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An Adaptive Neuro-Fuzzy Model for Quality Estimation in Wireless 2D/3D Video Streaming Systems

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Abstract: ***Delivering high Quality of Experience (QoE) is essential to the success of today's subscription for internet video streaming services. Quality of Service (QoS) metrics are considered by the research community as the most influential factor on video QoE. Therefore, establishing QoS-QoE correlation becomes critical for improving video QoE estimation. This paper presents experimental development of effective correlation between QoE and QoS for both 2D and 3D video streaming services. This is then used to build an objective QoE estimation model for real-time streaming of both 2D and 3D video contents over wireless networks. This model is based on using Adaptive Neural Fuzzy Inference System (ANFIS) to estimate the perceived video QoE. The proposed QoE model was trained with a set of media and packet layers' metrics, taking into account the effect of video content type, dimension, and different packet loss metrics. The performance of the proposed QoE estimation model shows a considerable estimation accuracy with a correlation coefficient of 92% and 0.167 RMSE.***

Keywords: ***QoE, QoS, MOS, Quality Estimation, ANFIS, Video Streaming.***

I. INTRODUCTION

Over the last decade, there has been growing interest by both users and service providers in video streaming services. Today, a variety of video streaming services and a wide scope of video content have emerged. The global Internet traffic is expected to be more dominated by different video streams which would be mostly generated by mobile devices and streamed over wireless links [1]. Therefore, there is a pressing need for adding to the flexibility and scalability of video streaming systems. It is also critical to maintain high level of service quality to ensure satisfactory user experience. Accordingly, service providers tend to perform real-time quality measurement for video streaming services in a scalable and adaptable manner.

In this context, Quality of Experience (QoE) has emerged as a critical user-centric measure of video service expectation and satisfaction. In challenging setups such as wireless video streaming, QoE provides effective performance indication for end users and service providers.

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However, there are varying elements at different levels such as network and applications would have impact on the QoE of video streaming services. This would make video QoE estimation a challenge, particularly in wireless environments.

It is perceived by the research community that the assessment of users' QoE can be carried out subjectively and objectively [2], [3]. The subjective approach is based on user interaction to assess the experienced video service in a controlled setup. In contrast, objective QoE assessment is based on a quantitative measurement of certain application and network metrics. This approach can be adopted with full-reference or reference-free measurement. Non-reference objective QoE assessment would be a feasible approach for real-time video streaming as the reference video object is difficult to be effectively obtained by the receiver. It typically operates at the client side to only inspect received video signals. This approach can provide reliable QoE measurement for real-time video streaming using low amount of data.

Developing a reference-free objective video QoE estimation model requires the establishment of a correlation between video quality and certain session parameters. This is a challenging requirement, and even more challenging if we also consider that changes to video quality would be dynamic [4]. Therefore, it is critical to build a video quality estimation model that is capable of capturing such a significant correlation in a real-time manner. The different metrics of Quality of Service (QoS) has been recognized by the research community as the most influential factor in this context [5]. This makes QoE-influencing QoS metrics important components for building QoE estimation models for video streaming systems. Therefore, establishing effective QoS-QoE correlation is considered a key requirement for the development of the proposed QoE estimation model in this research work.

The development of objective QoE estimation models has been mostly approached by the research community using a wide range of machine learning techniques. There have been a number of machine learning models examined for objective QoE estimation [6]. Recently, adopting a hybrid neuro-fuzzy model for estimating QoE objectively has become one of the feasible approaches in video quality systems. However, there are only a few previous quality evaluation studies conducted in the field of quality estimation for wireless 2D and 3D video streaming.

This research work proposes an objective QoE estimation model for non-intrusive 2D and 3D visual quality assessment. The proposed QoE model was developed based on effective QoS-QoE correlation established after conducting a number of experimental wireless video streaming tests. The proposed method in this work assesses the quality of wireless 2D and 3D video streaming by using the Adaptive Neuro Fuzzy Inference System (ANFIS) [7] which is a hybrid neuro-fuzzy system. NR objective video quality measurement is adopted as it requires no video references to be obtained for the estimation of QoE.

Following this section, Section II presents and discusses the related research works in the literature. Section III thoroughly presents how the proposed ANFIS-based QoE estimation model was developed. In Section IV, the results of the evaluation of the proposed model is provided and discussed. Section V discusses a potential usage of the proposed model and Section VI concludes this paper.

II. RELATED WORK

QoE measurement of video streams can be conducted by using subjective or objective methods. In subjective QoE assessment, the experienced service is assessed by the users using the Mean Opinion Score (MOS) method [2]. This approach can provide accurate QoE estimation but at the limitation of costly and time-consuming processes. In contrast, objective QoE assessment follows a quantitative approach to measure certain network metrics and indicators which correlate to the user perceived QoE [3]. This is based on applying mathematical calculation and algorithmic computation. If the reference object can be obtained completely or partially, objective assessment can be carried out according to the Full-Reference (FR) and Reduced-Reference (RR) models, respectively. Otherwise, the No-Reference (NR) model would be the most applicable for the objective assessment [8]. Therefore, NR objective QoE assessment would be a feasible approach for real-time video streaming as the reference video object is difficult to be effectively obtained by the receiver. It typically operates at the client side to only inspect received video signals. Although it requires less data thus would be considered less accurate in measuring QoE, the NR method can provide sufficient measurement reliability for real-time video streaming [8][9].

For NR objective video QoE estimation, it is effective to consider QoS performance as a key input to estimate video impairments [6]. However, there is still no standardized model establishing objective QoS/QoE correlation in the context of video streaming services. Studies such as in [10] considered the mapping QoS/QoE correlation models for multimedia services that use objective methods.

The measurement of QoS is typically performed at the application and network layers for the video streaming services. Several review studies in the literature, such as in [11], thoroughly discussed objective video quality assessment using media layer models (application level). Other studies such as in [12] focused on packet layer/bit-stream models (network level). In [13], a performance comparison study of different models was conducted using a huge video QoE dataset. Their results show that a feasible QoE estimation approach for video streaming is to factor in the QoS packet layer metrics, such as delay, packet loss, jitter, and bandwidth. On the other hand, the most complex approach is based on the hybrid methods combining QoS metrics from both media layer and packet layer, which shows higher performance than the others [14].

Different AI techniques have been used for the development of objective quality estimation models. Examples of these techniques are Fuzzy Inference System (FIS), Decision Trees, Adaptive Neural Network (ANN), and Support Vector Machines, etc. [15]-[20]. The study in [15] presented a video quality estimation model using fuzzy logic. The research work in [17] also used the fuzzy logic method for video quality estimation but only for 2D video and one type of video content. Moreover, both studies in [18] and [19] considered the development of prediction models for video quality using the ANFIS. The results show that the two proposed models gave high estimation accuracy. However, these research works did not consider 3D video traffic.

Most of existing video quality estimation models in the literature consider 2D video traffic. The QoE evaluation and prediction of 3D video is more challenging than 2D video due to additional factors including comfort levels and depth perception. The work in [21]-[23] studied how the packet loss affects the 3D video quality by using a subjective test. They found that the 3D video perception highly affected when packet loss rates increase. Nevertheless, none of these studies considered the 3D video evaluation in terms of burst loss as well as varying video content types.

It can be concluded that video QoE is highly influenced by varying values of the QoS metrics. This makes it necessary to investigate the correlation between video QoE and QoS metrics associated with the content type and video dimension against the packet loss. The main objectives of the proposed study herein are firstly considering the effect of QoS metrics on the QoE of 2D/3D video streaming over wireless network. Secondly, a neuro-fuzzy hybrid model for video quality estimation based on ANFIS is proposed in this study.

III. DEVELOPMENT OF THE PROPOSED MODEL

The methodology of developing the proposed QoE model is presented in this section. It firstly shows the simulation setup that was designed for building the required dataset for the development of the proposed model. The setup was based on running 2D and 3D video streaming over wireless network. The quality of the decoded video frames was then assessed using an objective quality metric that was mapped to the subjective quality metric (MOS). The measured objective dataset was used as a learning set to build the proposed ANFIS-based model. Also, in this section a brief description of the ANFIS theory is given, and followed by the proposed model design and experiment.

A. Simulation Setup

Table I shows the considered 2D and 3D video sequences; each has a length of 300 frames and different Temporal Index (TI) and Spatial Index (SI). Two video content classes, low motion and high motion,

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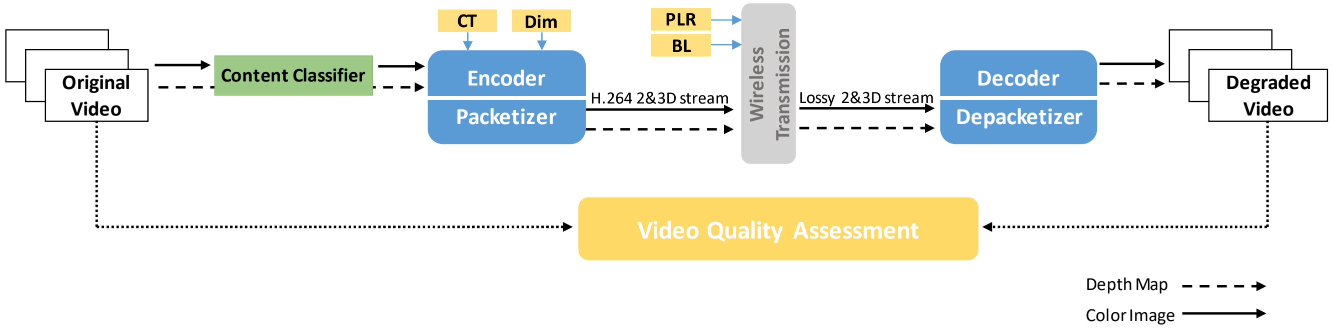


Fig. 1.Overview of the Simulation Setup

was considered according to the classification approach provided in the recommendation ITU-T P.910 [24]. H.264/AVC [25] was adopted to code the chosen 2D and 3D video streams including the 2D color image and depth map (2D and 3D). The coding process was configured to a fixed frame rate of 25 fps and a Group of Picture (GOP) size of 15 frames. The codec output then went through a packetization process to encapsulate video data into RTP/UDP/IP packets at a Variable Bit Rate (VBR). This is a typical setup for video streaming services over wireless networks [26].

After the coding process, the coded and packetized video sequences were streamed over a wireless transmission environment. Rayleigh-fading propagation environment was assumed for the wireless channel. Transmitted video packets were experimentally affected by simulated transmission errors. The Gilbert-Elliot model [27] was used to simulate the error scenarios by varying BL and PLR metrics. For the concealment of such errors, the decoder applied a simple replacement method considering previous frame in order to maintain low processing delay.

Fig. 1 provides an overview of the simulation scene. The bitrate rate was fixed to 2 Mbps in order to simulate a more realistic scenario. A collection of media and packet layer QoS metrics, namely dimension (D), content type (CT), packet loss rate (PLR) and burst loss (BL), was considered. These are illustrated in Table II. The simulation of each case of CT, D, PLR, and BL was repeated 10 times and then the average was taken to achieve high confidence.

Table- I: Video Sequences

Video Sequence	SI	TI	Class
Fencing clip (2D)	77.20	7.78	Low Motion
Music clip (3D)	74.41	4.90	
Pantomime clip (2D)	104.43	37.17	High Motion
BMX (3D)	99.42	22.35	

Table- II: The Considered QoS Parameters

Parameters	Values
Video Content Type (CT)	Low Motion / High Motion
Dimension (D)	2D / 3D
Packet Loss Rate (PLR)	0%, 0.1%, 1%, 2.5%, 5%, 7.5%
Mean Burst Length (BL)	1, 2.5, 5, 7.5

Table- III: Subjective MOS [2]

Quality	Bad	Poor	Fair	Good	Excellent
MOS	1	2	3	4	5

B. *QoE Measurement*

After decoding the video stream, following the process described in the previous section, the quality of the degraded video frames was measured by two objective full-reference perceptual quality metrics. The Video Quality Metric (VQM) [28] was used for the 2D video streams, while the 3D video streams were evaluated by the 3D video quality metric (Q) [29]. The VQM scale was set from score 0 indicating original quality and score 1 for a complete loss. The VQM and Q quality metrics were mapped to the subjective MOS Score, as illustrated in Table III, using the following equations (1) and (2), respectively:

$$MOS = 5 - 4\ VQM \quad (1)$$

$$MOS = 5 - 4\ (1\text{-}Q) \quad (2)$$

Table IV shows a sample of the collected objective dataset. The collected dataset identifies the relationship between the QoS metrics that affect video quality and the overall perceived QoE. The resulting objective dataset was then used as a learning set to build the proposed ANFIS-based model, as described in the following section.

Table- IV: Subjective MOS [2]

CT	D	PLR	BL	MOS
1	2	0.1	1	4.58
1	2	1	2.5	2.95
1	2	2.5	5	1.32
1	3	1	7.5	2.04
1	3	2.5	1	2.41
1	3	0.1	5	4.61
2	2	1	7.5	4.09
2	2	2.5	1	3.57
2	3	2.5	7.5	3.30

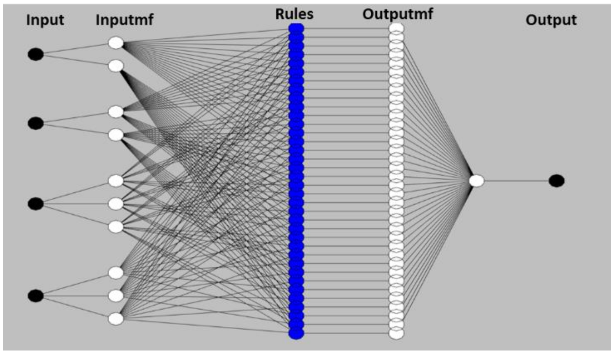


Fig. 2.ANFIS architecture

C. QoE Estimation Model Based on ANFIS

The proposed QoE estimation model was developed by using a hybrid neuro-fuzzy system, namely the Adaptive Neuro Fuzzy Inference System (ANFIS). It combines the concept of the ANN and FIS, and overcomes their limitations on missing capabilities of knowledge representation and automated learning. The neuro-adaptive learning techniques build a fuzzy rule base (in the shape of if-then rules) and run the input parameters of the membership functions from a certain set of I/O dataset using the back propagation or hybrid algorithm [7].

ANFIS consists of 5 layered structure. These are the fuzzy, product, normalized, de-fuzzy and output layers. Each layer includes a number of nodes which are connected with the previous level, as shown in Fig. 2. It should be noted that the number of input variables and values have an effect on the complexity of the rule base. A set of development steps were conducted to build the proposed ANFIS-based model for video QoE estimation. These steps are as follows:

Step 1: defining the input (CT, D, PLR and BL) and output (MOS) variables.

Step 2: initializing and training the fuzzy rule base by using the subtractive clustering algorithm.

Step 3: evaluating the proposed system performance by using the testing dataset and according to two measures: the RMSE (Root Mean Square Error) and R^2 (Coefficient of Determination).

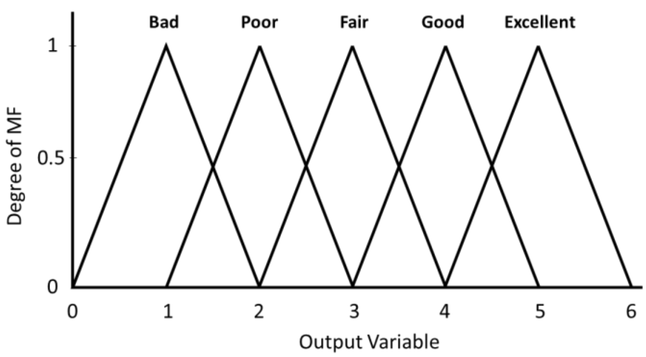


Fig. 3.The proposed ANFIS model

The fuzzy rule base was initialized in the proposed model by using the subtractive clustering algorithm, which is a one-pass algorithm for estimating the clusters number and the cluster centers in the dataset. The I/O dataset was separated into two portions. One contains 70% of the data for training and the other has 30% of the data for testing the proposed QoE estimation model. After the training process was completed, the initial MFs were identified and the proposed model was ready to be tested. The MF of the output metric is presented in Fig 4.

In this paper, the novelty of the proposed approach is that the objective QoS metrics (CT, Dimension, PLR and BL) together with the objective quality metric (VQM) were determined as input and output, respectively, to the proposed ANFIS-based model. The Neuro-Fuzzy Toolbox in Matlab software was used to build, train and evaluate the proposed ANFIS system. Fig 3 illustrates the functional block of the proposed model.

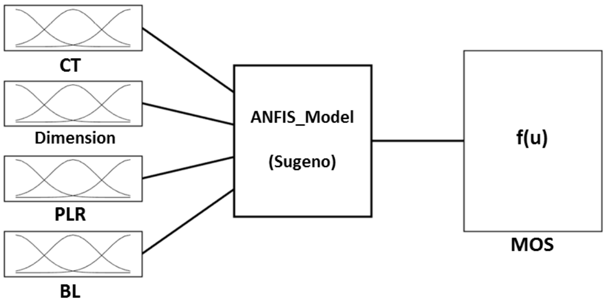
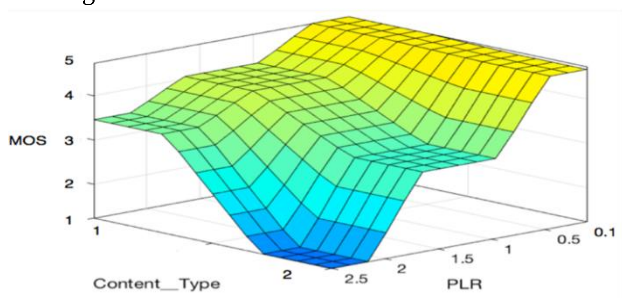


Fig. 4.The proposed ANFIS model

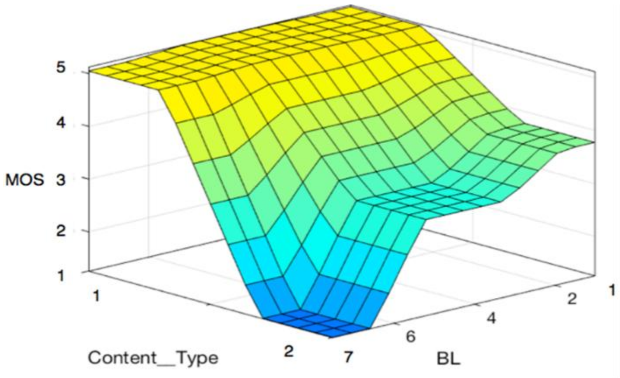
IV. RESULTS AND DISCUSSION

A. Impact of QoS Metrics on wireless 2D and 3D Video Streaming

This section presents the non-linear distortion impacts that lossy wireless networks have on the transmitted 2D and 3D video streams. Moreover, this study shows how 3D video streams can be more sensitive to low network performance than 2D video streams. The impact of QoS metrics on the 2D and 3D video streams are depicted by the surfaces provided in Fig. 5 and 6. It can be seen in Fig. 5 that video quality is highly dependent on the video content type. Accordingly, high motion video was more affected by PLR and BL than the case of lower motion video. It also can be noticed that the PLR's impact on both video streams is more obvious than BL. This is a result of the higher impact of the total packet loss on the resulting video degradation. When a wireless network has a PLR that varies randomly, transmission errors would be affected by inter-frame dependencies. For BL, on the other hand, transmission errors would be less affected by such a property, particularly in the case of having the average burst length increases.

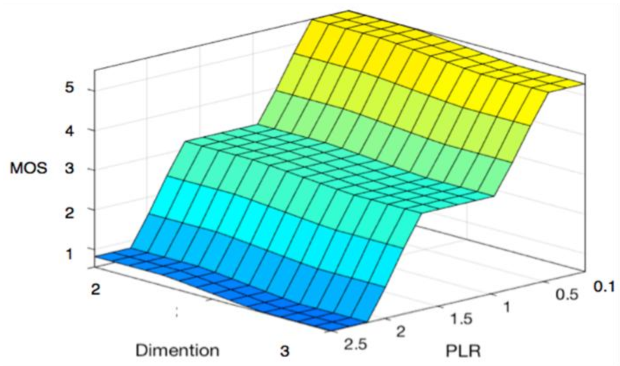


(a)

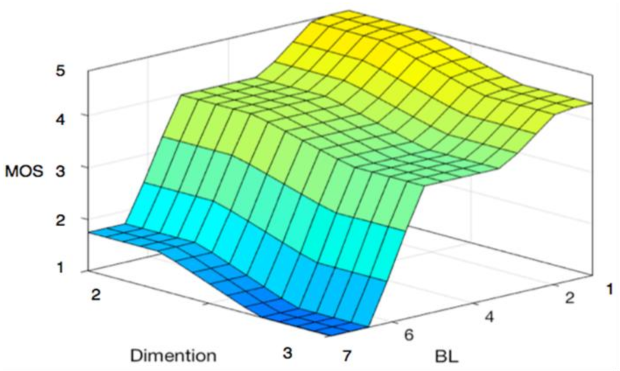


(b)

Fig. 5.The Impact of PLR and BL on Video CT



(a)



(b)

Fig. 6.The Impact of PLR and BL on 2D and 3D Video

In case of video dimension, Fig. 6 shows that including a depth image sequence in the case of 3D video streams adversely affected video quality. Missing packet in 3D videos caused blockiness artifacts in different regions of each view. These observations were also made in [30], [31], which confirms that the requirements for 3D video are more stringent than those for 2D video. This is because the 3D video (both color and depth) consumes a larger portion of the network Bandwidth. Generally, in order to maintain good balance between high quality of images and remaining bandwidth, it is critical to configure the optimal parameters for both 2D and 3D video encoding. One important consideration in this context is that video streams need to be encoded with optimal Quantization Parameter (QP).

B. QoE Estimation

The performance of the ANFIS-based model was evaluated using two measures which are RMSE and R^2. The R^2 scored was 92% and the RMSE reached 0.167. Fig 7 presents the validation of the proposed model. The stars represent the measured MOS scores, whereas the estimated MOS scores represented by the points. It is clear that the estimated MOS scores is greatly correlated with the measured MOS scores. This observation confirms the efficiency of the proposed ANFIS-based model in estimating user's perception.

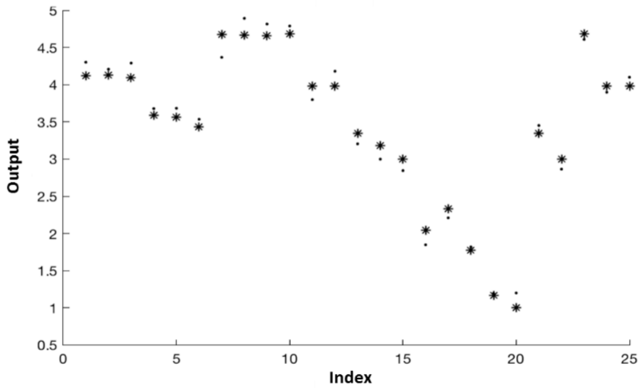


Fig. 7.Estimated MOS vs. Measured MOS

In addition, a performance comparison was conducted between the proposed ANFIS-based model and two other well-known machine learning methods. There were the Support Vector Machine (SVM) and Linear Regression (LR). For this purpose, a LR- and SVM-based models were also developed and tested. The comparison was carried out based on two measure: RMSE and R^2. Table V presents the comparison results of the proposed ANFIS-based model and the considered models. It can be seen that the ANFIS-based model outperformed the other two model in regards to estimation accuracy rate. The result confirms that the ANFIS model outperforms other methods due to its capabilities on modelling, learning and human behavior representation.

Table- V: Performance Comparison

Model	RMSE	R2
ANFIS-based model	0.167	92%
LR-based model	0.281	81%
SVM-based model	0.327	78%

V. POTENTIAL USAGE OF THE PROPOSED QOE MODEL

Fig. 8 shows how the proposed QoE estimation model can be suitably applied to provide effective wireless 2D/3D video streaming services. A QoE monitoring entity can be incorporated in the network architecture of service providers. The entity can be run at the controller of a Software Defined Network (SDN) as shown in Fig. 8. R1-R5 are SDN routers controlled by the SDN controller. This enables the QoE monitoring entity to estimate QoE of the videos streamed over the network.

Based on the estimated quality, network configurations can be effectively adjusted by the controller to enhance the provided video streaming service.

The QoE monitoring entity obtains the required QoS metrics from the controller to assess QoE of running video streams. These metrics could include delay and jitter in addition to PLR and BL. This process is carried out every certain assessment time interval. According to the current QoE estimation, the controller can then apply appropriate traffic policing and shaping. This is performed transparently to the running video stream traffic.

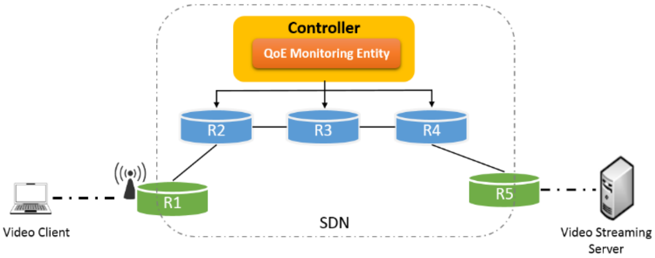


Fig. 8.Overview of a QoE-controlled Video Streaming Network System

VI. CONCLUSION

This paper presents the development of a hybrid NF model based on ANFIS for estimating the quality of 2D and 3D video traffic in the domain of wireless networks. Moreover, this paper also considered the QoS metrics' impact on the quality of wirelessly streamed 2D and 3D video in the context of video content type and video dimension. The perceived video quality was assessed according to VQM after mapping it to the MOS.The presented results made it clear that the ANFIS-based estimation model is a reliable methodology for 2D and 3D video quality estimation. In addition, the results confirm that estimating the video quality is affected by choosing the appropriate QoS metrics. As a future work, the work will be extended to evolved other QoS metrics (jitter, latency, etc.) and higher video resolution (4k/8K). This would help to further propose a general tool that can incorporate a QoS-centric wireless network planning and performance optimization platform.

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