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Development of a Path-loss Prediction Model Using Adaptive Neuro-fuzzy Inference System

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Abstract

The prediction of wireless communication signals is of paramount importance for proper network planning. The existing prediction models such as Okumura-Hata, Co-operative for Scientific and Technical Research (COST-231) and free space are less accurate for predicting path-loss values of wireless signals due to differences in propagation environments. Hence, this paper develops a path-loss model using Adaptive Neuro-Fuzzy Inference System (ANFIS) for accurate prediction of wireless High Speed Packet Access (HSPA) network signal in Ibadan, Nigeria. This is achieved by measuring the Received Signal Strength (RSS) from three Base Transmitting Stations (BTS) operating at 2100 MHz frequency in Ojo (longitude E 3' 53.1060', latitude N 7'27.2558'), Dugbe (longitude E 3'50.4361', latitude N 7' 23.0678') and Challenge (longitude E 3' 53.1060', latitude N 7' 21.258') areas of Ibadan using the Drive Test. Ericson Test Equipment for Mobile System (TEMS) phone, Global Positioning System (GPS) and Computer System are used to obtain RSS data at different distances. Base station parameters such as the transmitting antenna height, receiving antenna height, carrier frequency and distance are used as input variables to train ANFIS to develop a model. These base station parameters are also used to investigate the suitability of Okumura-Hata, COST-231 and free space model. A five layer ANFIS structure is developed and trained using Least Square Error (LSE) and Gradient Descent (GD) method to adjust the consequent and premise parameters. The performance of the developed ANFIS model is evaluated using Mean Square Error (MSE) and Root Mean Square Error (RMSE) and compared with Okumura-Hata, COST 231 and free space. The results obtained for ANFIS give lower RMSE and MSE indicating the suitability of ANFIS model for path-loss prediction. The developed ANFIS model can be used for network planning and budgeting in these environments.

Index Terms: HSPA, ANFIS, Least Square Error, Gradient Descent method

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1. Introduction

Wireless communication is the transmission of signals over a wireless channel that has no physical connection between the transmitter and the receiver [1]. There is reduction in signal strength as the distance increases indicating the loss in signal along the path. To determine the actual path-loss, path-loss models have been developed for predicting the values. These models are mathematical expressions used to predict the radio signal characteristics of a place [2]. The models are categorized into three; random, deterministic and empirical models [1,7,9]. Random models generate predictions randomly without proper considerations of all the physical environmental phenomena which make it unreliable when applied to environment that has complex structure and many obstacles [9,12]. Deterministic models rely on ray optical laws for prediction and are computationally complex and time consuming [11, 12]. Although these models seem to be accurate than other existing model but are difficult to implement especially in environments where there are many obstacles along the signal paths.

Nomenclature

AI	Artificial Intelligence
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
BTS	Base Transmitting Stations
COST	Co-operative for Scientific and Technical Research
FL	Fuzzy Logic
GD	Gradient Descent
GPS	Global Positioning System
HSPA	High Speed Packet Access
LSE	Least Square Error
MSE	Mean Square Error
RMSE	Root Mean Square Error
RSS	Received Signal Strength
SM	Stochastic Model
SUI	Stanford University Interim

On the other hand, Empirical models are dependent on the environment where the measurement is taken. To make these models applicable to other environments, optimization approach must be carried out on the models for proper adaption [3,8,12, 18, 19]. The measured data is used as reference for comparison with optimized models. A major limitation of the models is large deviation when compared to the measured data. Therefore, this paper investigates the applicability of the existing models in Ibadan, Nigeria and the development of a new model using Adaptive Neuro-Fuzzy Inference System (ANFIS). The investigation is carried out using the drive test method. Drive test equipment such as Test Equipment for Mobile System (TEMS), a computer system and a Global Positioning System (GPS) are used to carry out the measurement along three different locations in Ibadan, Nigeria. Path-loss values obtained from measured RSS are used to determine the deviation from path-loss values of the existing models. An ANFIS structure was developed and trained with transmitting antenna height, receiving antenna height, carrier frequency and distance as the input variables. Least Square Error (LSE) and Gradient Descent (GD) method are used to adjust the consequent and premise parameters. The new model developed using ANFIS is compared to the measured path-loss values.

2. Related works

In [7], Fuzzy Logic (FL) approach was used for path-loss prediction in Mehuwala, India. A path-loss exponent was assigned to each propagation environment. The authors classified the propagation medium into several propagation environments. A path-loss exponent (n) was assigned to each propagation environment. The result was compared to Hata model using path-loss exponent. Path-loss increased at the rate of 26.7 dB per decade with distance for FL Model. The rate of increase of path-loss per decade with distance for Hata model is 114.8 dB. The authors concluded that FL Approach is more efficient in path-loss prediction than theoretical analysis. In [10], a model was developed for Hyderabad city using Artificial Neural Network (ANN). The authors trained the measured data using Feed Forward Neural Network (FFNN). Leverberg Marquart algorithm was used for the training. The result was presented and compared to Hata, COST-231 and Walfisc model. ANN results were found to be better than other models.

In [16], FL was used to estimate path-loss in Dehradum and Uttarakh environments at India. The authors assigned a mean path-loss exponent (n) to each of the environment such as free space terrain, flat area terrain, heavy terrain and light terrain. Data was taken in three Zones within 1km to 5km Transmitter-Receiver separation distance. Path-loss exponent (n) was calculated by linear regression such that the error between measured and estimated path-loss is minimized. Finally, FL model was compared to Hata, COST-231 and Electronic Communication Committee (ECC-33) models using path-loss exponents (n). FL method proved a different method in path-loss prediction. The author concluded that, theoretical analysis is said to be different from practical analysis and to achieve a better result, the two must be combined. In [17], Adaptive Neuro-Fuzzy Inference System approach was used for path-loss prediction at VHF band. A five layer ANFIS structure was trained with frequency and distance as the input variables. Performance of the developed ANFIS model was compared to COST-231, Egli and ECC-33 models. ANFIS was found to have better predictions in terms of RMSE, Spread Corrected RMSE (SC-RMSE) Mean Error (ME), and Standard Deviation Error (SDE). Artificial Intelligence (AI) techniques have experienced great success in the field of path-loss predictions in recent time. Majority of the researches conducted on path-loss predictions using AI techniques have been done at VHF and GSM frequency (900 MHz), very few have been done at UHF band indicating that AI techniques have not been majorly investigated at higher frequency. Based on this assertion and the peculiarity of the environment under consideration, it is therefore necessary to investigate the efficiency of ANFIS for its adaptability in Ibadan, Nigeria at 2100 MHz.

2.1 Determination of path-loss models

Path-loss models are mathematical expressions used in design and predictions of radio signal attenuation. These models determine path-loss by calculating the difference between the transmitted power and the received power at any distance [8]. These models are categorized into three; deterministic, random and Empirical model [9,13].

2.1.1 Deterministic model

These models are based on ray optical laws. They approximate reflection, diffraction and scattering of the signal using simple geometric equations. There must be adequate knowledge of the position of obstacles for this model to be accurate. However, the model has computational complexity which makes it inapplicable as a general tool for path-loss modeling except in indoor environments and rural areas where obstacles are very minimal [3,13, 19].

2.1.2 Random models

These models are derived from randomness of the environment due to propagation mechanisms which make the wireless signal unpredictable [6,8]. As a result of this, statistical approach is adopted to predict the signal. The approach is known as random models.

2.2.3 Empirical models

Empirical models are based on real time measurement at a certain frequency range and a given distance, these models are limited to the geographical locations where the measurements are taken which makes their accuracy questionable when applied to other environments [2, 11, 18]. Therefore, optimization approach must be carried out for proper adaptation of these models to other environment. The optimized model is the used as a reference for comparison with the measured data

2.2 Applicability of path-loss models in Ibadan, Nigeria.

In this session, the applicability of some existing models for path-loss prediction in the environment under consideration is investigated using the base station parameters of the three BTSs (BTS_1 , BTS_2 and BTS_3) inIbadan. Details of the transmitting parameters are contained in Table 1.

Table 1. Test Site Parameters

Parameters	BTS_1 - Ojo	BTS_2 - Challenge	BTS_3 - Dugbe
Operating Frequency	2100 MHZ	2100 MHZ	2100 MHZ
Transmitting Antenna Height	28m	35m	30 m
Receiving Antenna Height	2dBi	2dBi	2dBi
Receiving Antenna Height	1.5 m	1.5 m	1.5m

2.2.1 Applicability Okumura-Hata Model

Okumura-Hata model developed empirical formulas valid over a frequency range of 150 MHz-1500 MHz [1,5]. Path-loss 'P_{Loss}' model described by Okumura-Hata model for urban environment is given by [1,16] as:

$$P_{Loss(oku)}(dB) = 69.55 + 26.16log_{10}f_c - 13.82log_{10}h_t - a(h_r) + (44.9 - 6.55log_{10}h_t)log_{10}TR_D \quad (1)$$

where:

h_r is the receiving antenna height
h_t is the transmitting antenna height
f_c is the frequency in MHz,
TR_D is the separation between the transmitter and the receiver,
$a(h_r)$ is the correction factor mobile station.

Inserting the site parameters of BTS_1into equation (1) gives;

$$P_{Loss(oku)}(dB) = 136.46 + 35.42 log_{10} TR_D \tag{2}$$

Where

$$a(h_r) = 3.2(log_{10} 11.75 h_r)^2 - 4.97\ dB \quad f_c > 300$$

Path-loss is obtained for BTS_2 as;

$$P_{Loss(oku)}(dB) = 135.12 + 34.79 log_{10} TR_D \tag{3}$$

Path-loss is obtained for BTS_3 as;

$$P_{Loss(oku)}(dB) = 136.04 + 35.22 log_{10} TR_D \tag{4}$$

2.2.2 Applicability of COST-231 Extension to Hata Model

COST 231 Extension to Hata Model operates over a frequency range of 500 MHz to 2000 MHz. Though, there is correction factor for adjustment. The 'P_{Loss}' model is given by [1, 5] as:

$$P_{Loss(cost)}(dB) = 46.3 + 33.9 log_{10} f_c - 13.82 log_{10} h_t - a(h_r) + (44.9 - 6.55 log_{10} h_t) log_{10}(TR_D) + K_m \tag{5}$$

where:

h_r is the receiving antenna height
h_t is the transmitting antenna height
f_c is the frequency in MHz,
TR_D is the separation between the transmitter and the receiver,
$a(h_r)$ is the correction factor mobile station.
K_m is the correction factors, and has a value of '3' for urban areas.

Inserting the site parameters of BTS_1 in equation (5) gives;

$$P_{Loss(cost)}(dB) = 141.92 + 35.42\ log_{10} TR_D \tag{6}$$

For BTS_2 , path-loss 'P_{Loss}' is obtained as;

$$P_{Loss(cost)}(dB) = 140.58 + 34.79\ log_{10} TR_D \tag{7}$$

For BTS_3 , path-loss 'P_{Loss}' is obtained as;

$$P_{Loss(cost)}(dB) = 141.51 + 35.22\ log_{10} TR_D \tag{8}$$

2.2.3 Free space models

Free space propagation assumes there is no obstruction along the path and the signal propagate on a straight line. The 'P_{Loss}' for free space propagation is given by [1,12] as:

$$P_{Loss(free)}(dB) = 32.48 + 20\,log_{10}TR_D + 20\,log_{10}(f) \tag{9}$$

Where (TR_D) is the separation between the transmitter and the receiver in meters (m) and 'f' is the frequency in MHz.

Inserting the site parameters, path-loss 'P_{Loss}' is obtained for BTS_1, BTS_2 and BTS_3 as;

$$P_{Loss(free)}(dB) = 98.92 + 20\,log_{10}TR_D \tag{10}$$

3. Methodology

The procedure for data collection involves Equipment Setup inside a vehicle. Information related to the BTS such as gains of the transmitting and receiving antennas, height of antennas and transmitted power are recorded for link budgeting.

3.1 Equipment Setup

Three BTSs in Ibadan, Nigeria at (longitude E 3' 53.1060' and latitude N 7'27.2558'), (longitude E 3'50.4361'and latitude N 7' 23.0678') and (longitude E 3' 53.1060' and latitude N 7' 21.258') that have omni-directional antennas and transmit a continuous wave signal are used for the investigation. The mobile receiver used is a 3G Ericson (W995) TEMS Phone connected to a dual core computer system as shown in Fig. 1. The computer system is integrated with TEMS software capable of mapping Received Signal Strength (RSS) with Global Positioning System (GPS). During the Drive Test campaign, transmitting parameters such as transmitted power, antenna gain, antenna height and the carrier frequency are recorded for every base station. TEMS software is locked on each of the transmitting base station to record RSS and the coordinate of each test point in the direction of the sectors. The receiver is kept at height of 1.5 m. The vehicle is driven away from the base stations at an average speed of 40km/h. 10 Measurements samples of RSS are taken for each BTS between 100m and 1km. Seventy percent (70%) of the data is used for training and 30% for testing. Details of the measurement are presented in Table 2.

Fig.1. Equipment Set-up

Table 2. Measured values at different distances for BTS_1 – Ojo, BTS_2 – Challenge and BTS_3 – Dugbe

Distance (m)	BTS_1 – Ojo	BTS_2 - Challenge	BTS_3 – Dugbe
100	97	98	96
200	105	103	102
300	110	105	106
400	113	109	110
500	117	112	113
600	120	116	117
700	122	120	121
800	124	123	126
900	129	126	128
1000	133	129	136

3.2 Development of Adaptive Neuro-Fuzzy Inference System

ANFIS is the combination of ANN and FL [4,14,15]. ANFIS structure has five layers driven by feed forward neural network that utilizes Sugeno 'If-then-rules' [14,15]. Fig. 2 shows the basic ANFIS structure with a single input layer, three hidden layers and one output layer. There are two fuzzy sets used in classifying each of the input. Input 'x_1' has fuzzy sets 'A_1' and 'A_2', input 'x_2' has fuzzy sets 'B_1'and 'B_2', input 'x_3' has fuzzy sets 'C_1'and 'C_2 and input 'x_4' has fuzzy sets 'D_1' and 'D_2'. There are sixteen (16) Sugeno 'If then rule' defined of the form;

R^1: If $x_1 = A_i, x_2 = B_i, x_3 = C_i , x_4 = D_i,$ then $Y_l = A_i x_1 + B_i x_2 + C_i x_3 + D_i x_4 + E_i$ *for l= 1,…,16*

Where $(A_i, B_i, C_i , D_i, E_i)$ are called consequent parameters.

Layer 1

This layer defines the membership grades for each set of input vectors. Usually, it is represented by a Gaussian function. The ith node of Layer 1has an output "$OP_{1,i}$" defined by [15] as:

$$\text{For input } x_1 ; OP_{1,i} = \mu_{Ai}(x) = \exp\left(-\left(\frac{x_1 - c_i}{\sigma_i}\right)^2\right) \quad \text{for i} = 1,2 \tag{11}$$

$$\text{For input } x_2; OP_{1,i} = \mu_{Bi}(x) = \exp\left(-\left(\frac{x_2 - c_i}{\sigma_i}\right)^2\right) \quad \text{for i} = 1,2 \tag{12}$$

$$\text{For input } x_3; OP_{1,i} = \mu_{Ci}(x) = \exp\left(-\left(\frac{x_3 - c_i}{\sigma_i}\right)^2\right) \quad \text{for i} = 1,2 \tag{13}$$

$$\text{For input } x_4; OP_{1,i} = \mu_{Di}(x) = \exp\left(-\left(\frac{x_4 - c_i}{\sigma_i}\right)^2\right) \quad \text{for i} = 1,2 \tag{14}$$

where :

(σ_i, c_i) are called premise parameters that define the shape of the membership functions,
$\mu_{Ai}, \mu_{Bi} , \mu_{Ci} \text{ and } \mu_{Di}$ are the input membership grades defined,
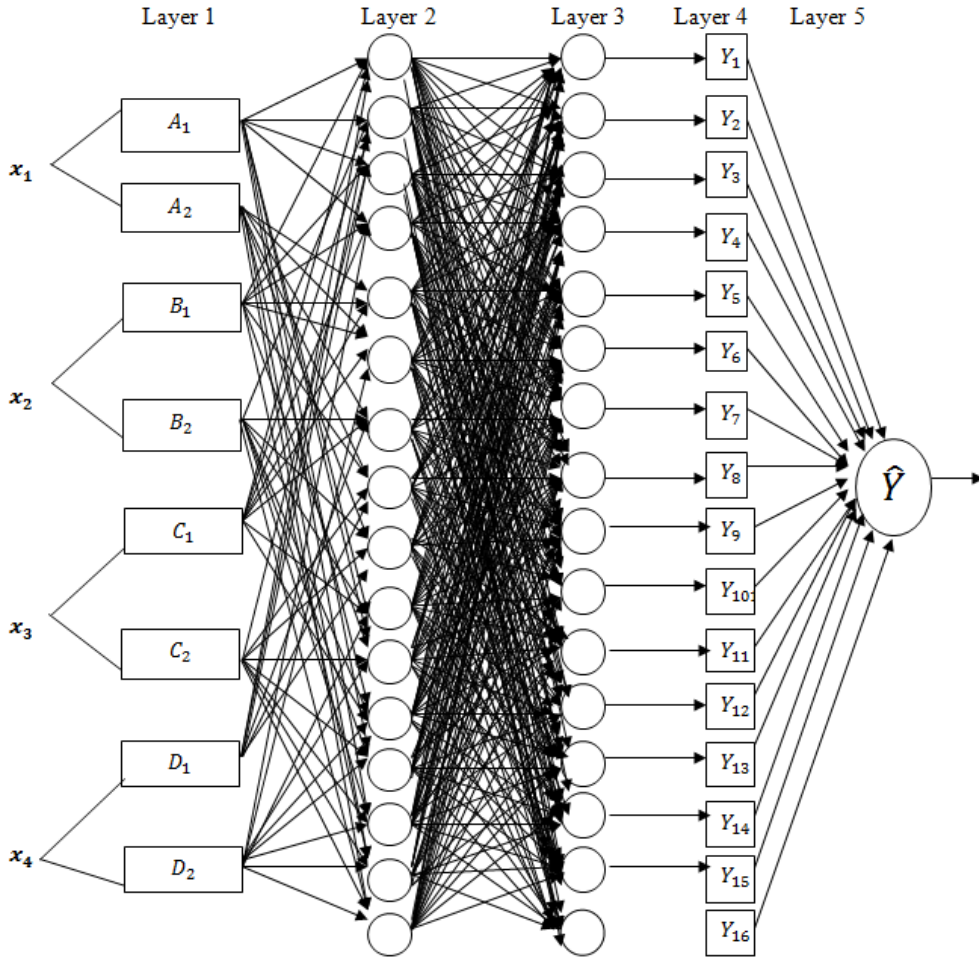c_i determines the center of the corresponding membership function.

Fig. 2. ANFIS Structure

Layer 2 (Product layer)

Takes the product of the incoming membership grades with the output " $OP_{2,i}$" of the ith node given by [15] as:

$$OP_{2,i} = w_l = \mu_{Ai}(x_1) * \mu_{Bi}(x_2) * \mu_{Ci}(x_3) * \mu_{Di}(x_4) \qquad for \ l = 1, ..., 16 \tag{15}$$

Layer 3 (Normalized layer)

The layer determines the ratio of the ith rule's firing strength to the sum of all rules' firing strength. The output ' $OP_{3,i}$' is defined as:

$$OP_{3,i} = \overline{w_l} = \frac{w_l}{\sum_{l=1}^{n=16} w_l} \qquad for \ l = 1 ... 16 \tag{16}$$

where; $\overline{w_i}$ is the normalized firing strength,
w_l is the firing strength of the ith rule,

Layer 4

The layer computes the contribution of each rule to the overall output and provides output values resulting from the inference of the rules. The output ' $OP_{4,i}$ ' of the node is given as:

$$OP_{4,i} = \overline{w_i}Y_l = \overline{w_i}\ (A_ix_1 + B_ix_2 + C_ix_3 + D_ix_4 + E_i) \qquad for\ l = 1,...,16 \tag{17}$$

where:

$(A_i, B_i, C_i, D_i, E_i)$ are called consequent parameters,
x_1, x_2, x_1 and x_2 are the input variables,
$\overline{w_i}$ is the output of layer 3.

Layer 5 (Final Output)

This layer computes the overall output as a summation of all incoming signal. The output of the ith node of this layer '$OP_{5,i}$' is given as:

$$OP_{5,i} = \sum_{l=1}^{16} \overline{w_i}Y_l \tag{18}$$

Where Y_l is the final part of the inference rule governing the path-loss defined as;

$$Y_l = (A_ix_1 + B_ix_2 + C_ix_3 + D_ix_4 + E_i)$$

In Training ANFIS for the path loss model development, the input variables are height of the transmitting antenna, height of the receiving antenna, frequency and distance represented as ($x_1,\ x_2, x_3, x_4$). Hybrid learning algorithm that combines LSE and GD method is used for the training. LSE are used to update the sets of consequent parameters while GD updates the premise parameters [14,15]. The training continues till error between the predicted and the measured values are minimized based on the relation. The performance of the developed model is compared to Okumura-Hata, COST-231 and free space model.

4. Results and discussion

Figs. 3. to 5. present path-loss versus distance for ANFIS model, Okumura-Hata model, COST-231 model, free space model and measured values for BTS_1 (Ojo), BTS_2 (Challenge) and BTS_3 (Dugbe). Fig. 3. presents path-loss against distance for ANFIS, measured, Okumura-Hata, COST 231 and free space models for BTS_1. At 500 m from the base station, path-loss values obtained are 117,114, 122, 127 and 91 dB for ANFIS, measured, Okumura-Hata, COST-231 and free space. Fig. 4 depicts path-loss values against distance for ANFIS, measured, Okumura-Hata, COST-231 and free space models for BTS_2. At 500m from the base station, path-loss values obtained are 115, 112, 126, 131 and 93 dB for ANFIS, measured, Okumura-Hata, COST 231 and free space models, respectively. Fig. 5 shows path-loss values against distance for ANFIS, measured, Okumura-Hata, COST 231 and free space models for BTS_3. At 500 m from the base station, path-loss values obtained are 117, 113, 125, 131 and 93 dB for ANFIS, measured, Okumura-Hata, COST 231 and free space models, respectively.
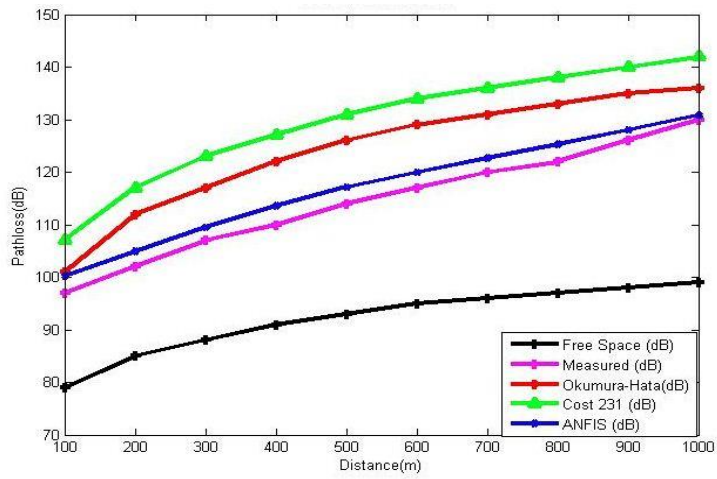
Fig. 3. Path-loss versus distance for ANFIS, Measured, COST 231, Okumura-Hata and Free space models for BTS_1 (Ojo)
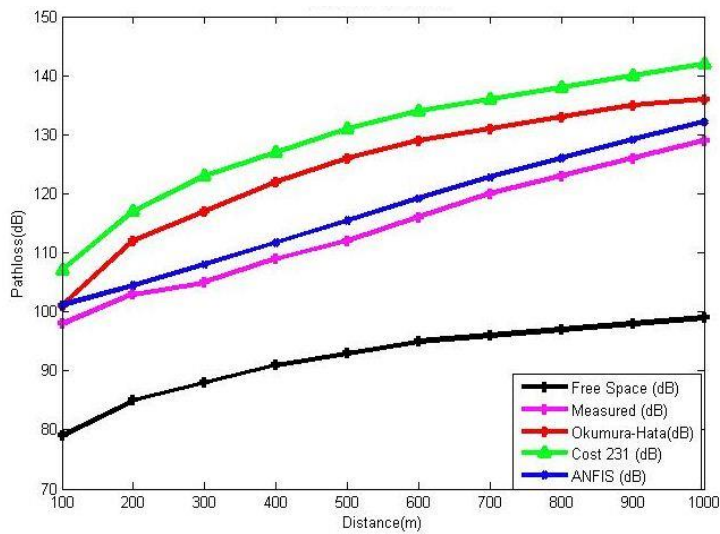

Fig. 4. Path-loss versus distance for ANFIS, measured, COST-231, Okumura-Hata and Free space models for BTS_2 (Challenge)
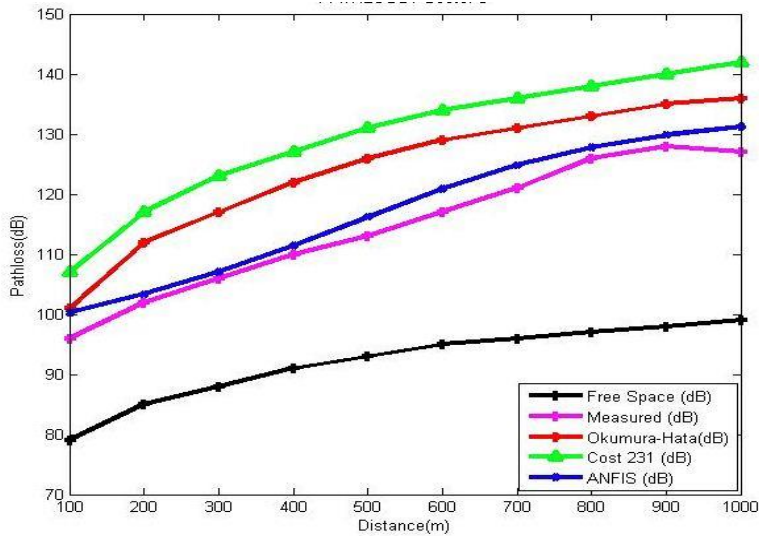
Fig. 5. Path-loss versus distance for ANFIS, measured, COST-231, Okumura-Hata and Free space models for BTS_3 (Dugbe)

The Average MSE (AMSE) obtained at BTS_1 are 106.16, 232.03, 500.13 and 7.99 for Okumura-Hata, COST-231, free space and ANFIS models, respectively. For BTS_2, AMSE values are 124.96, 261.30, 515.53 and 8.71 for Okumura-Hata, COST-231, free space and ANFIS models, respectively while the corresponding values for BTS_3 are 131.80, 199.10, 521.47 and 8.74, respectively. The average RMSE (ARMSE) values obtained from BTS_1 are 10.30, 15.23, 22.36 and 2.82 for Okumura-Hata, COST-231, free space and ANFIS models, respectively while ARMSE values of 11.18, 16.17, 22.70 and 2.95 are obtained from BTS_2 for Okumura-Hata, COST 231, free space and ANFIS models, respectively. The corresponding values of 11.48, 14.11, 22.84 and 2.96 are obtained from BTS_3. The results are also contained in Tables 3 and 4 for BTS_1 to BTS_3. ANFIS models give the lowest AMSE and ARMSE indicating the best model to predict the path loss in these environments. This is due to reduction in error by ANFIS.

Table 3. Average MSE results for the three BTS

BTS	Okumura-Hata	COST-231	Free Space	ANFIS
BTS_1 (Ojo site)	106.16	232.03	500.13	7.99
BTS_2 (Challenge site)	124.96	261.30	515.53	8.71
BTS_3 (Dugbe site)	131.80	199.10	521.47	8.74

Table 4. Average RMSE results for the three BTS

BTS	Okumura-Hata	COST-231	Free Space	ANFIS
BTS_1 (Ojo site)	10.30	15.23	22.36	2.82
BTS_2 (Challenge site)	11.18	16.17	22.70	2.95
BTS_3 (Dugbe site)	11.48	14.11	22.84	2.96

5. Conclusions

Adaptive Neuro-Fuzzy Inference Systems approach has been used to develop a path-loss model for HSPA network signal in Ibadan, Nigeria. RSS data are measured from three selected BTSed from three selected BTSs located at Ojo, Challenge and Dugbe areas of Ibadan using drive test. A five layer ANFIS structure is developed and trained using LSE and GD algorithm. HSPA base station parameters such as antennas height, carrier frequency, and separation of the transmitting and receiving antennas are used as input variables to train ANFIS. The development platform is MATLAB R2012a version on 64 bits' dual core computer system. The base station parameters are used to investigate the suitability of Okumura-Hata, COST-231 and free space model. The performance of the developed model is evaluated using RMSE and MSE and compared with Okumura-Hata, COST-231 and free space model. The results show that, errors related to ANFIS model is greatly reduced when compared with the existing models.

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