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ANFIS Model for Path Loss Prediction in the GSM and WCDMA Bands in Urban Area

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Abstract: Path loss propagation is a vital concern when designing and planning networks in mobile communication systems. Propagation models such as the empirical, deterministic and theoretical models, which possess complex, inconsistent, time-consuming and non-adaptable features, have proven to be inefficient in designing of wireless systems, thereby resulting in the need for a more reliable model. Artificial Intelligence methods seem to overcome the drawbacks of the propagation models for predicting path loss. In this paper, the ANFIS approach to path loss prediction in the GSM and WCDMA bands is presented for selected urban areas in Nigeria. Furthermore, the effects of the number of Membership Functions (MFs) are investigated. The prediction results indicated that the ANFIS model outperformed the Hata, Cost-231, Egli and ECC-33 models in both Kano and Abuja urban areas. In addition, an increase in the number of MFs conceded an improved RMSE result for the generalized bell-shaped MF. The general performance and outcome of this research work show the efficiency and usefulness of the ANFIS model in improving prediction accuracy over propagation models.

Keywords: Path loss prediction, artificial intelligence, ANFIS, urban environment, heuristic algorithm, generalized bell.

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1. INTRODUCTION

Path loss is the degradation in the signal strength as radio wave propagates from the source to destination. Electromagnetic wave propagation prediction is of high significance in the planning and designing process of wireless communication systems. The prominence of propagation models is significant since it can be used as the standard for the performance of the system as well as for precise reception of radio signals in a wireless network. Electromagnetic waves propagation is distinct in nature and exhibits certain mechanisms such as reflection, refraction, and diffraction. They incite signal fading, scattering, and shadowing in the line of the path of the radio signal [1].

The path loss propagation models in existence have been broadly grouped into empirical or statistical, site-specific or deterministic, and the theoretical models [2] ; empirical models are dependent on measurement campaign carried out in an area, the prediction of theoretical models' is of great value since it is capable of determining the optimal base station locations so as to obtain data rates that are suitable. The deterministic models, on the other hand utilize the physical environmental phenomenon to explain the propagation of radio wave signals in the area of interest [3]- [4].

Empirical path loss models have been found to be the most broadly used models due to their simplicity and ease of use, as the implementation of the models do not require much computational efforts, and, are not too responsive to the geometrical and physical composition of the environments [5]- [6]. These make them attractive, although, a major drawback of utilizing the model is the inaccuracies, specifically when used in another environment other than the one where the measurements were taken. For example, [7]; [8]; [9]; [10] tested several of these models in a typical urban and rural Nigeria terrain and found them to be inconsistent in prediction, aside having high prediction errors. [11]; [12]; [13] tuned some of the most performing models to minimize errors and improve the prediction accuracy and yet, the tuned models were found to be site-specific. On the other hand, the deterministic models seem to have better prediction accuracy because of the availability of detailed information about the propagation environment. However, they are computationally intensive and time-consuming [14] . Moreover, despite the inclusion of site-specific information, the deterministic models' efficiency in prediction is not always better than the empirical models [14]- [15]. This, therefore raises more questions as to which model can provide optimum prediction with minimal complexity, as such, the need to incorporate Artificial Intelligence (AI) and heuristic algorithms to improve path loss prediction.

Different Artificial Intelligence (AI) techniques for path loss prediction have been adopted, as evident in the literature. Although, application of heuristic algorithms for predicting path losses in urban macrocellular environment is gaining momentum [16]; [17]; [18]; [11]; [19]; [20]; [21] ; [22]; [23]; [24], however, most of the works that focus on the investigation of the suitability of the Adaptive Network based Fuzzy Inference System (ANFIS) technique for path loss prediction in the Ultra High Frequency (UHF) bands are very limited. Moreover, due to the peculiar nature of our terrain environment and the wide deployment of cellular mobile systems operating on the GSM and WCDMA bands, there is a need to test the efficacy and applicability of the ANFIS method for path loss prediction using our own terrain.

Therefore, this paper introduces the ANFIS method approach to path loss prediction in the UHF bands (GSM and WCDMA frequencies) within the Nigerian propagation terrain, which uses expert learning for its training so as to mimic a given data set. The predictions of the ANFIS were used to compare with those of the commonly employed empirical models. The models used are: Hata [25], COST 231 [26], Egli [27], and ECC-33 [28] models. These models were chosen as they are the most widely applicable empirical models. The performances of the models were examined employing the Root Mean Square Error (RMSE), Mean Error (ME), Spread Corrected RMSE (SC-RMSE), and Standard Deviation Error (SDE), relative to the measured data. Furthermore, the paper investigates the impact of system parameters such as the membership functions (MF) and epoch size on the performance of the method.

2. MATERIALS AND METHOD

This section provides the architecture of the ANFIS method used and the description of the measurement procedure used during the path loss propagation measurements.

2.1 Structure of Adaptive Network Based Fuzzy Inference System (ANFIS)

ANFIS was proposed by J. S. R. Jang in the early 1990s [29]. It is an Artificial Neural Networks (ANN) that uses the Fuzzy Inference System (FIS) for its prediction. It is also referred to as an adaptive network [30]. ANFIS being a multilayer feed forward network with different nodes is able to perform specified functions on input signals as well as the parameters attributed to these nodes. There is variation in the formulas from one node to another and the decision of each function of the nodes is dependent on the entire input-output function that is required by the adaptive network to be executed. Commonly, the popular feed-forward structure is employed in conjunction with the back propagation training method [31]. A disadvantage of multilayered feed-forward networks which contains many neurons per layer is the training period required. In addition, an excessively complex ANFIS can lead to data over fitting and, as a result, problems generalization [32]. The general structure and functions of each layer of the ANFIS method is shown in Figure 1.

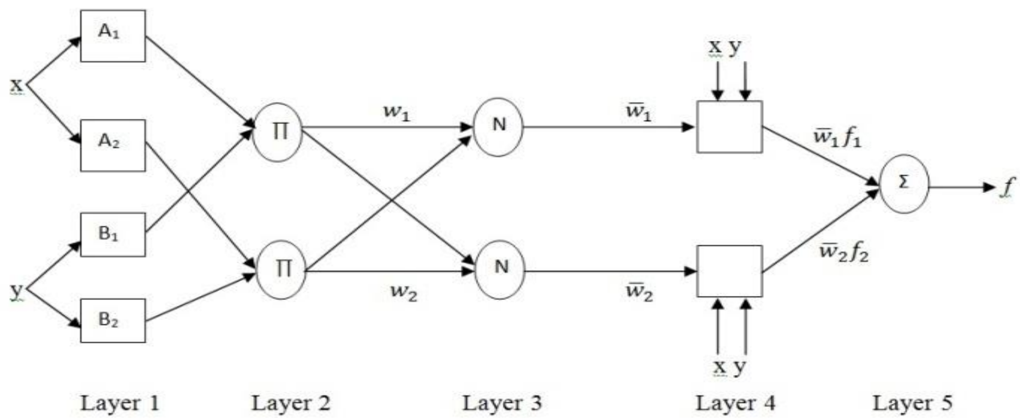

Figure 1. Two Inputs and Two Rules ANFIS Structure

Rules

If x is A_1 and y is B_1 then $f_1 = p_1x + q_1y + r_1$ (1)

If x is A_2 and y is B_2 then $f_2 = p_2x + q_2y + r_2$ (2)

where x and y are the inputs, which are also referred to as premise part, f is the output, A1, A2 , B1, B2 are the membership functions of each input. The variables p1, q1, r1 , p2, q2, r2 are linear parameters for the if-Then rule of the Takagi–Sugeno model. These are also called consequent parts.

The structure in Fig 1 consists of five layers. The first and fourth layers of the structure consists of adaptive nodes, while, second, third and fifth layers contain fixed nodes. The description of the structure is done with a first order sugeno because the output is a crisp value. A sugeno based ANFIS has a rule of the form [33]. Each layer is briefly described as follows:

Layer 1: A node in this layer is adaptable and the output of this layer (L_i^1) is given as;

$$L_i^1 = \mu A_i(x) \quad i = 1,2 \tag{3}$$

$\mu A_i(x)$ is the membership function (MF), in this work we used generalized bell MF which is taken normally as;

$$\mu A_i(x) = \frac{1}{1+\left|\frac{x-c_i}{a_i}\right|^{2b}} \tag{4}$$

$\{a_i, b_i, c_i\}$ is the antecedent variables set that change the shape of the MF and $A_i(x)$ is the degree of membership.

Layer 2: This layer is made up of the stable nodes which solve the firing power w_i also known as the synaptic weight of a rule. The output of each node is the multiplication of the incoming signals given by;

$$L_i^2 = w_i = \mu A_i(x) \times \mu B_i(y), \;\; i = 1,2 \tag{5}$$

Layer 3: The output of each node in this layer is constant which is given by;

$$L_i^3 = \overline{w_i} = \frac{w_i}{\sum w_i}, \;\; i = 1,2 \tag{6}$$

Layer 4: The changeable output of this layer is given by;

$$L_i^4 = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i), \;\; i = 1, 2 \tag{7}$$

$\{p_i$, q_i *and* $r_i\}$ is the consequent variables set and they are computed using the least squares estimates method.

Layer 5: The addition of all the input signals from layer 4 is the output of this layer and is given by;

$$L_i^5 = f = \sum_{i=1}^{2} \overline{w_i} f_i = \frac{\sum w_i f_i}{\sum w_i} \tag{8}$$

The ANFIS optimization combines both the least square errors estimate and back propagation algorithms which establish the output and input parameters respectively until the training is completed.

2.2 Least Square Errors Estimate (LSE)

It is a statistical approach employed in determining a line of best fit through the minimization of the sum of squares of a mathematical function. Eqn. (8) can be rewritten as;

$$f = z_p^k = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2$$

$$z_p^k = \sum_{i=1}^{2} \overline{w_i} f_i = \overline{w_1}(p_1 x) + \overline{w_1}(q_1 y) + \overline{w_1}(r_1) + \overline{w_2}(p_2 x) + \overline{w_2}(q_2 y) + \overline{w_2}(r_2) \tag{9}$$

Eqn. (9) in matrix form can be expressed as [34]

$$\begin{bmatrix} \overline{w_1}^{(1)} x^{(1)} & \overline{w_1}^{(1)} y^{(1)} & \overline{w_1}^{(1)} & \overline{w_2}^{(1)} x^{(1)} & \overline{w_2}^{(1)} y^{(1)} & \overline{w_2}^{(1)} \\ \overline{w_1}^{(2)} x^{(2)} & \overline{w_1}^{(2)} y^{(2)} & \overline{w_1}^{(2)} & \overline{w_2}^{(2)} x^{(2)} & \overline{w_2}^{(2)} y^{(2)} & \overline{w_2}^{(2)} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \overline{w_1}^{(n)} x^{(n)} & \overline{w_1}^{(n)} y^{(n)} & \overline{w_1}^{(n)} & \overline{w_2}^{(n)} x^{(n)} & \overline{w_2}^{(n)} y^{(n)} & \overline{w_2}^{(n)} \end{bmatrix} \begin{bmatrix} p_1 \\ q_1 \\ r_1 \\ p_2 \\ q_2 \\ r_2 \end{bmatrix} = \begin{bmatrix} z_p^{(1)} \\ z_p^{(2)} \\ \vdots \\ z_p^{(n)} \end{bmatrix} \tag{10}$$

where $[p_1, q_1, r_1, p_2, q_2, r_2]^T$ are calculated using eqn. (11) and z_d^k are the desired outputs. $\left[x^{(k)}, y^{(k)}, z_d^{(k)}\right]$ are the k_{th} training pairs, *k=1,2,.....,n*, and $\overline{w_1}^{(k)}$ and $\overline{w_2}^{(k)}$ are the normalized synaptic weights of layer 3 in relation with inputs $x^{(k)}$ and $y^{(k)}$.

$$\begin{bmatrix} \overline{w_1}^{(1)} x^{(1)} & \overline{w_1}^{(1)} y^{(1)} & \overline{w}^{(1)} & \overline{w_2}^{(1)} x^{(1)} & \overline{w_2}^{(1)} y^{(1)} & \overline{w_2}^{(1)} \\ \overline{w_1}^{(2)} x^{(2)} & \overline{w_1}^{(2)} y^{(2)} & \overline{w_1}^{(2)} & \overline{w_2}^{(2)} x^{(2)} & \overline{w_2}^{(2)} y^{(2)} & \overline{w_2}^{(2)} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \overline{w_1}^{(n)} x^{(n)} & \overline{w_1}^{(n)} y^{(n)} & \overline{w_1}^{(n)} & \overline{w_2}^{(n)} x^{(n)} & \overline{w_2}^{(n)} y^{(n)} & \overline{w_2}^{(n)} \end{bmatrix} \begin{bmatrix} p_1 \\ q_1 \\ r_1 \\ p_2 \\ q_2 \\ r_2 \end{bmatrix} = \begin{bmatrix} z_d^{(1)} \\ z_d^{(2)} \\ \vdots \\ z_d^{(n)} \end{bmatrix} \tag{11}$$

$$\begin{bmatrix} p_1 \\ q_1 \\ r_1 \\ p_2 \\ q_2 \\ r_2 \end{bmatrix} = \begin{bmatrix} \overline{w_1}^{(1)} x^{(1)} & \overline{w_1}^{(1)} y^{(1)} & \overline{w_1}^{(1)} & \overline{w_2}^{(1)} x^{(1)} & \overline{w_2}^{(1)} y^{(1)} & \overline{w_2}^{(1)} \\ \overline{w_1}^{(2)} x^{(2)} & \overline{w_1}^{(2)} y^{(2)} & \overline{w_1}^{(2)} & \overline{w_2}^{(2)} x^{(2)} & \overline{w_2}^{(2)} y^{(2)} & \overline{w_2}^{(2)} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \overline{w_1}^{(n)} x^{(n)} & \overline{w_1}^{(n)} y^{(n)} & \overline{w_1}^{(n)} & \overline{w_2}^{(n)} x^{(n)} & \overline{w_2}^{(n)} y^{(n)} & \overline{w_2}^{(n)} \end{bmatrix}^{-1} \begin{bmatrix} z_d^{(1)} \\ z_d^{(2)} \\ \vdots \\ z_d^{(n)} \end{bmatrix} \tag{12}$$

2.3 Back Propagation Algorithm

The errors to be reduced between the measured and ANFIS predicted output is given by [35];

$$E_k = \tfrac{1}{2} \sum_{k=1}^{n} (z_d^k - z_p^k)^2 \tag{13}$$

The errors for the *ith* node are back propagated in order for the synaptic weights, $\overline{w_i}^{(k)}$ to be updated using the gradient descent equation given by [35];

$$\overline{w_i}^{(k)}(M+1) = \overline{w_i}^{(k)}(M) - \frac{\partial E_k}{\partial \overline{w_i}^{(k)}} \tag{14}$$

where $\Delta w_i = -\frac{\partial E_k}{\partial \overline{w_i}^{(k)}}$ is the weight increment, and $\overline{w_i}^{(k)}(M)$ is the previous value of $\overline{w_i}^{(k)}$ and $\overline{w_i}^{(k)}(M+1)$ is the updated value.

The weight update for the next backward layer through to the input is generally given as;

$$w_i^{(k)}(M+1) = \begin{cases} w_i^{(k)}(M)x + \overline{w_i}^{(k)}(M+1) \\ w_i^{(k)}(M)y + \overline{w_i}^{(k)}(M+1) \end{cases} \tag{15}$$

Fig 2 provides a flow chat of the step by step taken during the model development.

2.4 Empirical Path Loss Propagation Models

In order to gauge the performance of the developed ANFIS model, the results of the ANFIS prediction is compared with the standard and popular empirical path loss propagation models. The models considered are: Hata Model, COST 231 model, Egli Model and ECC-33 model. These models were selected because aside they are widely used, the operation propagation parameters for the models, fall within the operating regions of the transmitters used.

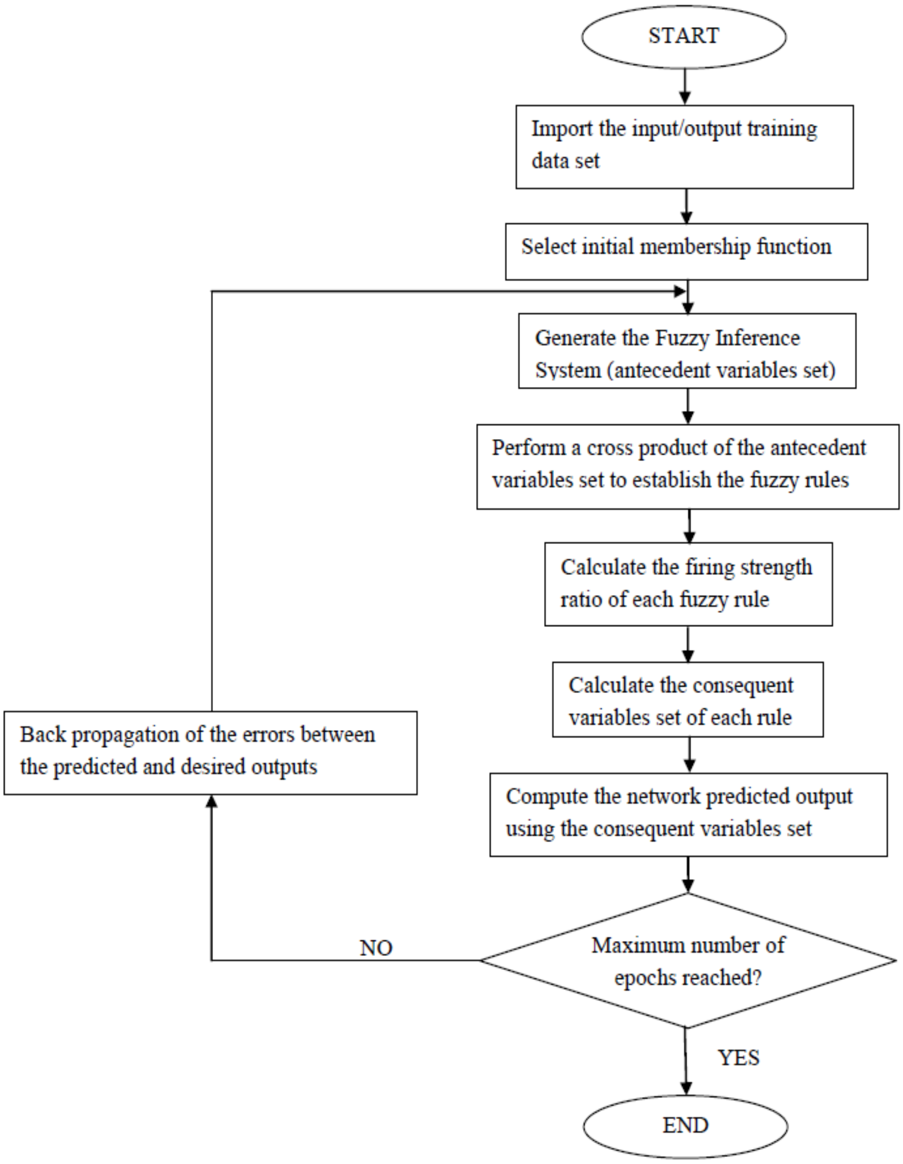

Figure 2. ANFIS Algorithm

3.0 METHOD OF DATA COLLECTION

3.1 Measurement Locations

Propagation measurements used by the models were taken in two urban cities of Nigeria; Kano (11°30′N 8°30′E 11.5°N 8.5°E), and Abuja (9°4′0″N 7°29′0″E). The measurement campaign covered the cellular frequencies, which are within the UHF bands. A tota of 10 cellular base stations (i.e., 5 in the GSM, and 5 in the WCDMA bands).

3.2 Measurement Set-up

The GSM band measurements were carried out in Kano, while those for the WCDMA band were conducted in Abuja. The measurements were done on a dual-band handset with special configuration, a GPS, and a Probe Dongle which was attached to a laptop equipped with a Huawei Genex Probe v 6.0 drive test software. All the drive tests were conducted within the metropolis. During the drive test, an automatic configuration was done on the handset making calls to a constant destination number. Each of the calls took 30 seconds of hold time and then dropped. The phone was kept inactive for 5 seconds and afterwards, subsequent calls were made. At the end of each drive test, log files containing signaling data including received signal strength, frequencies, scrambling codes (for 3G Node Bs), longitude, latitude, elevation, etc were obtained. For the GSM tests, the operating frequency for the individual Base Transceiver Stations (BTS) was in the 1800 MHz band, with centre frequencies ranging from 1835.2 MHz to 1838.6 MHz. The Absolute Radio Frequency Channel Numbers (ARFCN) for the GSM is 679, 668, 662, 672, and 677. The operating frequency for all the WCDMA was 2112.4 MHz with primary scrambling codes (PSC) of 132, 188, 484, 485, and 486. For all the measurement routes, 1.5 m was assumed as the average receiver antenna height. Fig 3 shows the screenshot the software used during data collection. Table 1 provides a detailed description of the cellular transmitters used during the drive test.

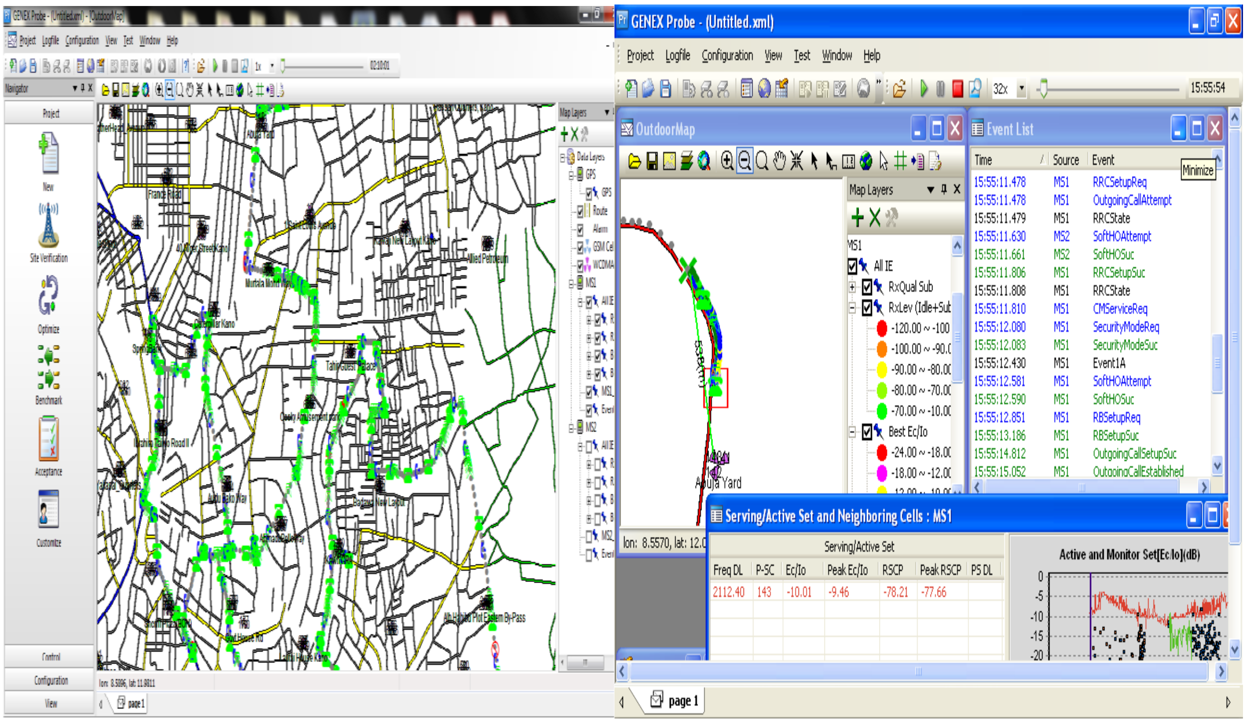

Figure 3. Screenshot showing the software used during data collection

Table 1. Description of the Cellular Transmitters

Transmitter	Band	BTS/ ARFCN	Frequency (MHz)	Antenna height (m)	Peak power (W)
GSM, Kano	UHF	1/679	1838.6	30	20
	UHF	2/668	1836.4	30	20
	UHF	3/662	1835.2	30	20
	UHF	4/672	1837.2	30	20
	UHF	5/677	1838.2	30	20
WCDMA, Abuja	UHF	1/484	2112.4	30	20
	UHF	2/486	2112.4	30	20
	UHF	3/132	2112.4	30	20
	UHF	4/485	2112.4	30	20
	UHF	5/188	2112.4	30	20

4. RESULTS AND DISCUSSION

4.1. GSM, Kano BTS

Figures 4 to 6 show the prediction of ANFIS against the empirical models. The ANFIS method mimicked the measured path loss across the five BTS while the prediction patterns exhibited by the Hata, COST 231, and ECC-33 models were quite similar across the routes as they are generally over predicted. The prediction of the Egli model in Figure 4 for BTS 1 was quite better than the other empirical models as it undulated between over and under estimation with respect to the measured path losses; however, it entirely under predicted across BTSs 1, 2, 4, and 5.

Table 2 shows how each of the models performed with respect to their statistical analysis for these BTS. It is evident that the ANFIS gave the best average RMSE and ME of 0.96 dB and -0.0000426 dB respectively in comparison to the empirical models which is quite an excellent fit for modeling the coverage area of the five BTS. The average RMSE for the empirical models are not fit for modeling this coverage area as they overshot the acceptable limit for an urban area since this environment is urban. Interestingly, the RMSE for BTS 3 for the Egli model gave a good fitness with a value of 6.80 dB as well as the SC-RMSE for BTS 2 of the Hata model with a value of 4.99 dB.

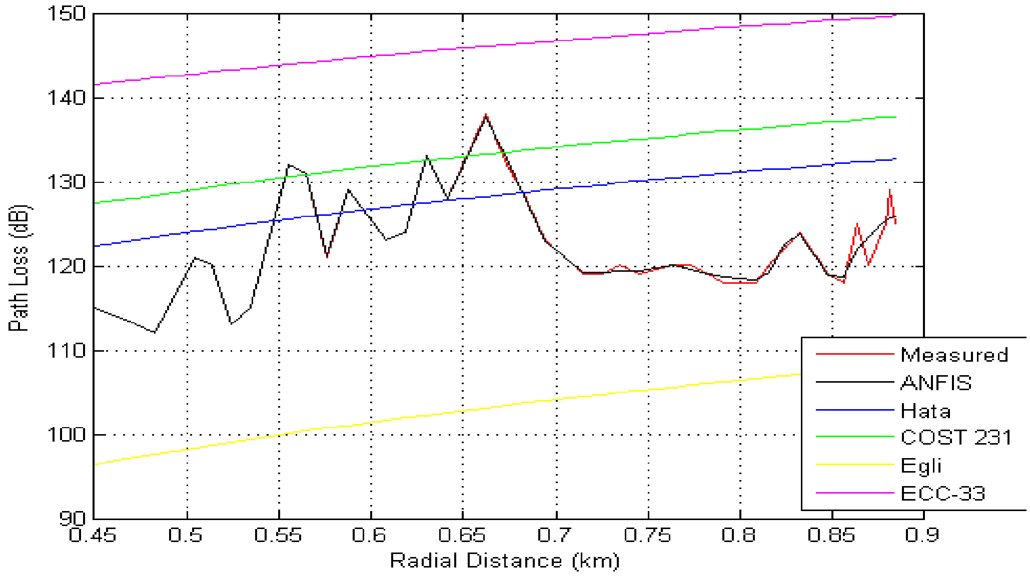

Figure 4. Comparison of Predicted and Measured Path Losses for BTS 1

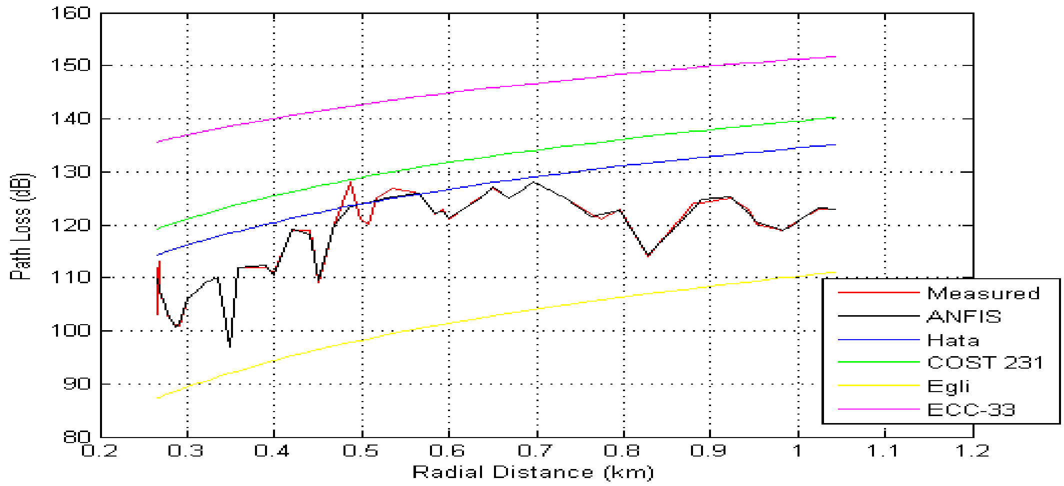

Figure 5. Comparison of Predicted and Measured Path Losses for BTS 2

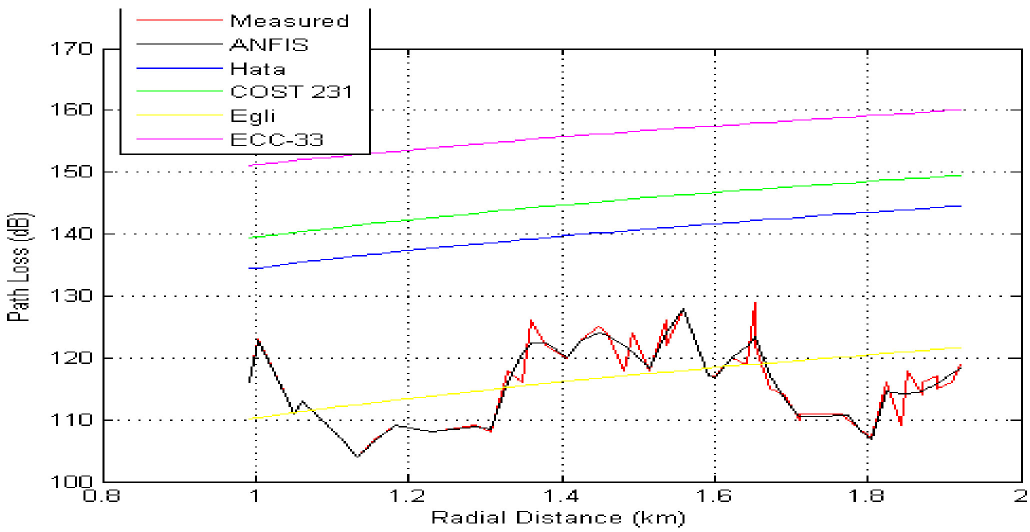

Figure 6. Comparison of Predicted and Measured Path Losses for BTS 3

Table 2. Performance Metrics for the Models of the GSM Band, Kano

MODEL		BTS 1	BTS 2	BTS 3	BTS 4	BTS 5	AVERAGE
ANFIS	RMSE (dB)	0.9752	1.5355	1.8482	0.0087	0.4276	0.9590
	SC-RMSE (dB)	5.4429	7.5735	4.9469	4.7948	6.0194	5.7555
	ME (dB)	-4.34E-05	-3.88E-05	-9.92E-06	-4.61E-05	-7.50E-05	-4.26E-05
	SDE (dB)	5.8538	8.2235	5.8578	4.801	6.2343	6.1941
COST 231	RMSE (dB)	12.9353	13.5229	30.3927	15.3682	12.9113	17.0261
	SC-RMSE (dB)	10.1265	7.6687	27.5364	12.4072	8.5107	13.2499
	ME (dB)	11.4031	12.4156	29.6806	14.7893	9.4639	15.5505
	SDE (dB)	3.1891	6.9304	2.9323	3.1068	4.9072	4.2132
HATA	RMSE (dB)	8.8359	9.1389	25.522	10.6303	9.8446	12.7943
	SC-RMSE (dB)	6.07	4.9903	22.7001	7.7145	5.9998	9.4949
	ME (dB)	6.386	7.4025	24.6697	9.7747	4.4475	10.5361
	SDE (dB)	3.1891	6.9304	2.9323	3.1068	4.9072	4.2132
EGLI	RMSE (dB)	19.6891	19.018	6.804	16.4187	23.4857	17.0831
	SC-RMSE (dB)	16.296	11.7124	4.3033	13.044	18.497	13.3705
	ME (dB)	-18.6689	-18.1983	1.2606	-15.8553	-21.5786	-14.6081
	SDE (dB)	3.6214	7.8699	3.3298	3.528	5.5724	4.7843
ECC-33	RMSE (dB)	24.9016	26.7843	41.1128	28.7737	25.1872	29.3519
	SC-RMSE (dB)	22.4446	21.6015	38.5451	26.4314	21.7693	26.1584
	ME (dB)	24.1801	26.2047	40.6044	28.4793	23.9178	28.6773
	SDE (dB)	2.5388	5.3263	2.602	2.3687	3.6307	3.2933

4.2. WCDMA, Abuja NodeBs

The pictorial representations of the path loss for the WCDMA band, Abuja are shown in Figures 7 to 8. For the Nodes B3 and B5, the ECC-33 and COST 231 models majorly overestimated the path losses, the Egli model under estimated while the Hata model fluctuated between over and under prediction. For the Node B5 in Figure 4.46, the Egli, Hata, and COST 231 models largely under estimated the losses, while the ECC-33 model wavered between over and under estimation of the losses. The ANFIS generally followed an imitative pattern of the measured data across all the nodes which suggest a better prediction in comparison to the empirical models. Table 3 shows how the ANFIS and each of the empirical models performed with relevance to the selected performance metrics. The average RMSE of 1.03 dB for the ANFIS method showed that it is a good fit for the coverage area of the nodes. Even though the average SC-RMSE increased the RMSE to 5.8850 dB, it is insignificant because it is still within the acceptable RMSE for an urban environment. The empirical models generally performed badly in terms of their average RMSE, but the RMSE for Node B1 of the Hata fell within the acceptable range for an urban settlement with a value 5.72 dB and therefore provided a good fit for this node as well as the SC-RMSE of Node B4 with 6.29 dB. The ECC-33 model for Node B5 also gave a good fitness of 6.60 dB after the deviation errors were negated from the RMSE.

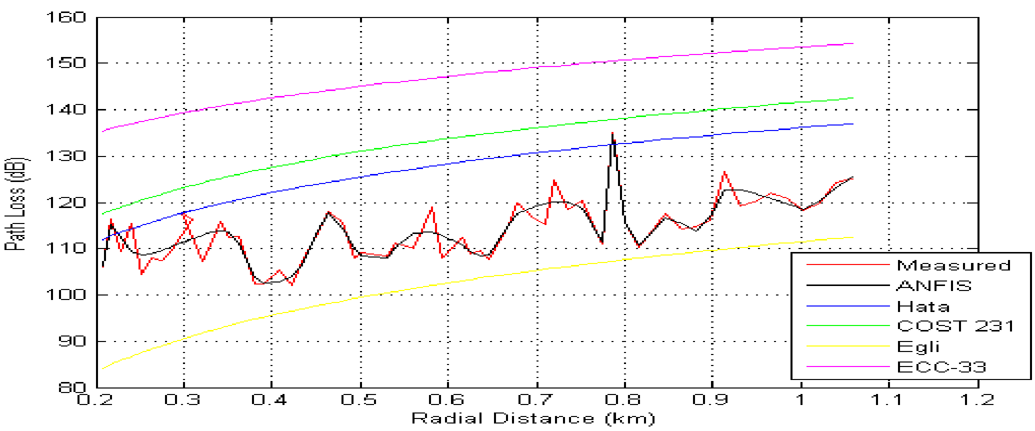

Figure 7. Comparison of Predicted and Measured Path Losses for Node B3

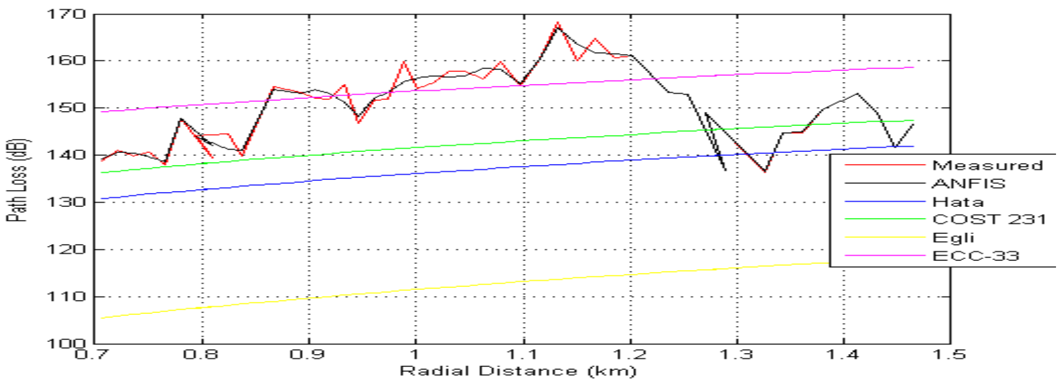

Figure 8. Comparison of Predicted and Measured Path Losses for Node B5

Table 3. Performance Metrics for the Models of the WCDMA Band, Abuja.

MODEL		Node B1	Node B2	Node B3	Node B4	Node B5	AVERAGE
ANFIS	RMSE (dB)	0.0214	0.419	2.5023	0.6663	1.5378	1.0294
	SC-RMSE (dB)	5.7097	6.5257	4.4881	5.7406	6.9608	5.8850
	ME (dB)	-4.70E-05	1.49E-05	9.83E-06	-4.26E-05	4.98E-05	-3.01E-06
	SDE (dB)	5.7231	6.8117	6.0535	5.9596	7.885	6.4866
COST 231	RMSE (dB)	10.1754	17.1655	19.2429	11.9745	11.4189	13.9954
	SC-RMSE (dB)	7.4025	14.1739	12.7105	9.7079	8.8783	10.5746
	ME (dB)	9.1997	15.1685	18.1463	9.4265	-8.3274	8.7227
	SDE (dB)	3.1789	3.4925	7.1665	2.6436	3.2418	3.9447
HATA	RMSE (dB)	5.7194	12.5843	14.1895	8.3711	15.868	11.3465
	SC-RMSE (dB)	3.4453	9.9659	8.2223	6.2872	13.0621	8.1966
	ME (dB)	3.716	9.6848	12.6625	3.9427	-13.8112	3.2390
	SDE (dB)	3.1789	3.4925	7.1665	2.6436	3.2418	3.9447
EGLI	RMSE (dB)	22.8239	17.1266	14.9676	22.0654	39.1608	23.2289
	SC-RMSE (dB)	19.2911	13.4993	8.6419	19.2763	35.5626	19.2542
	ME (dB)	-22.4133	-14.9848	-13.2447	-20.7063	-38.3588	-21.9416
	SDE (dB)	3.6098	3.9659	8.138	3.002	3.6813	4.4794
ECC-33	RMSE (dB)	23.8567	28.3609	32.6382	22.6382	8.5976	23.2183
	SC-RMSE (dB)	21.4866	25.5535	27.2611	20.5389	6.597	20.2874
	ME (dB)	23.4267	27.2782	32.1514	21.4926	3.6387	21.5975
	SDE (dB)	2.4185	2.9319	5.4751	2.2237	2.7553	3.1609

Table 4. Effects of the Number of Membership Functions on the RMSE for the Generalized Bell-shaped Membership Function

Number of Membership Functions	RMSE of Transmitters (dB)	
	GSM (BTS 4)	WCDMA (Node B4)
2	2.2154	3.3670
4	0.9058	2.1063
6	0.2266	0.9849
8	0.1922	0.8893
10	0.0087	0.6663

Table 4 gives an insight into how the number of MFs affects the RMSE. It is evident for the randomly selected BTS, and NodeBs that an increase in the number of MFs yielded a better result of the RMSE; however, care must generally be taken in the selection of the numbers so as to avoid over fitting of the results.

5. CONCLUSIONS AND RECOMMENDATIONS

This research experiment the use of AI in path loss prediction. The ANFIS method was used to predict path losses in the UHF bands and the RMSE, ME, SC-RMSE, as well as the SDEs of the used method were compared to that of four widely used empirical models (Hata, COST 231, Egli, and ECC-33 models). In general, the following conclusions are drawn from this research:

i. The ANFIS method generally performed better with least RMSE and ME across all the transmitters in comparison with the empirical models considered.

ii. The SDEs and the SC-RMSE for the empirical path loss models were dependent on the terrain composition and clutter cover of the measurement routes and system parameters of the transmitters while those of the ANFIS method were dependent on the measurement data because of the fact that ANFIS mimics a given set of data.
iii. The work also showed how the number and different types of membership functions, as well as the increment in epochs size, affected the RMSE; the higher the number of epochs, the lower the RMSE and vice versa.
iv. The data density had a significant impact on the ANFIS method as well; the lower the data density, the lower the RMSE and vice versa.
v. In terms of SDEs, the empirical models generally performed better than the ANFIS method as they provided least SDEs.
vi. Within the UHF bands considered, the ANFIS method generally seems to be more efficient than the empirical path loss prediction models considering RMSE as the performance criterion.

REFERENCES

[1] N. Zia and I. A. Muhammed, "RF Coverage and Path Loss Forecast Using Neural Network.," in *Advances in Intelligent Systems and Computing*, Switzerland., Springer International Publishing, 2014, p. 240.

[2] S. Sotiroudis, K. Siakavara and J. Sahalos, "A Neural Network Approach to the Prediction of the Propagation Path-Loss for Mobile Communication Systems in Urban Environment," in *Progress In Electromagnetics Research Proceedings (PIERS) proceedings*, Prague, Czech Republic, 2007.

[3] N. Faruk, A. Adeseko and Y. Adediran, "On the Study of Empirical Path Loss Models for Accurate Prediction of TV Signal for Secondary Users," *Progress in Electromagnetic Research (PIER),* vol. 49, pp. 155-176, 2013.

[4] N. Faruk, W. B. Olayiwola, A. Abdulkarim, N. Surajudeen-Bakinde, O. Obiyemi, A. Lukman, M. A. Maaruf and J. Abdulhameed, "Clutter and terrain effects on path loss in the VHF/UHF bands," *IET Microwaves, Antennas & Propagation*, vol. 12, no. 1, pp. 69-76, 2018.

[5] J. Parsons, The Mobile Radio Propagation Channel. 2nd Edition, John Wiley & Sons Ltd., 2000.

[6] O. Abdul-Aziz and T. Rahman, "Investigation of Path Loss Prediction in Different Multi-Floor Stairwells at 900 MHz and 1800 MHz," *Progress In Electromagnetics Research,* vol. 39, pp. 27-39, 2014.

[7] O. Onidare, N. Faruk, W. Olayiwola, M. Muhammad, O. Sowande and A. Adeseko, "Practical Error Bounds for Empirical Models at VHF/UHF bands," *Bayero Journal of Engineering and Technology,* vol. 11, no. 1, pp. 28-39, 2016.

[8] N. Faruk, Y. Adediran and A. Adeseko, "Error Bounds of Empirical Path Loss Models at VHF/UHF Bands in Kwara State, Nigeria," in *Eurocon,2013 IEEE*, Zagreb, Croatia., 2013.

[9] A. Oloyede, N. Faruk and W. Bello, "Variation of Clutter Height and its Impact on Path Loss in the VHF/UHF Bands," in *Advances in Wireless and Optical Communications (RTUWO)*, Riga, Latvia., 2016.

[10] A. Jimoh, N. T. Surajudeen-Bakinde, N. Faruk, A. Adeseko, O. Obiseye and W. Olayiwola, "Performance Analysis of Empirical Path Loss Models in VHF and UHF bands," in *IEEE 6th International Conference on Information and Communication Systems (ICICS), Jordan University of Science and Technology*, Amman, Jordan, 2015.

[11] I. Segun, A. Aderemi, N. Charles, E. Francis, N. Faruk and T. Carlos, "Calibrating the Standard Path Loss Model for Urban Environments using Field Measurements and Geospatial Data.," in *The International Conference of Wireless Networks*, London, U.K, 2017.

[12] N. Faruk, A. Ayeni, Y. Adediran and N. Surajudeen-Bakinde, "Improved Path Loss Model for Predicting DTV Coverage for Secondary Access," *Int. J. Wireless and Mobile Computing,* vol. 7, no. 6, pp. 565-576, 2014.

[13] J. Zang and X. Wang, "Measurements and Modeling of Path Loss Over Irregular Terrain for Near-Ground and Short-Range Communications," *Progress In Electromagnetics Research,* vol. 57, pp. 55-62, 2017.

[14] D. Kifle, L. Gimenez, B. Wegmann, I. Viering and A. Klein, "Comparison and Extension of Existing 3D Propagation Models with Real-World Effects Based on Ray-Tracing. A Basis for Network Planning and Optimization," *Wireless Personal Communication,* vol. 78, pp. 1719-1739, 2014.

[15] E. Greenberg and E. Klodzh, "Comparison of deterministic, empirical, and physical propagation models in urban environments," in *Microwaves, Communications, Antennas and Electronic Systems (COMCAS)*, 2005.

[16] O. Eichie, D. Oyedum, A. O.M. and A. M.A, "Comparative Analysis of Basic Models and Artificial Neural Network Based Model for Path Loss Prediction," *Progress in Electromagnetic Research M (PIER),* vol. 1, pp. 133-146, 2017.

[17] P. S. Sotirious, K. Sotirious, A. G. Konstantinos, S. Katherine and N. S. John, "Optimal Artificial Neural Network Design for Propagation Path-Loss Prediction Using Adaptive Evolutionary Algorithm," in *7th European Conference on Antennas and Propagation (EuCAP)*, 2013.

[18] J. C. Dela-Cruz and F. S. Caluyo, "Dela Cruz, J. C. & Caluyo, F. S. (2013). Heuristic modelling of outdoor path loss for 9m, 3m and 1.5m antenna at 677 MHz," in *IEEE Conference on Cybernetics and Intelligent Systems (CIS)*, Manila, Phillipines, 2013.

[19] N. Surajudeen-Bakinde, F. N., S. I. P., M. A. S., A. A. O., L. A. O. and C. T. C. , "Path Loss Predictions for Multi-Transmitter Radio Propagation in VHF Bands using Adaptive Neuro-Fuzzy Inference

System," *International Journal Engineering Science and Technology (JESTECH), Elsevier,* vol. 21, pp. 679-691, 2018.

[20] A. Tamma, A. Rabbie and K. Mustafa, "Neural Network Approach to Model the Propagation Path Loss for Great Tripoli Area at 900, 1800, and 2100 MHz frequency bands," in *16th International Conference on Sciences and Techniques of Automatic Control and Computer Engineering-STA*, Tunisia, 2015.

[21] A. S. Muhammed, I. P. Segun, N. Faruk, Surajudeen-Bakinde, N.T., A. Abdulkarim and A. O. Lukman, "Adaptive Neuro-Fuzzy Model for Path Loss Prediction in the VHF Band," in *IEEE International Conference on Computing, Networking and Informatics (ICCNI 2017) in Covenant University*, Ota, Nigeria, 2017.

[22] S. Muhammed, N. Faruk, N. Surajudeen-Bakinde, S. P., A. O. and O. Lukman, "On Adaptive Neuro-Fuzzy Model for Path Loss Prediction in the VHF Band", The ITU Journal: ICT Discoveries, Special issue 1," in *Special issue 1 - The impact of Artificial Intelligence (AI) on communication networks and services,*, International Telecommunication Union (ITU), 2018, pp. 1-9.

[23] A. Ozdemir, A. Mustapha, K. Mehmet and M. Gulsen, "The Prediction of Propagation Loss of FM Radio Station Using Artificial Nueral Network.," *Journal of Electromagnetic Analysis and Applications,* vol. 6, pp. 358-365, 2014.

[24] P. Gilbert, J. Leni and M. Joao, "Improvement of Outdoor Signal Strength Prediction in UHF Band by Artificial Neural Network," *IEEE Transactions on Antennas and Propagation,* vol. 64, no. 12, pp. 5404-5410, 2016.

[25] M. Hata, "Empirical formula for propagation loss in land mobile radio ser-vicest," *IEEE Trans. on Vehicular Technology, VT,* vol. 29, pp. 317-325, 1980.

[26] C. 231, "Urban transmission loss models for mobile radio in the 900 and1800 MHz bands (revision 2), COST 231," The Hague, , the Netherlands, 1991.

[27] J. J. Egli, "Radio Propagation above 40 MHz Over Irregular Terrain," *Proc IRE,*, vol. 45, no. 10, pp. 1381-1391, 1957.

[28] V. Abhayawardhana, I. Wassell, D. Crosbsy, M. Sellars and M. Brown, "Comparison of Empirical Propagation Path loss Models for Fixed Wireless Access Systems," in *IEEE Vehicular Technology Conference*, Spring, 2005.

[29] B. Kosko, Neural Networks and Fuzzy Systems: A Dynamical Systems Approach to Machine Intelligence, Prentice Hall, 1992.

[30] E. Turkan, Y. Berna and A. Aysen, "Fuzzy Adaptive Neural Network Approach to Path Loss Prediction in Urban Areas at GSM-900 band," *Turk J Elec Eng & Comp Sci,* vol. 18, no. 6, pp. 1077-1094, 2010.

[31] B. Mrinal, "daptive Network based Fuzzy Inference System (ANFIS) as a Tool for System Identification with Special Emphasis on Training Data Minimization," Ph.D Thesis, Department of Electronics and Communication Engineering Indian Institute of Technology, Guwahati, India, 2008.

[32] O. Erik, Z. Hans-Jurgen and S. Hajime, "Macrocell Path-Loss Prediction Using Artificial Neural Network," *IEEE Transactions on Vehicular Technology,* vol. 59, no. 6, pp. 2735-2747, 2010.

[33] D. Rupanwita, "Optimal Power Control for Cognitive Radio in Spectrum Distribution Using ANFIS," in *IEEE International Conference on Signal Processing, Informatics, Communication and Energy Systems(SPICES)*, Kozhikode., 2015.

[34] J. JongKoo, "Fuzzy and Neural Network Models for Analyses of Piles," Department of Civil Engineering,, Raleigh North Carolina University, 2007.

[35] S. Roland, Advanced Control Engineering. 1st Edn., Oxford: Reed Educational and Professional Publishing Ltd, 2001, pp. 351-364.