A New Algorithm For Prediction WIMAX Traffic Based On Artificial Neural Network Models

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Abstract— **In this paper, WIMAX traffic forecasting system for predicting traffic time series based on the traffic data recorded (TRD) along with Artificial Neural Networks (ANN) was proposed. The data used in this work are the maximum online user, minimum online user, traffic of MIMO-A and traffic of MIMO-B. These data are available from LibyaMax network (WiMAX technology) motorized by Libya Telecom and Technology over a period of 90 days. The quality of forecasting WIMAX traffic obtained by focusing on the ANN design through comparing different configurations of and models that consist of investigating different topology and learning algorithms. The decision of changing the ANN architecture is essentially based on prediction results to obtain the best ANN model for flow traffic prediction model. Testing the different configurations using real traffic data recorded at base stations (A, B and AB) that belong to a Libyan WiMAX Network. Statistical measurement is used to evaluate the different ANNs configuration to selected best model based on higher performance resulting. Outcome founded indicate that ANN model using maximum and minimum online user as inputs, gives good accurate results for predicting traffic by employing *TrainLM* with all considered cases.**

Keywords— WIMAX traffic , ANN model , Forecasting System

I. Introduction

Network traffic prediction represents a simple function throughout characterizing the network performance which is of significant interests in various network applications, for example admission control or network management. globally for a radio network and WIMAX network, predicting the future traffic level is usually obligatory in order to keep a reasonable quality connected with services. The decision of changing the network architecture (i.e. increase base stations) is actually determined by prediction effects and results. Models of which properly capture the characteristics of actual traffic are helpful intended for research as well as simulation and they assist with understand the network dynamics also to design as well as management and control the network. The key concept of the traffic forecasting is to specifically predict traffic in the future, considering the tested and measured traffic history. The options from the prediction technique will be based upon the actual prediction phase, prediction malfunction along with computational cost.

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Exploration time series data is probably the toughest issues throughout data mining research [1] and in order to feature an ideal summary and suitable conclusion regarding what prediction technique to for this purpose, several types of predicting methods are considered by researchers. The standard methods to time series predicting assume that the time series usually are given by linear procedures; however they may be completely inappropriate if the procedure is usually non-linear [2]. On the approach will be based upon Box-Jenkins method that is helpful to develop enough time series model within a sequence of steps which are replicated prior to the ideal model will be accomplished.

One more class of models works by using the structural state space methods along with enable you to estimate the actual stationary, trend, seasonal, and cyclical data. These kinds of methods capture the particular findings as a sum of separate components. Between each of the forecasting models, artificial neural networks (ANNs) are actually shown to make superior final results [3], [4] and [5]. The performance along with the computational intricacy of ANNs is balanced with those acquired using ARIMA in addition to fractional ARIMA (FARIMA) predictors [6]. Wavelet based predictors and as well as ANNs. The final results on this research indicate the actual important advantages of the actual ANN approach. In the research given by [7] demonstrate the advantage of the ANN more than standard rule-based systems will be proved. In addition the researcher of [8], [9] and [10] recommend a time delayed neural network (TDNN).

Generated traffic flow is the integration of the whole network system which establishes a connection that includes the traffic source (depending on the QoS classifiers) [11] and presents a forecasting technique for forward energy prices, one day ahead. The final results illustrate that the use of Wavelet Transform as a pre-processing associated with forecasting data boosts the performance of prediction strategies. The originality of the proposed forecasting model [12] is based on time series decomposition in wavelet domain and the use of ANNs in the transform domain, this model was developed as result of an Alcatel-Lucent study [13] and it aim is to compare different configurations of the ANN in order to find the highest prediction performance.

The paper is organized as follows: Section 2 provides a methodology presentation of the forecasting structure including some theoretical considerations regarding the data collection, the ANNs and its theory. In addition we present the configuration of the artificial neural network, and the ANN implementation. The next section describes the measures used for the performance evaluation. Results of the experimental

work presented in section 3. Finally, the last section is dedicated to conclusions and further work.

II. Methodology

A. *Data Collection*

In this study, the capital city of Libya, Tripoli, was selected as source of traffic data required for ANN based implementation of WIMAX traffic forecasting analysis. Indicated in figures (1), (2) and (3) are the daily data input/output recorded data during 90 days which includes the maximum and minimum online of user-A, user-B and user AB along with their WiMAX traffic of MIMO-A, MIMO-B and MIMO-AB .
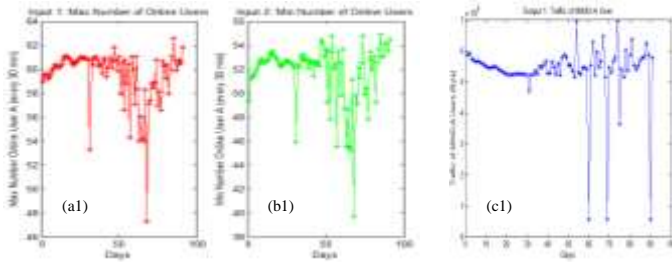

Figure 1.   Daily data input/output include (a1) Max number online of user-A (b1) Min number online user A and (c1) traffic of MIMO-user A
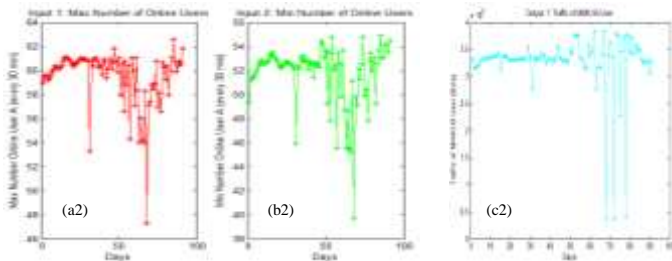

Figure 2.   Daily data input/output include (a2) Max number online of user-B (b2) Min number online user B and (c2) traffic of MIMO-user B
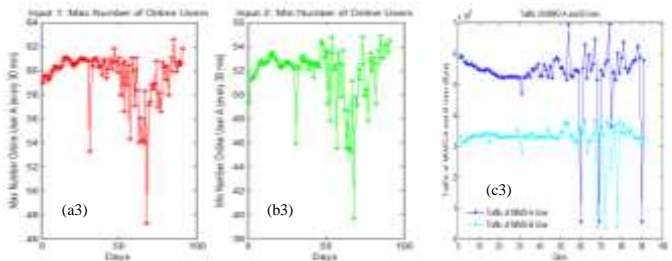

Figure 3.   Daily data input/output include (a3) Max number online of user-B (b3) Min number online user B and (c3) traffic of MIMO-user AB

From the illustrated figures, it can be seen that the daily maximum number of online users were found to vary between approximately (47.29) and (62.53) and the daily minimum number of online users were found to vary between approximately (39.73) and (54.89), while the daily traffic of MIMO-A user were found to vary between approximately (-5.698e7) and (6.954e8). During the same period of observation, the traffic of MIMO-B user was found to vary between approximately (3.632e7) and (3.837e8).

B. *ANN based Implementation of WIMAX Traffic Forecasting*

The ANN model selected for forecasting WIMAX traffic was a multi-layered feed forward perceptron. Three kinds of this model were designed. For each model, the network architecture consisted of an input and output layers, and hidden layers between them. The hidden layer contained a number of neurons as shown in Figure 4. The input layer consisted of the following data: Maximum and minimum number of online users, where the output layer consisted as the traffic of multi-input/multi-output of user A and B short form (MIMO-A, MIMO-B and MIMO-AB). The neurons in the layers were interconnected with weights characteristic of the information passing through them; the learning algorithm of error back propagation determined the weights. In this study, the three kinds configuration patterns (models) of training, called case (1), case (2) and case (3) were used and presented to the network as the following form:

- **Case (1):** WIMAX traffic of MIMO-A users

  In the case 1, trying to estimate the WiMAX Traffic from MIMO-A users using the daily recorded data includes the maximum and the minimum number of online users only, so the Traffic from MIMO-A users of daily data give as:

$$T_{Daily(A)} = f_A(X_{user(Max)}, X_{user(Min)}) \qquad (1)$$

- **Case (2):** WIMAX traffic of MIMO-B users

  Here, considering the estimation of the WiMAX traffic from MIMO-B users using the daily recorded data includes the same maximum and the minimum number of online users only, so the traffic from MIMO-B users of daily data give as:

$$T_{Daily(B)} = f_B(X_{user(Max)}, X_{user(Min)}) \qquad (2)$$

- **Case (3):** WIMAX traffic of MIMO-AB users

  In this case we combine both cases (1) and (2) as indicated above to estimation of the WiMAX traffic from MIMO-AB users using the same daily recorded data, so the Traffic from MIMO-AB users of daily data give as:

$$T_{Daily(AB)} = f_{AB}(X_{user(Max)}, X_{user(Min)}) \qquad (3)$$

Where, $T_{Daily(A,B,AB)}$ represent the WiMAX traffic from MIMO-A, MIMO-B and MIMO-AB users (byte) respectively. $(X_{user(Max)})$, $(X_{user(Min)})$ represent the maximum and the minimum number of online (Max-o

respectively, $f_{A,B,AB}$ is the function model depend on the architecture of the neural network as indicated in Figure 4
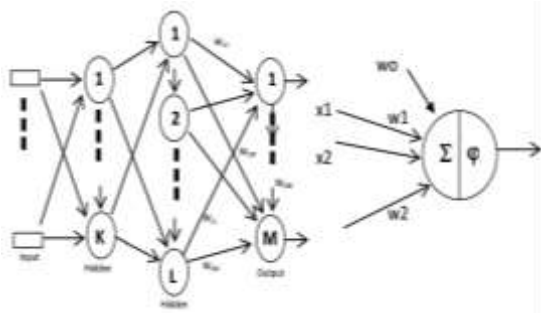

Figure 4. Genaral ANN configuration patterns

Considering our ANN architecture, it is noted that all models lead to the estimation of the traffic from MIMO-users as traffic flow index (output), which allows one to know the daily traffic flow index of the WIMAX network; but the difference between the three models lies in the function of number of MIMO-users (Number-MIMO). This is because Number-MIMO exhibits a marked variation due to the flow traffic in the Network. For this reason, Number-MIMO variations can be represented using ANN models and this procedure allows not only an optimal learning, but also uncovers the effect of Number-MIMO on the daily data recorded prediction.

Training Process

In the training process, neurons were trained and adjusted using the error back propagation rule (algorithm) to adjust the adaptation of the synaptic weights. The outputs are dependent on variables produced for the corresponding input. This algorithm is a supervised iterative training method commonly applied for multilayer feed forward nets, with nonlinear sigmoidal threshold units. The nonlinear sigmoidal transfer used and given as the following:

$$f(x) = \frac{1}{(1 + e^{-x})} \quad (4)$$

In this modeling stage, training data (2/3 entire data) are used in set of input–output vectors that characterize the problem. The output was produced and compared with the output of the training set. If there was a difference between the experimental output and the desired output, the connection weights were altered and the training process was updated until the error was minimized and reached the required tolerance level. Minimizing the error resulted in adjusting the weights of the connections between neurons. Once the tolerance level was reached, the network held the weights constant and used the trained network to make decisions. When the mean average error between the measured output and the desired output remained unchanged for a number of epochs, the network ceased to be trained. The output obtained

to be tested and compared with the desired value (target) by calculating the error function, which is the average of the square difference between the output of each neuron in the output layer and the desired output.

This procedure was conducted on the training and testing datasets. The following training parameters were set during the training process: Epochs of training was set to 10e4 , Training goal was set to 10-3, Maximum time of training the network is depend on the learning algorithm, Momentum constant=0.92, number of neurons = [20 10 1]. In order to suit the consistency of the model, input and output data were firstly normalized in the (0, 1) range, and then returned to the original values after the simulation using the following formula:

$$x' = \frac{x - x_{Min}}{(x_{max} - x_{Min})} \quad (5)$$

Where (x) represent the inputs/outputs of the network, and (x') is normalized inputs or outputs of the network. The value of normalized input or output is 1 when the input or output is x_{max} , and the value of normalized input or output is 0 when the input or output is x_{Min}.

The activation function applied in the designed ANN was the sigmoid function. In this study, the "Tansig" transfer function was used in the hidden layer and a linear activation function, and the "Purelin" transfer function in the output layer. The "Tansig" transfer function is defined as:

$$\tan sig(x) = \frac{2}{1 + e^{(-2x)}} - 1 \quad (6)$$

ANN Models Error Analysis

Initially, the recorded data collected from LibyaMax network was used for training, validating, and testing the designed feed-forward back-propagation neural networks. The estimated value of WIMAX traffic was tested for its accuracy. The predicted value resulted from the training and testing data for each model type was compared with the true (measured) data in order to verify the performance of the prediction model (for training and testing stages). The comparison between measured and estimated value was evaluated by statistical error of mean square error (*MSE*) to check the stability of the model measured by the following formula:

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (X_M - X_E)^2 \quad (7)$$

Where (N) is the number of input-output pairs and X_M , X_E are the desired (target) and estimated values, respectively. In addition, another statically measurement was obtained as an evaluation support known as model efficiency (M_{eff}) of the ANN prediction results from training and testing stage measured by the following formula:

$$M_{eff} = 1 - (\frac{MSE}{Var}) \qquad (8)$$

Where variance (Var) equals the square of standard deviation (STD^2). The best model that gave the lowest errors (MSE) and best fit (off) was selected as the stable and suitable model. The final step was to apply the result of the best proposed ANN model, with estimated value and solar radiation data value for Aqaba city.

III. Result and Discussions

This section discusses the modelling results of the daily WiMAX traffic for Tripoli city when the three types of learning algorithms are applied in the ANN model, and the performance of the prediction is evaluated by checking the (*MSE*) and Model efficiency (*Eff*) indicators. The results of the modeling are represented and discussed as following :

A. Modeling results: WiMAX traffic of MIMO-A users

Figures 5 (a), (b) and (c) illustrate the results from modeling the WiMAX traffic of MIMO-A users (case1) when applying an ANN topology of [20 10 1] with the three learning algorithms; Where the result obtained are extracted from Figure 4 which represent the modeling results of WiMAX traffic of MIMO-A using (a) *TrainLM* (b) *TrainGDX* and (c) *TrainSCG* learning algorithms. In this ANN model case, the prediction data showed generally excellent accuracy when plotted against the measured data and the performances of the ANN training and testing efficiencies are Summarize in Table.1.

TABLE I.   CROSS-VALIDATION REPORT OF ANN MODELING RESULTS OF WIMAX TRAFFIC OF MIMO-USER A

[20 10 1]	$T_{Daily(A)} = f_A(X_{user(Max)}, X_{user(Min)})$				
	Training			**Testing**	
Algorithms	MSE	M$_{eff}$	R	MSE	M$_{eff}$
TrainLM	1.16e-5	0.9992	0.99962	**3.515e-4**	**0.9823**
TrainGDX	0.0016	0.8920	0.94538	0.0072	0.6378
TrainSCG	1.08e-4	0.9929	0.99638	0.0054	0.7285

As illustrated in the Figures 5 (a, b, c) and cross-validation report from Table I, it was noted that the average testing efficiency of the model was (0.7829), and the learning algorithm of *trainLM* had the lowest MSE (3.515e-4) and highest efficiency (0.9823) compared to the other algorithms. *trainGDX* has the highest MSE (0.0072) and the lowest efficiency (0.6378), with *trainSGD* being somewhere in between.
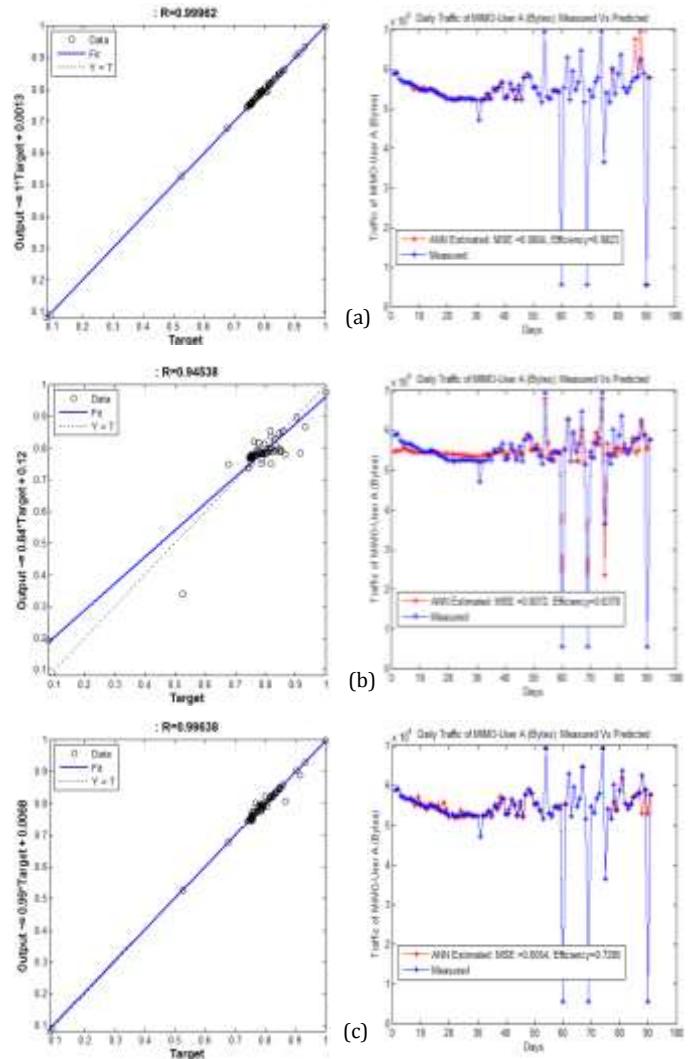

Figure 5.   Illustrate the results of modeling the Wimax traffic of MIMO-A users with (a) trainLM (b) trainGDX and (c) trainSCG

B. Modeling results: WIMAX traffic of MIMO-B users

In this case , illustrated in Figures 6 (a), (b) and (c) are the results of modeling the WiMAX traffic of MIMO-B users (case2) when applying the three learning algorithms; *LM*, *GDX* and S*CG*, respectively. Within this ANN model case, the prediction data showed boost accuracy while plotted against the measured data and the performances of the ANN training and testing efficiencies are summarize in Table.2.

TABLE II.   CROSS-VALIDATION REPORT OF ANN MODELING RESULTS OF WIMAX TRAFFIC OF MIMO-USER B

[20 10 1]	$T_{Daily(B)} = f_B(X_{user(Max)}, X_{user(Min)})$				
	Training			Testing	
Algorithms	MSE	M_{eff}	R	MSE	M_{eff}
TrainLM	1.17e-5	0.9995	0.99389	**0.0007**	**0.9690**
TrainGDX	0.0103	0.5784	0.75758	0.0098	0.5701
TrainSCG	9.27e-4	0.9619	0.98146	0.0014	0.9402

While illustrated from the Figures 6 (a, b, c) and cross-validation report as in from Table II, it was observed that the average testing efficiency of the model was (0.8264) along with the *trainLM* learning algorithm the lowest MSE (0.0007) and highest efficiency (0.9690) when compared to the various algorithms. GDX has the highest MSE (0.0098) and lowest efficiency (0.5701), with SGD being anywhere between.
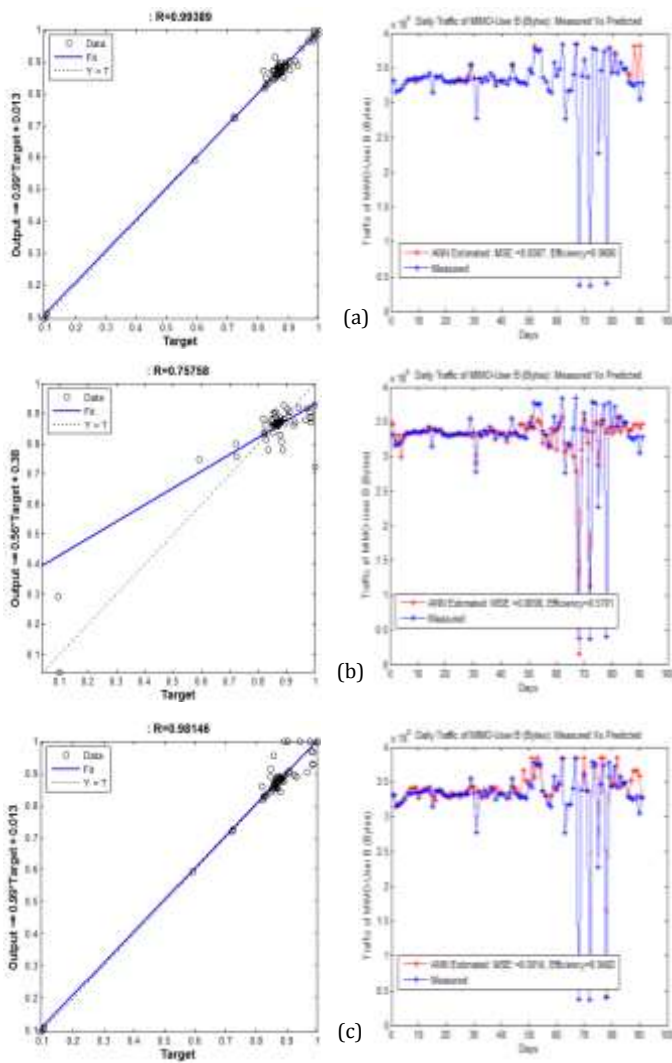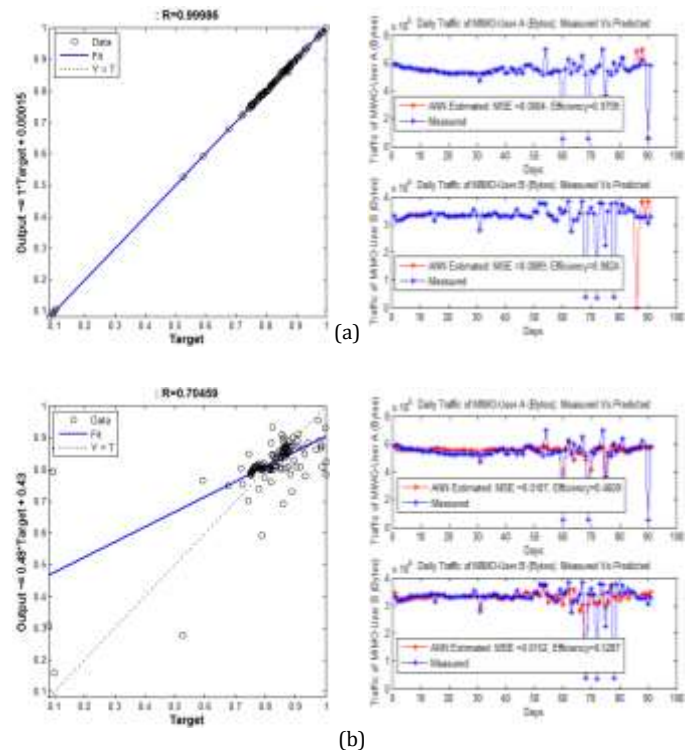
C. *Modeling results: WIMAX traffic of MIMO-AB users*

Considering the result from Figures 7 (a), (b) and (c) which illustrate the modeling the WiMAX traffic of MIMO-AB users (case3) by applying same three learning algorithms; mentioned above. In this ANN model case, the prediction data showed improvement and great accuracy when plotted against the measured data as indicated and summarize in Table.3.

TABLE III.   CROSS-VALIDATION REPORT OF ANN MODELING RESULTS OF WIMAX TRAFFIC OF MIMO-USERS AB

[20 10 1]	$T_{Daily(AB)} = f_{AB}(X_{user(Max)}, X_{user(Min)})$				
	Training			Testing	
Algorithms	MSE	M_{eff}	R	MSE	M_{eff}
TrainLM	5.85e-6	0.9998	0.99986	**0.0046**	**0.9812**
TrainGDX	0.0106	0.7329	0.70459	0.0130	0.4948
TrainSCG	0.0011	0.9638	0.97417	0.0044	0.6670

As shown in the Figures 7 (a, b, c) and cross-validation report, the average testing efficiency of the model was (0.7143), and both the learning algorithm *TrainLM* with *Train SCG* had the lowest MSE (0.0044) and (0.0046) respectively with highest efficiency (0.9363) and (0.6670) compared to the other algorithms. GDX has the highest MSE (0.0130) and the lowest efficiency (0.4948).
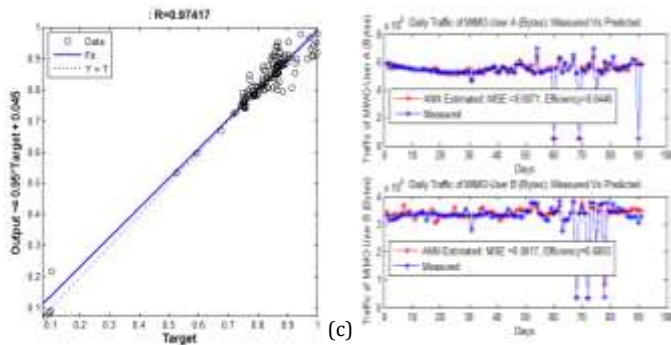

(a)

(b)

(c)

Figure 6.   Illustrate the results of modeling the Wimax traffic of MIMO-B users with (a) trainLM (b) trainGDX and (c) trainSCG

(a)

(b)

Figure 7. Illustrate the results of modeling the Wimax traffic of MIMO-AB users with (a) trainLM (b) trainGDX and (c) trainSCG

IV. **Conclusion**

In this paper we carried out a technique in which includes WIMAX traffic data recorded with the ANN model. The main challenge was to verify that using the ANNs with Maximum and Minimum user on-line allow us to obtain better results for predicting traffic flow based MIMO-A, B and AB. We made comparisons with the results from each learning algorithm. Founded, that forecasting technique discussed in this paper can be effectively used for building prediction models for WIMAX Traffic flow. Nonetheless, to be able to have higher performance and to reduce the prediction errors, we'd advocate getting more data for ANN training and analysis.

Acknowledgment

References

[1] Q. Yang W. Xindong, "10 Challenging Problems in Data Mining Research" International Journal of Information Technology and Decision Making, vol. 5(4), pp. 597-604, 2006.

[2] G. Zhang, B. E. Patuwo, M. Y. Hu, "Forecasting with artificial neural networks: The state of the art" International Journal of Forecasting 14, pp.35-62, 1998.

[3] S. Armstrong, M. Adyaa, "An application of rule based forecasting to a situation lacking domain knowledge" International Journal of Forecasting ,vol. 16, pp. 477-484, 2000.

[4] A.Mitra, S. Mitra, " Modeling exchange rates using wavelet decomposed genetic neural networks," Statistical Methodology, vol. 3, issue 2, pp. 103-124, 2006.

[5] G. Ibarra-Berastegi, A. Elias, R. Arias, A. Barona, "Artificial Neural Networks vs Linear Regression in a Fluid Mechanics and Chemical Modelling Problem: Elimination of Hydrogen Sulphide in a Lab-Scale Biofilter," IEEE/ACS International Conference on Computer Systems and Applications, pp.584-587, 2007.

[6] H. Feng, Y. Shu, "Study on Network Traffic Prediction Techniques" Proceedings of the International Conference on Wireless Communications, Networking and Mobile Computing, Vol. 2, pp. 1041- 1044, 2005.

[7] N. Clarence,W. Tan, " Incorporating Artificial Neural Network into a Rulebased Financial Trading System" The First New Zealand International Two Stream Conference on Artificial Neural Networks and Expert Systems (ANNES), University of Otago, Dunedin, New Zealand, November 24-26, 1993.

[8] T. Taskaya-Temizel, M.C. Casey, "Configuration of Neural Networks for the Analysis of Seasonal Time Series," Proceedings of the 3rd International Conference on Advances in Pattern Recognition (ICAPR 2005), Lecture Notes in Computer Science 3686, vol. 1, pp. 297-304, 2005.

[9] Daniel S. Clouse, C. Lee Giles, Bill G. Horne, Garrison W. Cottrell, "Time-Delay Neural Networks: Representation and Induction of Finite-State Machines, IEEE Transaction on Neural Networks," vol. 8, no. 5,September 1997.

[10] G. Peter Zhang, Min Qi, "Neural network forecasting for seasonal and trend time series," European Journal of Operational Research 160, pp. 501-514, 2005.

[11] Daw Abdulsalam Ali Daw, Kamaruzzaman Bin Seman, "Gateway To Wimax Profiling Services In Libya" International Journal of Engineering   Research and Development.vol. 7, PP. 63-68, 2013.

[12] D. Ion Railean, C Stolojescu, S Moga, P Lenca, "WIMAX Traffic Forecasting based on Neural Networks in Wavelet Domain" Ion Research Challenges in Information Science (RCIS), 2010 Fourth International Conference on. pp. 443-452, 2010

[13] I. Firoiu, C. Stolojescu, A. Isar, Forecasting of WiMAX BS Traffic: Observations and Initial Models, Alcatel Lucent technical report, January, 2009.

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