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Neural Network Models for Traffic Estimation in Mobile Networks in Lagos, Nigeria

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ABSTRACT

The network providers are now being challenged with their inability to accurate estimate and characterize traffic in a particular area, due to the increasing number of mobile communication services being rendered by the network providers Hence, this has been greatly undermining their design and planning processes and as such increasingly affected the Quality of Service(QoS).This research work addresses the traffic estimation in mobile communication network using Artificial Neural Network (ANN) approach using measured data collected in Lagos State,Nigeria.The Multilayer Perceptron (MLP) and Radial Basis Function (RBF) ANN techniques were used in the traffic modeling. The results of the ANN modeling showed that the Model 1 of MLP performed better than other models with Coefficient of Determination (R^2) of 99%, Root Mean Square Error(RMSE) of 5.456 and Mean Bias Error(MBE) of 0.94.It is recommended that the dataset used in developing the ANN models be increased by collecting and using not more than 12months traffic data for ANN modeling .An appropriate design of the models should also be given a serious concern by choosing appropriate number of neurons at the hidden units of the neural networks .This will provide a good traffic estimation which the mobile network provider can be used in network design and planning.

Keyword: Quality of Service, Mobile Communication, Traffic Estimation, Artificial Neural Network, Radial Basis Function

I. INTRODUCTION

Presently, there is tremendous worldwide increase in the demand for mobile communication services which include voice, data, video e.t.c.There are challenges facing Quality of Service (QoS) in the mobile network [1,2].The QoS is necessary especially in this present economic situation, and indeed a high competitive business environment in telecommunication industry. Therefore, for a survival, network operators must consider the effective use of their available resources (channels), which leads to effective network design and planning.

The pattern of the traffic and the analytical activities of mobile users are necessary to be carried out in order to realize the critical assignment of planning which is to plan for the best network which gives the highest number of traffic at a specified level of blocking probability and for a specified number of channels. The modeling of traffic and measurements are the major characterization of traffic being performed by network providers .But ,the modeling of traffic concerns the budgeting of the demand of traffic in a particular locality and handing over. The fact that this task is one of serious areas of tasks of traffic engineering, most network providers make use of it for planning purposes. Traffic intensity and holding time are some of the important factors to be considered in traffic characterization.

According to [3], Traffic in mobile communication is the amount of voice or data calls or both, which is over a channel within a particular time. Channel according to [4] is a medium of physical transmission such as logical transmission or a wire over a medium (multiplexed) and channel conveys an information signal. But, according to [5], the channel is either measured by data rate i.e bit per second or bandwidth (Hertz). Owing to high traffic generated by a number of subscribers which are trying to gain access to mobile network ,this cause transmission channel to experience block calls(congestion).Many of the subscribers receives no response from the network when number of subscriber exceeds maximum network capability(which results to block calls or congestion) .

As described by [4] ,traffic load is known from the amount of intensity of calls and holding time average. The offered, carried and block traffic can be characterized. The aggregation of carried and block traffic is the offered traffic. But, traffic load is usually affected by the various factors which are; cell area, number of circuits, size of cluster, efficiency of spectrum and bandwidth per channel. It is worthy to note also in [4], in nature, the technology of the cell is the same and also applicable to communication network entirely.

For an efficient design of mobile network design and planning,and as in [6] , the useful factors are Grade of Service(GoS) i.e probability of blocking , handover blocking and the rate of channel utilization e.t.c.The blocking probability which is the GoS is used to control the amount of block calls experienced in a network and this block calls arises from unavailability of network resources i.e transmission channels, to accommodate all the calls at a given time. The amount of available circuit and traffic load in erlang determine the blocking probability. Also in [6], it was established that in order to carry-out performance evaluation of handover blocking probability; handover rate, dropping probability, probability of handover, holding time (call) and holding time (channel) are the factors that must be considered.

However, the Artificial Neural Network (ANN) is a neural networks model which is stimulated biologically, and consists of artificial neurons which are interconnected together [7] and it is for information processing and computation using connectionist approach. The model structurally changes during learning phase due to its adaptivity [8]. A complex relationship between inputs and outputs can be modeled with ANN or to find the distribution of data [9]. An ANN is an interconnection of nodes(group), and similar to the neurons network in the brain of human. Because of their characteristics and capacity, in cases where methods and approach (traditional) have not been able to solve underlying problems, the ANN are being applied and is found to be effective. Capacity for memorizing, performing actions and ideas relation are some of the features which the ANNs imitate from human beings [10,2].

By associating outputs with the distribution of inputs, the neural network can establish a nonlinearity relationship in a set of data during a training process. Also, the use of neural networks to Traffic Engineering can be used to realize its generic purpose of "intelligent" agents or systems capable of adapting dataflow according to available resources. In [10], Neural Networks was applied in Internet Traffic Engineering, and the results showed that ANNs has a potential application in communication networks field. The neural network showed a good application in the major tasks of the Traffic Engineering which are prediction, monitoring, control, and resources performance [10].

Owing to the increase in demand of mobile communication services by the users, operators are often challenged with their inability to accurately estimate and characterize the traffic in terms of users' communication rate and their movements, thereby affecting inputs to network design and planning, and network performance. These are crucial elements of traffic engineering that remain necessities for effective and efficient mobile networks. This research paper therefore present Artificial Neural Network models to estimate traffic in mobile communication network in Lagos, Nigeria and specifically evaluate performance of the models statistically.

II. LITERATURE REVIEW

A. Theoretical Framework

This section contains theoretical background of Multilayer Perceptron (MLP)
and Radial Basis Function(RBF).

B. Multilayer Perceptron

The network of simple neurons called perceptron is MLP. In 1958, Rosenblatt introduced single percentron in 1958 as a basic concept. The linear combinations with inputs weights and outputting via nonlinear activation functions, results to the computation of single output from a multiple inputs(real-valued) by perceptron.Mathematically, it is as shown below;

$$y=\varphi(\sum_{i=1}^{n} w_i x_i + b) = \varphi\ (w^T x + b) \qquad (1)$$

where w represents weights,
x denotes inputs,
bdenotes bias
andφ denotes activation function. (Both w and x are vector)

Fig. 1 shows signal-flow graph.Heaviside step function (an activation function) i.e φ is used by original Rosenblatts percentron.

In multilayer networks these days, the φ. is often chosen as hyperbolic tangent tanh(x) or logistic sigmoid$1/(1+e^{-x})$or .

Both are related by $(\tanh(x)+1)/2=1/(1+e^{-2x})$ (2)

The functions are used due to the fact that, mathematically they are close to linear (near origin) and convenient but saturate when moving away from origin quickly. This makes the networks of MLP strong and mild modeling of nonlinear mappings.

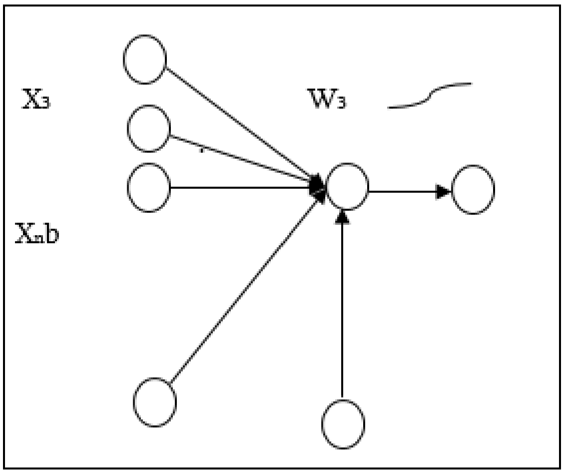


Figure 1: Signal-flow graph of the perceptron

Owing to the limited ability to map, single perceptron is not really useful. Perceptron represents only ridge-like function(oriented) irrespective of the activation used. The Perceptrons is usable as building blocks of much more larger practical structure. Typically, MLP consists of input ,hidden and output layers. Propagation of input signal is through layer by layer of network. The propagation of input signal is layer by layer in the network. A One(1) hidden layer signal-flow of the network is as shown in Fig. 2 below.

Mathematically, computations that are performed by the network(feedforward) of a single(1) hidden layer network with activation functions (nonlinear) and output layer (linear) are written as;.

$$x=f(s)=B\varphi\ (As+a)+b \qquad (3)$$

In eq. 3 above, x a denotes vector of outputs,s denotes vector of inputs ,B denotes weight matrix of second layer, b denotes bias vector of second layer. A denote matrix of weights of first layer, a denotes bias vector of first layer. The function φ represents element wise nonlinearity. Obviously, there is model generalization to a more hidden layer(s).

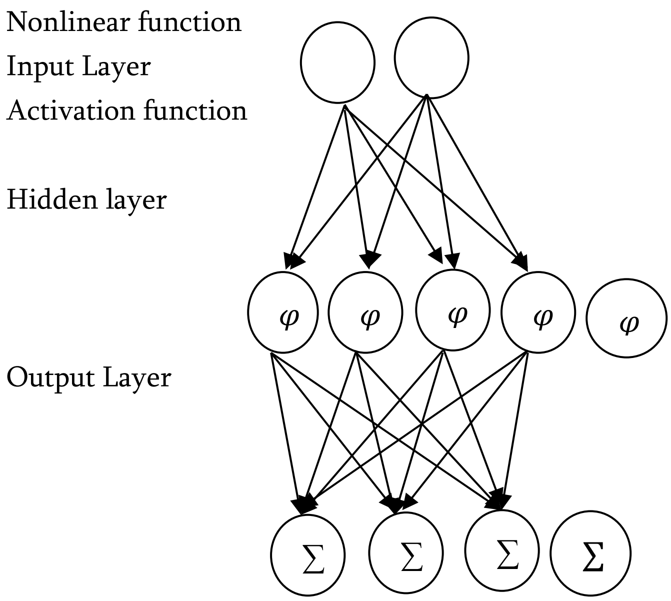


Figure 2: Signal-flow graph of an MLP

The single-layer network with its composition of parallel perceptron(s) are limited in the kind of mappings they can possibly represent, with one hidden layer only, the MLP network power is large surprisingly. In equation (3) above, the network has the capability to approximate to any given accuracy, any function which is continuous, $f{:}R^n \quad R^m$, with the condition that many hidden units are sufficiently available.

MLP networks are used for supervised learning problems typically. Therefore, a training set which involves input-output pairs and network has to undergo learning in order to model dependency between pairs. The training is adaptation of weights and biases (A, a, and b) to the optimal values for pairs (s(t),x(t)) in the Equation (3) above. Optimization criterion typically is squared reconstruction error :

$$\sum_t \| f(s(t))-x(t) \|^2.$$

Using back-propagation algorithm [11] problem in supervised learning of MLP can be solved. There are two steps involved in the algorithm. This algorithm is of two(2) steps. There is evaluation of predicted outputs which corresponds to input as in equation 3 above in forward pass. On other hand in backward pass, there is backpropagation of partial derivatives (cost function) through network with respect to different parameters. The chain rule of differentiation results to related computational rules for backward pass as forward pass.By using any of gradient-based optimization algorithms , network weights can be adapted. There is iteration of the whole process until the convergence of all the weights.

Also, by using auto-associative structure, MLP can be used for unsupervised learning. By setting values (same) for inputs and outputs of network. The sources (extracted) are emerged from values of hidden neurons. The approach is computational but rather intensive. For any representation reasonably, MLP network should have at least three(3) hidden layers ,the training of such network is time consuming [12].

III. METHODS

Estimation of traffic in mobile communication network using the ANN can be reliably achieved by using traffic data collected (network experience),and building of models using the data. Although some methods have been used to estimate traffic, but the ANN promises a quicker and better approach, due to its capability by efficiently finding relationships between non-linear data.

A. Data Collection for the Research Work

A purposive random sampling of the Base Station Controller (BSC) carrying the highest traffic intensity in Lagos State was used. This was selected out of the BSCs in the research work area. Having found out that the peak busy hour in Lagos State is 19:00(7.00pm).daily Busy Hour (BH) of necessary traffic data were collected as a secondary data from the BSC carrying the highest traffic intensity in Lagos State. The data were obtained from the OMC of one of the leading mobile networks for a period of six (6) months i.e from December,2012 to May,2013.An in-built OMC within the mobile network assist in measuring and monitoring all the entire event in the mobile communication system. The OMC-counter was used for measurement, and the traffic is characterized by two major components which are stochastic and deterministic.

B. Study Area

The Lagos State was chosen for this research work because of its features. It is one of the states, which is situated in the southwest geo-political zone. Lagos is the smallest state; one of the commercial nerve centres, and one of the administrative states in Nigeria.It is also the social hub of the country. It is the second to kano in terms of population among the states in Nigeria. Lagos State is divided into five divisions, and twenty Local Government Areas and thirty seven Area. The divisions are Epe, Badagry, Ikeja, Ikorodu and Lagos .The LGAs under each division includes Epe (Epe and Ibeju-Lekki), Badagry (Badagry,Amuwo-odofin ,Ajeromi-Ifelodun, and Ojo), Ikeja (Oshodi-Isolo, Ifako-Ijaiye, Agege, Alimosho,Ikeja, Mushin, kosofe and Shomolu), Ikorodu (Ikorodu) and Lagos(Surulere, Apapa,Lagos Mainland and Eti-Osa).

Population in Lagos State is growing at about 600,000 per year with density of about 4,193 persons per sq.km. As at the last census , Lagos State population was 18million in 2006.But, according to the United Nation Research work carried in 1999, it was revealed that Lagos State's population would be 24.5million by 2015,and would be ranked as a populous city in the world by ranking. The most industrialized state in Nigeria is Lagos State and this accounts for its highest number of companies ,firms, and businesses in Nigeria, hence its choice as a case. The Lagos as the case of this research paper as activity areas which include shopping centers ,business centers ,industrial zone, highways ,campuses, downtown, tourist zone and residential district. These characteristics of Lagos are needful so as to realize the objectives of this research paper.This is because a high level of traffic is expected in an area like Lagos State.

Previous literature had indicated some of the high traffic intensity areas in Lagos State. These include Mushin, Apapa, Alaba, Oyingbo. The fig. 3 below shows the geographical map of Mushin in Lagos State with some cells and streets in Mushin.

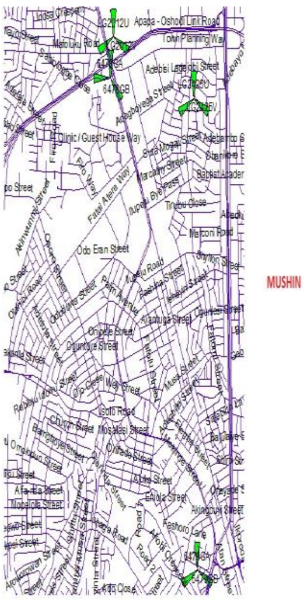


Figure 3: Geographical map of Mushin in Lagos (south west of Nigeria) at latitude 6.55^0 and longitude 3.36^0 with some cells.

Source: Field Survey(2013)

C. Traffic Predictors

Out of the many traffic parameters in the data collected ,only five(5) showed good correlation with the dependent variable i.e offered traffic. These include Traffic Channel, Seizure Traffic ,Utilization Rate, Call Completion Traffic and Handover Success rate.

Each of the predictors is shown mathematically below:

Traffic Channel according to [13] is used for communication by Mobile Station (MS). The TCH availability which is measured at busy hour (BH) and is a measure of the congestion of the traffic channel .

TCH Availability =

$$\frac{\text{BH TCH Traffic-Average TCH Traffic}}{\text{BH TCH Traffic}} \times 100\% \quad (4)$$

Handover Success Rate(HSR) is ratio of completed handovers (successfully) to total initiated handovers.

$$\text{HSR}=\frac{\text{successfully completed handovers}}{\text{Initiated handovers}} \times 100\% \quad (5)$$

Utilization Rate is the rate at which a traffic channel is successfully used.The channel utilization rate recommended by Nigerian Communication Commission is 60% i.e less than or equal to 60%.

Call Completion Rate is ratio of number of successive call(s) to number of call attempts. This is related to call completion traffic measured in erlangs

Call Completion Rate =

$$\frac{\text{Successful calls}}{\text{Call attempts}} \quad (6)$$

Offered Traffic (OT) measured in erlangs is the totality of carried traffic (flow) and block traffic

Block traffic is seizure traffic in erlangs, the relationship between block traffic and offered is given below:

$$\text{OT} = \text{Carried traffic} + \text{Block traffic} \quad (7)$$

$$\text{But,OT , } A = \lambda \times \mu \quad (8)$$

Where λ = calls intensity(Number)

μ= Mean holding time

Twenty-Six (26) combinations of traffic predictors were considered,this is shown in table 1 so as carry-out their effects on offered traffic.MLP and RBFNNare applied for estimation of offered traffic in Lagos State using the combinations shown in table 1 below.

TABLE I : MODELS BASED ON DIFFERENT COMBINATIONS OF INPUT PARAMETERS

Model No	Input Parameters	Model No	Input Parameters
1	TC,ST, UR ,CCT & HSR	14	UR,CCT & HSR
2	TC, ST ,UR & CCT	15	ST,UR & HSR
3	TC, ST,UR & HSR	16	ST,CCT & HSR
4	TC, UR ,CCT & HSR	17	TC & ST
5	ST,UR , CCT & HSR	18	TC & UR
6	TC ,ST,CCT,HSR	19	TC & CCT
7	TC ,ST & UR	20	TC & HSR
8	TC,ST & CCT	21	ST & UR
9	TC, UR &CCT	22	ST & CCT
10	ST ,UR & CCT	23	ST & HSR
11	TC,ST & HSR	24	UR & CCT
12	TC,UR & HSR	25	UR & HSR
13	TC,CCT & HSR	26	CCT & HSR

KEY: TC = TRAFFIC CHANNEL , ST = SEIZURE TRAFFIC , UR =UTILIZATION RATE, CCT = CALL COMPLETION TRAFFIC & HSR= HANDOVER SUCCESS RATE

D. ANN Model Formulations

In order to map vector of an input into output, ANN models can be designed in a classical way, this is according to [14]. A simple ANN model architecture (Fig. 4) is the collection of the nodes distributed over a one layer each of input, hidden and output of the model.

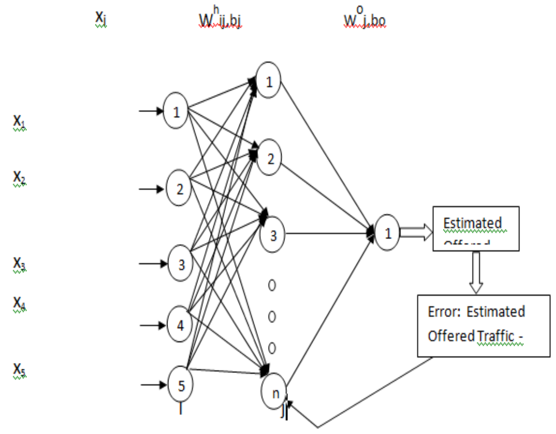


Figure 4: Generalized MLP flow diagram for the research work

$$O(x_1,\ldots\ldots,x_5) = f_o[b_o + \sum_{j=1}^{n}\{ W^{o}{}_{j} f_h(b^h{}_j + \sum_{i=1}^{5} W^{h}{}_{ij} E_i)\}] \quad (9)$$

Where i denotes the subscript for the input layer, and j denotes subscript for the hidden layer, five (5) input variables i.e $x_1,\ldots\ldots,x_5$, n denotes number of node(s) in the hidden layer , f_h= transfer function (hidden layer) f_o= transfer functions (output layer), $W^h ij$ = weight factors for the hidden layer, W^o=weight factors for the output layer, b^h= bias factor for the hidden layer, E_i=Input variables and O=Output value(Offered Traffic).

One input, hidden and output layers i.e a three (3)-layer network was used. Input layer contains independent variables (M 1: 5, M 2: 4, M 3: 4, M 4:4, M 5:4, M 6:4, M 7:3,M 8: 3,M 9:3,M 10:3, M 11:3, M 12: 3, M 13: 3, M 14: 3, M 15:3, M 16:3, M 17:2, M 18:2, M 19:2,M 20:2, M 21:2, M22:2, M 23:2, M 24:2,M 25:2 and M 26:2) and output layer contains dependent variables(Offered traffic). Equation 3.1 was used to calculate these outputs .

In determiningthe best MLP architecture (coefficient of determination(highest), mean bias error(lowest) andthe root mean square error(lowest), combination of input variables(the designs) were investigated.Levenberg –Marquardt training algorithm was used but changes were made to the amount of neurons in hidden layers. Also,activation (transfer) functions which include log sigmoid, tangent sigmoid and the linear functions were used.This was automatically determined by the MATLAB.

E. Designing and Programming ANN Models

The number of procedure(s) for the design of ANN models are the following five(5) steps are:

- Collection of Data
- Preprocessing of Data
- Building of Network
- Training of Network
- Testing Performance of Model

I) Data Collection for ANN Design:

The collection of data and preparation of sample are first procedure in design process of ANN models. Data collected from measurements for a period of six(6) months.Only five (5) parameters were considered as traffic predictors, these are Call Completion Traffic , Seizure Traffic ,Traffic Channels ,Utilization Rate and Handover Success Rate .This data was collected within Lagos State ,and was provided by a friend working with one of the leading mobile networks from December,2012 to May,2013.The data from December,2012 to April,2013 was used for training the models,but the data from 24th to 31st May,2013 was used for the testing the models.

II) *Data Preprocessing:*

The next step after the data collection is the preprocessing of data ,which involves three(3) procedures. The preprocessing of data procedures were carried out to train NN more efficiently. The procedures are:

- Missing data
- Normalization
- Randomization

Missing data were replaced by taking average of neighboring values in the same week so as to solve problem with missing data. Normalization of the data was carried in line with what [15] pointed that, data normalization is necessary before network is presented with input data because learning algorithm may get confused by mixing of variables with small and large magnitudes. This lays emphasis on how important each variable is and finally can force rejection of variable with smaller magnitude. The fig. 5 below shows the basic flow of ANN Model Design.

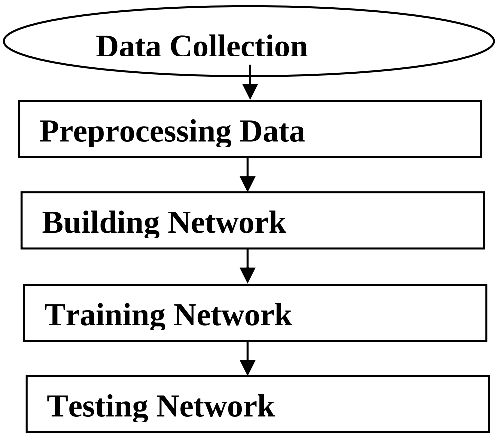


Figure 5: The basic flow of ANN model design

III) *Building the Network:*

This is 3rd stage of ANN model design which involves specification of neurons, hidden layer,training and weight/bias learning function.It also involves specification of transfer function in each layer andthe performance function.

IV) *Training the Network:*

This stage of ANN model design involves training of network for fitting of inputs and targets. After considering some backpropagation algorithms, Levenberg-Marquardt(LM) backpropagation (trainlm) was employed.In making actual output close to target output of network during training, weights are adjusted .A six(6) months data period from December,2012 to May,2013 are used for the training.Table 2 showstransfer functionsused which are provided by MATLAB.Table 2 below shows the various function name, and the mathematical form of function(s).

TABLE II : BUILT-IN TRANSFER FUNCTIONS ADAPTED FROM

Function Name	Mathematical form
Linear	$f(x) = x$
Hyperbolic Tangent Sigmoid	$= \frac{e^x - e^{-x} f(x)}{e^x + e^{-x}}$
Logistic Sigmoid	$f(x) = \frac{1}{1+e^{-x}}$
Gaussian RBF	$\varphi_j(x)=\exp\left[\frac{1}{-\|x-x_j\|2\sigma_j^2}\right]^2$

SOURCE: [15]

Backpropagation Algorithms [11] is most widely and popular used ANN training algorithm.It is an error back propagation based on error correlation learning rule. Interestingly, backpropagation uses gradient of transfer function of neurons so as to propagate error backward which is measured at the networkoutput ,after which output error gradients over each weight. In order to update the network , gradients are used [16].

Levenberg-Marquardt(LM) backpropagation, an optimization algorithm most widely used was employed.This technique finds minimum of multivariante function which is expressed as a sum of squares of real valued functions (non-linear).It provides a solution for the least squares(non-linear) minimization problems. Approximation of Hessian matrix is possible when performance function is in sum of squares form [16].

$$H=J^T J \tag{10}$$

Where J =Jacobian matrix

The J contains gradient and first derivates of network error(s) and as in equation 11 below:

$$g_w = J^T e \tag{11}$$

The J corresponding to weight and biases, and e is a vector.

LM algorithm makes use of approximation to Hessian matrix which is Newton-like update Samira (2010):

$$W_{k+1}=W_k- [J^TJ + \mu I]^{-1}J^Te \tag{12}$$

Where μ denotes constant and *I* denotes Identity matrix. After the success of each step, the performance function reduces as μ decreases, and as tentative step increases performance function, μ increases. The performance function reduces at every iteration of algorithm [16].

At the stop of training automatically, the improvement of generalization stops, and vice versa .an increase in MSE(validation samples) show this. At different sampling and initial conditions, different results will be generated on multiple times training.

The average squared difference between targets and outputs is MSE.Lower values of MSE are better.Zero means there is no error. The error was computed after the training process.Regression i.e R values shows the measurement of correlation between targetsandoutputs.R is 0 means random relationship and 1 means close relationship.

V) *Testing the Network:*

Testing the network involves testing performance of developed models.The new set of data wereentered to the model at this stage.

For quantitative evaluation and verification of possibility of underlying trend in performance statistical analysis such as Coefficient of Determination i.eR^2,Root Mean Square Error i.e RMSE and Mean Bias Error i.e MBE were conducted.The R^2 gives fraction of variance of a variable which is predictable from the other variable. RMSE is a measurement of the variation of predicated values around the measured data; short term performance information is provided. The accuracy of the estimation depends on how low is RMSE.MBE shows deviation(average) of predicted values from corresponding data(measured) ;long term performance information is provided. Long term model prediction depends on how low is MBE. The amount of overestimation in the predicted offered traffic is indicated by positive MBE value and vice versa .The MBE, RMSE and R^2 are as given below:

$$\text{MBE} = \frac{1}{n}\sum_{i=1}^{n}(\text{Ip,i} - \text{Ii}) \tag{13}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\text{I p,i-Ii})^2} \tag{14}$$

$$R^2 = \text{Square}(\ r\ ) \tag{15}$$

Where r is the linear correlation coefficient which is the measurement of direction and strength between the two(2) variables.

The r is given as:

$$r = \frac{n\sum \text{Ip, iIi} - (\sum \text{Ip, i})(\sum \text{Ii})}{\sqrt{n(\sum(\text{Ip, i } 2)^2\text{-}(\sum \text{Ip, i})^2}\sqrt{n(\sum(\text{Ii}^2)\text{-}(\sum \text{Ii})^2}}$$

The r can be computed using a correlation function i.e CORREL,as below:

$$r = \text{CORREL(I p,i-Ii)} \tag{17}$$

$$R^2 = r^2 \tag{18}$$

$I_{p,I}$ represent predicted offered traffic in Erlangs, I_i represent measured offered traffic in Erlangs, and n denotes number of observations.

F. Samples for Training ,Validation & Testing

Three(3) kinds of samples were used for training, validation and testing designed network. Training samples wereinputted during thetraining,and the network was adjusted in line with its error.Also, some samples were used for validation so as measure the network generalization,and also to stop training when generalization seizes to improve.However, some samples were used for testing which do not have effect on the training and they also provide an independent network performance measure during and after the training. Also, percentages of samples used are;70 for training, 15 for validationand15 for Testing respectively.

G. Programming the Models

In this research paper, MATLAB (R2010b) was used to generate the script files for development of ANN Models (MLP and RBF) and determination of statistics of performance error (R^2, RMSE and MBE).

I) Multilayer Perceptron:

The nftool ,which is the Neural Network Fitting tool (Graphical User Interface(GUI) toolbox) in MATLAB for MLP program was used.The inputs and target data of each model were first entered at the command window for convenience and simplicity.The inputs could be all the input variable i.e Call Completion Traffic (CCT) , Seizure Traffic (ST), Traffic Channels (TC) , Utilization Rate (UR) and Handover Success Rate (HSR),or two or more depending on a particular model while the target remains the Offered Traffic (Erlangs).The nftool was issued at the command window, after the MLP window was launched, the inputs and target of each model were selected .The inputs and target were then normalized.The normalization for training and testing data was to normalize inputs and target so as to yield zero(0) mean and unity standard deviation.The tool automatically divides inputs and target data as samples for MLP ANN,and Percentages are 70, 15 &15 respectively for training,validation and testing.The total number of samples used was 170.Then,neurons in the hidden layer was set.This usuallydepends on design of network.Thereafter, the network was trained to fit the inputs and targets.; it was trained using LM Backpropagation.

However, designer can still specify the neurons (each layer),number of hidden layers, transfer function(each layer), and other functions (training,weight/bias learning and performance) to be used.Neurons (each layer), transfer function (each layer),training function, weight/bias learning function were automatically selected ,but the Regression value i.e R and Mean Square Error were computed for each model window.

If network performance is not good enough, network can be optionally tested on more data.The results from the nftool was saved so as to be used on command window.Then, script was generated from the tool.

The saved network was accessed on the command window through its network , this was done for each model. Network performance was checked with unseen data ,sincethe training was completed ; this data was exposed to network.The testing simulation command was issued to simulate the network with the test data. Fig. 6 shows thescreen shot of MLP training.

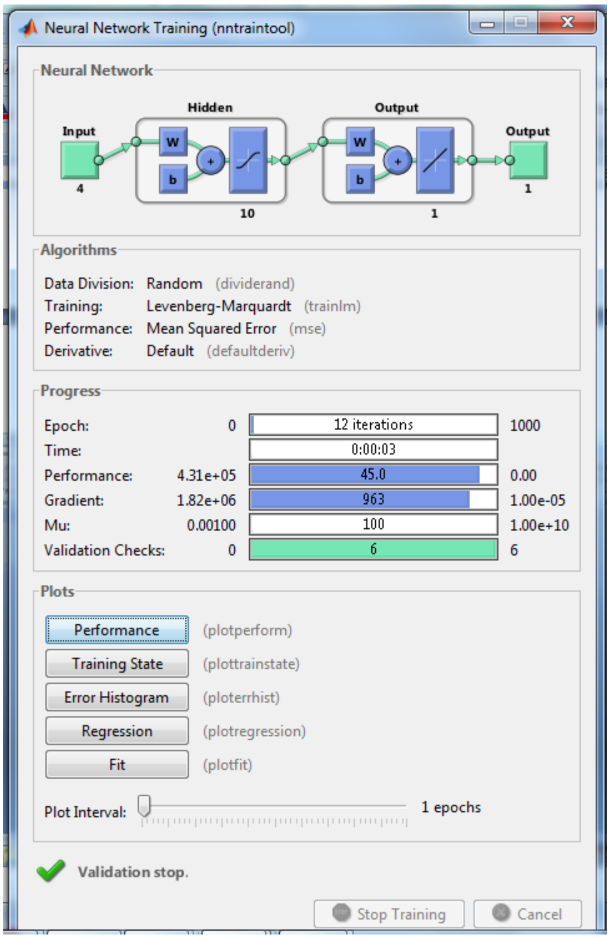


Figure 6: Training window

The output from network was denormalized for comparison with the measured data. Results of the simulation gave the predicted data of the offered traffic.This was later processed with measured data to compute the error statistics. And this was achieved on the Microsoft Excel 2007.

II) Radial Basis Function (RBF):

The “newrb” was employed for creation of RBF network continuously, with addition of one(1) neuron one at a time .Neurons were added until sum squared error is minute or when maximum number of neurons were attained. Function call which was used is:

nameofnetwork = newrb(in,tn,goal,spread,mn,df);

But,thein and tn represent input and target .Meanwhile, “goal” ,as an argument represents MSE goal , which was set to 0.01 in this research work, and “spread” denotes spread of RBF was changed between 1 and 2000. ‘mn’ refers to number of neurons (maximum),which was changed between 5 and 1200, while ‘df’refers to maximum number of neurons to include between the display and this df was fixed at 50. The fig. 7 above is the RBF training window for model 1.

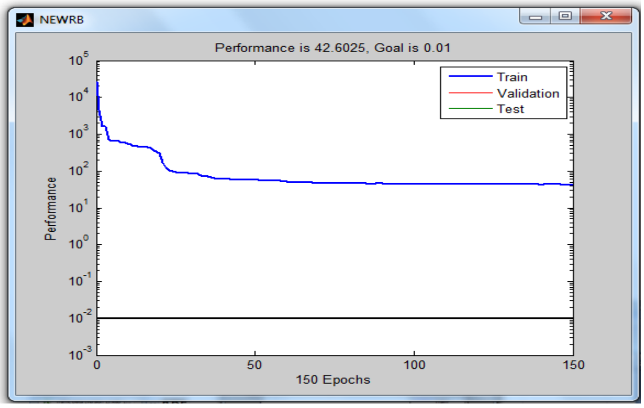


Figure 7. RBF training window

The recurrence of the above procedure continuously was carried out, witha number of neurons and hidden layer for MLP, and spread and number of neurons for RBF. However, results were thoroughly checked, stored, and compared ;this was done for all models that were tested so as obtain the best network structure with the lowest MBE ,highest R^2,and and lowest RMSE.

IV. RESULTS AND DISCUSSION

The ANN models considered in this research work i.e MLP and RBF were developed for traffic estimation for the traffic data collected in the research work area; this is for the different network structures by using traffic predictors as input parameters of the models. The statistical error parameters were computed for each of the ANN models.

The Table 3 and 4 are the results of ANN models i.e MLP and RBF obtained in this research work.The tables which are for MLP and RBFANN models developed, also show computed values of R^2 ,MBE and RMSE for network structures. The tables have the same fields which are Model, Network Structure, R^2, MBE and RMSE.The second (2^{nd}) field of the tables is the network structure, in which 1^{st}number represents number of neurons in (input layer),middle number represents neurons in (hidden layers) while the last number denotes neuronsin (output layer) of network.

TABLE III: STATISTICAL ERROR PARAMETERS OF ANN MODELS(MLP) FOR DIFFERENT NETWORK STRUCTURES

Model	Network Structure	R^2	RMSE	MBE
1	5-10-1	0.99	5.456	0.94
2	4-10-1	0.71	88.255	-48.99
3	4-10-1	0.97	17.759	14.61
4	4-10-1	0.98	24.058	22.19
5	4-10-1	0.98	24.058	22.19
6	4-10-1	0.84	39.338	28.27
7	3-10-1	0.98	23.193	-16.74
8	3-10-1	0.53	565.496	380.13
9	3-10-1	0.99	37.315	35.07
10	3-10-1	0.96	19.512	0.51
11	3-10-1	0.95	63.229	-44.72
12	3-10-1	0.97	38.627	31.26
13	3-10-1	0.93	31.962	-18.09

14	3-10-1	0.96	107.463	106.52
15	3-10-1	0.94	16.422	-3.40
16	3-10-1	0.97	11.991	4.98
17	2-10-1	0.96	32.580	-20.77
18	2-10-1	0.98	45.871	44.93
19	2-10-1	0.55	80.784	65.45
20	2-10-1	0.05	132.188	110.98
21	2-10-1	0.83	29.02	9.68
22	2-50-1	0.88	36.276	-3.33
23	2-10-1	0.06	173.512	118.41
24	2-10-1	0.95	98.770	97.64
25	2-10-1	0.95	96.80	95.88
26	2-10-1	0.09	132.17	114.74

It can be deduced from the table 3 that Model 1 is the best of MLP models developed for estimation, since it results to coefficient of determination of 99% ,lowest values of RMSE (lowest value of 5.456) and MBE of 0.94.The input parameters employed in Model 1 are Call Completion Traffic, Seizure Traffic,Traffic Channel, Utilization Rate and Handover Success Rate.

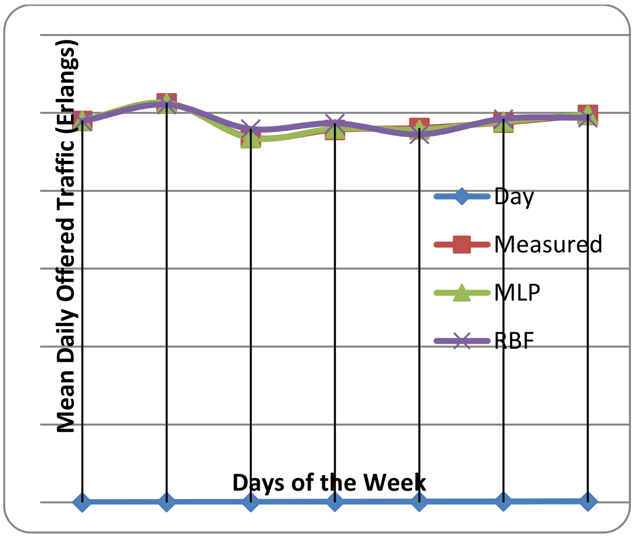
TABLE IV. STATISTICAL ERROR PARAMETERS OF ANN MODELS (RBF) FOR DIFFERENT NETWORK STRUCTURES

Model	**Network Structure**	**R^2**	**RMSE**	**MBE**
1	5-2500-1	0.77	32.387	7.14
2	4-3000-1	0.90	31.6678	-15.46
3	4-1150-1	0.90	73.970	-50.15
4	4-1900-1	0.84	26.177	2.42
5	4-1900-1	0.84	26.177	2.42
6	4-1700-1	0.53	55.905	5.05
7	3-1950-1	0.98	14.551	-4.94
8	3-2100-1	0.84	30.587	5.32
9	3-2500-1	0.95	34.876	31.41
10	3-2400-1	0.96	22.138	-2.82
11	3-5400-1	0.95	26.290	-13.46
12	3-5700-1	0.98	27.285	25.45
13	3-5400-1	0.81	35.997	-18.26
14	3-1510-1	0.60	110.485	72.77
15	3-2300-1	0.98	48.890	47.94
16	3-2400-1	0.97	11.706	0.51
17	2-6000-1	0.96	13.08	-1.94
18	2-6000-1	0.96	39.132	36.96
19	2-5400-1	0.98	12.954	4.09
20	2-12000-1	0.30	135.213	120.55
21	2-7000-1	0.99	32.680	31.16
22	2-6400-1	0.98	8.318	1.85
23	2-6400-1	0.97	15.130	10.68
24	2-2000-1	0.96	100.696	99.86
25	2-6400-1	0.96	100.945	100.11
26	2-7000-1	0.90	84.788	80.49

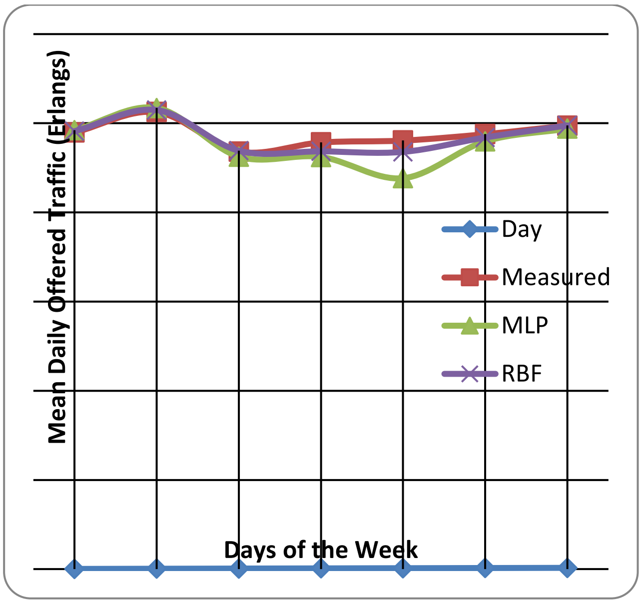
For the RBF models(Table 4) , Model 22 is the best of RBF models;input parameters are Call Completion Traffic and Seizure Traffic.

However, Model 10, 15 and 16 of MLP models showed good accuracy for estimation of daily mean offered traffic as compared to the RBF. The computed values of MBE are 0.51, -3.40 and 4.98 for these models.Also ,someof the RBF models performed well in terms of their low values of MBE.

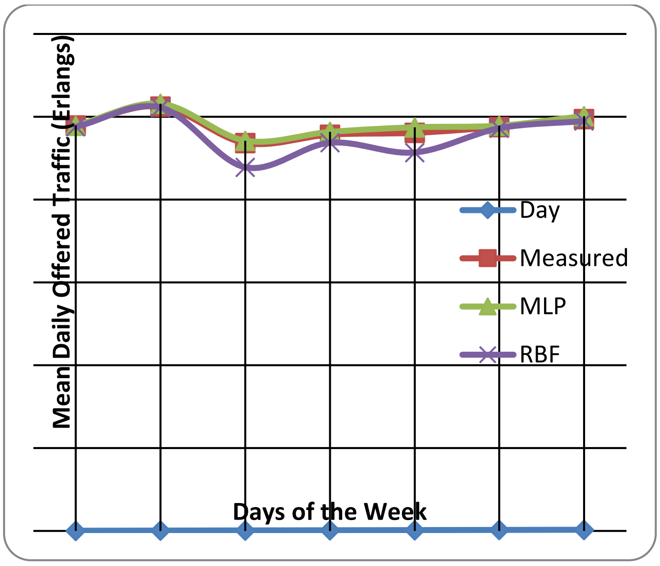
The developed ANN models were used to estimate offered traffic experienced during the last seven (7) days of May,2013.. The graphical comparisons between measured data and ANN models of estimated values of offered traffic are illustrated in fig.8 below.Each graph clearly indicated the measured,MLP and RBF.The graph is the mean daily offered traffic in Erlangs against the days of the week.



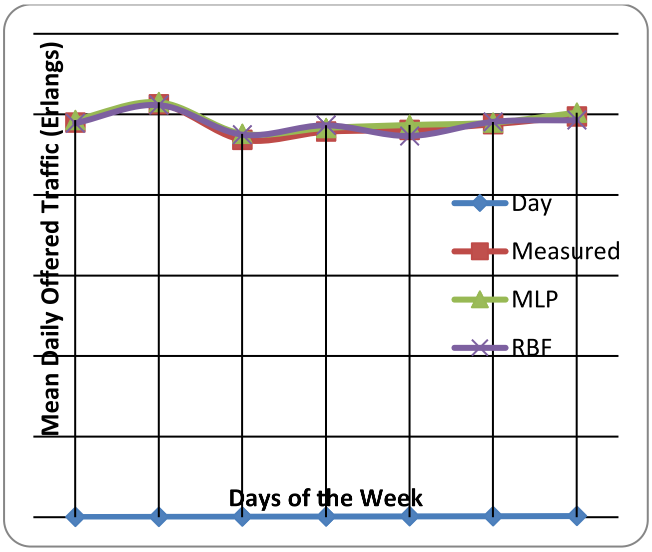
(a)


Mean Daily Offered Traffic (Erlangs)
Days of the Week
Day
Measured
MLP
RBF

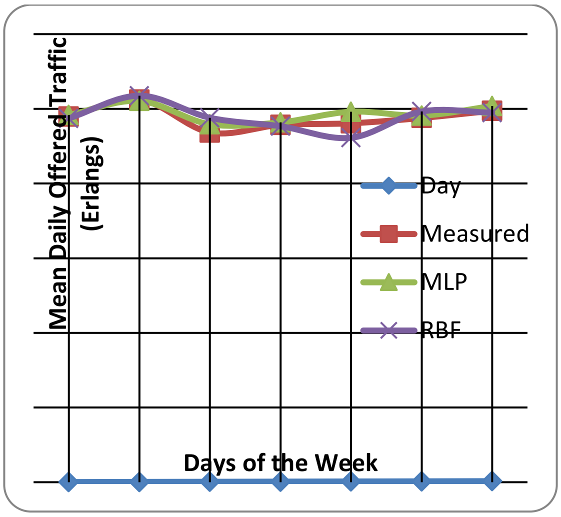
(b)


Mean Daily Offered Traffic (Erlangs)
Days of the Week
Day
Measured
MLP
RBF

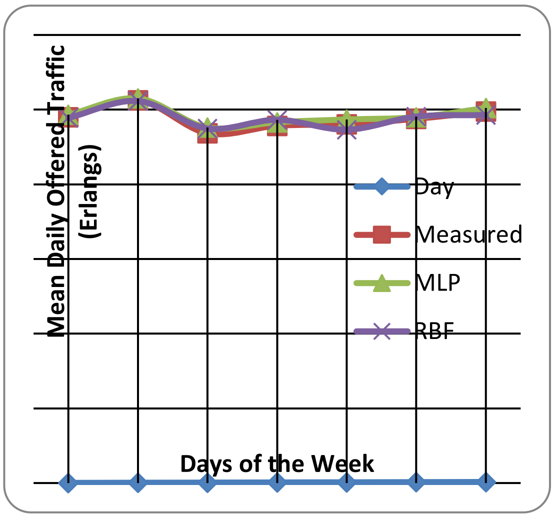
(c)


Mean Daily Offered Traffic (Erlangs)
Days of the Week
Day
Measured
MLP
RBF

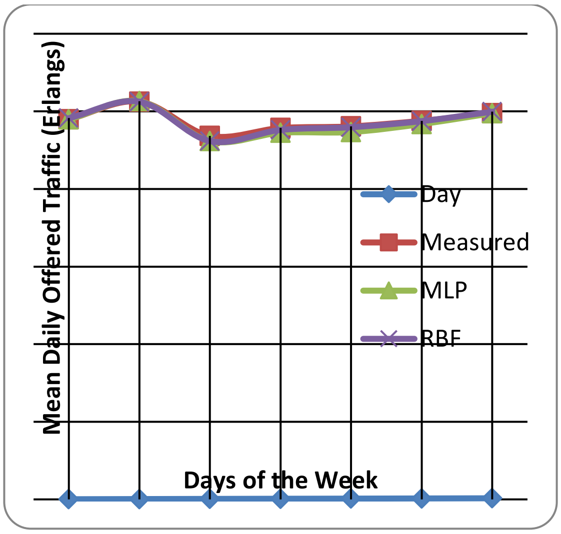
(d)

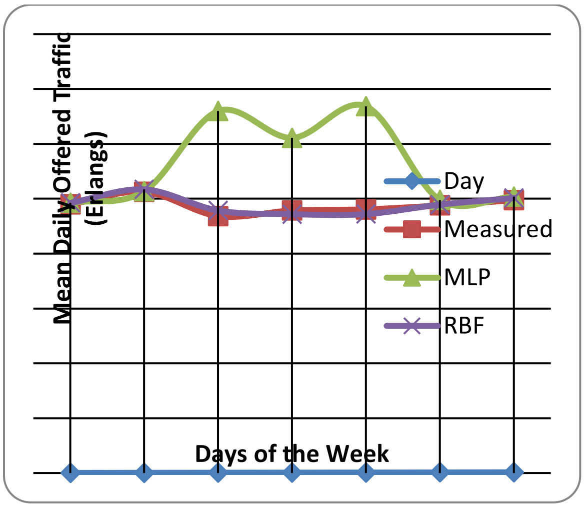

Mean Daily Offered Traffic (Erlangs)
Days of the Week
Day
Measured
MLP
RBF

(e)


Mean Daily Offered Traffic (Erlangs)
Days of the Week
Day
Measured
MLP
RBF

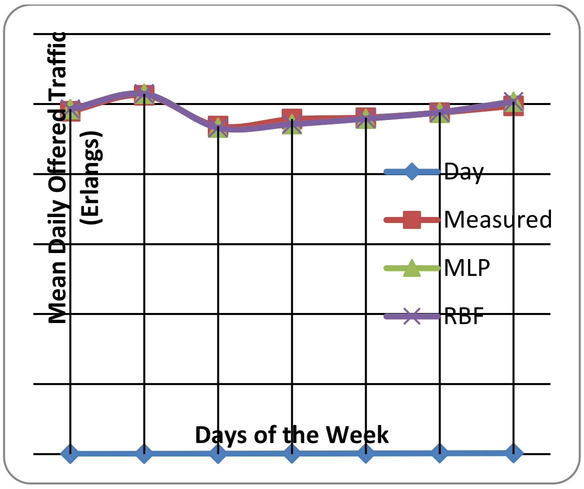
(f)


Mean Daily Offered Traffic (Erlangs)
Days of the Week
Day
Measured
MLP
RBF

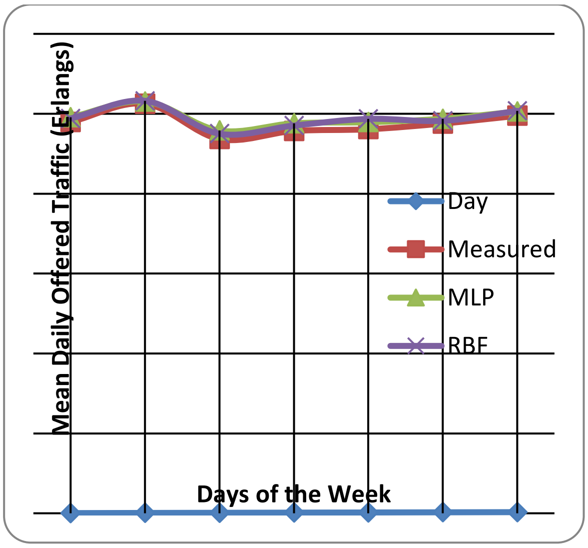

Mean Daily Offered Traffic (Erlangs)
Day
Measured
MLP
RBF
Days of the Week

(g)

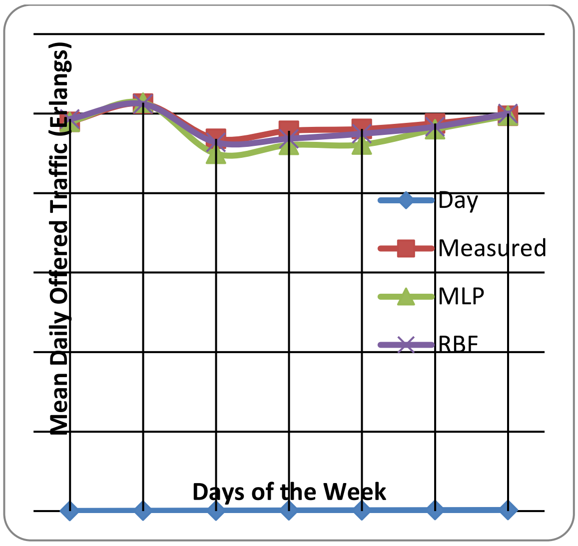
(h)


Mean Daily Offered Traffic (Erlangs)
Day
Measured
MLP
RBF
Days of the Week

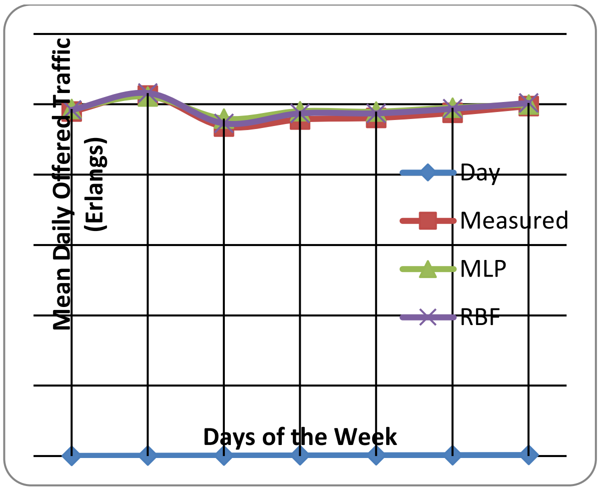
(i)


Mean Daily Offered Traffic (Erlangs)
Day
Measured
MLP
RBF
Days of the Week

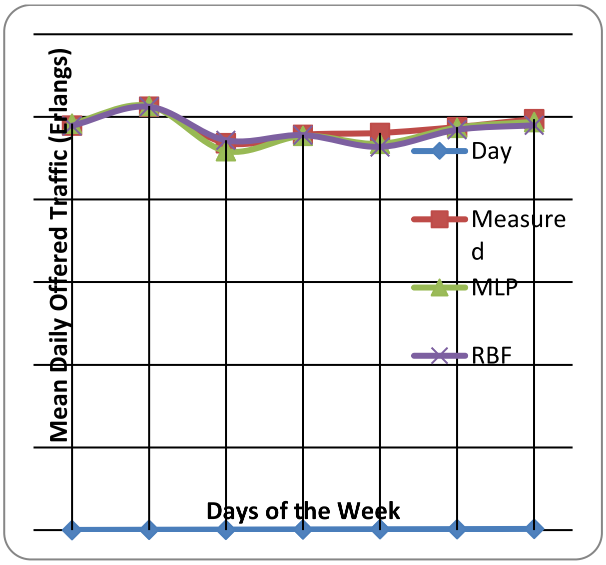
(j)


Mean Daily Offered Traffic (Erlangs)
Day
Measured
MLP
RBF
Days of the Week

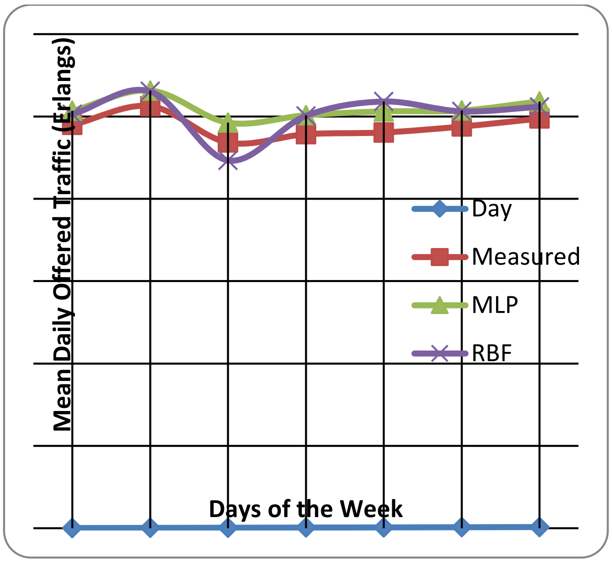
(k)


Mean Daily Offered Traffic (Erlangs)
Day
Measured
MLP
RBF
Days of the Week

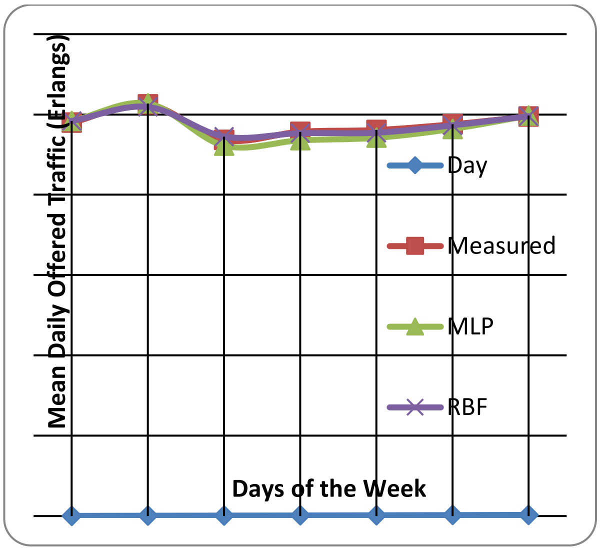
(l)


Mean Daily Offered Traffic (Erlangs)
Day
Measure
d
MLP
RBF
Days of the Week

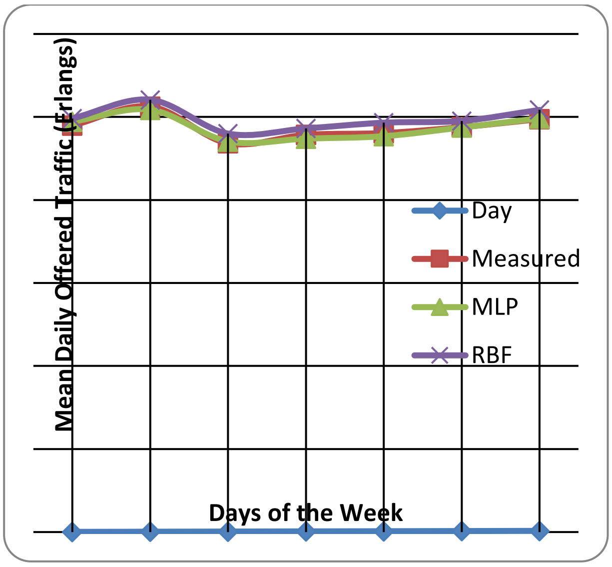
(m)


Mean Daily Offered Traffic (Erlangs)
Day
Measured
MLP
RBF
Days of the Week

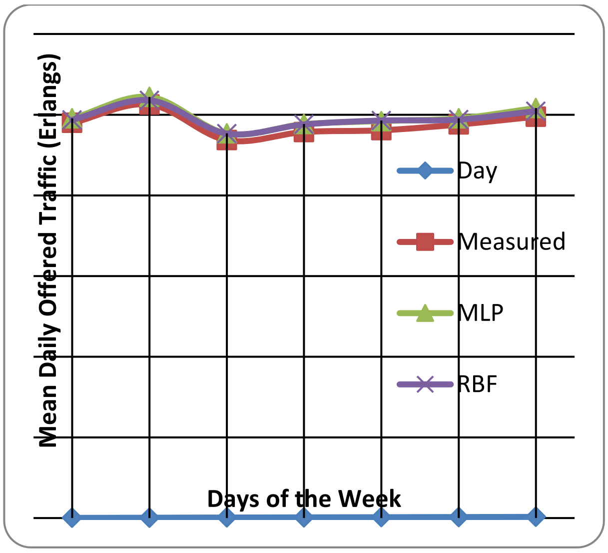
(n)


Mean Daily Offered Traffic (Erlangs)
Day
Measured
MLP
RBF
Days of the Week

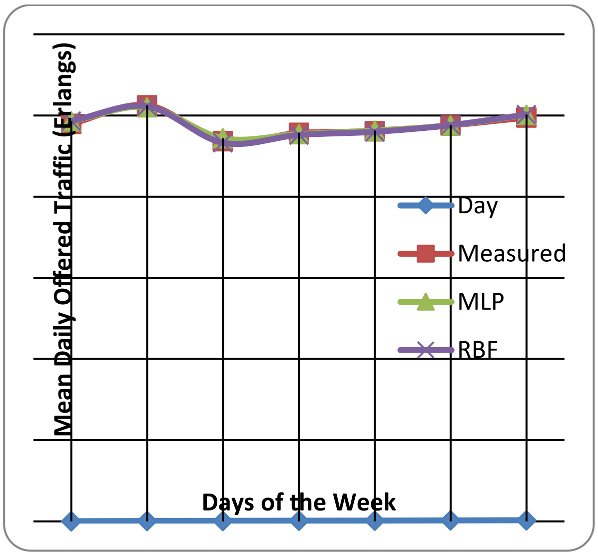
(q)


Mean Daily Offered Traffic (Erlangs)
Day
Measured
MLP
RBF
Days of the Week

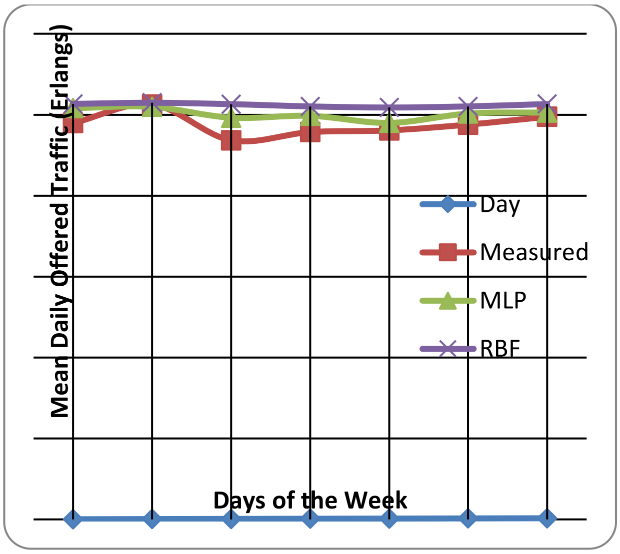
(o)


Mean Daily Offered Traffic (Erlangs)
Day
Measured
MLP
RBF
Days of the Week

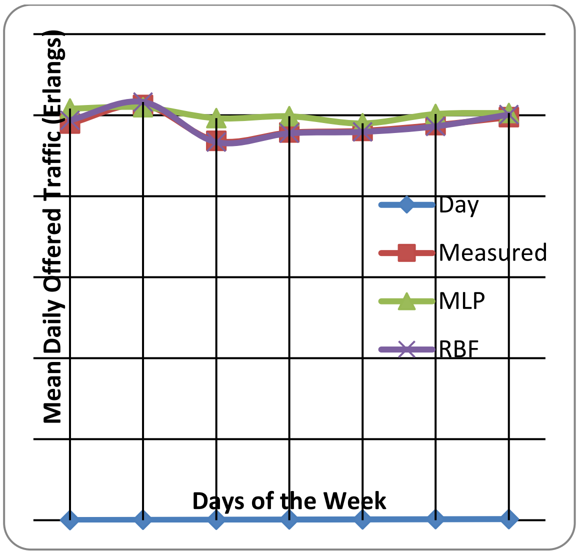
(r)


Mean Daily Offered Traffic (Erlangs)
Day
Measured
MLP
RBF
Days of the Week

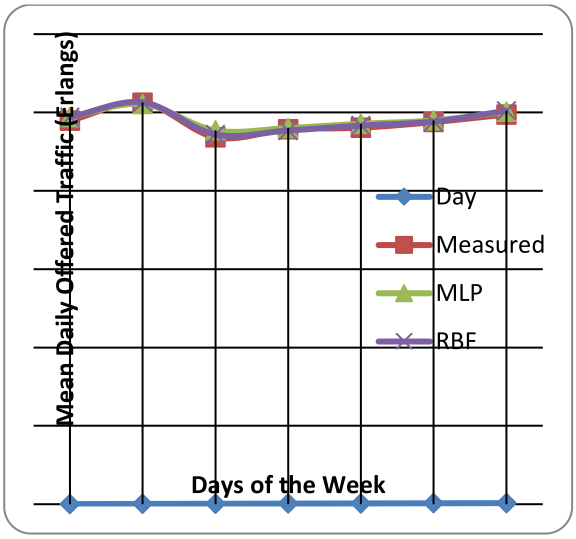
(p)


Mean Daily Offered Traffic (Erlangs)
Day
Measured
MLP
RBF
Days of the Week

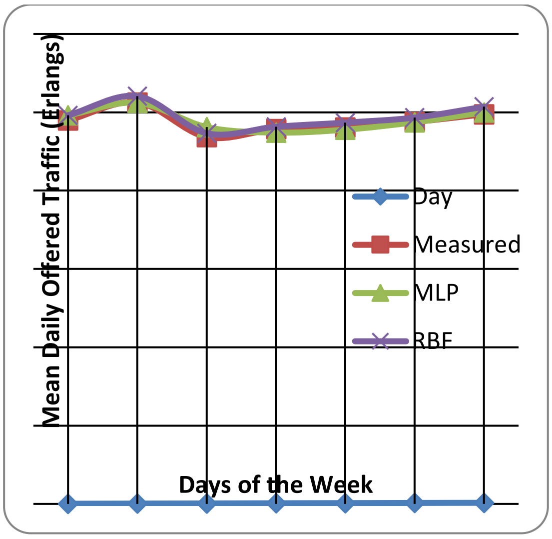
(s)


Mean Daily Offered Traffic (Erlangs)
Day
Measured
MLP
RBF
Days of the Week

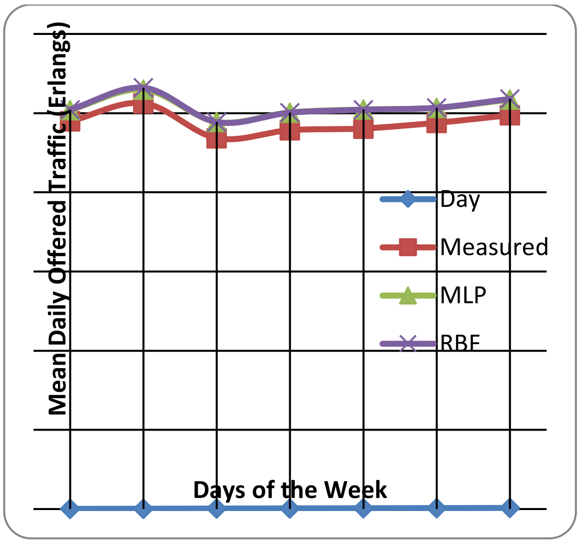
(t)


Mean Daily Offered Traffic (Erlangs)
Day
Measured
MLP
RBF
Days of the Week

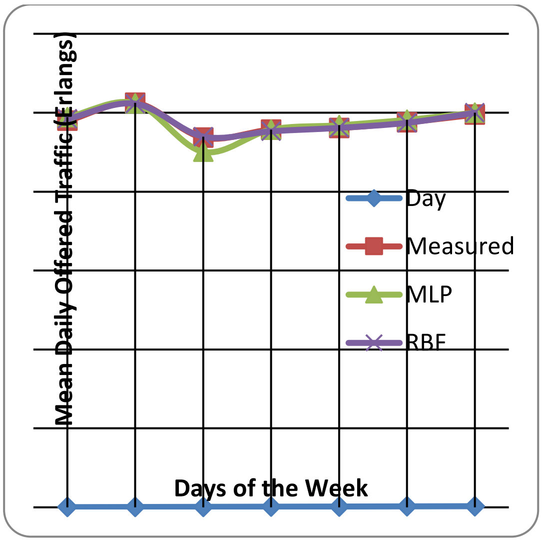
(w)


Mean Daily Offered Traffic (Erlangs)
Day
Measured
MLP
RBF
Days of the Week

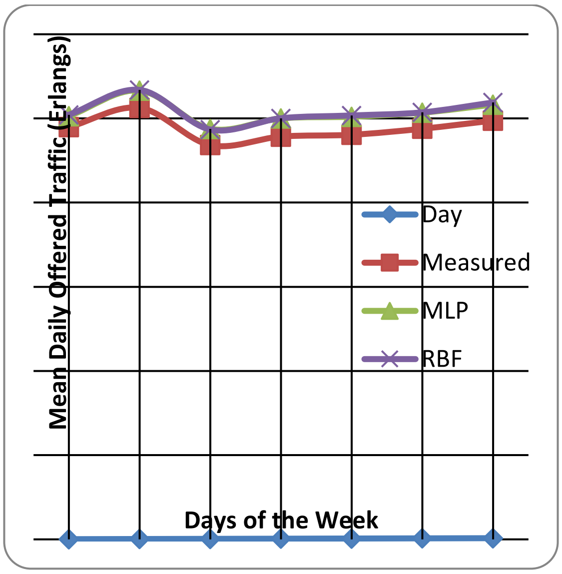
(u)


Mean Daily Offered Traffic (Erlangs)
Day
Measured
MLP
RBF
Days of the Week

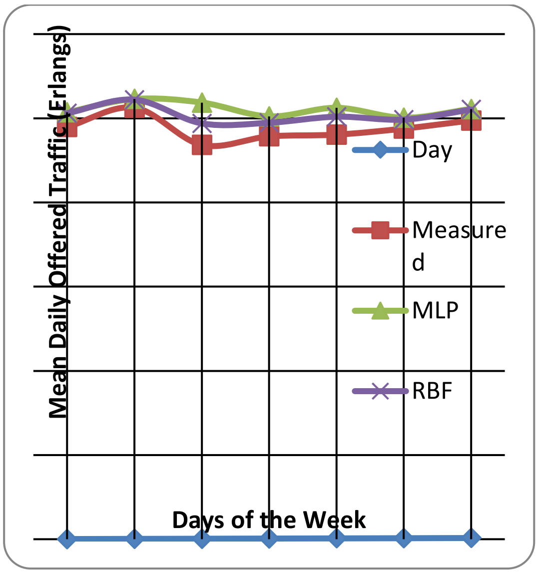
(x)


Mean Daily Offered Traffic (Erlangs)
Day
Measured
MLP
RBF
Days of the Week

(v)


Mean Daily Offered Traffic (Erlangs)
Day
Measured
MLP
RBF
Days of the Week

(y)



(z)

Figure 8: The comparison between measured and estimated ANN (MLP and RBF) models: (a) model 1; (b) model 2; (c) model 3; (d) model 4; (e) model 5; (f) model 6; (g) model 7; (h) model 8; (i) model 9; (j) model 10; (k) model 11; (l) model 12; (m) model 13; (n) model 14; (o) model 15; (p) model 16; (q) model 17; (r) model 18; (s) model 19;(t) model 20; (u) model 21; (v) model 22; (w) model 23; (s) model 24; (y) model 25; and (z) model 26

The fig. 8 above shows comparison between traffic data(measured) and estimated ANN modelsfor all the twenty-Six (26) MLP and RBF based network models. The validation was carried out with the use of traffic data(measured) of last seven days in May,2013 . In the developed models i.e (1-26), the ANN models were able to estimate traffic data as close to the ANN models .The best estimation was found with the model 1 as shown in the figure 8.This indicates that the model can be used to estimate the offered traffic favourably well ;given the measured data of the traffic predictors .And with this , network provider can improve in their network design and planning.However, there are cases where the MLP performed better than RBF such as Model 3,6,15 ,16,18 whereas RBF performed well and better in some models such as 2,9,11,19,22 & 26.Meanwhile, Some ANN models did perform well ,and as such not good for estimation of traffic data, these include Model 14,20,23,24.

V. CONCLUSION

In this research paper, the ANN models forestimating average daily traffic in Lagos, Nigeria was carried out using the MATLAB tools.The traffic data from 1st December to 31st May,2013was used proportionally for the training(70%), validation(15%) and testing(15%) of the neural network.With different combinations of input parameter(s Twenty-Six(26) models of MLP ANN were developed. Results obtained showed superiority of MLP over RBF especially (1,10, 15 and 16),with the deterministic coefficients above 90% and low RMSE and MSE values despite working with busy hour traffic data. The ANN models still showed good performance despite the unavailability of input parameter(s).

However, Call Completion Traffic, Seizure Traffic, Traffic Channel, Utilization Rate and Handover Success Rate are parameters used for ANN modeling among other parameters unused for the modeling are Carried traffic, Call drop rate, Holding time, Grade of Service among others, these are important measured data collected at the OMC of one of the leading mobile networks.

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doi : https://doi.org/10.32628/IJSRSET207555

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