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Forecasting of Traffic Load for 3G Networks Using Conventional Technique

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ABSTRACT

The degrading performance of network coverage, resource allocation, and utilization is due to the rapidly increasing number of cellular subscribers, which is immensely difficult to predict the traffic load in Nigeria. The available developed algorithms and models did not well consider the behavior of the traffic load using the adopted input variables of this research. This paper arguably constructs an Artificial Neural Network (ANN) as Conventional technique to forecast the instantaneous traffic load per cell or eNodeB of 3G networks in Kano Metropolis. Four Active 3G networks data was extracted and recorded with the aid of W995 TEMS Pocket Phone over thirty five cells. The forecasted models when tested apparently tracked the measured traffic load with RMSE of 0.148365%, 0.21878%, 0.3327% and 1.32220%, thus achieved MAPE of 0.00394%, 0.00696%, 0.00109% and 0.03978% for A, B, C and D networks respectively. These validated that the Conventional technique can be a valuable tool in forecasting traffic load in Nigeria and could also be adopted in forecasting of large-scale metropolis cellular networks.

KEYWORDS: Artificial Neural Network (ANN), traffic load, RSCP, Path loss, SIR.

1 INTRODUCTION

One of the most significant revolutions of mobile communications is that subscribers can use their mobile phones to access the subscribed services as long as they are in the operator's coverage area [1]. However, this revolution results in an exponential increase of service demands. The multifarious service demands brought up research development in areas of power control, handover procedures, frequency hopping, discontinuous transmission, spectrum efficiency, multiple access technology, cluster size and frequency re-use [2]. These techniques were developed aimed to increase the number of subscribers that can access the limited transmission channels in the mobile communication networks [3]. Therefore leads to development of different cellular standards from the second generation (2G) to third generation (3G) and now beyond, but still the subscribers' voice and data traffic demands are rapidly increasing. In order to reduce the pressure of circuit switched networks (2G), high switched packet networks (3G) are introduced to provide higher quality signal with balance traffic load to subscribers. Universal Mobile Telecommunication System (known as UMTS) is a third generation (3G) telecommunications technology. The most common form of UMTS makes use of WCDMA (Wideband Code Division Multiple Access, which is an air interface standard and compulsory feature of any mobile telecommunications device of the 3G network) and this is the type of 3G technology employed in Nigeria. The transmitting (Tx) and receiving (Rx) Frequencies, measures in Mega Hertz (MHz) of the four active 3G mobile networks in Kano as well as Nigeria in general were given in table 1 below.

Table 1: 3G Band Plan [4]

Networks	Tx Frequency (MHz)	Rx Frequency (MHz)
A	2140-2150	1950-1960
B	2110-2120	1920-1930
C	2120-2130	1930-1940
D	2130-2140	1940-1950

The four active 3G networks in Kano have voice connection of more than 7, 811, 290 subscribers. Therefore the subscribers of these networks are very aggressive with the abysmal services receiving from the operators. One of the core concepts to solve the conflictions and inherent problems between multifarious service demands and limited radio resource is to increase the number of eNodeBs in order to get higher total capacity. But the major issues of employing more eNodeBs into the networks were among others expensive and maintenance/installation cost, thus necessitated the need of having a very good tool in forecasting the behavior of traffic load. The major challenge of forecasting traffic load in cellular network is the non-linearity behavior of the network parameters. However, as bandwidth is cheap forecasting in networking often relies on simple techniques and/or over provisioning. A precise forecast of traffic loads in the 3G network is an essential task for a network carrier, as the upgrade path for network equipment needs two to four month time to be implemented [5]. This work established that traffic load in Kano is much lower than reported from the Nigeria Communication Commission (NCC), likely due to more expensive 3G infrastructure deployment plans in Nigeria. Traffic load is moderately correlated between the nodes belonging to the eNodeB. Finally the work also contributed in the construction of ANN linguistic models and when tested apparently tracked the measured traffic load, which could be adopted as a valuable tool in forecasting traffic load in 3G cellular network.

In recent times several research works were conducted on traffic load some based on statistical approaches, mathematical modellings, adaptive neuro fuzzy interference system (ANFIS), algorithm adoption, and fuzzy logic, as in [6] presented statistical methods, the random and the "best carrier" were analyzed and the results showed significant similarities in certain conditions subscribers per cell of SINR. Traffic cell analysis was carried out, traffic characteristic was determined and also traffic performance parameters were depicted in [2]. Similarly, [3] presents different methods to predict the load increase in a 3G live network, the DHR delivers a better MAE (Mean Absolute Error) performance. [1] Statistically modeled the downlink throughput per cell distributions over time and over different cells of an existing 3G network based on real network throughput data. Likewise [7] collected data from measurements on live 3G networks and compared the measured cell loads and number of users with the values estimated by the models. [8] Presented the design and implementation of a Fuzzy Logic multi-criteria handoff algorithm based on signal strength, path-loss and traffic load of base stations and the received signal to interference ratio as to balance traffic in all the neighboring sites at any time. The limitations of intelligent methods include the appropriate selection of membership function and choice of structure among others [9]. Therefore, to the best of our knowledge, up to now, this is the first paper dealing with the forecast of traffic load in a 3G cellular network using ANN.

The paper is organized in the following: Section 1 presents the nature of the problem, purpose, contributions and the previous literature. The methodology, measurement setup and the forecasting method formed section 2. The results and discussion is covered in section 3 and also validation of the models is also cover in this section. Finally section 4 formed the conclusion.

2 MATERIALS AND METHODS

2.1 Typical 3G network

Typical 3G network comprised of a Radio Access Network (RAN) and a core network (CN). Radio Network Controllers (RNCs) control multiple Base Stations (NodeBs), which connects with multiple User Equipments (UEs). Each NodeB is basically configured with multiple sectors (commonly 3 and up to 6 sectors) in different directions. The core network consists of Serving GPRS Support Nodes (SGSN) and Gateway GPRS Support Nodes (GGSN) to perform data access and charging functionality. The combination of HSDPA and HSUPA is called High Speed Packet Access (HSPA) [10], the network structure is depicted in Figure 1.

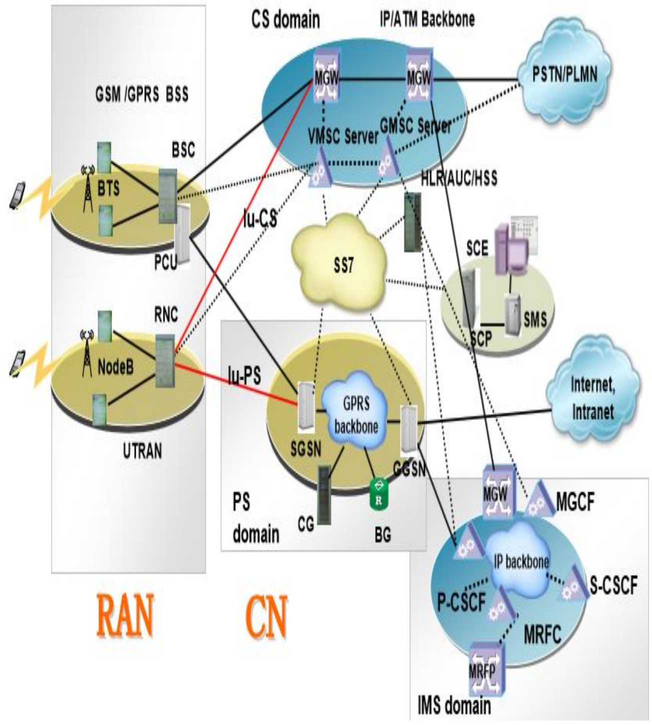

Figure 1: The 3G WCDMA network architecture [11]

2.2 Definitions of Important Parameters

a) RSCP (Received Signal Code Power): This is the downlink power/signal strength received by the UE on the pilot channel and measured in dBm. A higher RSCP indicates a better channel [12].

b) Transmitting Power (Tx power): This is the performance metric used to measure the transmitting ability of a cell/nodeB [12].

c) Path Loss: The path loss is the difference (dB) between the transmitted power and the received power. It represents signal level attenuation caused by free space propagation, reflection, diffraction and scattering [13]. Total path loss increases only substantially and appreciably with an increase in path-length, foliage distance, and reduction in transmitted frequency. Also occurs even when there are no obstacles between the transmitting and receiving antenna [14].

d) Signal-to-Interference Ratio (SIR): This is defined as the power of a certain signal of interest divided by the sum of the interference power (from all the other interfering signals) and the power of some background noise. Received Total Wideband Power (RTWP) measures the total level of noise within the 3G frequency band of any cell and captures uplink interference. A lower RTWP indicates a better channel and unloaded network [10].

e) Traffic Load: Traffic is the minutes of calls in Erlang [14]. Therefore Traffic is determined from the number or volume of calls intensity and service time (mean holding time, MHT) [2]. As in [2] traffic can be categorized into offered traffic, carried traffic and block traffic. Thus [2],

Offered traffic = carried traffic + block traffic (1)

The following formula could be adopted by the RF engineers to calculate the number of calls or Erlangs [13]:

$$ErlangB = \frac{Establish\,ed\ callsX\ MHT}{3600} \qquad (2)$$

2.3 Experimental Setup

The experimental setup is represented using flow chart as shown in figure 2. Step 1: The four carriers in consideration were examined using the same technique and at the same locality of thirty five cells/NodeBs with the aid of TEMS Pocket. TEMS Pocket is an advanced cellular network diagnostics tool for both indoor and outdoor measurement built into a Sony Ericsson W995 phone. TEMS Pocket is suitable for day-to-day verification, maintenance and troubleshooting of cellular networks but is also handy for many cell planning tasks. Some further key features of these devices are: GSM/GPRS quad-band, WCDMA/HSPA , 8.1 megapixel camera, Integrated GPS and in-built scanner [15]. Step 2: The data was collected for a period of 16 weeks (4 months), various times a day at an interval time of different hours. Informations such as RSCP, Tx power, pathloss, SIR, traffic load, etc were obtained and recorded for both intra and inter calls on a research’s designed form. Step 3: the artificial neural network was constructed with the above informations. Step 4: here, the voice traffic load was predicted and finally Step 5: the models were evaluated using error criteria.

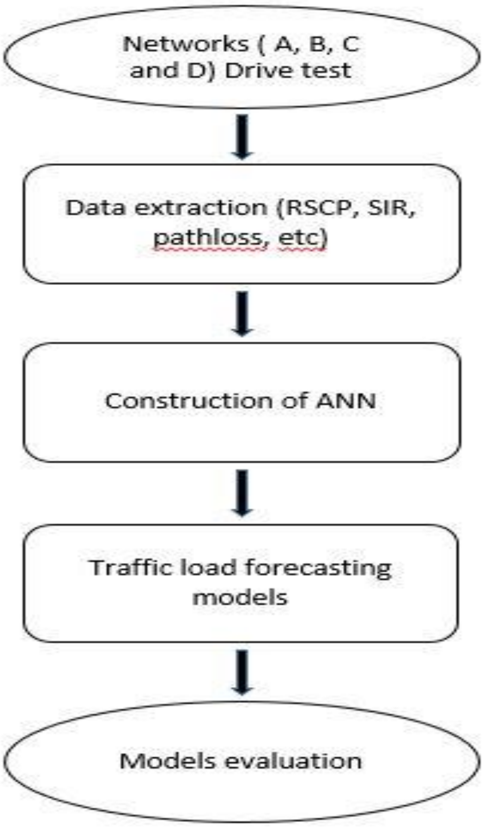

Figure.1: The experimental Setup flow chart

2.3 Study Location

Kano metropolis, Kano Nigeria is situated between latitudes 11° 25'N to 12° 47'N and longitude 8° 22' E to 8° 39' E east and 472m above sea level. Kano metropolis is boarded by Madobi and Tofa Local Government Areas (LGAs) to the southwest, Gezawa LGA to the east, Dawakin Kudu LGA to the southeast, and Minjibir LGA on the northeast. The study area of this research is made up of eight local government areas (LGAs): Dala, Fagge, Gwale, Kano Municipal, Nassarawa, Tarauni and parts of Kumbotso and Ungogo Local Governments. This location was chosen based on the fact that the population of the people in the area continue to grow substantially due to education, marketing and trading has been the dominant economic activity of the populace of the metropolitan Kano that is why it is referred as the Centre of Commerce in the country due to long flourished marketing activities. Kano metropolis is the third largest town in Nigeria after Lagos and Ibadan. It has a population of 2,826307 people [15].

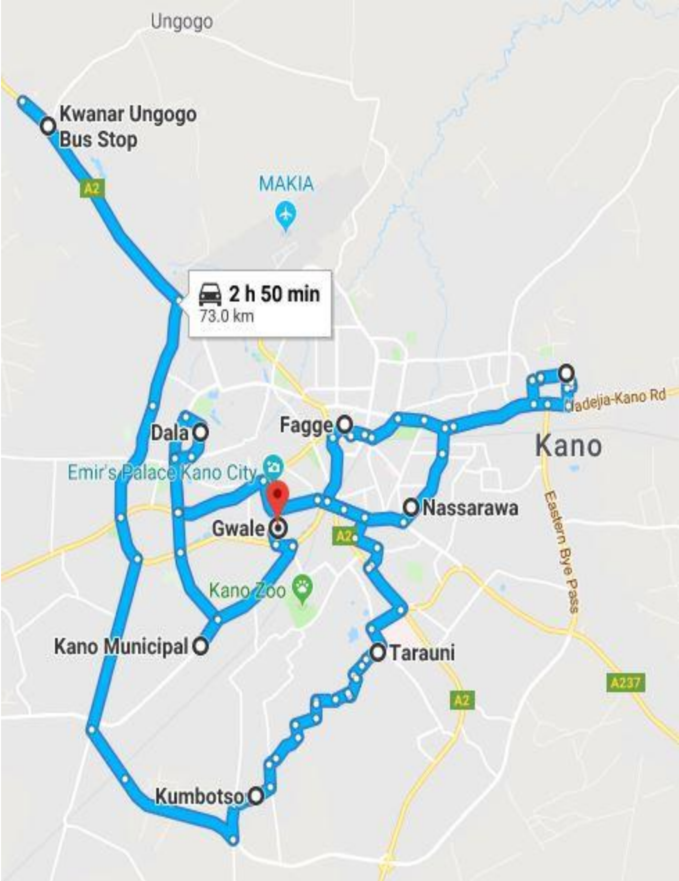

Figure 3: Research location

2.4 Methodology

An artificial neural network (ANN) is a computational model based on the structure and functions of natural neurons [16]. The technique of adjusting the weights is called training or learning. ANN is considered nonlinear statistical data modeling tools where the complex relationships between independents and dependents are mapped or modeled. The ANN considered here is used for engineering purposes, such as forecasting, data compression and pattern recognition. ANN has several advantages but one of the most recognized of these is the fact that it can actually learn from observing data sets. This gives it universal acceptability as a random function approximation tool. ANNs have three layers that are interconnected as shown in Figure 3. The first layer consists of input neurons; $x_1, x_2, \ldots x_n$. Those neurons send data on to the second layer (weights); $y_1, y_2, \ldots y_n$. Which in turn sends the output neurons to the third layer; z [16]. Training an artificial neural network involves choosing from allowed models for which there are several associated algorithms [17].

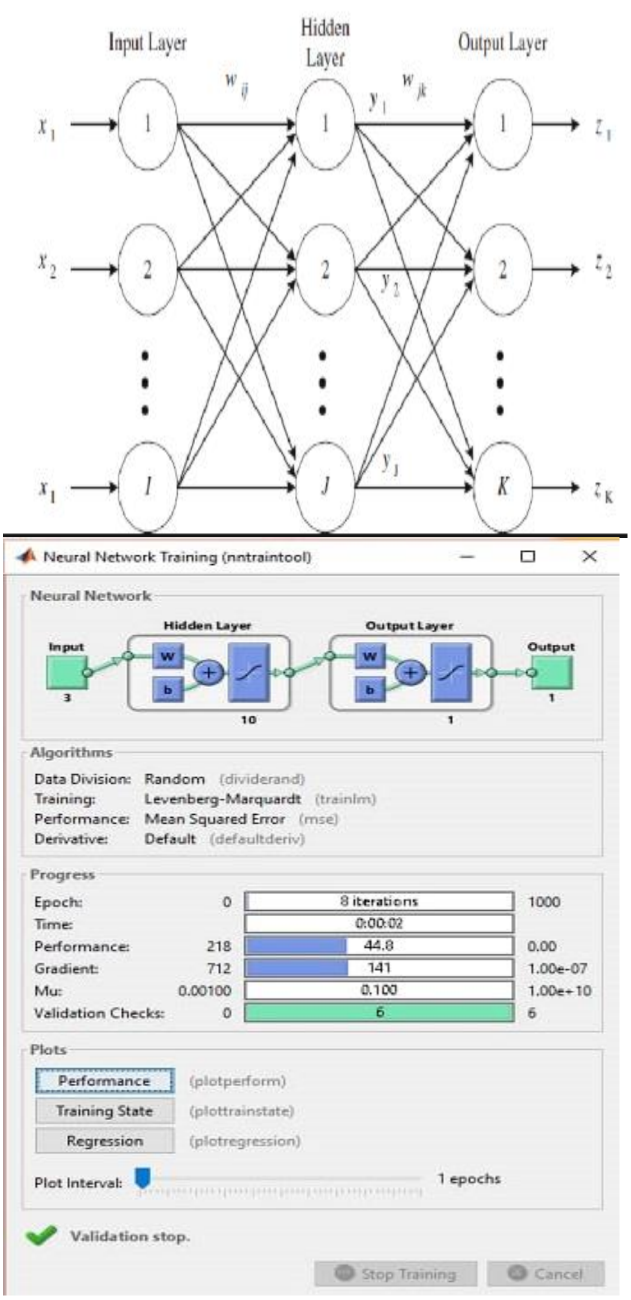

Figure 4: ANN Structure and it workspace

The data was extracted with the aid of W995 Transmission Environmental Monitoring System (TEMS) phone which recorded the RSCP, SIR, Pathloss, MHT, Established Calls, Hand over and traffic load files respectively. These data were refined and converted into an Excel format due to the likely unavoidable errors, outliers and missing values. The data was embedded into the ANN which is considered here as a conventional technique. The conventional technique model was developed using MATLAB (R2013a) with RSCP, SIR and pathloss as input data and the traffic load at enodeBs as the target output. Each data set consisted of three input columns and one output column. The construction was set as depicted in fig. 4 using 1 input layer with 3 inputs data, two hidden layers and one output layer. The first hidden layer consisted of 10 neurons, second consisted of 20 and the output consisted of 1 neuron layer, the output of the target is the eNodeBs' traffic load of the networks. The sampling interval is 1, completion time is 16.25sec and 10 maximum number of iterations were reached (epoch is 10). Thus each model is trained with one data set. The input data is normalized from the value of -1 to 1, these data set is further divided into two sets: 90% of these data are fed into the training process at random, while 10% was selected for testing phase. The output values were obtained when the input values were inserted into the first hidden layer, thus the output of the first hidden layer was fed into the second hidden layer, and the output of second hidden layer was fed into the input of the output layer. The value obtained at the output layer is the value of the network output. The models training were controlled by the following conditions: maximum epoch, minimum error and early stopping criteria.

The developed models were statistically analyzed using Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) as equated in (3) and (4). These are to compare the performance of the forecasting techniques and to consider the effect of the magnitude of the actual values so as to judge the models.

$$RMSE = \sqrt{\frac{\sum(x_i - y_i)^2}{N}} \quad (3)$$

$$MAPE = \frac{100\%}{N} * \sum_{i=1}^{N} \left| \frac{x_i - y_i}{x_i} \right| \quad (4)$$

Where x_i is the measured value, y_i is the forecast value and N is the number of samples.

3 RESULTS AND DISCUSSION

Figure 5, 6, 7 and 8 demonstrated the performance of the models during training phase of the three input variables of RSCP, Pathloss and SIR, for the four active 3G networks respectively. While figure 9, 10, 11 and 12 depicted the performance of the four 3G networks input variables during testing phase. The performance of the traffic data when evaluated using Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) during training and testing phases of the A, B, C and D Networks respectively are presented in Table 2.

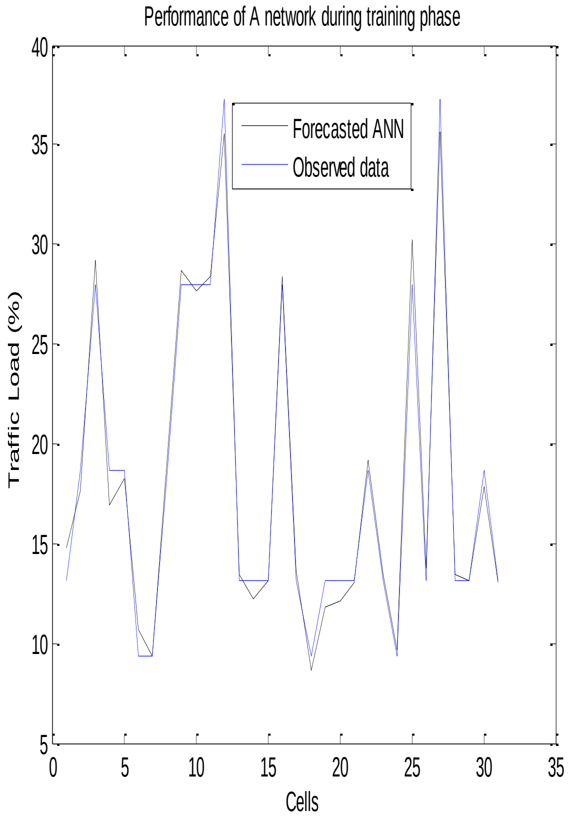

Figure 5: Performance of A Networks during Training

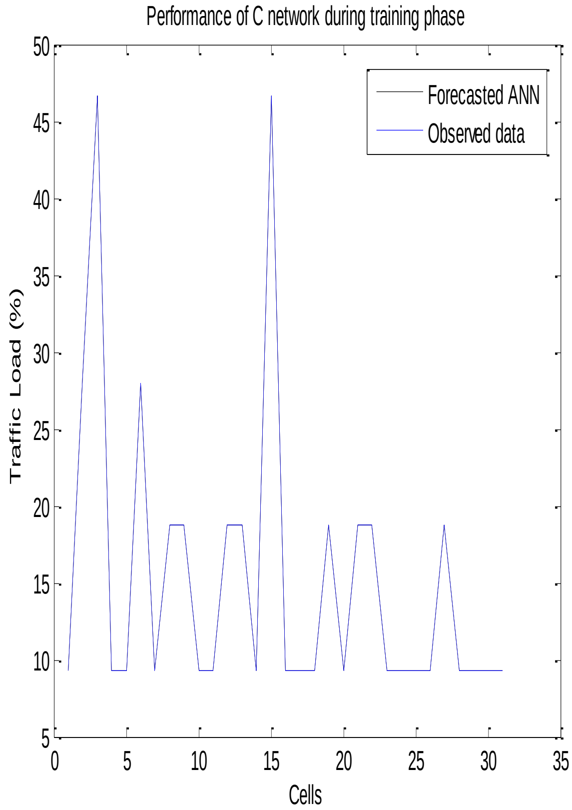

Figure 7: Performance of C network during training

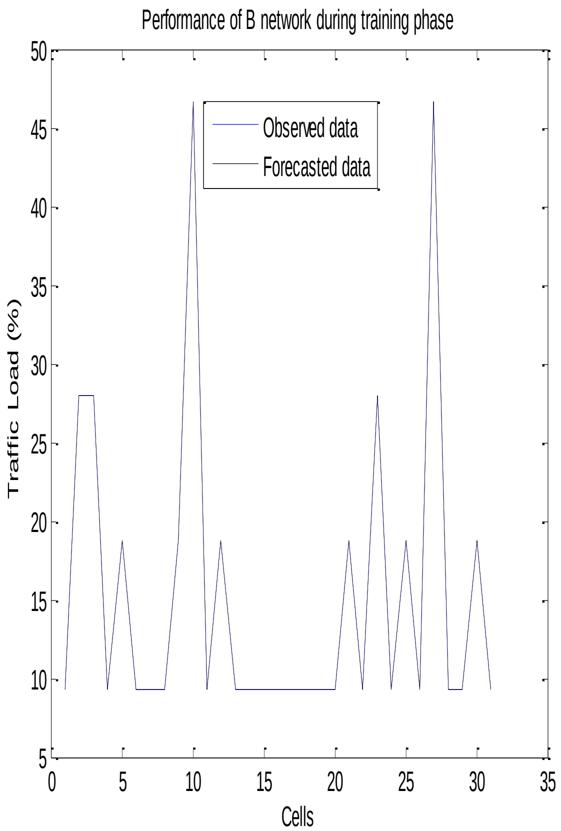

Figure 6: Performance of B network during training

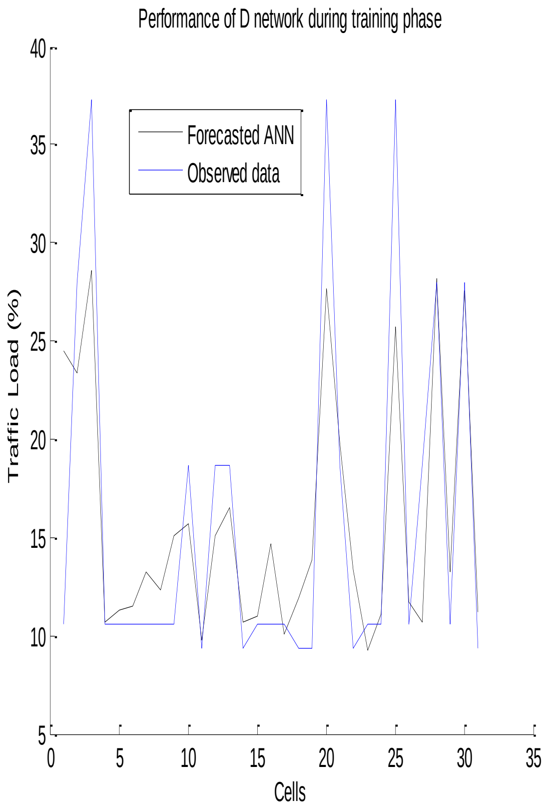

Figure 8: Performance of D network during training

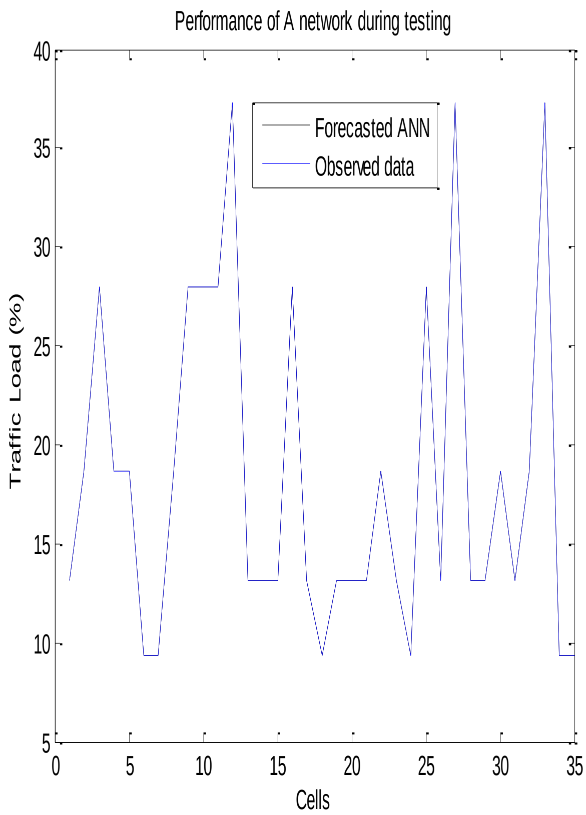

Figure 9: Performance of A network during testing phase

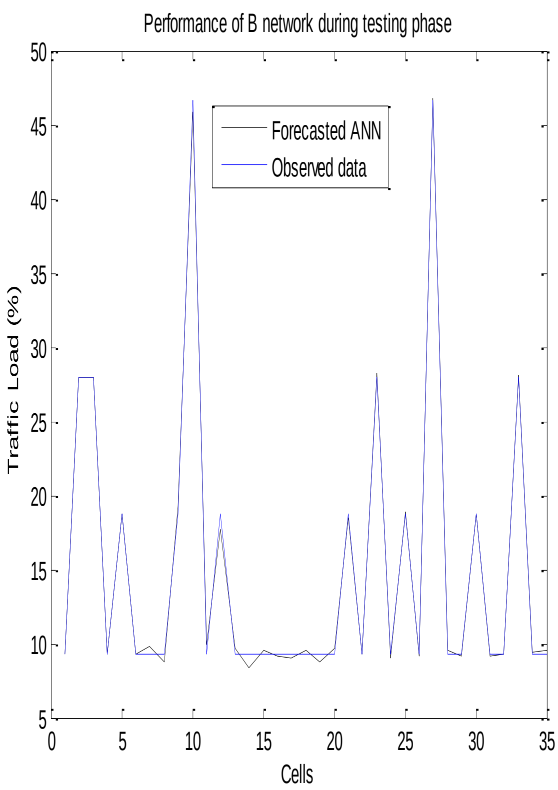

Figure 10: Performance of B network during testing phase

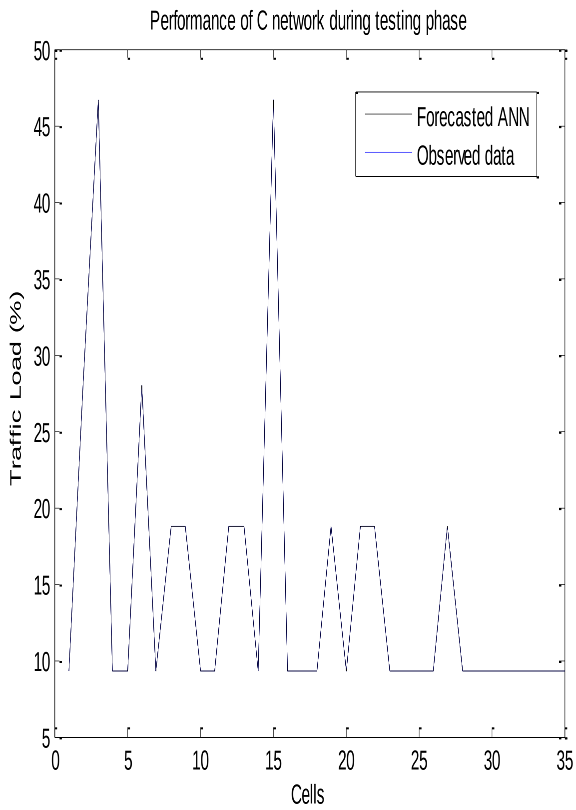

Figure 11: Performance of C network during testing phase

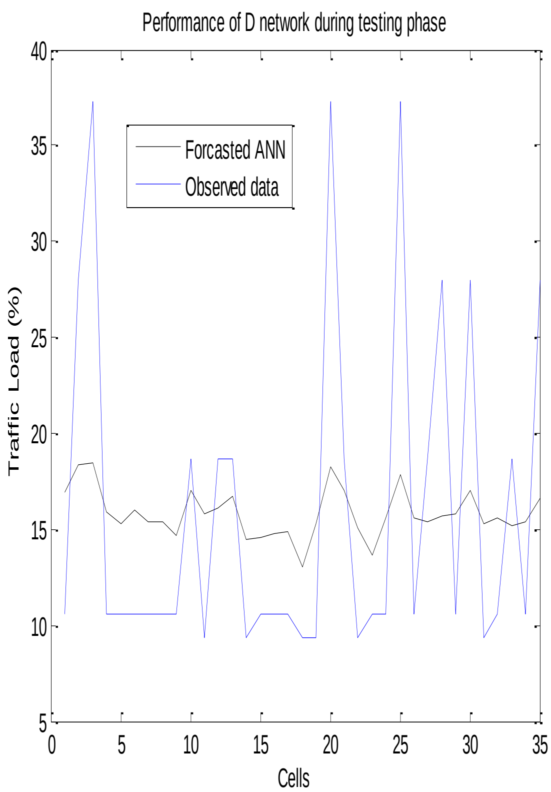

Figure 12: Performance of D network during testing phase

3.1 Validation of the Models

It is important to demonstrate how representative the models are for the simulations of networks with a given average traffic load and the models' ability to make representative of user estimations for different individual cell/eNodeB loads. Thus the forecasted models arguably demonstrated good fit to the traffic load when tested using equations (3) and (4) respectively. The result of the test is tabulated below in Table 2.

Table 2: Performance Evaluation of the Models

Networks	MAPE Training (%)	RMSE training (%)	MAPE Testing (%)	RMSE testing (%)
A	0.00437	0.13666	0.00394	0.14836
B	0.00132	0.03507	0.00696	0.21878
C	0.00065	0.01711	0.00109	0.03327
D	0.03240	0.89103	0.03978	1.32220

4. CONCLUSION

This paper predicted the traffic behaviors of four active 3G networks in Kano metropolis using Artificial Neural Networks as Conventional technique. The prediction error estimate is consistent at some certain levels. Whereby the traffic data for A, B and C networks when predicted were significantly accurate in tracking the observed data while D network did not track the observed data exactly but still is consistent with less than 2% error for both MAPE and RSME which is strongly recommended. The results proved that the conventional technique models could be served as valuable tools in forecasting voice traffic load in 3G networks at the case study location or any environment with similar network deployment.

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