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Nonlinear Autoregressive Recurrent Neural Network Model for Quality of Service Prediction

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Abstract*: Due to the advances in computer networks, Internet and multimedia communications, Quality of Service (QoS) monitoring and assessment become an increasingly important. The importance of assessing QoS stems from the fact it may reflect the resources availability of a network that may provide solutions for QoS provision, routing, monitoring, management … etc. In the literature, several monitoring and measurement approached and methods have been developed to quantify and predict the QoS of multimedia applications transmitted over such networks. In this research, a new QoS prediction system will be designed. The proposed system is based on using the Nonlinear Autoregressive with eXogenous input model (NARX) using recurrent neural network. This prediction system uses in addition to the QoS parameters; previous measured QoS values will used as inputs to this model. The expected output of this new model is the forecasted QoS. The proposed model will be trained, tested, validated and then optimized to provide a good estimate of the QoS provided by the given network. Simulation results are expected to show that the proposed model will have high accurate QoS prediction capabilities compared to other QoS assessment systems adopted in the literature.

Keywords: Computer Networks, QoS, Prediction, Nonlinear Autoregressive Exogenous Inputs (NARX), Multimedia, Videoconferencing.

I. INTRODUCTION

Modern networks are multi-traffic networks. That is because various kinds of traffic like voice, video and data can be transferred across them using the same network available resources. Due to this and due to the huge number of users and different network traffic types, network providers may encounter vital problems and difficulties in monitoring and engineering of these networks traffic. For this reason, networks performance and Quality of Service (QoS) are of vital importance for network providers and operators. Network performance is a key concept at the heart of network monitoring and controlling [1]. In the networking field, network performance refers to the performance of the network path between two end nodes in terms of several metrics used to characterize the performance of network like delay-related metrics and bandwidth-related metrics [2]. QoS is defined as "a set of service requirements to be met by the network while transporting a flow" [3]. A flow is a stream of packets from source to destination.

Advances in the current high speed networks have created many real-time multimedia applications like, text, graphics, audio, video, image, etc. QoS requirements of these applications vary from one application to another. Available network resources and performance may not guarantee the desired QoS requirements. That is because some of the network nodes may violate the service level agreement or requirements. Ensuring the performance of the network, definitely will improve the QoS. Therefore, network performance and QoS must be monitored appropriately to ensure the application QoS. Based on this, network performance prediction may play an essential role in achieving better control results. Nowadays, network performance prediction model shave become one of the key solutions for issues related to network management and measurements [4]. That is due to the fact that network performance prediction may be considered as a proactive approach rather than reactive, where network performance is monitored to ensure that network is performing well and no violation to any of the QoS requirements of the multimedia traffic transmitted across it. The predictability of the network performance is a significant stage in many areas like: congestion control and prevention, dynamic bandwidth allocation, network planning, network security schemes, call admission control... etc [5].

Network prediction models can be categorized in terms of prediction period into two categories: long and short period's prediction models [6]. Long period models provide a detailed predicting features of traffic performance which enable better planning and decisions. Short period prediction is linked to dynamic resource allocation used to improve QoS, congestion control and for optimal resource management. Several different techniques including time series models, modern data mining techniques, soft computing approaches, and neural networks are used for network traffic analysis and prediction.

Several approaches have been proposed to predict network performance and QoS based on different assumptions and designed for different metrics. These approaches can be categorized into two approaches: topology-based and model-based approaches. Topology-based approaches are based on using the network topology and the available routing information [7],[8],[9]. The idea of these approaches is only applicable for predicting additive metrics such as Round Trip Delay (RTT) and packet loss rates.

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Topology-based approaches showed good results in predicting these metrics but still suffer two main weaknesses. First, they are only employed in predicting additive metrics and fail for others like available bandwidth. Second, they depend on gathering and maintaining routing information which is a serious problem especially for large networks [2].On the other hand, model-based approaches depends on building models for network performance spaces, where the performance of a network can be predicted based on some features of the two end nodes in the network. These approaches are easier and more attractive than topology-based approaches in that they do not need routing information of the network and can be applied to predict several metrics without any limitation.

Moreover, prediction models in networks are categorized in terms of linear and nonlinear prediction models. Linear prediction models were used in several studies of network traffic prediction. These models were based on autoregressive (AR) and autoregressive integrated moving average (ARIMA) [10]. These models are simple in algorithm, but poor in adaptability. On the other hand, nonlinear models which are mainly based on intelligent algorithm like neural network, radial basis function (RBF) neural network, fuzzy logic, and genetic algorithms presented a good nonlinear mapping ability and effective way of learning in the field of prediction. But, nonlinear models are not suitable to be used in systems which include some linearity due its inabilities in capturing it. Therefore, none of them is superior to the other and the best solution is to combine them in one model [11]. Due to the limitations of both models, the proposed approach in this paper for network performance prediction and analysis is based on using both linear and nonlinear models. In this work, a nonlinear recurrent neural network autoregressive with exogenous input model (NARX) is used to predict and quantify the network performance. In this paper, we aim to address this niche and evaluate the suitability of this approach for QoS and network performance predicting. Here, network performance prediction can be considered as a tool used for ensuring minimal QoS level of multimedia traffic in packet network. Therefore, the purposed model may be used to provide a simple monitoring tool capable of predicting quantitative QoS according to network status. The developed model may deployed as an alternative to expensive monitoring tools necessary for predicting network performance and behavior.

II. LITRETURE SURVEY

Network performance evaluation can be deduced by assessing QoS which is derived from measurable QoS attributes [12]. These attributes are like delay, delay variation (jitter), loss ratio, and throughput. Measuring these attributes or parameters may give indication about network performance. The high volatility of these attributes results in degradation in the network performance and QoS which represents a challenge for the network service providers. Moreover, the measurement and monitoring of these parameters by service providers has shown to be unreliable [13]. Therefore, accurate prediction of QoS or network performance may be useful in lessening this problem. Many different predictors have been proposed. These predictors are like time series predictors and neural networks-based predictors.

To obtain an accurate, up-to-date network performance assessment and continuous QoS monitoring, most existing studies are based on time series predicting [14].A challenge for QoS or network performance prediction is to determine, which time series predicting method is the most suitable for predicting [15]. The suitability is determined by the accuracy that the forecasting methods can provide. These approaches have been successfully applied to forecast the network performance using different models to fit the past values and then predict their future changes [16]. In [17] used a QoS series model which includes three items, a trend, periodical and random items to determine the linearity, periodicity and uncertain changes in QoS measurements to extend the series into the future.

In [18] devised a technique which combines monitoring technologies with prediction methods using ARIMA models to forecast future network performance. The authors in [19] proposed an improved QoS prediction method which combines ARIMA with GARCH models to lessen the variation assumption constraint of ARIMA models. In [20], the authors presented an approach to compare different QoS prediction techniques based on ARIMA and linear time series forecasting models. In this study, ARIMA outperformed the other linear models in forecasting possible violations of QoS constraints and guaranteeing a low prediction error. In [21], an investigation of deploying a nonlinear autoregressive model to predict the QoS of multimedia traffic. The developed model showed that it is an effective approach to infer the network performance of any network topology. The obtained results revealed that it is an efficient method due to the high accuracy of the resulted forecasted QoS values.

Although time series models showed noticeable advantages in predicting network performance and QoS, their performance still have some limitations and drawbacks [22]. One of these is their inability to correct predictions timely by taking account of the up-to-date QoS measurements. In addition, they only forecast future values of QoS for each individual traffic in the network.

Several QoS and network performance studies have been conducted using artificial neural networks (ANNs). Some of these studies have shown that ANNs are a competitive model and superior to the classical time series prediction approaches such as ARIMA [23-25]. Consequently, some research studies combined these two approaches, which produced a dynamically prediction results [26]. In literature, several techniques have been proposed based on using the ANNs for assessing and forecasting of the QoS of multimedia traffic transmitted over IP networks [27-29]. In [30], an ANN was used to forecast RTT single-step-ahead between two nodes over the Internet. In [31], an improved neuro-based system was developed to predict the end-to-end delay and the RTT of the Internet traffic multi-step ahead with enhancement in the prediction accuracy.

Moreover, several QoS assessment techniques have employed fuzzy logic for the evaluating the network traffic performance of time-sensitive applications like audio and videoconferencing [32]. Moreover, in [38], a QoS assessment system was devised based on combining fuzzy C-means and regression model to estimate the QoS of VoIP traffic.

III. RECURRENT NEUERAL NETWORKS NARX MODEL

ANNs are very useful in a wide range of applications like recognition, optimization, data validation, Detection, approximation and prediction [33]. ANNs are mathematical models with great capabilities to learn, store, retrieve, and recall information. In addition, they possess the ability to simulate the biological neural system [34]. ANNs have the capacity to perform non-linear mapping of single or multi-inputs onto one or more outputs especially when the relationship between the input and output are unclear or unknown. There are several types of ANNs which are categorized according to their learning process and learning algorithm [35]. These are like feedback, or recurrent ANNs, and feed-forward ANNs.

Given that network traffic and QoS are both time series. Moreover, the NARX neural network is an efficient tool to forecast time series [36]. NARX is a nonlinear extension of the linear Autoregressive Exogenous (ARX). ARX is a linear tool used extensively in system identification [37]. Based on this, NARX are very useful in modeling, simulating and predicting of nonlinear dynamic systems in addition to time series modeling [38]. NARX can be classified as a recurrent dynamic neural network (RNN) consisting of several layers with feedback connections from the output to the input. The inputs of NARX are two kinds: the exogenous (i.e., external) and the previous outputs of the network [39].In nonlinear time series prediction, NARX neural network employ its memory ability to remember the past values of predicted time series. NARX neural networks are two architectures: series-parallel (open loop) architectures and the parallel (closed loop) architectures. These two models are shown in Figure 1 below and represent in equations 1 and 2, respectively.

$$\hat{x}(t) = f\begin{pmatrix} x(t-1), x(t-2), \dots, x(t-n_x), \\ u(t), u(t-1), u(t-2) \dots, u(t-n_u) \end{pmatrix} \quad (1)$$

$$\hat{x}(t) = f\begin{pmatrix} \hat{x}(t-1), \hat{x}(t-2), \dots, \hat{x}(t-n_x), \\ u(t), u(t-1), u(t-2) \dots, u(t-n_u) \end{pmatrix} \quad (2)$$

where,

f(.) is the mapping function of the neural network

$\hat{x}(t)$ is the predicted output of the system at time (t)

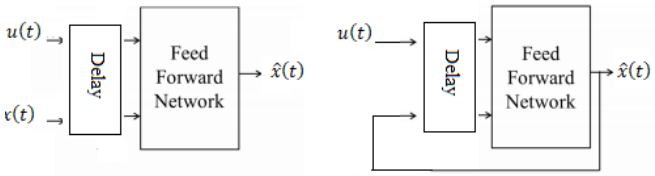
$u(t)$ is the current input

$x(t-1), x(t-2), \dots, x(t-n_x)$ are the original past outputs

$\hat{x}(t-1), \hat{x}(t-2), \dots, \hat{x}(t-n_x)$ are the predicted past outputs

$u(t-1), u(t-2) \dots, u(t-n_u)$ are the past inputs

n_x and n_u are the number of output and input delays, respectively.



(a) (b)

Fig. 1.NARX recurrent neural architecture: (a) Series-parallel architecture and (b) Parallel architecture

From the above Figure, it is clear that $\hat{x}(t)$, in the series-parallel model, is predicted based on past and present values of both the original output and input values $x(t)$ and $u(t)$, respectively. While in the parallel model, $\hat{x}(t)$ is predicted from the past values of the $\hat{x}(t)$ and the past and present values of the input $u(t)$.

Initially and for the prediction process, the function f(·) is not identified but approximated during the training phase. For NARX recurrent model, the Multi-Layer Perceptron (MLP) is used to approximate the mapping function f(·), especially for prediction of nonlinear systems. MLP comprises of three layers: input, hidden and output layer. In addition MLP includes neurons, activation functions and weights. Neuron multiplies the input vectors come from previous layer by the weights vector to give the scalar output. Figure 2 shows a typical architecture of NARX-ANN. Then using the activation function, each layer output is transformed and mapped to produce the neuron output which will be forwarded to the next layer. Activation functions are like: Linear, Sigmoid (Logsig) and Hyperbolic tangent (Tansig) [40].

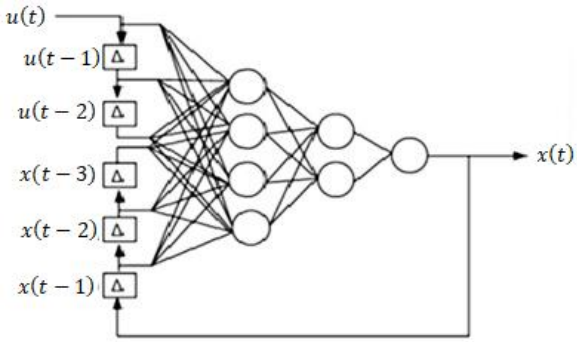


Fig. 2.Architecture of NARX-ANN model of two input delays and three output delays.

During the training process of the network, this includes modifying the weights based on an appropriate algorithm so that the neural network produces an output close to the target values. This is achieved by introducing some inputs and their associated output (target). Varying inputs and outputs during the training process will result an optimal solution which gives the best result.

Given the powerful performance of both NARX and the recurrent neural network in prediction process, the NARX-ANN is adopted to be used as prediction approach in this paper. Due to the availability of the past output values, the series-parallel model is used during the training phase of the prediction process.

This model is used due to the fact that introducing the original output values as input of the feed forward network will produce more precise results. Then, after finishing the training phase, the NARX-ANN will use the parallel architecture due to its capabilities in multi-step-ahead predictions [41].**METHODOLOGY**

In this work, delay, jitter, losses and QoS measurements were collected from the generated trace file of the simulated network. The collected data were used to train the NARX recurrent neural network with QoS as the target (output) variable and Delay, Jitter and Loss as the input variables. The NARX recurrent neural network was implemented by Matlab 2013a. The available dataset has to be divided into three different subsets: training, validation and testing sets. These need to be preprocessed and averaged using a blocking technique that combines every selected consecutive packet details in one block and calculates their average QoS parameters (i.e., delay, jitter and loss values. The averaged QoS parameters time-series are used as external inputs of the NARX recurrent neural network model. Another input for the model is the previous values of the QoS values. These values were obtained from our previous studies, which correspond to inputs QoS parameters which mean that every QoS value corresponds to specific QoS parameters values (i.e., Delay1, Jitter1 and Loss1 correspond to QoS1). Figure 3 illustrates the time-series plot of the QoS parameters (predictors), as well as assessed QoS values. This figure shows the relationship between the QoS and the three QoS parameters.

Several configurations were tested to determine the optimal NARX recurrent neural network architecture in terms of the number hidden layers in the model, number of neurons in each layer, transfer function used in each layer, training algorithm, and number of delays of the NARX model. The optimal model should have the best correlation coefficient (R) and the minimum root mean square error (RMSE). RMSE provides a measure of the difference between the predicated and the measured data. The R value represents the relationship between the predicted output and target values. The R value is in the range of [-1, 1]. If R = 1, then there is a very strong positive relationship between output and targets. In this work, the feed forward neural network was used. This network constructed using two layers: single hidden layer and an output layer. The transfer functions deployed in the network are as follows: the tangent sigmoid function in the hidden layer and linear function in the output layer. In addition, for the design of the network architecture, the delays of each input needs to be identified associated with the number of neurons in the hidden layer. Additionally, the Levenberg-Marquardt (LM) training algorithm was employed in the training phase of the recurrent neural network.

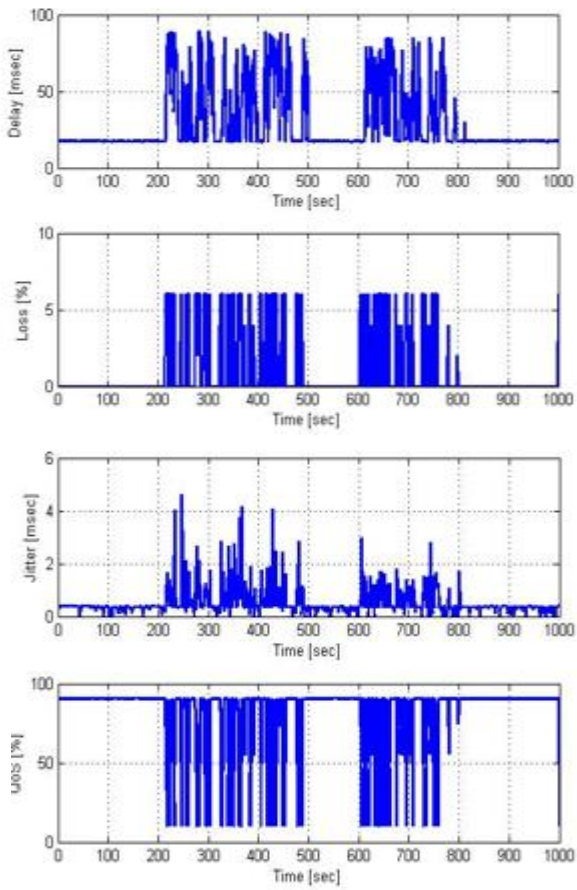


Fig. 3.Measured QoS parameters and the assessed QoS

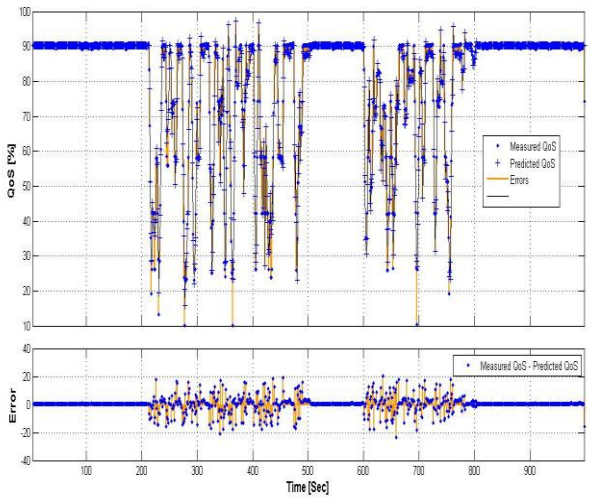
Several configurations were tested to determine the optimal NARX recurrent neural network architecture in terms of the number hidden layers in the model, number of neurons in each layer, transfer function used in each layer, training algorithm, and number of delays of the NARX model. The optimal model should have the best correlation coefficient (R) and the minimum root mean square error (RMSE). RMSE provides a measure of the difference between the predicated and the measured data. The R value represents the relationship between the predicted output and target values. The R value is in the range of [-1, 1]. If R = 1, then there is a very strong positive relationship between output and targets. In this work, the feed forward neural network was used. This network constructed using two layers: single hidden layer and an output layer. The transfer functions deployed in the network are as follows: the tangent sigmoid function in the hidden layer and linear function in the output layer. In addition, for the design of the network architecture, the delays of each input needs to be identified associated with the number of neurons in the hidden layer. Additionally, the Levenberg-Marquardt (LM) training algorithm was employed in the training phase of the recurrent neural network.

IV. RESULTS AND DISCUSSIONS

This section presents the results for using the NARX recurrent neural network model in predicting the QoS and network performance of a simulated network transmitting multimedia traffic.

The developed model was trained, validated and tested considering different recurrent neural network configurations in terms of number of neurons and delays. Selecting different number of number of neurons and delays produces different results of the predicted QoS in terms of R and RMSE values. Nevertheless, in general, all selected numbers of neurons and delays in each configuration provided nearly similar results. Based on this, several configurations have been simulated for different number of neurons and delays and different training, testing, and validation ratios of the available data.

Figures 4 and 5 show comparisons between predicted QoS using the NARX recurrent neural network model and the measured one for the simulated network based on varying the number of neurons and delays of the prediction model. In addition, Figure 6-8 show comparisons between predicted QoS and the measured one for the simulated network varying the data distribution ratios among the (training, validation and testing) stages of the prediction model.



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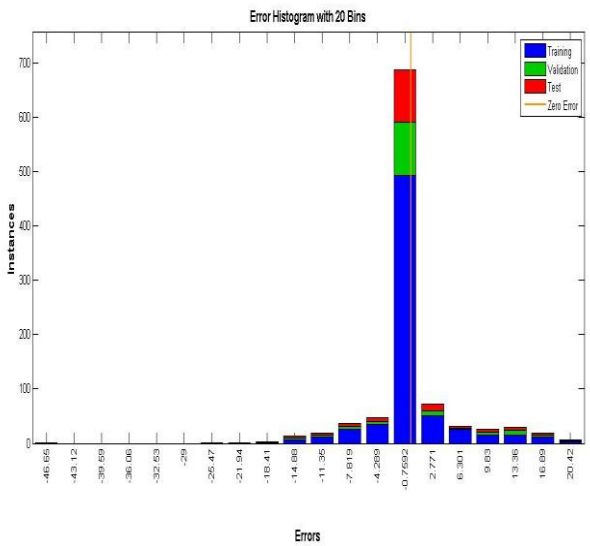

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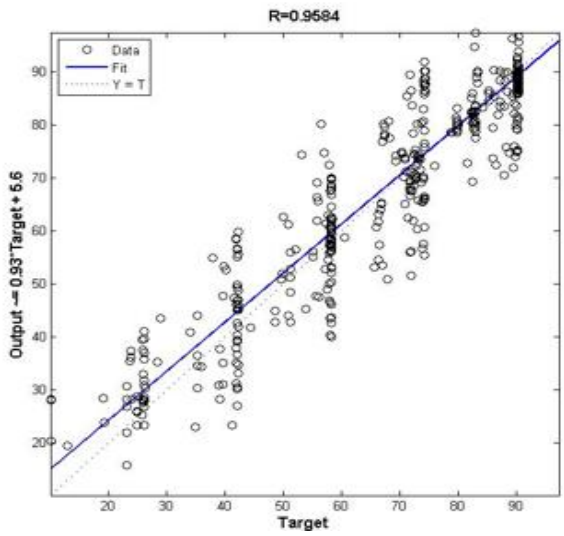

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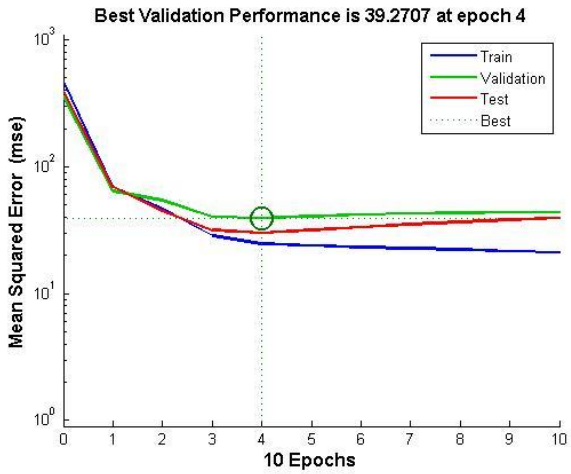
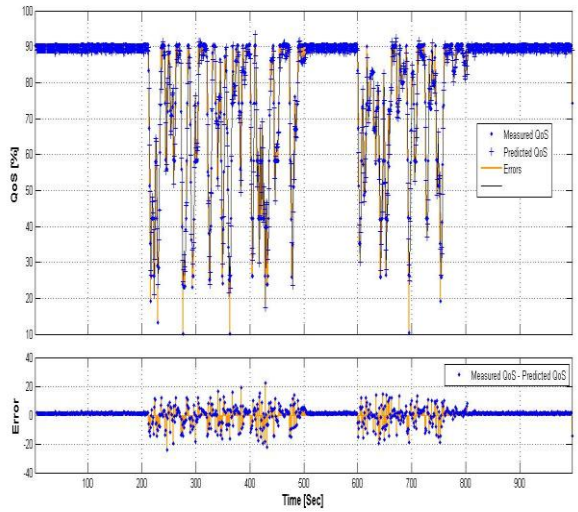


(d)

Fig. 4. (a) Response (b) Histogram of the error between the measured and the predicted QoS (c) Regression analysis, and (d) Best validation performance of using 2 delays and 20 neurons for the NARX recurrent neural network.



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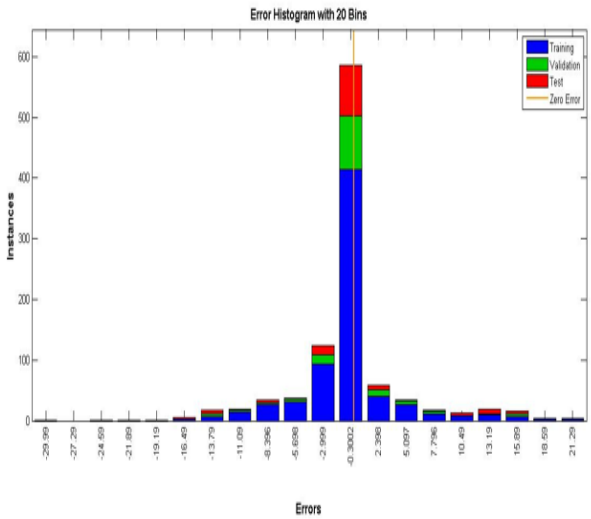

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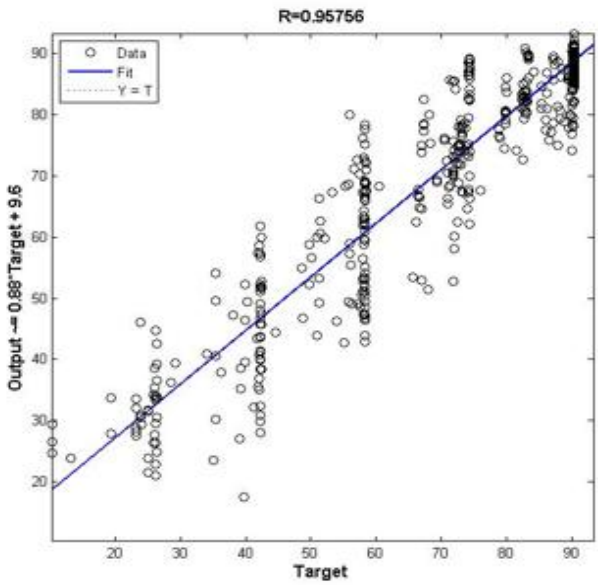

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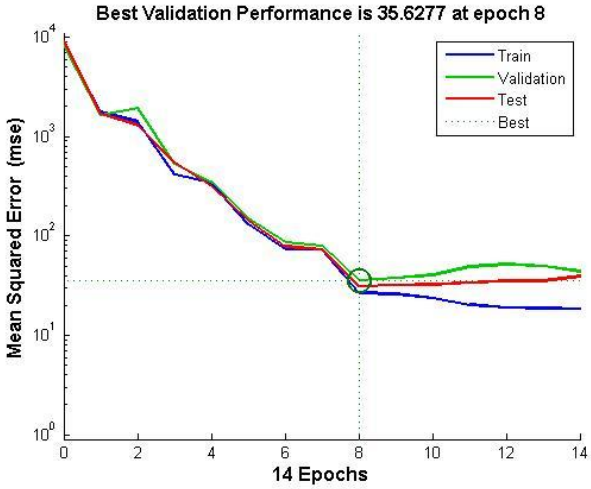

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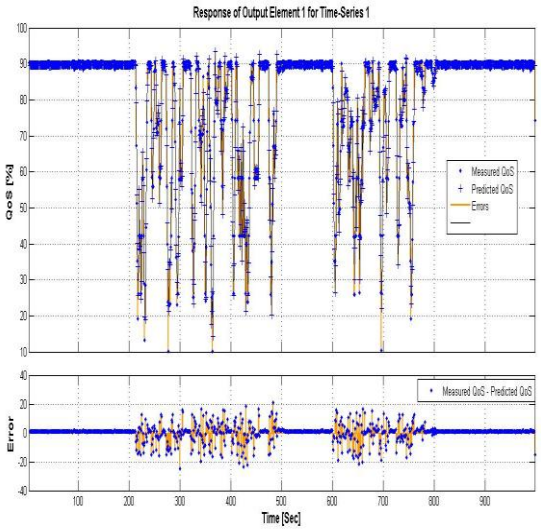
Fig. 5. (a) Response (b) Histogram of the error between the measured and the predicted QoS (c) Regression analysis, and (d) Best validation performance of using 3 delays and 10 neurons for the NARX recurrent neural network.



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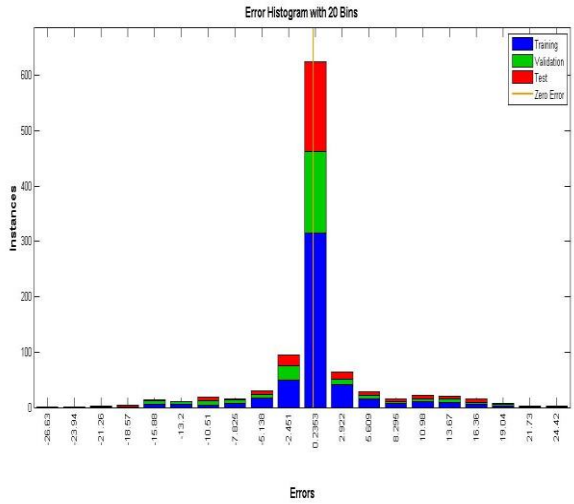

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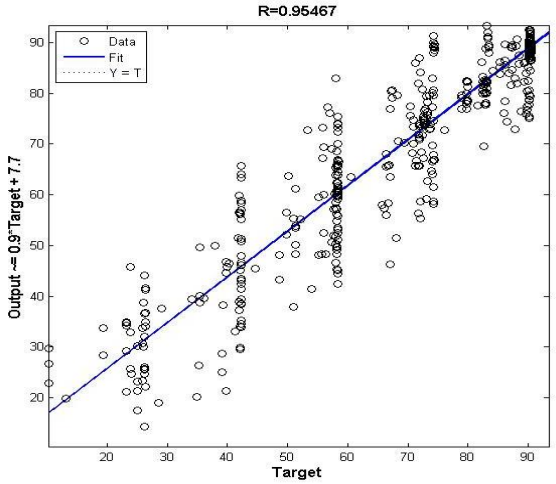

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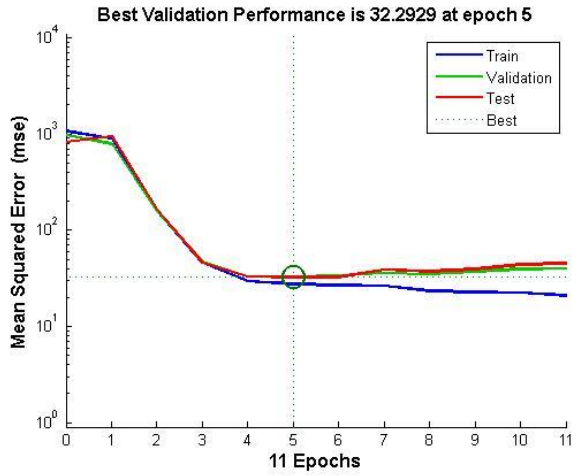

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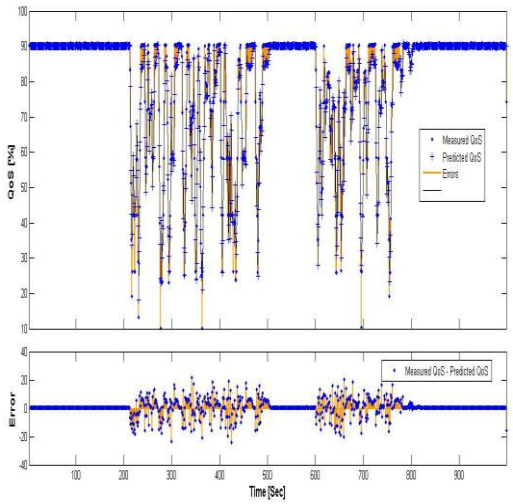
Fig. 6.(a) Response (b) Histogram of the error between the measured and the predicted QoS (c) Regression analysis, and (d) Best validation performance of using 50%, 25%, 25% training, validation and testing, respectively for the NARX recurrent neural network.



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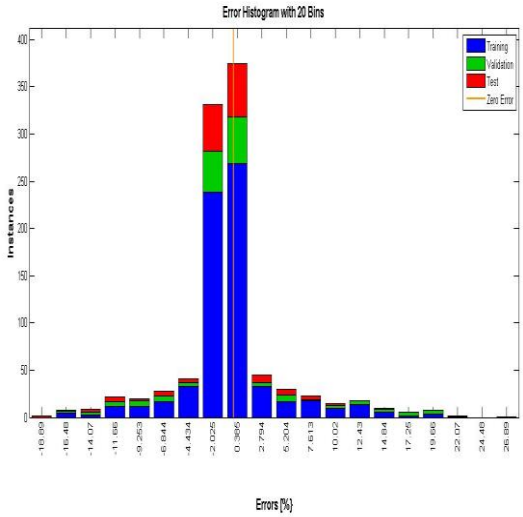

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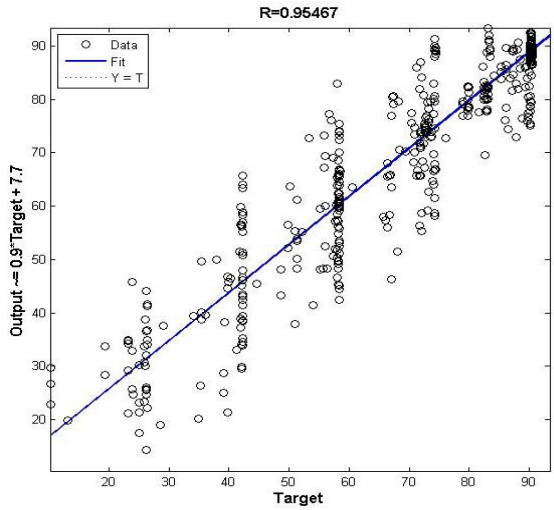

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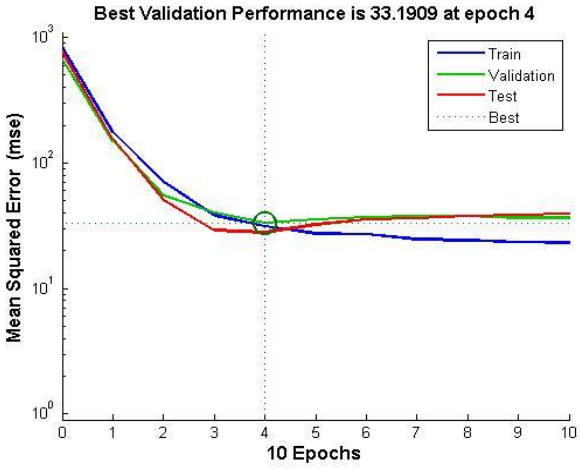
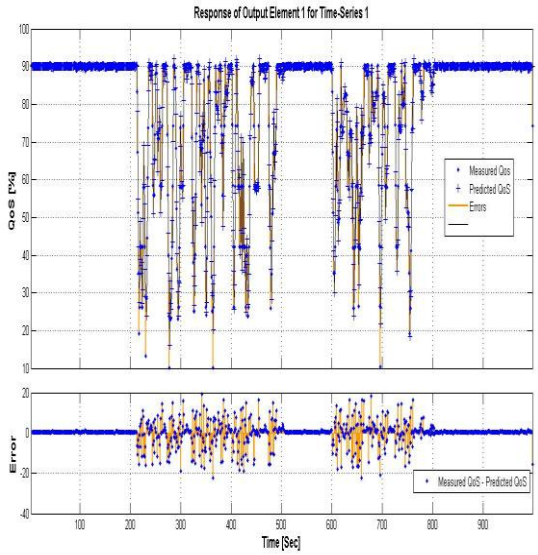


(d)

Fig. 7. (a) Response (b) Histogram of the error between the measured and the predicted QoS (c) Regression analysis, and (d) Best validation performance of using 75%, 15%, 15% training, validation and testing, respectively for the NARX recurrent neural network.



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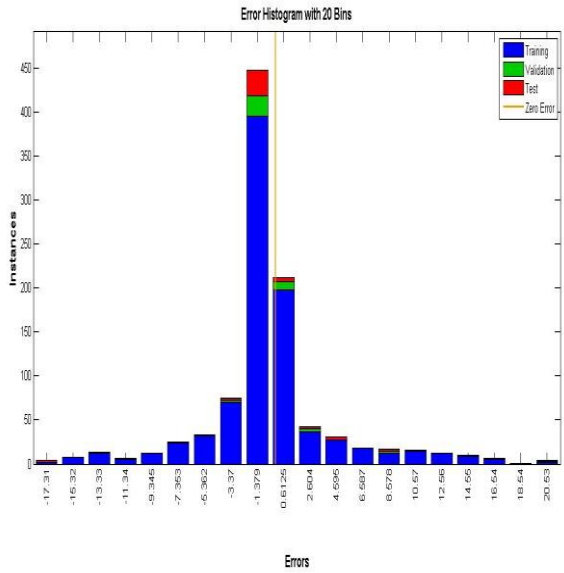

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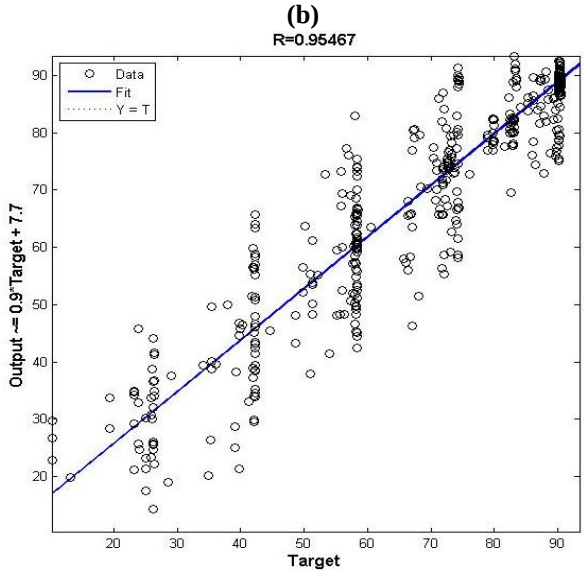

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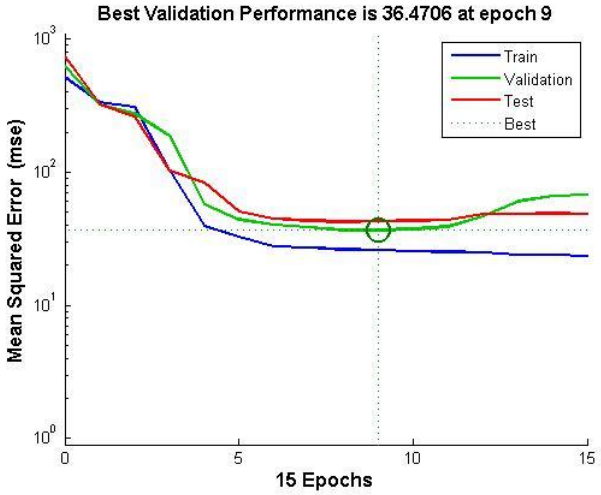

(d)

Fig. 8. (a) Response (b) Histogram of the error between the measured and the predicted QoS (c) Regression analysis, and (d) Best validation performance of using 90%, 5%, 5% training, validation and testing, respectively for the NARX recurrent neural network.

From the above Figures, and based on the selected number of neurons, delays and data distribution ratios (training, validation and testing) of the prediction model, it is clear that the predicted QoS using the developed predicting model offers a very good prediction of the experienced QoS and network performance by the multimedia application. Therefore, and based on the results, NARX recurrent neural network model provides an appropriate forecasting tool for multimedia application QoS and network performance.

V. CONCLUSIONS

In this work a QoS and network performance prediction model was developed based on the use of NARX recurrent dynamic neural network. This model was designed, trained, tested and validated based on the LM training algorithm and using a data collected from a simulated network to predict its performance and the QoS that this network can provide to multimedia application. From the obtained results, it was very clear that the devised QoS prediction model was very efficient where the predicted QoS values were very similar and comparable to the measured values. Additionally, further experimentation and examining for the developed model were conducted in terms number neurons and in terms of available data distribution (i.e., training, testing and validation). The obtained results (in terms of response, error distributions, regressions, and best validations) showed that the proposed NARX model can produce precise predictions of the network performance and its QoS.

Future work may be conducted in order to optimize the selection of the best number of neurons, delays and data distribution ratios (training, validation and testing) of the prediction model in terms of processing time the model takes to get the predicted QoS values.

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