ADDIS ABABA UNIVERSITY

SCHOOL OF GRADUATE STUDIES

ADDIS ABABA INSTITUTE OF TECHNOLOGY

ELECTRICAL AND COMPUTER ENGINEERING DEPARTMENT

Fine-tuning of Cost-231 Hata Path Loss Model for LTE Network: The Case of 4 Kilo Area

By:

Noah Fesseha

Advisor:

Dr.-Eng. Yihenew Wondie

A Thesis Submitted to the School of Graduate Studies of Addis Ababa University in Partial Fulfillment of the Requirements for the Degree of Masters of Science in Electrical Engineering

June, 2018

Addis Ababa, Ethiopia

ADDIS ABABA UNIVERSITY

SCHOOL OF GRADUATE STUDIES

ADDIS ABABA INSTITUTE OF TECHNOLOGY

SCHOOL OF ELECTRICAL AND COMPUTER ENGINEERING

A THESIS SUBMITTED TO THE SCHOOL OF GRADUATE STUDIES OF ADDIS ABABA UNIVERSITY IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTERS OF SCIENCE IN ELECTRICAL AND COMPUTER ENGINEERING (COMMUNICATION ENGINEERING)

Fine-tuning of Cost-231 Hata Path Loss Model for LTE Network: The Case of 4 Kilo Area

By: Noah Fesseha

Approval by Board of Examiners

____________________________ ____________________

Chairman, Dept. Graduate Committee Signature

Dr. -Eng. Yihenew Wondie ______________________

Advisor Signature

_______________ _____________________

Internal Examiner Signature

______________ ______________________

External Examiner Signature

Declaration

I, the undersigned, declare that this MSc thesis is my original work, has not been presented for fulfillment of a degree in this or any other university, and all sources and materials used for the thesis have been acknowledged.

Name: Noah Fesseha

Signature: _______________

Place: AAU, SECE, Addis Ababa

Date of submission: _______________

This thesis work has been submitted for examination with my approval as a university advisor.

Dr. -Eng. Yihenew Wondie _______________

Advisor's Name Signature

Abstract

The demand for increased mobile phone subscribers requires an efficient radio network planning that involves an accurate prediction of path loss. For Long Term Evolution (LTE) mobile network, empirical path loss models such as Cost-231 Hata model are used to predict the loss in a propagation environment. These models depend on frequency of operation, terrain profile of an environment, transmitter and receiver heights and distance from a base station. As the propagation environments continuously changes, these models need to be fine-tune continuously. In this thesis, LTE 1800 MHz mobile signals that are recorded experimentally, for four eNodeB in Addis Ababa 4Kilo area, are considered for path loss analysis. A drive test methodology was adopted for data collection and the measuring tools used for the test was a hand phone installed with Nemo Handy software. The received signal strength and path loss were recorded in the form of logs which can later be extracted with ACTIX software analyzer in to a suitable form of Excel sheet. The measured path loss is determined from the collected data. Cost-231 Hata model was optimized because it is the existing model in Ethio telecom. In order to improve the prediction accuracy, this model is statistically optimized using Least Square algorithm. The initial offset parameter and slope of the model curve in Cost-231 Hata model are considered and new model parameters are estimated. The optimized path loss predicting model is compared with the original Cost-231 Hata model and MATLAB R2016a Simulation software was used for this purpose. The performance of the optimized model is evaluated using Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). The optimized model gives a RMSE = 0.039 dB and MAPE = 0.037% as compared to Cost-231 Hata model with a RMSE = 0.49 dB and MAPE = 0.47%. The results show that the errors are least for the optimized Cost-231 Hata model, compared to the original Cost-231 Hata model. Hence, the optimized model is recommended for better deployment and gives an accurate path loss prediction in the urban area of 4Kilo**.**

Keywords: Path Loss Model, Long Term Evolution, Least Square Tuning Algorithm, Cost-231 Hata model, RMSE and MAPE.

Acknowledgments

First and foremost, I would like to thank the Almighty God who is always with me in each and every step of my life.

I would like to thank my advisor, Dr.-Eng. Yihenew Wondie for his sincere support, continuous encouragement, and meaningful guidance during the whole process from initial research to final thesis report. My thesis would not be completed well without my advisor's support. He has always been available and willing to help me. Besides; I would also like to thank my families and friends for their motivation, comments and suggestions.

I also would like to thank Dr. Beneyam Haile for his great advising in the process of developing this thesis idea.

Great thanks also to Ethio-telecom employees, especially to Mr. Ashagire, Mr. Futsum, Mr. Zelalem, Mr.Gebremedhin and Mr. Yeshitila as they were very cooperative in providing the necessary data for this work and very encouraging throughout the whole process.

Finally, I'm thankful for those who stood-by me throughout my work, giving me encouragements and valuable help. This work is fully dedicated for my family.

Table of Contents

List of Tables

List of Figures

Abbreviations

2G	Second Generations
3G	Third Generations
3GPP	3rd Generation Partnership Project
4G	Fourth Generations
CDMA	Code Division Multiple Access
dB	Decibel
dBm	Decibel-mill watt
DL	Downlink
EDGE	Enhanced Data Rates for GSM Evolution
EIRP	Effective Isotropic Radiated Power
EPC	Evolved Packet Core
EUTRA	Evolved UMTS Terrestrial Radio Access
E-UTRAN	Evolved UMTS Terrestrial Radio Access Network
FDD	Frequency Division Duplex
FDMA	Frequency Division Multiple Access
GSM	Global System for Mobile Communication
HSPA	High Speed Packet Access
ICI	Inter Carrier Interference
IP	Internet Protocol
ISI	Inter Symbol Interference
ITU	International Telecommunication Union
LOS	Line of sight

LSM	Least Square method
LTE	Long Term Evolution
MAPE	Mean absolute percentage error
MCM	Multicarrier modulation
MIMO	Multiple Input Multiple Output
MME	Mobility Management Entity
MME/GW	Mobility management entity/gateway
NLOS	None line of sight
OFDM	Orthogonal Frequency-Division Multiplexing
OFDMA	Orthogonal Frequency-Division Multiple Access
PAPR	Peak to Average Power Ratio
PCI	Physical cell identity
PCS	Personal communications systems
PDNs	Packet data networks
P-GW	Packet Gateway
PL	Path loss
QoS	Quality of Service
RAN	Radio Access Network
RF	Radio Frequency
RMSE	Root mean square error
Rx	Receiver
SAE	System Architecture Evolution
SC-FDMA	Single-Carrier Frequency-Division Multiple Access

S-GW	Serving Gateway
SINR	Signal-to-Interference and Noise Ratio
SNR	Signal-to-Noise Ratio
TDD	Time Division Duplex
TDMA	Time Division Multiple Access
Tx	Transmitter
UE	User Equipment
UL	Uplink
UMTS	Universal Mobile Telecommunications System
VoIP	Voice over IP
WCDMA	Wideband Code Division Multiple Access

Chapter One

Introduction

1.1 Background

The mobile radio channel sets unavoidable restrictions on the performance of wireless communication systems. Modeling the radio channel is generally one of the most challenging parts of mobile radio system design, and is normally done in a different approaches, based on measurements made in detail for an intended communication system or spectrum allocation. The transmission path between transmitter and receiver can differ from simple line of sight to one that is severely blocked by buildings, mountains and foliage [1].

Understanding the properties of radio wave propagation helps to get a better knowledge of propagation models. The basic mechanisms of electromagnetic wave propagation are reflection, diffraction and scattering. Propagation models are dedicated on predicting the average received signal strength at a certain distance from the transmitter, in addition to the unpredictability of the signal strength in close spatial closeness to a specific location [1, 2].

Generally, propagation prediction models can be classified in to small-scale and large-scale propagation models. Models that describe the rapid fluctuations of the received signal strength over very short travel distance (a few wavelengths) or short time duration (on the order of seconds) are termed small-scale fading models. On the other hand, propagation models that describe signal strength over large transmitter-receiver (T-R) separation distances (several hundreds or thousands of meters) are called large-scale propagation model [2, 1].

Under large-scale propagation model, there are numerous path loss models for predicting the path loss, which sequentially used for defining the signal strength at a location. But among the large-scale models mainly focus on the empirical propagation models such as Okumura model, Hata model and Cost-231 Hata model. Also, these models depend on the frequency of operation, terrain profile of an environment, transmitter and receiver heights and distance from the base station. Out of all these, Okumura model is one the most commonly used path loss predicting model, all other propagation models are enhanced forms of Okumura model [1]. But the objective of this study was Fine-tuning of the existing system Cost-231 Hata model for Addis

Ababa urban area of 4Kilo using the measured data acquired from Ethio-telecom with a carrier frequency of 1800MHz.

Wireless communication technologies have grown from day-to-day in to a more vigorous and vast applications. Based on this the new cellular technology Long Term Evolution (LTE) network was currently deployed in Addis Ababa 4Kilo area. Therefore, LTE are designed to offer mobile broadband services such as mobile TV, online gaming and live streaming with very high-speed internet. To protect this, 3GPP leads to new radio access technology known as LTE to support broadly high data rate and low latency system with better coverage and capacity performance. LTE standardization is being carried out in the 3rd Generation Partnership Project (3GPP), as per the case for Wideband CDMA (WCDMA), and the future phase of GSM evolution [3].

The first type of LTE was accomplished in March 2009 as part of Third Generation Partnership Program (3GPP) Rel-8 in addition to the first deployment was done in Sweden in 2010 tracked by nine different commercial launch efforts. LTE is established on flat radio access network architecture without a centralized network component. It offers flexible bandwidth options ranging from 1.4 to 20 MHz using orthogonal frequency-division multiple access (OFDMA) in the downlink and single-carrier frequency-division multiple access (SC-FDMA) in the uplink [4, 3].

Therefore the fine-tuning process in Addis Ababa 4 Kilo area can be done based on the integration of existing model Cost-231 Hata model and LTE network respectively. The model parameters becomes Fine-tune by considering the LTE data as an input.

1.2 Statement of the Problem

Environmental characteristics immensely affect wireless signal propagation. The strength of signal at any location from the transmitter mostly depends on the distance, frequency of transmission and obstacles along the path. This makes the signal strength unpredictable and exact analysis is so difficult to obtain in planning and expansion of any communication system. Therefore, modeling the path loss scenario is very important to ensure proper coverage of any wireless network for the services intended. Quality of service and system capacity enhancements are implicitly related to the associated path loss. This research work intends to Fine-tune of propagation path loss model suitable for the deployed 4G network, i.e. Cost-231 Hata model by using measurement data acquired from Ethio telecom. A busy area, 4 Kilo, is chosen for this purpose. The method, however, can be extrapolated to other coverage areas of Ethio telecom.

1.3 Objective of the Study

This thesis aims to achieve the following general and specific objectives.

1.3.1 General Objective

The general objective of the research is fine-tuning of Cost-231 Hata path loss model for LTE Network around 4Kilo area.

1.3.2 Specific Objectives

- To study different propagation models and their parameters.
- To predict the path loss using Cost-231 Hata model.
- To examine the level of Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) in each model.
- To propose better model for Path loss prediction in the urban area**.**

1.4 Methodology

The methodology encompasses the following activities:

- **Literature review**: includes reading books, articles, simulation tools and other resources related to the topic.
- **System modeling:** Involves the existing system Cost-231 Hata model for a better path loss prediction result of LTE network.
- **Simulation:** Simulating the Cost-231 Hata model using MATLAB R2016a, and then Fine-tuning with LSM algorithm.
- **Analysis and Interpretation of the results:** Finally, the results obtained from the simulation results analyzed and compared based on performance analysis criteria's.

1.5 Scope

This research is a case study and is expected to Fine-tuning the Cost-231 Hata path loss model for Addis Ababa, urban area of 4Kilo.The work only consider LTE Rel.8 at 1800MHz.The performance analyses and recommendation are based on path loss using RMSE and MAPE metrics. The simulation is done using entirely the MATLAB simulation tool by considering a measurement data acquired from Ethio telecom as inputs. Thus, implementation details of the model cannot be consider.

1.6 Contribution

The contribution of this study can be drawn as follows:

- This Fine-tuning of Cost-231 Hata path loss model studied for the LTE network in 4Kilo area of Addis Ababa can be starting point for other similar researches intended for planning and optimization.
- To the best of my knowledge, it is the first of its kind in the Ethiopian context. Therefore, its contribution is vast in the field in the country's context.
- It can be an input for Ethio-telecom for predicting coverage area, interference analysis, frequency assignments and cell parameters which are basic elements for network planning process in cellular systems in order to increase system performance.

1.7 Thesis Layout

The work of this thesis is organized in to Six Chapters. Chapter one presents the introduction, methods and objectives of this thesis work. In Chapter two, we are going to see some theoretical parts of radio wave propagation, small-scale path loss and large-scale path loss models have been described and in Chapter three, Advantages of LTE, multiple access schemes, LTE system architecture and multiple antenna technology are discussed. Then in the fourth Chapter we will see the possible optimization implementation algorithms. Chapter five contains simulation parameters, Simulation results and discussions. Finally, the last Chapter contains conclusions and recommendations for future works.

1.8 Literature Review

So far a lot of researches have been done regards to parameters optimization, most of the work mainly focused on the genetic algorithm based path loss optimization for LTE network, review on outdoor propagation models in radio communication, radio frequency attenuation path loss behavior in suburban coverage and comparison among different radio propagation models on the basis of path loss and signal strength for LTE network are among works [5, 6, 7, 8, 9].

In June 2016, K. Adeyemo Zachaeus *et al.:* explained "Genetic Algorithm Based Path loss Optimization for Long Term Evolution in Lagos, Nigeria" in order to investigate the suitability of Okumura-Hata model for LTE at 2.3GHz in Lagos, Nigeria. In addition to that, they argued that strength of signal depends on the environment and is being predicted by propagation path loss models. Besides, they use path loss to evaluate its performance. Finally, they achieve good performance in contrast to the existing system which is Evolved Universal Mobile Telecommunication Service Terrestrial Radio Access (E-UTRA) which developed by the 3rd Generation Partnership Project (3GPP) [5].

In March 2014, Sati Govind *et al.*: suggested that "A review on outdoor propagation models in radio communication" to study the different path loss models in radio communication (i.e. Radio propagation model) at different frequency band such as SUI model, Hata model, Okumura model, Cost-231 Hata model, ECC-33 model, Walfisch-Ikegami and they classified in to Empirical, Deterministic and Stochastic. Besides, they identify free space path loss model is basic models for finding the path loss in free space. Finally, they conclude that ECC-33 model is highly recommended for urban and sub-urban environments. However, relatively Walfisch-Ikegami models have high accuracy and generally use for urban environment [6].

In October 2010, Mardeni R. *et al.*: study on "RF attenuation path loss behavior in suburban coverage within Cyberjaya and Putrajaya areas, located in Selangor State in Malaysia", to develop and optimize a path loss model on the frequency range from 400MHz to 1800 MHz using a Hata model. Moreover, to optimize the pass loss and to calculate its performance they use Least Square method and they implement statistical analysis[1] with empirical result to

[1] such as relative error, standard deviation and variance

compare between the optimized models. Finally, they ensure Hata model has lowest error relatively to other models [7].

In December 2012, Singh Yuvraj: proposed “Comparison of Okumura, Hata and Cost-231 Models on the Basis of Path Loss and Signal Strength”, in order to choose the accurate radio propagation model which is essential for emerging technologies with appropriate design, deployment and management strategies for any wireless network; and he focuses on large-scale path loss model. He compares the above mentioned models based on path loss and signal strength by applying empirical result. After that, he concludes Okumura model has the least path loss and high signal strength in contrast to the other. Besides, relatively Cost-231 model has largest path loss and weak signal strength [8].

In September 2011, Shabbir Noman *et al*.: explained “Comparison of radio propagation models for Long Term Evolution (LTE) network”, to compare among different radio propagation models such as Stanford University Interim (SUI) model, Okumura model, Cost-231 Hata model, Cost Walfisch-Ikegami & Ericsson 9999 model which are used for the upcoming 4th Generation (4G) of cellular networks in different topography on the range of 1900 MHz and 2100 MHz frequencies experimentally based on path loss. Finally, they conclude, SUI model shows the lowest path lost in all the terrains while Cost-231 Hata model illustrates highest path loss in urban area and Cost Walfisch-Ikegami model has highest path loss for suburban and rural environments [9].

After reviewing most relevant works, it was proposed to Fine-tuning the existing model called Cost-231 Hata model using a Least Square method algorithm and evaluate the deviation in terms of the amount of error in each model using a root mean square error and mean absolute percentage error.

Chapter Two

Radio Wave Propagation

2.1 Introduction

The mobile radio channel can be well-defined as the behavior of radio waves when they are propagated from transmitter to receiver or numerous parts of the atmosphere. The transmission path between the transmitter and the receiver can vary from simple line of sight to one that is severely obstructed by building, mountains, moving object around the environment and foliage. Unlike wired channels that are stationary and predictable, radio channels are extremely random and present severe losses for wireless communication systems. These losses include distortions, noises, interferences and other weaknesses which are time-varying and unpredictable as a result of station movement. An understanding of radio propagation is vital for coming up with appropriate design, deployment and management strategies for wireless networks. Radio propagation is seriously site-specific and can fluctuate significantly dependent on the terrain, frequency of operation, velocity of mobile device, interferences and other vigorous factors. Accurate classification of the radio channel through key parameters and mathematical model is essential for the predicting signal coverage, analysis of interference from different systems and determining the optimum location for installing base station antennas [1, 2, 10].

In wireless communication received signal suffers from path loss and fading during propagation processes. Generally, mobile radio propagation has small-scale effects and large-scale effects on the received signal. The small-scale propagation effects refer to rapid fluctuations of the received signal power due to multipath and doppler spread, which are over relatively short distance, whereas the large-scale propagation effects refer to variations in the received power due to path loss and shadowing, which are over relatively long distance and vary slowly with time [1, 11].

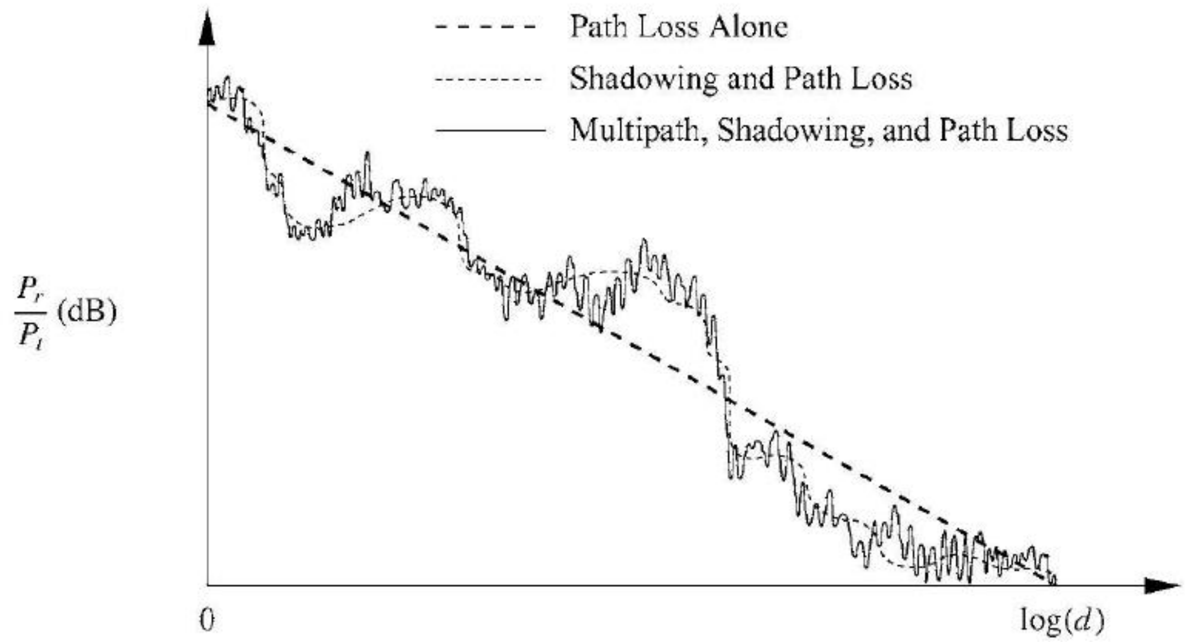


Figure 2.1: Path Loss, Shadowing and Multipath versus Distance [2].

Fig. 2.1 shows the ratio of the received to transmit power versus log distance for the combined effects of path loss, shadowing and multipath.

The Chapter is organized as follows: in Section 2.2 basic propagation mechanisms of radio wave has expressed. In Sections 2.3, 2.4, 2.5 the main difference between small-scale and large-scale effects are briefly described. Finally, path loss prediction models and their classification are discussed in Section 2.6.

2.2 Basic Propagation Mechanisms

Propagation mechanisms may generally be attributed to reflection, diffraction and scattering.

- ✓ Reflection occurs when a propagating wave impinges on an object which is very large compared to its wavelength. Typical examples of such kind of objects are surface of the earth, walls and buildings.
- ✓ Diffraction occurs when the path between the transmitter and the receiver is obstructed by an object that has sharp irregular edges. As a result, waves bend around and propagate behind the obstruction reaching the receiver even when there is no LOS. This phenomenon is called shadowing because the receiver is located in a shadowed region.

- ✓ Scattering occurs when objects are on the order or less of the wavelength of the radio signal. Typical examples of such kind of objects are street signs, foliage and lamp posts. When a radio signal reaches such objects, it scatters in many different directions [11, 12, 13].

2.3 Small-Scale Effects

These effects are used to describe the rapid variations of the amplitudes, phases and delays of a transmitter signal over a short period of time or short distance. There are so many factors which affect small scale fading like multipath propagation, Doppler shift, etc.

- ✓ Multipath fading is caused by random variation of signals due to constructive and destructive addition of different multipath components introduced by the channel.
- ✓ Doppler shift occurs due to the relative movement of transmitter and receiver over a short time interval. The rapid change in position causes the signal path to vary and that introduces a phase change on the received signal.

The two important special effects of small-scale fading are time dispersion caused by multipath propagation and frequency dispersion caused by Doppler spread. On the basis of time spread it is classified as flat fading and frequency selective fading. Unlike frequency selective fading, flat fading occurs where coherence bandwidth is greater than the signal bandwidth. Coherence bandwidth defines the frequency interval over which two frequencies of signal are likely to experience the comparable fading. Similarly on the basis of Doppler spread, the small scale fading is classified as fast fading and slow fading. Whenever the coherence time of channel is smaller than the time period of symbol then the signal will experience fast fading. Similarly, if time period of symbol is smaller than coherence time of channel then it causes slow fading. Coherence time may be defined as the time duration over which impulse response is considered to be not varying [13].

2.4 Large-Scale Effects

As explained earlier large-scale effects are used to define deviations in the received signal power due to complex terrains in suburban in addition to the density and height of buildings in urban areas. Large-scale effects can be described by path loss and shadowing. The effect of path loss and shadowing are separately explained as following below respectively [1, 2].

2.4.1 Path Loss

Path loss is the first type of large-scale effect and defined as a loss due to power dissipation of the transmitted signal reflected by objects over a long distance. Path loss is frequently expressed as a received power Pr (d) as a function of the distance (d) between the transmitter and receiver as illustrated by Equation 2.12.

$$P_r(d) \propto \frac{\lambda^2}{4\pi d^2}(P_t) \tag{2.1}$$

Where, P_r (d) is the received signal power, λ is the wavelength, P_t is the transmitted signal power and d is the distance between transmitter and receiver. Therefore from Equation (2.12) observe that the received signal is direct relationship (proportional) with a transmitted signal and inverse relationship (proportional) to the distance between transmitter and receiver [1, 2].

2.4.2 Shadowing

Shadowing also the second type of large-scale effect and is produced when the received signal power changes due to large objects, such as vegetation's (forest), mountains and buildings, which attenuates the signal power through reflection, diffraction and scattering [12, 13].

2.5 Propagation Models

Properly understanding of a propagation model has a great role in the designing and planning of wireless communication. Therefore, appropriate path loss prediction and received signal amount prediction are the basic important factors and the two faces of the same coin. In other words, if one is able to predict the average path loss then the average received signal amount is indirectly known. In addition to the above definition path loss can be simply stated as the difference between the transmitted signal and received signal power with a unit of decibels. Path loss comprises all possible losses which result from the free space propagation and other different propagation mechanisms. In general, it is also function of other parameters like antenna heights, carrier frequency, distance and environment type (urban, suburban or rural, etc.). From this point of view the classification of propagation models and their definition can be briefly explained as following below one by one [9, 1, 2, 18, 10, 17].

2.5.1 Classification of Propagation Models

Propagation models can be classified essentially into two extremes, i.e. entirely empirical models and Deterministic models. There are some models which have the features of both types. Those are known as Semi-empirical models.

2.5.1.1 Empirical Models

Are based on practically measured data. Subsequently few parameters are used, these models are simple but not very accurate. The models which are classified as empirical models for macro cellular environment. These contain Hata model, Okumura model and Cost-231 Hata model.

2.5.1.2 Deterministic Models

This model uses Maxwell's Equations along with reflection and diffraction laws. Likewise due to very accurate this model is better to find the propagation path losses. Some of the instances include Ray Tracing and Ikegami model.

2.5.1.3 Semi-Empirical Models

Are based on both empirical data and deterministic aspects. In some books and journals this model can be expressed by Statistical (Probability) model and Uses Probability analysis by finding the probability density function. Cost-231 Walfisch-Ikegami model is classified as a semi-empirical (statistical) model [6, 19, 8, 20, 11, 10].

From these classifications of path loss prediction models, empirical prediction models are our main focus, as this thesis is a case study and collection of measurement data using drive test is part of the analysis. But before proceeding to the explanation of empirical models it is necessary clarify the free space propagation model which is the basic (reference) model for all models.

2.6 Free Space Propagation Model

This channel model is an ideal model used to calculate the received signal strength when there is a direct LOS between a transmitter and a receiver unit, placed at distance d between them, without any obstacles near the line of sight. Satellite communication and microwave communications are among the best examples of free space propagation models. Free space model predicts that received power declines as a function of the Transmitter-Receiver separation distance raised to some power (i.e. a power law function).The free space power received by a receiver antenna which is separated from a radiating transmitter antenna by a distance d, is given by the Friis free space equation as:

$$P_r(d) = \frac{P_t G_t G_r \lambda^2}{(4\pi)^2 d^2 L} \tag{2.2}$$

Where P_t is the transmitted power, $P_r(d)$ is the received power, G_t is the transmitter antenna gain, G_r is the receiver antenna gain, d is the T-R separation distance in meters and λ is the wavelength in meters and L is the system loss factor (≥ 1, for example filter losses, antenna losses, etc.…). From now on, without loss in generality, it was assume L as unity. The Friis free space Equation shows that the received power falls off as the square of the transmitter-receiver separation distance. This implies that the received power decays at a rate of 20 dB/decade with distance [1, 13, 17, 21].

2.7 Empirical Models

As explained on the above section empirical models are models based on the practical measurement data. Under these model the Okumura model, hata model and Cost-231 Hata model are discussed respectively.

2.7.1 Okumura Model

Okumura’s model is one of the most frequently used macroscopic propagation models based on measured data with no analytical explanation. It was developed during the 1960’s as the result of large-scale studies conducted in and around Tokyo. It's the simplest and best in terms of path loss accuracy in cluttered mobile environment. It has a disadvantage of having a slow response to rapid terrain changes. Common standard deviations between predicted and measured path loss in this model lies between 10dB-14dB. The model was intended for use in the frequency range 200MHz to 1920MHz, although it can be extrapolated to 3GHz frequency. It's valid for coverage distances between 1Km-100Km. Base stations heights 30m-1000m can be analyzed through this model [1, 2].

The Okumura model path estimation is given as:

$$L_{P(Okumura)}(dB) = L_F + A_{mu}(f,d) - G(h_b) - G(h_m) - G_{AREA} \quad (2.3)$$

Where $L_{P(Okumura)}$ is the propagation path loss, L_F is the free space propagation loss, A_{mu} is the median attenuation relative to free space, $G(h_b)$ is the base station antenna height gain factor, $G(h_m)$ is the mobile antenna height gain factor and G_{AREA} is the gain due to the type of environment. Note that the antenna height gains are strictly a function of height and have nothing to do with antenna patterns [1, 2, 13].

It was found that the transmitting antenna height gain factor,$G(h_b)$ varies with 20 dB/decade and that the receiving antenna height gain factor,$G(h_m)$ varies with 10 dB/decade for height less than 3m.

$$G(h_b) = 20\log(h_b/200) \qquad 100m > h_b > 30m \quad (2.3(a))$$

$$G(h_m) = 10\log(h_m/3) \qquad h_m \leq 3m \quad (2.3(b))$$

$$G(h_m) = 20\log(h_m/3) \qquad 10m > h_m > 3m \quad (2.3(c))$$

The Okumura model can further be corrected for terrain undulation height, isolated ridge height, average terrain slope and mixed land/sea parameters. The following Figures 2.5 and 2.6 provide the values of $A_{mu}(f,d)$ and G_{AREA} (from set of curves), respectively [1, 2].

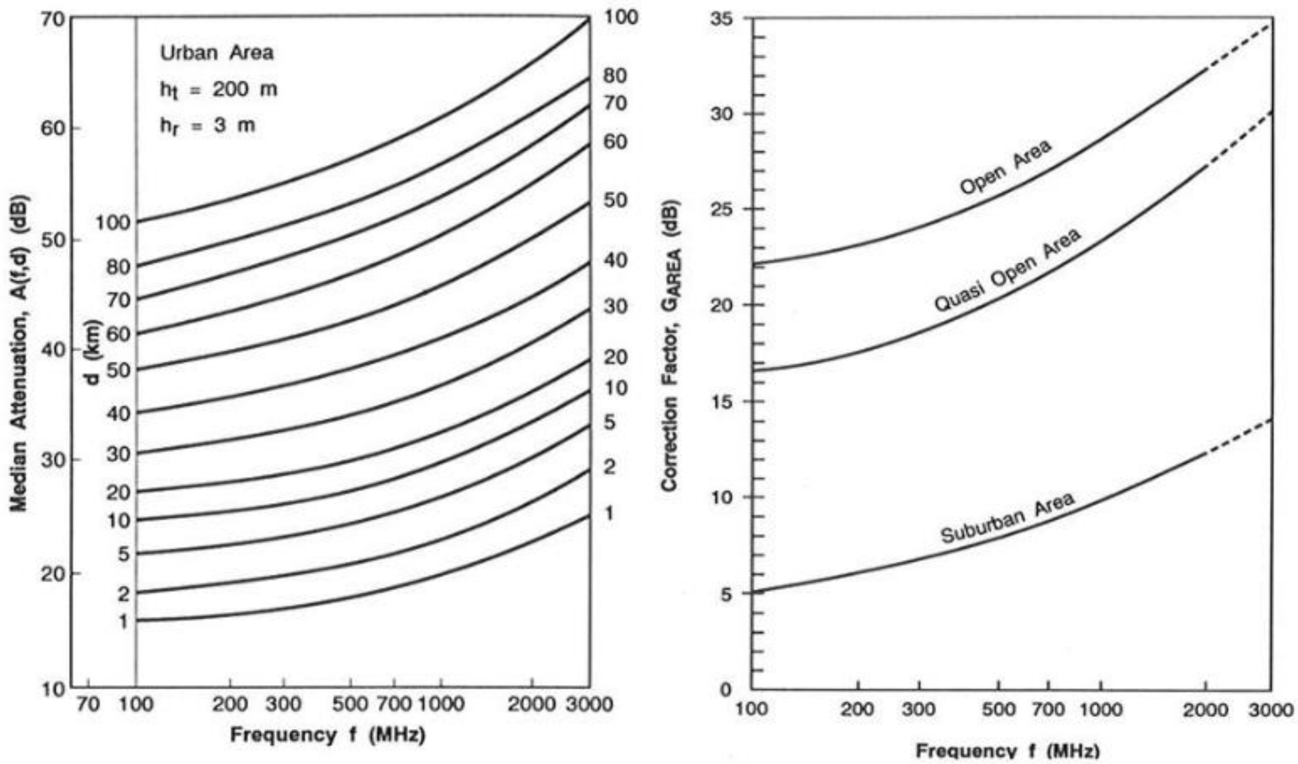


Figure 2.2: Curves plotted for Median Attenuation and Correction factors, [G_{AREA}] for different types of terrain *[1]***.**

2.7.2 Hata Model

Hata's Model established empirical mathematical relationships to describe the graphical information given by Okumura. It's limited to certain ranges of input parameters and is only over quasi-smooth terrain. Hata model is used for the frequency range (f_c) of 150 MHz to 1500 MHz to predict the median path loss for the distance (d) from transmitter to receiver antenna up to 20 km, and transmitter antenna height (h_b) is considered 30 m to 200 m and receiver antenna height (h_m) is 1 m to 10 m. It is used to calculate path loss in three different environments like urban, suburban and rural (flat) as following below.

a. **Urban area**: Built up city or large town with large building and houses.
b. **Suburban area**: Village Highway scattered with trees and house with some obstacles near the mobile but not very congested.
c. **Rural**: open space, no tall trees or building in path [7].

This model provides simple and easy ways to calculate the path loss. The basic path loss equation for urban area of Hata Model can be expressed as:

$$L_{P(Hata)}(dB) = 69.55 + 26.16 \log f_c - 13.82 \log h_b - a(h_m) + (44.9 - 6.55 \log h_b) \log d \quad (2.4)$$

$a(h_m)$ Is the correction factor for effective mobile antenna height which is a function of the size of the coverage area for a small to medium sized city, the mobile antenna correction factor is given by:

$$a(h_m) = (1.1 \log f_c - 0.7)h_m - (1.56 \log f_c - 0.8)\ dB \quad (2.4(a))$$

And for a large city it is given by

$$a(h_m) = 8.29(\log 1.54 h_m)^2 - 1.1\ dB \qquad for\ f_c \leq 300\ MHz \quad (2.4(b))$$

$$a(h_m) = 3.2(\log 11.75 h_m)^2 - 4.97\ dB \qquad for\ f_c \geq 300\ MHz \quad (2.4(c))$$

To obtain the path loss in a suburban area the standard Hata formula in $equation$ (2.15) is modified as

$$L_{P(Hata)}\ (dB) = L_{50}\ (urban) - 2\left[\log\left(\frac{f_c}{28}\right)\right]^2 - 5.4 \quad (2.5)$$

And for path loss in open rural areas, the formula is modified as

$$L_{P(Hata)}\ (dB) = L_{50}\ (urban) - 4.78\ (\log f_c)^2 - 18.33 \log f_c - 40.98 \quad (2.6)$$

These expressions have considerably enhanced the practical value of the Okumura method, although Hata’s formulations do not include any of the path specific corrections available in the original model [1, 2, 13, 17, 11].

2.7.3 Cost-231 Hata Model

The model was developed by the European cooperation in the field of scientific and technical research (Cost) Action 231 group: evolution of land mobile radio (including personal communication). The model is sometimes called Hata Model personal communication system (PCS) extension and is an extension of the Okumura–Hata model to be applicable for frequency(fc) ranging from 1500 MHz to 2000 MHz, base station antenna height(h_b) 30m to

200m, mobile station(h_m) 1m to 10 m and transmission radius(d) 100m to 20 Km [1, 2, 13, 17, 11].

The basic path loss Equation for Cost-231 Hata Model can be expressed as:

$$L_{P(COST)}(dB) = 46.3 + 33.9\log(f_c) - 13.82\log(h_b) - a(h_m) + \left(44.9 - 6.55\log(h_b)\right)\log(d) + C_K \quad (2.7)$$

The parameter C_K has different values for different environments like 0 dB for suburban and 3 dB for urban areas and the remaining parameter $a(h_m)$ is defined in Equation 2.4(c). Hata model for the different environment.

But from these empirical prediction models Cost-231 Hata model has been mainly consider because it is the existing model in Ethio telecom. Then by Fine-tuning the parameters the model becomes optimized using a Least Square method algorithms. Furtherly the detail explanation will be seen in the next Chapter Five Section 5.4.

Chapter Three

LTE: Long Term Evolution

3.1 Introduction

In this section an overview of the Long Term Evolution (LTE) is presented. LTE is an enhanced evolution of the Universal Mobile Telecommunications System (UMTS). It allows mobile users to access Internet through their devices (mobile telephones, laptop, etc.…). LTE plans to deliver high speed data and multimedia services to next generation. In the coming years LTE mobile broadband technology will be widely used by devices such as notebooks, smartphones, gaming devices and video cameras [4, 22].

The existing model in this research case study was Cost-231 Hata model. Four eNodeB station can be used for investigation purpose in the area. The aim is Fine-tuning of the Cost-231 Hata model parameters in order to get a better prediction path loss. LTE data was used for the purpose of Fine-tuning because it is the deployed network in Ethio telecom. The link between Cost-231 Hata model and LTE was the Fine-tuning is done based on the LTE measurement of Addis Ababa 4killo area. The carrier frequency and heights of eNodeB are among the basic LTE measurement parameters used in the model. In addition, the type of environment for Addis Ababa 4Kilo area was classified in to urban area. The classification was done based on the classification of Hata model and by asking to key informant of Ethio telecom. Generally the Fine-tuning process and result of the simulation was done by integrating the concept of Cost-231 Hata model and LTE network at the same time.

The LTE offers a high data rate and can operate in different bandwidths ranging from 1.4MHz up to 20MHz. For this case study 20MHz bandwidth was used. LTE supports high peak data rates (100 Mb/s in the DL and 50 Mb/s in the UL), low latency (10ms round-trip delay), improves system capacity and coverage and reduces operating costs. Moreover, it supports Multiple Input Multiple Output (MIMO) and allows seamless integration with existing systems [3, 4, 23].

The LTE uses orthogonal frequency-division multiple access (OFDMA) scheme for downlink and single carrier frequency-division multiple access (SC-FDMA) for uplink respectively.

Moreover, it uses packet switch multiple access technology. Furtherly discussed in briefly as following below [24, 25].

3.2 Advantages of LTE

The main advantage of long-term evolution (LTE) are put shortly as following:

- Better data rates: - The peak rate requirements for uplink and downlink were set at 50 Mbps and 100 Mbps respectively.
- Reduced delays, in terms of both connection establishment and transmission latency.
- Reduced cost per bit, implying High spectral efficiency.
- Spectrum flexibility with 1.25/2.5, 5, 10, 15 and 20 MHz allocations.
- Simplified network architecture.
- Seamless mobility, including between different radio-access technologies.
- Reasonable power consumption for the mobile terminal.

This can be made possible by reuse of the current spectrums, interoperability between current and upcoming system and reuse of existing sites [3, 4, 24, 25, 22, 26, 27, 23, 28, 29].

3.3 Multiple Access Schemes

Multiple access is essential for mobile communications. It allows several users access to the network and use it simultaneously. Based on this concept the applicant schemes for the downlink were Orthogonal Frequency-Division Multiple Access (OFDMA) and Multiple WCDMA. The selection of multiple-access schemes was made in December 2005, using OFDMA being selected for the downlink essentially because of the simplicity of the receiver [4, 22, 30].

In a similar fashion for the UL, selection was made in the approval of single-carrier-based frequency division multiple access (FDMA) solution using dynamic bandwidth. The elementary inspiration for this approach was to decrease power consumption of the user terminal. The elementary parameters, e.g. sub-frames and transmission time interval (TTI) were in line with those of the DL [3, 4, 31].

3.3.1 OFDMA for DL

In DL, the selected transmission scheme is OFDM using Cyclic Prefix (CP), mainly as a result of simplicity of the receiver. OFDMA spreads the multicarrier technology OFDM to offer a very flexible multiple access scheme. OFDM segments the bandwidth accessible for signal transmission into a multitude of narrowband subcarriers, organized to be mutually orthogonal, which either individually or in groups can transmit independent information streams. The arrangement between two sub-carriers is fixed at 15 KHz. As the arrangement of sub-carriers is fixed, the transmission bandwidth is diverse by varying the number of sub-carriers. A resource block is well-defined to consist of 12 sub-carriers in frequency and 14 infinite symbols in time. This creates one resource block to extent 180 KHz and 1ms in frequency and time correspondingly. This sub-frame is similarly the minimum transmission time interval (TTI) that helps to attain the necessities of low latency of LTE [4, 22, 23].

Based on their capacity demand and radio channel propagation conditions OFDMA is an extension of OFDM in which available sub-carriers are allocated to different users. To avoid ISI, a Guard Interval is put in between two successive symbols. The Guard Interval is then occupied with the CP. This means that a copy of fixed number of last samples is attached to the start of the symbol as shown in the Figure below [30, 23].

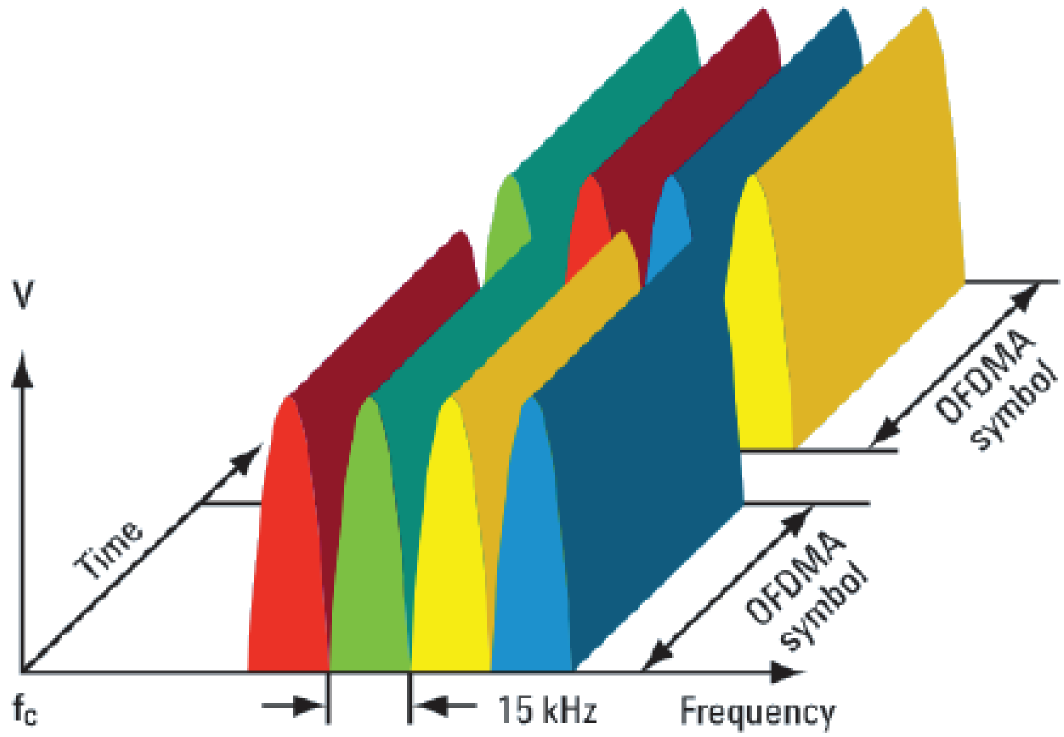


Figure 3.1: OFDMA scheme *[4]*.

Beyond the several advantages of the OFDMA technology, its strength to time-dispersive radio channels is the significant one. This strength is due to the division of the wideband transmitted signal into multiple narrowband subcarriers allowing inter-symbol interference to be largely constrained inside a guard interval at the beginning of each symbol. The key problem of OFDMA is the high Peak-to-Average Power Ratio (PAPR). Subsequently OFDMA consists of numerous sub-carriers in the frequency domain, which is numerous sinusoidal waves in the time domain, it is described by a strong variation of the signal envelope. This outcomes in a need for a highly linear RF power amplifier by means of low power consumption mainly at UE side [3, 4, 28].

Therefore high Peak-to-Average Power Ratio (PAPR) requires exclusive and incompetent power amplifiers with high requirements on linearity, which rises the cost of the terminal and drains the battery faster. Because of that, LTE uses Single Carrier Frequency Division Multiple Access (SC-FDMA) as the basic transmission scheme for the uplink [24, 22].

3.3.2 SC-FDMA for UL

The LTE uplink necessities differ from downlink necessities in numerous ways. Also the power consumption is a main consideration for UE terminals. The high PAPR and related loss of efficiency related with OFDM signaling are key concerns. Accordingly, an alternative to OFDM, SC-FDMA was required for use in the LTE uplink [29, 31].

The power efficient multiple access technology of SC-FDMA is the main difference with OFDM and is produced through a Discrete Fourier Transform OFDM (DFTS-OFDM). It offers a multiple-access technology which has greatly in common with OFDMA. Its resemblance in particular is its flexibility in the frequency domain and the combination of a guard interval at the start of each transmitted symbol to facilitate low-complexity frequency domain equalization at the receiver [22, 30, 29].

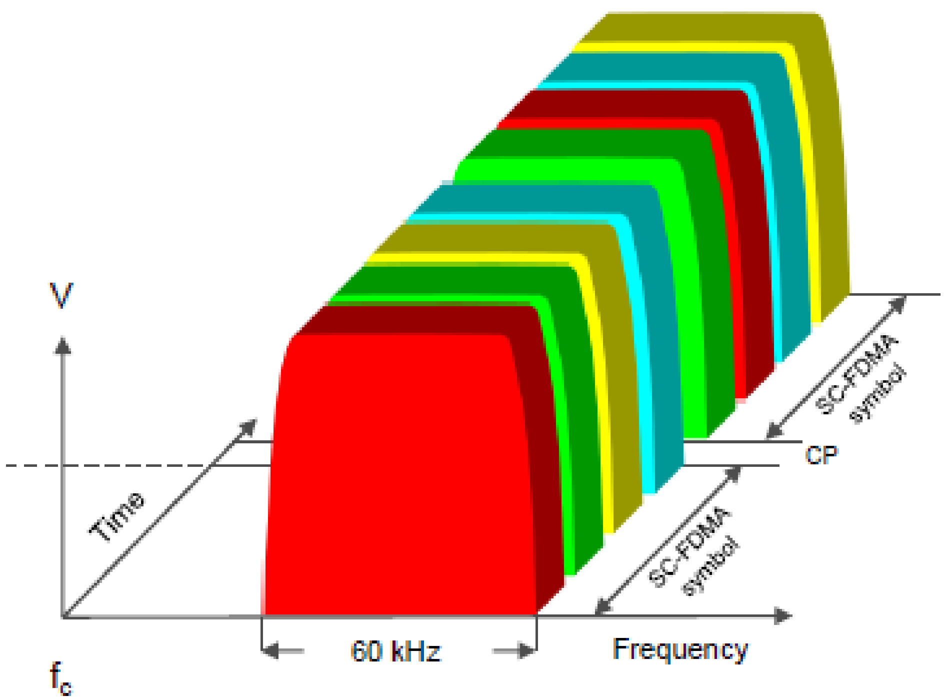


Figure 3.2: SC-FDMA scheme *[4]*.

Similar to OFDM, the channel bandwidth is subdivided into multiple sub-carriers. But, the sub-carriers are transmitted consecutively and not in parallel. In the uplink, a DFT pre-coder is used prior to the OFDM modulator to reserve the single-carrier properties. The DFT pre-coder does not negotiation orthogonally between subcarriers. Hence, PAPR is decreased and subsequently, a more efficient power amplifier implementation can be carried out [24, 25, 22, 30].

3.4 LTE System Architecture

LTE has been planned to support only packet-switched services which intention to offer seamless IP connectivity between UEs. Likewise the system architecture of LTE is designed to be more simplified and compressed compared to the previous 3GPP Releases. The LTE architecture is separated in to two, differentiating the radio access and non-radio access part as Evolved UMTS terrestrial Radio Access Network (E-UTRAN) and Evolved Packet Core (EPC), correspondingly, which together characterize the Internet Protocol (IP) Connectivity Layer or the Evolved Packet System (EPS) [32, 24].

The general E-URAN is said to be flat architecture as it is compared to GSM network architecture since a single centralized base station controller is misplaced and the radio controller function is completely integrated into the eNB. Even though the architecture is simplified and improved, the lack of decentralization also carried some disadvantages. For example, as the UE moves from one cell to another the network must transfer all information related to that particular UE organized with any buffered data from one eNB to another which will make transmission delay and data loss during handover. Basically, the LTE network architecture is briefly discussed below [22, 30].

3.4.1 E-UTRAN

The key part in the E-UTRAN architecture is the eNBs. It is the key access point in one site/location, which offers access for E-UTRA user plane (UP) and control plane (CP) protocol terminations to the UE. Two eNBs can be linked together by an interface known as X2 interface. The core advantage of connecting two eNBs is to increase the intelligence and decrease network. By doing this, eNBs can control the radio resource management, similar to radio bearer control, radio admission control, mobility control and some others. eNBs can correspondingly attain the security services of the users' authentication. The users' data stream is encoded and sent towards the users' gateway. Furthermore, eNBs involve in scheduling and paging of messages and broadcast of control channels (BCCH) [23, 28].

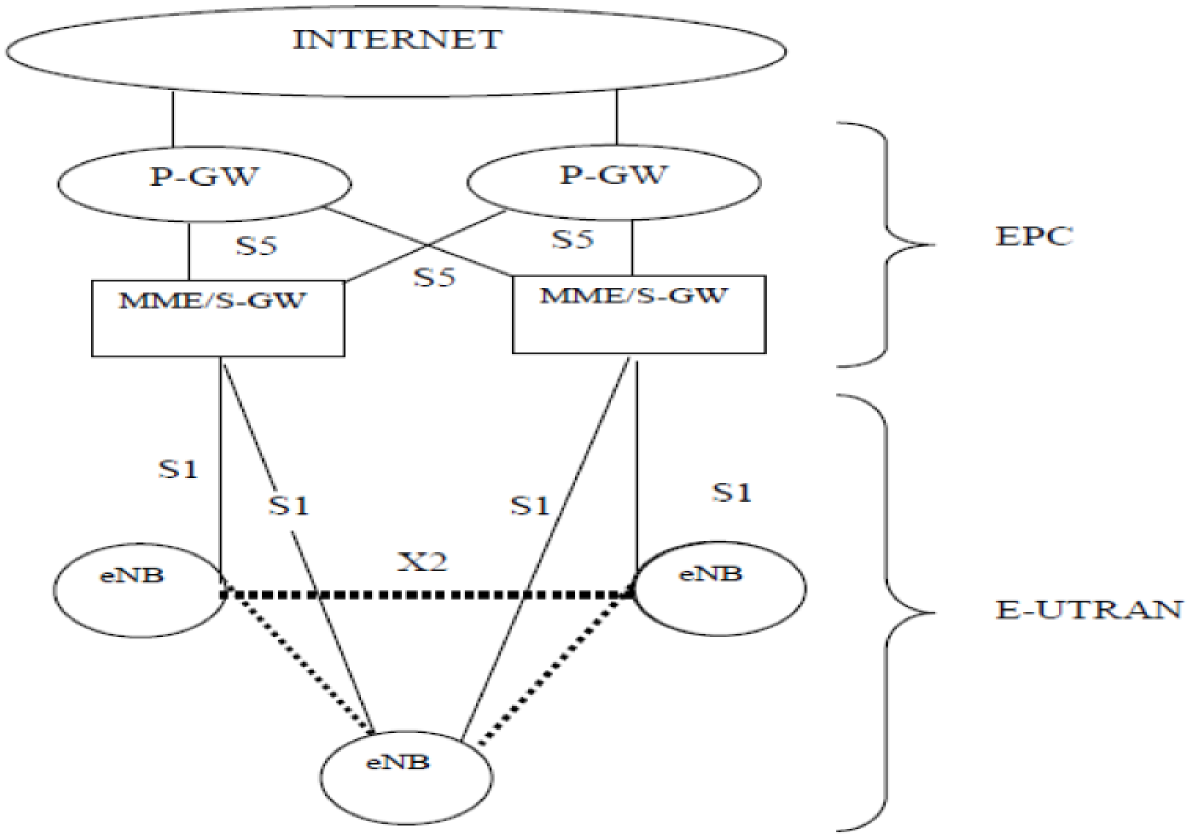


Figure 3.3: Simplified LTE Architecture *[29]*.

3.4.2 EPC

The EPC encompasses the functional units of Mobility management entities (MME) such as packet gateway service (PGWS), packet data network (PDN).The MME is accountable for the management of the control plane functionalities that are associated to subscribers and session management. It also makes the security control, the distribution of paging messages to eNBs and the integrity control of the none-access stratum (NAS) signals [27, 23].

The S-GW achieves data in the user plane for the close of packet data towards E-UTRAN. It work for a local mobility of exchanging packets with eNBs to the UE. Likewise, it serves as a transferring or routing unit towards other 3GPP technologies [31, 33].

The PDN-P-GW, joins the system with others PDNS. It simplifies IP related address assignments, policy implementations, packet grouping, and routing activities. Furthermore, it is used as a mobility frame for other none 3GPP access networks. The policy and charging rule function (PCRF) controls the charging scheme and the IP multimedia (IMM) configuration of each other [30, 27].

3.4.3 Main Interfaces

The chief objective of this simplified architecture is to decrease the number of interfaces between the different network elements as shown in Figure 3.4, there are two kinds of interfaces in the E-UTRAN and EPC system. The first interface is S1 which interfaces the eNBs with the MME/S-GW network elements to the many to many relationship schemes. The second part is X2 interface which links the different eNBs to each other. The third is the S5 interface which joins and offers access between the gateways of S-GW and S-PW [32, 24].

3.5 Multiple Antennas Techniques

The multi-input multi-output (MIMO) is a method used in mobile technologies so as to increase spectral efficiency, obtain higher data rates and enhanced coverage. It involves in the use of multiple antennas in both transmitter and receiver. LTE receipts benefit of MIMO to be successful the proposed aims in terms of peak data rates without requiring more transmitting power or bandwidth [24, 25, 22, 30, 34, 27].

Fundamentally MIMO offers different kinds of gains:

- ✓ **Array Gain:** upgrading of the average signal to noise ratio (SINR) using the same transmission power. It is achieved by coherent combining of different signals.
- ✓ **Power Combining Gain:** can be designated by the following expression$10\log(N)\ dB$. Where N represents the number of multiple transmitting antennas.
- ✓ **Spatial Multiplexing Gain:** development of the data throughput using the same bandwidth and transmission power.
- ✓ **Diversity Gain:** upgrading of the average signal quality, making the radio link stronger against the fading effects which are inherent to a wireless connection.

Moreover, can be existing in different configurations, which are better demonstrated by the following Figure:

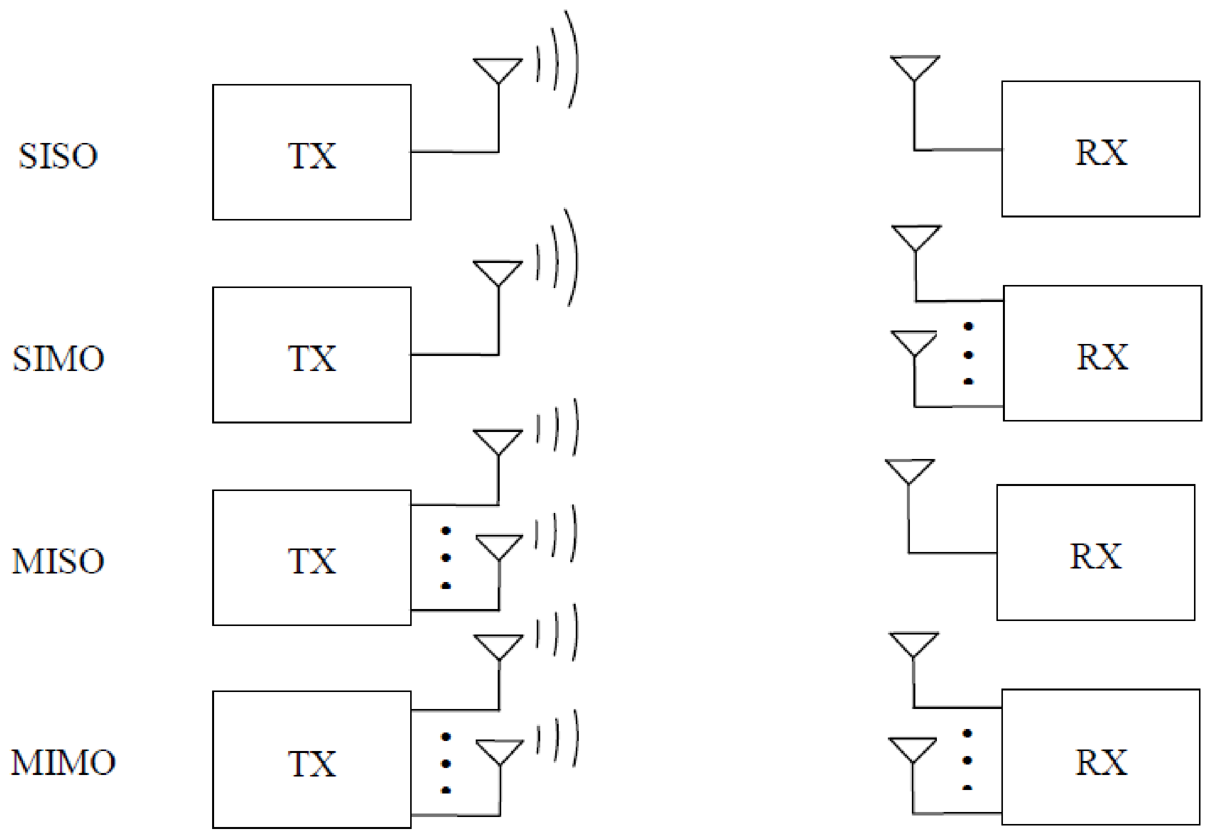


Figure 3.4: Different MIMO configurations *[22]*.

The “**S**” stands for Single, and the “**M**” for multiple, so there are 4 possibilities:

1. **Single-input-and-single-output (SISO) system**: It is uses only one antenna both at the transmitter and receiver.
2. **Single-input-and-multiple-output (SIMO) system**: It uses a single transmitting antenna and multiple receiving antennas.
3. **Multiple-input-and-single-output (MISO) system**: It has multiple transmitting antennas and one receiving antenna.
4. **Multiple-input-multiple-output (MIMO) system**: It uses multiple antennas both for transmission and reception. Multiple transmitting and receiving antennas will achieve antenna diversity without reducing the spectral efficiency. [35, 33, 36].

Chapter Four

4.1 Possible Optimization Implementation Algorithms

There are different kinds of path loss optimization algorithms used in different way including a propagation model. In this research, the Least Square method algorithm was used for optimization. Commonly used type of optimization algorithms can be discussed as follows.

- Genetic algorithm (GA).
- Particle swarm optimization (PSO) algorithm.
- Hybrid of GA and PSO (HGAPSO) algorithm.
- Least Square method (LSM) algorithm.

4.1.1 Genetic Algorithm (GA)

Genetic algorithm is an important computational tool for optimization and search technique based on the principles of genetics and natural selection. Genetic algorithms find better and better solutions to a problem iteratively repeated until some condition is satisfied. Due to random selection and reproduction procedure GA has a stochastic characteristics. In a search method GA finds appropriate solutions to the optimization process. Optimization is the process of adjusting the inputs to or characteristics of a device, Mathematical process, or experiment to find the minimum or maximum output or result. GA recombines different solutions to get a better one and is robust in dealing with sorting due to its ability to perform very well on a range of problems. Besides it can be applied to resolve any problem. The input in GA consists of variables; the process or function to be optimized is known as the cost function, objective function, or fitness function; and the output is the cost or fitness [5].

GA has a series of steps for solving a problem and explain using a flow chart other than explanation at the end. It works on a population of possible solutions with each representing a chromosome. The first mechanism is the coding of all the solutions into a chromosome. Subsequently the chromosome, a set of reproduction operators has to be obtained, the reproduction operators are applied to the chromosomes for performing mutations (i.e. Introducing new genetic structures in the population) and recombination. Selection compares individual in the population by using the fitness function. GA deals with the problems that maximize the fitness function. After which initial population of chromosomes is generated randomly [5, 37, 38].

In general, the basic GA consists of the following steps : first generating genetic random population of a chromosome, then evaluating the fitness *f* (*x*) of each chromosome *x* in the population and creation of new population by using the following: selecting two parent chromosomes based on their fitness, forming new offspring due to crossover of parents, acceptance of new offspring in the population, replacement of new generated population for sum of algorithm, finally stop when best solution is returned [5]. Furtherly look at the flow chart below.

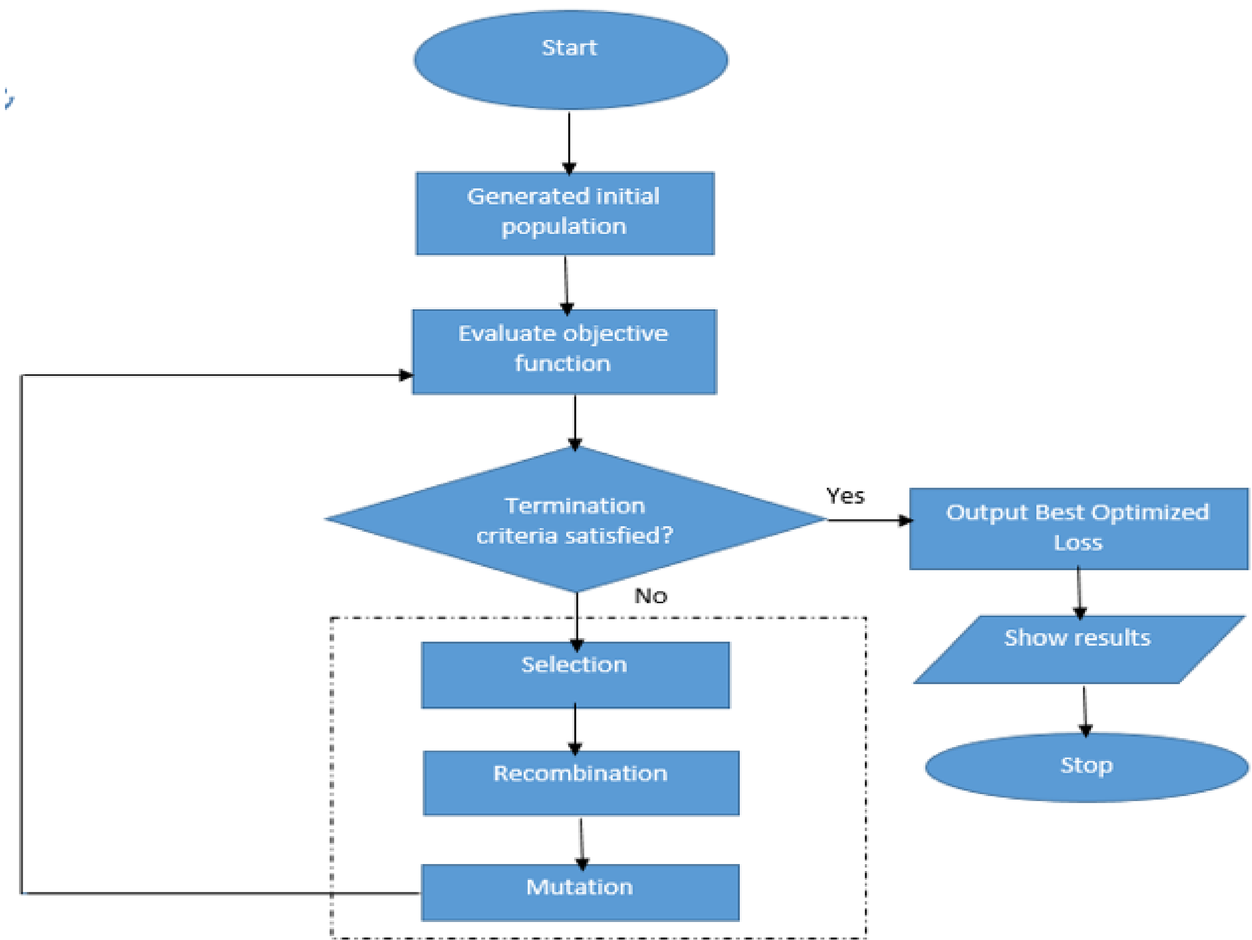


Figure 4.1: Flowchart of Genetic Algorithm *[5]*.

GA is more complex in the principle for the same work as compared to PSO algorithm. In addition, GA is discrete in nature, i.e. it converts the variables into binary 0's and 1's, and therefore it can easily handle discrete problems, besides PSO is continuous and hence must be modified in order to handle discrete problems. Unlike GA, the variables in PSO can take any values based on their current position in the particle space and the corresponding velocity vector. Genetic algorithms do not handle difficulty in an efficient way, because in such cases the number of elements undergoing mutation in very large which causes a considerable increase in the search space. So, in this case PSO is the best alternative as it requires small number of parameters and correspondingly lower number of iterations. GA usually converges towards a local optimum or even arbitrary point rather than the global optimum of the problem whereas PSO tries to find the global optima (i.e. lack of local optimum) [37].

Applications*:* Genetic algorithms can be used in a wide diversity of fields. It is mostly used to solve optimization problems. Some of the fields where GA is used are: bioinformatics, computational science, electrical engineering, manufacturing, and phyllo-genetics, etc. [37].

4.1.2 PSO Algorithm

The PSO method is a population-based random search technique for optimization, which was inspired by swarming behaviors observed in flocks of birds, schools of fish, or swarms of bees, and even human social behavior. It was originally proposed by Eberhart and Kennedy (1995) and has become popular for solving various optimization problems. Particles (potential solutions) are distributed throughout the searching space randomly in D-dimension and their positions and velocities are modified based on social behavior. The social behavior in PSO is a population of particles moving towards the most promising region of the search space. As express in the above section PSO has some advantages as compared to GA, such as fewer parameters needed to be adjusted and the rapid convergence speed under the same condition. Conversely its shortcoming is disposed to quick occurrence into a local optimum [37, 39, 40].

Finding how to map the problem solution into the PSO particle is the key issues for applying of PSO successfully, which directly affects its feasibility and performance. It also widely used to solve continuous problems and suitable for processing of computer programming. The fundamental idea of the PSO algorithm is set a group of random particles firstly, similarly it is known as random solutions. The location and speed of each particle are updated according to the current global optimal position (*pbest*) and current position (*gbest*). The process tends to the global optimal value of the gathered acceleration. Through continuous iteration, the optimal solution is found eventually [37, 40].

The model can be produced as follows. Suppose the $i-th$ particle's position (location) in the N dimensional search space is;

$$X_i = (X_{i,1}, X_{i,2}, X_{i,3}, X_{i,4}, X_{i,5}, \dots\dots\dots..X_{i,N})$$

Its speed is;

$$V_i = (V_{i,1}, V_{i,2}, V_{i,3}, V_{i,4}, V_{i,5}, \dots\dots\dots..V_{i,N})$$

In each iteration will yield, the $pbest$ will be produced through continuous tracking of $gbest$. The speed and location of all particles can be updated by expression (3.1) and expression (3.2).

$$V_{i,j} = wV_{i,j}(t) + c_1{}^*r_1{}^*\left(pbest_{i,j}(t) - x_{i,j}(t)\right) + c_2{}^*r_2{}^*\left(gbest_{i,j}(t) - x_{i,j}(t)\right) \quad (4.1)$$

$$x_{i,j}(t+1) = x_{i,j}(t) + v_{i,j}(t+1) \quad (4.2)$$

Expression (3.1) is used to update particle's speed, and expression (3.2) is used to update particle's location. Where w is weight coefficient, c_1 and c_2 are positive learning factors, r_1 and r_2 are the symmetrical distribution random numbers between 0 and 1.

According to the situation that the chromosome codes in evolutionary algorithm (EA) only can be 0 or 1, expression (3.3) is used as the commonly used fuzzy function for particle discretization.

$$sig(x_{i,j}) = \frac{1}{1+e^{-x_{i,j}}} \quad (4.3)$$

While the updating expression of every particle is given as expression (3.4).

$$x_{i,j}(t+1) = \begin{cases} 0, & rand < sig(x(i,:)) \\ 1, & rand \geq sig(x(i,:)) \end{cases} \quad (4.4)$$

When updating the particle's location, illegal codes may appear. In other words, the ith (i is odd) code and the $(i+1)th$ ($i+1$ is $even$) code cannot be "1" at the same time. Illegal codes must be deleted when it appear.

For further clarification look at the flow chart for particle swarm optimization algorithm as following below.

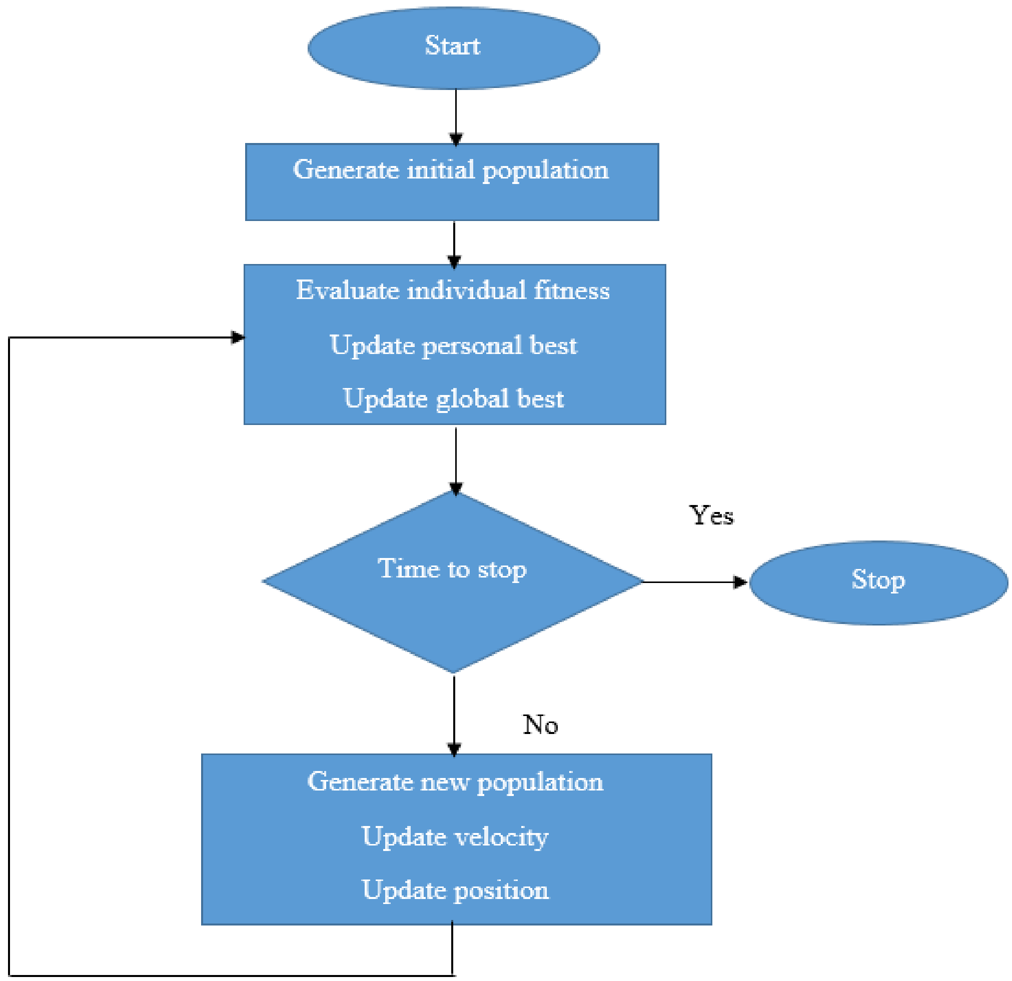


Figure 4.2: Flowchart for particle swarm optimization algorithm *[39]***.**

PSO Modifications: there are several versions of PSO algorithm can be obtained by combining it with other evolutionary algorithms (EA). There is a trend in research to make hybrid PSO algorithms to increase the overall optimization of the algorithm. Some of the commonly used modifications of PSO algorithm are mentioned below: [37].

- Discrete PSO.
- Constriction Coefficient.
- Bare-bones PSO.
- Fully informed PSO.

Applications: the first application of PSO originate in the field of neural network training. In addition to this it has been used in wide variety of fields including telecommunications, design, power systems, control and many others. PSO algorithms have been used extensively in dynamic tracking, Min Max problems and various optimization problems [37].

4.1.3 Hybrid of GA and PSO Algorithm

It can be also optimize a problem by combining (hybridize) of the genetic algorithm (GA) and particle swarm optimization (PSO). PSO performance is problem-dependent. This problem-dependent performance can be addressed through hybrid mechanism and combines different approaches to be benefited from the advantages of each approach. Hence to overcome the limitations of PSO, hybrid algorithms with GA are proposed. The root behind this is that such a hybrid approach is expected to have advantages of PSO with those of GA. One advantage of PSO over GA is its algorithmic simplicity. Another clear difference between PSO and GA is the ability to control convergence. The genetic operator’s crossover and mutation rates can slightly affect the convergence of GA, but these cannot be similar to the level of control achieved through deploying of the inertia weight. In fact, the decrease of inertia weight intensely increases the swarm’s convergence. The key problem with PSO is that it early converges to stable point, which is not necessarily maximum. To prevent the occurrence, position update of the global best particles is changed. The position update is done through some hybrid mechanism of GA. The idea behind GA is due to its genetic operator’s crossover and mutation. By applying crossover operation, information can be swapped between two particles to have the ability to fly to the new search area. The purpose of applying mutation to PSO is to increase the diversity of the population and the ability to have the PSO to avoid the local maxima [40, 41].

There are three different hybrid approaches are proposed

1. **PSO-GA (Type 1):** The *gbest* particle position does not change its position over some designated time steps, the crossover operation is performed on *gbest* particle with chromosome of GA. In this model both PSO and GA are run in parallel.
2. **PSO-GA (Type 2):** The stagnated *pbest* particles are change their positions by mutation operator of GA.
3. **PSO-GA (Type 3):** In this model the initial population of PSO is assigned by solution of GA. The total numbers of iterations are equally shared by GA and PSO. First half of the iterations are run by GA and the solutions are given as initial population of PSO. Remaining iterations are run by PSO.

4.1.4 Least Square Method (LSM) Algorithm

Least Square method (LSM) is one type of optimization algorithm among the mentioned possible optimization mechanism. This algorithm works based on the measured and theoretical (prediction) data of the study area. The LSM is a statistical tuning approach in which all environmental influences are considered. The basic principle of LSM is minimizing the difference between the measured and predicted data in a way of mean square error function. Due to its simplicity and easily implementation LSM algorithm was chosen for tuning purpose of this case study. In addition, the gradient of the Cost function can be easily obtained. Whereas the implementation of Genetic Algorithm and Particle Swarm Optimization are vast and more complex when we compare to LSM. In general, LSM is suitable for optimization of different propagation models [7, 42].

Mathematically it can be expressed the LSM in order to satisfy the condition of best fit for a theoretical (predicted) model with a given set of experimental data, the sum of deviation squares must be minimum.

$$E(a, b, c\ \ldots) = \sum_{i=1}^{n}[yi - PR, i\ (xi, a, b, c)]^2 \quad (4.5)$$

Where,

yi = experimentally measured path loss values at distance xi

$PR, i = (xi, a, b, c)$ = model predicted path loss values at distance xi based on tuning

Where a, b and c are the model parameters based on tuning, n represents number of experiment data set. This algorithm is discussed in detail in the next Chapter.

Chapter Five

Simulation Results and Discussions

5.1 Introduction

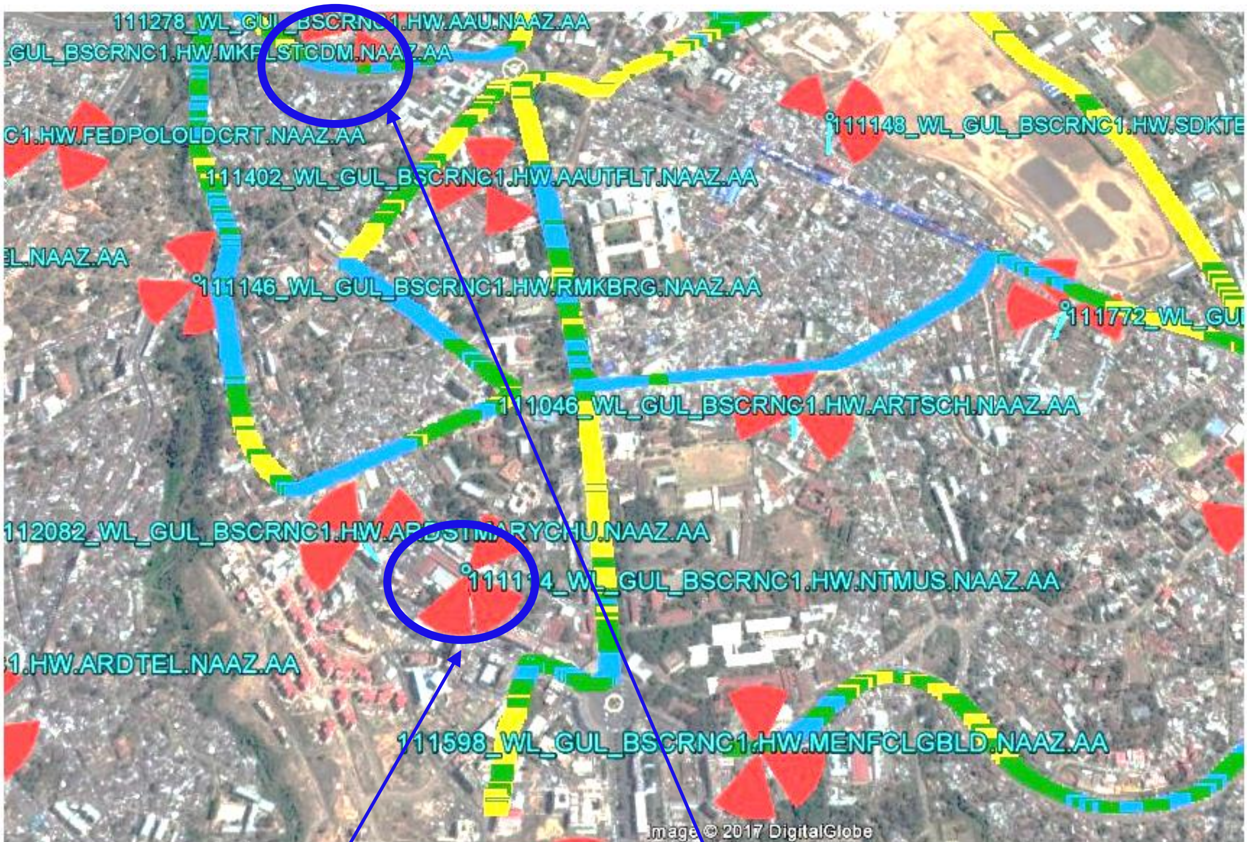
Different path loss prediction models were studied, as explained in Chapter two. This research is a case study and done based on measurement data. For this very reason, the empirical path loss prediction model has been considered. The first important task is determining the kind of path loss model in Addis Ababa. Based on queries done for Ethio telecom, Cost-231 Hata model is practiced in the deployment. The next and important task is Fine-tuning this path loss prediction model following which optimization of path loss will be done.

In this Chapter the necessary data and steps used in the study is briefly discussed. Here, four eNodeB stations in Addis Ababa, 4Kilo area are considered for investigation. These four eNodeB stations have a different location, longitude and latitude. Table 5.1 contains Site ID, PCI, height, and longitude- latitude of the eNodeB.

Table 5.1: LTE base stations location

LTE Base station	PCI	Longitude	Latitude	Height (m)
111114	271	E 38.7612801	N 9.0344801	27
111278	317	E 38.75874	N 9.04382	25
112082	306	E 38.76131	N 9.03777	35
111402	314	E 38.76113	N 9.04086	32
112082	307	E 38.76131	N 9.03777	35

Similarly, the pictorial view of the environment around the LTE eNodeB is shown in Figure 5.1 below.



Note some of the sites are indicated above

Figure 5.1: A pictorial view of urban environment around 4Kilo eNodeB

The implementation network parameters and assumptions used in the prediction and optimization of Cost-231 Hata model is shown in Table 5.2.

Table 5.2: Simulation Parameters

Parameters	**Value**
Frequency (Hz)	1800 MHz
Base Station Height (m)	30m
Receiver Antenna Height (m)	1.5m
Type of environment	Urban area
Type of existing model	Cost-231 Hata model

5.2 Data Collection Method and Measured Path Loss

Measurement Procedure

A drive test methodology was adopted for data collection from the study area. The measurements of path loss were conducted in Addis Ababa 4Kilo area and the measuring tools used for the drive test includes hand phone installed with a Nemo Handy software and vehicles. The transmitted power and received power are known by the Nemo Handy software when measurement was taken, then the software gives how much the deviation in the path loss. The ACTIX software was used to extract the log file into the appropriate format Excel sheet for analysis. The measurement was conducted in one sector for each LTE station by locking the interference coming from other sectors and the measurement was done until the strength of signal stops continuously measure along the path. After extracting the log file measurement in to the Excel format sorting (filtering) of data was done in average basis. Based on the measurement procedure the measured path loss data is shown in the following Table 5.3.

Table 5.3: Measured path loss for urban area of 4Kilo

Dist.(km)	Log scale(xi)	Measured path loss(dB)					Avera.PL(yi)
		PL111114-271	PL111278-317	PL112082-306	PL111402-314	PL112082-307	
0.075	0	90.3	92.5	88.6	88.4	87.6	89.48
0.095	6.7	102.2	98.3	102.5	90.6	90.5	96.82
0.115	7.5	100.2	98.1	92.1	98.6	106.8	99.16
0.135	8.2	92.5	106.4	100.2	92.3	96.5	97.58
0.155	8.8	99	94.2	90.4	101	95.7	96.06

This table shows sample data, but if it is necessary; the whole data of the measurement is shown in Appendix A.

5.3 Performance Measurement Metrics

In order to compare the performance between predicted and optimized Cost-231 Hata model performance error measurement metrics will be taken. The Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) is used to analyze the error of each eNodeB station with a predicted and optimized Cost-231 Hata model using the following formula.

$$RMSE = \frac{1}{n}\sum_{t=1}^{n}\sqrt{(P_{mt} - P_{Rt})^2} \tag{5.1}$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{(P_{mt} - P_{Rt})}{P_{mt}}\right| X\ 100\% \tag{5.2}$$

Where: P_{mt} is the mean value of measured data, P_{Rt} is the mean value of predicted path loss, n is the number of data points [43].

5.4 Optimization Process

The Least Square method (LSM) is the most appropriate tool for such optimization process. Hence, the LSM is a statistical method in which all environmental influences are considered. The Cost-231 Hata model for urban area is given in Equation (2.18) Section 2.7.3 of Chapter 2 and assume it contains three basic elements [7, 44]:

$$E_0 = 46.3 + C_K \tag{5.3}$$

$$E_{sys} = 33.9\log_{10}(f_c) - 13.82\log_{10}(h_b) - a(h_m) \tag{5.4}$$

$$\beta_{sys} = [44.9 - 6.55(\log_{10}(h_b))]\ \log_{10}(d) \tag{5.5}$$

Where,

E_0 = Initial offset parameter,

E_{sys} = Initial system design parameter

β_{sys}= slope of the model curve

Then total path loss of Cost-231 Hata model is given by

$$L_{P(COST)}(dB) = E_0 + E_{sys} + \beta_{sys}.\log_{10}(d) \tag{5.6}$$

Equation (5.6) may be written as

$$a = E_0 + E_{sys} \tag{5.7}$$

$$b = \beta_{sys}.\log_{10}(d) \tag{5.8}$$

Then the Cost-231 Hata model in Equation (2.7) is expressed as

$$L_{Predict(COST)} = a + b\log_{10}(d) \tag{5.9}$$

The simplified logarithm base $\log_{10}(d) = x$, so the above equation can be represented as

$$L_{Predict(COST)} = a + b.x \tag{5.10}$$

Where, $L_{Predict(COST)}$= predicted path loss model in decibels.

The parameters a and b represent constants for a given set of measured values. Tuning of Cost -231 Hata model would be achieved by considering the parameters E_0, E_{sys} andβ_{sys}.

The Least Square algorithm, to satisfy the condition of best fit for a theoretical model with a given set of experimental data, the sum of deviation squares must be minimum as given in (5.11).

$$E_p(a, b, c, \dots\dots) = \sum_{i=1}^{n}[y_i - F_R\ (x_i, a, b, c, \dots.)]^2 \tag{5.11}$$

Where,

y_i= experimentally measured path loss values at distance x_i

$F_R\ (x_i, a, b, c, \dots.)$ = model predicted path loss values at distance x_i based on optimization.

Where a, b and c are the model parameters based on tuning, n represents number of experiment data set. The error function $E_p(a, b, c, \dots\dots)$ must be least. To ensure this, all partial differentials of error function should be equal to zero.

$$\frac{\partial E}{\partial a} = 0, \qquad \frac{\partial E}{\partial b} = 0, \qquad \frac{\partial E}{\partial c} = 0 \tag{5.12}$$

The partial differential of error function with respect to parameter a can be described as

$$\frac{\partial E}{\partial a} = 0$$

$$\frac{\partial}{\partial a}\left(\sum_{i=1}^{n} \quad (y_i - (a + bx_i))^2\right) = 0$$

But the detail derivation is written on the Appendix C of this thesis. Then finally it can be expressed by the following equation:

$$na + b\sum_{i=1}^{n} x_i = \sum_{i=1}^{n} y_i \tag{5.13}$$

From Equation (5.13) the parameter a inters of b can be expressed as

$$na = \sum_{i=1}^{n} y_i - b\sum_{i=1}^{n} x_i$$

$$a = \frac{\sum_{i=1}^{n} y_i - b\sum_{i=1}^{n} x_i}{n} \tag{5.13(a)}$$

Similarly, the partial differential of error function with respect to parameter b can be briefly expressed in Appendix D of this thesis and finally it can be expressed by the following equation:

$$a\sum_{i=1}^{n} x_i + b\sum_{i=1}^{n}(x_i)^2 = \sum_{i=1}^{n} x_i y_i \tag{5.14}$$

Similarly, from Equation (5.14) the parameter b in terms of a can be expressed as

$$b\sum_{i=1}^{n}(x_i)^2 = \sum_{i=1}^{n} x_i y_i - a\sum_{i=1}^{n} x_i$$

$$b = \frac{\sum_{i=1}^{n} x_i y_i - a\sum_{i=1}^{n} x_i}{\sum_{i=1}^{n}(x_i)^2} \tag{5.14(b)}$$

By substituting the variables a and b in to Equations (5.13) and (5.14), the tuned statistical estimates of parameters a and b are described as:

From Equation (5.13)

$$\tilde{a} = \frac{\sum_{i=1}^{n}(x_i)^2 \,.\, \sum_{i=1}^{n} y_i - \sum_{i=1}^{n} x_i y_i \,.\, \sum_{i=1}^{n} x_i}{n\sum_{i=1}^{n}(x_i)^2 - (\sum_{i=1}^{n} x_i)^2} \tag{5.15}$$

If it is important; the tuned parameter of $\tilde{a}$ is shown in Appendix E.

In a similar way, from Equation (5.14)

$$\tilde{b} = \frac{n\sum_{i=1}^{n} x_i y_i - \sum_{i=1}^{n} y_i \,.\, \sum_{i=1}^{n} x_i}{n\sum_{i=1}^{n}(x_i)^2 - (\sum_{i=1}^{n} x_i)^2} \tag{5.16}$$

If it is important; the derivation of tuned parameter of $\tilde{b}$ is shown in Appendix F.

The tuned statistical estimates $\tilde{a}$ and $\tilde{b}$ are substituted into the original Cost-231 Hata model and the tuned values of the initial offset parameter and slope of the model can be obtained as the $\tilde{E}_{0(Tuned)}$ can be described from the expression of parameter a:

$$a = E_0 + E_{sys}$$

Then, E_0 becomes;

$$E_0 = a - E_{sys}$$

Therefore, $\tilde{E}_{0(Tuned)}$ will become;

$$\tilde{E}_{0(Tuned)} = \tilde{a} - E_{sys} \tag{5.17}$$

Therefore, $\tilde{\beta}_{sys}$ can be expressed as follows:

$$\tilde{\beta}_{sys} = \frac{\tilde{b}}{44.9 - 6.55\log_{10}(h_b)} \tag{5.18}$$

5.5 Implementation of Least Square Algorithm

The implementation of the Least Square algorithm is based on the tuned values of $\tilde{a}$, $\tilde{b}$,$\tilde{E}_{0(Tuned)}$ and $\tilde{\beta}_{sys}$ were determined by substituting measured data into Equations (5.15), (5.16), (5.17) and (5.18), respectively, and presented as followed; $\tilde{a} = 84.75$, $\tilde{b} = 1.92$ $\tilde{E}_{0(Tuned)} = 5.2$ and $\tilde{\beta}_{sys} = 0.06$. The tuned value of $\tilde{E}_0$ was introduced into Cost-231 Hata model and thus the optimized Cost-231 Hata model is presented as Equation (4.18) [7, 44]. After tuning the model 40dB gain can be obtain. This gain have two basic implication; the first one is it reduces the infrastructure cost by increasing the coverage area of a single base station and the second one is it reduces interferences or improve system throughput (data rate).

$$L_p(dB) = 5.2 + 33.9\log_{10}(f_c) - 13.82\log_{10}(h_b) - a(h_m) + (44.9 - 6.55\log_{10}(h_b))\log_{10}(d) + C_K \tag{5.19}$$

Table 5.4 contains the measured distance and average values of the measured data obtained from four different eNodeB station locations in Addis Ababa 4Kilo area. The comparative analysis of the existing models and optimized Cost-231 Hata model was also presented after substituting both measured and relevant network parameters of the models.

Table 5.4: Results of average path loss, predicted and optimized values of Cost-231 Hata model.

Dist.(km)	Log scale(xi)	Avera.PL(yi)	Cost-231 Hata model	Optimized Cost-231 Hata model
0.075	0	89.48	96.6	87.1
0.095	6.7	96.82	100.2	90.7
0.115	7.5	99.16	103.1	93.6
0.135	8.2	97.58	105.6	96.1
0.155	8.8	96.06	107.7	98.2
0.175	9.4	100.74	109.5	100

This table shows the sample data; if it is necessary; the whole data is shown in Appendix B.

Similarly, the existing and optimized Cost-231 Hata model can be compared based on the two performance measurement metrics that are explained in the above Section 5.3 that the RMSE and MAPE. Table 5.5 contains the outcome of error analysis for the different sites in Addis Ababa 4Kilo area.

Table 5.5: Performance analysis of the models

Measurement Site (Id-PCI)	Performance Metrics	Existing Model	Optimized Model
		Cost-231 Hata Model (dB)	Cost-231 Hata Model (dB)
111114-271	RMSE	0.5	0.022
	MAPE	0.48	0.021
111278-317	RMSE	0.49	0.028
	MAPE	0.48	0.027
112082-306	RMSE	0.5	0.022
	MAPE	0.48	0.021
111402-314	RMSE	0.55	0.026
	MAPE	0.53	0.025
112082-307	RMSE	0.43	0.096
	MAPE	0.41	0.091
Average	RMSE	0.49	0.039
	MAPE	0.47	0.037

5.6 Results and Discussion

In this study the Cost-231 Hata path loss model was optimized using a Least Square method algorithm. The measurement was taken using a drive test method as explained briefly in Section 5.2. It was taken a four eNodeB station in Addis Ababa 4Kilo area for investigation purpose and with a measurement at 20 meters away from the stations starting from 75meter to 415meter. The discussion of each site is shown one by one separately below.

From Figure 5.2 - Figure 5.7 the plots of predicted and optimized Cost-231 Hata models with measured for site 111114-271, 111278-317, 112082-306, 111402-314 and 112082-307 respectively are presented. The plot of the predicted and optimized path losses models are smooth as we observed from the Figure 5.2 - 5.7, whereas the plot of the measured ones shows variation due to the effect of large-scale fading, shadowing and multipath. The deviation of measured path loss from the predicted and optimized models can be expressed in terms of performance measurement matrices, root mean square error (RMSE) and mean absolute performance error (MAPE); respectively. These performance metrics can be calculated using the formula found in Section 5.3 and gave the deviation in mean rather than taking instance points in each distance.

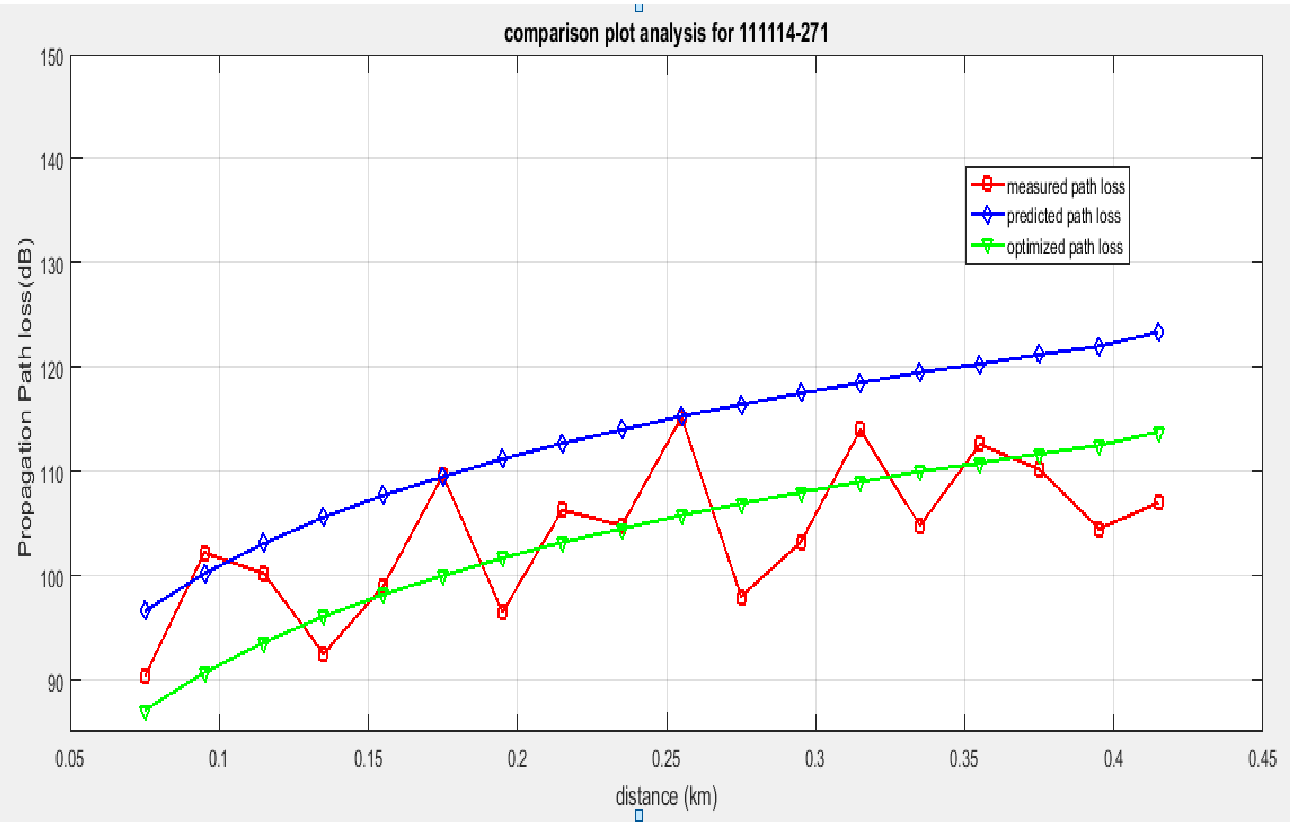


Figure 5.2: Comparative plot of measured, predicted and optimized Cost-231 Hata models for 111114-271

From the calculation as shown in Table 5.5; the predicted model result showed that RMSE was 0.5 dB and MAPE was 0.48 %, while the optimized model result showed that RMSE was 0.022 dB and MAPE was 0.021 %; respectively. Therefore, the optimized model gave better results as compared to the existing model.

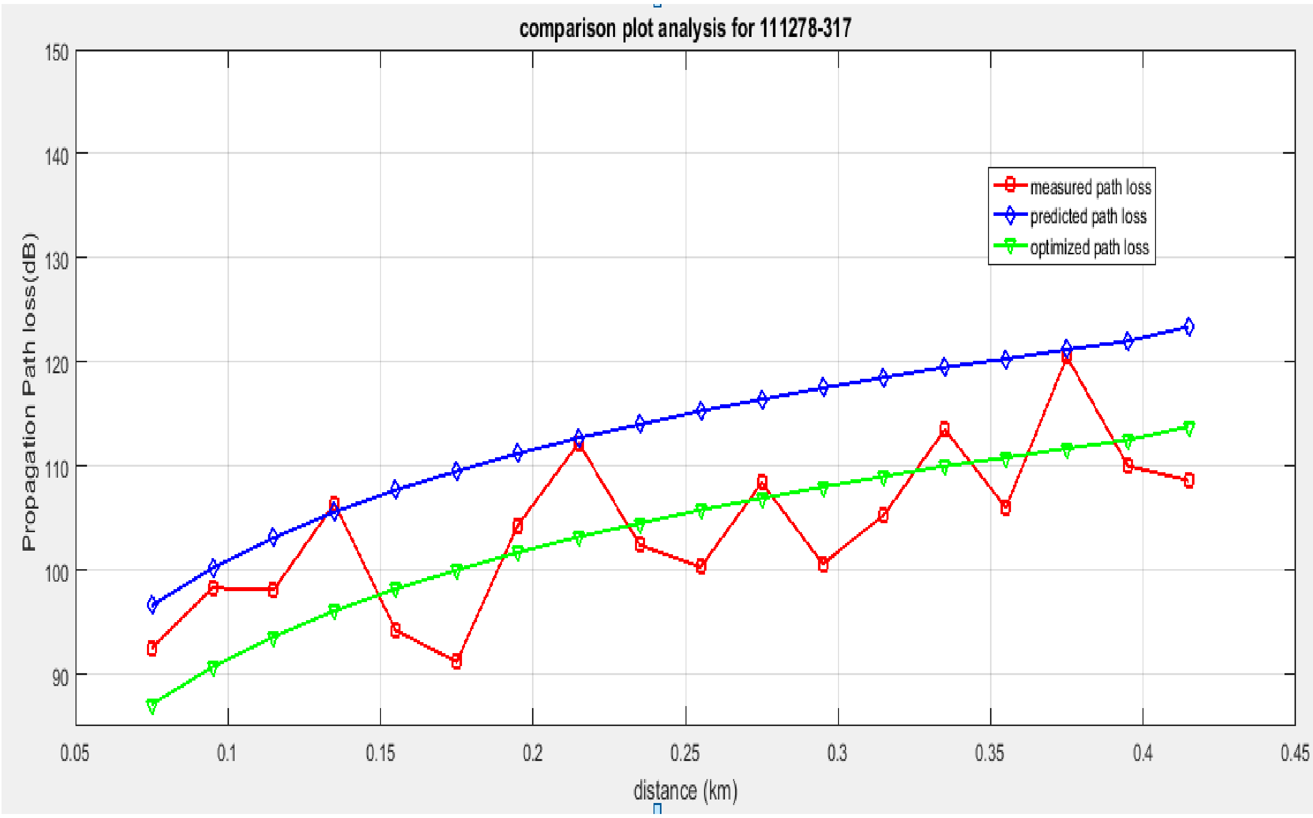


Figure 5.3: Comparative plot of measured, predicted and optimized Cost-231 Hata models for 111278-317

Based on the calculation as shown in Table 5.5; the predicted model showed a RMSE of 0.49 dB and MAPE of 0.48 %, whereas the optimized model has RMSE of 0.028 dB and MAPE of 0.027 %; respectively. Hence, the optimized model gave better results as compared to the existing model.

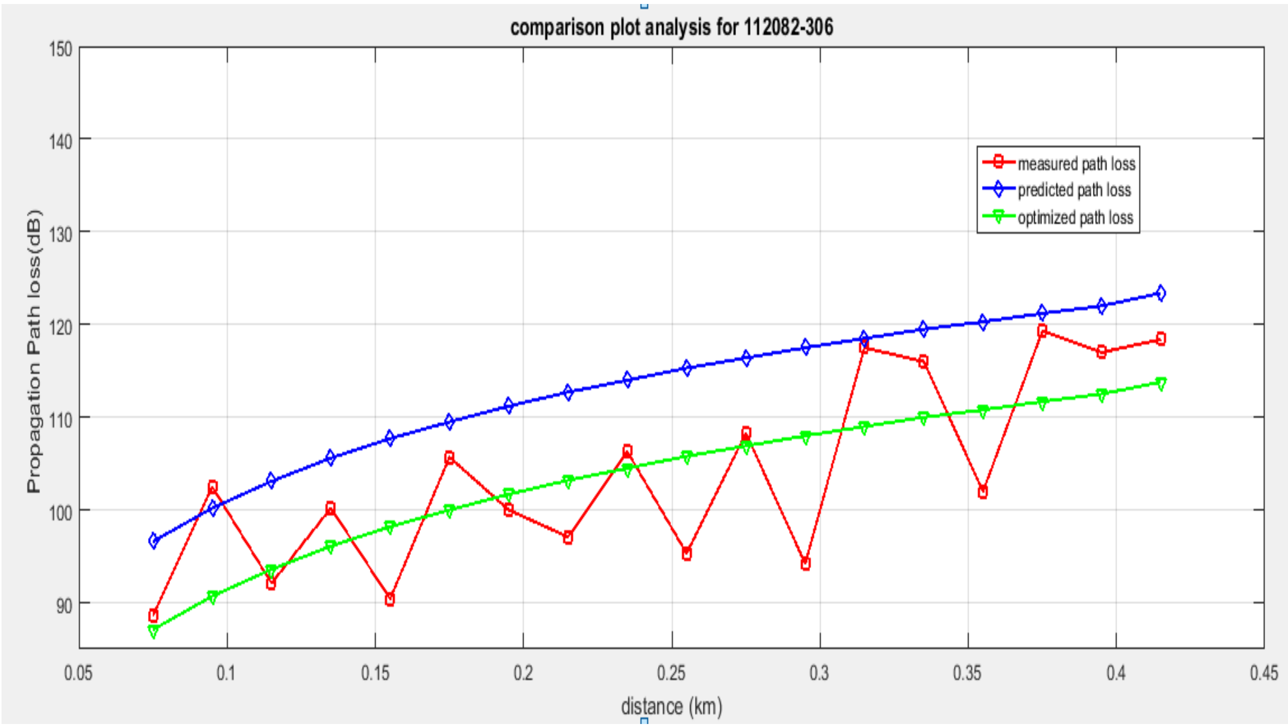


Figure 5.4: Comparative plot of measured, predicted and optimized Cost-231 Hata models for 112082-306

From the calculation as shown in Table 5.5; the predicted model result showed that RMSE was 0.5 dB and MAPE was 0.48 %, whereas the optimized model result showed that RMSE was 0.022 dB and MAPE was 0.021 %; correspondingly. Then the optimized model offered better results as compared to the existing model.

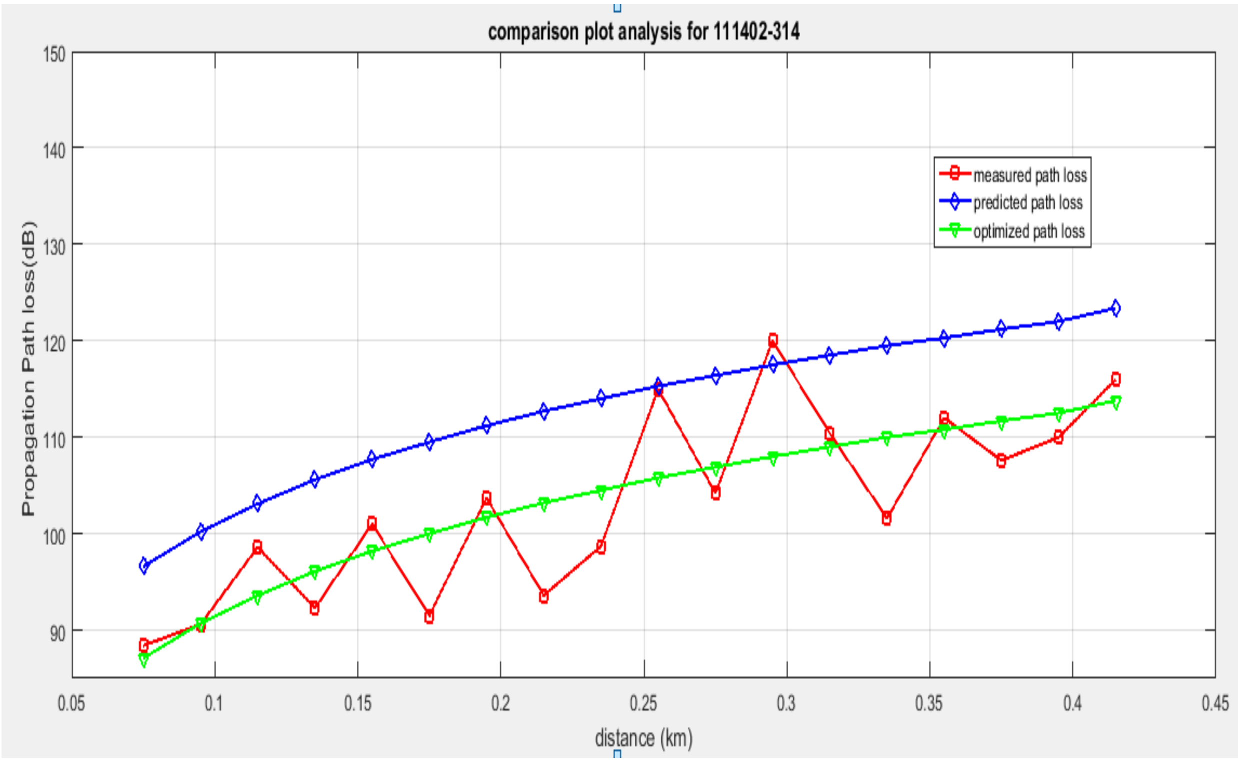


Figure 5.5: Comparative plot of measured, predicted and optimized Cost-231 Hata models for 111402-314

Based on the calculation as shown in Table 5.5; the predicted model showed a RMSE of 0.55 dB and MAPE of 0.53 %, whereas the optimized model has RMSE of 0.026 dB and MAPE of 0.025 %; respectively. Hence the optimized model gave better results as compared to the existing model.

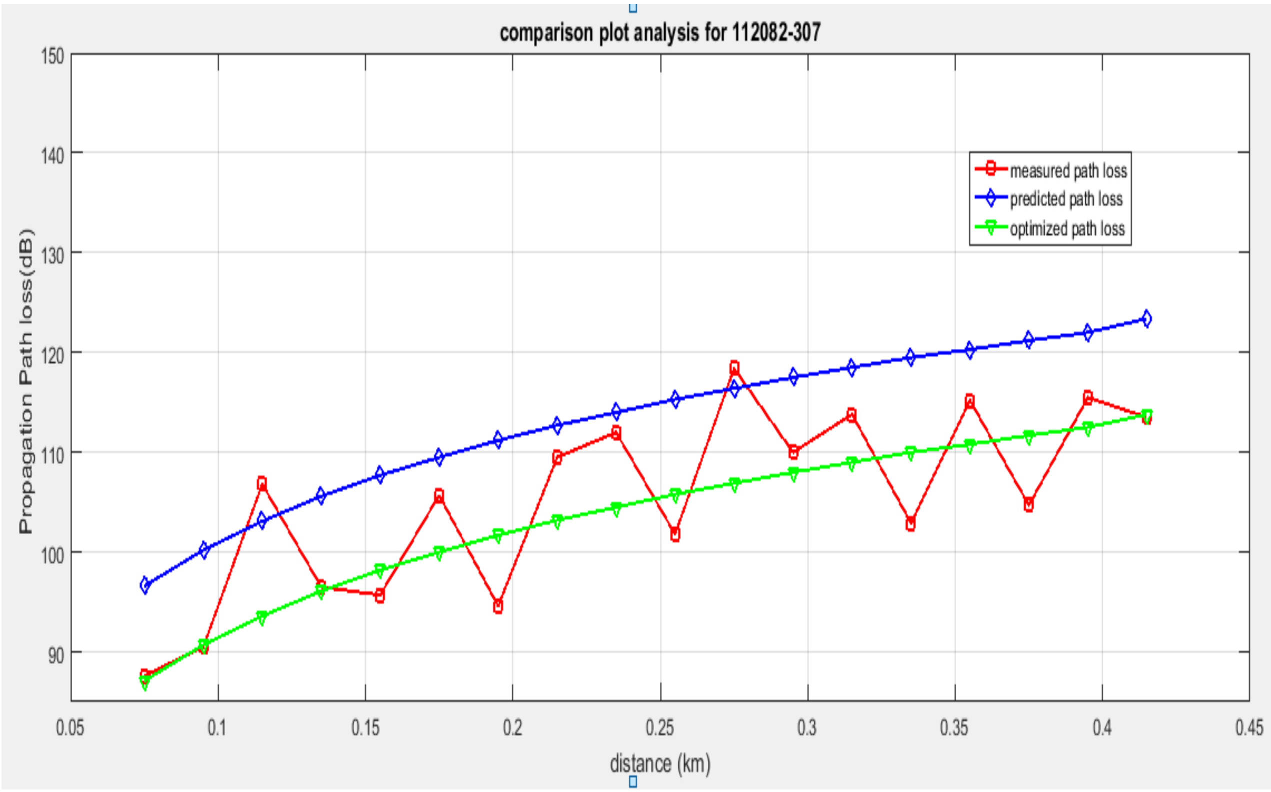


Figure 5.6: Comparative plot of measured, predicted and optimized Cost-231 Hata models for 112082-307

From the calculation as shown in Table 5.5; the predicted model result showed that RMSE was 0.43 dB and MAPE was 0.41 %, whereas the optimized model result showed that RMSE was 0.096 dB and MAPE was 0.091 %; respectively. Therefore, the optimized model provided better results as compared to the existing model.

Generally, the results as depicted in Figure 5.3 - 5.7 shows that optimized model gave a better performance compared to Cost-231 Hata model, thus the optimized model is successfully developed. Therefore, the optimized model can be used to the network planning and designing problems in the selected area and other areas as well in a similar manner.

Chapter Six

Conclusion and Recommendation

6.1 Conclusion

The aim of this thesis was Fine-tuning of Cost-231 Hata model, for LTE Rel.8 at 1800MHz for Addis Ababa urban area of 4Kilo. The measured path loss is obtained from experimentally collected derive test data. Cost-231 Hata model was tuned by implementing Least Square tuning algorithm. This model is selected to predict the path loss of the investigated area because, Ethio telecom used this model. Existing network parameters were fundamental inputs for this task.

In this work the path loss of the measured and predicted models are discussed. And also, the tuned model is compared with original Cost-231 Hata model in terms of root mean square error (RMSE) and mean absolute performance error (MAPE). In addition, the basic concepts of LTE and possible optimization implementation algorithms such as genetic algorithm (GA), particle swarm optimization (PSO) algorithm, hybrid of GA and PSO algorithm and Least Square method algorithm are discussed briefly. In this thesis Least Square method algorithm was used for optimization of Cost-231 Hata model because, gradient of the Cost function can be easily obtained.

From the overall average error analysis shown in Table 5.5, it is observed that, the performance of the tuned model gives a RMSE = 0.039 dB and MAPE = 0.037% as compared to Cost-231 Hata model with a RMSE = 0.49 dB and MAPE = 0.47% respectively. Hence, the tuned model is better, since it gives the least error. This indicates that the path loss predicted by the tuned model is more accurate compared to Cost-231 Hata model. Therefore, the tuned model can be used for accurate path loss prediction in urban area of 4Kilo to provide better coverage and optimization assessments.

6.2 Recommendation

Although in this study, Fine-tuning of Cost-231 Hata model for LTE Rel.8 at 1800MHz for the urban area of 4Kilo. The work can be further improved by incorporating the following points.

- The work can be extended for Addis Ababa and other cities such as: Bahirdar, Adama and so on.
- The performance comparison with other path loss models are not considered. Thus the work can be extended by including performance comparison.
- In this thesis the path loss model for outdoor case was optimized. The work can be developed for the case of indoor.

References

[1] T.S.Rappaport, wireless communication :principle and practice, singapor : pearson education, 2002.

[2] A.Goldsmith, Wireless communications, Cambridge University Press, 2005.

[3] B. Seifu, "LTE nominal radio network planning : modeling approaches for the case of Addis Ababa," AAiT, Addis Ababa, December 2012.

[4] H. Desalegn, "Techno-economic analysis of LTE deployment : a case study of Addis Ababa," AAiT, Addis Ababa, June 2014.

[5] K.Ogunremi K.Adeyemo , "Genetic algorithm based path loss optimization for Long Term Evolution in lagos,nigeria," *International Journal of Applied Science and Technology,* vol. 6, no. 2221-0997, June 2016.

[6] Govind Sati Sonika Singh, "A review on outdoor propagation models in radio communication," *International Journal of Computer Engineering and Science,* vol. 4, no. 2, pp. 64-68, March 2014.

[7] K.f.kwan R.mardeni , "Optimization of Hata propagation prediction model in suburban area in malaysia," *Progress in Electromagnetics Research c,* vol. 13, pp. 91-106, 2010.

[8] S. Yuvraj, "Comparison of Okumura, Hata and Cost-231 models on the basis of path loss and signal strength," *International Journal of Computer Applications,* vol. 59, no. 11, December 2012.

[9] Noman Shabbir Muhammad T.Sadiq, "Comparison of radio propagation models for Long Term Evolution (LTE) network," *International Journal of Next-Generation Networks,* vol. 3, no. 3, September 2012.

[10] T. Berhane, "Statistical modeling and simulation of small fast fading wireless channel," AAiT, Addis Ababa, June 2014.

[11] Z. Matewos, "Digital dividend and its opportunities for emerging wireless services: the case of ethiopia," AAiT, Adiss Ababa, March 2016.

[12] A. Arsal, "A Study on Wireless Channel Models: Simulation of Fading, Shadowing and

Further Applications," Izmir Institute of Technology, Auagust 2008.

[13] E. Ostlin, "On radio wave propagation measurments and modeling for cellular mobile radio networks," Blekinge Institute of Technology, Sweden, July 2009.

[14] B. Paudel, "On the effect of small scale fading and mobility in mobile wireless communication network," Missouri University of Science and Technology, 2009.

[15] J. Sammuel, "Wireless channel equalization in digital communication systems," Claremont Graduate University, California, 2012.

[16] N. Daniel, "Studying the impact of the environment on radio frequency signal quality:a case study of knust wireless local area network," Kwame Nkurmah University of Science and Technology, Kenya, May 2012.

[17] W. Mark, "Urban propagation modeling for wireless systems," Graduate Studies of Stanford University, February 2004.

[18] M.Moher S.S.Haykin , Modern wireless communication, Prentice Hall, 2004.

[19] Purnima K.Sharma R.K.Singh, "Comparative analysis of propagation path loss models with field measured data," *International Journal of Engineering Science and Technology,* vol. 2, no. 6, July 2013.

[20] Madhvi Soni P.K.Ghosh Kapil Gupta, "Review of data communication in wireless fading channel and a case study," *International Journal of Electronics and Communication Technology,* vol. 6, no. 1, March 2015.

[21] J.ramkumar R.gunasekaran, "A new path loss model for LTE network to address propagation delay," *International journal of computer and communication engineering,* vol. 2, no. 4, July 2013.

[22] M. J. Maria, "Performance enhancement in recently deployed LTE wireless networks," April 2014.

[23] E. I. Oludayo, "Analysis of handover decision making in downlink Long Term Evolution networks," Durban University of Technology, South Africa, July 2014.

[24] U. Toseef, "LTE optimization and resource management in wireless heterogeneous networks," University of Bremen, February 2013.

[25] A. Z. Yonis, "Design and implementation of MIMO Long Term Evolution - advanced to support larger bandwidth," Faculty of Electrical and Electronic Engineering University Tun Hussein Onn, Malaysia, 2013.

[26] G. A. Martinez, "Calculation of the coverage area of mobile broadband communications," Norwegian University of Science and Technology Department of Electronics and Telecommunications, Norwey, 2010.

[27] S. Mkrtchyan, "LTE- advanced :Technology and performance analysis," University of Vaasa Faculty of Technology, December 2011.

[28] S. Alotaibi, "3GPP Long Term Evolution LTE scheduling," University of North Texas, December 2013.

[29] T. Worku, "LTE technology deployment strategy for mobile telecom operators : a techno economic analysis," Korea Advanced Institute of Science and Technology, Korea, 2014.

[30] A. Helenius, "Performance of handover in Long Term Evolution," Aalto University School of Electrical Engineering, Finland, 2011.

[31] A. Basit, "Dimensioning of LTE Network Description of Models and Tool,Coverage and Capacity Estimation of 3GPP Long Term Evolution Radio Interface," Helsinki University, Finland, February 2009.

[32] T. Degefa, "QoS performance of LTE networks with network coding," Norwegian University of Science and Technology Department of Telematics, Norwey, June 2015.

[33] M. Sauter, From GSM to LTE: an introduction to mobile networks and mobile broadband, Germany: John Wiley and Sons, March 2011.

[34] 4G. Americas, MIMO and Smart Antennas for Mobile Broadband Systems, Americas, October 2012.

[35] S. M. Duarte, "Analysis of technologies for Long Term Evolution in UMTS," University of Tecnica, September 2008.

[36] 4G. Americas, Mobile Broadband Explosion, Americas: Rysavy Research, August 2012.

[37] Shahid Shabir Dr.Ruchi Singla, "A comparative study of genetic algorithm and the particle swarm optimization," *International Journal of Electrical Engineering,* vol. 9, no. 2, pp. 215-

223, May 2016.

[38] A. Getu, "Genetic algorithm based joint channel estimation and data detection for multi user MIMO," AAiT, Addis Ababa, April 2014.

[39] Kachitvichyanukul Vortas, "Comparison of three evolutionary algorithms:GA,PSO and DE," *Industrial Engineering and Management Systems*, vol. 11, no. 3, pp. 215-223, September 2012.

[40] Zhang Junbin Cai Jinyan,, "Genetic algorithm particle swarm optimization based hardware evolution strategy," *Wseas Transactions on Circuits and Systems*, vol. 13, 2014.

[41] K.Premalatha A.M.Natarajan, "Hybrid PSO and GA for global maximization," *International Journal Open Problems Comp.Math*, vol. 2, no. 4, December 2009.

[42] Dr. Aied Khalaf Mohammad, Ahmed A.Jaafar, "Performance evaluation of path loss in mobile channel for karada district in baghdad city," *Engineering and Technology Journal*, vol. 30, no. 17, December 2012.

[43] A. A.Olukunle, "Implementation of particle swarm optimization technique for enhanced outdoor network coverage in Long Term Evolution network in port harcourt,nigeria," *European Journal of Engineering Research and Science*, vol. 2, May 2017.

[44] A.ekeocha, "Optimization of Cost 231 model for 3G wireless communication signal in suburban area of port harcourt,nigeria," *International Journal of Engineering Sciences and Research Technology*, no. 2277-9655, May 2016.

[45] H. Zhen, "Performance evaluation of 2-D pilot aided OFDM system under hayper-rayleigh fading channel," University of Toledo, August 2014.

Appendix

Appendix A

Measured path loss data collected from the drive test for a different sites in 4Kilo area.

Dist.(km)	**Log scale(xi)**	**Measured path loss(dB)**					**Avera.pL(yi)**
		PL 111114-271	**PL 111278-317**	**PL 112082-306**	**PL 111402-314**	**PL 112082-307**	
0.075	0	90.3	92.5	88.6	88.4	87.6	89.48
0.095	6.7	102.2	98.3	102.5	90.6	90.5	96.82
0.115	7.5	100.2	98.1	92.1	98.6	106.8	99.16
0.135	8.2	92.5	106.4	100.2	92.3	96.5	97.58
0.155	8.8	99	94.2	90.4	101	95.7	96.06
0.175	9.4	109.6	91.2	105.7	91.5	105.7	100.74
0.195	9.8	96.5	104.3	100	103.7	94.6	99.82
0.215	10.3	106.3	112.2	97.1	93.6	109.5	103.74
0.235	10.7	104.8	102.4	106.3	98.7	112	104.84
0.255	11	115.2	100.3	95.3	115	101.8	105.52
0.275	11.3	98	108.4	108.3	104.2	118.4	107.46
0.295	11.6	103.2	100.6	94.2	120	110	105.6
0.315	11.9	114	105.3	117.5	110.4	113.8	112.2
0.335	12.2	104.8	113.5	116	101.6	102.9	107.76
0.355	12.4	112.6	106	102	112	115.2	109.56
0.375	12.7	110.2	120.5	119.3	107.6	104.7	112.46
0.395	12.9	104.5	110	117	110	115.5	111.4
0.415	13.1	107	108.6	118.4	116	113.5	112.7

Appendix B

The result of average measured path loss value from 4 eNodeB station, predicted and optimized path loss values of Cost-231 Hata models.

Dist.(km)	**Log scale(xi)**	**Avera.pl(yi)**	**Cost-231 Hata model**	**Optimized Cost-231 Hata model**
0.075	0	89.48	96.6	87.1
0.095	6.7	96.82	100.2	90.7
0.115	7.5	99.16	103.1	93.6
0.135	8.2	97.58	105.6	96.1
0.155	8.8	96.06	107.7	98.2
0.175	9.4	100.74	109.5	100
0.195	9.8	99.82	111.2	101.7
0.215	10.3	103.74	112.7	103.2
0.235	10.7	104.84	114	104.5
0.255	11	105.52	115.3	105.8
0.275	11.3	107.46	116.4	106.9
0.295	11.6	105.6	117.5	108
0.315	11.9	112.2	118.5	109
0.335	12.2	107.76	119.5	110
0.355	12.4	109.56	120.3	110.8
0.375	12.7	112.46	121.2	111.7
0.395	12.9	111.4	122	112.5
0.415	13.1	112.7	123.4	113.8

Appendix C

Derivation of error function of LSM algorithm with respect to a constant a.

$$\frac{\partial E}{\partial a} = 0$$

$$\frac{\partial}{\partial a}(\sum_{i=1}^{n} \quad (y_i - (a + bx_i))^2) = 0$$

$$\frac{\partial}{\partial a}(\sum_{i=1}^{n} \quad (y_i - a - bx_i)^2) = 0$$

$$\frac{\partial}{\partial a}(\sum_{i=1}^{n}(y_i - a - bx_i)\ (y_i - a - bx_i)) = 0$$

$$\sum_{i=1}^{n}\left(\frac{\partial}{\partial a}(y_i - a - bx_i)\ (y_i - a - bx_i)\right) = 0$$

$$\sum_{i=1}^{n}\left(\frac{\partial}{\partial a}(y_i - a - bx_i)(y_i - a - bx_i) + (y_i - a - bx_i)\frac{\partial}{\partial a}(y_i - a - bx_i)\right) = 0$$

$$\sum_{i=1}^{n}(-(y_i - a - bx_i) + -(y_i - a - bx_i)\ ) = 0$$

$$\sum_{i=1}^{n}(-y_i + a + bx_i - y_i + a + bx_i\ ) = 0$$

$$\sum_{i=1}^{n}(-2y_i + 2a + 2bx_i\ ) = 0$$

$$2(\sum_{i=1}^{n}(-y_i + a + bx_i\ )) = 0$$

$$(\sum_{i=1}^{n} -y_i + \sum_{i=1}^{n} a + \sum_{i=1}^{n} bx_i) = 0$$

$$(-\sum_{i=1}^{n} y_i + \sum_{i=1}^{n} a + b\sum_{i=1}^{n} x_i) = 0$$

$$(\sum_{i=1}^{n} a + b\sum_{i=1}^{n} x_i) = \sum_{i=1}^{n} y_i$$

$$na + b\sum_{i=1}^{n} x_i = \sum_{i=1}^{n} y_i$$

Appendix D

Derivation of error function of LSM algorithm with respect to a constant b.

$$\frac{\partial E}{\partial b} = 0$$

$$\frac{\partial}{\partial b}(\sum_{i=1}^{n} \quad (y_i - (a + bx_i))^2) = 0$$

$$\frac{\partial}{\partial b}(\sum_{i=1}^{n} \quad (y_i - a - bx_i)^2) = 0$$

$$\frac{\partial}{\partial b}\left(\sum_{i=1}^{n}(y_i - a - bx_i)\,(y_i - a - bx_i)\right) = 0$$

$$\sum_{i=1}^{n}\left(\frac{\partial}{\partial b}(y_i - a - bx_i)\,(y_i - a - bx_i)\right) = 0$$

$$\sum_{i=1}^{n}\left(\frac{\partial}{\partial b}(y_i - a - bx_i)(y_i - a - bx_i) + (y_i - a - bx_i)\frac{\partial}{\partial b}(y_i - a - bx_i)\right) = 0$$

$$\sum_{i=1}^{n}(-x_i(y_i - a - bx_i) + -x_i(y_i - a - bx_i)) = 0$$

$$\sum_{i=1}^{n}(-x_iy_i + ax_i + b(x_i)^2 - x_iy_i + ax_i + b(x_i)^2) = 0$$

$$\sum_{i=1}^{n}(-2x_iy_i + 2ax_i + 2b(x_i)^2) = 0$$

$$2\sum_{i=1}^{n}(-x_iy_i + ax_i + b(x_i)^2) = 0$$

$$\left(-\sum_{i=1}^{n}x_iy_i + \sum_{i=1}^{n}ax_i + \sum_{i=1}^{n}b(x_i)^2\right) = 0$$

$$a\sum_{i=1}^{n}x_i + b\sum_{i=1}^{n}(x_i)^2 = \sum_{i=1}^{n}x_iy_i$$

Appendix E

We can find the tuned value of constant a i.e. $\tilde{a}$ by expressing constant b in terms of a .

$$na + b\sum_{i=1}^{n}x_i = \sum_{i=1}^{n}y_i$$

$$na + \left(\frac{\sum_{i=1}^{n}x_iy_i - a\sum_{i=1}^{n}x_i}{\sum_{i=1}^{n}(x_i)^2}\right)\sum_{i=1}^{n}x_i) = \sum_{i=1}^{n}y_i$$

$$na + \left(\frac{\sum_{i=1}^{n}x_iy_i . \sum_{i=1}^{n}x_i - a(\sum_{i=1}^{n}x_i)^2}{\sum_{i=1}^{n}(x_i)^2}\right) = \sum_{i=1}^{n}y_i$$

$$na\sum_{i=1}^{n}(x_i)^2 + \sum_{i=1}^{n}x_iy_i . \sum_{i=1}^{n}x_i - a(\sum_{i=1}^{n}x_i)^2 = \sum_{i=1}^{n}(x_i)^2 . \sum_{i=1}^{n}y_i$$

$$a(n\sum_{i=1}^{n}(x_i)^2 - (\sum_{i=1}^{n}x_i)^2) = \sum_{i=1}^{n}(x_i)^2 . \sum_{i=1}^{n}y_i - \sum_{i=1}^{n}x_iy_i . \sum_{i=1}^{n}x_i$$

$$a(n\sum_{i=1}^{n}(x_i)^2 - (\sum_{i=1}^{n}x_i)^2) = \sum_{i=1}^{n}(x_i)^2 . \sum_{i=1}^{n}y_i - \sum_{i=1}^{n}x_iy_i . \sum_{i=1}^{n}x_i$$

$$\tilde{a} = \frac{\sum_{i=1}^{n}(x_i)^2 . \sum_{i=1}^{n}y_i - \sum_{i=1}^{n}x_iy_i . \sum_{i=1}^{n}x_i}{n\sum_{i=1}^{n}(x_i)^2 - \left(\sum_{i=1}^{n}x_i\right)^2}$$

Appendix F

We can find the tuned value of constant b i.e. $\tilde{b}$ by expressing constant a in terms of b.

$$\left(\frac{\sum_{i=1}^{n} y_i - b\sum_{i=1}^{n} x_i}{n}\right)\sum_{i=1}^{n} x_i + b\sum_{i=1}^{n}(x_i)^2 = \sum_{i=1}^{n} x_i y_i$$

$$\left(\frac{\sum_{i=1}^{n} y_i . \sum_{i=1}^{n} x_i - b\left(\sum_{i=1}^{n} x_i\right)^2}{n}\right) + b\sum_{i=1}^{n}(x_i)^2 = \sum_{i=1}^{n} x_i y_i$$

$$\frac{\sum_{i=1}^{n} y_i . \sum_{i=1}^{n} x_i - b\left(\sum_{i=1}^{n} x_i\right)^2 + bn\sum_{i=1}^{n}(x_i)^2}{n} = \sum_{i=1}^{n} x_i y_i$$

$$\sum_{i=1}^{n} y_i . \sum_{i=1}^{n} x_i - b\left(\sum_{i=1}^{n} x_i\right)^2 + bn\sum_{i=1}^{n}(x_i)^2 = n\sum_{i=1}^{n} x_i y_i$$

$$b\left(n\sum_{i=1}^{n}(x_i)^2 - \left(\sum_{i=1}^{n} x_i\right)^2\right) = n\sum_{i=1}^{n} x_i y_i - \sum_{i=1}^{n} y_i . \sum_{i=1}^{n} x_i$$

$$\tilde{b} = \frac{n\sum_{i=1}^{n} x_i y_i - \sum_{i=1}^{n} y_i . \sum_{i=1}^{n} x_i}{n\sum_{i=1}^{n}(x_i)^2 - \left(\sum_{i=1}^{n} x_i\right)^2}$$