ADAPTIVE HYBRID MODEL FOR PREDICTION OF ELECTROMAGNETIC SIGNAL PATH LOSS IN LONG TERM EVOLUTIONRADIO MICROCELLULAR NETWORK

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[1]PETER, I. G., [2]ASIEGBU, A. D.,[3]EKPE, O.
AND [4]EFURUMIBE, E. L.
Department of Physics,University of Agriculture,
Umudike, Abia State, Nigeria.
[1]*isaiahpeter@uniuyo.edu.ng,* [2]*danasiegbu@yahoo.com*
[3]*ekpe.obini@mouau.edu.ng,* [4]*efurumibe.ezinna@mouau.edu.ng*

ABSTRACT

Accurate path loss modeling and prediction will provide realistic information on the level of signal attenuation in a service area and contribute positively to better performance of cellular radio network. This will also support the tight fitting of cell fringe areas that are likely to be impacted negatively by interference around the cell edge/contour. A better predictive path loss model that will facilitate superb cellular network planning process will be of a great support to cellular radio network planners, stakeholders and end users. In this work we used a hybrid wavelet and Long Short Term Memory model for adaptive modeling and prediction of signal path loss in urban microcellular radio network. A measured signal data was obtained and routed through a wave let-based decomposition process with two decomposition levels. The decomposed measured signal data was converted into path loss values and then utilized as input data to Long Short Term Memory model where relevant extracted information were captured and trained for robust predictive adaptive learning and prediction. The degree of prediction accuracy using the proposed model over other prediction techniques were statistically quantified using four different first order statistical metricsSignal Pathloss model can accurately estimate pathloss which in turn are useful for maximizing of network quality and coverage area of base stations, frequency assignments, proper determination of electric field strength, interference analysis, handover optimization, power level adjustment, radio link budget design and analysis.

INTRODUCTION

One fundamental aim of Radio Frequency (RF) coverage planning is to resourcefully utilize the allotted frequency band. As a result, RF coverage planning and prediction tools are of immense significance as they assist radio network planners and designers to examine different system network configurations before and after deployment. The precision attained by the signal coverage prediction tool is also largely connected to the prediction accuracy of the radio propagation path loss model applied (Joseph and Konyeha, 2013; Isabona*et al.,* 2013). Classic statistical models such as the Least Square Regression (LSR) model and Least Absolute Deviation (LAD) model were used for path loss prediction (Drozdora and Akpasha, 2017). However, such models have limited capability in capturing non-linear and non-stationery signal dataset. Thus, the use of standard neural network and Deep Neural Network (DNN) methods such as Long Short Term Memory (LSTM) and Multilayer Perception (MLP) network is exploited in the last couple of years. In signal power coverage prediction using DNN learning model is presented for dense urban environment, (Ozyegen, *et al,* 2020). A practical prediction of shadowing factor and path loss exponent from satellite images at 900 MHz has been studied using Deep neural learning approach, (Hasan *et al.,* 2019).

In detailed reviews of different works which provide various path loss prediction techniques using different machine learning based methods are also shown, (Uceellari, *et al.,* 2016 and Cerri*et al.,* 2004). The standard neural network and DNN suffer major draw backs such as:

- Perform very poorly in noisy signal data sets.
- Lack abilities in handling incoherence signal data sets
- Perform poorly in predicting large and highly stochastic non linear data sets (Peng and Zhu, 2007; Wang, 2003; Isabona, and Srivastava, 2016; Isabona, 2020).

We proposed and practically applied combined wavelet and intelligent deep learning predictive modeling tools, which possess the capacity to adaptively learn and predict the relevant radio environment propagation features and path loss values through intensive training and learning.

MATERIALS AND METHOD

SIGNAL DATA COLLECTION AND PATH LOSS COMPUTATION METHOD

A field drive test based experimental set up was employed for the live signal data collection in this research work. The drive testing consists of carrying out a wide range Reference Signal Receive Power (RSRP) and service quality parameters measurement at the receiver terminal within the assessed Base station (eNodeB) of the coverage area.

The field drive test system tools used for this work are as listed:Global Positioning System (GPS), Two LTE Mobile phones, Dell Lab top, Data card, Power Inverter, Scanner, Direct Test Cables and Extension board, Map Info software andTelephone Mobile Software (TEMS).

All the tools were integrated together (Figure1). The map info software was specifically used for putting drive test location maps in view and creating route data (Figure 2). Aided by the field drive test system tools, live signal data were acquired around four Long Term Evolution (LTE) eNode B antenna sites, all which operates at 10 MHz band width across Uyo City, Akwa Ibom State, Nigeria.The path loss data was computed from the measured RSRP mathematically by (Joseph and Konyaha, 2013; Mallat, 1989).

$$PL_{mea}\,(dB) - E\,IRP - RSRP_{mea} \quad - \quad (1)$$

The E IRP can be calculated as:

$$E\,IRP = P_{TX} + G_{TX} - C_{LTX} \quad - \quad (2)$$

Where G_{TX} is the transmit antenna gain, PTX the transmitted power, and CLTX denotes transmission cable/connection loss, all in dB.

Table 1 shows some of the Key Bs antenna site parameters acquired during the field drive test.

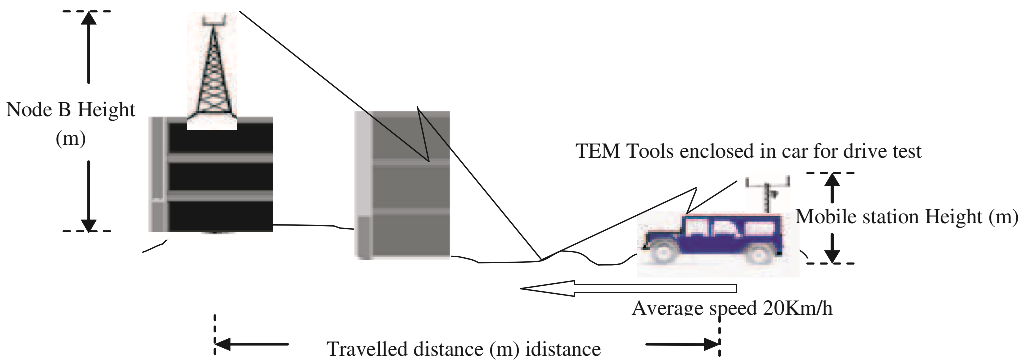

Figure 1: A sketch of TEMS Drive Test Configuration

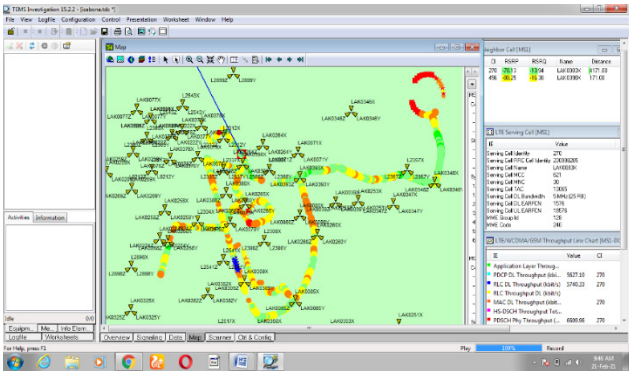

Figure 2: Snap shot of the drive test routes of the acquired RSRP data in eNodeB Site 1

Table 1: Transmission Antenna Engineering features of the eNodeB antenna Sites

	eNodeB 1	eNodeB2	eNodeB 3	eNode B 4
Transmission Frequency (MHz)	1,900	1,900	1800	1800
Transmission power (dBm)	43	43	43	43
Antenna heights (m)	30	28	26	32
Antenna gains (dB)	17.5	17.5	17.5	17.5
Cable /connection losses (dB)	0.5	0.5	0.5	0.5
Feeder loss (dB)	3	3	3	3

Multi-resolution Digital Wavelet Transform

A Wavelet Transform (WT) is a time-frequency decomposition transform which provides a useful means of analyzing spatial and temporal data in both time and frequency domain. Specifically, Multi-resolution Digital Wavelet Transform (MDWT) is considered in this research to provide superior support for multi-spatial scale non-stationary path loss modeling and analysis. The classical continuous wavelet transform is defined as (Ojuh and Isabona, 2018; Mallat, 1989).

$$W[\tau,\mu]=\frac{1}{\sqrt{\mu}}\int x[t]\psi[t]\left[\frac{t-\tau}{\mu}\right]dt \qquad (3)$$

where: $\psi(t)$ = mother wavelet function

τ =translator factor

μ =scale factor (which is the inverse of f_0)

$\frac{1}{\sqrt{\mu}}$ = signal energy normalization factor

In terms of DWT setting, the parameters τ and μ take on discrete values. The coefficients of *x(t)* in equation (3) can be expressed as:

$$W[k]=(x*\psi)[k]=\sum_{-\infty}^{\infty}x[k]\psi[n-k] \qquad (4)$$

Where k is the translation parameter, and n is an integer.

This work explores multi-resolution DWT decomposition and reconstruction methodology for the enhancement of measured LTE signals under noisy conditions. The proposed methodology is based on Mallat transform algorithm (Mallat, 1989). For DWT, the Mallat algorithm involves processing the reference signals using conjugate quadrature filters to produce signal wavelet approximation and detailed coefficients. Figure 3 shows the various steps employed to implement the proposed methodology. The measured noisy signal is the reference signal data. For a signal sample of length L, the DWT consistof $\log_2 L$ steps. The first stage entails the convolving of the signal sample simultaneously with both low-pass filter and high-pass filter to provide a number of approximation coefficients and detail coefficients correspondingly. The filter output of low-pass filter and the high-pass filter can be expressed as (Mallat, 1989).

$$W_{low}[n] == \sum_{-\infty}^{\infty} x[k]g[2n-k] \tag{5}$$

$$W_{high}[n] == \sum_{-\infty}^{\infty} x[k]h[2n-k] \tag{6}$$

After that, part of the signal samples was removed via a process termed down sampling. The signal decomposition was repeated over several levels to further upturn the frequency resolution. Figure 3 illustrates 3 decomposition levels and all the filters possesses a function for sub-sampling of the signal by 2.

$g(n)$ and $h(n)$ are dependent on each other by:

$$g[L-1-n] = (-1)^n.h(n) \tag{7}$$

where L is the length of the filter.

Next step was the reconstruction of the signal expressed as:

$$x(n) = \sum_{k=-\infty}^{\infty} \left(W_{high}[n]x[k].g[-n+2k]\right) + \left(W_{low}[k].h[-n+2k]\right) \tag{8}$$

The reconstruction was implemented using Inverse Discrete Wavelet Transform (IDWT).Whereas decomposition consist of convolution followed by dint of down sampling, reconstruction involves up sampling followed by means of convolution. Up sampling defines the signal lengthening process by injecting zeros amid the signal data points.

While carrying out the reconstruction, both the detail coefficients, cD and approximation coefficients, cAn were first up sampled. While the detail coefficients were convolved using a high pass filter, the approximation coefficients are convolved using the low-pass filter. Both sets of convolved data were then combined to obtain the next level of approximation coefficients, cA,-1

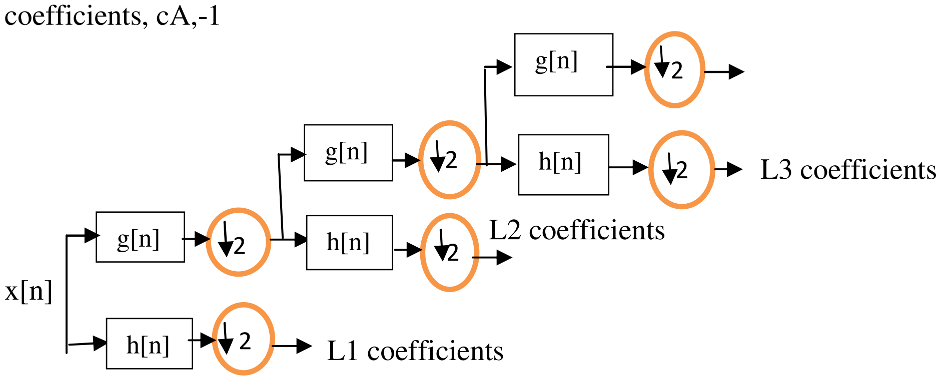

Figure 3: A Filter bank illustration of different level Decomposition with DWT

LSTM Architecture

Long Short Term Memory network, which is generally termed "LSTMs", is an exceptional type of recurrent neural network. It possesses the capacity to learn both long and short term memories. The LSTM was first devised by Hochreiter and Schmidhuber (1997) to solve complex long-term dependency and vanishing gradient problems. Thus, the LSTM has the capacity to learn sequence order dependency prediction and classification problems.

The LSTM architecture has three main parts. They are the forget gate, the input gate and the output gate (Figure 4). The forget gate is responsible for removing less important information or eliminating irrelevant information from the LSTM cell state through a multiplication by a filter. While the input gate is in charge of accepting and adding information to the cell state, output gate is responsible for outputting processed information from the cell state.

An input data sequence $x = (x_1, x_2, x_3,...x_T)$ can be mapped to the output data sequence $h = (y_1, y_2, y_3,...y_T)$ at t=1 to T iteratively in an LSTM network computing the unit activations using:

$$i_t = \ell\left(W_{ix}x_t + W_{im}m_{t-1} + W_{ic}c_{t-1} + b_t\right) \quad (9)$$

$$f_t = \ell\left(W_{fx}x_t + W_{fm}m_{t-1} + W_{fc}c_{t-1} + b_f\right) \quad (10)$$

$$c_t = f_t \otimes c_{t-1} + i_t\sigma\left(W_{cx}x_t + W_{cm}m_{t-1} + W_{cm}c_{t-1} + b_c\right) \quad (11)$$

$$o_t = \ell\left(W_{ox}x_t + W_{om}m_{t-1} + W_{oc}c_{t-1} + b_o\right) \quad (12)$$

$$m_t = o_t \otimes h(c_t) \quad (13)$$

$$h_t = \varphi\left(W_{ym}m_t + b_y\right) \quad (14)$$

W_{ix} represent the input weight matrix from the input gate, W_{oc} ,W_{ic} and W_{fc} are the connecting diagonal weight matrices. W denotes the weight matrix, b represent the bias vectors, $\otimes$ expresses the element wise product for the vectors. c , f , i and o denote the cell activation vectors, forget gate, input gate and the output gate, respectively. ℓ and φ denote the logistic sigmoid function and the activation function for the network output. h and σ represent the activation function for cell output and cell input, respectively.

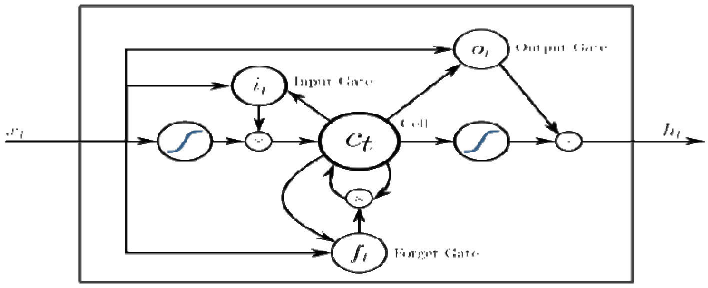

Figure 4: LSTM architecture

The Adaptive Hybrid Wavelet-LSTM Deep Neural Network Model

In this work, as illustrated in figure 5, a hybrid model which combines adaptive multi-resolution wavelet transform and LSTM neural network was designed to predict the path loss in Uyo metropolis, Akwa Ibom Sate, Nigeria. The wavelet transform method being employed to preprocess and decompose input path loss data, while LSTM neural network model is designed to adaptively learn and predict path loss data pattern (Figure 4). Shown in Table 2 is the hybrid wavelet-LSTM network training parameters. The predicted outcome of the proposed hybrid model has been compared to the conventional neural network models. Fig 5 depicts the architecture of the proposed adaptive Hybrid prediction model i.e. the wavelet transform and LSTM neural network model. The model is used for advance field data processing, path loss data computation, LSTM training and testing of path loss values and for updating hyperparameter for optimized path loss prediction. The overall resultant hybrid model is given by:

$$y(PL_w, W, \theta) = PL(RSRP_w, dist) + h_t([x_t, PL(RSRP_w, dist)], W, \theta) \quad (15)$$

Where $PL(RSRP_w, dist)$ is the computed path loss values using wavelet preprocess measured RSRP values. $h_t([x_t, PL(RSRP_w, dist)], W, \varphi)$ is adaptively predicted path loss output using deep neural network based LSTM training. W is the LSTM weight modelling marix, and θ is updating hyper optimization parameters.

Evaluation measurement and comparison of predicted path loss using Adaptive Hybrid model and conventional model

The four basic first order statistical indicators engaged to examine the prediction accuracy of the Adaptive Hybrid model include: Root Mean Squared Error (RMSE), Standard Deviation (STD), Mean Absolute Percentage Error (MAPE) and Mean Absolute Error (MAE).Both MAE and RMSE expresses the mean error magnitude between the actual observation and prediction.

The STD articulates the measure of dispersion between actual observation and prediction. MAPE expresses the Mean Percentage Error between the actual observation and prediction.The indicators are defined in Eq. (16) to Eq. (19) as follows:

$$MAE = \frac{1}{K_{test}} \sum_{k=1}^{Ktest} |t_k - y_k| \quad (16)$$

$$RMSE = \sqrt{MSE} = \frac{1}{K_{test}} \sqrt{\sum_{k=1}^{Ktest} \left[t_k - y_k \right]^2} \quad (17)$$

$$STD = \sqrt{\left(\frac{1}{K_{test}} \sum_{k=1}^{Ktest} |t_k - y_k| - MAE \right)^2} \quad (18)$$

$$MAPE = \frac{1}{N} \sum_{q=1}^{N} \left| \frac{t_k - y_k}{t_k} \right| \times 100 \quad (19)$$

the actual network value, $k = 1,2,...,\ K$ are values the signal path loss sample

Table 2: Key Hybrid Wavelet-LSTM Deep Neural Network Training Parameters

Path loss Data Training Parameters for Sites 1 and 2	Path loss Data Training parameters for Sites 3 and 4
Num Hidden Units = 300	Num Hidden Units = 200
MaxEpochs:300	MaxEpochs:200
GradientThreshold:1	Gradient Threshold:1
Initial Learn Rate: 0.005	Initial Learn Rate: 0.005
Learn Rate Schedule: piecewise	Learn Rate Schedule: piecewise
LearnRateDropPeriod:400	LearnRateDropPeriod:300
LearnRateDropFactor:0.2	LearnRateDropFactor:0.2
Training Options: adam (*adaptive moment estimation)*	Training Options: adam *(adaptive moment estimation)*

RESULTS AND DISCUSSION

The graphical results and the computed prediction error statistical values using the proposed hybrid wavelet-LSTM path loss prediction model and the conventional approach was accomplished using 2018a version of MATLAB software platform. Figures 6-13 shows the graphical prediction results using both the LSTM convectional and Hybrid LSTM approach. Specifically, while figures 6 to 9 displays the predicted path loss values at each measurement made using the conventional LSTM approach without updates, Figures 10 to 13 provide the path loss prediction using the hybrid wavelet-LSTM predictive path loss modeling approach with updates. Tables 2 and 3 show computed prediction performance results in terms of MAE, MAPE, RMSE and STD using the conventional approach and proposed hybrid wavelet-LSTM path loss prediction. While the attained MAE, MAPE, RMSE and STD predictive performance values range from 2.79 to 4.50, 2.05 to 3.26,4.19 to 6.32 and 3.89 to 5.79 dB, respectively, using the proposed Wavelet-LSTM model for the four eNodeB sites, indicating a better performance predictions; the prediction MAE, MAPE, RMSE and STD values made by conventional LSTM modeling approach range from7.53 to 15.77, 5.46 to 10.92, 9.99 to 19.77 and 9.68 to 18.86 dB.Tables3 and 4 also shows that the Wavelet-LSTM model attained the best prediction performances in locations 1-4 with MAPE, STD, and RMSE values compared to the ones made by ordinary LSTM neural network model.

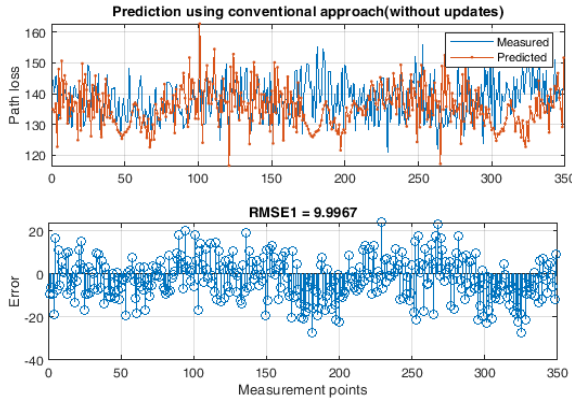

Figure 6: Conventional LSTM Path loss Prediction for eNodeB Site 1, (without updates)

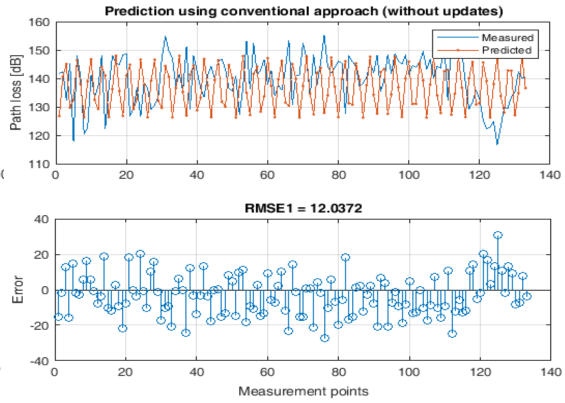

Figure 7: Conventional LTST Path loss Prediction for eNodeB Site 2, (without updates)

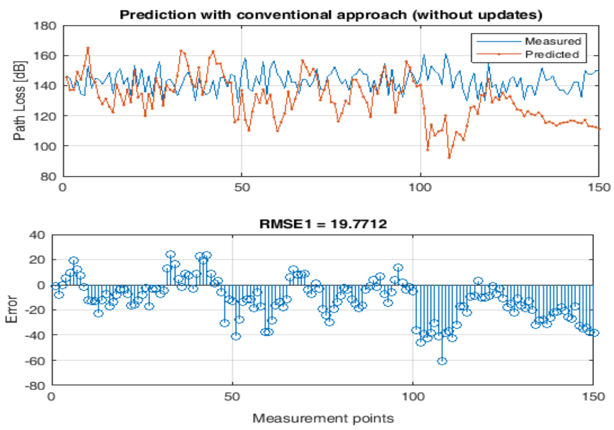

Figure 8: Conventional LSTM Path loss Prediction for eNodeB Site 3, (without updates)

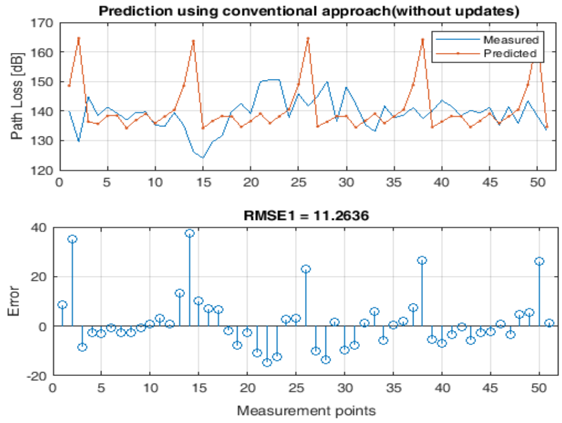

Figure 9: Conventional LSTM Path loss Prediction for eNodeB Site 4, (without updates)

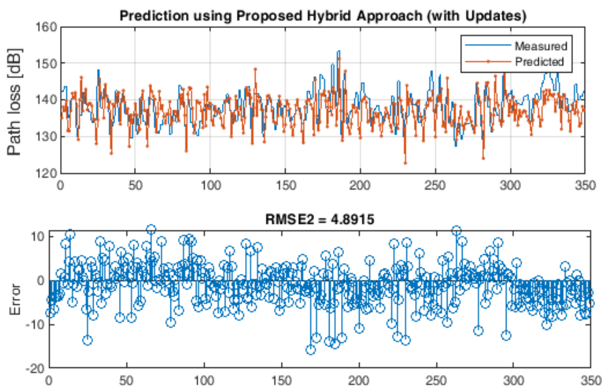

Figure 10: Proposed Hybrid Wavelet-LSTM Path loss Prediction for eNodeB, Site 1 (with updates)

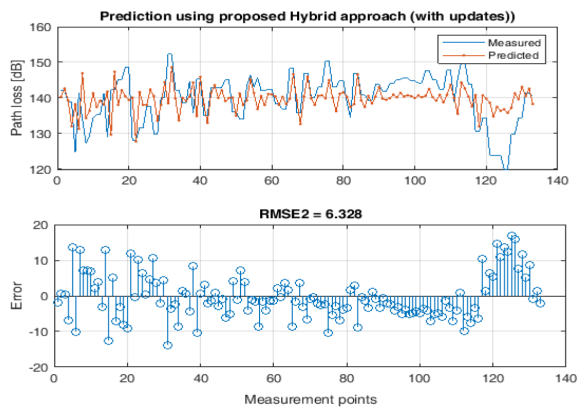

Figure 11: Proposed Hybrid Wavelet-LSTM Path loss Prediction for eNodeB Site 2, (with updates)

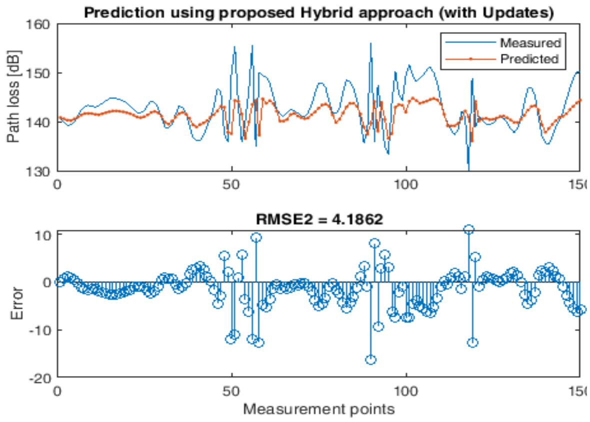

Figure 12: Proposed Hybrid Wavelet-LSTM Path loss Prediction for eNodeB Site 3, (with updates)

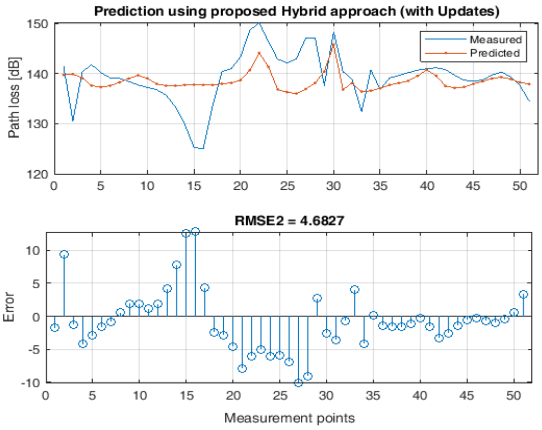

Figure 13: Proposed Hybrid Wavelet-LSTM Path loss Prediction for eNodeB Site 4 (with updates)

Table 3: Statistical error values attained using Convectional LSTM Path loss Prediction Approach

Performance Measure	eNodeB Site 1	eNodeB Site 2	eNodeB Site 3	eNodeB Site 4
MAE	8.12	10.01	15.77	7.53
MAPE	5.83	7.18	10.92	5.46
RMSE	9.99	12.06	19.77	11.26
STD	9.68	11.69	18.86	11.24

Table 4: Statistical error values attained using Hybrid wavelet-LSTM Path loss Prediction Approach

Performance Measure	eNodeB Site 1	eNodeB Site 2	eNodeB Site 3	eNodeB Site 4
MAE	4.17	4.50	2.79	3.47
MAPE	3.02	3.26	2.05	2.51
RMSE	4.89	6.32	4.19	4.68
STD	5.27	5.79	3.89	4.66

CONCLUSION

Accurate predictive analysis and modelling of signal path loss during and after cellular network planning process, presented in this work remained one key practical approach that can boost a successful and healthy cellular radio network performance improvement. Precise path loss modelling and prediction will provide realistic idea about the level of signal attenuation loss in the entire coverage service areas. It will also support in tight-fitting of cell fringe areas that are likely to be impacted negatively by interference around the cell edge/contour.

In this research, a joint wavelet and long short term model has been used for modelling and prediction of signal path losses in urban microcellular radio networks.The measured received signal strength data was first obtained and routed through a wavelet-based decomposition process employing two decomposition levels. The decomposed measured received strength constituents were converted to path loss values and then utilised as input data to LTSM deep neural network model where relevant extracted information is captured and trained for robust predictive adaptive learning. The degree of prediction accuracy using the Wavelet-LSTM model over other prediction techniques are also statistically quantified and provided using four different first order statistical metrics. The metric include: the Root Mean Squared Error (RMSE), Standard Deviation (STD), Mean Absolute Percentage Error (MAPE) and Mean

Absolute Error (MAE). In terms of RMSE, the proposed hybrid approach improves the mean prediction efficiency by 50% compared to the conventional prediction method.

REFERENCES

Cerri, G., Cinalli, M., Michetti, F and Russo, P. (2004). Feed forward neural networks for path loss prediction in urban environment. *IEEE Transactions on Antennas and Propagation,* 52(11):3137-3139.

Drozdova, V. G. and Akhpashev, R. V. (2017). "Ordinary least squares in COST 231 Hata key parameters optimization base on experimental data," *2017 International Multi-Conference on Engineering, Computer and Information Sciences (SIBIRCON),* Novosibirsk, pp. 236-238.

Hasan, H. F., Hashir, S. M., Baykas, T. andGunturk, B. K. (2019). Path Loss Exponent and Shadowing Factor Prediction from Satellite Images Using Deep Learning

Hochreiter, S. and Schmidhuber, J. (1997). Long short-term memory. *Neural Computation, 9*(8): 1735–1780.

Isabona, J. (2020). Wavelet Generalized Regression Neural Network Approach for Robust Field Strength Prediction in Open and Shadow urban Microcells. *Wireless Personal Communications,*114 (3):3635–3653.

Isabona, J. and Srivastava, V.M. (2016). A Neural Network based Model for Signal Coverage Propagation Loss Prediction in Urban Radio Signal Propagation Loss in Urban Microcells.*International Journal of Applied Engineering Research*, 11(22):11002-11008.

Isabona, J., Konyeha, C. C., Chinule, C. B. and Isaiah, G. P. (2013).‘‘Radio Field Strength Propagation Data and Pathloss calculation Methods in UMTS Network’’. *Advances in Physics Theories and Applications,* 21:54-68.

Joseph. I. and Konyeha, C. C. (2013). “Urban Area Path loss Propagation Prediction and Optimization Using Hata Model at 800MHz,” *IOSR Journal of Applied Physics (IOSR-JAP)*, 3(4):8–18.

Mallat, S. (1989). A Theory for Multiresolution Signal Decomposition: The Wavelet Representation. *IEEE Transactions on Pattern Analysis and Machine Intelligence,* 11(7): 674–693.

Mallat, S. (1989). Multiresolution approximation and wavelet orthonormal bases of L2. *Transaction of the American Mathematical Society,* 315(1):68-87.

Ojuh, D.O. and Isabona, J. (2018). Optimum Signal Denoising based on wavelet shrinkage thresholding techniques: White Gaussian Noise and White Uniform Noise case study. *Journal of Scientific and Engineering Research*, 5(6):179-186.

Ozyegen, O. 1.,Mohammadjafari, S.,Elmokhtari, K., Cevik, K. 1., Ethier, K. and Basar, J. (2020). A Deep learning approaches for fast radio signal prediction.

Peng, H. and Zhu, S. (2007). “Handling of incomplete data sets using ICA and SOM in data mining”. *Neural Computing* and *Applications*, 16(2):167–172.

Uccellari, M., Facchini, F., Sola, M., Sirignano, E., Vitetta, G. M., Barbieri, A. and Tondelli, S. “On the use of support vector machines for the prediction of propagation losses in smart metering systems," in *Proc. IEEE 26th International Workshop Mach. Learn. Signal Process,* Sep. 2016, pp. 1-6.

Wang, S. H. (2003). Application of self-organising maps for data mining with incomplete data sets. *Neural Computing* and *Applications*, 12(1):42–48,