Optimization Of Stanford University Interim Model For Enhanced Prediction Of Wireless Network Propagation Loss

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***Abstract*—The optimization of Stanford University Interim (SUI) model for enhanced prediction of wireless network propagation loss with signal in the 1800 frequency band is studied. The SUI model prediction performance is enhanced by tuning some of the model parameters. The first model tuning method used the root mean square error (RMSE) to adjust the shadowing factor of the SUI model. The second model tuning method used a function of the residue to simultaneously tune the path loss exponent and the shadowing factor. The study site is along Idoro road in Uyo metropolis in Akwa Ibom State. Nigeria. The measured path loss has maximum value of 153 dB at the path length of 1.851 km whereas the corresponding path loss was 132 dB for terrain A, 126 dB for terrain B and 111 dB for terrain C. The path length was from 0.272 km to 1.851 km. For terrain A, the results show that without model optimization, the SUI model realized 87 % prediction accuracy whereas the RMSE optimized model has 96 % accuracy and the best performance was realized using the optimal shadowing and path loss exponent-tuned SUI model with 99.6 % accuracy. Similar outstanding prediction performance was realized by the optimal shadowing and path loss exponent-tuned SUI model in the terrain B and C. Essentially, the optimal shadowing and path loss exponent-tuning method has shown constituent enhanced performance improvement over the RMSE method.**

Keywords*— *Optimization, Stanford University Interim Model, Path Loss, Wireless Network Propagation Loss Prediction, Path Loss Exponent, Shadowing Factor

1. INTRODUCTION

Today, wireless network communication systems have dominated the network industry [1,2,3]. Even the satellite communication system which is increasingly being adopted across the globe is one aspect of the wireless network system. One common challenge of these wireless communication systems is the propagation loss [4,5]. The propagation loss cause degradation in the signal strength as the signal propagates from the transmitter to the receiver [7,8]. The propagation loss increases with distance [9,10].

Apart from distance, there are several factors in the signal propagation environment which can affect the extent of propagation loss that will be experienced by the signal [11]. These factors makes it difficult to precisely define the propagation loss in every environment with a single analytical model. As such, in practice, the solution is to optimize the analytical model based on the empirically measured propagation loss dataset for the case study network coverage area [12,13].

Accordingly, in this work, the Stanford University Interim (SUI) model is studied [14]. The model is evaluated for its ability to accurately estimate the propagation loss in a location in Uyo Akwa Ibom State. The SUI model is then enhanced by tuning some of its model parameters to improve on its prediction performance. Specifically two different ways of model tuning are considered and their effectiveness in enhancing the model prediction performance are compared and the best model is recommended for application in the wireless network in the case study area.

2. METHODOLOGY

2.1 The Analytical Expression For The Stanford University Interim propagation loss Model

The Stanford University Interim (SUI) propagation loss model is an empirical propagation loss model developed by Stanford University in conjunction with 802.16 IEEE research group [15]. The SUI model is defined for the urban, suburban and the rural areas as well. According to the research group, if the propagation loss estimation by SUI model is denoted as $L_{SUI(dB)}$ then [14,15];

$$L_{SUI(dB)} = A + 10\gamma\left(\log_{10}\left(\frac{d}{d_0}\right)\right) + X_f + X_h + S \; for \; d > d_0 \quad (1)$$

Where, d represents the signal propagation path length in km, f represents the signal frequency expressed in MHz, d_0 =100 m , X_h represents receiving antenna height correction factor, γ represents the path loss exponent, X_f represents the frequency correction factor and S represents the shadowing correction factor with value between 8.2 and 10.6 dB. The analytical expression for the parameters A and γ are given as follows:

$$A = 20\left(\log_{10}\left(\frac{4\pi d_0}{\lambda}\right)\right) \quad (2)$$

$$\gamma = a + b(h_b) + \frac{c}{h_b} \quad (3)$$

Where

γ :

$$\begin{cases} \gamma = 2 & \text{for free space} \\ 3 < \gamma < 5 & \text{fof urban non line of sight environment} \\ \gamma > 5 & \text{for indoor propagation} \end{cases}$$

for free space propagation

Again, h_b represents the antenna height in meters for the base station. The values of a, b and c are dependent on the terrain, and their values are specified in Table 1 for the different terrains.

Table 1 The values of a, b and c terrain parameter in the SUI model [14,15]

Model Parameters	Terrain A	Terrain B	Terrain C
a	4.6	4.0	3.6
b (m^{-1})	0.0075	0.0065	0.005
C (m)	12.6	17.1	20

Also, the analytical expression for the parameters X_f and X_h are given as follows:

$$X_f = 6\left(\log_{10}\left(\frac{f}{2000}\right)\right) \quad (4)$$

$$X_h = \begin{cases} -10.8\left(\log_{10}\left(\frac{h_m}{2000}\right)\right) & \text{for terrain type A and B} \\ -20.8\left(\log_{10}\left(\frac{h_m}{2000}\right)\right) & \text{for terrain type C} \end{cases} \quad (5)$$

Where, f represents the frequency of the signal which is expressed in MHz, and h_m represents the antenna height of the receiver which is expressed in meter. The A terrain is appropriate for hilly environment having moderate to heavy foliage densities. The B terrain is appropriate for flat terrains having moderate to heavy tree densities. Terrain B can also apply to hilly terrains that have light tree densities. The C terrain is appropriate for flat terrain having light tree densities.

2.2 OPTIMIZATION OF THE STANFORD UNIVERSITY INTERIM (SUI) MODEL USING THE ROOT MEAN SQUARE ERROR (RMSE) METHOD OR OPTIMAL SHADOWING FACTOR METHOD

The Root Mean Square Error (RMSE) method is one of the commonest method used in optimizing empirical path loss models based on empirically acquired propagation loss dataset. The method requires the determination of the RMSE based on the empirically measured propagation loss at point k (denoted as $L_{meas(dB)(k)}$) and model predicted propagation loss at point k (denoted as $L_{SUI(dB)(k)}$) where there are n data points in the dataset. Then,

$$\text{RMSE} = \sqrt[2]{\left\{\frac{1}{n}\left[\sum_{i=1}^{i=n}\left(L_{SUI(dB)(k)} - L_{meas(dB)(k)}\right)^2\right]\right\}} \quad (6)$$

Let ε_k denote the error in the model prediction at point k, and $\bar{\varepsilon_k}$ denote the mean of ε_k for the n data points, then,

$$\varepsilon_k = L_{SUI(dB)(k)} - L_{meas(dB)(k)} \quad (7)$$

$$\bar{\varepsilon_k} = \frac{\sum_{k=1}^{k=n}\left(L_{SUI(dB)(k)} - L_{meas(dB)(k)}\right)}{n} \quad (8)$$

In the RMSE method of optimization of the model, the RMSE is added to the predicted propagation loss, $L_{SUI(dB)(k)}$ if the mean of the prediction error is negative; which means, the average of the measured propagation loss over the n data points is larger than the average of the model predicted propagation loss, hence the addition of the RMSE to each predicted value,$L_{SUI(dB)(k)}$. On the other hand, if the mean of the prediction error is positive, then the RMSE is subtracted from each predicted value, $L_{SUI(dB)(k)}$. The RMSE tuned SUI model is denoted as $L_{SUI-RMSE(dB)(k)}$. and it is expressed analytically as;

$$L_{SUI-RMSE(dB)(k)} = \begin{cases} L_{SUI(dB)(k)} + \text{RMSE} & \text{for } \bar{\varepsilon_k} \le 0 \\ L_{SUI(dB)(k)} - \text{RMSE} & \text{for } \bar{\varepsilon_k} > 0 \end{cases} \quad (9)$$

Since, S is the shadowing factor and is the only constant in the expression for SUI model shown in Equation 1, then, the addition of RMSE (which is a constant) is same as adjusting the shadowing factor. Hence, the RMSE-tuned SUI propagation loss can be given as;

$$L_{SUI-RMSE(dB)(k)} = A + 10\gamma\left(\log_{10}\left(\frac{d}{d_0}\right)\right) + X_f + X_h + (S + \text{RMSE}) \; for \; \bar{\varepsilon_k} \le 0, \; d > d_0 \quad (10)$$

$$L_{SUI-RMSE(dB)(k)} = A + 10\gamma\left(\log_{10}\left(\frac{d}{d_0}\right)\right) + X_f + X_h + (S - \text{RMSE}) \; for \; \bar{\varepsilon_k} > 0, \; d > d_0 \quad (11)$$

In view of this expression, the RMSE optimization method can be referred to as optimal shadowing factor method.

2.3 OPTIMIZATION OF THE STANFORD UNIVERSITY INTERIM (SUI) MODEL USING OPTIMAL SHADOWING AND PATH LOSS EXPONENT METHOD

In the case of optimal shadowing and path loss exponent method of optimizing the SUI model, the prediction error , ε_k is modeled as a linear function of $\left(10\log_{10}\left(\frac{d}{d_0}\right)\right)$. In this case, let $\varepsilon_{P(k)}$ denote the predicted error using the linear function of $\left(10\log_{10}\left(\frac{d}{d_0}\right)\right)$, hence,

$$\varepsilon_{P(k)} = (\varphi)(10)\left(\log_{10}\left(\frac{d_k}{d_0}\right)\right) + \delta \quad (12)$$

Where φ is the gradient and δ is the intercept of the linear function of $\log_{10}\left(\frac{d_k}{d_0}\right)$. The optimal shadowing and path loss exponent tuned SUI model is denoted as $L_{SUI-OSPLE(dB)(k)}$ and it is expressed analytically as;

$$L_{SUI-OSPLE(dB)(k)} = L_{SUI(dB)(k)} + \varepsilon_{P(k)} \quad (13)$$

$$L_{SUI-OSPLE(dB)(k)} = L_{SUI(dB)(k)} + (\varphi)(10)\left(\log_{10}\left(\frac{d_k}{d_0}\right)\right) + \delta \quad (14)$$

$$L_{SUI-OSPLE(dB)(k)} = A + (\gamma + \varphi)(10)\left(\log_{10}\left(\frac{d_k}{d_0}\right)\right) + X_f + X_h + (S + \delta)\ for\ ,\ d > d_0 \quad (15)$$

Again, the tuned model shows that both the shadowing factor and the path loss exponent are simultaneously adjusted. Hence, the method is referred to as optimal shadowing and path loss exponent method.

2.4 THE METRICS FOR PERFORMANCE EVALUATION

The following three metrics are used to evaluate the prediction performance of the model;

i. Root Mean Square Error (RMSE),

$$\text{RMSE} = \sqrt[2]{\left\{\frac{1}{n}\left[\sum_{k=1}^{k=n}\left(L_{ms(dB)(\text{i})} - L_{pred(dB)(\text{i})}\right)^2\right]\right\}} \quad (16)$$

ii. Mean Absolute Error (MAE),

$$\text{MAE} = \frac{1}{n}\left(\sum_{k=1}^{k=n}\left|L_{ms(dB)(\text{i})} - L_{pred(dB)(\text{i})}\right|\right) \quad (17)$$

iii. Prediction Accuracy or Mean Absolute Percentage Error (PAMAPE).

$$\text{PA} = \left\{1 - \frac{1}{n}\left(\sum_{k=1}^{k=n}\left|\frac{L_{ms(dB)(\text{i})} - L_{pred(dB)(\text{i})}}{L_{ms(dB)(\text{i})}}\right|\right)\right\} * 100\% \quad (18)$$

2.5 SITE SURVEY DATA COLLECTION AND ANALYSIS

Site survey data collection was conducted whereby, the receive signal strength (RSS) from the target wireless network base station was captured along with the longitude and latitude of the measurement points. About 27 data points were collected over a distance of about 1.8 km from the base station. The wireless network considered in the study operates in the 1800 frequency. The base station longitude is 7.86406 while the latitude is 5.024373. The visualization of the site survey path on Google map is presented in Figure 1 while the geo-coordinates of the measurement points and the measured RSS are presented in Table 1. The study site is along Idoro road in Uyo metropolis in Akwa Ibom State. Nigeria.

The Haversine formula is used to determine the distance , d_k of each of the measurement point k from the base station, which is computed as follows;

$$d_k = 2(R_{earth})\left\{\sqrt[2]{\sin\left(\frac{LAT_m(k) - LAT_{b(k)}}{2}\right)^2 + \cos\left(LAT_{b(k)}\right)\cos\left(LAT_m(k)\right) \text{si}}\right. \quad (19)$$

$$LAT_{rad(k)} = \frac{(LAT_{\deg(k)} * 3.142)}{180} \quad (20)$$

$$LONG_{rad)k)} = \frac{(LONG_{\deg(k)} * 3.142)}{180} \quad (21)$$

Where the parameters are the earth radius, R_{earth}; base station latitude, $LAT_{b(k)}$; the mobile device latitude, $LAT_{m(k)}$; the base station longitude, $LONG_{b(k)}$; the mobile device longitude , $LONG_{m(k)}$; the latitude expressed in radians, $LAT_{rad(k)}$ and the longitude in degrees is denoted as $LONG_{\deg(k)}$.

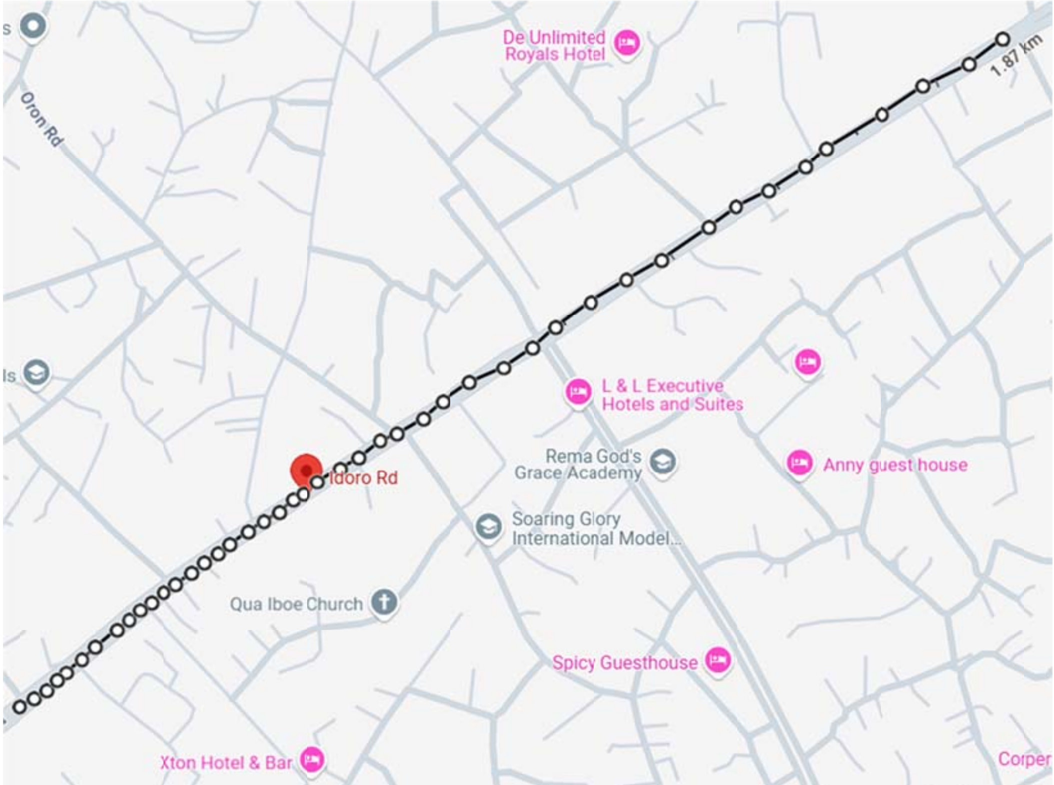


Figure 1 The visualization of the site survey path on Google map

Table 2 The geo-coordinates of the measurement points and the measured RSS

S/N (k)	Longitude	Latitude	RSSI (dBm)	S/N	Longitude	Latitude	RSSI (dBm)
1	7.86637	5.0252	-62.4646	14	7.87218	5.02974	-103.217
2	7.866939	5.025535	-70.423	15	7.87253	5.02998	-105.281
3	7.86725	5.025948	-73.165	16	7.872858	5.03015	-105.648
4	7.868077	5.026578	-80.9817	17	7.87323	5.03058	-106.898
5	7.868403	5.026838	-84.2946	18	7.874032	5.030908	-108.706
6	7.86884	5.02727	-87.9218	19	7.87408	5.03097	-108.927
7	7.869207	5.027509	-89.3781	20	7.87451	5.03134	-111.115
8	7.869598	5.027747	-91.2399	21	7.874858	5.031536	-111.944
9	7.86995	5.02816	-93.1278	22	7.875293	5.031839	-113.933
10	7.870467	5.028396	-95.8693	23	7.875771	5.032185	-114.907
11	7.870772	5.028764	-98.1948	24	7.876336	5.032618	-115.692
12	7.871228	5.029219	-99.25	25	7.87714	5.032878	-117.077
13	7.87158	5.02946	-101.727	26	7.87751	5.03329	-119.021
14	7.87218	5.02974	-103.217	27	7.878075	5.033398	-119.843

The measured propagation loss, $L_{ms(dB)(k)}$ is determined from the measured Received Signal Strength Intensity (RSSI) values which is denoted as $P_{m(dB)(k)}$, where;

$$L_{ms(dB)(k)} = EIRP_{b(dB)} + P_{m(dB)(k)} \quad (22)$$

$$EIRP_{b(dB)} = P_{b(dB)} + G_{b(dB)} + G_{m(dB)} - L_{OT} \quad (23)$$

where $P_{b(dB)}$ is the base station transmitter power, $G_{b(dB)}$ is the base station transmitter antenna gain, $G_{m(dB)}$ is the mobile device antenna gain, L_{msc} is the sum of miscellaneous losses that includes losses at the feeder cable, combiner and filter loses. The case study parameters values are; $P_{b(dB)} = 30.0$dBm , $G_{b(dB)} = 10.0$ dBi , $G_{m(dB)} = 0$ dBi , $L_{msc} = 6.5$ dBm. Then;

$$EIRP_{b(dB)} = 30 + 10.0 + 0 - 6.5 = 33.5 \quad (24)$$

Therefore

$$L_{ms(dB)} = P_{m(dB)} + 28.5 \quad (25)$$

3. RESULTS AND DISCUSSION

The results in Table 3 show the computed path length, and the measured path loss along with the tuned and un-tuned model-predicted path loss for the three terrain categories. The measured path loss has maximum value of 153 dB at the path length of 1.851 km whereas the corresponding path loss is 132 dB for terrain A, 126 dB for terrain B and 111 dB for terrain C. The path length is from 0.272 km to 1.851 km.

Table 3 The results of the computed path length, and the measured path loss along with the tuned and un-tuned model-predicted path loss for the case study

S/N (k)	d (km)	Field Measured Path Loss (dB)	Predicted Path Loss Using the Un-tuned SUI For Class A Terrain (dB)	Predicted Path Loss Using the Un-tuned SUI For Class B Terrain (dB)	Predicted Path Loss Using the Un-tuned SUI For Class C Terrain (dB)
1	0.272	96	93	91	78
2	0.345	104	98	96	82
3	0.395	107	101	98	85
4	0.509	114	106	103	89
5	0.554	118	108	104	90
6	0.621	121	110	106	92
7	0.669	123	111	108	93
8	0.720	125	113	109	95
9	0.777	127	114	110	96
10	0.840	129	116	112	97
11	0.891	132	117	113	98
12	0.961	133	119	114	100
13	1.008	135	120	115	100
14	1.081	137	121	116	102
15	1.128	139	122	117	102
16	1.169	139	122	118	103
17	1.230	140	124	119	104
18	1.324	142	125	120	105
19	1.332	142	125	120	105
20	1.395	145	126	121	106
21	1.439	145	127	121	106
22	1.498	147	127	122	107
23	1.563	148	128	123	108
24	1.642	149	129	124	109
25	1.732	151	130	125	110
26	1.792	153	131	125	110
27	1.851	153	132	126	111

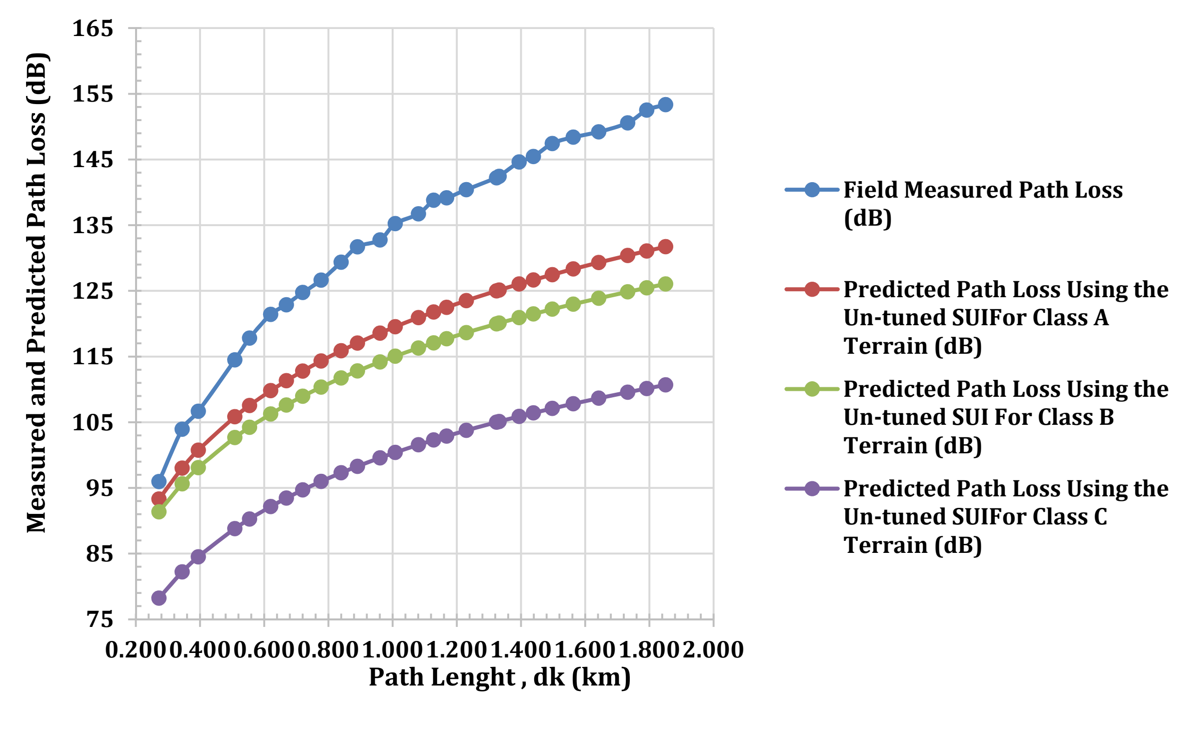


Figure 2 The line chart of the measured path loss, and the model predicted path loss

The prediction performance evaluation results for the models in terrain A is presented in Table 4 and Figure 3. The results show that without model optimization, the SUI model realized 87 % prediction accuracy whereas the RMSE optimized model has 96 % accuracy and the best performance is realized using the optimal shadowing and path loss exponent-tuned SUI model with 99.6 % accuracy.

Table 4 The prediction performance evaluation results for the models in terrain A

	UNTUNED SUI FOR CLASS A TERRAIN	RMSE-TUNED SUI FOR CLASS A TERRAIN	OPTIMAL SHADOWING AND PATH LOSS EXPONENT-TUNED SUI FOR CLASS A TERRAIN
RMSE	15.6	5.0	1.3
Mean Absolute Error (MAE)	14.8	4.0	0.5
Prediction Accuracy, PA (%)	87.8	96.9	99.6

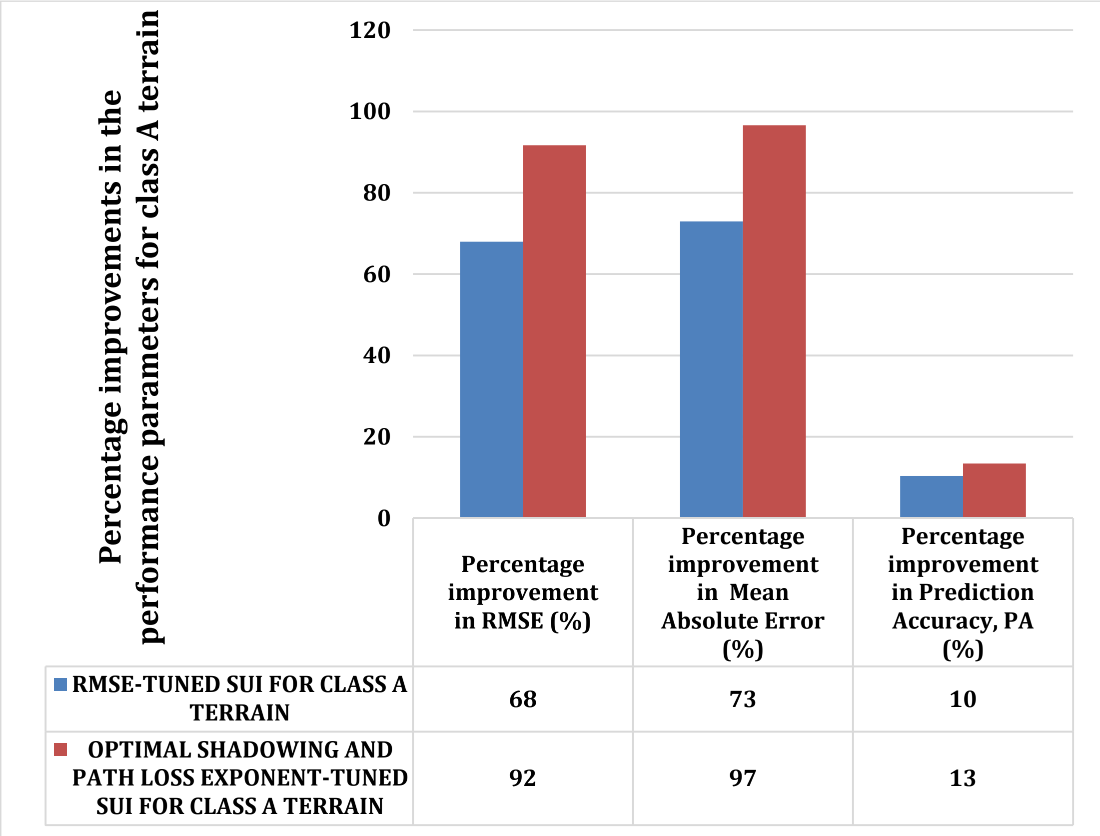


Figure 3 The Percentage improvements in the performance parameters for class A terrain

The prediction performance evaluation results for the models in terrain B is presented in Table 5 and Figure 4. The results show that without model optimization, the SUI model realized 83.5 % prediction accuracy whereas the RMSE optimized model has 96.3 % accuracy and the best performance is realized using the optimal shadowing and path loss exponent-tuned SUI model with 99.7 % accuracy.

Table 5 The prediction performance evaluation results for the models in terrain B

	UNTUNED SUI FOR CLASS BTERRAIN	RMSE-TUNED SUI FOR CLASS B TERRAIN	OPTIMAL SHADOWING AND PATH LOSS EXPONENT-TUNED SUI FOR CLASS B TERRAIN
RMSE	20.1	6.0	1.3
Mean Absolute Error (MAE)	19.2	4.8	0.4
Prediction Accuracy	83.5	96.3	99.7

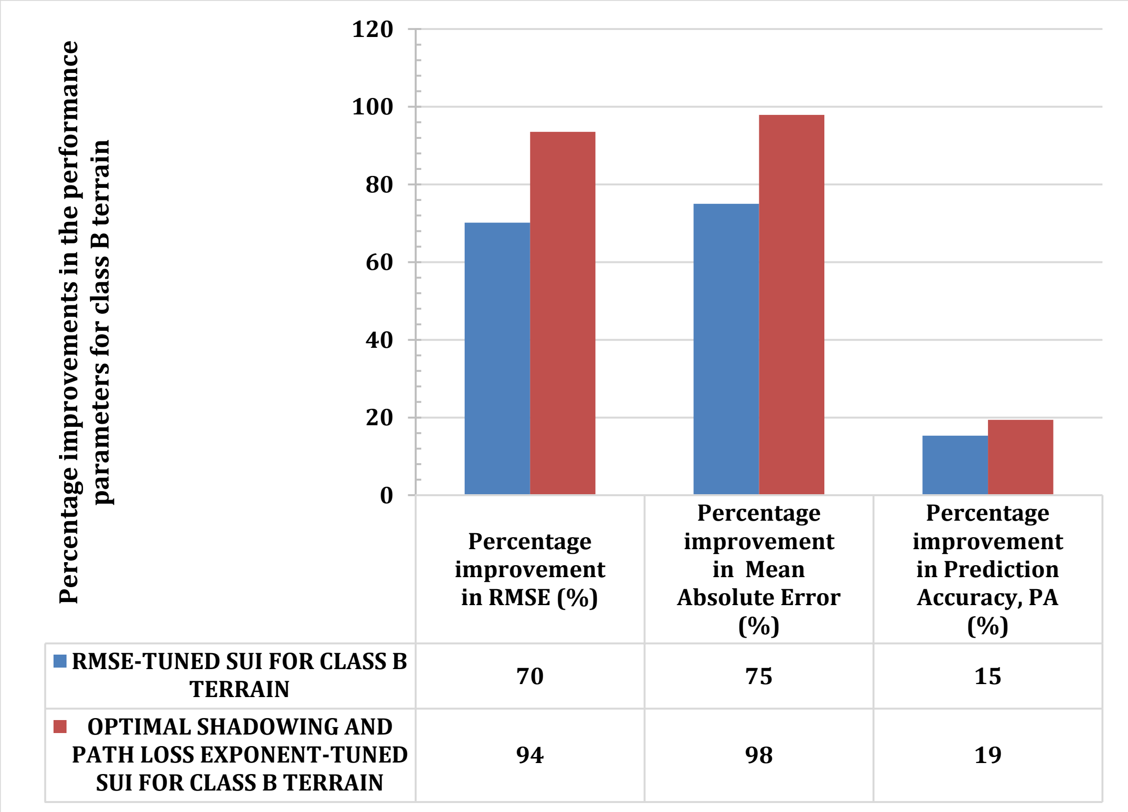
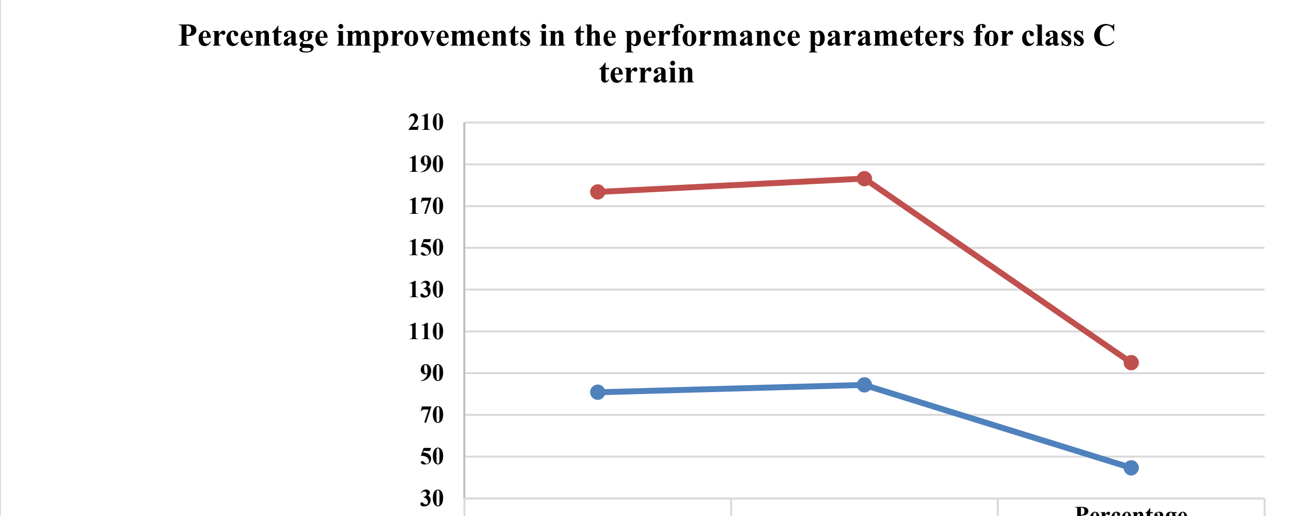


Figure 4 The Percentage improvements in the performance parameters for class B terrain

The prediction performance evaluation results for the models in terrain C is presented in Table 6 and Figure 5. The results show that without model optimization, the SUI model realized 66.3 % prediction accuracy whereas the RMSE optimized model has 95.9 % accuracy and the best performance is realized using the optimal shadowing and path loss exponent-tuned SUI model with 99.7 % accuracy. In all, the optimal shadowing and path loss exponent-tuned SUI model consistently displayed exceptional performance when compared to the RMSE-based method

Table 6 The prediction performance evaluation results for the models in terrain C

	UNTUNED SUI FOR CLASS C TERRAIN	RMSE-TUNED SUI FOR CLASS C TERRAIN	OPTIMAL SHADOWING AND PATH LOSS EXPONENT-TUNED SUI FOR CLASS C TERRAIN
RMSE	34.4	6.6	1.4
Mean Absolute Error (MAE)	33.8	5.3	0.4
Prediction Accuracy	66.3	95.9	99.7



	Percentage improvement in RMSE (%)	Percentage improvement in Mean Absolute Error (%)	Percentage improvement in Prediction Accuracy, PA (%)
OPTIMAL SHADOWING AND PATH LOSS EXPONENT-TUNED SUI FOR CLASS C TERRAIN	96	99	50
RMSE-TUNED SUI FOR CLASS C TERRAIN	81	84	45

Figure 5 The Percentage improvements in the performance parameters for class C terrain

4. CONCLUSION

The Stanford University Interim (SUI) propagation loss model is studied. The SUI model is used for estimating the propagation loss in wireless communication system having signal that can propagate in three different terrain categories. The class A is equivalent to the urban environment with the highest expected propagation loss than the class B and class C. The model prediction performance is enhanced by tuning some of the model parameters. The first method used the root mean square error (RMSE) to adjust the shadowing factor of the SUI model. The second method used a function of the residue to simultaneously tune the path loss exponent and the shadowing factor. The results showed that the second method greatly enhanced the prediction performance of the SUI model in all the three terrains considered.

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