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Tuning and Cross Validation of Blomquist-Ladell Model for Pathloss Prediction in the GSM 900 Mhz Frequency Band

Njoku Chukwudi Aloziem, Ozuomba Simeon, Afolayan J. Jimoh

Department of Electrical/Electronic and Computer Engineering, University of Uyo, Akwa Ibom, Nigeria

Email address:
simeonoz@yahoo.com (O. Simeon)

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Abstract: In this paper, Blomquist-Ladell model is tuned and used for the prediction of total pathloss for GSM signal in the 900 MHz band. The model combined free-space loss, excess plane-earth loss and tunable multiple knife-edge diffraction loss to give the total loss. Pathloss data captured from two drive test conducted in Uyo suburban area are used in the study. The first drive test dataset are used to tune the Blomquist-Ladell model, particularly to select the value of the statistical terrain diffraction loss that minimizes the root mean square error (RMSE) of the model prediction. The tuned Blomquist-Ladell model is then cross validated with the second drive test dataset. The results show that the Blomquist-Ladell model performed very well; with the training data (first drive test dataset) the model has RMSE of 2.935598 dB and Prediction Accuracy of 98.16323% and in the cross validation data (the second drive test dataset) the model has RMSE of 3.398141dB and Prediction Accuracy of 97.82251%. In both cases, the RMSE is below 3.5 dB which is below the acceptable maximum value of 7dB for such pathloss prediction model.

Keywords: Blomquist-Ladell Model, Pathloss, Plane-Earth Loss Model, Cross Validation Test, Diffraction Loss

1. Introduction

As radio waves propagates through space their signal strength decreases due to losses that exist in the signal path. The reduction in power density (attenuation) of an electromagnetic wave as it propagates through space is called path loss or path attenuation [1, 2, 3]. Path loss plays vital role to decide the quality of service (QoS) for wireless communication at network planning level. Consequently, wireless network planners find it necessary to determine the extent of the signal loss for a given radio path [1, 3].

Path loss may be due to many effects, such as free-space loss, refraction, diffraction, reflection, aperture-medium coupling loss, and absorption. Path loss is also influenced by terrain contours, environment (urban or rural, vegetation and foliage), propagation medium (dry or moist air), the distance between the transmitter and the receiver, and the height and location of antennas [1, 2].

In order to predict the path loss that is inherent in a given area, pathloss prediction models are developed. The most common approaches to propagation modeling are empirical models that use measurement data to define a model path loss equation and physical models that use physical radio wave principles such as; free space transmission, reflection or diffraction (Kumar, 2011). However, in practice, experts have noted that the most appropriate path loss model depends on the location of the receiving antenna [1, 3, 4].

While free space loss is likely to give an accurate estimate of path loss in Location 1, Location 2, a strong line-of-sight is present alone with ground reflections which can significantly influence path loss. In this case, the plane earth loss model appears appropriate. Furthermore, in Location 3, plane earth loss needs to be corrected for significant diffraction losses and foliage loss, caused by trees cutting into the direct line of sight. On the other hand, in Location 4, a simple diffraction model is likely to give an accurate estimate of path loss. In addition, in Location 5, path loss prediction is fairly difficult and unreliable since multiple diffraction are involved. In any case, a typical mobile phone in motion may find itself in a number of those 5 scenarios before.

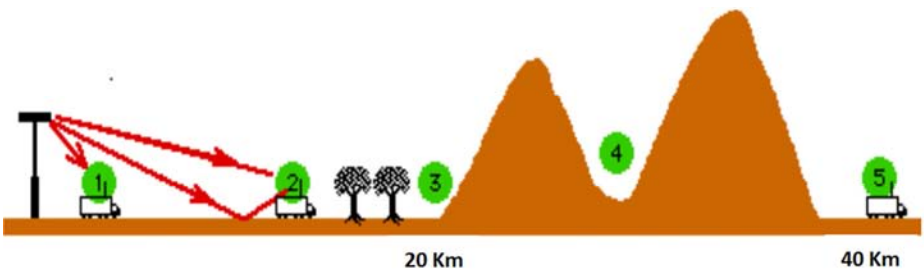

Figure 1. *Path loss model depends on the location of the receiving antenna.*

In this paper, Blomquist-Ladell model is used for the prediction of total pathloss for GSM signal in the 900 MHz band [5, 6, 7, 8]. The model combined free-space loss, excess plane-earth loss and tunable multiple knife-edge diffraction loss to give the total loss. Pathloss data captured from two drive test conducted in Uyo suburban area are used in the study. The first drive test dataset are used to tune the Blomquist-Ladell model, particularly to select the value of the statistical terrain diffraction loss that minimizes the root mean square error (RMSE) of the model prediction. The tuned Blomquist-Ladell model is then cross validated with the second drive test dataset [9, 10, 11].

2. Methodology

Blomquist-Ladell model combined the free-space loss (L_{FSL}), excess plane-earth loss (L_{EPEL}), and multiple knife-edge loss (L_{KEDL}) to give the total loss (L_{TL}). The excess plane-earth loss is given as [12, 13];

$L_{EPEL} = 10\mathrm{Log}(|a_{tx}a_{xr}|) + Y$

Where d is the link distance in meters, Y is the correction factor,

$$a_{tx} = \frac{4\pi(h_{tx})^2}{\lambda d_m} + \frac{\lambda(\epsilon_r)^2}{\pi d(\epsilon_r - 1)} \quad (1)$$

$$a_{rx} = \frac{4\pi(h_{rx})^2}{\lambda d_m} + \frac{\lambda(\epsilon_r)^2}{\pi d(\epsilon_r - 1)} \quad (2)$$

$$Y = \begin{cases} -2.8x & x < 0.53 \\ 6.7 + 10\mathrm{Log}_{10}(x) - 10.2x & x \geq 0.53 \end{cases} \quad (3)$$

$$x = d\left(\frac{2\pi}{\lambda}\right)^{1/3}(KR)^{-(2/3)} \quad (4)$$

Where

h_{tx} is the height of transmitter above ground in m

h_{rx} is the height of receiver above ground in m

d is the distance between transmitter and receiver along line of sight path in km

d_m is the distance between transmitter and receiver along line of sight path in m (1000d)

f is the carrier frequency in MHz

λ is the carrier wavelength in m

ϵ_r is the dielectric constant (relative permittivity) of the ground (Delisle recommends ϵ_r =10 for dry earth [12].

R is the radius of the earth in m (≈ 6.371 x 10^6)

k is the earth radius factor (typically 4/3),

c is the speed of light in m/s (≈ 299.792 x 10^6)

The free-space loss (L_{FSL}) in dB is given as;

$$L_{FSL} = 32.45 + 20\log(f) + 20\log(d) \quad (5)$$

Where

f is transmitted frequency in MHz and d is path length in km.

Finally, the total loss (L_{TL}) according to Blomquist-Ladell is given as follows:

$$L_{TL} = \begin{cases} L_{FSL} + \sqrt[2]{(L_{EPEL})^2 + (\mathrm{Ld}(\Delta h))^2} & L_{EPEL} \leq 0 \\ L_{FSL} + \sqrt[2]{(L_{EPEL})^2 + (\mathrm{Ld}(\Delta h))^2} & L_{EPEL} > 0 \leq \mathrm{Ld}(\Delta h) \\ L_{FSL} - \sqrt[2]{(L_{EPEL})^2 - (\mathrm{Ld}(\Delta h))^2} & L_{EPEL} > 0 > \mathrm{Ld}(\Delta h) \end{cases} \quad (6)$$

Where $\mathrm{Ld}(\Delta h)$ is the statistical terrain diffraction loss estimate which describes the “roughness” of the terrain as presented by Delisle, Lefevre, Lecours and Chouinard [12]. A value of ≈15 is considered minimal, ≈ 200 is used for hilly terrain, and ≈ 400 for very rugged terrain.. Delisle proposed the method for computing an estimate of additional losses due to terrain [12]. L_{FSL} is the basic free-space loss.

2.1. Drive Test Measurement Campaign and Determination Measured Pathloss

A handheld Samsung I9500 Galaxy S4 mobile phone was used to take measurement of received signal strength (RSS) from the UMTS 2100 GHz network. The RSS measurements were taken two times along dual lane tarred road in a suburban part of Uyo metropolis. The Samsung I9500 Galaxy S4 has CellMapper Android application installed [14]. The CellMapper captures and displays advanced GSM/CDMA/UMTS/LTE current and neighbouring cells’ low level data and can also record and export the data as comma-separated values (CSV) file. Data captured by the CellMapper comprises the current and neighbouring cells RSS in decibels (dB), the current cells cell ID (CID), local area code (LAC). The RSS along with the respective longitudes and latitudes were recorded at each measurement (receiver) point. In addition, the UMTS base station (transmitter) was located, and its longitude and latitude were recorded.

2.2. Calculation of the Measured Pathloss From the Measured RSS

After the measurements, Haversine formula was used to determine the distance between the mast (transmitter) and of the receiver locations.

The RSS value recorded at each of the receiving point is converted to measured pathloss (PL_m (dB) by using the formula:

$$PL_m\,(dB) = \left(PBTS + GBTS + GMS - LFC - LAB - LCF\right) - RSS\,(dBm) \quad (7)$$

where

PL_m (dB) is the measured pathloss for each measurement location at a distance d (km) from the base station.

PBTS = Base transceiver station power (dBm),

GBTS = Base transceiver station antenna gain (dBi),

GMS = Mobile station antenna gain (dBi),

LFC = Feeder cable and connector loss (dB),

LAB = Antenna body loss (dB) and

LCF = Combiner and filter loss (dB).

The values of these parameters are given by as:

$P\ BTS = 40\,W = [30 + 10\log_{10} 40] = 46\,dBm$; GBTS = 18.15 dBi, GMS = 0 dBi, LFC = 3 dB, LAB = 3 dB, LCF = 4.7 dB. The measured path loss value in dB obtained for each of the measurement points is recorded in Table 1. The receiver locations, distance, RSS, measured path loss and Okumura-Hata model predicted Pathloss are also given in Table 1.

2.3. Prediction Performance Analysis of the Model

In order to evaluate the prediction performance of the model, the root mean square error (RMSE), prediction accuracy (PA), the absolute minimum prediction error (AMNPE) and the absolute maximum prediction error (AMXPE) are calculated for the models.

Let $PL_{(measured)(i)}$ be the measured path loss (dB), let $PL_{(predicted)(i)}$ be the predicted path loss (dB) and let $\overline{PL_{(measured)}}$ be the mean of measured path loss and let n be the number of measured data points. The RMSE is estimated as:

$$RMSE = \sqrt{\left\{\frac{1}{n}\left[\sum_{i=1}^{i=n}\left|PL_{(measured)(i)} - PL_{(predicted)(i)}\right|^2\right]\right\}} \quad (8)$$

Then, the prediction accuracy based on mean absolute percentage error (MAPE) is calculated as:

$$\text{Prediction Accuracy} = \left\{1 - \frac{1}{n}\left(\sum_{i=1}^{i=n}\left|\frac{\left|PL_{(measured)(i)} - PL_{(predicted)(i)}\right|}{PL_{(measured)(i)}}\right|\right)\right\} \times 100\,\% \quad (9)$$

The absolute minimum prediction error (AMNPE) is given as;

$$AMNPE = \text{minimum}\left(\left|PL_{(measured)(i)} - PL_{(predicted)(i)}\right|\right) \text{ for all I} \quad (10)$$

the absolute maximum prediction error (AMXPE) is given as;

$$AMXPE = \text{maximum}\left(\left|PL_{(measured)(i)} - PL_{(predicted)(i)}\right|\right) \text{ for all I} \quad (11)$$

3. Result

Two drive tests were conducted. The data captured in the two drive tests are presented in table 1 and table 2 as well as in figure 2 and figure 3.

The dataset of the first drive test is used to train or tune the Blomquist-Ladell model parameters. Specifically, the Delisle statistical terrain diffraction loss estimate (Ld(Δh) is selected by running Microsoft Excel Solver's nonlinear optimization tool on the first drive test data. According to Delisle et al (1985), Ld(Δh) value of 15 is set as the minimum and 400 as the maximum. The Microsoft Excel's Solver nonlinear optimization is run with the condition that $15 \leq Ld(\Delta h) \leq 400$ and the objective is to minimize the root mean square error between the measured pathloss in the first drive test and the Blomquist-Ladell model predicted pathloss. The Microsoft Excel's Solver optimization gave optimal value of the statistical terrain diffraction loss estimate (Ld(Δh) as 35.19764 dB.

Afterwards the tuned Blomquist-Ladell model (with (Ld(Δh) = 35.19764 dB) based on the first drive test is cross validated by using the model to predict the pathloss at the same measurement points in the second drive test dataset. The measured and the predicted pathloss for the two drive test datasets are presented in table 3 and table 4 as well as in figure 4 and figure 5. The prediction performance of the Blomquist-Ladell model for the two datasets is shown in table 5.

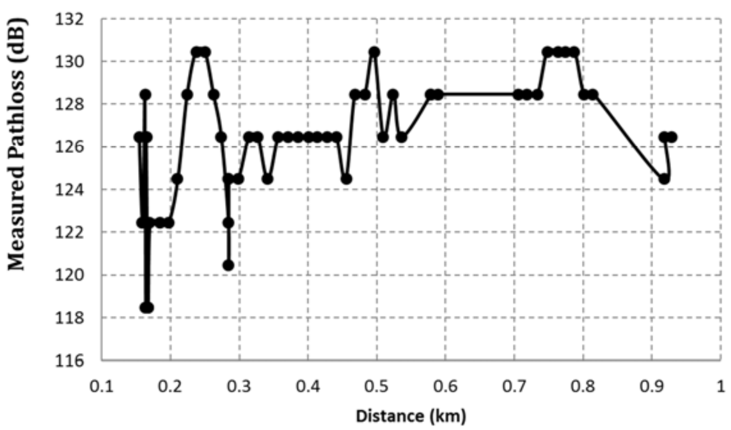

Figure 2. *Measured Pathloss (dB) Versus Distance (km) For The First Drive Test Dataset In Table 1.*

Table 1. *First drive test dataset that includes Received Signal Strength (RSSI), the measured pathloss and the distance (d) of the measurement points from the transmitter base station.*

S/N	d (km)	RSSI(dB)	Measured Pathloss (dB)	S/N	d (km)	RSSI(dB)	Measured Pathloss (dB)
1	0.1545	-73	126.5	29	0.385	-73	126.5
3	0.1626	-75	128.5	31	0.4131	-73	126.5
5	0.163	-73	126.5	33	0.4412	-73	126.5
7	0.1645	-73	126.5	35	0.468	-75	128.5
9	0.1675	-65	118.5	37	0.4955	-77	130.5
11	0.1836	-69	122.5	39	0.524	-75	128.5
13	0.2106	-71	124.5	41	0.5792	-75	128.5
15	0.237	-77	130.5	43	0.5896	-75	128.5
17	0.2624	-75	128.5	45	0.7196	-75	128.5
19	0.2843	-69	122.5	47	0.7474	-77	130.5
21	0.2848	-71	124.5	49	0.7742	-77	130.5
23	0.2984	-71	124.5	51	0.8009	-75	128.5
25	0.3269	-73	126.5	53	0.917	-71	124.5
27	0.3568	-73	126.5	55	0.9285	-73	126.5

Table 2. *The Cross Validation Data (The Second drive test dataset) that includes measured Received Signal Strength (RSSI), the measured pathloss and the distance (d) of the measurement points from the transmitter base station.*

S/N	d (km)	RSSI (dB)	Measured Pathloss (dB)	S/N	d (km)	RSSI (dB)	Measured Pathloss (dB)
1	0.1525	-73	126.5	29	0.3781	-75	128.5
3	0.1625	-75	128.5	31	0.4061	-73	126.5
5	0.1638	-73	126.5	33	0.4341	-73	126.5
7	0.1641	-65	118.5	35	0.4627	-71	124.5
9	0.1671	-65	118.5	37	0.4889	-75	128.5
11	0.1776	-69	122.5	39	0.5163	-73	126.5
13	0.2044	-71	124.5	41	0.5416	-73	126.5
15	0.2306	-75	128.5	43	0.5842	-77	130.5
17	0.2563	-77	130.5	45	0.7279	-75	128.5
19	0.2794	-71	124.5	47	0.7544	-77	130.5
21	0.2844	-67	120.5	49	0.7808	-77	130.5
23	0.2899	-71	124.5	51	0.8091	-75	128.5
25	0.3208	-73	126.5	53	0.8545	-69	122.5
27	0.3494	-73	126.5	55	0.9257	-73	126.5

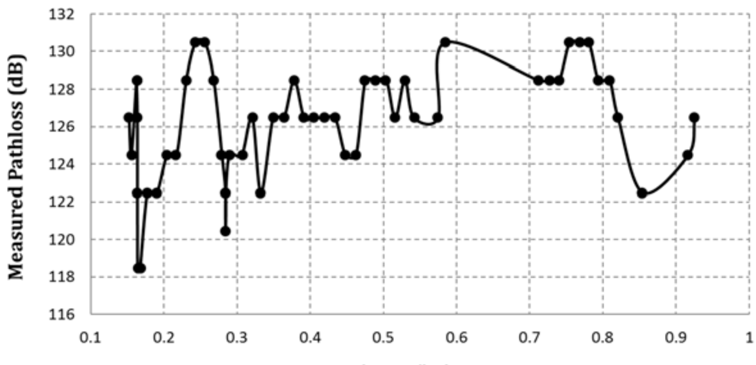

Figure 3. *Measured Pathloss (dB) Versus Distance (km) for the Cross Validation Data (the Second Drive Test Dataset) in Table 2.*

Table 3. *Measured Pathloss (dB) and Predicted Pathloss Versus Distance (km) Based On The First Drive Test Dataset in Table 1.*

S/N	d (km)	Measured Pathloss (dB)	Predicted Pathloss (dB)	S/N	d (km)	Measured Pathloss (dB)	Predicted Pathloss (dB)
1	0.1545	126.45	125.1	29	0.385	126.45	127.7
3	0.1626	128.45	125.2	31	0.4131	126.45	128
5	0.163	126.45	125.2	33	0.4412	126.45	128.2
7	0.1645	126.45	125.2	35	0.468	128.45	128.4
9	0.1675	118.45	125.3	37	0.4955	130.45	128.6
11	0.1836	122.45	125.5	39	0.524	128.45	128.8
13	0.2106	124.45	125.9	41	0.5792	128.45	129.2
15	0.237	130.45	126.2	43	0.5896	128.45	129.3
17	0.2624	128.45	126.5	45	0.7196	128.45	130.1
19	0.2843	122.45	126.8	47	0.7474	130.45	130.2
21	0.2848	124.45	126.8	49	0.7742	130.45	130.4

S/N	d (km)	Measured Pathloss (dB)	Predicted Pathloss (dB)	S/N	d (km)	Measured Pathloss (dB)	Predicted Pathloss (dB)
23	0.2984	124.45	126.9	51	0.8009	128.45	130.5
25	0.3269	126.45	127.2	53	0.917	124.45	131.1
27	0.3568	126.45	127.5	55	0.9285	126.45	131.2

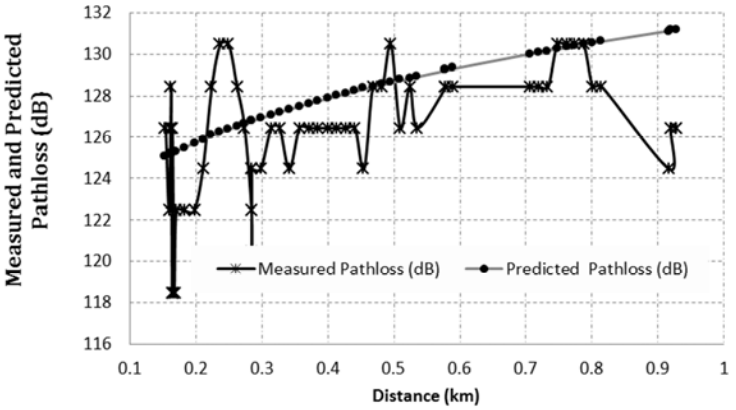

__Figure 4.__ Measured Pathloss (dB) and Predicted Pathloss Versus Distance (km) Based on the First Drive Test Dataset in Table 1 and Table 3.

__Table 4.__ Measured Pathloss (dB) and Predicted Pathloss Versus Distance (km) Based on the Cross Validation Data (the Second Drive Test Dataset) in Table 2.

S/N	d (km)	Measured Pathloss (dB)	Predicted Pathloss (dB)	S/N	d (km)	Measured Pathloss (dB)	Predicted Pathloss (dB)
1	0.1525	126.45	125.03	29	0.3781	128.45	127.69
3	0.1625	128.45	125.19	31	0.4061	126.45	127.93
5	0.1638	126.45	125.21	33	0.4341	126.45	128.16
7	0.1641	118.45	125.22	35	0.4627	124.45	128.39
9	0.1671	118.45	125.26	37	0.4889	128.45	128.58
11	0.1776	122.45	125.42	39	0.5163	126.45	128.78
13	0.2044	124.45	125.81	41	0.5416	126.45	128.96
15	0.2306	128.45	126.15	43	0.5842	130.45	129.25
17	0.2563	130.45	126.46	45	0.7279	128.45	130.13
19	0.2794	124.45	126.72	47	0.7544	130.45	130.28
21	0.2844	120.45	126.77	49	0.7808	130.45	130.42
23	0.2899	124.45	126.83	51	0.8091	128.45	130.57
25	0.3208	126.45	127.15	53	0.8545	122.45	130.81
27	0.3494	126.45	127.42	55	0.9257	126.45	131.16

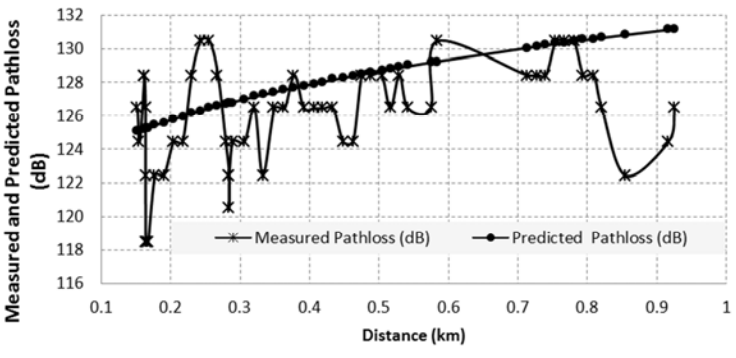

__Figure 5.__ Measured Pathloss (dB) and Predicted Pathloss Versus Distance (km) Based on the Cross Validation Data (The Second Drive Test Dataset) in Table 2 and Table 4.

__Table 5.__ Performance of the Blomquist-Ladell model when applied to the training data (the first drive test dataset)and when applied to the cross validation data (the second drive test dataset).

Performance Parameter	Performance of the prediction model based on the first drive test dataset in Table 1 and Table 3	Performance of the prediction model based on the cross validation data (the second drive test dataset) in Table 2 and Table 4
Statistical terrain diffraction loss estimate ($L_d(\Delta h)$) in dB	35.19764	35.19764
RMSE	2.935598	3.398141
Prediction Accuracy (%)	98.16323	97.82251
Maximum Prediction Error (%)	5.756943	6.826954
Minimum Prediction Error (%)	0.006765	0.020969

In published literatures, RMSE value that is less or equal to 6dB is acceptable for pathloss models. Table 5 shows that the Blomquist-Ladell model performed very well in both the training data (first drive test dataset in Table 1 and Table 3) and in the cross validation data (the second drive test dataset) in Table 2 and Table 4. In both cases, the RMSE is below 3.5 dB.

4. Conclusion

Pathloss prediction using Blomquist-Ladell model is presented for GSM network in the 900 MHz band. The Blomquist-Ladell model which is a semi empirical model gave very good prediction for the study area and the frequency band. Cross validation result also shows that the model gives good result when applied to other set of data captured around the study area. The key feature that makes the Blomquist-Ladell model useful for practical applications is that it incorporates the free space and the plane earth (reflection) model along with diffraction loss. It also has a tunable diffraction parameter that can be used to make the model prediction suitable for different environment.

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