Original Research Article

Path Loss Modeling for Next Generation Wireless Network Using Fuzzy Logic - Spline Interpolation Technique

Abstract

Appropriate path loss mathematical models help in reducing the complexity of the co-channel interference of Global System for Mobile Communication and Wireless Networks. This work proposes, to adapt and modify Hata model using fuzzy logic and spline interpolation techniques. Mean absolute errors of 1.55 dB and 0.4 dB were obtained using the techniques respectively. It was found that, using fuzzy logic - spline interpolation model, path loss is minimized by 1.94 dB in the study area. Therefore, fuzzy logic - spline interpolation is recommended for path loss prediction for next generation wireless networks in medium cities in Nigeria especially Yola. It is suggested that, neuro – fuzzy spline interpolation may be used to further minimize path loss error for medium cities.

Keywords: Radio path; Fuzzy logic; Carrier frequency, Path loss; Interpolation.

1.0 Introduction

Path loss is usually expressed as the losses (fading away of signal strength) in decibels (dB) between the base transceiver station (hb) and mobile station (hm)of Global System for Mobile Communication (GSM) and is one of the major factors that wireless network service providers (WNSP) such as Mobile Telephone Network (MTN), Airtel, 9 Mobile and Global Communications in Nigeria need to take into consideration before undertaking the design and planning of a wireless network (WN). The nature of terrain, vegetation, buildings or human and vehicular movements between the 'hb' and 'hm' antenna height, location of the antennas or distance between the antennas can significantly affect the magnitude of the GSM signal strength and Path loss may be characterized as slow, fast or multipath fading depending on the obstacles between 'hb'and 'hm'. Its significant increase reduces the spectral efficiency of the WN, which consequently may lead to frequent call drop, cross talk during call conversation, intra and inter connectivity difficulties. Therefore, there is a need to develop mathematical models in order to have accurate link budget on the WN because frequency allocation is a limited resource. The higher the frequency reuse in a complex environment such dense vegetation, mountains, large water surface and noisy areas. The greater the network quality of service (QoS) receives by the end user of GSM equipment. Developing

appropriate mathematical model of a specific area can tremendously reduce co-channel interference on a WN.

Several works on path loss prediction have been carried out. Magdy and Zhegqing, (2002) used ray-tracing technique to predict path loss for wireless communication system (WCS) [1]. Takahahi, (2010), worked on the relation between distance and path losses for multimeter wave inter – vehicle communication [2]. Abdullah (2010) utilized Kriging method to predict coverage area in wireless local area network (WLAN) [3]. Abdullah in (2011) again used two methods (i.e., Kringing and Neural Network) to predict the coverage area in WLANs [4]. Isobana et al, (2013) obtained path loss using empirical data in 2100MHz band and compared it with the known Okumura Hata model [5]. Yogita *et al,* (2013) discussed the nature of the area and the effects of human presence between the base transceiver station and mobile station [6]. Nnamani and Alumona, (2015) utilized COST 231Hata models and modified the models for their study area using empirical data [7]. Okumbo and Okonkwo, (2014) determined path loss using popular linear regression to characterize signal fading between the base transceiver station and mobile station in the southern of Nigeria [8]. Safina*et al,* (2015) applied log distance path loss, Joint Technical Committee (JTC) models and field measured data for comparative analysis in an indoor environment [9]. Nadir and Touati, (2008) utilized spline interpolation to recover a missing data in open areas of Oman [10]. Popoola *et al*, (2017) calibrates standard path loss model to estimate path loss in urban environment using field measured and geospatial data and obtained mean absolute error of 5.40 dB and root mean square error (RMSE) of 6.90 dB [11], Surajudeen *et al,* (2012) compared different path loss models such as COST 231 Hata, Okumura - Hata models to determine path loss of some selected urban areas in Nigeria. The authors obtained minimum RMSE as 11.58 dB. [12] Faruk *et al*, (2013) worked on error bound of empirical path loss models at VHF/UHF bands in Kwara State and obtained a MAE of 8.00 dB using Hata model [13]. Segun *et al,* (2014) evaluated path loss in suburban and urban areas of Nigeria using COST 231 Hata model and obtained average RMSE of 12.28 dB [14] and Ogbeide and Edeko, (2013) modified Hata using empirical data collected in Edo State, Nigeria, the authors arrived at average RMSE of 7.00dB [15]. However, these models developed cannot be used to capture accurately the network activities around globe due to the different nature of the environments across the world. Therefore, these models are considered as reference models that need adjustments based on empirical data obtained in the study areas of interest. This work proposes, to adapt and modify Hata path loss prediction model using fuzzy logic and spline interpolation

techniques for medium city, typically Nigeria with Yola in Adamawa State as the case study, and the following objectives shall be realized: determine mean square errors (MSE) using fuzzy logic and spline interpolation techniques, and use these errors obtained to modify the adapted model. Hata model is chosen for work because of its compatibility with the study area such as, base transceiver station is above all the roofs height in city, carrier frequency ranges from 500MHz to1500MHz, distance between the base transceiver station and the mobile station ranges from 1km to 20km, base Transceiver station height ranges from 30m to 200m, and mobile station height most be from 1m to 10m. [16, 17]. The Hata model is expressed in Eq. (1).

$$X(Suburban) = 69.55 + 26.16\log_{10}(f_c) - 13.82\log_{10}(h_b) - a(h_m) + (44.9 - 6.55\log_{10}(h_b)) \cdot \log_{10} D - 2\left\{\log_{10}\left(\frac{f_c}{28}\right)\right\}^2 \quad (1)$$

$$a(h_m) = \{1.1\log_{10}(f_c) - 0.7\}h_m - \{1.56\log_{10}(f_c) - 0.8\} \quad (2)$$

Where f_c = GSM operating frequency (MHz) and $a(h_m)$ = antenna correction factor of a medium city [18].

Fuzzy logic has been employed to solve complex practical problems in different areas such as multi objectives optimization of systems, facial pattern recognition and classification, unmanned helicopters, control of subway systems, nonlinear systems and functions approximation [19 - 22]. While, Spline interpolation is a simple curve referred to as piecewise polynomial, usually employed for testing of programs and calculating spline to eliminate errors (filter) in a set of data or use to recover missing information in a radio path [23]

2.0 Study area and method of data collection

Yola is a suburban city located at latitude 9.2035^{0}N and longitude 12.4954^{0}E, the city is approximately 10km in diameter and is characterized by short buildings, typically of height below 30m, it has indigenous trees scattered around city of roughly 20 to 25m height [24], several roads, with moderate width from10m to 15m, River Benue in the Northern part of the city and all the WNSP operate at 900MHz in GSM band. Data is collected using pathloss-link planner software installed on a personal computer (PC) which is mounted on a car to transverse within the city from 1000m to 6000m away from the base transceiver station. The

measurement was taken, three (3) times for a week at different time of the day, in the morning (9:00 am – 10:00 am), afternoon (12:00 noon – 1:00 pm), and evening (4:00 pm – 5:00 pm) at regular interval of‘50m, starting from 1000m. At the time of the measurements, the weather condition was clear with average temperature of 30^0C, 41^0C and 38^0C respectively and the measurement was conducted, when all human activities were at the peak. The average measured path loss (X_a) for one week and the predicted path loss (X_p) are plotted against distance as presented in Fig. 1.

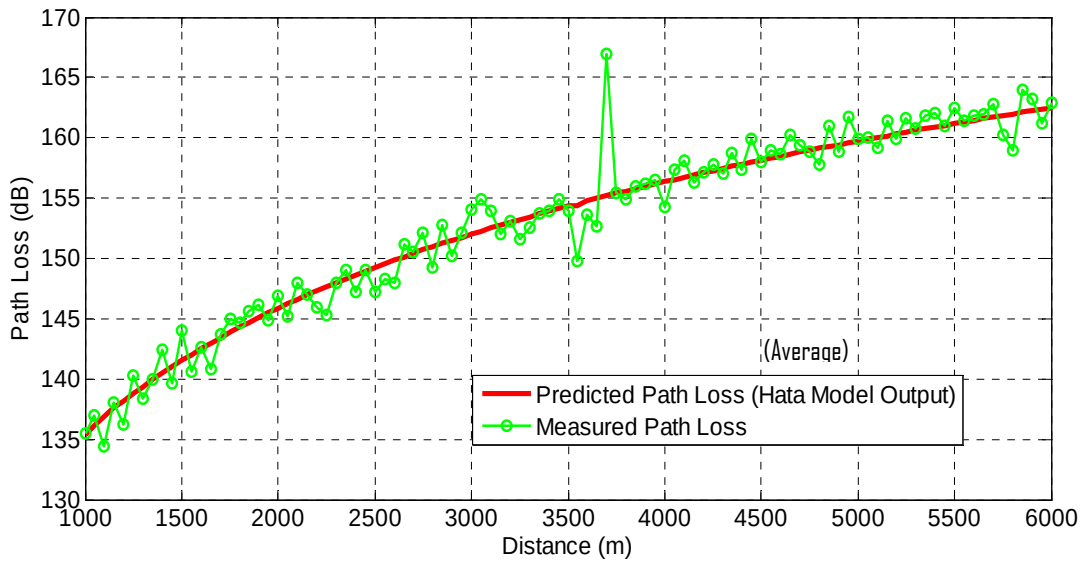

Fig. 1: Average Measured Path Loss and Predicted Path Loss against Distance

2.1 Method of data analysis

The data is analyzed in the following manner:

2.2 Determination of Mean Absolute Error using Fuzzy Logic

In order to obtain the mean absolute error of measured path loss, the following procedures in Fig. 2 have to be realized. The first layer is where fuzzification of inputs and outputs are performed. Usually, the inputs parameters are assigned an arbitrary class labels as short ‘s’, moderate ‘m’, ‘long ‘L’, ‘low ‘n’, and high ‘H’, with overlapping scales, such as short to moderate = ’sm’, moderate to high = ‘mH’, low to moderate = ‘nm’ and moderate to long = ‘mL’.

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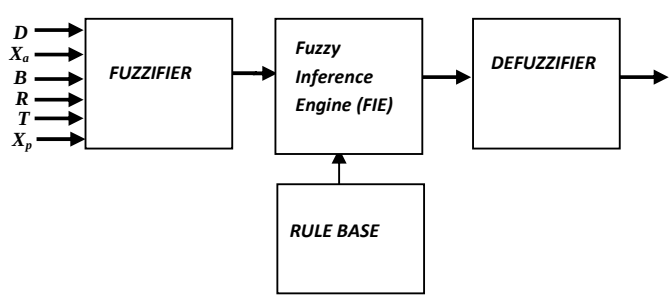

Fig. 2: Fuzzy logic model

The inputs are normalized as Distance = ‘D’, Average measured path loss =‘X_a’, predicted path loss = X_p, Buildings height = ‘B’, Roads width = ‘R’ and Trees height = ‘T’. Also, in this layer, classification of the input/output parameters based on data range, for example, sD = 1m – 500m, nD = 350m – 1500m, D = 1200m - 3000m, the other inputs can be classified in the same manner and assignment of membership function (MF) are performed. The inputs are fuzzified as shown in Table 1.

Table: 1 Fuzzified Inputs

Inputs	μ(sm)	μ(mH)	μ(nm)	μ(mL)	AND
D	0.35	-	-	0.13	0.13
X	-	0.66	0.45	-	0.45
B	0.82	0.70	-	-	0.70
R	0.34	-	-	0.58	0.34
T	0.46	0.55	-	-	0.46

There are many types of MFs which include; Gaussian, Generic and trapezoidal to mentioned but a few. However, in this work, an asymmetric triangular membership function distribution (TMFD) is chosen to map the input/output parameters (i.e., distance, buildings height, trees height, roads width, average measured and predicted path losses), because of its flexibility with the measured data. For example, information from Table 1 for input ‘D’ is illustrated in Fig. 3

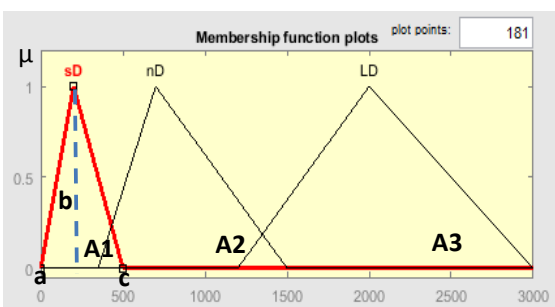

Fig. 3: Distance membership function

.Normally, the TMFD in Fig. 3 is expressed as

$$\mu(A) = D(a,b,c) \tag{3}$$

Where μ, is the MF of the cripts inputs ‘D’ in the triangular fuzzy set ‘A’, ‘ac’ is the base and ‘b’ is the height of the triangle. Layer 2 accepts two inputs (fuzzified output and the rule base). This is where the rule base is formulated in the expert domain. These rules act on the

fuzzified output using a firing strength (FS) before defuzzification is formed. For example, there are six (6) inputs, each having grade distribution (GD), the FIE takes only two maximum inputs at a time in order to compute their 'μ' values. The 'μ' most belongs to (0, 1), which means each value of 'μ'either has absolute belongingness (1) or non belongingness (0). Few examples of the rules may be formed as follows;

If D is sD AND B is sB then X is nX

If D is mD and B is sB then X is nX

If D is LD AND B is HB then X is HX

Then FS of the rules could be computed using Eq. (4).

$$FS = \min(\mu_{D1}(A1)), (\mu_{D2}(A2)), \ldots\ldots(\mu_{Dn}(A)) \quad (4)$$

In Eq. (4) μ_{D1}, μ_{D2}. . . μ_D are the MF values of each cripts inputs to the triangular fuzzy set, A_1. A_2 . . . A. [25]. In layer 3, Defuzzification is performed by combining the control action (C) of the fuzzy logic model as given in Eq. (5).

$$FAC = \frac{\sum_{i=1}^{n} FAj \times C}{\sum_{i=1}^{n} FAj} \quad (5)$$

where FAC denotes the deffuzzified output, FA_j is the firing areas of jth rule and C is the centroid [26] and the mean absolute error is computed using Eq. (6).

$$e = \frac{\sum_{I}(FAC)}{N} \quad (6)$$

where, N is the number of trainings [26], and the mean absolute error in Eq. (6) is applied to modify the Hata model of Eq. (1)

2.3 Determination of Mean Absolute Error using Spline interpolation

Spline interpolation is used to increase the sensitivity of the model obtained in Eq. (6) using Eq. (7) by eliminating the losses or recovering missing the information in radio path, given by

$$i = \rho \sum_{I} W_i (h_b - S(h_m))^2 + \left[1 - \rho \int \left(\frac{d^2 S}{d^2 k}\right)\right] dk \quad (7)$$

where ρ = piecewise interpolation parameter, W=weight of data measured, S=smoothing parameter and k=fuzzy modified path loss [17]. The mean absolute error between the output of the modified model and spline line is obtained using Eq. (8)

$$e_1 = \frac{1}{N}(|X_n - i|) \quad (8)$$

where X_n is the modified path loss [25].

Results and Discussion

Fig. 1 presents, the measured and the predicted path losses against distance. It is clearly shown that, measured experienced more losses than the predicted path loss. In general, it's observed that, as distance increases path loss increases. However, the spike between 3500m – 4000m is attributed to the complex environment along the road. Fuzzy logic was trained 64 times offline with several fuzzified inputs such as X_a,, X_p, D, B, R and T., and the rules acted on the inputs in the FIE under the influence of AND operation using Eq. (4) as shown in Table 1, before defuzzification is performed using Eq. (5) and mean absolute error is obtained using Eq. (6), as shown in Table 2. During the training, it is noticed that, the number of trainings performed is proportional to the number of the firing strength. In this work, $2^6 = 64$ rules were formulated and trained but only $2^4 = 16$ rules were fired. In another words, only 25% of the rules were fired while the 75% remained unfired, which means they belong to (0). So, they are discarded.

Table 2: FLM output computation

#FA	**FA**	**C**	**FAC**
FA1	0.42	24	10.08
FA2	0.18	12	2.16
FA3	0.33	28	9.24
FA4	0.28	40	1.12
FA5	0.46	32	14.72
FA6	0.22	50	1.10
FA7	0.10	31	3.10
FA8	0.28	29	8.96
Mean Absolute Error 'e'			**49.64/32=1.55**

The value of the mean absolute error obtained is then subtracted from Eq. (1) (i.e. e =1.55) to modify the Hata model as given in Eq (9)

$$X(Suburban) = 68 + 26.16\log_{10}(f_c) - 13.82\log_{10}(h_b) - a(h_m) + (44.9 - 6.55\log_{10}(h_b))\log_{10} D - 2\left\{\log_{10}\left(\frac{f_c}{28}\right)\right\}^2 \quad (9)$$

The modified model of Eq. (9) is then used to re-compute the path loss (X_r) of the study area and compared with the predicted path loss as depicted in Fig. 4. It is shown clearly that, path

loss is minimized, as reported by [21]

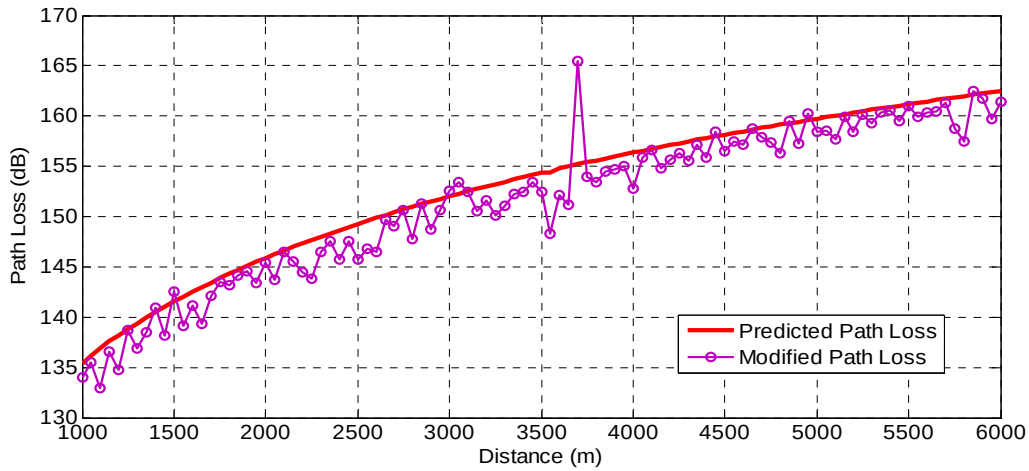

Fig. 4: Predicted and Modified Path losses against Distance

Eq. (7), interpolates Eq. (9) as depicted in Fig.5, and their mean absolute error is obtained as e_1=0.4dB using Eq. (8) and the error (e_1) is also subtracted from modified model of Eq. (9) to increase the sensitivity of the modified model as given in Eq. (10).

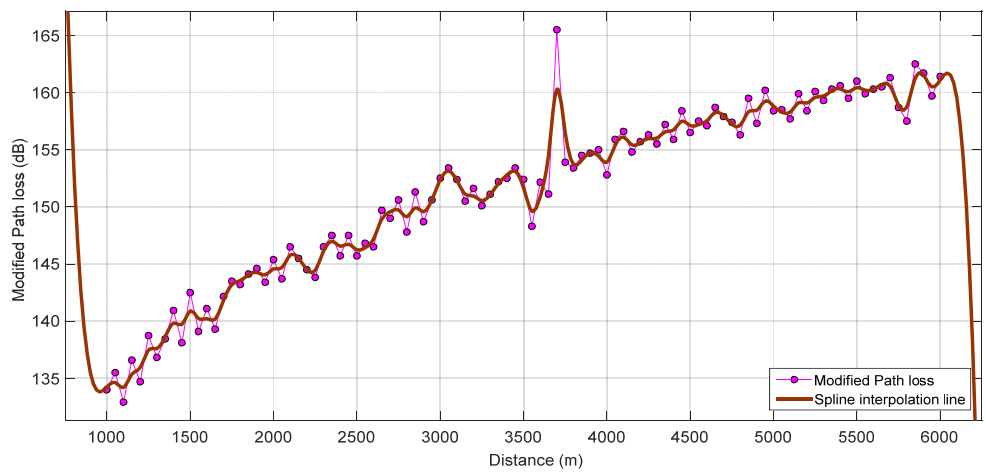

Fig. 5: Modified Path Loss Interpolaation

Therefore, Eq. (10) forms the new path loss model (Fuzzy Logic - Spline Interpolation Model) of the medium cities Nigeria, especially Yola in Adamawa State. Path loss (X_n) is further computed using Eq. (10) and compared with the predicted Path loss as depicted in Fig. 5. The computed becomes less than the predicted path loss appreciably, better than what is obtained by [27, 28]. In addition, the sum of the errors obtained in this work is 1.95dB and the value lies within acceptable range of 6.0dB [29, 30].

$$X(Suburban) = 67.6 + 26.16\log_{10}(f_c) - 13.82\log_{10}(h_b) - a(h_m) + (44.9 - 6.55\log_{10}(h_b))$$

$$\log_{10} D - 2\left\{\log_{10}\left(\frac{f_c}{28}\right)\right\}^2 \qquad (10)$$

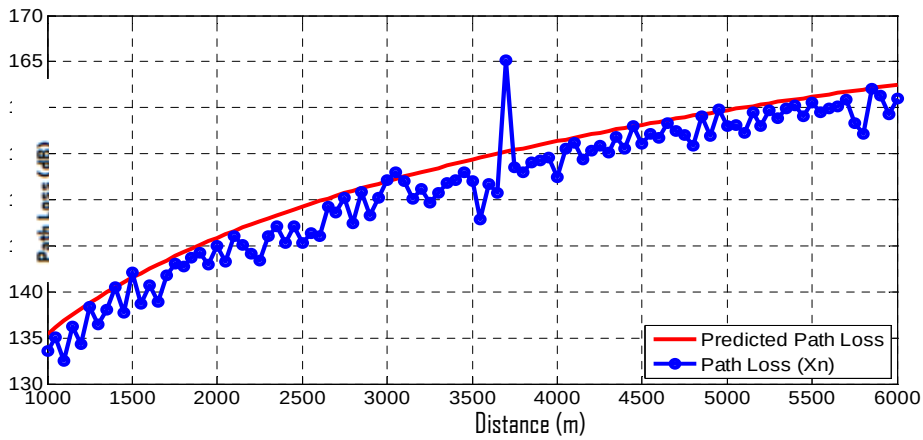

Fig. 6: Predicted Path Loss and Modified Path Loss against Distance

To validate the model, path loss (X_m) measurement was repeated after seven days and compared with the path loss (Xn) obtained from Eq. (10)., as depicted in Fig. 6. It can been seen that, measured path loss experienced more losses

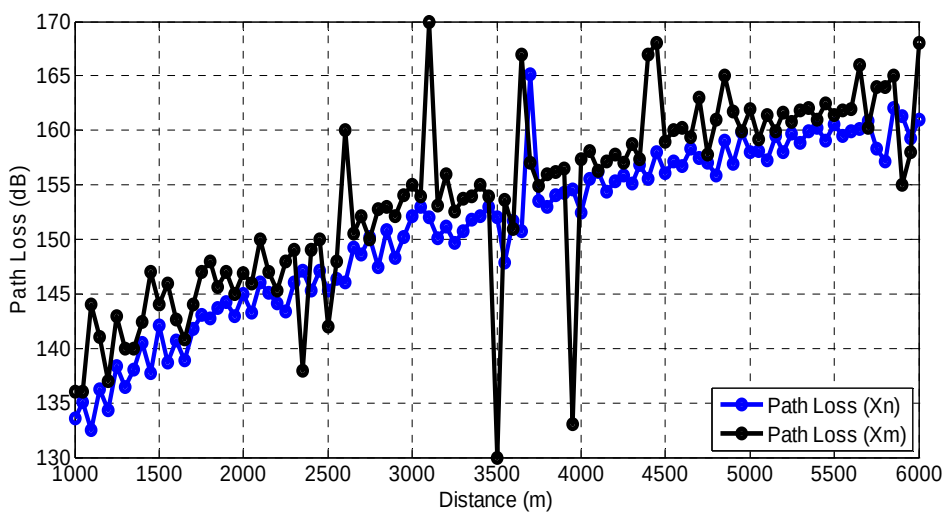

Fig. 6: Validation of Fuzzy Logic – Spline Interpolation Performance

4.0 Conclusion

Path loss is one of the important requirements that, GSM/WN needs to understand before taking the design of a WN. This work utilized a 'fuzzy logic - spline interpolation 'to modify Hata model using mean absolute error of 1.95 dB, for prediction of path loss in medium cities

in Nigeria especially, Yola in Adamawa State. It was found that, using fuzzy logic - spline interpolation model, path loss is minimized in the study area and the mean absolute error obtained falls within the acceptable range of 6.0dB as applied in radio frequency engineering. It is recommended that, neuro – fuzzy model and spline interpolation techniques may be integrated to further reduce the path loss prediction error for medium cities in Nigeria.

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