Addis Ababa University
Addis Ababa Institute of Technology
School of Computer and Electrical Engineering
Telecommunication Network Engineering Program

Outdoor Propagation Pathloss Model for UMTS Networks using Feedforward Backpropagation Neural Network: Case of Addis Ababa, Ethiopia

A Thesis Submitted to the School of Graduate Studies of Addis Ababa University in partial Fulfilment of the requirements for the degree of Master of Science in Telecommunication Network Engineering

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Declaration

I declare that this thesis is a presentation of my own research work and any materials used from any other sources have been clearly identified and acknowledged and it has not been presented to this university or to any other institution for a degree or other qualification.

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Name Signature

Place: Addis Ababa

Date of Submission: ____________________

Abstract

The ubiquity nature of mobile networks, growth in technology, and innovations in mobile services will attract more users with the growing expectation and satisfaction. To accommodate the increasing number of users', operators are investing more in infrastructure and service delivery. In order to get the right revenue with the appropriate investment, the network planning and optimization work has to be done properly. In this regard, propagation pathloss is one of the main inputs for the planning and optimization and it has to be predicted as accurate as possible.

Prediction of the propagation pathloss can be done using different models. These models are deterministic, empirical, and statistical models. From these models, the empirical pathloss models, such as, COST-231, ECC-33, Stanford University Interim (SUI) are more commonly used. Different environments own different model and accuracy. These models have got different accuracy and they are modeled for different environment. When they are applied for the environment other than the area they are modeled for, they lose their accuracy. Hence, searching for a better prediction model is essential. To this end, neural network-based model is one of the better solutions to empirical and deterministic models for predicting the propagation pathloss.

The dataset is collected from measurements through a drive-test and from low level design documents. Then, it is preprocessed before used in order to train and evaluate the network. The performance evaluation is done with metrics, such as Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2) and Regression coefficient (R). The result of the tthesis shows that the neural network-based model has improved the pathloss by 6.2 dBm, 4.85%, 8.98 dBm, 0.44 and 0.53. The achieved result for the empirical models considering values of MAE, MAPE, RMSE, R and R^2 are 10.57 dBm, 8.34%, 14.36 dBm, 0.38 and 0.14 respectively. On the other hand, the proposed approach achieved a value of 4,37 dBm, 3.49%, 5.38 dBm, 0.82 and 0.67 using the test dataset. To this end, the neural network-based model best fits the pathloss for the Addis Ababa city realistic case scenario.

Keywords: Pathloss, FFBP, modeling, neural network, performance metrics, Propagation, Propagation Models

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Contents

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List of Acronyms

ANN	Artificial Neural Network
BS	Base-Station
BTS	Base Transceiver Station
CN	Core Network
COST	Cooperation for Science and Technology
CS	Circuit Switching
DL	Downlink
ECC	Electronic Communication Committee
FDD	Frequency Division Duplex
FDMA	Frequency Division Multiple Access
FFBP	Feedforward Backpropagation
GPRS	General Packet Radio Service
GPS	Global Positioning System
GSM	Global System for Mobile Communication
LLSM	Linear Least Square Method
LOS	Line of Sight
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
ME	Mobile Equipment
MLP	Multilayer Perceptron
MSC	Mobile Switching Center
MSE	Mean Square Error
NLOS	Non-Line of Sight
NN	Neural Networks
PS	Packet Switching
QOS	Quality of Service
R	Regression Coefficient
RF	Radio Frequency
RMSE	Root Mean Squared Error

RNC	Radio Network Controller
RNS	Radio Network Subsystem
SD	Standard Deviation
SUI	Stanford University Interim
trainbr	Bayesian Regularization
traingd	Gradient Descent Backpropagation Algorithm
traingdm	Gradient Descent with Momentum
trainlm	Levenberg–Marquardt Backpropagation
UE	User Equipment
UL	Uplink
UMTS	Universal Mobile Telecommunication System
USIM	UMTS Subscriber Identity Module
UTRA	Universal Terrestrial Radio Access
WCDMA	Wideband Code Division Multiple Access

1 Introduction

1.1 Background

Worldwide, the growth of the telecom industry is considered as one of the important factors indicating the growth of a given country. Its social, economic and political importance is well accepted and understood in its ubiquitous penetration and use [1]. This industry provides a technological foundation for society to communicate. Communication has a central role in the operations of the society, organizations, and communities are distinguished from a collection of individuals by their communications. Web browsing, cell phone calls, instant messaging become increasingly integrated into how we work, play, and live today. In addition to this, this industry helps peoples or societies who do not get the chance because of geography to participate and take part in the development of their country [2].

With the emerging technology, the growing service deliveries, customer expectations and necessity to provide the demanded forced the telecom industry, especially cellular mobile communication to grow fast. Telecom operators are encouraged to invest more and satisfy the users' demand. Commercial companies and Business organizations are increasing to use the benefit of reliable and high-speed mobile services to offer new services with new frameworks and policies being developed to expand on current solutions and develop innovative modern solutions in various sectors [3].

The success in cellular mobile communication starting from its early deployment, the 1980s, has created interest in wireless communications engineers and professionals to know more about radio propagation and its difficulties in the propagation media [4]. The radio propagation characteristics in different areas become important study areas in communication engineering. As the fast growth of mobile communications continues, it is very valuable to have the capability of determining optimum base-station locations, obtaining suitable data rates, and estimating their coverage, without conducting a series of propagation measurements, which are very expensive and time-consuming. Therefore, it is important to develop effective propagation models for mobile communications [5].

In wireless communication, the transmission of information is between transmitter and receiver antenna by electromagnetic waves. The electromagnetic wave (signal) from the transmitter did not reach the receiver with its strength at the transmitter. This is due to the degradation in the strength of electromagnetic waves during propagation through the environment. This degradation is called pathloss. It is a result of the obstacles in the propagation medium, distance and losses in the environment. Terrain contours, environment or morphology type, propagation medium, and antenna height and location have a direct relation with the pathloss [6].

Radio wave propagation depends on different factors like transmitting power, antenna gain, antenna height, feeder cable, propagation environment, mobile station antenna height and antenna gain, operation frequency, the distance between the transmitter and receiver and so on [7]. The propagation environment contains natural and manmade obstacles that affect the propagating signal. Natural obstacles are mountain hills, water bodies, trees, and climate and the manmade obstacles are like buildings, roads cars, and other movable objects. Mobile radio coverage and signal quality in radio communication systems need investigation and identification of the radio propagation phenomena [8].

Pathloss is a major factor in the analysis and design of wireless communication system. Therefore, proper prediction of pathloss is important for reliable estimation of base-station (BS) locations, radio signal coverage and system performance optimization [9]. There are many propagation pathloss prediction models that are based on theory and experiment for the prediction of the pathloss of wireless communication systems. Propagation pathloss models are mathematical calculations derived to estimate the signal's pathloss during transmission and the connected losses in a given environment based on varying parameters such as frequency band, distance, and obstacles in the path of transmission [10]. These models can be commonly classified into three groups: the deterministic, empirical, and statistical models [11].

- Empirical models are based on observation and measurement data rather than mathematically expressed environment. These models are well suited for the areas where measurements were performed, but usually needs to be adapted for different places.
- Deterministic models are based on the physical law of electromagnetic wave propagation, consider all the propagation mechanisms and estimate the propagation pathloss analytically. These models require detailed data which describe the environment.

- Statistical models use random variables to characterize the propagation environment by assigning probability distributions to channel parameters such as delay spread or small scale fading factors

The radio propagation models are very important for planning and optimization of wireless communication system. The models describe the behavior of the signal transmitted from the transmitter to the receiver and the pathloss [12],[13]. The prediction of propagation pathloss during propagation through the propagation medium is propagation pathloss modeling. The pathloss modeling is used for predicting the received power, coverage area, and link budget, interference analysis and cell parameters which are basic elements for the planning process in cellular systems. There are several pathloss prediction models available. Empirical models are the commonly used propagation pathloss models in many areas [14] .

In this thesis, the Artificial Neural Network (ANN) based propagation pathloss modeling is employed. The study area is typical built-up urban environment with the mix of residential, commercial and open areas. ANNs are popular because of the commanding capacity that they have in modeling exceptionally complex nonlinear functions. The FFBP neural network is the common type of neural network is used in the modeling process. ANN is called simply Neural Network (NN). NN is used throughout this document. NN has the main advantage in the computation capability of large data and flexibility to adapt to the different environments.

1.2 Statement of Problem

Radio propagation pathloss is a key factor in the design of any radio communications system. Any signal that is propagating from a transmitter to a receiver faces signal degradation or pathloss. Understanding the various elements affecting radio propagation pathloss helps in predicting the loss for a given path, or to predict the coverage that may be achieved by the networks or base-station. In addition to this, it enables the system to be designed to perform to its best despite the various issues affecting it. Since pathloss is affected by different factors, it makes the received signal prediction difficult to analyze the pathloss to be used in the planning and optimization of the communication systems.

Pathloss modeling is important in ensuring the proper coverage of any wireless network for the service intended. For the enhancement of quality of service and optimization of the system capacity, the role of pathloss is significant. There are many models developed for this purpose. These models are modeled for a specific area and when they are used in areas other than those areas, they are modeled for, they lose their accuracy.

The propagation pathloss model used for Addis Ababa coverage planning of UMTS networks by ethio telecom is one of the common empirical model called COST-231. It is not adopted for the case of Addis Ababa. There are coverage problems, poor quality of service and poor quality of experience in the networks. This is because of the model is not developed for the case of Addis Ababa. Propagation models depend on environment through which the signal is propagated. They have to capture the behavior of the environment. ethio telecom will have network deployment and optimization in Addis Ababa and need a best fitted model for the area. This thesis is intended to develop the neural network based model that can solve the problem with the empirical models.

1.3 Objectives

1.3.1. General Objective

The main objective of the thesis is to develop an outdoor propagation pathloss model for UMTS networks based on the feedforward backpropagation neural network and compare results against well known radio propagation models.

1.3.2. Specific Objectives

- Identify radio propagation pathloss prediction models for UMTS networks.
- Selecting study area and identifying input features and target values for the neural networks
- Model development using the neural network-based for prediction of the propagation pathloss
- Performance comparison of a neural network-based model against the standard propagation pathloss models using the statistical performance metrics
- Recommend the model with better performance in the prediction of pathloss in the study area.

1.4 Literature Review

The authors in [15] presented the neural network approach to model the propagation pathloss in five different areas: dense urban, urban, dense suburban, suburban, and rural in Tripoli, Libya. Real measured Received Signal Strength (RSS) is taken on a range of distance from base station to one kilometer on each area at three bands of frequencies, namely 900 MHz, 1800 MHz, and 2100 MHz. The ANN model was trained using 120 input-output pairs for 900MHZ and evaluated using the other 30 measured data. For the other frequencies, 80 input-output pairs were used for training and 20 for evaluation. Distance between the transmitter and receiver and RSS is used as input output pair. Comparison was done based on the RMSE between the measured pathloss, ANN model and Hata model. The ANN model was much closer to the real measurement data and gives 7.1 to 28.8 dB improvements in the accuracy over the Hata model. The paper considers only distance between transmitter and receiver as input feature and the number of samples used is very small.

Optimal model for pathloss prediction using the FFNNs was presented on [16]. Drive test measurements were carried out in Canaanland Ota, Nigeria and Ilorin, Nigeria to obtain pathloss data at varying distances from 11 different 1,800 MHz base station. FFNNs with single hidden layer were trained with normalized terrain profiles (i.e. longitude, latitude, elevation, altitude, clutter height) and normalized distance to produce the corresponding pathloss values based on Levenberg-Marquardt algorithm. The number of the neurons in the hidden layer are varied to achieve the best prediction accuracy. The performance of the NN models was evaluated based on different metrics: MAE, MSE, RMSE, SD, and R. The FFNNs with tangential activations functions for both the hidden and output layer and 48 hidden neurons yielded a least prediction error. Comparison was done based on the metrics between the optimal NN model and Hata, COST-231, ECC-33 and Egli models. The predictions produced by the optimal NN model also showed significant improvements: MAE decreased from 36.01 to 4.74 dB; MSE decreased from 1,628.1 to 39.38 dB; RMSE decreased from 40.35 to 6.27 dB; standard deviation decreased from 18.42 to 6.27 dB; and *R* increased from 0.14 to 0.86, when tested with new data not previously included in the training process. The authors taken the largest error recorded by the Egli model for the empirical models to be compared with the optimal NN model. The difference between the empirical and the optimal model is reduced if they have used the model with the minimum error, ECC-33. In general, the optimal NN model performed better in terms of prediction accuracy and generalization ability.

Joseph Isabona and Viranjay M. Srivastava [17] studied different artificial neural network models that are very effective for the prediction of signal power loss in a microcell environment in Obio-Akpor, Port Harcort, Nigeria. Distance from the transmitter and the signal power loss are taken for the training of the NN. Feedforward backpropagation algorithm is used for the prediction of electromagnetic signals with the right combination of learning and training functions. The network was trained with nine training functions using training datasets. To determine the number of neurons in the hidden layer, the trial and error method is used. The result showed NN with 20 neurons producing the best result for most of the training functions. The training functions differ with the convergence speed and the number of training epoch. Comparing the training functions based on the epoch, gradient descent (traingd) and gradient descent momentum (traingdm) are performed best. Bayesian regularization (trainbr) is very suitable for the data set with the least RMSE, MAE and SD but it converges with the highest number of iteration and in higher time than other training functions. In this study, as input feature only distance between the transmitter and receiver and as a target value the signal loss taken and the dataset size used is small. I have got a good insight about training alorithms and functions.

1.5 Methodology

The methodology followed in this thesis contains literature review, data collection, data preprocessing, model development and model evaluation. Literature review includes reading books, journals, articles, reports and other resources related to the topic. The data collection is done using drive test tools in the selected areas and additional data are from the low level design documents. Since the data collected can have noises, outliers, missing data, corrupted and incorrect data, it must be inspected, rearranged, modified and transformed to minimize noises and error in data analysis. This means the collected data is preprocessed and analyzed in a way that it is ready to be feed to the artificial neural network. The final preprocessed dataset contains the input features include the distance between the transmitter and mobile terminal, the location of the mobile terminal, the altitude, base station antenna height, azimuth angle and as output or target the pathloss. The preprocessed data is classified in to training, validation and test data.

After making ready the data, the next step will be the model development. The model development can be explained using three stages network initialization, network training and validation. In network initialization phase the neural network design parameters are selected and settled. The network training phase is where the training of the network is done using the training dataset provided and based on the the feedforward backpropagation training algorithms. The last one is the validation phase, after the training is stopped the network is checked for generalization. This is done by using test dataset which is dufferent from the training dataset and not used in the training process. The developed model will be evaluated to check its performance. The statistical performance metrics RMSE, MAE, MAPE, Coefficient of correlation and determination used to measure the performance of the network in relation to the empirical pathloss models.

The tools used for the measurement and data collection are drive test tools such as a laptop with licensed Nemo software, mobile terminal with Nemo software, and a Global Positioning System (GPS) device. In addition to this, Google earth and Global mapper are used in the data collection. The preprocessing and analysis are done using the software, Actix analyzer, MS-Excel and MATLAB.

1.6 Scope and Limitation of the Thesis

This thesis work uses the data collected using drive test carried out in selected areas of Addis Ababa and site-specific parameters from the low level design documents. The neural network model is trained and tested using the collected dataset. The output of the thesis can be mostly applied to areas of Addis Ababa and the area having a similar environment as Addis Ababa. The limitation or the difficulties observed in this work is getting the measurement of the clutter loss and impact of climate on the pathloss. Both affect the signal transmission negatively and aggravate the pathloss in the area. In addition to this, there is some limitation during measurement in areas where there is no access road for the vehicle.

Contribution of the Thesis

One of the common problems with mobile networks is low coverage and poor quality of service (QoS). Most of the time this happens as a result of input parameters used in the network planning phase. Pathloss is one of the major parameters in network planning. Several models are available for pathloss prediction. Among this, the common empirical models are the COST-231, tuned

COST-231, ECC-33 and SUI. Their performance is not good as compared to the neural network-based model which is the output of this thesis. This will initiate engineers and professional in the field to do more research in propagation pathloss to improve the coverage and QoS of the network.

This thesis can be an input for ethio telecom for coverage planning and optimization in Addis Ababa and similar geographic areas in the country to improve coverage area, interference analysis, frequency assignments and cell parameters which are basic elements for network planning in mobile systems thereby improve the system performance. As of my knowledge, the neural network-based pathloss prediction model is the first model in the country. This will initiate researchers in this field and others to use the artificial neural network in their research.

1.7 Layout of the Thesis

This thesis develops a neural network-based model for outdoor propagation pathloss prediction for the UMTS network. The rest of the thesis work is divided into six chapters. The first chapter focuses on the introduction which consists of background, problem statement, objectives, the methodology of the thesis and literature review. The second chapter deals with the UMTS network technology. In this chapter, Basics of UMTS network, the architecture of UMTS, UMTS radio network planning and radio wave propagation. In the third and fourth chapters, an NN theory and the measurement and modeling are discussed in detail. The NN theories introduce types of NNs, elements of NNs, NN architecture, training of NNs and Benefits of NN. Measurement and modeling is the core of the thesis. It starts with data collection through measurement and ends with the modeled network. The fifth chapter is about the performance comparison of the Neural network model with empirical models. The result of the thesis is documented in this chapter. The last chapter is on the conclusion of the thesis. This includes overall results and their justifications.

2 Universal Mobile Telecommunication System

2.1 Basics of UMTS

UMTS is a third-generation mobile communication system specified by the 3rd Generation Partnership Project (3GPP) to support a wide range of applications with different QoS profiles. UMTS brings an evolution in terms of highly enhanced capacity, data rates and new service capabilities from 2G systems. It brings global mobility and high-speed transmissions with a wide range of services including voice telephony, messaging, images, video, Internet access, and broadband data, whereas traditional 2G mobile systems were built mainly for speech service [18],[19], [20].

On evolving from the second generation, Global System for Mobile Communication (GSM) to the 3G, UMTS provides three major areas technical, network, and services. In the technical area how the development path of network elements will be realized and with what kind of technology. The network evolves to support the changes that come with the evolution of the technical and this will have brought the evolution of the network elements. Service evolution is based on the real or imagined demands generated by the end-users.

The air interface of UMTS is based on wideband code division multiple access (WCDMA) technology that uses the direct-sequence spread-spectrum method of asynchronous code division multiple access to achieve higher speeds and support more simultaneous users compared to the implementation of Time division multiple access (TDMA) and frequency division multiple access (FDMA) used by the GSM networks. Within 3GPP, WCDMA is called universal terrestrial radio access (UTRA). It has two modes of operation, namely UTRA-FDD (Frequency Division Duplex) and UTRA-TDD (Time Division Duplex). UTRA-FDD uses paired frequency bands for uplink (UL) and downlink (DL) data transmissions, whereas UTRA-TDD uses a common frequency band for both directions and adjusts the time domain portion assigned for UL and DL transmissions dynamically [21],[22].

2.2 UMTS Architecture

A UMTS network contains three main parts: user equipment (UE), universal terrestrial radio access network (UTRAN), and core network (CN). Interfaces and functionalities of each are depicted in 3GPP standards. Figure 2.1 shows the detailed structure of the UMTS network architecture [21].

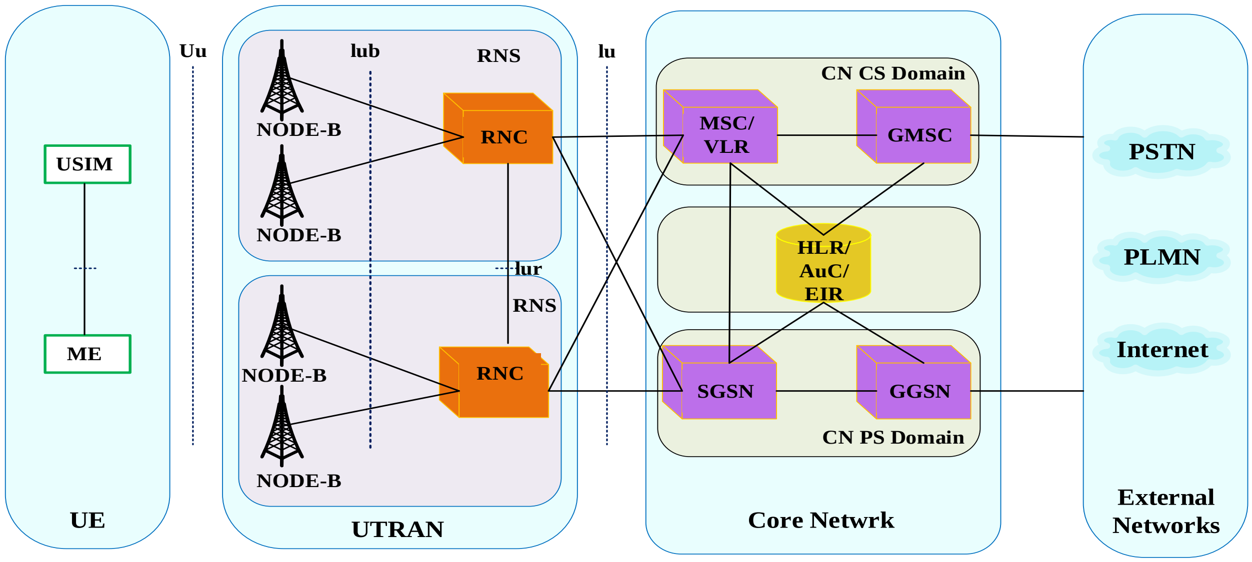


Figure 2.1 Architecture of UMTS network [21]

User Equipment (UE): interfaces with the user and consists of Mobile Equipment (ME) and UMTS Subscriber Identity Module (USIM). ME is the single or multimode terminal used for radio communication and USIM is a smart card that holds the subscriber identity, subscribed services, authentication, and encryption keys. UMTS UE can operate in either Packet Switching (PS) and Circuit Switching (CS) modes or only packet switch mode or only circuit switch mode of operation. USIM and ME communicate over the internal Cu interface. The UE accesses the fixed network via the Uu radio interface [23], [24][25].

UTRAN: establishes connectivity between the UE and the core network and is responsible for managing and operating the radio access to the UE. UTRAN contains several Node-Bs and Radio Network Controller (RNC). Node-B is equivalent to BTS in GSM/General Packet Radio Service (GPRS) and responsible for radio transmission/reception in one or more cells to/from the UE. It performs and reports radio measurements to the RNC. It also performs the air interface processing such as channel coding, rate adaptation, spreading, synchronization and power control [23], [25].

Radio Network Controller (RNC): is like a BSC in the GSM network and responsible for the integrity of the radio resource within Radio Network Subsystem (RNS) management and control of the Node B’s. Radio resource control, admission control, channel allocation, power control settings, handover control, macro-diversity, ciphering, segmentation/reassembly, broadcast signaling, and open-loop power control are functions for RNC. It is the central element of the UTRAN responsible for the control of the radio resources in all attached cells [24], [25].

The 3GPP standard defines four interfaces related to the UTRAN: Uu, Iu, Iub, and Iur. The Uu is the radio interface of UMTS based on WCDMA technology, located between the UTRAN and the UE. It realizes the radio connection between the UE and the Node B. The Iu interface is the interface that connects the UTRAN to the Core Network. Depends on the type of traffic, i.e. packet-switched or circuit-switched traffic, the Iu is divided into Iu-CS and Iu-PS. The Iub and Iur interfaces are used to connect the functional entities inside the UTRAN. The Iub interface connects RNC and Node B, while the Iur interface connects two RNCs with each other [24].

2.3 UMTS Radio Network Planning

UMTS radio network planning includes dimensioning, detailed planning and network optimization. The process of the UMTS radio network planning is illustrated in Figure 2.2. Dimensioning phase estimates the number of base stations and their configurations and other network elements, based on the operator’s requirements and the radio propagation in the area. The coverage, capacity, and QoS are done in accordance with the operator’s requirement [26].

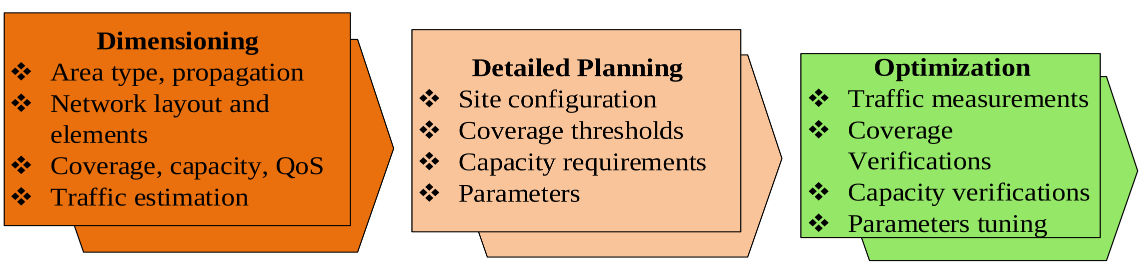


Figure 2.2 Radio network planning [22]

In detailed planning, real propagation maps and operator’s traffic estimates in each area are required. The base station locations and network parameters are selected by the planning tool and/or the planner. Capacity and coverage can be analyzed for each cell after the detailed planning. The third process of planning is when network is in operation, its performance can be observed by measurements, and the results of those measurements can be used to visualize and optimize network performance. The planning and optimization process can also be automated with intelligent tools and network elements [27].

The UMTS planning bases on the coverage, capacity, and QoS of the network to be deployed. Figure 2.3 shows the trade-off between the coverage, capacity, and QoS. Making the right balance between these three parameters will have a significant impact on the ability of the network to perform in an optimal manner, and in turn, will ensure the all-important return on investment can be achieved. If this is performed in a good way, both parties, the service provider or the operator and the user or the customer of the operator will be beneficiary. But if it is done in the other way means that an incorrect way, additional base stations will be required, and the business case will be negatively affected. When the three trade-offs are optimized, an individual balance is achieved to offer the best real-life scenarios [22].

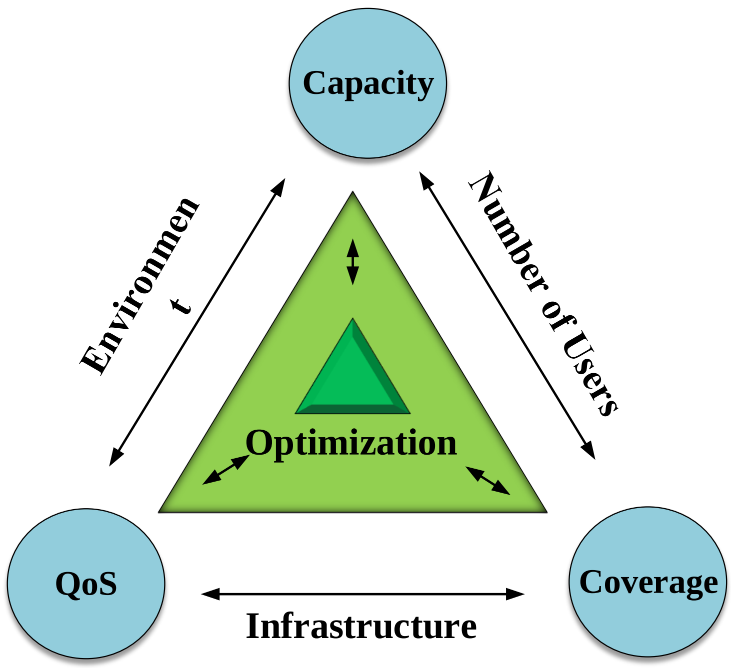


Figure 2.3 The Coverage, Capacity, and Quality Model (CCQ) [20].

The UMTS radio interface has special characteristics for different propagation environments that can be classified into outdoor macrocellular, outdoor microcellular, and indoor propagation types [28]. A macro cellular environment contains an urban, suburban and rural type of area, depending on the building or other obstacle density. Different propagation environments have different behaviors. These behaviors can be defined by some parameters: multipath propagation, angular spread, delay spread, fast fading and coherence bandwidth, slow fading, and propagation slope [22].

One of the factors that make the planning process difficult is the propagation environment. The signal propagation is not limited to the free space where there are no obstacles in the propagation environment between the transmitter and receiver. In areas where there are manmade and natural obstacles, no line-of-sight (LOS) between transmitter and receiver, the signal propagates through reflection, diffraction and scattering. The received signal is signals due to free space, reflection, diffraction and scattering. When these signals reach at the receiver, they will have different amplitude and arrival time. This will create multipath effect, which leads to the fading effect at the receiver. The fading effect is varying with the obstacles in the propagation environment thereby affect the received signal. Since signals reach at the receiver at different time, the result of their superposition is very difficult. This makes it hard the radio network planning process [22],[29],[30] . The next section deals with radio wave propagation.

2.4 Radio Wave Propagation

Radio propagation is the behavior of radio waves as it emits from the transmitter and propagates to the receiver through the communication media. Radio propagation plays a key role in the planning and optimization of coverage of radio systems. It influences the coverage, capacity and QoS of the communication systems. Figure 2.4 shows a typical mobile radio propagation system.

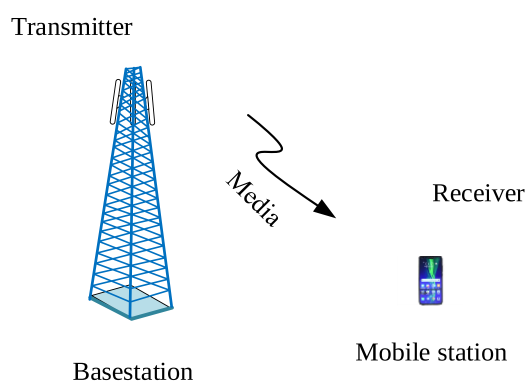


Figure 2.4 Typical radio propagation system

In mobile communication, when a mobile station or user moves, the radio wave propagation is affected by the distance moved by the mobile station from the transmitter and natural and man-made objects found in the direction of propagation. Man-made objects like buildings, cars, roads and trees and vegetation, and natural objects like atmospheric effects, hills, water bodies, and terrain of the earth surfaces can be listed as objects that affect the radio propagation. In addition to this, the time of the day and the season of the year have a great impact on the propagation [31].

As the distance from the base station increases, the signal strength decreases. This is caused by the fact that the signal spread out as a signal travels longer distance. It is termed as free space propagation. The area of the surface is proportional to the radius squared and the signal strength is inversely proportional to the area of the surface, and hence the signal strength is inversely proportional to the distance squared from the transmitter to the receiver. [32]. When there is a building or another obstacle is found between the transmitter and the receiver or mobile station, the signal will reach the mobile station slowly and reduced. This is called a slow fading. Another mobile radio phenomenon caused by the arrival of the signal from several paths creates a fast fading. One can directly from the base station to the mobile via a LOS path. The others are reflected off buildings and other obstacles behind the mobile and back into the mobile antenna.

2.4.1 Radio wave Propagation Mechanisms

Radio wave propagate from the transmitter to receiver via different propagation mechanisms. Theses mechanisms are shown in Figure 2.5. When the propagated signal reaches the receiver in a single path, without any obstruction, It is called propagation along LOS path. Among the received signals, LOS component has the shortest time of delay and usually the strongest received signal. Transmitted signals travels through propagation medium reaches the receiver in one or more indirect path, each with different attenuations and delays are known as NLOS propagation. The main NLOS propagation mechanisms are reflection, diffraction, and scattering. [20], [21], [22], [33].

Reflection is the phenomenon that occurs when propagating electromagnetic waves or Radio Frequency (RF) signal strikes or encounters the surface with a wavelength greater than that of the propagating signal wavelength. When radio waves traveling on between huge buildings or mountains, the signal is reflected due to the surface structure. The reflected signal is not as strong as the original, as an object can absorb some of the signal’s power [34][35].

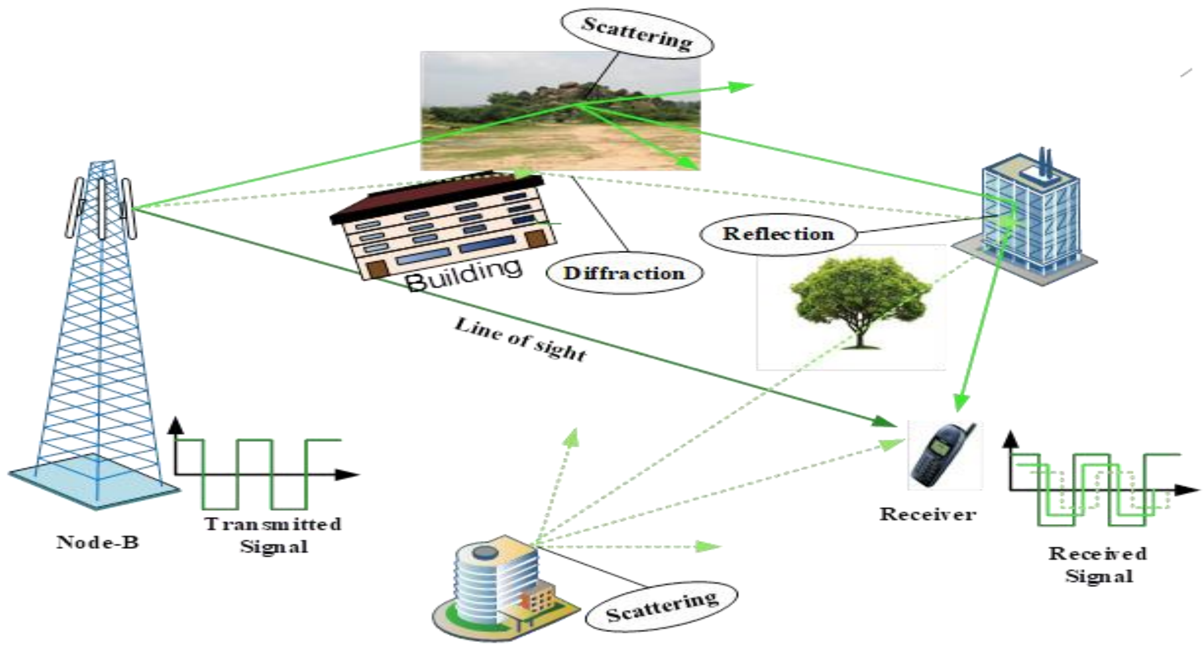


Figure 2.5 Radio wave propagation mechanism [23],[24].

Diffraction is ocuurs when a signal having wave length comparable to the size of an object impinges the object and if there are sharp edges, the signal 'diffracts' across the edges. Diffraction is also observed in a city with buildings [36]. Important examples of diffraction include waves bending over the tops of buildings, around street corners, and through doorways. Radio waves will be deflected at the edge and propagate in different directions. This can mean that a signal may be received from a transmitter even though it may be ''shaded'' by a large object between them. Diffraction is more pronounced when the obstacle becomes sharper and more like a ''knife-edge'' [33].

Scattering is the divergence of the electromagnetic wave when it strikes a rough surface or impurities in the environment. Dust, humidity, unevenness and other qualities in a material can cause a signal to scatter in all directions. This can have a significant impact on signal integrity and strength. The emitted energy can be channeled along a given direction using a waveguide. The propagation is achieved in this case by successive reflections of the waves off the surfaces of the waveguide. Certain environments, for instance, canyon streets, corridors, or tunnels behave like waveguides with respect to the propagation of radio wavesn [33].

A wave that is emitted from the transmitter may take different paths depending on the nature of the obstacles that it faces during their propagation. They are subjected to different phenomena like reflection, diffraction scattering, and refraction. This results in a multitude of elementary paths. Each such path is characterized at the receiver level by an attenuation, a delay, and a specific phase difference. This mode of propagation is referred to as multipath propagation. The different waves propagated along such multiple paths interfere at the receiver.

2.4.2 Radio Propagation Pathloss Models

Pathloss propagation models are mathematical formulas derived from experimental data for predicting a propagation pathloss in a given environment based on varying parameters such as frequency, distance and the obstacles in the path between transmitter and receiver. The models are developed to assist the prediction of path behavior and pathlosses when a variety of complex conditions exists that make the measurement of all the actual parameters impossible. There are several models to estimate pathloss[37].

Radio propagation models are divided into large-scale and small-scale models. Large-scale models occur in the order of thousands of meters in distance. It is used in network planning, in link budget calculations, network capacity prediction and they capture the loss in received signal strength as a function of distance. Small scale models are localized and occur temporally in the order of a few seconds or spatially in the order of a few meters. They are characterized by the rapid fluctuations of the received signal strength over short travel distances or short time durations [38][39]. Small-scale models influence physical layer link design, modulation schemes, and equalization strategies by capturing local constructive and destructive multipath effects [33],[40]. In this thesis work, we focus on the large-scale models.

In large-scale modeling, the transmitter and the receiver could be in line-of-sight or non-line of sight in an environment surrounded by buildings, trees and other objects. The receiver may receive a direct attenuated signal called a line of sight signal from the transmitter and indirect signals called the non-line of sight signal due to other physical effects like reflection, refraction, diffraction and scattering. The direct and indirect signals could also interfere with each other. Large-scale models can be divided in to three. These are deterministic, statistical and empirical models [41][42]. Figure 2.6 shows the classification of models.

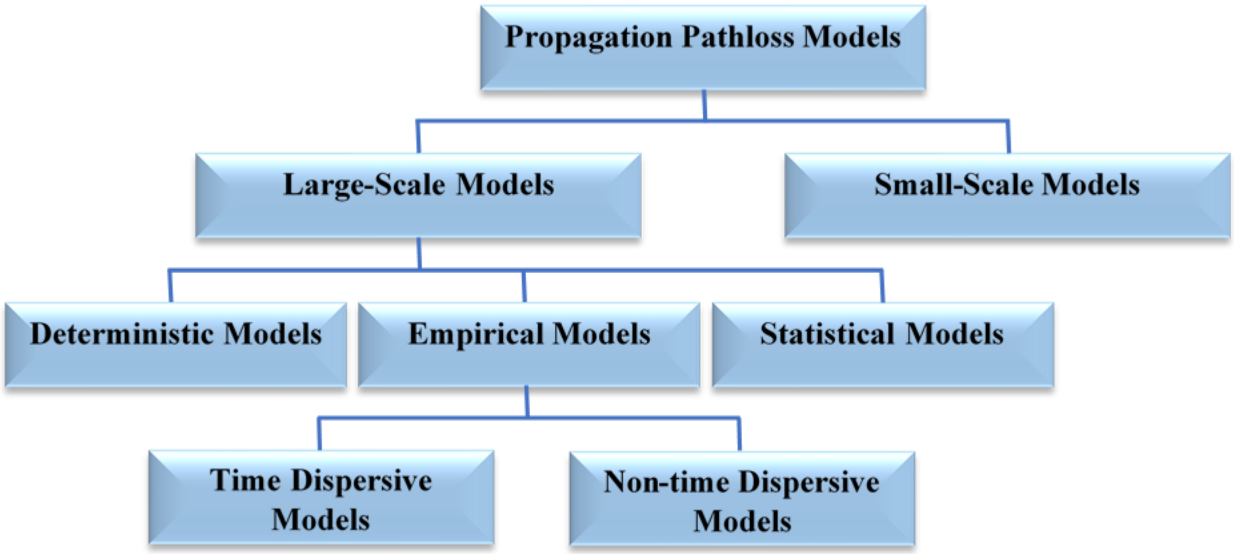


Figure 2.6 Classification of propagation pathloss models [42]

I. Deterministic Models

Deterministic models are based on the laws governing electromagnetic wave propagation to determine the received signal power at a particular location. They rely on basic principle of physics rather than statistical outcomes from the experiments. These model uses physical principles of electromagnetic waves propagation to predict signal levels in a generic environment in order to develop a simple relationship between the characteristics of that environment and propagation [43]. The feature that affects the capabilities and success of a deterministic model is the kind of information about the propagation environment. The quality of the model's predictions is a direct consequence of how the model maps the real propagation environment into the model propagation environment. Deterministic models require more computation and they are more accurate. An example of a deterministic model is a ray tracing model. They require more computation and are more accurate [5][44],[45][46],[47].

II. Empirical Models

Empirical models are models which are built upon the framework of the general pathloss formula and based on observation and measurement data. Mathematical expression that describe the pathloss is obtained by using the measurement data and regression techniques. They are used for the prediction of pathloss. These models are well suited for the areas where measurements were performed, but usually needs to be adapted for different places [48]. The accuracy of the empirical models depends on the environment in which the original data for the model is taken and how much this environment is universally applicable [47]. The common problem in usage of empirical pathloss models is using a model in areas where the propagation environment is widely different from the environment in which the model is developed. For example, Okumura tries to mitigate this problem by including correction factor, but unless the characteristics of ‘urban’, ‘suburban’, and ‘open are reasonably similar to those in Japan where the measurement data were taken, the problem sustains. Regardless of their limitation, empirical models are widely used since they are simple and allow fast computer calculations [47].

Empirical models are further classified as time dispersive and non-time dispersive models. Time dispersive provides information about time dispersive behavior of the channel, i.e., the multipath delay spread of the channel. Non-time dispersive models use some data sets and a statistical analysis of the data to construct a curve through the data. The main aim is to predict the average pathloss as a function of antenna heights, height above average terrain, terrain roughness, or other parameters such as local clutter (foliage and buildings). SUI, Hata [8] and the COST-231 Hata model [3]. are example for non-time dispersive model [42],[47][45].

Time dispersive is modeled to predict the pathloss from channel measurement results. It provides information about time dispersive behavior of the channel, that is the multipath delay spread of the channel. SUI model is an example of the time dispersion model. Non-time dispersive models use measurement data sets and a statistical analysis of the data to construct a curve through the data. The main aim is to predict the average pathloss as a function of antenna heights, height above average terrain, terrain roughness, or other parameters such as local clutter (foliage and buildings). Hata, COST-231 and Egli models are examples for non-time dispersive model [42][47][45].

III. Statistical Models

Statistical models use random variables to characterize the propagation environment by assigning probability distributions to channel parameters such as delay spread or small scale fading factors [42]. As in empirical modeling, propagation experiments and statistical analysis are performed to validate the goodness-of-fit each parameter distribution. Based on the fitness of data, as necessary the correction factor can be introduced. These models are commonly used in the planning of green field or open area deployments and evaluation since they rely on simple parameters. They offer simple single-slope log-distance expressions that are used to predict the mean pathloss induced at a given distance, *d* from the transmitter. Basic examples of statistical models include the Rayleigh and Rician fading models, which are based off of a set of commonly applied channel statistics and broadly applicable to many different environments [43].

Among the large-scale models, the commonly used models for the prediction of propagation pathloss for UMTS network are presented below. These models include the free space pathloss, Tuned COST-231, COST-231, ECC-33 AND SUI.

a) The free space pathloss

Pathloss in free space can be defined as the ratio of the transmitted power to receiver power in free air. It is expressed in decibels. Free space pathloss is depends on frequency and distance. Mathematically free space Pathloss is defined as [50],[51],[52].

$$PL = 10n\, log_{10}\, d + 10n\, log_{10}\, f + 32.44 \quad \text{------------------} \quad (2.1)$$

Where

n is the pathloss exponent. The value of n for free space pathloss is 2.

$$PL = 20\, log_{10}\, d + 20\, log_{10}\, f + 32.44 \quad \text{------------------} \quad (2.2)$$

f is the frequency of operation in MHz.

d is the distance between the transmitter and receiver in m.

b) COST-231 Hata Model

The COST-231 model was the extension of the Okumura Hata Model. It is widely used for the prediction of propagation pathloss in a mobile wireless system. The Cost-231model is designed to be used in the frequency band of 1500 MHz to 2000 MHz. It was made to be used in different terrains with correction. The common terrains types are: Rural or open area where the area is open space without tall buildings or trees, suburban area are paths with obstacles near the receiver such as village or high way with few trees and houses, and the other is the urban area which contains large buildings having more than two floors or large villages with congested houses and tall trees. Its simplicity and the availability of the correction factors have been made it widely used for wireless propagation pathloss prediction model. The basic equation for pathloss in dB is [53],[42],[54]:

$$PL = 46.3 + 33.9 \log_{10} f - 13.82 \log_{10} h_b - a(h_m) + (44.9 - 6.55 \log_{10} h_b) \log_{10} d + C_m \quad \text{----} \quad (2.3)$$

Where f is the frequency in MHz, d is the distance from the base station to the mobile antenna in (km), and h_b is the base station antenna height above ground level in meters, h_m is a mobile station antenna height. C_m is the correction factor for a suburban or open environment to be 0 dB and for urban environment 3 dB. The parameter $a(h_m)$ is defined for urban and suburban respectively as:

for urban:

$$a(h_m) = 3.2(\log_{10}(11.75h_m))^2 - 4.97\ , for\ \ f > 400MHz \text{ - - - - - - - - - } (2.4)$$

And

for subuarban or rural:

$$a(h_m) = (1.1\log_{10} f - 0.7)h_m - (1.5 \log_{10} f - 0.8) \text{ - - - - - - - - - - - - - - } (2.5)$$

Where h_m is the mobile antenna height above the ground level. It's quiet suitable for large cell mobile systems. The model requires the base station antenna to be higher than all adjacent rooftops.

c) Tuned COST-231

The tuned COST-231[55] is adapted from the normal COST-231 to fit the environment of Addis Ababa. The tuning is done using the Linear Least Square Method (LLSM) for the area. Assumption taken for the tuning is the tuned parameters of the pathloss models depend on variables of the pathloss model (MS and BTS antenna heights, frequency and distance) and the data measurement. The data measurement is taken at different frequencies (f), different MS and BTS antenna heights (h_m, h_b) and distances. To simplify the calculation, average MS and BS antenna heights and a fixed frequency are used.

The optimized (tuned) COST231 equation will be:

$$PL_{TC} = 49.36 + 33.9 \log_{10} f - 13.9 \log_{10} h_b - a(h_m) + [37.27 - 5.44 \log_{10} h_m] \log_{10} d \text{ - - - - } (2.6)$$

Where f is the frequency in MHz, d is the distance from the base station to the mobile antenna in (km), and h_b is the base station antenna height above ground level in meters, h_m is a mobile station antenna height. $a(h_m)$ is taken as in the case of COST-231.

d) Stanford University Interim (SUI) Model

Stanford University jointly with the 802.16 IEEE, Broadband Wireless Access working group carried out extensive work and developed the SUI model. SUI model is an extension of the Hata model for frequency greater than 1900MHz and the correction parameters allowed to extend up to 3,5GHz band. The base station antenna height of the SUI model can be used from 10 m to 80 m. The receiver antenna height is from 2 m to 10 m. The cell radius is from 0.1 km to 8 km [54]. The

SUI model defines the terrain as terrain A, terrain B, and terrain C. Terrain A can be used for hilly areas with moderate or very dense vegetation. This terrain presents the highest pathloss. Terrain B is characterized by the hilly terrains with rare vegetation or flat terrains with moderate or heavy tree densities. This is the intermediate pathloss scheme. Terrain C is suitable for flat terrains or rural with light vegetation, here pathloss is minimum. The basic pathloss expression of The SUI model with correction factors is presented as [46].

$$L = A + 10\gamma \log_{10}\left(\frac{d}{d_0}\right) + X_f + X_h + S, \quad for\ d > d_0 \text{ -------------- } (2.7)$$

where d is the distance between the base station and mobile antenna in (meters), d_0 =100m, X_f is the correction for frequency above 2GHz in (MHz), X_h is the correction for receiving antenna height, S is the correction for shadowing in dB and γ is the pathloss exponent. The random variables are taken through a statistical procedure as the pathloss exponent γ and the weak fading standard deviation S is defined. The log-normally distributed factor S, for shadow fading because of trees and other clutter on a propagation path and its value is between 8.2 dB and 10.6 dB. The parameters A and pathloss exponent γ is defined as

$$A = 20 \log_{10}\left(\frac{4\pi d_0}{\lambda}\right) \text{ ------------- ---- ----- -------- } (2.8)$$

and

$$\gamma = a - bh_b + \left(\frac{C}{h_b}\right) \text{ ---------- ------------------ --- } (2.9)$$

where, λ is the wavelength in (meters), h_b is the base station antenna height in meters. Takes the range between 10m to 80m. The constants a, b, and c depend on the type of the terrain and given in Table 2.1.

The value of pathloss exponent, γ is different for different terrains: $\gamma = 2$ for free-space propagation in the urban area, 3< γ<5 for urban Non-Line of Sight (NLOS) environment [54]. The frequency correction factor X_f and the correction factor for receiver antenna height X_h for the model are:

$$X_f = 6.0 \log_{10}\left(\frac{f}{2000}\right) \text{ ------ ------ ------------------ } (2.10)$$

and

$$X_h = \begin{cases} -10.8\log_{10}\left(\frac{h_r}{2000}\right), for\ terrain\ A\ and\ B \\ -20.0\log_{10}\left(\frac{h_r}{2000}\right), for\ terrain\ C \end{cases} \text{ - - - - - - - - - - - - (2.11)}$$

Where f is the operating frequency in MHz and h_r is the receiver antenna height in meters.

SUI uses these correction factors for pathloss prediction for the three terrain types defined. For our case, we use the terrain types: A, B, and C as urban, suburban and rural areas. Table 2.1: Different parameters for different terrain for SUI Model

Table 2.1 Different Parameters for Different terrain for SUI Model

Model Parameter	**Terrain A**	**Terrain B**	**Terrain C**
a	4.6	4	3.6
b(m-1)	0.0075	0.0065	0.005
c(m)	12.6	17.1	20

e) ECC-33 Model

The Electronic Communication Committee (ECC) developed ECC-33 pathloss prediction model by extrapolating the Okumura-Hate's unique measured data. The model is specially adapted for medium- and large cities and includes correction factors for suburban and open areas [40]. This model is effective in a frequency range from approximately 700 MHz to 3.5 GHz. The ECC-33 path-loss model is given by [56][57][16][3]:

$$PL[dB] = A_{fs} + A_{bm} - G_t - G_r \text{ - (2.12)}$$

where

A_{fs} is the free-space attenuation, A_{bm} is the elementary mean-pathloss, G_t is the source elevation gain factor and G_r is the receiver antenna gain factor.

Each of these factors is individually specified as:

$$A_{fs} = 92.4 + 20\log_{10} d + 20\log_{10} f \text{ - - - - - - - - - - - - - - - - - - - (2.13)}$$

where d and f are the distance between the source and the subscriber in km and the carrier frequency in GHz, respectively.

$$A_{bm} = 20.41 + 9.83\log_{10} d + 7.894\log_{10} f + 9.56(\log_{10} f)^2 \text{ - - - - } (2.14)$$

where d and f are the distance between the source and the subscriber in km and the carrier frequency in GHz, respectively.

h_t - transmitter antenna height (from 20 to 100 m):

$$G_t = \log_{10}(\frac{h_t}{200})(13.958 + 5.8(\log_{10} d^2)) \text{ - - - - - - - - - } (2.15)$$

Where, h_t is the height of the transmitting antenna

h_r- receiver antenna height (from 5 to 10m):

$$G_r = 0.795h_r - 1.862 \text{ - - - - - - - - - - - - - - - - - - } (2.16)$$

Where, h_r is the height of the receiver/subscriber antenna

NN-base models try to combine the advantages of empirical and deterministic models. The advantages of the empirical is ease of computation and that of deterministic is accuracy. NNs are composed of several nodes or neurons divided into different levels with connections between them. The neurons may receive several input signals which are combined using appropriate weights and passed through specific transfer functions. To specify the various weights, the network must be trained. Training is carried out using the measured data. Depending on the quality of the training process so will be the ability of the NN to make predictions in unknown situations: generalization property.

3 Neural network

3.1 Introduction

The NN is designed with the analogy of the biological nervous system with respect to architectural and information processing strategies. The network has three layers namely the input, the hidden and the output layers. The input layer represents predictor or independent variables, and the output layer represents the dependent or criterion variable. The hidden layer used to map the input independent variables to the output dependent variables. Neural networks are built and trained to find patterns in data that can be mapped to the output variable. Mapping in the hidden layer(s) of the network is where independent or input data are weighted, summed and applied as input to the transfer function. The output of the transfer function is weighted, summed and feed to the output layer transfer function. The transfer function in this layer is usually a linear transfer function. The predictor derived from the transfer function is compared to the target or the actual value from the dataset, the error is calculated, and backpropagated through the network. This process continues until the error falls into an acceptable range, the data pass through the network many times, weights are adjusted, and error is reduced. To handle the complex pattern of the nonlinearity, the activation function in the hidden layer has to be nonlinear like sigmoid [58].

The development of the models for the prediction or estimation of propagation pathloss that can describe the actual propagation condition is very important for the implementation of mobile communication systems. The drawbacks with the existing empirical models are that they are based on coarse/ rough approximations, and do not include the properties of the environment in which the signal is propagating through in an appropriate manner. NN comes as a solution for the propagation pathloss modeling and a very convenient alternative to the deterministic, empirical and ststistical models which often do not provide adequate results from the aspect of computation time, overhead and accuracy [8-12]. NN models based on the International Telecommunication Union (ITU)-R P370.7 recommendation, shown a high calculation rate and sufficient accuracy for the propagation pathloss prediction in terms of the macro propagation [59].

3.2 Types of Neural Networks

Neural networks can be classified as a single layer feedforward network, multilayer feedforward network and recurrent neural networks based on their topology. A brief explanation of each model is presented in the below sub-sections.

3.2.1 Single-layer feedforward network

A neural network in which the input layer of source nodes projects into an output layer of neurons but not vice-versa is known as a single layer feedforward network. In other words, a hidden layer is absent or not present in the network and there is no feedback from the output or hidden layer. In the single-layer network, 'single-layer' refers to the output layer of computation nodes as shown in Figure 3.1.

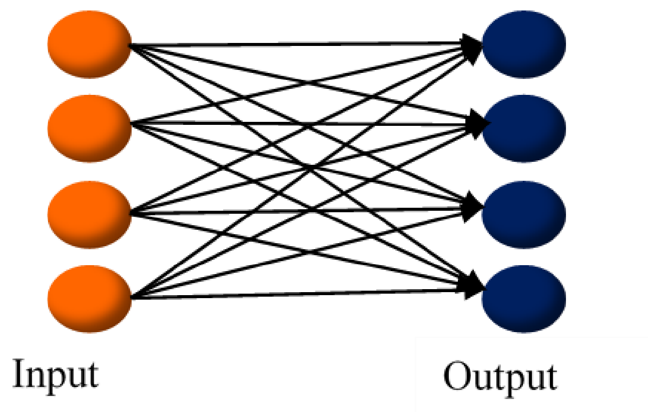


Figure 3.1 single layer feed-forward network [60]

3.2.2 Multilayer feed-forward network

This type of network consists of one or more hidden layers, whose computation nodes are called hidden neurons or hidden units. The function of hidden neurons is to interact between the external input and network output in some useful manner and to extract higher-order statistics. The source nodes in the input layer of the network supply the input signal to neurons in the second layer (1st hidden layer). The output signals of the second layer are used as inputs to the third layer and so on as in Figure 3.2.

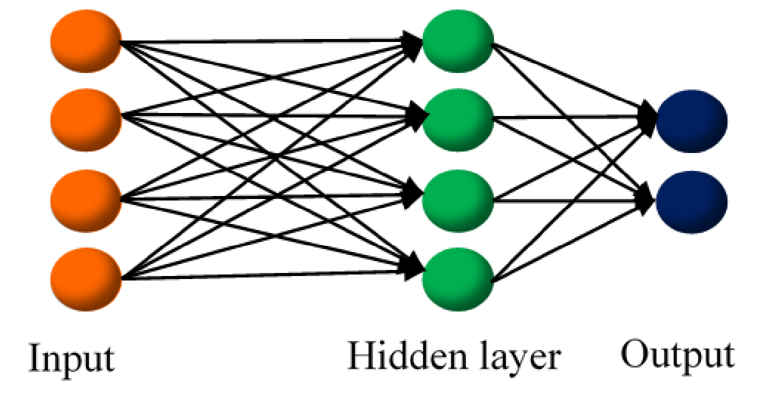


Figure 3.2 A multilayer feed forward network [61]

The overall response of the network to the activation pattern supplied by source nodes in the input first layer. Short characterization of feedforward networks:

1. Typically, activation is fed forward from input to output through ‘hidden layers.
2. Mathematically, they implement static input-output mappings.
3. Most popular supervised training algorithm: back-propagation algorithm
4. Have proven useful in many practical applications as approximates of nonlinear functions and as pattern classification.

3.2.3 Recurrent Network

A feedforward neural network having one or more hidden layers with at least one feedback loop is known as recurrent network as shown in Figure 3.3. The feedback may be a self-feedback, i.e., where the output of the neuron is fed back to its own input. Sometimes, feedback loops involve the use of unit delay elements, which results in nonlinear dynamic behavior, assuming that neural network contains nonlinear units.

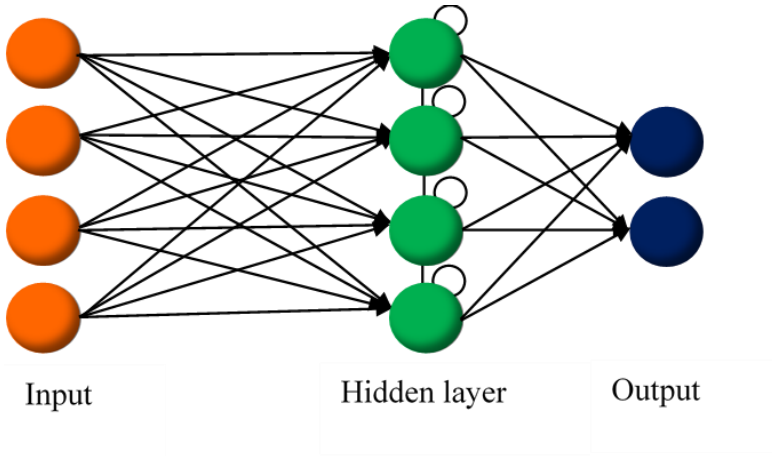


Figure 3.3 A recurrent network [62]

There are various other types of networks like; delta-bar-delta, Hopfield, vector quantization, counter propagation, probabilistic, Hamming, Boltzman, etc.

3.3 Neural network architecture

Neural network architecture refers to the arrangement of neurons in the layers and the connection patterns between layers, activation functions, and learning methods. The neural network model and the architecture of a neural network determine how the network transforms its input into an output. Figure 3.4 shows the architecture of the neural network used in this work [61].

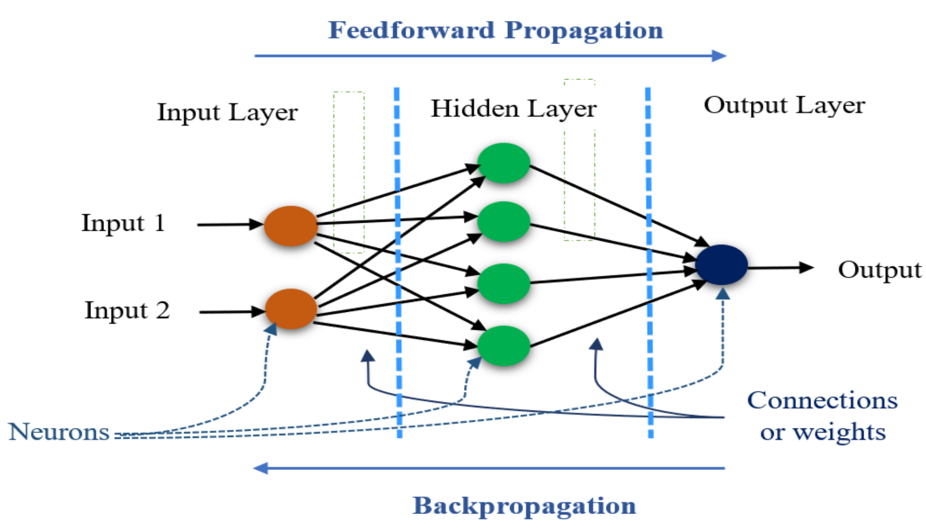


Figure 3.4 Architecture of neural networks [61]

Input Nodes (input layer): No computation is done here within this layer; they just pass the information to the next layer (hidden layer most of the time). A block of nodes is also called layer.

Hidden nodes (hidden layer): In hidden layers is where intermediate processing or computation is done, they perform computations and then transfer the weights (signals or information) from the input layer to the following layer (another hidden layer or to the output layer).

Output Nodes (output layer): Here we finally use an activation function that maps to the desired output format.

Connections and weights: The network consist of connections, each connection transferring the output of a neuron i to the input of a neuron j. In this sense, i is the predecessor of j and j is the successor of i, each connection is assigned a weight W_{ij}.
Neuron (artificial neuron) is the basic units of an artificial neural network. It receives inputs and generates an output which is a weighted combination of all the inputs. The basic artificial neuron is shown in Figure 3.5.

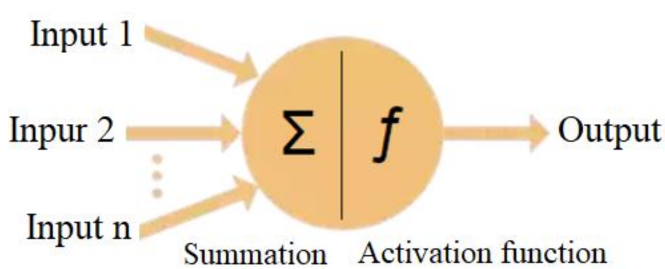


Figure 3.5 Basic artificial neuron

Activation function: the activation function of a node defines the output of that node given an input or set of inputs. A standard computer chip circuit can be seen as a digital network of activation functions that can be "ON" (1) or "OFF" (0), depending on the input. This is similar to the behavior of the linear perceptron in neural networks. However, it is the nonlinear activation function that allows such networks to compute nontrivial problems using only a small number of nodes. In artificial neural networks, this function is also called the transfer function.

3.4 Training of Neural Networks

3.4.1 Types of neural network training

Training is the process by which the parameters of the neural network are estimated to fulfill the work of the network as accurate and efficient as possible. Training can be categorized into three as supervised, unsupervised and reinforced training [63].

a) Supervised Training

In this method, both the inputs and associated outputs called desired or target output are provided. The network then processes the inputs and compares its resulting outputs against the desired outputs. The error between the network output and the desired value is computed. Then, errors are propagated back through the system, causing the system to adjust the weights, which control the network. This process will be repeated until the error drops in the acceptable range.

The set of data that are used for the training the network is called training dataset., during the training of a network, the same set of data is processed many times, as the connection weights are refined. Sometimes a network may never learn. This could be because the input data does not contain the specific information from which the desired output is derived.

In this training type part of the dataset is kept for testing. After training the network, it has to be evaluated whether the trained network is efficient and accurate enough to be used as a model for the application requested. If the trained network fails, inefficient and inaccurate then the designer has to review the input and outputs, the number of layers, the number of elements in the per layer, the transfer and the training functions and even the initial weights.

b) Unsupervised or adaptive training

The second type of neural network training is unsupervised training (learning). In this type, the network is provided with inputs but no desired or target outputs presented. The system itself must then decide what features it will use to group the input data. This is often referred to as self-organization or adaption. These networks use no external influences to adjust their weights. Instead, they internally monitor their performance. These networks look for regularities or trends in the input signals and make adaptations according to the function of the network. Even without being told whether it's right or wrong, the network still must have some information about how to organize itself. Competition between processing elements could also form a basis for training. The training of the network still must have some information about how to organize itself. Competition between processing elements could also form a basis for training. The training of the network should discover the similarities between the input features and translate them into new data representation. When competition for training is in effect, only the weights belonging to the winning processing element will be updated.

c) Reinforced Learning

Reinforced Learning: In Reinforced learning, the output is generated by the network. The output generated is further made to undergo comparison with hints as to whether the output is correct or incorrect. The network is rewarded for a computed correct answer, and a penalty is laid for an incorrect answer. In this work, we follow the supervised mode of learning is used to train the neural network.

3.5 Backpropagation Training Algorithm

The backpropagation training algorithm is a supervised training algorithm that is used to train the multilayer feedforward backpropagation neural network in many applications. It is used to update the network weights during training in order to improve network performance. It uses the gradient descent algorithms to reduce the performance function or the cost function through updating the neural network weights by moving them along the negative of the gradient of the performance function. The performance function is the error function computed as the difference between the network output and the desired or the target value. The term backpropagation refers to the manner in which the gradient is computed for nonlinear multilayer networks. The backpropagation algorithm needs the differentiable activation function when the weight update rule is based on the gradient of the error function which is defined in terms of the weight and activation functions.

3.6 Benefits of NN

NNs have some benefits which make them preferable to deal with certain problems that are complex and nonlinear in nature. Among these benefits of the NN their ability to learn and model complex nonlinear relationships. The generalization capability after learning from the initial inputs and their relationships, it can deduce unseen or covered relations in the data and making the model generalize and predict on the unseen data. Unlike other prediction techniques, NN does not impose any restrictions on the input variables on how they should be distributed. Additionally, many studies have shown that NNs can better model data with high randomness and non-constant variance, given its ability to learn hidden relationships in the data without imposing any fixed relationships in the data.

It uses very simple computational operations like additions, multiplication and fundamental logic elements to solve complex, mathematically ill-defined problems, nonlinear problems or stochastic problems. A conventional algorithm will employ complex sets of equations and will apply to only a given problem and exactly to it. The NN will be (a) computationally and algorithmically very simple and (b) it will have a self-organizing feature to allow it to hold for a wide range of problems. On the other way, neural networks are different and advantageous to conventional computers with their high parallelity which is element-wise whereas conventional digital computers are sequential [64].

4 Measurement and Modeling

4.1 Introduction

The details of the measurement and modeling realized in this thesis is presented in this section. The tools used for the data preparation, preprocessing, model development and evaluation are Global mapper, MS-Excel-2016 and Neural Network toolbox in MATLAB 2019a which is produced by Math works Inc. The data collection is done using drive test tools. The excellence and QoS of the network are assessed or examined by the satisfaction of the users of the network. To satisfy users, attention should be given during the network planning process. One of the main inputs for network planning is the propagation pathloss. To determine the pathloss, one must get or measure the received signal power using a drive-test. The drive-test provides insight into the performance of the network particularly in terms of radio frequency coverage.

Before going to start the testing process, the area where the test is carried out should be selected, the tools needed for the test which comprises the mobile equipment or mobile phone, drive test software installed on the laptop, GPS device and vehicle are to be checked. Using the mobile phone, the engineer will make a continuous call, in case if the call breaks, he will call again. The main use of this process is to collect enough samples at a reasonable speed and time.

4.2 Measurement Area and Feature Selection

4.2.1 Measurement Area Selection

The selection of the areas where the test is to be carried out is selected based on the features selected and their corresponding target value for the training of the neural networks. The features selected are used as input to the neural network and the output as a target or desired value for the neural network. Both are collected using the drive-test. The area selected for this study is as much as possible represent the Addis Ababa morphology. The morphology of Addis Ababa is not uniform. It includes urban, suburban and open areas. In addition to this, the selected area is the area, where there is coverage problem noticed. The measurement is done to collect the signal strength in the coverage area.

4.2.2 Feature selection

Selecting the input feature has great importance on the generalization performance of NN. It needs to have a clear understanding of the problems to be addressed. The propagation pathloss depends on several parameters. Among these, distance between the transmitter and receiver, altitude, latitude, longituude, transmit power, transmit antenna gain, feeder loss, Node B antenna, and mobile station antenna height, azimuth angle, electrical and mechanical tilt, and frequency are considered as input features for the study and the pathloss as target or output.

4.3 Measurement Setup and Data collection

4.3.1 Measurement Setup

The equipment set-up and drive-test methodology applied in the data collection are arranged to match a typical drive-test process used by RF field engineers. The measurement setup is shown in Figure 4.1. It consists of the Nemo Outdoor compatible test measurement mobiles, Laptop with Nemo Outdoor installed, Analysis software (Global Mapper, Actix Analyzer, etc.), and GPS, and License dongle.

- Nemo outdoor software is a drive test tool for measuring and monitoring the air interface of wireless networks with outdoor measurement options like voice, video and data quality and application testing option.
- The laptop is used to automatically log the phone measurements. Each measurement sample is associated with the time and position data obtained from the GPS receiver.
- Global positioning system (GPS): used in collecting the data of latitude and longitude for each point/measure data, time, speed, etc. It is also useful as a guide for implementing the correct routes.
- Mobile station: for mobile data collection, such as Received Signal Code Power (RSCP), Received Signal Strength Indicator (RSSI), Scrambling Code (SC), Received energy per chip divided by the total noise power density (Ec/No), Ue Tx Power, Throughput, Bit Error rate (BER), etc. One phone is used in free or idle mode, i.e. connected, but not on call.

Figure 4.1 Drive Test setup

4.3.2 Data Collection

The collection of data is very important for the accuracy and generalization of neural network-based models. The collection is done through measurement and considers the diversity and uniformity or even distribution of data during measurement. Measurement campaign is carried out in selected areas of Addis Ababa, Ethiopia. The measurement is used to collect features like location (i.e. latitude and longitude), the distance between transmitter and receiver and received power for UMTS frequency of 2100MHz. These are collected by using the drive test tools. The drive-test is performed on the pre-planned area. The drive test route is shown in Figure 4.2.

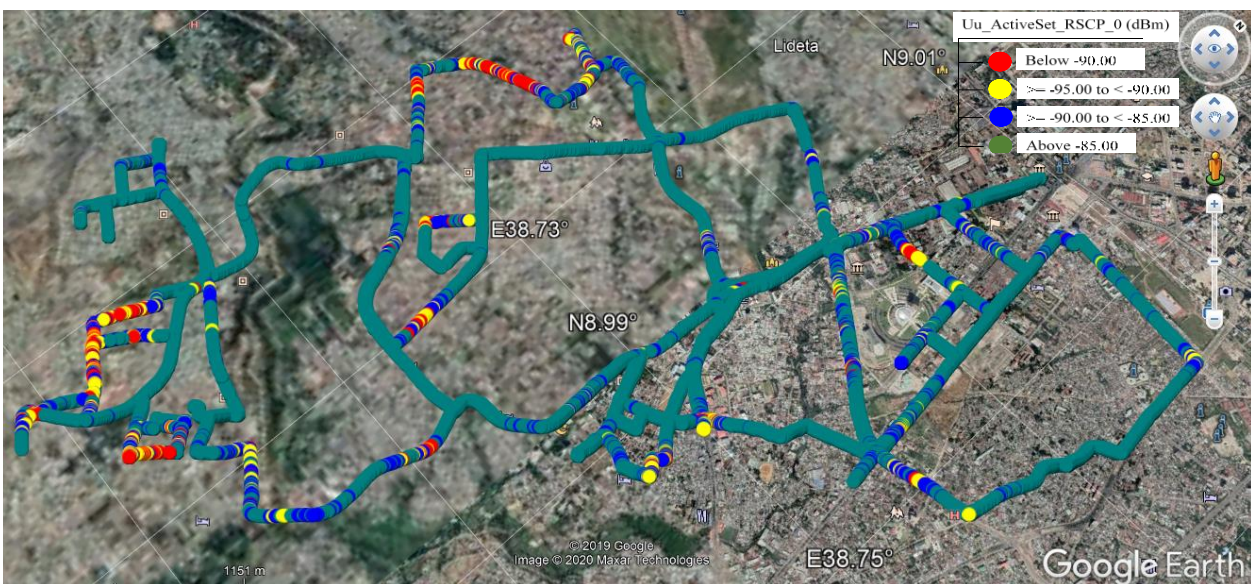
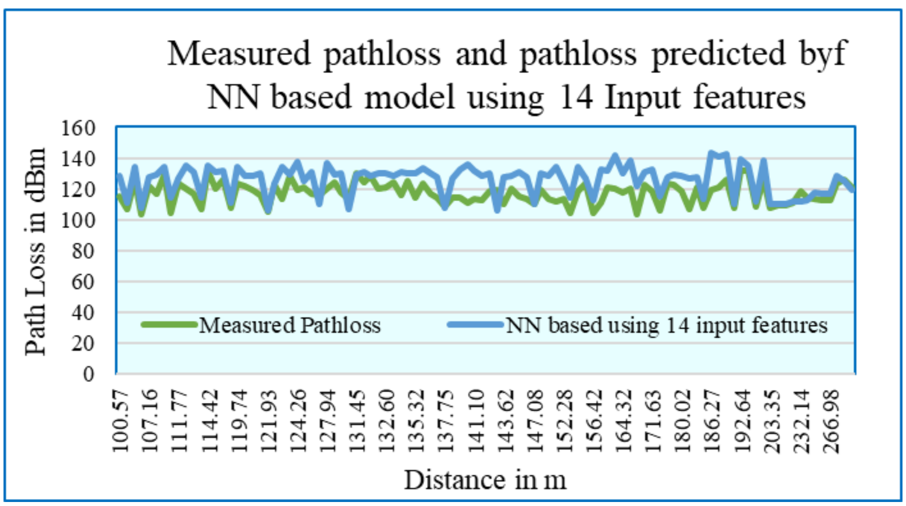


Figure 4.2 Data collection route and signal strength in the route

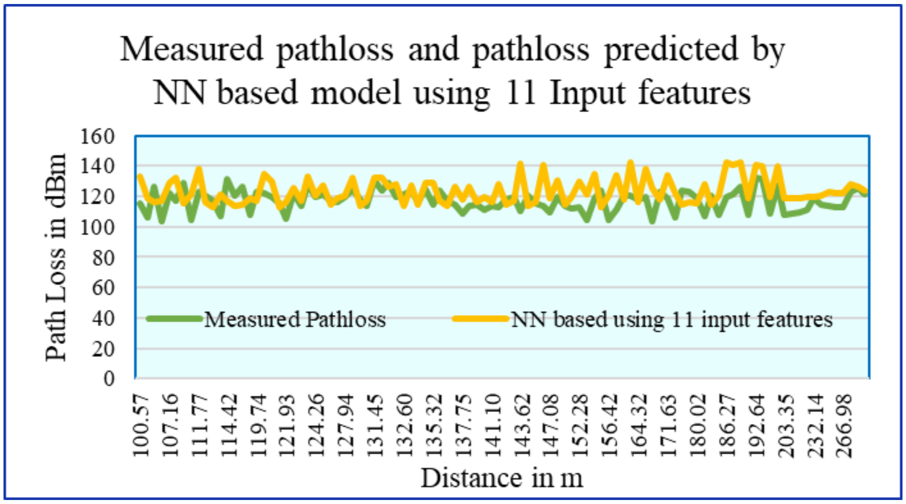
4.4 Pre-processing and data classification

4.4.1 Pre-processing of dataset

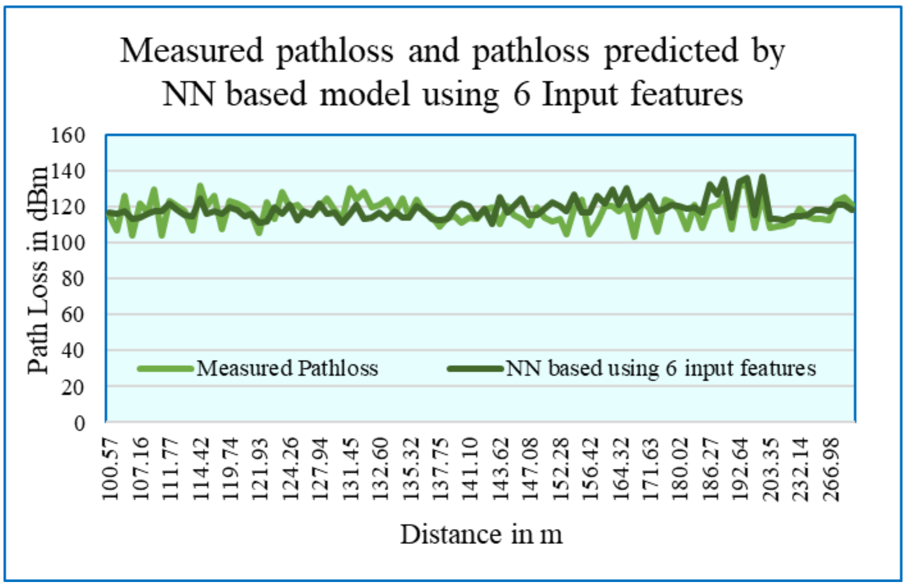
Data processing is the process of preparing the input features and target value for the purpose of minimizing noise, detecting trends, and flattening data distribution to assist the neural networks in learning the relevant patterns. It has a major impact on the generalization performance of a supervised machine learning algorithm. Removal of noise, corrupted and incorrect data is one of the most difficult problems in supervised machine learning. Data representation is very useful in designing an effective network since the neural networks are pattern matchers [65]. In some cases, raw inputs and outputs are fed to the neural networks. Instead, preprocessed data is used because it tends to help neural networks learn patterns better [66]. After identifying and removing the unnecessary noises, corrupted and incorrect data and outliers, the number of features is reduced from fourteen to seven by making an experiment and using the Pearson correlation algorithm. The result of the experiment and feature extraction algorithm is shown in Figures 4.3 and 4.4 and summarized in Table 4.1.



(a)



(b)



(c)

Figure 4.3 Graphs of measured & predicted pathloss using 14 (a), 11 (b) and 6(c) number of features

Figure 4.3 above show three models which are developed using 14, 11 and 6 features. In the three cases the green line indicates the measured pathloss. As can be seen from the graphs, the difference or the gap between the measured and predicted pathloss decreases as the number of features vary from 14 to 11 and from 11 to 6. The gap between the measured and predicted decreases mean that the error between the measured and predicted pathloss decreases. Table 4.1 compares the three models using the performance metrics MAE and RMSE. The minimum value for MAE and RMSE is recorded for the third model which is using 6 input features. Therefore, 6 number of features are used in this thesis to train and evaluate the neural network.

Table 4.1 Performance of models

Metric	14 Input features	11 Input features	6 Input features
MAE	9.51	9.48	6.26
RMSE	11.37	11.46	7.64

4.4.2 Dataset Classification

The data collection is done using drive test. It contains the input variables or the features and the output or the target value. For the neural networks, the dataset is categorized into three: training, validation, and testing dataset.

The training dataset is the part of the dataset which is used to train the machine learning algorithm and create the relation between the input features and output or target variables. The training data contain both the input features and their corresponding target values. The model runs with a training dataset and produces a result, which is compared with the target value for each input vector in the training dataset.

Validation is another part of the data, which is used to measure network generalization and to stop training when generalization stops improving. It provides an unbiased evaluation of a model fit on the training dataset while tuning the model's hyperparameters or design parameters.

The model has seen the training and the validation dataset, trained and create a relationship between the input and output to form a model. One cannot say that the model is accurate based on the dataset used during the training process. The test dataset is unseen or new data that is not used in the training or validation phase. It is used to evaluate and see the generalized accuracy of the model.

There is no general law for splitting the dataset proportion for training, validation, and testing. In different literatures, different proportion are taken [65][66][67][68],[69]. In this study, the MATLAB default for training, validation, and testing is 70%, 15%, and 15% respectively, followed [16].

4.5 Model Development

Once the dataset is made ready to be feed to the neural network, the next work will be the modeling of the network. The modeling of the network can be explained using three stages. These are the initialization or the hyper-parameter selection, training the network and the evaluation of the network.

4.5.1 The initialization or Hyper-parameter selection

The initialization phase is also called the hyper-parameter selection or the initial design parameter selection phase. The neural network design parameters include the type of network, number of layers, number of neurons in the hidden layer, activation or transfer function for the hidden layer, output transfer function, and the learning algorithm. Summarized design parameters are shown in Table 4.2.

Table 4.2 The summarized design parameters

No.	Neural Network design parameters	Specific for the research	Remark
1	Type of network	Backpropagation Neural Network	Feed forward with Back Propagation
2	Number of layers	2	Hidden and output layer
3	Number of neurons in the hidden layer	1 to 50	Varied from one to fifty but better result achieved at 45
4	Activation Function for hidden layer	Sigmoidal	tansig
5	Activation function for output layer	Linear	purelin
6	The learning algorithm	Levenberg-Marquardt algorithm	Fast to converge and memory intensive

- The network type and the number of layers can be determined through experiments and using related literature. This is done because there are several neural network types available. Different network types can fit different applications. In the same way, the number of hidden layers can vary depending on the type of application. The other way of determining the network type and a number of layers is through the experiment. The best network is chosen and used in the study. In addition to this, there are so many works in the literature that are done on the subject of interest and proposes the best network. Based on this method the network type can be selected. For this study, the second method is employed and the FFBP is selected [70], [16], [34].
- The number of hidden layers is also determined in the same way as the network type. The generalization ability of the neural network depends on the number of hidden layers. Hidden layer(s) provide the network with its ability to generalize. In practice, a neural network having one hidden layer and enough neurons in the hidden layer are commonly used and they have got a very good performance. Increasing the number of the hidden layer increases the computation time and can lead to overfitting which will decrease the performance of the model. Overfitting occurs when a predicting model has too small degrees of freedom. This means it has a few observations in relation to its parameters. It will be forced to memorize individual points rather than the patterns.
- Selecting the number of neurons in the hidden layer is one of the important parameters in neural network modeling which can decide the overall architecture of the network. This layer cannot directly connect to the input features, they have got a great impact on the output of the network. The number of hidden layer neurons must be set carefully. A fewer number of neurons in the hidden layer can give rise to the underfitting. Underfitting occurs when there is a very small number of neurons present in the hidden layer to sufficiently capture the patterns in the dataset. On the other hand, using a large number of neurons in the hidden layer will lead to an overfitting problem. Even it can happen when the training dataset is enough. As the number of neurons in the hidden layer getting large and large, the processing time of the network becomes large. To get the right number through an experiment by varying the number of neurons in the hidden layer it is advisable to start with fewer numbers and increase gradually until minimum error is reached by using the validation dataset.

- Accordingly, the number of neurons in the hidden layer for this network study is determined by varying the number of neurons from one to fifty. And obtained to be forty-five neurons. Figure 4.4 shows MSE for the different datasets.
- Activation or transfer function for hidden and output layer: The weighted sum of the inputs is transferred to the working output through an algorithmic process called transfer or activation function. The common types of transfer functions are logarithmic-sigmoidal (logsig), tangential-sigmoidal (tansig), and linear (purelin). The logarithmic-sigmoidal transfer function takes an input valued between negative infinity and positive infinity and outputs a value between zero and a positive one. The tangential-sigmoidal transfer function takes an input valued between negative infinity and positive infinity and outputs a value between negative one and positive one. And the linear transfer function produces a linear mapping of input to output. In this study, tansig for hidden and purelin for output layer are selected [71]. The graphical representation and mathematical form of the functions are shown in Table 4.3.

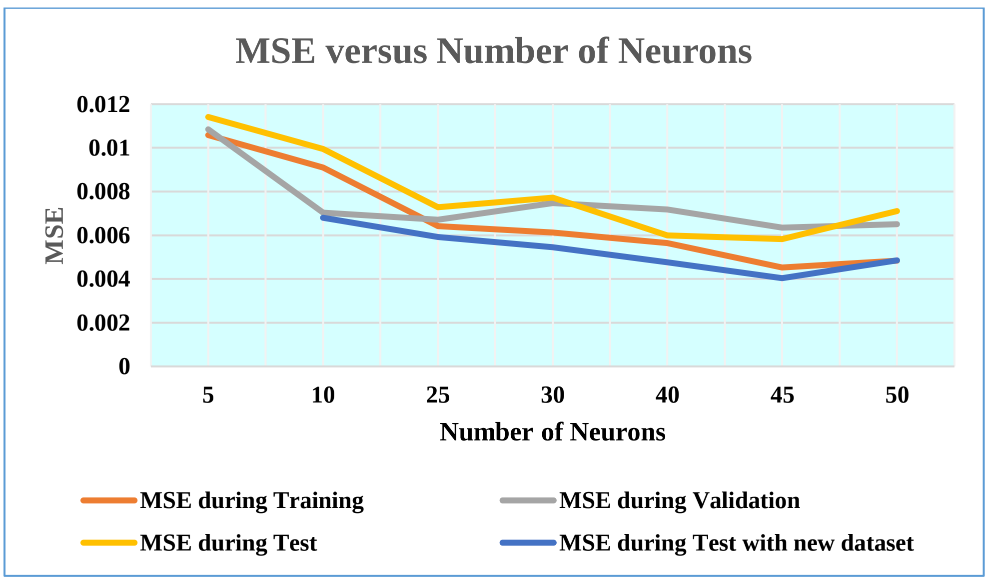
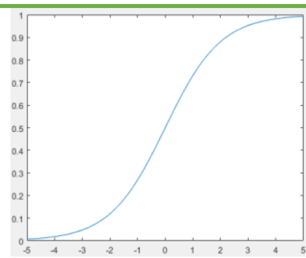
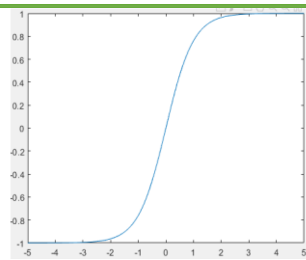
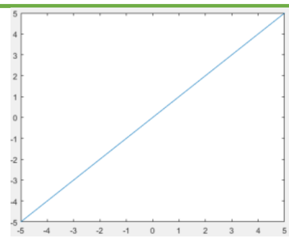


Figure 4.4 MSE for Training, Validation, and Testing

Table 4.3 Common transfer functions

Logistic Sigmoid		$f(x) = \dfrac{1}{1+e^{-x}}$
Hyperbolic Tangent Sigmoid		$f(x) = \dfrac{e^{x} - e^{-x}}{e^{x} + e^{-x}}$
Linear		$f(x) = x$

- A learning algorithm is a supervised training by which a network of computing units or neurons self-organizes to implement the desired behavior. The main learning algorithms for neural networks are Gradient descent, Newton's method, Conjugate gradient method, Quasi-Newton method, and Levenberg-Marquardt algorithm [72].

Gradient algorithm is one of the common training algorithms in the domain of neural networks. Its working principle is based on the measurement of output and computing the gradient of error and neural network weight adjustment in the downward gradient direction. The updates of the network weight are done after the presentation of each pattern from the training dataset.

Newton's method is a second-order algorithm because it makes use of the Hessian matrix. The objective of this method is to find better training directions by using the second derivatives of the loss function. It has got difficulty that the exact evaluation of the Hessian and its inverse are quite complex in computational terms.

The conjugate gradient method is motivated by the desire to fasten the slowness in convergence associated with gradient descent. It can solve the requirements of information related to the evaluation, storage, and inversion of the Hessian matrix, as required by Newton's method. The conjugate gradient is a method in between the gradient descent and Newton's method. In this method, the search is performed along with conjugate directions which produce generally faster convergence than gradient descent directions. These training directions are conjugated with respect to the Hessian matrix.

The quasi-newton method is emerged to solve the drawbacks of Newton's method. Newton's method needs several operations to evaluate the Hessian matrix and compute its inverse. The quasi-newton method developed an approximation to the inverse Hessian at each iteration of the algorithm, in place of computing the Hessian directly and then evaluating its inverse. This approximation is carried out based on only information on the first derivatives of the loss function. The Hessian matrix is composed of the second partial derivatives of the loss function. The core point of the quasi-Newton method is to approximate the inverse Hessian by another matrix.

The Levenberg-Marquardt (LM) algorithm is known by the name called damped least-squares method. It is developed particularly to work with the loss function that has the form of a square error sum. It does not calculate the exact Hessian matrix but works on the gradient vector and the Jacobian matrix. LM algorithm has got good performance when it works with the artificial neural network. Since the LM has contained the best features of the Gauss-newton method and the steepest-descent method and removes the limitations with them and has a fast convergence. Because of these, LM algorithm is selected for this study.

4.5.2 Network Model Training

The network training is a supervised type in which both the input and output are provided. The network takes the features as input and the measured value of pathloss as a target or desired value. The process of training a network is done by iteratively feeding the inputs and presenting it with a target value. The error is computed for each input and backpropagated through the system. Thereby adjusting the weight that controls the network. This process is repeated until a minimum error is reached. The training process is shown in Figure 4.5. The main goal of training the network is to reach the global minimum error function. In order to do this, the training algorithm is used. The training algorithm used is the Levenberg Marquardt algorithm. It is fast to converge as compared to others. It will save training time. The dataset used during the training process is a training dataset. In addition to this, the network training will also continue during the validation by using the validation dataset. Based on the MSE and regression output of the network after processing of the validation dataset, by varying the number of neurons and data size, the training is repeated and when minimum error and the regression value approaches one or if the MSE does not change the training is stopped and the network is ready.

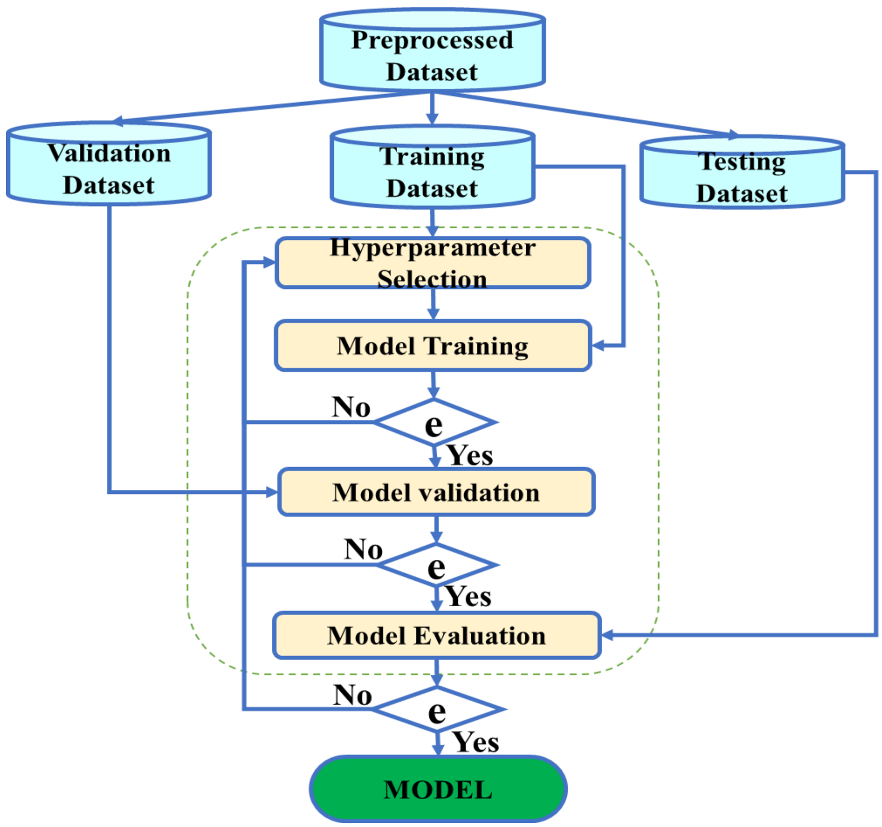


Figure 4.5 The training process of the neural network

4.5.3 Model Evaluation

To see the goodness of the model, it has to be evaluated. For the evaluation of the model, a new dataset that is not used before or seen by the network called the test dataset depicts how the model predicts the output on the test dataset or new dataset. The evaluation is based on the performance metric selected. There is different performance measuring metrics for NN prediction models like modeling time, training time and the most important, accuracy. In this study, the only accuracy is employed. The accuracy is measured terms of the prediction error which is the difference between the actual (desired) and the predicted (model output) value. There are a number of performance measuring metrics used for measuring the accuracy of the prediction models in the literature [34],[73][74],[75], [16]. The most frequently used metrics are: MAE, RMSE, MAPE, R and R^2. They can be mathematically represented as:

MAE: model evaluation metrics and it is the mean of the absolute values of the individual prediction errors overall instances. Mathematically expressed as:

$$\boldsymbol{MAE = \frac{1}{N}\sum_{i=0}^{n}\left|PL_i^m - PL_i^p\right|} \quad \text{------------------- 4-1}$$

Where

PL_i^m the measured pathloss at point i

PL_i^p the predicted pathloss at point i

RMSE: is the most popular prediction error measure and is a frequently used measure of the differences between values predicted by a model and the values observed. Mathematically expressed as:

$$\boldsymbol{RMSE = \sqrt{\frac{1}{n}\sum_{i=0}^{n}\left(PL_i^m - PL_i^p\right)^2}} \quad \text{------------------- 4-2}$$

MAPE: is the measure of prediction accuracy or measure of how far the model’s predictions are off from their corresponding outputs on average. MAPE has a clear interpretation since percentages are easier for people to conceptualize. Mathematically expressed as:

$$\boldsymbol{MAPE = 100 \times \frac{1}{n} \times \sum_{i=0}^{n}\left|\frac{PL_i^m - PL_i^p}{PL_i^m}\right|} \quad \text{------------------- 4-3}$$

Correlation coefficient (R) measures the strength of relation between predicted value and actual value. The value of a correlation coefficient ranges between -1 and 1. The greater the absolute value of a correlation coefficient, the stronger the linear relationship. The strongest linear relationship is indicated by a correlation coefficient of -1 or 1. The weakest linear relationship is indicated by a correlation coefficient equal to 0.

$$R = \sqrt{\frac{\sum_{i=1}^{n}(PL_i^m - PL_\mu^m)^2 - \sum_{i=1}^{n}(PL_i^m - PL_i^p)^2}{\sum_{i=0}^{n}(PL_i^m - PL_\mu^m)^2}} \quad \text{-------------------- 4-4}$$

The **coefficient of determination** (R^2) is a key output of regression analysis. It is interpreted as the proportion of the variance in the dependent variable that is predictable from the independent variable. It is the square of the correlation (R) between predicted values and actual values; thus, it ranges from 0 to 1. An R^2 of 0 means that the dependent variable cannot be predicted from the independent variable. An R^2 of 1 means the dependent variable can be predicted without error from the independent variable. An R^2 between 0 and 1 indicates the extent to which the dependent variable is predictable.

$$R^2 = \frac{\sum_{i=1}^{n}(PL_i^m - PL_\mu^m)^2 - \sum_{i=1}^{n}(PL_i^m - PL_i^p)^2}{\sum_{i=0}^{n}(PL_i^m - PL_\mu^m)^2} \quad \text{-------------------- 4-5}$$

4.5.4 Pathloss Computation

Sample of the pathloss is prediction using all models (i.e. Neural network-based model, Tuned COST-231, COST-231, ECC-33 and SUI model) is summarized in Table 4.4 below.

Table 4.4 Propagation pathloss prediction using different models

Distance	NN based Model	Tuned COST-231	COST-231	ECC-33	SIU
102.94	137.63	113.36	105.86	107.32	90.31
103.71	132.02	113.48	105.98	107.39	90.45
112.34	98.82	114.74	107.22	108.09	92.00
115.01	126.60	115.11	107.58	108.30	92.45
119.37	111.25	115.69	108.16	108.63	93.17
130.23	121.12	117.07	109.51	109.42	94.85
137.95	108.63	117.98	110.41	109.94	95.96
138.48	125.03	118.04	110.46	109.98	96.03
139.10	113.26	118.11	110.53	110.02	96.12
139.96	116.22	118.20	110.63	110.08	96.24
166.09	122.17	120.90	113.29	111.69	99.54
168.49	115.83	121.13	113.51	111.82	99.82
169.55	117.64	121.23	113.61	111.88	99.94
179.20	126.46	122.10	114.47	112.42	101.01

5 Performance analysis and result interpretation

Propagation pathloss models are important in the proper network planning and optimization. Most propagation models are developed from analytical and empirical methods. In this chapter, the performance of the neural network-based model and the common empirical models are analyzed. The analysis is carried out to compare the prediction results of the models by using data collected with drive tests in the selected areas of Addis Ababa. The analysis is done with the help of MATLAB and MS-Excel. The empirical models are mathematical formulae that handle the behavior of radio wave propagation as a function of frequency, distance, and other parameters.

The measured pathloss as a function of the distance between the transmitter and receiver is shown in Figure 5.1. From the Figure, one can see the nonlinear property of pathloss. This is because of the dependency of the pathloss not only on the distance but also on other features or parameters that affect the pathloss. At any point, it cannot be represented by using a mathematical formula.

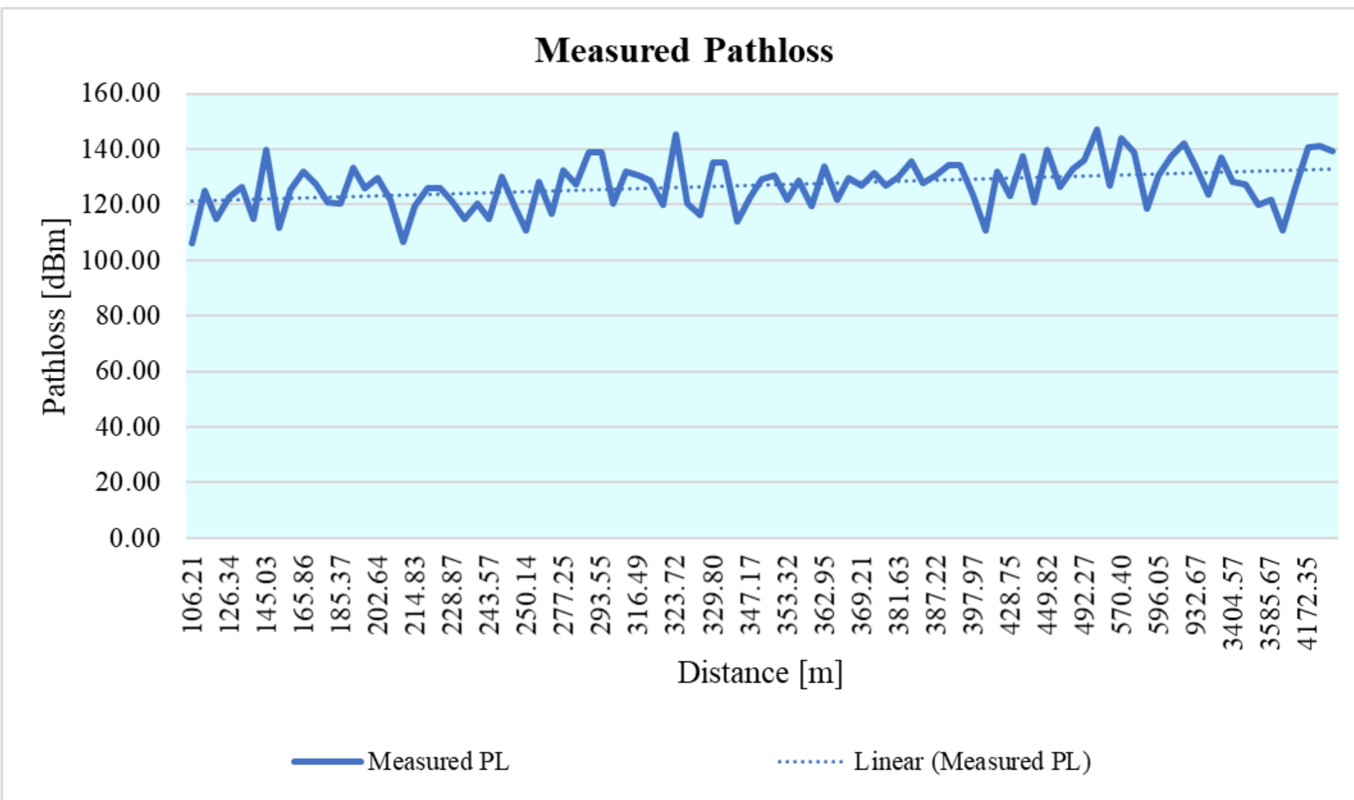


Figure 5.1 Measured pathloss vs distance

In the final model, the network type is feedforward with a backpropagation neural network having two layers (i.e. the hidden layer and output layer), a number of neurons in the hidden and output layer are 45 and 1, respectively. The activation function for the hidden and output layer are tansig and purelin and the training algorithm selected is the Levenberg-Marquardt algorithm. The network architecture of the neural network-based model is shown in Figure 5.2.

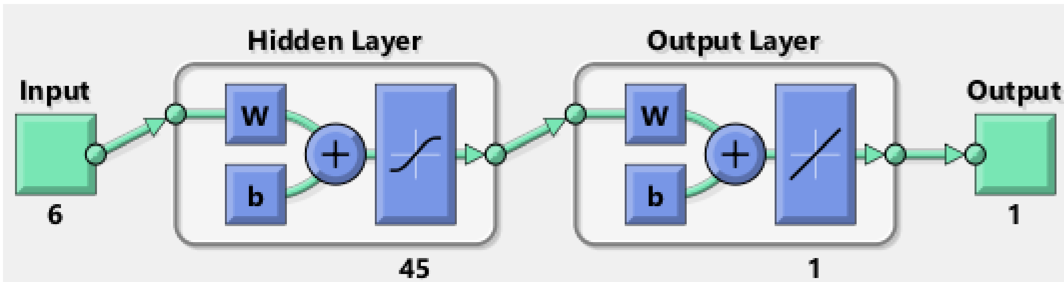


Figure 5.2 The network architecture of the neural network-based model

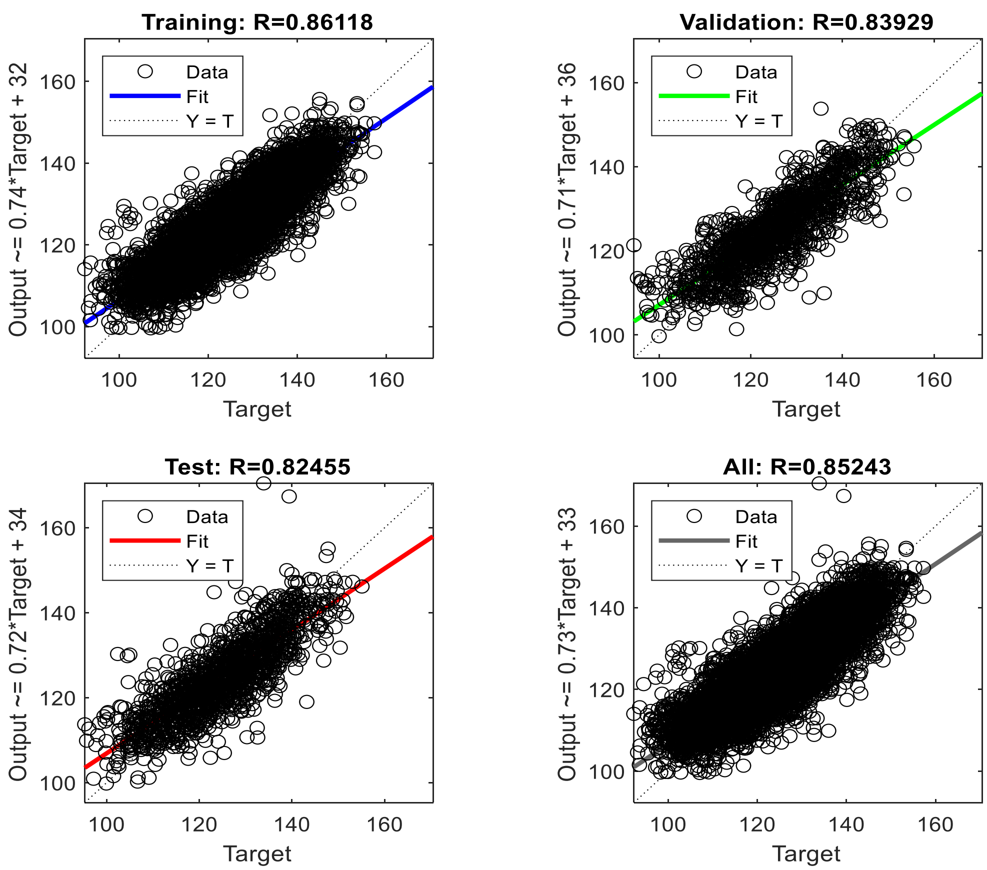


Figure 5.3 Correlation between the predicted and target during training

As discussed in Section 4.4.2, the dataset is divided into 70%, 15% and 15% training, validation and testing dataset respectively. Figure 5.3 shows the degree of correlation between the predicted value of the neural network model and the target or measured value for the three datasets. The values of R obtained for training, validation and testing are 0.86118, 0.83929 and 0.82455 respectively. The overall R-value for the model is 0.85243. R is between 0 and 1. R=1 means there is a perfect match between the predicted and measured values and R=0 mean there is no much between them. The value of R for this study is found to be 0.85243 which shows that the generalization ability of the model is good using the test dataset which is not used in the training process and can guarantee a high accuracy of pathloss prediction for radio network planning and optimization for Addis Ababa. The model is evaluated using the dataset that is not used during the model development or training. The correlation between the predicted and target is shown in Figure 5.4.

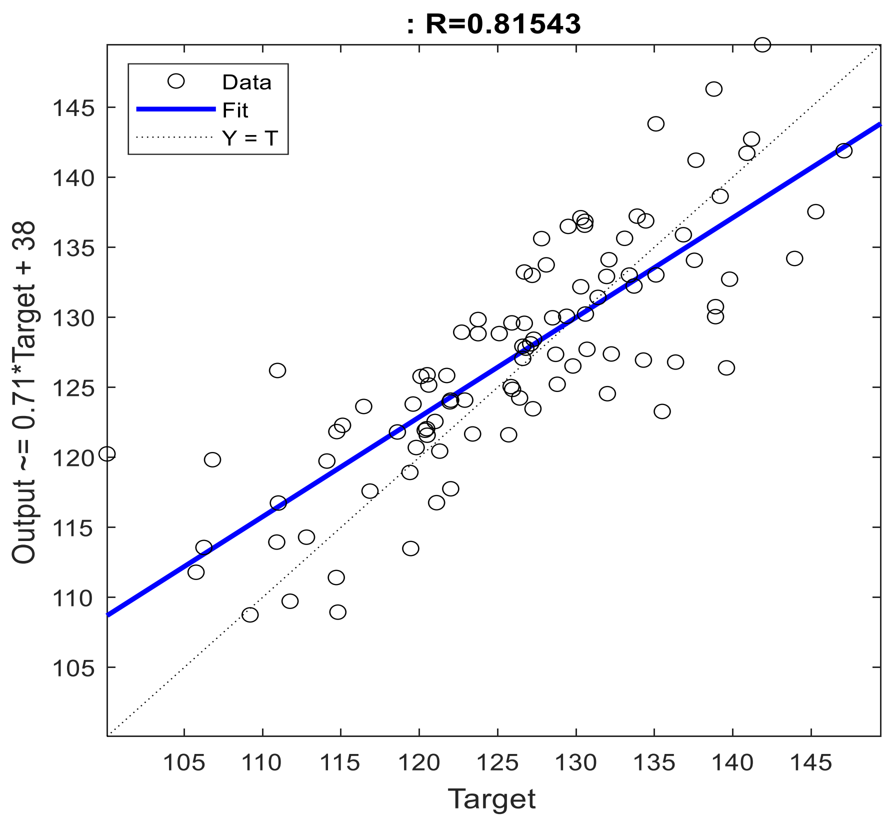


Figure 5.4 Correlation between the predicted and target during the evaluation

5.1 Comparison of models

To show that the neural network model is a better prediction model than the empirical models, it is necessary to do the comparison between the measured pathloss and the neural network, tuned-COST-231, COST-231, ECC-33 and SUI models based on their prediction results. Figure 5.5 shows that the plot of measured pathloss and the pathloss predicted by the neural network, tuned-COST-231, COST-231, ECC-33 and SUI against the distance between the transmitter and receiver. The overall characteristics of the empirical models are the same as it can be seen from the graph. The SUI model on average, under-predicted the pathloss and the tuned COST-231 over-predicted the pathloss along the distance covered by the data. On the other hand, the COST-231 and ECC-33 models prediction is around the average value of the measured pathloss. The neural network-based model is the best model as compared to the models described and its pathloss prediction result is much more similar to the measured pathloss. It also follows or imitates the fluctuations detected at different distances.

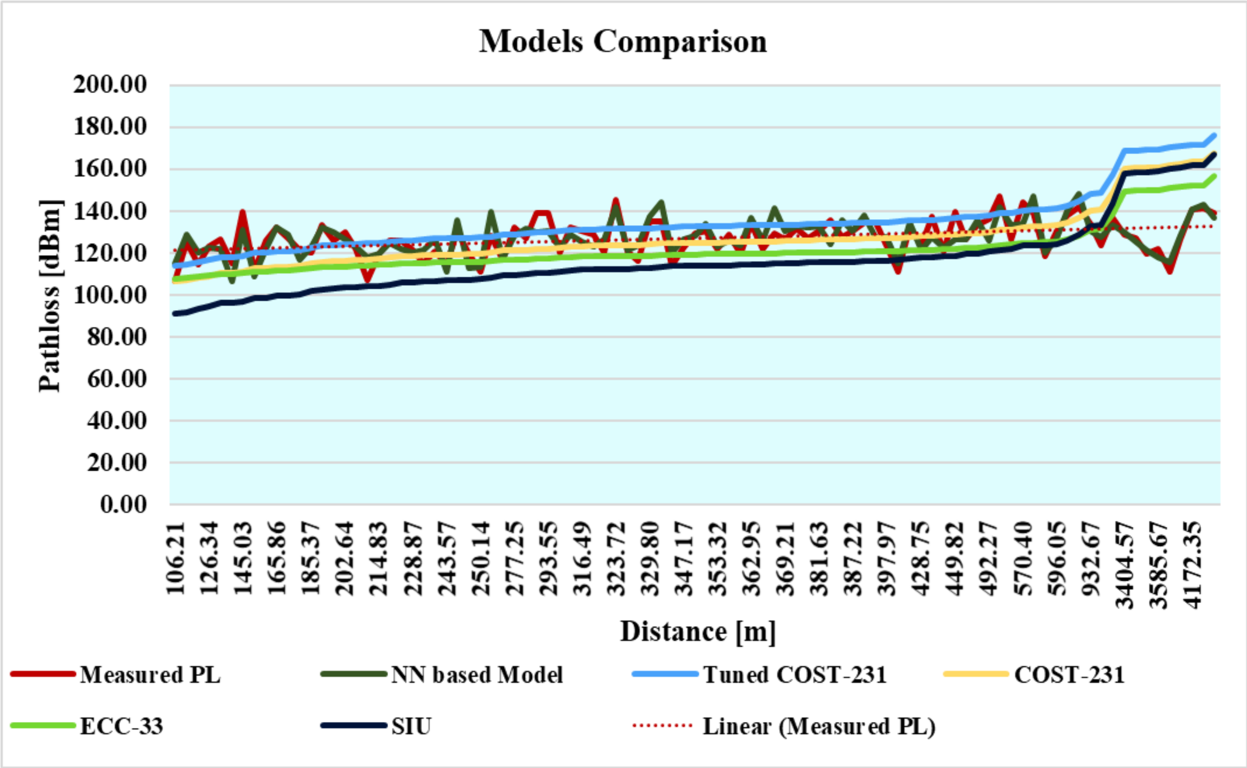


Figure 5.5 Plot of measured pathloss and models prediction

5.2 Performance Analysis of Models based on the Statistical Performance Metrics

The accuracy of the models can be seen from the error they incur during the prediction. In other words, measuring the accuracy of a model means measuring the error of the model. For the measurement of the error, there are statistical performance metrics discussed in Section 4.5.3. These metrics are MAE, MAPE, RMSE, R and R^2.

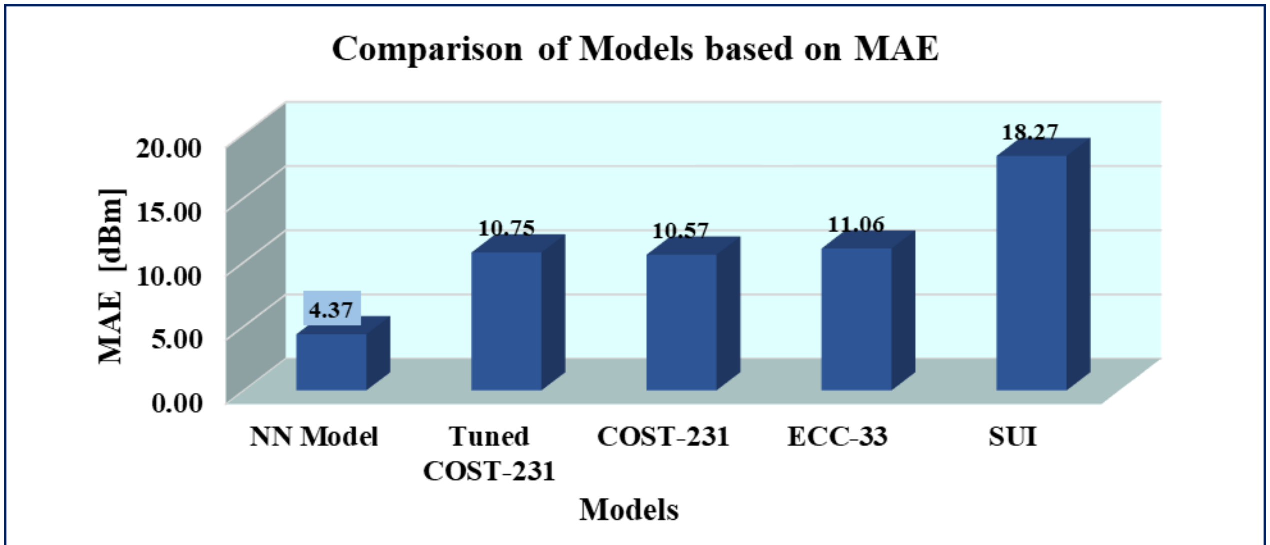
Table 5.1 the values of performance metrics for models

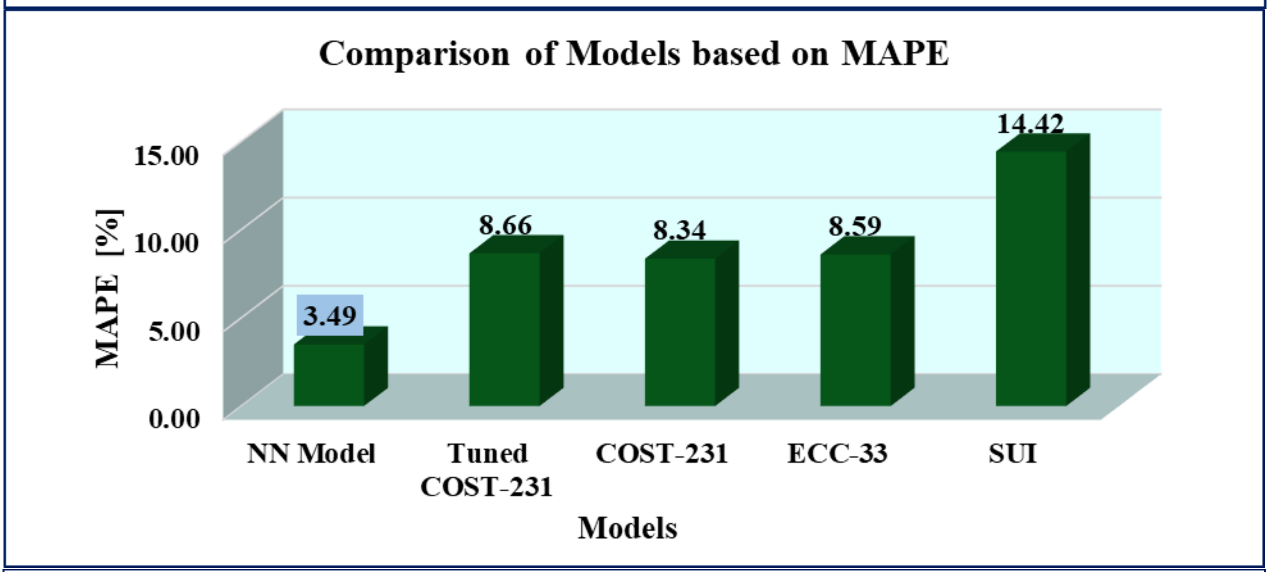
Models	MAE	MAPE	RMSE	R	R^2
NN Model	4.37	3.49	5.58	0.82	0.67
Tuned COST-231	10.75	8.66	16.01	0.38	0.14
COST-231	10.57	8.34	14.36	0.38	0.14
ECC-33	11.06	8.59	13.53	0.36	0.13
SUI	18.27	14.42	21.00	0.38	0.14

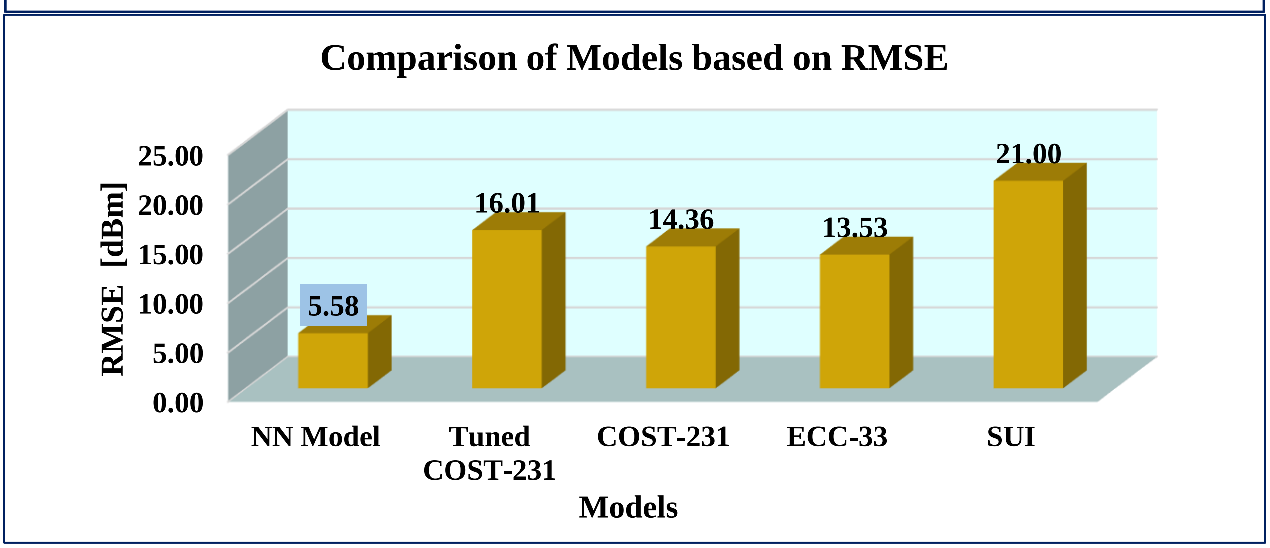
The result of the statistical performance evaluation is shown in Tables 5.1 and 5.2 based on the test dataset result. The test dataset is the sub-dataset which is not used in training and is a new dataset used only for testing or evaluating the models. As can be seen from Table 5.1 the performance of the neural network is better than the empirical models. The empirical models cannot represent the pathloss of Addis Ababa as accurately as that of the neural network model. The failure is associated with the environmental condition of Addis Ababa and the way the models are developed. Table 5.2 shows the bar chart representation of the performance metrics of the models.

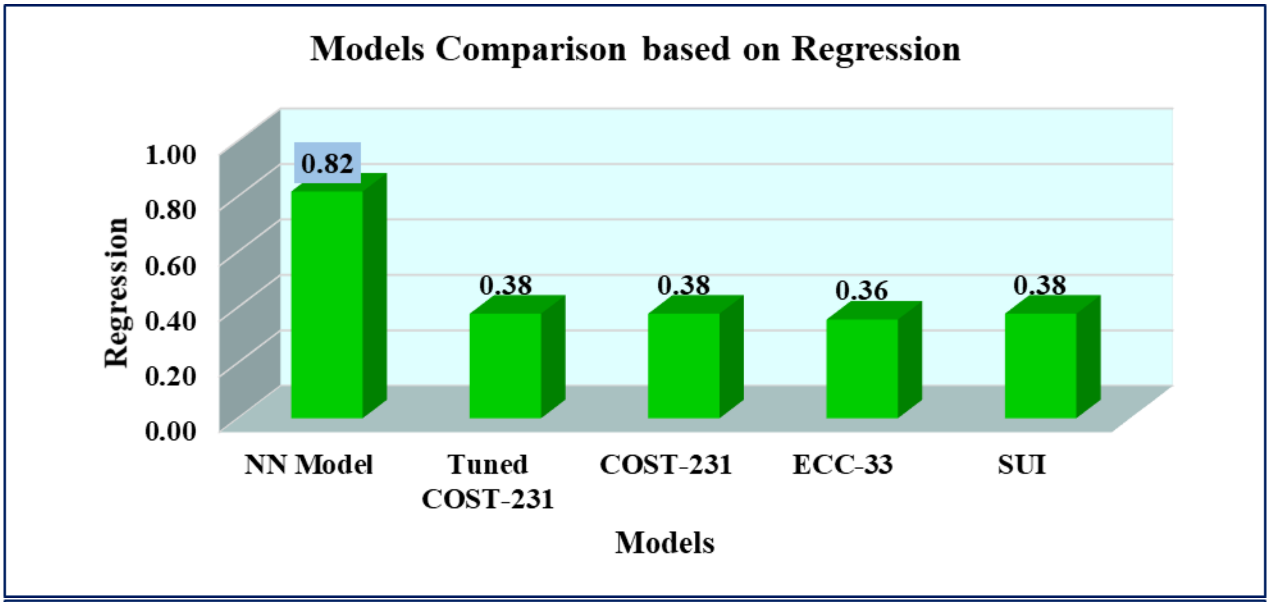
The findings showed that the neural network-based model has achieved the performance evaluation values for metrics: MAE, MAPE, RMSE, R and R^2 as 4.37 dBm, 3.49%, 5.58 dBm, 0.82 and 0.67 respectively. This shows that better prediction accuracy and generalization ability is achieved using the feedforward backpropagation neural network approach. On the other side, the lowest performance is registered with the prediction done using the SUI model: 18.27 dBm, 14.42%, 21.00 dBm, 0.38 and 0.14 dBm for MAE, MAPE, RMSE, R, and R^2respectively. The SUI model cannot be applied for the prediction of pathloss in Addis Ababa.

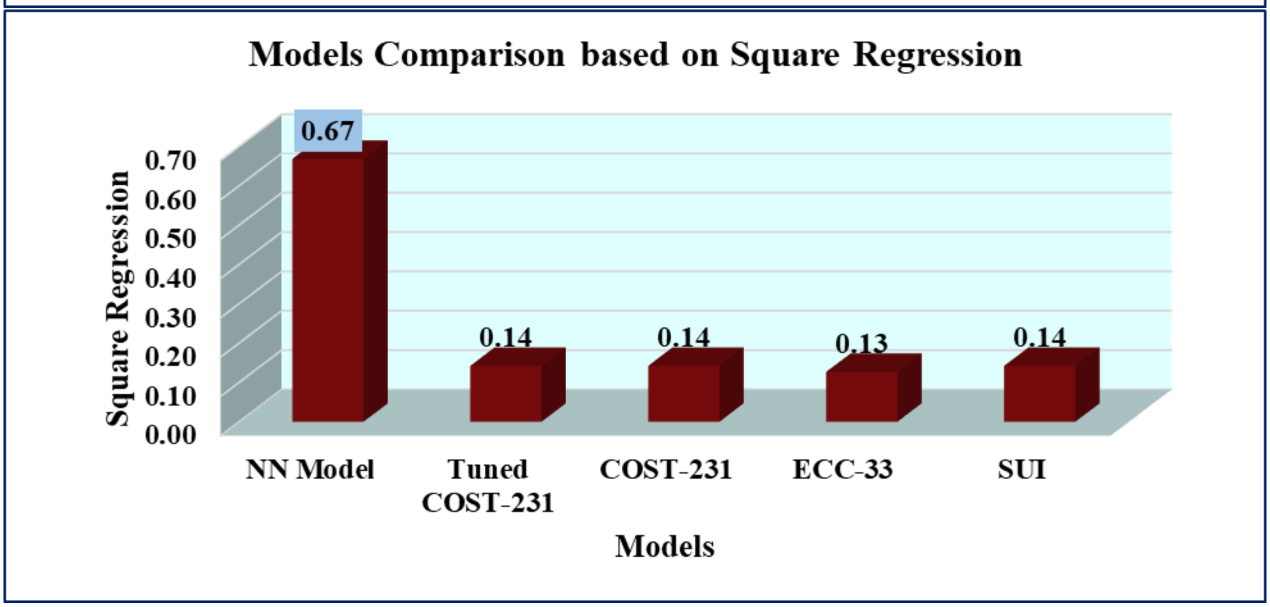
Table 5.2 Performance of models








Models Comparison based on Regression
1.00
0.80
0.60
0.40
0.20
0.00
Regression
0.82
0.38
0.38
0.36
0.38
NN Model
Tuned COST-231
COST-231
ECC-33
SUI
Models


Models Comparison based on Square Regression
0.70
0.60
0.50
0.40
0.30
0.20
0.10
0.00
Square Regression
0.67
0.14
0.14
0.13
0.14
NN Model
Tuned COST-231
COST-231
ECC-33
SUI
Models

6 Conclusion and Future Works

6.1 Conclusion

To satisfy the customer or user demand and increase the reachability of mobile network services, planning and optimization of the network are very essential. Since there are many areas which do not get the right service according to their need. This shows the need for improvement in network planning. One of the important parameters for the planning and optimization of the network is the propagation pathloss.

From the reality of cellular or mobile network coverage problem, the contribution of this study is vital. As it focused on the prediction model which is used to predict the pathloss in Addis Ababa using an NN based and the dataset collected through the drive-test in the selected areas of Addis Ababa for the UMTS network. More than 11,000 points, 6 selected features, around 13.3 square kilometers of the area and distance of 37.8 km is covered by this study. Four empirical models are used to validate the performance of the NN model. For all models, the system parameters and measured data are used. The accuracy of the empirical models are examined. The study shows that these models fail to correctly predict the pathloss in this area. In shorter distances, under-predict the pathloss and at longer distances, they over-predict the pathloss. To solve the problems with empirical models, FFBP neural network is trained using 6 features selected, forty-five neurons in the hidden layer, with tansig and purelin as activation functions for hidden and output layer, and Levenberg-Marquardt algorithm for training and come up with the NN based model with the best accuracy.

The performance comparison is done using the graphical method and statistical performance metrics: RMSE, MAE, MAPE, R and R^2. Graphical comparison depicts how the models behave with distance and compared with the measured pathloss. In general, all empirical models have got the same behavior. For short distance under-prediction and for longer distance over-prediction is noted. In the midway of the graphs, they almost average. The neural network-based model or the FFBP neural network model track and follow the way of the measured pathloss. This model is much nearer and resembles the measured pathloss. The performance metrics evaluation results showed a great improvement in pathloss prediction. The better MAE, MAPE, RMSE, R and R^2

for the empirical models are 10.57 dBm, 8.34%, 14.36 dBm, 0.38 and 0.14 respectively. The neural network model achieves these values 4.37 dBm, 3.49 %, 5.58 dBm, 0.82 and 0.67 using the test dataset which is not used during model development.

It can be concluded that the accuracy of the FFBP neural network model is shown to be the best model for Addis Ababa from a performance point of view as compared to the empirical models; tuned COST-231, COST-231, ECC-33 and SUI models.

6.2 Future Works

Pathloss has got a decisive role in mobile communication. Any error in pathloss prediction has an impact on network infrastructure and services performances. This is happening since the pathloss is one of the major inputs for network planning and optimization work. Pathloss will change with the growth of the cities or towns. Open areas are covered by a building, the small building is replaced by tall and large buildings, the size of roads, size of green area, number of trees etc. varies with time. This shows the research in the area of the pathloss is not to stop at one point. Proper selection of pathloss prediction models is important for mobile communication to attain its goal. therefore, the following area can be focused on future study areas.

- Performance analysis of machine learning algorithms for pathloss prediction
- Optimization of pathloss models using the machine learning algorithms

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