EMPIRICAL MOBILE NETWORK TRAFFIC PREDICTION: STATISTICAL COMPARATIVE PERFORMANCE ANALYSIS USING MIMO RBFN NETWORK MODEL

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Abstract. The exponential demand of telecommunication traffic require the development of different forecasting models in order to help industry players to plan for the future. The available forecasting traffic models are mostly developed for single-input single-output traffic data. The study applies multiple-input multiple-output (MIMO) radial basis neural network (RBFNN) model to instantaneously forecast five different time spans of telecommunication network traffic obtained from 4G and 3G networks operators. The data was taken from 3G uplink hourly, 3G daily voice, 4G weekly, 3G downlink monthly and 3G downlink quarterly from 2015 to 2017. The results prove that MIMO RBFNN (5-10-5) gives higher prediction accuracy than the other three MIMO models when subjected to different statistical tests.
Keywords: *4G, 3G, radial basis function neural network, multiple-input and multiple-output, forecasting*

Introduction

The rise in the volume of telecommunication network traffic due to enhanced services provided by operators well continue in the future. The forecast figures indicate an increase in subscription to 5.7 billion in 2023. This figure represent about 71% of the world population. The Middle East and Africa figure for monthly data traffic from mobile is expected to be 14 exabytes by 2023 (CISCO Official Portal, 2020). In the past several different forecasting models have been proposed to estimate the ever increasing volumes of telecommunication network traffic data (Zhang and You, 2020; Iqbal et al., 2019; Zhang et al., 2019; Zhang et al., 2017). However the concentration has centred on single-input single output models Multiple-input multiple-output (MIMO) models have also received massive attention by researchers in other fields. For example Soares Mayer et al. (2020) used MIMO Radial Basis Function Neural Network (RBFNN) to predict transmitter beamforming, Tripura et al. (2018) compared MIMO Nonlinear Autoregressive with Exogenous Inputs (NARX) and MIMO RBFNN models to forecast river flow with MIMO NARX model performing better than MIMO RBFNN.

The study adopted the MIMO RBFNN that integrated the direct MIMO method since it is capable of taking sequential stochastic dependencies of past data and generating forecast. The 5-input 5-output MIMO RBFNN provides another method for the prediction of different time spans of telecommunication network traffic data. RBFNN prediction is found in different fields such as pattern classification (Anifowose, 2010), network traffic (Szmit et al., 2013), telephone traffic prediction (Li et al., 2013), energy consumption (Staiano and Inneguale, 2017), financial time series (Wang et al., 2016), (Franco and Steiner, 2017). Biernacki (2017) used ARIMA, MLP, RBFNN and

FARIMA to forecast internet traffic and concluded that MLP, RBFNN and FARIMA models generally produced similar results which were better than ARIMA models. Wysocki and Ławryńczuk (2016) as well as Marček and Square (2015) suggested a hybrid ARIMA/RBFN network to forecast stock index data. ARIMA-RBFN for hydrological data (Xing and Lou, 2019).

Mohanty et al. (2014) also used a momentum based RBFNN for the pitch controller of an aircraft to obtain the desired pitch angle which is an important parameter for pilots. Huang (2014) applied the capabilities of RBFNN and Elman neural network in the analysis and design of hybrid generation system. The two neural networks were providing complimentary services to each other but not merely comparing their efficiency. Santhanam and Subhajini (2011) developed RBFNN and Back Propagation neural network (BPNN) models in forecasting the rainfall pattern using meteorological data. Zaleski and Kacprzak (2010) applied RBFNN model to predict short-term values of traffic volume generated by Transmission Control Protocol/Internet Protocol (TCP/IP) packet network users. Ozovehe et al. (2018) employed RBFNN, MLP, ANFIS models and Group Method of Data Handling (GMDH) to analysed the traffic of base station cells of GSM/GPRS. The prediction results showed that GMDH performed better than the three models.

Materials and Methods

Modelling multiple-input multiple-output radial basis function neural network for 4G and 3G network

Multiple-Input Multiple-Output (MIMO) method is basically the inter-relations of variables between inputs and outputs instantaneously. The MIMO methods are classified into two: (a) multi-stage MIMO (b) single-stage or direct MIMO.

Multi-stage MIMO

This approach is established on forecasting horizons which generates multi-step outputs at different horizons where learning is carried out by one multiple-output mode. The process is determined by Equation (1) as;

$$y_{n+1}, y_{n+2}, \dots, y_{n+k} = f(y_n, \dots\dots, y_{n-d+1}) + w \qquad \text{(Eq. 1)}$$

where; $y_{n+(.)}$ are the multiple-output and multiple-input per cycle; k is an integer (k>1), w represent the vector noise for zero mean and non-diogonal covariance; and d is the maximum embedded order. To determine k steps after learning process the Equation (2) is applied;

$$\hat{y}_{n+1}, \dots\dots\dots, \hat{y}_{n+k} = \hat{f}(y_n, \dots\dots, y_{n-d+1}) \qquad \text{(Eq. 2)}$$

In the process model restriction are encountered because prediction horizons are inside the same model structure.

Single-stage or direct MIMO

In this method one-step forecasting is provided in one segment in spite of the number of multiple outputs considered and the prediction is direct under varying time horizon. The factor of model restriction is non-existent with this method. The direct MIMO approach is determined from Equation (3) as;

$$y(n+h) = f\begin{cases} y(n-d_y), \dots\dots\dots, y(n-1), y(n) \\ u(n-d_u), \dots\dots\dots, u(n-1), u(n) \end{cases} \qquad \text{(Eq. 3)}$$

where; $u(n) = [u_1(n), \dots \dots \dots, u_r(n)]^T$ and $y(n) = [y_1(n), \dots \dots \dots, y_r(n)]^T$ are the input and output vectors, d_y and d_u represent the input and output time lags, h represents the prediction time horizon and $f(n) = [f_1(n), \dots \dots \dots, f_r(n)]^T$ is the nonlinear relation to be estimated. The basic architecture of the RBFN is a three layer (Suzuki, 2011) supervised feed-forward network (Xu et al., 2012) applied in interpolation, probability density function prediction etc. The input layer is composed of n input data. It is fully connected to the neurons in the second layer. The hidden layer transforms the data from the input space to the hidden space using a non-linear function (Anifowose, 2010). A hidden node has a radial basis function (RBF) as an activation function. The output layer, which is linear, yields the response, where the output value is determined from the weighted sum method and node number in the hidden layer network (Anifowose, 2010).

RBF is a real-valued function whose value depends only on the distance from some other point c called a centre (Giveki and Rastegar, 2019) and is given in Equation (4);

$$f(x, c) = f(\| x - c \|) \qquad \text{(Eq. 4)}$$

where; $\| x - c \|$ is the Euclidean distance between vector x and centre ci. The norm is often Euclidean distance, however other distance functions are also possible. The output of i'th neuron in the output layer of the RBFN is given in Equation (5) as (Suzuki 2011):

$$y_i(x) = \sum_{j=1}^{M} w_{ij}\varphi(\| x - c_j \|); \quad i = 1, \dots, m \qquad \text{(Eq. 5)}$$

The φ(.) is the basis function which is described using ||x-cj||. (w1i . . . ,wni) of connection weights between the n input nodes and the hidden node *i*.

Training of MIMO RBFNN model

The RBFN network training is in two phases (Dash et al., 2016): (1) the unsupervised learning phase which involves input layer and the hidden layer; and (2) the supervised learning phase which is applied from the hidden layer to the output layer. For this study, the LM algorithm was adopted as a learning rule to train the RBF network. LM is the most popular optimization algorithm. The LM algorithm provides a solution for nonlinear least squares minimization problem and the function to be minimized is given in Equation (6) as (Al-Mayyahi et al., 2015);

$$f(x) = \frac{1}{2}\sum_{j=1}^{m} r_j^2\,(x) \qquad \text{(Eq. 6)}$$

where; $x = (x_1, x_2, ..., x_n)$ is a vector and r_j are residuals. The derivatives of f can be written using Jacobian matric J of r defined as (Equation 7);

$$f(x) = \frac{\partial r_j}{\partial x_i}, 1 \le j \le m, 1 \le i \le n \qquad \text{(Eq. 7)}$$

The output of i'th neuron in the output layer of the RBFN is given as (Suzuki, 2011)(Equation 8);

$$y_i(x) = \sum_{j=1}^{M} w_{ij}\varphi(\| x - c_j \|); \quad i = 1, ..., m \qquad \text{(Eq. 8)}$$

For non-linear least squares, the minimization problems can be solved using LM algorithm. When the performance function has the form of a sum of squares, then the Hessian matrix, H can be approximated in Equation (9) as (Ramesh et al., 2008);

$$H = J^T J \qquad \text{(Eq. 9)}$$

where J is the Jacobian matrix that contains the first derivatives of network errors and the gradient, g_w can be computed in Equation (10) as;

$$g_w = J^T e \qquad \text{(Eq. 10)}$$

where e is a vector of network errors. The LM algorithm uses the approximation to the Hessian matrix Equation (11) (Ebrahimzadeh and Khazaee, 2010);

$$w_{k+1} = w_k - [J^T J + \mu I]^{-1} J^T e \qquad \text{(Eq. 11)}$$

where I is the identity matrix and μ is a constant. μ decreases after each successful step and increases only when a tentative step would increase the performance function. The RBF uses a radially symmetric function (e.g., Gaussian) expressed in Equation (12);

$$f(x) = e^{-\frac{(x-M)^2}{2\sigma^2}} \qquad \text{(Eq. 12)}$$

where M and σ are the mean and the standard deviation of the input variable x. The value on j output neuron network may be described as a function of the input vector x given by the Equation (13) (Suzuki, 2011);

$$y_j = \sum_{i=1}^{N} w_i f(\| x - c_i \|) \quad \text{(Eq. 13)}$$

Where; N is the number of neurons in the hidden layer; x is the input vector; ci is the centre vector for neuron i and wi is the weight of neuron i in the linear output neuron.

Creation and configuration of 5-input 5-output MIMO RBFNN

In the study, RBFN model of three layers was configured as multiple-input multiple-output (MIMO) that accepts five inputs of telecommunication network traffic of hourly, daily, weekly, monthly and quarterly time spans. The architecture for this study is illustrated in *Figure 1* with five inputs labelled as X_1, X_2, X_3, X_4 and X_5. The inputs denote telecommunication network traffic of five different time spans; X_1 = traffic measurement in hours; X_2 = traffic measurement in days; X_3 = traffic measurement in weeks; X_4 = traffic measurement in months; and X_5 = traffic measurement in quaters. The 5-input 5-output MIMO RBFN network model applied 3G uplink hourly traffic, 3G daily voice traffic, 4G weekly traffic, 3G monthly downlink traffic and 3G quaterly downlink as the input data. The normalisation procedure was performed on each data set which eventually gave the division of training = 70%, testing = 15%, and validation = 15%.

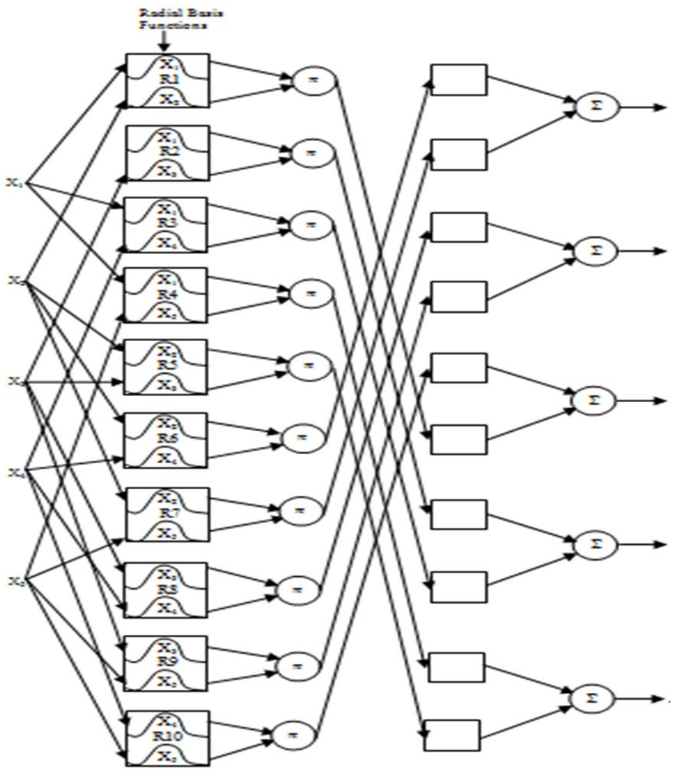

Figure 1. *RBFNN Architecture with 5-Input 5-Output Configuration.*

Training of 5-input 5-output MIMO RBFNN

The parameters utilised in the training of the MIMO RBFNN is given in *Table 1*. In the unsupervised phase, weight change was used for termination with a threshold value of 0.0001. The learning rate began at 0.01 and decayed to a low value of 0.001. With the MSE termination of the supervised phase, the increase function was utilised since the cross validation (CV) set was used. This was employed to monitor the generalisation process to be able to stop the network whenever the MSE of the CV set starts to rise.

Table 1. *Data used to calculate water demand.*

Parameters	5-input 5-output
Input PE	5
Output PE	5
Exemplars	1318
Hidden layer	1
Cluster centre	25
Competitive Rule	Conscience full
Metric	Euclidean
Supervised Learning	1100 Epochs
Unsupervised Learning	100 Epochs
Hidden layer	-
PE in Hidden layer	9
Transfer function	TanhAxon
Learning rule	LM
Output layer	-
Transfer function	TanhAxon
Learning rule	LM
Termination	MSE (Increase)
Weight update	Batch (supervised)

Results and Discussion

Measurement of mobile network data

The 4G network traffic data for the study was collected in 2017 from a network operator in Ghana (*Table 2*). The data was measured from the S5/S8 interface of the Packet Data Network Gateway (P-GW) in the 4G Evolved Packet Core where mobile data traffic is monitored from GPRS Tunnelling Protocol user plane (GTP-U). With the 3G data, it was collected on a large network in Ghana from 2015 to 2017. The network has three RNCs, two SGSNs and two MSCs. The study area covered the whole country which was divided into three (3) clusters (Northern Sector, Western Sector and Eastern Sector). The clusters were each designated with a Radio Network Controller (RNC). The descriptive statistics of the two networks and the corresponding values are provided in *Table 2*.The breakdown are 957 samples of 3G hourly uplink traffic, 707 samples of 3G daily voice traffic, 28 samples of 4G weekly traffic, 72 samples of 3G monthly downlink traffic and 15 samples of 3G downlink quarterly traffic. Table 3 shows the division of the samples into 70% for training, 15% for testing and 15% for validation and NeuroSolutions software was applied in the analysis.

Table 2. *Descriptive statistics of aggregated 4G and 3G network traffic data.*

Statistics	957 samples (hourly) 3G uplink	707 samples (daily) 3G voice	28 samples (weekly) 4G	72 samples (montlhy) 3G downlink	15 samples (quarterly) 3G downlink
Mean	71061.59	3121.063	82067313	3114591.0	13919290
Median	71967.59	3036.377	78350251	2383673.0	14087025

Maximum	235352.3	6424.421	2.16e+08	10691053	20920417
Minimum	14897.16	804.6220	3898517	270005.7	6388322.0
Std. Dev.	30059.34	1431.494	44639601	2839062	6582633.0
Skewness	0.702113	0.041234	0.605163	0.794602	-0.019465
Kurtosis	4.038581	1.925203	---	2.295719	1.100051
Jarque-Bera	121.6387	34.23028	4.440969	9.064749	2.257075

Table 3. *Training, testing and validation sample of 3G downlink traffic data*.

Data	3G uplink hourly (957 samples)	3G daily voice (707 samples)	4G weekly (28 samples)	3G monthly downlink (72 samples)	3G quarterly downlink (15 samples)
Training (70%)	671	495	20	50	9
Validation (15%)	143	106	4	11	3
Testing (15%)	143	106	4	11	3

MIMO RBFN network training for 4G and 3G traffic

The initial rate of unsupervised learning was 0.01 which decayed to 0.001 with an iteration of 100. In the modelling of the MIMO RBFN network, several configurations were performed each with 5-input and 5-output and application of varied cluster centres from 1 to 25. The Tanhaxon transfer function and LM learning rules were also applied in both hidden and output layers. In total four different MIMO RBFN networks were developed and the goodness of fit statistics values were compared as illustrated in *Table 4*. The MIMO RBFN network model is represented in bracket as first digit for input traffic, second digit for cluster centre and third digit for output traffic. For example, MIMO RBFN (5-13-5) implies 5 time spans as input traffic data, 13 as cluster centre and 5 time spans as output traffic data. From Table 4 the best model selected from the four obtained is MIMO RBFN (5-10-5) network.

Table 4. *5-input 5-output RBFN model selection criteria with 4G and 3G traffic data*.

MIMO RBFN architecture	MSE	NRMSE	R
5-13-5	0.00166	0.0226	0.9799
5-18-5	0.00415	0.0358	0.9699
5-10-5	0.000360	0.0105	0.9888
5-5-5	0.00151	0.0216	0.9537

MIMO RBFN network model forecasting

The predicted traffic of the MIMO RBFN (5-10-5) network model for five time span traffic are shown in *Figure 2*, *Figure 3*, *Figure 4*, *Figure 5* and *Figure 6*. The performance of the model was validated with 3G hourly uplink traffic, 3G daily voice traffic, 4G weekly traffic, 3G monthly downlink traffic and 3G downlink quarterly traffic.

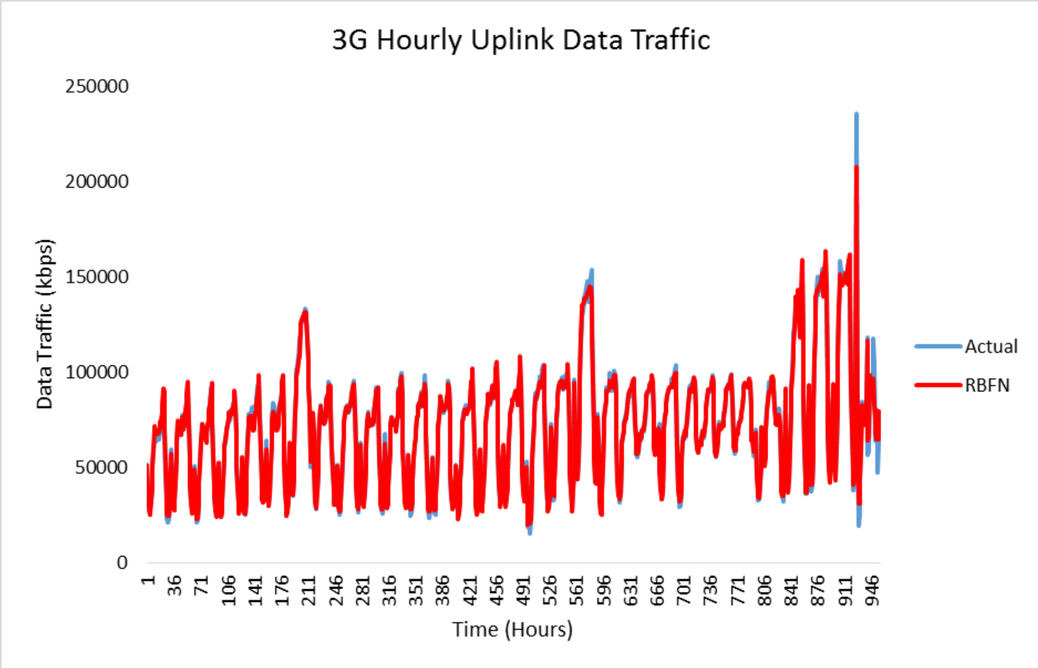

Figure 2. *Prediction performance of five model using 3G hourly uplink traffic data.*

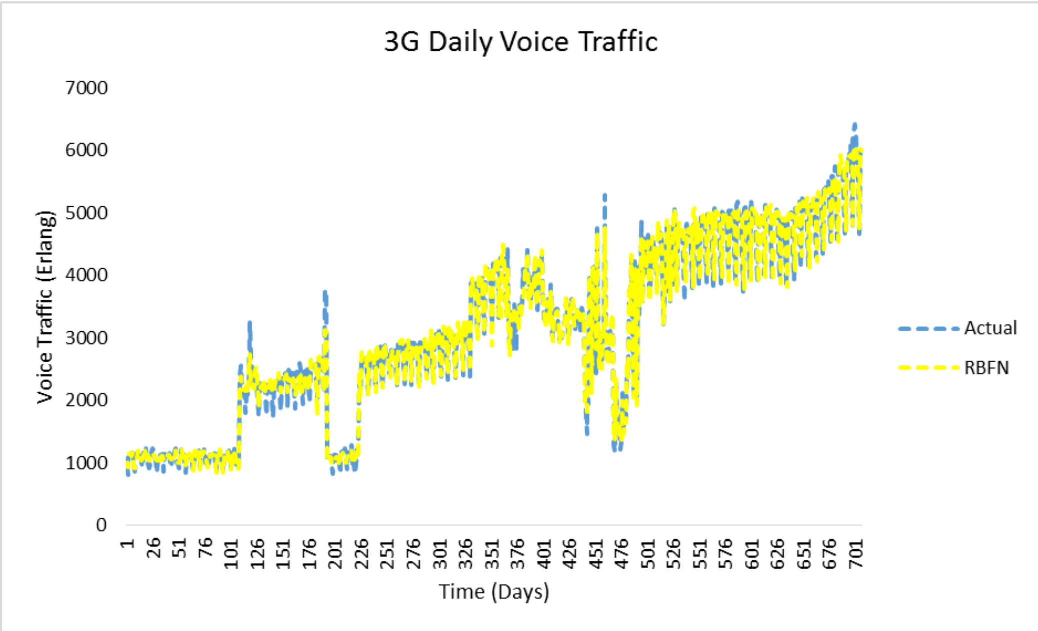

Figure 3. *Perdiction performance of five models using 3G daily voice traffic data.*

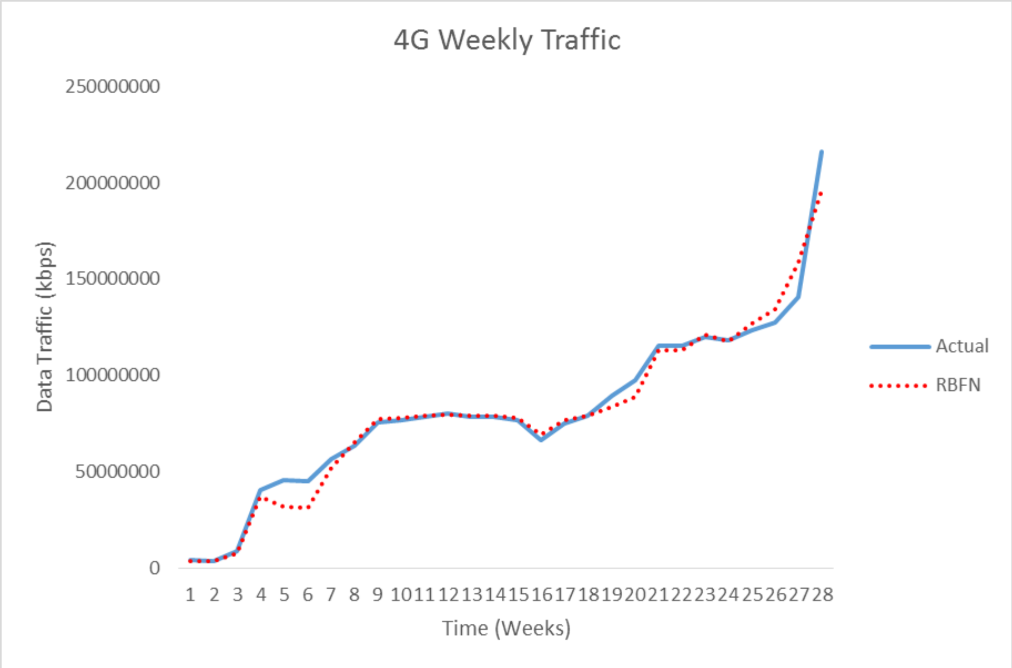

Figure 4. *Prediction performance of five models using 4G weekly traffic data.*

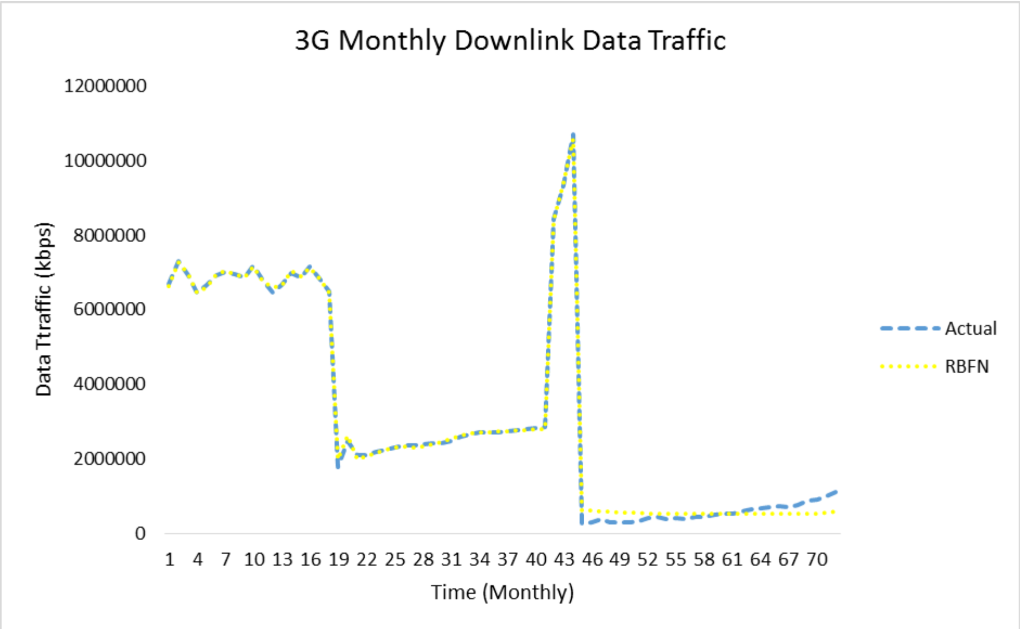

Figure 5. *Prediction performance of five models using 3G monthly downlink traffic data.*

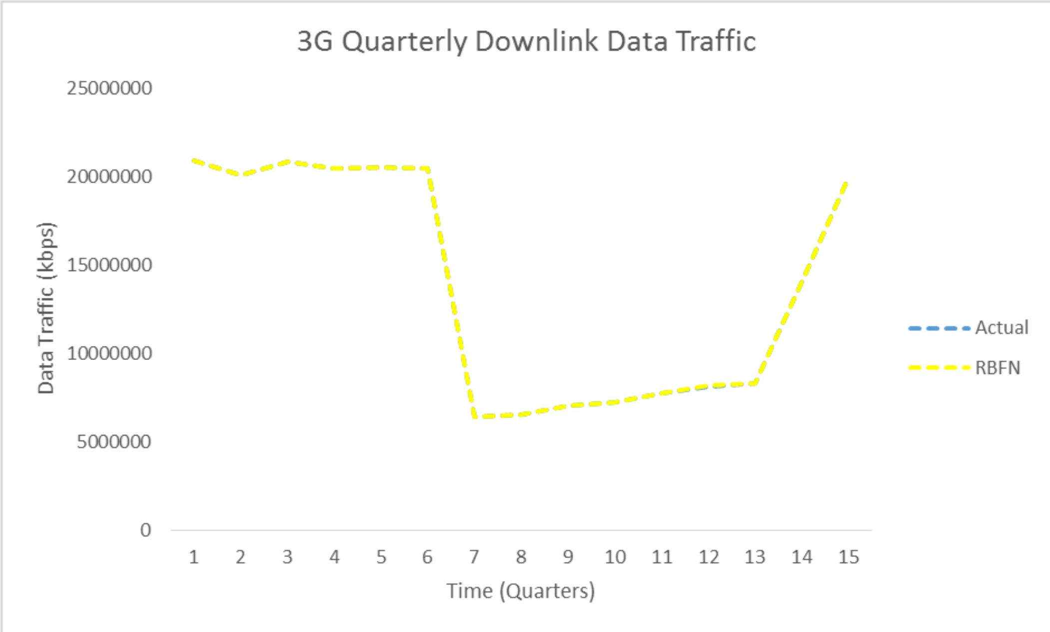

Figure 6. *Prediction performance of five models using 3G quarterly downlink traffic data.*

Conclusion

The study developed the direct MIMO RBFN model of 5-input 5-output configuration with Tanhaxon transfer function and learning rule of Levenberg-Marquardt in both the hidden and output layers. The four best fit models chosen for the five time spans of 3G uplink hourly, 3G daily voice, 4G weekly, 3G downlink monthly and 3G downlink quarterly were MIMO RBFN (5-13-5), MIMO RBFN (5-18-5), MIMO RBFN (5-10-5) and MIMO RBFN (5-5-5). The goodness of fit statistics such as MSE, NRMSE and R were used to select the best model out of the four provided. Observing the goodness of fit statistics of all models, MIMO RBFN (5-10-5) model was found with the least values and could be used to simultaneously predict five time spans of 4G and 3G traffic.

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Conflict of interest

The author confirm there are no conflict of interest involve with any parties in this research.

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