Hindawi
Computational Intelligence and Neuroscience
Volume 2023, Article ID 5236566, 9 pages
https://doi.org/10.1155/2023/5236566

Research Article

Statistical Characterization and Modeling of Radio Frequency Signal Propagation in Mobile Broadband Cellular Next Generation Wireless Networks

Joseph Isabona,[1] **Lanlege Louis Ibitome**,[2] **Agbotiname Lucky Imoize**,[3,4] **Udit Mamodiya**,[5] **Ankit Kumar**,[6] **Montaser M. Hassan**,[7] **and Isaac Kweku Boakye**[8]

[1]*Department of Physics, Federal University Lokoja, Lokoja 260101, Nigeria*
[2]*Department of Mathematical Sciences, Federal University Lokoja, Lokoja 260101, Nigeria*
[3]*Department of Electrical and Electronics Engineering, Faculty of Engineering, University of Lagos, Akoka, Lagos 100213, Nigeria*
[4]*Department of Electrical Engineering and Information Technology, Institute of Digital Communication, Ruhr University, Bochum 44801, Germany*
[5]*Department of Electrical Engineering, PIET-AICTE Idea Lab, Poornima Institute of Engineering and Technology, Jaipur, Rajasthan, India*
[6]*Department of Computer Engineering and Applications, GLA University Mathura, Mathura, Uttar Pradesh 281406, India*
[7]*Department of Biology, College of Science, Taif University, P.O. Box 11099, Taif 21944, Saudi Arabia*
[8]*Kwame Nkrumah University of Science and Technology (KNUST), Kumasi, Ghana*

Correspondence should be addressed to Isaac Kweku Boakye; ikboakye3@st.knust.edu.gh

Received 19 August 2022; Revised 3 October 2022; Accepted 24 November 2022; Published 27 January 2023

Academic Editor: N. Rajesh

An accurate assessment of the spatial and temporal radio frequency channel characteristics is essential for complex signal processing and cellular network optimization. Current research has employed numerous models to figure out how much signal propagation loss occurs along the propagation paths. However, there are issues in finding the right model for a particular terrain because these models are not universally applicable. By employing the lognormal function and the Maximum Likelihood model, a hybrid probabilistic statistical distribution model was evolved. Three LTE cell site locations in Port Harcourt, Nigeria, were used to create a hybrid model that describes the functional stochastic signal propagation loss in the area. The evaluated Maximum Likelihood model accurately estimates the relevant wireless channel properties based on observed field data. The minor square regression approach and the proposed hybrid parameter estimation methodology are compared. When it comes to estimating standard deviation errors as well as the root mean square errors, the ML-based approach consistently outperforms the least square regression model. Finally, the proposed hybrid probabilistic statistical distribution model would be useful for mobile broadband network planning in related wireless propagation conditions.

1. Introduction

Adequate knowledge of spatial radio frequency channel parameters is critical to cellular network engineering [1–4]. Accurate estimation of the network parameters is necessary for estimating the location probability and shadow margin computations, aiding effective network planning and optimization processes [5–9]. The work in [5] investigated macrocell path loss prediction employing artificial intelligence techniques. On the measurements of radio field strength and pathloss determination in UMTS networks, Isabona et al. [6] characterized the signal propagation loss in typical 3G wireless networks. In the built-up area of South-South Nigeria, Isabona and Peter [7] described signal propagation loss based on field measurements at 1.9 GHz. In [8], the authors presented radio frequency measurements and capacity analysis for industrial indoor environments. The work presented focuses on measurements campaign, including field testing, modeling, and a comparative analysis of multifrequency band propagation characteristics for cellular networks. By using experimental and simulated propagation data, estimating the spatial and temporal radio frequency channel parameters is key to addressing the proliferating issues in complex signal processing, cellular network systems design, and optimization [10–14].

In order to address the problem of determining the most suitable model for a specific environment, several parameter estimation approaches have been exploited recently [15–20]. Specifically, the work in [15] examined transmit power estimation focusing on the signal strength of the wireless network with cooperative receiver nodes using the Maximum Likelihood (ML) estimation [21, 22]. The authors applied the experimental findings to validate the explored ML estimation. In [16], the authors investigated the Maximum Likelihood estimation combined with signal statistics to determine the performance of intensity-modulated fibre optic links.

In related work, the authors in [17] reported realistic predictive modeling of stochastic path attenuation losses in wireless channels over microcellular urban, suburban, and rural terrains using probability distribution functions. Their study revealed that the normal distribution was most suitable for the statistical predictive modeling of signal path loss data. Similar predictive analyses have been reported [18–20]. Specifically, the work in [18] presented a study on empirical path loss models to accurately predict TV signals for secondary users. The authors of the work in [19] posed and answered a question on why is shadow fading lognormal. In [20], the authors investigated the fading characteristics of wireless channels on a high-speed railway in hilly terrain. In [23–25], the least square and absolute deviation regression methods were applied to estimate the parameters of the deployed radio frequency channel measurements from different wireless propagation environments. In particular, the work in [23] reported an experimental study of UMTS radio signal propagation characteristics, employing field measurements in the GSM band. In [24], the authors presented RF propagation measurement and modeling to facilitate network planning of outdoor wireless local area networks operating in the 2.4 GHz band.

Similarly, the work in [25] examined path loss propagation prediction and optimization, employing the popular Hata model at 800 MHz in an urban area. In a similar study, Gentile et al. [26] proposed a suitable methodology for benchmarking radio-frequency channel sounders through a system model. The current contribution exploited an efficient parameter-based ML estimation model combined with the lognormal distribution function to estimate spatial variations of wireless propagated signals. The study focused on practical field tests performed on a commercial mobile broadband network. The findings of this work demonstrated that the proposed ML-based model estimates the relevant wireless channel parameters for the tested environments, in comparison with the measured data, with minimal errors. The main contributions of the paper are outlined as follows:

(i) An efficient parameter-based ML estimation model combined with the lognormal distribution function to estimate spatial variations of wireless propagated signals is proposed

(ii) The performance of the proposed hybrid parameter estimation model compared with the least square regression method was examined

(iii) The cumulative hazard plots of propagation loss distribution of ML and LS models with the measurement obtained from different site locations were demonstrated

(iv) The mean prediction error with ML and LS estimated parameters on measured pathloss loss data were determined

The remainder of this paper is organized as follows: in Section 2, the preliminaries are highlighted briefly. Section 3 gives an overview of the simulated and experimental measurements and analyses. Section 4 presents the results and discussions. Finally, Section 5 provides a concise conclusion to the paper.

2. Materials and Methods

This section briefs the measurement campaign, signal propagation model, and maximum-likelihood estimators.

2.1. Measurements Campaign and Signal Propagation Modeling. The measurement campaign was conducted in the built-up areas of Port-Harcourt, Nigeria. The tested 4G LTE network operates at 1900 MHz. Field measurements were taken using drive test tools in and around the investigated environment [27–29]. Real-time 4G LTE signal strength obtained from the evolved base station (eNodeBs) was processed and analyzed in MATLAB. In particular, the Reference Signal Received Power (RSRP) was extracted from the logged files and processed similarly to earlier works [30–32]. According to Rappaport [33], the experimental received signal power and propagation loss are logarithmically related to the propagation distances, d_i, and transmit power P_{TX} is defined by the following equation:

$$P_{\mathrm{dBm},i} = P_{\mathrm{TX}} - L_{\mathrm{off}} - 10\alpha \log_{10}(d_i) - X_i, \tag{1}$$

where X_i and L_{off} express the location-specific fading and offset parameters, respectively. Equation (1) describes the signal propagation loss model. Specifically, it is assumed that L_{off} can be precisely achieved using a small reference measurement number. In the model, the shadow fading parameter X_i is assumed to be a specific random variable such that $X_i \sim N(0, \sigma^2)$. The key attenuation model parameters such as α and σ^2 are derived relative to their dependence on the actual wireless propagation environment [27, 29, 34, 35].

2.2. Maximum Likelihood Estimators. The Maximum Likelihood (ML) estimation is an indispensable and effective channel parameter estimation method that finds practical application in signal processing [36–39]. The ML method can be deployed to examine the behaviour of channel data parameters. This study employs the likelihood function [40–42] to determine the ML estimation parameters in the measured pathloss data. Specifically, the likelihood function of the lognormal distribution for P_i ($i = 1, 2, 3, \ldots, n$) dataset is achievable by considering the product of the probability densities expressed in equations (2) to (6):

$$f\left(\frac{P,\theta}{\mu,\omega^2}\right) = \prod_{i=1}^{n}\left[f\left(\frac{P_i}{\mu,\omega^2}\right)\right], \tag{2}$$

$$= \prod_{i=1}^{n}\left(\left(2\pi\omega^2\right)^{-1/2} P_i^{-1}\exp\left[\frac{-(\ln P_i-\mu)^2}{2\omega^2}\right]\right), \tag{3}$$

$$= \left(2\pi\omega^2\right)^{-1/2}\prod_{i=1}^{n}\left(P_i^{-1}\exp\left[\sum_{i=1}^{n}\frac{-(\ln P_i-\mu)^2}{2\omega^2}\right]\right), \tag{4}$$

$f(\cdot)$ signifies the lognormal distribution with parameters:

$$\widehat{\omega} = c\omega, \mathrm{c} := \frac{10}{\ln(10)}, \tag{5}$$

and

$$\mu_i = cP_{\mathrm{TX}} - L_{\mathrm{off}} - 10\alpha\log_{10}(d_i). \tag{6}$$

The lognormal distribution log-likelihood function for P_i ($i = 1, 2, 3, \ldots, n$) dataset can be obtained by exploring the natural log of the likelihood function (7) to (11):

$$L\left(\frac{P}{\mu,\omega^2}\right) = \ln\left(\left(2\pi\omega^2\right)^{-1/2}\prod_{i=1}^{n}P_i^{-1}\exp\left[\sum_{i=1}^{n}\frac{-(\ln P_i-\mu)^2}{2\omega^2}\right]\right), \tag{7}$$

$$= -\frac{n}{2}\ln\left(2\pi\omega^2\right) - \sum_{i=1}^{n}\ln P_i - \frac{\sum_{i=1}^{n}-(\ln P_i-\mu)^2}{2\omega^2}, \tag{8}$$

$$= -\frac{n}{2}\ln\left(2\pi\omega^2\right) - \sum_{i=1}^{n}\ln P_i - \frac{\sum_{i=1}^{n}-\left(\ln (P_i)^2 - 2\ln P_i\mu + \mu^2\right)}{2\omega^2}, \tag{9}$$

$$= -\frac{n}{2}\ln\left(2\pi\omega^2\right) - \sum_{i=1}^{n}\ln P_i - \frac{\sum_{i=1}^{n}\ln (P_i)^2}{2\omega^2} + \frac{\sum_{i=1}^{n}\ln P_i\mu}{2\omega^2} - \frac{\sum_{i=1}^{n}\ln\mu^2}{2\omega^2}, \tag{10}$$

$$= -\frac{n}{2}\ln\left(2\pi\omega^2\right) - \sum_{i=1}^{n}\ln P_i - \frac{\sum_{i=1}^{n}\ln (P_i)^2}{2\omega^2} + \frac{\sum_{i=1}^{n}\ln P_i\mu}{\omega^2} - \frac{n\mu}{2\omega^2}. \tag{11}$$

The next step is to find μ and ω^2, which maximize $L(P/\mu,\omega^2)$. Thus, for μ, we have the following equation:

$$\frac{\delta L}{\delta\mu} = \frac{\sum_{i=1}^{n}\ln P_i\mu}{\omega^2} - \frac{2n\mu}{2\omega^2} = 0. \tag{12}$$

Equation (11) also implies that equations (13) and (14) hold:

$$\frac{n\mu}{\omega^2} = \frac{\sum_{i=1}^{n}\ln P_i\mu}{\omega^2}. \tag{13}$$

So

$$\mu = \sum_{i=1}^{n}\ln P_i/n. \tag{14}$$

Similarly, to find ω^2, which maximize $L(P/\mu,\omega^2)$, according to (15) to (17):

$$\frac{\delta L}{\delta\omega^2} = -\frac{n}{2}\frac{1}{\sigma^2} - \frac{\sum_{i=1}^{n}(\ln P_i-\mu)^2\sum_{i=1}^{n}(\ln P_i-\mu)^2}{2}\left(-\omega^2\right)^{-2}, \tag{15}$$

$$= -\frac{n}{2\sigma^2} - \frac{\sum_{i=1}^{n}(\ln P_i-\mu)^2}{2\left(\omega^2\right)^2} = 0, \tag{16}$$

$$-\frac{n}{2\sigma^2} = \frac{\sum_{i=1}^{n}(\ln P_i-\mu)^2}{2\omega^4}. \tag{17}$$

Equation (17) implies the definitions in (18) and (19):

$$n = \frac{\sum_{i=1}^{n}(\ln P_i-\mu)^2}{\omega^2}, \tag{18}$$

and

$$\omega^2 = \frac{\sum_{i=1}^{n}(\ln P_i-\mu)^2}{n}. \tag{19}$$

By applying the expression in equations (15) and (19) can also be written as follows:

$$\omega^2 = \frac{\sum_{i=1}^{n}\left(\ln P_i - \sum_{i=1}^{n}\mathrm{In}P_i/n\right)^2}{n}. \tag{20}$$

Therefore, the ML estimation model parameters are defined in (21):$\mu = \sum_{i=1}^{n}\ln P_i/n$ and

$$\omega = \sqrt{\frac{\sum_{i=1}^{n}\left(\ln X_i - \sum_{i=1}^{n}\mathrm{In}P_i/n\right)^2}{n}}. \tag{21}$$

3. Results and Discussions

The results of the characterized parameters and predictive analysis of the propagation loss data using the ML estimate approach are briefed. The parameters of the pathloss data obtained via the least square (LS) regression estimation are provided for deductive comparison [15, 16]. The cumulative hazard plots are presented in Figures 1–3. Table 1 shows the measured loss estimated parameters and their estimation accuracies using the two approaches. The cumulative hazard plots are employed to visually examine the ML and LS models and their distributive prediction and reliability on the measured propagation loss. From the plotted mean prediction graphs of Figures 4–9 and the summarized prediction results in Table 2, it is evident that the ML estimation is superior to the LS approach. In Table 2, for

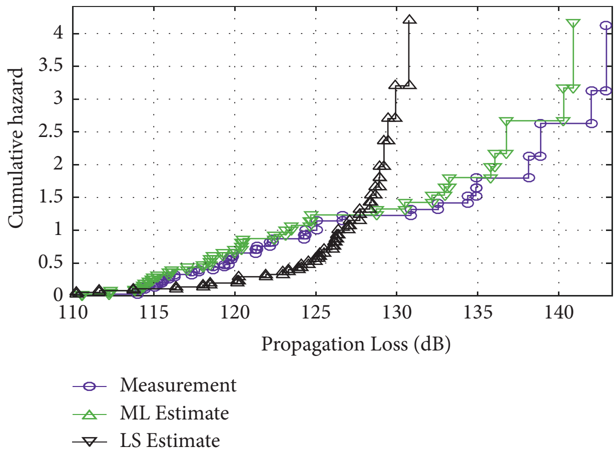

Figure 1: Cumulative hazard plots of propagation loss distribution of ML and LS models with the measurement obtained from site location 1.

Table 1: Estimated propagation loss parameters with the ML and LS models.

	Model estimated loss parameters	μ	ω	α
Site 1	ML	134.3	7.48	2.6
	LS	134.2	6.17	2.0
Site 2	ML	123.5	7.45	2.6
	LS	123.5	5.81	1.4
Site 3	ML	123.8	9.12	2.8
	LS	123.8	5.77	2.2

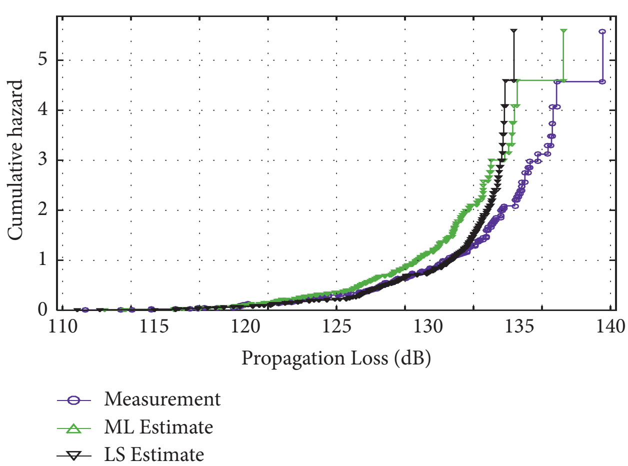

Figure 2: Cumulative hazard plots of propagation loss distribution of ML and LS models with the measurement obtained from site location 2.

instance, employing the mean absolute error (MAE), mean percentage error (MAPE), root mean square error (RMSE), and standard deviation error (SDE) statistics, the ML model, attains 1.82, 3.97, 1.99, and 0.79, respectively, in site location 1. In contrast, the LS model achieved 2.70, 11.85, 3.44, and 2.13, respectively. The ML posed similar parameter estimation and prediction performance over the LS approach, as revealed in Table 2 for site locations 1 and 2.

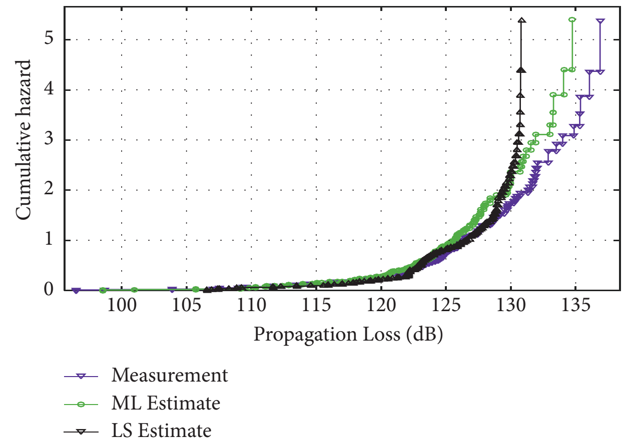

Figure 3: Cumulative hazard plots of propagation loss distribution of ML and LS models with the measurement obtained from site location 3.

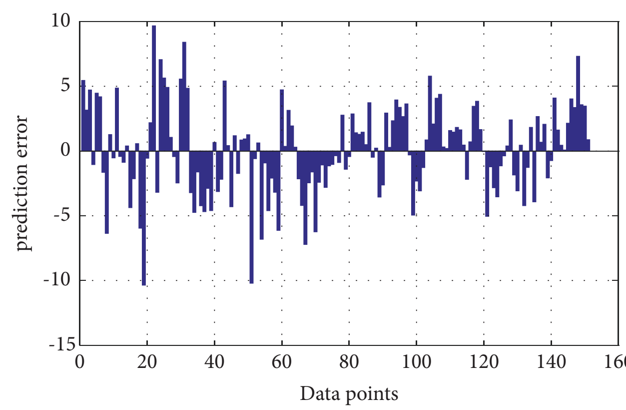

Figure 4: Mean prediction error with ML estimated parameters on measured loss data obtained from site location 1.

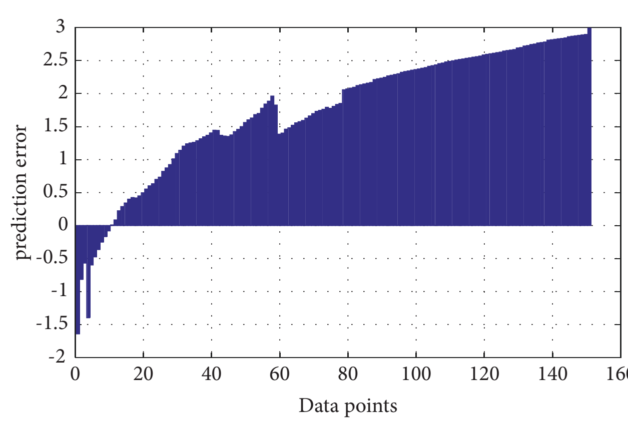

Figure 5: Mean prediction error with LS estimated parameters on measured loss data obtained from site location 1.

Figures 10–12 show exponential CDF plots to demonstrate the accuracy attained by the ML approach in estimating (predicting) the measured path loss values acquired over three study locations. It can be found from the three graphs that the ML-based estimation closely maps the

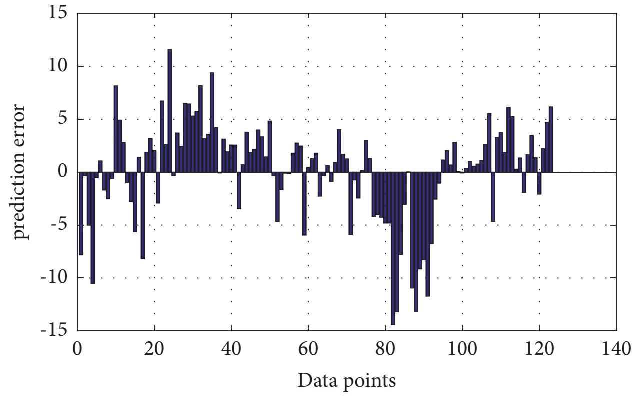

Figure 6: Mean prediction error with ML estimated parameters on measured loss data obtained from site location 2.

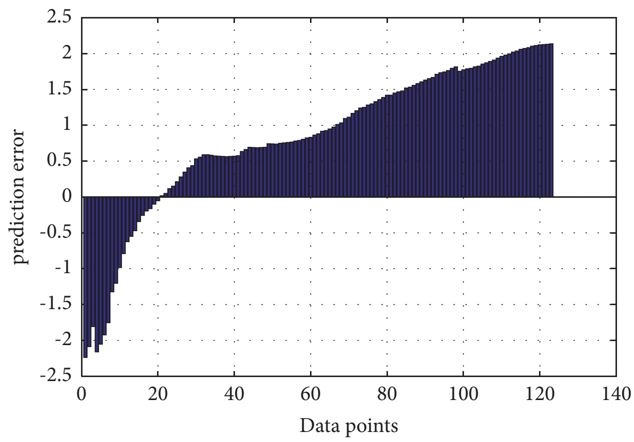

Figure 7: Mean prediction error with LS estimated parameters on measured loss data obtained from site location 2.

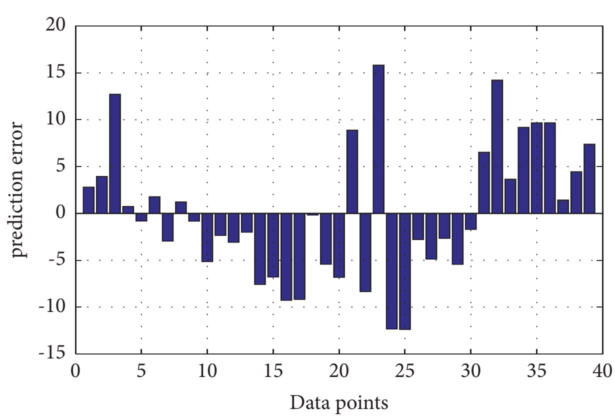

Figure 8: Mean prediction error with ML estimated parameters on measured loss data obtained from site location 3.

measured path loss values up to 70% each before deviations. In contrast, the LS-based approach could only accurately predict 30–50% of the measured path loss values sample. The prediction error attained by engaging the ML-based and ML-based estimation approaches is quantitively defined in Table 3.

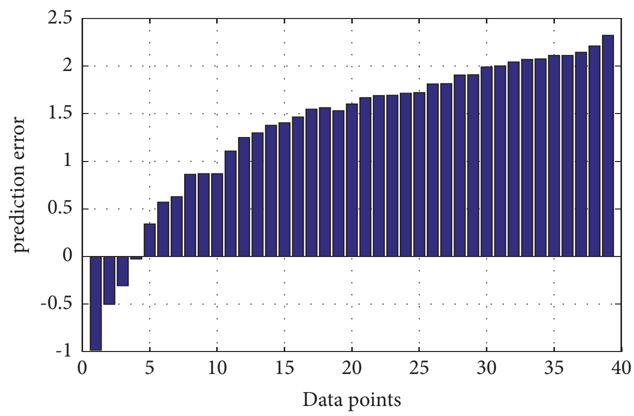

Figure 9: Mean prediction error with LS estimated parameters on measured loss data obtained from site location 3.

Table 2: Estimated propagation loss parameters with ML and LS models using standard metrics.

	Model and loss estimation error	MAE	MRE	RMSE	SDE
Site 1	ML	1.82	3.97	1.99	0.79
	LS	2.70	11.8	3.44	2.13
Site 2	ML	1.18	0.95	1.34	0.63
	LS	3.51	2.86	4.69	3.11
Site 3	ML	1.46	3.75	1.58	0.59
	LS	5.81	14.9	7.11	4.10

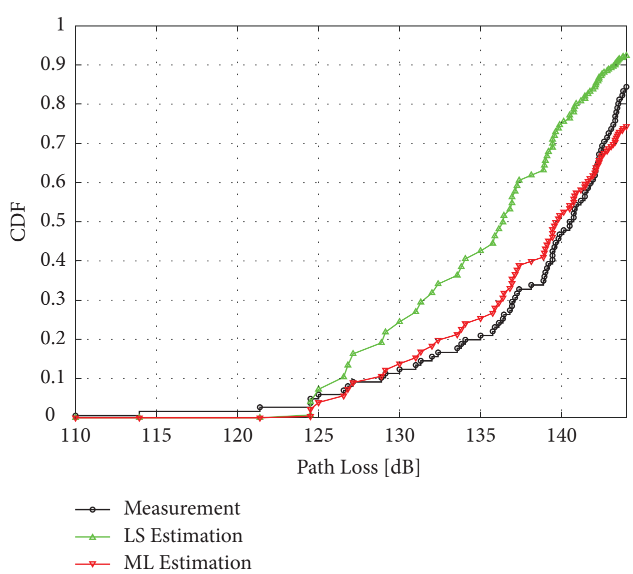

Figure 10: Path prediction attained with LS-based estimation and ML-based estimation approaches from site location 1.

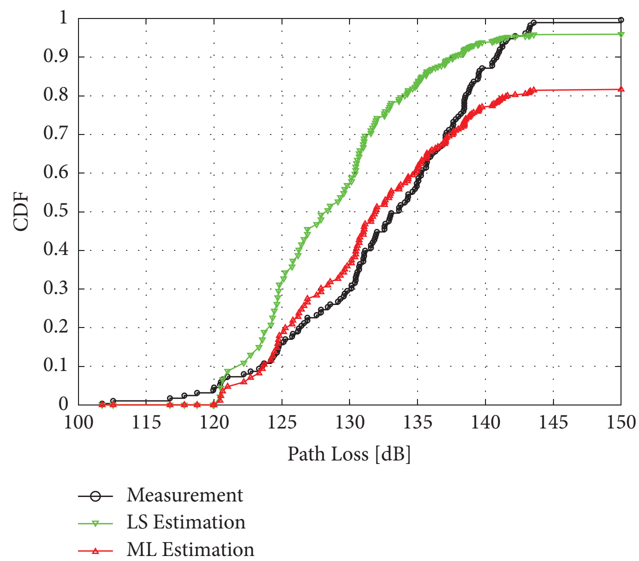

Figure 11: Path prediction attained with LS-based estimation and ML-based estimation approaches from site location 2.

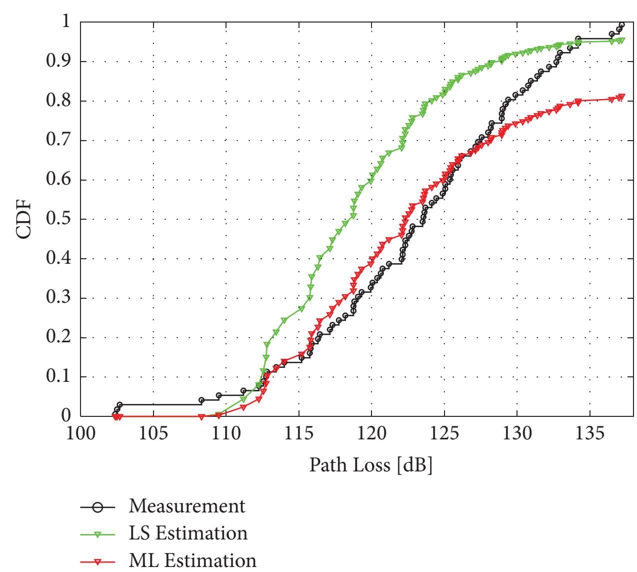

Figure 12: Path prediction attained with LS-based estimation and ML-based estimation approaches from site location 3.

Table 3: Precision estimation accuracy attained by LS-based estimation and ML-based estimation at different study locations.

Location	Locations	MAE	MRE	STE	RMSE
LS-based estimation	1	0.169126	11.39	0.0966802	0.19481
	2	0.174385	12.17	0.1007700	0.201407
	3	0.164623	10.92	0.0964925	0.190818
ML-based estimation	1	0.0604279	1.58	0.0457335	0.0726338
	2	0.0558125	1.42	0.0401722	0.0687666
	3	0.0539799	1.39	0.0413426	0.067993

4. Conclusions

This study considers parameter estimation for spatial variations of a radio frequency channel based on experimental measurements derived from an operational 4G LTE broadband network. The work developed a combined maximum-likelihood estimation model and a lognormal distribution function. The explored ML-based model reliably estimates the specified wireless channel parameters compared with measured field data for the investigated environments. In order to test the validity of the proposed model, standard statistical metrics were employed for benchmarking. Regarding the mean absolute error (MAE), Mean percentage error (MAPE), root mean square error (RMSE), and standard deviation error (SDE) statistics, the ML model approach attains 1.82, 3.97, 1.99, and 0.79 in site location 1. In contrast, the LS model achieved 2.70, 11.85, 3.44, and 2.13 values, respectively, for the same site location. Similar parameter estimation and prediction performance of the ML method over the LS approach are demonstrated for site locations 1 and 2. Future work would focus on optimizing the parameters of the proposed hybrid model for optimal performance in a related wireless propagation environment.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

The work of Agbotiname Lucky Imoize was supported in part by the Nigerian Petroleum Technology Development Fund (PTDF) and in part by the German Academic Exchange Service (DAAD) through the Nigerian-German Postgraduate Program under Grant no. 57473408. The authors extend their appreciation to Taif University for funding the current work via Taif University Researchers Supporting Project number (TURSP-2020/119), Taif University, Taif, Saudi Arabia.

References

[1] M. R. Akdeniz, Y. Liu, M. K. Samimi et al., "Millimeter wave channel modeling and cellular capacity evaluation," *IEEE Journal on Selected Areas in Communications*, vol. 32, no. 6, pp. 1164–1179, 2014.

[2] D. Vasisht, S. Kumar, H. Rahul, and D. Katabi, "Eliminating channel feedback in next-generation cellular networks," in *Proceedings of the 2016 ACM SIGCOMM Conference*, New York, NY, USA, August 2016.

[3] B. H. Fleury, M. Tschudin, R. Heddergott, D. Dahlhaus, and K. Ingeman Pedersen, "Channel parameter estimation in mobile radio environments using the SAGE algorithm," *IEEE Journal on Selected Areas in Communications*, vol. 17, no. 3, pp. 434–450, 1999.

[4] A. Richter, "Estimation of Radio Channel Parameters," *Models and Algorithms*, vol. 19, no. 4, 2005.

[5] A. U. Usman, O. U. Okereke, and E. E. Omizegba, "Macrocell path loss prediction using artificial intelligence techniques," *International Journal of Electronics*, vol. 101, no. 4, pp. 500–515, 2014.

[6] J. Isabona, C. C. Konyeha, C. B. Chinule, and G. P. Isaiah, "Radio field strength propagation data and pathloss calculation methods in UMTS network," *Advances in Physics Theories and Applications*, vol. 21, pp. 54–68, 2013.

[7] J. Isabona and I. G. Peter, "CDMA2000 radio measurements at 1.9 GHz and comparison of propagation models in three built-up cities of SouthSouth-South, Nigeria," *Am. J. Eng. Res*, vol. 2, no. 05, pp. 96–106, 2013.

[8] Y. Ai, M. Cheffena, and Q. Li, "Radio frequency measurements and capacity analysis for industrial indoor environments," in *Proceedings of the 2015 9th European Conference on Antennas and Propagation (EuCAP)*, Lisbon, Portugal, April 2015.

[9] H. Xu, C. Shi, W. Zhang, and Y. Yang, "Field testing, modeling and comparison of multi frequency band propagation characteristics for cellular networks," in *Proceedings of the 2016 IEEE International Conference on Communications (ICC)*, Kuala Lumpur, Malaysia, May 2016.

[10] A. R. Mishra, *Fundamentals of Cellular Network Planning and Optimisation*, John Wiley & Sons, Hoboken, New Jersey, United States, 2018.

[11] S. O. Ajose and A. L. Imoize, "Propagation measurements and modelling at 1800 MHz in Lagos Nigeria," *International Journal of Wireless and Mobile Computing*, vol. 6, no. 2, pp. 165–174, 2013.

[12] A. L. Imoize, E. M. Otuokere, S. O. Ajose, and A. O. Adegbenro, "Experimental validation of a best-fit model for predicting radio wave propagation through vegetation," *Arid Zo. J. Eng. Technol. Environ*, vol. 15, pp. 172–186, 2019.

[13] A. L. Imoize, A. E. Ibhaze, P. O. Nwosu, and S. O. Ajose, "Determination of best-fit propagation models for pathloss prediction of a 4G LTE network in suburban and urban areas of lagos, Nigeria," *West Indian J. Eng*, vol. 41, no. 2, pp. 13–21, 2019.

[14] A. L. Imoize and A. I. Oseni, "Investigation and pathloss modeling of fourth generation long term evolution network along major highways in Lagos Nigeria," *IFE Journal of Science*, vol. 21, no. 1, pp. 39–60, 2019.

[15] X.-L. Hu, P.-H. Ho, and L. Peng, "Performance analysis of maximum likelihood estimation for transmit power based on signal strength model," *Journal of Sensor and Actuator Networks*, vol. 7, no. 3, p. 38, 2018.

[16] N. Alić, G. C. Papen, R. E. Saperstein, L. B. Milstein, and Y. Fainman, "Signal statistics and maximum likelihood sequence estimation in intensity modulated fiber optic links containing a single optical preamplifier," *Optics Express*, vol. 13, no. 12, pp. 4568–4579, 2005.

[17] C. I. Abiodun and J. S. Ojo, "Determination of probability distribution function for modelling path loss for wireless channels applications over micro-cellular environments of Ondo State, Southwestern Nigeria," *World Sci. News*, vol. 118, pp. 74–88, 2019.

[18] N. Faruk, A. Ayeni, and Y. A. Adediran, "On the study of empirical path loss models for accurate prediction of TV signal for secondary users," *Progress In Electromagnetics Research B*, vol. 49, pp. 155–176, 2013.

[19] J. Salo, L. Vuokko, and P. Vainikainen, "Why is shadow fading lognormal?" in *Proccedings of the International Symposium on Wireless Personal Multimedia Communications*, Aalborg, Denmark, September 2005.

[20] F. Luan, Y. Zhang, L. Xiao, C. Zhou, and S. Zhou, "Fading characteristics of wireless channel on high-speed railway in hilly terrain scenario," *International Journal of Antennas and Propagation*, vol. 2013, pp. 1–9, Article ID 378407, 2013.

[21] C. Gustafson, T. Abbas, D. Bolin, and F. Tufvesson, "Statistical modeling and estimation of censored pathloss data," *IEEE*

Wireless Communications Letters, vol. 4, no. 5, pp. 569–572, 2015.

[22] R. Sari and H. Zayyani, "RSS localization using unknown statistical path loss exponent model," *IEEE Communications Letters*, vol. 22, no. 9, pp. 1830–1833, 2018.

[23] J. Isabona, "Experimental study of UMTS radio signal propagation characteristics by field measurement," *Department of Basic Sciences Benson Idahosa University PMB*, vol. 2, no. 07, pp. 99–106, 2013.

[24] J. Isabona and K. Obahiagbon, "RF propagation measurement and modelling to support adept planning of outdoor wireless local area networks in 2.4 GHz Band," *Am. J. Eng. Res*, vol. 3, no. 1, pp. 258–267, 2014.

[25] J. Isabona Joseph and C. C. Konyeha, "Urban area path loss propagation prediction and optimisation using Hata model at 800MHz," *IOSR Journal of Applied Physics*, vol. 3, no. 4, pp. 8–18, 2013.

[26] C. Gentile, A. F. Molisch, J. Chuang et al., "Methodology for benchmarking radio-frequency channel sounders through a system model," *IEEE Transactions on Wireless Communications*, vol. 19, no. 10, pp. 6504–6519, 2020.

[27] J. Isabona, R. Kehinde, A. L. Imoize, S. Ojo, and N. Faruk, "Large-scale signal attenuation and shadow fading measurement and modelling for efficient wireless network design and management," in *Proceedings of the 2022 IEEE Nigeria 4th International Conference on Disruptive Technologies for Sustainable Development (NIGERCON)*, Lagos, Nigeria, April 2022.

[28] S. Ojo, A. Imoize, and D. Alienyi, "Radial basis function neural network path loss prediction model for LTE networks in multitransmitter signal propagation environments," *International Journal of Communication Systems*, vol. 34, no. 3, pp. 1–26, 2021.

[29] J. Isabona, A. L. Imoize, S. Ojo et al., "Development of a multilayer perceptron neural network for optimal predictive modeling in urban microcellular radio environments," *Applied Sciences*, vol. 12, no. 11, p. 5713, 2022.

[30] A. L. Imoize and A. I. Dosunmu, "Path loss characterization of long term evolution network for," *Jordan J. Electr. Eng*, vol. 4, no. 2, pp. 114–128, 2018.

[31] A. L. Imoize and O. D. Adegbite, "Measurements-based performance analysis of a 4G LTE network in and around shopping malls and campus environments in lagos Nigeria," *Arid Zo. J. Eng. Technol. Environ*, vol. 14, no. 2, pp. 208–225, 2018.

[32] A. E. Ibhaze, A. L. Imoize, S. O. Ajose, S. N. John, C. U. Ndujiuba, and F. E. Idachaba, "An empirical propagation model for path loss prediction at 2100MHz in a dense urban environment," *Indian Journal of Science and Technology*, vol. 10, no. 5, pp. 1–9, 2017.

[33] T. S. Rappaport, *Wireless Communications: Principles and Applications*, Prentice-Hall, Upper Saddle River, New Jersey, 2nd ed edition, 2002.

[34] T. S. Rappaport, F. Gutierrez, E. Ben-Dor, J. N. Murdock, Y. Qiao, and J. I. Tamir, "Broadband millimeter-wave propagation measurements and models using adaptive-beam antennas for outdoor urban cellular communications," *IEEE Transactions on Antennas and Propagation*, vol. 61, no. 4, pp. 1850–1859, 2013.

[35] J. Isabona, A. L. Imoize, P. Rawat et al., "Realistic prognostic modeling of specific attenuation due to rain at microwave frequency for tropical climate region," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 8209256, 10 pages, 2022.

[36] D. G. Kleinbaum and M. Klein, "Maximum likelihood techniques: an overview," *Logist. Regres*, vol. 101, pp. 103–127, 2010.

[37] A. E. Waadt, C. Kocks, S. Wang, G. H. Bruck, and P. Jung, "Maximum likelihood localization estimation based on received signal strength," in *Proceedings of the 2010 3rd International Symposium on Applied Sciences in Biomedical and Communication Technologies (ISABEL 2010)*, Rome, Italy, November 2010.

[38] Y. T. Chan, B. H. Lee, R. Inkol, and F. Chan, "Received signal strength localization with an unknown path loss exponent," in *Proceedings of the 2011 24th Canadian Conference on Electrical and Computer Engineering (CCECE)*, pp. 000456 -000459, Niagara Falls, ON, Canada, May 2011.

[39] I. Valera, B. T. Sieskul, and J. Míguez, "On the maximum likelihood estimation of the ToA under an imperfect path loss exponent," *EURASIP Journal on Wireless Communications and Networking*, vol. 2013, no. 1, pp. 1–21, 2013.

[40] G. Jacinto, P. A. Filipe, and C. A. Braumann, "Weighted maximum likelihood estimation for individual growth models," *Optimization*, vol. 71, no. 11, pp. 3295–3311, 2022.

[41] R. Orellana, G. Bittner, R. Carvajal, and J. C. Agüero, "Maximum Likelihood estimation for non-minimum-phase noise transfer function with Gaussian mixture noise distribution," *Automatica*, vol. 135, Article ID 109937, 2022.

[42] C. Cheng, S. Liu, H. Wu, and Y. Zhang, "An Efficient Maximum-likelihood-like Algorithm for Near-Field Coherent Source Localization," *IEEE Transactions on Antennas and Propagation*, vol. 70, no. 7, pp. 6111–6116, 2022.