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Radio Spectrum Measurement Modeling and Prediction based on Adaptive Hybrid Model for Optimal Network Planning

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Abstract: Path loss model is fundamental to effective network planning. It provides adequate information on the extent of signal loss and help to improve the quality of service of cellular communication in an area. In this paper we used a hybrid wavelet and improved log-distance model for modeling and prediction of propagation path loss in an irregular terrain. The prediction accuracy of the proposed model was quantified using five statistical metrics. As seen presented in Table 2 and Table 3, the proposed model outperformed the standard log-distance model, the COST234 Hata and Okumura Hata models by an average of 20%.

Index Terms: Communication, Path Loss, log-distance, Wavelet, Levenberg-Marquart, communication.

1. Introduction

The mobile radio communication system has become an essential part of our everyday life—the police, ambulance services, fire services, and many more can effectively carry out their operations with the help of mobile radio systems. Likewise, individuals can communicate over a distance and access the internet with the use of these devices. Meanwhile, since mobile devices are carried around, they could be taken inside buildings, factories, vehicles, and so on, which affects the mean received signal. For clarity, buildings, foliage, antenna height, carrier frequency, and the nature of the terrain are some of the factors that affect or influence signal strength. Another major limitation of mobile radio propagation systems is their transmission channels. This is so because, unlike the wire-line channel, the wireless channel is unstable and unpredictable due to shadow fading, multipath fading, Doppler shift, and delay spread [1]. More so, it is easily affected by noise and interference. Noise degrades the performance of any wireless communication system [2,3], and corrupts the transmitted data. To mitigate some of these challenges, network engineers need to understand how their environment of interest will affect the received signal power (RSP) over distance after signal transmission.

A path loss model is one of the vital tools needed for the characterization and design of mobile communication networks. It is required for conducting feasibility studies before deployment. Path loss propagation models are classified into deterministic, statistical, and empirical models. Due to the complexity, irregularity, and variability of most transmission environments, it is mostly difficult to develop a path loss model using a deterministic or statistical approach [1]. The development of an empirical model, on the other hand, is relatively easy. It is derived from in-depth field measurements over a certain distance with a certain frequency. Examples of some commonly used empirical model types are the free space model**,** Hata model, Egli model, SUI model and so on [4,5]. However, the predictive accuracy of these models is limited to the environment in which they were developed and will fail if applied in any other environment, most especially an irregular environment.

In view of these, this paper seek to address the following:

- Conduct a detailed measurement of signal power data over irregular transmission terrains.
- Proposed a modified standard Log-distance path loss model, which is to enable it captures signal attenuation losses due to local terrain clutter features and irregularities.
- Adaptive tuning of influencing parameters of the modified path loss models for improved prediction performance
- Validation of the optimized path loss model to ascertain the level of its prediction accuracies in other locations

2. Literature Review

In wireless communication, the subject of path loss modelling, development, and optimization has been a vital research topic for years. It is mainly due to its importance for predicting signal coverage, network planning, and estimation of cell radius. A number of works involving different approaches to predict path loss can be found in the literature [6–8]. Most of them differ in the environment in which they were developed and in the parameters employed in the model development. Examples of such parameters are antenna height, transmitter-receiver distance, building heights, street widths, and so on. In [9], the authors proposed ordinary least square regression for the prediction of path loss in the city of Uyo, Nigeria. However, the major limitation of ordinary least square is that it is not adaptive, that is, it performs poorly in the face of non-linear and non-stationary datasets. In [10], the authors used the Levenberg-Marquart (LM) algorithm to tune the Egli model and enhance its predictive accuracy for two cities in Nigeria. The researchers used six statistical indicators for comparative analysis and found that the adaptive Egli model outperformed the classical Egli model for the studied locations. The authors of [11] analyzed the performance estimation of different path loss models using simulators. They consider an operating frequency of 1800 MHz for different mobile antenna heights for rural and urban clutter. They concluded that COST 231(W-I) performs better than the others. Daubechies, one of the wavelet families was employed in [12] for modeling and prediction of the spectrum. In [13], the authors affirmed that noise is one of the factors affecting the performance of wireless ultraviolet optical communication systems, and they applied discrete wavelet transform for the de-noising of the UV signals. Meanwhile, in [14], some wavelet thresholding techniques were compared using both the hard and soft methods, and Rigrsure was said to outperform the others. In [15], the authors developed a signal strength prediction model, and the features used are transmitter-receiver distance, frequency of transmission, terrain, and degree of urbanization. They carried out some measurement campaigns in the City of London at different frequencies and employed the technique of multiple regressions to develop a model. Their model is developed for urban areas with flat terrain, and most especially for the city of London. This simply means that the model will perform poorly if applied to other environments and terrain types. A model for prediction at 2100MHz was developed in the dense urban environment of Lagos [16].

This paper, propose a hybrid propagation path loss model that jointly combines wavelet transform and an improved Log-distance Path Loss Model. When applied to any environment, particularly one with irregular terrain, the model can learn, adapt, and predict.

3. Methodology

3.1. Measurement Campaign

3.1.1. Investigated Environment

The investigation took place in the ancient city of Lokoja, the capital of the Northern Nigeria Protectorate until 1903, and presently, Lokoja is the capital of Kogi State. Lokoja has a land mass of approximately 3180 km^2 and a population of approximately 692,000 as of 2020 [17]**.**

The city lies at a latitude of 7.8023^{o}N and a longitude of 6.7333^{o}E. The residential buildings of the city are of varying densities and heights. The city is bounded in the north by a mountain (Mount Patti) and rocky hills with surrounding trees, and in the south by the confluence of the river Niger and river Benue. These topographic features make Lokoja's terrain irregular [18].

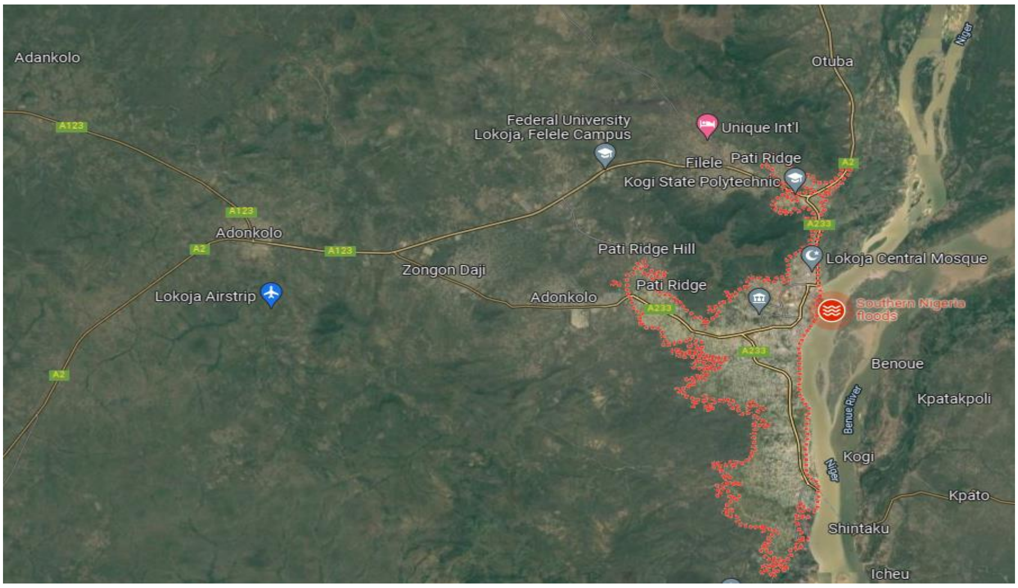

Fig. 1. Pictographic view of Lokoja, Kogi State

3.1.2. Radio Frequency (RF) Measurement

The data used for this paper was obtained from two main LTE networks. The two networks are tagged as network A and network B all through this paper operating in the study location – Lokoja. The tools used for measurement are one Dell Laptop and two TEMS pocket phones. Both were equipped with Ericson Telephone Mobile software. Other tools include GPS, Lexus 300RX car, inverter, and connecting cables. The car was used for mobility round the route selected for the study. The GPS was for taking location coordinates at every point of the drive test. The RF measurements were achieved by making constant calls to the networks at every drive test location. The operating frequency of network A is 801 MHz and that of network B is 2600 MHz.

To obtain the path loss from the measured data for network A and network B, we employ equation (1)[19].

$$P_L(dB)_{measured} = P_t + G_t + G_r - F_l - C_l - RSRP \tag{1}$$

where P_t is the base station transmit power in (dBm), G_t is the base station antenna gain in (dBi), G_r is the mobile station antenna gain in (dBi) and, F_l and C_l are the feeder loss and cable loss respectively. The value of these parameters and other relevant parameters for both networks are listed in Table 1

Table 1. Measurement setup parameters

Parameters	Definition	Numerical Values
P_t	Base station transmit power	43dB
G_t	Base station antenna gain	17.5dB
G_r	Mobile station antenna gain	0dB
F_l	Feeder loss	3gB
C_l	Cable loss	2dB
H_t	Base station antenna height	30m
H_r	mobile antenna height	1.5m
F_r	Transmit frequency	801/2600 MHz

Noise is one of the major factors that impinge on the performance of any wireless communication system[3], thereby affecting the accuracy of many propagation models. Noisy signal is any signal that is already corrupted by unwanted modifications of the original signal before and after transmission.

Hence, for a real case scenario, Equation (1) will be expressed as:

$$P_L(dB)_{measured} = P_t + G_t + G_r - F_l - C_l - RSRP + \chi \tag{2}$$

where χ is an Additive White Gaussian Noise (AWGN) with zero mean and variance of σ^2 [20].

3.2. Log-distance Path Loss Model

Log-distance path loss model in telecommunication is a generic model for the prediction of the path loss a transmitted signal encounters as it travels through obstacles such as building or densely populated area. It is an extension of free space model.

$$P_L(dB) = 130 + 20\log(f) + 20\log(r) \tag{3}$$

where PL(dB) is the path loss, f, the carrier frequency and r is the path length.

Eqn(3) is Friis free space model; it is used to predict propagation loss in an unobstructed path between the transmit station and the mobile station (MS). However, propagation path is not always unobstructed.

Eqn (4) is the general log-distance path loss model.

$$P_L(dB) = q_1 + q_2\log(f) + q_3\log(r) \tag{4}$$

Researchers have made efforts to tune the loss coefficients (q_1, q_2 *and* q_3). However, the determined coefficient cannot generalize to other environments, that is, log-distance signal degradation model is best applied in the location/environment wherein it was developed.

3.3. Wavelets Theoretical Background

Wavelets are mathematical tools applied for decomposing signals into different frequencies components. Thus, eliminating the noise in the signal [17, 18]. Mathematical representation is given as:

$$W(b,a) = \frac{1}{\sqrt{a}}\int_{-\infty}^{\infty}\psi(t)\left(\frac{t-b}{a}\right)P_L(t)\,dt \tag{5}$$

where $\psi(t)$ is the analyzing function (mother wavelet), a is the scale parameter and b is a position in time (translator factor).

To achieve the objectives of this work, the measured noisy signal, in equation (2) were passed through the three stages of wavelet data processing, that is, decomposition, thresholding and reconstruction. The raw data were decomposed into 4 level of frequencies scale by means of the 4th order Daubenchies (‘db4’) wavelet family [21] in MatLab R2018a software platform. The rigrsure thresholding method was applied.

3.3.1. Improved Log-distance Path Loss Model

In addition to the fact that log-distance path loss yields significant errors when applied to environment outside the environment wherein it was developed, it is also non-adaptive and does not have the capacity to handle the noise signals. It performs poorly when applied to a stochastic dataset, especially those influenced by irregular terrain features.

In order to cater to all its deficiency, there is need for it to be modified.

Let the improved version of equation (2) be defined as:

$$PL(dB) = q_1 + q_2\log(f) + q_3\log(r) + P \tag{6}$$

where $P = \sum_{n=1}^{N} a_n r^n$ for N = 2, therefor, $P = a_2r^2 + a_1r$

For the sake of convenience equation (6) can be written as.

$$PL(dB) = q_1 + q_2\log(f) + q_3\log(r) + q_4r^2 + q_5r \tag{7}$$

3.3.2. Tuning of the Improved Log-distance Path Loss Model

Given the measured signal data points (r_i, P_{Li}), the goal is to determine

$$y = P_L(r_i, q) \tag{8}$$

where q is the parameter vector [q_1, q_2, q_3, q_4, q_5] and y , a non-linear equation is the model output.

To obtain the vector q for best fit, the sum of squares is applied

$$S = \sum_{i=1}^{5}\left|P_{Li} - P_L(r_i, q)\right|^2 \tag{9}$$

The Jacobian Matrix, J of equation (9) is required to solve the minimization problem.

$$J = \begin{pmatrix} \frac{\partial P_L(r_1|q)}{\partial q_1} & \frac{\partial P_L(r_1|q)}{\partial q_2} & \cdots & \frac{\partial P_L(r_1|q)}{\partial q_5} \\ . & . & \cdots & . \\ . & . & \cdots & . \\ \frac{\partial P_L(r_5|q)}{\partial q_1} & \frac{\partial P_L(r_5|q)}{\partial q_2} & \cdots & \frac{\partial P_L(r_5|q)}{\partial q_5} \end{pmatrix} \tag{10}$$

In addition, the vector of all the residual is given

$$res = \begin{pmatrix} P_{Li} - P_L(r_1|q) \\ P_{Li} - P_L(r_1|q) \\ . \\ . \\ . \\ P_{L_N} - P_L(r_N|q) \end{pmatrix} \tag{11}$$

Hence, putting everything together we obtain the weighted least square of the LM method in equation (12). According to [10], Levenberg-Margaurdt Method is a very powerful and reliable tool for analyzing many minimization problem as it combines the benefits of the gradient-descent and Gauss-Newton methods.

$$LM = (J^T \cdot W \cdot J + \mu \cdot I) - 1 \cdot J^T \cdot W \cdot r \tag{12}$$

Where W is a diagonal matrix.

$$W = \begin{pmatrix} w_1 & 0 & 0 & \dots & 0 \\ 0 & w_2 & 0 & \dots & 0 \\ 0 & 0 & \ddots & \dots & \vdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 0 & w_N \end{pmatrix} \tag{13}$$

4. The Proposed Hybrid Model

To cater for all the limitations of log-distance path loss model, we proposed a hybrid path loss model – a combination of the wavelet transform and weighted non-linear least square (WNLLS). Figure 2 shows the implementation block diagram for the proposed hybrid model.

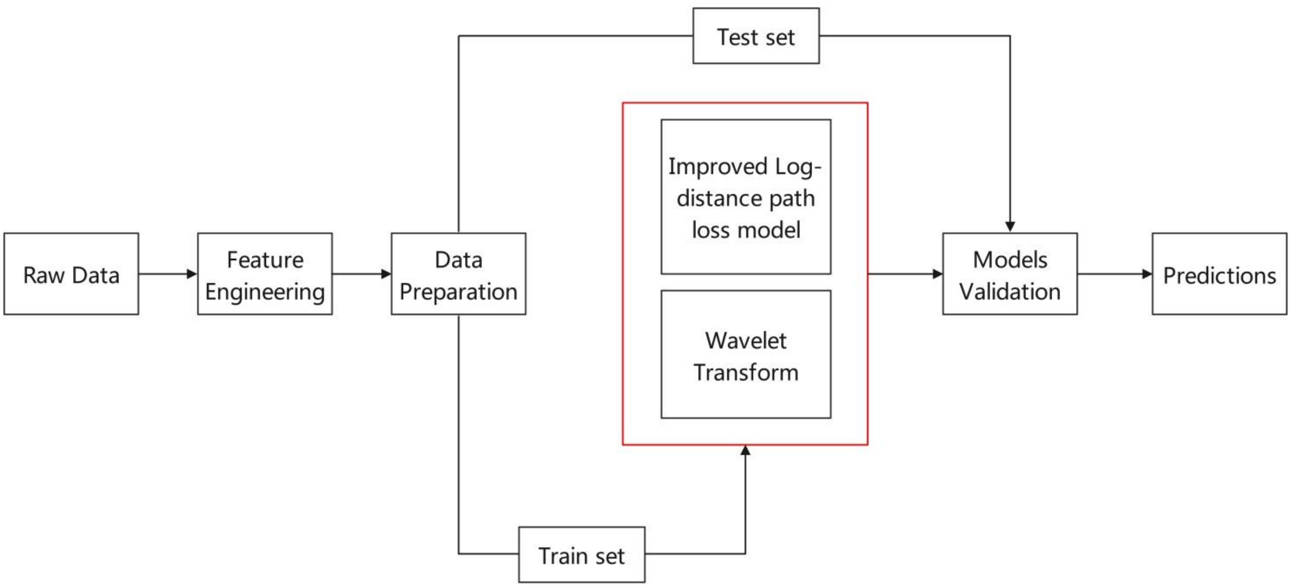

Fig. 2. block diagram for the implementation of the proposed model

4.1. *Performance statistical metrics*

Four statistical metrics were engaged to examine the prediction accuracy of the adaptive hybrid model developed using the following mathematical calculations: The coefficient of determination (R square), mean absolute square (MAE), root mean square error (RMSE), and the standard deviation (STD).

- **RMSE:** The square root of the mean square error. It tells how close the measured received signal strength (RSS), $f(x)$ values are to the values predicted $\bar{f}(x_i)$ by the fitted models. It is given as

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(f(x) - \bar{f}(x))}{n}} \tag{14}$$

where n = total number of measured data

- **R-square** tells the proportion of variation between the measured signal and the proposed hybrid model.
-

$$R^2 = 1 - \frac{\sum_i (f(x)_i - \bar{f}(x)_i)^2}{\sum_i (f(x)_i - \bar{y})^2} \tag{15}$$

where $\bar{y}$ is the mean of the measured signal

- **MAE** gives the absolute difference between measured data that is the received signal strength (RSS) values and the predicted values. It is defined as:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left\| f(x) - \bar{f}(x_i) \right\| \tag{16}$$

MAE metric is good at handling outliers.

- **STD** is the measure of the amount of dispersion of a set of data. A low STD is an indication that the result is closed to the mean of the data set.

$$STD = \sqrt{\frac{f(x) - \bar{f}(x_i)}{n-1}} \tag{17}$$

5. Results and Discussions

Figure 4 and figure 5 are plotted to show the level of signal attenuation in the study locations, and to compare the prediction accuracy of the proposed model and the COST 234 and Okumura Hata models. Specifically, figure 4 displays the measured path loss in three locations by Network A and compared the values to those made by COST234 and Okumura Hata models. While, figure 5 shows the measured path losses in three locations by Network B and compared the values to those made by COST234 and Okumura Hata models.

It is clear from figure 4 and figure 5 that COST 231 and Okumura Hata models over-predicted the propagation loss in our environment of interest.

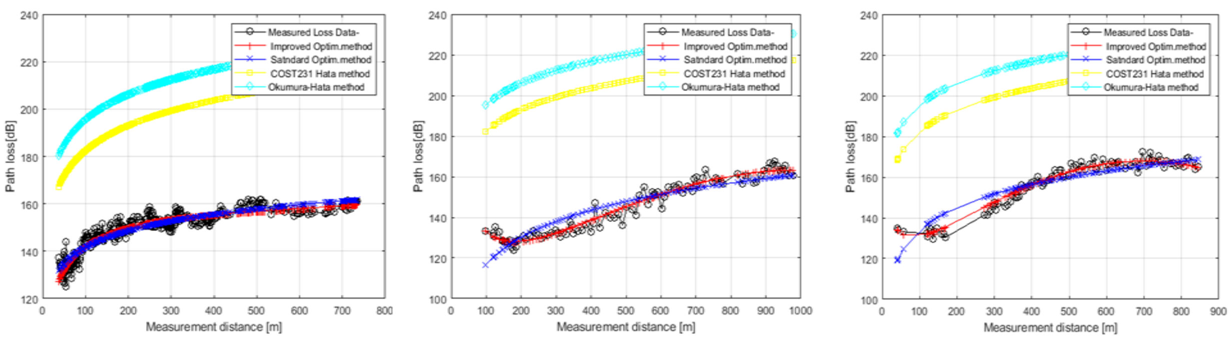

Fig. 4. Comparison of the measured path loss values, the ones predicted by COST231, Okumura Hata path loss, and the hybrid model for the three locations of Network-A

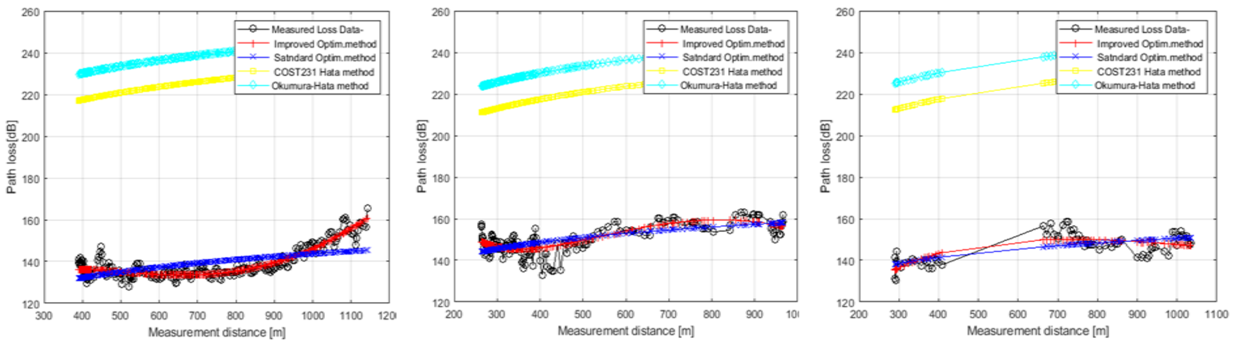

Fig. 5. Comparison of the measured path loss values, the ones predicted by COST231, Okumura Hata path loss, and the hybrid model for the three locations of Network-B

Figure 6 and figure 7 represent the prediction capabilities of the hybrid model (wavelet-WILM) developed in section 4 over the standard log-distance model. Specifically, figure 6 compares the measure path loss value to those predicted by the hybrid model (wavelet-WILM) and the standard optim.method. While figure 7 presents the measured path loss value to the predicted by the hybrid model (wavelet-WILM).

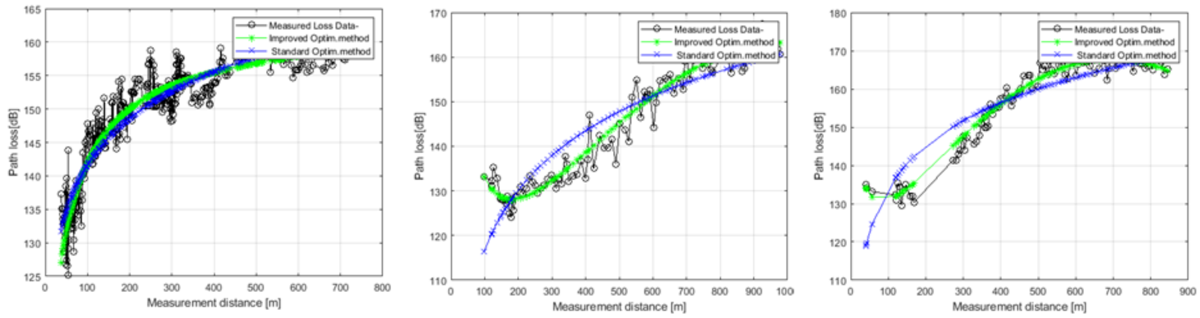

Fig. 6. Comparison of the measured path loss values, the standard log-distance model and the hybrid model for the three locations of Network-A

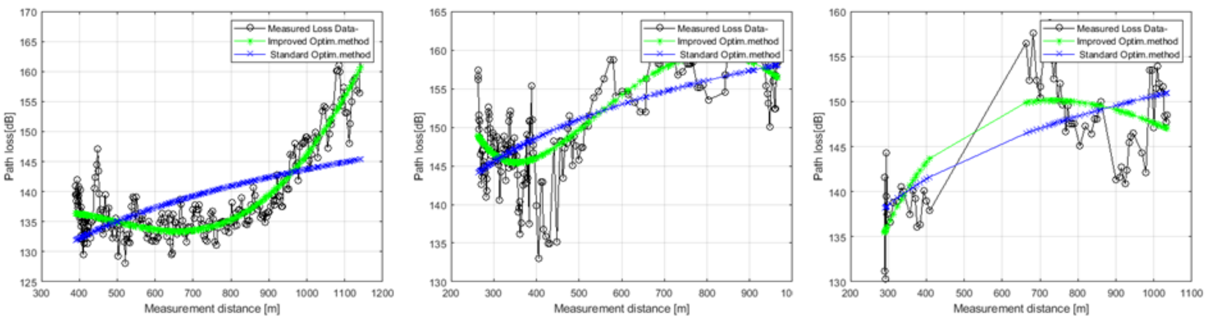

Fig. 7. Comparison of the measured path loss values, the standard log-distance model and the hybrid model for the three locations of Network-B

Table 2 displays the results for the three locations for Network A. For the three locations, the MAE for the improved optim.method is between 1.889-2.26 dB values the standard optim.method has a MAE between 2.415 – 4.01 dB values. Also, the RMSE for the improved optim.method for the three locations ranges between 2.3 – 2.9dB while for the standard model, it is between 3.06 – 5.37 dB, for COST234 it is between the range of 45.2 – 60.11 dB.

Table 2. Prediction Accuracy for Network A for location 1 – 3.

		MAE	RMSE	STD	R2
Location 1	Proposed Method	2.20149	2.79916	2.80239	0.960381
	Standard Method	2.41578	3.05925	3.06319	0.929133
	COST234-Hata method	44.9594	45.2433	5.06735	0.929133
	Hata method	58.0779	58.298	5.06735	0.929133
Location 2	Proposed Method	2.26536	2.90335	2.90997	0.991189
	Standard Method	4.23507	5.37042	5.3983	0.916315
	COST234-Hata method	59.8179	60.1117	5.96721	0.916315
	Hata method	72.9364	73.1776	5.96721	0.916315
Location 3	Proposed Method	1.88897	2.36515	2.34889	0.988331
	Standard Method	4.01604	5.26607	5.2943	0.905312
	COST234-Hata method	47.2051	47.5029	5.33973	0.905312
	Hata method	60.3236	60.557	5.33973	0.905312

Table 3. Prediction Accuracy for Network B for location 1 – 3

		MAE	RMSE	STD	R2
Location 1	Proposed Method	2.27355	2.9057	2.91108	0.964241
	Standard Method	4.73093	5.77013	5.78204	0.594649
	COST234-Hata method	86.6447	86.8416	5.85794	0.594649
	Hata method	99.3074	99.4793	5.85794	0.594649
Location 2	Proposed Method	3.08979	4.05663	4.04785	0.927865
	Standard Method	3.68221	4.95467	4.96889	0.674655
	COST234-Hata method	69.4023	69.6059	5.33446	0.674655
	Hata method	82.065	82.2373	5.33446	0.674655
Location 3	Proposed Method	3.5431	4.31682	4.34889	0.84201
	Standard Method	3.80708	4.89895	4.93537	0.66605
	COST234-Hata method	78.6293	78.8147	5.44287	0.66605
	Hata method	91.292	91.4517	5.44287	0.66605

Figure 8 – 10 and Figure 11 – 13 presents the prediction capacity of the hybrid method over the standard log-distance model for Network A and Network B respectively. The plots show that the hybrid method performed better than the standard method in all the locations.

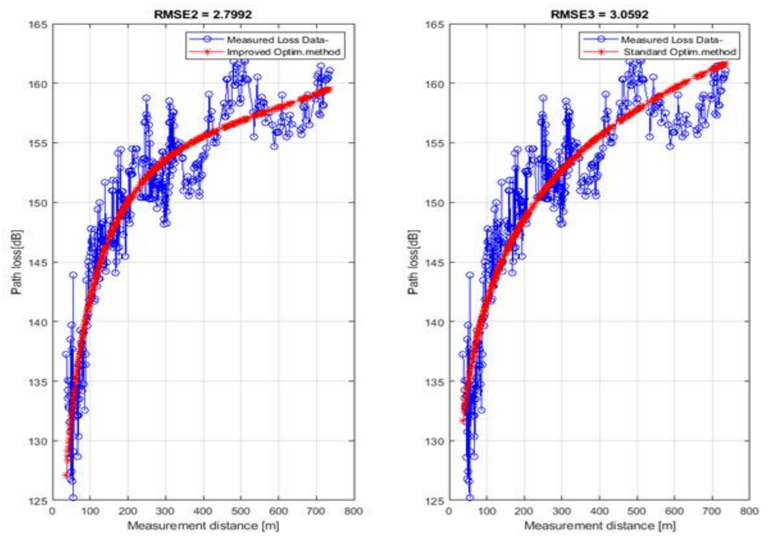

Fig. 8. Measured path loss values compared to the ones predicted using standard and proposed hybrid path loss models for Network A in Location 1

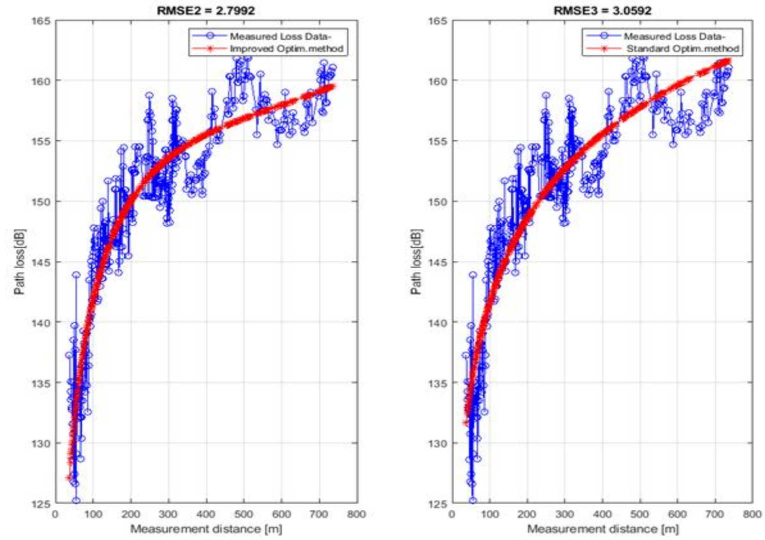

Fig. 9. Measured path loss values compared to the ones predicted using standard and proposed hybrid path loss models for Network A in Location 2

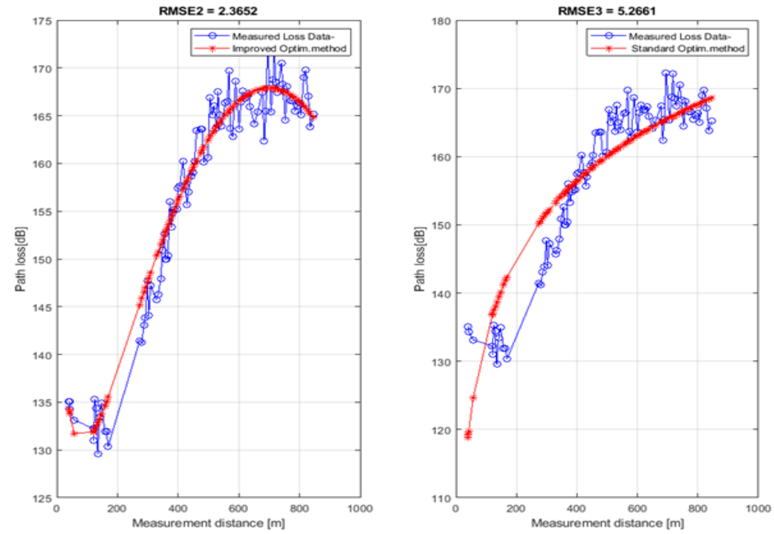

Fig. 10. Measured path loss values compared to the ones predicted using standard and proposed hybrid path loss models for Network A in Location 3

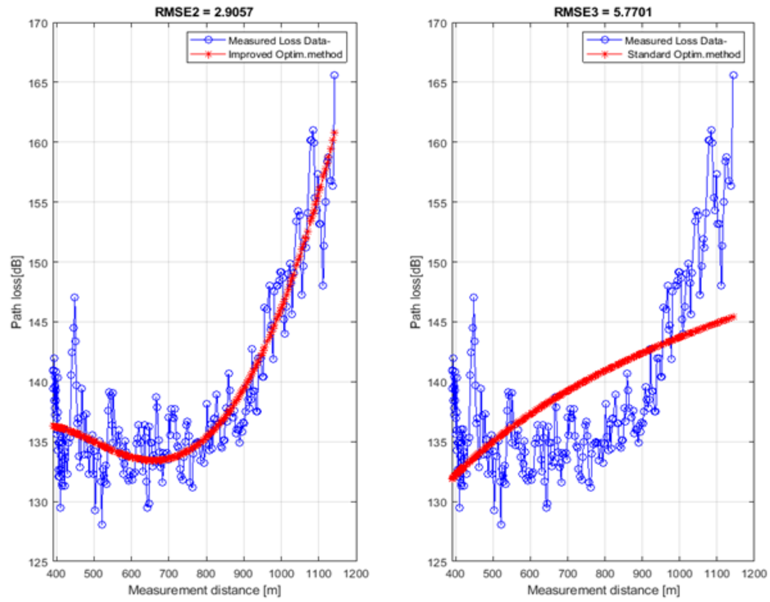

Fig. 11. Measured path loss values compared to the ones predicted using standard and proposed hybrid path loss models for Network B in Location 1

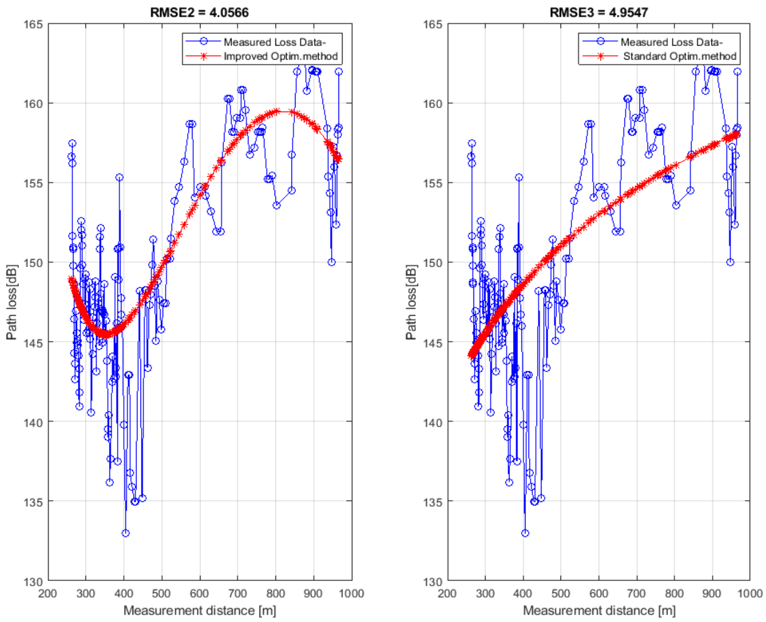

Fig. 12. Measured path loss values compared to the ones predicted using standard and proposed hybrid path loss models for Network B in Location 2

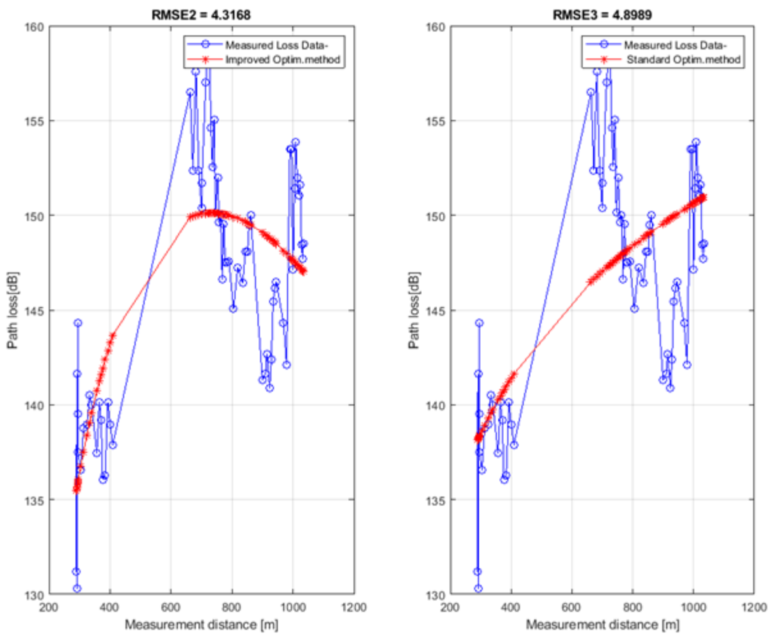

Fig. 13. Measured path loss values compared to the ones predicted using standard and proposed hybrid path loss models for Network B in Location 3

Figure 14 – 19 display the coefficient of correlation (R) results. The plots are to further compare the precision accuracy of the proposed hybrid model and the standard log-distance model. Figure 14 to 16 display the coefficient of correlation for the three locations of Network A, and figure 17 to 19 shows the plots for the coefficient of correlation for the three locations in Network B. The graphs show that the R-value of the hybrid model for both networks 99.1%. On the other hand the R-value for the standard model is in the range of 90.5 to 92.9 for both networks. The performances of the models for all the six locations are summarized in Table 2 and Table 3.

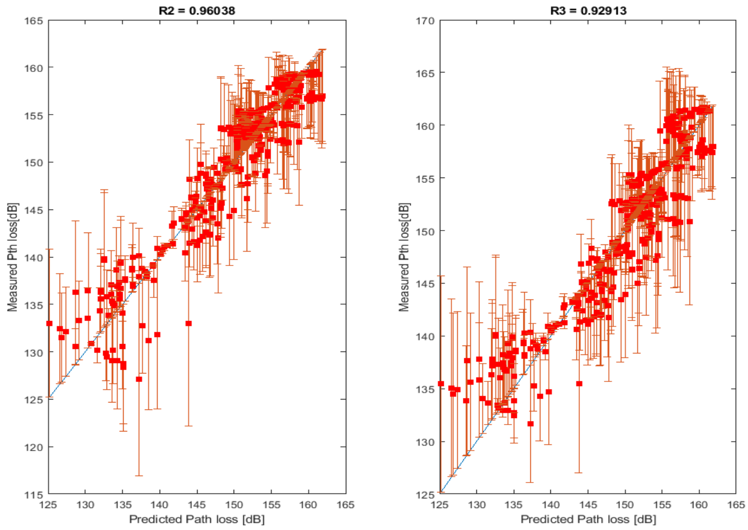

Fig. 14. Quantified Correlation coefficient values attained using the proposed hybrid path loss model in comparison with ones obtained using standard for Network A Location 1

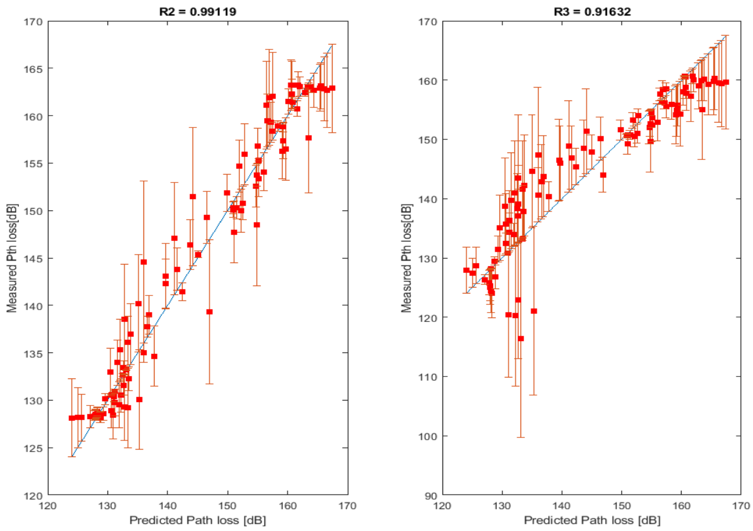

Fig. 15. Quantified Correlation coefficient values attained using the proposed hybrid path loss model in comparison with ones obtained using standard for Network A Location 2

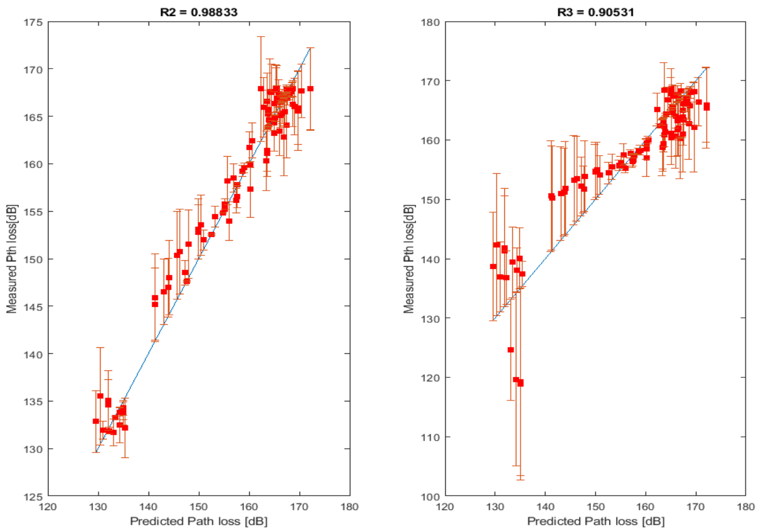

Fig. 16. Quantified Correlation coefficient values attained using the proposed hybrid path loss model in comparison with ones obtained using standard for Network A Location 3

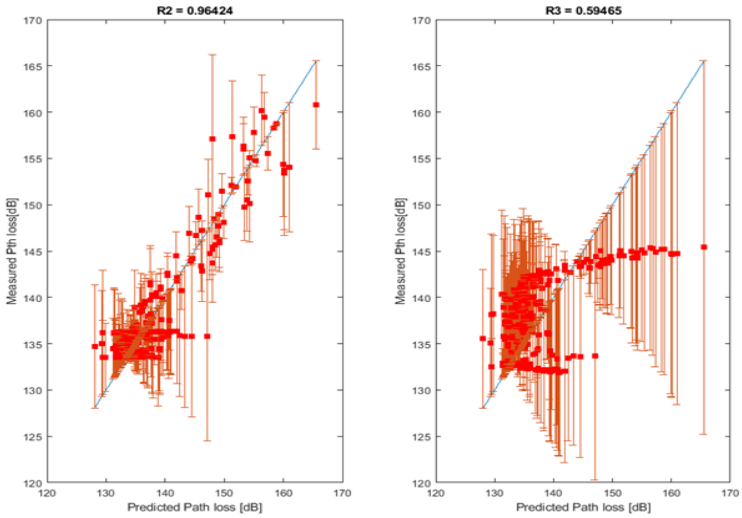

Fig. 17. Quantified Correlation coefficient values attained using the proposed hybrid path loss model in comparison with ones obtained using standard for Network B Location 1

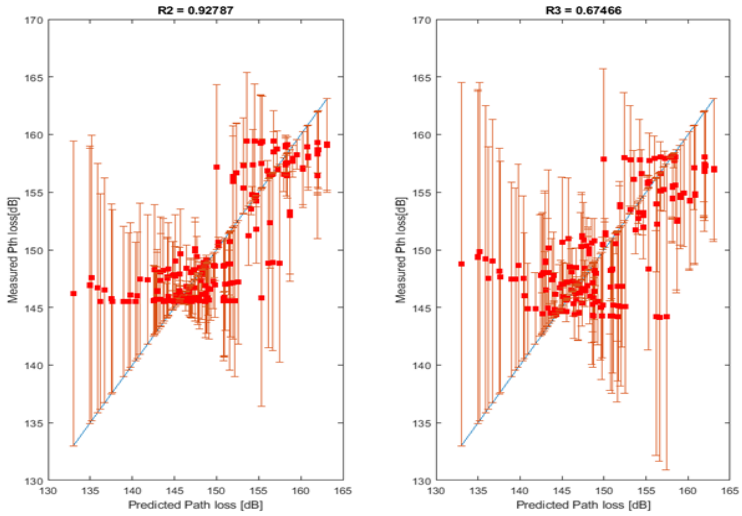

Fig.18. Quantified Correlation coefficient values attained using the proposed hybrid path loss model in comparison with ones obtained using standard for Network B Location 2.

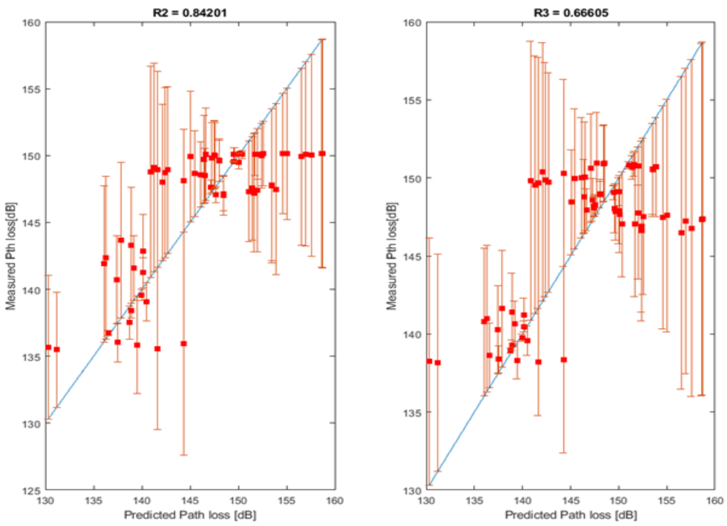

Fig. 19. Quantified Correlation coefficient values attained using the proposed hybrid path loss model in comparison with ones obtained using standard for Network B Location 3

Furthermore, the outcome of this research showed that standard log-distance model, COST234 model and the Hata model over-predicted the path loss signal for the two networks under consideration in this area. However, the developed hybrid model predicted the path loss with the smallest deviations from the actual measured signal. Hata model has the highest MAE and RMSE in all the three locations of the two networks followed by COST234 and the standard log-distance model. The limitation of Hata model is that it does not consider shadowing. More so, path loss propagation models perform better in the environment where they were developed. As shown in Table 2 and Table 3, the proposed hybrid model is well suited to the environment of interest. It has the least deviations and its proportion of variation to the measured signal is the best.

6. Conclusion

The propagation loss over irregular terrain is a complex function of frequency, path geometry, vegetation density and other less significant variables. Every physical entity or object transmitted radio signals encounters over their communication paths affect the direction and coverage quality level. The physical entities include the man-made terrain structures (buildings, houses and towers), natural terrain irregularity clutter features (mountains, valleys and hills), and atmospheric variables (other gaseous media). While the physical refracts (bends) the propagated radio signal, others diffract (scatters) and absorb the radio signals. Scattering effects generally weaken the radio signals, while bending incurs directional path changes in the radio signals. The resultant negative effects of these physical entities are large signal path losses. In this paper, a robust approach was employed for the development of a propagation path loss model for an irregular terrain. First, the standard log-distance model was improved by adding a polynomial function to cater for the uniqueness of the terrain. Secondly, the parameters of the improved models were tuned using the Levenberg-Marquart (LM) algorithm. Finally, the improved log-distance model was engaged for practical predictive analysis of signal attenuation of an LTE data collected from two main network operators in Nigeria. Network Operator A operates at 801 MHz and Network Operator B operate 2600 MHz. The measured signal was de-noised using a wavelet family – Daubechies (db4), and the improved log-distance model was used to predict the resulting signal. The hybrid model (wavelet+improved log-distance) indicates very high prediction accuracy when compared to other existing models like Okumural Hata and COST234 model.

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