

Effect of Training Algorithms and Network Architecture on the Performance of Multi-Band ANN-Based Path Loss Prediction Model

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Abstract: The propagation of Electromagnetic waves signal in terrestrial frequency bands in a build-up environment is affected by many factors, leading to signal degradation, diffraction, reflection, scattering, among others. Furthermore, the physical layer interface is one of the most critical factors needed to be carefully analyzed for optimum design of wireless systems. In view of these, several channel models were proposed to optimally predict how radio waves behaves in a typical built-up and complex environments. In the case of Nigeria, when these propagation models are considered at disparate environment, a many of them are susceptible to tremendous prediction error. Hence, there is a need to develop a model suitable for such an environment to minimize errors. This paper used Scale Conjugate and Levenberg-Marquardt algorithms to develop a multi-frequency bands ANN-based path loss prediction model. Furthermore, the paper investigated the effect of ANN system parameters on the model's performance. Findings revealed that Standard Deviation Error (SDE) and the Correlation Coefficient (R) depend on the model's network architecture. In addition, the Levenberg-Marquardt algorithm fits the network with complex structures compared to the scale conjugate algorithm. It was further discovered that increment of the number of hidden neurons, ordinarily, does not, in the same way, means an increase in the performance of the model.

Keywords— Hidden Neurons, Training Algorithms, ANN, Path Loss, VHF, UHF.

I. INTRODUCTION

The mobility concept is one of the key strengths in the wireless system, which consumers widely accept, and its application spans different economic sectors, including health, education, agriculture, to mention a few. Over two decades, mobile communication system have been the most dominant amongst the wide range of wireless systems been deployed [1]. The bedrock of successful deployment of wireless system rely on good designing and adequate planning. When a radio signal propagates between two end (i.e. transmitter and receiver) it will always experiences diverse environmental conditions. The radio wave signal propagating in an non-obstructed medium

will experience minimal propagation loss, which is known as the free-space model (FSPL) [2].

The radio signal that travels along a path or medium is always subjected to the nature of the environment, which greatly have an influence on the received power at the receiver [3-4]. Therefore, a radio designer or engineer requires to know the topology of the environment, frequency of operation, and location in order to estimate the received signal based on accurate path loss model. Therefore, there is a need to optimize and enhance a well-developed path loss, which will depend on a specific area. Optimizing a path loss model can enrich an RF engineer to fine-tune and choose appropriate system parameters and values for effective network deployments. These system parameters may include the base transceiver station, height, power and operating frequency [5-6]. Path loss models are broadly classified into three categories and these are: Deterministic, Experimental or measurements and Physical Models.

The empirical models have been extensively used to estimating the behaviour of RF signals due to their ease of use and non-complexity. Empirical models requires less computational effort but does not totally examine all the physical composition of the environments. As such, they are susceptible to high prediction errors when applied to a disparate environments, and this has been attended by the works presented in [7-15], when some of the models were tested in typical Nigerian terrain. This, thus, necessitated the need to tune some of the model parameters in other to minimize the errors [3][5][6][14]. Deterministic and physical models, on the other hand, are computationally expensive. This, therefore, leads to the evolution of computational methodologies like the Artificial Neural Networks (ANN) based models [1][16][17-25] for path loss predictions. In recent times, considering its hardy performance, much focus has been beamed into using computational intelligence technique for path loss prediction. This paper, therefore, investigated the effect of the Neural network system parameters such as the hidden neurons,

network architecture and training algorithms on the performance of ANN-based models for path loss prediction in the multi-frequency bands within different complex terrain environments.

II. ARTIFICIAL NEURAL NETWORK (ANN)

Artificial Neural Network (ANN) is a suitable technique for solving prediction issues and developing path loss models [21].

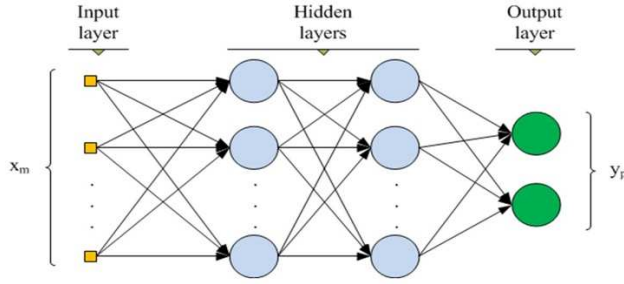


Fig 1: MLP Artificial Neural Network

A multilayer perceptron can be sub-divided into three parts: the input layer (i.e source nodes), hidden layers (which can be one or more), and an output layer shown in Figure 1; that consists of one or more neurons. A typical ANN as a stimulus $\mathbf{x}(m)$ which is applied to the input layer, and transverses different neurons, to produce a functional output signal y_p at the output layer j of the neuron. The error at the output layer p of the neuron is defined in (1):

$$e_p(m) = d_p(m) - y_p(m) \quad (1)$$

Where $d_p(m)$ is the i th member of the desired-response vector $\mathbf{d}(m)$. In (2), the instantaneous error energy of neuron p is defined as:

$$\mathcal{E}_p(n) = \frac{1}{2} e_p^2(m) \quad (2)$$

Adding the error-energy of all neurons in y_p , will produce a total instantaneous error energy for the ANN, which is shown in (3) and (4):

$$\mathcal{E}_p(m) = \sum_{j \in C} \mathcal{E}_j(m) \quad (3)$$

$$= \frac{1}{2} \sum_{j \in C} e_p^2(m) \quad (4)$$

Where all neurons in y_p are members of set C , and m training samples are contained in M , and the average energy error $\mathcal{E}_{av}$ over the training sample is defined in (5) and (6):

$$\mathcal{E}_{av}(M) = \frac{1}{M} \sum_{m=1}^M \mathcal{E}(m) \quad (5)$$

$$= \frac{1}{2M} \sum_{m=1}^M \sum_{j \in C} e_p^2(m) \quad (6)$$

III. TRAINING ALGORITHMS

The training algorithm works by updating the weights of the network at each iteration by the decision function. It is an

excellent bottleneck to decide the particular training algorithm to produce the best results [25-26]. The at the end of each iteration, the algorithms update the network weights and biases which then act as a new feedback to the input to produce another output until there is no significant change at the output any. This paper considered two training algorithm which are:- scale conjugate and Levenberg-Marquardt, were considered to develop the model.

A. SCALE CONJUGATE ALGORITHM

Scale conjugate is a supervised learning algorithm introduced as part of the training algorithm benchmarked against that of the back propagation algorithm [26]. The idea is to estimate the second order term in conjugate with a non-symmetric approximation of the form as explained in [29].

$$S_k = E'(w_k) p_k \approx \frac{E''(w_k + \sigma_k p_k - E''(w_k))}{\sigma_k} ; \quad 0 < \sigma_k < 1 \quad (7)$$

where $E'(w_k)$, S_k , p_k and σ_k is the Hessian matrix, second order term, search direction and step size respectively.

B. LEVENBERG-MARQUARDT ALGORITHM (LMA)

LMA also popularly called damped least square (DLS), provides numerical solutions to nonlinear function problems. One of the advantages of this algorithm is its fast and stable convergence when training different sizes of problems that can be solved by an ANN [26]. The Hessian matrix and gradient functions can be computed as:

$$H = J^T J \quad (8)$$

$$g = J^T \hat{e} \quad (9)$$

Where $\hat{e}$ and J is the vector of network errors and Jacobian matrix function respectively. When back propagation technique is employed, Jacobian matrix becomes less complex when compared to Hessian matrix. Therefore, by employing this approximation to the Hessian matrix, the following is obtained:

$$X_{K+1} = X_K - [J^T J + \mu I]^{-1} J^T \hat{e} \quad (10)$$

C. OPERATION OF ANN NEURONS

The basic element required in an ANN are the neuron. Let us assume that we have an inputs of N with k neuron and an output of y as shown below [27]:

$$v_k = \sum_{i=1}^N x_i w_{ki} + b_i \quad (11)$$

$$y_k = \varphi(\sum_{i=1}^N x_i w_{ki} + b_i) \quad (12)$$

$$y_k = \varphi(v_k) \quad (13)$$

$$\varphi = \frac{1}{1 + e^{-av_k}} \quad (14)$$

Where:

V_k = Input layer neuron, φ = Activation function, y_k = Output layer

IV. RESEARCH METHODOLOGY

In this study, a mobile wave radio propagation measurement dataset was used spanning UHF, VHF transmitters (30-340m) transmitting at frequencies of 900, 1800 & 2100MHz and 89.3, 103.5, 203.25, 429.25, 529.25, 615.25 and 629.25MHz (VHF and UHF) at a maximum distance of 60km. The measurement campaign for the broadcasting frequencies was carried out along different routes of FCT, Lagos, Osun, Kwara, and the Kano States. The receiver unit consists of an inbuilt GPS enables handheld N9432C Agilent spectrum analyzer (SA), a laptop and an external storage device that can store up to 32 GB data. A specially configured dual band mobile phone, GPS enabled, and a Probe dongle are connected to a USB of a laptop to measure the desired cellular frequencies. A Huawei Genex Probe v6.0 drive test software is installed on the laptop, to easy transfer the data set from the mobile phone into the laptop for further analysis. The data set are fed into an artificial neural network (ANN) and trained accordingly to develop a model that will be used to predict path losses. A total of 453 base stations were used during the data collection. The base stations considered were 147 for GSM, 299 for UMTS, 3 in the VHF, and 4 in the UHF bands resulting to over 1 million entries of path loss data.

The input layer is made up of five neurons that were used as input variables these are: the operating frequency (f), elevation (e), separation distance (d) and, the heights of the transmitter (ht), and receiver (hr). The ANN architecture used for the model development has a single node in the hidden layer in the number of neurons are varied from 5 to 30 and a single output layer, as shown in Fig 2. The total data set has 5 columns of (f , e , d , ht , and hr), with each column having 200,000 rows corresponding to one million (1,000,000) data density. Logistic and hyperbolic tangent functions were also utilized as the activation function, while Scale Conjugate and Levenberg-Marquardt as the training algorithms. The trained network used a back propagation algorithm in which the inputs values were transmuted to a version adapted to the hidden layer. The ANN model development employed linear activation (*logsig*) function at the input to hidden layer while hyperbolic tangent sigmoid transfer function (*tansig*) from the hidden to output layer. Data generated from the measured data from different locations were partitioned into training, testing and validation. The dataset was partitioned into 70% for training, 15% for testing and the reserved 15% for validation as a new measured dataset. The ANN model development considers two training algorithms; scale conjugate and Levenberg Marquardt (LM) algorithm, varying across the increase of hidden layer neurons through multiple runs.

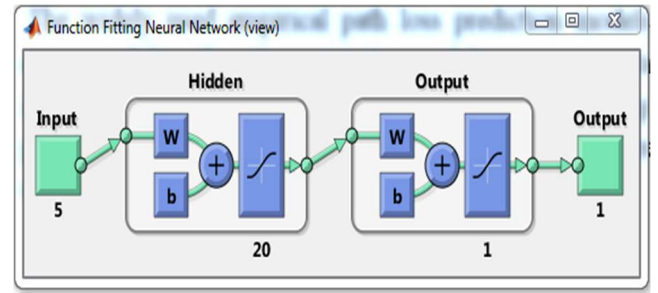


Fig 2: The network diagram for the model

V. RESULTS

Fig 3 depicts the performance of scale conjugate and Levenberg-Marquardt algorithms as a function of the number of neurons in the hidden layer. This was achieved by varying the number of hidden nodes from 5 to 30 in the step of 5.

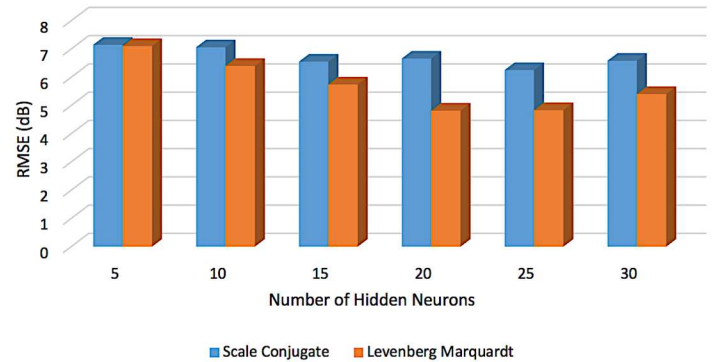


Fig 3: Graph of RMSE (dB) against Number of Hidden Neurons of both algorithms

For each scenario, the RMSE was computed. It was observed that the RMSE for scale conjugate and LM for 5-5-1 architecture revealed 7.14 dB and 7.10 dB, respectively. However, this was reduced to 6.58 dB and 5.4 dB, respectively, for 5-30-1 network configuration. It is worthy to note that the 5-20-1 network configuration gives the best performance with RMSE for SC and LM of 6.6 dB and 4.81, respectively.

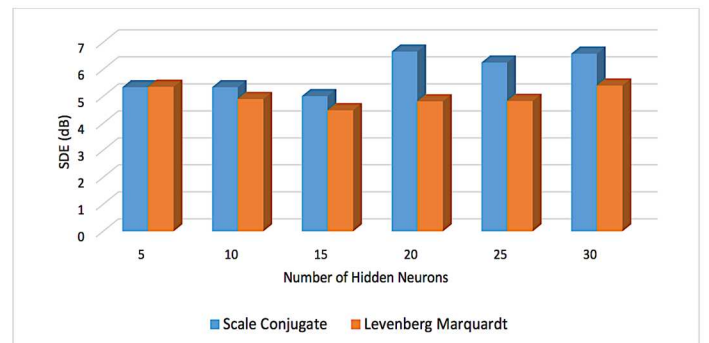


Fig 4: Graph of SDE (dB) against Number of Hidden Neurons of both algorithms

Investigation was conducted on how the network architecture affected errors and the correlation coefficient (R). Fig 4 shows the output performance metrics for both scale conjugate and Levenberg-Marquardt algorithms. It was observed from the comparison that reduction or increment of the number of hidden neurons has little or no effect on the output of the developed model. Furthermore, the LM algorithm gives the least value for SDE in almost all the number of hidden neurons compared to the scale conjugate algorithm

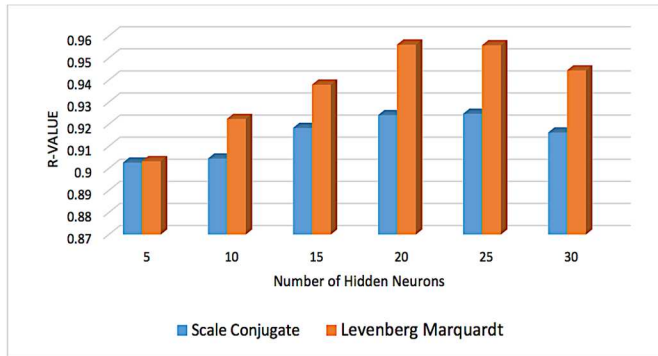


Fig 5: Graph of R-Value against Number of Hidden Neurons of both algorithms

It was deduced from the graphical representation of Fig 5 that an accretion of amount of hidden neurons increases the correlation coefficient for both algorithms, with LM achieving higher accuracy compared to SC. However, 5-20-1 gives the best accuracy and decreases when 5-30-1 is used. The best correlation coefficient produces 0.96 at the 5-20-1 hidden neurons architecture for the LM algorithm.

VI. CONCLUSIONS

Findings from this work revealed that the SDE and the R were affected by the network architecture. The Levenberg-Marquardt algorithm produces the least SDE, RMSE and accuracy compared with scale conjugate. It was observed that increment of the number of hidden neurons ordinarily does not, in the same way, mean increase in the performance of the model, as a tradeoff must be achieved to attain the optimal architecture. Hence, avoid using a less accurate architecture.

VII. ACKNOWLEDGEMENT

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