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MULTI-LAYER PERCEPTRON NEURAL NETWORK UHF FIELD STRENGTH PREDICTION MODEL FOR MAIDUGURI METROPOLIS.

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ABSTRACT
This paper investigates the application of a Multi-layer Perceptron Neural Network (MLP-NN) based model for field strength prediction across the Maiduguri metropolis at an operating frequency of 1800MHz. Received power values obtained from multiple Base Transceiver Stations situated within the city were used to train, validate and test the MLP-NN for ability to generalize. Results indicate that the MLP-NN model with a Root Mean Squared Error (RMSE) value of 5.29dB offers an improvement over the COST 231 Walfisch-Ikegami model, which has an RMSE value of 7.95dB.

INTRODUCTION

Network coverage and quality delivery of service are of paramount importance in the process of planning mobile communication networks. Hence, it is necessary to determine radio propagation characteristics within the limits of a given service area. Various terrains offer specific conditions that affect the propagation of radio waves depending on the nature and size of obstacles that perturb the propagation. Hence, deep knowledge of channels propagation characteristics of radio signals within a service area is highly necessary when developing effective communication systems.

Empirical and deterministic models are some of the most widely used means of predicting path loss in a given terrain. However, the validity of empirical models is limited only by the accuracy with which individual measurements are made and by the extent to which the environment of the measurements adequately represents the physical environment in which the model is to be applied (Popescu *et al*., 2001). On the other hand, deterministic models, though more accurate, are computationally inefficient and require more detailed site-specific information which is often difficult to come by (Abhayawardhana *et al*., 2005).

Existing literature have revealed that computational intelligence techniques are the recent alternative approaches used to predict the path loss at a particular location in an investigated area (Ostlin, 2010). Such techniques include Artificial Neural Networks (ANNs). ANNs have the ability to handle non-linear function approximation with a greater accuracy than those techniques which are based on linear regression. As described in (Faria *et al.*, 2009), neural networks can learn to approximate any function to a given accuracy and behave like associative memories by using just example data that is representative of the desired task, operating then as model free estimators. This gives them a key advantage over traditional approaches to function estimation such as the statistical methods. Hence, computational intelligence techniques have been applied recently to predict path loss with greater accuracy, such as in (Ostlin, 2010; Ignacio *et al*., 2012; Abraham *et al*., 2014; Joseph *et al*., 2014; Callistus *et al.*, 2015 etc). Popescu *et al*., (2001) demonstrated the use of a neural network based model for field strength prediction in an indoor environment.

In this study, the applicability of the Multi-layer Perceptron Neural Network (MLP-NN) based model for field strength prediction within the Maiduguri metropolis at an operating frequency of 1800MHz, is investigated. The accuracy of prediction results of the MLP-NN based model are statistically compared with those of the COST 231 Walfisch-Ikegami model. The choice of the COST 231 Walfisch-Ikegami model is informed by its suitability for path loss prediction in built-up environments.

THE MULTI-LAYER PERCEPTRON NEURAL NETWORK

An Artificial Neural Network (ANN) is a mathematical model that tries to simulate the structure and functionalities of biological neural networks (Andrej *et al.*, 2011). ANNs have the ability to derive meaning from complicated or imprecise data, and as such, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. ANNs as tools for non-linear data modeling are widely used in function approximations, pattern recognition, prediction/ forecasting, adaptation, system identification, classification, image processing, etc.

Gaurang *et al.,* (2011) describe MLP-NN as a feed forward neural network trained with the standard back propagation algorithm. They are supervised networks so they require a desired response to be trained. They learn how to transform input data into a desired response, so they are widely used for pattern classification. With one or two hidden layers, they can approximate virtually any input-output map. They have been shown to approximate the performance of optimal statistical classifiers in difficult problems.

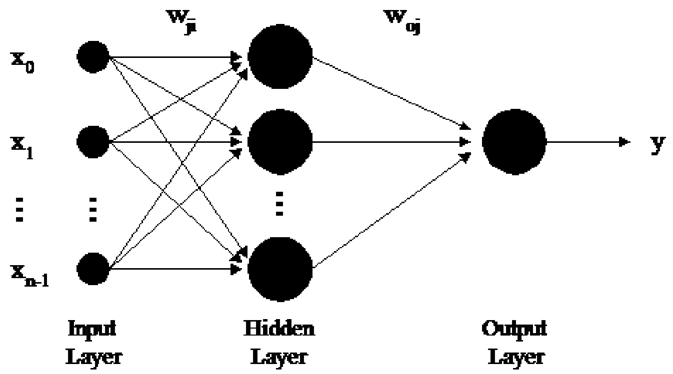

Figure 1: Multilayer Perceptron Neural Network with one hidden layer (Popescu *et al*., 2001)

As the name implies, a MLP-NN is a network that comprises of an input layer, one or more hidden layers and an output layer. Figure 1 shows that each neuron of the input layer is connected to each neuron of the hidden layer, and in turn, each neuron of the hidden layer is connected to the single neuron of the output layer. As a result, signal transmission across the entire network can only be in the forward direction, i.e, from the input layer, through the hidden layer and eventually to the output layer. Signals arriving at the inputs propagate forward from neuron to neuron, until they finally arrive at the output neuron and emerge as output signals. Error signals propagate in the opposite direction from the output neuron across the network.

As described in (Popescu *et al.*, 2001), the output of the MLP-NN is describe by the expression

$$\mathbf{y} = \mathbf{F_o}\left(\sum_{j=0}^{M} \mathbf{w_{oj}}\left(\mathbf{F_h}\left(\sum_{i=0}^{N} \mathbf{w_{ji}}\mathbf{x_i}\right)\right)\right) \qquad \text{........(1)}$$

where:

w_{oj} represents the synaptic weights from neuron j in the hidden layer to the single output neuron,

x_i represents the i^{th} element of the input vector,

F_h and F_0 are the activation function of the neurons from the hidden layer and output layer, respectively,

w_{ji} are the connection weights between the neurons of the hidden layer and the inputs.

The learning phase of the network proceeds by adaptively adjusting the free parameters of the system based on the mean squared error E, described by equation (2) between predicted and measured path loss for a set of appropriately selected training examples:

$$\mathbf{E} = \frac{1}{2}\sum_{i=1}^{m}(\mathbf{y_i} - \mathbf{d_i})^2 \qquad \text{...........(2)}$$

where, y_i is the output value calculated by the network and di represents the expected output. When the error between network output and the desired output is minimized, the learning process is terminated and the network can be used in a testing phase with test vectors. At this stage, the neural network is described by the optimal weight configuration, which means that theoretically ensures the output error minimization.

According to Östlin (2004), a neural network with only one hidden layer can approximate any function with finitely many discontinuities to an arbitrary precision, provided the activation functions of the hidden units are non-linear. Problems that require two or more hidden layers are rarely encountered in practice. Even for problems requiring more than one hidden layer theoretically, most of the time, using one hidden layer performs much better than using two hidden layers in practice (Syed, 2010).

THE COST 231 WALFISCH-IKEGAMI MODEL

As described in (Chhaya Dalela, 2013), this empirical propagation model was created on the bases of the models from J. Walfisch and F. Ikegami and further developed by the COST 231 project. Now referred to as the Empirical COST-Walfisch-Ikegami Model, it was developed and used in Europe. The model has high prediction accuracy in urban environments because it considers multiple diffraction losses over rooftops of buildings in the vertical plane between the Base and Mobile Stations. However, the model does not take into account path loss due to multiple reflections. The Model is valid for the following parameters:

- Frequency Range: 500 MHz to 2000 MHz
- Transmitter Height (hb): 4m to 50 m
- Link distance: 0.02km to 5km
- Mobile Station (MS) height (hm): 1m to 3m
- Mean height of buildings (hroof)
- Mean Street Width (w)
- Mean building separation (b)

The Line of Sight (LOS) path loss equation is given by (Mardeni and Kwan, 2010):

$$PL = 42.64 + 20\log f + 26\log d \qquad \text{...............(3)}$$

However, when there is No Line of Sight (NLOS) the equation is (Mardeni and Kwan, 2010)

$$PL = L_{FS} + L_{RTS} + L_{MSD} \qquad \text{..................(4)}$$

Where,

L_{FS} is free-space path loss and is expressed as:

$$L_{FS} = 32.45 + 20\log f + 20\log d \qquad \text{.................(5)}$$

L_{RTS} is path loss due to rooftop to street diffraction and is expressed as:

$$L_{RTS} = -16.9 - 10\log w + 10\log f + 20\log(h_b - h_m) + L_{ori} \qquad \text{.............(6)}$$

L_{ori} in (9) is path loss due to orientation angle φ (in degrees), between incident wave and street, expressed as:

$$L_{ori} = \begin{cases} -10 + 0.354\varphi & \text{for } 0 \le \varphi < 35 \\ 2.5 + 0.075(\varphi - 35) & \text{for } 35 \le \varphi < 55 \\ 4 - 0.114(\varphi - 55) & \text{for } 55 \le \varphi < 90) \end{cases} \qquad \text{............(7)}$$

L_{MSD} is path loss due to multi-screen diffraction, and is expressed as:

$$L_{MSD}=L_{BSH}+k_a+k_d\,logd+k_f\,logf-9logb \quad ....(8)$$

Where,

$$L_{BSH}=\begin{cases}-18\log(1+h_b-h_{roof}) & \text{for } h_b>h_{roof}\\ 0 & \text{for } h_b\leq h_{roof})\end{cases}$$

$$k_a=\begin{cases}54 & \text{for } h_b>h_{roof}\\ 54-0.8(h_b-h_{roof}) & \text{for } d\geq 0.5\text{km and } h_b\leq h_{roof}\\ \dfrac{54-0.8(h_b-h_{roof})}{0.5} & \text{for } d<0.5\text{km and } h_b\leq h_{roof}\end{cases}$$

$$k_d=\begin{cases}18 & \text{for } h_b>h_{roof}\\ 18-15(h_b-h_{roof}) & \text{for } h_b\leq h_{roof}\end{cases}$$

$$k_f=\begin{cases}-4+0.7(\dfrac{f}{925}-1) & \textit{for medium size city and suburban area}\\ -4+1.5(\dfrac{f}{925}-1) & \textit{for metropolitan area (i.e.large city)}\end{cases}$$

PERFORMANCE EVALUATION STATISTICS

The performance indices considered are as follows:

i) **Root Mean Square Error** (RMSE): This is a frequently used measure of the differences between values predicted by a model and the values actually observed (Olasunkanmi *et al*., 2014). The smaller the RMSE, the more accurate the prediction is. RMSE given by

$$RMSE=\sqrt{\sum_{(i=1)}^{N}\frac{(M-P)^2}{N}} \quad ....(9)$$

Where,

M – Measured Path Loss
P – Predicted Path Loss
N- Number of paired values

ii) **Coefficient of Determination** (R^2): As described in Abraham (*et al*., 2014), R-squared measures how successful the fit is in explaining the variation of the data- the goodness of fit. It is also called the square of the multiple correlation coefficients or the coefficient of multiple determinations and given by

$$R^2=1-\frac{(\sum_{(i=1)}^{N}(y_i-\hat{y}_i)^2}{(\sum_{(i=1)}^{N}(y_i-\bar{y}_i)^2} \quad ....(10)$$

where y_i is the measured path loss, $\hat{y}_i$ is the predicted path loss and $\bar{y}_i$ is the mean of the measured path loss. R^2 can take on any value between 0 and 1, but can be negative for models without a constant, which indicates that the model is not appropriate for the data. A value closer to 1 indicates that a greater proportion of variance is accounted for by the model.

MATERIALS AND METHODS

Received Power Measurement

Received power measurements were taken from multiple Base Stations of the mobile network service provider, Mobile Telecommunications Network (MTN), Nigeria, situated within the Maiduguri metropolis. The instrument used was a Cellular Mobile Network Analyser (SAGEM OT 290) capable of measuring signal strength in decibel milliwatts (dBm). The received power (PR) readings were recorded at a mobile height of 1.5 meters within the 1800MHz frequency band at intervals of 0.2km away from the Base Station, after an initial separation of 0.1kilometer as shown in Figure 2.

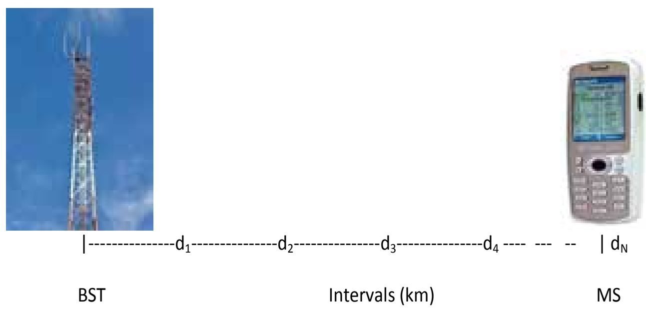

Figure 2: Measurement Procedure

Mobile Network Parameters obtained from the Network Provider (MTN) include the following:

(i). Mean Transmitter Height, HT= 40 meters
(ii). Mean Effective Isotropic Radiated Power, EIRP = 43dBm

Creating the MLP-NN Based Model

The MLP-NN architecture is defined by establishing the number of hidden layers to be used, the number of neurons contained in each layer, the activation function type, etc. In this paper, a MLP-NN with 1 hidden layer with a variable number of neurons in the hidden layer is initially adopted. The number of neurons in the hidden layer and other parameters such as the number of training iterations and the desired error goals are all determined by trial and error. The adjustable weights are based on the Root Mean Square Error (RMSE). The supervised learning algorithm considered is the Levenberg-Marquardt (trainlm) algorithm. Other parameters are based on MATLAB default settings. The MLP-NN is created using the MATLAB Neural Network ToolBox function newff, and simulated using the function sim.

In this study, the MLP-NN model final parameters adopted are as follows:

i. Number of neurons in hidden layer= 3
ii. 1 linearly activated output layer
iii. Training Algorithm: Levenberg-Marquardt
iv. Number of iterations=100
v. Error goal=0.001
vi. Stopping condition: dependent on error goal or number of iterations

Field strength Prediction using the MLP-NN Model

The techniques adopted in this study include the following:

a. Splitting Base Station Data into 60% Training, 10% Validation and 30% Testing

This basically involves analyzing each base station by randomly splitting path loss data obtained from it into 60% training, 10% validation and 30% training. It is pertinent to note the split is specified in the MATLAB application. This technique simultaneously carries out a performance comparison of the MLP-NN based models with the COST 231 Walfisch-Ikegami model on each base station. Field strength values based on the COST 231 Walfisch-Ikegami model were computed using equation (11)

$$P = EIRP - PL \quad \text{....................}(11)$$

Where, **P** is the received power, **EIRP** is the Effective Isotropic Radiated Power, and PL is the predicted path loss from equation (4).

b. Training with one Base Station data set and testing with a set from another

This is a test for generalization as described in (Abraham *et al.*, 2014). The technique involves randomly training with data set from one Base Station and testing with data set from another Base Station. By implication, a given data set can both be used for training and testing.

RESULTS AND DISCUSSION

Sample field strength prediction comparisons based on the first comparative technique are presented in Figures 3 to 6. These Figures are essentially MATLAB generated graphical performance comparisons of the MLP-NN model relative to the COST 231 Walfisch-Ikegami model. It can be observed that the MLP-NN model exhibits a more accurate prediction than the COST 231 Walfisch-Ikegami in Figures 4 and 5, while the reverse is the case in Figure 6. There is a slight convergence in performance between the two models in Figure 3. However, results in Table 1 indicate that the MLP-NN outperforms the COST 231 Walfisch-Ikegami model on all Base Stations with the exception of Base Station 7, culminating in a mean RMSE value of 4.88dB for the MLP-NN and 7.78dB for the COST 231 Walfisch-Ikegami model. On the other hand, the COST 231 Walfisch-Ikegami model exhibits better fit and correlation based on its higher R2 value.

Table 1: Splitting data into 60% training, 10% validation and 30% testing

MODEL	STAT.	BST 1	BST 2	BST 3	BST 4	BST 5	BST 6	BST 7	BST 8	BST 9	BST 10	GEOM. MEAN
MLP-NN	RMSE (dB)	3.82	6.23	5.92	4.79	4.55	3.97	7.67	4.52	5.87	3.06	4.88
	R^2	0.85	0.40	0.55	0.77	0.24	0.68	0.03	0.76	0.33	0.50	0.39
COST 231 W-I	RMSE (dB)	7.00	6.66	6.27	7.74	7.04	8.22	5.89	12.16	8.38	10.33	7.78
	R^2	0.80	0.82	0.81	0.72	0.77	0.69	0.87	0.31	0.70	0.38	0.66

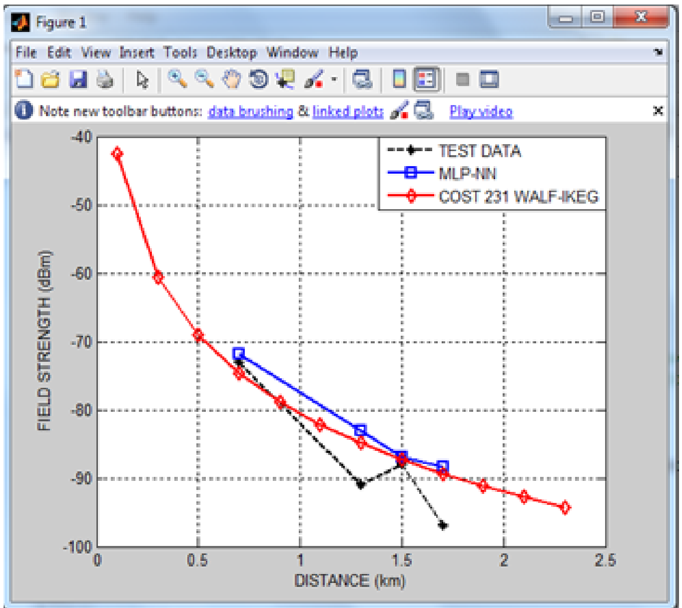

Figure 3: BST3 Comparison

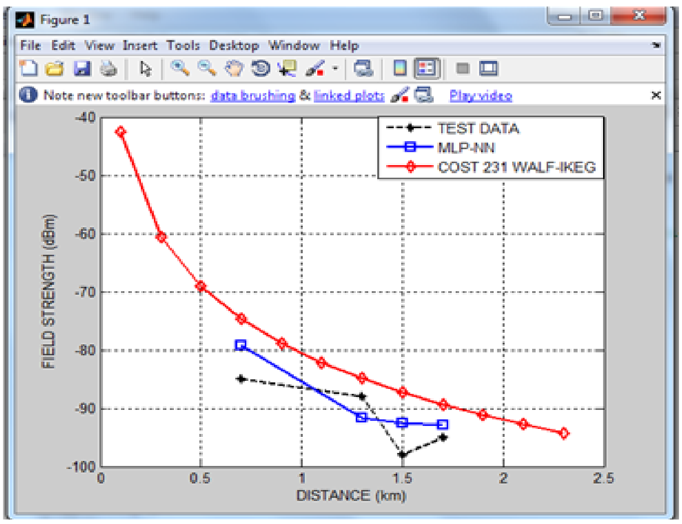

Figure 4: BST5 Comparison

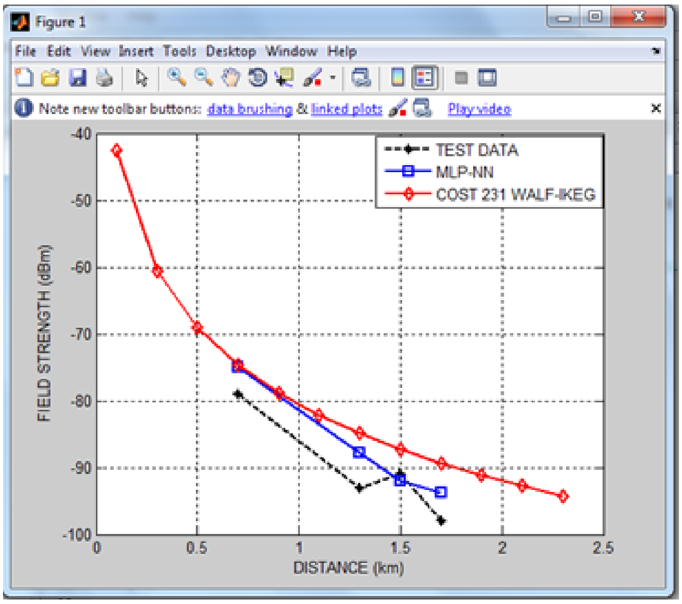

Figure 5: BST6 Comparison

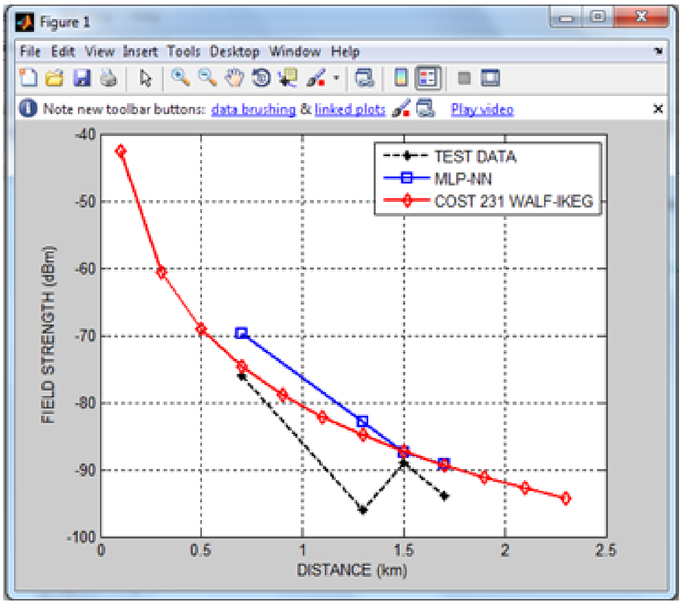

Figure 6: BST7 Comparison

Figures 7 to 10 show sample graphical comparisons based on the second comparative technique. It can be observed that while MLP-NN exhibits a much more accurate prediction than the Walfisch-Ikegami model in Figures 9 and 10, there is a slight convergence in performance in Figures 7 and 8.

Table 2: Training with one Base Station data set and testing with a set from another

MODEL	STAT.	BST7 / BST4	BST9 / BST2	BST1/ BST10	BST5/ BST8	BST6 / BST3	BST4 / BST8	GEOM. MEAN
MLP-NN	RMSE (dB)	5.65	6.82	5.69	4.91	8.04	4.10	**5.73**
	R2	0.85	0.81	0.81	0.89	0.68	0.92	**0.82**
COST 231 W-I	RMSE (dB)	7.74	6.66	10.33	12.16	6.27	7.04	**8.12**
	R2	0.72	0.82	0.38	0.31	0.81	0.77	**0.59**

However, results of Base Station Train-Test pairings in Table 2 indicate the MLP-NN outperforms the COST 231 Walfisch-Ikegami model on all but BST9/ BST2. On the geometric mean, MLP-NN based model with an RMSE value of 5.73dB outperforms the COST 231 Walfisch-Ikegami model, which has an RMSE value of 8.12dB. Moreover, the MLP-NN exhibits better fit and greater correlation with the test data as indicated by its R2 value of 0.82 and this suggest better generalisation to other environments.

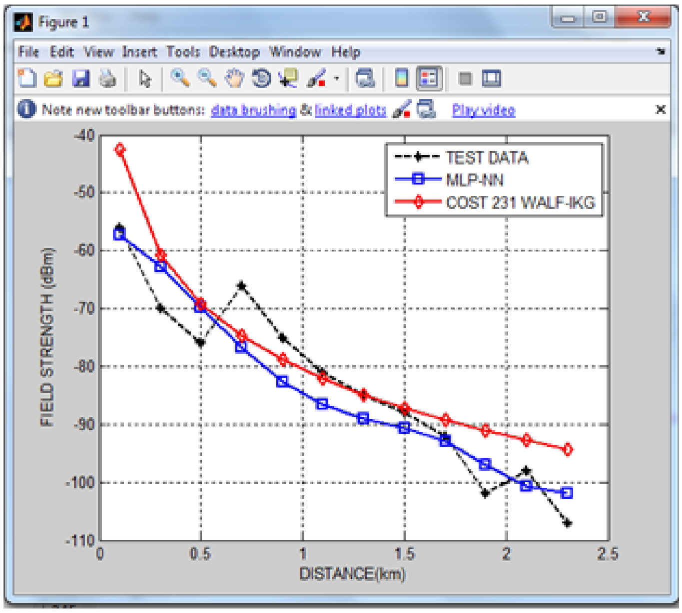

Figure 7: BST7/BST4 Pairing

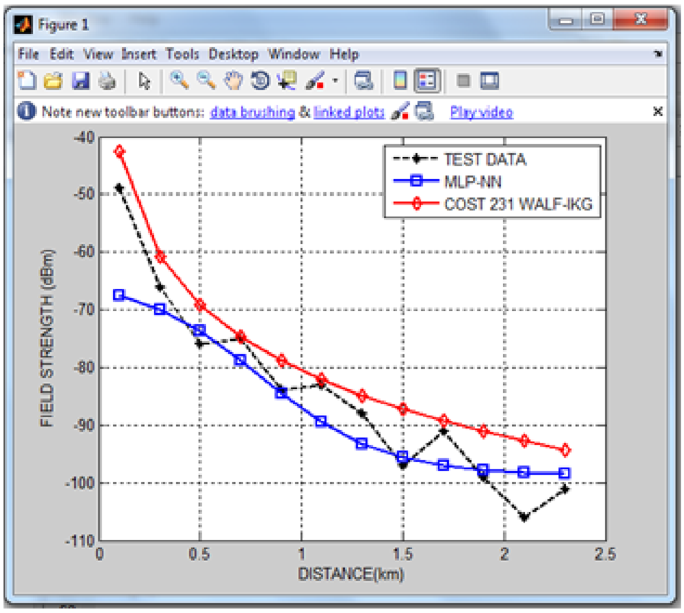

Figure 8: BST9/BST2 Pairing

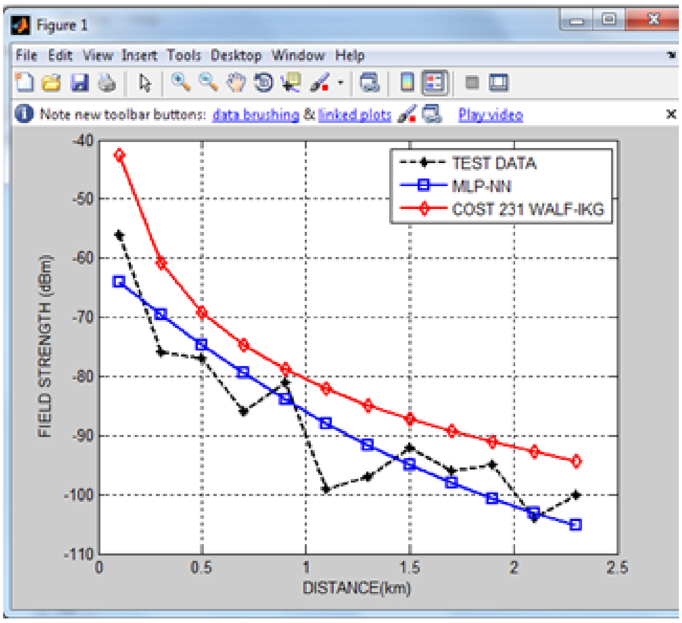

Figure 9: BST1/BST10 Pairing

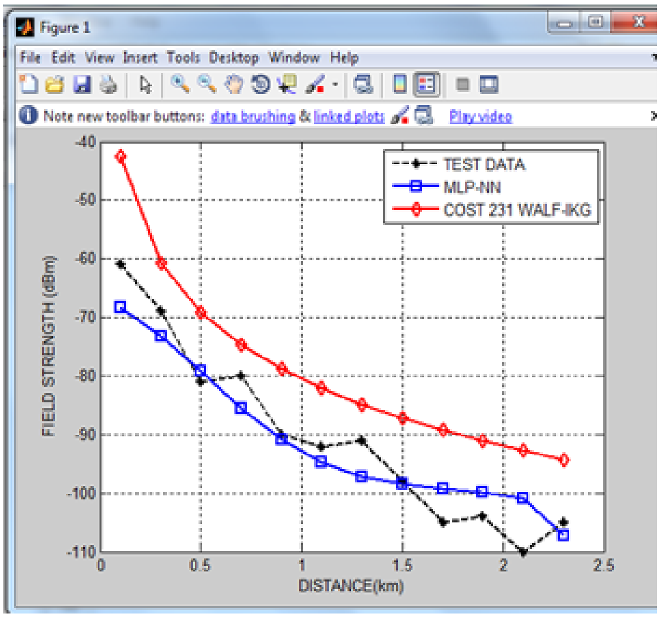

Figure 10: BST5/BST8 Pairing

Finally, a combined performance evaluation shows that on the geometric mean, the MLP-NN model with an RMSE value of 5.29dB offers a significant improvement over the COST 231 Walfisch-Ikegami model, which has an RMSE value of 7.95dB.

CONCLUSION

An Ultra High frequency (UHF) field strength prediction model based on the Multilayer Perceptron Neural Network (MLP-NN) was created and compared for prediction accuracy with the COST 231 Walfisch Ikegami model across the Maiduguri metropolis. Results indicate that the MLP-NN offers an improvement in prediction accuracy of about 2.74dB over the COST 231 Walfisch Ikegami model in terms of Root Mean Square Error (RMSE). Hence, the MLP-NN based model with an RMSE value of 5.29dB, which is less than the acceptable maximum of 6dB (Wu and Yuan, 1998; Obot *et al.,* 2011). Also, the better fit exhibited by MLP-NN using the test data from a different base station suggest better generalisation to other environments. It is therefore, recommended for field strength prediction within the terrain under investigation.

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