Mathematical and Software Engineering, Vol. 3, No. 1 (2017), 1-12.
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Empirical Valuation of Multi-Parameters and RMSE-Based Tuning Approaches for the Basic and Extended Stanford University Interim (SUI) Propagation Models

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Abstract

In this paper, the prediction performance evaluation of Stanford University Interim (SUI) Model and the extended SUI model are presented. More importantly, the effectiveness of two model tuning approaches, namely, RMSE-based tuning and multi-parameter tuning are assessed based on empirical pathloss data obtained for a suburban area in Uyo, Akwa Ibom state. Although the RMSE tuning is quite simple, the results showed that in some cases it does not minimize the prediction error to an acceptable level (6dB to 7dB) for practical applications. However, in the two models, the multi-parameter tuning effectively minimized the prediction error to an acceptable level with mean prediction error of about 0.00001dB, RMSE that are less than 2.45 dB and prediction accuracies above 98.2%. On the other hand, the RMSE-tuned models have mean prediction error of above ± 1.5dB, RMSE that above 8.8dB and prediction accuracies less than 94.3%. In all, the SUI model performed better than the extended SUI.

Keywords: Pathloss; Model Tuning; Empirical Pathloss Models; Stanford University Interim (SUI) Model; Multi-parameter tuning; RMSE-based Tuning

1 Introduction

Generally, wireless communications involves transmission of information in the form of electromagnetic (EM) wave [1]. Such transmitted information incurs path loss as electromagnetic wave propagates from the transmitter to the receiver [2, 3]. Path loss refers attenuation in the electromagnetic wave or degradation in signal strength as the signal propagates from between transmitter and receiver [4]. Path loss can be caused by effects such as diffraction, refraction, reflection, free space loss, among others [5]. Also, obstacles along the radio path cause pathloss. Such degradation in signal strength can result in call drop and other degradation in quality of service in cellular networks. As such, in wireless communication systems, path loss prediction is required during network planning for the effective tuning of transmitted power, maximization of coverage area and realization of highest quality of service [6-9].

Consequently, several pathloss models have been developed and used to predict the pathloss that can be experienced by wireless signals propagating at diverse frequencies and terrains. The pathloss models are classified into three categories, namely; empirical, semi-deterministic and deterministic models [10-12]. Empirical models such as Okumura model and Hata model are based on measurement data and statistical properties. Semi-deterministic models, such as Cost-231 and Walfish-Ikegami models are based on empirical models and deterministic aspects. Deterministic models are site-specific, requires enormous number of geometry information about the city.

In view of their simplicity, empirical models are the most popular models used in the wireless communication industry [13]. However, the existing empirical models require tuning or adjustment of their parameters to minimize the prediction error when they are employed in different terrain other than the one in which they are developed [14-16]. Several model tuning and optimization approaches have been presented in published literatures. The simplest approach is the one the utilities the root mean square error (RMSE) between the measured and the predicted pathloss prediction to minimize the prediction error by adding or subtracting the RMSE from the original model [17-20]. Other methods can adjust the coefficient of one or more model parameters in order to minimize the error. Yet another method adds a correction factor to the original model. This is one of the major ways new models are developed from existing models. The RMSE-based approach is limited in its ability to minimize the prediction error. As such, in some cases it fails to reduce the error to within the acceptable pathloss prediction error threshold for network planning [21-27].

Consequently, in this paper, comparative study of prediction performance of the RMSE-based tuning approach and the multi-parameter tuning approach is conducted. The study is performed for the Stanford University Interim (SUI) model and the Extended Stanford University Interim (EXSUI) model for a suburban area. The study is meant to show the disparity in prediction performance of the simple RMSE-based approach and the multi-parameter tuning approach. The study will demonstrate that in the situation where the RMSE-based tuning approach fails to meet the pathloss prediction error threshold value, the multi-parameter tuning approach can be used to improve on the prediction performance of the pathloss model.

2 Theoretical Background

2.1 The Stanford University Interim (SUI) Model

The basic Stanford University Interim (SUI) model with correction factors is jointly developed by the 802.16 IEEE group and Stanford University. The model is an extension of an early model developed by AT&T Wireless and then further analyzed by Erceg et al. [25]. The model is defined for the frequency bands below 11 GHz, particularly, 2.5 GHz to 2.7 GHz. Furthermore, SUI model is defined for three different terrain categories. Category A has the maximum pathloss suitable for hilly terrain with moderate to heavy tree densities. Category B is the intermediate path-loss category suitable for flat terrains. The minimum path-loss category for flat terrains with less tree densities is Category C. The following mathematical expressions are used to determine the median pathloss, $P(dB)$ with respect to the SUI model with correction factors [27-33]:

$$P(dB) = A + 10\,\gamma Log\left(\frac{d}{d_0}\right) + X_f + X_{h_r} + s \quad \text{for} \quad d > d_0 \tag{1}$$

$$A = 20Log\left(\frac{4\pi d_0}{\lambda}\right) \tag{2}$$

X_f is the frequency correction factor given as:

$$X_f = 6.0Log\left(\frac{f}{2000}\right) \tag{3}$$

X_{h_r} is the receiver antenna height correction factor given as [33-35]:

$$X_{h_r} = \begin{cases} -10.8Log\left(\frac{h_r}{2}\right) & \text{for terrain categories A and B} \\ -20Log\left(\frac{h_r}{2}\right) & \text{for terrain category C} \end{cases} \quad (4)$$

where:

f : Frequency of transmission in MHz and λ is the wavelength, in m;

h_t is the height of the base station antenna in meter where *10 m <* h_t*< 80 m*

h_r is the height of the mobile station antenna in meter.

d is the distance from base station antenna in m.

d_0 is the reference distance in m; d_0 = 100m

γ is the path-loss exponent

s is the shadowing effect where *8.2 dB < s < 10.6 dB*

a, b, c are constants dependent on the terrain category given in Table 1.

Table 1: SUI Model Parameters ([33-35])

	Terrain Category A	Terrain Category B	Terrain Category C
a	4.6	4	3.6
b	0.0075	0.0065	0.005
c	12.6	17.1	20

2.2 Extended Stanford University Interim (EXSUI) Model

The IEEE 802.16 group developed the extended SUI model [34] whereby the receiver antenna height correction factor (X_{h_r}) is modified correction factor *is* modified according to that proposed by Okumura. A new reference distance $\left(\delta_0'\right)$ is defined as follows [34]

$$\delta_0' = d_0\left(10^{\left(X_{f_r}+X_{h_r}\right)}\right) \quad (5)$$

The following equations are used to determine the median pathloss, $P(dB)$ in the case of the EXSUI model [34]:

$$P(dB) = \begin{cases} 20Log\left(\frac{4\pi d}{\lambda}\right) & \text{for} \quad d \le \delta_0' \\ A + 10\gamma Log\left(\frac{d}{d_0}\right) + X_f + X_{h_r} + s & \text{for} \quad d > \delta_0' \end{cases} \quad (6)$$

$$A = 20Log\left(\frac{4\pi\delta_0'}{\lambda}\right) \quad (7)$$

X_f is the frequency correction factor given as:

$$X_f = 6.0Log\left(\frac{f}{2000}\right) \quad (8)$$

X_{h_r} is the receiver antenna height correction factor given as [34]:

$$X_{h_r} = \begin{cases} -10Log\left(\frac{h_r}{3}\right) & \text{for } h_r \le 3\,m \\ -20Log\left(\frac{h_r}{3}\right) & \text{for } h_r > 3\,m \end{cases} \quad (9)$$

d_0, γ, s and the constants *a, b, c* are the same as the original SUI model given in Eq. 1 above.

3 Empirical Measurements

CellMapper Android application is installed in Samsung I9500 Galaxy S4 phone which was used to capture the values of the received signal strength (RSS) from UMTS (Universal Mobile Telecommunications System) cellular network operating at 2100MHz. The RSS measurements were taken in a suburban area in Uyo metropolis. The CellMapper application captures advanced GSM/CDMA/UMTS/LTE current and neighbouring cells' low level data. It also exports the data as comma-separated values (CSV) file. Data captured by the CellMapper includes the current and neighbouring cells RSS in decibels (dB), the current cell's cell ID (CID), local area code (LAC), the coordinates (e latitude and longitude) of the current location of the mobile phone (receiver). Furthermore, the GSM base station (transmitter) cited in the CellMapper record (by their Cell ID) were located and their longitudes and latitudes were recorded. The CellMapper dataset are exported from the handset to the laptop where the data are used for the analysis presented in this paper. The measured Received Signal Strength (RSS) in dBm at various distances (d) in km from the base station is shown in Table 1.

4 The Simulation Process and Performance Analysis for Pathloss Prediction Models

4.1 Performance Analysis for Pathloss Prediction Models

The performance of the model are evaluated in terms of mean prediction error ($\overline{\Delta}$), mean of the absolute prediction error ($\overline{\Delta}$), standard deviation or errors (σ), prediction accuracy (Pa%), Root Mean Square Error (RMSE), minimum prediction error and maximum prediction error.

The prediction error (Δ_i) for each location is given as

$$\Delta_i = P_{measured(i)} - P_{predicted(i)} \text{ , I = 1,2,3,…,n} \qquad (10)$$

Where n is the number of measurement points.

Mean prediction error ($\overline{\Delta}$) is given as:

$$\overline{\Delta} = \frac{1}{n}\left[\sum_{i=1}^{i=n} |\Delta_i|\right] \qquad (11a)$$

Mean of the absolute prediction error ($|\overline{\Delta}|$) is given as:

$$|\overline{\Delta}| = \frac{1}{n}\left[\sum_{i=1}^{i=n} |\Delta_i|\right] \qquad (11b)$$

Standard deviation (σ) is given as:

$$\sigma = \sqrt[2]{\frac{1}{n}\left[\sum_{i=1}^{i=n} (\Delta_i - \overline{\Delta})^2\right]} \qquad (12)$$

Prediction accuracy (Pa%) is given as:

$$\text{Pa}(\%) = 100\ (1 - \left(\frac{1}{n}\left[\sum_{i=1}^{i=n} \frac{|P_{measured(i)} - P_{predicted(i)}|}{P_{predicted(i)}}\right]\right) \qquad (13)$$

The Root Mean Square Error (RMSE) is given as:

$$\text{RMSE} = \sqrt{\left\{\frac{1}{n}\left[\sum_{i=1}^{i=n} \left(PL_{(measured)(i)} - PL_{(predicted)(i)}\right)^2\right]\right\}} \qquad (14)$$

4.2 The Simulation Process

4.2.1 The Un-tuned Models

Equation 15 is used to convert the measured received signal strength ($RSS_{(i)}$) to measured pathloss, $PL_{(measured)(i)}$) for each of the measurement point i. The longitude and latitude of each of the measurement point and the longitude and latitude of the base station are used with haversine formula to determine the distance of each of the measurement points from the base station. The measured pathloss is used to evaluate the prediction performance of the SUI model and the EXSUI model:

$$PL_m\ (dB) = P_{\mathrm{BTS}} + G_{\mathrm{BTS}} + G_{\mathrm{MS}} - L_{\mathrm{FC}} - L_{\mathrm{AB}} - L_{\mathrm{CF}} - \mathrm{RSS} \tag{15}$$

where

- P_{BTS} is the base transceiver station power (dBm), = $40\ dBm$
- G_{BTS} is the base transceiver station antenna gain (dBi), = $24dBi$
- G_{MS} is the mobile station antenna gain (dBi)) = $0\ dBi$
- L_{FC} is the feeder cable and connector loss (dB), = $3.02dB$
- L_{AB} is the antenna body loss (dB) = $3.02dB$
- L_{CF} is the combiner and filter loss (dB) = $4.5dB$
- RSS is the measured received signal strength (dBm)
- $PL_m\ (dB)$ is the measured pathloss for each measurement location at a distance d (km) from the base station.

4.2.2 The RMSE-Tuned Models

As part of the performance analysis of the un-tuned models, the RMSE is computed for each of the models. Then the RMSE-based tuning is performed by adding the RMSE between the measured and the predicted pathloss so as to minimize the prediction error. The prediction performance of the RMSE-tuned SUI model and the RMSE-tuned EXSUI model are performed.

$$PL_{SUI} = A + 10\,\gamma Log\left(\frac{d}{d_0}\right) + X_f + X_{h_r} + s + RMSE_{SUI} \quad \text{for SUI model} \tag{16}$$

$$PL_{EXSUI} = A + 10\,\gamma Log\left(\frac{d}{d_0}\right) + X_f + X_{h_r} + s + RMSE_{EXSUI} \quad \text{for EXSUI model} \tag{17}$$

4.2.3 The Multi-parameter-Tuned Models

Two model tuning factors K1 and K2 are introduced to adjust the coefficient of the model components that contains distance (d) and the receiver antenna height (h_r) respectively. Microsoft Excel solver tool is used to adjust and obtain the values of K1and K2 that minimize the RMSE. The procedure is carried out for the SUI model and the EXSUI model. Again, the prediction performance of the tuned SUI model and the tuned EXSUI model are conducted.

For SUI model;

$$PL_{SUI} = A + K1\left[10\,\gamma Log\left(\frac{d}{d_0}\right)\right] + X_f + K2\left[X_{h_r}\right] + s \tag{18}$$

For EXSUI model;

$$PL_{EXSUI} = A + K1\left[10\,\gamma Log\left(\frac{d}{d_0}\right)\right] + X_f + K2\left[X_{h_r}\right] + s \tag{19}$$

Where K1and K2 are the model tuning parameters.

5 Results and Discussions

Table 2 shows the measured Received Signal Strength (RSS) in dBm and the measured pathloss (PL_m) in dB at various distances (d) in km from the base station. The graph of measured pathloss (PL_m) in dB versus distances (d) in km from the base station is given in figure 1.

Table 2. The measured Received Signal Strength (RSS) in dBm and the measured pathloss (PL_m) in dB at various distances (d) in km from the base station.

d (km)	RSS (dBm)	PL_m (dB)	d (km)	RSS (dBm)	PL_m (dB)	d (km)	RSS (dBm)	PL_m (dB)
0.1543	-73	126	0.2844	-67	120	0.5267	-75	128
0.1622	-69	122	0.2846	-69	122	0.5401	-73	126
0.1626	-75	128	0.2875	-71	124	0.5773	-75	128
0.1627	-73	126	0.3033	-71	124	0.5875	-77	130
0.1634	-73	126	0.3183	-73	126	0.7092	-75	128
0.1641	-65	118	0.3303	-69	122	0.7238	-75	128
0.1644	-73	126	0.3463	-73	126	0.7378	-75	128
0.167	-65	118	0.3612	-73	126	0.7516	-77	130
0.1676	-65	118	0.3753	-75	128	0.7652	-77	130
0.1749	-69	122	0.389	-73	126	0.7781	-77	130
0.1877	-69	122	0.4032	-73	126	0.7914	-75	128
0.2016	-71	124	0.4172	-73	126	0.8051	-75	128
0.2146	-71	124	0.4312	-73	126	0.8192	-75	128
0.2281	-75	128	0.4455	-71	124	0.8675	-65	118
0.2407	-77	130	0.4588	-71	124	0.9166	-71	124
0.2538	-75	128	0.4723	-75	128	0.9219	-73	126
0.2658	-75	128	0.4864	-75	128	0.9219	-73	126
0.2772	-71	124	0.4997	-75	128			
0.2843	-69	122	0.5137	-73	126			

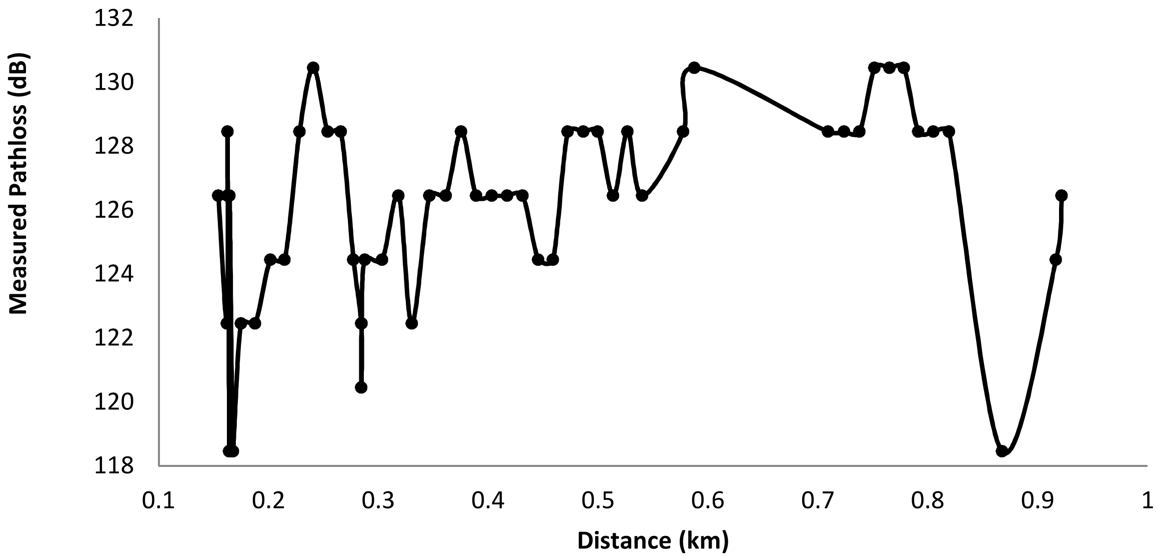

Figure 1.The measured pathloss (PL_m) in dB versus distances (d) in km from the base station

The graph of Figure 1 shows that the measured pathloss does not vary linearly with distance. Other factors affect the pathloss causing maximum pathloss to be witnessed not at the maximum distance of about 0.94km, but at about 0.25km, 0.6km and 0.78km.

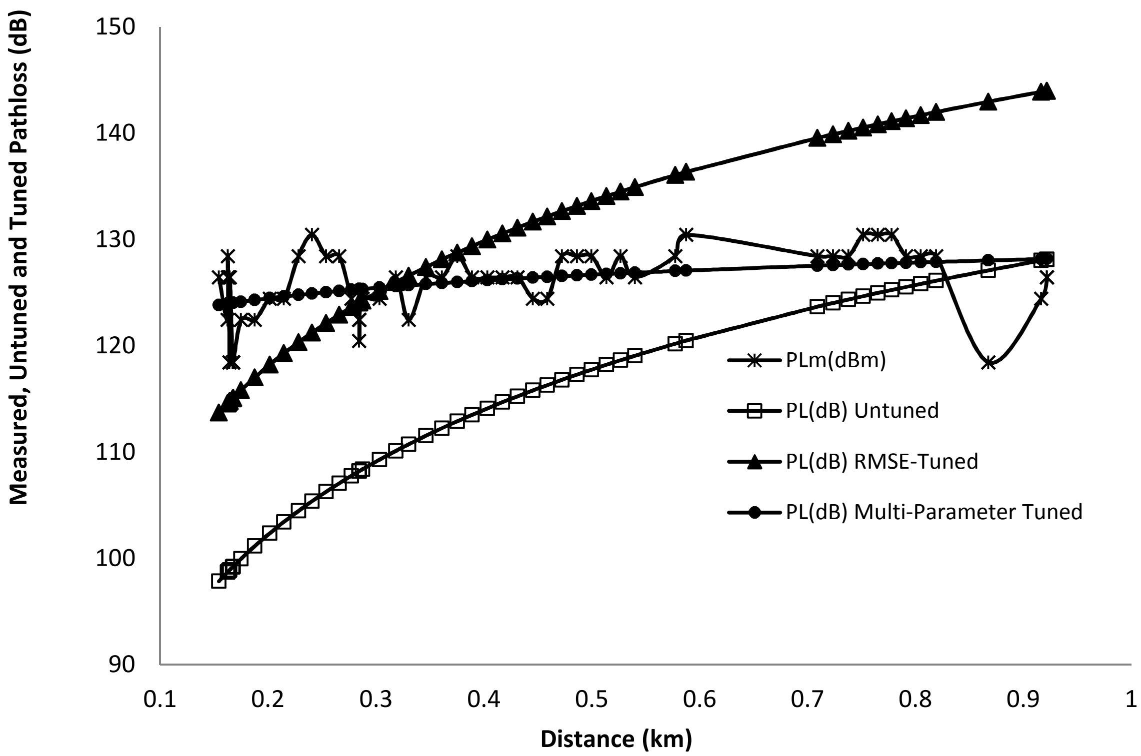

Figure 2. Measured, Untuned and Tuned Pathloss (dB) versus distance (km) for the SUI Model

Table 3. The prediction performance of the unturned SUI model, RMSE-tuned SUI model and multi-parameter tuned SUI model

Performance Parameter	Unit	Untuned SUI	RMSE-Tuned SUI	Multi-Parameter Tuned SUI
RMSE	dB	15.86241581	9.14916449	2.846932635
Standard Deviation	dB	8.760440739	8.76044074	4.026163247
Prediction Accuracy	%	89.007559	94.049663	98.24591005
Mean Error	dB	13.2238766	-2.6385392	0.00001
Absolute Mean Error	dB	13.7917181	7.51223167	2.187883051
Minimum Error	dB	-1.685863552	0.18751331	-0.04003758
maximum Error	dB	29.70310412	-24.51812	-9.58659255

Figure 2 shows the measured, untuned SUI model, RMSE-tuned SUI model and multi-parameter tuned SUI model. Table 3 shows the prediction performance of the unturned SUI model, RMSE-tuned SUI model and multi-parameter tuned SUI model. In Table 3 and Figure 2, the untuned SUI model under estimated the pathloss with mean prediction error of 13.2238766 dB, RMSE of 15.86241581 dB, Standard Deviation of error of 8.760440739 dB and prediction accuracy of 89.007559%. When RMSE is used to tune the SUI model, the prediction performance improved with mean prediction error of -2.6385392 dB , RMSE of 9.14916449 dB and prediction accuracy of 94.049663%. However, the RMSE approach does not improve on the standard deviation of error. Also, the RMSE overestimated pathloss although with a smaller error margins. Furthermore, the prediction performance of both the untuned and the RMSE tuned SUI model fail to meet the maximum acceptable RMSE of 6dB to 7dB for pathloss prediction models. From Eq. 16 and Table 3, the RMSE- tuned SUI is given as:

$$PL_{SUI} = A + 10\,\gamma Log\left(\frac{d}{d_0}\right) + X_f + X_{h_r} + s + 15.86241581 \quad \text{for SUI model} \tag{20}$$

The 15.86241581 accounts for other factors that affect the pathloss which are not explicitly captured in the SUI model.

The multi-parameter tuned SUI model has very good prediction performance; it slightly under estimated the pathloss with mean prediction error of 0.00001 dB, RMSE of 2.846932635 dB, standard deviation of error of 4.026163247 dB and prediction accuracy of 98.24591005%. The valued of the tuning parameters are K1= 0.143484264 and K2=13.91550936. Consequently, the multi-parameter tuned SUI model is given as:

$$PL_{SUI} = A + 0.143484264\left[10\,\gamma Log\left(\frac{d}{d_0}\right)\right] + X_f + 13.91550936\left[X_{h_r}\right] + s \tag{21}$$

Figure 3 shows the measured, untuned EXSUI model, RMSE-tuned EXSUI model and multi-parameter tuned EXSUI model. Table 4 shows the prediction performance of the unturned EXSUI model, RMSE-tuned EXSUI model and multi-parameter tuned EXSUI model. In Table 4 and Figure 3, the untuned EXSUI model under estimated the pathloss with mean prediction error of 14.32129283 dB , RMSE of 16.78823249 dB, Standard Deviation of error of 8.760440739 dB and prediction accuracy of 88.26474687%. When RMSE is used to tune the EXSUI model, the prediction performance improved with mean prediction error of -1.541122982 dB, RMSE of 9.14916449 dB and prediction accuracy of 94.2448662%. However, the RMSE approach does not improve on the standard deviation of error.

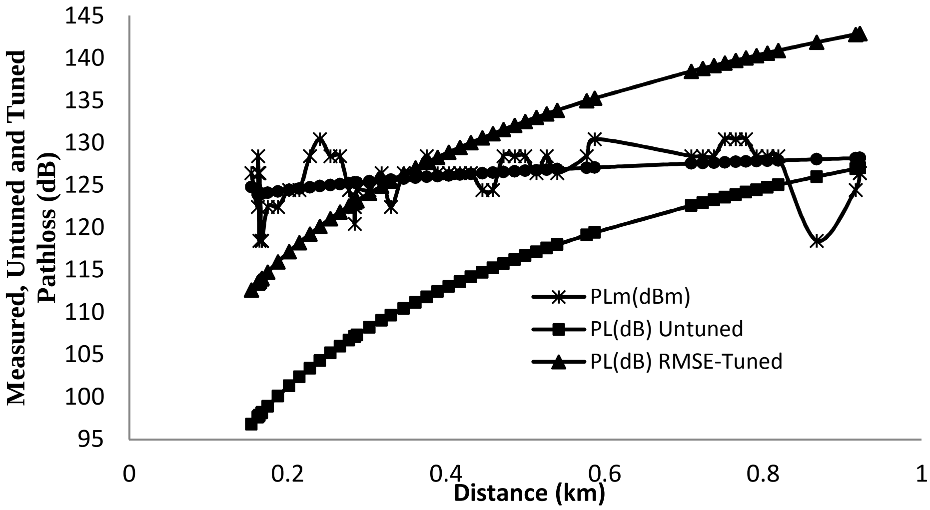

Figure 3. Measured, Untuned and Tuned Pathloss (dB) versus distance (km) for the EXSUI model

Also, the RMSE overestimated pathloss although with a smaller error margins. Furthermore, the prediction performance of both the untuned and the RMSE tuned EXSUI model fail to meet the maximum acceptable RMSE of 6dB to 7dB for pathloss prediction models. Then from Eq. 17 and Table 4, the RMSE-tuned EXSUI is given as:

$$PL_{EXSUI} = A + 10\,\gamma Log\left(\frac{d}{d_0}\right) + X_f + X_{h_r} + s + 8.894963855 \qquad (22)$$

Table 4. The prediction performance of the unturned EXSUI model, RMSE-tuned EXSUI model and multi-parameter tuned EXSUI model

Performance Parameter	**Unit**	**Untuned Extended SUI**	**RMSE-Tuned Extended SUI**	**Multi-Parameter Tuned Extended SUI**
RMSE	dB	16.78823249	8.894963855	2.833230647
Standard Deviation	dB	8.760440739	8.760440739	4.006792122
Prediction Accuracy	%	88.26474687	94.2448662	98.26207254
Mean Error	dB	14.32129283	-1.541122982	0.000002
Absolute Mean Error	dB	14.72951014	7.259590223	2.167873109
Minimum Error	dB	-0.588447365	0.133158438	0.008075
maximum Error	dB	30.80052031	-23.42070425	-9.609877201

The 8.894963855 accounts for other factors that affect the pathloss which are not

explicitly captured in the EXSUI model. The multi-parameter tuned EXSUI model has very good prediction performance; it slightly under estimated the pathloss with mean prediction error of 0.000002 dB, RMSE of 2.833230647 dB, standard deviation of error of 4.006792122 dB and prediction accuracy of 98.26207254 %. The valued of the tuning parameters are K1= 0.146372817 and K2 = 12.0580176. Consequently, the multi-parameter tuned EXSUI model is given as:

$$PL_{EXSUI} = A + 0.146372817 \left[10\, \gamma Log\left(\frac{d}{d_0}\right)\right] + X_f + 12.0580176\left[X_{h_r}\right] + s \qquad (23)$$

6 Conclusion

Prediction performance evaluation of SUI and EXSUI model are presented as well as the effectiveness of two model tuning approaches, namely, RMSE-based tuning and multi-parameter tuning. Although the RMSE tuning is quite simple, in some cases it does not minimize the prediction error to an acceptable level for practical applications. In that case, other model tuning approaches are required. The multi-parameter tuning can effectively minimize the prediction error to an acceptable level. The challenge is that it is a little more complex than the RMSE approach. Also, it requires experience to know what parameters to adjust to achieve the optimal prediction performance.

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