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Quality of Service Evaluation and Assessment Methods in Wireless Networks

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***Abstract*— Wireless networks are capable of facilitating a reliable multimedia communication. The ease they can be deployed is ideal for disaster management. The Quality of Service (QoS) for these networks is critical to their effectiveness. Evaluation of QoS in wireless networks provides information that supports their management. QoS evaluation can be performed in multiple ways and indicates how well applications are delivered. In this work, fuzzy c-means clustering (FCM) and Kohonen unsupervised neural networks were compared for their abilities to differentiate between Good, Average and Poor QoS for voice over IP (VoIP) traffic. Fuzzy inference system (FIS), linear regression and multilayer perceptron (MLP) were evaluated to quantify QoS for VoIP. FCM and Kohonen successfully classified VoIP traffic into three types representing Low, Medium, and High QoS. FIS, regression model and MLP combined the QoS parameters (i.e. delay, jitter, and percentage packet loss ratio) with information from the generated clusters and indicated the overall QoS.**

Keywords- Quality of service, wireless network; regression model; fuzzy logic; Neural Networks; disaster management.

I. INTRODUCTION

Wireless networks such as Mobile Ad-hoc Network (MANET) and satellite networks are valuable for disaster sites due to their flexibility [1]. Reliable and high data-rate wireless multimedia communication among public safety agencies are important necessity for efficient rescue and recovery missions in the aftermath of natural disasters [2][3][4]. Quality of Serive (QoS) performance is associated with the quality of user experience (QoE) and they provide important information about the network performance and the user's perception of the network performance [5]. A routing approach for offering reliable MANET-satellite hybrid networks for disaster management was proposed [1]. It considered the successful delivery of packets as the highest impact factor because in disaster management each packet may contain data for a survivor. A limitation of this approach was not considering QoS parameters such as delay, jitter and packet loss ratio. QoS monitoring techniques for voice over internet protocol (VoIP) that evaluated the connection characteristics based on active measurement and used Mean Opinion Score (MOS) model (the user experience) were reported [6][7]. Techniques were reported to evaluate overall QoS for multimedia applications using artificial intelligence that included fuzzy logic and neural networks. They reported that the measured QoS as an indicator of network condition and bandwidth availability [8]. Neural networks enabled assessment of QoS in wired and wireless networks. An innovative QoS evaluation method that used neural networks to analyse and assess QoS for VoIP transmitted traffic (VoIP) in NS-2 simulated networks was proposed [9][10]. The traffic parameters were initially classified into different categories of QoS by an unsupervised learning Kohonen neural network. The resulting information was then processed by a supervised learning multilayer perceptron (MLP) neural network to determine the overall QoS. The QoS determined by the approach correlated closely with other QoS assessment approaches based on fuzzy logic, Euclidean distance and regression model. Techniques to evaluate and improve QoS in IEEE 802.11 wireless network protocol were reported [11][12]. A wireless transmission parameter called *minimum contention window* (CWmin) was optimised. The value of CWmin affects the transmission waiting time for a wireless transmitter. Fuzzy and hybrid genetic fuzzy logic techniques were developed to assess and improve QoS. In their proposed scenario real-time applications were transmitted that included a video and an audio and the QoS for the networks was improved by optimising the CWmin. The study showed that QoS improved by 42.8% and 14.5% using fuzzy logic and for audio and video respectively. While the hybrid genetic fuzzy logic approach improved the QoS by 35.7% for the audio and by 16.5% for the video traffic.

A limitation of some previous studies is addressing QoS based on a single traffic parameter such as end-to-end delay or packet delivery. In this study artificial intelligence techniques were used for QoS classification and overall QoS assessment. Fuzzy c-means and Kohonen neural network techniques were developed to classify QoS parameters into High, Medium and Low QoS. This was then followed by assessing fuzzy inference system (FIS), regression model and multilayer perceptron to quantify overall QoS for VoIP traffic over a wireless network. The main contribution of this study is different QoS assessment techniques that can allow network administrators evaluate their networks' performance.

II. METHOD

A modular network was designed using the network simulation package called NS-2. NS2 is an open access network simulator that provides comprehensive facilities for simulation of wired and wireless networks, facilitates mobility and incorporates many transmission protocols and traffic types. The network used in this study is shown in Figure 1. It follows the hierarchical network design that divides the architecture into core, distribution and access tiers and conforms to the Open Source Interconnection (OSI) network model [13].

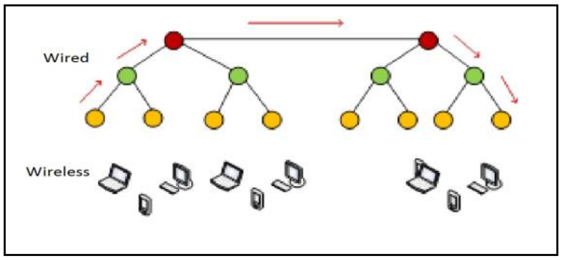

Fig.1. The topology of the network used in the study.

The wired part of the network contained the core tier and had a capacity of 10 Mbps. The wireless parts contained the distribution and access tiers and were configured in the IEEE 802.11e protocol with the Enhanced Distributed Channel Access (EDCA). The wireless channel capacity was 2 Mbps. The routing protocol in this scenario was Destination-Sequenced Distance Vector (DSDV) and the queuing mechanism for all scenarios was First-In-First-Out (FIFO). The queue size was 50 packets. The traffic type was VoIP. This was chosen as its transmission is time sensitive. It used a packet size 160 bytes. G711 protocol was used for audio coding with 64 kbps transmission rate. The NS-2 scenarios ran for 400 msec. Following each simulation, a trace file was generated by NS-2 that contained the network and traffic transmission measurements such as the packet types, transmitted and received times and packet sizes, transmission protocol and whether the packet was successfully delivered. A Perl language based tool was developed to read the packet transmission information from the trace file and determine the traffic parameters: delay, jitter, and percentage packet loss ratio. These measurements were performed using equations explained below.

Delay (D_i) for the i^{th} packet was measured as in equation (1) where R_i and S_i are the times for a packet to be received and sent respectively [14][15].

$$D_i = R_i - S_i \tag{1}$$

The absolute value for the Jitter (J_i) was determined using equation (2) where D_i and D_{i-1} are the delays associated with the currently and previously received packets respectively.

$$J_i = absolute\ (D_i - D_{i-1}) \tag{2}$$

The percentage packet loss ratio ($\%PLR_i$) was determined using equation (3) where R_i and S_i are i^{th} packets received and sent respectively and n is number of packets sent.

$$\%PLR = \left(1 - \frac{\sum_{i=1}^{n} R_i}{\sum_{i=1}^{n} S_i}\right) \times 100 \tag{3}$$

III. EVALUATION OF QOS APPROACHES

Two QoS classification methods and three QoS quantification methods were developed and evaluated.

A. Analysis of QoS Using Fuzzy C-means Clustering Algorithm

FCM was used to group the QoS parameters (delay, jitter, and percentage packet loss ratio) of the VoIP traffic into clusters based on their similarities and so to provide an interpretation of the traffic related to QoS. The measured QoS parameters values were represented by a matrix (QoS_p) for processing by FCM as

$$QoS_p = \begin{bmatrix} D_1 & J_1 & \%PLR_1 \\ D_2 & J_2 & \%PLR_2 \\ . & . & . \\ D_n & J_n & \%PLR_n \end{bmatrix} \tag{4}$$

Where D_i, J_i, $\%PLR_i$, i=1, 2,…, n are the measured delay, jitter, and percentage packet loss ratio respectively. FCM operated on the matrix in (4) and minimised the FCM objective function in equation (5) in order to classify the contents of QoS_p into three (C) clusters, generated the membership matrix (U) and determined the matrix clusters centres (V).

$$J\left(\mathrm{QoS_p}; U, V\right) = \sum_{i=1}^{C} \sum_{j=1}^{n} \left(\mu_{ij}{}^{m} D_{ij}{}^{2}\right) \tag{5}$$

D_{ij}^2 is the Euclidian distance between D_j, J_j, PLR_j to the centre V_i of cluster i. The parameter m allows the degree of fuzziness for the clusters' memberships to be set [16]. This value was kept at 2 as other values either introduced insufficient or large overlap between the clusters. The degrees of membership of n^{th} example case, (μ_{nk}) belonging to cluster k was indicated by membership matrix U as

$$U = \begin{bmatrix} \mu_{11} & \mu_{12} & \cdots & \mu_{1k} \\ \mu_{21} & \mu_{22} & \cdots & \mu_{2k} \\ . & . & & . \\ \mu_{n1} & \mu_{n2} & \cdots & \mu_{nk} \end{bmatrix} \tag{6}$$

The clustering process was terminated when the objective function improvement between two consecutive iterations was less than the minimum amount (in this study this was 10^{-5}). The number of clusters C was set to three and were chosen based on the Xie-Beni index cluster validity method [17]. The FCM algorithm portioned the traffic data into *High*, *Low*, and *Medium* QoS clusters. These clusters were represented by their clusters by the matrix V as

$$V = \begin{bmatrix} D_{c1} & J_{c1} & \%PLR_{c1} \\ D_{c2} & J_{c2} & \%PLR_{c2} \\ D_{c3} & J_{c3} & \%PLR_{c3} \end{bmatrix} \tag{7}$$

where D_{ci}, J_{ci}, $\%PLR_{ci}$, i=1,2,3 are the cluster centres for three types of QoS (poor, average and good).

B. *Evaluation of QoS using Kohonen Neural Network*

The self-organising map of Kohonen neural network with 100 neuros (10×10) shown in Figure 2 was used. It was trained to group the QoS parameters of VoIP traffic into *Poor*, *Average* and *Good* QoS.

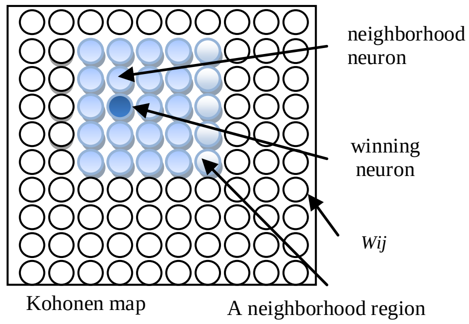

Fig. 2 The Kohonen map.

The values of QoS parameters i.e. delay, jitter, and percentage packet loss ratio were measured by equations (1)-(3). QoS parameters for the VoIP traffic were classified by applying the recommended QoS values indicated in Table I to form examples to train the Kohonen neural network prior to the training process. These classified values were arranged to form examples to train the Kohonen neural network.

Table I VoIP QoS Requirements [6].

Range	Delay (ms)	Jitter (ms)	%PLR
Low (good quality)	<150	<1	<2
Medium (average quality)	150-400	1-3	2-4
High (poor quality)	>400	>3	>4

The VoIP QoS parameters (delay, jitter and percentage packet loss ratio) were labelled as H (*High*), M (*Medium*) and L (*Low*) ranges for delay, jitter, and percentage packet loss ratio. The matrix shown in equation (8) represents the QoS parameters and their labels to train the Kohonen network.

$$QoS\ parameters = \begin{bmatrix} D_1 & J_1 & \%PLR_1 & L_1 \\ D_2 & J_2 & \%PLR_2 & L_2 \\ D_n & J_n & \%PLR_n & L_n \end{bmatrix} \tag{8}$$

where D_i, J_i, $\%PLR_i$, and L_i labels, i=1, 2,$\cdots$,n are respectively the measured delay, jitter, packet loss ratio, and their associated labels for *Low*, *Medium* ,and *High* QoS. Each input, representing one of the traffic parameters, was connected to all 100 neurons in the Kohonen map. The connections were associated with their respective weights, w_{ij}, i.e., the weight from input i to neuron j. During the training of the neural network, the Euclidean distance between the inputs and each neuron's weights was calculated and the neuron with the smallest Euclidean distance was considered as the winning neuron and its weight was updated using

$$w_{updated} = w_{current} + \eta(x - w_{current}) \tag{9}$$

where $\boldsymbol{w}_{current}$ and $\boldsymbol{w}_{updated}$ are the current and updated connection weights for the winning neuron, η is the learning rate that controls the speed of convergence and $\boldsymbol{x}$ is the input vector containing the three traffic parameters. A number of neurons around the winning nodes, called neighbourhood neurons (shown in Figure 2) had also their weights updated with an amount less than that for the winning neuron. The learning process ensured the weights for selected winning neurons moved closer to the respected category of the inputs. In this study the training was performed for 1000 iteration, this process classified the traffic data to *Poor*, *Average* and *Good* QoS values.

C. *Fuzzy Inference System Based Classification of QoS*

The fuzzy logic method for classifying QoS was based on fuzzy inference system (FIS). It consisted of fuzzifier, knowledge base, inference engine and defuzzifier. Three fuzzy sets were used for each traffic input (delay, jitter and percentage packet loss ratio). In this study, eleven rules were incorporated into the FIS knowledge base as shown in Table II. These mapped the three inputs to the QoS output of the FIS, indicating *Good, Average* and *Poor* QoS.

Table II Rules used for the FIS knowledge base.

No.	Delay	Jitter	%Packet Loss Ratio	QoS
1	Low	Low	Low	Good
2	Low	Low	Medium	Good
3	Low	Medium	Low	Good
4	Medium	low	Low	Good
5	Low	Medium	Medium	Average
6	Medium	Low	Medium	Average
7	Medium	Medium	Low	Average
8	Medium	Medium	Medium	Average
9	High	Any	Any	Poor
10	Any	High	Any	Poor
11	Any	Any	High	Poor

The membership function type for the inputs and output was Gaussian that provided flexibility to represent the information [18]. These membership functions are shown in Figure 3.

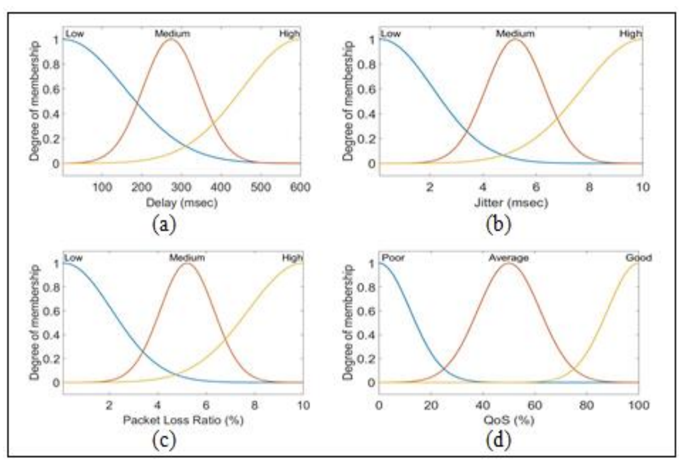

Fig. 3 Membership functions, (a-c) for delay jitter and percentage packet loss ratio. (d) Membership function for FIS output.

Each fuzzy rule was applied to the associated membership functions and the rule's consequence was mapped to the associated output membership functions. The output membership functions were aggregated and the centroid was used for defuzzification and obtaining the QoS output

D. QoS Assessment Using Linear Regression

Linear regression model is shown in (10) which defines the relationship model between independent variables (***X***) and dependent variable (***Y***) [18][19].

$$\boldsymbol{Y=XB+E} \tag{10}$$

B is the regression coefficients and ***E*** is associated with measurement error which was considered as zeros in this study. In the developed linear regression the independent variables were traffic parameters delay, jitter, and percentage packet loss ratio respectively whereas the dependent variable was QoS. Equation (10) can be rewritten as in (11). The regression expression was determined by considering the QoS requirements listed in Table II in order to provide the outputs that reflected the overall QoS. The QoS parameters shown in Table II were categorised as: *Low*, *Medium*, and *High*. The overall QoS was classified as *Good*, *Average*, and *Poor*. The overall QoS was between 0 (worse) to 100% (best) QoS.

$$\begin{bmatrix} QoS_1 \\ QoS_2 \\ . \\ QoS_n \end{bmatrix} = \begin{bmatrix} 1 & D_1 & J_1 & \%PLR_1 \\ 1 & D_2 & J_2 & \%PLR_2 \\ . & . & . & . \\ 1 & D_n & J_n & \%PLR_n \end{bmatrix} \begin{bmatrix} b_0 \\ b_1 \\ . \\ b_n \end{bmatrix} + \begin{bmatrix} e_0 \\ e_1 \\ . \\ e_n \end{bmatrix} \tag{11}$$

The regression model for VoIP was designed by arranging the values of independent and dependent variables into matrices as follows: *Low* QoS parameters (i.e. delay less than 150 ms, jitter less than 1 ms, and percentage packet loss ratio less than 2%) corresponding to *Good* overall QoS which ranged between (67-100%), *Medium* QoS parameters (i.e. 150 < delay < 400 ms, 1 < jitter < 3 ms, and 2% < packet loss ratio < 4%) corresponding to *Average* QoS (i.e. 33% < QoS < 67%), whereas *High* QoS parameters (i.e. delay > 400 ms, jitter > 3 ms, and packet loss ratio > 4%) corresponded to *Poor* QoS (i.e. QoS 33%). After the mapping of QoS parameters to the overall QoS, the matrices of QoS parameters and the overall QoS were formed for the regression model as

$$QoS_i = b_0 + b_1 D_i + b_1 J_i + b_3 PLR_i \tag{12}$$

D. QoS Assessment Using Multilayer Perceptron

A multilayer perceptron (MLP) had been used by [9] and [20] to evaluate and assess the network QoS due to its suitability ability to model nonlinear input-output relationships. In this study the proposed MLP consisted of an input layer with three neurons, a hidden layer with three neurons, and an output layer with one neuron as shown in Figure 4. The inputs were D_i, J_i, and $\%PLR_i$ i.e. delay, jitter and percentage packet loss ratio respectively, The MLP output was the overall QoS. The MLP inputs and output were set up based on the recommended ITU values shown in Table (II) in order to provide output represent the overall QoS. Using the information in Table I a training file consisting examples of traffic parameters (delay, jitter, percentage packet loss ratio) for different levels of QoS were set up to train the MLP. For each example the level of QoS was specified.

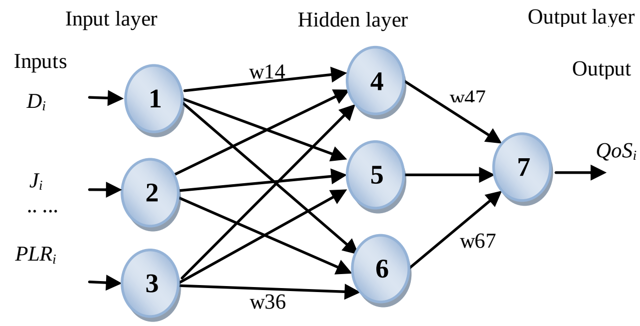

Fig. 4 The MLP used in the study

During the MLP training, the inputs traffic parameters were multiplied with their associated neurons' connection weights and the results are summed. A sigmoid activation function then used this summed value to generate the output for each neuron. In this study, the commonly used gradient descent with momentum was used for learning algorithm. The function of this algorithm was to use the calculated error (i.e. the difference between the MLP calculated output and the provided desired output) to reduced the magnitude of the error in the following training iteration. Training process was terminated when the error between MLP output and desired QoS values became less than 0.0001 or when the maximum training iteration which set to 1000 was reached. The examples to train the MLP were prepared by using the examples already classified into different QoS categories by the fuzzy c-means clustering or the Kohonen neural network.

IV. Results and Discscssions

The values of QoS parameters (i.e. delay, jitter, and packet loss ratio) for the VoIP traffic were classified into three clusters, representing *Low*, *Medium*, and *High* values. Each cluster was represented by its own centre as shown in Figure 5(e). The FCM membership matrix specified the degrees of memberships of each set of measured traffic parameters to the three clusters. Figures 5(a-c) show the degree of membership for a sample VoIP traffic. During the clustering of VoIP, the objective function indicated the progress of FCM over the number of iterations performed as shown in Figure 5(d).

Figures 6(a-c) show the QoS output of Kohonen neural network. It has classified the traffic into three clusters. Low, Medium and High QoS were indicated by three regions. The darker colour (dark red) illustrates low value regions (Good QoS) and lighter (light yellow) illustrates high value regions (Poor QoS). The jitter values for VoIP were not changing rapidly which justify its colour distribution in the map. The grouping of QoS values (H:high, M:Medium, L: Low) provided by the Kohonen network is shown in Fig.6(d).

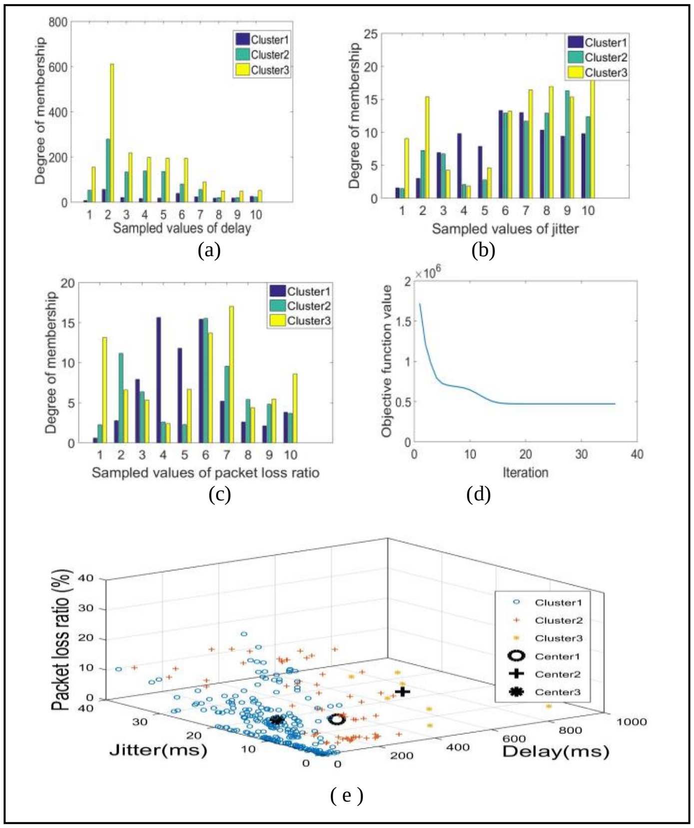

Fig. 5 (a-c): The degree of membership between sampled delay, jitter and percentage packet loss ratio and the cluster centres for: (d) FCM objective function (e) FCM clusters and centres.

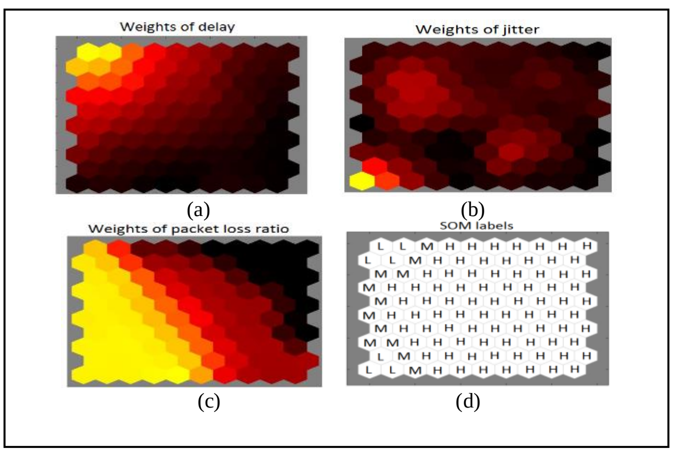

Fig. 6 Classification of QoS parameters for VoIP using Kohonen neural network: (a) Delay, (b) Jitter, (c) %Packet loss ratio, (d) QoS parameters labels.

Figures 7 (a) and (b) show the QoS evaluation as percentage using the FIS and the regression model respectively based on three input parameters (delay, jitter and percentage packet loss ratio). It can be noticed that both methods illustrates similar results and trend. From the start of the simulation until 100 msec the QoS was very high. Then due to heavy load on the network at 270 msec the network restored its high QoS. The network has provided a good QoS for most of the 400 ms.

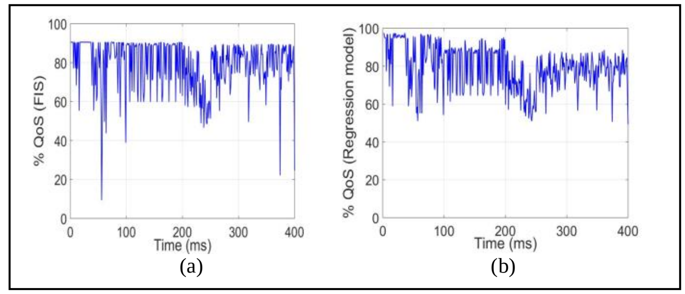

Fig. 7 QoS evaluation of VoIP using (a) FIS (b) regression model

To train the MLP, the classified QoS results which were processed by fuzzy C-means and Kohonen neural network were used as training examples. The quantitative QoS by MLP is shown in Figure 8(a). Figure 8(b) shows the comparison between QoS examples and measured MLP outputs during its training to evaluate QoS of VoIP traffic. Figures 8(c) and 8(d) show the MLP behaviour with regard to least error square error and weight update respectively during training. It can be observed from Figures 8(a) and (b) that the actual output values used to train MLP and the output values following the termination of its training are similar. The results show the QoS of VoIP from MLP during the test phase are similar to those obtained using the FIS and regression model.

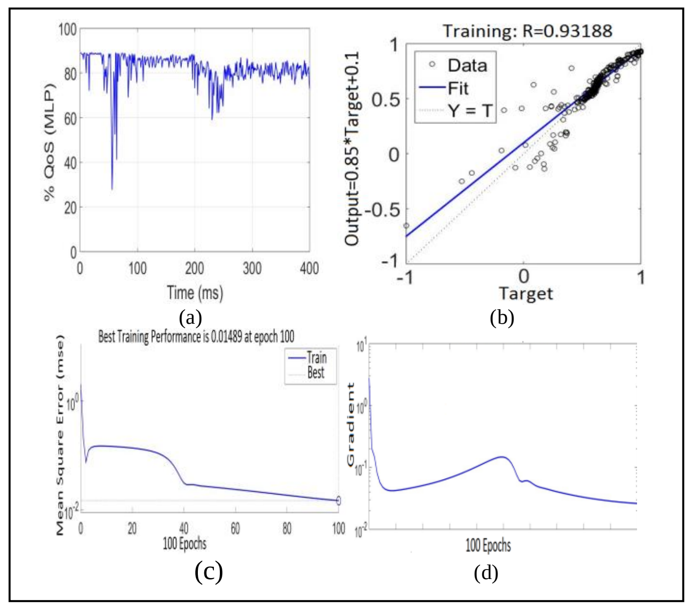

Fig. 8 (a) QoS evaluation of VoIP using MLP (b) Comparison between trained QoS and calculated MLP outputs (c) Mean Squared Error (d) gradient plot

QoS evaluation methods for VoIP traffic provided results which were closely comparable as illustrated in Table III. Even in cases that their QoS values were slightly different, they were in the same QoS class. The values of QoS obtained from the MLP and the regression model ranged from (1% - 100%), whereas the range of QoS values produced by the FIS were between (10%-90%). This indicates that the MLP and regression can better in covering the full range of QoS.

Table III QoS parameters of VoIP and its QoS using: Fuzzy Inference System (FIS), Regression Model and Multi-Layer Perceptron (MLP)

Delay (ms)	**Jitter (ms)**	**%Packet loss ratio**	**QoS: Fuzzy inference system**	**QoS: Regression model**	**QoS: MLP**
5.8	0.1	0.06	90.5	97.3	87.8
7.6	0.1	0.04	90.5	97.3	87.8
35	0.7	0.04	90.5	95.8	87.5
120	3.1	10	83.9	81.9	82.6
190	3	2	89.0	86.6	85.2
160	2.5	2.7	89.6	87.5	85.3
160	2.5	2.7	89.6	87.5	85.3
130	3	2.1	90.0	88.7	85.7
190	11.9	25	62.2	59.0	80.3
100	9.7	0.05	86.9	86.3	85.5
169	12	0.02	80.3	82.0	83.8
163	5.7	0.04	89.5	87.2	85.7
185	32	10	58.0	56.6	66.5
194	11.8	9	80.5	73.2	81.0

The QoS classification methods based on fuzzy c-means and the Kohonan network successfully classified QoS into three classes that represent *High*, *Medium* and *Low* values. The fuzzy c-means did not require training examples but Kohonan needed sufficient training examples.

V. CONCLUSION

The QoS parameters for VoIP traffic were processed and analysed by FCM and Kohonen neural network to differentiate them as *Low*, *Average* and *Good* QoS. The capability and robustness of these techniques to handle complex characteristic patterns made them effective for QoS evaluation. For quantitative QoS assessment, the fuzzy inference system, regression model and multilayer perceptron combined the QoS parameters (i.e. delay, jitter, and packet loss ratio) and produced a single value that represented the overall QoS. The values of evaluated QoS using the three methods were compared and they showed to be similar. Although some QoS values differed slightly, they were in the same QoS category.

VI. ACKNOWLEGEMENTS

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