



ORIGINAL RESEARCH ARTICLE

ARTIFICIAL NEURAL NETWORK (ANN) PATHLOSS PREDICTION MODEL FOR LTE NETWORK FOR MICROCELLS IN AN URBAN ENVIRONMENT

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ABSTRACT

One of the challenges faced by telecommunication service providers is capacity. The capacity of a cell depends on the model used in planning the cell during deployment stage. This paper presents Artificial Neural Network (ANN) Pathloss Prediction model for Long Term Evolution (LTE) network for microcells in Benin city, Edo state, Nigeria. Received signal strength data collected with respect to distance, mobile station antenna height and base station antenna height was used to create a data base with pathloss estimated from the measured data. A feature variable consisting of 80% of measurement data collected was used to train a 4-32-1 multilevel perceptron artificial neural network with pathloss as the label using python language on Scientific python development environment interface (SPYDER). The result of the 20% test data shows that artificial neural network is suitable for predicting pathloss in Benin City. This is as a result of root mean square error (RMSE) values and mean absolute error values of $0.59dB$ and $0.42dB$ obtained respectively which are less than the $6dB$ error value allowed for network planning. It is recommended that the result of the study be adopted in designing or expanding LTE network capacity in the areas studied in this work.

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1.0 Introduction

The demand trend for mobile communication services has shown that as population increases coupled with technological advancement, the demand for mobile communication services increases (Bi *et al.*, 2001). The mobile communication technology has advanced from first generation (1G) to (4G) in Nigeria. The brand name for the fourth generation of mobile wireless cellular communication standard is long term evolution (LTE). LTE, a successor to both 2G and 3G developed by the 3rd generation partnership project (3GPP) committee to improve Universal mobile telecommunications services (UMTS) communication standard is a highly flexible radio interface. The demand for telecommunication services necessitates the need for proper planning of cellular networks. The performance of cellular networks depends on the propagation model deployed during planning stage. Due to the complex and diverse nature of the radio propagation environment, the power of a propagating signal fluctuates with respect to time and space. Thus, a model that will work best is that which is developed using propagation data gotten from that environment. The use of empirical and deterministic models for deployment of mobile networks presents a compromise between accuracy and simplicity (Ojo *et al.*, 2021). Example of empirical models in literature are the Okumura-Hata model, Walfisch Ikegami model, Stanford University interim model, Egli model and COST 231 Hata model (Zhang *et al.*, 2019 and Jo *et al.*, 2020).

Although the empirical models are simple to use because of the few parameters needed to predict the path loss in a given environment, they provide unsatisfactory results when applied to a more general radio propagation environment since they are mostly site specific (Zhang *et al.*, 2019 and Jo *et al.*, 2020). Deterministic models are more accurate but quite complex to develop and lack computational accuracy with an example being the ray tracing method. In order to develop models that can predict pathloss with high accuracy and computationally efficient, researchers in recent times have looked into machine learning based path loss prediction models.

A lot of researchers have contributed knowledge in the area of developing pathloss models for cellular network planning. While some have develop models for different mobile network technologies, others have simulated cellular networks at different frequencies. Shoewu *et al.* (2019) presented the result on a study conducted in wetland and dry land areas in Lagos state, Nigeria using received signal strength data collected with TEMS investigation software installed on mobile phone via drive test for 4G cellular networks. Their result show that existing empirical model such as ECC-33 model, COST 231 Hata model, Free space model, Okumura model and Davidson-Hata model are not suitable for pathloss prediction in Lagos. Sulyman *et al.* (2014), Sree Vardhan *et al.* (2016), Ubaidillah *et al.* (2020) and Atanasoy *et al.* (2017) also carried out propagation studies on different locations. Sharma *et al.* (2018) presented a report on optimization of propagation pathloss model in 4G wireless communication system was presented. The authors in this study carried out data collection at 1800MHz in India and compared their result with predictions made by COST-231 Hata, Egli, Walfich-bertoni, ECC-33 and SUI models with pathloss values obtained from the measured field strength data. The authors reported that COST-231 Hata, is best model based on the closest agreement to the measured path loss exponent. Thus, the COST 231 Hata model was optimized. Among the various studies reviewed, it is worthy of note that propagation models are environment specific and existing empirical models are mostly not suitable for use in planning cellular networks in environment where the terrain characteristics is not similar with that in which the model is built for.

In wireless communication, pathloss prediction is treated as a supervised learning task with the received signal strength, distance between the mobile station and the base station, mobile station antenna height and base station antenna height as the feature variables and the path loss values as the label. Artificial Neural Network (ANN) is a one of the artificial intelligence algorithms that can be used in developing pathloss models based on data collected in a typical radio propagation environment and trained with it (Eichie *et al.*, 2017). The flexibility of ANN to learn from a given data set without being explicitly programmed can be seen from researches in recent times.

An artificial neural network (ANN) is a learning algorithm whose design is inspired by the behavior of neurons in the human brain. An ANN is based on a collection of connected units or nodes called artificial neurons. A neuron is the fundamental processing element of a neural network. Each neuron transmits its output via a connection of weights like the synapses in a biological neural network to another neuron in the next layer. Weights are assigned to a neuron based on its relative importance against other inputs. Shown in Figure 1 is the structure of an artificial neuron.

A neural network consists of several layers. The outer most layers that receive the input to the network are called the input layers. The next layer is called the hidden layer. This layer does further processing of the signal and passes it to the output layer. Shown in Figure 1 is the structure of an artificial neuron with weights and bias.

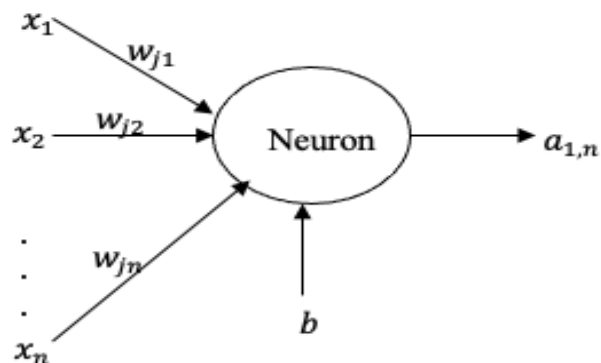


Figure 1: Analysis of a single neuron with weights and bias

A neuron (a) is presented in Figure 1 with a vectorial input $= [x_1, x_2, \dots, x_n]$. These inputs are multiplied with weights $W = [w_{j1}, w_{j2}, \dots, w_{jn}]$ alongside the summation of a bias term to produce a weighted sum as in equation (1).

$$O_j = \sum_{i,j=1}^n x_i w_{ji} + b \quad (1)$$

The weighted sum in equation (1) is fed into a non-linear mapping function f called the activation function which produces a scalar output $a_{1,n}$ as in equation (2) [11].

$$a_{1,n} = f\left(\sum_{i,j=1}^n (x_i w_{ji}) + b\right) \quad (2)$$

The ANN learning is obtained by updating the weights along the MLP artificial neural network in consecutive iterations of feed forward and back-propagation procedures with the matrix of neurons in the hidden layer as in equation (3).

$$z_n^{(l)} = f(a_n^{(l)}) = [f(a_{1,n}^{(l)}), f(a_{2,n}^{(l)}), f(a_{3,n}^{(l)}), \dots, f(a_{k,n}^{(l)})]^T \quad (3)$$

$$\text{where } a_n^{(l)} = \begin{cases} w^{(l,n)} \cdot X_n & \text{for } l = 1 \\ w^{(l,n)} \cdot z_n^{(l-1)} & \text{for } 2 \dots L - 1 \end{cases}$$

For m features, the weight matrix for layer $l = 1$ and for layers $l = 2, 3, \dots, L - 1$ associated with $X_n = [x_{1,n}, x_{2,n}, \dots, x_{D,n}]$ are given by

$$w^{(1,n)} = \begin{bmatrix} w_{1,1}^{(1,n)} & w_{1,2}^{(1,n)} & \dots & w_{1,m}^{(1,n)} \\ w_{2,1}^{(1,n)} & w_{2,2}^{(1,n)} & \dots & w_{2,m}^{(1,n)} \\ \vdots & \vdots & \ddots & \vdots \\ w_{k,1}^{(1,n)} & w_{k,2}^{(1,n)} & \dots & w_{k,m}^{(1,n)} \end{bmatrix} \text{ and}$$

$$w^{(l,n)} = \begin{bmatrix} w_{1,1}^{(l,n)} & w_{1,2}^{(l,n)} & \dots & w_{1,m}^{(l,n)} \\ w_{2,1}^{(l,n)} & w_{2,2}^{(l,n)} & \dots & w_{2,m}^{(l,n)} \\ \vdots & \vdots & \ddots & \vdots \\ w_{k,1}^{(l,n)} & w_{k,2}^{(l,n)} & \dots & w_{k,m}^{(l,n)} \end{bmatrix}$$

Using equation 3, the feed forward computation of Figure 1 is performed as given in equation 4 as;

$$z_n^{(L-1)} = f \left(w^{(L-1,n)} \cdot f \left(w^{(L-2,n)} \cdot f \left(\dots w^{(2,n)} \cdot f \left(w^{(1,n)} \cdot X_n \right) \right) \right) \right) \quad (4)$$

The prediction value y_p from the final layer of the feedforward procedure is a linear output of $z_n^{(L-1)}$ and $w^{(L,n)}$ as in equation (5).

$$y_p^{(L)} = w^{(L,n)} \cdot z_n^{(L-1)} \quad (5)$$

Where:

$$w^{(L,n)} = [w_{1,1}^{(L)}, w_{1,2}^{(L)}, w_{1,3}^{(L)}, \dots, w_{1,k}^{(L)}]$$

f: is the activation function from one neuron to another

X_n : represents the nth column of the $m \times n$ matrix in the input layer

$a_n^{(l)}$: represents the output of neuron a in layer l

y_p : is the output of the neural network

2. Materials and method

This section presents the description of the study area as well as materials and method adopted in this work which includes the data measurement setup, data acquisition process, data pre-processing and model development.

2.1 Description of study area

Edo state is one of the 36 states in Nigeria. It lies on latitude 6°30'N and 6°00'E. The state is in the south geopolitical zone of Nigeria, bounded by Kogi state to the North East, Anambra State to the East, Delta State to the South and Ondo State to the west with a total land area of 17.802km² as shown in Figure 2. Edo State has 18 local government areas with Benin city as the State capital and the largest urban Centre. NIFOR is one of rural communities in Edo state. For the purpose of this study, Benin City will be referred to as location 1 and NIFOR location 2.

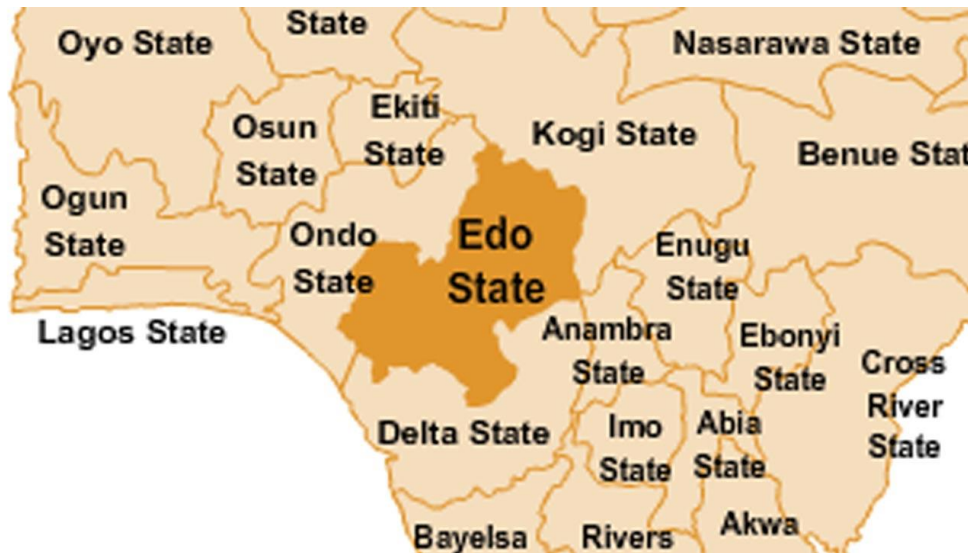


Figure 2: Map of Nigeria showing location of Edo state (<https://www.guardian.ng/news> accessed 10th July, 2020)

2.2 Measurement Set-Up and Data Collection

In order to develop suitable model for LTE cellular network situated in Benin city, Benin city was divided into ten sub locations which reflect the major areas of the city. This is because of the large number of base stations in Benin City. An experimental set up was designed and implemented to measure and record received signal strength data from one of the mobile network providers. The base station transmits signals using sectorial antennas spaced at 120° apart with antenna heights ranging from 32 to 38 meters. The measurement set-up consists of base stations, an acer smart phone, a Global Positioning System and a personal computer as shown in Figure 3.

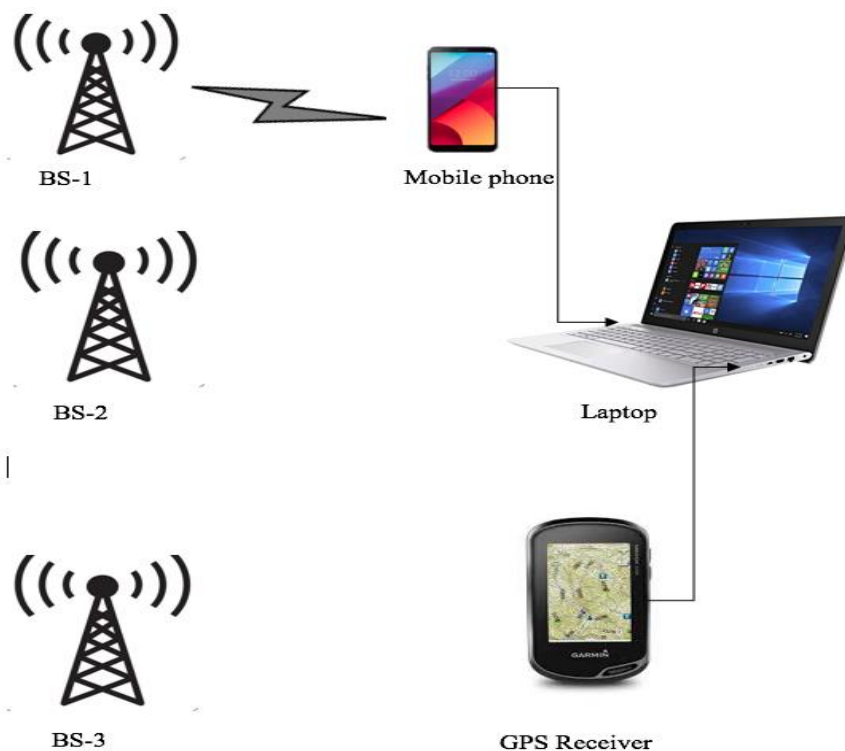


Figure 3: Received Signal Strength Measurement Set up

2.2.1 Measurement Campaign

In order to study the network from subscribers' point of view, a network cell info lite software installed on an acer phone was used to collect RSS data at intervals of 50m away from the base station during a download from the network. The measured data were transferred to the laptop through a Universal Serial Bus (USB) interface. In addition, a handheld GPS (GARMIN GPS 76CS) receiver was used to obtain the spatial coordinates of the measuring points in degrees. RSS collected was used to calculate the pathloss of the transmitted signals. (Omoze, 2021).

2.3 Data Pre-processing

Data pre-processing is an important step in preparing data set for ANN algorithm to enhance performance of the learning algorithm. The step taken to pre-process the field data collected in this work is feature normalization.

2.3.1 Feature Normalization

Normalization is a data pre-processing step in which the data collected are rescaled to lie between 0 and 1. This is necessary to avoid weight appropriation bias. In this work, the normalization technique used is the standard scaler technique presented in equation (6).

$$\bar{x}_i = \frac{x_i - \bar{x}}{\sigma} \quad (6)$$

where \bar{x}_i is the standardized of x_i , \bar{x} is the expected value of the feature given denoted as $E(x)$;

$$E(x) = \bar{x} = \frac{1}{n} \sum_{i=1}^n x_i \quad (7)$$

and σ is the standard deviation of a feature given as ;

$$\sigma = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2} \quad (8)$$

where the subscript i denotes the sample number and n the number of samples.

Feature scaling is done on the features of the dataset using the StandardScaler module imported from sklearn library using the fit transform command on the feature.

2.4 Model Development

In order to develop model with high accuracy and generalization ability, the RSS data collected with respect to distance (d), base station antenna height h_{tx} and mobile station antenna height h_{rx} was divided into 80% training data set and 20% test data set using the stratified shuffle split technique in the Scientific Python Development Environment software (SPYDER). Figure 4 is the flow chart of model development adopted in this study.

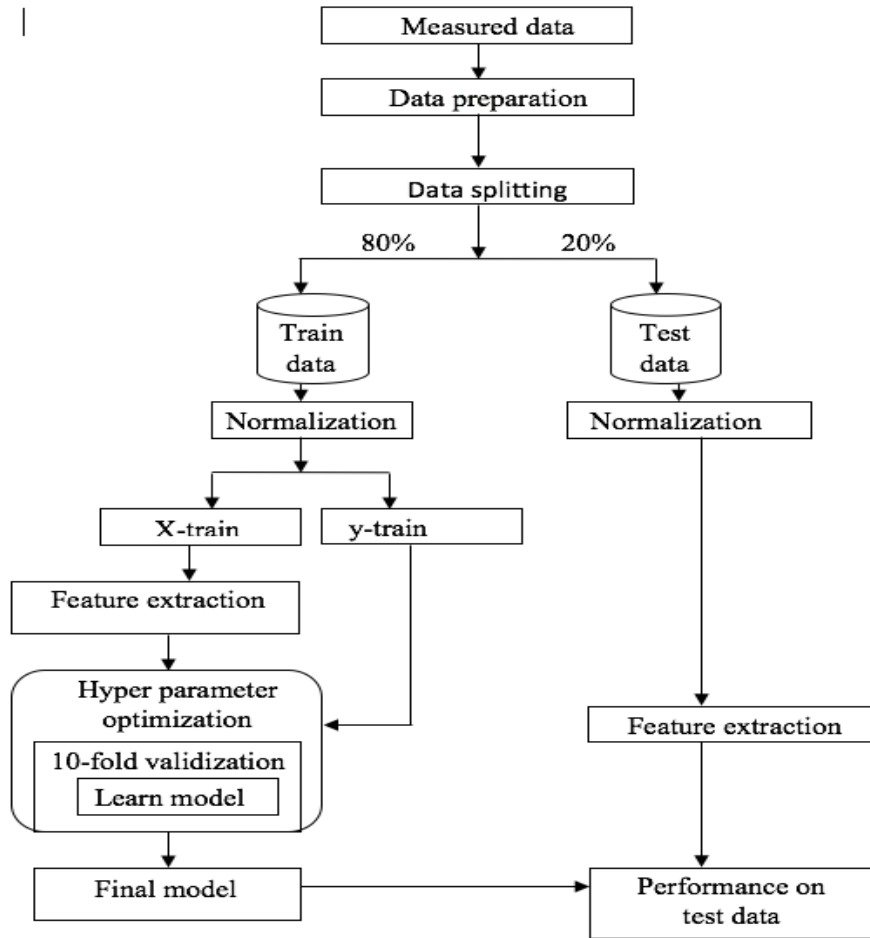


Figure 4: Flow chart of model development adopted in this study

2.4.1 Artificial Neural Network (ANN) Training

In this work, a 4-32-1 multi-level perceptron neural network was used to train the training data set. The input to the network is a feature matrix of distance $(d)m$, received signal strength values $(RSS)(dBm)$, base station antenna height $(h_{tx})m$ and mobile station antenna height $(h_{rx})m$ while the output is the pathloss values $(P_L)dB$. Where pathloss (P_L) is given in equation (9).

$$P_{L(dB)} = P_{tx}(dBm) - P_r(dBm) \quad (9)$$

where P_{tx} is the transmitted power by the base station antenna and P_r is the measured power (RSS). Figure 5 shows the artificial neural network architecture used in this work.

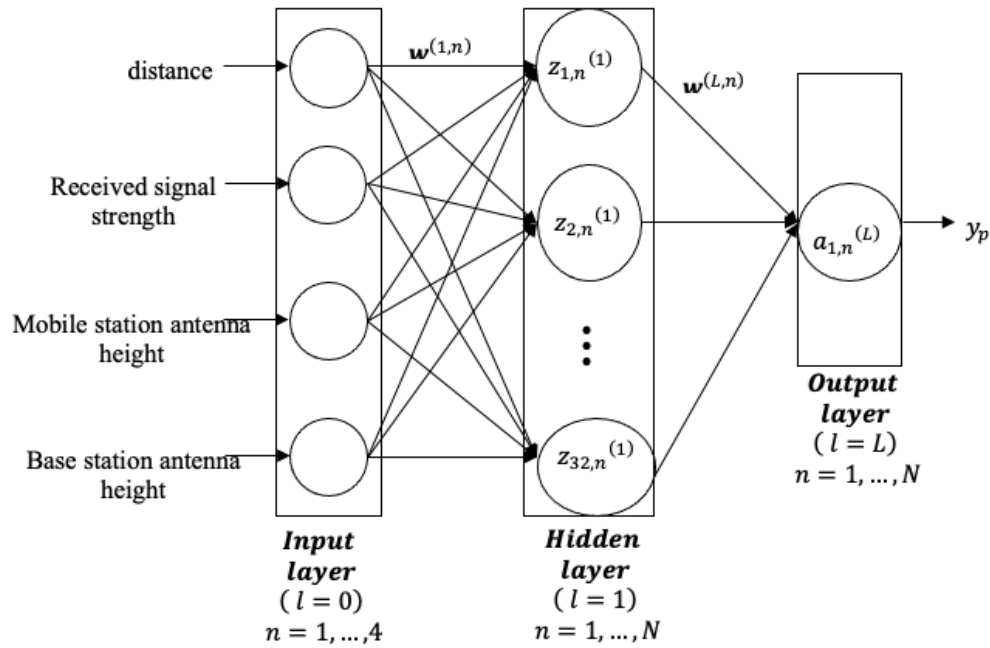


Figure 5: Block diagram of a MLP-artificial neural network with 4 features

The hidden layer activation function is the rectified linear unit (relu) as presented in equation (10) while the output layer activation function is the linear activation function as given in equation (11).

$$f(x) = \begin{cases} x & x > 0 \\ 0 & x \leq 0 \end{cases} \quad (10)$$

$$f(x) = ax \quad (11)$$

where $a = 1$

2.4.2 Cross validation

Cross Validation (CV) is a process that provides continuous monitoring of the generalization performance of the model over the learning process. CV requires splitting the data into 2–3 non-overlapping subsets: the training set which is used for parameter learning, the validation set on which the prediction error is used to approximate the generalization error, and the test set on which the prediction error is used to approximate the unbiased generalization error after the learning is completed. In this work, Early Stopping technique was adopted. To utilise early stopping, 10% of the training set was used as a validation set with a patience of 10 and the validation mean square error was monitored during the training process.

2.5 Model Validation

The validation of the developed model is a vital aspect of the modeling process; essential to its evaluation are the values of the goodness of fit indices obtained from the analysis of the given model. In this section, the artificial neural network model is validated to ascertain its suitability for the data collected in the environment investigated. The Root mean square of errors (RMSE) and mean absolute error (MAE) are computed using equation (12) and equation (13) and are used to evaluate the goodness of fit of the developed model.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - y_{p(i)})^2} \quad (12)$$

$$MAE(y_i, y_p) = \frac{1}{n} \sum_{i=1}^n |y_i - y_{p(i)}| \quad (13)$$

Where y_i is the pathloss estimated from the measured received signal strength data and $y_{p(i)}$ is the pathloss predicted using the developed artificial neural network model.

By computing equations (12) and (13), RMSE and MAE error values of 0.59dB and 0.42dB respectively.

3. Results and Discussion

This section presents the results obtained from training received signal strength data collected in real time from LTE (4G) mobile networks in Benin city. Because of the problem of overfitting, the data collected for the 10 zones were merged and used to train the artificial neural network. Table I shows descriptive statistics of the data collected in this study.

Table I: Table of Descriptive Statistics of Data Collected for LTE (4G) Cellular Network

Index	d	RSS	H_{rx}	H_{tx}	P_L
count	294	294	294	294	294
mean	309.18	-77.33	1.5	35.22	107.83
std	178.69	7.16	0	2.86	7.16
min	50	-96	1.5	30	92.17
25%	150	-82.86	1.5	34	102.74
50%	300	-78.19	1.5	36	108.19
75%	450	-72.74	1.5	36	112.86
max	800	-62.17	1.5	40	126

It presents received signal strength data collected from 294 sample points for a maximum cell radius of 800m with average RSS value of -77.33dBm. The average base station antenna height at this location for the 700MHz network was 35.22m with 126dBm pathloss value obtained at the cell edge. It is clear that the 700MHz cells in location 2 are micro cells.

From literature, pathloss prediction for mobile communication systems is often treated as a supervised learning problem, thus the data collected for this investigation was divided into feature DataFrame and target DataFrame using DataFrame indexing techniques in the scientific python development environment.

In order to develop models with high generalization ability on unseen samples, the 80% training data was trained using a 4-32-1 multi-layer perceptron feedforward neural network built using the keras functional API on tensorflow backend and learning was done by back propagating the errors. The input to the neural network is the normalized values of the feature DataFrame with the distance, received signal strength, mobile station antenna height and base station antenna height as feature variables. In the neural network architecture perspective, three key factors are considered, the type of activation function, the number of hidden layers and the number of hidden nodes on each layers.

In order to avoid overfitting of the training dataset, dropout regularization technique was adopted in the hidden layer with a dropout probability of 0.3. Since the aim of training is to predict real value number as the pathloss, the output layer is made up of a single neuron with the linear activation function.

The artificial neural network model was compiled using the Adams optimizer with the mean square error as the loss function. Training was done using a batch size of 32 for dataset for 100 epochs.

Figure 6 shows a comparative analysis of prediction made using artificial neural network (ANN) and pathloss values obtained from measured data with respect to distance while Figure 7 shows training history of artificial neural network for 100 epochs.

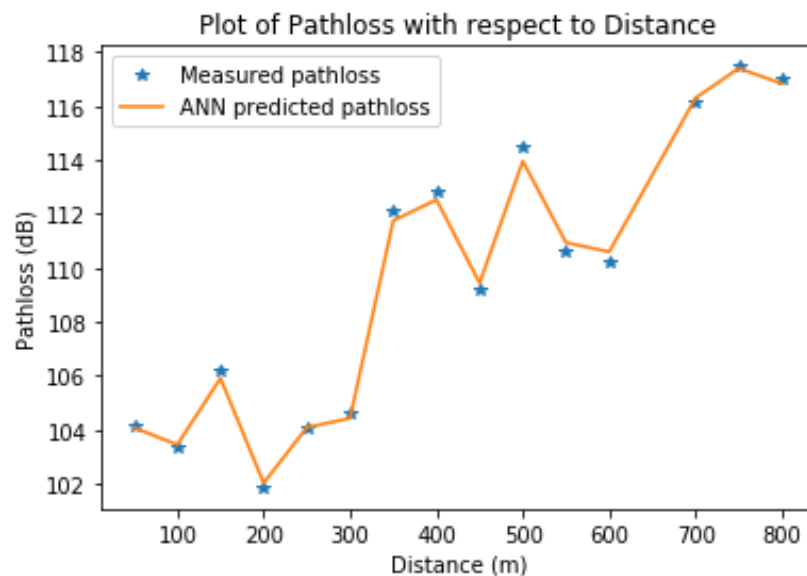


Figure 6: Plot of Measured Pathloss and Pathloss predicted using Artificial Neural Network

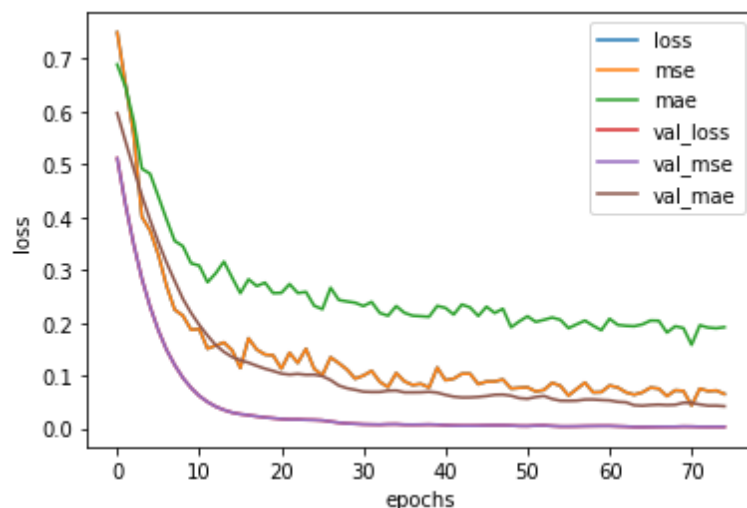


Figure 7: Performance curve of trained neural network history for pathloss prediction for 700MHz network at location 2.

3.1. Discussion

The artificial neural network model was compiled using the Adams optimizer with the mean square error as the loss function. Training was done using a batch size of 32 for dataset for 100 epochs. Figure 6 is a plot of pathloss measured with respect to distance. This plot shows that pathloss increases with respect to distance. It also shows that artificial neural network was able to learn and predict the behaviour of the network.

Figure 7 is a plot of Performance curve of trained neural network history for pathloss prediction for 700MHz network. Here, the network was trained for 100 epochs. At 0 epoch, the network had not learnt the variation in the measured data thus the high loss, mean absolute error and mean square error values. As the number of epoch increases, the network learns more about the data set and this can be seen in the lower high loss, mean absolute error and mean square error values obtained at 70 epoch. The plot also shows that at 70 epoch, the network has fully learnt the variation in the data set presented.

4. Conclusion

This study presents ANN pathloss model development for LTE network in an urban environment. Using received signal strength data measured with respect to base station antenna height, mobile station antenna height and distance from the base station, pathloss was estimated. A feature matrix consisting of 4×240 elements was used to train a 4-32-1 multilevel perceptron artificial neural network with pathloss values as the label. The hidden layer activation function is the rectified linear unit activation function while the activation function for the output layer is the linear activation function. By performing cross validation with a validation set of 10%, ANN training was achieved at the 74th epoch with a mean square error value of 0.0058dBm and a validation mean square error value of 0.00086dBm.

The result obtained from this study shows that artificial neural network with RMSE and MAE values of 0.59dB and 0.42 dB respectively were obtained when compared with pathloss estimated from the measured data. This shows that the developed artificial neural network algorithm will provide good of LTE networks if deployed during design stage in the Benin City.

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