International Journal of Trend in Scientific Research and Development (IJTSRD)
Volume 4 Issue 2, February 2020 Available Online: www.ijtsrd.com e-ISSN: 2456 – 6470

Mobile Network Coverage Determination at 900MHz for Abuja Rural Areas using Artificial Neural Networks

Deme C. Abraham

Department of Computer Science, University of Jos, Jos, Nigeria

ABSTRACT

This study proposes Artificial Neural Network (ANN) based field strength prediction models for the rural areas of Abuja, the federal capital territory of Nigeria. The ANN-based models were created on bases of the Generalized Regression Neural network (GRNN) and the Multi-Layer Perceptron Neural Network (MLP-NN). These networks were created, trained and tested for field strength prediction using received power data recorded at 900MHz from multiple Base Transceiver Stations (BTSs) distributed across the rural areas. Results indicate that the GRNN and MLP-NN based models with Root Mean Squared Error (RMSE) values of 4.78dBm and 5.56dBm respectively, offer significant improvement over the empirical Hata-Okumura counterpart, which overestimates the signal strength by an RMSE value of 20.17dBm.

KEYWORDS: *Field Strength; Generalized Regression Neural Network; Multi-Layer Perceptron Neural Network; Hata-Okumura*

How to cite this paper: Deme C. Abraham "Mobile Network Coverage Determination at 900MHz for Abuja Rural Areas using Artificial Neural Networks" Published in International Journal of Trend in Scientific Research and Development (ijtsrd), ISSN: 2456-6470, Volume-4 | Issue-2, February 2020, pp.1119-1123, URL: www.ijtsrd.com/papers/ijtsrd30228.pdf

IJTSRD30228

INRODUCTION

An Artificial Neural Network (ANN) is a mathematical model that mimics the structure and functionalities of biological neural networks [1]. The Artificial neural network is a system of interconnected artificial neurons that mimic the human brain to form a complex programming structure for neural processing. Each neuron interconnects to, and receives signals from multiples of neurons. The neuron is structured such that if the resulting sum of the signals surpasses a certain threshold, a response is sent through the axon. ANNs are widely used in areas such as data mining fields, classification, forecasting, functional approximation, rule extraction, pattern recognition and medical applications [2].

As described in [3], neural networks can learn to approximate any function to a given accuracy and behave like associative memories by using just example data that is representative of the desired task. Given large amounts of training data, ANNs are capable of solving complex problems. This gives them a key advantage over traditional approaches to function estimation such as the statistical methods. Neural networks estimate a function without a mathematical description of how the outputs functionally depend on the inputs.

In this paper, an ANN-based approach to network coverage prediction across the rural areas of Abuja, Nigeria, is presented. The problem of field strength prediction is viewed as a function approximation problem consisting of a nonlinear mapping from a set of input variables containing information about the potential receiver onto a single output variable representing the predicted field strength [4]. Network coverage prediction is a crucial aspect of wireless network planning. Over the years, Deterministic Models have been widely used for signal strength prediction in a given environment. As described in [5], Deterministic Models make use of the laws governing electromagnetic wave propagation to determine the received signal power at a particular location. The field strength is calculated using the Geometrical Theory of Diffraction (GTD) as a component comprising of direct, reflected and diffracted rays at the required position. Deterministic models such as [6] often require a complete 3-D map of the propagation environment. Recent approaches to field strength prediction are based on computational intelligence as clearly documented in [7], [8]. This study considers the use of the Generalized Regression Neural Network (GRNN) and the Multi-Layer Perceptron Neural Network (MLP-NN) in field strength prediction across the terrain question.

The Generalized Regression Neural Network

As described in [9], the Generalized Regression Neural Network (GRNN) was proposed by [10]. It is type of Artificial Neural Network (ANN) that is capable solving a variety of problems such as function approximation, prediction, control, plant process modeling or general mapping problems [11. Unlike back-propagation neural networks, which may require a large number iterations to converge to the desired output, the GR-NN does not require iterative training, and usually requires a fraction of the training

Samples a back-propagation neural network would need [10]. As shown in Fig. 1, the GRNN comprises of four layers:

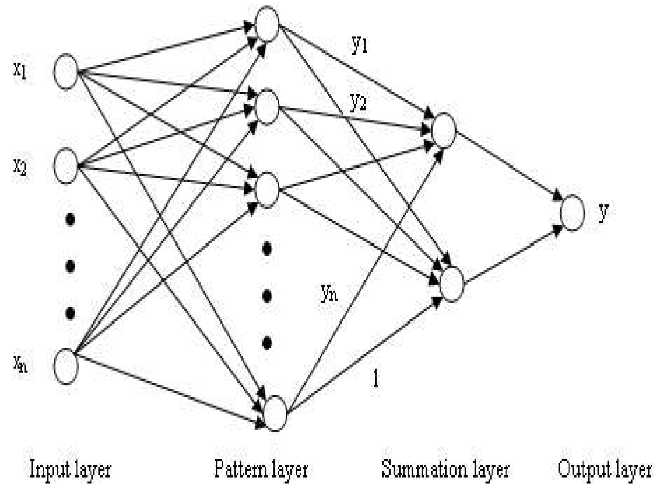

Fig. 1: Generalized Regression Neural Network Architecture [12]

Input layer: This is the first layer and it is responsible for sending inputs to the next layer called the pattern layer

Pattern layer: This layer computes the Euclidean distance between input and training data, and also the activation function.

Summation layer: This layer comprises of two parts: the Numerator and the Denominator. The Numerator sums up products of training data and activation function, while the Denominator sums up activation functions.

Output layer: The single neuron contained in this layer generates the output through division of the Numerator by the Denominator obtained from the previous layer.

The general regression as described by [10] is as follows: given a vector random variable, x, and a scalar random variable, y, and assuming X is a particular measured value of the random variable y, the regression of y on X is given by (1)

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

If the probability density function $\hat{f}(x,y)$ is unknown, it is estimated from a sample of observations of x and y. The probability estimator $\hat{f}(X,Y)$, given by (9) is based upon sample values X^{i} and Y^{i} of the random variables x and y, where n is the number of sample observations and p is the dimension of the vector variable x.

$$\hat{f}(X,Y) = \frac{1}{(2\pi)^{(p+1)/2}\sigma^{(p+1)/n}} \cdot \frac{1}{n}\sum_{i=1}^{n} \exp\left[\frac{(\mathrm{X}-\mathrm{X}^{\mathrm{i}})^{T}(\mathrm{X}-\mathrm{X}^{\mathrm{i}})}{2\sigma^2}\right] . \exp\left[\frac{(\mathrm{Y}-\mathrm{Y}^{\mathrm{i}})^2}{2\sigma^2}\right] \quad (2)$$

A physical interpretation of the probability estimate $\hat{f}(X,Y)$, is that it assigns a sample probability of width σ (called the spread constant or smoothing factor) for each sample X^{i} and Y^{i}, and the probability estimate is the sum of those sample probabilities.

The scalar function $\mathrm{D}_{\mathrm{i}}^2$ is given by (3)

$$D_i^2 = (X - X^i)^T (X - X^i) \quad (3)$$

Combining equations (1) and (2) and interchanging the order of integration and summation yields the desired conditional mean $\acute{Y}(X)$, given by (4)

$$\acute{Y}(X) = \frac{\sum_{i=1}^{n} Y^i exp\left(-\frac{\mathrm{D}_{\mathrm{i}}^2}{2\sigma^2}\right)}{\sum_{i=1}^{n} exp\left(-\frac{\mathrm{D}_{\mathrm{i}}^2}{2\sigma^2}\right)} \quad (4)$$

It is further stated in [10] that when the smoothing parameter σ is made large, the estimated density is forced to be smooth and in the limit becomes a multivariate Gaussian with covariance σ^2. On the other hand, a smaller value of σ allows the estimated density to assume non-Gaussian shapes, but with the hazard that wild points may have too great an effect on the estimate.

The Multi-Layer Perceptron Neural Network

The Multi-Layer Perceptron Neural Network (MLP-NN) is a feed forward neural network trained with the standard back propagation algorithm [13]. As described in [14], the MLP-NN is a supervised network so it requires a desired response to be trained. With one or two hidden layers, the MLP-NN can approximate virtually any input-output map. They have been shown to approximate the performance of optimal statistical classifiers in difficult problems.

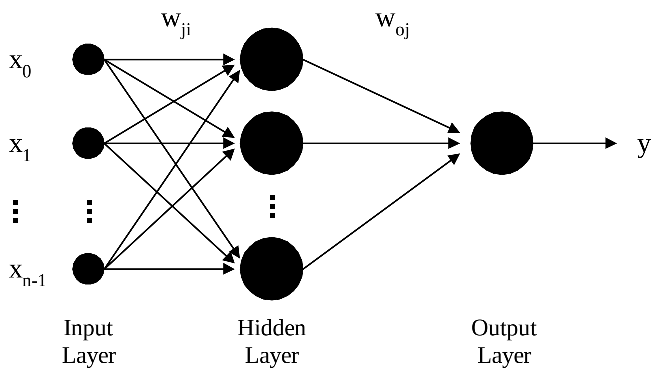

Fig.2: Multilayer Perceptron Neural Network with one hidden layer [14]

The MLP-NN comprises of an input layer, one or more hidden layers and an output layer. Fig. 2 shows an architecture with 1 hidden layer. It can be observed that each neuron of the input layer is connected to each neuron of the hidden layer, and in turn, each neuron of the hidden layer is connected to the single neuron of the output layer. Signal propagation across the entire network is always in the forward direction, i.e, from the input layer, through the hidden layer and eventually to the output layer. Error signals propagate in the opposite direction from the output neuron across the network. As described in [14] the output of the MLP-NN is given by (5)

$$y = F_0\left(\sum_{j=0}^{M} w_{0j}\left(F_h\left(\sum_{i=0}^{N} w_{ji}x_i\right)\right)\right)$$

where:
- w_{oj} represents the synaptic weights from neuron j in the hidden layer to the single output neuron,
- x_i represents the i^{th} element of the input vector,
- F_h and F_0 are the activation function of the neurons from the hidden layer and output layer, respectively,
- w_{ji} are the connection weights between the neurons of the hidden layer and the inputs.

The learning phase involves adaptively adjusting the free parameters of the system based on the mean squared error E, between predicted and measured path loss for a set of appropriately selected training examples. The mean squared error is given by (6),

$$E = \frac{1}{2}\sum_{i=1}^{m}(y_i - d_i)^2$$

Where, y_i is the output value computed by the network and d_i is the desired output. When the error between network output and the desired output is minimized, the learning process is terminated and the network can be used in a testing phase with test vectors. At this stage, the neural network is described by the optimal weight configuration, which means that theoretically ensures the output error minimization.

The Hata-Okumura Model

As described in [15] the Hata-Okumura Model incorporates the graphical information from the Okumura Model. The Hata Model is a widely used propagation model for predicting path loss in urban areas, and also has formulations for predicting path loss in Suburban and Open Areas. The Hata Model for Urban Areas is valid for the following parameters:

Frequency Range: 150 MHz to 1500 MHz
Transmitter Height: 30 m to 200 m
Link distance: 1 km to 20 km
Mobile Station (MS) height: 1 m to 10 m

Hata Model for Urban Areas is formulated as (7).

$$L_U = 69.55 + 26.16 log f - 13.82 log h_B - C_H + (44.9 - 6.55 log h_B) log d \quad (7)$$

For small or medium sized cities (where the mobile antenna height is not more than 10 meters),

$$C_H = 0.8 + (1.1 log f - 0.7)h_M - 1.56 log f$$

and for large cities,

$$C_H = \begin{cases} 8.29(log(1.54h_M))^2 - 1.1, & for\ 150MHz \le f \le 200MHz \\ 3.2(log(11.75h_M))^2 - 4.97, & for\ 200MHz \le f \le 1500MHz \end{cases}$$

Where,
L_U - Path loss in Urban Areas
h_B - Height of base station antenna in meters (m)
h_M - Height of mobile station antenna in meters (m)
f - Frequency of Transmission in megahertz (MHz).
C_H - Antenna height correction factor
d - Distance between the base and mobile stations in kilometers (km).

The Hata Model for Suburban Areas is given by (8)

$$L_{SU} = L_U - 2(log\frac{f}{28})^2 - 5.4 \quad (8)$$

Hata model for open areas is formulated as (9)

$$L_O = L_U - 4.78(log f)^2 + 18.33 log f - 40.94 \quad (9)$$

Materials and Methods

A. Received Power Measurement and Path Loss Computation

Received power measurements were recorded from multiple Base Transceiver Stations (BTSs) situated within the Abuja rural areas between Abaji and Gwagwalada, as well as Gwagwalada and Zuba. The BTSs belong to the mobile network service provider, Mobile Telecommunications Network (MTN), Nigeria. The instrument used was a Cellular Mobile Network Analyser (SAGEM OT 290) capable of measuring signal strength in decibel milliwatts (dBm). Received power (P_R) readings were recorded within the 900MHz frequency band at intervals of 0.15km, after an initial separation of 0.1km. Mobile Network Parameters obtained from the Network Provider (MTN) include Mean Transmitter Height of 33 meters and Mean Effective Isotropic Radiated Power (EIRP) of 45dBm.

Statistical Indices for Performance Comparison

The performance comparison indices adopted in this study are based on the Root Mean Square Error (RMSE), given by (10), and the Coefficient of Determination (R^2), given by (11). The RMSE is a measure of the differences between predicted and observed values. The smaller the RMSE value, the higher the prediction accuracy of the model. R^2 ranges from 0 to 1, but can be negative, which indicates the model is inappropriate for the data. A value closer to 1 indicates a greater correlation of the model with the test data, and hence, greater fit.

$$RMSE = \sqrt{\sum_{i=1}^{N}\frac{(M-P)^2}{N}} \quad (10)$$

Where,
M – Measured Path Loss
P – Predicted Path Loss
N- Number of paired values

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y}_i)^2} \quad (11)$$

Where
y_i is the measured path loss,
$\hat{y}_i$ is the predicted path loss and
$\bar{y}_i$ is the mean of the measured path loss values.

Results and Discussion

Figures 3 to 8 clearly indicate that the empirical Hata-Okumura model overestimates the signal strength across all the BTSs considered in this investigation. On the contrary, it can be observed that the ANN-based predictors are convergent towards the test data, indicating greater prediction performance. The statistical performance indices in Table 1 indicate that on the average, the GRNN-based predictor is the most accurate of the three predictors with a RMSE value of 4.78dBm and R^2 value of 0.82. The MLP-NN model has a RMSE value of 5.56dBm and R^2 value of 0.68. The Hata-Okumura model with a RMSE value of 20.17dBm clearly overestimates the signal strength as earlier stated.

TABLE1. Statistical Performance Comparison of Predictors

MODEL	STATS.	BST 1	BST 2	BST 3	BST 4	BST 5	BST 6	MEAN
GRNN	RMSE(dBm)	5.08	5.49	4.86	5.34	3.58	4.31	4.78
	R^2	0.82	0.75	0.84	0.86	0.80	0.87	0.82
MLP-NN	RMSE(dBm)	6.12	5.22	5.00	4.35	8.17	4.51	5.56
	R^2	0.74	0.78	0.83	0.91	-0.02	0.85	0.68
Hata - Okumura	RMSE(dBm)	22.15	19.82	21.63	19.84	17.18	20.40	20.17
	R^2	-2.55	-1.95	-2.02	-0.92	-2.81	-2.06	-2.05

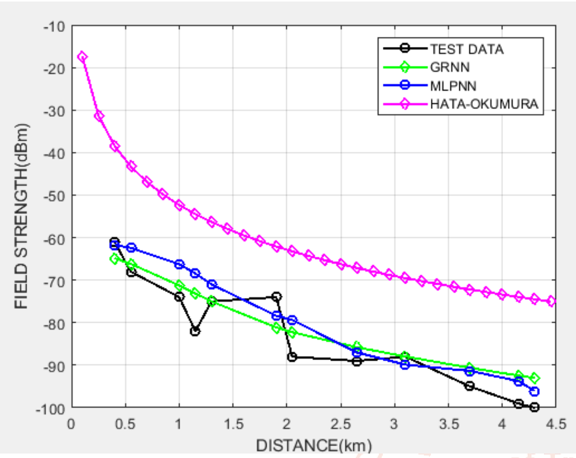

Fig. 3: Model Comparison for BTS 1

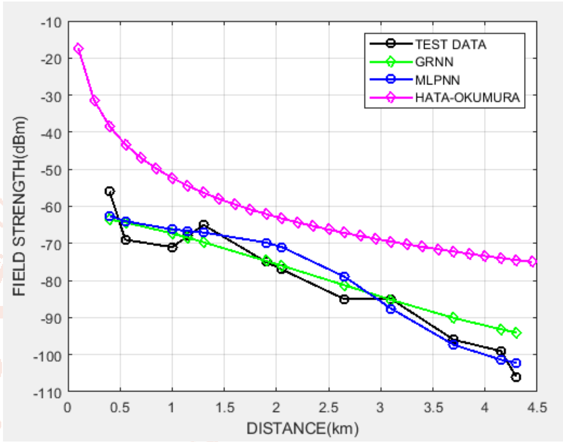

Fig. 6: Model Comparison for BTS 4

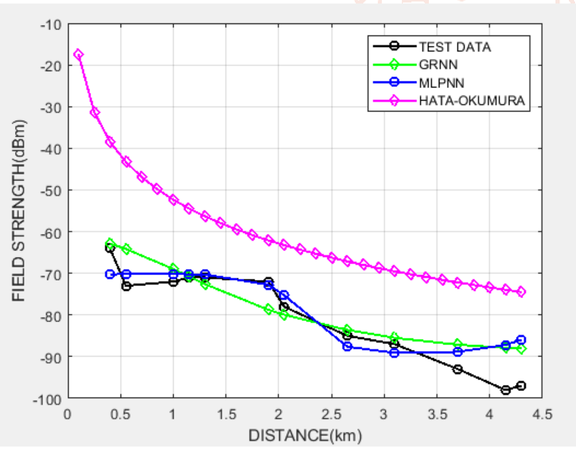

Fig. 4: Model Comparison for BTS 2

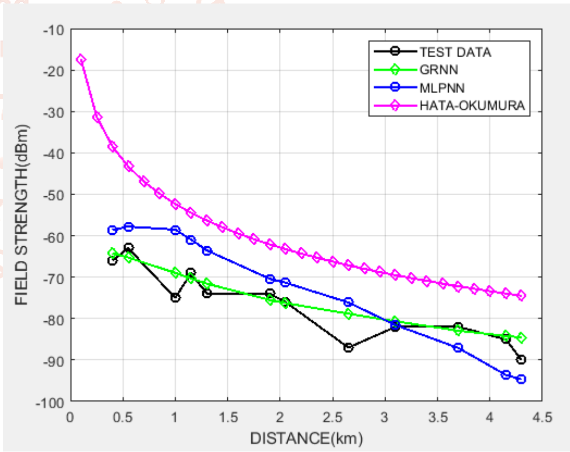

Fig. 7: Model Comparison for BTS 5

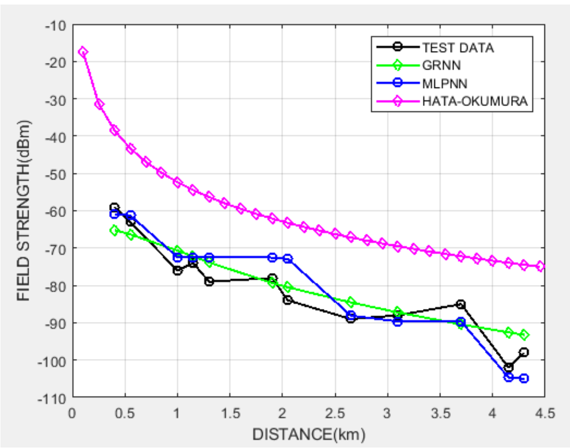

Fig.5: Model Comparison for BTS 3

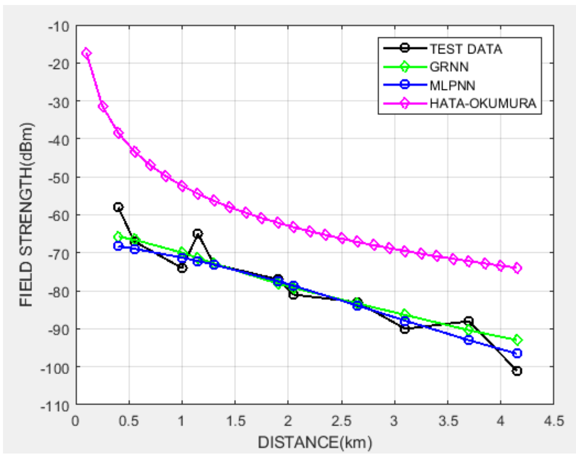

Fig. 8: Model Comparison for BTS 6

Conclusion

Field strength prediction models for the rural areas of Abuja, Nigeria, were created on the bases of two types of ANN, which were trained and tested with received power data recorded at an operating frequency of 900MHz from multiple Base Transceiver Stations situated across the rural areas. The two deep learning networks considered were the Generalized Regression Neural network (GRNN) and Multi-Layer Perceptron Neural Network (MLP-NN). Results indicate that the ANN-based models offer significant improvement over the empirical Hata-Okumura model.

References

[1] Andrej K., Janez B. and Andrej K. Introduction to the Artificial Neural Networks, Artificial Neural Networks - Methodological Advances and Biomedical Applications, Prof. Kenji Suzuki (Ed.), ISBN: 978-953-307-243-2, pp 1, 2011

[2] Janmenjoy N., Bighnaraj N. (2015). A Comprehensive Survey on Support Vector Machine in Data Mining Tasks: Applications & Challenges. *International Journal of Database Theory and Application* Vol.8, No.1 (2015), pp.169-186, 2015.

[3] Faria P., Zita V., Joao P., Khodr H. (2009). ANN Based Day-Ahead Spinning Reserve Forecast for Electricity Market Simulation. Center of the Electr. Eng., Polytech. Inst. of Porto (IPP), Porto, Portugal DOI: 10.1109/ISAP.2009.5352930 Conference: Intelligent System Applications to Power Systems, 2009. ISAP '09. p. 2.

[4] Popescu I., Naforni I., Gavriloaia G. Field Strength Prediction in Indoor Environment with a Neural Network Model: FACTA UNIVERSITATIS (NIS), Series: Electronics and Energetics. Vol. 14, No. 3, 2001, pp 329-336.

[5] Sumit J. and Vishal G. A Review on Empirical Data Collection and Analysis of Bertoni‟s Model at 1.8 GHz. International Journal of Computer Applications (0975 – 8887) Volume 56, No.6, 2012, pp 17- 23.

[6] Athanasiadou G.E., Nix A.R., McGeehan J.P. „A Microcellular Ray-Tracing Propagation Model and Evaluation of its Narrowband and Wideband Predictions‟, IEEE Journal on Selected Areas in Communications, Wireless Communications series, vol. 18, no 3, 2000, pp. 322-335.

[7] Popescu I., Naforni I., Gavriloaia G. Field Strength Prediction in Indoor Environment with a Neural Network Model: FACTA UNIVERSITATIS (NIS), Series: Electronics and Energetics. Vol. 14, No. 3, 2001, pp 329-336.

[8] Deme A. C. Field Strength Determination in a Tropical Metropolitan Environment Using Computational Intelligence Techniques. American Journal of Engineering Research (AJER) e-ISSN: 2320-0847 p-ISSN: 2320-0936 Volume-5, Issue-8, pp-276-284, 2016

[9] Deme C. A. A Generalized Regression Neural Network Model for Path Loss Prediction at 900 MHz for Jos City, Nigeria. *American Journal of Engineering Research (AJER)*. E-ISSN: 2320-0847 p-ISSN: 2320-0936 Volume-5, Issue-6, pp-01-07, 2016.

[10] Specht D. F.A. A general regression neural network. *IEEE Transactions on Neural Networks*. 2, 1991, 568-576.

[11] Leszek R. Generalized Regression Neural Networks in Time-Varying Environment. *IEEE Transactions on Neural Networks, Vol. 15, No. 3*, 2004, pp. 576-596.

[12] Sun G., Hoff S. J., Zelle B. C., Nelson M. A. Development and Comparison of Back propagation and Generalized Regression Neural Network Models to Predict Diurnal and Seasonal Gas and PM_{10} Concentrations and Emissions from Swine Buildings. *American Society of Agricultural and Biological Engineers ISSN 0001-2351. Vol. 51(2):2008,* pp. 685-694

[13] Gaurang P., Amit G., Y P Kosta and Devyani P. “Behaviour Analysis of Multilayer Perceptrons with Multiple Hidden Neurons and Hidden Layers”, *International Journal of Computer Theory and Engineering*, Vol. 3, No. 2, 2011, pp. 332-337.

[14] Popescu I., Naforni I., Gavriloaia G. Field Strength Prediction in Indoor Environment with a Neural Network Model: FACTA UNIVERSITATIS (NIS), Series: Electronics and Energetics, 2001. Vol. 14, No. 3, pp 329-336.

[15] Yuvraj S. (2012). Comparison of Okumura, Hata and COST-231 Models on the Basis of Path Loss and Signal Strength. *International Journal of Computer Applications* (0975 – 8887) Volume 59, No.11, 2012, pp. 37-41.