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Okumura-Hata Propagation Model Tuning Through Composite Function of Prediction Residual

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Abstract

In this paper, an innovative composite function of prediction residual-based approach for tuning Okumura-Hata propagation model in the 800-900MHz GSM frequency band is presented. The study is based on empirical measurements conducted at University Of Uyo (UNIUYO) town-campus located at latitude and longitude of 5.042976, 7.919046 respectively. The proposed path loss tuning approach is compared with RMSE based tuning approach. According to the results, the composite function of prediction residual tuned Okumura-Hata model has the lowest RMSE value of 2.164, the highest Coefficient Of Determination (R^2) value of 0.967 and the highest prediction accuracy of 98.64%. On the other hand , the RMSE- tuned Okumura-Hata model has a higher RMSE value of 5.3, lower R^2 value of 0.814 and the lower prediction accuracy of 96.87%. Essentially, in all the three performance measures used , the composite function of prediction residual based tuning approach performed better than the RMSE based tuning approach. However, in pathloss tuning studies, RMSE value below 7dB is acceptable for the urban area. As such, the RMSE based tuning approach gave tuned model with acceptable RMSE value but with lower prediction accuracy than the model produced by the composite function of prediction residual based tuning approach.

Keywords: Pathloss, Residual, Pathloss Model, Okumura-Hata Model, Model Tuning, RMSE Based Tuning, Composite Function, Composite Function of Residual

1 Introduction

Path loss models are generally classified into three categories: empirical, deterministic and stochastic [1,2]. Empirical models are those based on observations and measurements alone. The deterministic models determine the received signal strength at a particular location by using the laws governing electromagnetic wave propagation [1,3]. Stochastic models, on the other hand, model the environment as a series of random variables [1,3]. Among these three categories of models, empirical models are the most popularly used because of their simplicity.

Undeniably propagation environments are too complex to model accurately. In practice, empirical models are mostly developed based on empirical measurements taken over a given distance, specific frequency range and particular topology. Consequently, the empirical models give high prediction errors when they are applied in another environment other than the one for which they have been designed [4,5]. Consequently, empirically measured data is usually used to investigated and tune the empirical models in respect of any desired environment the model will be used. The tuning process seeks to improve the prediction accuracy of the model with regards to the measured data. One popular way of tuning path loss model is by adding a constant value, usually, the Root Mean Square Error (RMSE) to the model so as to minimize the prediction error [6, 7,8,9]. Another way is to minimize the model's prediction error by modifying the coefficient of one or more parameters in the model [10,11,12,13,14]. Among the different model tuning approaches, the use of RMSE is the most popular because it is simple and easy to employ. In this paper, model tuning approach that uses composite function of the prediction model residual is proposed. Instead of adding the RMSE to the empirical model, the prediction error is minimized by adding a composite function of the empirical model prediction residual. The tuning approach is demonstrated by using empirical measure conducted for GSM network at 900MHz within and around University of Uyo (UNIUYO) town campus located in Uyo, Akwa Ibom state at latitude and longitude of 5.042976, 7.919046 respectively.

The study is carried out with Hata-Okumura model which is one of the most commonly used empirical path loss models [15,16]. The prediction efficiency of the composite function-based tuning approach is compared to that of the RMSE-based tuning approach. Specifically, statistical error analysis parameter such as RMSE, coefficient of determination, otherwise called R^2 and Prediction Accuracy (PA) are used in the comparative error analysis.

2 Review Of Okumura-Hata Propagation Model

The Okumura-Hata Model, as known as Hata model, is a widely used propagation model for predicting path loss in urban, suburban and open areas. This model takes into account the effects of diffraction, reflection and scattering caused by city structures [16]. The Okumura-Hata model uses four parameters for estimating the path loss, namely, carrier frequency, distance, base station antenna height and mobile antenna height. The model is based on Okumura's measurements in Tokyo, which were fitted into a mathematical model by Hata. The following equations are used for the computation of the path loss (in dB) according to the Okumura-Hata model [17]:

$$LP_{OK\_HATA(urban)} = A + B * \log_{10}(d) \qquad for\ Urban\ Area \tag{1}$$

$$LP_{OK\_HATA(suburban)} = A + B * \log_{10}(d) - C \qquad for\ Suburban\ \text{Area} \tag{2}$$

$$LP_{OK\_HATA(open/rural)} = A + B * \log_{10}(d) - D \qquad for\ Open\ Area/\text{Rural} \tag{3}$$

$$A = 69.55 + 26.16 * \log_{10}(f) - 13.82 * \log_{10}(h_b) - a(h_m) \tag{4}$$

$$B = 44.9 - 6.55 * \log_{10}(h_b) \tag{5}$$

$$C = 5.4 + 2 * \left[\log_{10}\left(\frac{f}{28}\right)\right]^2 \tag{6}$$

$$D = 40.94 + 4.78 * [\log_{10}(f)]^2 - 18.33 * \log_{10}(f) \tag{7}$$

$$a(h_m) = [1.1 * \log_{10}(f) - 0.7] * h_m - [1.56 * \log_{10}(f) - 0.8] \tag{8}$$

Eq (8) is for $small\ city, medium\ city, open\ area, rural\ area\ and\ sububan\ area$

$$a(h_m) = 8.28 * [\log_{10}(1.54 * h_m)]^2 - 1.1 \quad for\ large\ city\ \ \text{f} \leq 200\text{MHz} \tag{9}$$

$$a(h_m) = 3.2 * [\log_{10}(11.75 * h_m)]^2 - 4.97 \quad for\ large\ city\ \ \text{f} \geq 400\text{MHz} \tag{10}$$

Where

- f is the centre frequency f in MHz: 150 MHz≤ f≤ 1000MHz
- d is the link distance in km: 1 km ≤ d ≤ 20kmh_b is the base station antenna height(in metres) : 30m ≤h_b ≤ 200m
- h_m is the mobile antenna height (in meters) : 1m≤ h_m≤ 10 m
- $a(h_m)$ is an antenna height-gain correction factor that depends upon the environment
- C and D are used to correct the small city formula for suburban and open areas.

3 Methodology

Handheld Samsung I9500 Galaxy S4 was used to take measurement of Received Signal Strength along from GSM network. The RSS measurements are taken along a route that started inside UNIUYO town campus and ended around Oron road and Nwaniba road junction in Uyo metropolis (Figure 1). The Samsung I9500 Galaxy S4 has CellMapper and My GPS Coordinates Android applications installed. CellMapper is an Android application that displays advanced GSM/CDMA/UMTS/LTE current and neighboring cells' low level data and can also record and export the data as CSV file. Among the data captured by CellMapper are the current and neighboring cells Received Signal Strength (RSS) in dB, the current cells CID, LAC. My GPS Coordinates is an android application that gives the latitude and longitude of the current location of the mobile phone in both decimal format and sexagesimal (degrees/minutes/seconds) format. The RSS along with the longitude and latitude are reads at each measurement point. In addition, the GSM base station was located and its longitude and latitude are recorded.

After the measurements, haversine formula was used along with the longitude and latitude of each of the measurement points and the longitude and latitude of the mast location to determine the distance between the mast and each of the measurement points [18,19].

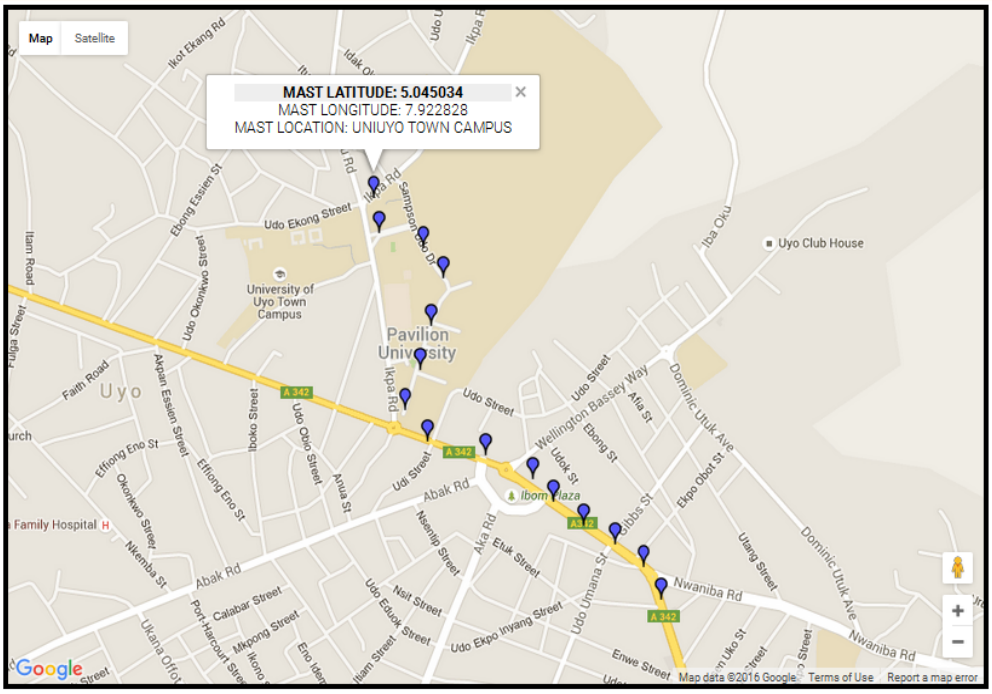

Figure 1. The Map Plot of the Measurement Points and Route Use in the Study

The haversine formula is given as follows:

$$d = 2 \times r \left\{ \sqrt[2]{\left[\sin\left(\frac{LAT_2 - LAT_1}{2}\right)^2 + \cos(LAT_1) \times \cos(LAT_2) \times \sin\left(\frac{LONG_2 - LONG_1}{2}\right)^2 \right]} \right\} \quad (11)$$

$$\text{LAT in Radians} = \frac{(\text{LAT in Degrees} \times 3.142)}{180} \quad (12)$$

$$\text{LONG in Radians} = \frac{(\text{LONG in Degrees} \times 3.142)}{180} \quad (13)$$

Where: r = radius of the Earth = 6371 km

LAT_1 and LAT_2 are the latitude of the coordinates of point1 and point 2 respectively

$LONG_1$ and $LONG_2$ are the longitude of the coordinates of point1 and point 2 respectively

d = the distance between the two point specified by their coordinates LAT_1 , $LONG_1$ and LAT_2 , $LONG_2$.

3.1 Calculation of the Measured Pathloss from the Measured RSS

Each of the RSS value recorded at each of the measurement point is converted to Measured Path Loss ($PL_{m(dB)}$) using the formula [6,20,21]:

$$PL_{m(dB)} = \text{EIRP}_t(\text{dBm}) - \text{P}_r(\text{dBm}) \quad (14)$$

where

$PL_{m(dB)}$ is the measured path loss for each measurement location at a distance *d* (km) from the base station.

EIRP_t is the Effective Isotropic Radiated Power in dBm and

P_r is the mean Received Signal Strength (RSS) in dBm which is the measured received signal strength.

The effective isotropic radiated power EIRP_t (dBm) is given as:

$$\text{EIRP}_t = \text{P}_{BTS} + \text{G}_{BTS} + \text{G}_{MS} - \text{L}_{FC} - \text{L}_{AB} - \text{L}_{CF} \quad (15)$$

where

P_{BTS} = Transmitter Power (dBm),

G_{BTS} = Transmitter Antenna Gain (dBi),

G_{MS} = receiver antenna gain (dBi),

L_{FC} = feeder cable and connector loss (dB),

L_{AB} = Antenna Body Loss (dB) and

L_{CF} = Combiner And Filter Loss (dB).

The values of these parameters are given as [6,22,23]:

P_{BTS} = 40 W = [30 + 10Log$_{10}$ 40] = 46 dBm,

G_{BTS} = 16 dBd = [16 + 2.15] = 18.15 dBi,

G_{MS} = 0 dBi, L_{FC} = 3 dB, L_{AB} = 3 dB, L_{CF} = 4.7 dB.

Substituting these values into equation (5) gives

EIRP_t = 46 + 18.15 – 3 – 3 – 4.7 = 53.5 dBm.

The measured path loss values in dB are obtained in Table 1 by substituting the calculated value of EIRP_t(dBm) and the measured values of P_r (dBm) into equation 4 for each of the measurement points recorded in Table 1.

3.2 Performance Analysis of the Model

In order to evaluate the effectiveness of the Okumura-Hata model, Root Mean Square Error (RMSE) , coefficient of determination, otherwise called R^2 and Prediction Accuracy (PA) are calculated based on the Okumura-Hata model predicted path loss and the measured path loss.

Let $PL_{(measured)(i)}$ be the measured path loss (dB);

Let $PL_{(predicted)(i)}$ be the predicted path loss (dB);

Let $\overline{PL_{(measured)}}$ be the mean of measured path loss and let n be the number of measured data points. Then, the Root Mean Square Error (RMSE) is calculated as follows:

$$\mathrm{RMSE} = \sqrt[2]{\left\{ \frac{1}{n} \left[\sum_{i=1}^{i=n} \left| PL_{(measured)(i)} - PL_{(predicted)(i)} \right|^{2} \right] \right\}} \quad (16)$$

Then, the prediction accuracy based on Mean Absolute Percentage Error (MAPE) is calculated as follows:

$$\text{Prediction Accuracy} = \left\{ 1 - \frac{1}{n} \left(\sum_{i=1}^{i=n} \left| \frac{\left| PL_{(measured)(i)} - PL_{(predicted)(i)} \right|}{PL_{(measured)(i)}} \right| \right) \right\} * 100\% \quad (17)$$

The Coefficient Of Determination, otherwise called R^2 is given as:

$$R^2 = 1 - \frac{SSE}{SST} = 1 - \frac{\left(PL_{(measured)(i)} - PL_{(predicted)(i)}\right)^2}{\left(PL_{(measured)(i)} - \overline{PL_{(measured)}}\right)^2} \quad (18)$$

3.3 Model Optimization

In most literatures examined, path loss model tuning is performed by adding or subtracting to the original model the RMSE between the measured and the predicted path loss [6, 7,8,9]. In some other cases, the model tuning is done by adjustment of the coefficients of one or more parameters contained in the model [10,11,12,13,14]. In each case, the aim is to reduce the prediction error or residual. In this paper, a different model tuning approach is presented. The proposed tuning approach is based on the functional composition or composite function of the model prediction residual.

Functional composition or function of function is the application of one function to the results of another function [24,25]. Functional composition has been applied in filter sharpening [25] and in signal processing [24]. In some literature functional composition is also known as composition of functions or composite function which refers to the combination of functions in such a way that the output from one function becomes the input for the next function. In path loss model studies, the predicted path loss as a function of distance can be stated as $PL_{Predicted(d)} = PL_{Predicted}(d)$; the measured path loss as a function of distance can be stated as $PL_{measured(d)} = PL_{measured}(d)$; and the path loss prediction residual as a function of distance can be stated as $Re_{(d)} = Re(d)$. Then, composite functions of prediction residual in respect of the predicted path loss can be expressed as:

$$\left(Re \; o \; PL_{Predicted(d)}\right) = Re\left(PL_{Predicted}(d)\right) \quad (19)$$

With the composite functions of prediction residual, $Re\left(PL_{Predicted}(d)\right)$ the error due to the model's inadequacies concerning the particular environment being studied can be minimized by adding the $Re\left(PL_{Predicted}(d)\right)$ to the predicted path loss, $PL_{Predicted}(d)$.

3.4 Model Tuning as Functional Composition Process

Every path loss prediction model has error associated with it when its predictions are compared with the actual measured path loss. The prediction error or residual consists of both random and predictable components. Model tuning or optimization process seeks to adjust the model so that the tuned model can as well predict the predictable components of the error thereby reducing the error to only the random component. For instance, consider a pathloss study that uses a model and empirically measured data, whereby, $\hat{Y}(d)$ is the model predicted pathloss at distance d from the transmitter, Y(d) is the empirically measured pathloss at distance d from the transmitter and e(d) is prediction residual at distance d from the transmitter. Hence,

$$Y(d) = \hat{Y}(d) + e(d) \tag{20}$$

$$e(d) = Y(d) - \hat{Y}(d) \tag{21}$$

The prediction residual consists of both predictable and random error components. The predictable component of the residual at distance d from the transmitter is denoted as E(d) whereas the random component is denoted as $\mathcal{E}$. The random component ($\mathcal{E}$) is not a function of d so it is modeled as a lump sum of all the random errors associated with the measurement. Hence,

$$e(d) = E(d) + \mathcal{E} \tag{22}$$

$$Y(d) = \hat{Y}(d) + E(d) + \mathcal{E} \tag{13}$$

Hence the tuned model denoted as $\hat{Y}T(d)$ is given by:

$$\hat{Y}T(d) = \hat{Y}(d) + E(d) \tag{24}$$

The predictable component of the residual can be predicted with respect to the distance alone or with respect to any particular parameter (such as antenna height, frequency, etc.) or combination of parameters in the path loss model. The drawback of predicting the predictable component of the residual with respect to distance alone or using a subset of the whole parameters in the path loss model is that such approach will ignore the contributions of the omitted model parameters towards the prediction residual. Therefore, E(d) is modeled as a function of the predicted path loss, where:

$$E(d) = F\big(\hat{Y}(d)\big) \tag{25}$$

$$Y(d) = \hat{Y}(d) + F\big(\hat{Y}(d)\big) + \mathcal{E} \tag{26}$$

$$\hat{Y}T(d) = \hat{Y}(d) + F\big(\hat{Y}(d)\big) \tag{27}$$

In most literatures examined, path loss model tuning is performed by adding or subtracting the RMSE to the original model [6, 7,8,9]. In this case, E(d) which is the predictable component of the residual is approximated by a constant, namely, the RMSE between the measured and the predicted path loss. Hence,

$$E(d) = RMSE \tag{28}$$

$$Y(d) = \hat{Y}(d) + RMSE + \mathcal{E} \tag{29}$$

$$\hat{Y}T(d) = \hat{Y}(d) + RMSE. \tag{30}$$

4 Results and Discussion

The measurement point locations, distance, RSS, measured path loss and Okumura-Hata model predicted Pathloss are given in Table 1.

The un-tuned Okumura-Hata in Table 1 has RMSE of 15.99 with R^2 value of -0.68 and Prediction Accuracy of 89.0%. However, the performance of model is deemed acceptable if it provides an overall RMSE of about 6-7 dB for urban areas and 10 to15 dB for suburban and rural areas [26,27]. In this wise, the Okumura-Hata requires tuning to minimize the error.

In this paper, the Okumura-Hata model tuning is done in two ways, one, by adding the RMSE to the original Okumura-Hata model path loss prediction and two by adding the composite function of the Okumura-Hata model prediction residual to the original Okumura-Hata model path loss prediction.

Table 1. The measurement point locations, distance, RSS, measured path loss and Okumura-Hata model predicted Pathloss

S/N	Longitude	Latitude	d (km)	RSS (dBm)	Measured Pathloss (dB)	Okumura-Hata Predicted Pathloss (dB)
1	7.923032	5.043714	0.148692	-69	122.5	94.9086
2	7.924781	5.043172	0.299812	-55	108.5	105.3305
3	7.925575	5.04198	0.456531	-71	124.5	111.6462
4	7.925106	5.040165	0.598065	-77	130.5	115.6879
5	7.924655	5.038487	0.756541	-80	133.5	119.177
6	7.924054	5.036948	0.910456	-82	135.5	121.8901
7	7.924955	5.035794	1.055424	-84	137.5	124.1607
8	7.92723	5.035238	1.194907	-85	138.5	126.1529
9	7.929118	5.034362	1.377801	-87	140.5	127.9865
10	7.929958	5.03349	1.50901	-90	143.5	129.4658
11	7.93116	5.032613	1.663195	-92	145.5	130.9522
12	7.932404	5.031865	1.810383	-97	150.5	132.2474
13	7.93352	5.031	1.961469	-99	152.5	133.4257
14	7.934185	5.029754	2.116707	-102	155.5	134.5304

The composite function of the Okumura-Hata model prediction residual is generated by fitting a trend line equation on the graph of the prediction residual versus the Okumura-Hata model path loss prediction. The residue, e (d) as given in Eq. (11) is the difference between the measured pathloss, Y(d) and the predicted path loss, $\hat{Y}$(d) at each of the measurement point, d. Xuru's online nonlinear regression tool (http://www.xuru.org/rt/NLR.asp#CopyPaste) is used to fit nonlinear equation , E(d) to the graph of e(d) versus $\hat{Y}$(d) as shown in Table 3 and Figure 2 where E(d) is given as:

$$\mathrm{E(d)} = \frac{\left(\mathbf{0.1457466236}(\hat{\mathrm{Y}}(\mathbf{d}))\right) - \left(\mathbf{0.641993705}(\hat{\mathrm{Y}}(\mathbf{d}))\right)}{\hat{\mathrm{Y}}(\mathbf{d}) - \mathbf{99.3737369}} \qquad (31)$$

Table 2 shows the results of tuning of the Okumura-Hata model by addition of the RMSE to the original model and by addition of E(d) which is the composite function of the Okumura-Hata model prediction residual . From Table 3, the composite function of prediction residual tuned Okumura-Hata model has the lowest RMSE value of 2.164, the highest Coefficient Of Determination (R^2) value of 0.967 and the highest prediction accuracy of 98.64%. On the other hand, the RMSE- tuned Okumura-Hata model has a higher RMSE value of 5.3, lower R^2 value of 0.814 and the lower prediction accuracy of 96.87%.

Essentially, the composite function of prediction residual based tuning approach performed better than the RMSE based tuning approach. However, in pathloss tuning studies, RMSE value below 7dB is acceptable for the urban area.

As such, the RMSE based tuning approach gave tuned model with acceptable RMSE value but with lower prediction accuracy than the model produced by the composite function of prediction residual based tuning approach.

Table 3. Prediction Residual (e(d)), Composite Function Of The Okumura-Hata Model Prediction Residual (E(d)) Versus Okumura-Hata Predicted Pathloss , $\hat{Y}(d)$

Okumura-Hata Predicted Pathloss , $\hat{Y}$(d) in dB	**Prediction Residual , e(d) in dB**	**Composite Function Of The Okumura-Hata Model Prediction Residual, E(d) in dB**
94.9086	27.5914	27.4784883
105.3305	3.1695	3.99950712
111.6462	12.8538	10.4316515
115.6879	14.8121	12.3085794
119.177	14.323	13.506096
121.8901	13.6099	14.2897012
124.1607	13.3393	14.8801838
126.1529	12.3471	15.3620165
127.9865	12.5135	15.7819263
129.4658	14.0342	16.1071384
130.9522	14.5478	16.4235681
132.2474	18.2526	16.6919367
133.4257	19.0743	16.9308234
134.5304	20.9696	17.1507

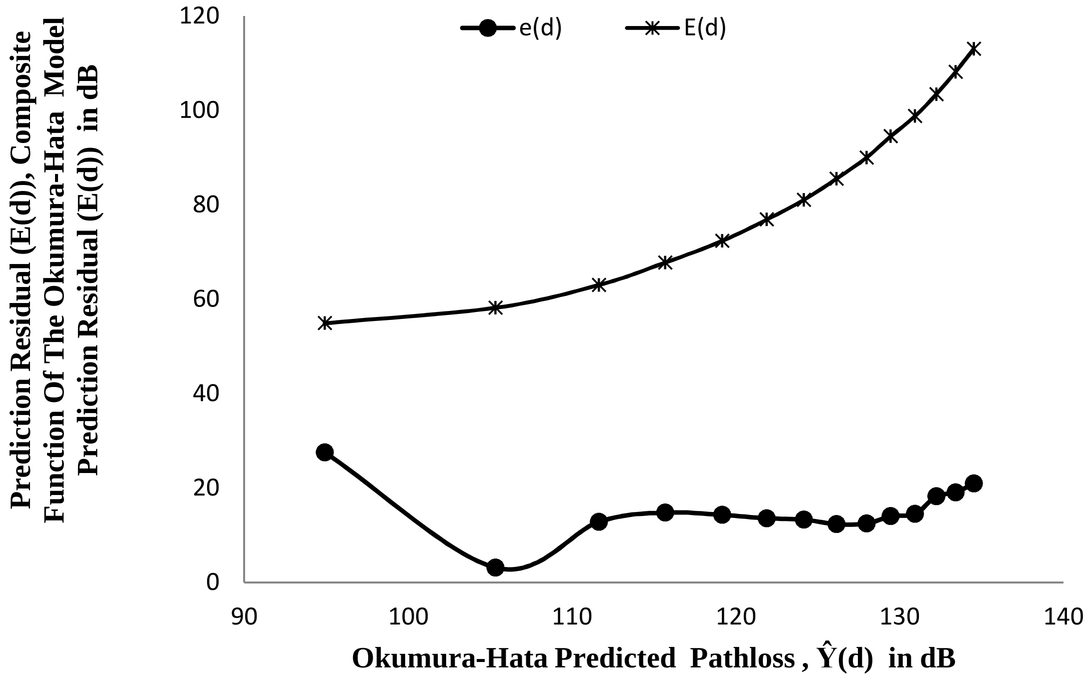

Figure 2. Graph of prediction residual (e(d)), composite function of the Okumura-Hata model prediction residual (E(d)) versus Okumura-Hata predicted pathloss , $\hat{Y}(d)$

Table 3. The results of tuning of the Okumura-Hata model by addition of the RMSE and by addition of E(d) which is the composite function of the Okumura-Hata model prediction residual.

d (km)	Measured Pathloss (dB)	Un-tuned Okumura-Hata Predicted Pathloss , $\hat{Y}(d)$ in dB	RMSE Tuned Okumura-Hata Predicted Pathloss, in dB	Composite Function of Prediction Residual Tuned Okumura-Hata Predicted Pathloss, in dB
0.148692	122.5	94.9086	110.8965653	122.3870883
0.299812	108.5	105.3305	121.3184653	109.3300071
0.456531	124.5	111.6462	127.6341653	122.0778515
0.598065	130.5	115.6879	131.6758653	127.9964794
0.756541	133.5	119.177	135.1649653	132.683096
0.910456	135.5	121.8901	137.8780653	136.1798012
1.055424	137.5	124.1607	140.1486653	139.0408838
1.194907	138.5	126.1529	142.1408653	141.5149165
1.377801	140.5	127.9865	143.9744653	143.7684263
1.50901	143.5	129.4658	145.4537653	145.5729384
1.663195	145.5	130.9522	146.9401653	147.3757681
1.810383	150.5	132.2474	148.2353653	148.9393367
1.961469	152.5	133.4257	149.4136653	150.3565234
2.116707	155.5	134.5304	150.5183653	151.6811
RMSE		**15.98796526**	**5.32038487**	**2.163692849**
Coefficient of Determination (R^2)		**-0.680549661**	**0.813897992**	**0.969220881**
Prediction Accuracy (%)		**89.04896912**	**96.87009956**	**98.6363852**

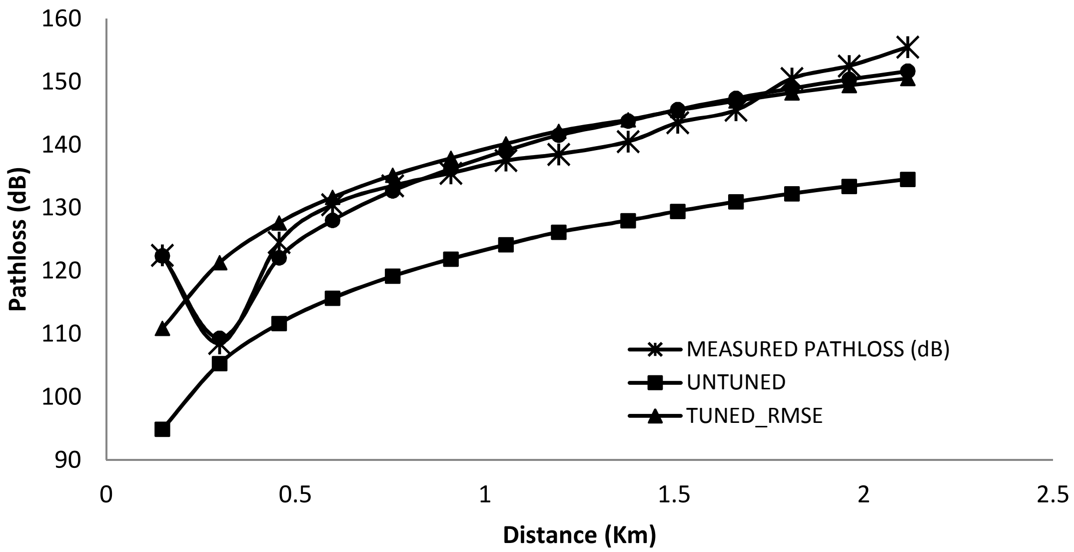

Figure 2. Tuned and Untuned Pathloss Versus Distance

From Eq. 1, the un-tuned Okumura-Hata path loss model for urban area is given as $LP_{OK\_HATA(urban)} = A + B * \log_{10}(d)$. The RMSE based tuning approach has RMSE value of 15.98796526. Then, by equation (25), the predictable error component is given as:

$$E(d) = RMSE = 15.98796526 \quad (32)$$

By equation (27), the RMSE based tuned Okumura-Hata path loss model for urban area is given as:

$$LP_{OK\_HATA\_RMSE\_TUNED(urban)} = A + B * \log_{10}(d) + 15.98796526 \quad (33)$$

Similarly, the composite function of prediction residual based tuning approach gave the predictable error component by equation (31) as $E(d) = \frac{\left(\mathbf{0.1457466236}(\hat{Y}(\mathbf{d}))\right) - \left(\mathbf{0.641993705}(\hat{Y}(\mathbf{d}))\right)}{\hat{Y}(\mathbf{d}) - \mathbf{99.3737369}}$. Hence, by equation (24), the composite function of prediction residual tuned Okumura-Hata path loss model for urban area is given as:

$$LP_{OK\_HATA\_\mathrm{CF}\_TUNED(urban)} = A + B * \log_{10}(d) + \frac{\left(0.1457466236(\hat{Y}(\mathbf{d}))\right) - \left(0.641993705(\hat{Y}(\mathbf{d}))\right)}{\hat{Y}(\mathbf{d}) - 99.3737369} \quad (34)$$

5 Conclusion

Composite function of prediction residual based path loss model tuning approach has been presented and compared with RMSE based tuning approach. The study is conducted for Okumura-Hata path loss model for the GSM network in the 800-900MHz frequency band. The study is based on empirical measurements conducted at University Of Uyo (UNIUYO) town-campus located at latitude and longitude of 5.042976, 7.919046 respectively. Root Mean Square Error (RMSE), coefficient of determination, otherwise called R^2 and Prediction Accuracy (PA) are used in the comparative error analysis. In all the three performance measures used , the composite function of prediction residual based tuning approach performed better than the RMSE based tuning approach.

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