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An Adaptive Hybrid Outdoor Propagation Loss Prediction Modelling for Effective Cellular Systems Network Planning and Optimization

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Abstract: The frequent poor service network experienced by some mobile phone users within some deadlock areas in Nigeria is an issue which has been identified by different researchers due to wrong positioning and planning of the evolved NodeB (eNodeB) transmitter using existing propagation loss models. To effectively contribute towards this potential issue constantly experienced in some part of Nigeria, an adaptive hybrid propagation loss model that is based on wavelet transform and genetic algorithm methods has been developed for cellular network planning and optimization, with the capacity to resolve the problems absolutely. First, the signal strengths were measured within four selected eNodeB cell sites in long term evolution (LTE) at 2600MHz using drive-test method. Secondly, the measured data were denoised through wavelet tools. Thirdly, COST231 model was optimize and deduced to generic model with parameters. Fourthly, genetic optimization algorithm automatically developed the propagation loss models for denoised signal data (designated as wavelet-GA model) and unprocessed signal data (designated as GA model). The hybrid wavelet-GA propagation loss model, GA propagation loss model, and COST231 propagation loss model were compared based on three error metrics such as root mean square error (RMSE), mean absolute error (MAE) and correlation coefficient (R). The developed hybrid wavelet-GA model estimated the lowest RMSEs of 2.8813 dB, 3.9381 dB, 4.7643 dB, 6.9366 dB, whereas, COST231 model gave highest value of RMSE. The developed hybrid wavelet-GA model also derived the least value of MAE as compared with COST231 and the GA models, such as, 2.2016 dB, 2.8672 dB, 3.4766 dB, 5.8235 dB. The correlation coefficients were also compared, and it showed that the developed hybrid wavelet-GA model were 90.04%, 78.61%, 92.21% and 91.23% for the four cell sites. The developed hybrid wavelet-GA model was also validated to account for the performance level by checking for the correlation coefficient using another measured signal data from different eNodeB cell sites other than the once used for the developed of the hybrid wavelet-GA model. It was noticed that the developed hybrid wavelet-GA propagation loss model is 97.41% valid. Existing standard COST231 model are not able to predict propagation loss with high level of accuracy, as such not efficient to be applied within part of Port Harcourt, Nigeria. The proposed hybrid wavelet-GA model has proven to achieve high performance level and it is relevant to be utilized for cellular network planning and optimization. In future purposes, more regions and locations should be considered to form a broader view in the development of more robust propagation loss models.

Index Terms: Adaptive, Hybrid, Propagation Loss, Prediction Modeling, Cellular Network, Wavelet, Genetic Algorithm.

1. Introduction

The radio frequency based cellular network systems have gone through five different generations of deployments which includes the first generation (1G), second generation (2G), third generation (3G), fourth generation (4G), and fifth generation (5G) and is now evolving toward the sixth generation (6G). Examples of different generation standards include Nordic Mobile Telephone (NMT), Global System for Mobile Communications *(*GSM*),* Universal Mobile Telecommunication Systems (UMTS), Long Term Evolution (LTE) and New Radio (NR) [1]. The evolution and deployment of these different cellular network systems have been driven by the subscribers' increasing demand and technological development in the telecommunication sector. Today, we are in the era where billion of portable wireless cellular network devices, such as smart phones and palmtops, which are competing for the already limited radio spectrum (RF) to obtain connectivity. The rapid increase in the number of portable communication devices and their teeming private/public users have resulted in increase in total daily traffic in telecom system networks, globally. This, in turn, have a strong nose-diving bearing on the Quality of Service (QoS) offered to the end-users, especially in Sub-Sahara Africa [2].

In Nigeria, subscribers' satisfaction and quality of service (QoS) is still far below expectation. There has been series of complaints arising from frequent call outages, call conversation echoes, drop calls, among others, from mobile subscribers [3]. Some users even resort to the option of subscribing to more than one service provider, just to maintain seamless connectivity, thereby losing a fortune to the telecom system network operators [4].

All the aforementioned problems have been linked to poor network coverage planning and optimization. One of the most important tools, cellular network engineer use in solving poor network coverage planning problem is conducting regular signal measurements to develop propagation loss models, which are in turn used for effective signal coverage propagation loss predictive analysis between the transmitters and receivers of cellular communication paths [5]. An accurate propagation loss model helps in determining the cell radius, cell coverage area and locations where the cell sites or a base station transmitter should be located in order to achieve best network performance. However, if an inaccurate propagation loss model is employed in calculating signal loss between antennas, it will result to error in placing cell sites correctly and the probability of wrong deployment or placement the cell sites will be very high [6].

One of the significant contributions to remedy the problem of poor quality of service experienced by the wireless communication users due to inappropriate planning or positioning of transmitter cell is to adequately collect data and carried out proper computational analysis. However, existing literature have recorded that several methods in view to resolving the issues. For this purpose genetic algorithm is distinctively one of the best computational analyses that can reproduce the best offspring among several iterations of the optimizing parameters [7].

The main objective of this paper is to develop a hybrid wavelet-genetic algorithm (wavelet-GA) propagation loss model for cellular network planning and optimization in Nigeria. The developed hybrid wavelet-GA was computationally formulated by genetic optimization algorithm method to achieve the best off spring solution suitable for the generic parameters.

Outline

Section 1 contains the overview introduction of the research paper and the main objective for the research paper. Literature review and various contributions relating to this research paper were identified and detailed in section 2. Furthermore, we presented the methodology adopted for this study in section 3, which involves all the materials used for the drive test data collection method, processing of the data, and the method for the wavelet-GA model development. In section 4, we presented the results achieved in the various eNodeB cell sites. Finally, section 5 contains the concluding part of the research.

2. Literature Review

Several researchers have contributed immensely towards the development of propagation loss model where some of the challenges were addressed. Some of these studies were specifically channeled for the comparison of existing predicted propagation loss model to ascertain the best existing standard model suitable for the study area, while others focused to the develop propagation loss model using different methods.

For this purpose, propagation loss modeling has taken different dimensions of optimization of existing predicted model in view of an effective transmitter planning and accurate estimation of the propagation loss to address the constant poor quality of service (QoS) experienced in most environments. Base on the improvement, [8] optimized an existing COST231 propagation loss model and developed a propagation loss model using hybrid Weighted Least Square and genetic algorithm approach. The proposed hybrid optimization propagation loss model estimated the lowest mean square error (MSE), root mean square error (RMSE), percentage relative error when compare with existing standard model and can be utilized to achieve an effective enhance QoS and appropriate transmitter planning at 900MHz.

[9] optimized Okumura-Hata propagation loss model to develop a more robust propagation loss model using Second Order Newtons Algorithm Method. Based on this optimized model development, the measured signals were achieved within 800MHz through drive test method. Existing standard Okumura-Hata propagation loss model was compared with the developed Second Order Newtons Algorithm Model based on RMSE. It was concluded that the

develop Second Order Newton Algorithm Model performed much better that the existing standard Okumura-Hata model, as such should be adopted and utilized for network planning within Yaounde city of Cameroon.

COST231 Model

COST231 model is an extension of the Okumura-Hata model and it is utilized to derive path loss during cellular network planning and optimization, of which the frequency of operation ranges from 1.8GHz to 2GHz. Equation (1) is the COST231propagation path loss model [10].

$$y_p(dB) = 46.3 + 33.9\log(f) - 13.82\log(h_t) - a(h_r) + \left[44.9 - 6.55\log(h_t)\right]\log(d) + C_m \qquad (1)$$

Where

y_p = propagation path loss in decibel
$a(h_r) = 3.2[\log(11.75h_r)]^2 - 4.97$
f = frequency of transmission
ht = transmitter height
hr = receiver height
d = transmitter receiver distance
Cm (correction factor) = 0dB for medium and suburban environments, and 3dB for urban cities

3. Methodology

The tools employed for measurements are; TEMS software, MATLAB 2020a software, MTN SIM card, Del Laptop, GPS. Other relevant field test supporting devices are car for the drive-test measurement, inverter and connecting cables.

3.1. Practical Test Routes Survey

In this research, the locations in which field works are conducted were first visited to survey the area (that is, have good knowledge of the terrain) and know which the drive test routes to take when collecting signal strength data. It also provided means of knowing the number of eNodeBs antennas the LTE cellular systems network provider have in the study locations.

3.2. Signal Measurement

Field measurements will be conducted using a popular commercial LTE cellular networks air interface, propagating on the 2600MHz band in Port Harcourt, Nigeria. The building clusters in the area are a mixture of residential/commercial bungalows, two- or three-story buildings encompassed with medium density user and vehicular traffics as earlier described. Precisely, the measurement routes were selected along the main streets and sideway of the roads of the area, where the LTE eNodeB transceivers are deployed.

3.3. Signal Data Collection

One of the main LTE radio networks data to be collected during measurement is RSRP (i.e., Reference Signal received Power). Technically, the RSRP is an indicator of signal power level at the UE terminal in LTE networks. Generally, the stronger RSRP level received at UE, better signal coverage quality can be achieved in the radio network. There exist sundry factors that can impact the RSRP levels at the UE terminals, among which are transmitter-receiver (Tx-Rx) communication distance, RF channel conditions, signal propagation loss, UE location, total radiated eNodeB power, etc. the RSRP were extracted from four commercial eNodeB cell sites within Port Harcourt.

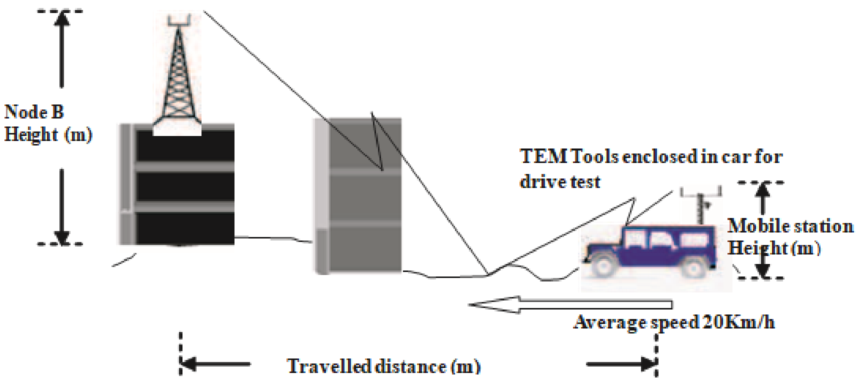

Fig.1. A sketch of tems drive test configuration

The field drive-test employed for the signal data collection is shown in Fig.1. The drive testing consists of carrying out wide-ranging signal strength measurement and service quality parameters at the receiver terminal within the assessed BS coverage area. Thus, the drive-test system provides a means of getting deep insight to the cellular networks performance.

3.4. *Measured Propagation Path Loss Estimation*

For the estimation of the measured propagation path loss, equation (2) was used

$$L_m\,(dB) = P_t + G_r + G_r - L_F - L_A - RSRP \tag{2}$$

Where

L_m = measured propagation path loss in decibel
P_t = transmitting power
G_t = transmitter gain
G_r = Receiver gain
L_F = feeder loss
L_A = antenna loss

3.5. *Fitness Function Evaluation*

During evaluation, the utmost fundamental task is to design a fitness function, *f(x)* of each *x* in the population that takes into account all the guiding objectives as highlighted below. The fitness function is then applied to evaluate the quality of the generated solutions and results during the GA optimization process. Accordingly, a fitness function must be formulated or design for any specific problem to be resolved.

Model optimization is a procedure in which a theoretical propagation loss model is optimized using measured data from the drive test [11]. The essence of the optimization is to have the optimized propagation loss values that are very close to the measured propagation loss values for the area of study [12]. The propagation loss model chosen for optimization is the COST231 model and its mathematical equation is given in equation (1).

The COST231 model is divided into three portions: the first parameter, P_0, the first system parameter, P_{sys}, and the model curve gradient, $G_{sys}\log(d)$. So, from equation we have:

offset parameters, $P_0 = 46.3 - 13.82\log(h_t) - a(h_r) + C_m$
system design parameter, $P_1 = 33.9\log(f)$
slope of the model curve, $P_2 = [44.9 - 6.55\log(h_t)]\log(d)$
Equation (1) can be written as;
Therefore; $y_p = P_0 + P_1 + P_2$
Let: $P_0 = Z_1$
$P_1 = Z_2\log(f)$
$P_2 = Z_3\log(d)$
$y_p\,(Z_1, Z_2, Z_3) = Z_1 + Z_2\log(f) + Z_3\log(d)$

Where; y_p = generic propagation loss of the COST231 model in dB, Z_1, Z_2, and Z_3 are parameters for a given set of measurements. Here, the best fit of the theoretical model curve to a given set of experimental data would be met by using the genetic algorithm, when the sum of squares function is minimal, as shown in equation. The objective or fitness function is defined as the sum of the squares of the difference between the measured and COST231 propagation loss [11]. Thus, the objective function f(z) for the research work can be expressed as equation.

$$F(z) = \sum_{i=1}^{N} [L_m - y_p]^2$$

Where; $y_p = y_p(x_i, z_1, z_2, z_3)$ denote the expression of the COST231 propagation loss model in equation.

3.6. *Wavelet Transform*

The wavelet transform (WAT) is a special mathematical method of denoising, wherein the noisy signal is decomposes into different resolution levels by regulating the wavelet function (i.e. mother wavelet) shifting and scaling factors. Mathematically, the classical continuous WAT is defined as [13, 14].

$$W(\tau, s) = \frac{1}{\sqrt{s}} \int x(t)\Psi(t)[\frac{t-\tau}{s}]dt \tag{3}$$

Where:

S = scale factor

τ = translator factor

$\Psi(t)$ = mother wavelet function

$x(t)$ = signal function

$\frac{1}{\sqrt{s}}$ = normalization factor for the signal

3.7. Genetic Algorithm

The GA is defined as a search heuristic method for survival of the fittest. It has been discovered as a useful tool for search and optimization problems. It searches for the best solution among all possible solutions represented by a point in the search space, that is, searches the search space for the best solution. GA is a stochastic algorithm since selection and reproduction require random methods. It also considers a population of solutions and considers many solutions at each iteration [15]. The algorithm recombines different solutions to get better ones. It's robust when it comes to dealing with sorting, as it works very well on a number of issues. It can be applied to solve any problem. GA is a series of steps to solve a problem, that is, a problem-solving technique that uses genetics as a problem-solving model. GA is a search method to find suitable solutions for optimization. In the optimization technique, the problem is to find the solution that fits best, that is, the one that pays off out of all possible solutions. GA works on a population of possible solutions, each representing a chromosome. The first is the encoding of all solutions into one chromosome. After the chromosome, a set of reproductive operators must be obtained; the reproductive operators are applied to the chromosomes to perform mutations and recombination.

3.8. Performance of Spatial Interpolation

Three performance accuracy methods are applied accordingly. The RMSE, MAE and R are estimated to assess or measure the spatial interpolation between the measured values and predicted values [16].

$$RSRP = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(L_m - y_p\right)^2} \tag{4}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left(L_m - y_p\right)^2 \tag{5}$$

$$R = \frac{\sum_{i=1}^{n}\left(L_m - L_{m(mean)}\right)^2 - \sum_{i=1}^{n}\left(y_p - L_m\right)^2}{\sum_{i=1}^{n}\left(L_m - y_{p(mean)}\right)^2} \tag{6}$$

4. Results and Discussion

The results attained by applying measured propagation loss with hybrid Wavelet-GA optimization method, proposed GA optimization method achieved without denoising the signal, and existing propagation loss method such as COST 231 are provided. Another standard propagation loss model used to compare the results obtained by our proposed hybrid propagation loss model is the optimized COST231 model using only GA. Thus, for the purpose of benchmarking the proposed propagation loss model using the Hybrid Wavelet-GA model, the prediction results attained by using ordinary GA and COST231 model, are engaged for comparative performance comparisons across the study locations. The performance of the proposed hybrid model over the standard approaches are evaluated and revealed using three key performance indicators. The indicators include RMSE, MAE, and correlation coefficient (R).

Table 1. The developed propagation loss models for wavelet-GA and GA models

Sites/Locations	Proposed Hybrid Wavelet-GA	GA Model
1	-4.3+22.0log(d)+29.3log(f)	5.3+20.7log(d)+27.5log(f)
2	9.3+14.9log(d)+28.7log(f)	-0.6+14.5log(d)+30.8log(f)
3	-7.0+30.0log(d)+25.3log(f)	0.4+26.5log(d)+25.8log(f)
4	-7.5+30.0log(d)+24.1log(f)	-8.5+30.0log(d)+24.3log(f)

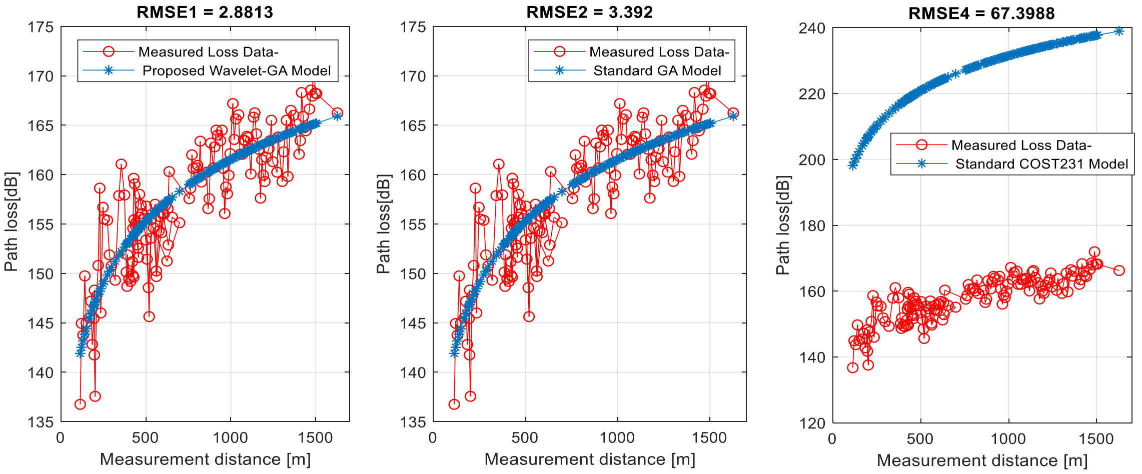

Fig.2. RMSE Difference using hybrid Wavelet-GA model, GA Model, and COST231 model, in eNodeB Site 1

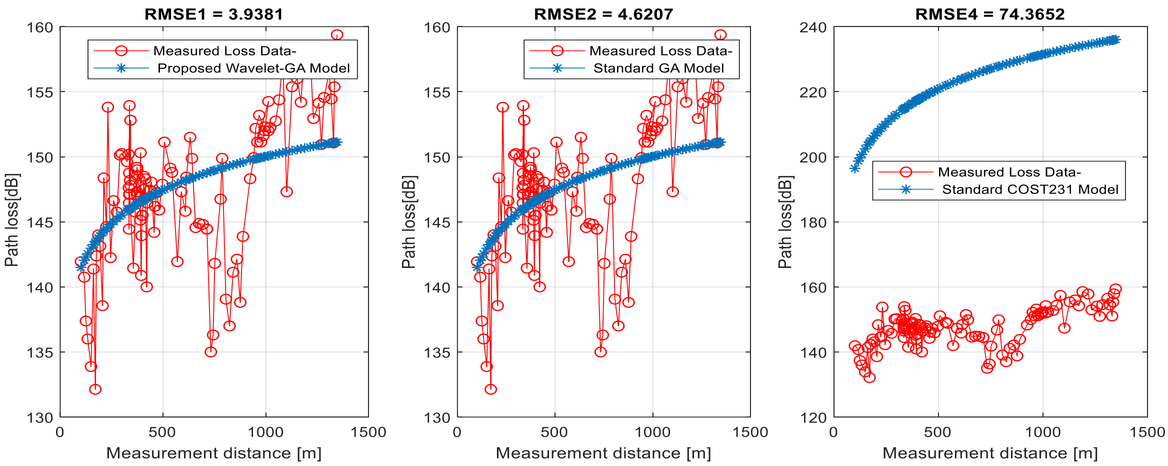

Fig.3. RMSE Difference using hybrid Wavelet-GA model, GA Model, and COST231 model, in eNodeB Site 2

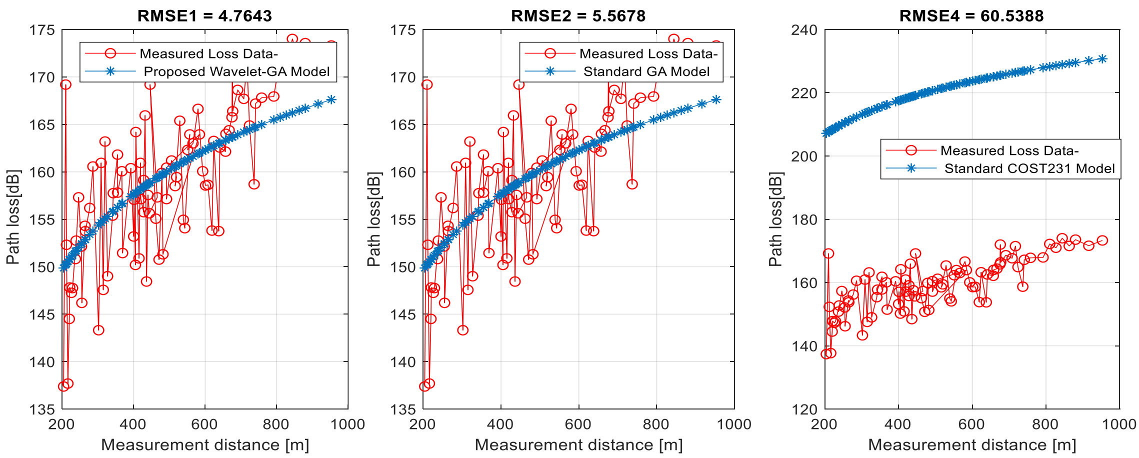

Fig.4. RMSE Difference using hybrid Wavelet-GA model, GA Model, and COST231 model, in eNodeB Site 3

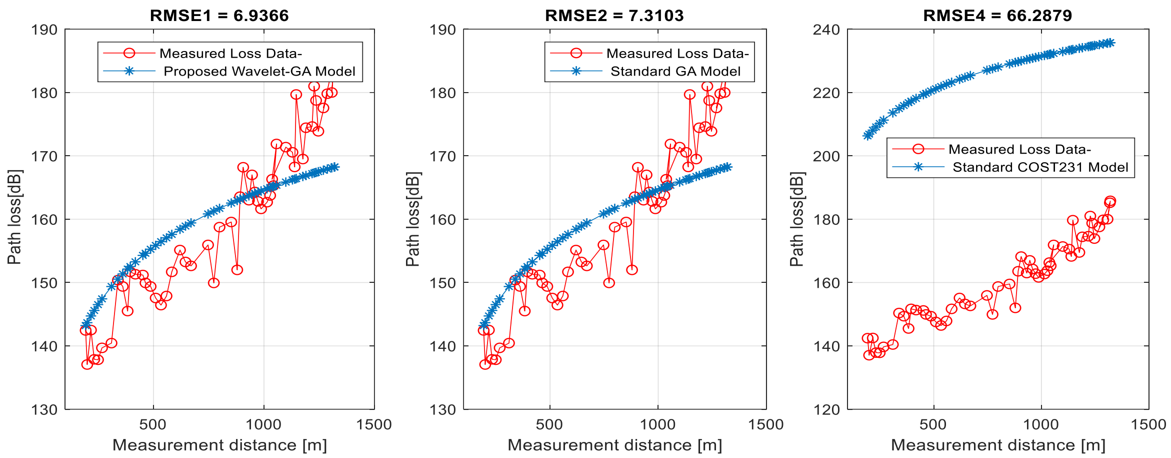

Fig.5. RMSE Difference using hybrid Wavelet-GA model, GA Model, and COST231 model, in eNodeB Site 4

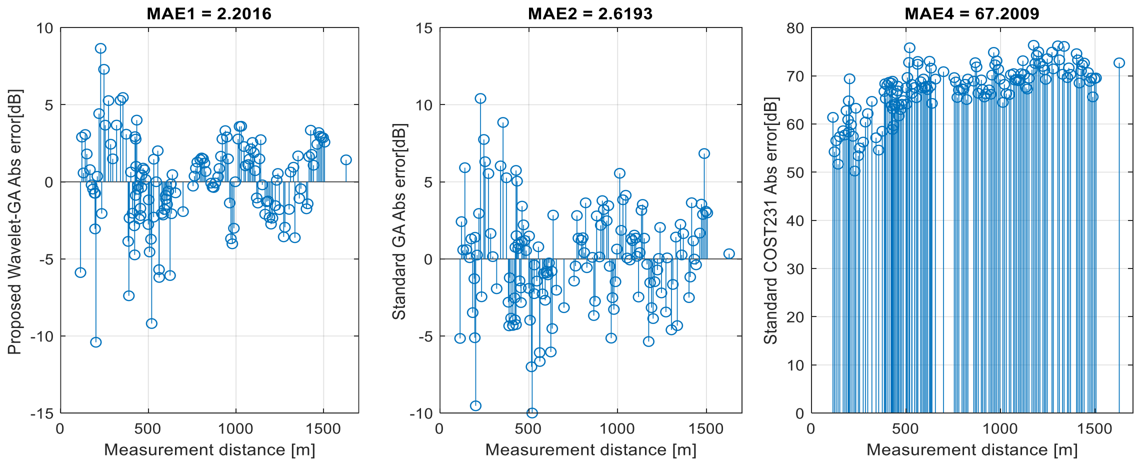

Fig.6. MAE difference using hybrid Wavelet-GA model, GA Model, and COST231 model in eNodeB Site 1

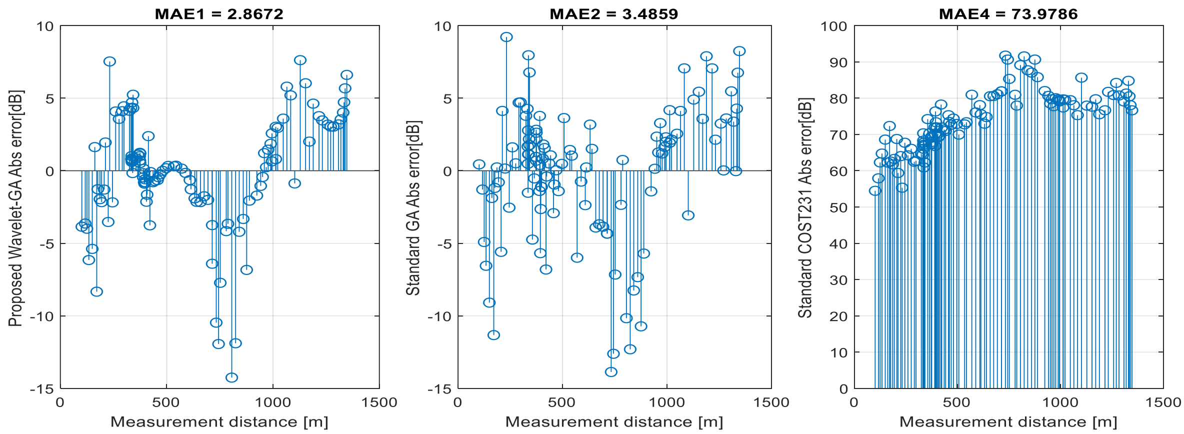

Fig.7. MAE difference using hybrid Wavelet-GA model, GA Model, and COST231 model in eNodeB Site 2

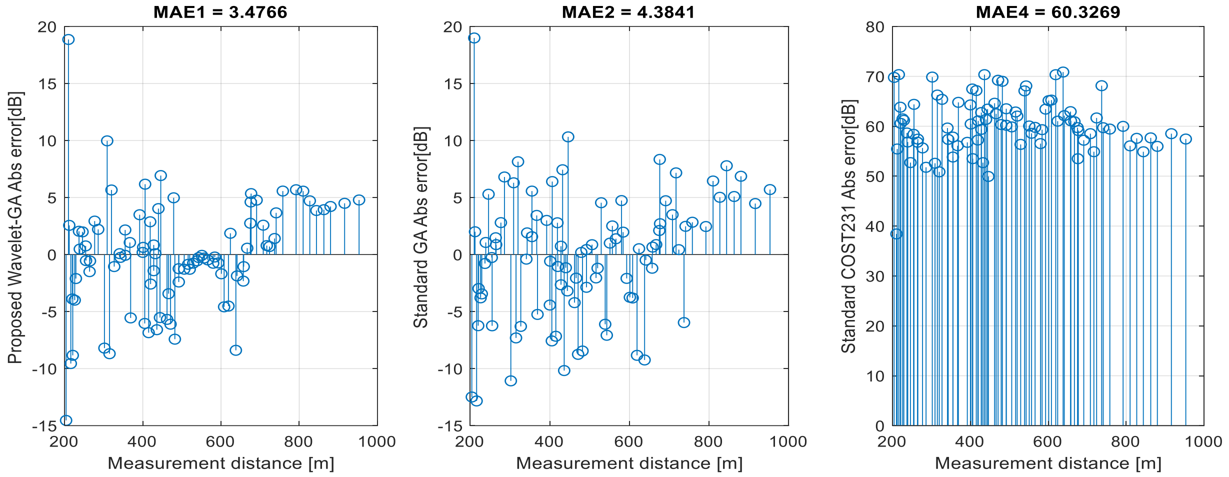

Fig.8. MAE difference using hybrid Wavelet-GA model, GA Model, and COST231 model in eNodeB Site 3

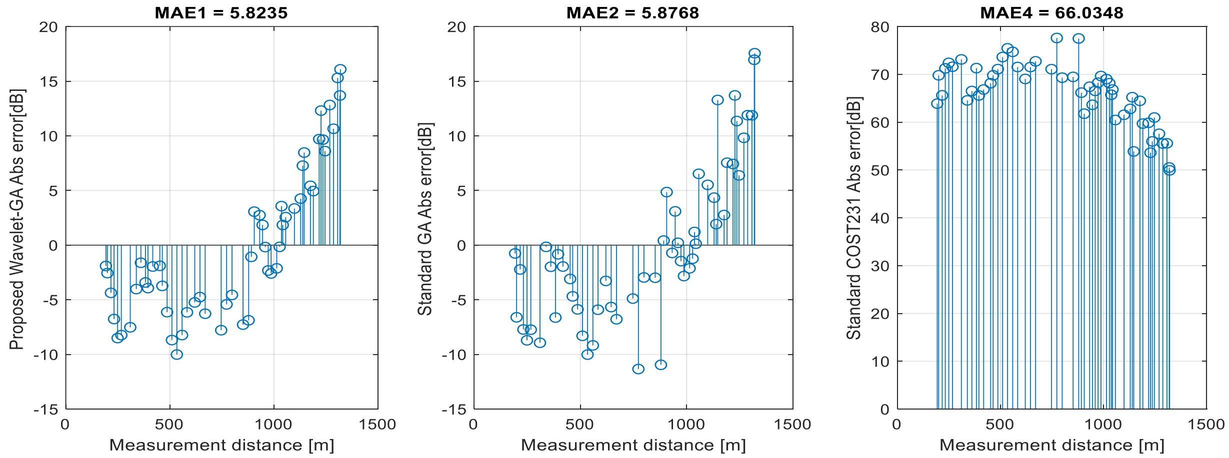

Fig.9. MAE difference using hybrid Wavelet-GA model, GA Model, and COST231 model in eNodeB Site 4

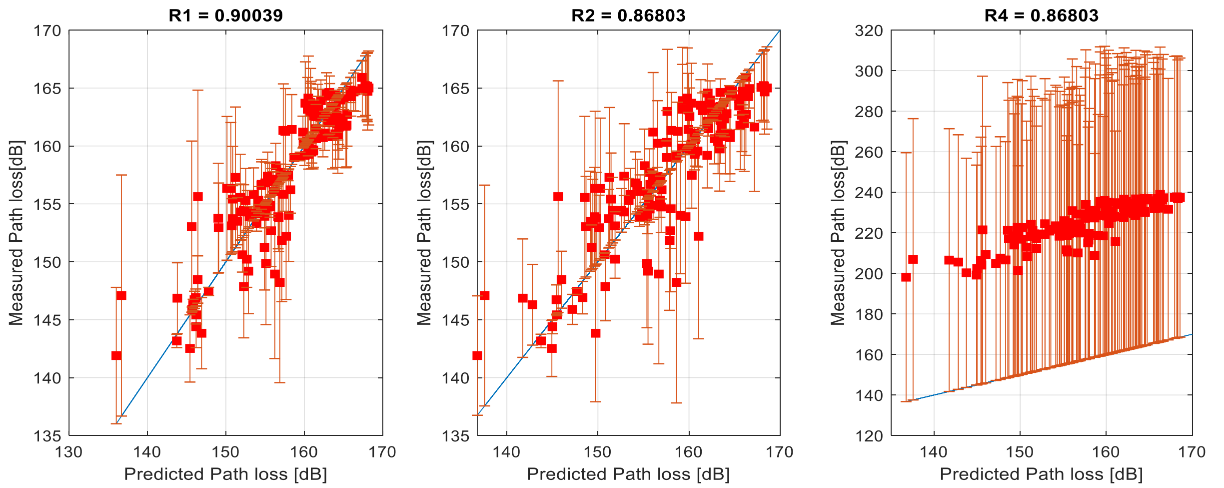

Fig.10. Correlation of wavelet-GA, GA and COST231 models to measured data in eNodeB Site 1

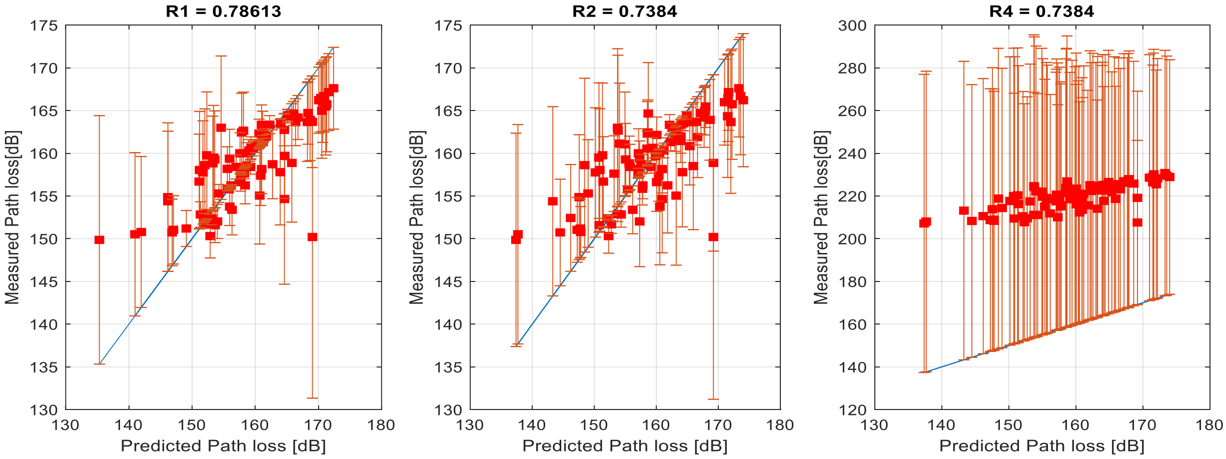

Fig.11. Correlation of wavelet-GA, GA and COST231 models to measured data in eNodeB Site 2

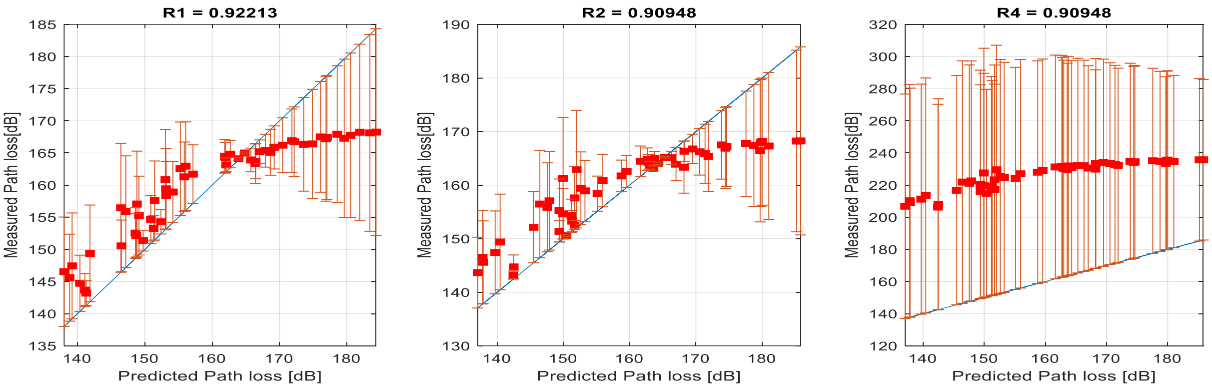

Fig.12. Correlation of wavelet-GA, GA and COST231 models to measured data in eNodeB Site 3

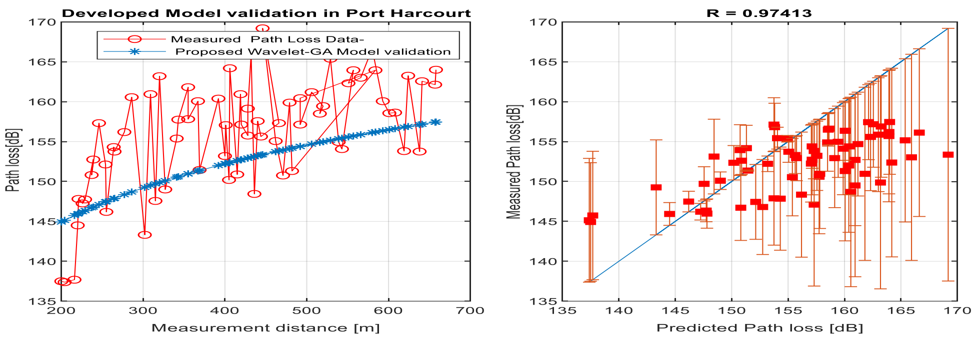

Fig.13. Validation of proposed hybrid wavelet-GA model using another eNodeB Site

Table 2. Summary Comparison of the Obtained Outcomes

Models	eNodeB Sites	RMSE	MAE	R
Proposed Wavelet-GA	1	2.8813	2.2016	0.9004
	2	3.9381	2.8672	0.7861
	3	4.7643	3.4766	0.9221
	4	6.9366	5.8235	0.9823
GA	1	3.3920	2.6193	0.8680
	2	4.6207	3.4859	0.7384
	3	5.5678	4.3841	0.9095
	4	7.3103	5.8768	0.9022
Standard COST231	1	67.3988	67.2009	0.8680
	2	74.3652	73.9786	0.7384
	3	60.5388	60.3269	0.9095
	4	66.2879	66.0348	0.8932

Fig. 2 showed that the proposed wavelet-GA model estimated the least RMSE of 2.8813 dB, whereas GA and standard COT231 models determined 3.3920 dB and 67.3988 dB respectively in site 1. The analysed result in fig. 3 indicated that wavelet-GA model also predicted the lowest RMSE of 3.9381 dB and that GA and COST231 models estimated 4.6207 dB and 74.3652 dB respectively in site 2. In fig. 4 COST231 model derived the highest RMSE of 60.5388 dB while wavelet-GA has the least RMSE of 4.7643 dB and GA model estimated 5.5676 dB. In site 4, the analysed result presented in fig. 5, wavelet-GA model estimated the least RMSE while COST231 model estimated the highest value of RMSE.

The MAEs were also evaluated for wavelet-GA, GA and COST231 Models in all the four sites. The fig. 6 of site 1 proved that wavelet-GA model has high performance level with the least 2.2016 dB MAE value, as compared to GA model and COST231 model with RMSE values of 2.6193 dB and 67.2009 dB respectively. In fig. 7, COST231 model estimated the highest MAE value of 73.9786 dB where as wavelet-GA model estimated the least of 2.8672 dB. Also in fig. 8 the lowest MAE value of 3.4766 dB was determined by wavelet-GA model whereas GA and COST231 models determined 4.3841 dB and 60.3267 dB respectively. The analysed results in fig. 9 showed that wavelet-GA model estimated the least MAE while COST231 model estimated the highest in sit 4.

The correlation coefficients (R) with the measured value were also examined. It examined how close the propagation losses of these models are to the measured propagation loss. Fig. 10 showed that wavelet-GA model estimated the highest correlation coefficient of 90.039% with the measured value whereas GA and COST231 models estimated 86.803% each. Again, in fig. 11 GA and COST231 models determined R of 73.84% each as compared to wavelet-GA model with highest value of 78.613 %. Also, in fig. 12, wavelet-GA model has 92.213% correlated with measured value, while GA and COST231 models estimated 90.948% each correlation coefficient with the measured value.

Fig. 13 showed the validation prediction performances level of the proposed Wavelet-GA model using another cell site measured data. To validate a developed propagation loss model means to test the model prediction performance level in another terrain other than which it was initially developed. The proposed wavelet-GA model attained a correlation coefficient value of 97.41% as such confirmed to have high performance level. This again validates the efficiency of the hybrid wavelet-GA signal propagation loss predictive modeling approach, which is proposed in this research.

5. Conclusions

This study focused on optimizing COST231 model for improved propagation loss prediction through signal denoising and GA approach. The estimated RMSE, MAE, and correlation coefficient using the developed hybrid denoised wavelet-GA model, unprocessed GA model, and existing standard COST231 model were compared. The proposed wavelet-GA model estimated the lowest RMSEs of 2.8813 dB, 3.94 dB, 4.76 dB, 6.94 dB, whereas, COST231 model gave higher value of RMSE. The developed wavelet-GA model also derived the least value of MAE as compared with COST231 and the unprocessed GA models, such as, 2.20 dB, 2.87 dB, 3.48 dB, 5.82 dB. The correlation coefficient were also compared, and it showed that the developed hybrid wavelet-GA model are 90.04%, 78.61%, 92.21% and 91.23% relatively close with the measured propagation loss. The developed wavelet-GA model was also validated to account for the performance level by checking for the correlation coefficient using another signal data from different eNodeB cell sites other than the once used for the developed wavelet-GA model. It was noticed that the developed wavelet-GA propagation loss model is 97.41% valid. COST231 model are not able to predict propagation loss with high level of accuracy, as such not efficient to be applied within part of Port Harcourt. The proposed wavelet-GA model could be very useful for network planners and network planning engineers to improve network quality in a similar environment. The proposed wavelet-GA model has proven to achieve high performance level and it is relevant to be utilized for cellular network planning and optimization. In future more regions and locations should be considered to form a broader view in the development of more robust propagation loss models.

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