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Field Strength Determination in a Tropical Metropolitan Environment Using Computational Intelligence Techniques

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ABSTRACT: *This study proposes computational intelligence based models for field strength prediction across the tropical metropolitan environment of Abuja, the federal capital territory of Nigeria. The three networks considered were the Multilayer Perceptron Neural Network (MLP-NN), the Radial Basis Function Neural Network (RBF-NN) and the Adaptive Neuro-Fuzzy Inference System (ANFIS). Prediction models based on these networks were created, trained and tested for field strength prediction using received power signals recorded at an operating frequency of 900MHz from multiple Base Transceiver Stations (BTS) distributed across the city. Results indicate that the RBF-NN and the ANFIS based models gave predictions with Root Mean Squared Errors (RMSE) values less than 5dBm. The RBF-NN based predictor gave the highest prediction accuracy based on RMSE value of 4.41dBm, closely followed by the ANFIS model with 4.69dBm.*

I. INTRODUCTION

On cellular networks, radio signals propagate from transmitter to receiver via multiple paths, based on a phenomenon termed multipath propagation. The signals undergo multiple diffractions, refractions, reflections, scattering, transmission and absorption. In line of sight situations, part of the signal, known as the direct component travels directly to the receiving device. In any case, the radio signal strength reduces as the signal propagates towards the receiver and this is called attenuation. Hence, the strength of the signal at the receiver depends significantly on the nature of the terrain, atmospheric conditions, transmitting power, transmitting frequency, height of transmitter, mobile station height, etc. As a result, it is necessary to determine signal strength at various locations away from the transmitter in order to ensure quality delivery of service.

Quite a number of techniques have been successfully implemented in order to predict received signal power at various locations away from the transmitter. Deterministic models are some of the widely used techniques for signal strength prediction. As described in [1], these 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.

Recent approaches to field strength prediction are based on computational intelligence as clearly documented in [3], [4]. Computational intelligence encompasses various computing techniques including artificial neural networks, genetic algorithms, fuzzy sets, neuro-fuzzy systems, etc. These techniques are quite efficient in handling problems associated with uncertainty, imprecision, approximation, etc. Hence, computational intelligence techniques attempt to find acceptable solutions to complex real world problems such as pattern recognition, speech processing, function approximation, signal processing, forecasting, etc.

The problem of field strength prediction is viewed as a function approximation problem consisting of a nonlinear mapping from a set of input variables containing information about the potential receiver onto a single output variable representing the predicted field strength [3]. Hence, the study is aimed at exploring the remarkable abilities to handle such tasks. The study presents computational intelligence based models for field strength determination across Abuja, the federal capital territory of Nigeria. The computational intelligence networks considered are the Multilayer Perceptron Neural Network (MLP-NN), the Radial Basis Function Neural Network (RBF-NN), and the Adaptive Neuro-Fuzzy Inference System (ANFIS). Models based on these networks are created, trained, validated and tested for field strength prediction using received power signals recorded at an operating frequency of 900MHz from multiple Base Transceiver Stations (BTS) distributed across the city.

II. THE MULTI-LAYER PERCEPTRON NEURAL NETWORK

The artificial neuron or simply neuron is an essential processing unit that processes weighted inputs to produce an output. The Multilayer Perceptron Neural Network (MLP-NN) comprises of fully interconnected layers of such neurons. The MLP-NN is made up of an input layer, one or more hidden layers and an output layer. In such architecture as depicted in Fig. 1, each neuron in a given layer is connected to each neuron in the next layer, in such a way that only forward transmission of signals is possible, i.e, from the input layer, through the hidden layer and eventually to the output layer. Hence, the MLP-NN is a type of feed forward neural network. However, error signals propagate in the opposite direction from the output neuron across the network. The MLP-NN is typically trained with the standard back propagation algorithms. The conjugate gradient back propagation (traincgb) and the Levenberg-Marquardt back propagation algorithm are typical examples of supervised learning methods used in MLP-NN.

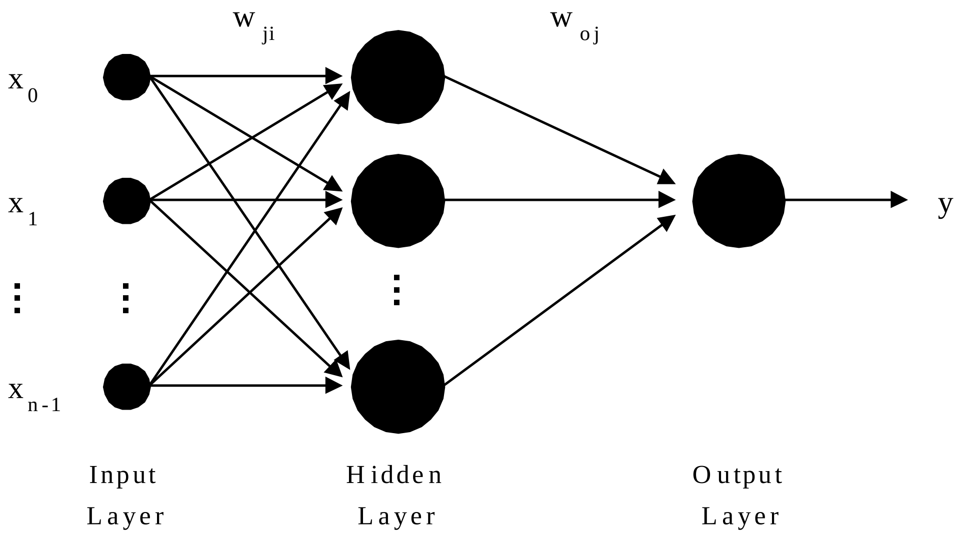

Figure 1: Multilayer Perceptron Neural Network with one hidden layer [3]

With one or two hidden layers a MLP-NN can approximate virtually any input to the desired output map. According to [5], 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 [6].

As described by Popescu et al, (2001), the output of the MLP-NN is given by (1):

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

Where:

- W_{0j} 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 (2) between predicted and measured path loss for a set of appropriately selected training examples:

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

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

III. THE RADIAL BASIS FUNCTION NEURAL NETWORK

The Radial Basis Function Neural Network (RBF-NN) is described by [7] as 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. With respects to categorical variables, n-1 neurons are used where n is the number of categories. 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.

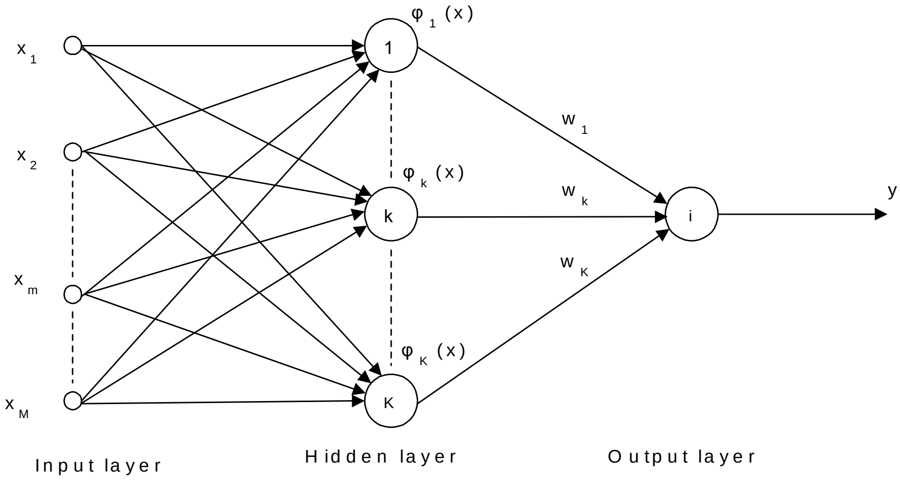

Figure 2: The Radial Basis Function Neural Network [8]

As described by [8], 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 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 (3):

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

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 [9], 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 (4):

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

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. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEMS

An Adaptive Neuro-Fuzzy Inference System (ANFIS) is an intelligent system created by the fusion of an Artificial Neural Network (ANN) with a Fuzzy Inference System (FIS). ANFIS was first proposed by [10] to combine the learning ability of ANNs with the ability of fuzzy systems to interpret imprecise information. ANNs are quite useful in modeling systems where there is no mathematical relationship between input and output patterns. This stems from the fact that, as systems that mimic the human brain, ANNs can be trained using input patterns and target output, and then used to predict a result given new set of inputs. Based on the concepts of fuzzy set theory, fuzzy if-then rules, and fuzzy reasoning, FIS is a computational network capable of modeling human knowledge and reasoning. Hence, ANFIS is an intelligent adaptive system capable of solving complex non-linear problems.

The ANFIS model considered in this study is based on the model proposed by [11], referred to as the First Order Sugeno Fuzzy Model (or simply TS Model) shown in Fig. 3. Fig. 4 presents an ANFIS architecture based on the TS model, with two inputs, *x* and *y* and one output which is a function of the inputs.

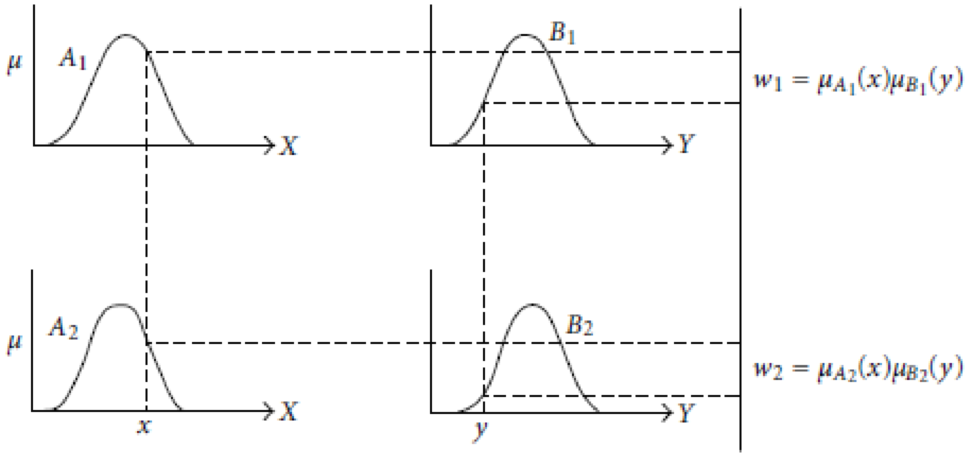

Figure 3: First Order Sugeno Model [12]

Based on the TS Model, the two *if-then-else* rules are as follows:

i) If (x is A_1) and y is B_1, THEN $f_1 = p_1 x + q_1 y + r_1$

ii) If (x is A_2) and y is B_2, THEN $f_2 = p_2 x + q_2 y + r_2$

The linguistic labels A_i and B_i are fuzzy sets associated with the input nodes *x* and *y* respectively, and f_i is a non-fuzzy function which depends on the inputs *x* and *y*.

As shown in Figure 4, the ANFIS architecture comprises of five layers and each layer is defined by specific nodes, which can either be fixed or adaptive. A fixed node is denoted by a circle while a square represents an adaptive node.

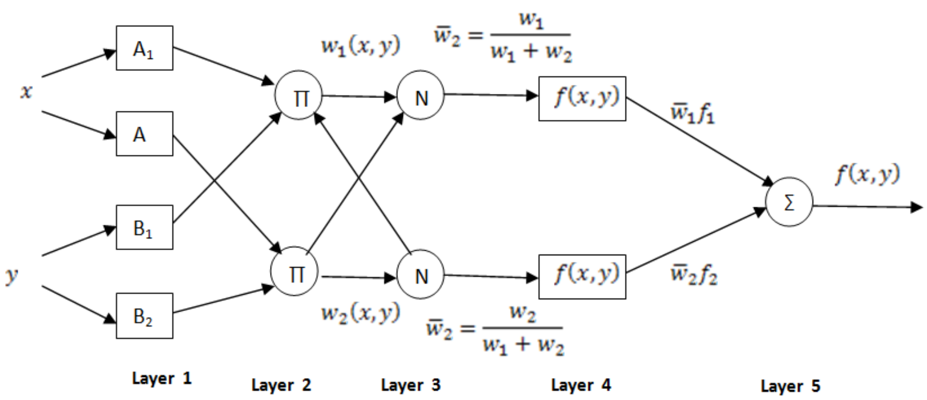

Figure 4: The Architecture of an Adaptive Neuro-Fuzzy Inference System

Layer 1 : In this layer, every node is an adaptive node with a node function given by:

$$O_{1,i} = \mu_{A_i}(x) \quad for\ i = 1,2 \tag{5}$$

$$O_{1,i} = \mu_{B_{i-2}}(y) \quad for\ i = 3,4 \tag{6}$$

These functions are defined by Membership Functions (MF) which can either be Bell, Gaussian or Triangular. The most widely used MF is the Bell MF given by (7):

$$\mu_{Ai}(x) = \frac{1}{1 + \left[\frac{x - c_i}{a_i} \right]^{2b_i}} \tag{7}$$

Layer 2: This layer comprises of fixed nodes and the output of every node is the product of all the incoming signals into the node as given by (8). These node outputs are the firing strengths of the rules.

$$w_i = \mu_{Ai}(x_i) X \mu_{Bi}(y_i) \tag{8}$$

Layer 3: This layer also comprises of fixed nodes, which are denoted by N. This is the normalization layer where the ratio of the firing strength of each rule is calculated with respect to the sum of the firing strengths of all rules, using (9). Hence, the outputs of this layer are referred to as normalized firing strengths.

$$\overline{w_i} = \frac{w_i}{\sum_{j=1}^{2} w_j} \tag{9}$$

Layer 4: The nodes in this layer are adaptive nodes. The output of each node is the product of the normalized firing strength and a first order polynomial (for the first order TS model), given by (10):

$$\overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i) \tag{10}$$

The parameters p_i, q_i and r_i are called consequent parameters.

Layer 5: This is the output layer and it has a single fixed node labeled ∑. The layer computes the overall output as the summation of all incoming signals, to produce a crisp output given by (11):

$$f(x, y) = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{11}$$

According to Jang (1993), ANFIS uses a hybrid learning algorithm comprising of gradient descent back-propagation and the least-squares approximation method. During network training the back-propagation algorithm determines the premise parameters while the least-squares approximation method determines the consequent parameters.

V. MATERIALS AND METHODS

5.1 Received Power Measurement and Path Loss Computation

Received power measurements were recorded from multiple Base Transceiver Stations (BTSs) situated within the Central Business District, Maitama and Wuse areas of Abuja, the federal Capital Territory of Nigeria. The Base Stations belong to the mobile network service provider, Mobile Telecommunications Network (MTN), Nigeria. The instrument used was a Cellular Mobile Network Analyser (SAGEM OT 290) capable of measuring signal strength in decibel milliwatts (dBm). Received power (P_R) readings were recorded beyond the computed Fraunhofer far field radius of 24meters, within the 900MHz frequency band at intervals of 0.05km away from the Base Station, after an initial separation of 0.05 kilometer. Mobile Network Parameters obtained from the Network Provider (MTN) include Mean Transmitter Height of 28 meters and Mean Effective Isotropic Radiated Power (EIRP) of 45dBm.

5.2 Development of Prediction Models

The MLP-NN architecture adopted comprises of an input layer with number of neurons dependent on data input vector size, one hidden layer, and one linearly activated output layer. The number of neurons in the hidden layer and other parameters such as 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*.

The RBF-NN is created using the MATLAB function *newrb*. The key network parameter is basically the spread constant, determined by trial and error.

Creating the ANFIS network involved specifying the number of network inputs, the number of fuzzy membership function (MF) per each input, the type of fuzzy MF, and the number of epochs as described by [13]. In this paper, the type of the MF chosen is the bell-shaped function.

VI. RESULTS AND DISCUSSION

Two distinct approaches to field strength prediction were adopted using the considered computational intelligence models. 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 computational networks are trained for optimum performance. The second approach involves training the networks with a data set obtained from one Base Station and then testing with a set from another Base Station in a random manner [14]. By implication, a given data set can both be used for training and testing.

The statistical indices for model performance evaluation were based on the following:

i) Root Mean Squared Error (RMSE) given by (12)

$$RMSE = \sqrt{\sum_{i=1}^{N} \frac{(M-P)^2}{N-1}} \tag{12}$$

Where, M is the Measured received power, P the Predicted received power and N the Number of paired values.

ii) The coefficient of determination (R^2), also called the square of the multiple correlation coefficients or the coefficient of multiple determinations, given by (13):

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y}_i)^2} \tag{13}$$

Based on the first comparative approach, Fig. 5 depicts the performance of each of the models on BTS 7. It can be observed that the RBF-NN and the ANFIS models exhibit a much closer prediction than the MLP-NN. Results in Table 1 show that this performance trend is sustained across most of the BTSs. Geometric Mean performance across all the BTSs shows that the RBF-NN is the most accurate with an RMSE value of 4.03dBm. This is closely followed by the ANFIS model with 4.29dBm. However, the ANFIS model has a higher R^2 value of 0.61, indicting a great fit, resulting from higher correlation. With the highest prediction RMSE value of 6.83dBm, the MLP-NN is simply not in the class of the other two models.

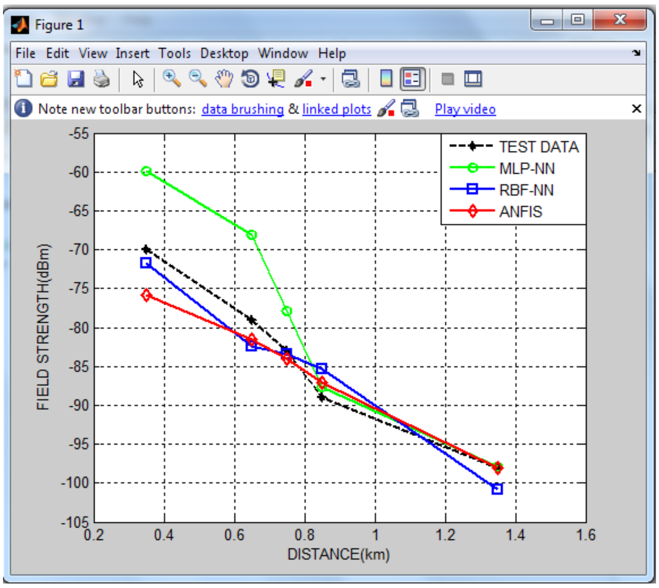

Figure 5: Data splitting into 60% training, 10% validation and 30% testing on BTS 7

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

BASE TRANSCEIVER STATION	STATS.	MLP-NN	RBF-NN	ANFIS
BTS1	RMSE(dBm)	7.11	0.88	2.37
	R^2	0.51	0.99	0.95
BTS2	RMSE(dBm)	13.25	5.08	7.05
	R^2	-1.26	0.67	0.36
BTS3	RMSE(dBm)	5.57	4.93	5.81
	R^2	0.50	0.61	0.46
BTS4	RMSE(dBm)	8.89	7.07	5.06
	R^2	-0.55	0.02	0.50
BTS5	RMSE(dBm)	2.31	4.74	2.12
	R^2	0.82	0.24	0.85
BTS6	RMSE(dBm)	9.61	4.87	4.78
	R^2	-0.29	0.67	0.68
BTS7	RMSE(dBm)	7.04	2.71	3.01
	R^2	0.44	0.92	0.90
BTS8	RMSE(dBm)	10.99	5.72	5.53
	R^2	-1.02	0.45	0.49
BTS9	RMSE(dBm)	5.00	4.48	4.23
	R^2	0.60	0.68	0.71
BTS10	RMSE(dBm)	5.55	4.56	5.99
	R^2	0.12	0.41	0.53
GEOM. MEAN	RMSE(dBm)	6.83	4.03	4.29
	R^2	0.01	0.41	0.61

Based on the second approach to field strength prediction, Fig. 6 presents a scenario where the networks are trained with BTS 9 data and tested with data from BTS 10. Again, it can be observed that RBF-NN and the ANFIS models exhibit a closer prediction than the MLP-NN.

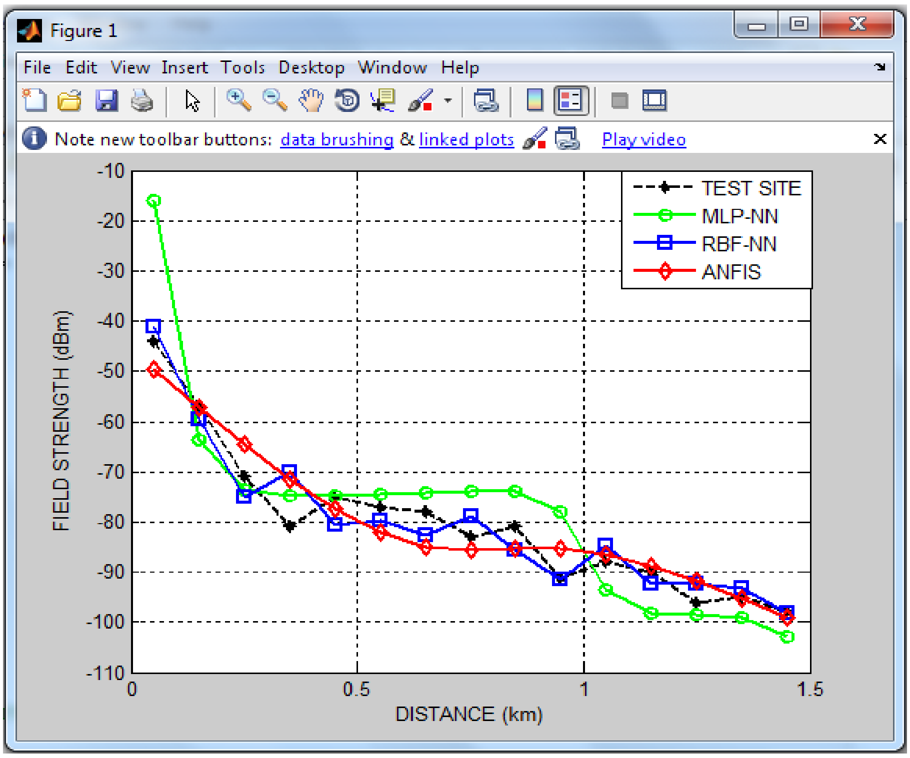

Fig.6: Training with BTS 9 data and Testing with data from BTS 10

Similarly, results in Table 2 show that this performance trend is sustained across most of the train/test pairings. Geometric Mean performance across all train/test pairings shows that again, the RBF-NN is the most accurate with an RMSE value of 4.82dBm and an the highest R^2 value of 0.9. The RBF-NN is closely followed by the ANFIS model with 5.12dBm. The MLP-NN still maintains an RMSE value above 6dBm.

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

TRAIN/TEST PAIRINGS	STATS.	MLP-NN	RBF-NN	ANFIS
BTS7/BTS3	RMSE(dBm)	2.46	5.54	4.97
	R^2	0.98	0.88	0.90
BTS2/BTS8	RMSE(dBm)	8.09	5.51	5.32
	R^2	0.72	0.87	0.88
BTS10/BT1	RMSE(dBm)	3.75	4.92	3.77
	R^2	0.95	0.91	0.95
BTS4/BTS5	RMSE(dBm)	7.12	4.51	4.49
	R^2	0.80	0.92	0.92
BTS6/BTS9	RMSE(dBm)	16.09	5.07	5.04
	R^2	-0.19	0.88	0.88
BTS1/BTS7	RMSE(dBm)	6.97	3.33	3.83
	R^2	0.82	0.96	0.95
BTS8/BTS4	RMSE(dBm)	5.26	5.31	5.85
	R^2	0.89	0.89	0.86
BTS3/BTS6	RMSE(dBm)	9.17	5.03	6.80
	R^2	0.60	0.88	0.78
BTS5/BTS2	RMSE(dBm)	6.90	5.08	7.76
	R^2	0.82	0.90	0.77
BTS9/BTS10	RMSE(dBm)	8.62	4.34	4.64
	R^2	0.63	0.91	0.89
GEOM. MEAN	RMSE(dBm)	6.66	4.82	5.12
	R^2	0.69	0.90	0.88

A combined performance assessment based on the two approaches shows that on the geometric mean, the same performance trend is observed with the RBF-NN model being the most accurate with an the lowest RMSE value of 4.41dBm and the highest R^2 value of 0.73. Just a fraction less accurate than the RBF-NN counterpart is the ANFIS model with an RMSE value of 4.69dBm and an R^2 value of 0.61. The MLP-NN is the least accurate with an RMSE value of 6.74dBm and an R^2 value 0.08, indicating a poor fit resulting from poor correlation.

VII. CONCLUSION

Field strength prediction models for the metropolitan city of Abuja, Nigeria, created on the bases of computational intelligence networks, were trained and tested with received power data recorded at an operating frequency of 900MHz from multiple Base Transceiver Stations situated across the city. The three networks considered were the Multilayer Perceptron Neural Network (MLP-NN), the Radial Basis Function Neural Network (RBF-NN) and the Adaptive Neuro-Fuzzy Inference System (ANFIS). Results indicate that the RBF-NN based predictor gave the highest prediction accuracy based on RMSE value of 4.41dBm, closely followed by the ANFIS model with 4.69dBm. The MLP-NN is the least accurate with an RMSE value of 6.74dBm.

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