# Performance Evaluation of Generalized Regression Neural Network Path loss Prediction Model in Macrocellular Environment

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***Abstract*— A path loss prediction model for macrocellular environment is presented. The model consists of generalized regression neural network (GRNN). Compared with some conventional path loss prediction models like the Free Space, Hata and Egli models, the proposed model shows superior prediction results. The GRNN model gives accurate prediction even in environments different from where the training samples were obtained**.

***Keywords—Path loss prediction, generalized regression neural network, macrocellular environment.***

## I. INTRODUCTION

Path loss prediction is a major consideration in the analysis and design of telecommunication systems. The propagation of radio waves is strongly influenced by the nature of the environment. One of the difficulties in mobile communication systems is that at least one of the mobile units is situated in a very low height of between 1.5m to 3.0m above the ground, and so the propagation of radio waves will be substantially influenced by the surface of the terrain such as hills, buildings and vegetations. In such cases the calculation of only free space path loss does not have sufficient accuracy because other factors in the environment were not considered in the calculation. To achieve a reasonable accuracy, other things in the environment and the effects of reflection, diffraction, etc, should be considered in the calculation. Outdoor propagation environments can be classified into three: urban, suburban and rural environments.

Several models have been proposed for predicting path loss. The conventional models can be grouped into two categories: empirical and deterministic models. Empirical models, which include Okumura, Hata, Egli, and COST-231 [1, 2], are based on measurement campaigns carried out in specific representative environments. These models have the advantage of computational efficiency, but they may not be very accurate when applied without modification in different propagation environments [3]. In the deterministic models, field strength is calculated using such techniques as the geometrical theory of wave diffraction and ray-tracing technology. The major advantage of deterministic approach is its precision, but it requires detailed information about the propagation environment, and very long computation time [2, 4, 5].

In recent studies, artificial neural network (ANN) models have successfully been applied in the prediction of path loss in rural, urban, and indoor environments [6, 7, 8, 9, 10, 11]. ANN models bring together the gains of empirical and deterministic models. Because of its intrinsic parallelism, ANN has high processing speed and can process large volume of data [12]. ANN models have the flexibility to adapt to different environments; they can be trained to perform well in environments similar to where the training data are collected.

## II. GRNN ARHITECTURE

An alternative method to path loss prediction based on generalized regression neural network (GRNN) is also proposed. By definition, the regression of a dependent variable $\boldsymbol{y}$ on an independent variable $\boldsymbol{x}$ estimates the most probable value for $\boldsymbol{y}$, given $\boldsymbol{x}$ and a training data. The regression method will produce the estimated value of y that minimizes the mean square error, *mse,* [13, 14, 15]. GRNN is based on nonlinear regression theory for function estimation.

GRNN is a special case of radial basis function (RBF). The characteristic feature of the radial basis functions is that their response decreases (or increases) monotonically with distance from a central point. Functions that depend only on the distance from a centre vector are radially symmetric about that vector, hence the name radial basis function. The radial basis function has a maximum of 1 when its input is 0 [16]. As the distance between weights $\boldsymbol{w}$ and input $\boldsymbol{x}$ decreases the output increases. The major difference between GRNN and RBF is the method that the weights $w_{ij,}$ are determined. Instead of training weights, the GRNN assigns the target value directly to the weights, $w_{ij}$, from the training set associated with input training vector and a component of its corresponding output vector [14].

Compared with the standard feedforward neural networks, GRNN has a relatively simple and static structure [16]. It is made up of the input layer, one hidden radial basis layer, and an output linear layer

[16, 17, 18]. The transformation of data from the input layer to the hidden layer is non-linear, while the transformation from the hidden layer to the output layer is linear. GRNN is a one-pass learning algorithm with a highly parallel network. GRNN does not require an iterative training procedure, and it trains rapidly without any training pathologies such as paralysis or local minima problems that characterize standard feedforward network [14, 19, 20].

It is generally used for function approximation. It approximates any arbitrary function between input and output vectors, drawing the function estimate directly from the training data. Unlike the standard feedforward network, GRNN trains the weight by assigning to $w_{ij}$ the target value directly from the training set associated with input training vector, *i* and component *j* of its corresponding output vector [14, 20].

The regression of ***y*** on ***x*** is given by [13, 15, 20]

$$E[y|X] = \frac{\int_{-\infty}^{\infty} y f(X,y)dy}{\int_{-\infty}^{\infty} f(X,y)dy} \quad (1)$$

where E[y|X] is the expected value of output, given the input vector; ***x*** is the input vector; ***y*** is the output vector; f(X,y) is the joint probability density function (pdf) of ***x*** on ***y***.

The function value is estimated optimally as [19]

$$y_i = \frac{\sum_{i=1}^{n} h_i w_{ij}}{\sum_{i=1}^{n} h_i} \quad (2)$$

where $w_{ij}$ = the target output corresponding to input training vector $x_i$ and output *j*; $h_i = \exp[-D^2/(2\sigma^2)]$, the output of a hidden layer of neuron; $D_i^2 = (x-u_i)^T(x-u_i)$, the squared distance between the input vector *x* and the training vector *u; σ* = smoothing factor, a constant controlling the size of the receptive region; *n* is the number of samples.

The input parameters strongly influence the performance of GRNN model. The model presented in this paper has the following as input parameters: distance between base station transmitter and mobile receiver *(d, in metres)*, carrier frequency (*f, in MHz*), street orientation (*ɵ, in degrees*), height of base station antenna *($h_{BS}$, in metres,)*, height of building ($h_b$, in metres), separation distance between buildings ($\Delta h_e$, *in metres*), difference between base station antenna height and building height *($\Delta h_f$,* in metres*)*, height of mobile antenna *($h_{ms}$,* in metres*)*, difference between building height and mobile antenna height *($\Delta h_g$,* in metres*)*, street width *(sw,* in metres*)*, base station transmitter output power *($BS_{pr}$,* in dB*)*, transmitter antenna gain *($G_t$,* in dB*)*, receiver antenna gain *($G_r$,* in dB*)*, free space transmission path loss *($L_{fs}$,* in dB*)*.

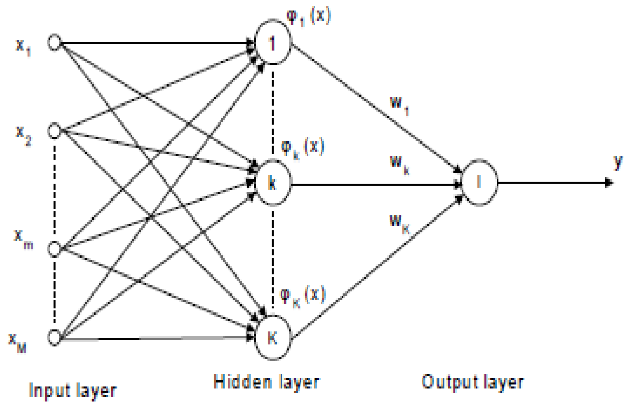


**Fig.1** Generalized Regression Neural Network Architecture [19]

The proposed model used the neural network toolbox of *MATLAB 7.5* [16], Non-linear radbas and special linear activations are used at the hidden and output layers respectively. The GRNN model is trained on measurement data set of propagation path loss taken in an urban environment. The learning process is equivalent to finding a surface in a multidimensional space that provides a best fit to the training data; the criterion for 'best fit' being measured in statistical sense. The generalization is equivalent to the use of this multidimensional surface to interpolate the data set [18].

## III. METHODOLOGY

To evaluate and tune the network model, measured data is needed [5, 21]. With the aid of a laptop computer, *Hewlett Packard, Model HP 620*, the proposed model was trained with physical data that characterized the input parameters. The work presented in this paper used the field strength measurement conducted in Uyo, Akwa Ibom State Nigeria, at a carrier frequency of 870.52MHz [22]. A set of path loss data recorded at distances of 1km to 5km between transmitter and receiver was used in the training. 2100 measurement samples were used to test the model and to compare it with Free-space, Hata, Egli, and MLP-ANN models.

Particular to the GRNN is the use of the smoothing factor, *σ,* which alters the degree of generalization of the network. Therefore, a range of smoothing factors and methods for selecting smoothing factors are tested in the study in order to determine the optimum smoothing factors for model inputs. In this network, there are no training parameters such as the learning rate, momentum, optimum number of neurons in the hidden layer, and learning algorithm as in backpropagation network, but there is a smoothing factor which its optimum value is gained by trial and error. The smoothing factor has to be greater than 0 and can usually range from 0.1 to 1 with good results [23]. Tables 1(a) and (b) give a summary of the execution time (in seconds) and the different values of *σ* (the smoothing factor) for training the network, and their corresponding *mse* values.

**Table 1(a)** Summary of the smoothing factor, *mse* value and execution time for the network training.

| S/N | Smoothing factor, $\sigma$ | *mse* value (dB) | Execution time (sec) |
|---|---|---|---|
| 1 | 0.10 | 0.0 | 0.112 |
| 2 | 0.15 | 0.0 | 0.115 |
| 3 | 0.20 | 0.0 | 0.109 |
| 4 | 0.25 | 0.0 | 0.113 |
| 5 | 0.30 | 0.0 | 0.114 |
| 6 | 0.35 | 0.0 | 0.108 |
| 7 | 0.40 | $1.23 \times 10^{-253}$ | 0.124 |
| 8 | 0.45 | $2.67 \times 10^{-187}$ | 0.143 |
| 9 | 0.50 | $7.55 \times 10^{-140}$ | 0.121 |
| 10 | 0.55 | $9.71 \times 10\text{-}^{105}$ | 0.115 |
| 11 | 0.60 | $4.89 \times 10^{-78}$ | 0.111 |
| 12 | 0.65 | $2.96 \times 10^{-57}$ | 0.109 |
| 13 | 0.70 | $9.13 \times 10^{-41}$ | 0.131 |
| 14 | 0.75 | $1.83 \times 10^{-27}$ | 0.112 |
| 15 | 0.80 | $1.41 \times 10^{-16}$ | 0.112 |
| 16 | 0.85 | $1.49 \times 10^{-7}$ | 0.123 |
| 17 | 0.90 | 5.43 | 0.101 |
| 18 | 0.95 | $1.48 \times 10^{3}$ | 0.125 |
| 19 | 1.00 | $1.48 \times 10^{3}$ | 0.110 |

**Table 1(b)** Summary of the smoothing factor, *mse* value and execution time for the network training.

| S/N | Smoothing factor, $\sigma$ | *mse* value (dB) | Execution time (sec) |
|---|---|---|---|
| 1 | 0.850 | $1.49 \times 10^{-7}$ | 0.123 |
| 2 | 0.855 | $9.76 \times 10^{-7}$ | 0.132 |
| 3 | 0.860 | $6.19 \times 10^{-6}$ | 0.126 |
| 4 | 0.865 | $3.80 \times 10^{-6}$ | 0.114 |
| 5 | 0.870 | $2.26 \times 10^{-3}$ | 0.113 |
| 6 | 0.875 | 0.0013 | 0.119 |
| 7 | 0.880 | 0.0073 | 0.117 |
| 8 | 0.885 | 0.0398 | 0.111 |
| 9 | 0.890 | 0.2108 | 0.120 |
| 10 | 0.895 | 1.0844 | 0.123 |
| 11 | 0.900 | 5.4293 | 0.126 |
| 12 | 0.905 | 26.4691 | 0.113 |
| 13 | 0.910 | 125.73 | 0.126 |
| 14 | 0.915 | 582.16 | 0.110 |
| 15 | 0.920 | $1.4811\times 10^{3}$ | 0.116 |
| 16 | 0.925 | $1.4811 \times 10^{3}$ | 0.121 |
| 18 | 0.930 | $1.4811 \times 10^{3}$ | 0.116 |
| 19 | 0.935 | $1.4811 \times 10^{3}$ | 0.121 |
| 20 | 0.940 | $1.4811 \times 10^{3}$ | 0.118 |
| 21 | 0.945 | $1.4811 \times 10^{3}$ | 0.114 |
| 22 | 0.950 | $1.4811 \times 10^{3}$ | 0.131 |

## IV. RESULTS

Table 2 represents the test and performance results of Free space path loss, Hata, Egli [22], MLP-ANN [11] and GRNN models. GRNN with different input parameters is evaluated by comparing its prediction error statistics of mean square error, *mse.* With *mse* value of 1.0844dB, the proposed GRNN model shows superior path loss prediction results.

**Table 2**. Path performance results:

| Prediction models | Mean square error *(mse)* |
|---|---|
| Free space | 16.24dB |
| Hata | 2.37dB |
| Egli | 8.40dB |
| MLP-ANN | 1.68dB |
| GRNN | 1.0844dB |

## V. OBSERVATIONS

From Table 1(a) it was seen that the GRNN network has far less execution time when compared with the MLP-ANN network which has execution time of 0.912seconds [11]. It was also noticed that the *mse* values were approximately 0.0dB for $\sigma$ values of 0.10 to 0.85, and then it increased rapidly from 0.0dB to $1.48 \times 10^3$dB for $\sigma$ values of 0.85 to 1.00. Because of that the, $\sigma$ values of 0.85 to 1.00 were further increased by a step of 0.005, and the result of the computation was as shown in Table 1(b). From the Table 1(b) $\sigma$ value of 0.895 was chosen and a corresponding *mse* value of 1.0844dB was obtained for the GRNN structure. This *mse* value was superior to the one that was obtained with the MLP-ANN model.

## VI. CONCLUSION

The proposed GRNN model is for path loss prediction in urban macrocellular propagation environment. Superior results were obtained when its performance was compared with the predictions made by different empirical models. Another important advantage of the model is the fact that unlike the deterministic approach, the GRNN model is simpler and computationally faster. It achieved the stated improvement without going through the rigorous problems of having a substantial and precise knowledge of the propagation environments.

Also the GRNN model does not require an iterative training procedure like the MLP-ANN model. It trains rapidly without encountering the problems of local minima that characterize standard feedforward network.

## VII. RECOMMENDATIONS

The GRNN model is just introduced in a simple way. To further improve the performance and the generalization property of the model, more input variables such as land usage, terrain clearance angle and vegetation density can be incorporated in the system.

Based on the relative advantages of the model over the conventional models, telecommunication companies can improve their services by the GRNN model in the design and analysis of their budget link.

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