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Comparative evaluation of single constant tuning method and function of residue tuning method for the Early ITU foliage propagation loss model

Enyenihi Henry Johnson[1], Ibanga, Ekerette Bernard[2], Ezuruike Okafor S.F.[3]
[1] Department of Electrical/Electronic Engineering, Akwa Ibom State University Mkpat Enin, Akwa Ibom State, Nigeria
[2] Department of Electrical/Electronic and Computer Engineering, University of Uyo, Akwa Ibom, Nigeria
[3] Department of Electrical/Electronic Engineering, Imo State Polytechnic, Umuagwo, Nigeria
([1] gentlejayy@yahoo.com)

***Abstract*— This paper presented a comparative evaluation of single constant tuning method and function of residue tuning method for the Early ITU foliage propagation loss model. The study was conducted on a 3G mobile network coverage area that is within a Terminalia Mantaly tree park located in Uyo, Akwa Ibom state. The relevant data (RRSI, base station information, measurement point longitude and latitudes) were collected using a Netmonitor 1.5.84 android app installed on a Infinix S3 mobile phone. Two sets of measurements were conducted and one of the datasets was used to train or develop the proposed models while the second dataset was used for cross-validation purpose. The root mean square error (RMSE) and prediction accuracy were used to assess the prediction performance of the models. The four tuning methods considered are ; the RMSE-based tuning method, the coefficient of foliage depth tuning , the coefficient of Early ITU foliage model tuning and the error function of foliage depth-tuning methods. The results showed that the error function of foliage depth-tuning method the best prediction performance with a RMSE of 2.92 dB and a prediction accuracy of 97.22 % for the training dataset and a RMSE of 3.71 dB and a prediction accuracy of 96.6 % for the validation dataset. Also, among the four tuned models, the RMSE-tuned ITU foliage model had the least prediction performance for both the training and validation datasets. The ideas presented in this paper will guide network designers in the selection of model tuning approach that will ensure more accurate path loss prediction, especially in areas covered with vegetation.**

***Keywords*— Path Loss, Foliage Path Loss Model, Model Tuning, Empirical Path Loss Model, Early ITU Model**

I. INTRODUCTION

As wireless signals propagate through the atmosphere, they are subjected to both free space path loss and other path losses that depend on the kinds of obstructions present in the signal path [1,2,3,4,5,6,7,8,9]. Over the years, experts have developed empirical models to estimate the propagation loss that wireless signals experience in different environments [10,11,12,13]. Among the empirical models, there are some propagation loss models that are developed specifically for regions that are covered with foliage [14,15,16,17]. Such models are referred to as foliage path loss models and one of the most popular is the Early ITU model [18,19,20,21], where ITU stands for the International Telecommunication Union.

The Early ITU foliage propagation loss model estimates the additional propagation loss due to the presence of vegetation in the signal path [18,19,20,21]. In essence, the effective propagation loss is the sum of the free space path loss and the path loss estimated by the Early ITU foliage propagation loss model. Although the Early ITU model has been widely studied, experts have noted that empirical models need to be optimized before they can provide acceptable path loss prediction accuracy when they are employed in an environment other than the environment where they were developed [22,23,24,25,26,27,28,29]. In this study, the Early ITU foliage propagation loss model is employed in predicting the path loss for a Terminalia Mantaly [30,31] tree park located in Uyo, Akwa Ibom State. More importantly, the study in this paper is set to present and comparatively evaluate different path loss model tuning approaches based on the empirical data and the Early ITU foliage propagation loss model. The essence of the study is to present alternative path loss model tuning approaches that relatively simple but can give better prediction performance than the widely used root mean square tuning method. The relevant mathematical expressions and methodology for the models development and evaluation are presented in the paper.

II. FOLIAGE PROPAGATION LOSS BASED ON THE EARLY ITU MODEL

One of the most popular foliage propagation loss models developed by the International Telecommunication Union (ITU) is referred to as the Early ITU model which specifies the foliage propagation loss as follows [18,19,20,21]:

$$\mathrm{PL}_{\mathbf{ITU}}\,(dB) = \begin{cases} 0.2F^{0.3}\left(d_f\right)^{0.3} & for \quad 0 \le d_f \le 14\mathrm{m} \\ 0.2F^{0.3}\left(d_f\right)^{0.6} & for \quad 14 \le d_f \le 400\mathrm{m} \end{cases} \tag{1}$$

Where d_f in meters is the foliage depth along the signal path and f in GHz is the signal frequency. The overall propagation loss ($\mathrm{PL}_{\mathbf{EL}}$) is obtained by adding Early ITU estimated propagation loss ($\mathrm{PL}_{\mathbf{ITU}}$) to the free-space propagation loss ($\mathrm{PL}_{\mathbf{FSP}}$). Hence;

$$\mathrm{PL}_{\mathbf{EL}} \;=\; \mathrm{PL}_{\mathbf{FSP}} \;+\; \mathrm{PL}_{\mathbf{ITU}} \tag{2}$$

where ;

$$\mathrm{PL}_{\mathbf{FSP}}\,(dB) \;= 32.5 + 20 * \log(\mathrm{f}) + 20 * \log(\mathrm{d}) \tag{3}$$

Where d is the path length in km while f is the signal frequency in MHz.

Furthermore, root mean square error (RMSE) is used to assess the prediction performance of the model and it is given as;

$$e_{(i)} = P_{m(i)} - P_{ITU(i)} \tag{4}$$

$$\mathrm{RMSE} = \sqrt[2]{\left\{\frac{1}{n}\left[\sum_{i=1}^{i=n}\left|e_{(i)}\right|^2\right]\right\}} \tag{5}$$

Where $P_{m(i)}$ is the path loss measured at data point i and $P_{ITU(i)}$ is the ITU model predicted path loss at data point i. Also, prediction accuracy (PA) is used to assess the prediction performance of the model and it is given as ;

$$\mathbf{PA} = \left(1 - \left(\frac{1}{n}\left(\sum_{i=1}^{i=n}\left|\frac{P_{m(i)} - P_{ITU(i)}}{P_{m(i)}}\right|\right)\right)\right) * 100\ \% \tag{6}$$

III. THE FIELD MEASUREMENT AND THE EARLY ITU FOLIAGE MODEL TUNING METHODS

In most case, empirical propagation loss models need to be tuned based on empirically measured data to make them more effective in predicting the propagation loss in the given area. The model tuning entails adjustment of one or more model parameters such that the resultant root mean square error is minimized. Also, the model can be tuned by adjusting the model parameter by sung a composite function in respect of the parameter. In this paper, different single constant tuning methods and the composite function of the prediction residue method are considered and their prediction performances are compared. Specifically, single constant tuning means that only one constant value is adjusted to minimize the RMSE. The constant can be the coefficient of a factor or parameter in the path loss model or it can be a standalone constant that is added or subtracted to the model path loss prediction so as to minimize the RMSE. On the other hand, the composite function of prediction residue involves the derivation of a mathematical expression that can estimate the path loss prediction error based on the value of a single parameter in the model. Particularly, in this paper, the model developed estimates the prediction error based on the value of the field measured foliage depth.

The field measurement was carried out on an 1800 GHz cellular network and the network's coverage area considered is a Terminalia Mantaly tree park located in Uyo, Akwa Ibom State. The relevant data (RRSI, base station information, measurement point longitude and latitudes) were collected using a Netmonitor 1.5.84 android app installed on a Infinix S3 mobile phone. Two sets of measurements were conducted and one of the datasets was used to train or develop the proposed models while the second dataset was used to evaluate the prediction performance of developed models with respect to independent dataset captured within the study area. The measured RSSI values were used to determine the measured path loss. . Figure 1 shows the measured path loss versus foliage depth for the training and validation datasets.

Importantly, the selection of the parameters or the single constant to be adjusted depends on the correlation coefficient (r) results pertaining to the parameter. Table 1 shows the correlation coefficients of the field measure path loss and prediction error with the foliage depth and untuned ITU foliage model predicted path loss.

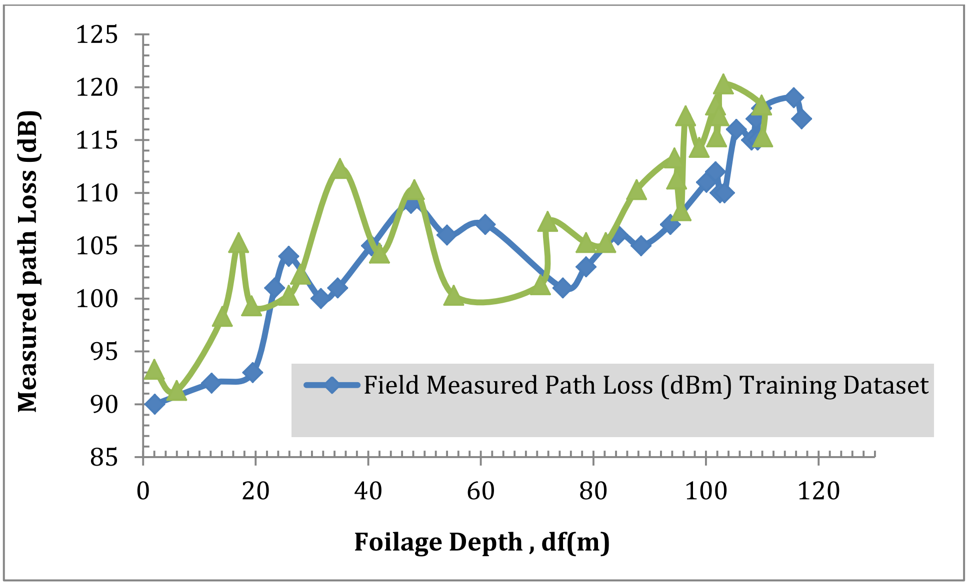


Figure 1 The measured path loss versus foliage depth for the training and validation data

Table 1 The Correlation Coefficient of the field measure path loss and prediction error with the foliage depth and untuned ITU model path loss prediction

	Field Measured Path loss			*Error ,e*
Field Measured Path loss	1		Error ,e	1
df (m)	0.886749		df (m)	0.832185
Untuned ITU Model	0.893345		Untuned ITU Model path loss	0.838058

The r values in Table 1 show that both the field measure path loss and prediction error are very strongly correlated to untuned ITU foliage model predicted path loss and also to the foliage depth. Consequently, the tuning methods adopted in this paper involve adjustment of the coefficients of the foliage depth and the untuned ITU foliage model. The tuning models are as follows:

I) The RMSE-based tuning is given as

$$\mathrm{PL}_{\mathbf{ITU-RMSE}} = \left\{ \begin{array}{ll} 0.2F^{0.3}(d_f)^{0.3} & for \quad 0 \le d_f \le 14\mathrm{m} \\ 0.2F^{0.3}(d_f)^{0.6} & for \quad 14 \le d_f \le 400\mathrm{m} \end{array} \right\} + \text{RMSE for } \sum e_{(i)} \ge 0 \quad (7)$$

$$\mathrm{PL}_{\mathbf{ITU-RMSE}} = \left\{ \begin{array}{ll} 0.2F^{0.3}(d_f)^{0.3} & for \quad 0 \le d_f \le 14\mathrm{m} \\ 0.2F^{0.3}(d_f)^{0.6} & for \quad 14 \le d_f \le 400\mathrm{m} \end{array} \right\} - \text{RMSE for } \sum e_{(i)} < 0 \quad (8)$$

II) The coefficient of foliage depth-tuned (CFD-tuned) ITU foliage model is given as;

$$\mathrm{PL}_{\mathbf{ITU-CFD}} = \left\{ \begin{array}{ll} 0.2F^{0.3}\left((d_f)K_{CFD}\right)^{0.3} & for \quad 0 \le d_f \le 14\mathrm{m} \\ 0.2F^{0.3}\left((d_f)K_{CFD}\right)^{0.6} & for \quad 14 \le d_f \le 400\mathrm{m} \end{array} \right\} \quad (9)$$

Where K_{CFD} is the coefficient of foliage depth tuning parameter.

III) The coefficient of Early ITU foliage model-tuned (CEITU-tuned) ITU foliage model is given as;

$$\mathrm{PL}_{\mathbf{ITU-CEITU}} = \left\{ \begin{array}{ll} K_{\mathbf{CEITU}}\left(0.2F^{0.3}(d_f)^{0.3}\right) & for \quad 0 \le d_f \le 14\mathrm{m} \\ K_{\mathbf{CEITU}}\left(0.2F^{0.3}(d_f)^{0.6}\right) & for \quad 14 \le d_f \le 400\mathrm{m} \end{array} \right\} \quad (10)$$

Where $K_{\mathbf{CEITU}}$ is the coefficient of Early ITU foliage model tuning parameter.

IV) The error function of foliage depth-tuned (EFFD-tuned) ITU foliage model is given as;

$$\mathrm{PL}_{\mathbf{ITU-EFFD}} = \left\{ \begin{array}{ll} 0.2F^{0.3}\left((d_f)K_{CFD}\right)^{0.3} & for \quad 0 \le d_f \le 14\mathrm{m} \\ 0.2F^{0.3}\left((d_f)K_{CFD}\right)^{0.6} & for \quad 14 \le d_f \le 400\mathrm{m} \end{array} \right\} + f(e \; of \; d_f) \quad (11)$$

where $f(e \; of \; d_f)$ is the function used to estimate the path loss prediction error from the foliage depth.

IV RESULTS AND DISCUSSIONS

The results of the measured and predicted path loss versus foliage depth using the four different tuning methods based on the training dataset is shown in Figure 2. Similar results for the validation dataset are shown in Figure 3. The prediction performance of the four different tuning methods based on the training and the validation datasets are given in Figure 4. According to the results in Figure 4, the error function of foliage depth-tuned (EFFD-tuned) ITU foliage model had the best prediction performance for the training and the validation datasets. It has RMSE of 2.92 dB and prediction accuracy of 97.22 % for the training dataset and RMSE of 3.71 dB and prediction accuracy of 96.6 % for the validation dataset. Also, among the tuned models, the RMSE-tuned ITU foliage model had the least prediction performance for both the training and validation datasets.

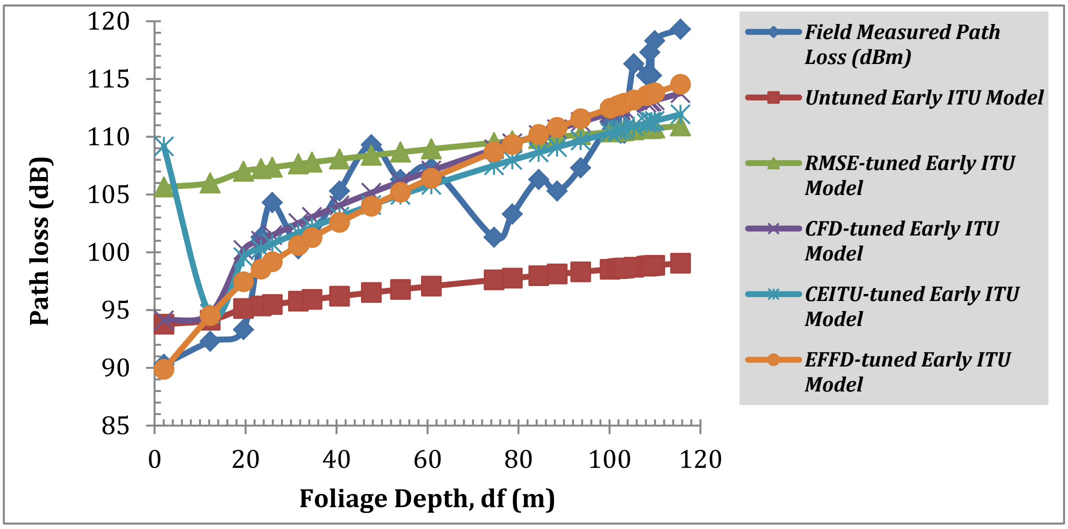


Figure 2 The measured and predicted path loss using the four different tuning methods based on the training dataset

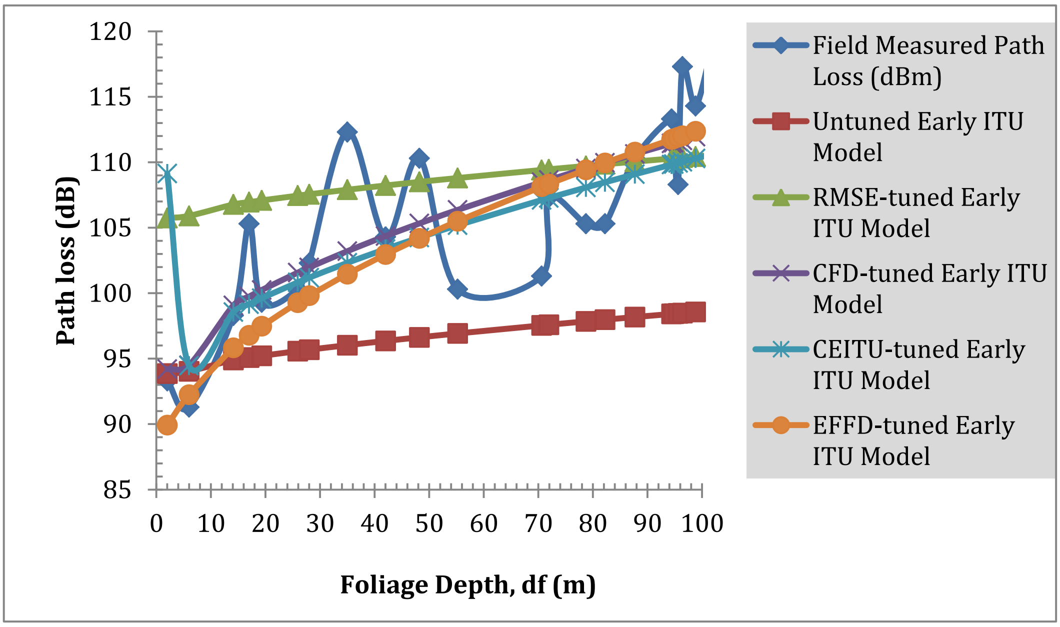
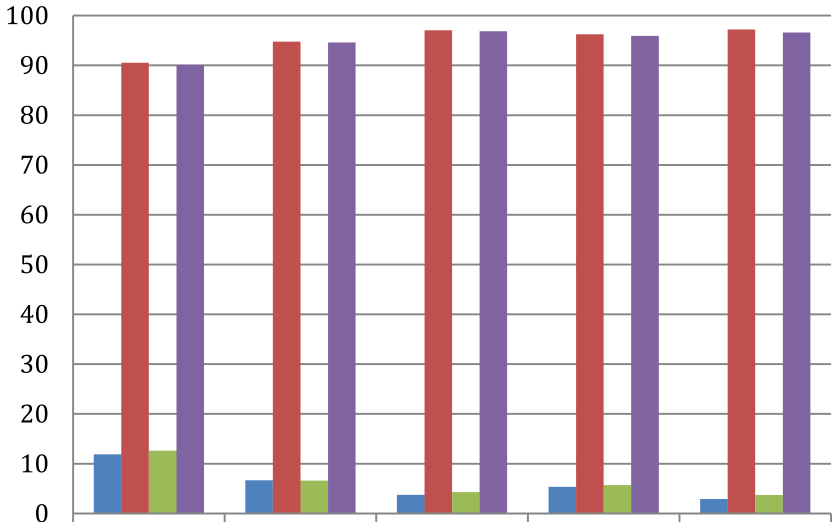


Figure 3 The measured and predicted path loss using the four different tuning methods based on the validation dataset



	Untuned Early ITU Model	RMSE-tuned Early ITU Model	CFD-tuned Early ITU Model	CEITU-tuned Early ITU Model	EFFD-tuned Early ITU Model
RMSE (training dataset)	11.87018	6.688147	3.739522	5.34603	2.9201
Prediction Accuracy (%) (training dataset)	90.51815	94.77687	97.05465	96.24522	97.21261
RMSE (validation dataset)	12.61697	6.606709	4.282761	5.704403	3.713809
Prediction Accuracy (%)(validation dataset)	90.12446	94.60754	96.84961	95.92586	96.60108

Figure 4 The prediction performance of the four different tuning methods based on the training and the validation datasets

The models based on the different tuning methods are given as follows:

I) The RMSE-based tuning is given as

$$PL_{\mathbf{ITU-RMSE}} = \begin{Bmatrix} 0.2F^{0.3}(d_f)^{0.3} & for \quad 0 \le d_f \le 14\text{m} \\ 0.2F^{0.3}(d_f)^{0.6} & for \quad 14 \le d_f \le 400\text{m} \end{Bmatrix} + 11.87 \quad (12)$$

II) The coefficient of foliage depth-tuned (CFD-tuned) ITU foliage model is given as;

$$PL_{\mathbf{ITU-CFD}} = \begin{Bmatrix} 0.2F^{0.3}(14.7(d_f))^{0.3} & for \quad 0 \le d_f \le 14\text{m} \\ 0.2F^{0.3}(14.7(d_f))^{0.6} & for \quad 14 \le d_f \le 400\text{m} \end{Bmatrix} \quad (13)$$

III) The coefficient of Early ITU foliage model-tuned (CEITU-tuned) ITU foliage model is given as;

$$PL_{\mathbf{ITU-CEITU}} = \begin{Bmatrix} 13.42\left(0.2F^{0.3}(d_f)^{0.3}\right) & for \quad 0 \le d_f \le 14\text{m} \\ 13.42\left(0.2F^{0.3}(d_f)^{0.6}\right) & for \quad 14 \le d_f \le 400\text{m} \end{Bmatrix} \quad (3)$$

IV) The error function of foliage depth-tuned (EFFD-tuned) ITU foliage model is given as;

$$PL_{\mathbf{ITU-EFFD}} = \begin{Bmatrix} 0.2F^{0.3}\left((d_f)K_{CFD}\right)^{0.3} & for \quad 0 \le d_f \le 14\text{m} \\ 0.2F^{0.3}\left((d_f)K_{CFD}\right)^{0.6} & for \quad 14 \le d_f \le 400\text{m} \end{Bmatrix} + 2.08\,(d_f)^{\frac{1}{2}} - 6.88 \quad (14)$$

In all, the EFFD-tuned Early ITU foliage model is the preferred foliage path loss model for the case study site.

V CONCLUSION

The ability of different path loss model tuning methods to optimize the Early ITU foliage model parameters for more effective path loss prediction is studied. The study was based on field measurement conducted on a 3G mobile network coverage area that is within a Terminalia Mantaly tree park. Four different model tuning methods were studied and the prediction performance of the various tuned Early ITU foliage models was also compared. The four tuning methods considered are ; the RMSE-based tuning method, the coefficient of foliage depth tuning, the coefficient of Early ITU foliage model tuning and the error function of foliage depth-tuning methods. In all, the composite error function of foliage depth gave the best prediction performance in both the training and the cross-validation datasets. On the other hand, among the tuned models, the RMSE-tuned ITU foliage model had the least prediction performance for both the training and validation datasets. The ideas presented in this paper will guide network designers in the selection of model tuning approach that will ensure more accurate path loss prediction , especially in areas covered with vegetation.

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