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An Artificial Intelligence Approach to Ultra-High Frequency Path Loss Modelling of the Suburban Areas of Abuja, Nigeria

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ABSTRACT

This study proposes Artificial Intelligence (AI) based path loss prediction models for the suburban areas of Abuja, Nigeria. The AI-based models were created on the bases of two deep-learning networks, namely the Adaptive Neuro-Fuzzy Inference System (ANFIS) and the Generalized Radial Basis Function Neural network (RBF-NN). These prediction models were created, trained, validated and tested for path loss prediction using path loss data recorded at 1800MHz from multiple Base Transceiver Stations (BTSs) distributed across the areas under investigation. Results indicate that the ANFIS and RBF-NN based models with Root Mean Squared Error (RMSE) values of 5.30dB and 5.31dB respectively, offer greater prediction accuracy over the widely used empirical COST 231 Hata, which has an RMSE of 8.18dB.

KEYWORDS: *Path Loss; Adaptive Neuro-Fuzzy Inference System; Generalized Radial Basis Function Neural Network; Multi-Layer Perceptron Neural Network; Hata-Okumura*

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INRODUCTION

Artificial intelligence (AI) refers to the ability of programmed computers or control systems to mimic or simulate human intelligence. In recent times, AI is widely used in diverse technological areas to proffer increased performance and efficiency. Some of the widely used AI tools are the Deep-Learning networks, termed soft computing or computational intelligence tools. As described by [1], Soft Computing exploits the remarkable ability of the human mind to reason and learn in an environment of uncertainty and imprecision. Soft Computing encompasses a collection of computing methodologies, which include artificial neural networks, genetic algorithms, fuzzy sets, neuro-fuzzy systems, etc. Soft Computing exploits the tolerance for imprecision, uncertainty, approximate reasoning and partial truth in order to achieve tractability, robustness and low-cost solutions [2]. Hence, these techniques are quite efficient in finding acceptable solutions to problems such as prediction, pattern recognition, speech processing, function approximation, signal processing etc.

In recent times, mobile communication networks have become the most common media for wireless communications. In order to establish a cellular network, adequate knowledge of radio propagation characteristics across a specific terrain is an essential requirement. Path loss modeling is commonly used in network coverage determination. Path loss refers to the loss of power as radio waves propagate between receiver and transmitter. Path loss is dependent on operating frequency, transmitter height and transmitter-receiver separation, nature of the terrain, etc. Path loss usually results from reflections, diffraction, refractions, scattering, free space loss, etc. Empirical models [3] are some of the most widely used means of predicting path loss in a given terrain. Unfortunately, existing empirical models though easier to implement, are less sensitive to the environment's physical and geometrical structures and not so accurate while the deterministic models which though are more accurate are computationally inefficient and require more detailed site-specific information which is often difficult to come by [4]. Recent approaches to radio propagation modelling such as [5][6][7] and [8] are based on the application of soft computing techniques.

This study presents an AI-based approach to path loss prediction across the suburban areas of Abuja, the federal capital territory of Nigeria. The two Soft Computing networks considered are the Adaptive Neuro-Fuzzy Inference System (ANFIS) and the Radial Basis Function Neural Network (RBFNN). These predictors are compared for performance accuracy with the Hata Okumura and the COST 231 Hata empirical models.

Adaptive Neuro-Fuzzy Inference Systems

As described in [5], the Adaptive Neuro-Fuzzy Inference System (ANFIS) is a hybrid system created by combining a Fuzzy Inference System (FIS) and an Artificial Neural Network (ANN). ANFIS was first proposed by [9] to combine the learning ability of ANNs with the ability of fuzzy systems to interpret imprecise information, and it was based on the first-order Takagi–Sugeno (TS) model. ANFIS is an intelligent adaptive system capable of solving complex non-linear problems. ANNs are quite useful in modelling 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 sets of inputs. Based on the concepts of fuzzy set theory, fuzzy if-then rules, and fuzzy reasoning, FIS, on the other hand, is a computational network capable of modelling human knowledge and reasoning.

The ANFIS predictor considered in this study is based on the model proposed by [10], referred to as the First Order Sugeno Fuzzy Model (or simply the TS Model) shown in Fig 1. The ANFIS architecture based on the TS model is presented in Fig. 2, with two inputs, *x* and *y* and one output which is a function of the inputs.

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

1. If (x is A_1) and y is B_1, THEN $f_1 = p_1 x + q_1 y + r_1$
2. 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 Fig. 2, 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.

Layer 1 : In this layer, every node is an adaptive node with a node function given by (1) and (2):

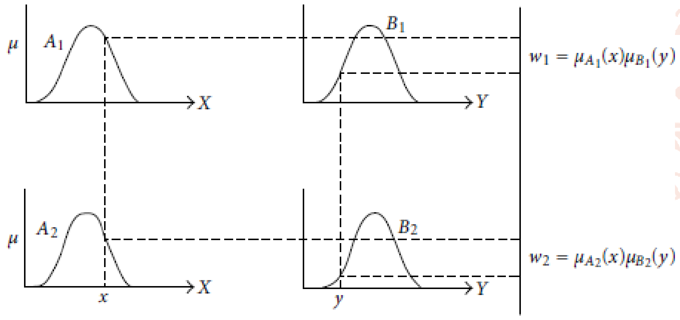

Fig. 1: First Order Sugeno Model (Liang et al, 2012)

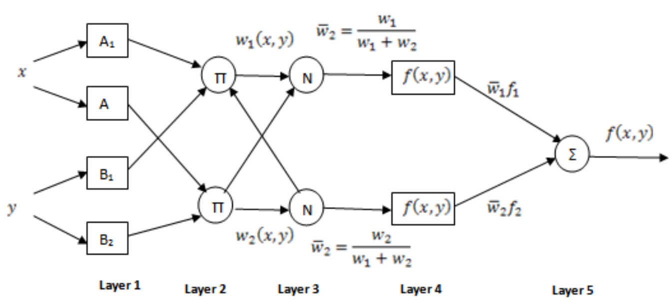

Fig. 2: The Architecture of an Adaptive Neuro-Fuzzy Inference System

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

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

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 (3).

$$\mu_{Ai}(x) = \frac{1}{1 + \left[\frac{x - c_i}{a_i}\right]^{2b_i}} \qquad (3)$$

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 (4). These node outputs are the firing strengths of the rules.

$$w_i = \mu_{Ai}(x_i) X \mu_{Bi}(y_i) \qquad (4)$$

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 (5). Hence, the outputs of this layer are referred to as normalized firing strengths.

$$\overline{w_i} = \frac{w_i}{\sum_{j=1}^{2} w_j} \qquad (5)$$

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 (6):

$$\overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i) \qquad (6)$$

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 $\sum$. The layer computes the overall output as the summation of all incoming signals, to produce a crisp output given by (7).

$$f(x,y) = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \qquad (7)$$

According [9], 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.

The Generalized Radial Basis Function Neural Network

The generalized Radial Basis Function Neural Network (RBF-NN) is also widely used in solving function approximation problems. The generalization is equivalent to the use of this multi-dimensional surface to interpolate the test data [11]. As described in [11], a RBF-NN network comprises of the input layer, hidden layer and 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. 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 RBF–NN layers are shown in Fig. 3.

1. The input layer
2. The hidden layer, where input data undergoes nonlinear transformation
3. The linear output layer, where the outputs are produced

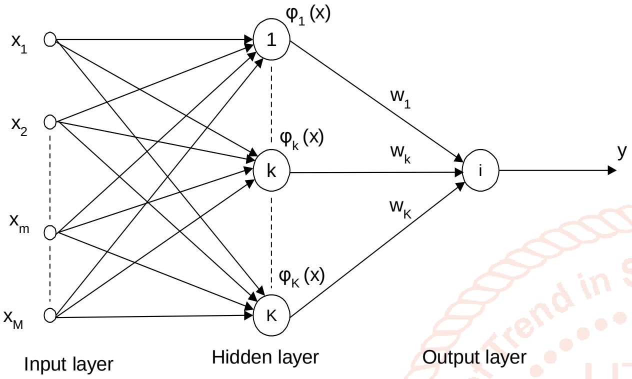

Fig. 3: ***The Generalized Radial Basis Function Neural Network [11].***

The most popular choice for the function φ is a multivariate Gaussian function with an appropriate mean and auto covariance matrix [11]. The output of a Radial Basis Function Neural Network is given by (8).

$$Y_i(X) = \sum_{i=1}^{K} w_{ik}\varphi_k(X) \qquad (8)$$

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 [12], 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 (9)

$$\varphi_k = \exp\left(-\frac{\left\|X-\mu_k\right\|^2}{2\sigma_k^2}\right) \qquad (9)$$

Where,
μ_k denotes the center vector
σ_k denotes the spread (width) of the function

The learning process is equivalent to finding a surface in a multidimensional space that provides a best fit to the training data, with the criterion for the "best fit" being measured in some statistical sense [11]. The training of a RBFNN 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.

The Cost 231 Hata Model

As described in [6], the COST 231 Hata Model was derived from the Hata Model by the European Cooperative for Scientific and Technical research, to suit the European environments taking into consideration the frequency range 0.5GHz to 2GHz. This model is suitable for path loss prediction in urban, semi-urban, suburban and rural areas. The model expression is given by (10)

$$L = 46.3 + 33.9\log f - 13.82\log h_B - a(h_m) + (44.9 - 6.55\log h_B)\log d + C \qquad (10)$$

Where,

- L = Median path loss in Decibels (dB)
- C=0 for medium cities and suburban areas
- C=3 for metropolitan areas
- f = Frequency of Transmission in Megahertz (MHz)(500MHz to 200MHz)
- h_B = Base Station Transmitter height in Meters (30m to 100m)
- d = Distance between transmitter and receiver in Kilometers (km) (up to 20kilometers)
- h_m = Mobile Station Antenna effective height in Meters (m) (1 to 10metres)
- $a(h_m)$ = Mobile station Antenna height correction factor as described in the Hata Model for Urban Areas.
- For urban areas, $a(h_m) = 3.20(\log10(11.75hr))^2 - 4.97$, for f > 400 MHz
  For sub-urban and rural areas, $a(h_R) = (1.1\log(f) - 0.7)h_R - 1.56\log(f) - 0.8$

Materials and Methods

A. Received Power Measurement and Path Loss Computation

Received power measurements were recorded from multiple Base Transceiver Stations (BTSs) situated within the suburban areas of Abuja, namely Kubwa and Kuje, with average building heights mostly below 15m. 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 milli watts (dBm). Received power (P_R) readings were recorded within the 1800MHz frequency band at intervals of 0.05km away from the BTS. Corresponding path loss values (L_P), were computed using (11).

$$L_P = EIRP - P_R \qquad (11)$$

Where,

- L_p is the computed path loss
- EIRP is the Effective Isotropic Radiated Power
- P_R is the received signal power

Mobile Network Parameters obtained from the Network Provider (MTN) include Mean Transmitter Height of 28 meters and Mean Effective Isotropic Radiated Power (EIRP) of 43dBm.

Results and Analysis

The performance comparison of the AI-based models and the empirical model is based on the Root Mean Square Error (RMSE), given by (12), and the Coefficient of Determination (R^2), given by (13). The RMSE is a measure of the differences between predicted and observed values. R^2 ranges between 0 and 1, but can be negative, which indicates the model is inappropriate for the data. A value closer to 1 indicates that a greater correlation of the model with test data.

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

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

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

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 values.

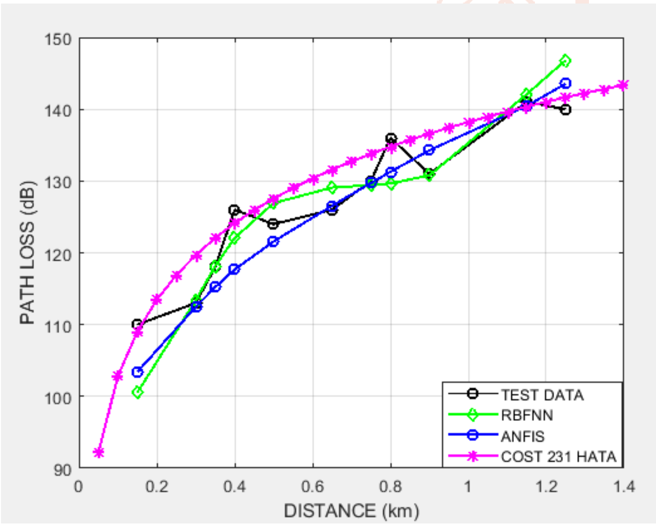

Fig. 4: ***Model Comparison for BTS 1***

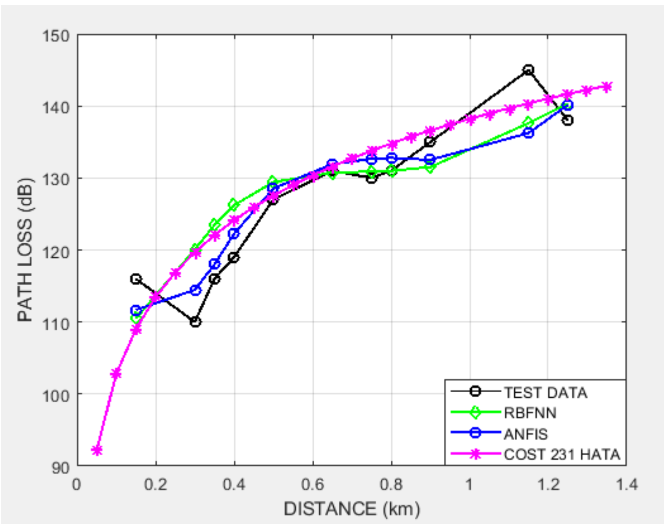

Fig. 5: ***Model Comparison for BTS 2***

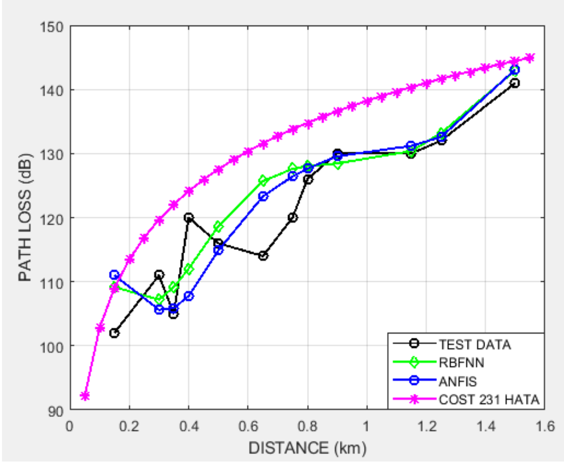

Fig. 6: ***Model Comparison for BTS 3***

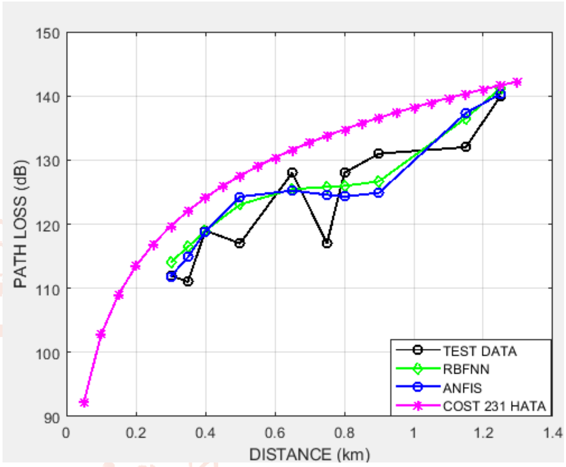

Fig. 7: ***Model Comparison for BTS 4***

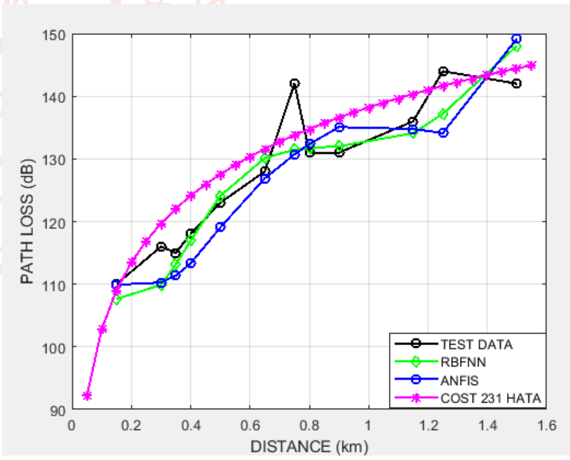

Fig. 8: ***Model Comparison for BTS 5***

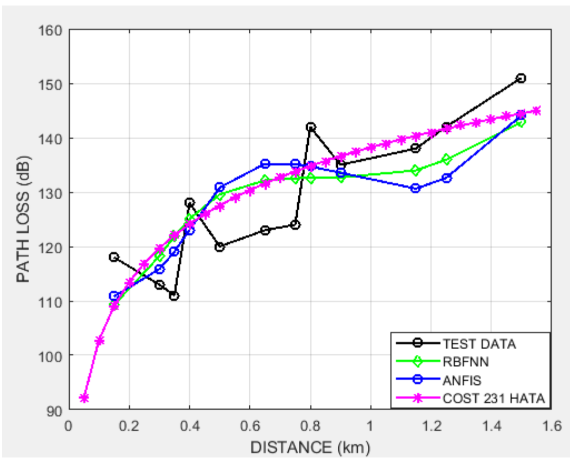

Fig. 9: ***Model Comparison for BTS 6***

Table 1: Statistical Performance Comparison of Predictors

MODEL	STATS.	BST 1	BST 2	BST 3	BST 4	BST 5	BST 6	MEAN
RBF-NN	RMSE(dB)	4.38	5.38	5.48	4.47	4.59	7.59	5.31
	R^2	0.80	0.72	0.76	0.76	0.83	0.61	0.75
ANFIS	RMSE(dB)	3.97	3.74	5.76	4.61	5.64	8.08	5.30
	R^2	0.83	0.87	0.73	0.75	0.74	0.56	0.75
COST 231 Hata	RMSE(dB)	4.80	6.96	11.22	11.08	7.30	7.70	8.18
	R^2	0.88	0.59	0.16	-0.19	0.65	0.58	0.44

During neural network training, validation and testing, the set of recorded path loss values from each BTS was randomly split into 50% for training, 10% for validation and 40% for testing. Figs. 4 to 9 depict graphical performance comparisons of all predictors considered. It can be clearly observed that the COST 231 Hata slightly overestimates the path loss in figures 6 and 7. However, a convergence in performance of the three predictors can be observed in the other figures. The performance indices in Table 1 indicate that the AI- based predictors with a mean RMSE value of 5.3dB offer greater prediction accuracy over the COST 231 Hata. Furthermore, with R^2 values of 0.75, the AI-based models exhibit greater fit over the COST 231 Hata, which has 0.44.

Conclusion

Artificial Intelligence based models were trained, validated and tested using data obtained at an operating frequency of 1800MHz, from multiple Base Stations located within the suburban areas of Abuja, Nigeria. The AI-based models were created on the bases of two deep learning networks, namely, the Adaptive Neuro-Fuzzy Inference System (ANFIS) and the Generalized Radial Basis Function Neural network (RBF-NN). A performance comparison of the AI-based models with the widely used COST 231 Hata empirical counterpart indicate that on the average, the AI-based techniques offer an improvement of about 3dB over the COST 231 Hata. Hence, the AI-based models are recommended for path loss prediction at 1800MHz, across the terrain under investigation.

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