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Quality of Service Evaluation using a Combination of Fuzzy C-Means and Regression Model

Aboagela Dogman, Reza Saatchi, and Samir Al-Khayatt

Abstract**—**In this study, a network quality of service (QoS) evaluation system was proposed. The system used a combination of fuzzy C-means (FCM) and regression model to analyse and assess the QoS in a simulated network. Network QoS parameters of multimedia applications were intelligently analysed by FCM clustering algorithm. The QoS parameters for each FCM cluster centre were then inputted to a regression model in order to quantify the overall QoS. The proposed QoS evaluation system provided valuable information about the network's QoS patterns and based on this information, the overall network's QoS was effectively quantified.

Keywords**—**Fuzzy C-means; regression model, network quality of service

I. Introduction

THE growth in transmission of critical real-time applications such as videoconferencing and VoIP over computer networks means that their qualities of service (QoS) needs evaluating in an effective manner. The evaluation of QoS is currently carried out either by analysis or measurement techniques. The analysis techniques are used to examine the characteristics of the traffic [1-4], whereas the measurement techniques are applied to determine how well the network treats the ongoing traffic [5-12].

The contribution of this paper is the development of a mechanism that combines analysis and measurement techniques to evaluate QoS. The analysis technique was based on Fuzzy C-Means (FCM) clustering in order to discover the characteristic information from network QoS parameters and based on this information; a regression model was developed to quantify the QoS in order to determine network performance.

Pervious published studies have analysed network traffic based on several mechanisms. FCM is one of the explorative techniques used to analyse the statistical characteristics of network traffic. Several studies have addressed the use of FCM clustering in network traffic domain. For instance, a network administrator assistance system was proposed based on FCM.

A. Dogman, PhD student, Sheffield Hallam University, Sheffield, United Kingdom (e-mail: aadogman@ my.shu.ac.uk).

R. Saatchi, Sheffield Hallam University, Sheffield, United Kingdom (e-mail: r.saatchi@shu.ac.uk).

S. Al-Khayatt, Sheffield Hallam University, Sheffield, United Kingdom (e-mail: s. alkhayatt @ shu.ac.uk).

The proposed system utilised a FCM method to analyse users' network behaviors and traffic-load patterns based on the measured traffic data of an IP network. Analysis results can be used to assist administrators to determine efficient controlling and configuring parameters of the network management [1]. FCM was also used to cluster network traffic and produce application profiles which contained significant information about the current status of the network in order to manage network resources [2]. In wireless sensor networks, an FCM algorithm was used in order to create clusters which reduced the spatial distance between sensors nodes [3]. An FCM clustering algorithm was also developed to detect routing attacks caused by abnormal flows in a wireless sensor network. The study demonstrated that FCM can be a valuable tool for intrusion detection [4].

However, none of the previous studies have addressed the use of FCM to cluster QoS parameters (delay, jitter, and packet loss ratio). A novel aspect of our study is that QoS parameters of multimedia applications were intelligently clustered. In situations such as network QoS, FCM algorithm can be an efficient technique to cluster QoS patterns because the natural characteristics of network QoS parameters partly cover more than a single cluster.

The generated clusters by FCM in turn allowed the QoS parameters for each cluster centre to be combined together. A regression model was developed to combine the QoS parameters (i.e. delay, jitter, and packet loss ratio) for each cluster centre to estimate the overall QoS. This is because a single QoS parameter could not reflect an application's transmission requirements [12]. For instant, delay, jitter, and packet loss ratio could all have significant effect on VoIP quality.

Regression model is a widely employed statistical method due to its effectiveness for creating functional relationships among variables [13-14]. A number of studies were conducted based on regression models in network domain. For instance, a regression model was used to predict the collision ratio, collision rate variation, and queue status ratio in participant wireless nodes in a mobile ad-hoc network and to subsequently adjust the Contention Window (CW), Distributed Inter-Frame Space (DIFS) and transmission rate in order to improve the network performance [15].

Regression models were developed from simulation data to predict network behaviour in terms of throughput, mean delay, missed deadline ratio, and collision ratio. The overall results showed that the predictions were within the expected confidence interval [16]. An adaptive regression algorithm was proposed to monitor two arbitrary sensor nodes and dynamically learn the linear relation among their measurements. Subsequently, the algorithm eliminated the redundant node, and estimated the deficient data without the need for base station assistance. The simulation results showed that the proposed scheme could save significant amount of energy in a dynamic environment [17].

This paper is organized as follows: section II explains Fuzzy C-means clustering algorithm, regression model, and QoS parameters included in the measurements. Section III explains the clustering of QoS parameters using FCM algorithm and how regression model was devised to quantify the overall QoS. Section IV describes network simulation and traffic models. The results are discussed in section V. Finally, conclusion is provided in section VI.

II. Theoretical Background

A. Fuzzy C-means Clustering Algorithm

Fuzzy C-means (FCM) clustering algorithm can be defined as a mechanism to discover certain features in a set of data and classify each element of data into a number of clusters with different degree of memberships [18-19]. The operation of FCM is as follows:

X is matrix of size $n \times N$.

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1N} \\ x_{21} & x_{22} & & x_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nN} \end{bmatrix}$$

Each $x_j \in R^p, j = 1,2, \ldots, n$ is a given set of feature data representing by a number of features *p*. FCM operates on the matrix *X* and minimises the FCM objective function given in Equation (1) in order to partition matrix *X* into *C* clusters.

$$J\,(X; U, V) = \sum_{i=1}^{C}\sum_{j=1}^{n} (\mu_{ij})^m \; D_{ij}^2 \qquad (1)$$

The value *m* controls the degree of fuzziness for the membership of the cluster where $m \in [1, \infty]$. As the value of *m* decreased, the membership of the cluster becomes closer to the binary clustering.

U is the membership matrix expressed as:

$$U = \begin{bmatrix} \mu_{11} & \mu_{12} & \cdots & \mu_{1N} \\ \mu_{21} & \mu_{22} & & \mu_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ \mu_{n1} & \mu_{n2} & \cdots & \mu_{nN} \end{bmatrix}$$

Each value of matrix *U* indicates the degree of membership between vector x_j and cluster C_i and must meet the following criteria:

- $\mu_{ij} \in [0,1], \forall_i = 1, \ldots, C, \forall_j = 1, \ldots, n$
- $\sum_{i=1}^{C} \mu_{ij} = 1,\ \forall_j = 1, \ldots, n$

During the clustering process, the elements of *U* are updated using Equation (2).

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{C}\left(\frac{\|x_j - v_i\|}{\|x_j - v_k\|}\right)^{\frac{2}{m-1}}} \qquad (2)$$

where $1 \le i \le C, 1 \le j \le n$. The clusters' centres $V = \{v_1, v_2, \ldots, v_C\}$ are calculated according to Equation (3).

$$v_i = \frac{\sum_{j=1}^{n}(\mu_{ij})^m x_j}{\sum_{j=1}^{n}(\mu_{ij})^m} \quad , \forall_i = 1, \ldots, C \qquad (3)$$

The distance D_{ij}^2 is the Euclidian distance between x_j to the centre v_i of cluster i which defined by equation (4).

$$D_{ij}^2 = \|x_j - v_i\|^2 \qquad (4)$$

Equations (2)-(4) are repeated until the maximum number of iteration is reached or the objective function improvement between two consecutive iterations is less than the minimum amount of improvement.

B. Regression Models

Regression models aim to analyse the relationship between several variables. One variable is considered to be dependent or response variable and the others are considered to be independent or descriptive variables [13]. Equation (5) defines the regression model between dependent variable (y) and independent variables ($x_1, x_2, \ldots, x_n$) as follows:

$$y = b_0 + b_1x_1 + b_2x_2 + \cdots + b_nx_n + e \qquad (5)$$

In vector notation, the regression model can be written as in equation (6).

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} 1 & x_{11} & \cdots & x_{k1} \\ 1 & x_{12} & & x_{k2} \\ \vdots & & \ddots & \vdots \\ 1 & x_{1n} & \cdots & x_{kn} \end{bmatrix} \begin{bmatrix} b_0 \\ b_1 \\ \vdots \\ b_n \end{bmatrix} + \begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_n \end{bmatrix} \qquad (6)$$

Or Y=Xb + e

where $b = \{b_0, b_1, b_2, \ldots b_n\}$ are the regression coefficients determined from recorded data and *e* is a column vector of *n* error terms. The regression coefficients are calculated using equation (7).

$$b = (X^TX)^{-1}X^TY \qquad (7)$$

The vector of residual (i.e. error terms) is given by equation (8).

$$e = Y - Xb \qquad (8)$$

In order for the regression model to be valid and accurate predictor, there are some assumptions that need to be followed. These are [14]:

- *X* and *Y* are linearly related.
- *X* is non-stochastic and measure without error.
- Errors are independent and normally distributed.

The prediction accuracy of regression model can be measured using correlation coefficient. The value of correlation coefficient (*R*) is between 0 and 1. The values closest to 1 indicate a perfect correlation whereas a correlation less than 0.5 would be described as weak correlation. The correlation between the actual values (y_A) and predicted values (y_P) can be calculated using equation (9).

$$R_{y_A\,,\,y_P} = \frac{\sum(y_{Ai} - \overline{y_A})(y_{Pi} - \overline{y_P})}{\sqrt{\sum(y_{Ai} - \overline{y_A})^2 \sum(y_{Pi} - \overline{y_P})^2}} \qquad (9)$$

where y_A is the actual value, $\overline{y_A}$ is the mean of the actual values, y_P is the predicted value, and $\overline{y_P}$ is the mean of the predicted values.

C. An Overview of QoS Parameters

In this study, VoIP traffic was considered because its sensitivity to QoS parameters such as delay, jitter, and packet loss ratio. Table I illustrates the QoS requirements of VoIP where delay, jitter, and packet loss ratio requirements are listed [20].

TABLE I
VOIP QOS REQUIREMENTS

Range	Delay(ms)	Jitter(ms)	Loss ratio (%)
Low (good quality)	0-150	0-1	0-2
Medium(average quality)	150-400	1-3	2-4
High (poor quality)	>400	>3	>4

A brief description of QoS parameters as follows [21]:

- **Delay**: this is defined as the elapsed time for a packet to travel from its source to its destination. Delay is calculated using equation (10).

$$D_i = R_i - S_i \qquad (10)$$

where, D_i is the delay for the i^{th} packet and R_i and S_i are the arrival and sending times of the i^{th} packet respectively.

- **Jitter**: it is the absolute value of the variations in delays between two consecutive packets for a given traffic flow. Equation (11) is used to calculate the jitter.

$$J_i = |\, D_i - D_{i-1} \,| \text{ while } i>0 \qquad (11)$$

where, J_i is the jitter of the i^{th} packet, D_i and D_{i-1} are the delay of two consecutive packets.

- **Packet loss ratio**: this is defined as the percentage of transmitted packets failing to reach their destinations. Packet loss ratio is calculated using Equation (12).

$$PLR_i(t) = \left(1 - \frac{\sum R_i(t)}{\sum S_i(t)}\right) \times 100 \qquad (12)$$

where, $PLR_i(t)$ is the percentage loss ratio during the i^{th} interval. $\sum R_i(t)$ and $\sum S_i(t)$ are the total number of received and transmitted packets during the i^{th} time interval respectively.

III. DESCRIPTION OF PROPOSED METHODS

A schematic diagram of the proposed network QoS evaluation system is shown in Fig. 1. The system uses a combination of FCM algorithm and regression model to evaluate network QoS.

The QoS parameters (i.e. delay, jitter, and packet loss ratio) were obtained from the generated trace file of the simulated network. The extracted QoS parameters were then used as inputs to the FCM algorithm to be clustered. The centres of generated clusters by FCM were then used to quantify the overall QoS. The QoS parameters (i.e. delay, jitter, and packet loss ratio) for each cluster centre were combined using the developed regression model. The devised regression model processed the inputs of each centre and estimated the overall QoS. The following subsections explain this operation.

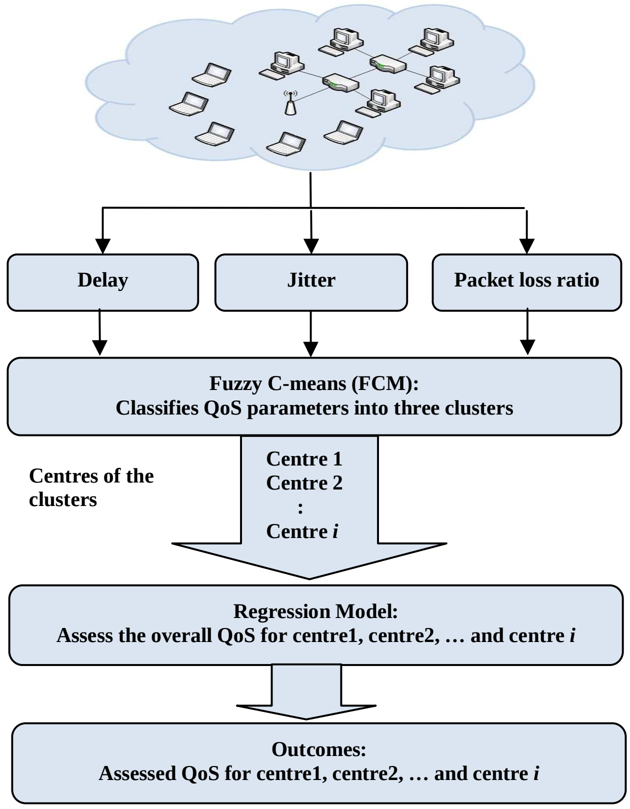

Fig. 1 QoS Evaluation System

A. QoS clustering using Fuzzy C-means Algorithm

FCM was developed to partition the QoS parameters of VoIP applications (delay, jitter, packet loss) into clusters. This classification provided an informative view about traffic behavior and consequently discovered valuable information from ongoing traffic.

The values of QoS parameters (delay, jitter, and packet loss ratio) were measured using equations (10), (11), and (12) respectively. The measured values were represented in matrix notation to be used as inputs to FCM algorithm as follows:

$$QoS\ parametres = \begin{bmatrix} D_1 & J_1 & PLR_1 \\ D_2 & J_2 & PLR_2 \\ \vdots & \vdots & \vdots \\ D_n & J_n & PLR_n \end{bmatrix}$$

where D_i, J_i, PLR_i, $i = 1,2,\dots,n$ are the measured delay, jitter, and packet loss ratio respectively. FCM was employed at predefined time interval (i.e. every 50 seconds). The exponent value for partition was 2 (i.e. m=2). This value is suitable for fuzzification [1]. The maximum number of iterations was 200, and the minimum amount of improvement was 1e-5. These parameters were chosen experimentally, i.e. different values were experimented to monitor the FCM clustering response and the best values were selected. The clustering process of FCM terminated when it reached the maximum number of iterations or the objective function improvement between two consecutive iterations was less than the minimum amount of improvement.

The FCM algorithm produced three clusters classifying the QoS parameters into three levels low, medium, and high. The number of clusters C was chosen based on Xie-Beni index cluster validity method [22]. Equation (13) defines the function of Xie-Beni index method.

$$S = \frac{\sum_{i=1}^{C}\sum_{j=1}^{n} \mu_{ij}^{2}\left\|v_i - x_j\right\|^2}{n\, min_{i,j}\left\|v_i - v_j\right\|^2} \qquad (13)$$

The optimal number of clusters was three, associated with small Xie-Beni index *S=0.0014*. Each cluster was represented by its own centre as follows:

$$Clusters\ centres = \begin{bmatrix} D_{c1} & J_{c1} & PLR_{c1} \\ D_{c2} & J_{c2} & PLR_{c2} \\ D_{c3} & J_{c3} & PLR_{c3} \end{bmatrix}$$

where D_{ci}, J_{ci}, PLR_{ci} , $i = 1,2,3$ are the centres of delay, jitter, and packet loss ratio for each cluster respectively. The centres D_{ci}, J_{ci}, PLR_{ci} , $i = 1,2,3$ for each cluster were then combined using regression model in order to quantify the overall QoS.

B. QoS assessment using Regression Model

Due to the relevance of VoIP quality to the QoS parameters (delay, jitter, and packet loss ratio) as shown in Table I, the values of independent variables (x_1, x_2, x_3) in regression model were represented by delay, jitter, and packet loss ratio respectively and the values of dependent variable (y) were represented by the overall QoS. The values of QoS parameters (i.e. delay, jitter, and packet loss ratio) were obtained using equations (10), (11), and (12). These values were then normalised in order to have the same contribution for measuring overall QoS. The normalisation process considered limits for QoS parameters where the overall QoS is poor. For VoIP, these limits are 600 ms for delay, 5 ms for jitter, and 6% for packet loss ratio.

The regression formula was calculated based on QoS requirements listed in Table I in order to provide the outputs that reflect the overall QoS. The QoS parameters shown in Table I were categorized as: Low, Medium, and High. The overall QoS on the other hand was classified as Good, Average, and Poor quality corresponding to the categories of QoS parameters. The overall QoS spans between (0%-100%). Low QoS parameters (i.e. delay $\leq$150 ms, jitter $\leq$1 ms, and packet loss ratio $\leq$ 2%) corresponded to good overall QoS which ranged between (67%-100%), medium QoS parameters (i.e. 150 < delay $\leq$400 ms, 1 < jitter $\leq$3 ms, and 2% < packet loss ratio $\leq$4%) corresponded to average QoS (i.e.33% < QoS $\leq$ 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 $\leq$ 33%).

The QoS parameters and the overall QoS were then arranged in matrices to feed them to the regression model as follows:

$$\begin{bmatrix} QoS_1 \\ QoS_2 \\ \vdots \\ QoS_n \end{bmatrix} = \begin{bmatrix} 1 & D_1 & J_1 & PLR_1 \\ 1 & D_2 & J_2 & PLR_2 \\ \vdots & \vdots & \vdots & \vdots \\ 1 & D_n & J_n & PLR_n \end{bmatrix} \begin{bmatrix} b_0 \\ b_1 \\ b_2 \\ b_3 \end{bmatrix} + \begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_n \end{bmatrix}$$

where D_i, J_i, PLR_i, QoS_i , $i = 1,2, \ldots, n$ are delay, jitter, packet loss ratio, and overall QoS respectively. The regression coefficients b_0, b_1, b_2, b_3 were determined from the recorded data using equation (7). The vector of residual (i.e. error terms) was then calculated using equation (8). The calculated errors were normally distributed indicating that the mean of error terms e_i , $i = 1,2, \ldots, n$ should be zero. This implies that the estimated regression model determined was as follows:

$$QoS_i = b_0 + b_1 * D_i + b_2 * J_i + b_3 * PLR_i$$

where QoS_i , D_i, J_i, PLR_i , $i = 1,2, \ldots, n$ are the overall QoS delay, jitter, packet loss ratio for i^{th}packet respectively.

IV. Modeling and Simulation

A. Network Model

A wireless-cum-wired network topology illustrated in Fig. 2 was simulated using the Network Simulator- 2 (ns-2) [23]. The network topology consisted of 8 wireless nodes, 2 wired nodes, and 2 base stations. The bandwidth of wired connections was 5 Mbps and 2 ms propagation delay. The WLAN was based on IEEE 802.11e standard and implemented enhanced distributed channel access (EDCA) technique. The main parameters that modeled the wireless channel are presented in Table II [24].

The queue management mechanism was Drop-Tail and the queue size was 50 packets. Different types of traffic were transmitted over the simulated network. These were: VoIP, video-conferencing and best effort traffic. Constant Bit Rate (CBR) traffic was adapted to model VoIP, videoconferencing, and data. VoIP modeled as G.711 voice encoding scheme with 160 packet size and 64 kbps generation rate. The packet size of the video traffic was 512 bytes and the inter-packet interval was 10ms. This generated a packet transmission rate of 384 kbps. The best effort traffic was modeled using different packet sizes and generation rates that corresponded to non-video-conferencing or VoIP usage. All traffics were transmitted using UDP.

The simulation time was 500 seconds. Simulations were repeated 10 times for each experiment. Each time a different initial seed was used in order to randomly manage which node transmitted first as all the nodes were requested to transmit at a given time. The randomness introduced using the different seeds avoided the bias of random number generation.

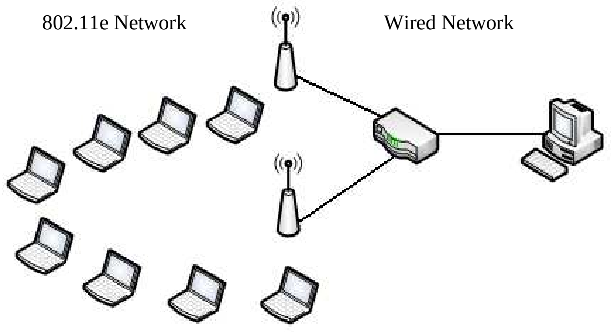

Fig. 2 Simulated network

TABLE II
IEEE 802.11E PARAMETERS VALUES

Parameter	Value
SlotTime	20 μsec
SIFS	10 μsec
Preamble Length	144 bits
PLCP Header Length	48 bits
RTS Threshold	3000 bytes
PLCP Data Rate	1 Mbps
Data Rate	2 Mbps

B. Network QoS Settings

The transmitted traffic (VoIP, video-conferencing, and best effort traffic) were mapped into three access categories (ACs) to represent three priorities level as shown in Table III. VoIP had the highest priority, whereas best effort traffic had the lowest priority [25]. However, due to the high sensitivity of VoIP quality to the QoS parameters as shown in Table I, in this study, the quality of VoIP traffic was evaluated.

TABLE III
IEEE 802.11E ACCESS CATEGORIES

Parameters	AC_0 (VoIP)	AC_1 (Video-conferencing)	AC_2 (best effort traffic)
Arbitration Inter-Frame Space (AIFS)	2	2	3
Minimum Contension Window value (CW_{min})	7	15	31
Maximum Contension Window value (CW_{max})	15	31	1023
Transmit Opportunity TXOP (ms)	3.008	6.016	0

V. RESULTS AND DISCUSSIONS

A. FCM Clustering Algorithm

FCM was applied at predefined regular time intervals, set to be 50 seconds. FCM analysis results are shown in Fig. 3. The values of QoS parameters (i.e. delay, jitter, and packet loss ratio) of transmitted VoIP were grouped into three clusters representing low, medium, and high values of QoS respectively. Each cluster was represented by its own centre.

The fuzzy partition matrix produced by FCM algorithm indicated that each value of QoS parameter had a degree of membership to different clusters. Fig 4 shows the degree of membership between a sample of delay and the produced clusters. As indicated by the figure, each value had different degree of membership to the three clusters between 0 and 1 with the total being 1. This feature made FCM a valuable clustering tool, because the characteristics of QoS parameters do not allow crisp (binary) partition.

During the clustering process, the objective function clarified the progress of FCM clustering algorithm across the iterations as shown in Fig.5. The clustering process of FCM stopped when it reached the maximum number of iterations or when the objective function improvement between two consecutive iterations was less than the predefined minimum amount of improvement. As shown in Fig. 5, FCM stopped when the objective function improvement between two consecutive iterations was less than 1e-5 (preset minimum improvement). This value was chosen experimentally and the best value was selected.

Fig. 6 illustrates the centres of the clusters for 50 seconds time intervals. The FCM algorithm classified the QoS parameters of VoIP into three levels at each time interval. During the first third of the simulation, three applications were transmitted over the network (two VoIP, and one video-conferencing). During this interval the network was able to meet the QoS requirements of the VoIP application. The values of delay, jitter, and packet loss ratio were at low range of QoS parameters. As the number of transmitted applications increased to four VoIP, video-conferencing, and best effort traffic during the second third of the simulation, the values of QoS parameters were increased accordingly. When the network load became heavy during the final third of the simulation, the network was incapable of meeting even minimum QoS requirements for VoIP application. The values of QoS parameters were in the high range, 600 ms for delay, 5 ms for jitter, and 6% for packet loss ratio, indicating poor quality of VoIP.

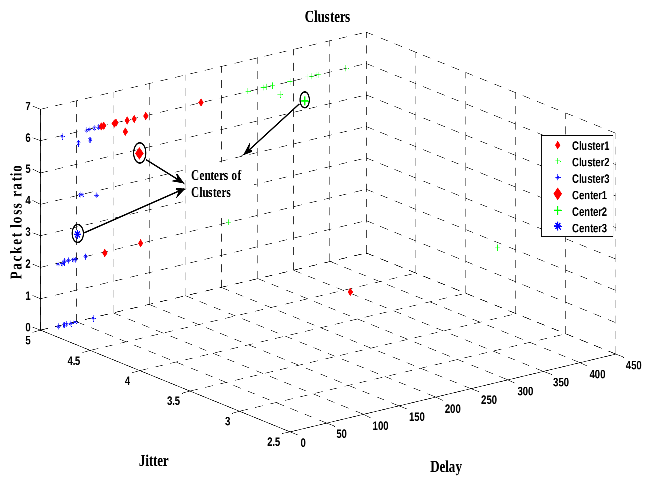

Fig. 3 Clustering QoS parameters of VoIP at predefined time interval

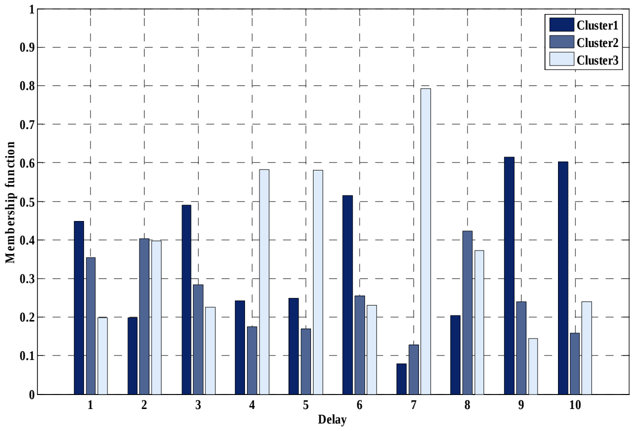

Fig. 4 The degree of membership between a sample of delay and the clusters

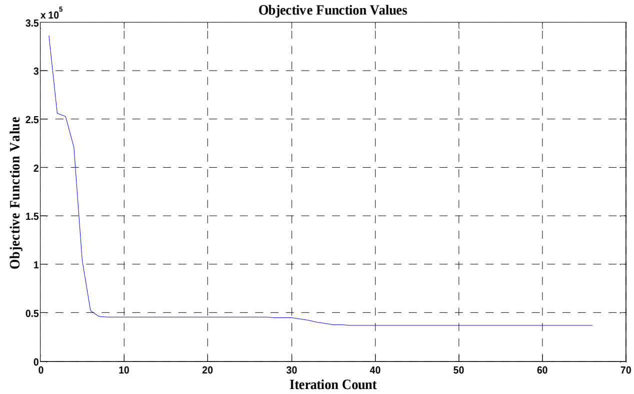

Fig. 5 The progress of objective function

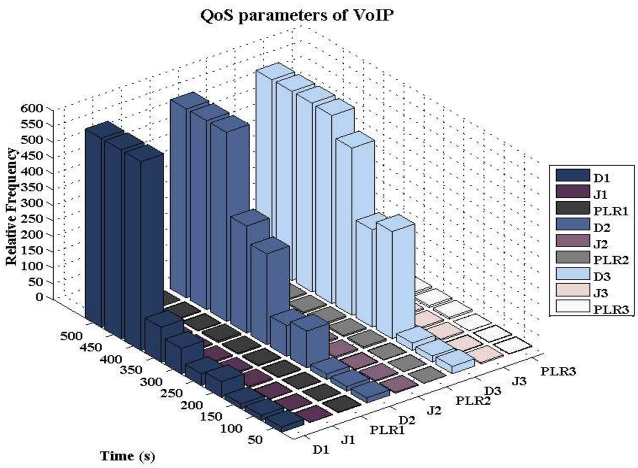

Fig. 6 Clustering QoS parameters of VoIP

B. Regression Model

Fig.7 shows the results from the devised regression model. The results show the predicted QoS for clusters centres for each time interval. From the figure, it can be observed that the QoS values reflected the corresponding QoS parameters shown in Fig.6.

In other words, as the values of QoS parameters increased, the values of overall QoS decreased accordingly.

The results obtained from the devised regression model were compared using another assessment method (i.e. the developed Fuzzy Inference System FIS mechanism for quantifying QoS) [12]. FIS consisted of four main components: fuzzification, fuzzy inferencing, fuzzy rules, and defuzzification. The inputs to FIS were delay, jitter, and packet loss ratio. The output produced by FIS was the overall QoS [26]. Fig.8 shows the results obtained from FIS mechanism.

From Figs.7, 8 and the values of expected QoS provided in Table IV, it is indicated that both assessment methods provided results which were comparable. Although some outputs were slightly different, they are in the same region (i.e. poor, average, or good). The discrepancies were due to the fact that each method followed a different operation. However, the values of QoS obtained from devised regression model spanned between (0%-100%) whereas the range of QoS values produced by FIS was between (10%-90%). This indicates that the devised regression model could provide more accurate results.

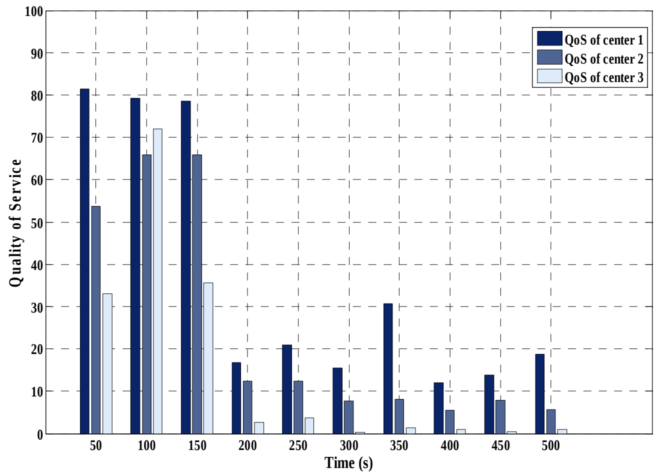

Fig. 7 The QoS of VoIP using regression model

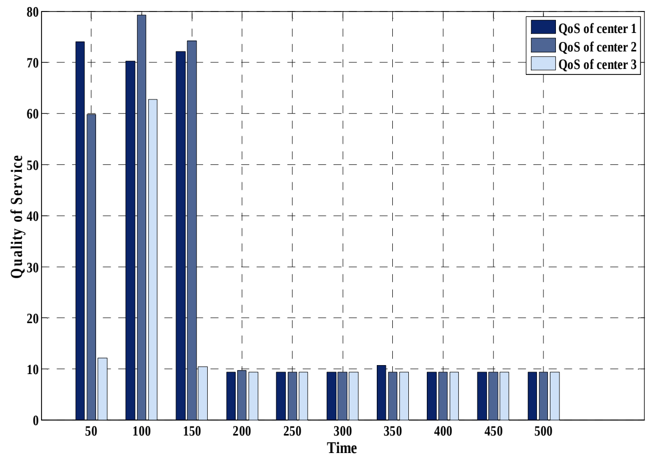

Fig. 8 The QoS of VoIP using FIS mechanism

TABLE IV
QOS PARAMETERS AND THE EXPECTED QOS USING FUZZY INFERENCE SYSTEM AND REGRESSION MODEL

QoS parameters			**Expected QoS**	
Delay(ms)	***Jitter (ms)***	***Packet loss ratio (%)***	***FIS mechanism***	***QoS evaluation System***
16.70	1.06	2.13	74	81.52
16.49	3.19	0.65	59.83	53.71
16.13	1.4	1.46	72.1	78.6
16.15	1.30	1.71	70.15	79.17
65.55	4.93	3.50	9.29	16.79
288.22	4.94	5.17	9.29	7.64
289.94	4.64	5.09	9.57	12.43
339.43	5	4.49	9.28	8.1
600	5	2	9.28	12.12
600.00	5.00	5.99	9.28	1.01

The regression analysis shown in Fig. 9 indicates that regression model was strongly correlated with fuzzy inference system. The prediction accuracy of regression model was measured using correlation coefficient. The value of correlation coefficient (R) was 0.94 indicating a high correlation.

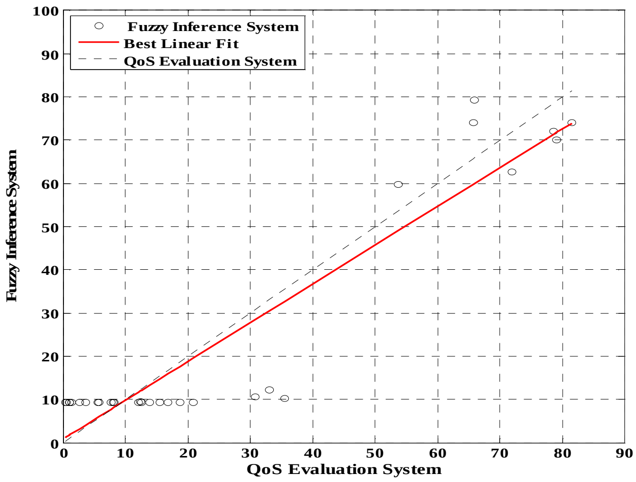

Fig. 9 Comparison between QoS assessment methods: fuzzy inference system, and QoS evaluation system

VI. CONCLUSION

This study presented a new QoS evaluation system. A combination of fuzzy C-means and regression model was used to analyse and measure the QoS of VoIP traffic transmitted over a simulated network. The robustness of FCM to cope with imprecise QoS patterns made it an en excellent clustering mechanism. The values of QoS parameters of transmitted VoIP were classified into three clusters representing low, medium, and high values of QoS respectively. The regression model in turn combined the QoS parameters (i.e. delay, jitter, and packet loss ratio) for each centre of generated clusters and produced a single value that represented the overall QoS. The overall QoS was a good indication of network performance. The overall QoS can be used to monitor the network and to avoid congestion.

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