RADIO PROPAGATION MODELING OF JOS SUBURBS AT 900MHZ USING AN ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

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Date Manuscript Received: 07/01/15Date Accepted: 06/07/15Published: December 2015

ABSTRACT

This study investigates radio propagation modeling of the suburbs of Jos, Nigeria, at an operating frequency of 900MHz, using an Adaptive Neuro-Fuzzy Inference System (ANFIS) Technique. Path loss values computed based on received power measurements obtained from Base Transceiver Stations situated across the suburbs of the city were used to train, validate and test the ANFIS model for capacity to predict path loss. Results indicated that the ANFIS model with a Root Mean Square Error (RMSE) value of 4.74dB offers an improvement in prediction accuracy over the COST 231 Hata model, which has an RMSE value of 5.90dB.

INTRODUCTION

Transmission between the base station and the mobile station is usually accompanied by some power loss, and this loss is known as path loss and it depends particularly on the carrier frequency, antenna height and distance (Ashis, 2012). There is a variety of models used by researchers and radio engineers to predict path loss across a particular terrain. A model that suits a given terrain (or environment) may not necessarily be suitable to another. Hence, radio engineers and researcher have been evolving new techniques for accurate prediction of path loss.

For the purpose of path loss prediction, a wide range of radio propagation models have been usedglobally. Some of these models include empirical and deterministic models. Empirical models are path loss prediction models that are based on observations and measurements alone. Unfortunately, these 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 (Abhayawardhana et al. 2005).

An Adaptive Neuro-Fuzzy Inference System (ANFIS) is an intelligent computation technique that is highlyefficient in handling complex non-linear problems. Because artificial intelligence is adaptive andrelies on observed data rather than on an analytical modelof the system, the resulting scheme is robust, efficient andcapable of reflecting changes in the wireless signal behavior and hence they mitigate the error in wireless signal prediction(Alotaibi et al., 2008).

Alotaibi *et al.* (2008) used ANFIS as wireless signal predictor on a private mobile network-terrestrial trunked radio (TETRA) network, where it was shown to outperform some empirical models and to be marginally better than RBF-NN predictor. Also, ANFIS was used by Turkan *et al.* (2010) to predict path loss based ondata obtained in the 900 MHz band in Harbiye region of Istanbul, Turkey. ANFISprediction error was shown to be less than that obtained using Bertoni–Walfish model. Faihan *et al.* (2007) developed a robust ANFIS based prediction model for the city of Riyadh city – Saudi Arabia. ANFISprediction error was shown to be less than that obtained using Bertoni–Walfish model (Walfisch and Bertoni, 1998).

This study investigated the applicability ofan ANFIS based predictor for path loss prediction across the suburbs of Jos, Nigeria. The ANFIS predictor is developed and trained on measured data obtained from Base Stations situated within the terrain. The prediction accuracy of the ANFIS predictor is compared with that of the empirical COST 231Hata based on root mean square error (RMSE) and the square of multiple correlations,R-square (R^2).

ADAPTIVE NEURO-FUZZY INFERENCE SYSTEMS

An ANFIS is a combination of an Artificial Neural Network (ANN) and a Fuzzy Inference System (FIS) to form an intelligent adaptive system capable of solving complex non-linear problems. 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.

ANFIS was first proposed by Jang (1993) to combine the learning ability of ANNs with the ability of fuzzy systems to interpret imprecise information (Abraham *et al.*, 2013). ANFIS is based on the first-order Takagi–Sugeno–Kang (TSK) model. A brief ANFIS architecture as described in (Abraham et al.,2013) is as follows: Figure 1 shows n example of such fuzzy inference system with two inputs, x and y and one output which is a function of the inputs. For the TSK inference system, the rule is constructed as follows:

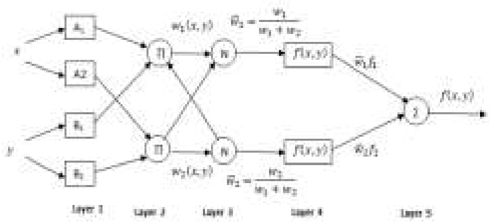

Figure 1: *The Architecture of an Adaptive Neuro-Fuzzy Inference System*

If x is A_i and y is B_i, THEN $f_i = p_i x + q_i y + r_i$

Where A_i and B_i are linguistic labels in the input spaces x and y respectively and f_i is a local function which depends on x and y.

Layer 1 is the fuzzification layer which generates membership grades for each linguistic label for any input value; these values are defined by membership functions. The common membership functions are the bell and triangular functions depicted in Figure 2. The bell function used in this work is described by the three parameters, a, b and c in equation (1).

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

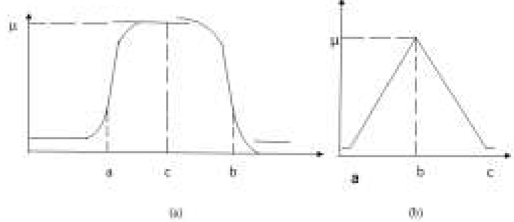

Figure 2: *(a)bell and (b) triangular membership functions*

Layer 2 is the application of the fuzzy operator and the output of every node in this layer is the product of all the incoming signals into the node as given by equation (2).

$$w_i = \mu_{A_i}(x_i) X \mu_{B_i}(y_i) \qquad (2)$$

Layer 3 produces an output which is the so-called normalized firing strength of each rule according to equation (3):

$$\overline{w_i} = \frac{w_i}{\sum_{j=1}^{2} w_j} \qquad (3)$$

Layer 4 is a layer of adaptive nodes each with a node function described by equation (4):

$$\overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i) \qquad (4)$$

where, p_i, q_i and r_i are called consequent parameters and the least-squares method is used to identify their optimal values.

Layer 5 is the defuzzification layer,that generates a crisp output given by equation (5).

$$f(x, y) = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \qquad (5)$$

where, $\overline{w_i f_i}$ is the output of node *i* in layer 4 denoting the consequent part of rule *I*.

In the training algorithm suggested by Jang (1993), ANFIS uses a hybrid learning algorithm which is a combination of gradient descent and the least-squares approximation method in order to train the network. Gradient descent back-propagation algorithm is used for training the premise parameters and least-squares approximation is used for training the consequent parameters. The optimal consequent parameters are estimated in the forward pass, while the premise parameters remain fixed. In the backward pass, premise parameters are tuned, while the consequent parameters remain fixed.

THE COST 231 HATA MODEL

The COST 231 Hata (Purnima, 2010) Model is an extension of the Hata Model, which is also an extension of the Okumura Model. It was formulated to suit the European environments taking into consideration a wide range of frequencies (500MHz to 200MHz). The COST 231 Hata Model is one of the most widely used radio propagation models because of suitability for urban, semi-urban, suburban and rural areas. The COST 231 Hata Model is given by(Purnima, 2010).

$$L = 46.3 + 33.9\log f - 13.82\log h_B - a(h_R) + (44.9 - 6.55\log h_B)\log d + C \qquad (6)$$

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 Antenna effective height in Meters (30m to 100m)
- d = Link distance in Kilometers (km) (up to 20kilometers)
- h_R = Mobile Station Antenna effective height in Meters (m) (1 to 10metres)
- $a(h_R)$ = Mobile station Antenna height correction factor as described in the Hata Model for Urban Areas.
- For urban areas, $a(h_R)$ = 3.20(log10(11.75hr))2- 4.97, for f >400 MHz

For sub-urban and rural areas, $a(h_R) = (1.1\log(f) - 0.7)h_R - 1.56\log(f) - 0.8$

PERFORMANCE EVALUATION INDICES

The statistical indices that form the bases for performance evaluation are based on Root Mean Squared Error (RMSE) and the square of multiple correlations, (R^2).

The RMSE is given by (Olasunkanmi *et al.*, 2014)

$$RMSE = \sqrt{\sum_{i=1}^{N} \frac{(M-P)^2}{N}} \qquad (7)$$

Where,

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

The square of multiple correlations is given by (Abraham *et a*l., 2013)

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y}_i)^2} \qquad (8)$$

Where y_i is the measured path loss, $\hat{y}_i$ 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

Measurements were taken from 8 different Base Stations of the mobile network service provider (Mobile Telecommunications Network (MTN), Nigeria), situated within the within the Jos suburbs. The instrument used was a Cellular Mobile Network Analyser (SAGEM OT 290) capable of measuring signal strength in decibel milliwatts (dBm). Readings were taken within the 900MHz frequency band at intervals of 0.2 kilometer, after an initial separation of 0.05kilometer away from the Base Station.

The mobile network parameters obtained from the service provider include the following:

I) Mean Transmitter Height, H_T= 34 meters

ii) Mean Effective Isotropically

Radiated Power, EIRP = 47dBm

iii) Transmitting Frequency, f_c = 900MHz

Creating the ANFIS Model Predictor

According to Alotaibi et al (2008), creating an ANFIS network involves 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. In this paper, the type of the MF chosen is the bell-shaped function, and the number of fuzzy MF per each input is 2 and the number of iterations is 30.

Path Loss Prediction using the ANFIS 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 separately by randomly splitting path loss data obtained from it into 60% training, 10% validation and 30% training. The essence of validation is to further refine the network construction. This technique simultaneously carries out a performance comparison of the ANFIS based models with the COST 231 Hata model on each base station.

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 then testing with a data set from another Base Station. By implication, a given data set can both be used for training and testing.

RESULTS AND DISCUSSION

As stated in the previous section, the first comparative technique involves analyzing each base station data separately, by randomly splitting the data into 60% training, 10% validation and 30% training. Figures 3 to 6 show prediction comparisons ofthe ANFIS-based model with the COST 231 Hata model relative to the test output. It can be observed from Figures 3, 5 and 6 that the ANFIS based model exhibits a closer prediction, while Figure 2 shows that the COST 231 Hata outperforms the ANFIS model.

MODEL	STAT.	BST1	BST2	BST3	BST4	BST5	BST6	BST7	BST8	GEOM. MEAN
ANFIS	RMSE(dB)	1.06	7.78	4.98	5.05	3.35	4.18	5.53	5.85	**4.18**
	R^2	0.99	0.11	0.78	0.73	0.92	0.78	0.69	0.56	**0.60**
COST 231 Hata	RMSE(dB)	4.89	6.32	6.03	6.62	6.52	5.32	6.08	5.42	**5.87**
	R^2	0.27	-0.75	0.04	-0.41	0.06	-0.06	-0.13	-0.14	**-0.10**

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

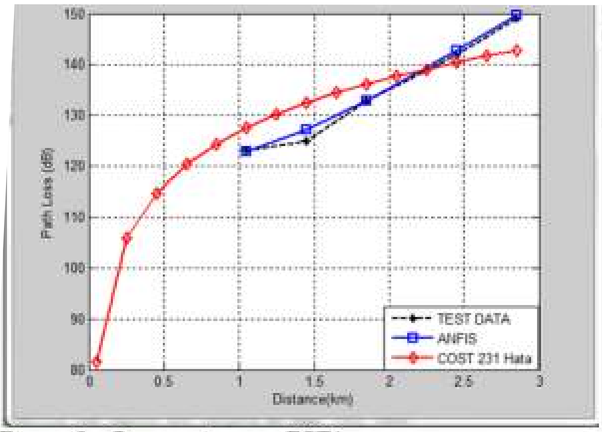

Figure 3 : Comparison on BST1

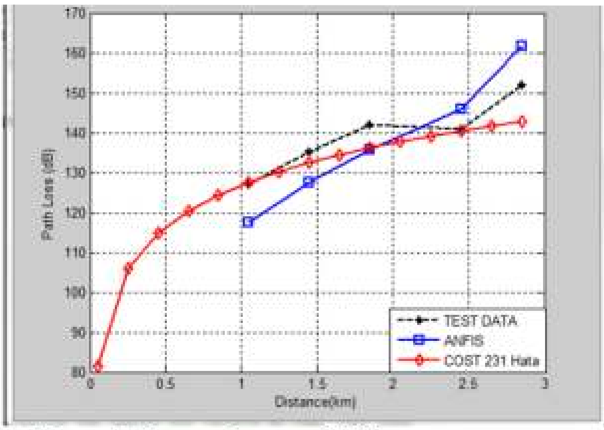

Figure 4 : Comparison on BST2

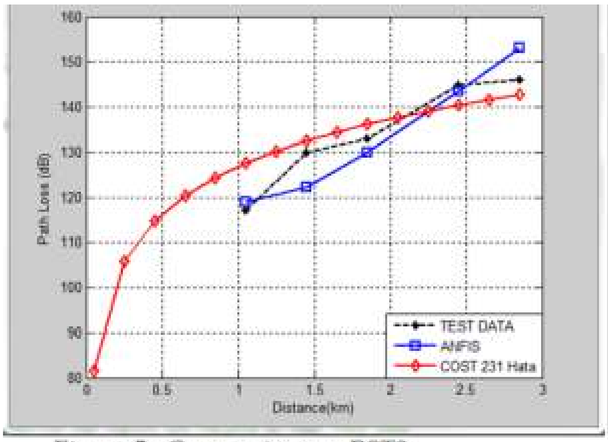

Figure 5 : Comparison on BST3

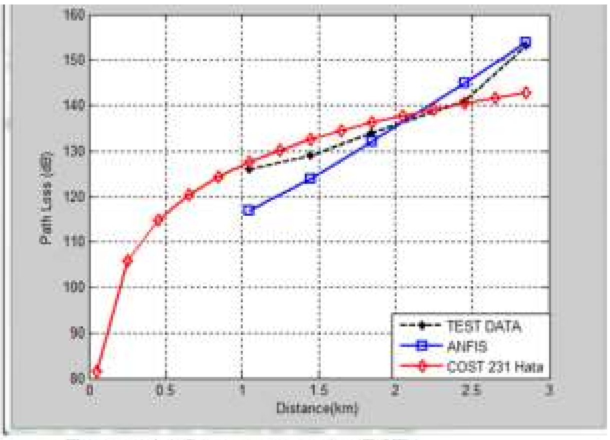

Figure 6 : Comparison on BST4

The performance statistics of the two models across all the Base Stations are presented in Table 1, which shows that the ANFIS model outperforms the COST 231 Hata counterpart on all but Base Stations 2 and 8. Geometric mean values show that the ANFIS model with an RMSE value of 4.18dB and R^2 of 0.6 is more accurate than the COST 231 Hata counterpart, which has an RMSE value of 5.87dB and a very poor R^2value of -0.10.

The sample graphical comparisons shown in Figures 7 to 10 are based on the second comparative technique. It can be observed that the ANFIS model exhibits a slightly closer prediction than the COST 231 Hata model as far as all the Figures are concerned. Results in Table 2 show that the ANFIS model gives a better prediction on all train/test pairings with the exception of BST6/BST2. Mean performance shows that there is a slight convergence in performance, with the ANFIS model just fractionally more accurate by about 0.56dB.

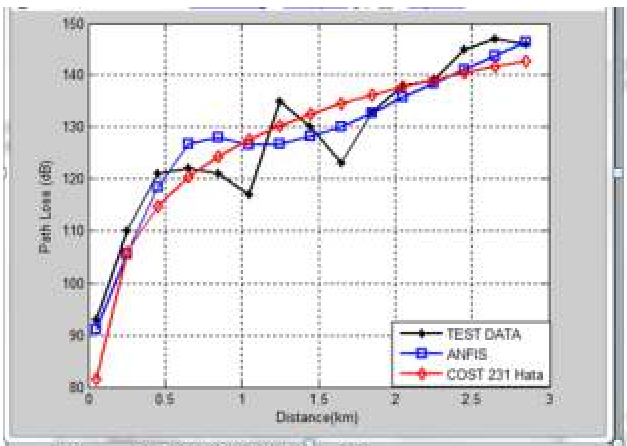

Figure 7: BST3/BST6 Pairing

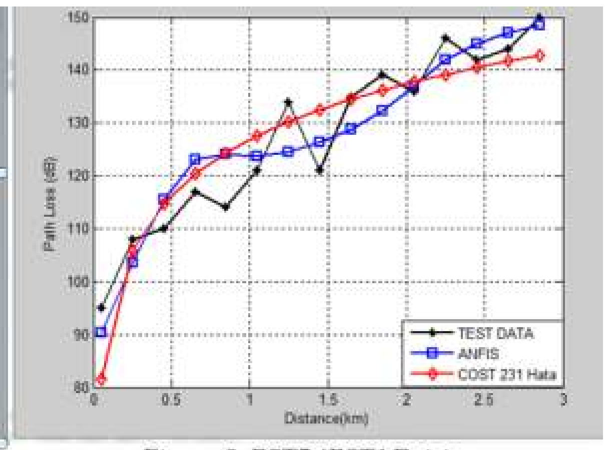

Figure 8: BST5/BST1 Pairing

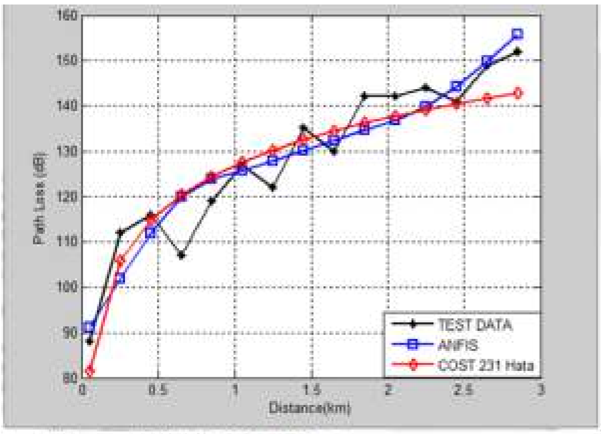

Figure 9: BST2/BST8 Pairing

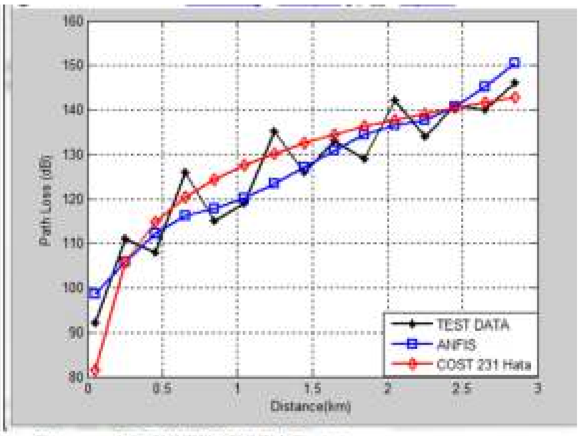

Figure 10: BST7/BST4 Pairing

MODEL	STAT.	BST3 /BST6	BST5 /BST1	BST2 /BST8	BST7 /BST4	BST6 /BST2	BST8 /BST5	GEOM. MEAN
ANFIS	RMSE(dB)	4.82	5.52	5.81	5.50	6.08	4.62	**5.37**
	R^2	0.89	0.88	0.89	0.86	0.83	0.9	**0.87**
COST 231 Hata	RMSE(dB)	6.03	6.52	6.32	6.08	5.33	5.42	**5.93**
	R^2	0.82	0.83	0.87	0.82	0.87	0.86	**0.84**

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

Finally, a combined performance evaluation based on the two comparative techniques shows that on the geometric mean, the ANFIS model with an RMSE value of 4.74dB offers an improvement over the COST 231 Hata model, which has an RMSE value of 5.9dB. Moreover, the ANFIS model's superior R^2 value of 0.72 indicates that it has higher correlation with the test data, compared with the COST 231 Hata model's R^2 value of 0.29.

CONCLUSION

This study has successfully demonstrated the applicability of an Adaptive Neuro-Fuzzy Inference System techniquefor path loss prediction across the suburbs of the city of Jos, Nigeria.Prediction results based on the two comparative techniques implemented show that the ANFIS model with an acceptable RMSE value of 4.74dBis more accurate than the commonly used empirical COST 231 Hata model, which has an RMSE value of 5.9dB. Hence, the ANFIS model is recommended for path loss prediction across the area under investigation.

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