

# Investigating Predictive Capabilities of RBFNN, MLPNN and GRNN Models for LTE Cellular Network Radio Signal Power Datasets

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**Abstract-** Efficient radio frequency signal coverage planning with well configured transmitters and receivers' communication channels, is the heart of any cost-effective cellular network design, deployment and operation. It ensures that both network quality and coverage are simultaneously make best use of (i.e. maximized). This work aim to appraise the adaptive learning and predictive capacity of three neural network models on spatial radio signal power datasets obtained from commercial LTE cellular networks. The neural network models are radial basis function neural network (RBFNN), multilayer perceptron neural network (MLPNN) trained with Bayesian regulation algorithms and general regression neural network (GRNN) models. Largely, it is established from the results that ANN prediction methods can tolerate and adapt to measurement errors of attenuating LTE radio signals. Performance comparisons reveal that all the neural network models can predict the propagated LTE radio signals with considerable errors. Specifically, RBFNN delivered the overall best performance with the smallest mean absolute percentage error, root mean square error, mean absolute error and standard deviation values. The GRNN model also gave better prediction results with marginal errors compared to the MLPNN. Thus, the predictive abilities of RBFNN and GRNN models can be explored as a useful tool to successfully plan or fine-tune mobile radio signal coverage area.

**Keywords-** Neural networks; Signal power; attenuating radio signals; radial basis function multilayer perceptron, general regression neural network, Adaptive signal prediction

## 1 INTRODUCTION

A number of researchers from both the science and engineering field across the globe have come up with various theories, models and procedures to predict attenuating propagated signals and estimate their path losses between two or more transmitting antennas and their respective receivers in radio frequency (RF) cellular networks. The main intents and tasks of radio network planning process are clearly to achieve or exceed the minimum radio signal network coverage needed to guarantee the required service quality at the user equipment terminals with minimal costs within cellular networks. This is particularly essential when introducing or deploying Mobile Broadband cellular networks on existing ones.

Thus far, the existing signal path loss estimation and prediction models as well as their theories and procedures have not been to acceptably predict the actual attenuating signal power when implemented for cellular network planning and deployment in propagation environment, other than the one with which they were initially designed (Neskovic et al., 2002; Mardeni & Kwan, 2010). For example, results from previous research works (e.g, Isabona & Isaiah, 2013; Isabona et al., 2013, Popescu, 2003), show that large prediction error exist between conventional prediction loss models and measurement signal loss data. The pressing need to surmount the above signal prediction challenges have in the past few years, led researchers to the domain of artificial neural network (ANN) modeling outfits. In most cases, the ANN has shown to be a better and preferred approach for nonlinear signal coverage data modeling (Neskovic, 2000; Baghirli, 2015; Isabona & Srivastava, 2016.). This can be ascribed to one of the key features on ANN, which is its capacity to extract and establish connection between input and output vectors, irrespective of the physical process involved.

The application of ANN models for predictive modelling and regression analysis in general, has become largely acknowledged and explored virtually in all disciplines. This is clearly seen from the rising number of publications in previous research works/academic literatures. This work aim to appraise the adaptive learning capacity of RBFNN, GRNN and MLPNN models on spatial signal power prediction. The objective is to validate their adaptive prediction efficiency and accuracy on the landscape of attenuating and fluctuating propagated radio signal power in LTE urban microcellular terrain.

## 2 METHODOLOGY

In this work, seven basic workflow processes as summarised in fig. 1, were explored to actualize the above highlighted research goal. The first stage is data collection, which was specified in input vector form. Then, the collected data is preprocessed to enhance systematized network learning. This is followed by building and configuring the relevant network. The network building/configuring comes after the weights and biases initializing. The next stage is training and validation.

This work considered a configured 2 hidden layered MLPNN, 0.001 error goal, 0.1 momentum value, 0.3 learning rate transig/purelin activation function for hidden/output layer, and the Bayesian regulation as training algorithm; a two layered RBFNN with a spread of 9, and 0.2 error goal; and a two layered GR-NN with 9 as spread. A 70%:15%:15% data division technique is adopted for optimal neural networks learning. The inputs and targets datasets were scaled to reside in the range [-1, 1] to enhance training and testing speed. Also, to avert overtraining, eliminate contemptuous impact stimulated by the initial values, and develop robust adaptive predictive ability, the early stopping measures were engaged for training and testing. Lastly, the neural

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network workflow process is finalized, ready for use and performance testing.

The adaptive prediction performances of the respective ANN model have been appraised using four experimental data sets obtained from the four LTE base station sites as described in the field test data collection procedure in fig.1. Also, for a deeper evaluation of the respective NN model's prediction accuracy with the experimental signal data, five different key statistical indexes as expressed in section 2.6

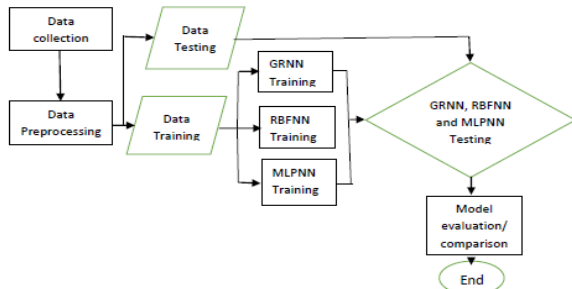


Fig. 1: Predictive Modelling Process Flowchart

### 2.1 FIELD MEASUREMENT

In cellular mobile networks, the user equipment (UE) or a moving mobile device makes continuous cell selection and handover so as to keep and maintain the best possible communication link in the network. In LTE mobile networks standard, the UE measures two relevant parameters to establish connection either in idle mode when waiting for a call or active mode during a call (Benedicic et al., 2014). The parameters are the Reference Signal Received Quality (RSRQ) and Reference Signal Received Power (RSRP). The radio signal power coverage prediction involves forecasting or estimating the outlook trends of underlying signal coverage data over a specific area.

Thus, for this work, the Reference Signal Received Power (RSRP) is the main signal data employed for signal coverage analysis and prediction. The RSRP data was collected from four operational base station (BS) transceivers, all which located in Waterline areas of Port Harcourt City with 4.8165° N, 7.0093° E coordinates. The Waterline is a typical urban area with a flat topography and mixed commercial and residential building edifices. With the aid of one Sony Ericson mobile phone, Samsung mobile phone, HP Laptop, scanner, all equipped with TEMS test software and housed in small Gulf car, field measurements round the four BS sites. The tools were connected, before embarking on the drive test. Every measurement locations with respect to longitude, latitude and measurement data points were acquired with the aid of a Garmin Etrex 10 GPS tool. The measurements covered all the major accessible parts of the LTE network target area, with over 5,000 data points, collected around the four base station sites. To eliminate or curtail small-scale fading effect on the measured RSRP values, all field test measurements were post-processed to a single median value (Belloul & Saunders, 2003). At every measurement distance ( $d$ ) from the BS, the RSRP is related to effective radiated power (ERP)

and propagation loss ( $PL_{mi}$ ) by the expressions in equations (1) and (2) (Ebhotu et al, 2018):

$$RSRP = ERP - PL_{mi} \quad (1)$$

$$ERP = P_{TX} - G_{TX} - CL_{TX} \quad (2)$$

where:  $G_{TX}$ , is the transmit antenna gain,  $P_{TX}$ , the transmitted power, and  $CL_{TX}$ , denotes transmission cable loss, all in dB.

### 2.2 MODEL EVALUATION

The following six performance indexes, namely, mean absolute percentage error (MAPE), root mean square error (RMSE), mean absolute error (MAE), standard deviation (STD), and correlation coefficient, have been engaged to evaluate the MLPNN, RBFNN and the GRNN prediction models. The mathematical definitions of these performance indexes are expressed in equations (3) to (7):

$$MAE = \frac{1}{N} \sum_{q=1}^N |y_q - d_q| \quad (3)$$

$$RMSE = \sqrt{MSE} = \frac{1}{N} \sqrt{\sum_{q=1}^N [y_q - d_q]^2} \quad (4)$$

$$MAPE = \frac{1}{N} \sum_{q=1}^N \left| \frac{y_q - d_q}{y_d} \right| \quad (5)$$

$$STD = \sqrt{\left( \frac{1}{N} \sum_{q=1}^N |y_q - d_q| - MAE \right)^2} \quad (6)$$

$$R = \frac{\sum_{q=1}^N (y_q - \bar{y}_k)(y_q - \bar{d}_k)}{\sqrt{\left[ \sum_{q=1}^N [(y_k - \bar{y}_k)^2] \right] \left[ \sum_{q=1}^N [(y_k - \bar{d}_k)^2] \right]}} \quad (7)$$

### 3 RESULTS AND ANALYSIS

For results comparative analysis, figs. 2 to 5 were plotted to show at how each of the NN prediction model adaptively match the measured signal power for site I to IV. The plotted graphs reveal that the RBFNN model prediction values are much closer to the measured signal data compared with the GRNN and MLPNN models. Tables 1 to 4 reveal the detailed summary of each NN model prediction accuracy on the signal data employing the six statistical indexes for the four sites. A high fluctuation of signal power along the coverage area in the graphs can be ascribed to the strong influence of the terrain obstructions such as vast density and tall building of blocks as well as the effect of non-uniform distribution of the buildings and other terrain features on the propagated radio signals.

The displayed graphs in figs. 6 to 11 are presented to reveal correlation coefficient performance fittings on the measured signal data along the test points. The prediction errors of each investigated models in terms of MAE, RMSE, MAPE and STD are provided in tables 1 to 4. The higher the distribution of prediction error in the scatter plots, the poorer the prediction performance. A large value of STD clearly reveals higher deviations of the predicted NN model values to that of the measured signal data. It is apparent from the results summary in

tables 1 to 4 that RBFNN delivered the overall best prediction performance in terms of MAE, RMSE, MAPE and STD values in all the study base station sites. RBFNN also attained best performance by having the highest R values. The optimum and superb performance of RBFNN can be attributed to its ability to adaptively make enhanced nonlinear mapping between input and output vector variables in dataset, provided that there are adequate amount of data samples. The GRNN model gave a preferable prediction marginal error results compared to the MLPNN. The poorer performance of MLPNN may be attributed its local minimum problem.

Table 1. GRNN, RBFNN and MLPNN Prediction Accuracy on Signal Power, site I

Parameter	GRNN,	RBFNN	MLPNN
MAE	1.309	0.066	1.686
MAPE	$1.30 \times 10^{-2}$	$6.57 \times 10^{-4}$	$2.58 \times 10^{-2}$
RMSE	1.806	0.575	1.742
STD	1.245	0.571	1.083
R	0.970	0.997	0.931

Table 2. GRNN, RBFNN and MLPNN Prediction Accuracy on Signal Power, site II

Parameter	GRNN,	RBFNN	MLPNN
MAE	0.846	0.339	1.859
MAPE	$9.30 \times 10^{-2}$	$3.70 \times 10^{-3}$	$8.80 \times 10^{-3}$
RMSE	1.363	0.896	3.840
STD	1.068	0.827	3.746
R	0.979	0.990	0.856

Table 3. GRNN, RBFNN and MLPNN Prediction Accuracy on Signal Power, site III

Parameter	GRNN,	RBFNN	MLPNN
MAE	3.016	0.327	3.438
MAPE	$2.94 \times 10^{-2}$	$3.70 \times 10^{-3}$	$3.29 \times 10^{-2}$
RMSE	4.420	0.734	4.964
STD	3.231	0.657	3.942
R	0.848	0.996	0.806

Table 4. GRNN, RBFNN and MLPNN Prediction Accuracy on Signal Power, site IV

Parameter	GRNN,	RBFNN	MLPNN
MAE	0.755	$3.73 \times 10^{-14}$	2.738
MAPE	$7.30 \times 10^{-3}$	$1.15 \times 10^{-16}$	$2.04 \times 10^{-2}$
RMSE	1.259	$4.19 \times 10^{-14}$	2.907
STD	1.008	$1.90 \times 10^{-14}$	2.808
R	0.995	0.999	0.969

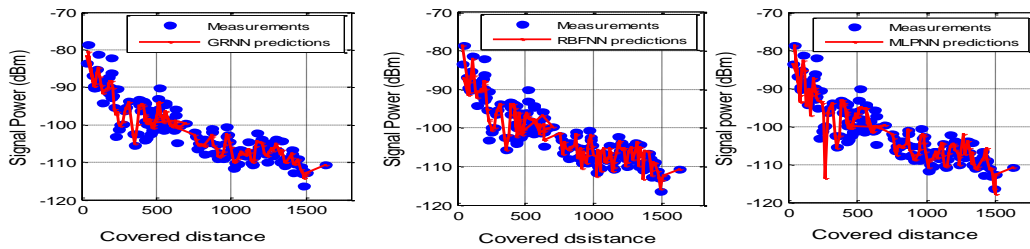


Fig. 2: Signal power prediction performance with GRNN, RBFNN and MLPNN models as function covered measurement distances in site I

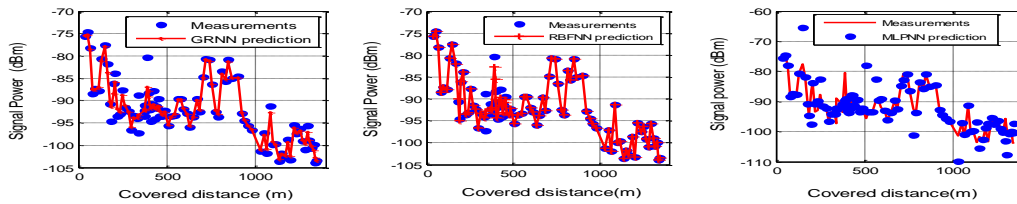


Fig. 3: Signal power prediction performance with GRNN, RBFNN and MLPNN models as function covered measurement distances in site II

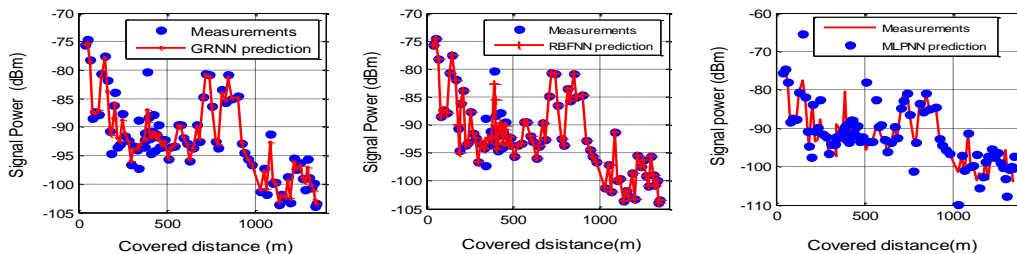


Fig. 4: Signal power prediction performance with GRNN, RBFNN and MLPNN models as function covered measurement distances in site III

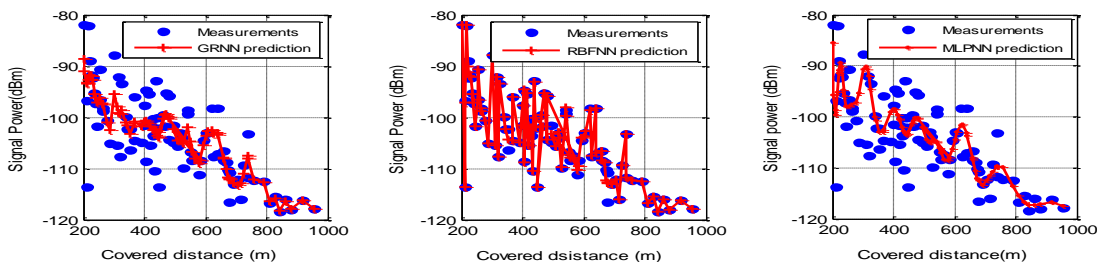


Fig. 5: Signal power prediction performance with GRNN, RBFNN and MLPNN models as function covered measurement distances in site III

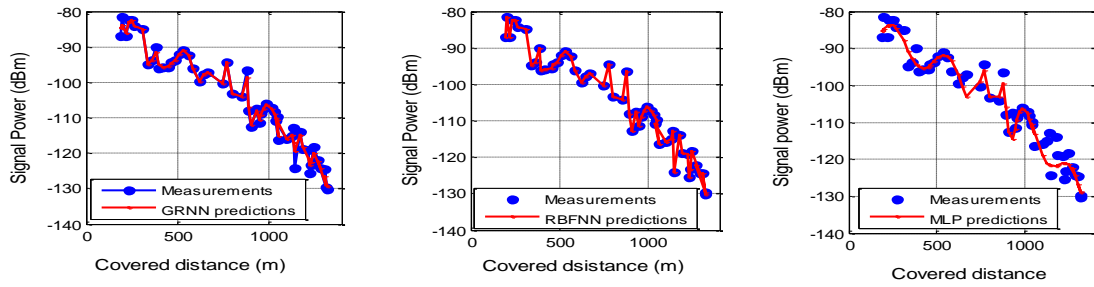


Fig. 6: Signal power prediction performance with GRNN, RBFNN and MLPNN models as function of covered measurement distances in site IV

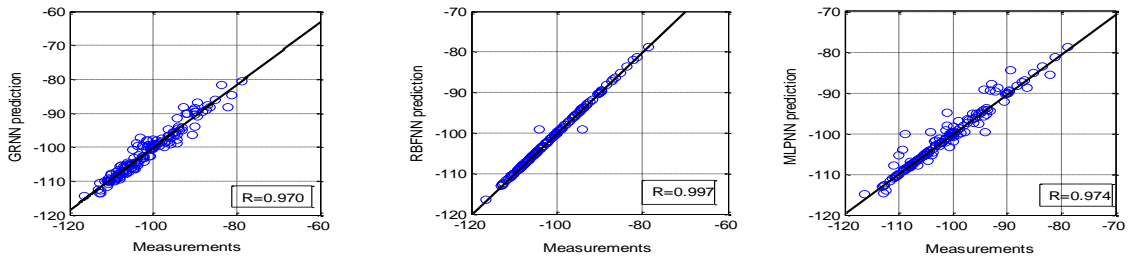


Fig. 7: prediction against measured signal power with GRNN, RBFNN and MLPNN models in site I

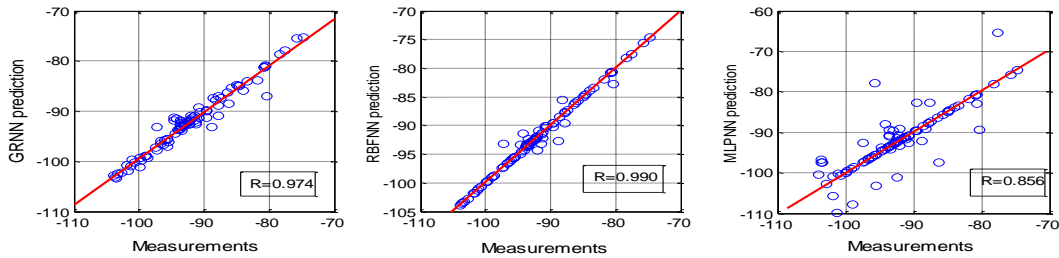


Fig. 8: prediction against measured signal power with GRNN, RBFNN and MLPNN models in site II

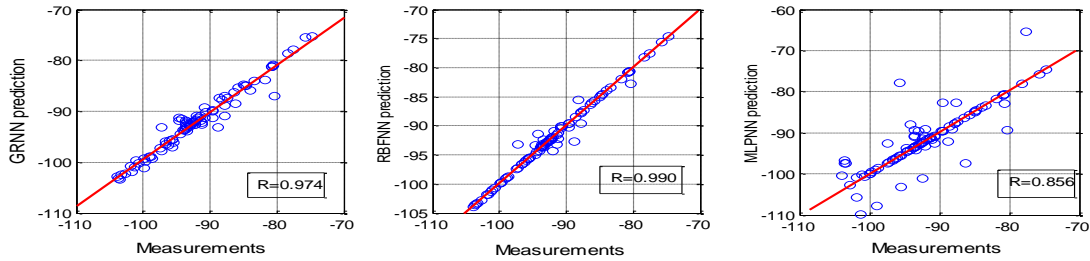


Fig. 9: prediction against measured signal power with GRNN, RBFNN and MLPNN models in site II

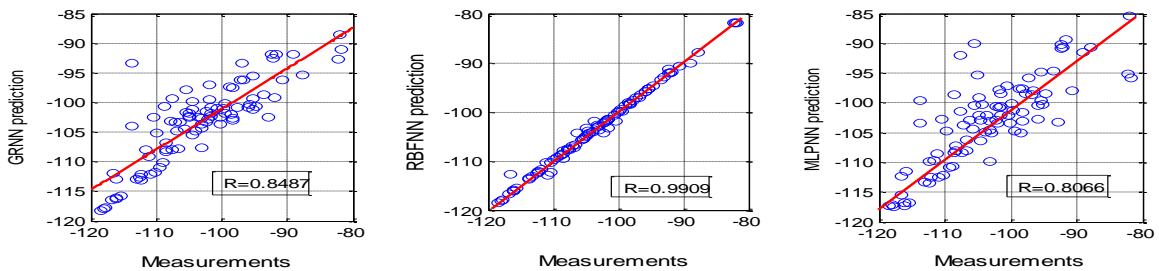


Fig. 10: prediction against measured signal power with GRNN, RBFNN and MLPNN models in site III

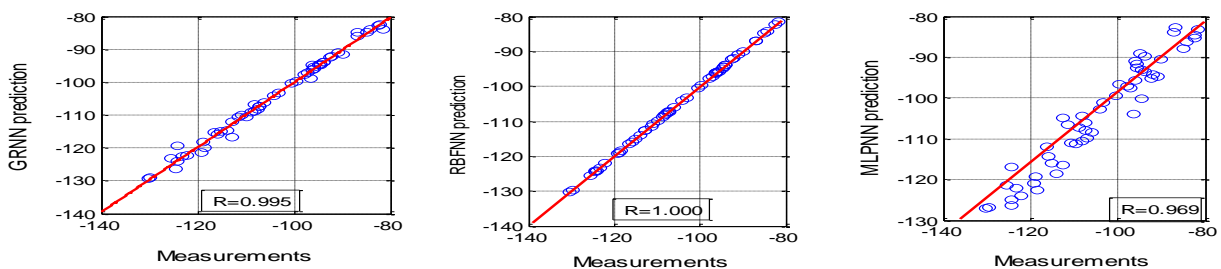


Fig. 11: prediction against measured signal power with GRNN, RBFNN and MLPNN models in site IV

## 4 CONCLUSION

Accurate prediction of propagated signal power play key role in planning an efficient signal coverage planning with well configured transmitters and receivers. Three different ANN soft computing methodologies have been explored in this work to predict the propagated radio signal power dataset of LTE cellular networks. Largely, it can be established from results that ANN prediction methods can tolerate and adapt to measurement errors of attenuating LTE radio signal datasets. Performance comparisons reveal that all of the ANN models used in this paper can predict propagated LTE radio signals with considerable errors. RBFNN delivered the overall best performance with the smallest MAE, RMSE, MAPE and STD values of training results. The GRNN model also gave better prediction results with marginal errors compared to the MLPNN. Thus, predictive abilities of RBFNN and GRNN models can be explored to successfully plan or fine-tune LTE radio signal coverage area.

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