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Soft Computing Techniques for Path Loss Estimation at 1800MHz in a Tropical Metropolitan Environment: Case Study of Abuja-Nigeria

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***Abstract*—This study proposes path loss prediction models based on Soft Computing Techniques, for a tropical metropolitan environment, using Abuja, the federal capital territory of Nigeria, as case study. The two Soft Computing networks considered are the Adaptive Neuro-Fuzzy Inference System (ANFIS) and the Generalized Regression Neural network (GRNN). Prediction models based on these networks were created, trained and tested for path loss prediction using path loss data recorded at 1800MHz from multiple Base Transceiver Stations (BTSs) distributed across the city. Results indicate that the ANFIS and GRNN based models gave predictions with Root Mean Squared Error (RMSE) values of 5.76dB and 5.17dB respectively. A comparison of prediction results indicate that on the average, the two Soft Computing Techniques offer an improvement of about 4.71dB over the linear regression based methods comprising of the COST 231 Hata and COST 231 Walfisch-Ikegami models.**

I. INTRODUCTION

Radio signals propagating from a transmitter to a receiver are usually accompanied by loss of power. This loss of power is referred to as path loss. Path loss is not only dependent on operating frequency, transmitter height and transmitter-receiver separation, but also on the nature of the terrain. Path loss usually results from reflections, diffraction, refractions, scattering, free space loss, etc. Since path loss is quite an essential factor in radio link characterization, there is need for accurate path loss prediction so that the radio link can be optimally engineered for acceptable delivery of service. Empirical and deterministic models 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 [1].

Recent approaches to path loss prediction are based on the application of soft computing techniques. As described by [2], Soft Computing is an emerging approach to computing which parallels the remarkable ability of the human mind to reason and learn in an environment of uncertainty and imprecision. Soft Computing is a term that encompasses a collection of computing methodologies, which include artificial neural networks, genetic algorithms, fuzzy sets, neuro-fuzzy systems, etc. Soft Computing is aimed at exploiting the tolerance for imprecision, uncertainty, approximate reasoning and partial truth in order to achieve tractability, robustness and low-cost solutions [3]. Hence, these techniques are quite efficient in finding acceptable solutions to complex real world problems such as pattern recognition, speech processing, function approximation, signal processing, forecasting, etc.

Since the problem of path loss prediction is viewed as a function approximation problem this study is aimed at exploiting the remarkable abilities of Soft Computing techniques to handle such tasks. This study presents path loss prediction models for Abuja, the federal capital territory of Nigeria, based on two Soft Computing networks: the Adaptive Neuro-Fuzzy Inference System (ANFIS) and the Generalized Regression Neural Network (GRNN). The prediction results of the two Soft Computing networks are compared with those of the COST 231 Hata and the COST 231 Walfisch-Ikegami models, which are widely deemed suitable for urban path loss prediction.

II. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEMS

An Adaptive Neuro-Fuzzy Inference System (ANFIS) is a hybrid system created by combining different soft computing techniques in order to exploit the properties of the different techniques. It is a fusion of an Artificial Neural Network (ANN) with a Fuzzy Inference System (FIS). ANFIS was first proposed by [2] to combine the learning ability of NNs 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 set 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 model considered in this study is based on the model proposed by [4], referred to as the First Order Sugeno Fuzzy Model (or simply TS Model) shown in Fig 1. 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.

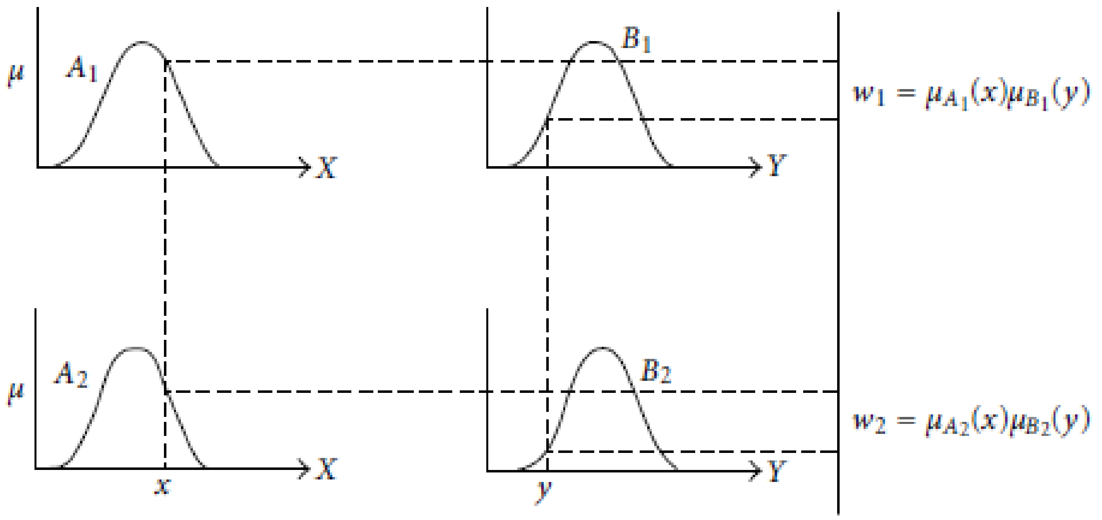


Fig. 1: First Order Sugeno Model (Liang et al, 2012)

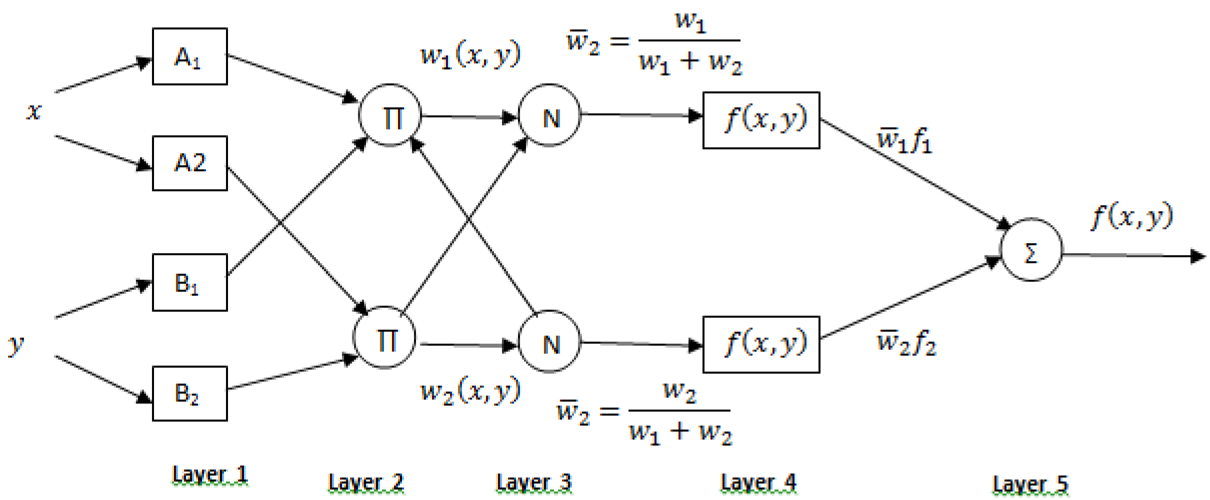


Fig. 2: The Architecture of an Adaptive Neuro-Fuzzy Inference System

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 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):

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

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

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).

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

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.

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

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.

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

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):

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

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).

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

According [2], 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.

III. THE GENERALIZED REGRESSION NEURAL NETWORK

The Generalized Regression Neural Network (GRNN), proposed by [5] is type of Artificial Neural Network (ANN) that is capable of approximating virtually any function given sufficient data. 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 [5]. The GRNN is used to solve a variety of problems such as prediction, control, plant process modeling or general mapping problems [6]. As shown in Fig. 3, the GRNN comprises of four layers:

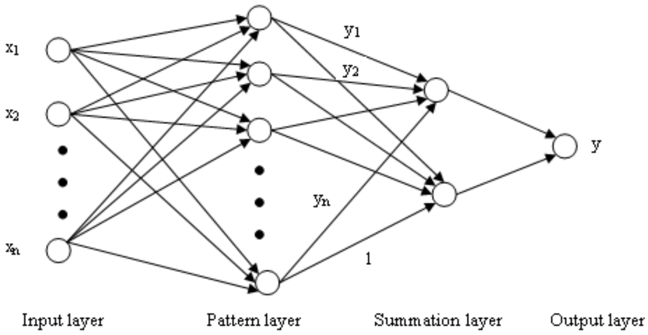


Figure 3: Generalized Regression Neural Network Architecture [7]

Input layer: This is the first layer and it is responsible for sending inputs to the next layer called the pattern layer

Pattern layer: This layer computes the Euclidean distance between input and training data, and also the activation function.

Summation layer: This layer comprises of two parts: the Numerator and the Denominator. The Numerator sums up products of training data and activation function, while the Denominator sums up activation functions.

Output layer: The single neuron contained in this layer generates the output through division of the Numerator by the Denominator obtained from the previous layer.

The general regression as described by [5] is as follows: given a vector random variable, x, and a scalar random variable, y, and assuming X is a particular measured value of the random variable y, the regression of y on X is given by (8)

$$E[y|X] = \frac{\int_{-\infty}^{\infty} y f(X,y) dy}{\int_{-\infty}^{\infty} f(X,y) dy} \quad (8)$$

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 (9) 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.

$$\hat{f}(X,Y) = \frac{1}{(2\pi)^{(p+1)/2}\sigma^{(p+1)/n}} \cdot \frac{1}{n}\sum_{i=1}^{n} \exp\left[\frac{(X-X^i)^T(X-X^i)}{2\sigma^2}\right] \cdot \exp\left[\frac{(Y-Y^i)^2}{2\sigma^2}\right]$$
(9)

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 (10)

$D_i^2 = (X - X^i)^T(X - X^i)$ (10)

Combining equations (8) and (9) and interchanging the order of integration and summation yields the desired conditional mean $\acute{Y}(X)$, given by (11)

$$\acute{Y}(X) = \frac{\sum_{i=1}^{n} Y^i exp\left(-\frac{D_i^2}{2\sigma^2}\right)}{\sum_{i=1}^{n} exp\left(-\frac{D_i^2}{2\sigma^2}\right)} \quad (11)$$

The only free network parameter is the smoothing parameter. Neural network training involves finding the optimal value of the smoothing parameter, for which the mean squared error is minimum. As a key advantage over standard feed-forward neural nets, the GNN always converges to a global minimum and hence, has no issues with local minima. It is further stated in [5] that 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.

IV. THE COST 231 HATA MODEL

The COST 231 Hata Model was formulated from the Hata Model by the European Cooperative for Scientific and Technical research, to suit the European environments taking into consideration a wide range of frequencies (500MHz to 200MHz). The Hata model in turn is an extension of the Okumura Model. As a result of its proven suitability path loss prediction in urban, semi-urban, suburban and rural areas, it is one of the most widely used models. The model expression is given by (12)

$L = 46.3 + 33.9logf - 13.82logh_B - a(h_m) + (44.9 - 6.55logh_B)logd + C$ (12)

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, $a(h_R) = (1.1\log(f) - 0.7)h_R - 1.56\log(f) - 0.8$

V. THE COST 231 WALFISCH-IKEGAMI MODEL

The COST-Walfisch-Ikegami Model is a semi-empirical propagation model created on the bases of the models from J. Walfisch and F. Ikegami [8] and further developed by the COST 231 project. The model is suitable for path loss prediction 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 (h_b): 4m to 50 m
- Link distance: 0.02km to 5km
- Mobile Station (MS) height (h_m): 1m to 3m
- Mean height of buildings (h_{roof})
- Mean Street Width (w)
- Mean building separation (b)

The Line of Sight (LOS) path loss equation is given by (13)

$PL = 42.64 + 20logf + 26logd$ (13)

However, when there is No Line of Sight (NLOS) the equation is (14)

$PL = L_{FS} + L_{RTS} + L_{MSD}$ (14)

Where,

L_{FS} is free-space path loss and is expressed as (15):

$L_{FS} = 32.45 + 20logf + 20logd$ (15)

L_{RTS} is path loss due to rooftop to street diffraction and is expressed as (16):

$L_{RTS} = -16.9 - 10logw + 10logf + 20\,log(\,h_b - h_m) + L_{ori}$ (16)

L_{ori} in (16) is path loss due to orientation angle φ (in degrees), between incident wave and street, expressed as (17):

$$L_{ori} = \begin{cases} -10 + 0.354\varphi \; for \; 0 \le \varphi < 35 \\ 2.5 + 0.075(\varphi - 35) \; for \; 35 \le \varphi < 55 \\ 4 - 0.114(\varphi - 55) \; for \; 55 \le \varphi < 90 \end{cases} \quad (17)$$

L_{MSD} is path loss due to multi-screen diffraction, and is expressed as (18):

$$L_{MSD} = L_{BSH} + k_a + k_d logd + k_f logf - 9 \log b \quad (18)$$

Where,

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

$$k_a = \begin{cases} 54 \; for \; h_b > h_{roof} \\ 54 - 0.8(h_b - h_{roof}) \; for \; d \ge 0.5km \; and \; h_b \le h_{roof} \\ 54 - \frac{0.8(h_b - h_{roof})}{0.5} \; for \; d < 0.5km \; and \; h_b \le h_{roof} \end{cases}$$

$$k_d = \begin{cases} 18 \; for \; h_b > h_{roof} \\ 18 - 15(h_b - h_{roof}) \; for \; h_b \le h_{roof} \end{cases}$$

$$k_f = \begin{cases} -4 + 0.7\left(\frac{f}{925} - 1\right) \; for \; medium \; size \; city \; and \; suburban \; area \\ -4 + 1.5\left(\frac{f}{925} - 1\right) \; for \; metropolitan \; area \; (i.e. \, large \; city) \end{cases}$$

VI. 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 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 48meters, within the 1800MHz frequency band at intervals of 0.05km away from the Base Station, after an initial separation of 0.05 kilometer. Corresponding path loss values (L_P), were computed using (19).

$$L_P = EIRP - P_R \quad (19)$$

Where,

EIRP is the Effective Isotropic Radiated Power, determined from (20)

$$EIRP = P_T - L_F + G_T \quad (20)$$

Where,

- P_T - Transmitted power
- L_F - Feeder Loss
- G_T – Transmitter gain

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.

B. Path loss Prediction Procedure

Path loss prediction using the considered Soft Computing networks is based on two distinct approaches. The first involves separately analyzing each BTS 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 splitting path loss obtained from all BTSs into two sets: 50% training (BTSs 1 to 5) and 50% testing (BTSs 6 to 10). In performance evaluation, the geometric mean is preferred to the arithmetic mean because it is less sensitive to extreme values [9]. Hence, the Geometric Mean (GM) of the training set values at each receiver-transmitter separation is obtained from the training set using equation (21), and then used to train the network based models. The trained networks are then tested with data from the testing set.

$$GM = \sqrt[n]{X_1 . X_2 . X_{3,} . , X_n} \quad (21)$$

In both cases, the network based models are simultaneously compared for path loss prediction with the COST 231 Hata and the COST-Walfisch-Ikegami models.

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

i) Root Mean Squared Error (RMSE) given by (22)

$$RMSE = \sqrt{\sum_{i=1}^{N} \frac{(M-P)^2}{N-1}} \quad (22)$$

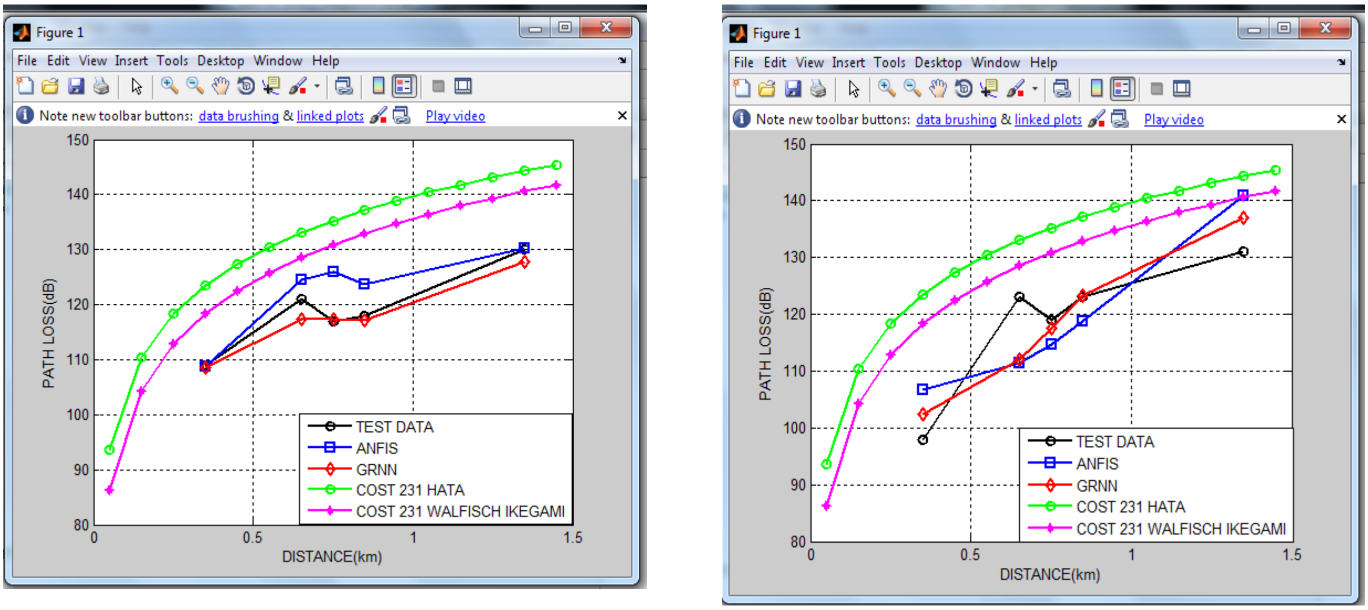
Where, M is the Measured received power, P the Predicted received power and N the Number of paired values.

ii) The coefficient of determination (R^2), also called the square of the multiple correlation coefficients or the coefficient of multiple determinations, given by (23):

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y}_i)^2} \quad (23)$$

VII. RESULTS AND DISCUSSION

Based on the first comparative approach, Fig. 4a) and Fig. 4b) depict the performance of the network based predictors relative to the empirical models on BTS1 and BTS2 respectively. It can be observed that the network based models exhibit a much closer prediction than the empirical models. Prediction results in Table 1 show that this performance trend is sustained across all the BTSs. Geometric Mean performance across all the BTSs shows that the GRNN based model is the most accurate with an RMSE value of 4.54dB. The ANFIS based model with an RMSE value of 5.52bB is about 1dBm less accurate than the GRNN. The COST 231 Hata and the COST-Walfisch-Ikegami models with 12.24dB and 9.08dB respectively, are simply outperformed by the network based counterparts.



a) BTS1 Analysis

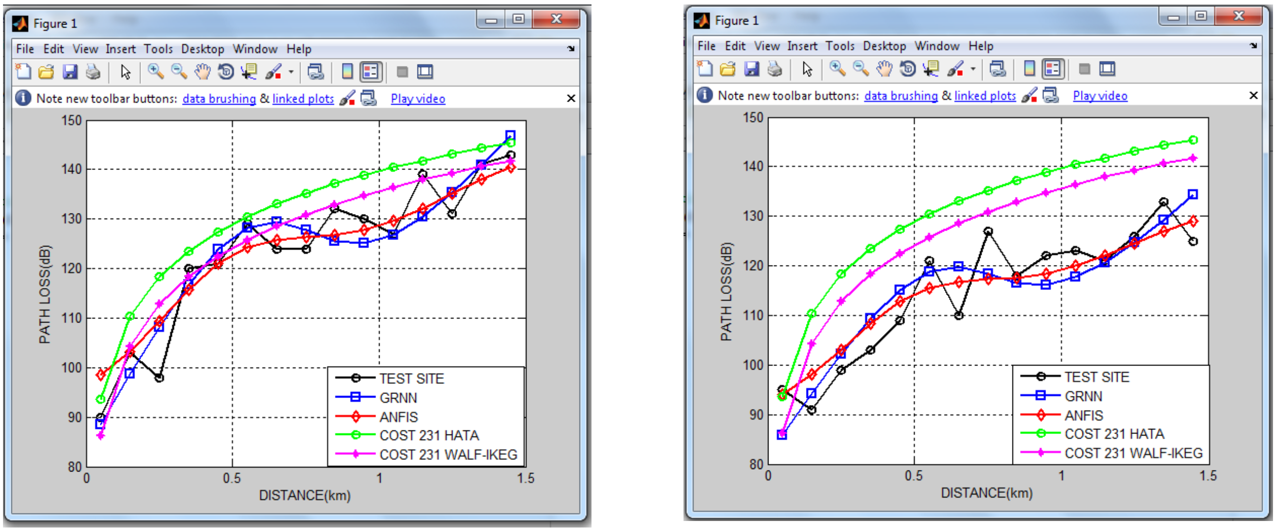
b) BTS 2 Analysis

Fig. 4: 60% training, 10% validation and 30% testing

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
ANFIS	RMSE(dB)	4.99	8.30	5.29	4.49	2.87	4.75	8.06	6.99	4.90	7.13	5.52
	R^2	0.46	0.44	0.22	0.69	0.69	0.60	0.45	0.48	0.67	0.08	0.41
GRNN	RMSE(dB)	2.02	5.97	4.60	3.75	4.93	3.52	6.61	5.11	4.36	7.01	4.54
	R^2	0.91	0.71	0.41	0.78	0.08	0.78	0.63	0.72	0.74	0.11	0.46
COST 231 Hata	RMSE(dB)	18.06	15.17	13.97	12.63	8.33	8.94	17.17	12.46	8.26	11.84	12.24
	R^2	-1.11	0.13	0.06	0.41	0.73	0.64	-0.91	0.28	0.71	0.13	0.11
COST 231 W-I	RMSE(dB)	14.41	11.07	11.09	9.69	6.56	5.80	13.22	8.64	5.63	9.09	9.08
	R^2	-0.35	0.54	0.41	0.65	0.83	0.85	-0.13	0.65	0.87	0.49	0.48

Based on the second approach, Fig. 5a) depicts a scenario where the network based models are trained with the geometric mean and tested with BTS6 data, while in Fig. 5b), testing is with BTS7 data. In both cases, the network based models exhibit more accurate predictions. Again, geometric mean performance indices in Table 2 show that the network based models outperform their empirical counterparts. It can be observed that the GRNN only slightly outperforms the ANFIS based model. Table 2 also shows that the COST-Walfisch-Ikegami out performs the COST 231 Hata by about 3dB.



a) Testing with BTS 6 data b) Testing with BTS 7 data

Fig. 5: Training with geometric mean and testing with BTS6 and BTS7 data

Table 2: Splitting entire data into 50% training and 50% testing.

MODEL	STAT.	GM / BST6	GM/ BST7	GM/ BST8	GM/ BST9	GM/ BST10	GEOM. MEAN
ANFIS	RMSE(dB)	4.88	5.90	7.64	5.61	6.43	6.02
	R^2	0.89	0.77	0.73	0.87	0.74	0.80
GRNN	RMSE(dB)	4.95	4.90	7.00	6.43	6.53	5.89
	R^2	0.89	0.84	0.77	0.82	0.74	0.81
COST 231 Hata	RMSE(dB)	8.94	17.17	12.46	8.26	11.84	11.33
	R^2	0.64	-0.91	0.28	0.71	0.13	0.17
COST 231 Walfisch-Ikegami	RMSE(dB)	5.80	13.22	8.64	5.63	9.09	8.05
	R^2	0.85	-0.13	0.65	0.87	0.49	0.54

A combined performance assessment based on the two approaches shows that on the geometric mean, the same performance trend is sustained with the GRNN model being the overall best predictor with an RMSE value of 5.17dB. With an RMSE value of 5.76dB, the ANFIS based model is less accurate by about 0.59dB. As further proof of its performance superiority, the GRNN based model has the highest R^2 value of 0.61, giving it the best fit, resulting from the highest correlation. Again, the COST-Walfisch-Ikegami with 8.55dB outperforms the COST 231 Hata by about 3.22dB, making the COST 231 Hata the least accurate.

VIII. CONCLUSION

Path loss prediction models for the metropolitan city of Abuja, Nigeria, created on the bases of two Soft Computing networks, were trained and tested with path loss data recorded at an operating frequency of 1800MHz from multiple Base Transceiver Stations situated across the city. The two networks considered were the Adaptive Neuro-Fuzzy Inference System (ANFIS) and the Generalized Regression Neural network (GRNN). Results indicate that the GRNN based predictor with an RMSE value of 5.17dB gave a more accurate prediction than the ANFIS based model which has 5.76dBm. A comparison of prediction results indicate that on the average, the two Soft Computing Techniques offer an improvement of about 4.71dB over the linear regression based methods comprising of the COST 231 Hata and COST 231 Walfisch-Ikegami models.

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