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Impact of noise reduction on Path Loss Model development and Tuning using Wavelet Transform

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Abstract: Accurate path-loss estimation is an essential part of wireless network planning. It is achieved through extensive measurement of the received signal strength (RSS) in the target area. The measured data is mostly corrupted by noise, which affects the accuracy of the path loss model it is used for. Therefore, the purpose of this paper is to highlight the impact of noise on the dataset used for the development of path loss model. In this paper, a wavelet transform was used for the de-noising of the RSS data, and the outcome was used for the tuning of the standard log-distance model. The standard model, the tuned standard model and the wavelet+tuned-standard model were compared. As expected, the wavelet+tuned-standard model outperforms the others.

Keywords: path loss, wavelet, noise, model, communication

1. Introduction

One of the significant drawbacks of wireless communication systems is the loss of signal strength as the signal propagates from the transmitter to the receiver. The loss is first a result of the spreading out of the signal from the transmitter and then due to the interaction of the signal with various blockades along its path. These blockades reflect, scatter, and diffract the signal.

For network engineers to plan any wireless network, a transmission path loss model is required. This model is engaged to ascertain the level of loss suffered by the transmitted signal and allow the engineers to optimize the cell tower distribution.

Noise in the transmission of wireless communication has an adverse impact on the overall quality of service (QoS) of the system [1]. However, understanding the properties and effects of noise on wireless communication links is vital for the development of reliable path loss models for accurate network planning by engineers and designers [2]. The corruption of signals by noise occurs during signal production, propagation, reception, and reproduction [3]. If the signal that is sullied with noise is used to develop or tune a propagation path loss model, the performance of the model will be poor, hence the need for noise reduction. The main objectives of this work include the following:

- Detail data acquisition using a professional TEMs tool
- Adaptive tuning of the standard log-distance model using the Levenberg-Marquardt Algorithm (LMA)
- Effect of noise reduction of the measured signal on the LM–tuned model

2. Related works

In [3, 4], the authors classify and explain the different types of noise, their sources, and their effects on communication systems. They pointed out that noise reduction in telecommunication is divided into passive noise control and active noise control. The authors in [5,6] argued that noise reduction is a vital aspect of data cleaning, and it enhances data analysis. Meanwhile, there exist many de-noising techniques: rough sets and neural networks [8], wavelets transform [9], Hybrid slantlet transform [10] and so on. However, wavelet transform is considered in this paper due to its ability to effectively analyze data in both frequency and temporal domain [11]. The author in [3] compared the de-noise ability of four thresholding wavelet transform techniques and concluded that Rigrsure outperformed the others. In [9], the authors consider noise reduction on the received signal in wireless ultraviolet communications using wavelets. And they concluded that wavelet transforms can improve the signal-to-noise ratio (SNR) at the receiver.

Thus, to enhance the prediction accuracy of the standard log-distance model and provide better path-loss prediction capability, we propose a dimensionality reduction of the signal dataset to filter out noise before using it for path-loss model development.

3. Methodology

The block diagram in Fig 1 presents the methodology wherein this work is guided. We start by defining the standard log-distance model, and then the Levenberg-Marquardt algorithm is engaged for the tuning of the standard log-distance model. This is followed by engaging the wavelet transform techniques for noise reduction and the results were evaluated.

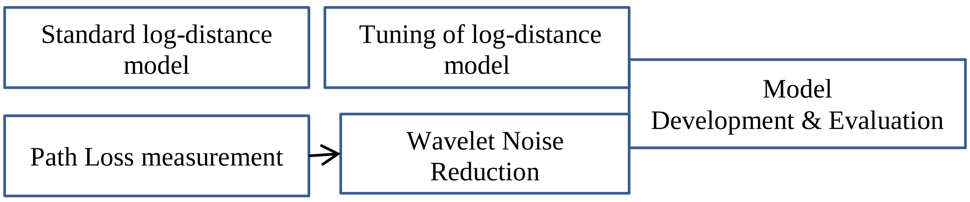

Fig.1. Block diagram of the research methodology

3.1. RF network data measurement

The data used for this paper was obtained from a network provider in Nigeria. The tools used for measurement are one Dell laptop computer and two TEMS pocket phones. Both were equipped with Ericsson Telephone Mobile software. Other tools include GPS, a Lexus 300RX car, an inverter, and connecting cables. The car was used for mobility around the selected route in the study location. The GPS was for taking location coordinates at every point of the drive test. The RF measurements were achieved by making constant calls to the networks at every drive test location. The operating frequency of the network provider is 801 MHz.

To obtain the path loss (P_L) from the measured data for network A and network B, we employ the equation (1)[12].

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

where RSRP is the reference signal received power. The value of these parameters and other relevant parameters for the network is listed in Table 1

Table 1. Measurement setup parameters

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

3.2. Model tuning with LM

The value of signal power attenuation (P_L) in free space is given without proof as:

$$P_L(dB) = 147.56 + 20\log(f) + 20\log(d) \tag{2}$$

where f is the signal frequency, and d is the distance between the transmitter and the receiver. Meanwhile, equation (2) will perform badly in other propagation environments, such as urban and sub-urban areas, hence the need for tuning. Equation (2) can be re-written as equation (3)

$$P_L(dB) = x_1 + x_2\log(f) + x_3\log(d) \tag{3}$$

For the sake of this work, equation (3) will be referred to as standard model. x_1, x_2 and x_3 are the loss coefficients.

Given the measured path loss data points (d_i, P_L) , the goal is to determine the vector **x** that can provide an optimal prediction model $y = P_L(r_i, \mathbf{x})$ with high accuracy. where **x** is the parameter vector [x_1, x_2, and x3] and $P_L(d_i, x)$, a linear equation is the model output.

3.3. Levenberg-Marquardt Algorithm (LMA)

The Levenberg-Marquardt Algorithm (LMA) [11–13], is a major optimization algorithm for providing robust global solutions to complex least-square approximation problems.

The Jacobian Matrix, J of equation (3) is required to solve the minimization problem.

$$J = \begin{pmatrix} \frac{\partial P_L(d_1|x)}{\partial x_1} & \frac{\partial P_L(d_1|x)}{\partial x_2} & \cdots & \frac{\partial P_L(d_1|x)}{\partial x_3} \\ . & . & \cdots & . \\ . & . & \cdots & . \\ \frac{\partial P_L(d_1|x)}{\partial a_1} & \frac{\partial P_L(d_2|x)}{\partial a_2} & \cdots & \frac{\partial P_L(d_3|x)}{\partial a_3} \end{pmatrix} \tag{4}$$

In addition, the vector of all the residual is given

$$res = \begin{pmatrix} P_{Li} - P_L(r_1 \mid x) \\ P_{Li} - P_L(r_2 \mid x) \\ . \\ . \\ . \\ P_{LN} - P_L(r_N \mid x) \end{pmatrix} \tag{5}$$

Hence, putting everything together we obtain the LM method in equation (6). According to [16], [17], Levenberg-Marquardt Method is a very powerful and reliable tool for analyzing many minimization problem as it combines the benefits of the gradient-descent and Gauss-Newton methods.

$$LM = (J^T \cdot W \cdot J + \mu \cdot I)^{-1} \cdot J^T \cdot W \cdot r \tag{6}$$

where J is the Jacobian matrix, J^T, the transpose of the Jacobian, μ is the damping parameter, W is the weight matrix, I is the identity matrix, and r is the residual vector representing the difference between the observed and the predicted values.

3.4. Signal De-noising with Wavelet Transform

Assuming that the path loss signal $P_L(n)$ is corrupted with noise χ, the noise model is expressed as:

$$y(n) = P_L(n) + \sigma\chi(n) \tag{7}$$

Where σ is a Gaussian white noise, representing the noise intensity, and n = 1, 2, 3, . . . , N represents the length of the signal.

To obtain good and reliable datasets for the model development, wavelet transform is used to filter the noise in the measured data.

Equation (8) defines wavelet transform:

$$P(b,a) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} \psi^* \left(\frac{t-b}{a} \right) y(n)\, dt \tag{8}$$

where a is the dilation parameter, b is the translational parameter and $\frac{1}{\sqrt{a}}$ is a weighting function. $\psi^*(t)$ is the complex conjugate of the mother wavelet $\psi(t)$ and $y(n)$ is the corrupted signal .

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}} \psi \left(\frac{t-b}{a} \right) \tag{9}$$

4. Result and discussions

This section presents the results and valuable discussions. As shown in Figs. 1, 2 and 3, the top parts of the plots, that is, Figs. 1a, 2a and 3a show how the standard model in equation (2) predicts the acquired path loss data relative to the measured distance across the routes of interest. It is clear from the plots in Figs. 1, 2, and 3 that the unturned standard model overpredicted the measured path loss with very high MAE, RMSE, and STD values at all the sites. This type of error is to be expected because the model is developed for a free space scenario thus, the need to tune the standard model to fit the measured data. The LMA-tuned standard model predicted the measured path-loss well, but it performed best with the de-noised path loss signal. Tables 2, 3, and 4 present the estimated errors for the standard model, the tuned standard model, and the tuned standard model plus wavelet in all the study areas.

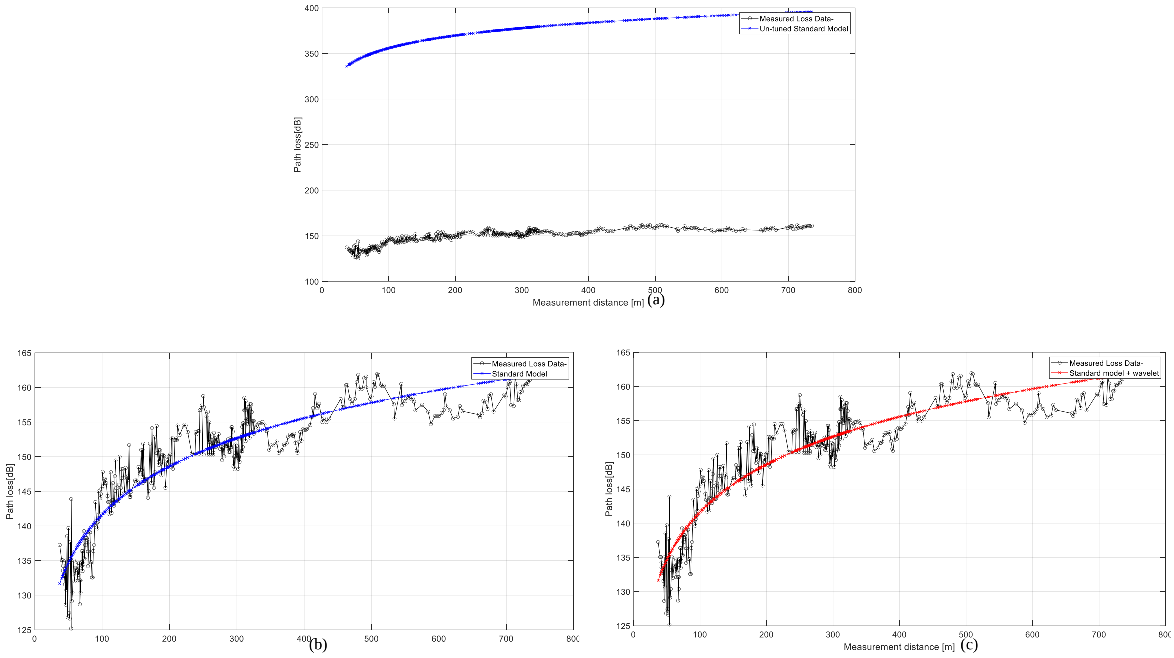

Fig. 1. Measured link loss prediction plots for Route_1

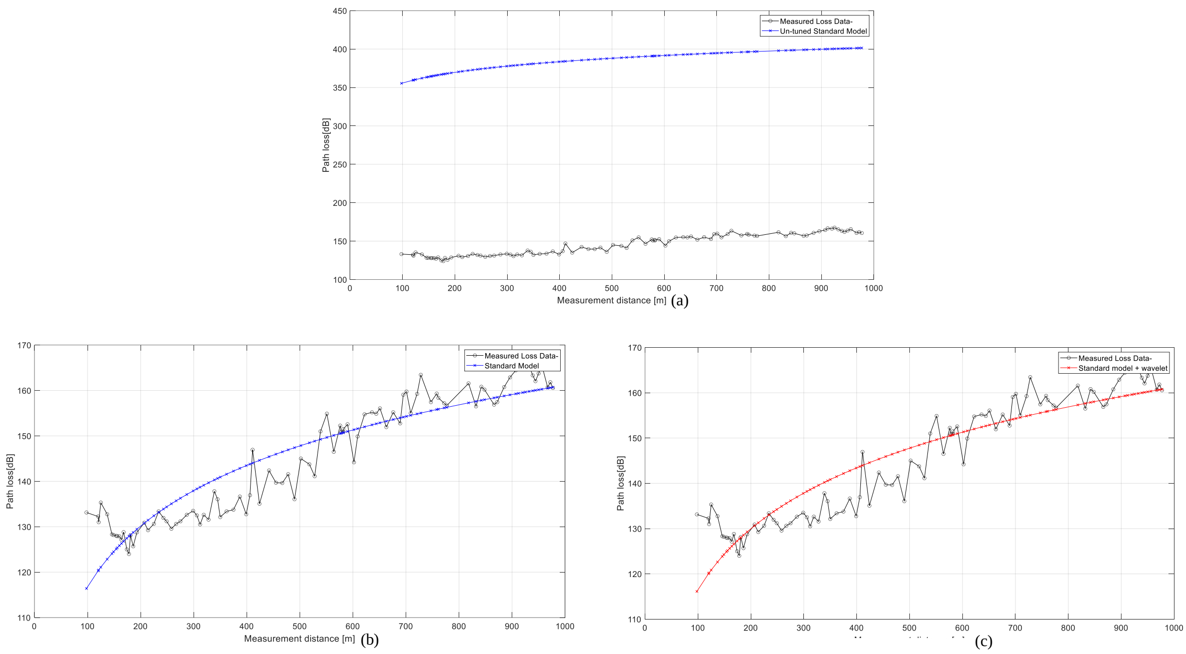

Fig. 2. Measured link loss prediction plots for Route_2

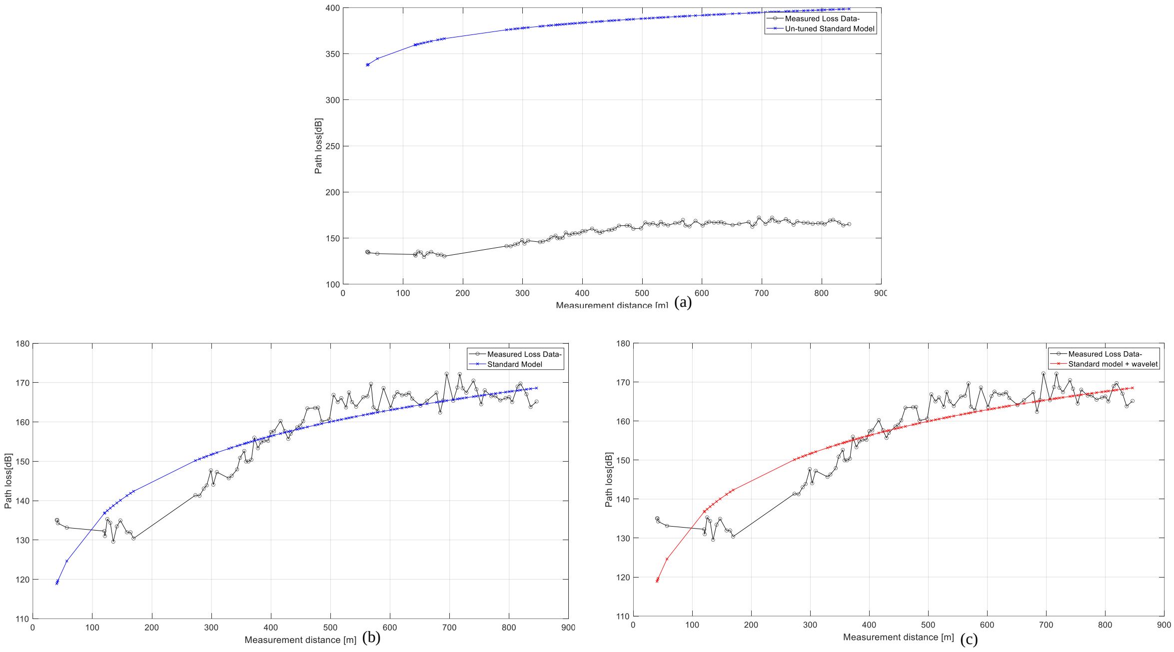

Fig. 3. Measured link loss prediction plots for Route_3

Figs. 4 – 6 also show the performance fits of the standard model, tuned standard model, and the tuned standard model + wavelet performance fits on the acquired path loss data in each study route. The closer the R-squared value is to one, the better the fit between the model's estimations and the measured data is. A negative r-squared, on the other hand indicates that the model fits is worse than the mean of the target values, which is the case for the standard model in all the selected routes. The correlations for the tuned standard model range from 0.90 to 0.92 while the correlations for the tuned standard model + wavelets range from 0.91 to 0.94. It may be deduced from the foregoing that data denoising is vital before engaging in the development of a propagation loss model.

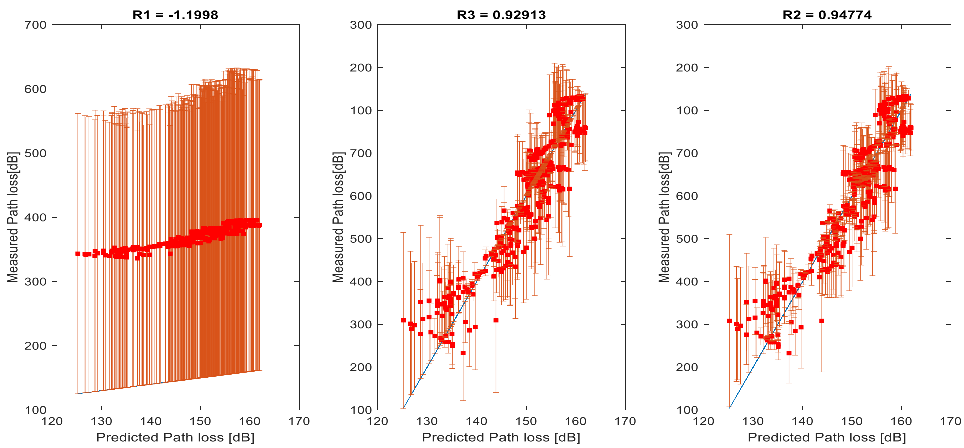

Fig. 4. Path loss estimation performance regression plots in route_1

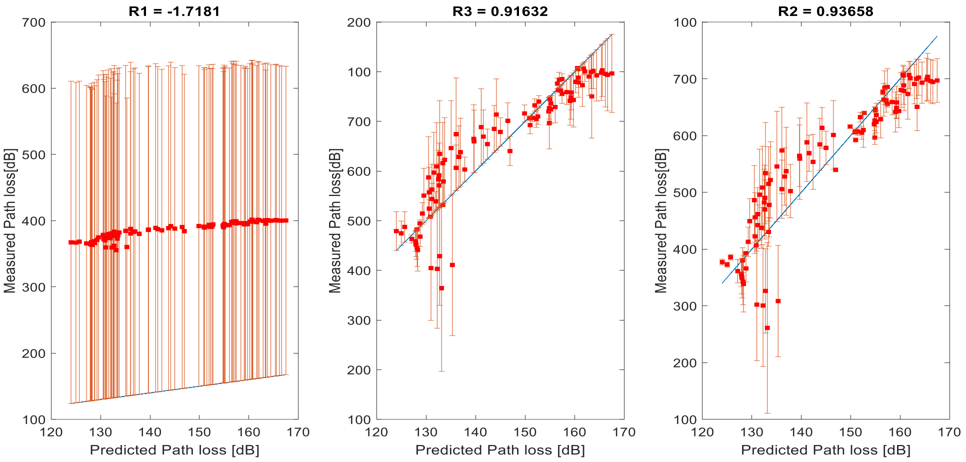

Fig. 5. Path loss estimation performance regression plots in route_2

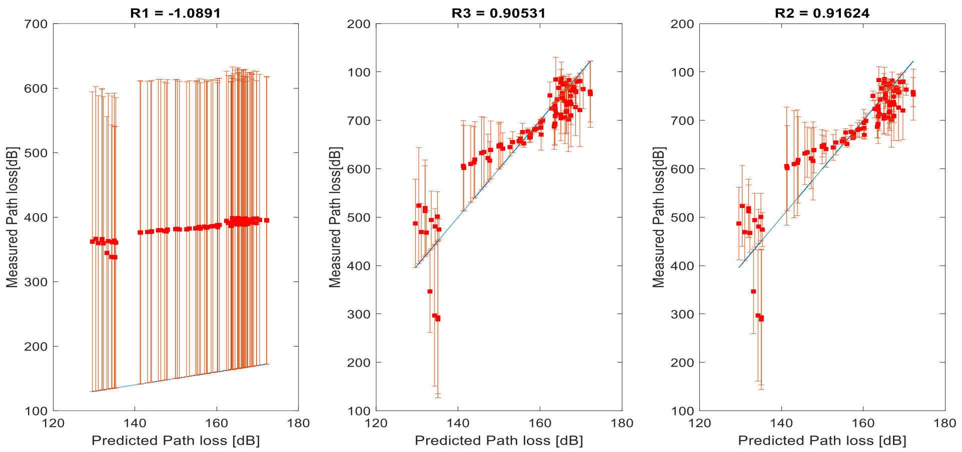

Fig. 6. Path loss estimation performance regression plots in route_3

Furthermore, the three in one set of graphs in Figs. 7 – 9 are plotted to examine the mean absolute error values as compared with the standard model, the tuned standard model and the tuned standard model + wavelet. The mean absolute error for the standard model is outrageously high, followed by the tuned standard model. The tuned standard model + wavelet have the least MAE. This also attests to the fact that, noise reduction is necessary before engaging any datasets for the development of a fresh propagation loss model or the tuning of an existing model.

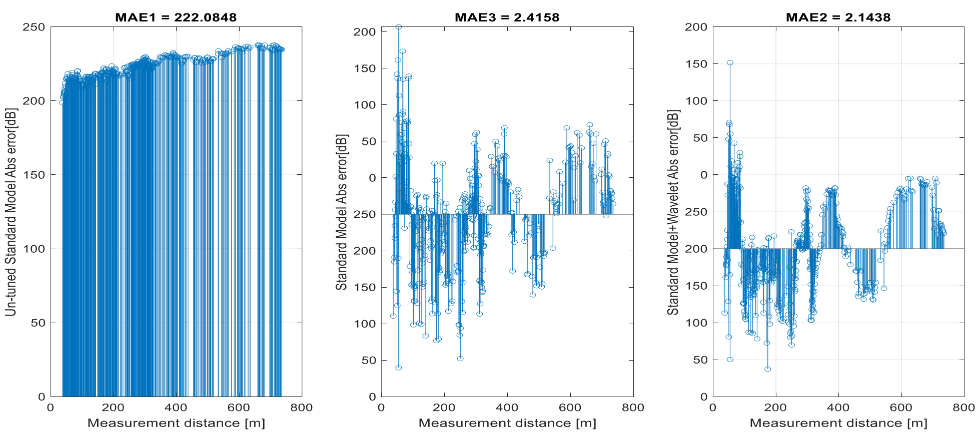

Fig. 7. Quantified estimation of mean absolute error attained in route_1

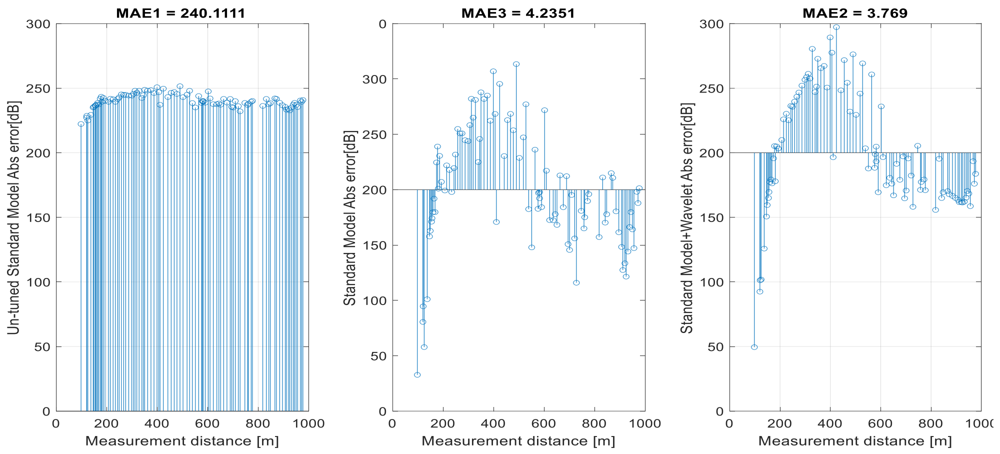

Fig. 8. Quantified estimation of mean absolute error attained in route_2

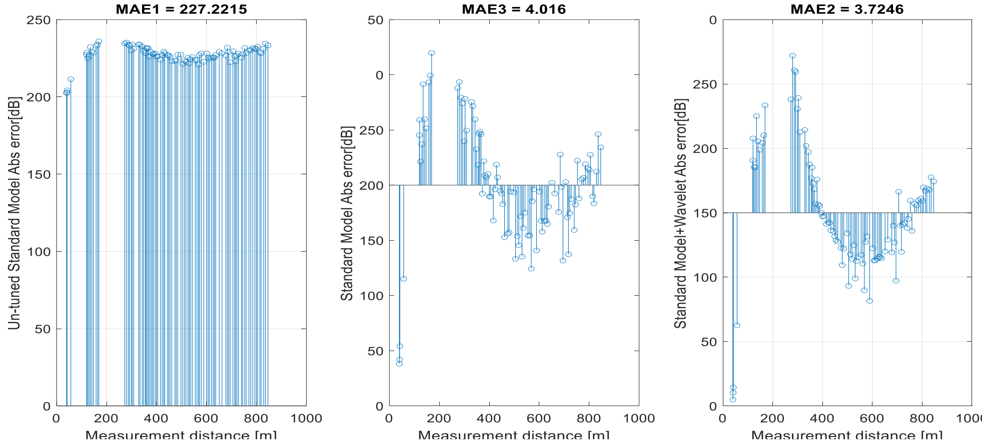

Fig. 9. Quantified estimation of mean absolute error attained in route_3

Table 2. Computed first order estimates statistic for Route_1

	Standard model	Tuned Standard model	Tuned Standard model+Wavelet
MAE	222.085	2.41578	2.14384
RMSE	222.237	3.05925	2.59486
STD	8.23431	3.06319	2.5982
R^2	-1.1998	0.929133	0.94774

Table 3. Computed first order estimates statistic for Route_2

	Standard model	Tuned Standard model	Tuned Standard model+Wavelet
MAE	240.111	4.23507	3.76899
RMSE	240.172	5.37042	4.63376
STD	5.41894	5.39831	4.65784
R^2	-1.71809	0.916315	0.936579

Table 4. Computed first order estimates statistic for Route_3

	Standard model	Tuned Standard model	Tuned Standard model+Wavelet
MAE	227.222	4.01604	3.72458
RMSE	227.297	5.26607	4.89745
STD	5.88066	5.2943	4.92371
R^2	-1.08906	0.905312	0.916236

5. Conclusions

A comparison investigation to ascertain the impact of noise reduction in the development or tuning of existing propagation loss model is presented in this paper. This work can form the foundation upon which the development of a reliable propagation path-loss model is built. And, this will enhance the planning and designing of wireless communication system in any terrain.

We first demonstrated that the tuned standard model can achieve better estimation performances than the untuned standard model in the study environment of interest. In addition, we show that the combination of a wavelet and the tuned standard model can achieve a better signal attenuation prediction. Future research may explore other denoising techniques and compare for different propagation environments.

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