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A LEAST ABSOLUTE DEVIATION TUNING METHOD TO REDUCE SIGNAL COVERAGE LOSS PREDICTION ERROR IN ELECTROMAGNETIC WAVE PROPAGATION CHANNEL

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ABSTRACT

The demand for increased mobile phone subscribers require an efficient radio network planning that involves an accurate prediction of propagation loss. Although various empirical loss models are in use, they are suitable for a particular environment or a specific cell radius. The tuning of a model is a process in which the parameters of the theoretical propagation model are adjusted with the help of measured values obtained from the experimental data. In this process, several model parameters can be changed. The objective of tuning is to obtain the values of the predicted model parameters to have a closest match with minimal prediction error to the experimentally measured data. In this paper, we have introduced a tuned least absolute deviation (LAD)-based Walficsh/Ikegami (W/I) model using measured UMTS strength data carried out in GRA, Benin City, Nigeria. We found that the performance of the tuned W/I model is the best as root mean square error is lower compared to least square based regression technique. The tuned model with LAD method best fit into BS 2 and BS 3 with an RMSE of 5.41 as compared to least square tuning method which has an average RMSE of 16.68 with BS 2 and BS 3. This successfully validates our tuning methodology and suggests that the tuned model is more accurate for the specified environment.

KEYWORDS: Optimization, Propagation Model Tuning, least absolute deviation regression method, prediction error, electromagnetic waves, environment.

INTRODUCTION

In wireless communication technologies, information is sent by electromagnetic waves. Electromagnetic wave propagation in real space is very complicated and much more complex in the mobile communication system, which are mainly displayed in three aspects (Tiegang, (2013):

(i) The openness of wireless channel- When electromagnetic wave transmits in open space, the wireless channels are easily affected by all kinds of interference signals.

(ii) The complexity and diversity of propagation environment- The mobile communication system works both in big cities with high buildings and small villages in mountains.

(iii) The random mobility of users-Users might call anywhere, such as in rooms, in a high-speed train or car.

Above three aspects have a great influence on the propagation of electromagnetic wave in a mobile communication system; during propagation an interaction between waves and environment attenuates the signal level. It causes path loss and finally it limits coverage area. Generally, wireless propagation models are built to predict the path loss, so as to estimate the field strength coverage of received signals. The accurate signal coverage prediction using propagation pathloss models is a crucial element in the first step of network planning. The capability of determining optimum Base-Station (BS) locations, obtaining suitable data rates and estimating coverage without conducting a series of propagation measurements (what is very expensive and time consuming) can be achieved with propagation models.

Propagation models commonly used in mobile communication network planning are mostly empirical models, which are mathematical model summarized from a large number of measured data, for example, Okumura-Hata's model, COST231-Hata model, COST231-Walfisch-Ikegami model and SPM model, etc.

Empirical propagation models are designed for a specific type of communication systems, specific system parameters and types of environment. This is due to the different propagation characteristics which are in different areas. Thus, if empirical models are mechanically copied in all areas, a great error will generate between calculation results and actual values.

Especially in Nigeria, because of the vast area of the country and various types of geography in different places, if you want to apply a model in different regions, some parameters must be modified, which means that a model correction is needed. This is to reduce its propagation prediction errors. There are mainly two sources causing the errors (Tiegang, 2013): errors from test data for correction and error from correction algorithm. Errors from test data are mainly composed of three aspects: GPS errors, digital map errors, and CW (Continuous Wave) test equipment errors. GPS errors depend on the measuring accuracy of GPS equipment; digital map Errors depend on the resolution of digital maps; CW test equipment errors, on one hand, result from the test device itself, on the other hand, from improper operation.

In this paper, the Least Absolute Deviation (LD) method is introduced to effectively reduce the errors via propagation model tuning procedure. We will describe the method through the example of COST-231 Walficsh-Ikegami (W/I) model correction.

MATERIALS AND METHODS

With the rapid growth of the telecommunication industry in Nigeria, all operators are paying more and more attention to the matching extent between propagation model and local environment. In this environment, high quality of service is a competitive advantage for a service provider. The radio propagation environment is very complicated, and the otherness between different areas is great, so it is necessary to carry actual propagation model testing and tuning, and then obtain the propagation model which reflects radio propagation characteristic exactly (Wenxiao and Mingjing, 2008).

In recent times, operators usually use special planning software to finish propagation model tuning. Now, there are several kinds of popular radio network planning software, such as ASSET software of AIRCOM Company in England, PLANET software of MARCONI Company in England and ATOLL software of FOSK Company in France (Lui *et al.*, 2007)). Though using planning software to model tuning is convenient, this software depend on digital map badly, the cost is expensive, especially in some small and medium-sized cities (Wenxiao and Mingjing, 2008). Thus, the process of tuning propagation models is very important, and can have major impact on their accuracy.

A statistical tuning method based on least-square theory for adjusting the Walfisch-Bertoni model parameters for generalized conditions in the CDMA2000 signal propagation environments was previously proposed (Isabona and Azi, 2012). However, this method relates to many tuning parameters, the iterative tuning process is relatively complicated.

In this paper, we engage simple linear-iterative Least Absolute (LAD) method for automatics model tuning and obtaining an exact outdoor propagation model fitting for UMTS signal propagation data in the studied environment. This method, as the name suggests, minimizes not the sum of squared deviations but the sum of absolute values of the deviations. Consequently it does not put excessive weight on highly deviating observations like the least squares does, and hence produces more robust estimators with respect to outliers. This is important to direct a more robust planning of present and future cellular wireless communication systems in Nigeria.

Theory of Propagation Model Tuning

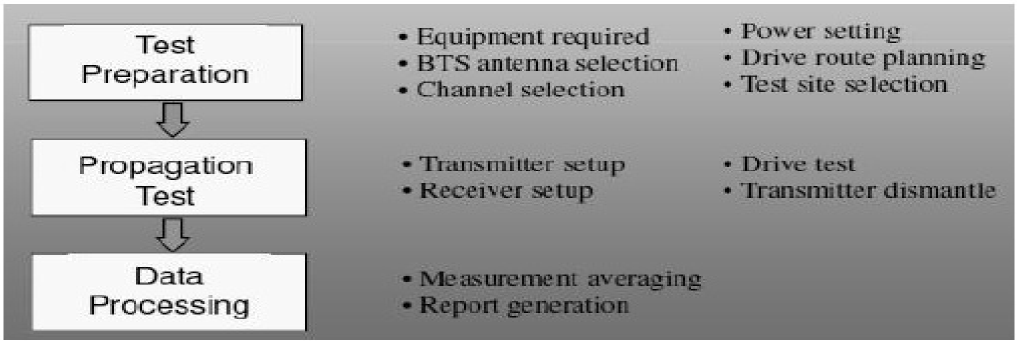
The quality of a network plan is dependent on the accuracy of the propagation model used to produce coverage plots and conduct interference analysis. An unreliable propagation model will result in a poor network plan, with too many sites (i.e. investing too much) or too few sites (i.e. not meeting the service requirements and a huge cost to rectify the situation). Propagation model tuning includes defining the clutter classes, CW measurements of those different clutter classes, statistical analysis of the measurements, tuning of the planning propagation models and parameters and final selection of propagation models, clutter classes and tuned parameters. Tuning the propagation model is an iterative process which requires defining new clutter classes to obtain better results.

The objective of propagation model tuning is to obtain values for model parameters that are in agreement with measured data. When using these tuned parameters, the median of the predicted path loss shall have a minimum difference and variance when compared to median of measured path loss. The tuning or calibration process can be achieved either manually or automatically. The manual tuning process consists of adjustment of the model parameters in order to set the error between measured and predicted signals near or equal to zero. We then increment the parameters one by one. These processes are repeated manually until any change in parameters will increase error value. The manual tuning process requires a large number of repetitions before a near global minimum is obtained.

CW Measurement and Measured Propagation loss Data Totaling

The CW measurements were conducted from a UMTS network base station (BS) transmitters, located at the BIU Campus, Ugbor and Gapiona Avenues, all evenly distributed in Government Reserved Area (GRA), Benin City, Edo Sate, Nigeria. Each of the BSs in the three study locations are tagged BS 1, BS 2 and BS 3 in this paper. The measured CW received signal strength data which is the Received Signal Code Power (RSCP) and transmitter-receiver (T-R) separation distance (d) are recorded in dBm and m. Every measurement points of received signal strength and T-R separation distance are recorded evenly from all the predefined routes of three base stations. Each measurement point is represented in an average of a set of samples taken over a small area ($10m^2$) in order to remove the effects of fast fading (Takahashi, 2004). A CW drive-test system was used to collect and record signal level data at various locations in a form of logs which were later processed with a communication network analyzer. The CW drive test process used here is broken down as shown in fig. 1.

Fig. 1: CW Measurement process (www.telecomsource.net)



The data collection tool consisted of ERICSSON TEMS (Test Mobile Systems) Cell-Planner tool with an antenna mounted on a moving vehicle 1.5 meter above ground level, Global Positioning System Receiver Set (GPS system) and a personal computer and a piece of compass. The personal computer houses the operating system and the data collection software (ERICSSON TEMS Investigation 8.0). The personal computer serves as the communication hub for all other equipment in the system. The GPS operates with global positioning satellites to provide the location tracking for the system during data collection position on a global map which has been installed on the personal computer. The compass help to determine the various azimuth angles of the base station transmitters. Average height of transmit antenna is about 30–32 meters above ground level, with the same transmit power. Sampling rate of the collected data, on the average, is about 2–3 samples per meter. The transmission parameters are given in table 1.

Table 1: Transmission parameters

Antenna parameters	Specific values
Operating frequency	2100MHz
RF Power Tx	43dB
Tx Antenna Gain	18dB
MS Handset Gain	0dB
Antenna Height	20/40m
MS Height	1.5m

The propagation loss is derived from the measured received signal power $\mathbf{P_r}$ at the mobile station (MS) by the expression in given by

$$\mathbf{PL = EIRP - P_r} \qquad (1)$$

The transmitter EIRP refers to the total amount of power density that transmits from the base station into the propagation medium. *EIRP* is given by:

$$\mathbf{EIRP = P_r + G_r + G_R - L_T - L_R} \qquad (2)$$

applying equation (2) in equation (1) yields:

$$\mathbf{PL = P_r + G_r + G_R - L_T - L_R - P_r} \qquad (3)$$

where $\mathbf{P_r}$ is BS transmitted power, $\mathbf{P_r}$ is measured received signal strength in dBm, G_T and G_R are the gain of transmitting and receiving antenna, respectively, and L_T and L_R are feeder losses, all in dB scale.

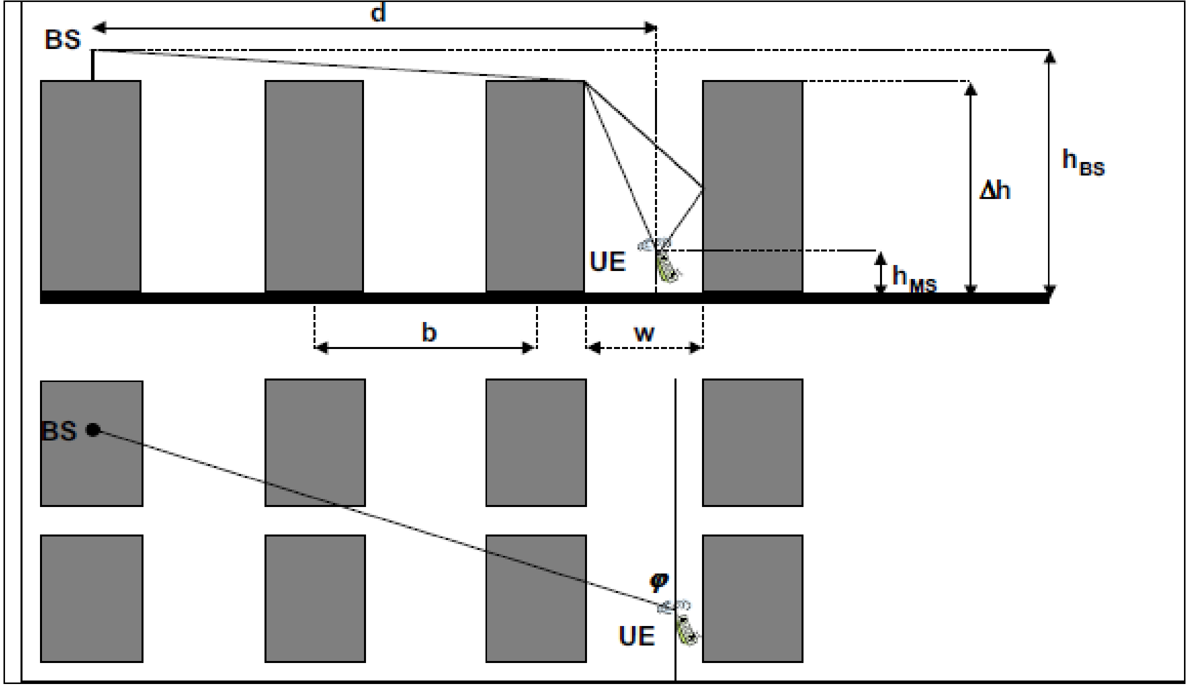
Here, we follow recommendation in literature in which approximately 1/3 of the measurements is used to tune the parameters of the pathloss model and the other 2/3 to compare measurements and predictions in order to validate the optimisation carried out. Thus, the propagation loss data from BS 1 was used for tuning procedure.

Cost 231(Walfisch - Ikegami)

The parameters, excess path loss from Walfisch-Bertoni model and final building path loss from Ikegami Model are combined in this model with a few empirical

correction parameters. This model is statistical and not deterministic because you can only insert a characteristic value, with no considerations of topographical database of buildings. The model is restricted to flat urban terrain.
The parameters used in Cost 231 Walfisch- Ikegami are denoted in fig. 2

Fig. 2: Geometry of Cost 231 Walfisch- Ikegami



The COST-Walficsh-Ikegami Model

This model is combination of J. Walfisch and F. Ikegami model. Now it is known as a COST 231 Walfisch-Ikegami (W-I) model. This model can be used in cases when the BTS (Base Transceiver Station) antenna is placed either above or below roof line in urban or suburban areas (Alexander, 2011).

This model is most suitable for flat suburban and urban areas that have uniform building height. The W-I model gives more precise path loss predictions among other models like the Hata. This is a result of the additional parameters introduced which characterized the different environments. The additional parameters as listed by Mohammed and Ahmed (2012) are as follows;

- Average heights of buildings (hr).
- Average width of roads (w).
- Average building separation (b).
- Road orientation with respect to the LOS (φ).

This model is restricted to the following range of parameters:

- f = 800 to 2000 MHz
- h= 4 to 50 m
- h = 1 to 3 m
- d= 0.02 to 5 km

This model distinguishes between LOS and non-LOS paths as follows.

For LOS paths the equation is as below:

$$L_{los} = 42.6 + 26\log d + 20\log f \qquad d \geq 20\text{m} \qquad (4)$$

Walfisch Ikegami (NLOS)
The validity of the model is given as follow:
Parameter ranges for this model are:
Frequency f= 800… 2000MHz
Height base station h_{BS}= 4… 50m
Height Mobile station h_{MS}= 1… 3m
Distance d= 0.02… 5km
Further parameter:
Mean building height: Δhin m
Mean street width: *w* in m
Mean building spacing: ***b*** in m
Mean angle between propagation path and street: ϕ in °

Table 2 Validity of the Cost 231 W-I Model

Frequency (MHz)	800-2000 MHz
Base Station Height (h_{base})	4-50 m
Mobile Height (h_{mobile})	1-3 m
Distance d, km	0.02-5 km

If a non-LOS exists, path loss defined as follow

$$L_b = \begin{cases} L_{FS} + L_{rts} + L_{msd} & \\ FS & \text{if } L_{rts} + L_{msd} < 0 \end{cases} \qquad (5)$$

$$L_{rts} = \begin{cases} -16.9 - 10\log w + 10\log f + 20\log \Delta h_{mobile} \\ L_{ori} \end{cases} \qquad (6)$$

L_{FS} represents free space loss, L_{rts} is rooftop to street diffraction and scatter loss, L_{rts} is the multi-screen loss.
The rooftop to street diffraction and scatter loss L_{rts} represents the coupling of wave propagating along the multi-screen path into the street mobile located.
where L_{ost} is defined as

$$L_{OST} = \begin{cases} -10 + 0.354\left(\frac{\varphi}{deg}\right), & 0 \leq \varphi < 35 \\ 2.5 + 0.075\left[\left(\frac{\varphi}{deg}\right) - 35\right], & 35 \leq \varphi < 55 \\ 4 - 114\left[\left(\frac{\varphi}{deg}\right) - 55\right], & 55 \leq \varphi \leq 90 \end{cases} \qquad (7)$$

Where φ is the angle between incidences coming from base station and road, in degrees.

The multiscreen diffraction loss L_{msd} is an integral for which Walfisch-Bertoni model approximate a solution to this for the cases base station antenna height is greater than the average rooftop. COST 231 extended this solution to the cases base station antenna height is lower than the average rooftop by including empirical functions.

$$Lmsd = L_{bsh} + k_a + k_d \log(d/km) + k_f \log(f/MHz) - 9 \log(b/m) \tag{8}$$

$$L_{rts} = \begin{cases} -18\log(1 + \Delta h_{base}) & \text{for } h_{base} > h_{roof} \\ 0 & \text{for } h_{base} \le h_{roof} \end{cases} \tag{9}$$

$$K_f = \begin{cases} -4 + 0.7\left[\left(\frac{f}{925}\right) - 1\right] & \textit{medium sized nd suburban centres with moderate density} \\ 15[\left(\frac{f}{925}\right) - 1 & \text{Metropolitan centers} \end{cases} \tag{10}$$

$$K_a = \begin{cases} 54 & \text{for } h_{base} > h_{roof} \\ 54 - 0.8\Delta h_{base} & \text{for } d \ge 0.5 \text{ km } \textit{and } h_{base} \le h_{roof} \\ 54 - 0.8\Delta h_{base}\frac{R}{0.5} & \text{for } d \le 0.5 \text{ km and } h_{base} \le h_{roof} \end{cases} \tag{11}$$

$$K_d = \begin{cases} 18 & \text{for } hbase > hroof \\ 18 - 15\ \Delta hbase / hroof & \text{for } hbase \le hroof \end{cases} \tag{12}$$

where

$\Delta h_{mobile} = h_{roof} - h_{mobile}$

$\Delta h_{Base} = h_{base} - h_{roof}$

The term k_a denotes the increase of the path loss for base station antennas below the rooftops of adjacent buildings. The terms k_d and $k_{f\ control}$ the dependence of the multi-screen diffraction loss versus distance and radio frequency.

Finally, the total W/I pathloss model, $L_{(W/I)}$ can be written as

$$\begin{aligned} L\left(\frac{W}{I}\right) = {} & 32.4 + 20\log_{10}(d) + 30\log_{10}(f) - 16.9 + 10\log_{10}(w) + 20\log_{10}(h_{roof} - h_m) \\ & + L_{ori} + 18^{*}\log_{10}(1 + (h_b - h_{roof})) + K_a + K_d\, 18\log_{10}(d) + K_f \log_{10}(f) \\ & - 9\log_{10}(S) \end{aligned} \tag{13}$$

It is impossible to represent with total reliability all the features of an environment; consequently, the propagation models use approximations and suppositions (they consider buildings as half edges, they approximate to zero the absorption of the walls, etc), those suppositions cause error in simulation results. Although Walfisch Ikegami model of equation (11) was designed for BS antennas placed below the mean building height, however, the model show often considerable inaccuracies. This is especially true in cities with an irregular building pattern like in historical grown cities. Also the model was designed for cities on a flat ground. Thus for cities in a hilly environment the model is not applicable

Model Tuning Process

Overview

This work proposes a method that consists of statistical model correction through the multiple linear regression of the absolute difference from the propagation loss data obtained by the W/I (11) in relation to the environment and the propagation loss data collected in the studied environment

The W/I propagation model equation is multivariate, one variable, L. In order to correct the W/I model to field data, we will multiply the model's default parameters in Eq.1 with variables and this gives:

$$\begin{aligned} L(\text{Proposed}) = {} & 32.4 + \beta_1^{*} K_d\, 18 \log_{10}(d) + \beta_2^{*}\, 20 \log_{10}(d) + \beta_2^{*}\, 20 \log(h_{roof} - h_m) + \beta_3^{*}\, 9 \log(S) \\ & + 30 \log_{10}(f) - 16.9 + \beta_3^{*}\, 10 \log_{10}(w) + \beta_4^{*} L_{ori} + 18^{*} \log_{10}(1 + (h_b - h_{roof}) \\ & + K_a + K\Pi og_{10}(f) - \beta_5 \qquad (14) \end{aligned}$$

In equation (14), the parameters β1, β2, β3, β4 and β5, must be tuned to minimize difference between the predicted and measured propagation loss.

The mathematic method used for the tuning of model to the realized measurements is the Least

Absolute Deviation (LAD) Technique

Linear regression has long been dominated by least squares (LS) techniques, mostly due to their well-designed theoretical footings and ease of application. The assumption in this method is that the model has normally distributed errors. In many applications, however, heavier-than-Gaussian tailed distributions may be encountered, where outliers in the measurements may easily ruin the estimates (Bloomfield and Steiger, 1983). To address this problem, robust regression methods have been developed so as to mitigate the influence of outliers. Among all the approaches to robust regression, the least absolute deviations (LADs) method is considered putatively the modest one since it require a simpler "tuning" mechanism like most of other robust regression procedures (Yinbo and Gonzalo, 2004). As a result, LAD regression has drawn significant attentions in science, engineering, and other statistics related area as detailed in a series of studies on LAD methods (Bloomfield and Steiger, 1983; Yinbo and Gonzalo, 2004). LAD regression is based on the assumption that the model has Laplacian distributed errors (Yinbo and Gonzalo, 2004).

Given the pathloss data set, $y_n$with n measurements, which depend on the input variables $x_1, x_2 \ldots x_p$, $x \in N$, then we consider a LAD regression model

$$y = \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n = \sum_{i=1}^{n} \beta_i X_i \qquad (15)$$

This model is to be fitted of n, $n \in N$ points
$y_i, x_{i1}, x_{i2}, \ldots, x_{ip}$, $i = 1, 2, \ldots, n$.

The observations y_i, where $i = 1, 2\ldots, n$ will be represented by a vector Y. The unknowns $\beta_1, \beta 2 \ldots \beta_p$ will be represented by a vector Y. Let X be a matrix.
For a given β, the vector of fitted or predicted values, L_p, can be written $L_p = X\beta$. Using the LAD estimation we will pick the coefficients $\beta = (\beta_1, \beta_2 \ldots \beta p)^T$ to minimize the residual sum of absolute values (RSA), i.e,

$$\mathrm{RSA} = \min\left[\delta = \sum_{i=1}^{n}\left|y_i - \sum_{j=1}^{p} x_{ij}\right|\right] = \|Y - X\| \qquad (16)$$

Differentiating RSA with respect to β, we get

$$\frac{\partial RSA}{\partial \beta} = -X^T \operatorname{sign}(Y - X\beta), \qquad (17)$$

For all real vectors β for which the function is differentiable, sign is the sign of the variables.
Thus, RSS is minimal for $X^T X\beta - XY^T$
Here, the differential correction in equation (17) is implemented using JavaScript program. It involves expanding the function to be fitted in a Taylor series around current estimates of the parameters, retaining first-order (linear) terms, and solving the resulting linear system for incremental changes to the parameters. The program computes finite-difference approximations to the required partial derivatives, and then uses a simple elimination algorithm to invert and solve the equations.

RESULTS

The tuned Walficsh-Ikegami (W/I) model parameters with measured propagation loss data using LAD regression method are given in table 3. Shown in table 4 are the tuned parameters of W/I model using LS regression technique; this was done for comparison and to verify the correctness of our proposed tuning approach utilized in this paper.

Table 3: Tuned parameters by LAD Regression technique

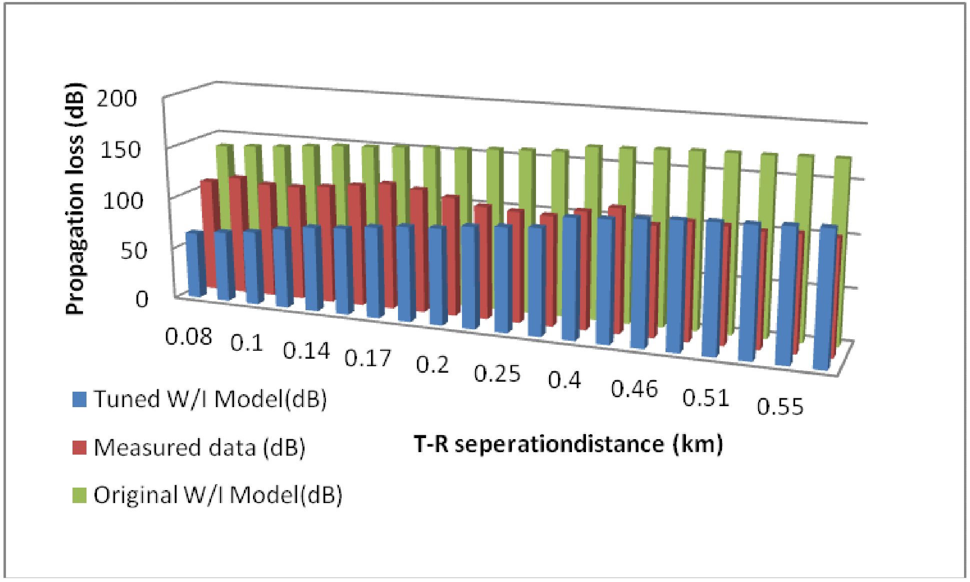
Parameters	Average values
β_1	2.68
β_2	-2.68
B_3	-5.58
B_4	2.88
B_5	11.53

Table 4: Tuned parameters by LS Regression technique

Parameters	Average values
β_1	3.80
β_2	-2.40
B_3	-5.01
B_4	3.68
B_5	11.96

In figure 3, the propagation loss analysis is shown with tuned W/I model. It can be observed from the graph that the iteratively tuned model agree well with measured loss data especially at higher T-R separation distances.

Fig. 3: Propagation loss data analysis for BS1



Next, root mean square error (RMSE) between tuned model and measured data is computed for other base stations (BSs) in order to validate the correctness of the proposed LAD tuning method for accurate propagation loss prediction in the study locations as shown in figures 4 and 5 using radar plots. It is shown that the base stations fit into the tuned model. The tuned model with LAD method best fit into BS 2 and BS 3 with an RMSE of 5.41 as compared to LS tuning method which has an average RMSE of 16.68 with BS 2 and BS 3. Thus the find-tuned model is successfully carried out with proper calibration procedure.

Fig. 4: Propagation loss data analysis for BS1

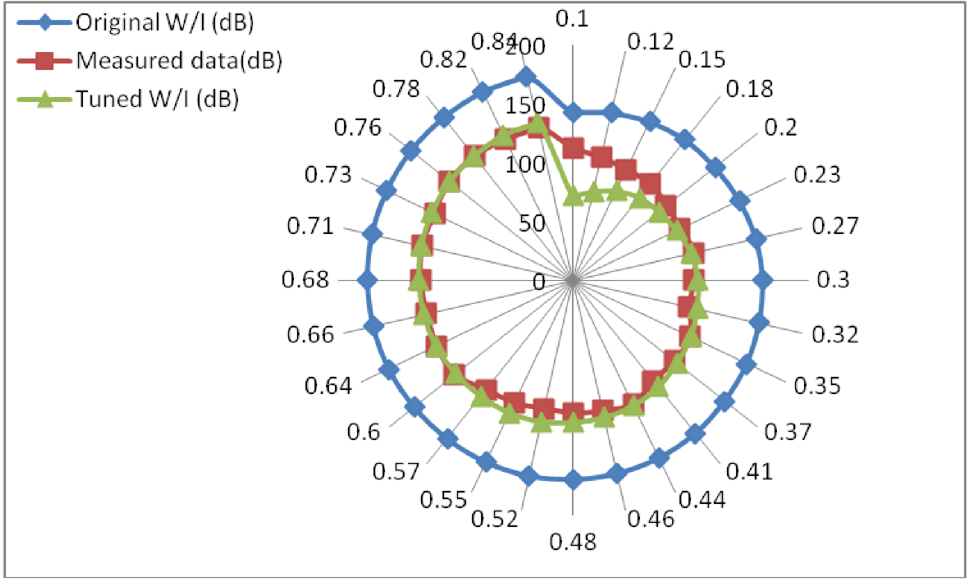
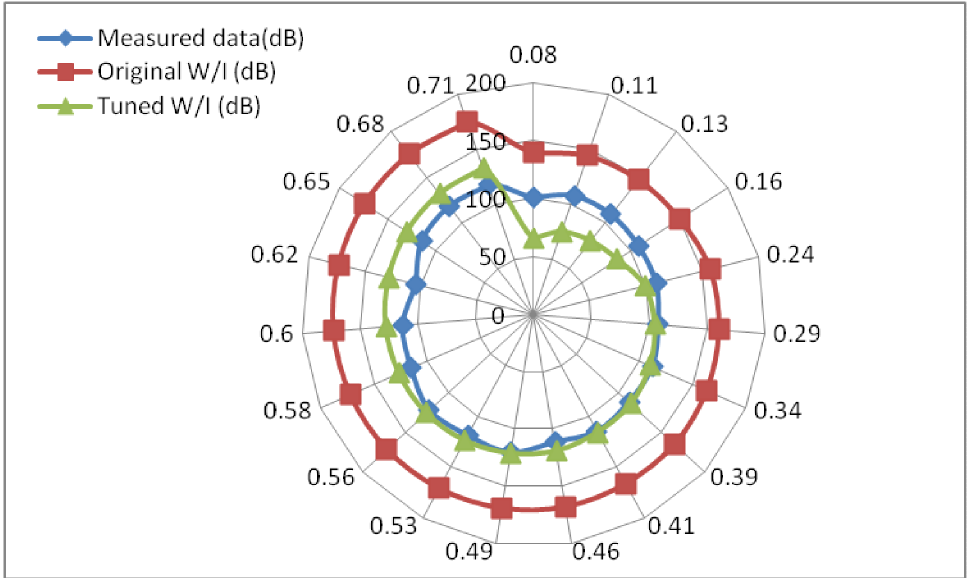


Fig. 5: Propagation loss data analysis for BS1



DISCUSSION

The demand for increased mobile phone subscribers requires an efficient radio network planning that involves an accurate prediction of propagation loss. Most propagation loss models are suitable for either particular areas (Urban, Suburban, Rural, etc.), or specific cell radius (Macro cell, Micro cell, Pico cell). To overcome this drawback, the empirical models' parameters can be adjusted or tuned according to a targeted environment. The propagation model tuning must optimize the model parameters in order to achieve minimal error between predicted and measured signal strength. This will make the model more accurate for received wireless signal predictions.

In this paper, we have introduced a tuned LAD-based W/I model using measured UMTS strength data carried out in GRA, Benin City, Nigeria We found that the performance of the tuned W/I model is the best as root mean square error is the lower compared to least square based regression technique. The tuned model with LAD method best fit into BS 2 and BS 3 with an RMSE of 5.41 as compared to LS tuning method which has an average RMSE of 16.68 with BS 2 and BS 3. The tuned model is found suited to the built-up terrain, which can be used to predict the signal strength of mobile phone due to base station. This model is useful for Nigeria telecommunication provider to improve their service for better signal coverage and better mobile user satisfaction

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