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Original Article

Machine Learning Approach for Propagation Attenuation Evaluation in 4G LTE Wireless Communication Networks

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Abstract *- This study focused on developing signal propagation attenuation models using a machine learning approach. Four commercially installed LTE base-stations in Port Harcourt that operated at 2600 MHz were considered with the extraction of signal data for the study. A field drive-test method was utilized to collect signal data within the environment. The measured signal data were denoised through the rigrsure thresholding method using the wavelet tool in Matlab. The measured denoised propagation attenuation values were estimated using measured unprocessed signal data. The developed hybrid model using the denoised data was designated as the wavelet-GA model, whereas the genetic algorithm (GA) model was used through the unprocessed data designated as the GA model. The RMSE, MAE, and correlation coefficient (R) were used as evaluation metrics to compare the machine learning hybrid Wavelet-GA model with the GA model and the standard COST231-Hata model. The COST231-Hata and GA models were not as predictive as the machine learning hybrid Wavelet-GA model. The machine learning model outperformed the GA and COST231-Hata models in all the base stations in terms of R, RMSE, and MAE values. The corresponding MAE values for base stations 1, 2, 3, and 4 were 1.68 dB, 3.30 dB, 3.02 dB, and 3.34 dB, respectively, while the machine learning hybrid Wavelet-GA model estimated RMSE values of 2.27 dB, 4.61 dB, 3.77 dB, and 3.93 dB. Its high performance was confirmed by the examined R, which showed a strong alignment between the machine learning hybrid Wavelet-GA values and the measured propagation attenuation values. However, the COST231-Hata model showed the lowest R and the highest RMSE and MAE values, suggesting a lower degree of accuracy and reliability. The R was also compared with measured propagation attenuation data, and it proved the efficiency of the machine learning model estimated at 94.49%, 84.85%, 92.17% and 93.25% for the base stations, respectively. Validation with data from a different base station confirmed the efficiency of the machine learning propagation attenuation model based on denoised signal data, providing valuable insights for network planning. When evaluated, it showed that the developed machine learning was 97.41% valid within Port Harcourt. Conclusively, it showed that the machine learning propagation attenuation model outperformed existing propagation attenuation models and such recommended for cellular network planning within Port Harcourt as it can remedy the poor quality of service experienced within the areas.*

Keywords *- Machine-Learning, Propagation, Attenuation, Wireless, Communication, Networks.*

1. Introduction

Poor Quality of Service (QOS) experienced by communication users within Nigeria and the African continent at large has become a factor of concern. On a regular basis, users complained of several challenges, such as drop calls, voice echoes during calls, inability to connect or place calls and delays in downloading/uploading files during usage of the wireless communication system [1].

These problems have been identified as effects of inadequate planning network systems due to the improper estimation of signal propagation path attenuation of communication network within these areas; as such the need to embrace an optimized machine learning approach for communication network planning to checkmate these issues. Propagation path attenuation prediction is crucial for planning and implementing a 4G LTE to achieve significant improvements in network efficiency [1]. Estimating propagation path attenuation in a mobile environment can be done using simulations of empirical propagation attenuation models. As the demand for wireless and mobile communication services grows, mobile service providers need to ensure high-quality data and network services [2]. This requires meticulous network planning to avoid challenges such as network congestion and interference. Propagation path attenuation models are invaluable tools in this planning process, enabling providers to estimate and predict network coverage in specific locations, thus facilitating cost-effective network planning [3]. When building wireless communication systems, propagation attenuation must be taken into account. Signal attenuates or deteriorates as it moves from a transmitter to a receiver through a wireless communication channel. It is feasible to estimate the expected attenuation for a given route and forecast the coverage that networks or base stations can achieve by knowing the numerous factors that affect signal propagation path attenuation. Additionally, by using this knowledge, systems can be designed to function optimally even in the face of obstacles brought on by these factors. To effectively plan and optimize wireless communication systems, it is difficult to predict the received signal due to the multiple influences on path loss, which complicates analysis [4].

Several propagation attenuation models were optimized to suit specific areas under consideration to ensure optimal performance [5]. However, simulation-based models often fall short of predicting the propagation environment with high accuracy. Numerous studies have explored propagation attenuation, leading to various conclusions. Many models performed well in the intended primary environments of development, with the effectiveness largely dependent on the geographical or topographical characteristics of those areas. Considerable attention has been given to propagation attenuation predictions in several areas, resulting in different propagation attenuation models [6]. However, there has been limited discussion on propagation attenuation modeling utilizing machine learning within the environment of study, and this paper aims to contribute to the existing literatures in this area. This necessitates the use of measurement-based propagation attenuation models for more precise predictions.

However, [7] developed and compared path loss values based on regression analysis using regression analysis. To obtain channel responses, measurements were made using a spectrum analyzer FSH6 at 3.5 GHz operating frequency in urban and suburban areas. The findings showed that pathloss could be expressed as a function of distance and that, in practical measurements, a breakpoint distance of 32 meters was particularly accurate. Path loss exponents (n) for urban and suburban areas were identified and computed. To determine how the measurement results would affect particular environments, they were examined and contrasted. It has been noted that a variety of phenomena that contribute to radio path loss cause radio signals to attenuate as they move from the transmitter to the receiver. Again, [8] determined the best probability distribution function for simulating RF signal pathloss in Ondo State's urban, suburban, and rural areas during both wet and dry seasons is determined. The normal distribution in the rural setting during the rainy season had an RMSE of 7.06 dB, a relative error of 12.48 percent, and an R of 0.99. The RMSE during the dry season was 9.06 dB, with R of 0.99 and a relative error of 13.45 percent. These results provided important information for future wireless propagation channel planning in the areas under study. [9] developed propagation attenuation models utilizing 4G LTE data within urban and suburban terrains in Lagos, Nigeria. The COST231-hata and Ericsson models, which had RMSEs of 5.13 dB and 7.08 dB, respectively, among the different models assessed, performed the best in both urban and suburban environments. With RMSEs of 6.20 dB in urban areas and 5.90 dB in suburban areas, the optimized models produced promising prediction results that were in good agreement with propagation measurement results from comparable regions. According to the results, these models have the potential to greatly enhance coverage areas, which will raise the performance level of network systems in these regions. This work contributes by introducing a machine learning approach for solving the challenges faced by mobile users due to inadequate signal coverage. It compared the developed machine learning propagation attenuation models with the standard COST231-hata model based on RMSE, MAE, and R. The accuracy of the machine learning hybrid model enhances propagation attenuation prediction within the terrains of consideration.

2. Materials and Methods

The main components of the research involved the collection of data, preprocessing of data in Matlab, modeling, evaluation, and validation. Tools like a laptop with licensed TEM software, a modem with a data SIM card, and a GPS device were used for measurement and data collection. MATLAB and MS Excel were used for data analysis and preprocessing. The drive test method was used to collect data in pre-designated areas within Port Harcourt, and the recorded data were then extracted. The measured propagation attenuation was extracted from a recorded drive-test route, as shown in Figure 1.

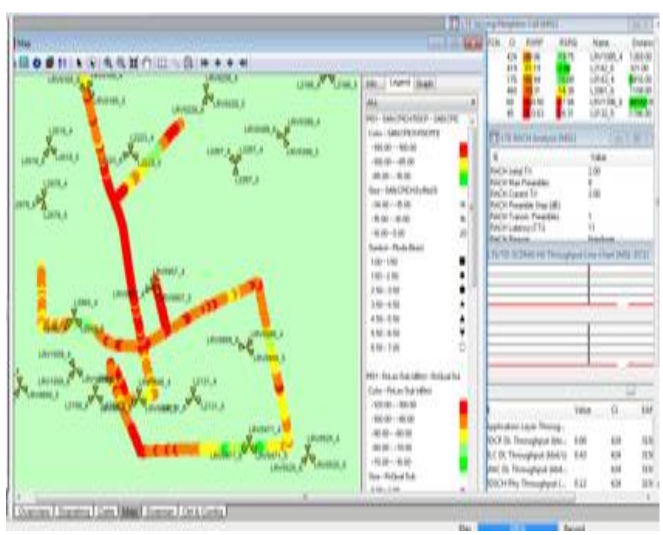

Fig. 1 Drive test route

2.1. Standard Propagation Attenuation Models

Design engineers and wireless network planners have developed a number of propagation models to enhance broadband services. The impact of path loss on signal propagation is addressed by these models, providing precise forecasts that are necessary for efficient network planning [10, 11].

2.1.1. COST231-Hata Model

An expansion of the original Hata model, which was created to forecast signal propagation in urban settings, especially for wireless communication systems, is the COST231-Hata model [12]. In mobile communication engineering, the COST231-Hata model is still an essential tool that offers a useful way to estimate propagation attenuation in a variety of scenarios.

The frequencies covered by the COST231-Hata model range from 1.5 GHz to 2 GHz [13]. This means that it is compatible with GSM and UMTS, among other contemporary mobile communication systems. The model may not be accurate for long-range scenarios or extremely complex environments, and it is primarily useful for medium-range communications between 1 km to 20 km [14].

It might not take into consideration all the factors that influence signal propagation, such as particular topographical features or transient obstructions, as many empirical models do. Engineers can use the COST231-Hata model to help plan and optimize wireless communication networks by figuring out where and how high to place antennas for optimal coverage [15].

It helps with base station coverage area prediction, which is important for customer satisfaction and service quality. The model offers a foundation for contrasting various propagation environments, enabling customized solutions depending on particular urban and geographic features. Its propagation attenuation estimation is in accordance with three various terrains, such as rural, suburban, and urban environments [16]. Its path attenuation in decibels can be estimated for the urban environment using equation (1)

$$\hat{y}_p(\mathrm{dB}) = 46.3 + 33.9\log_{10} f - 13.82\log_{10} h_t - \alpha(h_r) + (44.9 - 6.55\log_{10}(h_t))\log_{10}(d) + C_m \qquad (1)$$

Where
h_t = transmitter height
d = the distance between the transmitter and receiver
$\hat{y}_p$ = predicted value

$$\alpha(h_r) = \begin{cases} 0 & (\text{if } h_r \leq 1\text{m}) \\ 3.2(\log_{10}(11.75h_r))^2 - 4.97 & (\text{if } h_r > 1\text{m}) \end{cases}$$

The value of C_m is designated as 0 dB for suburban areas, whereas 3 dB for large cities.

2.1.2. Okumura-Hata Model

It is an empirical model frequently utilized to forecast propagation attenuation within urban settings. It has been a mainstay in mobile communications, offering insightful information about propagation attenuation behavior in diverse settings [17]. The frequency range covered by the Okumura-Hata model can be between 150 MHz to 1500 MHz; higher frequencies required by more recent mobile technologies are not compatible with this model [17]. Its formula for propagation attenuation calculation can be evaluated using equation (2);

$$\hat{y}_p(\mathrm{dB}) = 69.55 + 26.16\log_{10}(f) - 13.82\log_{10} h_t - \alpha(h_r) + (44.9 - 6.55\log_{10} h_t)\log_{10}(d) \qquad (2)$$

To minimize errors and enhance the caliber of the analysis, the acquired data were carefully extracted and preprocessed because they might include noise. By undergoing this preprocessing step, the data was readily loaded for the genetic algorithm to analyze. Model development becomes the primary focus after the data is prepared. In this phase, the genetic algorithm-based propagation attenuation model was comparatively evaluated with other existing propagation attenuation models considering the RMSE, MAE, and R.

2.2. Measured Propagation Attenuation Estimation

The measured propagation attenuation was calculated by utilizing the formulation in equation (3).

$$\hat{y}_m = p_t + G_t + G_r - L_f - L_a - \mathrm{RSRP} \qquad (3)$$

Where
$\hat{y}_m$ = measured path loss value
p_t = power from the transmitter
G_t = transmitter gain
G_r = receiver gain
L_f = loss due to feeder cable
L_a = loss due to antenna
RSRP = measured signal

2.3. Genetic Algorithm

Natural evolution serves as the inspiration for a class of optimization and search methods known as genetic algorithms (GAs). It is particularly useful for resolving complex issues where more conventional optimization techniques might falter, which belongs to the broader category of evolutionary algorithms [18]. Their resemblance to natural selection makes it possible for them to efficiently explore intricate solution spaces. Despite the drawbacks, it is useful in a variety of applications due to its versatility and worldwide search capabilities. Practitioners can use GAs to solve challenging problems in a variety of domains by having a basic understanding of the technique's components and guiding principles [18-20]. A population of viable answers to the current problem is the starting point for a genetic algorithm. Every solution is commonly depicted as a chromosome, which is normally encoded as a series of binary numbers. Next, each chromosome's performance in solving the problem can be assessed by the fitness function [21]. The probability of a solution being chosen for replication is ascertained by its fitness score. A solution that has a higher fitness score is superior.

It also goes through a selection process in which chromosomes from the current population are chosen in order to produce offspring. The roulette wheel selection method was utilized for the purpose of this research. The chromosomes cross over, and the chosen chromosomes are paired to create offspring. By combining both parents' genetic information, Crossover may be able to produce better results. Mutation was performed, which is merely the recombination of genes within the chromosomes [21]. The best solution can be found at the end of the iteration, and if this is met, GA ends.

2.4. Metric Evaluation

The accuracy and performance of predictive models, particularly regression models, are evaluated using a variety of metrics [22]. The correlation coefficient, MAE, and RMSE were utilized to evaluate the performance level. Each offers distinct perspectives on the performance of the models.

$$\mathrm{RSRP} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\hat{y}_m - \hat{y}_p\right)^2} \tag{4}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|\hat{y}_m - \hat{y}_p\right| \tag{5}$$

$$R = \frac{\Sigma(\hat{y}_m - y_m)(\hat{y}_p - y_p)}{\sqrt{\Sigma(\hat{y}_m - y_m)^2\,\Sigma(\hat{y}_p - y_p)^2}} \tag{6}$$

Where;
n = number of data points
y_m and y_p are measured and predicted mean, respectively.

3. Results and Discussion

The analyzed results shown in Figures 2 to 13 demonstrated the prediction accuracy of the machine learning hybrid Wavelet-GA model in comparison to the GA model and the standard COST231-Hata model.

The machine learning hybrid Wavelet-GA model demonstrated superior accuracy in forecasting propagation attenuation by achieving the lowest RMSE values for all the sites. The machine-learning hybrid wavelet-GA model derived the lowest RMSE values of 2.27 dB, 4.61 dB, 3.77 dB, and 3.93 dB for sites 1, 2, 3, and 4, respectively. The highest prediction errors were shown by the COST231-Hata model, with RMSE values of 67.40 dB, 74.37 dB, 60.54 dB, and 66.29 dB.

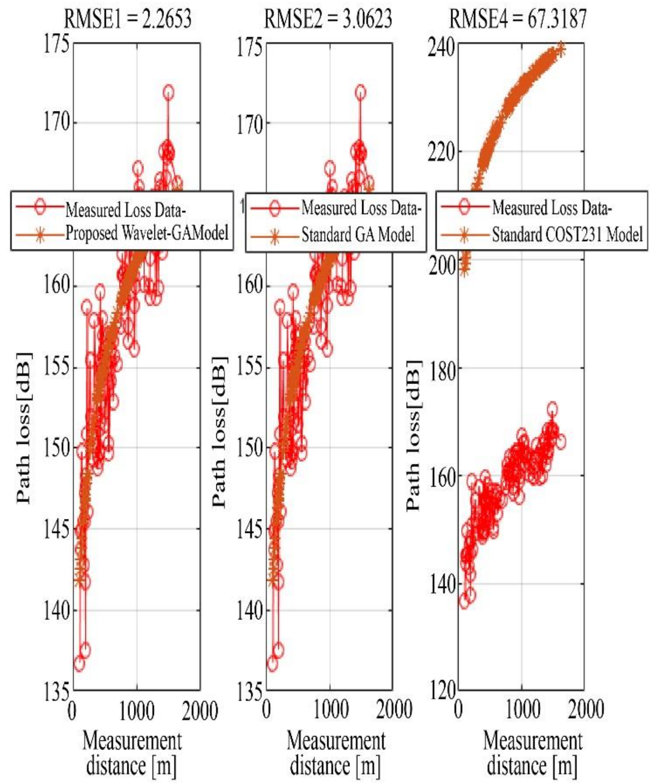

Fig. 2 RMSE of Wavelet-GA Model Vs GA and Cost231 Models for Site 1

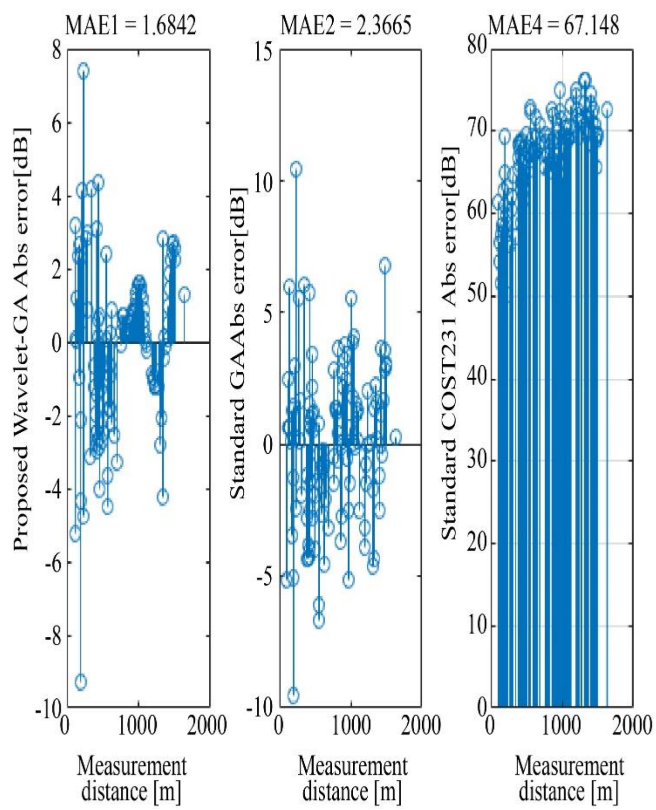

Fig. 3 MAE of Wavelet-GA Model Vs GA and Cost231 Models for Site 1

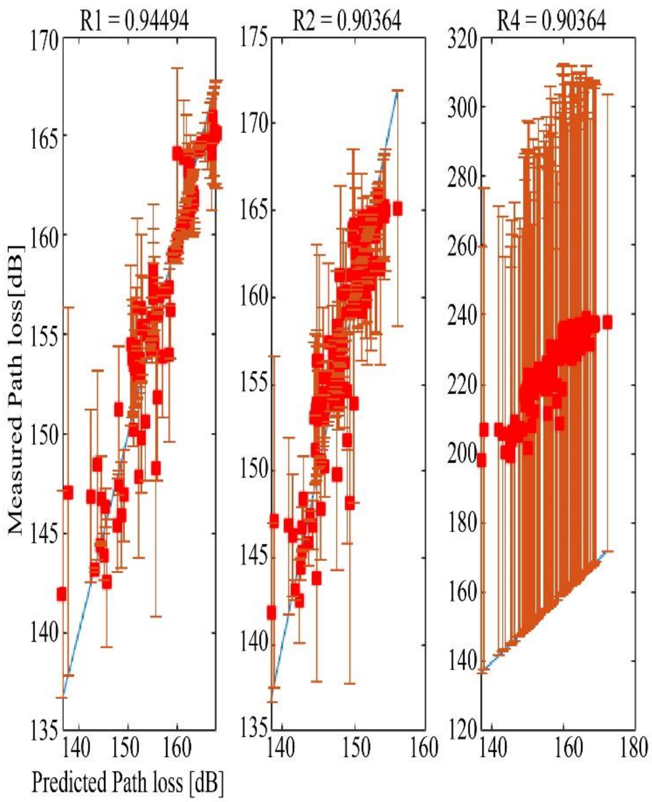

Fig. 4 R of Wavelet-GA Model Vs GA and COST231 Models for Site 1

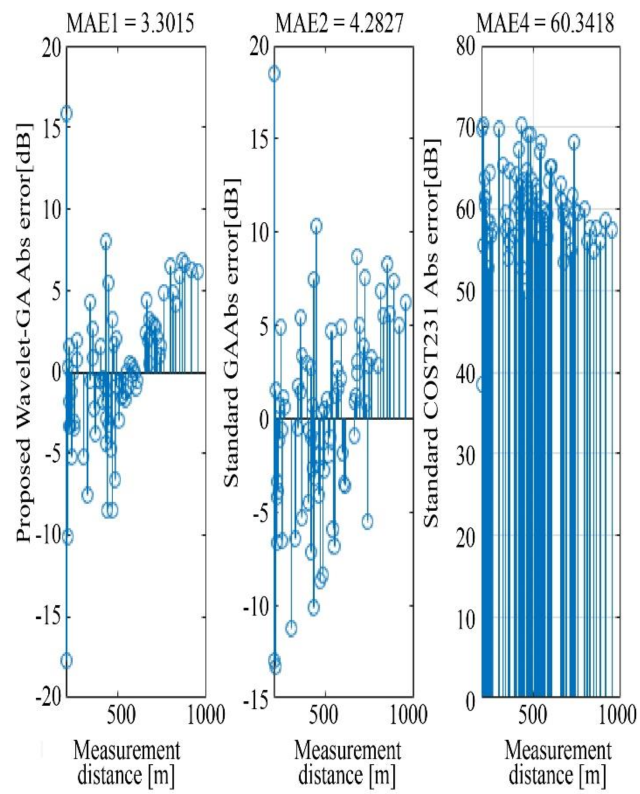

Fig. 6 MAE of Wavelet-GA Model Vs GA and COST231 Models for Site 2

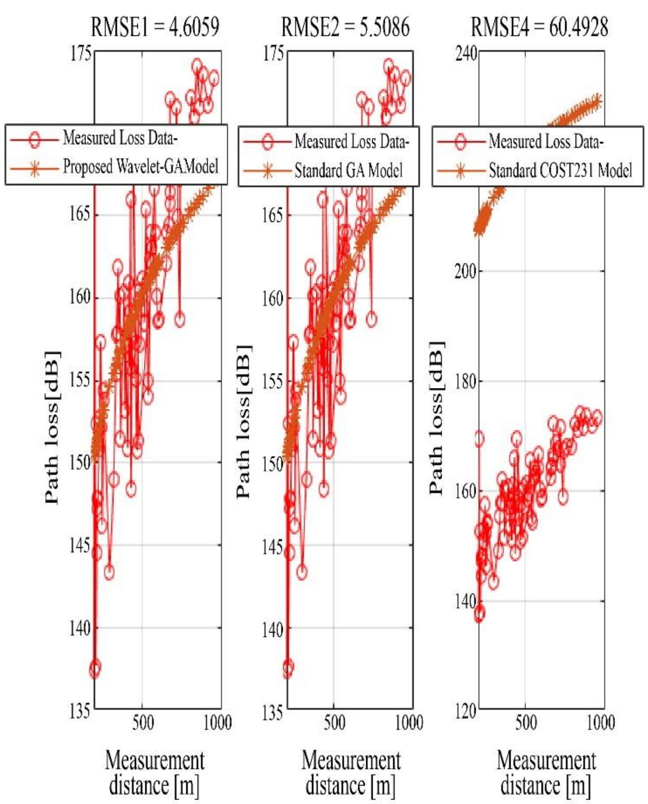

Fig. 5 RMSE of Wavelet-GA Model Vs GA and COST231 Models for Site 2

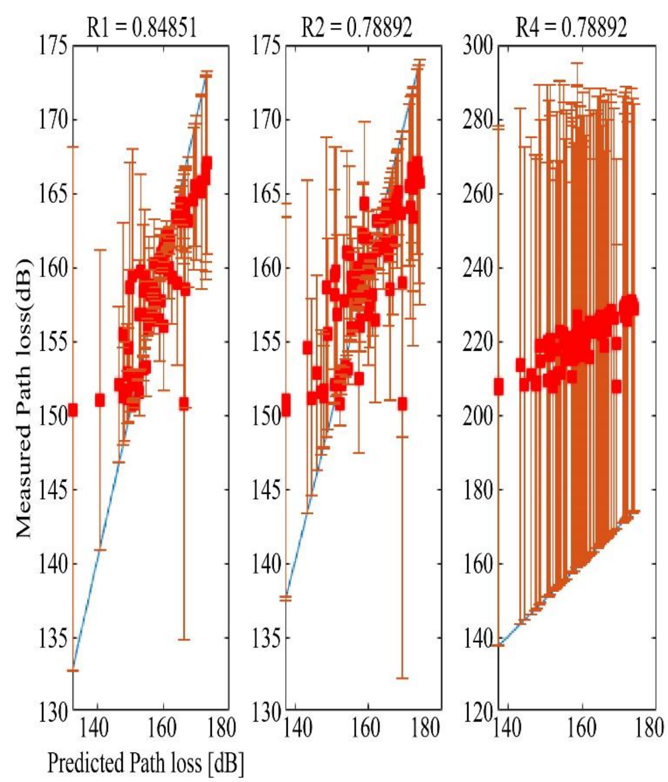

Fig. 7 R of Wavelet-GA Model Vs GA and Cost231 Models for Site 2

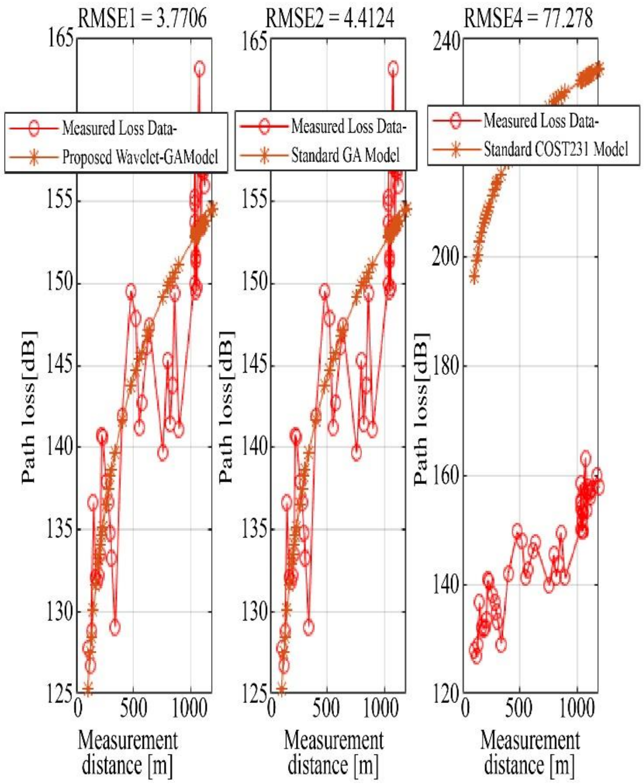

Fig. 8 RMSE of Wavelet-GA Model Vs GA and COST231 Models for Site 3

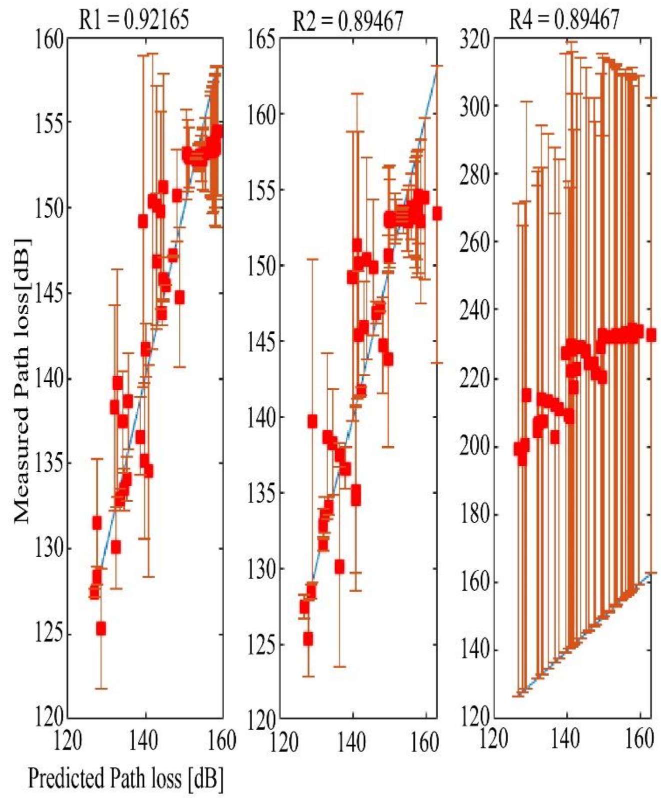

Fig. 10 R of Wavelet-GA Model Vs GA and COST231 Models for Site 3

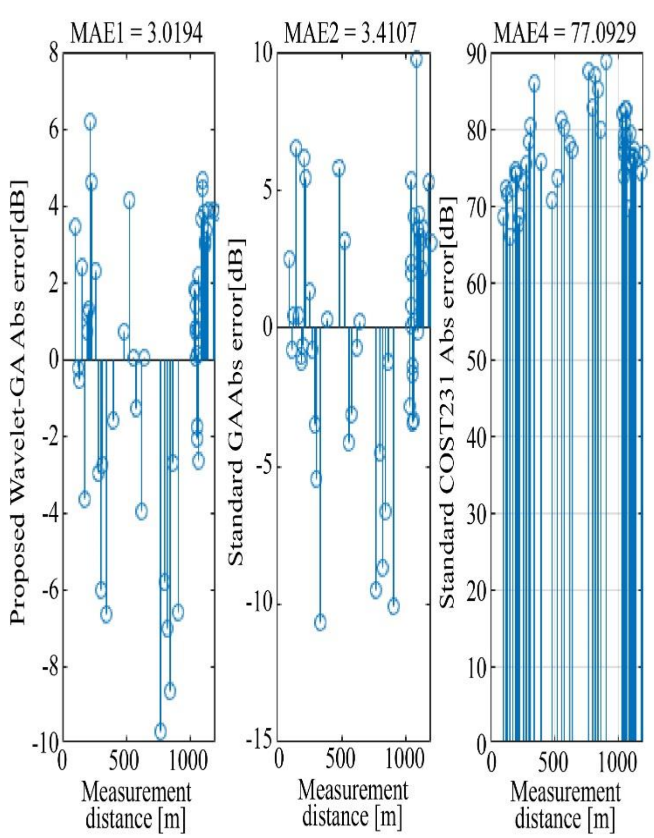

Fig. 9 MAE of Wavelet-GA Model Vs GA and Cost231 Models for Site 3

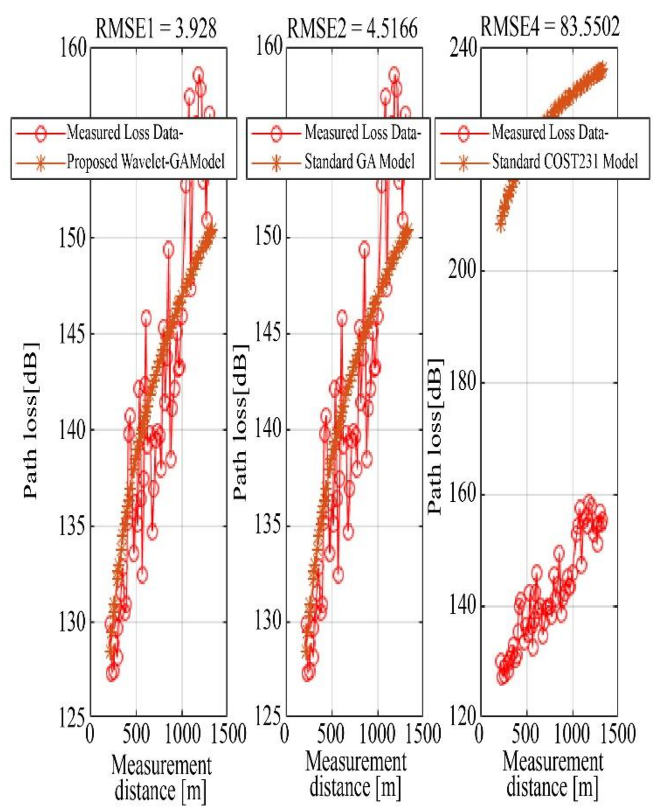

Fig. 11 RMSE of Wavelet-GA Model Vs GA and COST231 Models for Site 4

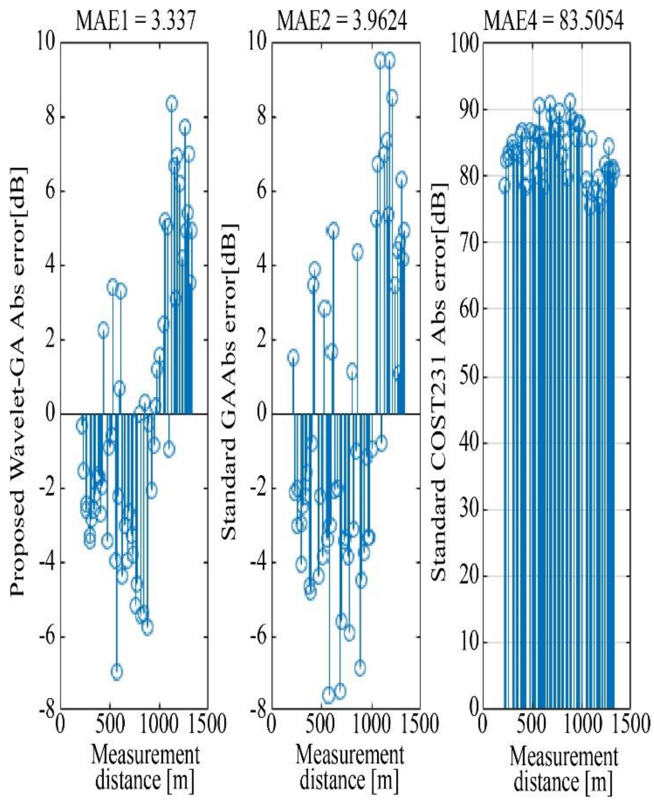

Fig. 12 MAE of Wavelet-GA Model Vs GA and COST231 Models for Site 4

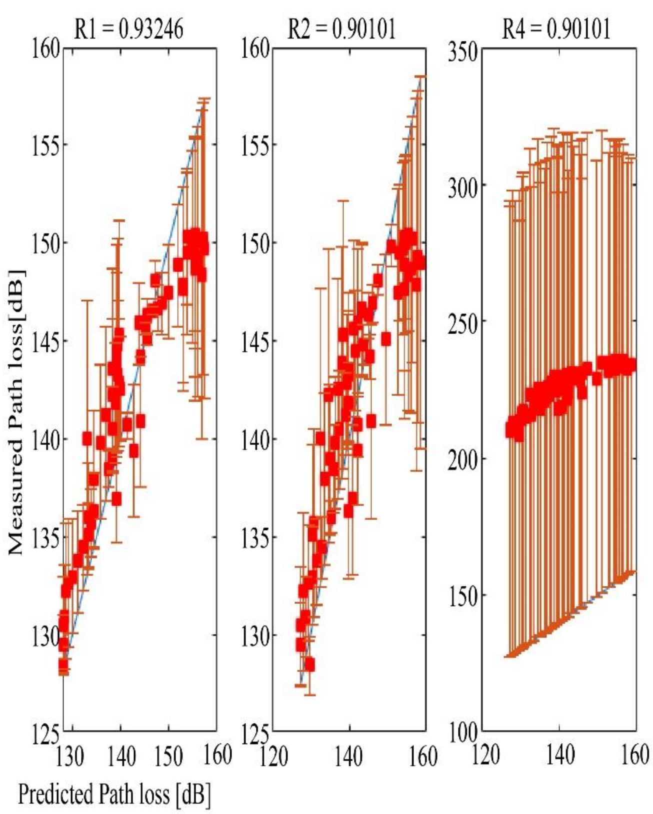

Fig. 13 R of Wavelet-GA Model Vs GA and COST231 Models for Site 4

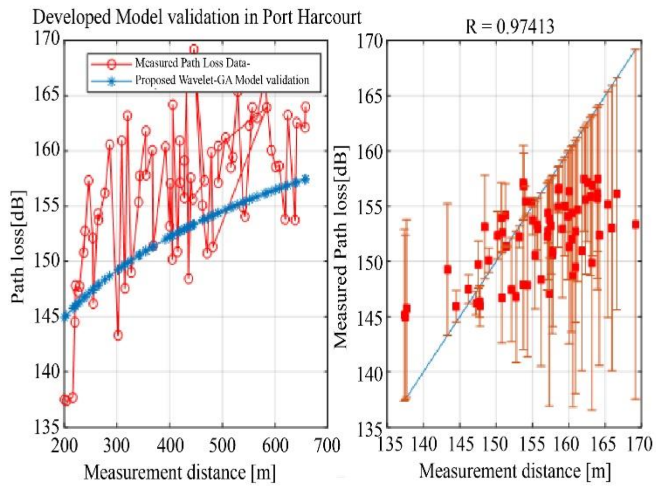

Fig. 14 Validation of the hybrid Wavelet-GA model

The machine learning model evaluated the least MAE values of 1.68 dB, 3.30 dB, 3.02 dB, and 3.34 dB for sites 1, 2, 3, and 4, respectively, whereas the COST231-Hata model, on the other hand, showed the highest MAE values with values ranging from 67.20 dB to 84.36 dB. It showed strong correlations between measured propagation attenuation and the machine-learning hybrid Wavelet-GA model. Correlation coefficients for all the sites were 94.49%, 84.85%, 92.17% and 93.25% respectively. Figure 14 shows the validation results, which demonstrated the level of performance of the machine learning hybrid Wavelet-GA model when the test ran with another dataset. In order to demonstrate the model's versatility and dependability, this method evaluates its capacity to forecast propagation losses across different cell sites. The machine learning hybrid Wavelet-GA model showed a prediction accuracy of 97.41% in Figure 14.

4. Conclusion

It proved that the machine learning hybrid Wavelet-GA model is more accurate at predicting signal propagation attenuation than both the GA and the COST231-Hata models. Its superior efficiency and effectiveness in forecasting propagation attenuations are highlighted by the results, which validate the machine learning hybrid Wavelet-GA model's robustness and reliability for dynamic scenarios. On all cell sites, the machine learning hybrid Wavelet-GA model consistently obtained the highest correlation coefficients and the lowest RMSE and MAE values when compared to the GA and COST231-Hata models. The correlation analysis demonstrated the high predictive accuracy of the machine learning hybrid Wavelet-GA model by showing a strong alignment between the measured values and its predictions. In contrast, the COST231-Hata model performed worse, showing the lowest correlation coefficients and the highest RMSE and MAE values. The efficiency of the machine learning hybrid Wavelet-GA model was further validated using different datasets since it provides a workable solution to the problems of low quality of service in the area. The machine learning hybrid Wavelet-GA model performed better than conventional models and is advised for cellular network planning within Port Harcourt; as such, network providers should benefit greatly from this improved model's increased capacity and coverage, which will ultimately raise end users' quality of service. Since the data utilized in this work was limited to only four sites in Port Harcourt, as such, for future work, it is recommended that more cell sites should be considered to cover Nigeria as a whole for a broader coverage area.

Conflicts of Interest

The outcome of this research work was achieved without any conflicts existing between the authors.

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