International Journal of Advanced Research in Physical Science (IJARPS)
Volume 5, Issue 10, 2018, PP 35-42
ISSN No. (Online) 2349-7882
www.arcjournals.org

Generalized Regression Neural Network: an Alternative Approach for Reliable Prognostic Analysis of Spatial Signal Power Loss in Cellular Broadband Networks

Kingsley Obahiagbon[1], Joseph Isabona[2]

[1]*Department of Computer Sciences, Benson Idahosa University, Benin City, Nigeria*

[2]*Department of Physics, Federal University, Lokoja, Kogi State, Nigeria*

Corresponding Author:** ***Kingsley Obahiagbon, *Department of Computer Sciences, Benson Idahosa University, Benin City, Nigeria*

Abstract: *Realistic signal coverage loss-centric modeling and predictive analysis are key means of boosting upcoming cellular networks planning and optimizing existing ones. This work presents the results of our studies regarding the applications of the probabilistic Generalized Regression Neural Networks (GRNN) to the predictive analysis and modelling of spatial signal power loss data collected over commercial LTE networks interface in outdoor environment. The explored GRNN model is trained with the measured spatial signal power loss data obtained in three different outdoor signal propagation environments. The results of the prediction made by the proposed model showed a greater agreement with the measurements compared to the conventional least square (LS) regression modelling approach.*

Keywords: *Probabilistic GRNN modelling, LS regression modelling, spatial signal power loss, LTE networks interface, outdoor environment.*

1. Introduction

The deployment of Long Term Evolution (LTE) cellular systems started in Nigeria some fey years ago, with the aim of enhancing the existing cellular communication systems such as Universal Mobile Telecommunication System (UMTS), Global Systems for Mobile Communication (GSM) and High-Speed Packet Access (HSPA). LTE is designed to provide improved cellular communication systems, like superior sector capacity and coverage, flexible bandwidth operation, enriched user experience with full mobility, enhanced end-user throughputs, compact user plane latency, robust multi-antenna support, equitable operating costs, and seamless integration with existing systems [1]. Accordingly, the LTE can provide up to 50 Mbps peak data rates for uplink and 100 Mbps for downlink, at 20 MHz bandwidth (BW)). In terms of spectral efficiency, it can provide up to 2.5 bps/Hz for uplink and 5 bps/Hz for downlink [1, 2].LTE is also designed to provide better cell edge coverage performance and scalable BW capacity (between 1.25 and 20 MHz).

Realistic signal power coverage loss-centric modeling and predictive analysis are of key means of planning new cellular networks like LTE and optimizing existing ones. One conventional method of signal power coverage loss-centric predictive modeling in literature is the use of least square (LS) regression [3-12]. But a major problem with LS regression approach is that it demands varying and incrementing one after another repeatedly in steps, before reaching a near global minimum [13-15].

In contemporary times, different computational intelligent methods have been exploited to predictively and analytically model the stochastic behaviour of propagated radio signal from the base station transmitters in different terrain [16-19]. Of these computational intelligent methods are artificial neural networks (ANNs). ANNs models have been widely used in handling multifaceted non-linear function approximation problems with a superior predictive accuracy than the aforementioned conventional technique such as LS regression, which are based on linear regression.

In our previous works [20-22], we concentrated on linear adaptive and multilayer perception neural networks. In this paper, we provide a predictive mathematical analysis of stochastic behaviour of propagated radio signal loss data obtained from deployed LTE networks in urban microcell using GRNN modelling approach. The predictive modelling techniques characterizes the coupling relation between the spatial signal coverage data and the communication distance, taking into account both line of sight and non-line of sight propagated signal scenarios. Detailed predictive analysis of the signal loss data obtained at 1900 MHz from three Base Transceiver Stations using the GRRN model in comparison with least square regression technique are also provided.

2. Least Square Regression Method

Regression method remained a well-known conventional technique that has been widely explored for statistical predictive analysis in literature for approximating the values of dependent variable (e.g. signal power) in correspondence with the values of the independent variables.

The influence of independent variables on the on dependent ones can conveyed mathematically with a response function *f*:

$$y = f(x_1, x_2, ..., x_n; \beta_1 \beta_2, ...\beta_m) \tag{1}$$

The regression model is given by:

$$w = y + \varepsilon = f(x_1, x_2, ..., x_n; \beta_1, \beta_2, ...\beta_m) + \varepsilon \tag{2}$$

where y is the dependent (observed response) variable; $x_1, ..., x_n$ expresses the input variables, n is the input variable number, $\beta_1, \beta_2, ..., \beta_m$ and ε articulate the unknown regression model parameters and the error term.

The unknown model parameters can be obtained in least square sense by:

$$S(\beta_1, \beta_2, ..., \beta_m) = \sum_{j=1}^{n} (w_j - y_j)^2 = \sum_{j=1}^{n} [(w - f(x_1, x_2, ..., x_n; \beta_1, \beta_2, ...\beta_m) + \varepsilon)]^2 \tag{3}$$

where $S(\beta_1, \beta_2, ..., \beta_m)$ is the error function.

Specifically, to estimate $\beta_1, \beta_2, ..., \beta_m$, we minimized S by solving the system of equations:

$$\frac{\partial S}{\partial \beta i} = 0, i = 1,2, ..., m \tag{4}$$

3. General Regression Neural Network (GRNN)

General Regression Neural Networks (GRNNs), are distinctive class of probabilistic neural networks (PNNs). Largely, the application of PNNs is particularly advantageous owing to their capability to converge and congregate to the core function to the given data, even if the training sample number is small. Furthermore, the information required to obtain satisfying fit of their networks to data is reasonably small and can be accomplished with or without extra input by the handler. As a result, this makes GRNN a distinctive and resourceful tool to carry out predictive task robustly in practice [23, 24].

Specifically, the GRNN comprises of four key layers viz., input layer, summation layer, pattern layer, and output layer as revealed in figure 1. As can be seen in the figure, the input and the pattern layer are completely connected to each other and also link up to the summation layer, where each unit defines the training implementation pattern. The summation layer calculates the sum of the weighted outputs from the input layer via the pattern layer to the output; and the output is the resultant destination of the training process. Summation layer contains two focal sub-parts, which are numerator part and denominator part. While the formal part sums the multiplication of activation function and output data training, the later caters for the summation of the entire activation function [23]. The summation layer values are fed through the summation layer to the output layer. During training, each data sample is catered for as the average of normal distribution, and the output can be expressed as:

$$\hat{y}_i = \frac{\sum_{i=1}^{n} y(i)\phi_i}{\sum_{i=1}^{n} \phi_i} \tag{5}$$

$$\phi_i = \exp\left(-\frac{\|x - x_i\|^2}{2\sigma_i^2}\right) \tag{6}$$

where σ indicates spread constant and it determines the smoothness; ϕ_i is the basis function and is relates the data training sample number; y(i) indicates the values of training outputs.

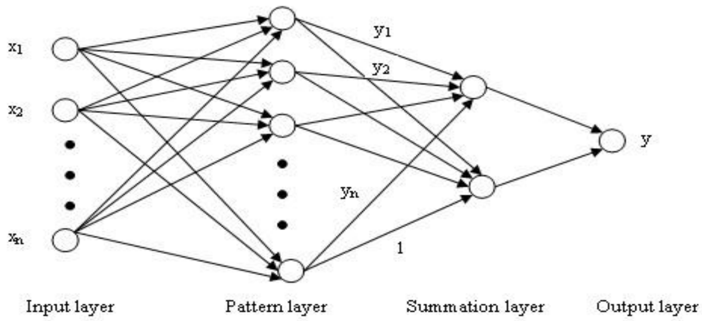

Figure1. *The GRNN architecture*

4. Data Collection Methodology

The measured values of RSRP signal loss data employed to build the GRRN model were obtained using drive-test tools in commercial LTE cellular networks and the networks belongs to MTN Telecommunication Company located in the City Port Harcourt. The LTE network operates at 1900MHz frequency Band. A drive-test tools possess the capability to access, generate and acquire real-time LTE RSRP data automatically and uniformly from the base station transmitters. The tools include: Two LTE proficient mobile handsets (i.e. Sony Ericson and Samsung Y-4), Network Scanner, external GPS devices, Compass, HP Laptop and some key computer software such as MapInfo, Matlab 2015a, Excel spread, that were utilized for post-processing of acquired signal testing log files and data analysis. The LTE mobile phones and the HP laptop were both engrained with mobile testing software (a.k.a. TEMS) which enable it to access, record and extract the signal data along the measurement test routes. The GPS and Compass are used for matching up the mobile station (i.e. user equipment) measurement locations in correspondent to field test environment and the base station transmitter. The field signal power measurements were carried out in three selected locations with special concentration on built-up busy urban streets, roads and open areas with mixed residential and commercial building structures. The measured signal power loss values, S_{Loss} can be expressed mathematically using:

$$S_{Loss} = EIRP - RSRP \tag{7}$$

where:

EIRP= Effective Isotropic Radiated Power,

RSRP=Received Signal Power

5. Training and Prediction

All written GRNN program, computations and implementation were carried with the aid of MATLAB2015a software and platform. To beat over fitting problem that usually impact ANN predictive learning and training capability negatively, the early-stopping method was utilised. Accordingly, the field data was shared into three sets by means of ratio 75%: 15%:15%, which are for training, testing and validation respectively. In the GRNN implementation, the centers of the Gaussian are selected equal to the signal data training input patterns, and a spread parameter of 9 was employed for the training.

Also, by means of the expression in equation (8), the input data sets were normalized to enhance the generalization of ANNs [14].

$$Qn = \frac{(Q_o - Q_{\min})}{(Q_{\max} - Q_{\min})} \tag{8}$$

where

Q_n = normalized value

Q_o = original value of the parameter

Q_{min} = Minimum parameter value

Q_{max} = Maximum parameter value

For the purpose performance comparative investigation between the conventional least regression method and the GRNN method, statistical parameters, namely root mean squared error (RMSE), standard deviation error (SDE), mean squared error (MSE) and mean absolute error (MAE).The parameters can be quantified mathematically as follows:

$$MAE = \frac{1}{K_{test}} \sum_{k=1}^{Ktest} |t_k - y_k| \tag{9}$$

$$RMSE = \sqrt{MSE} = \frac{1}{K_{test}} \sqrt{\sum_{k=1}^{Ktest} [t_k - y_k]^2} \tag{10}$$

$$SDE = \sqrt{\left(\frac{1}{K_{test}} \sum_{k=1}^{Ktest} |t_k - y_k| - MAE \right)^2} \tag{11}$$

where t_k denotes the target value, y_k indicates the actual network value, $\bar{y}_k$ is the mean of the actual network value, $k = 1,2,..., K$ are values the signal loss sample

6. Results and Analysis

Presented in figures 2a-4a and 2b-4b are the respective predictions made using the conventional LS regression model and the proposed GRNN model on Measured Signal loss Data in three outdoor LTE network environments. In the figures, while the RMSE between the Measured Signal loss Data and the GRNN model were found to1.85, 2.36and 4.06 dB in site 1 to 3, the LS regression model attained 3.85, 5.20 and 6.29dB respectively. The above results reveals a superior prediction adaptation of GRNN model to the signal loss data; such performance can be to GRRN ability to learn and captures the non-linear behaviour of input signal variables over the propagation LTE network area.

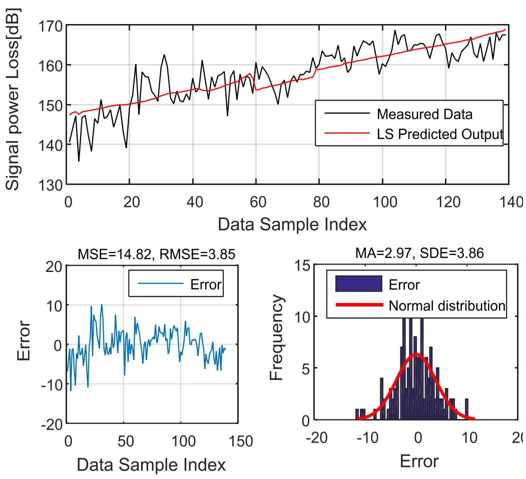

Figure2a. *Measured Signal loss Data and LS predicted Output in Site 1*

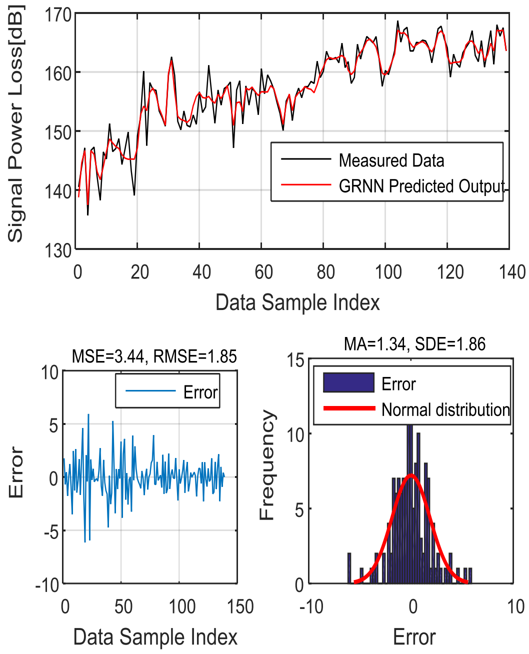

Figure2b. *Measured Signal loss Data and GRNN predicted Output in Site 1*

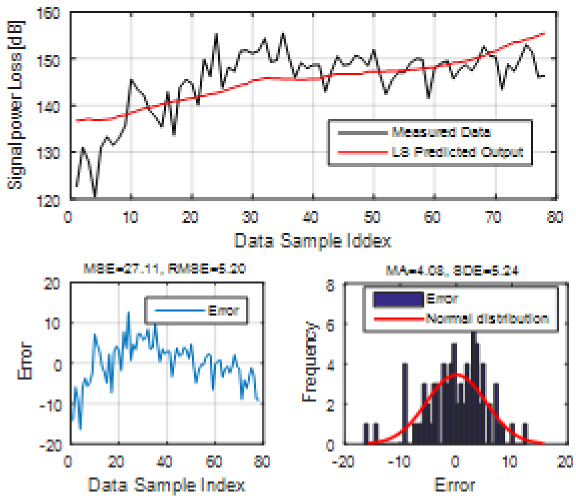

Figure3a. *Measured Signal loss data and LS predicted Output in Site 2*

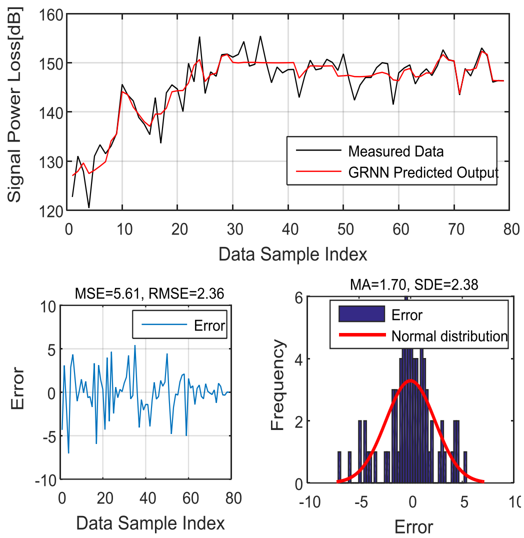

Figure3b. *Measured Signal loss Data and GRNN predicted Output in Site 2*

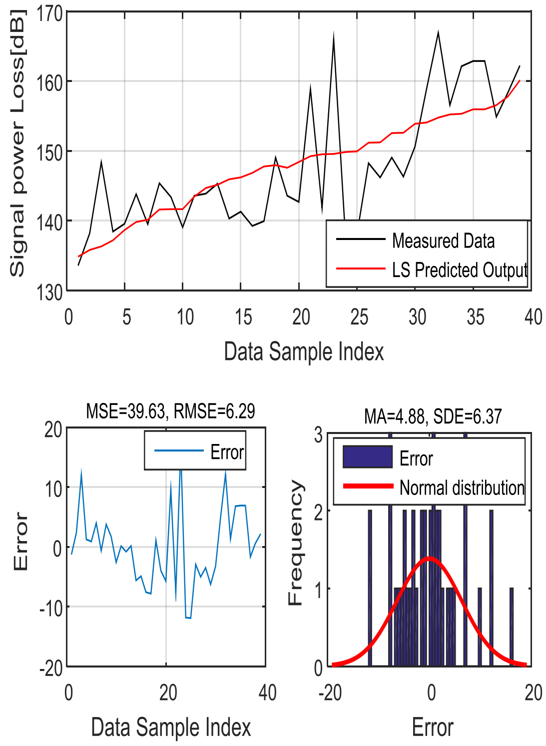

Figure4a. *Measured Signal loss Data and LS predicted Output in Site 3*

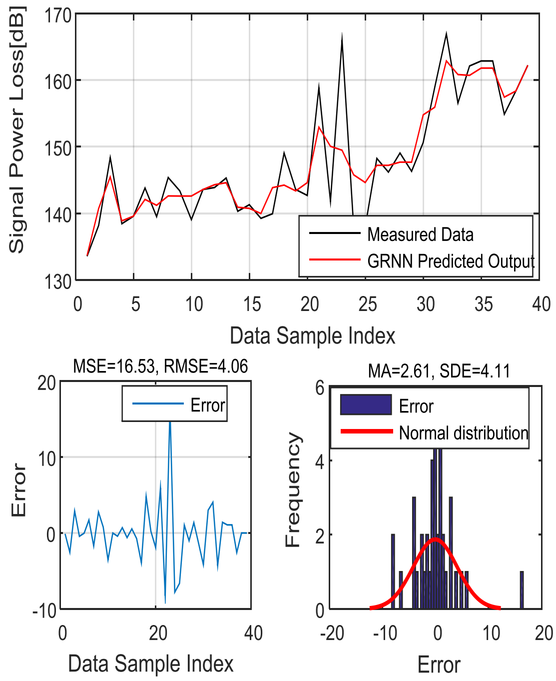

Figure4b. *Measured Signal loss Data and GRNN predicted Output in Site 3*

7. CONCLUSION

Realistic signal coverage loss-centric modeling and predictive analysis are of key means of planning new cellular networks like LTE and optimizing existing ones.

In this study, we have provided a predictive mathematical analysis of stochastic behaviour of propagated radio signal loss data obtained from deployed LTE networks in urban microcell using GRNN modelling approach. Detailed predictive of analysis of the signal loss data obtained at 1900 MHz from three Base Transceiver Stations using the GRRN model in comparison with least square regression technique have also been provided. The predictive analysis has been evaluated by four key performance indexes, which are root mean square error, standard deviation error correlation coefficient and mean absolute error. In the figures, while the root mean square error between the Measured Signal loss Data and the GRNN model were found to1.85, 2.36and 4.06 dB in site 1 to 3, the LS regression model attained 3.85, 5.20 and 6.29dB respectively.

REFERENCES

[1] Holma, H. and A. Toskala, 2009. LTE for UMTS Evolution to LTE-Advanced, 2nd Edition, Wiley.

[2] Mahjabeen, D., A. Ahmed and S. Rafique, 2011. Use of LTE for the Interoperability between Different Generations of Wireless Communication, Int. J. Communications, Network and System Sciences (IJCNS), 4(7): 424-429.

[3] Mingjing Yang and Wenxiao Shi. A linear least square method of propagation model tuning for 3G radio network planning. In Fourth International Conference on Natural Computation, vol. 5, pp.150–154. IEEE, 2008.

[4] R.E. Schumacker, M.P. Monahan, and R. E. Mount., A comparison of OLS and robust regression using S-PLUS. Multiple Linear Regression Viewpoints, vol. 28(2), pp.10-13, 2002.

[5] Isabona, J, and K. Obahiagbon (2014) ‘‘RF Propagation Measurement and Modelling to Support Adept Planning of Outdoor Wireless Local Area Networks in 2.4 GHz Band, American Journal of Engineering Research, vol. 3, Issue-1, pp 58-67.

[6] Isabona, J and Konyeha. C.C (2013) ‘‘Urban Area Path loss Propagation Prediction and Optimisation Using Hata Model at 800MHz’’, IOSR Journal of Applied Physics (IOSR-JAP), Vol. 3, Issue 4, pp.8-18.

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

[8] Isabona, J and Isaiah. G.P (2013) ‘‘CDMA2000 Radio Measurements at 1.9GHz and Comparison of Propagation Models in Three Built-Up Cities of South-South, Nigeria’’, American Journal of Engineering Research (AJER), vol. 2, Issue-05, pp-96-106.

[9] Isabona, J, and Azi. S.O, (2013) ‘‘Enhanced Radio Signal Loss Prediction with Correction Factors for Urban Streets in the IMT-2000 Band’’, Elixir Space Science, vol. pp.15958-15962.

[10] Isabona, J, and Babalola, M (2013) ‘‘Statistical Tuning of Walfisch-Bertoni Pathloss Model based on Building and Street Geometry Parameters in Built-up Terrains’’. American Journal of Physics and Applications, vol. 1, pp. 10-16.

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

[12] Isabona, J and Konyeha. C.C. (2013) ‘‘Experimental Study of UMTS Radio Signal Propagation Characteristics by Field Measurement’’, American Journal of Engineering Research, vol. 2, Issue-7, pp. 99-106.

[13] Isabona, J, and Enagbonma, O.(2014) A Least Absolute Deviation Tuning Method to reduce Signal Coverage Loss Prediction Error in Electromagnetic Wave Propagation Channel optimization, International Journal of Basic and Applied Sciences, vol. 1, Issue 1, pp. 44-55.

[14] Isabona, J, and Azi. S.O, (2013) ‘‘Enhanced Radio Signal Loss Prediction with Correction Factors for Urban Streets in the IMT-2000 Band’’, Elixir Space Science, vol. pp.15958-1596233.

[15] Isabona, J, and Azi. S.O, (2012). ‘‘Optimised Walficsh-Bertoni Model for Pathloss Prediction in Urban Propagation Environment’’, International Journal of Engineering and Innovative Technology (IJEIT) Vol. 2, Issue 5, pp. 14-20.

[16] Östlin, E., Zepernick, H.J., and Suzuki, H. Macrocell Path loss Prediction Using Artificial Neural Networks: IEEE Transactions on Vehicular Technology, vol. 59, No. 6, 2010, pp. 2735-2744

[17] Abraham U. U., Okereke O. U. and Omizegba E. E. Macrocell path loss prediction using artificial intelligence techniques: International Journal of Electronics, 2013, pp 1-16.

[18] Joseph M. M, Callistus O. M, and Gabriel A. I. (2014). Application of Artificial Neural Network for Path Loss Prediction in Urban Macrocellular Environment. American Journal of Engineering Research-ISSN: 2320-084, 2014, pp. 270-275

[19] V.C. Ebhota, Isabona, J, and Srivastava, V.M. (2018), Base line knowledge on propagation modelling and prediction techniques in wireless communication networks, Journal of Engineering and Applied Sciences (JEAS),Vol. 13 (4), pp. 235-240.

[20] Ebhota, V.C. J. Isabona and V.M. Srivastava, (2018) Investigating Signal Power loss Prediction in A Metropolitan Island Using ADALINE and Multi-Layer Perceptron Back Propagation Networks, International Journals of Applied Engineering Research, vol. 13, (18), pp. 13409-13420.

[21] V.C. Ebhota, Isabona, J, and Srivastava, V.M. (2018), Improved Adaptive Signal Power loss Prediction using Combined Vector Statistics based Smoothing and Neural Network approach, Progress in Electromagnetic Research C, Vol. 82, 155–169.

[22] Isabona, J and V. M. Srivastava, "Hybrid neural network approach for Predicting Signal Propagation Loss in Urban Microcells," 2016 IEEE Region 10 Humanitarian Technology *Conference (R10-HTC), Agra, India, 2016, pp. 1-5.*

[23] C. Christodoulou, and M. Georgiopoulos, Applications of Neural Networks in Electromagnetics, Artech House, 2001

[24] S. Haykin, Neural Networks: A Comprehensive Foundation, IEEE Press, McMillan College Publishing Co., 1994.

Citation: *Kingsley Obahiagbon & Joseph Isabona, " Generalized Regression Neural Network: an Alternative Approach for Reliable Prognostic Analysis of Spatial Signal Power Loss in Cellular Broadband Networks", International Journal of Advanced Research in Physical Science (IJARPS), vol. 5, no. 10, pp. 35-42, 2018.*