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MODIFICATION OF LOG-NORMAL PREDICTION MODEL FOR HSPA NETWORK USING ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

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ABSTRACT

The transmission of radio signals over a channel for proper path-loss prediction is a core aspect of planning in wireless communication. Some conventional path-loss prediction models such as Log-normal, Okumura-Hata and COST 231 models are not appropriate for predicting the path-loss values due to differences in frequencies of operation which, therefore, need adaptation before employing. This paper, therefore, modifies the Log-normal prediction model for High Speed Packet Access (HSPA) using Adaptive Neuro-fuzzy Inference System (ANFIS). The modification is carried out by measuring the Received Signal Strength (RSS) using drive test at Ayetoro area of Lagos, Nigeria on (Longitude 3.19647E and Latitude 6.59167 N). The drive test equipment consists of a computer system integrated with Test Equipment for Mobile System (TEMS) software, Ericson TEMS phone and Global Positioning System (GPS). Suitability of the conventional models is determined using Base Station (BS) parameters of the network after which the modification of Log-normal prediction model is carried out by obtaining the path-loss exponent. The path-loss exponent is used to determine the deviation for proper modification. The modified model is further enhanced using ANFIS model which is developed by training five layer ANFIS architecture for adaptation. The models are evaluated using path-loss values and Root Mean Square Error (RMSE) to determine the performances. The results obtained show that ANFIS, COST 231, and modified Log-normal models give the lowest RMSE values with their path-loss values closest to the measured values. Therefore, these models are suitable for predicting the HSPA signal in this area and can be used for future planning of wireless network.

***Key words**: ANFIS, Log normal, Least Square Error, Gradient Descent*

INTRODUCTION

Wireless communication has become an acceptable means of communication in recent times owing to its flexibility and adaptability. The acceptability of wireless communication as a general tool for communication is highly dependent on the ability to communicate while moving (Megha and Rohit, 2004). However, a major challenge of wireless communication is loss in signal strength as distance increases between the transmitter and the receiver. This affects the quality of the received signal by the mobile station and therefore, requires serious attention during network planning and budgeting (Adeyemo, Fawole and Akande, 2017).

Path-loss models have been developed to determine the actual path-losses along the propagation channel. These models are experimental, stochastic and deterministic (Dominic, Musa and Tonga, 2015). However, the acceptability of these models in path-loss prediction is dependent on their accuracy, time consumption and complexity. Experimental models are based on empirical measurement taken at some distances over a period of time at a particular frequency (Okorogu, Onyishi, Nwalozie and Utebor, 2013). Although, these models are simple but are limited in terms of applicability to other environments due to differences in environmental terrains. Therefore, the models have to be optimized in order to make them applicable to other environments (Okorogu *et al.,* 2013).

Deterministic model is based on ray tracing method for path-loss prediction along the propagating channel (Goldsmith, 2004). These models are sometimes accurate than experimental model but has high computational complexity and computational time (Omae, Ndungu, and Kibet, 2014). Stochastic models assume the environments behave in a random manner and therefore generate predictions randomly using statistical distribution. These models exclude the real behavior of the environment in terms of the environmental terrain and other physical phenomenon (Abhayawardhan, Wassell, Crosby, Sellars, and Brown, 2009). The predictions of these models are unreliable because the terrain and the structure of the environment are not inclusive. Therefore, there is a need to propose a better model that can give more accurate predictions with proper adaptability.

Adeyemo *et al.* (2017) investigated some existing path-loss prediction models and developed a modified path-loss model for Universal Mobile Telecommunication System (UMTS) signal in Owerri, Nigeria. The modified path-loss model was developed using regression analysis by obtaining the path-loss exponent from the measured data. The results were compared to COST 231, LEE and SUI (Stanford University Interim) models. It was confirmed that, the developed modified model has better predictions than other models. The paper focuses on Log-normal model with shadowing effect for path-loss prediction without optimization. Ogbeide and Edeko (2013) modified Hata model for path-loss prediction at Very High Frequency (VHF) band in Edo State, Nigeria using Log-normal model. The result was compared with the conventional Hata model using RSME to determine the suitability. It was confirmed that, an RMSE value of 7 dB was obtained from Hata model while the modified model has RMSE value of 4.6 dB.

Versaci, Salvano, Fabio and Biagiano, (2012) developed a path-loss model using ellipsoidal rules and Fuzzy inference systems (EFIS). A sugeno FIS was structured into three different sections: membership functions, Fuzzy operators and If-then rules. The input to the ellipsoidal Fuzzy inference considered are transmitting antenna gain, receiving antenna gain, carrier frequency, distance from the radio base station, the height of the building, length of the street and the height of the transmitting antenna. The performance of the network was compared to Okumura-Hata and ray-tracing Model using Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). It was deduced that, EFIS gave a better performance than Okumura-Hata and ray tracing.

Dominic, Musa and Tonga (2015) developed a model from log normal model for path-loss prediction in Kaduna town, Nigeria. The aim was to address the problem of poor network signal quality received by the subscribers. Path-loss exponent was obtained to develop a model for some service providers. The developed models were modified by obtaining the standard deviation about a mean for proper modification. It was also confirmed that, different path-loss values were obtained for different service providers. The authors concluded that, path-loss is a major cause of poor quality of signal received by the customers.

Although, some of the researches done on path-loss prediction have employed adaptive algorithm but very few have investigated ANFIS for path-loss prediction at 2100 MHz. It is, therefore, pertinent to investigate the applicability of ANFIS as an adaptive algorithm for path-loss prediction in this peculiar environment of Aiyetoro, Lagos. This paper addresses the issue of large deviations posed by existing prediction models when compared to the measured data by optimizing the modified Log-normal model using ANFIS for proper adaptation to the environment

MEASUREMENT AND EQUIPMENT SETUP

The research was carried out in Aiyetoro area of Lagos, Nigeria. Data is collected from an HSPA Base Stations (BS) that transmit signal at a frequency of 2100 MHz with 42 dBm transmit power. A computer system integrated with Test Equipment for Mobile System TEMS software, TEMS Phone and a Global Positioning System (GPS) were set up for data collection. TEMS software records RSS and the coordinates of each test point. The receiver was kept at height of 1.5 m in the vehicle throughout the experiment and vehicle was moving at an average speed of 40 km/h. RSS values were recorded for the three sectors of the BS and the results were averaged. Fig. 1a, b, c and d show the tower photograph of the BS and panoramic view of the environment across the three sectors. Table 1 contains the path-loss values obtained from RSS and the corresponding distances.

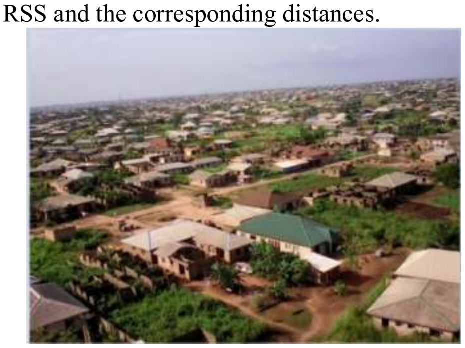

Fig. 1: (a) Tower Photograph (long 3.19647 E lat 6.59167 N) (b) panoramic view of sector 1 environment (c) panoramic view of sector 2 environment (d) panoramic view of sector 3 environment.

Table 1: Measured RSS with their corresponding Path-loss values in Aiyetoro, Lagos.

Distance (m)	RSS (dBm)	Measured L_M(dB)
100	-68	110
200	-85	127
300	-91	133
400	-86	128
500	-90	132
600	-91	133
700	-98	140
800	-92	134
900	-99	141
1000	-104	146

Suitability of some prediction path-loss models

Using the BS parameters, suitability of Okumura-Hata , COST 231 and Log-normal models were investigated for their adaptability in Aiyetoro, Lagos environment.

Suitability of Okumura-Hata model to BS of Aiyetoro, Lagos

Okumura-Hata models provide some empirical formulas at an approximate frequency range of 150 MHz-1500 MHz to predict signal strength. Path-loss 'L_P'described by Okumura-Hata model for an urban area is given by (Costa, 2008) as:

$$L_P(dB) = 69.55 + 26.16log_{10}f_c - 13.82log_{10}h_t - a(h_r) + (44.9 - 6.55log_{10}h_t)log_{10}D \quad (1)$$

where: D is the distance
h_r is the receiving antenna height ranging from 1m to 10m,
f_c is the frequency in MHz,
$a(h_r)$ is the correction factor for effective mobile antenna height.
h_t is the transmitting antenna height ranging from 30 m to 200 m.
Correction factor for large cities is given by:

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

Substituting HSPA base station parameters into equation (1) gives (3).

$$L_P(dB) = 136.05 + 35.22\log D \quad (3)$$

Suitability of Cost 231 Extension to Hata Model to the BS of Aiyetoro, Lagos.

This model is an extension to Okumura-Hata model designed to be used in frequency bands of 500 MHz to 2000 MHz (Isabona and Azi, 2013). The P_L formula is described by (Costa, 2008) as:

$$L_P(dB) = 46.3 + 33.9log_{10}f_c - 13.82log_{10}h_t - a(h_r) + (44.9 - 6.55log_{10}h_t)log_{10}(D) + C_m \quad (4)$$

where: *a(hr)* is the correction factor,
h_r is the effective receiving antenna height from 1m to 10m,
C_m is the correction factor and the parameter that defines the type of the terrain,
f_c is the frequency in MHz,
D is the distance between the transmitter and the receiver
h_t is the height of the transmitting antenna from 30 m to 200 m,
After the substitution of the HSPA parameters into equation (4), (5) is obtained as;

$$L_P(dB) = 141.50 + 35.22\log\ D \quad (5)$$

Log- Normal Path-loss Model

The Log-normal path-loss model $L_{PP}\ (d_i)$ is expressed by Dominic *et al., (2015)* as:

$$L_{PP}\ (d_i) = L_P\ (d_0) + 10n\ log_{10}\left(\frac{d_i}{d_0}\right) \quad (6)$$

Path-loss exponent "n" is obtained as:

$$n = \frac{L_P(d_i) - L_P(d_0)}{10\, log_{10}(\frac{d_i}{d_0})}$$

(7)

where : 'n' is the path-loss exponent,
'd_0' is the reference distance of 100 meters,
$L_P\ (d_0)$ is free space path-loss at reference distance of 100 meters
At 200 m, predicted path-loss value (L_{PP}) is obtained from equation (6) as;

$$L_{PP}(d_i) = 110 + 10\, nlog(\frac{200}{100})$$

$$L_{PP}(d_i)dB = 110 + 3.01n \quad (8)$$

$L_P\ (d_0)$ is obtained from the measured path-loss values as 110 dB.
The analysis repeated at other distances and the result is presented in Table 2.
Error 'E' related to the network is calculated with respect to the path-loss exponent 'n' as:

$$E = L_M(d_i)dB - L_{PP}(d_i)\ dB \quad (9)$$

The square of error is also calculated and presented in Table 2 as:

$$E\ (n) = (L_M(d_i) - L_{PP}(d_i))^2 dB \quad (10)$$

Summation of the square errors in Table 2 gives;

$$E\ (n) = 5893 - 3455.84n + 521.39n^2 \quad (11)$$

The square error is differentiated and equated to zero in order to obtain the value of 'n' which minimizes the squared error.

$$E\ (n) = 5893 - 3455.84n + 521.39n^2$$

$$\frac{\partial e(n)}{\partial(n)} = 2(521.39n) - 3455.84$$

$$\frac{\partial e(n)}{\partial(n)} = 2(521.39n) - 3455.84 = 0$$

$$n = \frac{3455.84}{1042.78} = 3.31$$

A modified form of this model is when the shadowing effect which occurs over a large measurement location is included (Nwalozie, Ufoaroh, Ezeagwu and Ejiofor, 2014). Path-loss '$L_{PP}\ (d_i)$' in equation (6) when shadowing factor is included becomes:

$$L_{PP}\ (d_i) = L_P\ (d_0) + 10n\ log_{10}\left(\frac{d_i}{d_0}\right) + \delta \quad (12)$$

where: δ is a Zero-Mean Gaussian distributed random variable (in dB) with standard deviation σ (in dB). The standard deviation is determined from the square error obtained in equation (11) as:

$$\sigma = \left(\frac{1}{N}\sum_{i}^{n}(L_m(d_i) - L_p(d_i))^2\right)^{\frac{1}{2}}$$

$$\sigma = \left(\frac{1}{10}\ 521.39\ (3.31)^2 - 3455.84\ (3.31) + 5893\right)^{\frac{1}{2}}$$

$$\sigma = (16.66)^{\frac{1}{2}}$$

$$\sigma = 4.08$$

The resultant Path-loss model is obtained as:

$$L_{PP} = 110 + 10(3.31)\log(\frac{d_i}{d_0})(dB)$$

$$L_{PP} = 114.08 + 33.1 logD(dB) \quad (13)$$

Table 2: Measured values, Predicted values and the corresponding square errors

$L_M\ (d_i)\ dB$	$L_{PP}(d_i)dB$	$L_M(d_i)$ - $L_{PP}(d_i)$	$(L_M(d_i) - L_{PP}(d_i))^2$
110	110	0	0
127	110 + 3.01n	17 – 3.01n	289 – 102.34 – 9.06n^2
133	110 + 4.77n	23 – 4.77n	529 –219.42 – 22.94n^2
128	110 + 6.02n	18 – 6.02n	324 – 216.72 + 36.24n^2
132	110 + 6.99n	22 – 6.99n	489 – 307.56 + 48.36n^2
133	110 + 7.78n	23 – 7.78n	529 – 357.88 + 60.53n^2
140	110 + 8.45n	30 – 8.45n	900 – 507.00 + 71.40n^2
134	110 + 9.03n	24 – 9.03n	576 – 433.44 + 81.54n^2
141	110 + 9.54n	31 – 9.54n	961 – 591.48 + 91.01n^2
146	110 + 10.00	36 – 10.00n	1296 – 720.00 +100.00n^2

Adaptive Prediction models

The conventional prediction models are adapted to other environment other than where they are developed using adaptive algorithms such as Genetic Algorithm, Particle Swamp Optimization and Adaptive Neuro-Fuzzy Inference system (ANFIS). In this paper, ANFIS is employed because of few researches on it in this area to the best of authors' knowledge (Nazmat, Nasir, Segun, Muhammed, Abdulkarim, Lukman and Carlos, 2018).

Adaptive Neuro-Fuzzy Inference Systems

Adaptive Neuro-Fuzzy Inference Systems builds a system that utilizes Fuzzy Logic (FL) and Artificial Neural Network (ANN) to generate predictions (Hazlina, 2013). ANFIS combines the strength of both ANN and FL to build a better system capable of giving a more accurate intelligence (Nauk, 1997). ANN's are designed to understand the human brain and develop computer programs that can solve difficult and abstract problems (Syed and Muhhamed, 2015). Fuzzy Logic (FL) is a branch of science which rationalizes uncertain events (Hazlina, 2013). ANFIS structure is a five layers feed forward neural network that utilizes Sugeno and Takagi If-then-rules (Jang, 1993). Fig. 2 shows the basic ANFIS structure with

two inputs and one output. The Sugeno and Takagi ANFIS structure has rules of the form:
Rule 1: If z_1 is C_1 and z_2 is D_1 then $Y_1 = C_1 z_1 + D_1 z_2 + E_1$

(14)

Rule 2: If z_1 is C_2 and z_2 is D_2 then $Y_2 = C_2 z_1 + D_2 z_2 + E_2$

(15)

where 'z_1'and 'z_2', are the input variables. C, D and E are consequent parameters, and 'Y' is the final output.

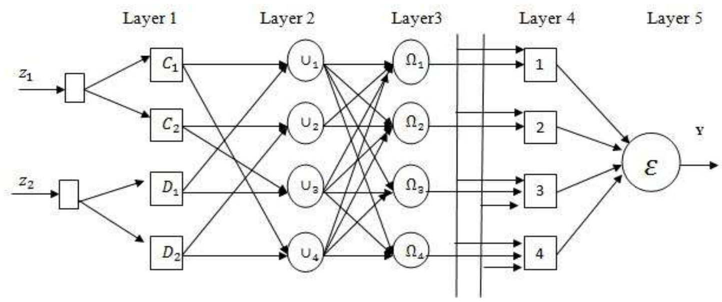

Figure 2: Basic ANFIS Structure with five layers

(a) Layer 1 (Fuzzification layer):
The layer contains adaptive nodes defining the membership grades of input. It is usually represented by Gaussian function. The output is given in term of membership functions 'μ_{Ci}' and 'μ_{Di}' by (Jang, 1993) as:

$$\mu_{Ci}(z_1) = \exp\left(-\left(\frac{z_1 - c_i}{\sigma_i}\right)^2\right) \quad \text{for i= 1, 2} \tag{16}$$

$$\mu_{Di}(z_2) = \exp\left(-\left(\frac{z_2 - c_i}{\sigma_i}\right)^2\right) \quad \text{for i= 1, 2}$$

(17)

(b) Layer 2 (Product Layer):
The output of this layer 'w^l' is the product of the incoming membership functions:

$$w^l = \mu_{Ci}(z_1).\mu_{Di}(z_2)$$

for i= 1,2
(18)

(c) Layer 3 (Normalized Layer)
The output of the layer 3 '$\overline{w_l}$' is the ratio of 'w^l' to the sum of all the firing strengths:

$$\overline{w_l} = O_{3,i} = \frac{w^l}{\sum_{l=1}^{n} w^l}, \quad \text{for } l = 1,2,3,4$$

(19)

(d) Layer 4 (Deffuzification layer):
This computes the contribution of each rule to the overall output and provides output values resulting from the inference of the rules.

$$\overline{w_l} y_i = O_{4,i} = \overline{w_l}(C_i^l z_1 + D_i^l z_2 + E_0^l)$$

(20) where: y_i is the final part of the fuzzy inference rules.
$\overline{w_l}$ is the output of layer 3.
C, D_i, E_i are called consequent parameters
$z_1$and z_2 are the input variables

(e) Layer 5 (Output Layer)
The final output is computed as the summation of the entire incoming signals.

$$O_{4,i} = \sum_{i=1}^{4} \overline{w_l} Y_i$$

(21)

ANFIS Training

In this study, ANFIS network was trained to map input data (path-loss exponent and distance) to the corresponding path-loss values using Least Square Error (LSE) and Gradient Descent (GD) method to adjust the consequent and the antecedent parameters, respectively (Namzat *et al., 2018)*. The input data signals propagate forward till the sets of consequent parameters are identified by LSE while the error signal measured propagates backward till the premise parameters are updated by GD method. 100 measurement samples were taken over one kilometer and seventy percent (70 %) of the data was used for training while thirty percent was used (30 %) for testing. Training proceeds until the error between the measured and the predicted value is minimized. The performance of the ANFIS based model is compared to Okumura-Hata, COST 231 and modified log normal model.

RESULT AND DISCUSSION

Fig. 3 presents path-loss versus distance for measured, COST 231 and Okumura-Hata. At 600 m away from the BS, path-loss values obtained for measured, COST 231 and Okumura-Hata are 138, 134 and 128, respectively. Fig. 4 depicts path-loss versus distance for, measured, COST 231, Okumura-Hata, ANFIS and Log-normal models. At 400 m away from the BS, path-loss values obtained for, measured, COST 231, Okumura-Hata, ANFIS and modified models are 128, 127, 122, 130 and 134 dB respectively. Similarly, at 600 m away from the BS, path-loss values obtained for measured, COST 231, Okumura-Hata, ANFIS and modified Log-normal models are 140, 136, 131, 143 and 142, respectively.

Table 3. presents path-loss values obtained for measured, modified Log-normal and ANFIS models. At 400 m away from the BS, path-loss

values obtained for measured, modified Log-normal and ANFIS models are 128, 134 and 130 dB, respectively. Corresponding values of 138, 140 and 134 dB were obtained at 600 m away from the BS.

The results are justifiable in that, path-loss values obtained from ANFIS are the closest to the measured value and are, therefore fit for path-loss prediction in this environment. Path-loss values obtained from the modified Log-normal models and COST 231 are also relatively close to the measured values showing that both models can also be used for path-loss prediction in the environment. Path-loss values obtained from Okumura-Hata are lower than the measured values indicating that the model under predicted path-loss in the environment. Table 4 presents the RMSE obtained for COST 231, Okumura-Hata, ANFIS and modified Log-normal models. 5.32, 10.40, 3.18 and 5.00 are RMSE values obtained for COST 231, Okumura-Hata, ANFIS and the modified Log-normal models respectively, confirming the suitability of ANFIS, COST 231 and the modified Log normal models for path-loss prediction in the environment.

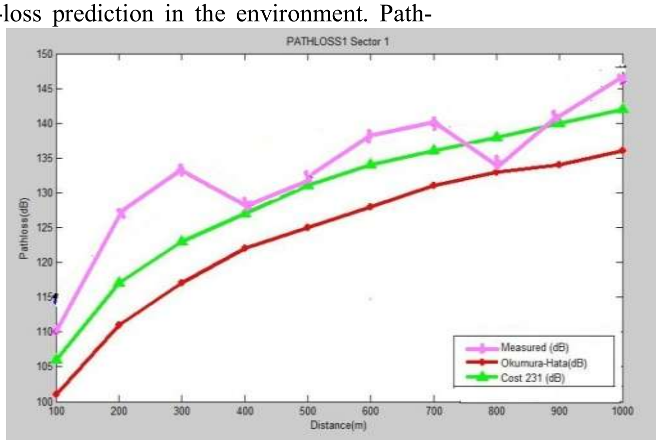

Figure 3: Path-loss (dB) models versus Distance (m) for measured, COST 231, and Okumura-Hata

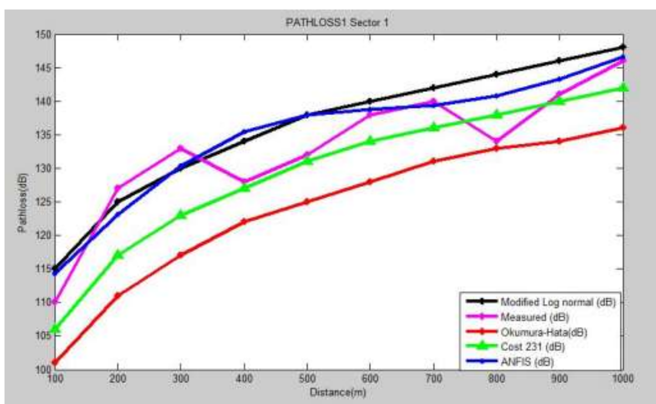

Figure 4: Path-loss (dB) models versus Distance (m) for measured, COST 231, Okumura-Hata, ANFIS and modified Log normal model.

Table 3: Path-loss values of the prediction models

Measured (dB)	ANFIS (dB)	Modified Log-normal (dB)	110
114	115		
127	130	125	
133	137	130	
128	130	134	
132	136	138	
138	134	140	
140	143	142	
134	137	144	
141	143	146	
146	149	148	

Table 4: RMSE results

Models	RMSE
Okumura-Hata	10.9
Cost 231	5.32
Modified	5.00
ANFIS	3.18

CONCLUSION

ANFIS approach is used for path-loss prediction in Aiyetoro, Lagos, Nigeria. RSS data was measured from an HSPA BS through the Drive Test. A modified model was developed from Log-normal model; Path-loss exponent 'n' is obtained to calculate the path-loss formula. The path-loss formula was modified by obtaining the standard deviation. A five layer ANFIS structure is developed and trained using LSE and GD to further Optimized the modified Log normal model using path-loss exponent and distances as the input variables. The suitability of Okumura-Hata and COST 231 are also investigated using the BS parameters. The performance of the optimized model is evaluated using path-loss values and RMSE and compared with Okumura-Hata and COST 231.The results show that ANFIS, COST 231 and the modified Log normal models are the most suitable for path-loss prediction in this environment.

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