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Application of Artificial Neural Network For Path Loss Prediction In Urban Macrocellular Environment

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Abstract: **-** An artificial neural network model for the prediction of path loss in urban macrocellular environment is presented. The model consists of a multilayer perceptron trained with measured data using Scaled Conjugate Gradient algorithm. Comparison between the proposed model on one hand, and the free space, Hata and Egli models on the other hand shows a better prediction result. With the proposed ANN model a good generalization is achieved, and it is accurate in environments different from the one used in training the network.

Keywords:- *Artificial neural network, path loss, prediction, macrocellular environment.*

I. INTRODUCTION

Path loss prediction is a crucial task in the design and planning of network in modern mobile communication system. A great variety of models has been proposed for predicting path loss. These models can generally be grouped into two categories; empirical models and deterministic models. Empirical models like the Okumura, Hata and COST-231 models [1, 2] are based on measurements of electric field strength carried out in specific representative environment. The empirical models are computationally efficient, but they may not be very accurate in different propagation environment without modifications [3]. On the other hand, the deterministic models such as the geometrical theory of wave diffraction, ray-tracing technology are very accurate. But the problem with the deterministic models is that it requires excessive computational time, and it needs detailed information of the environment [2, 4].

In recent studies, artificial neural network (ANN) models have successfully been applied in the prediction of path loss in rural, urban, and indoor environments [5, 6, 7, 8, 9]. 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. ANN models have the flexibility to adapt to different environments. An ANN prediction model can be trained to perform well in environments similar to where the training data are collected.

To develop an ANN model that is accurate and generalizes well, measurement data from different environments are applied in the training process. There are many methods of improving the performance of the training process. These include Resilient Backpropagation, Scaled Conjugate, Fletcher-Powell Conjugate Gradient, Conjugate Gradient with Powell/Beale Restarts, Levenberg-Marquardt and BFGS Quasi-Newton algorithms. Each algorithm has its advantages and disadvantages, but their suitability depends on actual application situations.

Also the input parameters strongly influence the performance of ANN model, therefore the choice of inputs to be used become imparative. The ANN model presented in this paper has the following inputs: distance between base station transmitter and mobile receiver *(d)*, carrier frequency (f), street orientation (θ), height of base station antenna (h_{BS}), height of building (h_b), separation distance between buildings (Δh_e), difference between base station antenna height and building height (Δh_f), height of mobile antenna (h_{ms}), difference between building height and mobile antenna height (Δh_g), street width *(sw)*, base station transmitter output power (BS_{pr}), transmitter antenna gain (G_t), receiver antenna gain (G_r), free space transmission path loss (L_{fs}).

II. ARTIFICIAL NEURAL NETWORK MODEL

The basic features of the ANN is for it to be able to create its own internal model of behavior of radio waves by just observing the measured data [10]. Measured data have inherent behavior of the network from where it was collected imbedded in it; as such some measured data are needed for the creation of ANN model. Later on, this internal model can be used for predicting path loss values in the places where the measurements were not made by generalizing the observed measured values.

The work presented in this paper is modeled as multilayer perceptron (MLP) consisting of input layer, one hidden layer and an output layer [11]. The tan-sigmoid and linear activation functions were used in the hidden layer and output layer respectively.

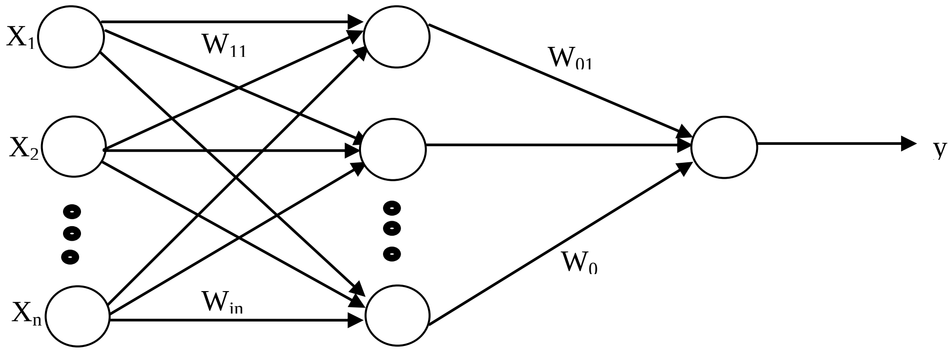


Figure 1. Configuration of multilayer perceptron.

Two kinds of signals propagate through the network [7]:

a. The input signals that are fed at the input port of the network, and propagate forward (neuron by neuron) through the whole structure and reach the output end as output signals.
b. The error signals that originate at the output port and proceed backward (layer by layer) through the structure.

The output of the system is described by the following equation [7, 12, 13]:

$$y = F_0\{\textstyle\sum_{j=0}^{M} w_{0j}\ [F_h \sum_{i=0}^{N}(w_{ij}\, x_{ij}\,)]\} \qquad (1)$$

where N = number of neurons in the input layer, M = number of neurons in the output layer
w_{0j} = synaptic weights from jthneuron in the hidden layer to the single output neuron.
w_{ij} = the connection weights between the neurons of the hidden layer and the input layer
x_{ij} = the ith element of the input vector
F_h = activation function of the hidden layer, F_0 = activation function of the output layer

The training parameters such as weight values, bias values, pre-processing and post-processing functions were selected in default way. The system parameters such as the weight and threshold values are adjusted by the training process. The training phase of the network continues by adaptively adjusting these parameters based on the mean square error, *mse*[4, 14], between the predicted value and the measured data for a selection of appropriate set of training examples.

$$mse = \frac{1}{N}\textstyle\sum_{i=1}^{N}(y_i - d_i)^2 \qquad (2)$$

where y_i = output value calculated by the network, d_i = expected or predicted output, N = number of samples.

When the error between the network output and the predicted output is minimized the training process is terminated. The network can then be used in a testing phase with test vectors. At that stage the network is described by the optimum configuration of the weights.MLP network of different sizes and six different algorithms were compared to determine the fastest algorithms, prediction accuracy, generalization properties and the optimal configuration for the proposed ANN model.

A **Hewlett Packard** laptop computer, ***Model HP 620***, was used for the experiments. Accordingly, 14 variables were presented to the input layer of the network structure, and the number of neurons in the hidden layer was varied from 9 to 20. Table 1 gives a summary of the execution time (in seconds) for training the network with different algorithms. Each entry in the table is the mean value of 10 different trials (with different random initial weights in each trial). For the BFGS Quasi-Newton algorithm, 5 trials were carried out in each entry. In each case, the network is trained until the minimum value of the mean squared error (***mse***) is obtained.

Table 1: Execution time (in seconds) for different training algorithms.

S/N	Types of Algorithm	NUMBER OF NEURONS IN THE HIDDEN LAYER											
		9	10	11	12	13	14	15	16	17	18	19	20
1	Scaled Conjugate Gradient	0.863	0.878	0.878	0.903	0.905	0.912	0.925	0.926	0.935	0.956	0.974	0.986
2	Resilient Backpropagation	0.890	0.905	0.919	0.920	0.922	0.928	0.932	0.937	0.942	0.962	0.977	0.998
3	Fletcher-Powell Conjugate Gradient	0.895	0.918	0.927	0.936	0.937	0.942	0.944	0.946	0.968	1.005	1.006	1.080
4	Conjugate Gradient with Powell/Beale Restarts	0.898	0.934	0.945	0.986	0.994	0.997	1.000	1.004	1.013	1.016	1.018	1.168
5	Levenberg-Marquardt	8.89	11.62	18.19	20.77	27.24	32.75	34.48	44.96	53.50	58.00	63.14	75.78
6	BFGS Quasi-Newton	51.96	79.36	82.78	151.71	155.90	204.60	292.94	99.44	354.53	356.74	413..60	491.43

For the network structures considered in Table 1, Scaled Conjugate Gradient is the fastest training algorithm, followed closely by Resilient Backpropagation, Fletcher-Powell Conjugate Gradient, and Conjugate Gradient with Powell/Beale Restarts algorithms in that order.

Scaled Conjugate Gradient and Resilient Backpropagation algorithms were further compared to find out which one of them had a lower **mse** value (using 1000m as the separation distance between the transmitter and receiver). The summary of the result is given in Table 2.

Table 2: Mean value of mse for a separation distance of 1000m between transmitter and receiver

S/N	Types of Algorithm	NUMBER OF NEURONS IN THE HIDDEN LAYER											
		9	10	11	12	13	14	15	16	17	18	19	20
1	Scaled Conjugate Gradient	*1.78*	*1.70*	*1.69*	*1.76*	*1.74*	*1.67*	*1.78*	*1.76*	*1.75*	*1.73*	*1.71*	*1.79*
2	Resilient Backpropagation	*2.08*	*2..00*	*2.05*	*\2.09*	*2.06*	*2.16*	*2.00*	*1.98*	*2.15*	*2.04*	*2.78*	*2.20*

From the data in Table 2, Scaled Conjugate Gradient algorithm had lower **mse** values for the respective network structures. This algorithm was selected for training the network and to create an effective model that can make proper path loss predictions. The optimal number of neurons in the hidden layer is obtained by searching for the best convergence of the network during the training process. From Table 2 the network structure with 14 hidden neurons had the least **mse** value, and as such it was chosen for the model.

III. METHODOLOGY

Measured data is needed to evaluate and tune the ANN model [10] so that the network can create its own model of behavior of radio waves. The network has to be trained by some examples of correct pairs of inputs/outputs. These pairs are based on measured samples of field strength in various conditions.

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 [14]. 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. The sample set was randomly divided into three sub-groups. 60% of the data for training the network, 20% was used to validate the network generalization. Training continues as long as it decreases the network's error on the validation vectors. When the network memorizes the training set, training is stopped to avoid the problem of over-fitting [6].

Finally, the last 20% of the data is used for performance evaluation of the network model; it is an independent test of network generalization of data that the network has not seen.

MLP network of different sizes were analyzed to determine the network complexity required to obtain accurate path loss predictions. To reduce the training time and still maintain the prediction accuracy and generalization property Scaled Conjugate Gradient algorithm was used to train the network. This algorithm is generally faster than the others and very ideal for the network model.

During the training phase the characteristics of the network were modified by this iterative algorithm until a minimum error is obtained, that is the error between the network (predicted) output and the desired (measured) output is minimized. The training phase operates based on the mean squared error (2) between predicted path loss and measured path loss for a set of properly selected training examples [3].

The purpose of the prediction model includes generation of minimal errors for the training examples, and to perform well with examples not used in the training operation. The generalization property of the network is very important in practical prediction situations where the intention is to use the path loss prediction model to find the coverage area of potential transmitter locations for which no or limited information are available [7].

IV. RESULTS

Our objective was to design an ANN model that can accurately predict propagation path loss. 2100 measurement samples, which were shared in the ratio of 60%, 20% and 20%, were used to respectively train, validate and test the network. The performance of the ANN model was evaluated by making a comparison between expected and measured values based on mean squared error, *mse*.

Table 3 represents the result of the ANN model in terms of *mse*. Also indicated in the table is the separation distance, (d), between the transmitter and the receiver, and the corresponding values of *mse*.

Table 3: Mean squared error values, *mse*, of the ANN model:

Separation distance (d)	***mse* (dB)**
1km	2.52
2km	2.35
3km	1.31
4km	1.53
5km	0.68
Average	1.68

Furthermore, Table 4 presents the *mse* value of the ANN model and those contained in [14]. The ANN model was shown to have a better performance.

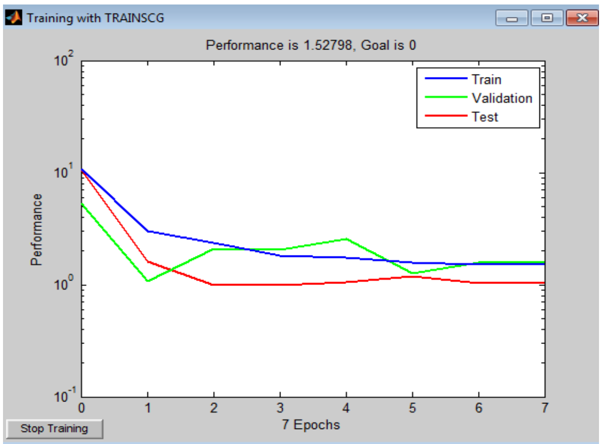
Table 4: *mse* values for Free space path loss, Hata, Egli and ANN models.

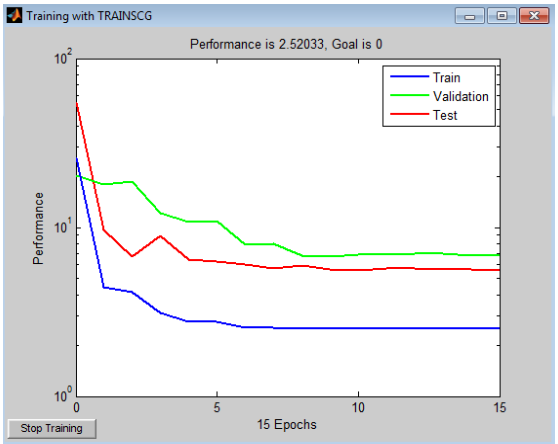
Free space path loss (dB)	**Hata model (dB)**	**Egli model (dB)**	**ANN model (dB)**
16.24	2.37	8.40	1.68

From Table 4, the ANN model has an average value of 1.68dB. This is acceptable because it is below the minimum value of 6dB for good signal propagation.

V. OBSERVATIONS

Some observations were made during the training process. It was noticed that different results were obtained each time the network was trained. This was as a result of different initial weight and bias values, and different divisions of measured data into training, validation and test sets [11]. Thus it is possible that different artificial neural structures trained on the same problem can generate different outputs for the same input. To actualize a neural network of good accuracy it is necessary to retrain several times. Another thing that should be noted is that the network is sensitive to the number of neurons in the hidden layer. When the number is few it leads to underfitting but when the number is too many it causes overfitting.





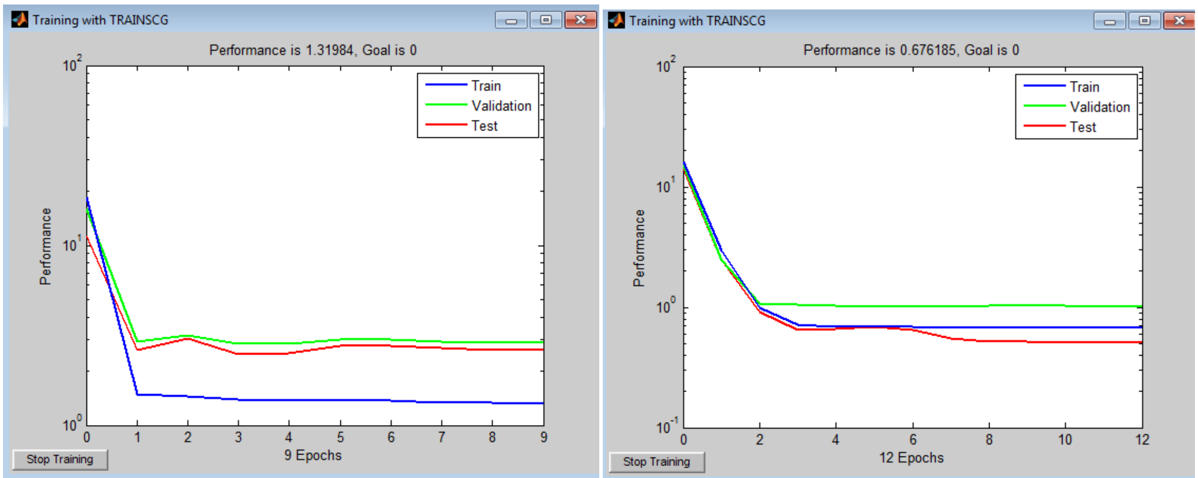


Figure 2. Some results of the network performance .

VI. CONCLUSION

The ANN model thus developed is for path loss prediction in urban macrocellular propagation environment. Its performance was compared with the predictions made by different empirical models. It is noticed that due to its generalization property the ANN model has significant improvement over the other models. The model has the ability to perform interpolation or extrapolation if test data exceed the training data space. Also because the model is trained with measured data, it makes the included propagation effect more realistic.

Another important advantage of the model is the fact that unlike the deterministic approach, the ANN 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.

VII. RECOMMENDATIONS

The ANN 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 empirical and deterministic models, telecommunication companies in Nigeria can improve their services by the ANN model in the design and analysis of their budget link.

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