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Adaptive Tuning of the Log-distance Model for Optimal Predictive Modeling of Pathloss Over Irregular Terrains

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Abstract: Recent technological development has facilitated the deployment of different Mobile Broadband Cellular Network Systems (MBCNS), such as Long Term Evolution (LTE) and 5G New Radio (NR), globally. This development aims at satisfying the ever-data-hungry multimedia applications to guarantee good quality of service for mobile subscribers. One way mobile subscribers can continuously access and enjoy the services provided by the MBCNS is to put in place a well-planned signal coverage area, wherein accurate path loss estimation is prioritized. Particularly, with the regular technological advancements and evolution of mobile communication systems, particularly fourth and fifth, the development of accurate précised path loss models has become more critical for robust planning and optimization purposes. In practice, the conventional log-distance path loss model is suitable for path loss predictive modeling and estimation in plain signal propagation environments. However, the model is not suitable for irregular terrains. In order to adapt this model for application in irregular terrains, this paper proposes a modified log-distance path loss model with an adaptive polynomial term. The modified long-distance path loss model provides efficient irregular terrain signal loss estimation parameters. In order to boost the prediction accuracy of the proposed model, two regression optimization methods, non-linear least square and weighted least square, were employed with the Levenberg-Marquardt (LM) algorithm to determine its relevant parameters. In terms of the coefficient of correlation and percentage error, the modified log-distance path loss model with the optimized parameters showed 40-60% improvement in accuracy over the standard log-distance model for the path loss prediction across the six different locations investigated. Furthermore, the validation of the proposed model has been provided in order to ascertain the level of its prediction accuracies in other locations. Overall, the modified log-distance model showed remarkable accuracy and efficiency when deployed in a related wireless propagation environment.

Keywords: Radio wave signals; Signal path loss, Irregular terrains; Log-distance model; Propagation loss; Levenberg-Marquart algorithm; Efficient network planning.

1. Introduction

The technological advancements in the telecom industry over the past decades have been enormous and steady [1]–[3]. This advancement has led to the introduction, spreading, and deployment roll-out of multimedia services by radio network providers. In these networks, the one key thing that is paramount to the mobile subscriber and constantly in the heart of the network provider is providing good signal coverage at every antenna deployment location. The network coverage of deployed antennas must be planned to reach the teeming number of present and prospective subscribers at every site [4]–[6]. It must also be deployed to subdue the stumbling blocks and provide a clear line of sight communication in the paths of propagated radio signals. In order to effectively optimize, plan and deploy the base station antennas, an optimal signal path loss

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model is essential. Path loss modeling is a method of characterizing, estimating and modelling the signal losses between a transmit antenna and receiver antenna in connection with the transmission distance, transmission frequency and other radio-environmental parameters [7]–[9]. The resultant model developed after the modeling process is termed path loss. Such path loss models are helpful to radio network providers in planning and optimizing their networks to attain optimal performance

quality. With the regular technological advancements and evolution of mobile communication systems, particularly fourth and fifth, the development of accurate precise path loss models has become more critical.

In general, standard path loss modeling techniques are of three main sets. The first is the stochastic path loss model. The environments and measured path loss parameters are modeled as a series of random variables in stochastic models. In terms of accuracy, they have low prediction performance. Also, the stochastic model is limited in generalization ability and cannot precisely estimate wave propagation characteristics [10]. The 3GPP 38.901 model, developed using a robust number of field measurement data [11], [12] is a typical example. Such model type is contained in [13]. The deterministic models [14] are the second path loss model type. These model types utilize topographical maps or architectural plans combined with environmental propagation variables and geometric theory to predict path loss characteristics [14]–[16]. Ray-tracing models are typical examples. Lastly, the third type is the *empirical* model. These models are solely built based on detailed field observations and measurement of path loss data. In terms of accuracy, *empirical* models are pretty good, but their prediction efficiency is often limited to the specific terrain they were developed. Examples of this model type are the Hata model, Lee model, etc.

The novelty of this paper is the provision of a detailed status analysis of measured loss data over irregular terrains. The second one is the successful optimization of the existing log-distance model with the addition of a polynomial term, which in turn resulted in optimal predictive analysis of measured signal losses. The third is the application of non-linear least squares and Levenberg- Marquardt methods to effectively determine the log-distance model parameters for studied irregular terrain signal prediction analysis. Fourthly, validation of the optimized path loss model to ascertain the level of its prediction accuracies in other locations has been provided.

Thus, our contributions to this research paper are as follows:

- Measurement-based estimation of path loss over irregular signal propagation terrains
- A detailed appraisal of prediction accuracy of commonly used standard log-distance path loss models on the measured signal path loss levels
- Modification of the standard Log-distance path loss model, which is to enable it to take into account (captures) signal attenuation losses due to local terrain clutter features and irregularities.
- Effective 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

The remaining part of this contribution is organized as follows. Section 1 provides the introductory framework. In Section 2, the related work is elaborated. Section 3 presents the materials and methods employed in the study. Section 4 gives a comprehensive description of the results and discussions. Finally, Section 5 concludes the paper and gives useful perspectives on future work.

2. RELATED WORK

Over any radio transmission path, the radio signal attenuation loss over the paths is caused by numerous factors. This often time makes precise path loss modeling and calculations very difficult. Developing a model that can reliably calculate or estimate propagated signal path loss at specific distances from the transmitter is crucial during network planning and continuous management. Particularly, such a model also helps us to determine the network cell radius and the coverage area of the transmitter. Another key distinctive application of path loss models is in the area of positioning.

Radio path loss modeling, development, and tuning (adaption) to meet the specific needs of cellular planning and management in a given terrain have been a subject matter and a research topic for decades, particularly in the early 70s when the first digital-based voice telephony such as the GSM came into public use. Radio frequency designers and planners utilize path loss models to estimate cell radius and extrapolative analysis of signal coverage in cellular communication networks. Some notable path loss models, such as the Okumura, Hata [17], and Egli [18] models, which were developed in European Countries, are mainly good and accurate for use in large urban-macro cells [19]–[21]. Besides, the models are designed specifically for the radio frequency range of 150-1500 MHz and for heights of transmit antenna above 30 m. The same limitation is valid for other classical models like SUI, LEE, and COST231- Hata, which were planned for usage up to 2000 MHz. Thus, applying the models out of their frequency range, antenna height, and terrain specification usually results in significant errors [20], [22], [23].

In [24], the authors used terrain-based field signal measurement techniques to conduct a thorough propagation path loss calibration for rural, urban and suburban CDMA and LTE as case studies in the USA. The researchers realized between 4.5 dB to 8 dB performance accuracies in terms of RMSE error for the case studied environment compared to the usual prediction models that achieved between 7.4 to 11 dB performance accuracy. In [25], the Standard Propagation Model, an extension of the Hata model, was calibrated (tuned) by the authors for 4G LTE networks using the suburban terrain of Indonesia as a case study. The resultant calibrated model achieved 79% accuracy for signal coverage prediction over the COST 231 model for studying suburban terrain.

In [26], an ATOLL network planning tool has been engaged to calibrate Hata automatically. The authors achieved an average of 6.90 dB and 4.40 dB values of RMSE and MAE over the typical Hata model that achieved lower prediction accuracies with 21.55 dB and 18.32 dB values of RMSE and MAE. 1n [27]–[29], the Quasi-Moment-Method-Based (QMM) Calibration technique has been explored to tune ECC-33 models using Ibadan and Abuja Cities in Nigeria as a case study. The results revealed that the calibrated EEC model outperformed the none calibrated ECC model.

The Statistical Calibration Method is employed in [30] to calibrate standard path models for efficient planning of mobile ad-hoc networks by considering atmospheric refractivity and terrain diffraction as key components. The researchers' aim was achieved using line-of-sight and non-line-of-sight signal propagation scenarios. In [31], the bounding error technique was engaged for antenna height correction of the Hata-Okumura model application [32]–[35], the adaption of Hata and Egli's model parameters using Least square and least absolute deviation approximation. The adaption of Hata and Egli model parameters was done to reduce their prediction error usage for CDMA, UMTS and LTE cellular network planning in Nigeria using some major Cities such as Benin, Uyo and Port Harcourt as case studies. Similar studies that explored the least square approximations technique for path loss model adjustment for different terrains or study locations are contained in [36]–[43].

Despite the number of huge works done by different researchers in the above previous works, none of them holistically considered irregular terrain features in calibrating the existing path loss models. Thus, our research work is therefore designed to timely bridge the gap between previous works. Particularly, this current study is an extension of recent work in [32], wherein the five parameters of the Egli path loss model were optimized based on practical field measurements for its adaptive usage in LTE networks, using Uyo and Port Harcourt cities, Nigeria.

3. MATERIALS AND METHODS

The block diagram in **Figure 1** displays the methodology wherein this research paper is guided. The stepwise method can be explored for a similar signal propagation environment where there is a need for optimal predictive path loss modelling. We start by defining the standard log-distance and modified log-distance path loss models. This is followed by engaging the Levenberg-Marquardt algorithm in combination with the measured pathloss data to tune the parameters of the modified log-distance model parameters in the non-linear and weighted non-linear least-square senses.

A. Log-distance Path loss Model

In free space, the transmitted signals through the communication channel to the receiving end are assumed to be in an empty atmospheric setting without impediments. The power density S_p attained over a communication distance *r* is related to the received power, P_r the transmit power P_t and the processing antenna gain G_{at} in equations (1) and (2) by [44]:

$$S_p = \frac{P_t g_t}{4\pi r^2} \tag{1}$$

$$P_r = S_p A_e = \frac{P_t G_{at}}{4\pi r^2}.A_e \tag{2}$$

with A_e being the antenna aperture area given by equation (3):

$$A_e = \frac{G_{ar}\lambda^2}{4\pi}. \tag{3}$$

P_r can be modified with respect to A_e in equation (4):

$$P_r = \frac{P_t G_{at}}{4\pi r^2}.A = \frac{\lambda^2}{(4\pi r)^2}.G_{at}P_t G_{ar} \tag{4}$$

where λ = transmission wavelength.

Thus, the path loss, $P_l(dB)$ over the free space channel can be computed from equation (4) using equation (5):

$$P_l(dB) = 20\log\left(\frac{4\pi r}{\lambda}\right). = 20\log\left(\frac{4\pi f_{ca} r}{C_{speed}}\right) \tag{5}$$

where C_{speed} and f_{ca} define the light speed and transmission frequency.

Given that $C_{speed} = 3\times 10^8 m/s, \pi = 3.142,$, then equation (5) turns to equation (6):

$$P_l(dB) = 130 + 20\log(f) + 20\log(r) \tag{6}$$

The expression in (6) reveals that signal loss in free space attenuates 20dB in value. However, this is certainly not so in other propagation environments such as built-up terrains, suburban areas or urban areas.

In more general form, equation (6) can be rewritten as equation (7)

$$P_l(dB) = a_1 + a_2 \log(f) + a_3 \log(r) \tag{7}$$

Thus, equation (6) is referred to as the general log-distance path loss model. In literature, many efforts have been explored to determine the loss coefficients: a1, a2 and a3, to reflect the true nature of the terrain the signal is propagated. This led to the introduction of the Hata path loss model, SUI path loss model, COST 231 Hata path loss model, and Ikegami path loss model, all of which were developed in countries such as Japan and the US. The application of the models mentioned above for path loss estimation outside the locations or environments wherein they were not developed has always yielded significant errors [25], [30], [31].

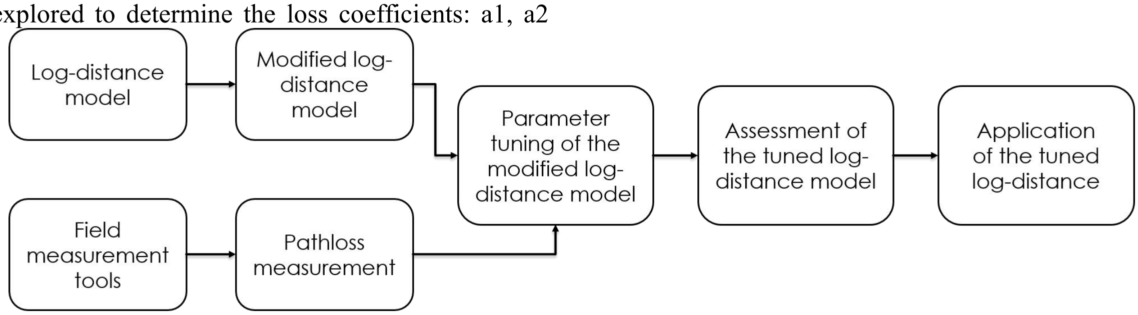

Figure 1: Block diagram of the research methodology

B. Modified Log-distance Path Loss Model

Another key reason why the general Log-distance model usually results in a large error during application is its non-adaptive nature. As a log-linear model type, it can hardly adapt to stochastic and highly fluctuating path loss data, particularly those highly influenced by non-uniform terrain profiles and uncontrollable atmospheric variables.

In order to cater to such a Log-distance model deficiency, a modified Log-distance model is proposed in this paper. It is termed the MLM path loss model. MLM model has been obtained by adding a polynomial term, P, to boost its adaptive path loss data modeling pattern. The modified version of the Log-distance model can be defined in equation (8):

$$P_l(dB) = a_1 + a_2 \log(f) + a_3 \log(r) + P \tag{8}$$

where $P = \sum_{n=1}^{N} b_n r^n$, b is the modeling coefficients.

For $N = 2, P = b_2 r^2 + br$ and expression in (8) would result in equation (9):

$$P_l(dB) = a_1 + a_2\, log\,(f) + a_3\, log\,(r) + b_2 r^2 + b_1 \tag{9}$$

For the sake of uniformity, equation (9) can be rewritten as equation (10):

$$P_l(dB) = a_1 + a_2\, log\,(f) + a_3\, log\,(r) + a_4 r^2 + a_5 r \tag{10}$$

C. Tuning of the Modified Log-distance Path loss Model

Given path loss data points (d_i, y_i) , the aim is to determine the vector **a** parameter that can provide an optimal prediction model $PL(d_i, a)$ with high accuracy in the least square sense given by equations (11) to (14):

$$\min_{\boldsymbol{a}} f(\boldsymbol{a}) \equiv \min_{\boldsymbol{a}} \frac{1}{2}\|r(\boldsymbol{a})\|^2 = \min_{\boldsymbol{a}} \frac{1}{2}\sum_{i}^{t} r_i(\boldsymbol{a})^2 \tag{11}$$

where,

$$\boldsymbol{a} = (a_1, a_2, a_3, a_4, a_5, a_6) \tag{12}$$

$$r_i(\boldsymbol{a}) = y_i - Pl(d_i, \boldsymbol{a}); i = 1,\dots,t \tag{13}$$

$$r(\boldsymbol{a}) = \begin{pmatrix} r_1(a) \\ r_2(a) \\ r_3(a) \end{pmatrix} \tag{14}$$

With y_i and d_1 indicating the measured loss data values and the covered distance during measurements. The expression in equation (12) is a minimization optimization problem.

In this paper, non-linear least square and weighted non-linear least square approaches have been engaged to solve the minimization optimization problem. To implement both approaches, we utilize the LM method. Thus, in the remaining part of this paper, the non-linear least square and weighted non-linear least square methods are proposed optim. method 1 and proposed optim. method 2.

D. Levenberg Marguardt Algorithm (LMA)

The Levenberg–Marquardt algorithm (LMA) [45]–[48] is one key distinctive optimization algorithm for providing robust global solutions to complex and intricate non-linear least-squares approximation problems [47], [49], [50]. Particularly, the optimal performance of the LMA over the gradient descent algorithm during application in finding local minima has been discussed in [8] and [32]. Thus, this paper engages the LMA algorithm to provide global solution to effective parameter tuning and predictive optimization existing path loss model in irregular terrains. The implementation flow chart of the Levenberg-Marquardt algorithm for parameter tuning of the modified log-distance model is shown in **Figure 2.**

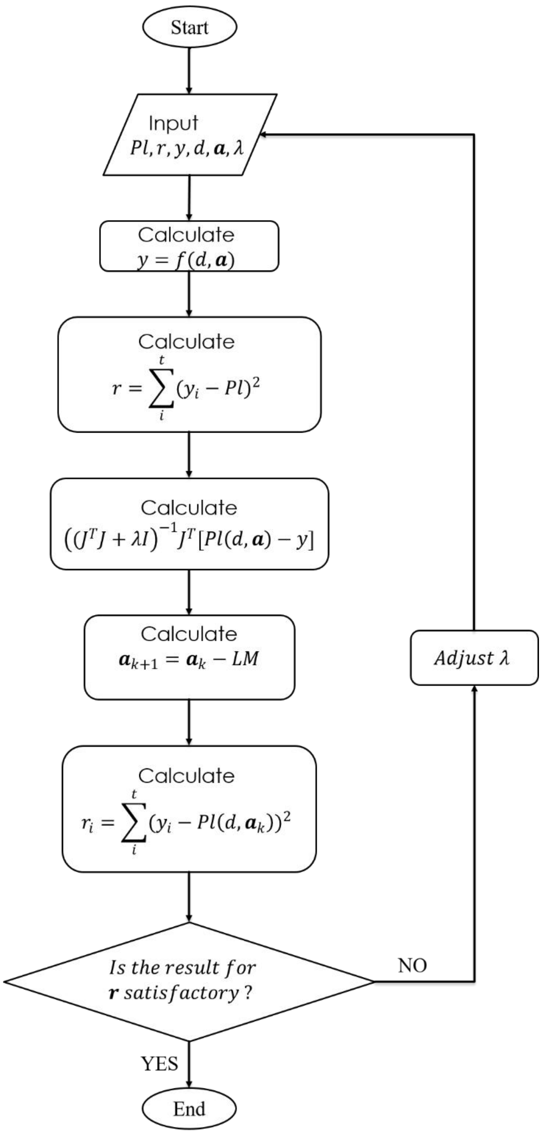

Figure 2: Flow diagram of Log-distance Parameter tuning the LM Algorithm

In order to engage the LMA, first, we define its constituent components, which are Gradient, Jacobian and Hessian matrices $r(\boldsymbol{a})$.

(a) **Jacobian and Gradient of** $r(\boldsymbol{a})$

The Jacobian $J(\boldsymbol{a})$ of the vector function $r(\boldsymbol{a})$ can be defined as in equation (15):

$$[J(\boldsymbol{a})]_{ij} = \frac{\partial r_i(\boldsymbol{a})}{\partial a_j} = \frac{\partial Pl(d_i, \boldsymbol{a})}{\partial a_j}; i = 1, \ldots, t, j = 1, \ldots, n.$$

(15)

The gradient $\nabla f(\boldsymbol{a})$ of the vector function $r(\boldsymbol{a})$ is given by equation (16):

$$[\nabla f(\boldsymbol{a})]_j = \sum_i^t r_i(\boldsymbol{a}) \frac{\partial r_i(\boldsymbol{a})}{\partial a_j} \quad (16)$$

It follows from equations (5) and (6) that equation (17) is evolved:

$$[\nabla f(\boldsymbol{a})]_j = J(\boldsymbol{a})^T r(\boldsymbol{a}) \quad (17)$$

since $[J(\boldsymbol{a})]_{i,:} = \nabla r_i(\boldsymbol{a})^T = \nabla Pl(d_i, \boldsymbol{a})^T$

(b) **Hessian matrix** $H_i(\boldsymbol{a})$ **of** $r(\boldsymbol{a})$

The hessian of $r(\boldsymbol{a})$ is the second derivative of equation (6) given by equation (18):

$$[\nabla^2 f(\boldsymbol{a})]_{kl} = \frac{\partial^2 Pl(\boldsymbol{a})}{\partial a_k \partial a_l} = \sum_i^t \frac{r_i(\boldsymbol{a})}{\partial a_k} \frac{\partial r_i(\boldsymbol{a})}{\partial a_l} + \sum_i^t r_i(\boldsymbol{a}) \frac{\partial^2 r_i(\boldsymbol{a})}{\partial a_k \partial a_l}$$

(18)

Following a similar expression in equation (7), the Hessian can be written in terms of the Jacobian given by equation (19) whose parameters are defined in equation (20):

$$H(\boldsymbol{a}) = \nabla^2 f(\boldsymbol{a}) = J(\boldsymbol{a})^T J(\boldsymbol{a}) + \sum_i^t r_i(\boldsymbol{a}) \nabla^2 r_i(\boldsymbol{a}) \quad (19)$$

where

$$[\nabla^2 r_i(\boldsymbol{a})]_{kl} = -[\nabla^2 Pl(d_i, \boldsymbol{a})]_{kl}$$

$$-\frac{\partial^2 Pl(d_i, \boldsymbol{a})}{\partial a_k \partial a_l}; k = l = 1, \ldots, t \quad (20)$$

From the above expressions, the LM method can be written as in equation (21):

$$LM = \left(J(\boldsymbol{a})^T J(\boldsymbol{a}) + \lambda I\right)^{-1} J(\boldsymbol{a})^T r(\boldsymbol{a}) \quad (21)$$

The values of the vector $\boldsymbol{a} = (a_1, a_2, a_3, a_4, a_5)$ can be determined iteratively using the LM method as in equation (22):

$$\boldsymbol{a}_{K+1} = \boldsymbol{a}_k - \left(J(\boldsymbol{a}_k)^T J(\boldsymbol{a}_k) + \lambda_k I\right)^{-1} J(\boldsymbol{a}_k)^T r(\boldsymbol{a}_k)$$

(22)

where λ_k is the damping parameter introduced by LM to control the direction and length of the iterations steps, k=1, 2,…, with I being the identity matrix.

(c) Weighted Model Function Jacobian

The weighted least version implementation of the LM method can be obtained by multiplying the Jacobian by the square root by the weighted parameter defined by equations (23) and (24):

$$J_w(\boldsymbol{a}) = W^{1/2} J(\boldsymbol{a}) \tag{23}$$

$$r_w(\boldsymbol{a}) = w_i^{1/2}\left(y_i - Pl(d_i, \boldsymbol{a})\right); i = 1,\ldots,t; w_i, i = 1,\ldots,t \tag{24}$$

Thus, the weighted least version of the LM method can be expressed using equation (25)

$$\boldsymbol{a}_{K+1} = \boldsymbol{a}_k - \left(J(\boldsymbol{a}_k)^T W^{1/2} J(\boldsymbol{a}_k) + \lambda_k I\right)^{-1} J(\boldsymbol{a}_k)^T W^{1/2} r(\boldsymbol{a}_k) \tag{25}$$

The proposed modified log-distance modelling the is given below

<u>Proposed log-distance modelling with LM Algorithm</u>

I. Initialise relevant parameters: *Pl, d,* λ_k , a, and k=1,2,….
II. Set the starting points, a_0, the Jacobian $J(\boldsymbol{a})$ and residual function $r(\boldsymbol{a})$
III. Compute $\boldsymbol{a}_{K+1} = \boldsymbol{a}_k - \left(J(\boldsymbol{a}_k)^T J(\boldsymbol{a}_k) + \lambda_k I\right)^{-1} J(\boldsymbol{a}_k)^T r(\boldsymbol{a}_k)$
IV. Compute the residual $r(\boldsymbol{a})$
V. Check the precision performance criteria
VI. If *K:=K*+1, repeat steps II to V till precision performance criteria is attained

E. Path Loss Prediction

One way mobile subscribers can continuously access and enjoy the services provided by broadband cellular networks is to steadfastly plan and replan (optimize) the well-planned signal coverage area of the network, wherein accurate path loss estimation is a key factor. At the same time, the conventional log-distance path loss model is good for path loss predictive modelling and estimation in normal signal propagation environments but not for irregular terrains. This paper proposes a modified log-distance path loss model with an adaptive polynomial term. The modified log-distance path loss model is projected to estimate the efficient signal loss in irregular terrain. To further boost the proposed model prediction efficacy, the two optimization methods, namely non-linear least square and weighted least square, are engaged to effectively determine the relevant optimization parameters to match measured path loss data.

F. Investigated Environment

These practical field drive tests took place in Lokoja, a well-known old city bounded by River Niger and Benue, Kogi State. Lokoja has been predicted to be the third (3rd) fastest-growing city in the African continent city by 2025, which is about a 5.93% upward growth [51]–[53]. The area coverage of Lokoja stands at 3,180 km^2, with a population of precisely 195,261 according to the 2006 census [54].

The old city lies about 7.8023° North and 6.7333° E east of the equator and Meridian. It is approximately 165 km Southwest of Abuja and 390 km Northeast of Lagos by road. The residential districts and buildings are of varying densities, accompanied by different suburbs like Felele, Ganaja, Otokiti, and Adankolo, Otokiti. The city is of Dry tropical savanna and Wet climate. One popular topography feature of the town is the presence of hiking Mountain Patti and rocky hills with surrounding trees, as displayed in **Figure 3.** The presence of hiking Mountain Patti and rocky hills surrounded by trees makes the Lokoja terrain irregular [55].

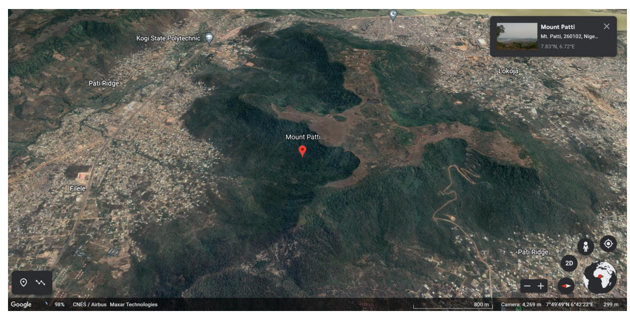

Figure 3: Pictographic view of Hiking Mount Patti, Lokoja, Kogi State

G. Ultra-high Radio Frequency Measurement

The ultra-high radio frequency (UH-RF) measurements were conducted using two main LTE networks operating in the study locations. The two networks called network A and network B all through this work. Though two networks were used for the study, the measurements pattern in drive test routes were almost the same. The measurement tools consisted of one EliteBook HP laptop and two TEMS-pockets phones, both of which were equipped with Ericson Telephone Mobile software. Other supporting tools include the GPS, Lexus 300RX car, Inverter, and connecting cables. The Lexus car was used for mobility and other tools during the drive tests. The GPS was primarily used to take location coordinates at every measurement point in correspondence with the transmitter [7]. The UH-RF measurements were done considering only the forward links and wherein constant calls were made to the networks at every drive test location. While network A operates at 2600MHz, network B operates at 800MHz. In the two networks, three eNodeBs were used for the study. The study environment was selected to represent a typical fast-growing urban area, consisting of light human and vehicular traffics, residential buildings, and a few commercial ones.

Most importantly, the presence of hiking Mountain Patti, rocky hills and rocky undulating topography with mixed structures of residential buildings and trees makes Lokoja terrain irregular in nature. 3500 and 4350 signal data samples were obtained via the network A and B drives.

In order to obtain the path loss values from the measured signal power (RSR) conducted in the respective location for Networks A and B, the expressions in (26) and (27) were used [19]–[21].

$$PL_{measured}(dB) = P_{total} + RSRP \tag{26}$$

$$Ptotal = P_t + G_t - F_l - C_l \tag{27}$$

where P_t, G_t, C_l, and F_l indicate the eNodeB transmits power, eNodeB antenna gain, cable loss and feeder loss, respectively. Other eNodeB transmission parameters for Networks A and B are provided in **Table 1**. A snapshot of the field drive test routes wherein the measurements were undertaken is displayed in **Figures 4 and 5.** In particular, Figure 4 is a snapshot drive test route and signal coverage quality of network A. Figure 5 is a snapshot drive test route and signal coverage quality of network B.

TABLE 1

eNode B Antenna parameters and Measurement setup parameters

Parameters	Definition	Numerical Values
P_t	eNodeB transmit power	40-43dB
G_t	eNodeB transmit antenna gain	17.5-18dB
C_l	Cable loss	2(dB)
F_l	Feeder loss	3 (dB)
F_c	eNodeB transmission frequency	801/1857 MHz
H_e	eNodeB transmit antenna height	26-34(m)
H_r	Mobile equipment height	1.5m

Figure 4: A snapshot drive test route and Signal coverage Quality of Network A.

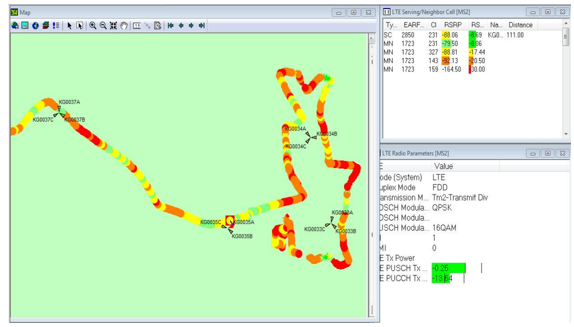

Figure 5: A snapshot drive test route and Signal coverage Quality of Network B.

4. RESULTS AND DISCUSSION

In this section, MATLAB software toolbox and user interface environment accompanied with the support of an Elitebook brand HP laptop running on Intel® Turbo Boost Technology plus Microsoft excel spreadsheets were used for every graphical plot, coding, computations, and implementation of the entire research objectives and results presentations.

A. Comparison of measured path loss and quantified path loss using the standard Log-distance model

The graphs in **Figures 6-11** are plotted to examine two things. The first is to quantify and reveal the levels of signal path losses across the study locations, and the second is to examine the precision accuracy that has been achieved using the standard log-distance models such as COST 231 Hata and Okumura Hata models in predicting the measured path loss values. The acquired path loss values were obtained from the measured signal power (RSR) conducted in the respective locations for networks A and B, the expressions in (26) and (27). Specifically, **Figure 6** shows the measured path loss values compared to those made by COST 231 Hata and Okumura Hata prediction models in location 1. **Figure 7** displays the measured path loss values compared to those made by COST 231 Hata and Okumura Hata prediction models in location 2. **Figure 8** provides the measured path loss values compared to those made by COST 231 Hata and Okumura Hata prediction models in Location 3. **Figure 9** shows the measured path loss values compared to those made by COST 231 Hata and Okumura Hata prediction models in Location 4. **Figure 10** displays the measured path loss values compared to those made by COST 231 Hata and Okumura Hata prediction models in location 5. Last, **Figure 11** gives the Measured path loss values compared to the ones made by COST 231 Hata and Okumura Hata prediction models in location 6.

For locations 1 to 3 belonging to operator A, path loss values acquired are ranged between 130.31-153.50dB, 142.63-163.13dB, and 129.50-172.21dB, respectively. For locations 4 to 6 belonging to operator B, the path loss values attained range between 125.19 to 169.09dB, 124.00 to 166.63dB, and 129.56-169.75dB, respectively. These high losses of propagated signals reveal that the terrain through which radio signals spread when being transmitted had a substantial effect on the strength and direction of the signals. Noticeably, higher path loss values can be seen at distances between 300 to 800m in Figure 4 and Figure 6, probably due to the presence of mountains and irregular terrain features along the transmitted radio signal paths. This is because of the weighty obstructs and attenuations of the signals received over the irregular paths, which causes weakling of the signals or higher path losses.

On the other hand, the path loss values attained employing the standard log-distance-based COST 231 Hata and Okumura Hata models across the six study locations are in the range of 180 to 230dB and 190-240dB, which are quite higher than all the measured path loss values. This is clear that the COST 231 Hata and Okumura Hata models over-predicted the measured loss values. In order to quantify the magnitude of the over-prediction realized with the standard models, six key indices are engaged. The evaluation indicators include the root mean square error (RMSE), Mean absolute percentage error (MAPE), Mean absolute error (MAE), coefficient of determination (R), and standard deviation (STD). While the MAE and RMSE express the mean absolute value and roots mean absolute differences between the measured path loss values and predicted values, the STD and R provide information on the level deviation and correlation between the measured and predicted loss values. Lower RMSE, MAE, and STD values imply better performance, while the reverse trend is for R values. The quantified levels of prediction estimation errors attained by the COST 231 Hata and Okumura Hata models in terms of RMSE, MAE, STD and MAPE are provided in Table 1. Such significant-high prediction error across the sites could result from clear physical terrain and topographical differences where the study locations are. Thus, the driver needs to fine-tune (i.e., adapt) the log-distance model to fit in the measured path loss data is evident.

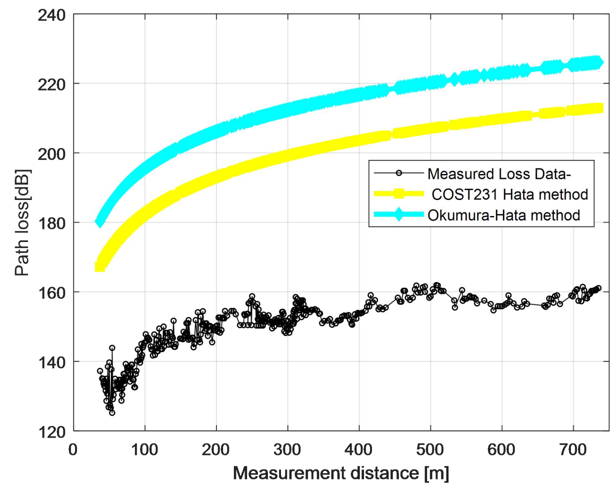

Figure 6: Measured path loss values compared to the ones made by COST 231 Hata and Okumura Hata prediction models in Location 1.

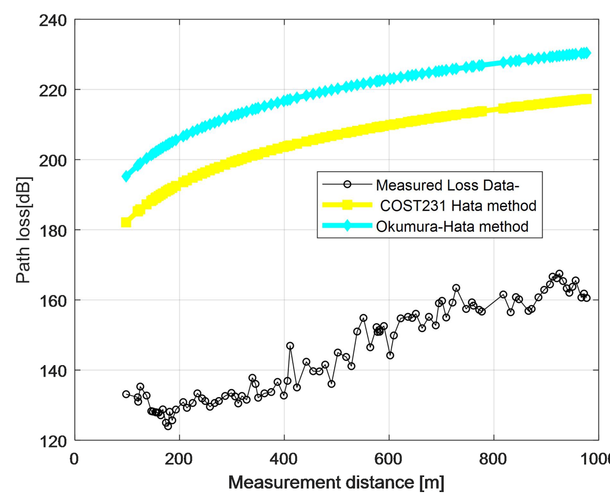

Figure 7: Measured path loss values compared to the ones made by COST 231 Hata and Okumura Hata prediction models in Location 2.

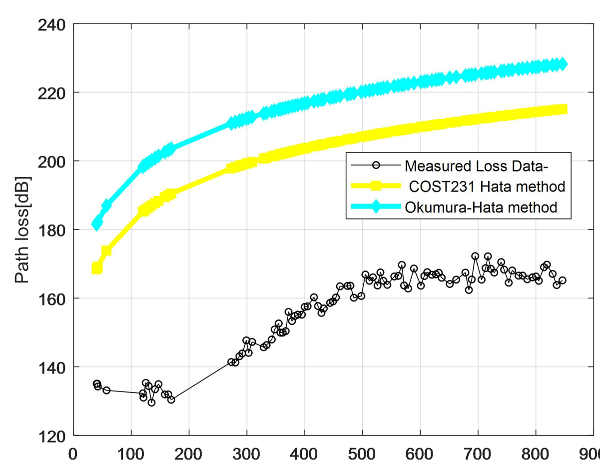

Figure 8: Measured path loss values compared to the ones made by COST 231 Hata and Okumura Hata prediction models in Location 3.

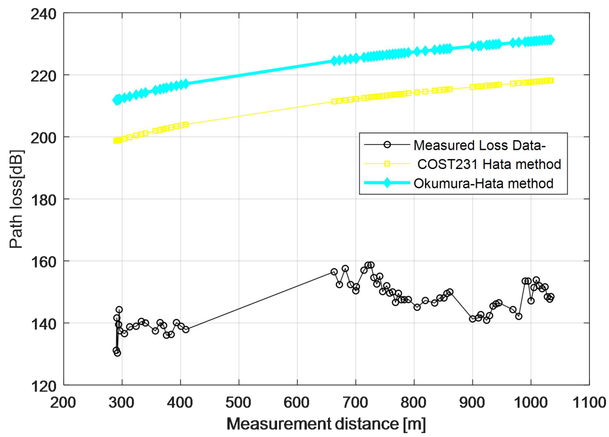

Figure 9: Measured path loss values compared to the ones made by COST 231 Hata and Okumura Hata prediction models in Location 4.

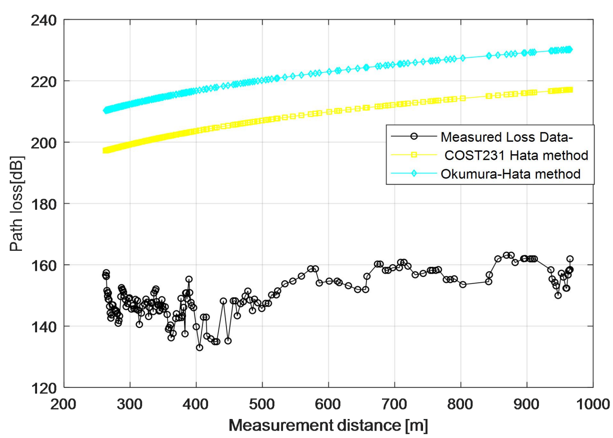

Figure 10: Measured path loss values compared to the ones made by COST 231 Hata and Okumura Hata prediction models in Location 5

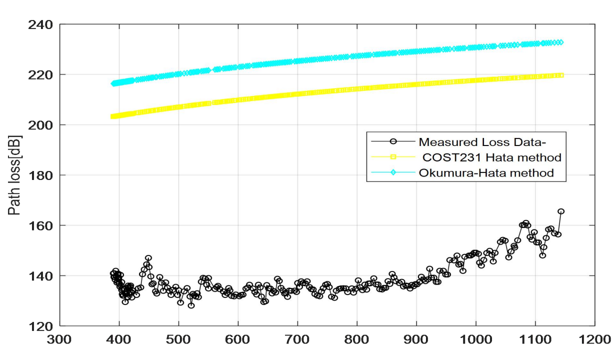

Figure 11: Measured path loss values compared to the ones made by COST 231 Hata and Okumura Hata prediction models in Location 6.

B. Results of proposed modified Log-distance path loss model tuned through NILS and WLILS methods in comparison with standard Log-distance model

One known crude method of enhancing existing path loss models for efficient predictive performance or reducing their prediction errors during application over terrain is to optimize their critical influencing parameters methods through the least square sense. This paper is termed the standard optimization method (or simply the standard method). However, there are times when concentration on only optimizing the models' key influencing parameters would not work, especially for irregular terrains.

To cater to this paper's above problem, we first modified the existing Hata model by adding a polynomial term. This is being done to improve its adaptive prediction level. Secondly, we proposed two methods, non-linear iterated least square (NILS) and weighted iterated least square methods, to optimize the key influencing parameters of the modified Hata models which are defined in section 2. The two proposed methods are termed as proposed optim. method 1 and proposed optim. method 2.

Figures 12–17 are plotted to specifically show the prediction capacity of adapted modified Log-distance model LM and WLM algorithms over the standard Log-distance model. In particular, **Figure 12** gives the measured path loss values compared to those predicted using standard and proposed optimized modified path loss models in location 1. **Figure 13** shows the measured path loss values compared to those predicted using standard and proposed optimized modified path loss models in location 2. **Figure 14** displays the measured path loss values compared to those predicted using standard and proposed optimized modified path loss models in location 3. **Figure 15** produces the measured path loss values compared to those predicted using standard and proposed optimized modified path loss models in location 4. **Figure 16** depicts the measured path loss values compared to those predicted using standard and proposed optimized modified path loss models in location 5. Last, **Figure 17** shows the measured path loss values compared to those predicted using standard and proposed optimized modified path loss models in location 6.

The results show that the adapted, modified Log-distance model attained better prediction precisions of measured path loss over the standard log-distance models, almost by 40%. As a case in point, while the adapted modified Log-distance model attained 1-4dB MAE values and 2.3-4.26 dB RMSE values, the adapted Standard Log-distance model attained 4.22-8.12 dB MAE values and 5.13 10.53 dB RMSE values. In terms of mean absolute percentage error, the adapted, modified Log-distance model attained 82.33 to 90.11% precision accuracy, while the adapted Standard Log-distance model only attained 52.43 to 80.71% precision accuracy.

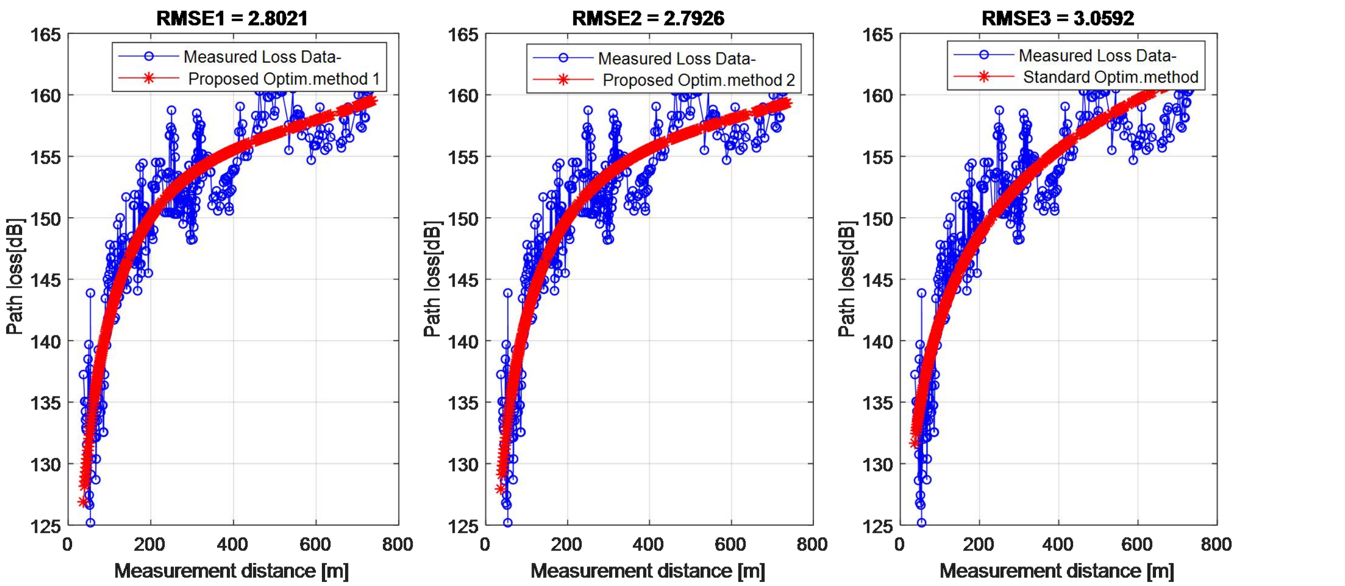

Figure 12: Measured path loss values compared to the ones predicted using standard and proposed optimized modified path loss models in Location 1

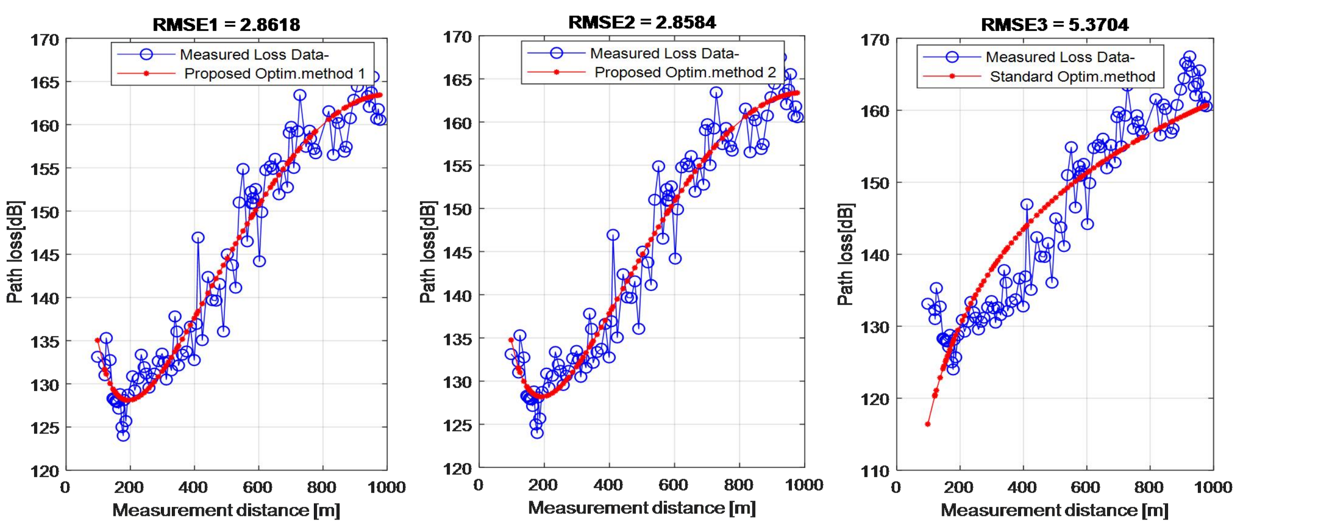

Figure 13: Measured path loss values compared to the ones predicted using standard and proposed optimized modified path loss models in Location 2

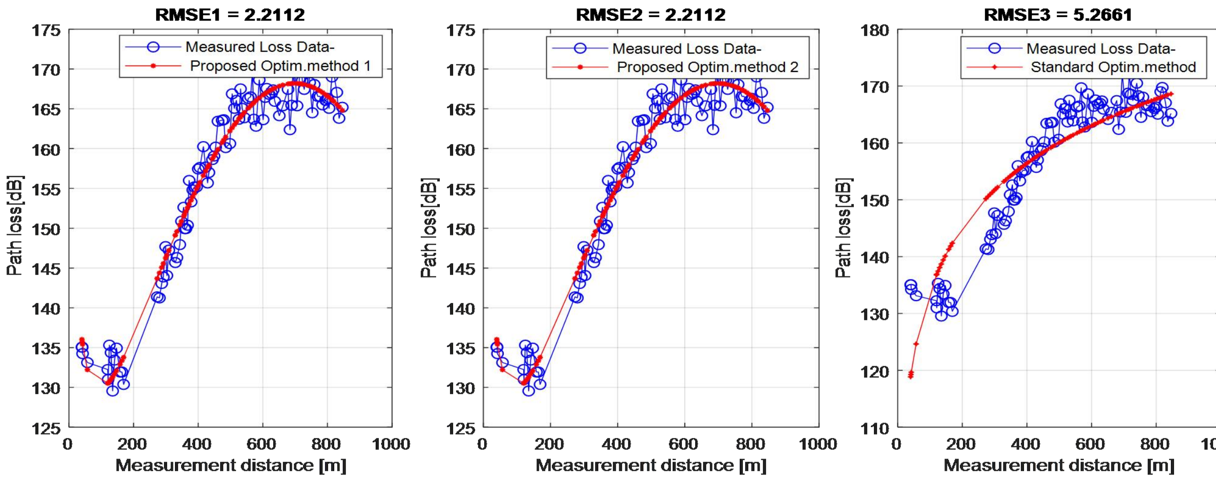

Figure 14: Measured path loss values compared to the ones predicted using standard and proposed optimized modified path loss models in Location 3

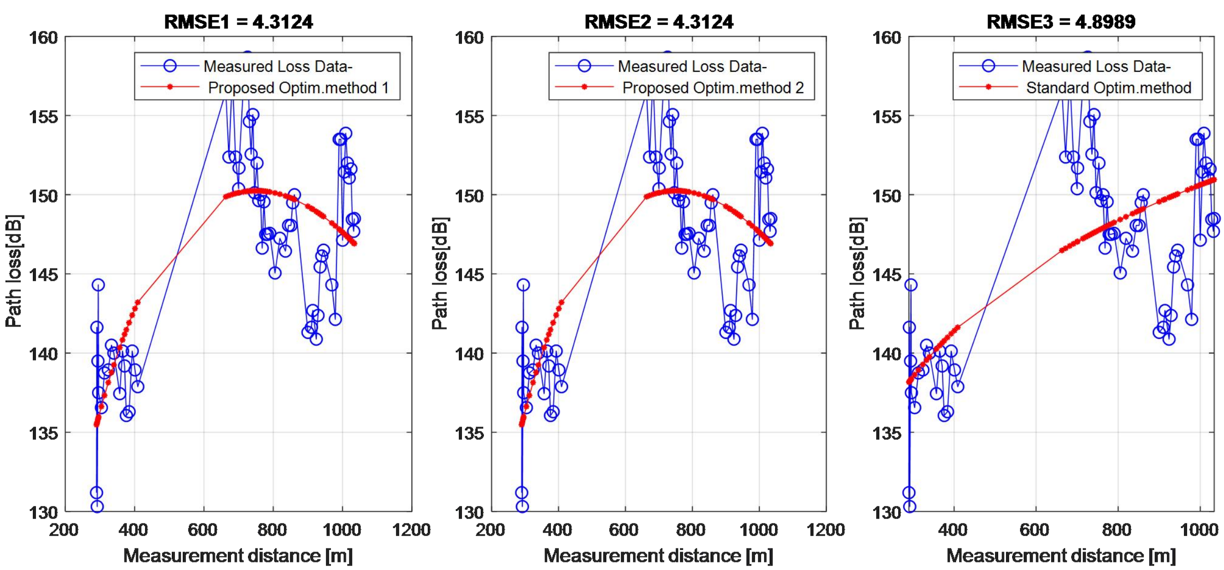

Figure 15: Measured path loss values compared to the ones predicted using standard and proposed optimized modified path loss models in Location 4

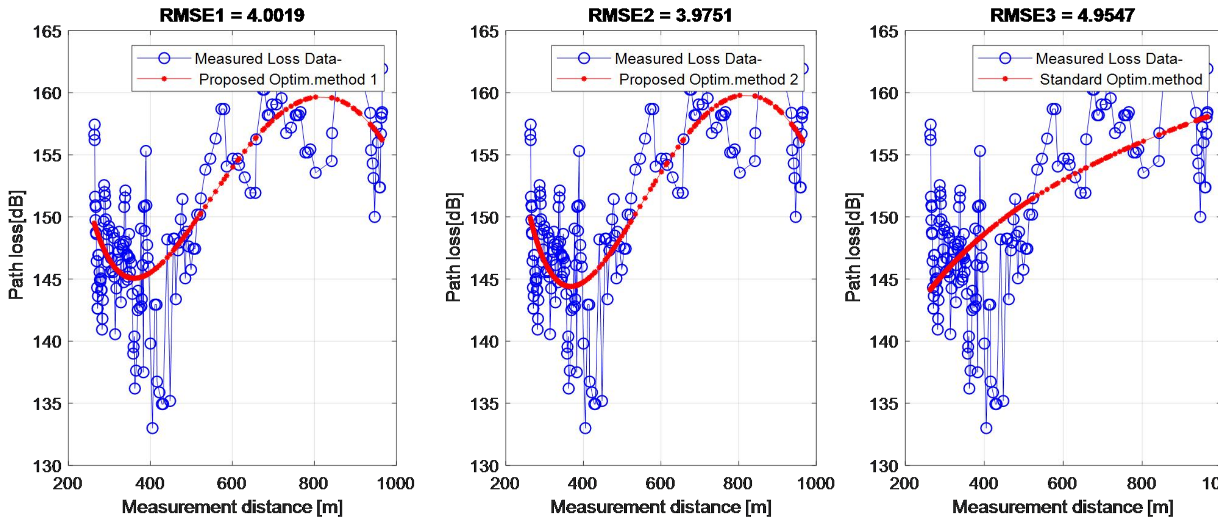

Figure 16: Measured path loss values compared to the ones predicted using standard and proposed optimized modified path loss models in Location 5

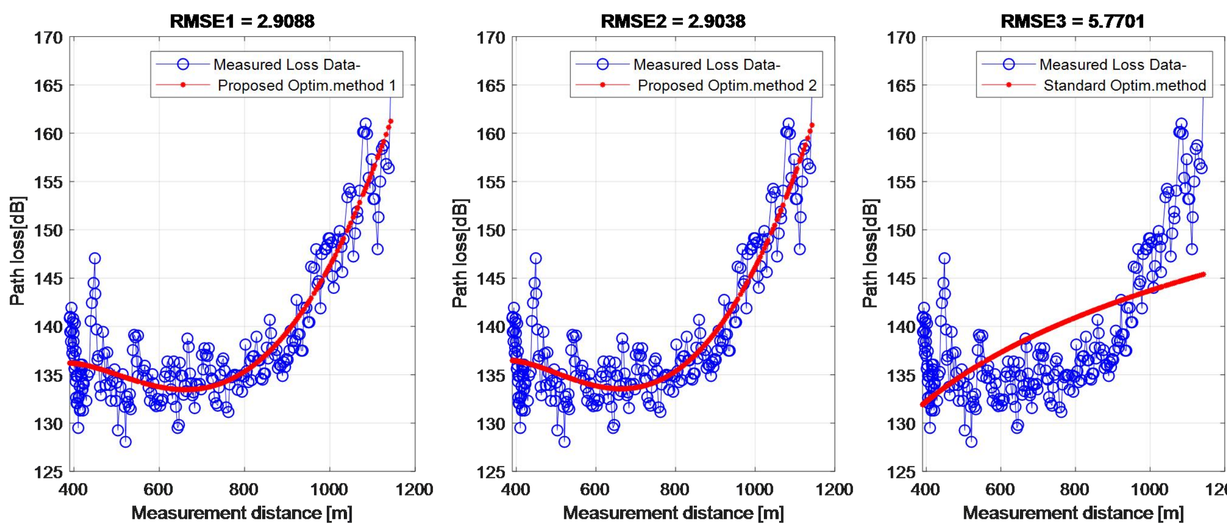

Figure 17: Measured path loss values compared to those predicted using standard and proposed optimized modified path loss models in Location 6.

Figures 18 to 23 are three in one set of graphs plotted to examine the absolute error values attained to compare the optimized models using the standard Log-distance model and modified Log-distance models, and classical unoptimized pathloss estimation methods using Hata, COST 231 Hata models. Specifically, **Figure 18** gives the quantified prediction absolute error values attained using the proposed optimized modified path loss models compared to those obtained using the standard in Location 1. **Figure 19** displays the quantified prediction absolute error values attained using the proposed optimized modified path loss models compared to those obtained using the standard in Location 2. **Figure 20** measures the quantified prediction absolute error values achieved using the proposed optimized modified path loss models compared to those obtained using the standard in Location 3. **Figure 21** provides the quantified prediction absolute error values attained using the proposed optimized modified path loss models compared to those obtained using the standard in Location 4. **Figure 22** displays the quantified prediction absolute error values achieved using the proposed optimized modified path loss models compared to those obtained using the standard in Location 5. **Figure 23** produces the quantified prediction absolute error values attained using the proposed optimized modified path loss models compared to those obtained using the standard in Location 6.

The proposed two modeling methods attained lower absolute error values than the standard model. In the second case, classical unoptimized pathloss estimation methods using Hata, COST 231 Hata models achieved up 23dB, 26dB and 30dB of the 75% pathloss data samples.

All the proposed optimized path loss modelling methods attained lower levels of absolute errors for the same 75% of the samples, thus indicating healthier stability in the predictive analysis.

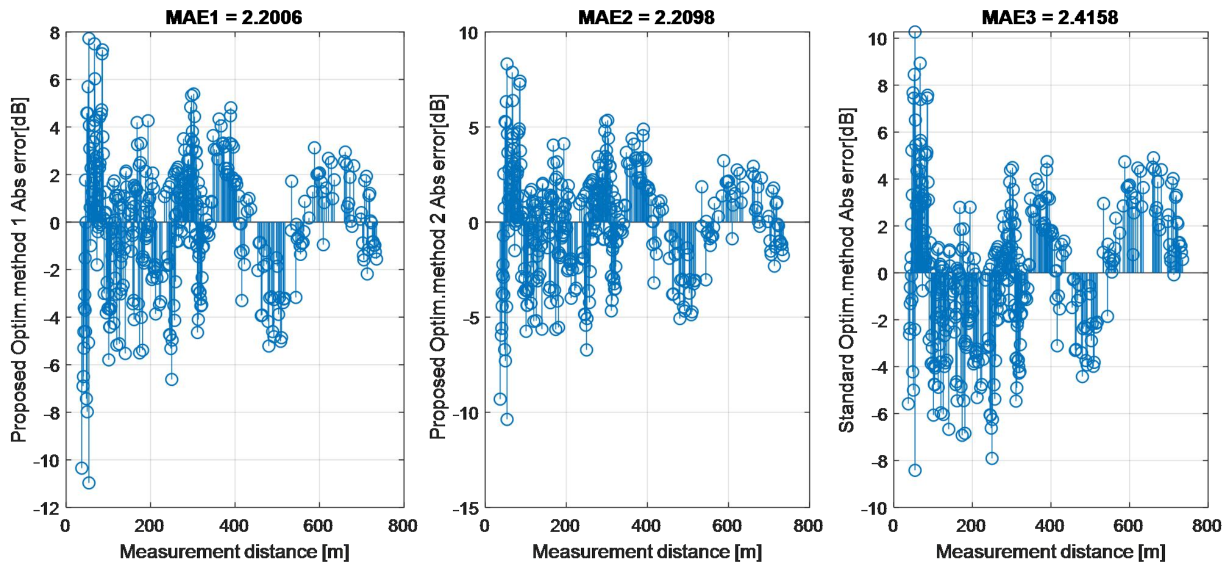

Figure 18: Quantified prediction absolute error values attained using the proposed optimized modified path loss models in comparison with ones obtained using standard in Location 1

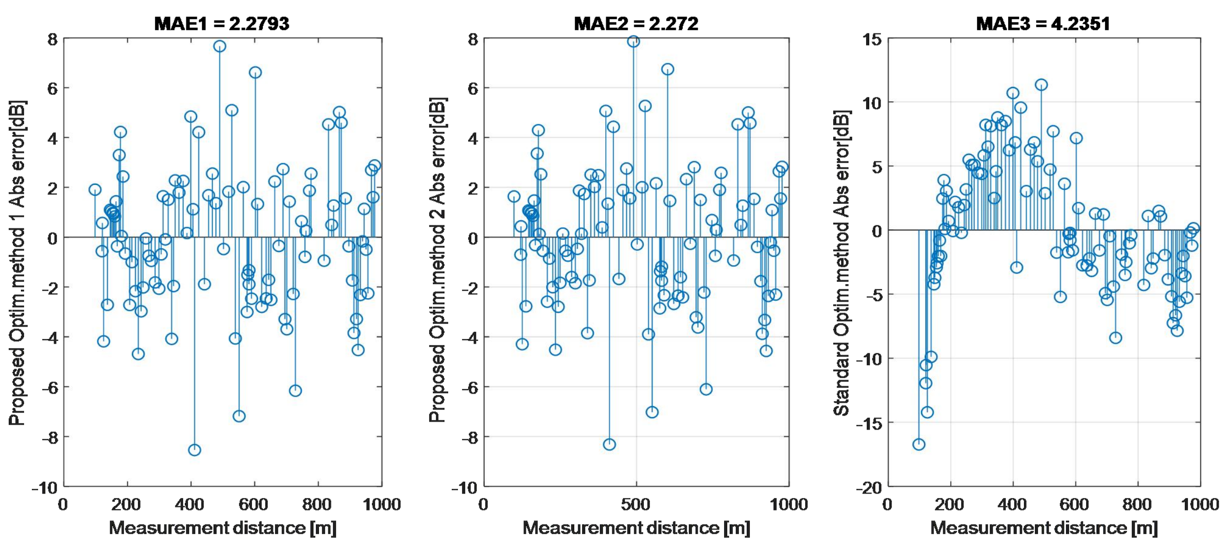

Figure 19: Quantified prediction absolute error values attained using the proposed optimized modified path loss models in comparison with ones obtained using standard in Location 2

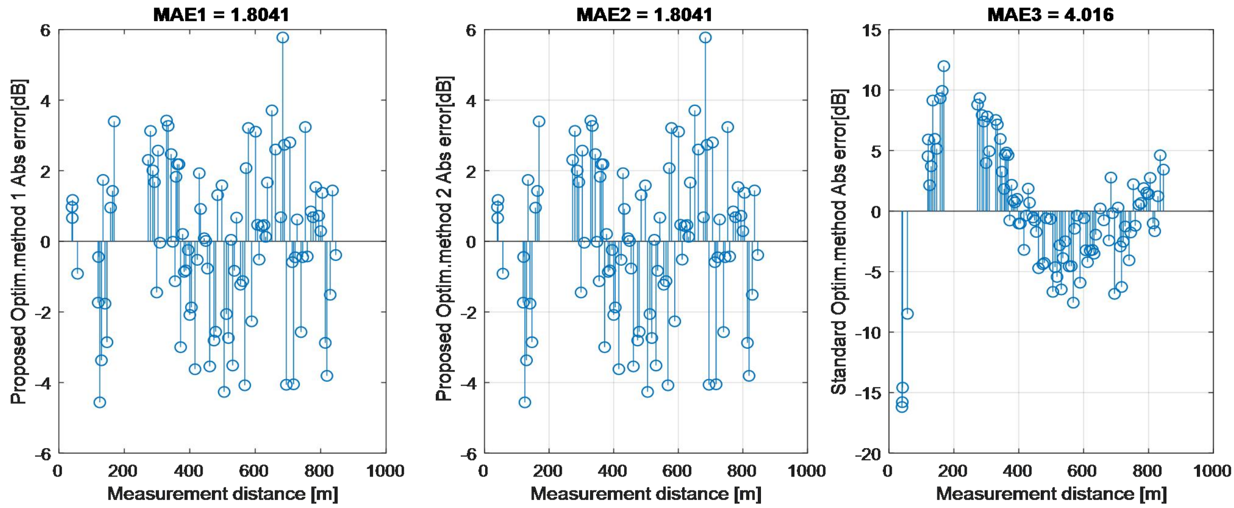

Figure 20: Quantified prediction absolute error values attained using the proposed optimized modified path loss models in comparison with ones obtained using standard in Location 3

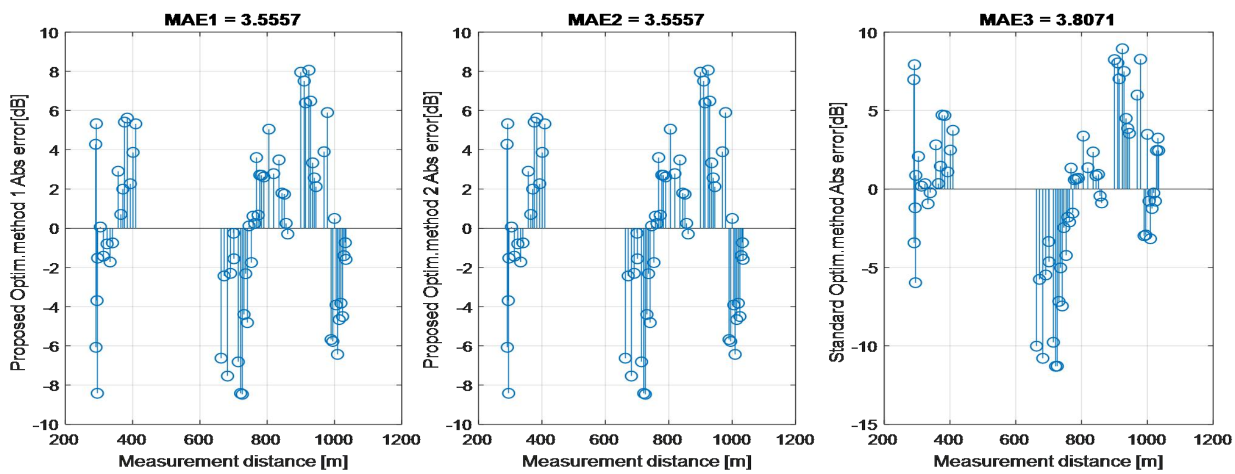

Figure 21: Quantified prediction absolute error values attained using the proposed optimized modified path loss models in comparison with ones obtained using standard in Location 4

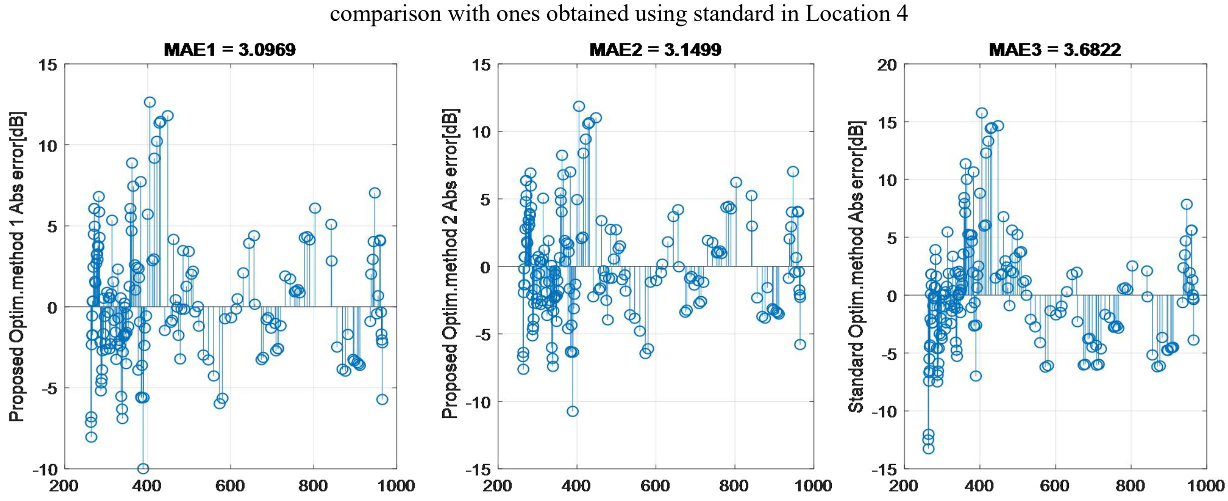

Figure 22: Quantified prediction absolute error values attained using the proposed optimized modified path loss models in comparison with ones obtained using standard in Location 5

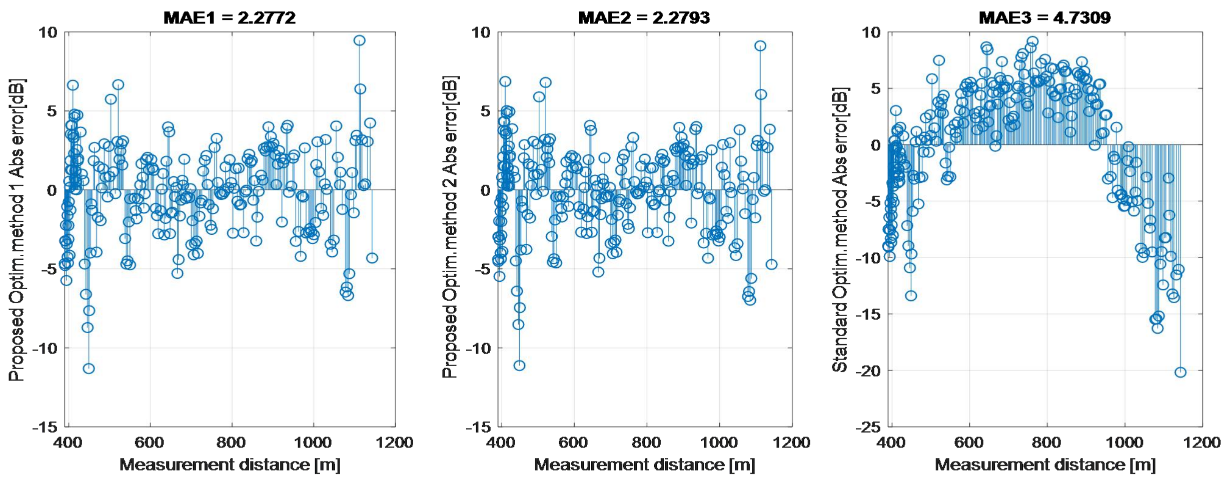

Figure 23: Quantified prediction absolute error values attained using the proposed optimized modified path loss models in comparison with ones obtained using standard in Location 6.

Figures 24 to 29 display the coefficient of correlation (R) results, plotted to compare further the precision accuracy between the proposed two-path loss and the standard optimization methods. **Figure 24** gives the quantified Correlation coefficient values attained using the proposed optimized modified path loss models compared to those obtained using the standard in Location 6. **Figure 25** produces the quantified Correlation coefficient values achieved using the proposed optimized modified path loss models compared to those obtained using the standard in Location 2. **Figure 26** displays the quantified Correlation coefficient values attained using the proposed optimized modified path loss models compared to those obtained using the standard in Location 3. **Figure 27** provides the quantified Correlation coefficient values achieved using the proposed optimized modified path loss models compared to those obtained using the standard in Location 4. **Figure 28** shows the quantified Correlation coefficient values attained using the proposed optimized modified path loss models compared to those obtained using the standard in Location 5. **Figure 29** gives the quantified Correlation coefficient values achieved using the two presented optimized modified path loss models in comparison with ones obtained using standard in Location 6

The graphs show that the R values realized by the proposed two-path loss optimization methods range from 0.9800 to 0.9999. On the other hand, the R values achieved by the standard optimization method are in the range of 0.9644 to 0.9944. **Table 2** gives the achieved prediction parameters for the network using the proposed methods and standard methods. **Table 3** shows the achieved prediction parameters for the network using the proposed methods and standard methods. The path loss prediction results using key performance evaluation indicators are summarized in **Tables 4 and 5.** These achieved path loss prediction performance enhancements in all six study location demonstrates the superiority of proposed two-path loss optimization methods over the standard optimization approaches.

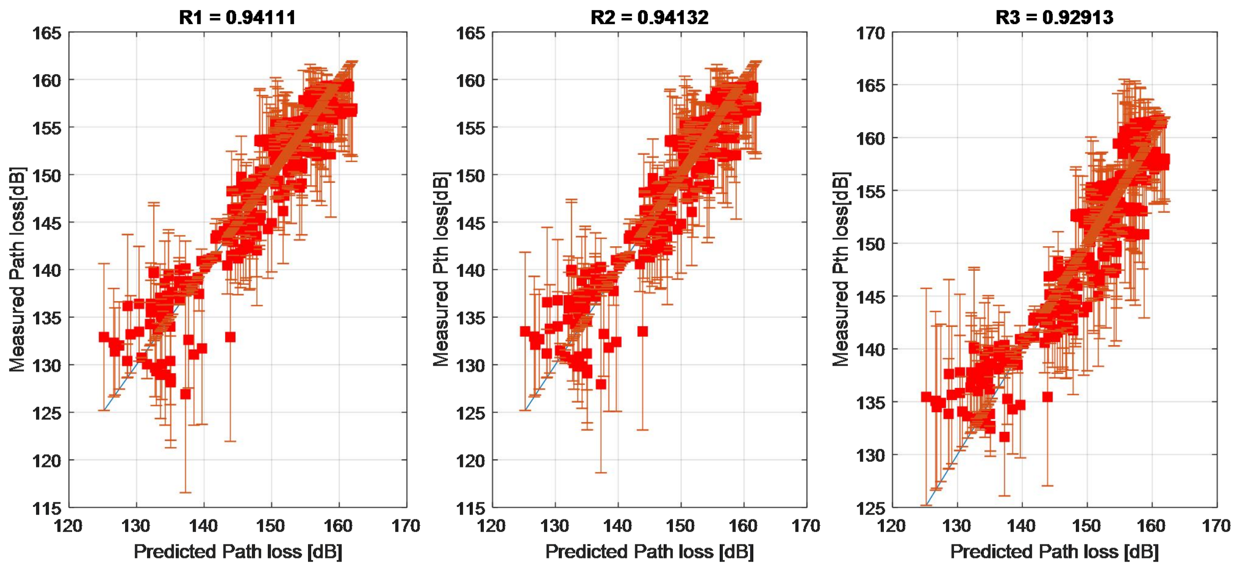

Figure 24: Quantified Correlation coefficient values attained using the proposed optimized modified path loss models in comparison with ones obtained using standard in Location 6

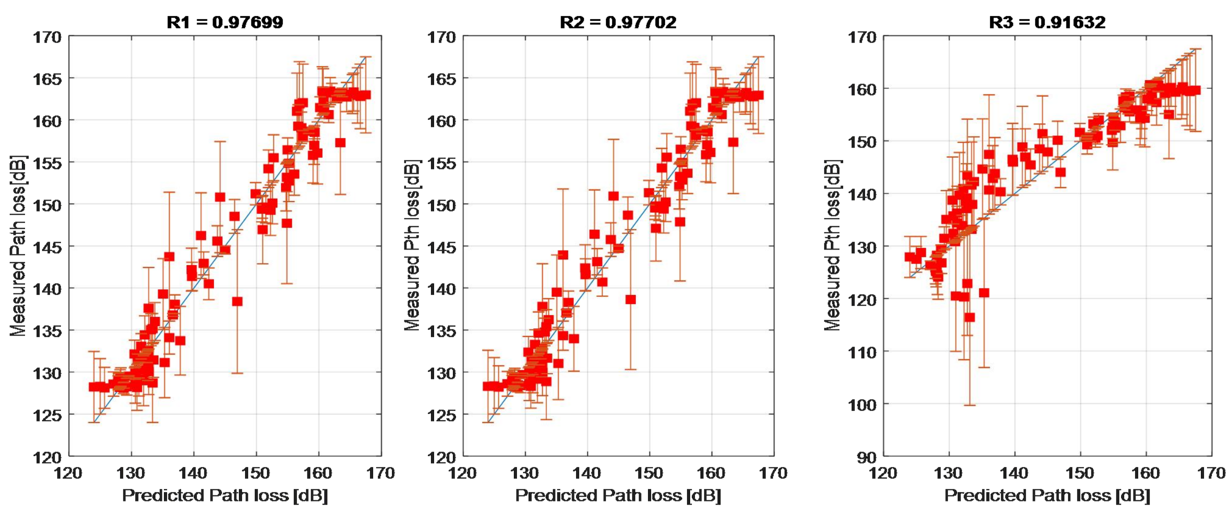

Figure 25: Quantified Correlation coefficient values attained using the proposed optimized modified path loss models in comparison with ones obtained using standard in Location 2

E-mail:olukannise@custech.edu.ng, joseph.isabona@fulokoja.edu.ng, ituabhor.odesanya@fulokoja.edu.ng, aimoize@unilag.edu.ng, cclee@mail.fju.edu.tw

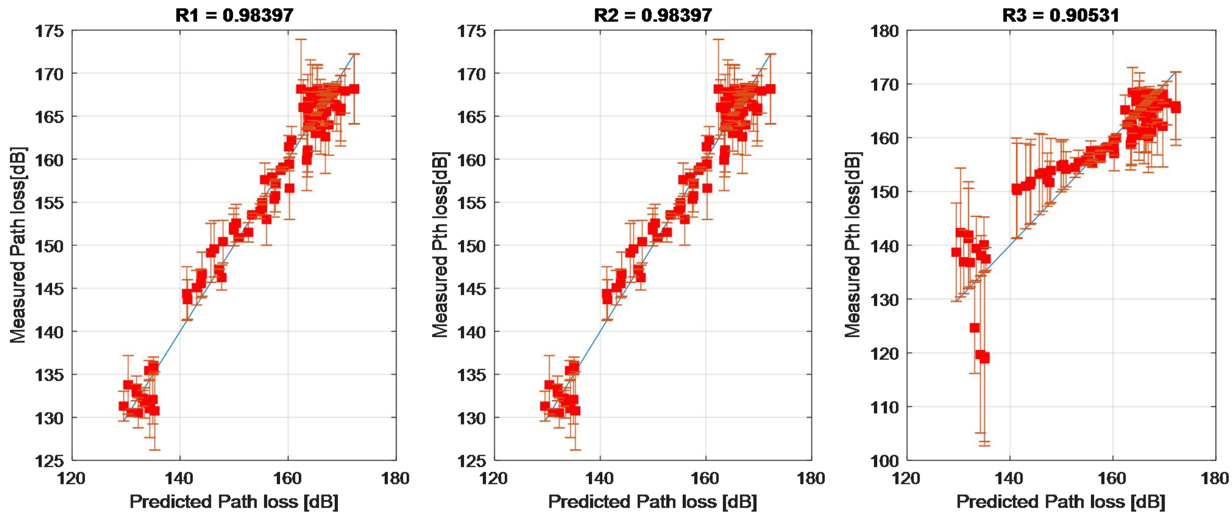

Figure 26: Quantified Correlation coefficient values attained using the proposed optimized modified path loss models in comparison with ones obtained using standard in Location 3

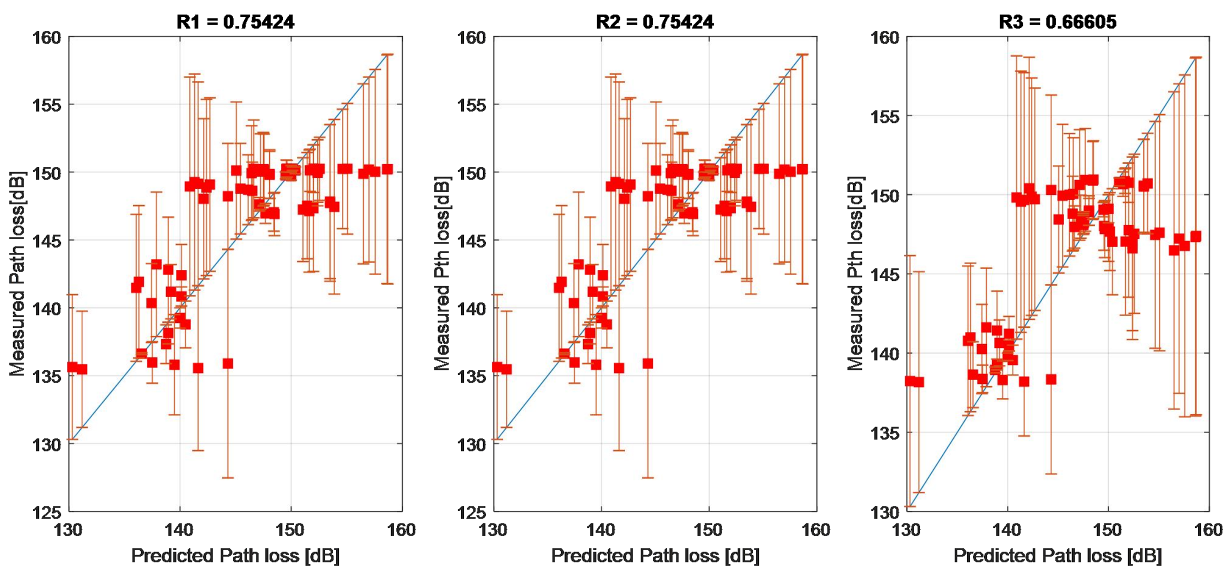

Figure 27: Quantified Correlation coefficient values attained using the proposed optimized modified path loss models in comparison with ones obtained using standard in Location 4

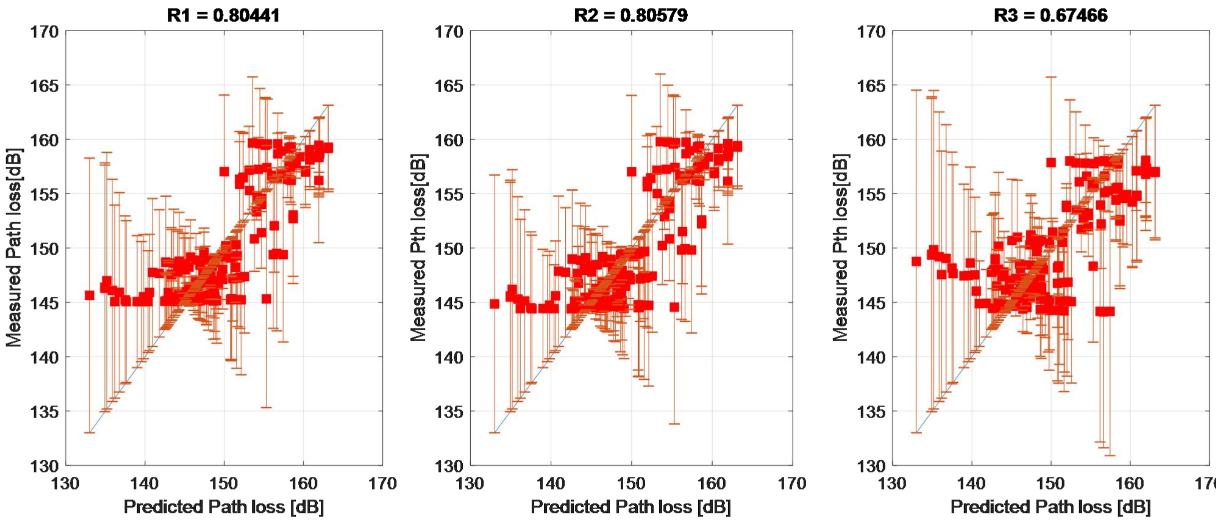

Figure 28: Quantified Correlation coefficient values attained using the proposed optimized modified path loss models in comparison with ones obtained using standard in Location 5

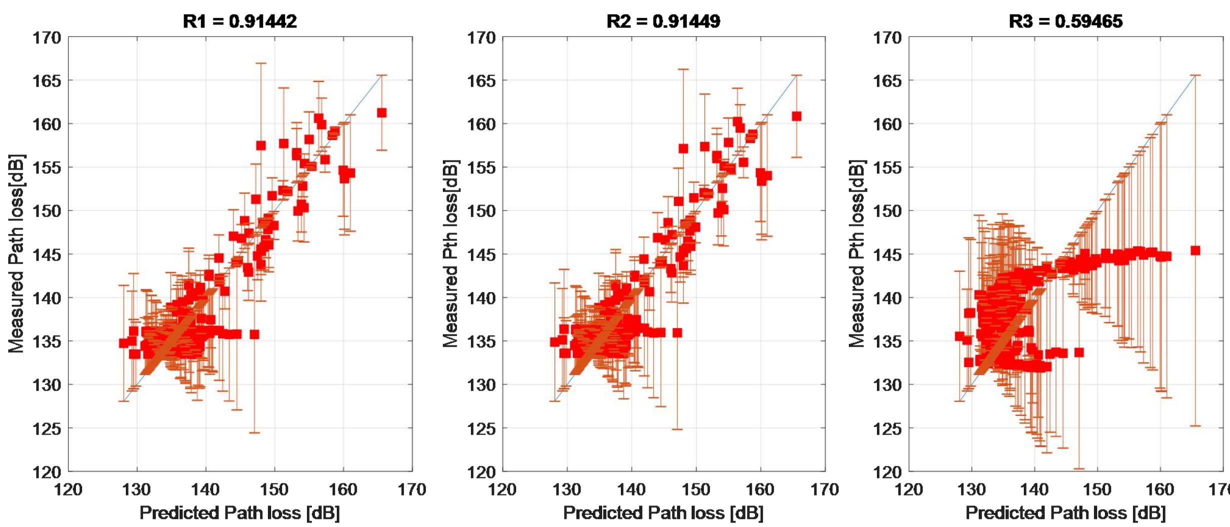

Figure 29: Quantified Correlation coefficient values attained using the two proposed optimized modified path loss models in comparison with ones obtained using standard in Location 6

Table 2

Achieved Prediction Parameters for Network A using Proposed Methods and Standard Method

Method	Location	a1	a2	a3	a4	a5
Proposed Method 1	Location 1	30.285	40.679	10.676	0.0000250	-0.048764
	Location 2	149.45	-96.76	53.035	-0.00010771	0.25803
	Location 3	104.45	-54.136	36.96	-0.00017789	0.28232
Proposed Method 2	Location 1	32.731	37.8	11.432	0.000018	-0.039406
	Location 2	147.45	-94.344	46.282	-0.00010642	0.25415
	Location 3	103.23	-54.136	33.202	-0.00017789	0.28232
Standard Method	Location 1	56.08	23.10	13.03		
	Location 2	22.41	44.35	1.73		
	Location 3	37.73	37.53	6.42		

Table 3

Achieved Prediction Parameters for Network A using Proposed Methods and Standard Method

Method	Location	a1	a2	a3	a4	a5
Proposed Method 1	Location 4	-20.52	74.15	-7.1127	-0.000019	-0.0151
	Location 5	431.22	-355.66	149.71	-0.00026215	0.61752
	Location 6	-178.03	241.07	-60.368	0.00020193	-0.42555
Proposed Method 2	Location 4	-20.52	74.15	-7.1127	-0.000018	-0.015136
	Location 5	476.28	-399.33	165.33	-0.00028839	0.68413
	Location 6	-159.14	223.88	-53.856	0.00019419	-0.40419
Standard Method	Location 4	48.93	23.16	9.85		
	Location 5	50.57	28.87	10.35		
	Location 6	36.91	28.86	6.17		

Table 4

Quantified Prediction Accuracies were achieved using the proposed two optimized modified path loss models in comparison with ones obtained using the standard for network A in Locations 1 to 3

Study Location	**Prediction Accuracy for Operator A**				
Location	MAE	RMSE	STD	R2	PE
Proposed method1	1.81	2.21	1.27	0.9998	1.16
Proposed method 2	1.80	2.21	1.27	0.9998	1.15
Standard method	4.02	5.26	3.41	0.9989	2.70
COST 231-Hata method	61.04	61.26	15.06	0.8482	28.10
Hata method	73.73	73.89	5.31	0.7792	32.06
Location 2					
Proposed method1	2.25	2.85	1.74	0.9996	1.53
Proposed method 2	2.25	2.85	1.74	0.9996	1.55
Standard method	4.23	5.37	3.30	0.9986	3.00
COST 231-Hata method	76.65	59.01	5.07	0.7427	33.29
Hata method	86.31	86.52	5.93	0.6473	37.41
Location 3					
Proposed method1	2.19	2.80	1.74	0.9996	1.49
Proposed method 2	2.20	2.79	1.70	0.9997	1.49
Standard method	2.41	3.06	1.87	0.9996	1.63
COST 231-Hata method	58.79	59.01	5.06	0.8449	28.19
Hata method	71.45	71.63	5.06	0.7714	32.31

Table 5

Quantified Prediction Accuracies were achieved using the proposed two optimized modified path loss models in comparison with ones obtained using the standard for Operator B in Locations 4 to 6

Study Location	**Prediction Accuracy for Operator B**				
Location 4	MAE	RMSE	STD	R2	PE
Proposed method1	2.25	2.9111	1.83	0.9996	1.62
Proposed method 2	2.27	2.90	1.81	0.9996	1.63
Standard method	4.73	5.77	3.30	0.9983	3.39
COST 231-Hata method	86.64	59.01	63.44	0.6085	38.47
Hata method	99.30	99.48	5.85	0.4862	41.75
Location 5					
Proposed method1	3.11	3.99	2.51	0.9993	2.07
Proposed method 2	3.15	3.97	2.42	0.9993	2.11
Standard method	3.68	4.96	3.32	0.9989	2.46
COST 231-Hata method	69.40	59.01	36.36	0.7849	31.64
Hata method	82.06	82.24	5.31	0.6998	35.37
Location 6					
Proposed method1	2.61	3.49	1.83	0.8742	1.78
Proposed method 2	2.63	3.18	1.76	0.8753	1.81
Standard method	3.80	4.90	3.08	0.9995	2.60
COST 231-Hata method	78.62	59.01	51.96	0.7104	36.95
Hata method	91.29	91.46	5.40	0.6101	38.42

C. Results of the proposed modified Log-distance model tuned using the NILS

The expressions in (28) and (29) describe the proposed modified Log-distance models developed for Networks A and B, enabling them to conduct optimal path loss predictive analysis and estimation for the studied irregular terrains. Only the resultant models attained using the NILS method are shown for brevity.

$$PL_{network\ A}(dB) = 126.95 - 75.45 \times \log_{10}(r) + 44.86 \times \log_{10}(f_c) - 0.00015 \times r^2 + 0.2707 \times r \quad (28)$$

$$PL_{network\ B}(dB) = 121.59 - 57.30 \times \log_{10}(r) + 44.67 \times \log_{10}(f_c) - 0.00003 \times r^2 + 0.096 \times r \quad (29)$$

Figures 30 and 31 are provided to reveal the accuracies attained in engaging the two models' path loss prediction in other eNodeB study locations for Network A and B for the sake of validity. In terms of RMSE, STD and MAE, the two models attained 6.76dB, 3.62dB, 5.78 dB and 5.82dB, 4.84dB, and 4.55dB precision accuracies, respective for network A and Network B. The results are quite better than those achieved with the standard models, affirming our study aim.

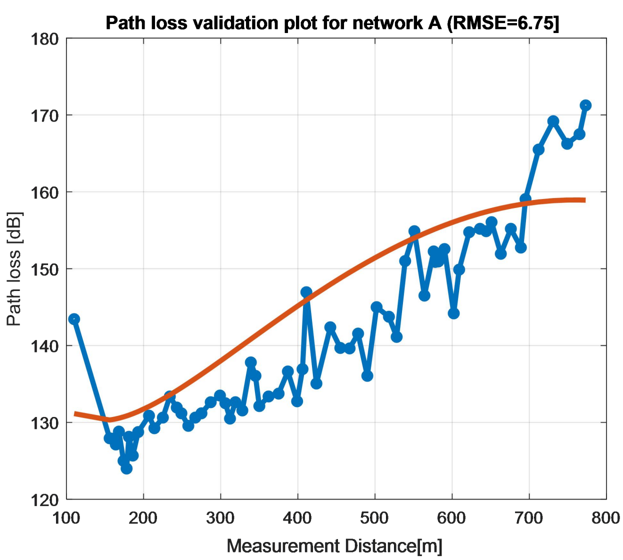

Figure 30: Validated Path loss prediction plot proposed optimized modified path loss models for Network A

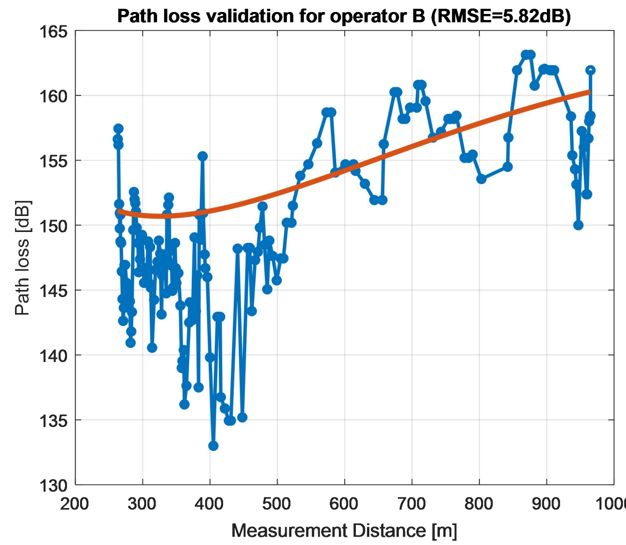

Figure 31: Validated Path loss prediction plot proposed optimized modified path loss models for Network B

5. CONCLUSIONS

The use of existing path loss models for optimal extrapolative analyses of path loss from propagated radio waves along different communication channels plays a vital role in optimal microcellular planning and management in a given terrain. This study has modified an existing model to cater to the optimal extrapolative analysis of path loss, particularly in complex terrains. The parameters of the modified model have been tuned using the Levenberg-Marquart (LM) algorithm to boost prediction accuracy. The modified Log-distance model was applied to practical predictive analysis of path loss data obtained from Nigeria's two main operational LTE broadband networks. Results indicate that the modified log-distance model demonstrates clear optimal prediction accuracy over the standard loss model. The modified log-distance model also indicates higher prediction in related microcellular environments than the preliminaries. The transmission loss over irregular terrain is a complex function of frequency, path geometry, vegetation density, and other variables. Every physical entity or object transmitted by radio signals encounters over the communication paths affects the direction and coverage quality. The physical entities include manmade 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. Future work would investigate the optimal characterization of the projected pathloss models over irregular terrains.

List of Abbreviations

CDMA	Code Division Multiple Access
LMA	Levenberg-Marquardt Algorithm
LTE	Long Term Evolution
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MBCNS	Mobile Broadband Cellular Network Systems
MLM	Modified Log-distance Model
NR	New Radio
QMM	Quasi-Moment Method
RMSE	Root Mean Square Error
STD	Standard Deviation
SUI	Stanford University Interim

Availability of Data and Material

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Competing Interests

The authors declare that they have no conflicts of interest.

Funding

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Authors' Contribution

The manuscript was written through the contributions of all authors. Conceptualization, S.E.O., J.I., and I.O.; methodology, S.E.O., J.I., I.O., and A.L.I.; writing—original draft preparation, S.E.O.; writing—review and editing, S.E.O., J.I., and I.O., A.L.I., and C.-C.L.; supervision, J.I.; project administration, J.I., A.L.I., and C.-C.L.; funding acquisition, A.L.I., and C.-C.L. All authors have read and agreed to the published version of the manuscript.

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References

[1] I. O. Ann, O. Itanyi, and I. U. Wilfred, "Managing innovations in telecommunications industry in Nigeria," *African J. Bus. Manag.*, vol. 6, no. 25, pp. 7469–7477, 2012.

[2] T. Hidayat, R. Mahardiko, and M. Alaydrus, "Mobile cellular technology forecast for the Indonesian telecommunications industry," *J. Telecommun. Digit. Econ.*, vol. 8, no. 1, pp. 37–48, 2020.

[3] G. Kalem, O. Vayvay, B. Sennaroglu, and H. Tozan, "Technology forecasting in the mobile telecommunication industry: A case study towards the 5G era," *Eng. Manag. J.*, vol. 33, no. 1, pp. 15–29, 2021.

[4] A. L. Imoize, S. O. Tofade, G. U. Ughegbe, F. I. Anyasi, and J. Isabona, "Updating analysis of key performance indicators of 4G LTE network with the prediction of missing values of critical network parameters based on experimental data from a dense urban environment," *Data Br.*, p. 108240, 2022, doi: https://doi.org/10.1016/j.dib.2022.108240.

[5] A. L. Imoize, K. Orolu, and A. A.-A. Atayero, "Analysis of key performance indicators of a 4G LTE network based on experimental data obtained from a densely populated smart city," *Data Br.*, vol. 29, no. 105304, pp. 1–17, 2020, doi: 10.1016/j.dib.2020.105304.

[6] A. L. Imoize and O. D. Adegbite, "Measurements-Based Performance Analysis of a 4G LTE Network in and Around Shopping Malls and Campus Environments in Lagos Nigeria," *Arid Zo. J. Eng. Technol. Environ.*, vol. 14, no. 2, pp. 208–225, 2018.

[7] J. Isabona *et al.*, "Development of a Multilayer Perceptron Neural Network for Optimal Predictive Modeling in Urban Microcellular Radio Environments," *Applied Sciences*, vol. 12, no. 11. p. 5713, 2022, doi: 10.3390/app12115713.

[8] J. Isabona and K. Obahiagbon, "RF propagation measurement and modelling to support adept planning of outdoor wireless local area networks in 2.4 GHz Band," *Am. J. Eng. Res.*, vol. 3, no. 1, pp. 258–267, 2014.

[9] A. Igbinovia and J. Isabona, "Empirical Investigation of Field Strength Spatial Coverage Variability in Mobile Radio Communication Networks," *Int. J. Res. Stud. Electr. …*, vol. 4, no. 4, pp. 33–41, 2018, doi: 10.20431/2454-9436.0404004.

[10] L. Wu *et al.*, "Received power prediction for suburban environment based on neural network," in *2020 International Conference on Information Networking (ICOIN)*, 2020, pp. 35–39.

[11] Z. Huang, X. Cheng, and N. Zhang, "An improved non-geometrical stochastic model for non-WSSUS vehicle-to-vehicle channels," *ZTE Commun.*, vol. 17, no. 4, p. 62, 2019.

[12] U. Karabulut, A. Awada, I. Viering, M. Simsek, and G. P. Fettweis, "Spatial and temporal channel characteristics of 5G 3D channel model with beamforming for user mobility investigations," *IEEE Commun. Mag.*, vol. 56, no. 12, pp. 38–45, 2018.

[13] J.-C. Brumm, H. Strohm, and G. Bauch, "A stochastic channel model for ultra wideband in-body communication," in *2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2019, pp. 4032–4035.

[14] D. He, B. Ai, K. Guan, L. Wang, Z. Zhong, and T. Kürner, "The design and applications of high-performance ray-tracing simulation platform for 5G and beyond wireless communications: A tutorial," *IEEE Commun. Surv. Tutorials*, vol. 21, no. 1, pp. 10–27, 2018.

[15] K. Chamberlin and R. Luebbers, "An evaluation of Longley-Rice and GTD propagation models," *IEEE Trans. Antennas Propag.*, vol. 30, no. 6, pp. 1093–1098, 1982.

[16] J. B. Andersen, "UTD multiple-edge transition zone diffraction," *IEEE Trans. Antennas Propag.*, vol. 45, no. 7, pp. 1093–1097, 1997.

[17] M. Hata, "Empirical Formula for Propagation Loss in Land Mobile Radio Services," *IEEE Trans. Veh. Technol.*, vol. 29, no. 3, pp. 317–325, 1980, doi: 10.1109/T-VT.1980.23859.

[18] J. J. Egli, "Radio Propagation above 40 MC over Irregular Terrain," *Proc. IRE*, vol. 45, no. 10, pp. 1383–1391, 1957, doi: 10.1109/JRPROC.1957.278224.

[19] V. C. Ebhota, J. Isabona, and V. M. Srivastava, "Environment-Adaptation Based Hybrid Neural Network Predictor for Signal Propagation Loss Prediction in Cluttered

and Open Urban Microcells," *Wirel. Pers. Commun.*, vol. 104, no. 3, pp. 935–948, 2019, doi: 10.1007/s11277-018-6061-2.

[20] J. Isabona and D. Ojuh, "Adaptation of Propagation Model Parameters toward Efficient Cellular Network Planning using Robust LAD Algorithm," *Int. J. Wirel. Microw. Technol.*, vol. 10, no. 5, pp. 13–24, 2020, doi: 10.5815/ijwmt.2020.05.02.

[21] S. O. Ajose and A. L. Imoize, "Propagation measurements and modelling at 1800 MHz in Lagos Nigeria," *Int. J. Wirel. Mob. Comput.*, vol. 6, no. 2, pp. 165–174, 2013, doi: 10.1504/IJWMC.2013.054042.

[22] J. Isabona and V. M. Srivastava, "Coverage and Link Quality Trends in Suburban Mobile Broadband HSPA Network Environments," *Wirel. Pers. Commun.*, vol. 95, no. 4, pp. 3955–3968, 2017, doi: 10.1007/s11277-017-4034-5.

[23] I. Joseph and C. C. Konyeha, "Urban area path loss propagation prediction and optimisation using Hata model at 800MHz," *IOSR J. Appl. Phys.*, vol. 3, no. 4, pp. 8–18, 2013.

[24] J. Zhang, C. Gentile, and W. Garey, "On the cross-application of calibrated pathloss models using area features: finding a way to determine similarity between areas," *IEEE Antennas Propag. Mag.*, vol. 62, no. 1, pp. 40–50, 2019.

[25] M. A. Amanaf, A. Hikmaturokhman, and A. F. Septian, "Calibrating the Standard Propagation Model (SPM) for Suburban Environments Using 4G LTE Field Measurement Study Case in Indonesia," in *IOP Conference Series: Materials Science and Engineering*, 2020, vol. 982, no. 1, p. 12029.

[26] S. I. Popoola, A. A. Atayero, N. Faruk, C. T. Calafate, E. Adetiba, and V. O. Matthews, "Calibrating the standard path loss model for urban environments using field measurements and geospatial data," in *Proceedings of the World Congress on Engineering*, 2017, vol. 1, pp. 5–7.

[27] M. A. Adelabu, A. A. Ayorinde, H. A. Muhammed, F. O. Okewole, and I. Mowete, "A Quasi-Moment-Method-Based Calibration of Basic Pathloss Models," *Elektr. Electr. Eng.*, vol. 19, no. 3, pp. 35–48, 2020.

[28] M. A. Adelabu, A. Ayorinde, and A. I. Mowete, "Prediction Characteristics of Quasi-Moment-Method Calibrated Pathloss Models," *Int. J. Comput. Appl.*, vol. 975, p. 8887, 2020.

[29] M. A. K. Adelabu, A. A. Ayorinde, H. A. Muhammed, F. O. Okewole, and A. I. Mowete, "An Evaluation of Quasi-Moment-Method Calibrated Pathloss Models for Benin City Nigeria," *Niger. J. Technol.*, vol. 40, no. 3, pp. 472–483, 2021.

[30] J. M. Kelner, M. Kryk, J. Łopatka, and P. Gajewski, "A statistical calibration method of propagation prediction model based on measurement results," *Int. J. Electron. Telecommun.*, vol. 66, 2020.

[31] C. Phillips, D. Sicker, and D. Grunwald, "Bounding the practical error of path loss models," *Int. J. Antennas Propag.*, vol. 2012, 2012.

[32] J. Isabona and A. L. Imoize, "Terrain-based adaption of propagation model loss parameters using non-linear square regression," *J. Eng. Appl. Sci.*, vol. 68, no. 1, pp. 1–19, 2021.

[33] L. Akhoondzadeh-Asl and N. Noori, "Modification and Tuning of the Universal Okumura-Hata Model for Radio Wave Propagation Predictions," in *2007 Asia-Pacific Microwave Conference*, 2007, pp. 1–4, doi: 10.1109/APMC.2007.4554925.

[34] Z. Nadir and M. I. Ahmad, "Pathloss determination using Okumura-Hata model and cubic regression for missing data for Oman," *Proc. Int. MultiConference Eng. Comput. Sci. 2010, IMECS 2010*, no. March, pp. 804–807, 2010.

[35] A. Akinbolati and M. O. Ajewole, "Investigation of path loss and modeling for digital terrestrial television over Nigeria," *Heliyon*, vol. 6, no. 6, p. e04101, 2020, doi: https://doi.org/10.1016/j.heliyon.2020.e04101.

[36] T. Jawhly and R. C. Tiwari, "The special case of Egli and Hata model optimization using least-square approximation method," *SN Appl. Sci.*, vol. 2, no. 7, pp. 1–10, 2020.

[37] B. S. L. Castro, M. R. Pinheiro, G. P. S. Cavalcante, I. R. Gomes, and O. De O Carneiro, "Comparison between known propagation models using least squares tuning algorithm on 5.8 GHz in Amazon region cities," *J. Microwaves Optoelectron.*, vol. 10, no. 1, pp. 106–113, 2011, doi: 10.1590/S2179-10742011000100011.

[38] D. Castro-Hernandez and R. Paranjape, "Local Tuning of a Site-Specific Propagation Path Loss Model for Microcell Environments," *Wirel. Pers. Commun.*, vol. 91, no. 2, pp. 709–728, 2016, doi: 10.1007/s11277-016-3489-0.

[39] M. Yang and W. Shi, "A Linear Least Square Method of Propagation Model Tuning for 3G Radio Network Planning," in *2008 Fourth International Conference on Natural Computation*, 2008, vol. 5, pp. 150–154, doi: 10.1109/ICNC.2008.188.

[40] I. Simi, I. Stani, and B. ZIRNI, "Minimax LS algorithm for automatic propagation model tuning," 2001.

[41] K. Ravindra, A. D. Sarma, and M. Prasad, "An adaptive polynomial path loss model at UHF frequencies for mobile railway communications," 2002.

[42] R. Mardeni and L. Y. Pey, "The optimization of Okumura's model for Code Division Multiple Access (CDMA) system in Malaysia," *Eur. J. Sci. Res.*, vol. 45, no. 4, pp. 508–528, 2010.

[43] E. AarnæS and S. Holm, "Tuning of Empirical Radio Propagation Models Effect of Location Accuracy," *Wirel. Pers. Commun.*, vol. 30, no. 2, pp. 267–281, 2004, doi: 10.1023/B:WIRE.0000049404.44405.82.

[44] J. Isabona, "Wavelet Generalized Regression Neural Network Approach for Robust Field Strength Prediction," *Wirel. Pers. Commun.*, vol. 114, pp. 3635–3653, 2020, [Online]. Available: https://doi.org/10.1007/s11277-020-07550-5.

[45] J.-S. R. Jang and E. Mizutani, "Levenberg-Marquardt method for ANFIS learning," in *Proceedings of North American Fuzzy Information Processing*, 1996, pp. 87–91, doi: 10.1109/NAFIPS.1996.534709.

[46] J. Fan, "The modified Levenberg-Marquardt method for non-linear equations with cubic convergence," *Math. Comput.*, vol. 81, no. 277, pp. 447–466, 2012, doi: 10.1090/s0025-5718-2011-02496-8.

[47] E. H. Bergou, Y. Diouane, and V. Kungurtsev, "Convergence and complexity analysis of a Levenberg–Marquardt algorithm for inverse problems," *J. Optim. Theory Appl.*, vol. 185, no. 3, pp. 927–944, 2020.

[48] N. Yamashita and M. Fukushima, "On the rate of convergence of the Levenberg-Marquardt method," in *Topics in numerical analysis*, Springer, 2001, pp. 239–249.

[49] J. Isabona and D. O. Ojuh, "Application of Levenberg-Marguardt Algorithm for Prime Radio Propagation Wave Attenuation Modelling in Typical Urban, Suburban and Rural Terrains," *Int. J. Intell. Syst. Appl.*, vol. 13, no. 3, pp. 35–42, 2021.

[50] Z. Yan, S. Zhong, L. Lin, and Z. Cui, "Adaptive Levenberg–Marquardt algorithm: A new optimization strategy for Levenberg–Marquardt neural networks," *Mathematics*, vol. 9, no. 17, p. 2176, 2021.

[51] I. O. Oluseyi and A. J. Olusegun, "Managing land use transformation and land surface temperature change in Anyigba Town, Kogi State, Nigeria," *J. Geogr. Geol.*, vol. 3, no. 1, p. 77, 2011.

[52] U. A. Saleh, Y. S. Haruna, S. M. Isa, and S. A. Jumaat, "Statistical Evaluation of Wind Speed Data for Power Generation at Anyigba, Kogi State, Nigeria," in *Proceedings of the 12th National Technical Seminar on Unmanned System Technology 2020*, 2022, pp. 1091–1101.

[53] M. H. Sani and U. Haruna, "Farm planning model for sustainable vegetable crop production in the Eastern part of Kogi State, Nigeria.," *J. Agron.*, vol. 9, no. 1, pp. 17–22, 2010.

[54] N. P. Commission, "Nigerian population census," *Publ. by NPC, Abuja*, 2006.

[55] E. O. Abubakar, "An integrated geospatial analysis of land

suitability for urban expansion in Lokoja, Nigeria," *An M. Sc Thesis Submitt. to Dep. Geogr. Obafemi Awolowo Univ. (OAU), Ile Ife, Osun State, Niger.*, 2013.

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