of either matching the same number of samples or having a very different number of samples.

To study the role of differing numbers of measurements on path loss estimation, we first examine the calculated $\gamma$ parameter from a particular sector of a base station in each region, when using uniform and non-uniform down-sampling. We gradually reduce the number of samples obtained by channel scanner to eventually reach the same number of samples recorded by WiEye. At each step, we calculate the error in path loss exponent calculation with respect to our reference value, which is obtained by considering the highest resolution in channel scanner data set. To do so, we reduce the number of samples by $i$, where $i \in 1, \ldots, n$ and $n = \frac{\#\text{Channel scanner records}}{\#\text{Phone records}}$. As we reduce the data set by $i$ samples, we are able to leverage $i$ data sets for a given $i$ to increase the confidence in the result and study the variation of error.

Figure 3.5: Impact of averaging on the $\gamma$ estimation in terms of mean and standard deviation in a period of 1 to 6 seconds.
Fig. 3.6a shows the error in path loss estimates by reducing the signal samples received from a cell sector of a base station in the downtown area. By increasing the time interval between samples, the $\gamma$ and resulting variation thereof are affected. We observe that the error caused by uniformly downsampling can reach up to 0.03 in this specific cell, which means the predicted value is very close to the reference $\gamma$. Although the MSE over each 10 steps has some variation, it does not increase the error dramatically. Furthermore, by decreasing the number of samples, the variation of channel characteristic estimation is not as stable as when we have more data points.

Fig. 3.6b shows the impact of uniformly downsampling the channel characteristics on each of the three different regions (single-family residential, multi-family residential, and downtown). The maximum variation over all three regions is depicted as the variation of the MSE at each point. Of particular note in this result is that downtown shows more sensitivity to downsampling, and the single-family residential region shows the least sensitivity.

Figure 3.6: Uniformly downsampling the measurements of a sector in downtown (left) and across all three regions (right).

**Non-Uniform Downsampling Impact.** In a second scenario, perhaps the crowdsourced measurements are not coming from a single user which has uniformly throttled the number of measurements recorded or reported but from multiple users in the same area.
Controlling for device differences for now (we will study this issue in Section 3.4.5), the newly composed data set for mobile phone measurements $Y$ has a non-uniform sampling period in time and space compared to drive testing the region with a channel scanner. As before, we quantify the accuracy of the estimate of $\gamma_Y$ to the estimated $\gamma$ when mobile phone signal strength readings are dispersed through time and space. We assume that a sufficiently large number of users in a similar area have crowdsourced measurements. We also assume that the number of measurements from the non-uniformly sampled data set matches that of the uniformly sampled data set.

The non-uniform distributed measurements are studied in two domains: (a) temporal and (b) spatial. For non-uniform temporal downsampling, we reduce the number of samples randomly based on the time stamp of the received signal measurements from the channel scanner data set. Fig. 3.7a depicts the impact of the non-uniform temporal downsampling on the path loss exponent from a cell sector in downtown and shows that by increasing the number of samples, the error with respect to the reference value decreases. However, in general, the non-uniform temporal downsampling has caused a higher value in terms of MSE for the same number of measurements as compared to uniform downsampling.

For non-uniform spatial downsampling, we select the most populated sector in each region. Then, we chose the measurements based on three clusters which are randomly distributed over the region. Then, we increase the number of the selected measurements in each cluster. Finally, we compare the $\gamma$ of the aggregated samples from non-uniformly distributed clusters with the $\gamma$ computed from all measurements from the channel scanner in the same region. A comparison between the uniform downsampling and non-uniform distributed measurements in space for three regions is depicted in Fig. 3.7b. The clustered scenario shows a higher error than the uniformly-distributed one. In addition, we observe that the error in the downtown region is higher than two other regions.

We have found that the location of the selected clusters in the non-uniform scenario is significant, as depicted in Fig. 3.8. To do so, we again select the most populated sector in a region. Then, we determine the location of three clusters of measurements based on Fig. 3.8.
We start by choosing 50 measurements in each cluster and we increase it by 50 until we have 3000 measurements. The left figure shows a model which is more dispersed through a sector. The middle scenario covers the left and top left area of the sector. In the right scenario, all measurements have a grouping on the left of the sector.

We measured the average of the MSE for each scenario. The results show the 0.007, 0.02, and 0.2 as the average of the MSE for each aforementioned scenario. In other words, a spatially well-distributed group of user measurements would contribute to a better result to predict the path loss exponent. Also, the type of cluster distribution has an impact on the number of measurements that are needed to estimate the channel condition. With this result and the current developments in the LTE standard (10) about the Minimization of Drive Test function [2], a carrier could more strategically poll users in a given area and/or at a certain time to reduce the resources necessary for their users to crowdsource and increase the likelihood of success of such an effort.

What is the required number of measurements? The number of measurements plays an important role in path loss prediction accuracy. Hence, we seek to find a sufficient number of measurements to provide a certain level of accuracy in channel characteristics.
prediction among three regions. To do so, we repeated the same procedure as before with our analysis with the following exception: we perform uniform downsampling, but his time, we consider more than one base station in each region and we select the sectors that contain the same number of signal measurements (about 4000 to 5000). We reduced the number of signal quality measurements and compared the path loss exponent results obtained from the new data set with the reference value. As we can see in Fig. 3.9, by decreasing the sampling size the averaged error is increased with greater fluctuations.

We depict three areas in each figure, where each area shows a certain level of accuracy in path loss prediction. The area on the far left of each graph shows the number of measurements that provides poor accuracy. The area towards the middle of each graph shows the range of the required number of measurements to obtain an acceptable error corresponding to the $\gamma$ estimation. Finally, the area on the far right of each graph represents a range of measurements where the error is monotonically decreasing with each additional measurement providing improved accuracy. As depicted across all the graphs of Fig. 3.9, the required number of measurements to provide an accurate estimation of channel characteristics is between 700 and 1500. We explain in Section 3.5 that an error in path loss exponent estimation, result in overestimation or underestimation in the probability of coverage of a targeted region. Overestimating and underestimating in network performance prediction result in gaps in coverage area and redundancy or even unwanted self-interference within the same network.
3.4.3.3. Quantization of the Received Signal Power

Android reports the quality of the common pilot channel received signal quality for LTE in terms of Arbitrary Strength Units (ASU) with 98 quantized levels. The received signal level has a range of -44 dBm to -140 dBm and is mapped to “0 to 97” with the resolution of 1 dBm. Since the obtained signal strength by a channel scanner has much greater granularity, the question becomes: what role does quantization have on the path loss exponent? We have considered the quantization impact on path loss estimation as defined as the difference between the estimated $\gamma$ compared to the highest resolution setting as measured by the channel scanner. To do so, we round each element of the received signal strength from the channel scanner to its upper bound or lower bound value. By comparing the result with the reference $\gamma$, we found the absolute error to be negligible (e.g., 0.0003). We show this effect in Fig. 3.10a of the following subsection, which considers the joint effect of all of these imperfections.

3.4.4. Joint Analysis of Mobile Phone Factors on Path Loss

Up to this point, we applied each of the challenges with phone measurements individually. We now jointly consider the mobile phone imperfections impact (averaging, uniform and non-uniform downsampling in space and time, and quantization) on the $\gamma$ estimation. To do so, we extract the collected data by the channel scanner obtained from a specific cell sector from three regions. Then, we apply the averaging on signal samples which are quantized already. Then, we downsampled (uniformly and non-uniformly in time and space) from the averaged and quantized values. At each step, we obtain the MSE from the path loss exponent calculated from the channel scanner’s samples with the highest resolution. Fig. 3.10a depicts the relative error caused by each shortcoming in comparison with the other studied issues for all 11 of our base stations. Fig. 3.10b shows the percentage of MSE caused by each individual issue with respect to the reference $\gamma$ for data from all base stations. Here, we observe that
non-uniformly downsampling has a dramatic effect on the results. However, each base station 
has a diverse measurement number, which could contribute to these results. Hence, we 
analyze the impact of each imperfection with mobile phone measurements individually on a 
data set for a single sector in each region with a comparable number of measurements (4000 
to 5000). As before, we applied averaging, uniform and non-uniform (spatial and temporal) 
downsampling, and quantization to the data. Fig. 3.11a shows the MSE of the path loss 
prediction due to each effect as compared to the prediction with all measurements of that
There are two interesting findings from these results: (i) either form of non-uniformly downsampling is clearly the most dominant effects considered when predicting the path loss exponent, and (ii) the two non-uniform downsampling techniques (time and space) have approximately equivalent performance (despite the noise of non-uniformly downsampling noted earlier). The latter finding offers great hope for crowdsourced data sets to be influential in characterizing the path loss characteristics of an environment.

3.4.5. Impact of Heterogeneous Mobile Phones and Users on Path Loss Characterization

When crowdsourcing signal quality from mobile phone users, there is a diversity in hardware and software of the devices. Even two co-located mobile phones at the same time may report very different signal qualities due to different RF front ends. In this section, we study the impact of heterogeneous devices on the estimated path loss exponent. Up to this point, we have considered a single type of mobile phone, Samsung Galaxy 5S, due to its ability to support both Qualipoc and WiEye. Here, we use WiEye across three other mobile phones (4 total) with a two-phase approach. First, we consider the signal strength samples from all the devices to calculate the path loss exponent and evaluate the accuracy compared to the path loss exponent from the channel scanner signal quality samples. Second, we consider
the differences in reported signal strength from each device introduced by each mobile phone in terms of dBm as compared to the raw measurements of the channel scanner. Lastly, we calculate the path loss exponent based on strictly crowdsourced data from WiEye users in different regions around the world and examine the geographical features of these areas.

3.4.5.1. Calibrating Diverse Phone Models and Setup

In this experiment, four Android phones described in Table 3.6 are used to collect signal strength data from the three aforementioned areas in Dallas (single-family residential, multi-family residential, and downtown). We installed our development version of WiEye, which logs signal strength samples at 1 Hz, on the following four phones: Samsung GS5, Nexus 5X, Samsung S8, and Google Pixel. Each phone was co-located alongside the channel scanner on the roof of a car. The duration of the experiment was 360 minutes.

Table 3.6: Measurement tools configuration and field-tested range of reported signal quality (dBm) from channel scanner (TSMW) and WiEye of four phones.

<table>
<thead>
<tr>
<th>Tool</th>
<th>Model/OS</th>
<th>Chipset</th>
<th>Min</th>
<th>Max</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Channel</td>
<td>TSMW/-</td>
<td></td>
<td>-130</td>
<td>-52</td>
<td>78</td>
</tr>
<tr>
<td>Scanner</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>W1</td>
<td>Samsung</td>
<td>GS5/A5</td>
<td>-118</td>
<td>-54</td>
<td>64</td>
</tr>
<tr>
<td>W2</td>
<td>Nexus</td>
<td>5X/A5</td>
<td>-119</td>
<td>-58</td>
<td>61</td>
</tr>
<tr>
<td>W3</td>
<td>Google</td>
<td>Pixel/A7</td>
<td>-120</td>
<td>-57</td>
<td>63</td>
</tr>
<tr>
<td>W4</td>
<td>Samsung</td>
<td>GS8/A7</td>
<td>-121</td>
<td>-54</td>
<td>67</td>
</tr>
</tbody>
</table>

We first analyze the RSRP differences of the four phones in terms of the minimum, maximum, and resulting range of dBm reported across all measurements to understand the relative sensitivities. While a few hours of driving does not guarantee the full range of signal strengths, during this time, we observe that the greatest range of values is achieved by the Samsung S8 (67 dBm) as reported by WiEye and the least range of values belonged to the Nexus 5X (61 dBm). As a point of comparison, the TSMW Channel Scanner achieved a
range of 78 dBm for the temporally-matched samples.

3.4.5.2. Inferring Path Loss Across Devices

We now use each phone to predict $\gamma$ for four observed base stations in aforementioned regions. The dBm offset bias between the average received signal level by each phone and the channel scanner is shown in Table 3.7 per region.

Table 3.7: Average signal quality bias reported from heterogeneous phones as reported by WiEye with matched channel scanner measurement.

<table>
<thead>
<tr>
<th>Device</th>
<th>Location</th>
<th>$W_1$ (GS5) dBm Diff. (Mean)</th>
<th>$W_2$ (N5X) dBm Diff. (Mean)</th>
<th>$W_3$ (Pixel) dBm Diff. (Mean)</th>
<th>$W_4$ (GS8) dBm Diff. (Mean)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Downtown</td>
<td>4.4 (-78.5)</td>
<td>2.1 (-76.2)</td>
<td>3.2 (-77.3)</td>
<td>1.6 (-75.7)</td>
<td></td>
</tr>
<tr>
<td>Single Family</td>
<td>3.8 (-85.0)</td>
<td>2.4 (-83.6)</td>
<td>2.5 (-83.7)</td>
<td>1.7 (-82.9)</td>
<td></td>
</tr>
<tr>
<td>Multi Family</td>
<td>4.1 (-80.3)</td>
<td>2.7 (-79.1)</td>
<td>3.5 (-80)</td>
<td>1.1 (-77.6)</td>
<td></td>
</tr>
</tbody>
</table>

We observe that on average the difference in reported received signal level by the scanner is 3 dBm higher versus the phones across the three regions with a range of 1.46 to 4.1 dBm. As we depicted before, the biases directly affect the path loss characterization. The lower reported channel quality corresponds to a higher value in obtained path loss exponent, while a higher reported channel quality corresponds to a lower path loss exponent. We now consider the calculated path loss exponent from the signal strength samples of each of the four phones, the calculated path loss exponent from the aggregated data set of the reported signal strength samples from all phones, and then the calculated $\gamma$ from the compensated signal strength samples of all phones, considering the bias.

Table 3.8 shows the obtained path loss characteristics of one specific sector in three different regions, when we consider only a single phone’s RSRP and all phones’ RSRP. As a point of reference, we also include the $\gamma$ from the channel scanner RSRP data. We observe that the obtained $\gamma$ using the data set of each phone are relatively close to one another. We see that the Samsung S8 phone has the closest $\gamma$ value between all four phones to the channel

40
scanner. In other words, the device that receives the larger range is more accurate in terms of the $\gamma$ estimation. The comparison shows that considering all RSRP data across device types actually increases the accuracy as compared to any given phone against the path loss exponent calculated from the channel scanner RSRP. Hence, we find that $\gamma$ is predicted by using the RSRP from a diverse set of mobile phones. In addition, we compensated the signal strength of the aggregated data set by using the 3 dBm obtained in the previous section. We find that the compensated results in terms of $\gamma$ are extremely close (with 2.7\%, 0.3\%, and 0.6\% error for single-family residential, multi-family residential, and downtown, respectively) to the obtained results by the channel scanner.

3.4.5.3. Inferring the Path Loss from Crowdsourcing

We now use crowdsourced measurements taken from our widely-distributed WiEye application on the Google Play store. We estimate the path loss exponent of regions around the world without physically drive testing those areas. Based on some of our highest user density, we have selected four environments with diverse geographical features: (i) tall buildings and trees in Dresden, Germany, (ii) low buildings and no trees in Artesia, New Mexico, (iii) mostly trees with a few homes in Macon, Georgia, and (iv) mostly free space in Thiersheim, Germany. The aerial view of each of these environments can be seen in the top figures of Fig 3.12.

In Fig. 3.12, the bottom figures show the number of crowdsourced signal strength samples and their spatial location as captured by our Android application overlayed on a more basic map of the same area displayed in the aerial view on the top. Using these signal quality measurements from each region, we have computed the path loss exponent $\gamma$, which can be seen in the caption of each subfigure. We have ordered the figures from left to right where we see the path loss exponent is decreasing from left to right. In particular, $\gamma_a$ equals 3.3 with the most diverse and complex environment with tall buildings and trees, $\gamma_b$ equals 2.7 with an environment that has similar, small building types but no trees, $\gamma_c$ equals 2.5 with mostly trees and a few homes, and $\gamma_d$ equals 2.1 with mostly free space.
Table 3.8: Path loss characteristics obtained by four devices in three modes: matched, aggregated, compensated mode.

<table>
<thead>
<tr>
<th>Device</th>
<th>Single Family</th>
<th>Multi-Family</th>
<th>Downtown</th>
</tr>
</thead>
<tbody>
<tr>
<td>Channel Scanner</td>
<td>3.01</td>
<td>3.33</td>
<td>3.61</td>
</tr>
<tr>
<td>W₁ (GS5)</td>
<td>3.21</td>
<td>3.50</td>
<td>3.80</td>
</tr>
<tr>
<td>W₂ (N5X)</td>
<td>3.18</td>
<td>3.54</td>
<td>3.78</td>
</tr>
<tr>
<td>W₃ (Pixel)</td>
<td>3.38</td>
<td>3.58</td>
<td>3.90</td>
</tr>
<tr>
<td>W₄ (GS8)</td>
<td>3.19</td>
<td>3.47</td>
<td>3.75</td>
</tr>
<tr>
<td>Aggregated</td>
<td>3.27</td>
<td>3.53</td>
<td>3.83</td>
</tr>
<tr>
<td>Compensated</td>
<td>3.09</td>
<td>3.34</td>
<td>3.63</td>
</tr>
</tbody>
</table>

(a) Location: Dresden, Germany with $\gamma_a=3.3$.
(b) Location: Artesia, New Mexico with $\gamma_b=2.7$.
(c) Location: Macon, Georgia with $\gamma_c=2.5$.
(d) Location: Thiersheim, Germany with $\gamma_d=2.1$.

Figure 3.12: Path Loss Analysis for Crowdsourced Data Sets in Four Different Regions.

Therefore, the geographical features and complexity in the environment match the $\gamma$ behavior we would expect, and the channel factors were derived strictly using crowdsourced measurements. Of particular note that in these measurements alone we saw a fairly dramatic change in the $\gamma$. In fact, we observed a range of 2.1 to 4.0 of the path loss exponent throughout this paper, which would constitute extremely different network designs across this range of propagation scenarios.

We find that a well-distributed signal measurement throughout a region would provide an accurate $\gamma$. Yet, we seek to achieve an acceptable accuracy level with less total mea-
measurements. In this experiment, we considered signal quality measurements obtained from various locations within a sector corresponding to a base station. The minimum and maximum distances from captured measurements regarding to a base station are 84 m and 2.5 km respectively. We divide the signal quality measurements into 3 groups for a particular sector based on distance: near, middle, and far (Fig. 3.13). We then perform the analysis on all combinations of two different regions of the three available, studying the role of distance away from the base station and its impact on our path loss prediction.

Table 3.9 shows the path loss slope for each cluster. As we expect, the variation of the $\gamma$ over a homogeneous region is less than a heterogeneous environment due to the difference between the geographical characteristics of each region. In addition, we aggregate signal measurements from different clusters and compare the results with our reference path loss slope. The results show that aggregating the signal measurements from the near and edge region results in a path loss exponent closest to our reference $\gamma$.

In the next step, we apply the same approach on our crowdsourced data set, depicted in Fig. 3.12. We select the case with a slope $\gamma_a = 3.3$ because of its complex environment with tall buildings and trees. The results show that the aggregated data sets from near and far regions ($\gamma = 3.29$) are the closest result to the reference slope ($\gamma = 3.3$).

Table 3.9: Field-tested path-loss exponent per cell from channel scanner (TSMW) and Corresponding Geographical Features.

<table>
<thead>
<tr>
<th>Region</th>
<th>Ref$\gamma$</th>
<th>NearCell$\gamma$</th>
<th>MiddleCell$\gamma$</th>
<th>EdgeCell$\gamma$</th>
<th>Average$\gamma$</th>
<th>Agg$\gamma_{1,2}$</th>
<th>Agg$\gamma_{2,3}$</th>
<th>Agg$\gamma_{2,3}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single-Family</td>
<td>3.55</td>
<td>3.58</td>
<td>3.59</td>
<td>3.5</td>
<td>3.55</td>
<td>3.52</td>
<td>3.6</td>
<td>3.61</td>
</tr>
<tr>
<td>Downtown</td>
<td>3.57</td>
<td>3.63</td>
<td>3.54</td>
<td>3.46</td>
<td>3.54</td>
<td>3.56</td>
<td>3.6</td>
<td>3.5</td>
</tr>
<tr>
<td>Dresden (Germany)</td>
<td>3.3</td>
<td>3.4</td>
<td>3.34</td>
<td>3.3</td>
<td>3.34</td>
<td>3.29</td>
<td>3.37</td>
<td>3.27</td>
</tr>
</tbody>
</table>

3.5. Coverage Estimation Impact from Prediction Error

In the previous sections, we evaluated the path loss exponent prediction accuracy using RMSE and the total difference in the $\gamma$ value. However, it is hard to interpret such error in
terms of operational network performance. To build such intuition, we examine the role of this prediction error on coverage estimation and Bit Error Rate (BER). Since the received signal level randomly varies due to shadowing effects, network operators must determine the probability that the received signal strength crosses the specified threshold at the cell edge, which is calculated according to [65]:

$$P_{x_0(R)} = Prob[x > x_0] = \int_{x_0}^{\inf} P(x)dx$$

$$= \frac{1}{2} - \frac{1}{2} \text{erf}\left(\frac{x_0 - \mu}{\sigma\sqrt{2}}\right)$$

(3.1)

Here, $x_0$, is the receiver sensitivity, which is a function of the UE hardware design and the required service quality. $x$ is the receive signal level at distance $d$, which can be obtained by applying a log-distance propagation model. It is a common approach to estimate the mean of the received signal level over a specific distance $d$ from the base station. The variation of the received signal level due to shadowing, represented here by $\sigma$.

Knowing $Prob[x > x_0]$, we can determine the percentage that the received signal level exceeds a certain threshold in an area with radius $R$ around the center of a base station, as shown in [18]:

$$F_{\gamma} = \frac{1}{\pi R^2} \int P(x_0)dA$$

(3.2)

The simplified version of the previous equation could lead to:

$$F_{\gamma} = \frac{1}{2} [1 - \text{erf}(a) + \exp\left(\frac{1 - 2ab}{b^2}\right)(1 - \text{erf}\frac{1 - ab}{b})]$$

(3.3)
Here, $a$ and $b$ are obtained from 3.4:

\[
\begin{align*}
a &= \frac{x_0 - \alpha}{\sqrt{2}\sigma} \\
b &= \frac{10\gamma \log_{10}(e)}{\sqrt{2}\sigma}
\end{align*}
\] (3.4)

Where $\alpha$ is determined from the transmitter power, antenna heights and gains. To investigate the impact of the path loss error prediction on the probability of cell area coverage estimation, we assume that the mobile network provider has a restriction on the receiver sensitivity $x_0$ at a certain distance $R$ to provide a particular service level. With respect to the above assumptions, we achieve the probability of exceeding the sensitivity level $x_0$ with probability $Prob_{x_0} = prob[x_R > x_0]$. Knowing this, we obtain the percentage of the useful area covered with a cell boundary of $R$ and the received signal level $x_0$.

We consider the case where the actual path loss exponent is 3.0. Then, we consider an error in path loss exponent value from -1.0 to +1.0 for a range between 2.0 and 4.0 for the predicted value. We assume the receiver sensitivity is fixed due while providing a particular service level at the cell edge. Then, we obtain $F_u$ corresponding to each $\gamma$, and we compare the estimated probability of coverage over the cell area with the reference $\gamma$. Fig. 3.14a shows the impact of the error in path loss exponent prediction on the probability of cell area coverage estimation when we are overestimating and underestimating the path loss exponent.

As we can see, in the case that a greater path loss exponent than actual is predicted ($\gamma > 3.0$), the coverage area probability drops from 79% to 20% by increasing the predicted $\gamma$ from 3.0 to 4.0. In this case, with a fixed transmission power, the network operator would cover 59% more than expected, thereby creating unwanted redundancy and self interference. In the case that a lower path loss exponent than actual is predicted ($\gamma \leq 3.0$), the coverage area probability rises from 79% to 99% as early as 2.6 and remains at 100% to 2.0. While this might seem like a positive effect for network operators, it could be an even greater problem. Namely, the network operator will think that the propagation environment is better than actual and so increase the spacing between nodes, thereby creating coverage holes. For
example, in the environment where an actual path loss exponent is 3.0 and the predicted path loss exponent is 2.6, there will be around 20% of the network that is not covered from the targeted area.

![Figure 3.14: Impact of the γ estimation’s error on the cell area coverage probability estimation.](image)

Lastly, we study the impact of the error in path loss exponent prediction on the network performance in terms of BER. Fig. 3.14b shows the variation of BER by changing the predicted path loss exponent from 2.0 to 4.0 with a step of 0.5 while the SNR is in a range of 8 to 24. We compare the BER of the estimated path loss exponents with our reference one (γ = 3.0). We observe that an error about 0.5 in path loss exponent prediction causes an order of magnitude change in the BER at an SNR of 20.

### 3.6. Summary

In this work, we take a first step towards crowdsourcing wireless channel characteristics in LTE cellular networks (and later generations of cellular technology) by considering the relationship between received signal strength measurements of diverse mobile phones at the firmware and API level versus advanced drive testing equipment. In particular, we performed extensive experimentation across four mobile phone types, two pieces of software,
and a channel scanner in three representative geographical regions: single-family residential, multi-family residential, and downtown. With these devices and in-field measurements, we evaluated the effects of averaging over multiple samples, uniform and non-uniform downsampling (in time and space), quantization, and crowdsourcing on the path loss exponent estimation. We showed that both types of non-uniform downsampling have the most dramatic effects on path loss calculation. Conversely, we showed the quantization impact can largely be ignored since it showed a negligible influence on our estimation. One key result of note stems from the spatial non-uniformity of clusters of measurements observed within our crowdsourcing database, which required far more measurements than more uniformly spaced measurements. Also, we addressed the required number of measurements to have a sufficient understanding about the average of the signal attenuation in a specific environment. Using the MDT specification of LTE release 11, carriers could request specific measurement locations and times from users to be far more efficient in polling signal quality. Furthermore, we showed four regions around the globe and predicted the channel characteristics of these regions from our crowdsourced data. In summary, we lay a strong foundation for intuitively understanding a large majority of the issues involved with crowdsourcing channel characteristics. For example, we found that even a prediction error of 0.4 for the path loss exponent would cause a 40% redundancy in the covered area or coverage holes for 25% of the targeted area based on whether the error was above or below the actual value, respectively. In summary, we lay a strong foundation for understanding a large majority of the issues involved with crowdsourcing channel characteristics. In future work, we will study the impact of the various contexts on the received signal quality and path loss estimation to precisely characterize the role of each geographical feature on the large- and small-scale fading effects.
4.1. Introduction

In the previous chapter, we addressed the accuracy and reliability of the collected data by a UE in terms of the received signal level as one of the most important Key Performance Indicators (KPIs) of the network. Network operators use KPIs to track network performance, including the received signal power, received signal quality, throughput, and delay. Historically, drive testing has been widely used by carriers and third party entities to collect a sufficient density of KPI data to accurately characterize the network performance. Despite providing detailed information at certain locations, this approach is costly in terms of manpower, time, and equipment.

As we mentioned earlier, MDT allows carriers to monitor the in-situ network performance of end users to detect variations of the provided quality of service (QoS) to perform such actions as handover if the problem is confined to a single user or self-organization if the problem extends to one or more towers. For the latter problem, changes to the antennae configuration in terms of transmit power, tilt, or height can alleviate some issues while more persistent effects necessitate smaller cell deployment in detected network holes.

For example, the physical range over which a wireless link can be established to reliably connect devices is called coverage. Coverage is an important performance metric the Mobile Network Operators need to consider when evaluating a wireless solution. There are three approaches to predicting the coverage and deciding whether to deploy additional infrastructure. This process consists of three possible approaches: empirical, deterministic, and semi-deterministic. Empirical or statistical models such as the Hata model [57], COST-231,
Walfisch-Ikegami model are usually the results of the campaign measurements corresponding to a specific environment. Although empirical models are easy to implement and their computational complexity is low, they are not often easily generalizable to regions of the same type.

In deterministic models such as the Ray Tracing technique and Finite-Difference Time-Domain (FDTD), the received signal strength is obtained using the Geometrical Theory of Diffraction. In these models, not only is the direct path used but also the reflected and diffracted rays are considered to predict the path loss model. Since they need detailed information about the region of interest to predict the path loss, the computational complexity of these approaches is high. The last category, semi-deterministic models, are based on empirical and deterministic models such as COST-231 and Walfish-Ikegami model [117].

Using neural networks has been recently studied in literature as an alternative approach to predict the path loss propagation of an arbitrary environment. These models can process a large amount of data in a reasonable time with the ability to learn the characteristics of a new environment. The results show that these models can provide a close estimation for the signal attenuation prediction in an area.

Since the propagation models highly depend on the environment, our solution uses some in-situ measurements to improve the accuracy of the models, which can be obtained by via crowdsourcing.

To make efficient use of the crowdsourced data (to preserve bandwidth and battery life of users), a natural extension of MDT is to interpolate the region’s performance from discrete user locations using propagation models [57, 87] and coverage maps [21, 92]. Other studies have used crowdsourced data to measure network metrics (e.g., [77, 86, 102, 114, 127]). However, none of these approaches directly considers geographical features of the environment in predicting the propagation characteristics and resulting KPIs. In this paper, we establish the relationship required by MDT efforts between geographical data and user-based data, from which we build a Regional Analysis to Infer KPIs (RAIK) framework. To do so, we predict the network coverage using neural networks alongside crowdsourced data.
collected by User Equipment (UEs) with an overlaid LiDAR dataset in that same region. RAIK is based on two feed-forward, back-propagation models, which employs multilayer perceptron (MLP) with the geographical features of a region to provide a KPI-based coverage map. The first model consists of conducting a customized 2D filter for the region of interest to limit the error which may happen due to the variation of geographical characteristics. For example, due to the difference of the geographical features within an area, we might receive a very strong signal adjacent to a dead zone in terms of the received signal level. We tune the grid size by taking advantage of the correlation between the received signal levels and geographical features.

Using the second model we predict the received signal level in each tile considering the objects surrounding the UE and the objects which intersect the direct path from the transmitter to the receiver. However, due to multipath, the direct path should have a width to account for reflections. To capture these objects, we conduct a 3D filter. Then, we tune the filter size using delay spread information of the concerned area. To evaluate RAIK, we perform extensive in-field measurements from urban and suburban regions with diverse geographical features such as type, density, and height of the buildings and trees. RAIK forms a generalized framework that allows prediction of the KPIs in areas that have yet to receive crowdsourced channel quality measurements from users, relying solely on the terrain and clutter information of a given area.

Our work consists of the following three contributions:

- We introduce the Regional Analysis to Infer Key Performance Indicators (RAIK) framework, a learning structure that can create interconnected relationships between geographical information and KPIs.

- To understand the impact of tile size on the prediction results, we provide a coverage map based on the path loss exponent using crowdsourced data. We find in all the results that there is a tradeoff between the larger tile size having too much area which has distinct terrain and too small area without sufficient measurements. We show that this tenuous relationship is magnified in the downtown area due to the diversity from
street to street.

- We conduct an appropriate filter according to the shape and size to extract the geodata for training the NN model. This area is chosen based on the angle of a cone shape around the direct path between the base station and UE.

- We consider the accuracy of predicting KPIs in areas in which the RAIK framework lacks any signal quality training, relying solely on the geographical features of the area. For sub-regions that are tested without prior training in that region, we find that the mean squared error (MSE) of the predicted path loss and the measured one (to test our prediction) can be as small as 0.01, which is a 7-fold reduction from state-of-the-art algorithms.

The remainder of the paper is organized as follows. In Section 4.3, we present our framework, measurement set up, and path loss evaluation using crowdsourced data. In Section 4.4, we present our prediction and in-field analysis of the relationship between geographical features and our path loss prediction model using a neural network. We present related work in Section 4.2 and conclude in Section 4.6.

4.2. Related Work

Many different propagation models have been used to predict the coverage area of a network, such as Okumura-Hata [57, 87] and the Longley-Rice irregular terrain model [61]. In these models, one must collect radio signal measurements from a specific region to be able to calibrate the model for that region to find the appropriate constants.

Recently machine learning algorithms have emerged as an alternative approach to overcome the low accuracy of empirical models and the complexity of deterministic models while predicting the path loss propagation of a given region. Several studies have addressed the prediction of urban, suburban [89, 115], and indoor environments [83, 93] using Neural Network algorithms.

It is well known that the performance of an ANN model is highly affected by the selected input features. Since the terrain type plays an important role in the propagation character-
istics of a channel, some studies trained the model consider more detailed information about the obstacles located in the area of interest.

As the input features, [123] just considered the distance between the transmitter and the receiver to predict the path loss. Also, [12] proposed an adaptive neuro-fuzzy inference system (ANFIS) approach to reduce the Radial Basis Function Neural Network (RFBNN). The author simplified the input by considering the distance between the transmitter and receiver because the percentages of the area covered by buildings for the urban and suburban base stations was fixed. The SVM and ANN models have been compared in [118], considering antenna-separation distance, terrain elevation, horizontal angle, vertical angle, latitude, longitude, horizontal, and vertical attenuation of the antenna as the input features. Geodata has not been considered in this model.

A Multilayer Perceptron (MLP) based ANN technique was implemented to predict the path loss at 900 MHz [82]. A 2D map was extracted from aerial photography to obtain geographical data. A General Regression Neural Network to predict the propagation path loss was used in [94]. They reported a significant improvement in the obtained prediction by neural models as opposed to empirical models considering the street width, rooftop height, and building block spacing.

All the above methods failed to consider essential items such foliage, the angle of a direct path between the base station and the UE to consider the objects that reflect or scatters the transmitted signal before reaching the UE, and the effective area surrounding the UE. Although [89] utilized geodata as the input features of the model and proposed a simple NN model to predict the path loss propagation the area size surrounding the UE, the direct path angle has not been optimized.

The other method to predict propagation coverage over an area is utilizing geostatistical modeling techniques, where the measurements are collected strategically and different interpolation techniques are applied to predict the propagation model of the uncovered locations. For example, a radio environment map of 2.5 GHz WiMax utilized geostatistical modeling and interpolation [92]. Still another work proposed a modified version of Kriging algorithm
to reduce the computational complexity of the spatial interpolation to produce the coverage map [21]. In contrast, we specifically target a relationship between the signal quality of a network at a given location and the geographical features in that area to predict the KPIs of that region and regions that lack accessibility or crowdsourced measurements.

4.3. Regional Analysis to Infer KPIs (RAIK)

To construct a coverage map from a region of interest, we build a framework depicted in Fig. 5.1, which consists of two phases: (A.) Conducting a customized grid over the concerning region and (B.) Refining the predicted path loss in each grid. These two phases are explained in detailed as follows:

(A.) Conducting a customized grid over the concerning region. The variation of the geographical characteristics of a region may cause observing very strong received signals just near a dead zone. This type of scenario frequently happens in the downtown area where the foliage and the tall buildings are non-uniformly distributed over the region. In previous studies, the size of the grid has been defined arbitrarily. In this work, we take advantage of the correlation between the signal attenuation and the geographical features to determine the grid size. This phase which is termed as A in Fig. 5.1 consists of the following steps.

(i.) We first build an Android-based crowdsourcing infrastructure, which allows the widespread collection of in-field signal quality data coupled with the location of that user at the time of the measurement.

(ii.) We then infer the propagation characteristics of a given region (regardless of the geographical features) by using the collected signal quality measurements through that area and a sliding square window of varying sizes.

(iii.) Since the received signal attenuation is affected by foliage and buildings surrounding the user equipment (UE), we consider 3-dimensional geographical data from the region of interest. For this purpose, we use Light Detection and Ranging (LiDAR) data, which includes detailed information of buildings and foliage such as height and surface area (see Section. 4.3.1 for more details).
(iv.) Then the prediction function will receive the estimated channel characteristics and corresponding geographical features of an area to construct a two-layer map consisting of: (a.) the network performance information obtained by the UEs, and (b.) their corresponding location information overlaid on a map containing the foliage and buildings in the area.

(v.) Lastly, to tune the grid size, we use an ANN model. To prepare the input data of the model, we change the filter size and move it over the region to extract the geographical features and the corresponding $\gamma_i$ of each sub-region. Then, we train the ANN model using the obtained datasets. The input feature and the target of the model are the geographical features of each sub-region (buildings and foliage) and $\gamma$, respectively. Finally, we consider the performance of the ANN model as an indicator to select the proper grid size.

(B.) Refining the Initiated Path Loss of Each Grid.

In wireless communication, the direct path between the transmitter and receiver can vary from a clear Line Of Sight (LOS) to Non-Line Of Sight due to blockage from obstacles. The obstacles along the direct path from the base station to the UE can have a large impact on the received signal level. Furthermore, due to multipath, there is a width of this direct path
that is relevant. The angle around this direct path might be larger or smaller depending on
the degree to which the multipath delay spread exists in the environment. To improve our
prediction results, we consider the objects along with the direct path from the transmitter
to the receiver in addition to the buildings and foliage surrounding the receiving antenna.

The steps of this phase are depicted in Fig. 5.1, which is labeled as $B$. In this phase,
we consider the information of each signal measurement in a certain tile as the input of the
second ANN model which is termed as $RAIK_2$.

(i.) We first consider the signal measurements captured in a certain tile that are coupled
with the location of that user at the time of the measurement.

(ii.) To extract proper input features, we conduct a cone-shaped filter to capture the
detailed geographical features along with the direct path from the transmitter to the receiver.

(iii.) After setting up the filter size we collect the proper information regarding the foliage
and buildings surrounding the user equipment (UE) along with the direct path using our
LiDAR database.

(iv.) Then, the prediction function will receive the received signal level of our signal
measurements and corresponding geographical features.

(v.) Lastly, we can infer the propagation model of the concerned area using the predicted
signal levels.

4.3.1. Data Acquisition Procedure for KPI Prediction

We now further describe the two data sets on which our RAIK model is based: (a.) re-
ceived signal quality data collected by Android phones, and (b.) LiDAR, which describes the
geographical features in the area. We consider these two data sets because the geographical
features directly impact the received signal quality in a given region.

(a) Android-Based Crowdsourced Data. We have a crowdsourced dataset, which is
built from voluntary participants that installed our publicly-available Android application
(WiEye) to collect global radio measurements. To limit the power and bandwidth consumed
by our app, signal quality from all visible cellular and WiFi base stations are recorded 10
times per day. We have a development version of our app that captures measurements at a
frequency of 1 Hz, which we have used to emulate a more concentrated user base in relevant
geographical regions in this paper. We specifically record received signal strength across all
available technologies, GPS coordinates, Mobile Country and Network Codes, base station
identification (CID, LAC), device identification, and velocity of the receiver (when locally
collecting data).

We have acquired hundreds of millions of crowdsourced signal strength data points using
WiEye. Locally, we collected an additional 10 million measurements with greater densities
in three representative geographical regions in Dallas: downtown, single-family, and multi-
family residential areas. We utilized obtained data from the downtown and single-family
residential areas to train the model. Then, we used the multi-family residential area as a
testing region, where the training from this area was not used. Generally, the density of the
foliage in the single-family area is higher than the other two regions, the downtown area is
mainly covered by tall buildings, and the multi-family area has a mixture of vegetation and
moderately-sized buildings (e.g., 2-3 stories).

(b) LiDAR-Based Geographical Features. To consider the vertical and horizontal
footprint of trees and buildings, we use LiDAR data, which creates 3-dimensional point
clouds of the Earths surface. Recently, LiDAR has been used in several applications, such
as digital elevation modeling (DEM), autonomous vehicles, micro-topography, agriculture,
modeling Pollution, and archaeology and building construction. Wireless communication
would be another potential use case of LiDAR since it provides detailed information about
the geographical features in an area of interest, which we know has impact on the received
signal level.

LiDAR employs a remote sensing method from airplanes or helicopters that transmits
pulses of light to detect the distance from the earth. The laser sends these pulses and
measures the time delay between the transmitted and the received pulse to calculate the
elevation. LiDAR systems are equipped with a laser scanner that measures the angle of
each transmitted pulse and the returned pulse from the surface, high precision clocks which
record the time that the laser pulse leaves and returns to the scanner, an Inertial Navigation Measurement unit (IMU) to measure the angular orientation of the scanner relative to the ground (pitch, roll, yaw), a data storage and management system, and a GPS detector.

The LiDAR sampling rate is 400,000 pulses per second, which creates millions of data points. Also, the accuracy of the collected points is about 15 cm vertically and 40 cm horizontally. Hence, LiDAR systems provide a high-resolution 3D geometric model for the earth, clutter, and foliage, with applicability across a broad range of fields such as geodesy, geometrics, archeology, geography, geology, geomorphology, seismology, forestry, atmospheric physics. [23]. Relevant to our work, we use LiDAR to represent a three-dimensional map of building and tree data in the three Dallas regions under test. Each record that corresponds to
a tree in our 3-D map includes coordinates of the object, height, and area. We have the same information for buildings. Fig. 4.2 shows the detected trees and buildings in suburban region in Dallas. The background of each figure is from OpenStreetMaps to verify the accuracy of the LiDAR information from the same area.

**KPI Metric for RAIK.** From all the KPIs in the standard, we specifically target the Reference Signal’s Received Power (RSRP) since: (i.) network providers seek to provide coverage over an area to deliver sufficient quality of service to customers, (ii.) a well-known relationship exists between the received signal power and the throughput [85], and (iii.) UEs regularly measure the received signal power to keep track of visible base stations in case of the handover, even if the phone is idle. Thus, the battery consumption to measure RSRP is low and conducive to MDT efforts.

4.3.2. Propagation Over Three Representative Region Types

Large-scale fading refers to the average attenuation in a given environment to transmission through and around obstacles in an environment for a given distance [97]. There are three well-known types of models to predict large-scale fading: empirical, deterministic, and semi-deterministic. Empirical models such as [57] and [87] are based on measurements and use statistical properties. These models are widely-used because of their low computational complexity and simplicity. However, the accuracy of these models is not as high as deterministic models to estimate the channel characteristics. Deterministic models or geometrical models using the Geometrical Theory of Diffraction to predict the path loss. To consider the losses due to diffraction, detailed knowledge of the terrain is needed to calculate the signal strength [62]. Despite the accuracy of their model, their computational complexity is high and need detailed information about the region of interest. The last one, semi-deterministic models, are based on empirical and deterministic models [25]. In this study, we use an empirical approach since it is the type of modeling that could best leverage crowdsourced data. Large-scale fading is a function of distance \(d\) between the transmitter and the receiver where \(\gamma\) is the path loss exponent. The path loss exponent typically varies between
2 in free space and 6 indoors, depending on the environmental type. Nominal values are in the range of 2.7-3.5 in typical urban scenarios and between 3 to 5 in heavily shadowed urban environments [97].

The large-scale path loss for an arbitrary distance $d_i$ between transmitter and receiver is defined according to:

$$L_p(d_i) = L_p(d_0) + 10n\log(d_i/d_0) \tag{4.1}$$

Here, $n$ is the path loss exponent, and $L_p(d_0)$ is the path loss at the reference distance $d_0$. To characterize propagation in a given region, we calculate the path loss exponent from mobile phone measurements, where a linear regression model is used to calculate the $n$. While mobile phones are not as precise as advanced drive testing equipment, we have shown that path loss is a recoverable parameter from UE signal quality measurements if the appropriate calibration is performed [36].

Fig. 4.3 depicts the collected RSRP in three representative geographical regions: downtown, single-family residential, and multi-family residential. In each region RSRP values are based on signals received from a single base station. The variation of the signal quality can be observed in each of the three regions. However, sudden changes on the received signal strength in the downtown area are more dramatic from street to street. In particular, we observe very strong signals adjacent to dead zones with respect to the RSRP. Since there are differing geographical features within each region, we calculate the path loss exponent ($\gamma$) obtained from received signal measurements taken by mobile phones in smaller sub-regions. To do so, we use a square window with an initial size of 200-m square. There is a tradeoff in the region size considered when considering the accuracy of the RAIK framework. If the sub-region considered is too large, the variation in the geographical features present imprecision in the inferred path loss. If the sub-region considered is too small, the amount of signal quality measurements is insufficient to infer a precise path loss exponent.

For example, Fig. 4.4 shows that the calculated $\gamma$ from the RSRP values over the entire region (3.1) is different from the one calculated from the RSRP of a 200-m square sub-region (3.4). Hence, we will use a filter over each region with sizes of 100-m, 200-m, and 300-m.
Figure 4.4: Path loss exponent ($\gamma$) calculated over entire downtown region (left) versus a 200 m x 200 m sub-region (right).

square in Section 4.4 to understand both the role of these window sizes and the resulting path loss exponent ($\gamma$) in each region and sub-region.

4.4. Prediction and In-Field Evaluation of KPIs

We now train and evaluate the RAIK framework with our signal quality measurements from the three region types discussed in Section 4.3.2. To do so, we first consider a performance metric and the impact of choosing different sizes of sub-regions (i.e., tile size) over which to compute those predicted metrics. We then consider homogeneous training and testing, where the neural network is trained and tested in the same region for the downtown and single-family residential region. Lastly, we consider heterogeneous testing where we use the training from these aforementioned region types but test on a different region type: multi-family residential.

4.4.1. MultiLayer Perceptron Components Used in RAIK

Neural network algorithms have been widely applied to predict the channel propagation in wireless networks [15,26,42,94]. In our study, we use a multilayer perceptron (MLP) artificial
neural network introduced in [20], and [58]. MLP performs the Levenberg-Marquardt back-
propagation algorithm as a supervised learning technique for training the network [56]. MLP
consists of three layers: input, output and hidden layers. A neural network in its general
form is described as:

\[ Z = f(\Sigma w_{i,j}^T x_i + b) \]  \hspace{1cm} (4.2)

where \( x_i \) is the input vector. Each node in a layer is connected to the nodes in the next
layer with certain weights \( w_{i,j} \). In neural network algorithms, the goal is finding the best
selection of weights as the inputs’ coefficients such that the difference between the predicted
values and the target values are minimized. Here, \( w_{i,j}^T \) is the transpose vector of the selected
weights by the model associated to the inputs \( (x_i) \) and \( b \) is the bias vector.

\[ w^T = w_1, w_2, .., w_n \]  \hspace{1cm} (4.3)

We employ the sigmoid function [101], which is easily differentiable with respect to the
network parameters, and this plays an important role in training of the neural network. It
is expressed as:

\[ S(x) = \frac{1}{1 + exp(-x)} \]  \hspace{1cm} (4.4)

4.4.2. Training and Performance Metrics of RAIK

The model’s performance highly depends on the selected features for the model’s input
and their accuracy. The selected input features are defined as: (a.) distance between the
transmitter and the receiver, (b.) percentage of the area covered by buildings (i.e., foot
print) [82], trees (i.e., canopy or crown), and free space (i.e., unoccupied by trees or build-
ings), (c.) number of buildings and trees, (d.) average height of the buildings and trees, and
(e.) standard deviation of the heights of the buildings and trees. All the input param-
ters have been provided from a 3-dimensional LiDAR database. The model’s output is the
path loss exponent acquired from radio measurements in each sub-region. To increase the
efficiency of the model, all features are normalized to fall in a range of \([0, 1]\).
Performance Metrics for Evaluating the RAIK Model. To evaluate the model, we apply first-order statistical metrics including the minimum and maximum difference between observed and predicted values and the standard deviation of the errors, denoted as $e_{\text{min}}$, $e_{\text{max}}$, and $e_{\sigma}$, respectively. The mean error, $e_{\text{mean}}$, shows the average error across all records, which indicates whether there is a systematic bias (a stronger tendency to overestimate or underestimate) in the model. We employ the linear correlation, $r$, between the predicted, $\gamma_i$, and actual values, $\hat{\gamma}_i$. This metric varies between -1.0 and +1.0. Linear correlation returns +1 if there is a perfect positive correlation between the two input variables, -1.0 if there is a perfect negative correlation, and 0.0 if there is no correlation. Finally, the performance of the model is evaluated by calculating the mean squared error (MSE), defined as:

$$\min \frac{i}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \quad (4.5)$$

Here, $y_i$ and $\hat{y}_i$ are the desired output and the obtained output calculated by the neural network, respectively [52].

4.5. Performance of The RAIK Model

In this section, we depict the results of conducting the indicated processes in Fig. 5.1, which are referred to as A and B. In the first section, we study the grid size of the 2D filter to divide a region to sub-regions.

4.5.1. The Results of the Phase ”A”: Two Dimensional Filter Calibration

To limit the impact of the variation of the geographical features on the received signal level, we design a two-dimensional filter over the concerned area. To do so, we need to address the following questions: What is the appropriate tile (filter) size to cover a cell site? What is the required number of measurements in each tile to find the corresponding path loss exponent? To answer these question we conduct a set of experiments as follows:

The Impact of Tile Size on RAIK Performance. We now consider the influence of tile or
sub-region size on the estimated path loss and the accuracy of the prediction model. To this end, we train the model on data obtained from tiles with three different sizes: 100-m square, 200-m square, and 300-m square. Table 4.1 shows the comparison between the performance metrics of RAIK for tiles with the three different sizes in tile’s side length. It is shown that by increasing the tile size to a value larger or smaller than 200-m square, the statistical metrics of the performance decrease in both regions, gradually. Of particular note, the tile size choice most affects the downtown area due to the diversity in height, area, and density of trees and buildings. In both region types, we see that the selection of too large or too small tile sizes impedes the ability of the model to capture the correlation between geographical characteristic changes and the resulting channel propagation, making the KPI prediction noisy. Since the 200-m square tile size showed the best performance in terms of MSE, $e_{min}$, $e_{max}$, $e_{mean}$, and $e_{\sigma}$ across region types, we will use this size for the remainder of the paper to study various other issues related to KPI prediction.

Table 4.1: Impact of tile size on RAIK performance.

<table>
<thead>
<tr>
<th>Region</th>
<th>Single-family</th>
<th>Downtown</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tile’s Side (m)</td>
<td>100 200 300</td>
<td>100 200 300</td>
</tr>
<tr>
<td>MSE</td>
<td>.03 .02 .02</td>
<td>0.07 0.02 0.05</td>
</tr>
<tr>
<td>$e_{min}$</td>
<td>-.61 -.13 -.4</td>
<td>-.7 -.32 -.43</td>
</tr>
<tr>
<td>$e_{max}$</td>
<td>.38 .21 .33</td>
<td>-.43 .23 .27</td>
</tr>
<tr>
<td>$e_{ave}$</td>
<td>.04 .02 .03</td>
<td>.1 .04 .07</td>
</tr>
<tr>
<td>$\sigma_{err}$</td>
<td>.21 .17 .16</td>
<td>.32 .23 .22</td>
</tr>
<tr>
<td>$r$</td>
<td>.78 .97 .92</td>
<td>.63 .90 .86</td>
</tr>
</tbody>
</table>

Impact of the Number of Measurements on RAIK Prediction. We now study the impact of the number of measurements in a given 200-m square tile on the accuracy of the KPI prediction using the RAIK framework. For this purpose, we consider tiles that have different ranges of measurements: 600-800, 800-1000, and 1000-1200 depicted as ‘A’, ‘B’ and ‘C’ respectively. A tile has to be within the range to be considered for training the RAIK framework. Table 4.2 shows the prediction accuracy for the single-family residential and
Table 4.2: Impact of Measurement Number in Propagation Prediction.

<table>
<thead>
<tr>
<th>Region</th>
<th>Meas #</th>
<th>Performance Metric</th>
<th>$e_{\text{min}}$</th>
<th>$e_{\text{max}}$</th>
<th>$e_{\text{mean}}$</th>
<th>$\sigma_{\text{err}}$</th>
<th>$r$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single Family</td>
<td></td>
<td>MSE</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>.02</td>
<td>-.17</td>
<td>.27</td>
<td>.03</td>
<td>.21</td>
<td>.85</td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>.01</td>
<td>-.18</td>
<td>.24</td>
<td>.02</td>
<td>.2</td>
<td>.93</td>
<td></td>
</tr>
<tr>
<td>C</td>
<td>.01</td>
<td>-.13</td>
<td>.2</td>
<td>.02</td>
<td>.13</td>
<td>.95</td>
<td></td>
</tr>
<tr>
<td>Downtown</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>.05</td>
<td>-.42</td>
<td>.3</td>
<td>.08</td>
<td>.32</td>
<td>.77</td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>.03</td>
<td>-.21</td>
<td>.24</td>
<td>.06</td>
<td>.23</td>
<td>.84</td>
<td></td>
</tr>
<tr>
<td>C</td>
<td>.02</td>
<td>-.15</td>
<td>.23</td>
<td>.02</td>
<td>.17</td>
<td>.87</td>
<td></td>
</tr>
</tbody>
</table>

downtown regions when such an approach is taken for the training. We observe that there is a trade-off that occurs. Increasing the minimum number of measurements forces tiles to be not considered, having fewer records for input into RAIK. On the other hand, increasing the minimum number allows for better accuracy of the channel characteristics for those tiles that are considered. The latter effect can be seen by the increase in the correlation coefficient as the minimum number of measurements required for each tile is raised. Overall, we see a net RAIK prediction benefit to increasing the measurement requirement for both regions considered for these ranges of measurement number.

**Homogeneous Training and Testing But in Adjacent Sub-Regions.** Next, we study RAIK performance when training and testing in the same region type, which we refer to as homogeneous training and testing. However, the training (70%) and testing (30%) data come from differing sub-regions in the same region type. As depicted in Fig. 4.5a, the downtown sub-region used for testing is adjacent to the sub-region used for training. This is emulating a crowdsourcing context in which a carrier lacks measurements from users in a certain area but has other users providing data nearby. Fig. 4.5b shows the results from this particular training/testing data combination. We show that the absolute error between the actual $\gamma$ and the predicted one is extremely bounded (0.18). In fact, the absolute error of the majority of the testing sub-region is below 0.1.

Table 4.3 depicts the results of the testing phase of homogeneous approach. In particular,
it can be seen that the model shows a better performance with collected data from the single-family region. This can be explained because the variation of the buildings’ height and terrain type in the single-family region is more self-similar as compared with the downtown area.

To evaluate RAIK in the context of the most relevant related works in predicting $\gamma$, we compared it with the Kriging algorithm, which is a common approach to address the spatial propagation prediction [71]. To predict the lost data in a region, Kriging employs regression of the surrounding values of that region by assigning weights to these values to capture the spatial correlation of field of interest. Many studies have used Kriging to estimate the path loss [68,69,92]. For example, an empirical Okumura-Hata model with Inverse Distance Weighting (IDW) and Kriging has been evaluated in prior work [68]. They have shown that the approach with Kriging shows an improved performance versus just Okumura-Hata model and IDW.
Fig. 4.6a shows the Kriging calculated path loss when all signal quality measurements are used. As we just performed for a downtown region, we introduce a measurement hole, emulating a lack of crowdsourced measurements, shown in Fig. 4.6b. The dots denote the available points, and the lack of dots denotes lack of signal quality measurements. Fig. 4.6c shows the Kriging prediction results with these signal quality measurements removed and find the MSE to be 0.07. We perform the same analysis on this region with RAIK and find the MSE to be 0.01. The use of geographical data to predict KPIs reduced the error seven-fold.

Heterogeneous Training and Testing. Since the aim is providing a generalized RAIK model to predict the channel characteristics based on geographical information alone, we consider the obtained input-output pairs from different base stations located in single-family residential and downtown environments as our data for training. We then test in an entirely new region (multi-family residential) but also test in the two regions that were used for training. There are two issues to evaluate here. First, up to this point, the training and testing has only taken place in the same region. Here, we have two different regions composing the
training set, which may confuse the model. Second, we would like to evaluate how well the RAIK framework can predict in region types that have received no training.

Table 4.4 shows the RAIK performance across the three regions. We observe that both the single-family residential region and downtown region perform slightly worse from their respective homogeneous training and testing performance described in Table 4.3. In particular, we observe that the variation of error for single-family and downtown increase from .13 and .21 to .21 and .27, respectively. Although, the MSE for single-family increased from .01 to .03 and downtown increased from .02 to .04, the model still shows an acceptable performance in comparison with the homogeneous model. Furthermore, the performance of the multi-family region that contributed no training data to the RAIK model is 0.03. The variation of error has increased slightly in comparison with two well-trained regions, but it is still comparable. In summary, while slight improvements in RAIK KPI prediction can be achieved when training data is available from adjacent regions of similar geographical features, RAIK can still predict KPIs across regions with distinct geographical features.

Table 4.4: RAIK with Heterogeneous Training and Testing.

<table>
<thead>
<tr>
<th>Region</th>
<th>MSE</th>
<th>$e_{\text{min}}$</th>
<th>$e_{\text{max}}$</th>
<th>$e_{\text{mean}}$</th>
<th>$\sigma_{\text{err}}$</th>
<th>$r$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single Family</td>
<td>.02</td>
<td>-.22</td>
<td>.24</td>
<td>.05</td>
<td>.21</td>
<td>.90</td>
</tr>
<tr>
<td>Downtown</td>
<td>.03</td>
<td>-.27</td>
<td>.3</td>
<td>.07</td>
<td>.27</td>
<td>.87</td>
</tr>
<tr>
<td>Multi Family</td>
<td>.03</td>
<td>-.3</td>
<td>.33</td>
<td>.09</td>
<td>.3</td>
<td>.82</td>
</tr>
</tbody>
</table>

4.5.2. The Results of the Phase "B": Extracting Effective Data Using a Cone-Shaped Filter to Improve Path Loss Prediction

In Section 4.5.1, we studied the appropriate region size to predict the path loss exponent. We predicted the path loss exponent of a specific region using the phone-based measurements and corresponding geographical features using a NN model and we chose the region size as
In this section, we reduce the standard deviation of the observed error in path loss exponent prediction estimated in Section 4.5.1. The objective is to conduct an $RAIK_2$ model to accurately predict the received signal level at any arbitrary location in a tile. The model should be simple, accurate, and generalizable. The most important step to achieve this goal is to train the NN model using proper information. Having the signal level information, we can conduct an accurate estimation of the propagation model of the corresponding region with high accuracy.

To achieve this goal, we first need to extract the data that affects the signal when it travels its path from the transmitter to the receiver. In our previous analysis, two important factors have not been addressed: 

a) The obstacles along the direct path from the base station to the UE have a significant effect on the propagation characteristics. 

b) We need to address the width of the direct path. The angle around this direct path depends on the environment. In wireless communication, we have a direct path (Line of Sight) and Non-Line of Sight (NLOS). In some environments, LOS rarely happens and the signals are mostly subject to the NLOS scenario in which a signal is exposed to the reflection and diffraction due to the buildings and foliage. In other words, the signal reaches to a UE from different paths, which are termed as multipath fading. Hence, the angle might be larger or smaller depending on the degree to which multipath delay spread exists in the environment. We expect that if the delay spread is large, the angle of relevance along the direct path would be larger, representing tall and more distant structures that produce reflections. In contrast, we expect that if the delay spread is small, the angle would likely be smaller. Concerning the above-mentioned cases, we need to design a cone-shaped filter that contains the objects along with the direct path from the base station and the UE with a calibrated angle according to the environment type.

**Acquiring the Delay Spread Information.** As we mentioned the maximum delay spread of the received signals implicitly shows the area which contains the objects that affect a signal while it is traveling through its direct path from the transmitter to the receiver. The
delay spread happens due to the multipath. Multipath can be modeled by a vector of relative delays and a vector of average powers depicted in 4.6:

$$h(t) = \sum_{i=0}^{L-1} a_i \sigma (t - \tau_i )$$  \hspace{1cm} (4.6)$$

Here, $L$ is the number of paths and $a_i$ and $\tau_i$ are the attenuation and delay of the $i^{th}$ path, respectively. However, a large number of spurious components reach the UE with negligible power. The delay between the paths depends on the geographical features of the environment. The difference between the arrival time of the last path and the first path is called delay spread, which can be obtained by 4.7.

$$\text{Delay-Spread} = \frac{\Delta t}{C}$$  \hspace{1cm} (4.7)$$

Here, Delay-Spread is the difference in time of arrival ($\mu$sec), $\Delta t$ is the difference in distance in meter, and $C$ is the speed of light ($3 \times 10^8$ m/s).

We use a channel scanner from Rohde & Schwarz called the TSMW, to measure the delay spread of the single-family, multi-family, and downtown areas. The TSMW provides detailed information of the delay spread of the received signals such as the difference between the first and the last peak.

Table 4.5 depicts the average, minimum, and maximum values of the delay spread observed in three regions and corresponding distances. In this table, we do not consider the LOS scenario, which the signal reaches to the UE with zero delay. To depict the delay spread in terms of distance we use 4.7.

As we expect, the largest and the smallest values correspond to the downtown and single-family regions, respectively.

**Impact of the Cone-Shaped Filter Angle Size on RAIK Performance.** In this section, we study the impact of the obstacles which scatter, reflect, and diffract from a transmitted signal while it is traveling along multiple path to the receiver. To extract the required objects in terms of foliage and building, we use a cone-shaped filter. However,
we need to find an appropriate angle for the cone-shaped filter. To do so, we perform the following steps:

(i). We change the angle size of the filter for each signal measurement in a tile according to the observed delay spread depicted in Table 4.5. We use a right triangle in between the transmitter and the receiver as depicted in Fig. 4.7. The hypotenuse of the triangle and the opposite side are determined by the distance between the base station and the UE and the delay spread in terms of distance, respectively. Using the Pythagorean Theorem, we obtain the length of the third side. Then, using the \( \cos \theta = \frac{a}{c} \), we can find the angle size of the filter, which should be doubled at the end.

(ii). Since the angle size varies due to the distance between the base station and UE, we consider the averaged distance observed in our dataset as the direct path length. Then, we change the opposite side length due to the maximum, minimum, and average distances corresponding to the maximum, minimum, and average delay spread as depicted in Table 4.5, respectively.

Fig. 4.8 shows three cone-shaped filters with different angles. The obtained angle corresponding the average delay spread is depicted as \( \theta_{\text{Ref}} \), and two other angles, \( \theta_1 \) and \( \theta_2 \) are the angles corresponding the minimum and the maximum delay spread values, respectively.

(iii) Then, we extract all the objects located within the range of the \( \theta_{\text{min}} \), \( \theta_{\text{max}} \), and \( \theta_{\text{ave}} \) for three regions. The selected objects’ heights intersect the cone-shaped filter. To compensate the vertical error of the LiDAR dataset, we consider an error margin about \( \pm X \) meters for each object’s height.
(iv) Then, we train the RAIK$_2$ with three different datasets obtained from three different regions to predict the received signal level as the output of the model. In this experiment, we exclude the objects surrounding the UE to evaluate the impact of the objects that intersects the direct path.

Table 4.7 depicts the performance of the NN model, which considers differing $\theta$.

The performance of the RAIK model is improved when the angle of the cone-shaped filter is calibrated according to the average delay spread of the channel. As depicted, the MSE increases and the correlation factor of the model decreases by changing the filters angle by a value smaller or larger than the $\Theta_{Ave}$. The reason is that a large number of spurious components reach the UE with negligible power and their impact on the received signal level is insignificant.

Impact of the Feature Selection on RAIK Performance. In this section, we calibrate the angle size of the cone-shaped filter in each region according to the obtained results from the previous section. Now we show the importance of the geographical features
Table 4.6: Delay Spread Corresponds to Three Different Environment.

<table>
<thead>
<tr>
<th>Region</th>
<th>$\Delta_{SF}$ (m)</th>
<th>$\theta$ (m)</th>
<th>$\Delta_{MF}$ (m)</th>
<th>$\theta_{MF}$ (m)</th>
<th>$\Delta_{DT}$ (m)</th>
<th>$\theta_{DT}$ (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min Delay Spread</td>
<td>3</td>
<td>89</td>
<td>3</td>
<td>89</td>
<td>60</td>
<td>86</td>
</tr>
<tr>
<td>Max Delay Spread</td>
<td>570</td>
<td>53</td>
<td>630</td>
<td>48</td>
<td>930</td>
<td>11</td>
</tr>
<tr>
<td>Mean Delay Spread</td>
<td>99</td>
<td>84</td>
<td>102</td>
<td>83</td>
<td>240</td>
<td>75</td>
</tr>
</tbody>
</table>

Figure 4.8: The reference area vs smaller and larger areas.

on the performance of the prediction model to estimate the propagation model of a particular area.

We train the $RAIK_2$ using three datasets as the input feature of the model include: a) The distance between the Tx and Rx ($NN_a$). b) The distance and the objects along the direct path, ($NN_b$). c) The distance and the obstacles surrounding the UE ($NN_c$). d) The distance, the objects along the direct path, and the objects around the UE ($NN_d$).

Table 4.8 shows a comparison between the performance metrics of $RAIK_2$ for four different datasets. It is shown that training the model considering the distance as the only input feature, degrades the $RAIK_2$ performance to predict the received signal level. We observe that considering the geodata improves the prediction performance.
Table 4.7: The impact of the one-shape filter angle on the $RAIK_2$ performance.

<table>
<thead>
<tr>
<th>Filter Angle Size</th>
<th>$\theta_{\text{min}}$</th>
<th>$\theta_{\text{ave}}$</th>
<th>$\theta_{\text{max}}$</th>
<th>$\theta_{\text{min}}$</th>
<th>$\theta_{\text{ave}}$</th>
<th>$\theta_{\text{max}}$</th>
<th>$\theta_{\text{min}}$</th>
<th>$\theta_{\text{ave}}$</th>
<th>$\theta_{\text{max}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Std</td>
<td>6.4</td>
<td>5.1</td>
<td>6</td>
<td>6.3</td>
<td>5.1</td>
<td>6.7</td>
<td>6.8</td>
<td>5.2</td>
<td>6.9</td>
</tr>
<tr>
<td>MAE</td>
<td>4.7</td>
<td>4.5</td>
<td>6.9</td>
<td>4.7</td>
<td>4.1</td>
<td>5.1</td>
<td>5.1</td>
<td>4.5</td>
<td>5.3</td>
</tr>
<tr>
<td>R</td>
<td>0.84</td>
<td>0.89</td>
<td>0.85</td>
<td>0.84</td>
<td>0.87</td>
<td>0.8</td>
<td>0.77</td>
<td>0.83</td>
<td>0.79</td>
</tr>
</tbody>
</table>

Of particular note, the surrounding objects affect the single-family due to the density of trees around the UE which scatter the received signal. In contrast, in the multi-family area, considering the obstacles along the direct path improves the model’s performance more than considering the objects around the UE. Also, we observe that the $NN_b$ and $NN_c$ are showing the same performance in the downtown area due to the diversity in height, area, and the density of trees and buildings.

Table 4.8: The impact of the input features on the NN performance.

<table>
<thead>
<tr>
<th>Area</th>
<th>Single Family</th>
<th>Multi Family</th>
<th>Downtown</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>$NN_a$</td>
<td>$NN_b$</td>
<td>$NN_c$</td>
</tr>
<tr>
<td>Std</td>
<td>7.2</td>
<td>6</td>
<td>5.4</td>
</tr>
<tr>
<td>MAE</td>
<td>5.5</td>
<td>4.5</td>
<td>4</td>
</tr>
<tr>
<td>R</td>
<td>0.76</td>
<td>0.86</td>
<td>0.89</td>
</tr>
<tr>
<td>MSE</td>
<td>17.2</td>
<td>11</td>
<td>12.5</td>
</tr>
</tbody>
</table>

4.5.3. Performance of the Kriging Versus $RAIK_2$

In this section, we assess the performance of the NN and Kriging Model in path loss prediction. We perform two algorithms to predict the received signal level of certain coordinates, and we compare the results in terms of the MSE. To compare the NN and interpolation-based Kriging algorithm, we select the largest group of measurements corresponding to a
base station in the downtown area. We then provide the coordinates of the UE capturing the measurements during the test as the input of the Kriging algorithm and the received signal strength level as the output of the model. The input of the NN model is the geographical features of the environment and the distance between the Tx and the Rx.

Since the Kriging algorithm is vulnerable to large distances we design two special cases as follows to compare the $RAIK_2$ and Kriging performance: (a) Considering the crowdsourcing base measurements, the distribution of the collected measurements usually do not follow a uniform pattern. In real life, adjacent to a large set of data, a region may lack information. To model this scenario, we intentionally provide a big gap in the middle of our concerned area as shown in Fig. 4.9.

![Figure 4.9: Non-uniform data selection.](image)

Fig. 4.10a shows the estimated received signal level by Kriging when all signal quality measurements are used. As we just mentioned, we provide a measurement hole, emulating a lack of crowdsourced measurements, shown in Fig. 4.9b. The dots show the available measurements, and the lack of dots denotes lack of signal quality measurements. Fig. 4.10b shows the results of Kriging prediction in the absence of the selected signal quality measurements and we find the MSE to be 7. We conduct the same analysis on this region with $RAIK_2$ and find the MSE to be 4.4. As we observe the use of geographical data to predict received
signal level reduced the error seven-fold.

![Image](image1.png)  
(a) Kriging interpolation on all signal measurements.  

![Image](image2.png)  
(b) Kriging interpolation on selected signal measurements.  

Figure 4.10: The impact of the clustered data on Kriging prediction performance.

(b) We select the measurement route in the downtown region which covers a distance of about 1000 meters. We train the \( \text{RAIK}_2 \) and Kriging models with measurements from a specific tile close to the transmitter. Then, we test the performance of the models using our test dataset. The test dataset contains the measurements which are out of the area of the selected tile, and their distance from the transmitter gradually increases.

Table 4.9 shows the performance evaluation of the test data obtained by Kriging and NN model. As depicted, \( \text{RAIK}_2 \) prediction shows higher performance in comparing with the Kriging prediction performance while we increase the distance of the test data to the BTS.

Table 4.9: Comparing the Performance of the \( \text{RAIK}_2 \) and Kriging.

<table>
<thead>
<tr>
<th>Region</th>
<th>( d_1 )</th>
<th>( d_2 )</th>
<th>( d_3 )</th>
<th>( d_4 )</th>
<th>( d_5 )</th>
<th>( d_6 )</th>
<th>( d_7 )</th>
<th>( d_8 )</th>
<th>( d_9 )</th>
<th>( d_{10} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>ANN</td>
<td>2.7</td>
<td>2.9</td>
<td>4.2</td>
<td>3.6</td>
<td>4</td>
<td>3.20</td>
<td>3.4</td>
<td>3.1</td>
<td>3.2</td>
<td>3.9</td>
</tr>
<tr>
<td>Kriging</td>
<td>2.2</td>
<td>2.5</td>
<td>4.5</td>
<td>4.7</td>
<td>4.8</td>
<td>5</td>
<td>10</td>
<td>10</td>
<td>15</td>
<td>15</td>
</tr>
</tbody>
</table>

4.6. Summary

In this paper, we used the knowledge of geographical features of a region to extend crowdsourced measurements such as those within the MDT effort of the 3GPP standard to
predict the KPIs in that region. To do so, we built an Android-based crowdsourcing infrastructure and performed in-field measurements to create a high density of UE measurements in three representative region types: downtown, single-family residential, and multi-family residential. With these RSRP measurements, we studied the relationship between the size of smaller, square sub-regions under consideration with regards to the calculated path loss exponent, showing the tradeoff of too large and too small sub-regions. We then used LiDAR data to extract tree and building data to build a Regional Analysis to Infer Key Performance Indicators (RAIK) framework, which created a relationship between these geographical features and the received signal level in different sub-regions. Using the RAIK framework, we showed that KPIs can be predicted with very low error in areas that lack access or users to produce crowdsourced measurements. We believe that this work will serve as a fundamental step in extending the reach of MDT measurements taken by carriers and thereby reduce the load on users and their devices.
5.1. Introduction

Accurate prediction of wireless propagation models is always a vital issue for mobile network operators. To predict the instantaneous received signal level at an arbitrary point, network operators often need the knowledge of both large- and small-scale fading. The large-scale models estimate the average of the received signal level due to the distance and small-scale channel models estimate the local variations of the average signal level [14, 17, 81, 88, 91, 98].

In previous chapters, we evaluated the obtained KPI via an MDT-like approach in terms of the received signal level to estimate the path loss propagation of a region. Most of the research has studied the capability of the UE to measure the network coverage and amount of dropped calls. In [37], we evaluated the estimated path loss exponent by phone measurements. Also, in [35], we depicted how we can predict the received signal level in an arbitrary point in a concerning area using the geographical features. Also, [11] quantified the error in MDT-based autonomous coverage estimation as a function of UE and base station positioning error.

However, the capability of an MDT-like approach to estimate the fast fluctuations of the wireless channel has rarely been addressed in prior studies. Estimating the multipath and fading characterization would help in different real-life scenarios such as channel characterization, link budget calculations, adaptive modulation, and geolocation applications, to enhance the network performance for the end user. However, currently this information is only achievable in a lab environment, and under controlled conditions [106]. Recently, [106] proposed a method to use UE measurements for characterizing multipath in terms of
coherence bandwidth and the Doppler shift of propagation channels in mobile networks.

A UE in an LTE network can measure the rapid fluctuations of the wireless channel condition using reference signals. MDT enables the UE to periodically send additional information to the transmitter according to the base station and infrastructure requirements. This information allows the Mobile Network Operator (MNO) to monitor the network performance from the end-user perspective. MDT is not an excessive burden on the phone load processing because a phone will automatically perform all of these tasks whether it is currently active or inactive on the network. There is, however, concerns over battery consumption if the MDT reporting becomes too frequent, memory concerns if the reporting becomes too infrequent (and yet the recording level stays high), and privacy concerns over providing location information.

In LTE networks, the UE measures a reference signal every 0.5 milliseconds. With MDT, a UE can log these KPIs of the network to report them to the MDT servers immediately or periodically. However, a mobile phone may average over multiple samples of received signal quality, which might affect the instantaneous observations of the channel variations. In this work, we study the capability of MDT measurements to estimate the channel fluctuation characteristics in the presence of phone measurements shortcomings include averaging over multiple samples, imprecise quantization, and non-uniform and/or less frequent channel sampling. We use outage probability as the performance metric, which is a function of the wireless channel variation. Outage probability defines as the point at which the receiver power value falls below a threshold. This threshold is the minimum signal-to-noise ratio within a channel to have a certain QoS.

We set up a framework to evaluate the fast fluctuations of the network in terms of outage probability in the presence of some imperfections of the phone measurements such as averaging over a few numbers of samples, the number of data selected in a uniform and non-uniform fashion over time, and quantization depicted in Fig. 5.1. To provide a repeatable experiment we use a channel emulator to generate Rayleigh fading channel.
Our contributions in this work are as follows: We study the non-ideal signal samples impact on fading estimation in terms of outage probability while the signals are averaged, downsampled (uniformly and non-uniformly), and quantized. We quantify the role of each imperfection on the fast-fading parameter estimation.

The remainder of the paper is organized as follows. In Section 5.2 we depict our data acquisition approach. In Section 5.3, we analyze the role of mobile phone imperfections in terms of fading parameter and outage probability and we conclude in Section 4.6.

5.2. Fast Fading Estimation in the Presence of Non-Ideal data

An accurate estimation of fast-fading can significantly enhance the propagation model prediction. To measure fast-fading, we need a relatively large amount of information provided over a short period of time. In this study, we want to evaluate the fast-fading parameter estimation using MDT measurements while the signal samples are induced by some factors such as averaging over multiple samples, imprecise quantization, and non-uniform and/or
less frequent channel sampling.

5.2.1. Characterization of Small-Scale Fading or Fading

Small-scale fading occurs because the difference in arrival time and phases of the same signal due to reflections off of surrounding objects and the direct path from the transmitter to the receiver. The reflected and scattered signals arrive at the receiver from different paths. The phases of the distorted signals are random variables because the distance of each path is diverse. Thus, these signals add up at the receiver constructively (high amplitude) or destructively (low amplitude) depending upon their random phases. Small-scale fading estimates the local variations of the average signal level. It is the variation of the measurements over a small period of time and short distances considering the impact of the environmental features.

So, the distribution of the arrived signals follows one of the Rayleigh, Rician, Nakagami, Weibul, and log-normal models. However, these models should be selected carefully to avoid any underestimating or overestimating for the network configuration. For example, in an open area with fewer scatterers, there is a dominant line of sight (LOS) between the Tx and the Rx. In this situation, the received signal strength follows a Rician distribution. In an urban area, there is no dominant LOS path between the Tx and the Rx, and the scattered signals can be modeled using a Rayleigh distribution.

The Rayleigh channel can be expressed by scattering components according to 5.1, where there is no direct path between BTS and the UE:

\[
h(t) = \sum_{l=1}^{L} a_n e^{j2\pi f_d t + \Phi_n}
\]  
(5.1)

Here, \( L \) is the number of paths and \( a_n \) is the gain of the \( l \)th path. The Doppler frequency shift and the phase of \( l \)th path are depicted as \( f_d \) and \( \phi_n \), respectively. The Doppler shift is the change in the frequency and phase of the electromagnetic wave due to the relative
motion between the transmitter and receiver, which can be obtained by 5.2.

\[ F_d = \frac{v \cos \theta}{c} F_c \]  \hspace{1cm} (5.2)

Here, \( C \) is the speed of light, \( F_c \) is the carrier frequency, and the receiver is moving at speed \( v \) at an angle \( \theta \). The probability density function (PDF) of received signal envelope can be depicted by a Rayleigh distribution 5.3.

\[ P(x) = \frac{x}{\sigma^2} e^{-\frac{x^2}{2\sigma^2}} \]  \hspace{1cm} (5.3)

Here, \( r \) depicts the received signal envelope, and \( \sigma^2 \) is the local-mean scattered power.

**Mobility Optimization in LTE.** LTE is optimized for different range of mobility scenarios include (a) a low mobile speed from 0 to 15 km/h, (b) a medium mobile speed between 15 and 120 km/h, and (c) a high mobile speed from 120 km/h to 350 km/h (or even up to 500 km/h depending on the frequency band) [1]. The Doppler shift determines the coherence time value, which shows the duration of time that the channel does not significantly change. The Doppler shift determines the maximum rate that will allow sampling the channel accurately. For the sampling rate to have an accurate estimation, the channel the sampling rate should be twice the Doppler shift. Hence, LTE has an interval between each pilot signal as 0.5 ms to combat the Doppler shift in the worst case scenario.

According to [119], we generate an ITU channel for pedestrian test environment using the channel emulator. A multipath fading propagation condition is defined by a combination of a multi-path power-delay profile and a maximum Doppler frequency, which is either 5 Hz.

5.2.2. Experimental Set-up: Emulating the Fading Channel

Fast fading varies according to the geographical features of a particular area. The higher environmental complexity, the more paths exist, which tends to have more severe fast-fading
effects. A wireless channel can be depicted as \( y(t) = x(t) * h(t) \) (5.4).

Let \( x(t) \) be the transmitted signal through the channel \( h(t) \). \( h(t) \) is the fading channel which varies due to the environment of the wireless channel. The received signal can be depicted as \( y(t) \), which is the combination of arrived signals from different paths. Thus, conducting a repeatable in-field experiment is not an easy or even possible task since there are many uncontrollable channel factors. Hence, we use a channel emulator to generate channel fading in a completely controlled environment.

In order to eliminate the impact of the other sources of noise and performing repeatable experiments, we use an Azimuth ACE-MX channel emulator. To generate a wireless channel we use the Wireless Open-Access Research Platform (WARP). The transmitter and receiver are connected with the Azimuth ACE-MX via cabling from the radio to the emulator input. WARP is used as both the transmitter and the receiver of the system along with an Azimuth ACE-MX channel emulator. The channel emulator generates fast-fading samples with the desired fading distribution. The hardware set up is depicted in Fig. 5.2. The channel emulator can be controlled over the Ethernet by the Director-II software which is installed on a PC. We can configure the channel characteristics such as model type, path-loss, Doppler, and input or output attenuation regarding the experiment requirements. We can implement different fading channels due to different geographical features and velocity using ITU-R empirical channel models \([63]\), referred to as pedestrian B, and vehicular A/B. Their significant differences are in the number, gain, and the delay of the channel taps which is termed as a power-delay profile.

**Evaluation Metric To Estimate the Fast Fading.** We choose the outage probability which is a function of fast fading to evaluate the accuracy of the fading parameter estimation. The instantaneous signal samples are affected by averaging, downsampling (uniformly and non-uniformly), and quantization. We obtain the absolute error between the ground truth
value and the estimated fading parameter.

Outage Probability Ratio for a Non-Ideal Dataset. In cellular networks, outage happens when the received signal strength drops below a certain threshold \([54, 64, 97]\), which can be obtained by \(5.5\).

\[
P_{\text{out}} = \int_{0}^{P_{\text{th}}} p(t) dt \tag{5.5}
\]

Accordingly, the outage would be determined with the duration of time that the received signal level stays below a threshold.

5.3. Fading Estimation Evaluation

In this section, we depict the evaluation results in terms of outage probability estimation in the presence of the phone imperfections. We study the impact of averaging, quantization, and downsampling on the reported outage probability using an MDT-like measurement approach.
5.3.1. Averaging Impact on Outage Probability Estimation

To study the impact of the averaging on the outage probability, we conduct a moving averaging window with various sizes. It averages $d$ number of input samples to provide a new data point at the output, where $d$ is the size of the moving averaging window size 5.6.

$$\mu s_n = \frac{1}{d} \sum_{i=0}^{d-1} s_{n+i}$$  \hspace{1cm} (5.6)

By applying the moving averaging filter with various sizes over the data samples, we provide new datasets. Then, we measure the outage probability of the new dataset and compare the obtained $\mu ave$ parameter with $\mu ref$. The $\mu ref$ is the outage probability obtained by considering all the samples of the original dataset. We repeat the experiment 50 times and depict the results in terms of MSE. The variation of the $p$ parameter of the channel is depicted in Fig. 5.3, where we increase the filter size to from one to 1000 samples.
As depicted, the error in outage probability estimation increases by increasing the averaging window size. By averaging over 12 samples, the error increases from 0.005 to 0.01.

5.3.2. Uniform Downsampling Impact on Outage Probability Estimation

To evaluate the impact of the uniform downsampling on the outage probability estimation, we reduce the number of samples to reach 40 number of samples. Then, we compare the obtained outage probability corresponding to each new dataset with our reference \( p_{\text{ref}} \), which has the highest resolution allowed by our dataset.

Fig. 5.4 depicts that the error in terms of outage probability estimation increases by decreasing the number of samples. We repeat the experiment 50 times. The results are depicted in terms of MSE. We depict the number of samples on the x-axis, average over the estimated error at each data point, and show the results on the y-axis. The standard deviation of the error is depicted by error bars.

We observe that by increasing the number of measurements to ten samples, the error increases up to 0.18. Also, by reducing the number of samples to 400, we experience an error about 0.008 compared to the \( p_{\text{ref}} \).

5.3.3. Non-Uniformly Sample Selection Impact on Outage Probability

In this section, we assume that a phone does not provide a periodic report of the channel quality. In other words, the distance between every two samples is not equal. To do so, we reduce the number of samples non-uniformly from 2000 to 40 samples. The number of samples at each step is chosen according to the selected number of samples in the previous section. Then, we compare the obtained outage probability corresponding to each new dataset with the reference \( p_{\text{ref}} \).

Fig. 5.5 depicts that the error in terms of outage probability estimation increases while we reduce the number of samples. We performed the experiment 50 times. We depict the average of the estimated error of all experiments on the y-axis at each data point. Also, we show the variation of the error observed in experiment by error bars around the average
values. We observe that by reducing the number of samples to 40, the error increases to more than 0.02, which depicts a higher error as compared with the uniform sample selection approach.

5.3.4. Quantization of the Received Signal Power

Android uses an Arbitrary Strength Units (ASU) to report the received signal level in LTE communication, which is quantized to 98 levels. There is a mapping with 1 dB from "0 to 97" to a range of -44 dBm to -140 dBm. In this experiment, we want to study the role quantization has on the fast-fading parameter.

To do so, we applied quantization on top of the averaging from the previous section. In other words, once we increased the averaging window size, we quantize the obtained samples and round each element to its closest upper or lower quantized value.

We compare the estimated $p_{\text{ave}}$ after applying the averaging with $p_{\text{quant,ave}}$. Here, $p_{\text{quant,ave}}$ is the channel fading parameter after averaging and quantization. By comparing the result
with the reference value, we notice that the absolute error imposed by quantization to be negligible.

**Comparing the Impact of the Phone Imperfections on the Outage Probability Estimation.** By comparing the observed errors from averaging and sample reduction, we notice that the averaging has a dominant impact of the outage probability estimation. Table 5.1 shows the impact of each individual imperfection on the outage probability.

Table 5.1: Comparing the Error Imposed by Phone Imperfection on Outage Probability Estimation.

<table>
<thead>
<tr>
<th>Item</th>
<th>Averaging</th>
<th>Non Uniform Selection</th>
<th>Uniform Selection</th>
<th>Quantization</th>
</tr>
</thead>
<tbody>
<tr>
<td>Error (MSE)</td>
<td>0.086</td>
<td>0.0093</td>
<td>0.0075</td>
<td>0.00001</td>
</tr>
</tbody>
</table>

5.3.5. Impact of the Outage Probability Estimation Error On the Network Performance
In the previous section, we evaluated the effects of averaging over multiple samples, uniform and non-uniform downsampling, quantization on the accuracy of the outage probability estimation using MSE.

In this section, we interpret the error in outage probability estimation of the network in terms of operational network performance, and we examine the role of this estimation error has on Bit Error Rate (BER).

BER is the number of bit errors that happen in a certain amount of bit transmissions. In a wireless network, the fluctuation of the received signal due to the multipath and Doppler effect the BER. Thus, network operators need to determine the probability that the received signal strength crosses a particular threshold level in certain areas.

In this particular example, we conduct a Binary Phase Shift Keying (BPSK) transmission through a Rayleigh fading channel. Then, we measure the outage probability of the channel, which is a function of the received signal fluctuations. To do so, we measure the average SNR of the channel as the threshold for the received signal level. Next, we obtain the outage probability of the channel and the corresponding BER. We perform the steps above for different SNRs.

Fig. 5.6a depicts the outage probability for various SNRs. The outage probability increase while we increase the outage threshold. Fig. 5.6b depicts the variation of the BER according to the channel gain variations. Then, we consider an error in outage probability value from -0.1 to +0.1 for a range between 0 and 0.7. We observe that an error about +/- 0.1 in outage estimation changes the required outage threshold in a step of 4dB. Fig. 5.6b shows the variation of BER by changing the estimated outage probability from 0 to .7 while the outage threshold is in a range of -10 to 15. We consider two SNR values with their corresponding BERs. For example, we select the SNR at 0 dBm and 4 dBm. We notice that 4 dB variation in SNR causes an error of less than 0.1 in BER estimation.
(a) Outage probability for different thresholds.

(b) BER estimation regarding to channel gain variations.

Figure 5.6: Impact of the $\gamma$ estimation’s error on the cell area coverage probability estimation.
6.1. Future Work

In this work, we used Lidar dataset to provide a 3-dimensional map from the area under the study. The availability of Lidar data points has been increased. This Lidar information improves the ability of wireless propagation model prediction in an unknown area. However, the processing time of the Lidar dataset is high. An efficient approach to collect and record the Lidar data points will increase the performance of the prediction approach.

Also, providing adequate coverage for an indoor environment is one of the main concerns of Mobile network operators. Crowdsourced measurements can be used to improve indoor coverage. However, there are still some difficulties in detecting the indoor and outdoor measurements in a crowdsourced dataset.
[1] 3GPP. Requirements for evolved utra (eutra) and evolved utran (eutran).


[3] 3GPP. ETSI TS 127 007 "UMTS;LTE AT command set for UE, TS 27.007 v.10.3.0 release 10", April 2011.


[40] ETSI, T. 127 007 v5. 3.0 (2003-03) digital cellular telecommunications system (phase2+). *UMTS*.


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[77] **Mobiperf.** Mobiperf, measuring network performance on mobile platforms, 2013.


[98] Rayleigh, L. Xii. on the resultant of a large number of vibrations of the same pitch and of arbitrary phase. The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science 10, 60 (1880), 73–78.


[113] Sklar, B. Rayleigh fading channels in mobile digital communication systems. i. characterization. IEEE Communications magazine 35, 7 (1997), 90–100.


[120] Unknon, A. Technical specification group radio access network; evolved universal terrestrial radio access (e-utra); radio resource control (rrc); protocol specification (release 12). Technical Specification 36.


[125] Yashkova, O. The metamorphosis of the wireless network testing market.
