APPLICATION OF CANFIS MODEL IN THE PREDICTION OF MULTIPLE-INPUT TELECOMMUNICATION NETWORK TRAFFIC

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Abstract *–Telecommunication network traffic prediction is an important approach that ensure efficient network planning and management. Telecommunication network traffic is univariate and prediction models have mostly been concentrated on single-input and single-output traffic. This study proposes a new approach, the multiple-input multiple-output Coactive Neuro-Fuzzy Inference System (CANFIS) model to predict a five time span univariate hourly, daily, weekly, monthly and quarterly time series of 3G downlink traffic simultaneously. In the modelling process several parameters were used in the configuration of the network. The best model for predicting five-input telecommunication traffic was CANFIS (5-2-5) which employed a Bell membership function, Axon transfer function and Momentum learning rule and the membership function per input of 2. The performance of the model was evaluated by comparing the predicted traffic with actual traffic obtained from a 3G network operator and the results indicate a minimum accuracy measure value of MSE = 0.000486, NRMSE = 0.01120 and percent error = 12.33%.*

Keywords – 3G downlink, CANFIS, multiple-input, multiple-output, prediction, telecommunication network traffic.

1. INTRODUCTION

Telecommunication network traffic prediction is an important approach that ensures efficient network planning and management. However, in research, the focus of forecasting mobile network traffic has mostly been on developing single models for each individual data set [1] [2][3][4]. Other research works that have applied individual traditional forecasting approaches for prediction are Kalman filtering [5], ARIMA and exponential smoothing [6] and voice traffic forecasting for GSM using feedforward neural network [7]. Reference [8] applied four different models, linear regression, simple exponential regression, ARMA and dynamic harmonic regression (DHR) to analyze hourly, daily and weekly telecommunication traffic. Reference [9] applied a neural network ensemble to 44160 hourly data of HSDPA traffic and indicated that the neural network ensemble predict the traffic with high accuracy.

Several methods have been used to develop high precision techniques in forecasting 3G network traffic [9] [10] [11]. Reference [10] applied data mining technique in predicting the air interface load of 3G network traffic while reference [12] established that 3G cellular network resource management is influenced by factors such as number of users, multipath propagation, congestion control, transport protocol flow, etc.

Reference [13] designed a multiple fuzzy system architecture which is connected side by side. The model is able to predict time series data at dissimilar inserting lengths and time intervals; however the system could not predict instantaneous multiple outputs.

In another study, [14] proposed a multiple-input multiple-output Adaptive Neuro Fuzzy Inference System (MANFIS) model that considered overtaking incidents of vehicles for dissimilar time steps in the future. This model however, predicted two different time steps of the future as output using five inputs. However to the best of our knowledge the Coactive

Neuro-Fuzzy Inference System (CANFIS) model has never been used to simultaneously predict hourly, daily, weekly, monthly and quarterly 3G downlink traffic.

CANFIS is a multiple-input multiple-output (MIMO) generalization of the Adaptive Neuro Fuzzy Inference System (ANFIS) structure [14]. Many researchers have explored the advantages of MIMO in the analysis and forecasting in several fields [14] [15] [16] [17]. For instance [17] used CANFIS with two inputs and three outputs in fault detection and diagnosis of railway track circuits. Reference [17] applied the CANFIS model to Australian regional flood and concluded that the model provided an accurate regional floods estimated level. The authors implemented multi-input single output (SISO) CANFIS architecture.

The ability of CANFIS models to work on multiple-input and multiple-output have been tested by other researchers: 7-input/4-output [18]; 9-input/6-output [16]. Reference [19] employed the CANFIS architecture with 6-inputs and 1-output to predict farm yields.

Reference [20] evaluated the capabilities of a CANFIS model for the prediction of flow through trapezoidal and rectangular rockfill dams. The authors in [21] predicted the electric load using the CANFIS and ANN models and concluded that the CANFIS model outperformed the ANN model.

The advantage of applying the CANFIS model is that it serves as a single model to predict five different time spans of telecommunication network traffic, unlike the traditional forecasting models, that use one model for each time span. In previous research no study has been conducted that has explored the forecasting of telecommunication network traffic using the multiple-input multiple-output CANFIS model with 5-input and 5-output: hourly, daily, weekly, monthly and quarterly data.

2. METHODOLOGY

The methodology section of this study highlights the approach adopted to instantaneously predict five-input 3G downlink traffic using the CANFIS network model and the selection of the best model.

2.1 CANFIS network architecture creation

CANFIS is an extension of the basic principles of the earlier Adaptive Neuro-Fuzzy Inference System with a multiple-input multiple-output (MIMO) architecture [21]. CANFIS is an improvement on the MISO ANFIS architecture to multiple-input multiple-output (MIMO) configuration. The CANFIS architecture for five-input five-output is shown in Fig. 1 with five layers. There are five inputs of 3G downlink traffic, $x_1 = hourly\ data, x_2 = daily\ data, x_3 = weekly\ data, x_4 = weekly\ data\ and\ x_5 = hourly\ data$ with predicted hourly, daily, weekly, monthly and quarterly outputs.

The CANFIS structure consists of five layers whereby each one can be adaptive or fixed in performance [22]: Layer 1, Layer 2, Layer 3, layer 4 and Layer 5.

Layer 1(Premise parameters): Every node in this layer is a complex-valued membership function (μ_{ij}) with a node function:

$$O_{1,j} = \mu_{Ai}(x_1), for\ i = 1, 2. \quad (1)$$

$$O_{1,j} = \mu_{Bi-2}(x_2), for\ i = 3, 4. \quad (2)$$

$$O_{1,j} = \mu_{Ci-4}(x_3), for\ i = 5, 6. \quad (3)$$

$$O_{1,j} = \mu_{Di-6}(x_4), for\ i = 7, 8. \quad (4)$$

$$O_{1,j} = \mu_{Ei-8}(x_5), for\ i = 9, 10. \quad (5)$$

where, $(A_1, A_2\ or\ B_1, B_2\ or\ C_1, C_2\ or\ D_1, D_2\ or\ E_1, E_2)$ represents the linguistic variable, $\mu_{Ai}(x_1), \mu_{Bi-2}(x_2), \mu_{Ci-4}(x_3), \mu_{Di-6}(x_4)$ $and\ \mu_{Ei}$ are some appropriate parameterized membership functions (MFs), $x_1, x_2, x_3, x_4\ and\ x_5$ are the input to the i^{th} node.

Each node in Layer 1 is the membership grade of a fuzzy set (A_{ij}) and identifies the degree to which the given input fits to one of the fuzzy sets, which is represented in general as equation (6)

$$O_{1,j} = |\mu_{ij}A_{ij}(z_i)| \llcorner\ \mu_{ij}A_{ij}(z_i)$$
$$for\ (1 \leq i \leq n, 1 \leq j \leq m) \quad (6)$$

where $O_{i,j}$ the membership grade of a fuzzy set A_{ij}, μ_{ij} is any suitable parameterized membership function and z_i is a real number.

Layer 2 (Firing strength): Every node in this layer is the product of all the incoming signals. This layer receives input in the form of all the output pairs from the first layer:

$$O_{2,j} = w_{ij} = \mu A_{i1}(z_i)\mu A_{i2}(z_2), \dots, \mu A_{i1n}(z_n)$$

$$for\ (1 \le i \le m) \quad (7)$$

$$O_{2,j} = \mu_{Ai}(x_1)\mu_{Bi}(x_2)\mu_{Ci}(x_3)\mu_{Di}(x_4)\mu_{Ei}(x_5), \quad for = 1,2,3,4,5. \quad (8)$$

where w_{ij} is the weights equivalent to the *j*th MF of input *i.*

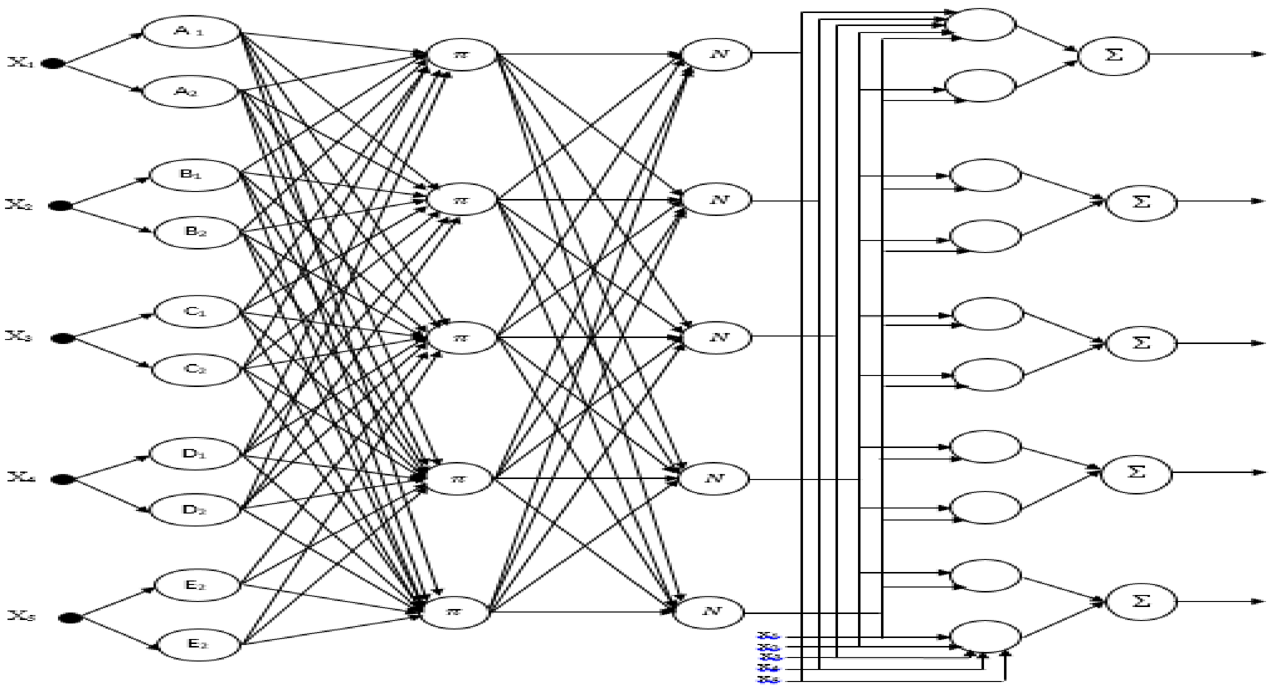

Fig. 1 – 5-input 5-output CANFIS architecture for telecommunication traffic

Layer 3 (Normalised firing strength): Every node in this layer calculates rational firing strength using the formula:

$$O_{3,j} = \overline{w_j} = \frac{w_j}{\sum_{j=i}^{m} w_j}\ for\ (1 \le j \le m) \quad (9)$$

where $\overline{w_j}$ is the output of layer 3.

Layer 4 (Consequence parameters): Every node in this layer is a multiplication of normalized firing strength from the third layer and output of the neural network given by:

$$O_{4,j} = \overline{w_j}\mu_j = \overline{w_j}(P_{J1}Z_1 + P_{J2}Z_2 + \cdots P_{Jn}Z_{2n} + q_j)\ \ for\ (1 \le j \le m) \quad (10)$$

where $\overline{w_j}$ is the output of layer 3, $(P_{J1} + P_{J2} + \cdots P_{Jn})$ is the parameter set or consequent parameters, n is the number of rules, j is the number of outputs.

Layer 5 (Overall output): This layer computes the output of the CANFIS network using equation (11) [20]:

$$O_{5,j} = \sum \overline{w_j}\,\mu_j \quad (11)$$

where $O_{5,j}$ is the overall output, *j*= 1,2,3,4,5.

The CANFIS model combines fuzzy input with a modular neural network to rapidly explain poorly defined intricate functions using a basic component of fuzzy axon which applies a membership function (MF) to the input [15].

2.2 Configuration of the CANFIS network

In modelling the five-input five-output CANFIS structure, a bell fuzzy axon with the bell-shaped curve as its MF was applied to the input telecommunication network traffic variable, hourly, daily, weekly, monthly and quarterly respectively as shown in equation (12). The fuzzy axon has the advantage of modifying the MF while the network training process continues over back propagation which ensures convergence. The MFs per input used were 3.

Bell function is given as [20]:

$$\mu_1(x) = \frac{1}{1 + \left|\frac{(x - c_1)}{a_1}\right|^{2b_i}} \qquad (12)$$

where x = input to the node and a_1, b_1 and c_1 are adaptable variables known as premise parameters.

From reference [23], the output of fuzzy axon is calculated using equation (13):

$$f_j(x, w) = min\forall_i \left(MF\left(x_i, w_{ij}\right)\right) \qquad (13)$$

where, i = input index, j = output index, x_i = input i, w_{ij} = weights (MF parameters) corresponding to the jth MF of input i and MF is the membership function of the particular subclass of the fuzzy axon.

The parameters applied for configuring the network are grouped under input and output as shown in Table 1. The momentum algorithm was chosen as the learning rule with the axon as the transfer function. The fuzzy model reasoning approach of the Tsukamoto model and the Sugeno model (TSK) were implemented.

Table 1 – Network parameter selection for configuration of CANFIS model

Input layer parameter		Output layer parameters	
Input PE	5	Transfer function	Axon
Output PE	5	Learning rule	Momentum
Exemplars	271	Step size	1
Hidden layer	0	Momentum	0.7
Membership function	Bell	Maximum epochs	1000
MFs per input	3	Termination	MSE (Increase)
Fuzzy model	TSK	Weight update	Batch

2.3 Initialization of the CANFIS network

For a model initialization, a common rule set with n input and m IF-THEN rules are used in equation (14), equation (15) and equation (16) as follows [23]:

$$Rule\ 1: If\ z_1\ is\ A_{11}\ and\ z_2\ is\ A_{12}\ \dots and\ z_n\ is\ A_{1n}$$

$$then\ u_1 = p_{11}z_1 + p_{12}z_2 + \cdots + p_{1n}z_n + q_1 \qquad (14)$$

$$Rule\ 2: If\ z_1\ is\ A_{21}\ and\ z_2\ is\ A_{22}\ \dots and\ z_n\ is\ A_{2n}$$

$$then\ u_2 = p_{21}z_1 + p_{22}z_2 + \cdots + p_{2n}z_n + q_2 \qquad (15)$$

$$\vdots$$

$$Rule\ m: If\ z_1\ is\ A_{m1}\ and\ z_2\ is\ A_{m2}\ \dots and\ z_n\ is\ A_{mn}$$

$$then\ u_m = p_{m1}z_1 + p_{m2}z_2 + \cdots + p_{mn}z_n + q_m \qquad (16)$$

2.4 Prediction measure of accuracy

In order to determine the goodness of fit of the CANFIS models the following statistical measures are used as shown mathematically in equation (17), equation (18) and equation (19). A model with a minimum value is selected for forecasting.

Mean squared error (MSE) is calculated as:

$$MSE = \frac{\sum_{j=0}^{P-1}\sum_{i=0}^{N-1}(d_{ij} - y_{ij})^2}{NP} \qquad (17)$$

Normalised root mean squared error (NRMSE) is given as:

$$NRMSE = \frac{\sqrt{MSE}}{\sum_{j=0}^{P-1}\frac{max\left(d_{ij}\right) - min\left(d_{ij}\right)}{P}} \qquad (18)$$

The percent error (%Error) is computed as:

$$\%Error = \frac{100}{NP}\sum_{j=0}^{P-1}\sum\nolimits_{i=0}^{N-1}\frac{|dy_{ij} - dd_{ij}|}{dd_{ij}} \qquad (19)$$

where, P is the number of output processing elements, N is the number of exemplars in the data set, y_{ij} is the network output for exemplar i at processing element j, d_{ij} is the desired output for exemplar i at processing element j, dy_{ij} is the denormalised network output for exemplar i at processing element j, dd_{ij} is the denormalised desired output for exemplar i at processing element.

3. ANALYSIS AND RESULTS

3.1 Data collection and specification

The data used for this study is obtained from a mobile network operator in Ghana with a nationwide coverage of three hundred and eighty (380) active NodeBs connected to three radio network controllers (RNCs). The network operator recorded an estimated figure of 3,889,821 data subscribers according to 2017 statistics [24].

The experimental 3G downlink traffic data was collected from 2015 to 2017. It consists of 957 samples of hourly traffic, 707 samples of daily traffic, 178 samples of weekly traffic, 72 samples of monthly traffic and 15 samples of quarterly traffic. The different samples of the 3G downlink traffic for modeling are illustrated in Table 2. Each sample is divided into three parts of 70% training, 15% for validation and 15% for testing. The data set analysis was carried out by NeuroSolutions software version 7.1 and Eviews software.

Table 4 shows the descriptive statistics of 3G downlink traffic under five classifications of hourly, daily, weekly, monthly and quarterly. The weekly and quarterly data had negative skewness while hourly, daily and monthly data produced positive skewness.

3.2 CANFIS network training

Table 4 illustrates the training results of the CANFIS network using the Momentum learning algorithm and an Axon transfer function. The data with 70%:15%:15% architecture was selected as the allocation with minimum percent error of 32.34 and MSE of 0.00298.

In Table 5, five different architectures of CANFIS were analysed with varying learning rule and transfer functions.

The best network with minimum values of MSE, NRMSE and percent error of 0.000406, 0.0112 and 12.33% respectively using Table 5 is the CANFIS (5-2-5) model with an Axon transfer function and Momentum learning rule.

Table 2 – Training, testing and validation sample of 3G downlink traffic

Data	Hourly (957 samples)	Daily (707 samples)	Weekly (178 samples)	Monthly (72 samples)	Quarterly (15 samples)
Training	671	495	126	50	9
Validation	143	106	26	11	3
Testing	143	106	26	11	3

Table 3 – Descriptive statistics of 3G downlink data traffic

Statistic	957 samples (Hourly)	707 samples (Daily)	178 samples (Weekly)	72 samples (Monthly)	15 samples (Quarterly)
Mean	413531.6	553128.8	1362434.0	3114591.0	13919290
Median	409333.4	431660.2	1619248.0	2383673.0	14087025
Maximum	1041087.0	3391268.0	2709330.0	10691053	20920417
Minimum	78563.67	205131.2	437722.6	270005.7	6388322.0
Std. Deviation	186704.9	329937.4	553089.7	2839062	6582633.0
Skewness	0.466702	1.819760	-0.105359	0.794602	-0.019465
Kurtosis	3.018888	10.54329	2.168778	2.295719	1.100051
Jarque-Bera	34.75510	2066.423	5.453709	9.064749	2.257075

Statistic	957 samples (Hourly)	707 samples (Daily)	178 samples (Weekly)	72 samples (Monthly)	15 samples (Quarterly)
Probability	0.000000	0.000000	0.065425	0.010755	0.323506

Table 4 – CANFIS architecture training results

CANFIS Architecture (Training: Validation: Testing)	MSE	NMSE	R	% Error
(70%:15%:15%)	0.00298	0.0303	0.71	32.34
(70%:10%:20%)	0.00373	0.0339	0.70	34.89
(80%:10%:10%)	0.00460	0.0377	0.698	36.70
(60%:10%:30%)	0.0034	0.0328	0.683	36.24

Table 5 – Selection of network architecture for forecasting

CANFIS Model	5-3-5	5-3-5	5-2-5	5-2-5	5-2-5
Transfer function	TanhAxon	TanhAxon	TanhAxon	Axon	TanhAxon
Learning Rule	Step	RProp	RProp	Momentum	Step
MSE	0.0092	0.0021	0.00108	0.000406	0.00559
NRMSE	0.0531	0.0252	0.01825	0.01120	0.0415
R	0.5968	0.7868	0.9268	0.9737	0.6262
% Error	48.37	21.05	17.82	12.33	52.55

The CANFIS (5-2-5) model testing window with convergence rate for the data is shown in Fig. 2. The active cost curve plot indicates that with testing data the algorithm has successfully undergone generalization and thereby converging to zero.

3.3 Network Validation

The CANFIS (5-2-5) network for five-input five-output data with 2 MFs per input, was validated by comparing the actual and predicted traffic as demonstrated in Fig. 3 for hourly traffic prediction.

The daily, weekly, monthly and quarterly prediction of 3G traffic are exhibited in Fig. 4, Fig. 5, Fig. 6 and Fig. 7. The CANFIS model employed the Bell membership function, Axon transfer function and Momentum learning rule. The membership function per input was varied between 2 and 7.

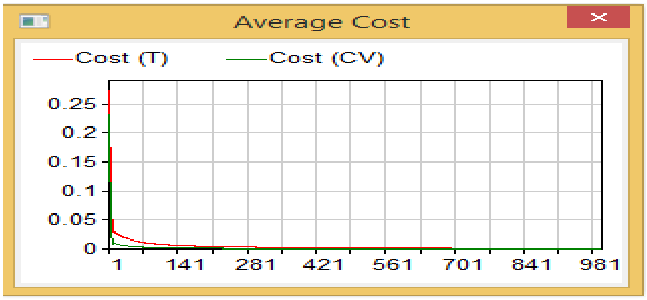

Fig. 2 – CANFIS (5-2-5) testing window

The study found out that with the increase in the number of inputs, the CANFIS model produce accurate traffic forecasting when membership functions per input are 2. Therefore the best model for predicting five-input telecommunication traffic was CANFIS (5-2-5).

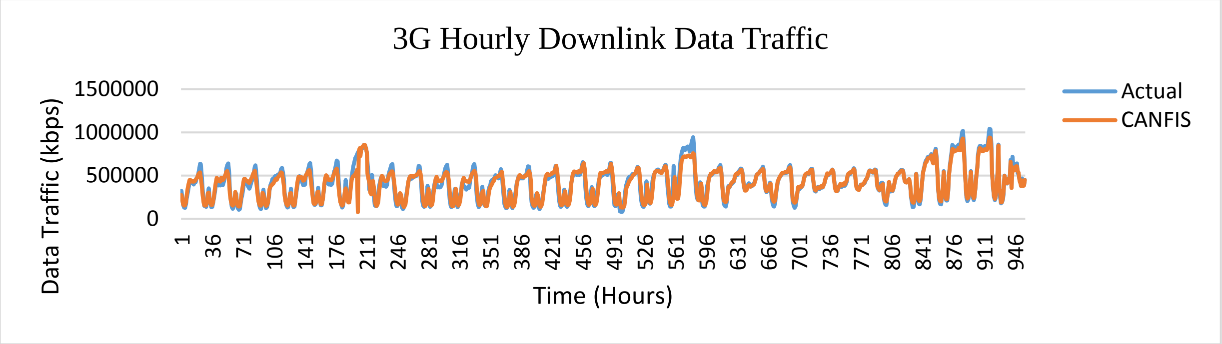

Fig. 3 – Actual and predicted 3G hourly traffic using the CANFIS (5-2-5) model

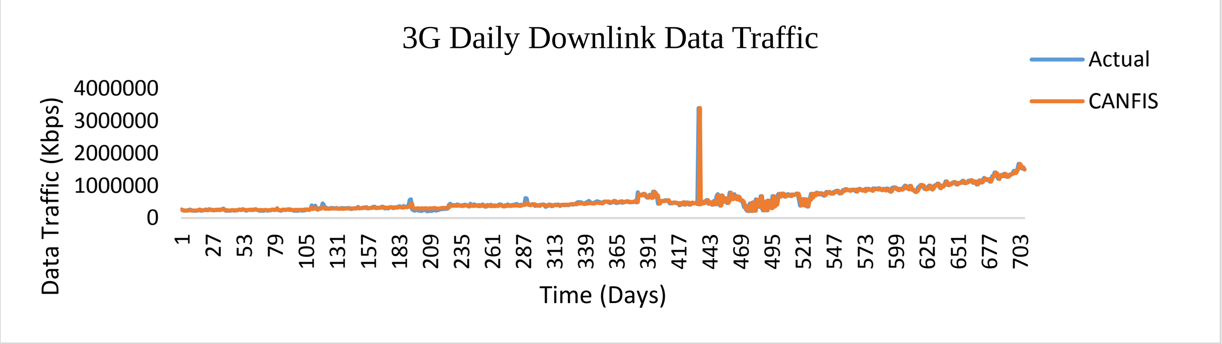

Fig. 4 – Actual and predicted 3G daily traffic using the CANFIS (5-2-5) model

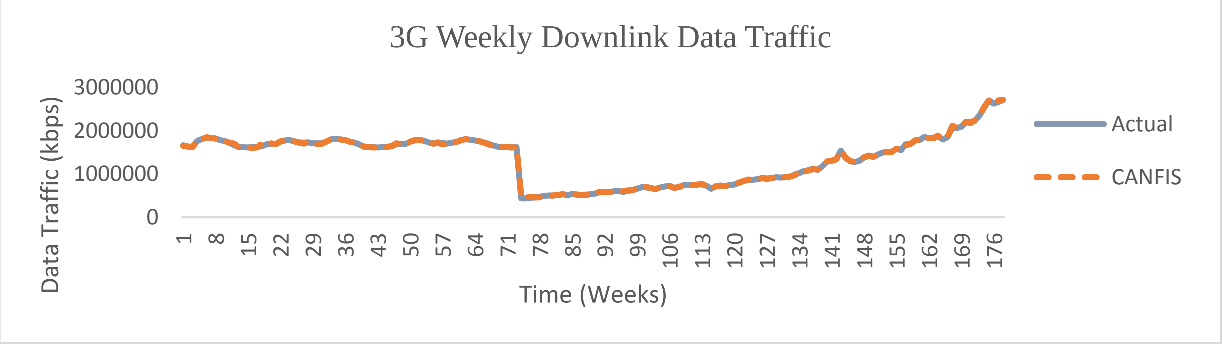

Fig. 5 – Actual and predicted 3G weekly traffic using the CANFIS (5-2-5) model

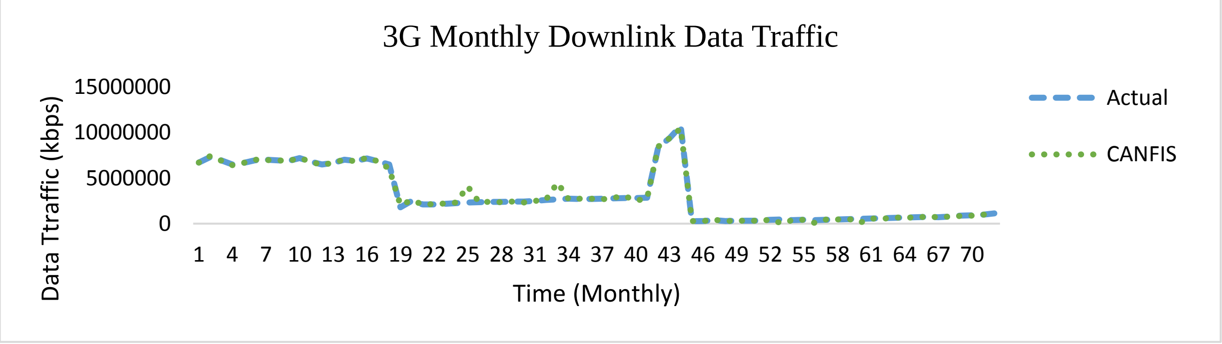

Fig. 6 – Actual and predicted 3G monthly traffic using the CANFIS (5-2-5) model

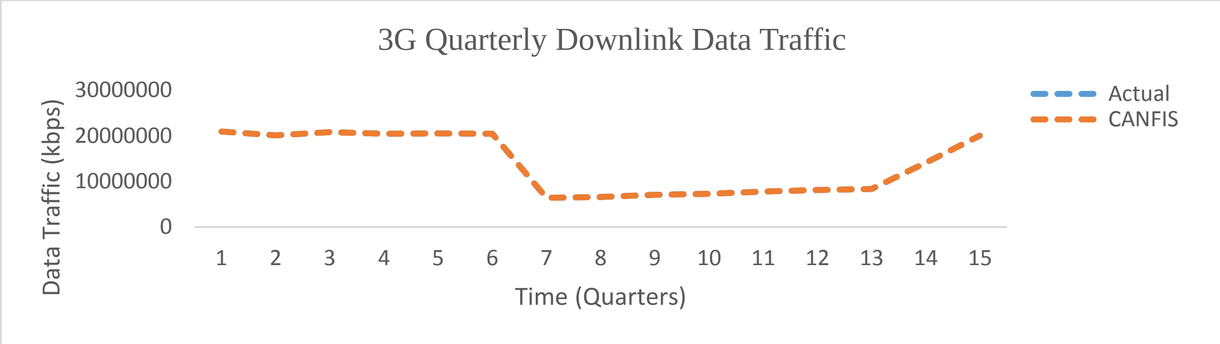

Fig. 7 – Actual and predicted 3G quarterly traffic using the CANFIS (5-2-5) model

4. CONCLUSION

The CANFIS model has been used to predict five time spans of hourly, daily, weekly, monthly and quarterly 3G downlink data simultaneously. In this approach five different CANFIS models were developed and the CANFIS (5-2-5) model was selected as the best. The model was evaluated by comparing the forecast with actual data obtained from 3G mobile operator and the results showed a good performance with minimum values of MSE, NRMSE and percent error of 0.000486, 0.01120 and 12.33%.

In the future, a genetic algorithm optimization technique will be explored to improve on the delay in training of the CANFIS model when membership function per input and multiple input data are increased.

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