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# Genetic Algorithm-based Path Loss Models: An Optimization Technique in LTE Wireless Communication Systems

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## Abstract

Signal path loss models play significant role in predicting signal strength, its attenuation, and enable characterisation of the radio frequency channel. Distance, transmitting frequency, and obstacles are critical elements that emphasize the signal strength variability affecting signal propagation at various areas. This study employs denoised data and unprocessed data to formulate path loss models using drive-test method. The signal strengths were measured, analyzed, and presented considering four base-stations (BS) within Port Harcourt using Long Term Evolution (LTE) at 2600MHz. A comparative analysis was performed between COST231-Hata model, Okumura-Hata model, and the developed models, based on metrics such as RMSE, MAE, and correlation coefficient (R). The developed model using denoised data exhibited excellent performance with the lowest RMSEs of 2.88dB, 3.94dB, 4.76dB, 6.94dB, demonstrating its accuracy in predicting path loss. Additionally, it yielded the least MAE values of 2.20dB, 2.87dB, 3.48dB, 5.82dB as compared to the existing standard models. The correlation coefficients of the developed model showed close alignment with the measured path loss of 90.04%, 78.61%, 92.21% and 91.23% for the BSs respectively. Validation of the developed models with data from different BSs confirms high efficiency of 97.41%. Conclusively, COST231-Hata and Okumura-Hata models exhibited limited accuracy in predicting path loss within Port Harcourt. The developed model illustrates exceptional performance and it's recommended for effective communication network planning and optimization in the area. Future research is encouraged to expand the study to include more BS, regions, and locations for an in-depth and robust model development.

**Keywords:** Genetic-algorithm, pathloss, model, optimization, wireless, communication, systems.

## 1. Introduction

The advent of 3G and 4G cellular-based wireless communication systems led to technological advances in video and Internet data that were not possible with the 2G-GSM introduction [1]. Despite the presence of numerous telecommunications companies operating 3G Universal Mobile Telecommunication System (UMTS) and 4G LTE in Nigeria, mobile user satisfaction and signal quality remain substandard. Users' complaints of weak or fluctuating signal strength, dropped calls, echoes during calls, and delays in downloading files, with pronounced problems occurring on broadband cellular networks [2].

[3] has observed that, inaccurate estimation of signal path loss when planning cellular networks is a major cause of dead or weak signal. To address dead zones and quality of service issues in cellular networks, one approach is to employ a reliable path loss model in cellular network planning [5][6].

The main objective of this study was to implement a proactive measurement-based hybrid technique, that combines discrete wavelet transform and genetic algorithms, to develop an adaptive hybrid path loss prediction model, for optimal mobile network planning, particularly in parts of Port Harcourt, Nigeria.

## 2 Existing Path Loss Models

Several path loss models exist and are replete in literature, they include;

### 2.1 Free-Space Path Loss Model

The Free-Space Path Loss (FSPL) model is a fundamental theoretical approach for estimating signal path loss in free space without obstacles [9]. It is characterized by the wavelength of signal propagation and depends on the distance between the base-station and mobile station. It is expressed as:

$$P_L(dB) = 20\log(d) + 20\log(f) + 20\log\left(\frac{4\pi}{c}\right) \quad (1)$$

Where; d is the distance, f is the frequency, and c is the speed of light. It is Ideal for predicting signal loss in unobstructed environments, such as, satellite communication or in open outdoor areas.

### 2.2 COST 231-Hata Model

The COST 231-Hata model is an empirical path loss model formulated for urban and suburban areas. It is an extension of the Hata model which includes additional factors for more accurate predictions [8]. Frequency, antenna height of the BS, antenna height of the mobile station and distance are taken into account. It is suitable for frequency range between 1500 MHz to 2000 MHz. and it is commonly used to predict signal path loss in urban and suburban areas, particularly in the context of cellular network planning [9]. It can be represented as [4]

$$PL\ (dB) = 46.3 + 33.9\log(f) - 13.82\log(h_t) + (44.9 - 6.55\log h_t)\log d + Cm \quad (2)$$

Where, Cm is the correction factor based on the type of environment (it is equal to 0 db, for median and sub urban cities; and equal to 3 db for metropolitan areas.

f = Frequency of Transmission in Megahertz (MHz)

$h_t$ = Base Station Antenna effective height in Meters (m)

d = Link distance in Kilometers (km)

### 2.3 Okumura-Hata Model:

The Okumura-Hata model is another empirical path loss model developed for urban and suburban environments, derived from the Hata model. It includes adjustments based on various environmental and geographical parameters [10][11]. It considers frequency, base-station antenna height, mobile-station antenna height, and distance. It can be suitable within frequency range of 150 MHz to 1500 MHz and it is commonly used in mobile network planning, of which it can provide reasonable and accurate predictions for signal propagation in several urban and suburban areas [12]. Its mathematical representation is as shown below;

$$P_{L(urban)}(dB) = 69.55 + 26.16\log f - 13.82\log h_t - a(h_r) + [44.9 - 6.55\log h_t]\log d \quad (3)$$

Where; $f$ = Frequency in megahertz and ranges from 150 MHz to 1000 MHz

$h_t$ = Effective transmitter antenna height (in meters): 30 m to 200 m

$h_r$ = Effective receiver antenna height (in meters): 1 m to 20 m

$d$ = Separation distance (in km): 1 km to 20 km

For small to medium areas,

$$a(h_r) = [1.1\log f - 0.7]h_r - [1.56\log f - 0.8]$$

For large environment,

$$a(h_r) = 8.29[\log(1.54h_r)]^2 - 1.1; \quad \text{for} \quad f < 300\text{MHz}$$

$$a(h_r) = 3.2[\log(11.75h_r)]^2 - 4.97; \quad \text{for} \quad f \geq 300\text{MHz}$$

For suburban environment,

$$P_{L(suburban)} = P_{L(urban)}(dB) - 2\left[\log\left(\frac{f}{28}\right)\right]^2 - 5.4 \quad (4)$$

For rural environment,

$$P_{L(rural)} = P_{L(urban)}(dB) - 4.78[\log f]^2 - 18.33\log f - 40.98 \quad (5)$$

These path loss models are valuable tools in the field of telecommunications for evaluating signal loss and supporting the planning and optimization of wireless communication systems. Selecting the most appropriate model depends on the specific characteristics of the area and the frequency range of interest [13].

## 3 Methodology

In this research, a field drive test setup was used to acquire real time signal data. The driving test included comprehensive measurements of received signal strength and quality of service parameters at the receiver terminal within the evaluated coverage area of which four base-stations were considered, identified as BS 1, BS 2, BS 3, and BS 4. Tools used for the field drive test system included the Global Positioning System (GPS), LTE modem, an MTN internet data SIM card, a HP laptop, an inverter, a scanner, direct test cables, Matlab software, MapInfo software and Telephone Mobile Software (TEMS). MapInfo software was specifically used to display test site maps and create route data. Using these field drive test system tools, real time signal data were collected around four BSs in Port Harcourt, Nigeria, all operating at a 2600 MHz bandwidth.

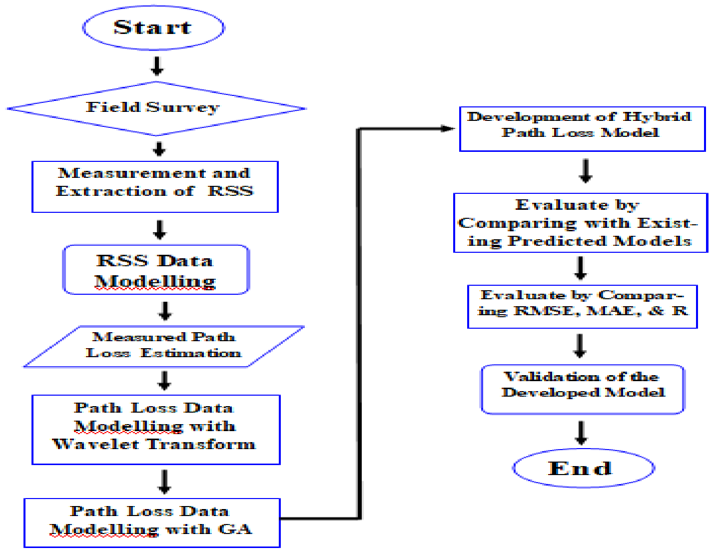


Fig.1: Flowchart of the proposed hybrid path loss model development

## 3.1 Estimation of the Measured Path loss

Path loss is the decrease in signal power level during propagation from the base-station to the receiver [14]. Estimation of the signal path loss can be achieved by;

$$PLm\ (dB) = Pt + Gt + Gr - L_{AB} - L_{FC} - RSS \quad (6)$$

Where;

PLm = measured path loss in dB

Pt = transmit power in dBm

Gt = transmit antenna gain (dBi)

Gr = receiving antenna gain (dBi)

$L_{AB}$ = antenna body loss (dB)

$L_{FC}$ = feeder cable loss (dB)

RSS = Received signal strength data (dBm)



## 3.2 Generic Model Formulation

The COST 231-Hata model is divided into three portions: the offset parameter, $P_0$, the system parameter, $P_1$, and the slope of the model curve parameter.

Hence, the formulation of the generic model in equation (2) was deduced as follows:

Offset parameters,

$$P_0 = 46.3 - 13.82 \log(h_t) - a(h_r) + Cm$$

Slope of the model curve,

$$P_1 = [44.90 - 6.550 \log(h_t)]\log(d)$$

System design parameter,

$$P_2 = 33.9 \log(f)$$

Therefore;

$$P L_p = P_0 + P_1 + P_2$$

Furthermore, let:

$$P_0 = Z_1$$

$$P_1 = Z_3 \log(d)$$

$$P_2 = Z_2 \log(f)$$

$$P_L\ (dB) = Z_1 + Z_3 \log(d) + Z_2 \log(f) \quad (7)$$

Where;

$P_L$ is generic path loss of the COST 231-Hata model.

$Z_1$, $Z_2$, and $Z_3$ are deduced parameters.

### 3.3 Genetic Algorithm (GA)

The problems associated in cellular network planning are resolved using the Darwin's law of nature or natural selection to solve optimization problems. So, it is possible to deploy GA optimization tool to resolve number of optimization issues, as such when the cellular network planning is well done, the performance level is highly effective and significant high QoS to the cellular network users can be achieved [15].

In this work, binary encoding type was utilized considering the problem. After encoding to binary chromosomes, some of the chromosomes were selected randomly. The next process was to evaluate the fitness function of the individual selected chromosomes. After which three criteria were carried out which involves crossover, selection, and mutation to achieve the second iteration and subsequently the best solutions to the issue are gotten. GA performs its optimization duty through iteration method. The iterations are designed to continue pending when the GA achieves the best solution of the iteration processes.

### 3.4 Metric Evaluation

In this paper, three metrics were used to evaluate the regression between actual data and predicted data. They are the root mean square error (RMSE), mean absolute error (MAE), and the correlation coefficient (R) of the developed model and predicted model were evaluated. The empirically expressions for the three metrics are;

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_m - y_p\right)^2} \tag{8}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_m - y_p\right|$$

And, (9)

$$R = \frac{\sum_{i=1}^{n}\left(y_m - y_{m(mean)}\right)^2 - \sum_{i=1}^{n}\left(y_p - y_m\right)^2}{\sum_{i=1}^{n}\left(y_m - y_{P(mean)}\right)^2} \tag{10}$$

## 4 Results and Discussion

**Table 1: Developed path loss models**

| Sites | Hybrid Wavelet-GA | GA |
|---|---|---|
| PH 1 | -4.3+22.0log(d)+29.2log(f) | 5.3+20.7log(d)+27.5log(f) |
| PH 2 | 9.3+14.9log(d)+28.6log(f) | -0.6+14.5log(d)+30.8log(f) |
| PH 3 | -7.0+30.0log(d)+25.2log(f) | 0.4+26.5log(d)+25.8log(f) |
| PH 4 | -7.5+30.0log(d)+24.0log(f) | -8.5+30.0log(d)+24.3log(f) |
| | **-2.4+24.2log(d)+26.8log(f)** | **-0.9+22.9log(d)+27.1log(f)** |

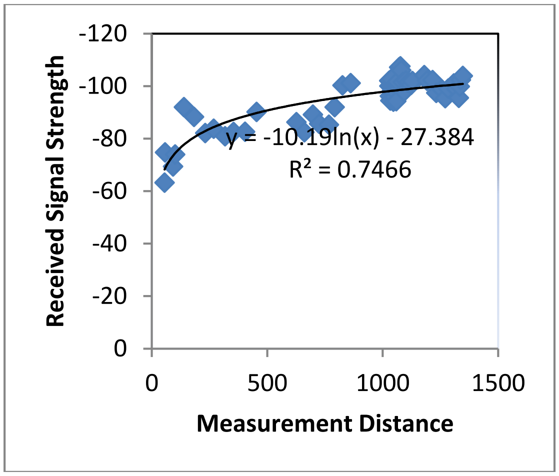


Fig.2: Measured signal data modeling for BS 1

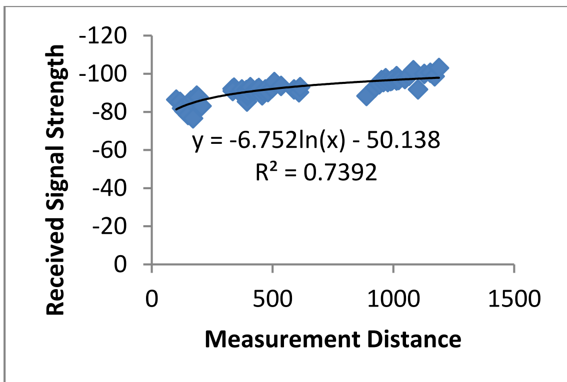


Fig.3: Measured signal data modeling for BS 2

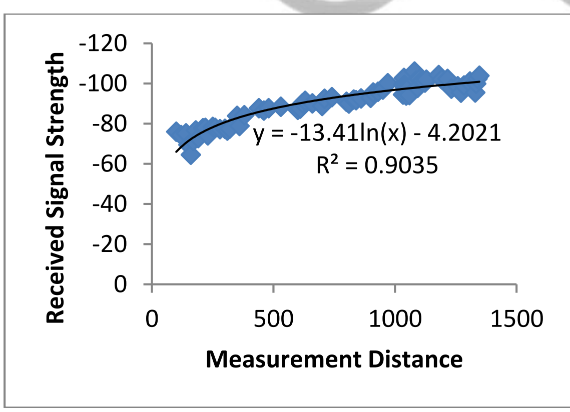


Fig.4: Measured signal data modeling for BS 3

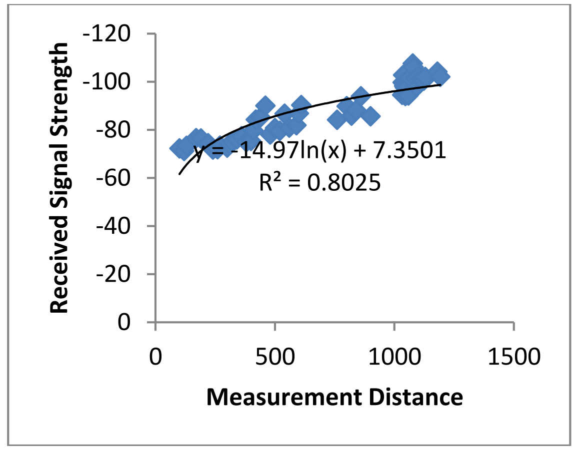


Fig.5: Measured signal data modeling for BS 4

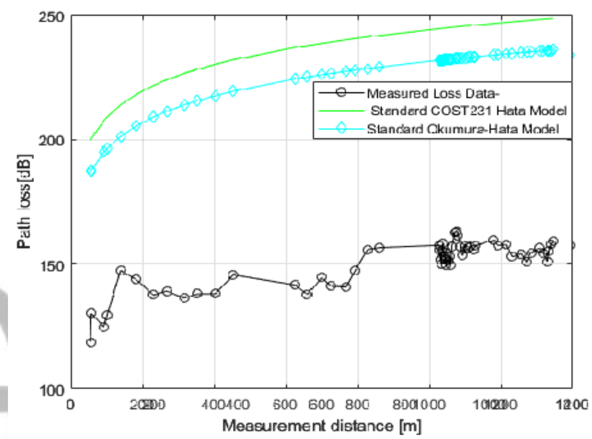


Fig. 6: Analysis of measured path loss data as compared with COST231-Hata and Okumura-Hata models for BS 1

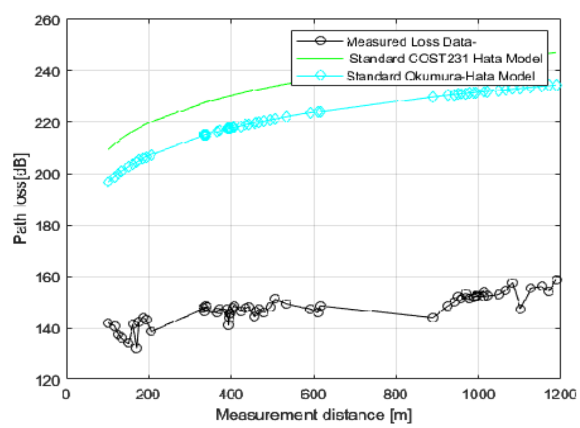


Fig.7: Analysis of measured path loss data as compared with COST231-Hata and Okumura-Hata models for BS 2

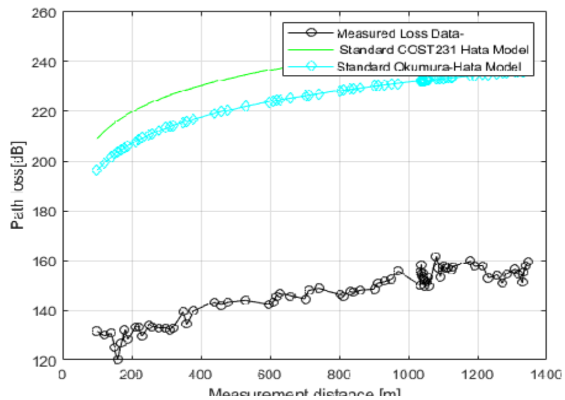


Fig. 8: Analysis of measured path loss data as compared with COST231-Hata and Okumura-Hata models for BS 3

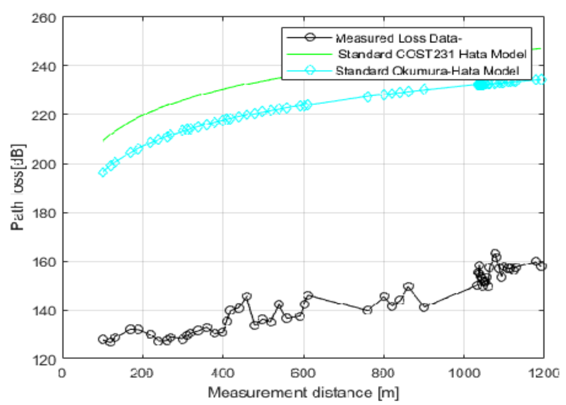


Fig. 9: Analysis of measured path loss data as compared with COST231-Hata and Okumura-Hata models for BS 4

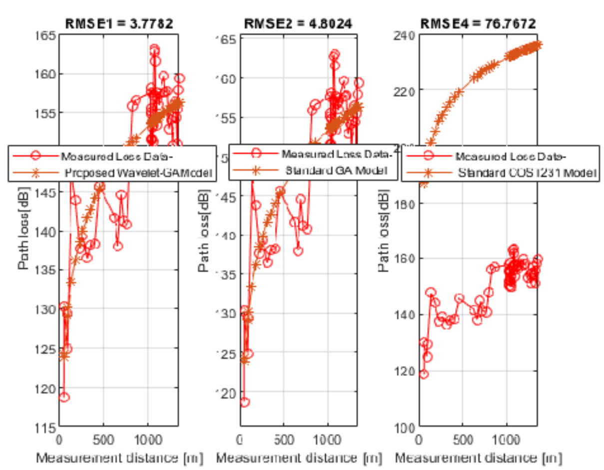


Fig. 10: RMSE of Wavelet-GA model, GA model, COST231-Hata model as compared to measured path loss data for BS 1

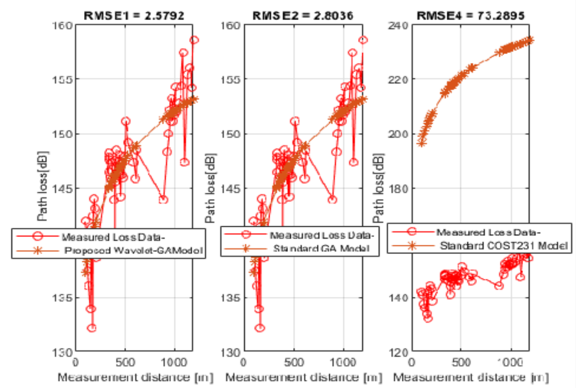


Fig. 11: RMSE of Wavelet-GA model, GA model, COST231-Hata model as compared to measured path loss data for BS 2

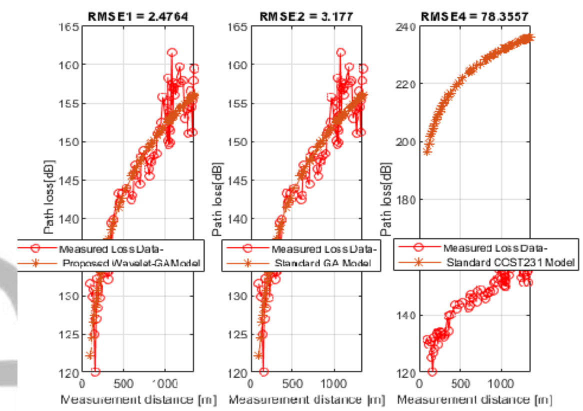


Fig. 12: RMSE of Wavelet-GA model, GA model, COST231-Hata model as compared to measured path loss data for BS 3

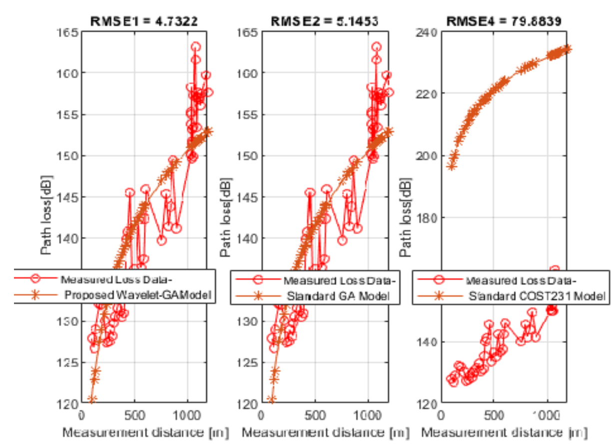


Fig. 13: RMSE of Wavelet-GA model, GA model, COST231-Hata model as compared to measured path loss data for BS 4

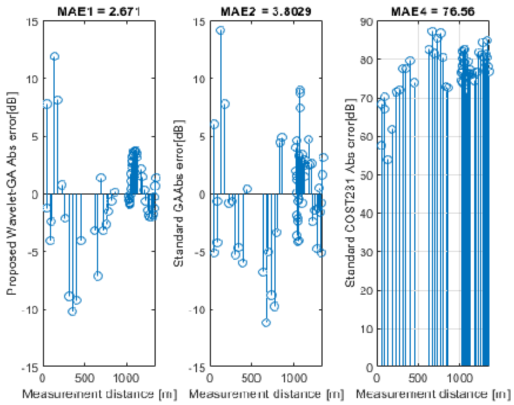


Fig. 14: MAE of Wavelet-GA model, GA model, COST231-Hata model as compared to measured path loss data for BS 1

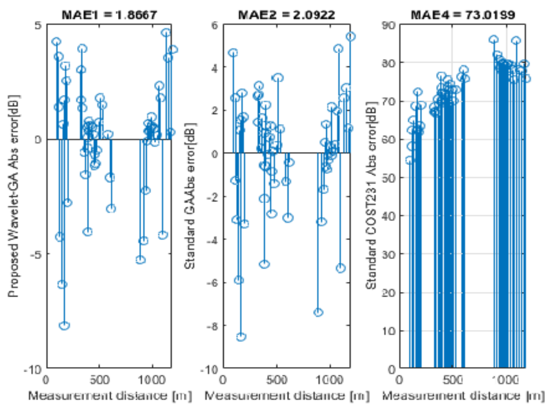


Fig.15: MAE of Wavelet-GA model, GA model, COST231-Hata model as compared to measured path loss data for BS 2

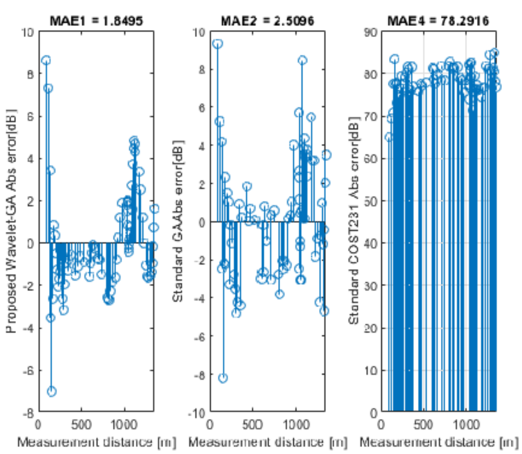


Fig. 16: MAE of Wavelet-GA model, GA model, COST231-Hata model as compared to measured path loss data for BS 3

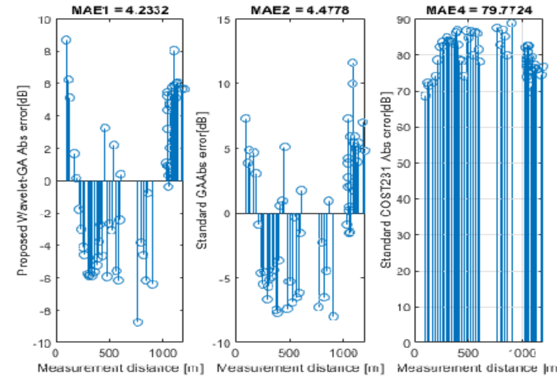


Fig. 17: MAE of Wavelet-GA model, GA model, COST231-Hata model as compared to measured path loss data for BS 4

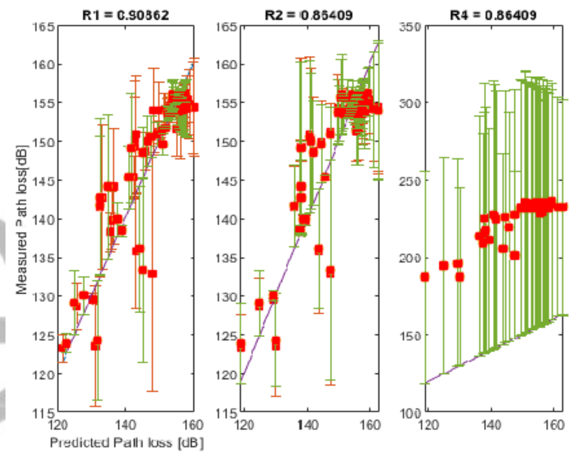


Fig. 18: Correlation coefficient of Wavelet-GA model, GA model and COST231-Hata model as compared to measured path loss data for BS 1

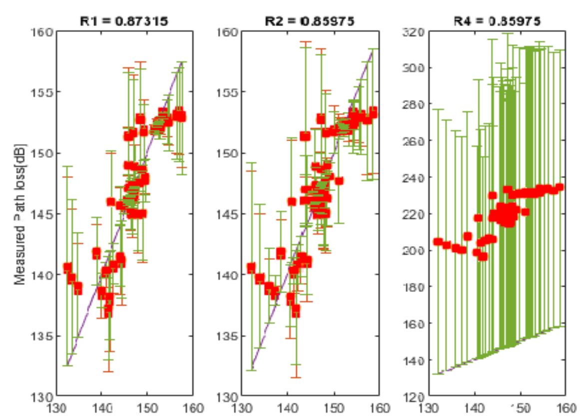


Fig. 19: Correlation coefficient of Wavelet-GA model, GA model and COST231-Hata model as compared to measured path loss data for BS 2

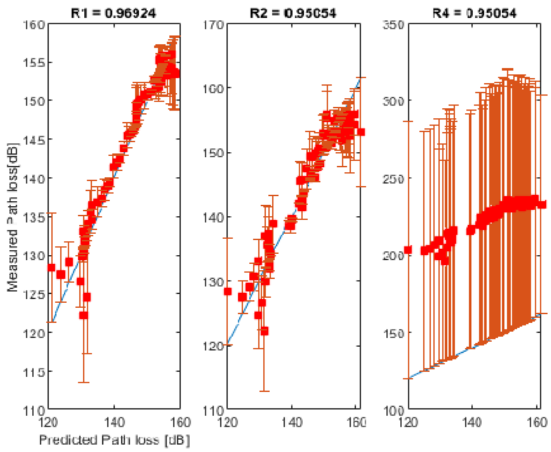


Fig. 20: Correlation coefficient of Wavelet-GA model, GA model and COST231-Hata model as compared to measured path loss data for BS 3

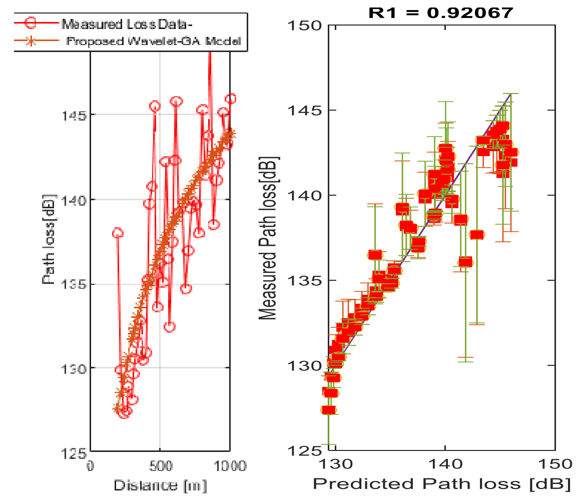


Fig. 22: Validation of proposed hybrid Wavelet-GA model considering another BS

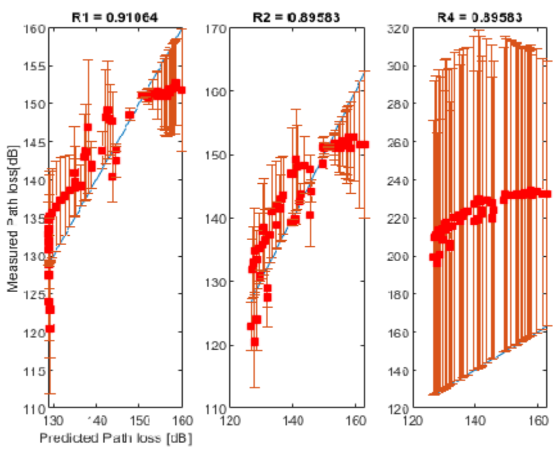


Fig. 21: Correlation coefficient of Wavelet-GA model, GA model and COST231-Hata model as compared to Measured path loss data for BS 4

Table 1 presents the developed models considering denoised and unprocessed measured signal data. The second column are the developed path loss model using denoised signal data (Wavelet-GA), where as the third column detailed the developed path loss model using unprocessed signal data (GA).

The analyzed results from Figs. 2 to 5 represent the measured signal data modeling with respect to the regression. The modeling showed very high correlation coefficient throughout the BSs, as such the extracted RSS data are observed to not be below standard.

The analyzed results from Figs. 6 to 9 compared the path losses of the existing Okumura-Hata model and the existing COST231-Hata model with measured path losses for the different BSs. It showed that the existing COST 231-Hata and Okumura-Hata models estimated higher values of path losses as against the measured path loss value. However, Okumura-Hata model performed better than COST231-Hata model in all the BSs.

The analyzed results in Figs. 10 to 13 revealed the RMSE prediction accuracies of the hybrid Wavelet-GA model, the GA model, and the COST231-Hata model compared to the measured path loss values. The results showed that the hybrid developed Wavelet-GA model have high performance accuracy and consistently estimated the lowest RMSE values throughout the BSs.

Furthermore, Figs. 14 to 17 presents the analyzed results using MAE. In this context, the developed hybrid Wavelet-GA model gave the lowest MAE values, while the COST231-Hata model consistently gave the highest values across all BSs.

Furthermore Figs. 18 to 2, again illustrated the correlation coefficient (R) in the comparison of the measured path losses with the developed hybrid Wavelet-GA model, GA model and the standard COST231-Hata model. The results showed that the developed hybrid Wavelet-GA model achieved the highest R values, indicating a strong correlation between the measured path loss and the developed hybrid Wavelet-GA model.

The analyzed results in Fig. 22, demonstrated the validation prediction capabilities of the newly formulated hybrid Wavelet-GA model. Validation of the developed path loss model involves evaluating its ability to predict path loss using a different dataset other than those used in its development phase. This evaluation allows for the determination of the effectiveness of the model in predicting path losses within different BSs and demonstrates its dynamic and efficient prediction performance. It is therefore evident that the hybrid Wavelet-GA model exhibited performance level of about 92.07%, indicating successful validation.

## 5 Conclusion

The results clearly proved that the developed Wavelet-GA model consistently outperformed existing standard models. It showed lower RMSE and MAE values as well as higher correlation coefficients. Therefore, one approach to addressing dead spots and quality of service issues in cellular networks is to use a hybrid Wavelet-GA path loss model when planning and optimizing wireless communication system. The developed path loss model in this study is reliable and promising and has the capacity in mitigating challenges such as dead signal zones, weak/fluctuating coverage signal strength, dropped calls, mid-call echoes, and file download delays for mobile phone users. Its efficiency suggests that there is potential to restore high signal levels within parts of Port Harcourt, Nigeria.



## 6 Acknowledgement

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## 7 Conflict of interest

The authors assert that there are no conflicts of interest in the execution of this study.

## 8 References

[1] Atanasov, P., & Kissovski, Z. (2017). Optimization of path loss models based on signal level measurements in 4G LTE network in Sofia. *Bulgaria Journal of Physics*, *44*(5), 145–154.

[2] Isabona, J., Zhimwang, J. T., & Risi, I. (2022). Cascade forward neural networks-based adaptive model for real-time adaptive learning of stochastic signal power datasets. *International Journal of Computer Network and Information Security, 3*(6), 63-74.

[3] Mardeni, R., & Priya, T. S. (2010). Optimised cost-231 hata models for wimax path loss prediction in suburban and open urban environments. *Modern Applied Science*, *4*(9), 75-89. https://doi.org/10.5539/mas.v4n9p75

[4] Matha, B., (1999). Radio Propagation in Cellular Networks. Artech House, Boston-London.

[5] Michel, D.E.D., & Emmanuel, T. (2015). Optimization of okumura hata model in 800mhz based on newton second order algorithm: Case of Yaoundé, Cameroon. *Journal of Electrical And Electronics Engineering, 10*(2), 2278–1676.

https://doi.org/10.9790/1676-10211624

[6] Mousa, A., Dama, Y., Najjar, M., & Alsayeh, B. (2012). Optimizing outdoor propagation model based on measurements for multiple RF cell. *International Journal of Computer Applications*, *60*(5), 5–10. https://doi.org/10.5120/9686-4121

[7] Nafea, S., & Hamza, E. K. (2019). Path loss optimization in wimax network using genetic algorithm. *Iraqi Journal of Computers, Communications, Control and Systems Engineering*, *20*(1), 24–30.

[8] Parmar, K. J., & Nimavat, V. D. (2015). Comparative analysis of path loss propagation models in radio communication. *International Journal of Innovative Research in Computer and Communication Engineering*, *3*(2), 840-844

[9] Peter, P. O. (2019). Optimized artificial neural network model for the prediction of domestic companies index direction under the botswana stock market. *International Journal of Science And Research,8*(10), 536–542.

[10] Popoola, S. I Adetiba, E., Atayero, A. A., Faruk, N., & Calafate, C. T. (2018). Optimal model for path loss predictions using feed-forward neural networks optimal model for path loss predictions using feed-forward neural networks. *Cogent Engineering*, *4*(1). 1-19.

[11] Tarkaa, N. S., Agbo, V. A., & Oglegba, S. O. (2017). Radio propagation path-loss analysis for an operative GSM network. *The International Journal of Engineering and Science, 6*(9),53–67. https://doi.org/10.9790/1813-0609035367

[12] Thakur, A., & Kamboj, S. (2016). Transmission and optimization of a 3G microwave network at 18GHz. *International Journal of Engineering Science and Computing, 6*(5), 5622–5626. https://doi.org/10.4010/2016.1372

[13] Wang, Y., Lu, W. J., & Zhu, H. B. (2012). An empirical path-loss model for wireless channels in indoor short-range office environment. *International Journal of Antennas and Propagation*, *20*(12), *1-8*. https://doi.org/10.1155/2012/636349.

[14] Zakaria, Y., Hosek, J., & Misurec, J. (2015). Path loss measurements for wireless communication in urban and rural environments. *American Journal of Engineering and Applied Sciences*, *8*(1), 94-99. https://doi.org/10.3844/ajeassp.2015.94.99.

[15] Zheng, Q., Feng, B. Liu, Z., & Chang, H. (2021). Application of improved particle swarm optimisation algorithm in hull form optimisation. *Journal of Marine Science and Engineering,9*(4), 1-20. https://doi.org/10.3390/ jmse9090955