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A Method for Real-time Adaptive Propagation Loss Modeling and Estimation Over LOS and NLOS Microcellular Radio Communication Links

Emmanuel Nwelih
Department of Computer Science, University of Benin, Benin City, Edo State, Nigeria
Email: emmanuel.nwelih@uniben.edu

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Abstract

Wireless cellular communication technology has developed into a very resourceful commodity worldwide. Today, people of all races can hardly live without means of voice and data cellular communication technology. Imprecise propagation loss estimation leads to high power waste, high co-channel interference and poor service quality in cellular communication system networks. This paper proposes a realistic adaptive fine-tuning method for distinctive propagation loss estimation over microcellular communication radio links based on signal power measurements from Long Term Evolution radio broadband networks, taking non-line of sight (NLOS) and line of sight (LOS) environments into consideration. The methodology is verified by measurements taken in non-line of sight and line of sight signal propagation scenarios. The results showed that the estimated propagation losses using the proposed realistic adaptive tuning models were more accurate than the existing Cost - 231 modelling estimation approach.

1. Introduction

The evolution and application of different wireless cellular communication technologies are on the rise daily at an exciting pace worldwide. Today, people of all races can hardly live without means of voice and data cellular communication technology. It all started when the second generation (2G) of wireless cellular communication standard which provides easy means of voice communication anytime and anywhere, was introduced in the mid 80's. A key example of such communication technology is the GSM. Since then, other cellular radio standards such as 3G and 4G, which provide better multimedia communications have evolved. Examples of 3G and 4G-based technologies include UMTS, WCDMA, CDMA2000, HSPA, Wimax and LTE. The latest of the above itemized different technologies, is the 4G LTE (Long Term Evolution). In terms of bandwidth, data speed, quality of service differentiation, latency, spectrum efficiency, enhancement to security, backward compatibility, etc., LTE provides considerable performance improvements over previous mobile technologies such as GSM, UMTS and HSPA. Imprecise propagation loss estimation during the cellular network design phase or optimisation phase, has been identified as the leading reason for high power waste, high co-channel interference and poor service quality in LTE cellular networks. The evolution of 4G cellular communication technology such as LTE some few years ago provided a great opportunity to enhance data speed, quality of service differentiation and spectrum efficiency.

However, some channel propagation challenges such as power outage, fading and signal path loss are also affecting the aforementioned great opportunities. One key way to solve some propagation challenges is by modelling, estimating and examining the behavior identified challenges. Prediction and estimation of channel parameters and behaviour, including propagation loss and signal attenuation, is the primary focus of radio channel modeling [1-3].

Over the years, some efforts have been made and reported in several studies on to examine, model and estimate the behavior of path loss over propagation channels. In [4], the authors compared ray tracing models with empirical models. From the results, the authors observed a difference of 12.6dB between the two compared models. An approach to adapt Standard Macrocell model and Bertoni-Walfisch model for GSM radio networks design is presented in [5], using city of Nablus, Palestine as a case study. From the results, Bertoni-Walfisch model outperforms the Standard Macrocell model by about 60%. Similar works on measurements based propagation channel modeling are also contained in [6-13], but none of them specifically looked into none line of sight (NLOS) and line of sight (NOS) propagation scenarios as considered in this work. By NLOS, we mean radio frequency (RF) propagation path between transmitter and receiver that is obscured (completely or partially) by a varied degree of obstacles like physical landscape, tall buildings, trees, etc, thus creating difficulties for efficient radio signal transmission. For LOS, there exist direct visual communication sight or links from the transmitter to the receiver. Under this condition, the rate of propagated signal fading is expected to quite lower than the NLOS case.

This paper proposes a realistic adaptive fine-tuning method for distinctive propagation loss estimation over a microcellular communication radio links based on signal power measurements from Long Term Evolution radio broadband networks. The methodology is verified by measurements taken in non-line of sight and line of sight signal propagation scenarios. The results showed that the estimated propagation losses using the proposed realistic adaptive tuning model was more accurate than the existing estimation approach.

1.1. Existing Propagation Loss Models

There exist a lot of propagation models for predictive path loss modelling and estimation, among which are Hata model, Free space model, Walficsh-Betroni model, Walficsh-Ikegami model, Lee Model, Egli model and Cost-231 Hata model. One of the most frequently explored one in literature is the COST-231 Hata model. The COST 231[ref] is a derivative of the Hata model. This model hinge on upon four core influencing parameters for propagation loss estimation and modelling. The parameters are frequency, receiver antenna height, transmitter height and Tx-Rx communication distance. Cost-231 Hata model has different correction parameters for suburban urban and rural (flat) environments. In this work, we concentrate on COST-234 Hata model for urban environment. It is given by:

$$PL_{COST\text{-}234}\ [dB] = 43.6 + 33.9*\log10\ (f_{ca}) + (44.9 - 6.55*\log10\ (bh))*\log10\ (d) - T \quad (1)$$

$$T=13.82*\log10\ (bh) - amh- 2*(\log10\ (f_{ca}/28)).\,\hat{}2 - 5.4) \quad (2)$$

where
$PL_{COST-234}$= COST-234 Hata Model
bh= eNode Height in meter
mb=mobile antenna height in meter
f_{ca}=Carrier Frequency in MHz
d=Tx-Rx communication distance in meter

Although the Cost-231 Hata model has been widely employed for propagation predictive analysis and modelling, but its efficacy is limited when employed in residential areas and built-up terrains environments other than which model was originally designed [1, 8, 9, 13].

2.0. Materials and Method

2.1. Measurements Campaign

(a) Measurement environment

Field measurements were piloted using commercial LTE cellular networks air interface, propagating on the 2600MHz band in Benin City, Edo State, Nigeria. The building clusters in the area are a mixture of residential/commercial bungalows, two or three story buildings encompassed with medium density user and vehicular traffics. Precisely, the measurement routes were selected along the main streets and sideways of the roads of the area, where the LTE eNodeB transceivers are deployed. Four accessible LTE eNodeB cell sites at close range were engaged in the measurements and the cell sites are designated as 'Cell_1, Cell_2, Cell_3, and Cell_4, in this work.

(b) Measurement tools

The tools employed for measurements consisted of two commercial user equipment (UE) Sony Ericson handsets, one HP Laptop, RF scanner, Dongle and other relevant field test supporting devices such as GPS, inverter and connecting cables. A real-time professional monitoring software called TEMS, which possesses the capacity to display and record different radio frequency data made in log files along each measurement routes. For the post processing measured log data files, Map info, MS Excel, MATLAB 2018a were used.

(c) RF network data measured

One of the main LTE radio network data collected during measurement is RSRP (i.e. Reference Signal received Power). Technically, the RSRP is an indicator of signal power level at the UE terminal in LTE networks. Generally, the stronger RSRP level received at UE, better signal coverage quality can be achieved in the radio network. There exist sundry factors that can impact the RSRP levels at the UE terminals, among which are transmitter-receiver (Tx-Rx) communication distance, RF channel conditions, signal propagation loss, UE location, total radiated eNodeB power, etc. In terms of propagation loss and total radiated eNodeB power, RSCP can be defined as:

$$\text{RSRP (dBm)} = \text{Path Loss [dB]} - \text{Ptot (dB)} \quad (3)$$

$$Ptot = Gt + Pt - Gr - Cl - Fl - (10*\log(Nrb) - 10*\log(12)) \quad (4)$$

where:
Ptot= total radiated eNodeB power in decibel
Gt = eNodeB antenna gain in decibel
Cl= connector losses
Fl=feeder losses
Nrb=No of resource blocks
Gr= Receiver antenna gain in decibel
Thus, in terms of propagation loss, the expression in (1) can be written as:

$$\text{Path Loss [dB]} = Ptot - RSRP \quad (5)$$

$$\text{Path Loss [dB]} = Gt + Pt - Gr - Cl - Fl - (10*\log(Nrb) - 10*\log(12)) - RSRP \quad (6)$$

2.2. Adaptive fine-tuning method for Cost-231 Hata model Parameters

In order to tune the Cost-231 model parameters, its expressions in (1) and (2) can be written as:

$$PL_{COST\text{-}234} = z_1 + z_2 * \log10\,(d) + z_3 * \log10\,(fca); \tag{7}$$

Where z_1, z_2 and z_3 designate the adaptive coefficients. The z_1, z_2 and z_3 can be obtained by solving the following parametric equations:

$$nz_o + z_1 \sum \log_{10}(d) + z_2 \sum \log_{10}(f_{ca}) = \sum \mathrm{PL}_{\mathrm{COST\text{-}234}} \tag{8}$$

$$z_o \sum \log_{10}(d) + z_1 \sum \log_{10}^2(d) + z_2 \sum \log_{10}(d)\log_{10}(f_{ca}) = \sum \mathrm{PL}_{\mathrm{COST\text{-}234}}\left[\log_{10}(d)\right] \tag{9}$$

$$z_o \sum \log_{10}(f_{ca}) + z_1 \sum \log_{10}(d)\log_{10}(f_{ca}) + z_2 \sum \log_{10}^2(f_{ca}) = \sum \mathrm{PL}_{\mathrm{COST\text{-}234}}\left[\log_{10}(f_{ca})\right] \tag{10}$$

where n specifies the number of observations

3.0. Results and Discussion

By exploring the non-linear regression function fitting tools in Matlab R2018a on measured propagation loss data and the standard Hata model: $PL_{COST\text{-}234}$, Table 1 displays the estimated adaptive coefficients and their descriptive statistical values. Provided in Table 2 is the measured loss data estimation errors with COST-231 Hata model before and after adaptation. The estimation errors are computed in terms root mean square error (RMSE), mean absolute error (MAE), percentage error (PE), standard deviation error (STD), maximum absolute error (Max.error), Coefficient of correlation (R^2) and signal error ratio (SRER). The lower the prediction errors, the better the accuracy, except for R^2 and SRER wherein higher values are preferred.

Table 1: Estimated Coefficients and Statistics for Cell_1 to Cell_4

		Estimate	SE	tStat	pValue
Cell_1	z_o	18.66	0.61	30.13	1.18e-43
	z_1	35.75	2.94	12.12	2.33e-19
	z_2	6.17	2.11	2.918	4.64e-3
Cell_2	z_o	21.07	0.90	23.38	6.36e-30
	z_1	31.34	4.03	7.77	2.28e-10
	z_2	6.87	3.07	2.23	2.95 e-3
Cell_3	z_o	16.841	0.62105	27.117	1.30e-43
	z_o	37.945	2.9505	12.861	1.21e-21
	z_o	5.6388	2.1209	2.6587	9.37e-3
Cell_4	z_o	39.76	0.22	178.69	2.70e-133
	z_1	19.222	0.99	19.26	2.08e-36
	z_2	12.35	0.75	16.25	1.50e-30

Based on the estimated adaptive coefficients, the $PL_{COST\text{-}234}$ for Cell_1 can be written as

$PL_{COST\text{-}234}$ *(Cell_1) = 18.66+33.75*log10 (d) + 6.17*log10 (fca)*

$PL_{COST\text{-}234}$ *(Cell_1) = 21.07+31.34*log10 (d) + 6.87*log10 (fca)*

$PL_{COST\text{-}234}$ *(Cell_3) = 16.84+37.95*log10 (d) + 5.63*log10 (fca)*

$PL_{COST\text{-}234}$ *(Cell_4) = 39.76+19.22*log10 (d) + 12.35*log10 (fca)*

The expressions above show that the rate of propagated signal attenuation (i.e. propagation exponent, n) for Cell_1 to Cell_3 are 3.3, 3.1 and 3.7, all which depicts the NLOS propagation environment. For Cell-4, which is a LOS environment, rate of propagated signal attenuation stands at 1.9. The mean n value $\left(\text{i.e.}, n = \frac{3.3+3.1+3.7}{3}\right)$, for Cell_1, Cell_2 and Cell_3 is 3.37. This value shows that the rate of signal attenuation obtained for the NLOS is about 78% higher than the LOS environment value, which is 1.92. This can be attributed to the varied building and other obstructions in the LOS terrains. Similarly, taking the mean value of other estimated parameters for Cell_1, Cell_2 and Cell_3 leads to us to obtain the proposed real-time adaptive tuned model for NLOS environment: $PL_{COST\text{-}234}\,(NLOS) = 18.86+33.7*\log 10\,(d) + 6.22*\log 10\,(fca)$. For the LOS environment, it is $PL_{COST\text{-}234}\,(LOS) = 39.76+19.22*\log 10\,(d) + 12.35*\log 10\,(fca)$

Shown in Figs 1-4 are the resultant measured propagation loss estimation using the original $PL_{COST\text{-}234}$ and the proposed adapted $PL_{COST\text{-}234}$.

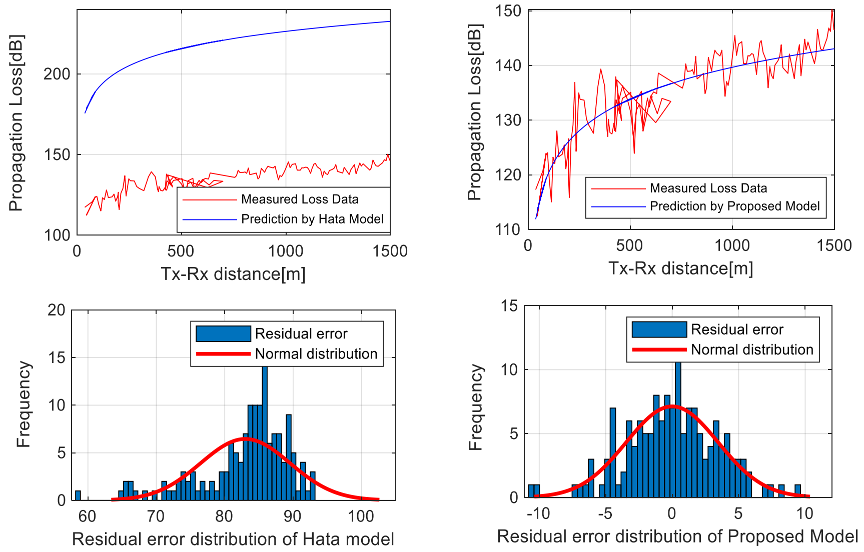

Fig 1: Measured propagation loss estimation using the original $PL_{COST\text{-}234}$ and the proposed adapted $PL_{COST\text{-}234}$ for Cell_1

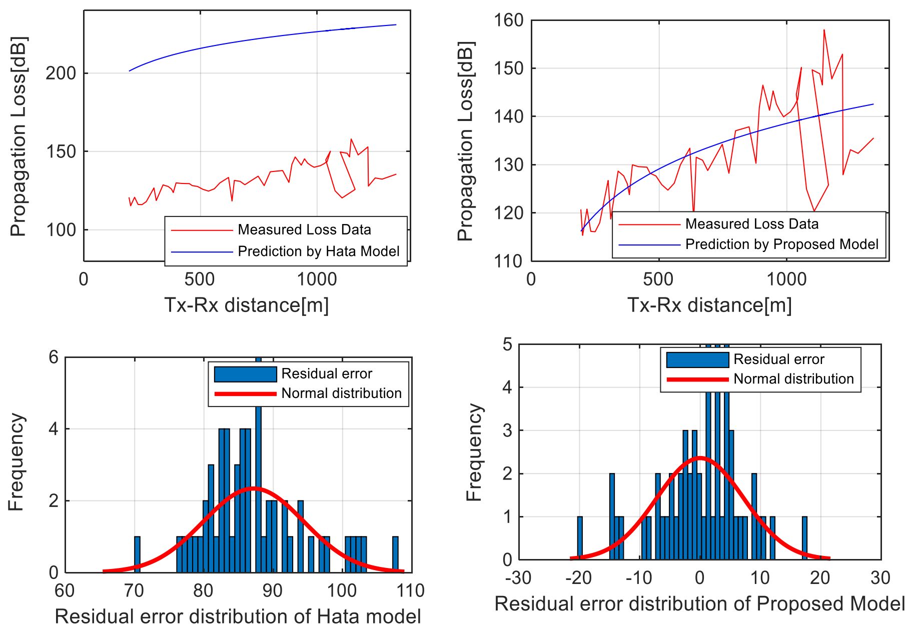

Fig 2: Measured propagation loss estimation using the original $PL_{COST\text{-}234}$ and the proposed adapted $PL_{COST\text{-}234}$ for Cell_2

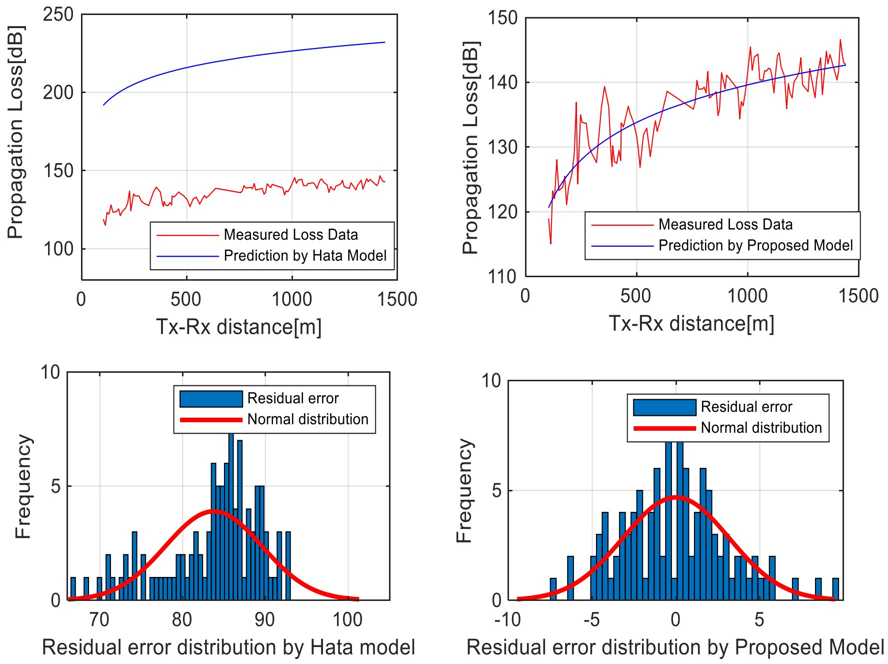

Fig 3: Measured propagation loss estimation using the original $PL_{COST\text{-}234}$ and the proposed adapted $PL_{COST\text{-}234}$ for Cell_3

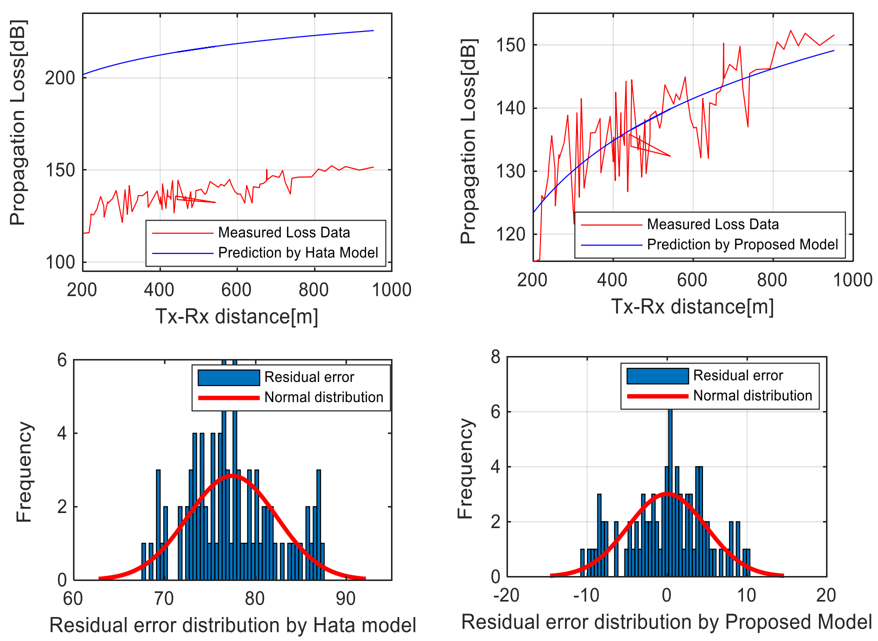

Fig 4: Measured propagation loss estimation using the original $PL_{COST\text{-}234}$ and the proposed adapted $PL_{COST\text{-}234}$ for Cell_4

Table 2: Computed First Order Statistics for Cell_1 to Cell_4

		Cell_1	Cell_2	Cell_3	Cell_4
Proposed Adaptive Model Estimation Statistics	MAE	4.80	5.52	2.47	3.83
	RMSE	7.06	7.12	3.19	4.84
	STD	4.02	4.50	1.94	2.96
	R^2	0.9973	0.9971	0.9995	0.9988
	Max.Error	17.60	19.61	9.66	10.47
	SRER	44.48	42.92	42.92	48.43
	PA	99.92	99.75	99.94	99.87
Cost-231 Hata Model Estimation Statistics					
	MAE	99.63	87.15	83.74	77.43
	RMSE	79.95	87.44	83.44	77.58
	STD	7.06	7.19	5.82	4.87
	R^2	0.8660	0.8424	0.8543	0.8692
	Max.Error	80.15	88.34	89.38	78.40
	SRER	27.42	25.51	28.62	28.23
	PE	86.06	84.23	85.42	86.92

4.0. Conclusion

Enhancing the estimation accuracy of standard propagation loss models will continue to remain a vital component for effective radio cellular network management or planning process. In this work, a realistic adaptive fine-tuning method has been proposed and explored for adaptive propagation loss estimation over microcellular communication radio links based on signal power measurements from Long Term Evolution radio broadband networks, taking non-line of sight (NLOS) and line of sight (LOS) environments into consideration. It is shown that an adapted propagation model provides a superior loss estimation than the existing standard empirical COST-234 Hata model.

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