Development and Comparison of Artificial Neural Network Techniques for Mobile Network Field Strength Prediction across the Jos-Plateau, Nigeria

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***Abstract*—Artificial Neural Networks have a tremendous ability to adapt to any environment given sufficient data and hence are quite useful in prediction. However, they differ in their capabilities due to their distinguishing characteristic features and training procedures. In this study the Multilayer Perceptron Neural Network (MLP-NN), the Radial Basis Function Neural Network (RBF-NN) and the Generalized Regression Neural Network (GR-NN) were created and analysed for field strength prediction using received power readings obtained at 1800MHz from Base Transceiver Stations (BTS) situated within the metropolis of Jos, Nigeria. Results indicate that the GR-NN gave the most accurate prediction with an RMSE value of 5.13dB.**

Keywords—Multilayer Perceptron Neural Network; Radial Basis Function Neural Network; Generalized Regression Neural Network; Field Strength Prediction

I. INTRODUCTION

Radio wave propagation from transmitter to receiver is usually accompanied by attenuation, which refers a drop or reduction in signal strength. This stems from the fact that the various obstacles along radio path cause wave diffraction, reflection, scattering, refraction and absorption. In addition to that, radio waves also undergo free space attenuation depending on atmospheric conditions. Attenuation is also dependent on signal frequency: the higher the frequency the higher the attenuation. As a result, the reach of a transmitter is dependent on transmitting power, terrain nature, antenna height, etc. Hence, determination of radio propagation characteristics of a given terrain is of paramount importance in network coverage prediction.

Deterministic models are widely used in signal strength prediction. As described by [1], deterministic models make use of the laws governing electromagnetic wave propagation to determine the received signal power at a particular location. The field strength is calculated using the Geometrical Theory of Diffraction (GTD) as a component comprising of direct, reflected and diffracted rays at the required position. Deterministic models often require a complete 3-D map of the propagation environment. The ray tracing model used by [2] in radio propagation modeling, is a typical example of deterministic models.

Artificial Neural Networks (ANNs) have successfully been implemented in field strength prediction due to their efficiency in handling complex function approximation problems and flexibility to adapt to any environment. For example, [3] developed a model for field strength prediction in indoor environments with neural networks. The predictor was an ANN based model for the prediction of electric field strength for mobile communication networks in indoor environment.

In this study, three types of ANN, namely the Multilayer Perceptron Neural Network (MLP-NN), the Radial Basis Function Neural Network (RBF-NN) and the Generalized Regression Neural Network (GRNN), are developed and compared for field strength prediction accuracy within the metropolis of Jos, the Plateau State capital, Nigeria.

II. THE MULTI-LAYER PERCEPTRON NEURAL NETWORK

As described in [4] the Multilayer Perceptron Neural Network (MLP-NN) is a feed forward neural network trained with the standard back propagation algorithm. 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. Fig. 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 feed forward network, signal transmission across the entire network is in the forward direction, i.e, from the input layer, through the hidden layer and eventually to the output layer. Error signals propagate in the opposite direction from the output neuron across the network.

With one or two hidden layers a MLP-NN can approximate virtually any input to the desired output map. According to [6], 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 [7].

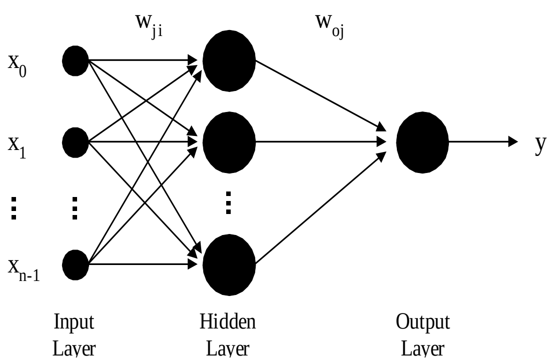


Fig. 1. *Multilayer Perceptron Neural Network with one hidden layer [5]*

As described in [5], the output of the MLP-NN is given by the expression

$$y = F_0\left(\sum_{j=0}^{M} W_{0j}\left(F_h\left(\sum_{i=0}^{N} W_{ji}X_{ij}\right)\right)\right) \quad (1)$$

where:

- W_{0j} represents the synaptic weights from neuron j in the hidden layer to the single output neuron,
- X_i is 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 (2) between predicted and measured path loss for a set of appropriately selected training examples:

$$E = \frac{1}{2}\sum_{i=1}^{m}(y_i - d_i)^2 \quad (2)$$

where,

- y_i is the output value calculated by the network
- d_i is 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, it ensures output error minimization.

III. THE RADIAL BASIS FUNCTION NEURAL NETWORK

The Radial Basis Function Neural Network (RBF-NN) can be used to solve any function approximation problems. As described by [8], the Radial Basis Function Neural Network (RBF-NN) is a type of feed-forward artificial neural network with three layers as shown in Fig. 2: an input layer, a hidden layer and an output layer. One neuron in the input layer corresponds to each predictor variable.

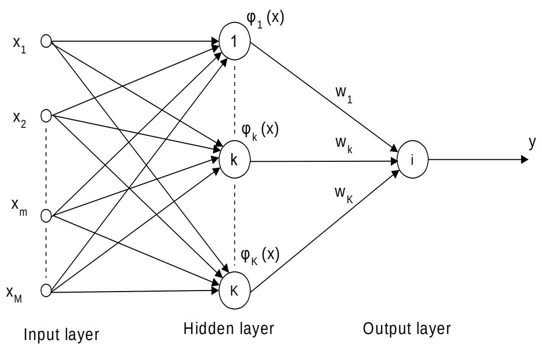


Fig. 2. *The Generalized Radial Basis Function Neural Network [9]*

The hidden layer has a variable number of neurons. Each neuron consists of a radial basis function centered on a point with the same dimensions as the predictor variables. The output layer has a weighted sum of outputs from the hidden layer to form the network outputs. As described by [9], the output of hidden-nodes are not calculated using the weighted-sum activation function; rather the output of each hidden-node, φ_k is obtained by the closeness of input vector X to an M-dimensional parameter vector μ_k associated with the k^{th} hidden node. The most popular choice for the function φ is a multivariate Gaussian function with an appropriate mean and auto covariance matrix. The output of a Radial Basis Function Neural Network is given by

$$Y_i(X) = \sum_{i=1}^{k} W_{ik}\varphi_k(X) \quad (3)$$

where,

- X is the input vector
- W_{ik} is the connection weight in the second layer (from hidden to output layer)
- k is the number of hidden nodes
- i denotes the i-th hidden node
- φ_k is the radial basis activation function.

As described in [10], the radial basis function is a multi-dimensional function that describes the distance between a given input vector and a pre-defined centre vector. The Gaussian function is a type of radial basis function given by

$$\varphi_k = exp\left(-\frac{\|X-\mu_k\|^2}{2\sigma_k^2}\right) \quad (4)$$

where, μ_k denotes the centre vector and σ_k denotes the spread (width) of the function.

The training of a RBF-NN is in two stages:

1. Determination of radial basis function parameters, i.e., Gaussian centre and spread width
2. Determination of output weight by supervised learning.

IV. THE GENERALIZED REGRESSION NEURAL NETWORK (GR-NN)

The Generalized Regression Neural Network (GR-NN) is a type of Radial Basis Function Neural Network (RBF-NN), classified under Probabilistic Neural Networks (PNN). Given sufficient input data, the GR-NN can approximate virtually any function. In contrast to back-propagation neural networks, which may require a large number iterations to converge to the desired output, the GR-NN does not require iterative training, and usually requires a fraction of the training samples a back-propagation neural network would need [11]. As shown in Fig.3, the GR-NN comprises of four layers: an input layer, a hidden layer (pattern layer), a summation layer, and an output layer.

According to [11], the GR-NN can approximate any arbitrary function between input vector and output vector directly from the training data. The general regression as described by [11] is as follows: given a vector random variable, x, and a scalar random variable, y. Assuming X is a particular measured value of the random variable y, the regression of y on X is given by

$$E[y|X] = \frac{\int_{-\infty}^{\infty} y f(X,y)dy}{\int_{-\infty}^{\infty} f(X,y)dy} \quad (5)$$

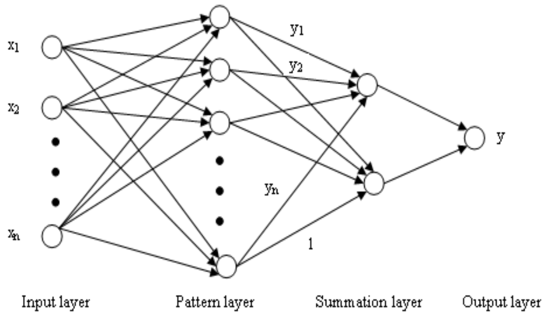


Fig. 3: *Generalized Regression Neural Network Architecture [12]*

If the probability density function $\hat{f}(x,y)$ is unknown, it is estimated from a sample of observations of x and y. The probability estimator $\hat{f}(X,Y)$, given by (6) is based upon sample values X^i and Y^i of the random variables x and y, where n is the number of sample observations and p is the dimension of the vector variable x.

$$\hat{f}(X,Y) = \frac{1}{(2\pi)^{\frac{p+1}{2}}\sigma^{\frac{p+1}{n}}}\cdot\frac{1}{n}\sum_{i=1}^{n} \exp\left[\frac{(X-X^i)^t(X-X^i)}{2\sigma^2}\right].\exp\left[\frac{(Y-Y^i)^2}{2\sigma^2}\right] \quad (6)$$

A physical interpretation of the probability estimate $\hat{f}(X,Y)$, is that it assigns a sample probability of width σ (called the spread constant or smoothing factor) for each sample X^i and Y^i, and the probability estimate is the sum of those sample probabilities.

The scalar function D_i^2 is given by

$$D_i^2 = (X - X^i)^T(X - X^i) \quad (7)$$

Combining (5) and (6) and interchanging the order of integration and summation yields the desired conditional mean $\acute{Y}(X)$, given by

$$\acute{Y}(X) = \frac{\sum_{i=1}^{n} Y^i exp\left(-\frac{D_i^2}{2\sigma^2}\right)}{\sum_{i=1}^{n} exp\left(-\frac{D_i^2}{2\sigma^2}\right)} \quad (8)$$

As further stated in [11], when the smoothing parameter σ is made large, the estimated density is forced to be smooth and in the limit becomes a multivariate Gaussian with covariance σ^2. On the other hand, a smaller value of σ allows the estimated density to assume non-Gaussian shapes, but with the hazard that wild points may have too great an effect on the estimate.

V. MATERIALS AND METHODS

Received power measurements were recorded from Base Transceiver Stations (BTS) of the mobile network service provider MTN (Mobile Telecommunications Network), Nigeria, situated within the metropolis of the city under investigation.

The instrument used was a Cellular Mobile Network Analyzer (SAGEM OT 290) capable of measuring signal strength in decibel milliwatts (dBm). Received power (P_R) readings were recorded within the radiating far field (propagation region) defined by the Fraunhofer far field radius (R_{ff}), given by $R_{ff} > \frac{2D^2}{\lambda}$, where D is the transmitting antenna length in meters and λ the wavelength of the transmitted signal derived from $\lambda = \frac{c}{f}$, where c is the velocity of light and f, the propagation frequency. For an antenna length of 2 meters, R_{ff} at 1800MHz was found to be greater than 48 meters. Hence, measurements were taken at an average mobile height of 1.5 meters within the 1800MHz frequency band at intervals of 0.05km away from the BTS, starting with a reference distance of 0.05kilometer. Mobile Network Parameters obtained from the Network Provider (MTN) include the following: Mean Transmitter Height, H_T= 34 meters, Mean Effective Isotropic Radiated Power, EIRP = 46dBm.

Field strength prediction was conducted using two basic approaches: the first involves separately analyzing each base station data by splitting the data into 60% training, 10% validation and 30% testing. This is to ensure that the neural networks are trained for optimum performance. The second approach involves training the GRNN with a data set obtained from one Base Station and then testing with a set from another Base Station [13]. By implication, a given data set can both be used for training and testing.

The statistical performance indices used in this study are based on the Root Mean Squared Error (RMSE) and the coefficient of determination (R^2). The RMSE is given by

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

where, M is the Measured Path Loss, P is the Predicted Path Loss and N the Number of paired values.

The coefficient of determination (R^2) is given by [13]

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

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 ranges from 0 to 1, but if negative for models without a constant, 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.

VI. RESULTS AND DISCUSSION

This study takes into consideration a MLP-NN with 3 hidden layer neurons, an error goal of 0.001 and the Levenberg-Marquardt back propagation as training algorithm; an RBF-NN with a spread of 0.8 and error goal of 0.1; and a GR-NN with 0.6 as spread. Based on the first comparative approach, Fig.4 graphically shows field strength prediction performance of each of the ANN based models for BTS1. It can be observed that the RBF-NN and the GR-NN plots are convergent. This stems from the fact that the GR-NN is a type of RBF-NN. However, the basic distinction between the two is that the GRNN assigns target values directly to the weights, from the training set associated with the input training vector and a component of its corresponding output vector, instead of training weights [14]. For BTS2 a similar trend can be observed from Fig.5. However, Table 1 shows that the GR-NN gave the most accurate predictions for BTS1 and BTS2. The prediction results of each of the ANN based models for the entire BTSs based on the first comparative technique are all presented Table 1. Considering the geometric mean, it can be observed that the GR-NN gave the least prediction error of 4.83dB and the best fit 0.84. In performance evaluation, the geometric mean is preferred to the arithmetic mean because it is less sensitive to extreme values [10] (Nicholas, 2002).

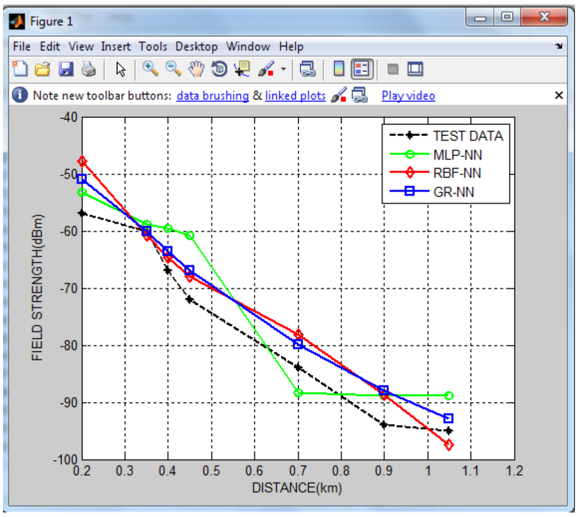


Fig. 4. *Analysis of Base Transceiver Station 1*

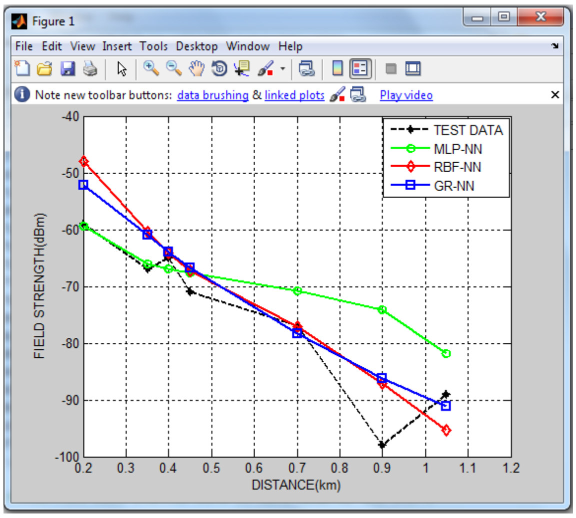


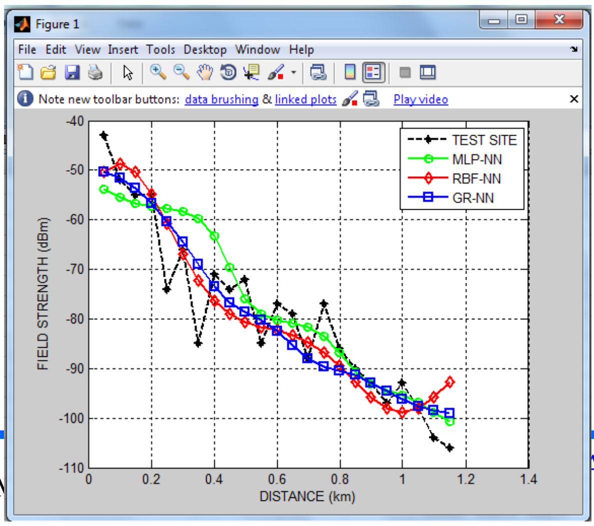
Fig. 5. *Analysis of Base Transceiver Station 2*

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

MODEL	STATS.	BTS 1	BTS 2	BTS 3	BTS 4	BTS 5	BTS 6	BTS 7	BTS 8	GEOM. MEAN
MLP-NN	RMSE(dB)	6.32	9.82	7.11	7.69	4.45	3.13	9.23	1.90	5.49
	R^2	0.81	0.42	0.50	0.69	0.88	0.94	0.56	0.99	0.69
RBF-NN	RMSE(dB)	5.00	6.95	4.88	6.47	5.64	3.15	6.92	2.70	4.96
	R^2	0.88	0.71	0.76	0.78	0.81	0.94	0.75	0.97	0.82
GR-NN	RMSE(dB)	4.30	5.92	4.89	6.62	3.62	4.06	6.93	3.57	4.83
	R^2	0.91	0.79	0.76	0.77	0.92	0.90	0.75	0.95	0.84

Sample prediction plots based on the second comparative technique are presented in Figs.6 and 7. Fig. 6 shows the plots resulting from training the ANN based models with data from BTS 8 and testing with data from BTS4. It can be observed that MLP-NN does not give a close prediction especially at distances close to the BTS. The plots in Fig. 7 derived from a BTS1/BTS6 pairing exhibit a similar trend. Prediction results in Table 2 show that for the BTS8/BTS4 pairing there is a slight convergence in performance between the RBF-NN and GR-NN while the MLP-NN is the least accurate. For the BTS1/BTS6 pairing the RBF-NN is most accurate.

Prediction results for all the random pairings are presented in Table 2. On the geometric mean, the GR-NN gave the most accurate prediction with an RMSE value of 5.45dB and the best fit as far as the second comparative technique is concerned. A combination of the two comparative techniques shows that on the geometric mean the GR-NN is the most accurate with an RMSE value of 5.13dB and R^2 value of 0.86. This is closely followed by the RBF-NN with 5.43dB and R^2 value of 0.84. The MLP-NN gave the least accurate prediction with an RMSE value of 5.73dB and R^2 value of 0.77.



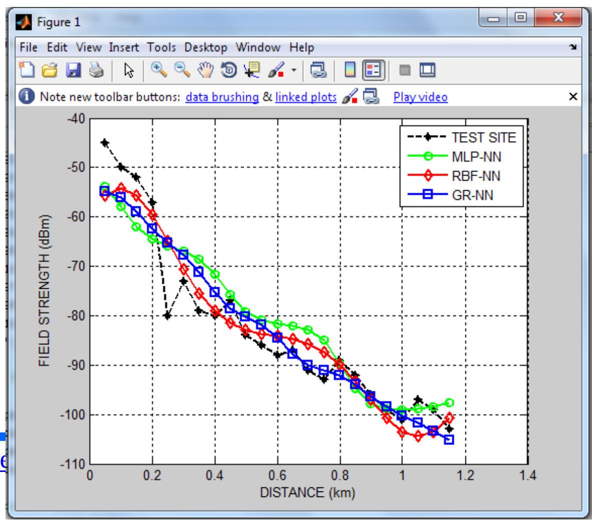


Fig. 6: *Training with BTS8, Testing with BTS4*

Fig.7: *Training with BTS1, Testing with BTS6*

Table 2: Random Training with data from one BST and Testing with data from another

MODEL	STAT.	BTS 8/4	BTS 1/6	BTS 3/2	BTS 7/5	BTS 6/3	BTS 4/1	BTS 2/8	GEOM. MEAN
MLP-NN	RMSE(dB)	7.80	6.62	6.04	6.51	5.79	5.05	4.64	5.99
	R^2	0.78	0.84	0.88	0.87	0.83	0.93	0.94	0.86
RBF-NN	RMSE(dB)	6.67	5.08	5.41	7.90	5.89	5.88	5.24	5.95
	R^2	0.84	0.91	0.90	0.80	0.83	0.90	0.92	0.87
GR-NN	RMSE(dB)	6.36	5.33	4.79	6.40	5.53	5.31	4.67	5.45
	R^2	0.85	0.90	0.92	0.87	0.85	0.92	0.94	0.89

VII. CONCLUSION

Three types of feed-forward Artificial Neural Network based models namely the Multilayer Perceptron Neural Network (MLP-NN), the Radial Basis Function Neural Network (RBF-NN) and the Generalized Regression Neural Network (GR-NN) were created and analyzed for field strength prediction using received power readings obtained at 1800MHz from Base Transceiver Stations (BTS) situated within the metropolis of Jos. This was carried out with a view to determining the most accurate in field strength prediction across the city. Results indicate that the GR-NN with an RMSE value of 5.13dB and R^2 value of 0.86 gave the most accurate prediction. This is closely followed by the RBF-NN with 5.43dB and R^2 value of 0.84.

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