Journal of Multidisciplinary Engineering Science and Technology (JMEST)
ISSN: 2458-9403
Vol. 12 Issue 1, January - 2025

Cellular Network Propagation Loss Characterization Using Standard Path Loss Model

Ifeagwu E.N.,[1]
Department of Electrical and Electronic Engineering,
Federal University Otuoke, Bayelsa State

Okafor Joyce Odu[2]
Department of Electrical and Electronic Engineering,
Federal University Otuoke, Bayelsa State

Amaechi, Justice Nzegwu[3]
Department of Science Laboratory Technology (Physics Electronics)
Imo State Polytechnic, Omuma, Imo State

***Abstract*—Cellular network propagation loss characterization using Standard Path loss (SP) model is presented. The work is based on empirical measurement of the received signal strength, evaluation of the SP model's ability to accurately predict the path loss and then tuning the SP model to optimize its prediction accuracy thereby minimizing the SP model's path loss prediction error for the given study area. The cellular network operating in the 1800 MHz frequency band was considered. The model was tuned using the root mean square (RMSE) method and also using the function of residue method. The measured path length range was 0.15 km to 2.26 km while the corresponding path loss range was 79.49 dB to 128.39 dB. The un-turned model had RMSE of 39.89 dB for the urban propagation environment. The RMSE–based tuned model had RMSE of 3.067 dB for the urban propagation environment which is about 92.3 % improvement over the un-tuned model prediction, while the function of residue-based tuned model had RMSE of 1.07896 dB which is about 97.3 % improvement over the un-tuned model prediction. Similar performance improvement in RMSE was experienced in the suburban and rural environments, with the function of residue-based tuned model giving the best performance. The results showed that the function of residue method performed much better than the RMSE method which is the most widely used method.**

Keywords— Cellular Network, Propagation Loss, Standard Path Loss Model, Path loss Model Tuning, Empirical Model

1. Introduction

The growing adoption of wireless networks and the rising demand for more bandwidth and enhanced quality of service is posing running challenges to wireless network designers and operators [1,2,3]. This is due to some inevitable challenges associated with wireless signal propagations. One of the problem is the propagation loss which is always suffered by wireless signals as they propagate over a communication environment [4,5,6]. The propagation loss, also known as path loss is dependent on several factors and hence varies from one communication environment to another [7,8].

In practice, wireless network designers and operators conduct site survey to estimate the expected propagation loss for their wireless signal [9,10]. The site survey can also be avoided if there is a propagation loss model that can accurately characterize the propagation loss in the given environment for the same signal frequency of interest. Hence, researchers always provide study reports of such empirical models that are optimized for wireless network installation in a given area.

Accordingly, in this study, the focus is to conduct the empirical propagation loss model evaluation and tuning for a cellular network in the 18000 MHz frequency band [11,12,13]. Specifically, the Standard Path loss model (SP model) is considered [14,15]. Most importantly, the approach for the model tuning approaches adopted are, one, the root mean square error (RMSE)-based method and two, the function of residue-based method. The performance of the models tuned using the two methods are compared and the best model is recommended for the case study cellular network in the given case study area.

2.0 METHOD

The focus in this work is to use the Standard Propagation (SP) model to characterize the propagation loss cellular network signal. The work is based on empirical measurement of the prevailing path loss, evaluation of the SP models ability to accurately predict the path loss and then tuning the SP model to optimize its prediction accuracy thereby minimizing the SP model's path loss prediction error for the given study area.

So, first, the analytical equations for computing the Standard Propagation (SP) model are presented followed by the data collection and analysis. Then other steps for the evaluation and optimization of the SP model based on the empirical dataset from the case study area are presented.

2.1 THE STANDARD PROPAGATION MODEL

The Standard Propagation (SP) Model is one of the empirical models for characterizing propagation loss that is experienced by wireless signal as it propagates from the transmitter to the receiver over a path length. Base on the SP model, the path loss, $LP_{SP(dB)}$ for a given path length, d is expressed in the following analytical models [14,15]:

$$LP_{SP(dB)} = A + B(\log_{10}(d)) + C_m \quad (1)$$

$$A = K_1 + K_3(\log_{10}(H_{TXeff})) + K_6(H_{TXeff}) + K_7(\log_{10}(H_{TXeff})) \quad (2)$$

$$B = K_2 + K_5(\log_{10}(H_{TXeff})) \quad (3)$$

$$C_m = K_4(Diffraction\ Loss) + K_{clutter}(f(clutter)) + K_{hillLOS} \quad (4)$$

Where, d is the path length in km, $K_{clutter}$ is the coefficient for clutter attenuation, hm denote the mobile device antenna height of antenna , hb denote the base station antenna height, K_1, K_2 , K_3 , K_4 , K_5 , K_6 and K_7 are various constants which are defined in Table 1 for various propagation environments. H_{TXeff} denotes the *mobile antenna height* (in m) while f(clutter) denotes the average of the weighted losses due to clutter.

Table 1 The K-Parameters specifications for the different propagation environments [14,15]

K Values	Dense Urban	Urban	Suburban	Rural	Highways
K_1	16.375	17.575	17.675	5.275	26.625
K_2	48	45.9	45.9	48	40.1
K_3	5.83	5.83	5.83	5.83	5.83
K_4	0.8	0.8	0.8	0.8	0.8
K_5	-0.655	-0.655	-0.655	-0.655	-0.655
K_6	0	0	0	0	0
K_7	0.8	0.8	0.8	0.8	0.8
$K_{clutter}$	1	1	1	1	1

2.2 DATA COLLECTION AND ANALYSIS

Empirical data collection was conducted through a test drive along the path within the case study area in Eket, in Akwa Ibom State, Nigeria. The TEst Mobile System (TEMS), core i5 laptop, and 4G Modem with SIM card of the target GSM service provider, GPS, and Python program written for the analysis of the data. The Google map visualization of the case study site is shown in Figure 1 while empirical measured data with the base station located at longitude of 7.94177 and latitude of 4.64657 are presented in Table 2. The cellular network considered operates in the 1800 MHz frequency band.

Figure 1 The Google map visualization of the case study site

Table 2 The empirical measurement data with the base station located at longitude of 7.94177 and latitude of 4.64657

Data point, i	Longitude	Latitude	RSSI (dBm)	Data point, i	Longitude	Latitude	RSSI (dBm)
1	7.942397	4.645414	-50.9915	14	7.94026	4.63706	-83.412
2	7.94298	4.6447	-65.4208	15	7.93901	4.63661	-88.6254
3	7.9432	4.64381	-68.2004	16	7.93888	4.6354	-90.2176
4	7.94338	4.64248	-71.4159	17	7.93892	4.6351	-87.0313
5	7.94382	4.64177	-77.985	18	7.93818	4.6343	-90.4016
6	7.94408	4.64075	-81.7754	19	7.9384	4.63413	-89.9097
7	7.94427	4.64017	-80.6482	20	7.93767	4.63314	-92.2763
8	7.94368	4.63917	-78.9148	21	7.93703	4.63206	-92.6083
9	7.94355	4.63904	-79.0846	22	7.93633	4.63163	-94.8689
10	7.94311	4.63821	-83.5667	23	7.93607	4.63101	-95.8166
11	7.94186	4.63768	-84.8455	24	7.93535	4.63021	-95.1633
12	7.94126	4.63737	-88.5572	25	7.93468	4.62877	-94.6366
13	7.94117	4.63737	-85.7314	26	7.93373	4.62798	-96.543
14	7.94026	4.63706	-83.412	27	7.93382	4.62784	-99.8945

2.3 DETERMINATION OF THE TRANSMISSION PATH LENGTH USING THE HAVERSINE FORMULA

After the drive test, each measurement point coordinates are used along with the base station coordinates to determine the transmission path length using the Haversine formula which is expressed as follows:

$$d = 2(R_{earth})\left\{\sqrt[2]{\sin\left(\frac{LAT_m - LAT_b}{2}\right)^2 + \cos(LAT_b)\cos(LAT_m)\sin\left(\frac{LONG_m - LONG_b}{2}\right)^2}\right\} \quad (4)$$

$$LAT_{rad} = \frac{(LAT_{deg} * 3.142)}{180} \quad (5)$$

$$LONG_{rad} = \frac{(LONG_{deg} * 3.142)}{180} \quad (6)$$

Where LAT_b and LAT_m denote the latitude of the base station and the mobile device respectively $LONG_b$ and $LONG_m$ denote the longitude of the base station and the mobile device respectively. Also, latitude in radians is denoted as LAT_{rad}, latitude in degrees is denoted as LAT_{deg}, longitude in radians is denoted as $LONG_{rad}$, and longitude in degrees is denoted as $LONG_{deg}$. In addition, R_{earth} denotes the earth radius which is 6371 km , while d is the transmission path length in km.

2.4 DETERMINATION OF THE MEASURED PATH LOSS USING THE EMPIRICALLY MEASURED RSSI VALUES

The empirically measured Received Signal Strength Intensity (RSSI) data values are converted to measured path loss $L_{ms(dB)}$ using the analytical expression as follows:

$$L_{ms(dB)} = EIRP_{b(dB)} + P_{m(dB)} \quad (7)$$

$$EIRP_{b(dB)} = P_{b(dB)} + G_{b(dB)} + G_{m(dB)} - L_{OT} \quad (8)$$

where $L_{ms(dB)}$ denotes the measured path loss, $P_{m(dB)}$ denotes the Received Signal Strength Intensity (RSSI) measured at the mobile device, $P_{b(dB)}$ denote the transmitter power at the base station, $G_{b(dB)}$ denote the transmitter antenna gain at the base station, $G_{m(dB)}$ denote the receiver antenna gain at the mobile device, L_{OT} denotes the sum of other losses which include feeder cable loss, combiner and filter loses , among others. Typical values used for the study are; $P_{b(dB)} = 30$ dBm, $G_{b(dB)} = 10.5$ dBi , $G_{m(dB)} = 0$ dBi , $L_{OT} = 7$ dBm. Then;

$$EIRP_{b(dB)} = 25 + 10.15 + 0 - 7 = 28.5 \quad (9)$$

Therefore

$$L_{ms(dB)} = P_{m(dB)} + 28.5 \quad (10)$$

2.5 THE PERFORMANCE METRICS

The metrics used for evaluation of the path loss model's prediction performance are; Root Mean Square Error (RMSE), Mean Absolute Error (MAE), R-Squared (R^2) value and prediction accuracy expressed as the Mean Absolute Percentage Error (PAMAPE).

The Mean Absolute Error (MAE) is computed using analytical expression as follows:

$$\text{MAE} = \frac{1}{n}\left(\sum_{i=1}^{i=n}\left|L_{ms(dB)(\text{i})} - L_{pred(dB)(\text{i})}\right|\right) \quad (11)$$

Where $L_{ms(dB)(\text{i})}$ and $L_{pred(dB)(\text{i})}$ are the ith measured and predicted path loss respectively while n denotes the number of data points in the dataset.

The Root Mean Square Error (RMSE) is computed using analytical expression as follows:

$$\text{RMSE} = \sqrt[2]{\left\{\frac{1}{n}\left[\sum_{i=1}^{i=n}\left(L_{ms(dB)(\text{i})} - L_{pred(dB)(\text{i})}\right)^2\right]\right\}} \quad (12)$$

The prediction accuracy expressed as the Mean Absolute Percentage Error (PA/MAPE) which is computed using analytical expression as follows:

$$\text{PA/MAPE} = \left\{1 - \frac{1}{n}\left(\sum_{i=1}^{i=n}\left|\frac{L_{ms(dB)(\text{i})} - L_{pred(dB)(\text{i})}}{L_{ms(dB)(\text{i})}}\right|\right)\right\} * 100\% \quad (13)$$

2.6 MODEL OPTIMIZATION

In practice, when the measured and model predicted path loss has RMSE > 6dB, then the model prediction performance is not acceptable and the model will require parameter tuning to optimize the prediction performance. In this study, two model optimization approaches are considered, namely;

Method 1: the RMSE –based model tuning and

Method 2: the function of residue-based method.

2.6.1 THE RMSE –BASED MODEL TUNING METHOD

Step 1: Compute the prediction error, e_i in data point i, where,

$$e_i = L_{pred(dB)(\text{i})} - L_{ms(dB)(\text{i})} \quad (14)$$

Step 2: Compute the mean of the prediction error, $\overline{e_i}$, where,

$$\overline{e_i} = \frac{\sum_{i=1}^{i=n}(e_i)}{n} \quad (15)$$

Step 3: Compute the root mean square of the prediction error RMSE, where,

$$\text{RMSE} = \sqrt[2]{\left\{\frac{1}{n}\left[\sum_{i=1}^{i=n}(e_i)^2\right]\right\}} \quad (16)$$

Step 4: Tune the model predicted path loss, denoted as $LT_{predM1(dB)(\text{i})}$ where,

$$LT_{predM1(dB)(\text{i})} = \begin{cases} L_{pred(dB)(\text{i})} + \text{RMSE} & \text{for } \overline{e_i} \leq 0 \\ L_{pred(dB)(\text{i})} - \text{RMSE} & \text{for } \overline{e_i} > 0 \end{cases} \quad (17)$$

The optimized path loss model using the method 1 is therefore defined as,

$$LP_{SPM1(dB)} = \begin{cases} A + B(\log_{10}(d_i)) + C_m + \text{RMSE} & \text{for } \overline{e_i} \leq 0 \\ A + B(\log_{10}(d_i)) + C_m - \text{RMSE} & \text{for } \overline{e_i} > 0 \end{cases} \quad (18)$$

2.6.2 THE FUNCTION OF RESIDUE-BASED METHOD

Step 1: Compute the prediction error, e_i in data point i, where,

$$e_i = L_{pred(dB)(\text{i})} - L_{ms(dB)(\text{i})} \quad (19)$$

Step 2: Plot the graph of e_i versus $\log(d_i)$, where d is the path length in km and insert linear trend line analytical expression to predict the error at d_i, where the predicted error eP_i at d_i is given as,

$$eP_i = \beta(\log_{10}(d_i)) + \delta \quad (20)$$

Where β is the slop or gradient of the line and δ is the intercept (a constant).

Step 3: Tune the model predicted path loss, denoted as $LT_{predM2(dB)(\text{i})}$ where,

$$LT_{predM2(dB)(\text{i})} = L_{pred(dB)(\text{i})} + eP_i \quad (21)$$

$$LP_{SPM(dB)} = A + B(\log_{10}(d_i)) + C_m + eP_i \quad (22)$$

$$LP_{SPM(dB)} = A + B(\log_{10}(d_i)) + C_m + \beta(\log_{10}(d_i)) + \delta \quad (23)$$

$$LP_{SPM(dB)} = A + (B + \beta)(\log_{10}(d_i)) + C_m + \delta \quad (24)$$

3. RESULTS AND DISCUSSION

The results of the path length computation using the Haversine formula and the measurement points' longitude and latitude are presented in Table 3 along with the measured path loss. The path length range is 0.15 km to 2.26 km while the corresponding path loss range is 79.49 dB to 128.39 dB.

Comparison of the line charts of the empirically measured path loss, the tuned and the un-tuned model predicted path loss for the urban environment is presented in Figure 3. Similar comparison for the suburban environment is presented in Figure 4 while that of the rural environment is presented in Figure 5. Again, the results of the performance parameters, namely, MAE, RMSE and PA/MAPE (%) for the un-tuned model, the RMSE–based tuned model and the function of residue-based tuned model are presented in Table 4.

Table 3 The results of the measured path loss and the path length computation using the Haversine formula

S/N	Path Length, d (km)	Field Measured Path Loss (dB)	S/N	Path Length, d (km)	Field Measured Path Loss (dB)
1	0.15	79.49	14	1.07	111.91
2	0.25	93.92	15	1.15	117.13
3	0.35	96.70	16	1.28	118.72
4	0.49	99.92	17	1.32	115.53
5	0.58	106.49	18	1.42	118.90
6	0.70	110.28	19	1.43	118.41
7	0.76	109.15	20	1.56	120.78
8	0.85	107.41	21	1.70	121.11
9	0.86	107.58	22	1.77	123.37
10	0.94	112.07	23	1.84	124.32
11	0.99	113.35	24	1.96	123.66
12	1.03	117.06	25	2.13	123.14
13	1.03	114.23	26	2.25	125.04
14	1.07	111.91	27	2.26	128.39

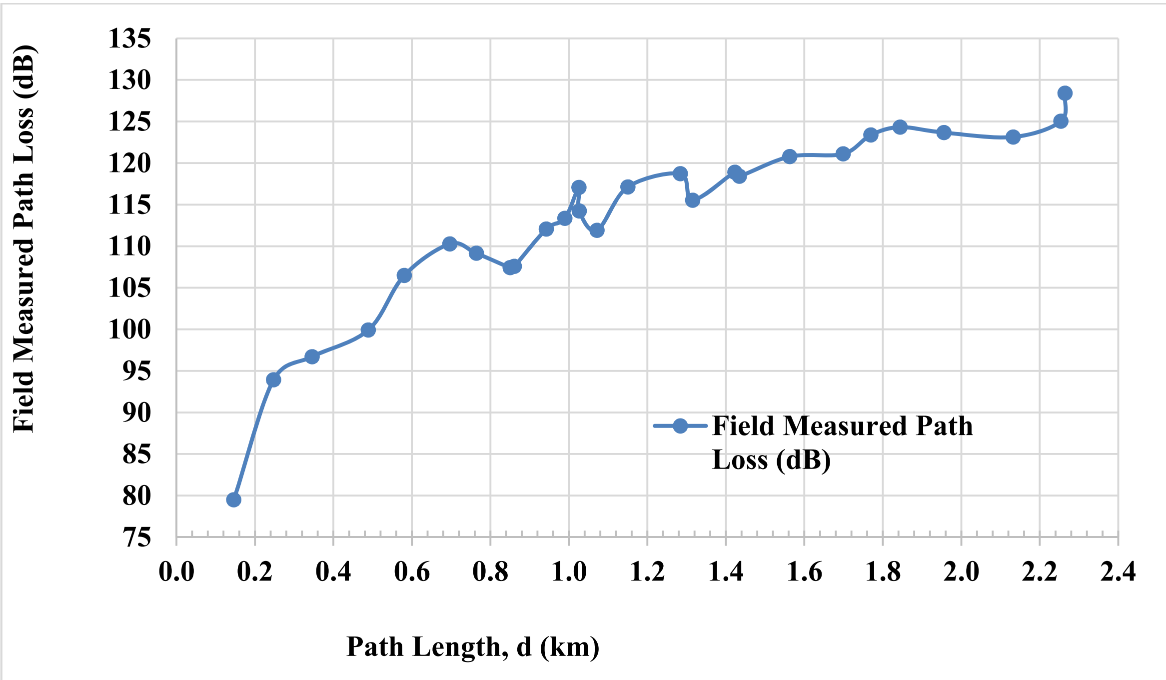


Figure 2 The line chart of the empirically measured path loss

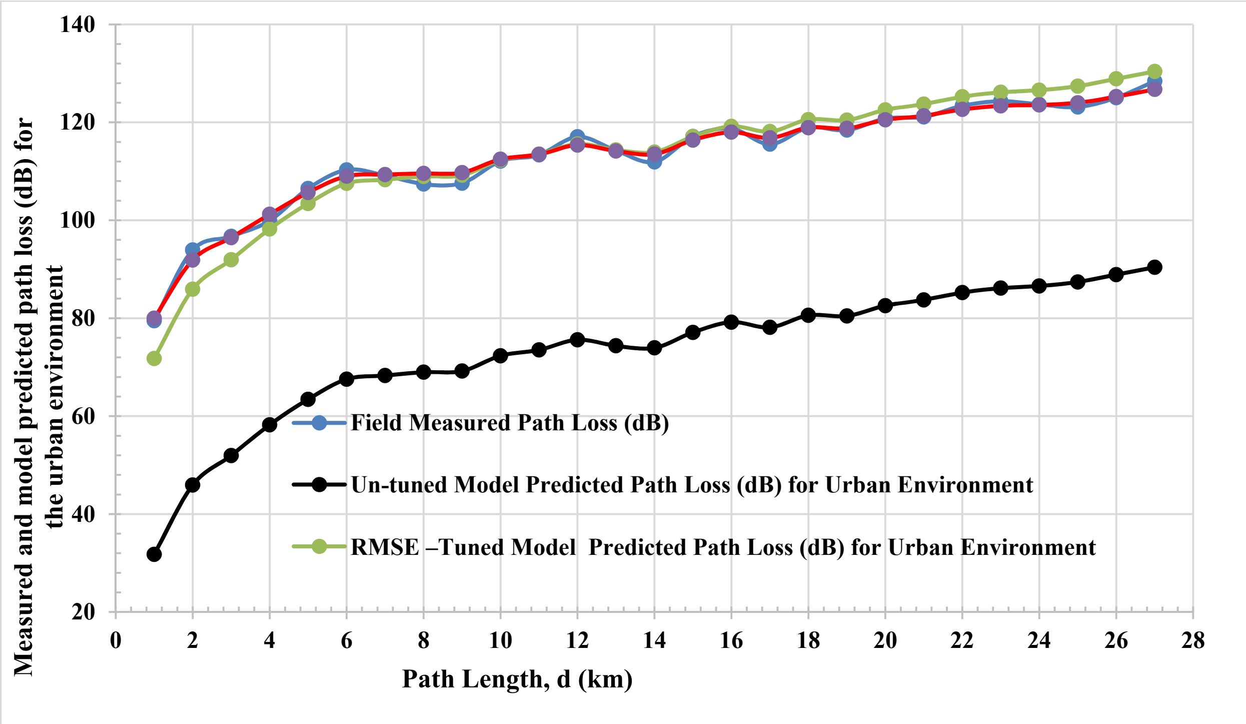


Figure 3
Comparison of the line charts of the empirically measured path loss , the tuned and the un-tuned model predicted path loss for the urban environment

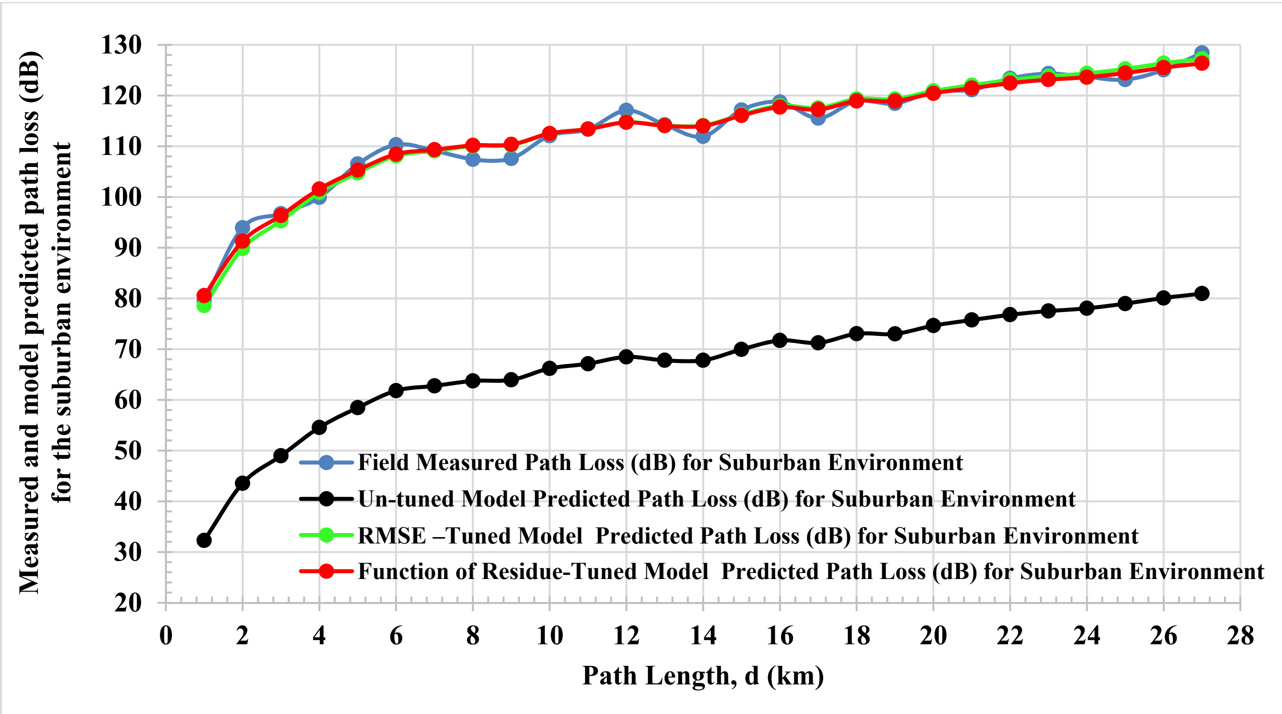


Figure 4 Comparison of the line charts of the empirically measured path loss , the tuned and the un-tuned model predicted path loss for the suburban environment

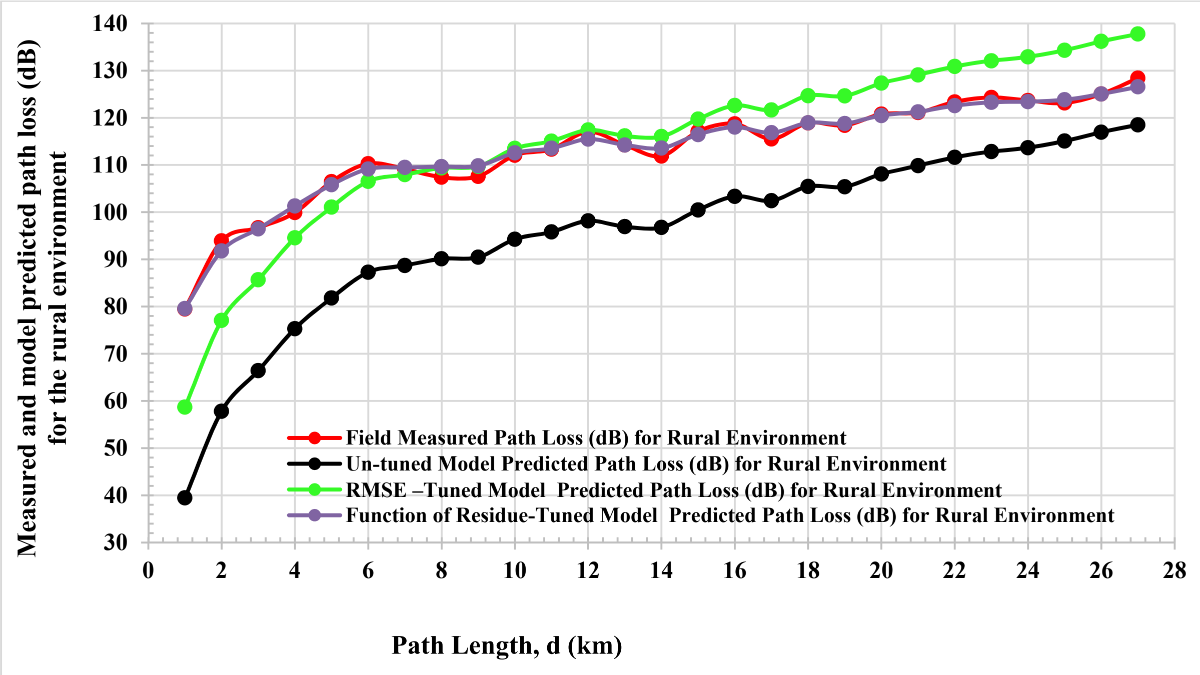


Figure 5
Comparison of the line charts of the empirically measured path loss , the tuned and the un-tuned model predicted path loss for the rural environment

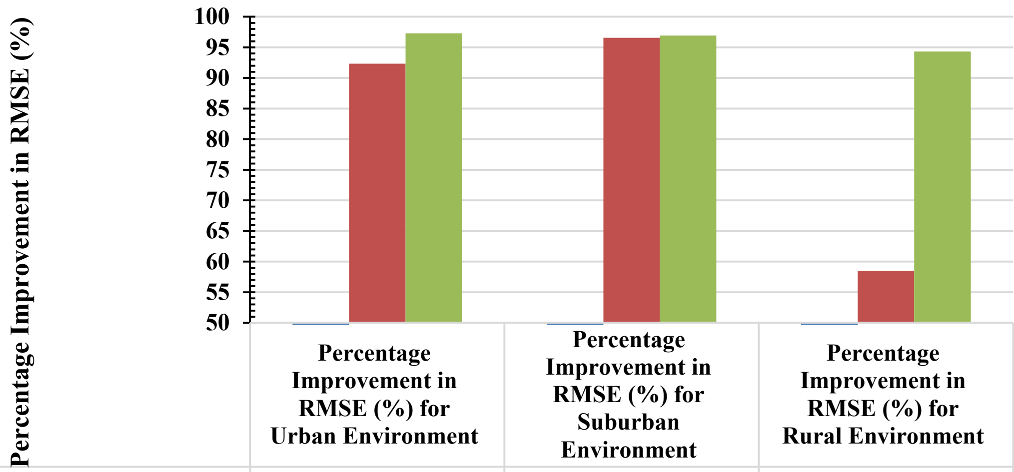
The results in Table 4 show that for the urban environment, the un-turned model, the RMSE is 39.89 dB which is far above the maximum acceptable value of 6 dB for model predicted path loss. Hence, the model tuning is required. The RMSE–based tuned model has RMSE of 3.067 dB which is about 92.3 % improvement over the un-tuned model prediction, as shown in Figure 6, while the function of residue-based tuned model has RMSE of 1.07896 dB which is about 97.3 % improvement over the un-tuned model prediction. Similar performance improvement in RMSE is experienced in the suburban and rural environments, as shown in Table 4 and Figure 6, with the function of residue-based tuned model giving the best performance.

Similar comparison of the percentage improvement in MAE (%) for the model tuning methods is presented in Figure 7 while the comparison of the percentage improvement in MA/MAP (%) for the model tuning methods is presented in Figure 8. Again, the function of residue-based tuned model has the best performance in all the performance parameters considered.

Table 4 The results of the performance parameters for the un-tuned model, the RMSE–based tuned model and the function of residue-based tuned model

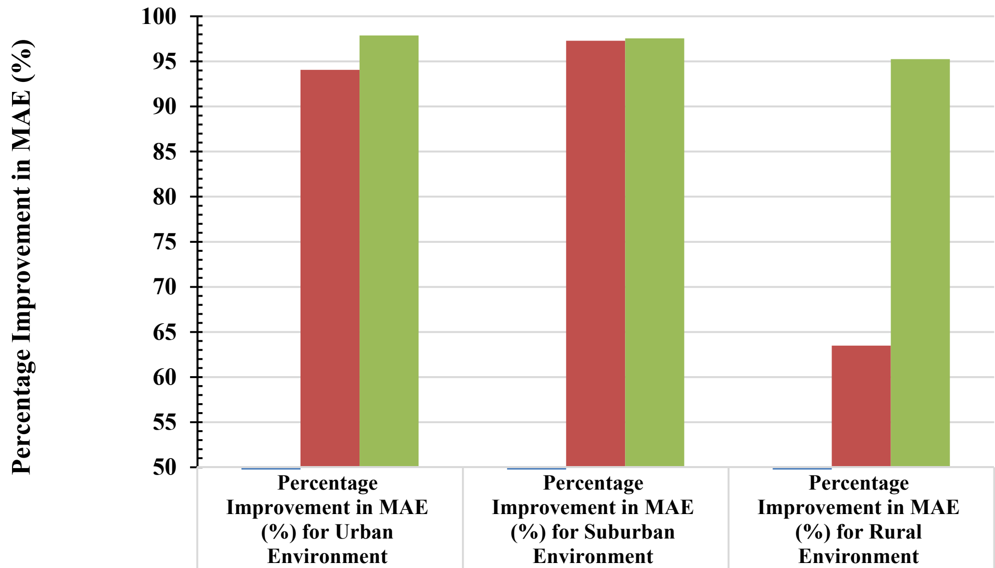
PROPAGATION ENVIRONMENT CATEGORY	MODEL TUNING METHOD	RMSE (dB)	MAE (dB)	PA/MAPE (%)
URBAN ENVIRONMENT	URBAN (ORIGINAL MODEL)	39.98812	39.87047	64.15765
	URBAN (RMSE –BASED MODEL TUNING)	3.067358	2.366157	97.76705
	URBAN (FUNCTION OF RESIDUE-BASED MODEL)	1.07896	0.843695	99.23599
SUBURBAN ENVIRONMENT	SUBURBAN (ORIGINAL MODEL)	46.29184	46.26468	58.67021
	SUBURBAN (RMSE –BASED MODEL TUNING)	1.585852	1.253635	98.85309
	SUBURBAN (FUNCTION OF RESIDUE-BASED MODEL)	1.427651	1.127791	98.97475
	RURAL (ORIGINAL MODEL)	19.24677	17.58846	83.56565

RURAL ENVIRONMENT	RURAL (RMSE –BASED MODEL TUNING)	7.989628	6.423645	94.0455
	RURAL (FUNCTION OF RESIDUE-BASED MODEL)	1.095101	0.833496	99.24996



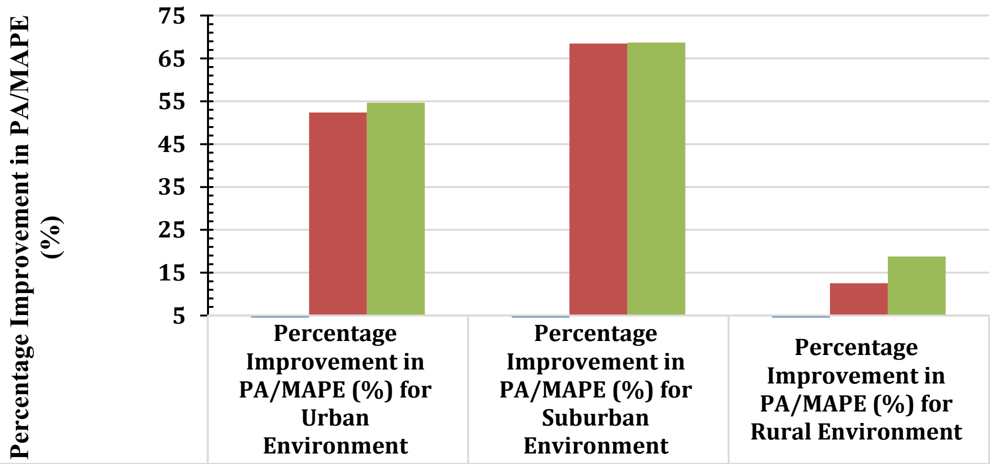
	Percentage Improvement in RMSE (%) for Urban Environment	Percentage Improvement in RMSE (%) for Suburban Environment	Percentage Improvement in RMSE (%) for Rural Environment
ORIGINAL MODEL (NOT TUNED)	0.0	0.0	0.0
RMSE –BASED MODEL TUNING	92.3	96.6	58.5
FUNCTION OF RESIDUE-BASED MODEL TUNING	97.3	96.9	94.3

Figure 6 Comparison of the percentage improvement in RMSE (%) for the model tuning methods



	Percentage Improvement in MAE (%) for Urban Environment	Percentage Improvement in MAE (%) for Suburban Environment	Percentage Improvement in MAE (%) for Rural Environment
ORIGINAL MODEL (NOT TUNED)	0.0	0.0	0.0
RMSE –BASED MODEL TUNING	94.1	97.3	63.5
FUNCTION OF RESIDUE-BASED MODEL TUNING	97.9	97.6	95.3

Figure 7 Comparison of the percentage improvement in MAE (%) for the model tuning methods



	Percentage Improvement in PA/MAPE (%) for Urban Environment	Percentage Improvement in PA/MAPE (%) for Suburban Environment	Percentage Improvement in PA/MAPE (%) for Rural Environment
ORIGINAL MODEL (NOT TUNED)	0.0	0.0	0.0
RMSE –BASED MODEL TUNING	52.4	68.5	12.5
FUNCTION OF RESIDUE-BASED MODEL TUNING	54.7	68.7	18.8

Figure 8 Comparison of the percentage improvement in PA/MAPE (%) for the model tuning methods

4. CONCLUSION

The Standard propagation (SP) model is presented for estimating the path loss in a cellular network operating in the 1800 MHz frequency band. The SP model prediction performance for the case study site is evaluated for the urban, the suburban and the rural environment using empirically measured received signal strength. The model was tuned using the root mean square (RMSE) method and also using the function of residue method. The results showed that the function of residue method performed much better than the RMSE method which is the most widely used method.

References

1. Ahmed, R., Mahmood, M. R., & Matin, M. A. (2023). Challenges in meeting QoS requirements toward 6G wireless networks: A state of the art survey. *Transactions on Emerging Telecommunications Technologies*, *34*(2), e4693.
2. Alimi, I. A., Patel, R. K., Muga, N. J., Pinto, A. N., Teixeira, A. L., & Monteiro, P. P. (2021). Towards enhanced mobile broadband communications: A tutorial on enabling technologies, design considerations, and prospects of 5G and beyond fixed wireless access networks. *Applied Sciences*, *11*(21), 10427.
3. Taufique, A., Jaber, M., Imran, A., Dawy, Z., & Yacoub, E. (2017). Planning wireless cellular networks of future: Outlook, challenges and opportunities. *IEEE Access*, *5*, 4821-4845.
4. Alobaidy, H. A., Singh, M. J., Behjati, M., Nordin, R., & Abdullah, N. F. (2022). Wireless transmissions, propagation and channel modelling for IoT technologies: Applications and challenges. *IEEE Access*, *10*, 24095-24131.
5. Serghiou, D., Khalily, M., Brown, T. W., & Tafazolli, R. (2022). Terahertz channel propagation phenomena, measurement techniques and modeling for 6G wireless communication applications: A survey, open challenges and future research directions. *IEEE Communications Surveys & Tutorials*, *24*(4), 1957-1996.
6. Oladimeji, T. T., Kumar, P., & Elmezughi, M. K. (2022). Path loss measurements and model analysis in an indoor corridor environment at 28 GHz and 38 GHz. *Sensors*, *22*(19), 7642.
7. Tang, W., Chen, X., Chen, M. Z., Dai, J. Y., Han, Y., Di Renzo, M., ... & Cui, T. J. (2022). Path loss modeling and measurements for reconfigurable intelligent surfaces in the millimeter-wave frequency band. *IEEE Transactions on Communications*, *70*(9), 6259-6276.
8. Ellingson, S. W. (2021, September). Path loss in reconfigurable intelligent surface-enabled channels. In *2021 IEEE 32nd Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC)* (pp. 829-835). IEEE.
9. Hmamouche, Y., Benjillali, M., Saoudi, S., Yanikomeroglu, H., & Di Renzo, M. (2021). New trends in stochastic geometry for wireless networks: A tutorial and survey. *Proceedings of the IEEE*, *109*(7), 1200-1252.
10. Hu, S., Chen, X., Ni, W., Hossain, E., & Wang, X. (2021). Distributed machine learning for wireless communication networks: Techniques, architectures, and applications. *IEEE Communications Surveys & Tutorials*, *23*(3), 1458-1493.

11. Ojo, S., Akkaya, M., & Sopuru, J. C. (2022). An ensemble machine learning approach for enhanced path loss predictions for 4G LTE wireless networks. *International Journal of Communication Systems*, *35*(7), e5101.
12. Shaibu, F. E., Onwuka, E. N., Salawu, N., Oyewobi, S. S., Djouani, K., & Abu-Mahfouz, A. M. (2023). Performance of path loss models over mid-band and high-band channels for 5G communication networks: A review. *Future Internet*, *15*(11), 362.
13. Adebowale, Q. R., Faruk, N., Adewole, K. S., Abdulkarim, A., Olawoyin, L. A., Oloyede, A. A., ... & Calafate, C. T. (2021). Application of computational intelligence algorithms in radio propagation: a systematic review and metadata analysis. *Mobile Information Systems*, *2021*(1), 6619364.
14. Popoola, S. I., Atayero, A. A., Faruk, N., Calafate, C. T., Olawoyin, L. A., & Matthews, V. O. (2017). Standard propagation model tuning for path loss predictions in built-up environments. In *Computational Science and Its Applications–ICCSA 2017: 17th International Conference, Trieste, Italy, July 3-6, 2017, Proceedings, Part VI 17* (pp. 363-375). Springer International Publishing.
15. Popoola, S. I., Atayero, A. A., Faruk, N., Calafate, C. T., Adetiba, E., & Matthews, V. O. (2017, July). Calibrating the standard path loss model for urban environments using field measurements and geospatial data. In *Proceedings of the World Congress on Engineering* (Vol. 1, pp. 5-7).