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A QoE Adaptive Management System for High Definition Video Streaming over Wireless Networks

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Abstract

The development of the smart devices had led to demanding high-quality streaming videos over wireless communications. In Multimedia technology, the Ultra-High Definition (UHD) video quality has an important role due to the smart devices that are capable of capturing and processing high-quality video content. Since delivery of the high-quality video stream over the wireless networks adds challenges to the end-users, the network behaviors 'factors such as delay of arriving packets, delay variation between packets, and packet loss, are impacted on the Quality of Experience (QoE). Moreover, the characteristics of the video and the devices are other impacts, which influenced by the QoE. In this research work, the influence of the involved parameters is studied based on characteristics of the video, wireless channel capacity, and receivers' aspects, which collapse the QoE. Then, the impact of the aforementioned parameters on both subjective and objective QoE is studied. A smart algorithm for video stream services is proposed to optimize assessing and managing the QoE of clients (end-users). The proposed algorithm includes two approaches: first, using the machine-learning model to predict QoE. Second, according to the QoE prediction, the algorithm manages the video quality of the end-users by offering better video quality. As a result, the proposed algorithm which based on the least absolute shrinkage and selection operator (LASSO) regression is outperformed previously proposed methods for predicting and managing QoE of streaming video over wireless networks.

Keywords: Adaptive streaming, QoE assessment and management, Smart algorithm, Prediction model, Wireless network.

1. Introduction

Multimedia streaming applications have become a common service for many IP (Internet Protocol) service providers, especially live and Video on Demand (VOD) streams. Video streaming service and IP traffics are highly grown in a wide variety of applications. Globally, IP video traffic will be estimated at 82% of all consumers' Internet traffic by 2021. Therefore, live Internet video will be accounted for 13% of Internet video traffic by 2021 based on the visual Networking Index of Cisco and forecasting of mobile data [1]. On the one hand, the development of ultra-high definitions equipment such as cameras, displays, and playback system is made easy viewing the resolutions of 2K, 4K, and 8K videos. On the other hand, video frame rates have also become higher. As consequences, improving the benefit of HD video quality playback (4K and 8K with 60 fps) by customers for both live and video-on-demand streaming over the available networking systems can introduce a question of how multimedia service providers can deliver adequate streaming services to the end-users [2]. Over the past few decades, Video-on-demand streaming services have obtained potential popularity. An elevation of the access network's speed has also led to a huge number of users that watch videos online. For the purpose of retaining the existing users and attracting new users, service providers try to satisfy the user's expectations and produce a satisfaction of viewing experience. The first step is to accomplish and quantify the users' perception of the current service level. The QoE is a quality measure that prepares a comprehensive measure of the users' perception of quality [3].

According to the description given by authors [4], the architecture of the IP network is not intended for immediate services such as audio or video. And the quality of the video as a part of multimedia technology has a vital role because of its growth. Furthermore, there are several causes that can impact service quality, particularly packet loss and delay variation. Laith et al. [5] approached to enhance QoE in multicast and unicast for real-time video streaming. Also, Moorthy et al. [6] presented a wide variety of objective video quality assessment (VQA) models; they focused on full-reference, reduced reference, and no-reference. Scalable Video Coding (SVC) and transmission rate scheduling exploited to improve the average video quality perceived by the multicast end-users [7]. The decision of Ron et al. [8] explained that, an optimal encoding scheme that maximizes viewer-perceived quality.

In this paper, a QoE-smart algorithm based on using a machine learning model is proposed. The required parameters of the proposed intelligent system consist of the video's characteristics, measurement of the network parameters, the device capacity, and assessment objective metrics. The machine-learning model in the system trains the dataset to find the future QoE-prediction when a video is streamed to a group of users. The model is based on a supervision machine learning approach to provide accurate real-time prediction through the LASSO regression model. The intelligent system can understand the information and it can provide accurate assessments according to the metrics are used in the training model.

The main contributions are as follows:

- Improving the QoE evaluation by involving more parameters to the model such as (video characteristics, service and network providers, and devices).

- A prediction model must be used to evaluate and manage the QoE of customers because popular mathematical measures for evaluating the perceived quality of the video are not completely correlated to the Human Vision System (HVS) due to the fact that these metrics are failed to detect and catch the packet loss in wireless networks.

The remaining part of the research paper is organized as follows; Section 2 discusses an overview of the high-quality videos streaming on the Internet then an explanation of some states of the arts. In Section 3, the system description and parameters are explained. We present our proposal smart prediction algorithm for assessing and managing QoE in Section 4. Experiment setup parameters and evaluation results depicted in Section 5. Finally, the conclusion and future work are presented in Section 6.

2. Related work

In this section, we state some related works considering the current problems are still existed in the assessing of high-quality video streaming in wireless networks.

In [9], M. Seufert et al. mentioned that the change in network conditions cause drastic problems to video streaming on the Internet. HTTP adaptive streaming (HAS) is a technology used by many video services that overcome these issues by adapting the video to the current network conditions. It can enable service providers to make better utilization of resources and Quality of Experience (QoE) by including information from different layers to deliver and adapt a video in its best possible quality. By that means, it allows taking into consideration end-user device capabilities, network conditions, available video quality levels, and current server load. For end-users, the main advantages of HAS compared to classical HTTP video streaming are reducing interruptions of the video playback and maximum bandwidth utilization, which both basically result in a higher QoE. An adaptation strategy is possible by changing the resolution, network conditions, frame rate, or quantization of the video, which can be performed with different strategies and related client- and server-side actions.

Generally, multicast streaming over wireless communication entails a group of end-users to monitor the content of video streaming on the shared throughput simultaneously. The channel capacity of the groups may be different. Moreover, the control of the perceived video quality in multicast channels is challenging for service providers. Chang et al. [10] described how the mobile network condition deteriorates delivering 4k videos over the HTTP. They presented a new and practical feasible system called MEV, with an adaptable pre-fetching technique in which the content of providers is embedded in a smart way. To achieve a better QoE assessment, an adaptive content-aware video streaming is proposed [11]. IEEE 802.11 standard has been considered as one of the most popular wireless access technologies due to its advantages of the high data rate, low cost, and easy deployment. In addition, most mobile devices, smart devices, laptops are equipped with the WLAN interface. The effect of Multicasting over IEEE 802.11 based WLANs has also been addressed by Wan-Seon et al. [11]. They addressed the two well-known problems of multicasting, which are poor reliability and low-rate transmission. They proposed a new Multicasting protocol (Mac-Level) for IEEE 802.11n which is named REMP. The difficulties faced by wireless and mobile networks for multimedia streaming are studied in [12]. Wide area network (WAN) encounters distinctive problems because of the qualities of the networks, for example, restricted resources, larger transmission delays and jitters, higher and burst bit error rates, and reduced and variable bandwidth. Additionally, the streaming quality experiences by end-users are measured by using objective and subjective metrics. Their study is to organize separated QoE metrics into various groups and investigate the significance and complication in video source coding and wireless networks. The accordance between the precision of QoE measurements and the use of resources in the system is perceived. A Module of QoE shows lower precision of true perceptual quality that needs fewer computation complications. Jaime et al. [13] described the specific problem of the measurement of the video quality (VQM). The measure of the video quality can be classified into objective and subject quality assessments. On the one hand, the objective assessment method indicates the measuring of VQ by objective assessment techniques. On the other hand, the subjective assessment method is used directly to initiate the performance of the system which is directly expecting the user's perceived quality of the videos. Additionally, the purpose of using objective methods depending on the characteristic of the multimedia content and which kind of measures should be taken. The objective assessment could be performed through the Full Reference (FR) of the video acting as an input compared to the processed signal of the system output. In Reduced Reference (RR), the selected parameters are uniquely deduced to compare both input and output images. It significantly minimizes bandwidth consumption. In [14], some QoS parameters are used such as (throughput, jitters, and packet loss). According to [15], they proposed a method based on quality measurement which is relied on an audio-visual quality evaluating approach that utilizes an equal signal-to-noise (S/N) ratio conversion method. No Reference (NR) could objectively calculate the VQ of the received video file. It is also known as the unique ended approach. Iñigo et al. [16] developed an approach to speed up the estimation QoE of the no-reference bitstreams. Their proposed method was based on the full-reference objective metrics, which make the process more convenient and better than using subjective tests. Consequently, the dynamic range of compression causes the process of tone-mapping, artifacts mix, and degraded images. This process could make quality evaluation becoming a challenge.

The authors of [17] in their approach extracted a set of features choosing from the tone-mapped image and its reference. This is to estimate a various view of tone-mapped images and its reference HDR image to measure different aspects of the tone-mapped image. Moreover, in [18], the problems of zoomable video streaming in multicast channels are highlighted. An efficient algorithm to solve this problem is proposed. The approach is focused on the video multicast allocation with heterogeneous link rate. Therefore, the presented multicasting approach refines the quality of video reconstruction up to 12dB, 6dB, and 3dB in terms of PSNR in comparison with three other schemes (baseline schemes, adaptive unicast, adaptive and approximate multicast. Kalpana et al. [19] studied objective and subjective for assessing QoE of uncompressed reference video of natural scenes and distorted video. The video database represented in their research, which called the Laboratory for Image and Video Engineering (LIVE) Video Quality Database to evaluate the performance of the proposed algorithm. A real-time cognitive video quality assessment method was proposed by the authors; it allows precise simultaneous analysis of the video quality that is delivered on the customer side and disconnected profound unsupervised learning process from the server-side.

In this paper, the proposed approach has different directions. First, a smart algorithm based on the machine learning method is proposed to improve the accuracy and adaptive management of the video quality over unreliable wireless channels. Secondly, the model is built up from learning characteristics of the different source metrics such as video, network service, and end-user device capacity. Finally, the attained results with the LASSO regression method are compared with other ML techniques and presented in Table 5.

3. System description and parameters

In this section, we explain the general architecture of streaming video over a wireless network from the service provider to the end-users. The distribution of streaming video can be a broadcast, multicast, or unicast. The architecture also describes the system service and application service to stream the video over different channels in wireless networks. Therefore, we reveal the all parameters that are involved to provide the videos and the impacts on delivering the videos in the transmission and explain mathematically the important metrics are used to assess the video's quality.

3.1 General system description

To carry an answer to our concern, a multicast application is designed and proposed for multimedia streaming over wireless networks [26]. We analyze high-quality video streaming for multicasting wireless networks. This can be released scenarios such as (live events interactive TV, university campus broadcasting for live lessons, improving stage in concerts, and multicast live cinema) as shown in Figure1. The multimedia provider uses a multicast application for streaming the video contents over network systems. The multimedia provider of video content can be either live or on-demanded.

On the one hand, in the live streaming scenario, the process contains capturing real events via high-quality cameras and then they are encoded with a high-quality codec system. On the other hand, the scenarios of video-on-demand streaming decide to encode the media content in standard quality. Video encoding processes consist of the bitrate stream, codec resolution types, frame rate per secondhand audio-video containers. The proposed multicast system can stream different scene events to the different conditions, each video can stream through a channel as illustrated in figure 1. Providers can also stream video content over multicast service; the stream can be either internal or external such as the internet or Intranet. In fact, multimedia service providers connect with the Internet to transmit these events to the range of desired receivers. Consequently, multimedia providers are using content distribution to attain a better performance when the media is delivered to the end-users. In addition, the network operators want to know if their networks are healthy and which paths are over or under-provisioned, whether better routes exist to certain destinations, and provisioning of resources is necessary. Cooperation plays an important role in the ISP's service providers. The ISPs cooperated with content service providers to determine the location of video content. The clients are connected to the server by using the wireless technology as mid-point to receive media streaming. The wireless networks may be available under heterogeneous capacity and the throughput capacity of these networks' devices is changed according to the power of the devices and the influence factors. The client application includes two sides: a side is to select the server address (Multicast address) and playback the streamed media over the current channels. The other side is, the media receiver application able to capture the GOP of the videos, when the end-users suffer from receiving degraded video quality, a message is sent to the service provider which contains the information of the GOP, according to the evaluation is decided by the smart assessment in the server-side. Therefore, the provider provides adaptive video streaming to users to integrate better streaming.

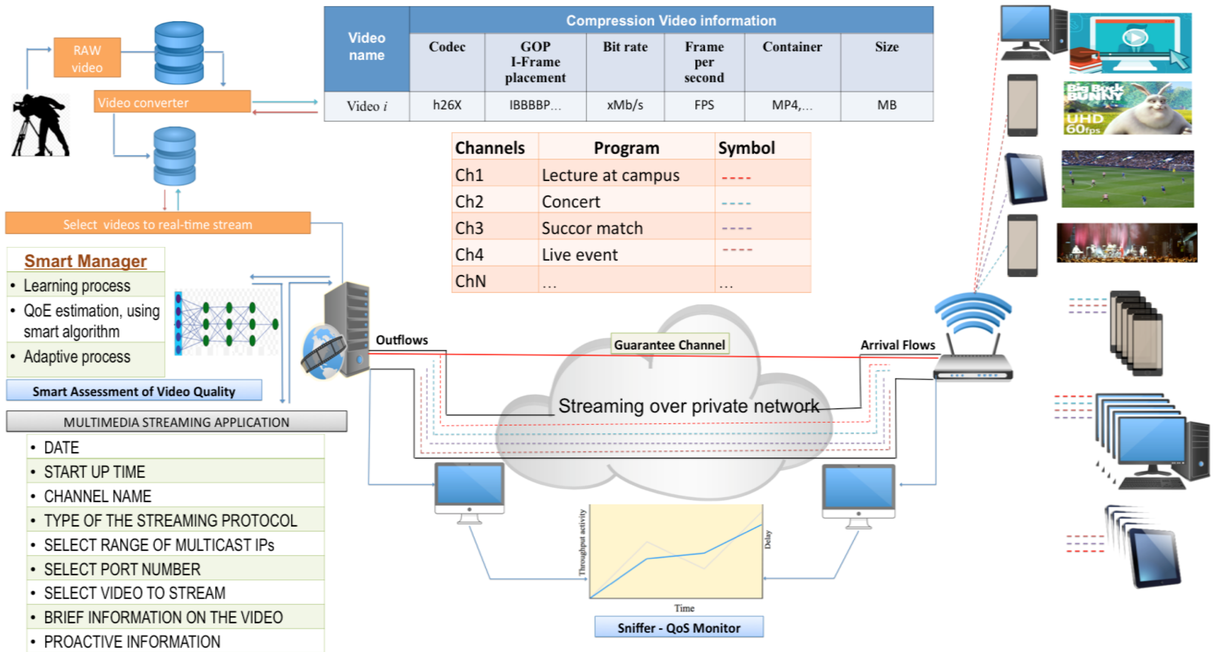

Fig. 1. General description of the system.

3.2 Metrics impact the QoE

QoE is a very holistic concept related to personal feelings because of the relation between user view and the concept of video quality. Nevertheless, it is crucial to provide a reliable strategy for measuring QoE as real as possible. The real-time automated measuring is enabled the network operator and service provider to learn the overall customer satisfaction. Therefore, it is necessary to identify the factors that are affected by the QoE. For this reason, we classified them into three groups, as follows.

A. Network metrics

QoE is affected by the metrics of QoS, which is significantly based on the availability of the network's performance. The key factors are delay, jitter, and packet loss. The impact of each individual or combined parameter leads to the artifact such as degrading quality, frames stalling, jerkiness, blocking, blurring, basic pattern, and staircase noise, of the, streamed video.

B. Media characteristic

The video characteristic has a direct impact on the QoE. The network parameters of a service provider minimize the bit streaming of video quality. The characteristics of the video are defined as codec, frames rate, resolution, bitrate, content, and motion. The parameters of frames per second, stream bitrate, and resolution also have a high impact on the user's satisfaction while the user is received the media over unreliable channels. When the raw video is compressed to a codec the preparation of the video codec is an important part to provide better QoE. The service provider should know about the characteristics of the connected clients in order to provide proper video codec. The transcoding of the video according to different values of the media parameters is set in the service provider or the relative content distributor. This is led to the adaptive delivery of the video to the end-users.

C. End-users terminal

The end-users are equipped with different electronic devices such as laptops, smart devices, personal computers, mobile phones, and tablets. These devices are available in a different capacity, screen size, processing power, usages, and other aspects. They could be categorized into two classes: The smart devices as mobile devices and tablets, personal computer. All these terminal devices have affected the user's satisfaction while receiving video streaming. The new generation of mobile devices can support playback of high-quality video streaming. The simplicity of using these devices makes the users consume high video quality on their devices. The finding of the QoE satisfaction on the mobile devices compare to other devices has a smaller screen size that can be different from aspect of the perceptual assessment.

3.3 Metrics assessing the video QoE

The essential QoE evaluation methods are used to assess media streaming delivery over network devices. This assessment lets providers getting a feedback service by learning from end-users. Generally, the QoE approach can be classified into the subjective and objective quality assessment. The detailed descriptions are as follows.

A. Objective measurement

A mathematical model for objective evaluation is used to assure the efficiency of the proposed algorithm. The objective model consists of being full-reference (FR), no-reference (NR), and reduce-reference (RR) respectively. The quality is calculated between the original and received videos aims to support the full-reference metrics. The original video signal is compared to the delivered signal for every pixel. FR is considerably precise at expense of computational complexity. Objective models can be evaluated using many parameters such as SNR, PSNR, APSNR, OPSNR, SSIM, MSE, MSAD, DELTA, and VQM. The difference between the original and modified pixels are mathematically determined to extract the errors using SNR, PSNR, APSNR, OPSNR, SSIM, MSE, MSAD, DELTA, NQI, and VQM metrics. They have shown a high-performance outcome in comparison with PSNR which is very equivalent to the HVS. The time and the accuracy of the objective evaluation are mainly depending on the selection of an appropriate metric as mentioned previously.

1) Average Peak-Signal-to-Noise-Ratio (PSNR)

APSNR is the average ratio between the streamed and the received video data. It is measured in (dB). APSNR is considered as an accurate metric to find out the perceptual quality of video streaming the wireless communication networks. The value depends on color space models. For example, it is equal to 100 for the L component in LUV model while for RGB and YUV models equal to 256 color levels as expressed in the following equation.

$$APSNR = 10\ log_{10} \frac{Max\_Error^2}{MSE\ (All\ Frames)} \quad (1)$$

Here Max_Error represents maximum (color components, H-video Height, and W-video Width) differences for all possible points. Where Max_Error is identical to MSE, while it could be used for more appropriate cases because of having the logarithmic scale. The MSE calculates the average of errors. An efficient way to determine APSNR for a given sequence by calculating the MSE for all consecutive frames (video frames MSE values are obtained by arithmetic mean algorithm).

2) Mean Absolute Difference (MSAD)

It is a measurement of the average similarity between blocks in a given image. It is basically used for video compression codecs and video filtering as given by:

$$d(X,Y) = \frac{\sum_{i=1,j=1}^{m,n} |X_{i,j} Y_{i,j}|}{mn} \quad (2)$$

Where $X_{i,j}$ describes the original color values for a given image while $Y_{i,j}$ represents color values for corresponding pixels in the block selected for comparison for R, G, and B channels separately.

3) Structural Similarity Index (SSIM)

SSIM utilized to compare two images based on metrics perspectives. In this context, structural similarity refers to sampling the signals with high correlation. HVS is essentially limited for extracting the visual information (structural) from the restricted point of view. The SSIM is given by

$$SSIM(i,k) = \frac{(2M_i M_k + C_1)(2\sigma_{ik} + C_2)}{(M_i^2 + M_k^2 + C_1)(\sigma_i^2 + \sigma_k^2 + C_2)} \quad (3)$$

Where M_i represents the mean value of the original image blocks, M_k is a mean value of the degraded image blocks, σ_i^2 is the block variance of the original image, σ_k^2 is the block variance of the degraded image, and σ_{ik}^2 represents a block covariance between the original and distorted images. C_1 and C_2 represent two variables that keep the division stable mainly for the weak value of denominator.

4) Video Quality Metric (VQM)

This metric modifies the Discrete Cosine Coefficient (DCT) constructed from Watson's proposed theory, which makes use of the visual perception property corresponding to the human perception. VQM outperforms the most situations as long as the root of MSE fails. The low complexity and the load of memory cause VQM more engaging for measuring the perceptual quality of video in wide range of applications.

$Mean_{\_dist} = 1000 * mean\ (|diff|)$ (4)

Where 1000 is presented with the standard ratio.

The maximum distance between the blocks in DCT transformation

The largest distance between the DCT blocks is $Max_{_dist}$and VQM ranking is written as follows:

$Max_{\_dist} = 1000 * Max\ (|diff|)$ (5)

$VQM\ = (Mean_{\_dist} + 0.005 * Max_{\_dist})$(6)

0.005 is described the selected weights of the greatest distortion which is depended on many basic psychophysics experiments.

B. Subjective measurement

The most used subjective metrics in the literature are the following***:***

1. **Mean Opinion Score (MOS):** The MOS is an accurate method to evaluate the perceptual quality of video in the field of QoE and is based on visual/psychological simulation experiments. Nevertheless, the subjective quality score set by a human is also dependent on the evaluation of experiences. Accordingly, it is considered as a reliable metric even though it is a most costly and complicated method for evaluating the users' QoE. The evaluation incorporates in building human observers, which assessed the video quality relying on the perspective and perception.
2. **Difference Mean Opinion Score (DMOS):** The DMOS method assists the evaluation of quality perception and processes via the determination of how much differences can be introduced in the distorted test video according to the subjective quality evaluation of the video frames.

3.4 Network measurements

The quantity detection of the packet switching between the sender (server) and the receiver (client)is allowed by the observer points. These points can identify the details of error rate, bit-rate, delay variation, and latency during the broadcasting. The real-time monitoring of the adopted points shows the diverse quantity of the packet numbers during the transmission and realizes the impact of QoS. Additionally, they are guaranteed the bit-rate to indicate the minimum and maximum bits transferring during each channel session. Furthermore, all data captured from the points are stored in a database to acquire bits of knowledge about the measurement analysis. The data flow property indifferent sense of the networking equipment is significant that one may understand the exact relation among QoE metrics.

3.5 Prediction model

The platform of the multicast video streaming is designed and developed based on machine learning (ML), having the ability to naturally improve the performance evaluation of the end-user experiences over time. The machine learning model is basically consisting of supervised and unsupervised learning techniques. On the one hand, supervised learning indicates the category structure and ranking of the data set. The learning phase needs a set of classes that should be labeled and returns a value that matches the data set to the predefined labeled classes. On the other hand, unsupervised learning refers to the task of choosing the hiding layer in non-labeled classes for categorizing into relevant classes. Consequently, the methods or models used are trained, recognized, generalized, adapted, and improved.

In the proposed system, as a regression model; LASSO (Least Absolute Shrinkage and Selection Operator) is used to train the dataset which contains video characteristics, device capacity, and network services. Information obtained from various resources is trained to predict the future QoE evaluation of the end-users. LASSO regression represents a type of linear regression that uses shrinkage the property where data values are shrunk and tending to a central point, like the mode and mean. The LASSO model provides simple, sparse models (i.e. models with fewer parameters). This distinction is well-suited for models showing high levels of muti-collinearity, like variable selection/parameter elimination.

LASSO uses a linear regression with the prediction standard standard $x_{ij}$and $y_i$as central response value for the iteration *i*=1, 2...N and *j*=1, 2...p, N represents the sample number and P describes the sample characteristic. In this research, different objective QoE metrics such as SSIM, VQM, APSNR and MSAD are extracted to attain a better prediction of LASSO model. To minimize β LASSO has proposed a solution for the$l_1$penalized regression issue offending $\beta = \{ \beta_j \}$ by the following formula:

$$\beta = \sum_{i=1}^{N} \left(y_i - \sum_j x_{ij} \beta_j \right)^2 + \lambda \sum_{j=1}^{p} |\beta_j| \quad (7)$$

The above equation is similar to reducing the sum of squares with a restriction of the form$\sum |\beta_j| \leq s$. It is also identical to the ridge regression with a limitation:$\sum_j \beta_j^2 \leq t$. Due to the l_1-penalty form, LASSO performs shrinking and selection while ridge regression model only shrinks. λ (tuning parameter) controls the strength of the l_1-penalty. λ is basically representing the amount of shrinkage: When λ = 0, no parameters are eliminated. When λ increases, more coefficients are set to zero and eliminated (theoretically, when λ = ∞, *all* coefficients are eliminated).Consequently, as λ increases, bias increases whereas when λ decreases, variance increases. For more general penalty form, q value that has been selected by LASSO is q=1 whereas q=2 for ridge regression model. In addition, subset selection is appeared as q→0, and LASSO employs a small value of q which is very close to the subset selection to get a convex problem. Convexity property is very useful in terms of the time complexity as shown in eq. (8).

$$q = \left(\sum_{j=1}^{p} \beta_j^q \right)^{1/q} \quad (8)$$

Therefore, LASSO function will report two critical parameter values: 1) the lambda value that minimizes the cross validated mean squared error. 2) The lambda value with the greatest amount of shrinkage whose CVMSE is within one standard error of the minimum.

4. Proposed algorithm

In this section, we approach designing an efficient algorithm for assessing and managing QoE problems. The approach is based on developing an algorithm on the video service provider. It decides on QoE evaluation of the streaming video for a group of end-users or a user per connection. The algorithm predicts the future QoE of the end-users whereas they are receiving video streaming service and it manages the QoE by providing better video stream quality. The proposed algorithm is shown in Figure 2. When the clients are connected to the media server, the server captures the information characteristic of the connected clients such as the device's name, operation system version, CPU, memory, and screen size. The group of connected users is clustered according to channels subscriber. Also, the characteristics of the channels are analyzed according to the QoS parameters. The restriction values of these QoS parameters are extracted from the server-side in order to diagnosis its effects on the QoE of the users. When the server starts to flow the video stream over the channels, it establishes a reliable channel to request a group of pictures (GOPs) from the group of users. When the server receives the GOP, it provides a comparison between the GOP received by clients and the original GOP on the server-side. In order to evaluate the QoE of end-users from the obtained GOPs of the delivered video which contains series of I-frame, P-frame, and B-Frame of the streaming video, some important full reference video assessment metrics are selected to provide the comparison such as APSNR, MSAD, SSIM, and VQM. The system uses deploying the accurate result by utilizing the accurate decision on the estimation of the QoE of the streaming video and from the output results of the prediction model. The server knows about the satisfaction of the end-users. If a user or group of users has an annoyance with the streaming video, the server provides adaptive bitrate, resolution, and frames per second in order to integrate better service of the video quality to its users.

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5. Experiment setup parameters and evaluation results

In this section, we explain the parameters and the tools are used for the test environment such as the design of the system application for streaming videos over the wireless networks, the real testbed design to implement the experiments, and the approaches to obtain the experiment results.

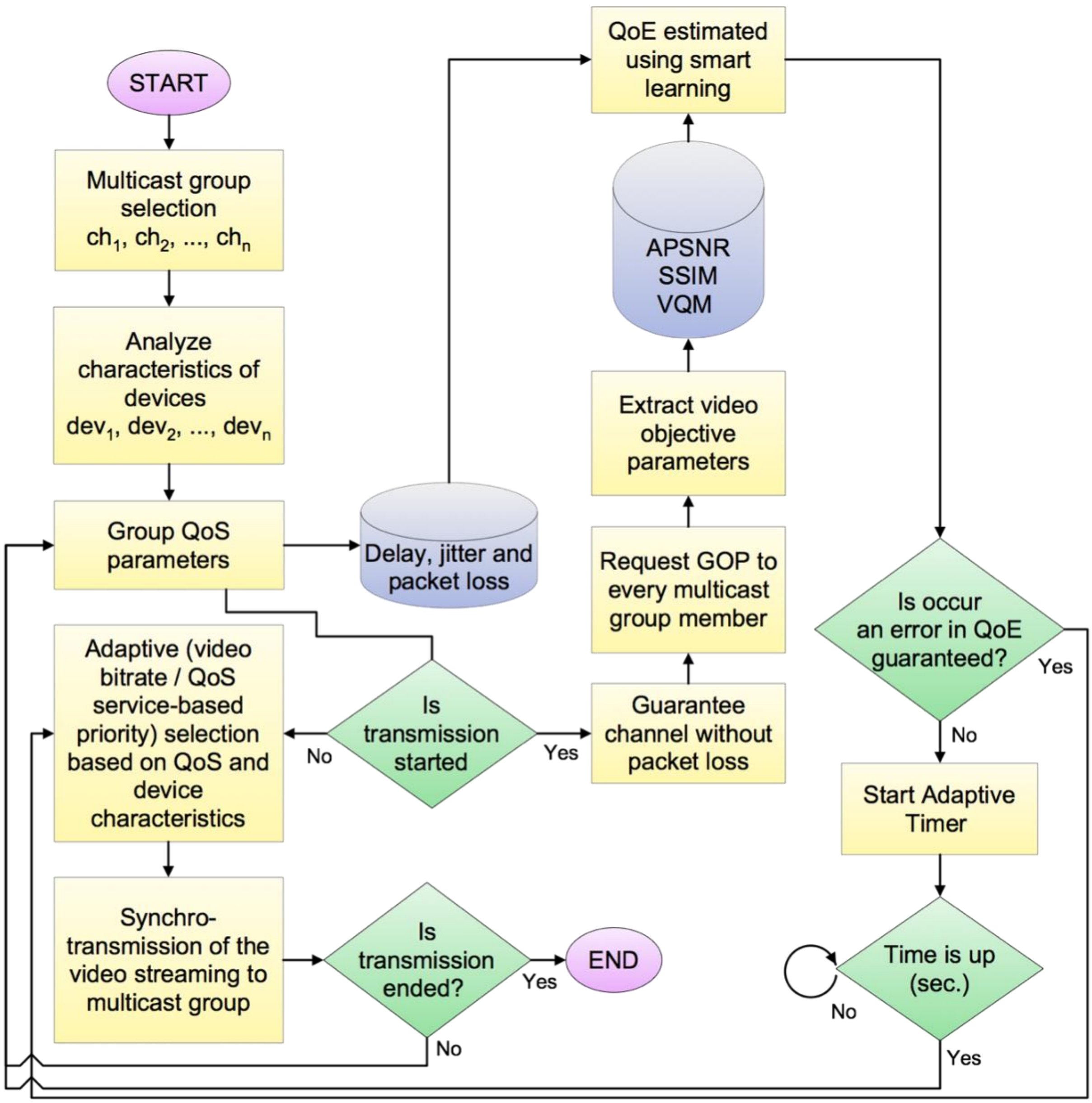


Fig. 2. Proposed algorithm for QoE prediction and management.

5.1 Multicast video streaming system application

In this paper, a multicast video streaming application is developed which permits the provider to stream the video signal to both a group and multiple groups of users. It is developed in Java. The application receives and reads video data from an MP4 container. The transportation layer of this application is based on UDP to contribute the technique for a one-to-many communication channel through an IP in an infrastructure network. It also supplies important features such as multicast (IPs and ports) address range, multicast video timetable, video transcoding if necessary, and multicast video timer for starting. As a result, the proposed application can simultaneously launch multiple videos for streaming to the different receivers. For that, FFMPEG is used in the case when the video requires a transcoding mechanism. The clients' applications involve utilizing. The VLC media player is an opensource and an engine that gives permission to the clients to transmit a GOP to the server.

5.2 Real Testbed experiments

For our experiments, University provided a laboratory with a real Testbed. Its components are the wireless and heterogynous devices such as hardware emulator device, multicast server, and mobile devices as explained in Table 2 and Table 3. It is also aimed at observing experimental test results in an accurate way and obtaining optimal values for video quality assessment. In figure 3, the real Testbed network topology is shown, which illustrates particular tree-based network access for a multicast server and twenty laboratory devices. To receive multimedia streaming data, the end-user devices are connected via the 802.11 access link. Differently, wireless devices are directly connected to the server. Moreover, the emulator point in the network is acting as a traffic shaper; it controls the available bandwidth throughput by using prior knowledge about network resources and guarantees a defined amount of bandwidth according to the predetermined policy rules. The concept of traffic grouping is used such as QoS, queue disciplines, and policy rules. The hardware emulator embedded with Hierarchy Token Bucket (HTB), traffic control (TC) queuing discipline, and network emulator (NetEm) so that modeling and controlling the network throughput, delay, and rate of packet lost. Therefore, to measure the availability and connectivity of the network, IPERF and Ookla speed tests are used.

5.3 Experiments results

Set of videos with different characteristics are provided and used for the first experiment as shown in Table 1. The video characteristics are available with bitrate variation, frame rate, resolution, motions' content and etc. FFMEG is used to encode 2000 frames of the raw video with various profiles and an ID is assigned to each encoded video as a labeled, ID_i, where i = 1 to 8. For example, BigBuckBunny and Star War movies which present as low and fast motion video content respectively are encoded. The video properties are HD resolution (2K and 4K), 30 and 60 frames per second, variable bitrate and GOP of size 16, which structured as IBBPBBPBBPBBI.

Table 1. Characteristic of the sequences.

Video Characterization				
Genre	**Resolution**	**FPS**	**Bitrate**	**Codec**
BigBuckBunny	2k/4k	30/60	Variable	H264
Star War	2k/4k	30/60	Variable	H264

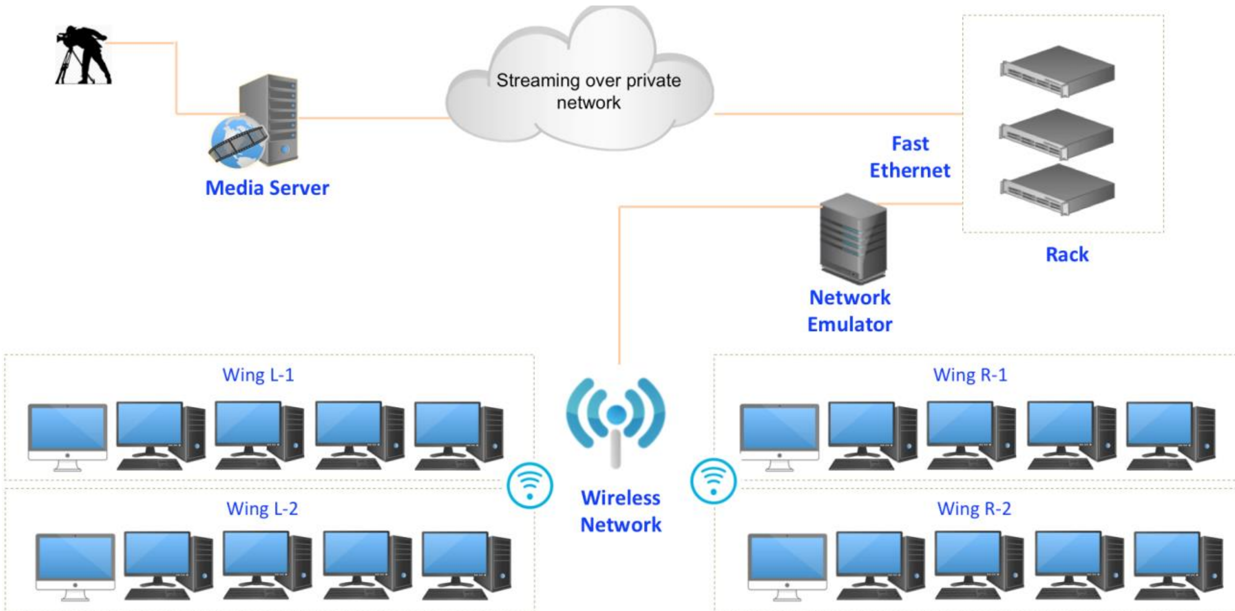


Fig. 3. Network testbed to apply experiments.

Table 2. Characteristics of the devices.

MacBook	**PCs**	**Server**
MacBook Pro retina	Cooler master	Cooler master
MacOS sierra	Windows	Ubuntu
2,4 GHz Intel Core i7	2,4 GHz Intel Core i5	2,4 GHz Intel Core i5
8 GB 1600 MHz DDR3	8 GB	8 GB
NVIDIA GeForce GT 650M	GeForce GTX 980	GeForce GTX 980
15 Inch	17 Inch	17 Inch
Airport Support 5GHz	Linksys Cisco Support 5GHz	Linksys Cisco Support 5GHz
Support 1Gbps	Support 1Gbps	Support 1Gbps
2880 x 1800 Retina, 32-bit color	2880 x 1800, 32-bit color	2880 x 1800, 32-bit color

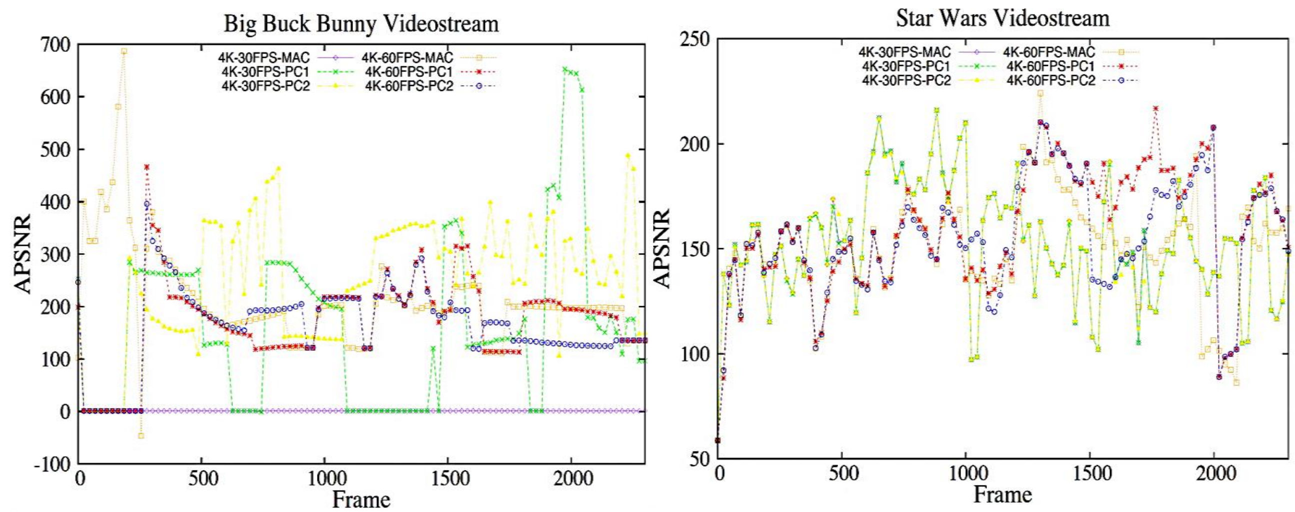
Table 3. Characteristic of the wireless device.

Technical specification	**Characteristics 802.11 (ac)**
Frequency	5GHz
Modulation scheme	OFDM
Channel Bandwidth	20,40,80 MHz
Data rate	1300Mbp
Aggregation Data rate	Up to 1.2Gbps (4x4)
PIRE	<20dBm (PIRE)
LAN interface	0/100/1000Mbps RJ45 LAN
Dimension (W X D X H)	(28mm x 175mm x 119 mm)
Maximum computer per wireless network	50-70 nodes

In this experiment, distinct values are provided for setting the QoS parameters, which are consisted of 280Mbps of throughput, 3ms of two ways packet latency and 0.001% for packet loss and jitter. The video provider streams different videos over the wireless network to the end-user devices. Among all of the devices, we choose randomly three equipment; MacBook and two PCs as their characteristics described in Table 2 (two devices from left-wing and other from right-wing). This is in order to capture and extract the observed information. The distance of the wireless access point is five meters away from the two heterogeneous devices (L-Wing) and the distance of the other device (R-wing) is ten meters as shown in Figure 3. To assess perceptual streamed videos, the objective metrics, such as, APSNR, SSIM, MSAD, and VQM, are chosen to observe the degradation of QoE over these devices. The obtained results of the objective evaluations are depicted for three devices in figures 4, 5, 6, and 7.

In Figure 4.a and 4.b, the impact of the video quality for different frames in two low and high motion video sequences is shown. It indicates that the APSNR values are slightly decreased when the frame numbers are increased in the low motion video (BigBuckBunny) using different frames per second. Furthermore, figure 5.a and 5.b illustrate the fluctuation of SSIM value versus frame numbers for the high motion video sequence (star war). As an overall trend, the quality of video received by end-users has an acceptable level for low quality while an artifact occurred in high motion video.

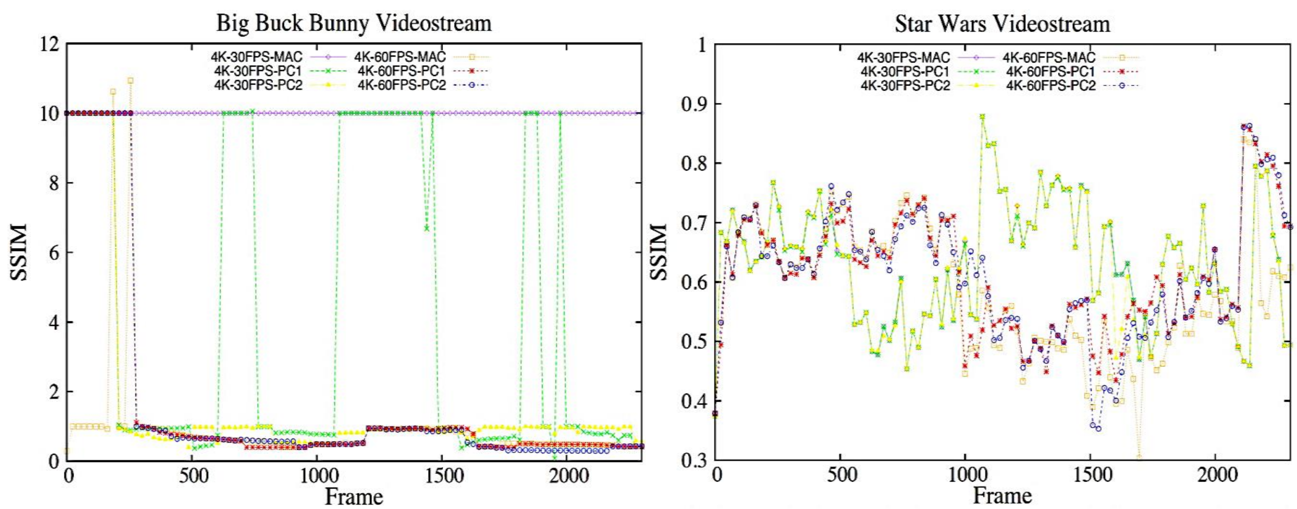
In figures 6 and 7, the same tests are performed using other quality measurements such as MSAD and VQM. The graph demonstrates that the MSAD and VQM have steadily changed for low motion sequences, whereas they have significant oscillation for fast video motion. Therefore, we observe the error (artifact) occurs in the representation of the videos. The purpose of this test is to show the kind of artifacts whereas performing the subjective assessment. Therefore, many artifacts appear when a video has been delivered over the degraded network service. The artifacts have been changed from one scene to another scene and from the type of the artifacts also to another type, the effect is changed according to the scenes. We provided two types of video to demonstrate the artifacts, as shown in Figure 8, the first row of the figure which is labeled as low motion content and the second row as high-motion content (dynamic content) are presented.



a. Big Buck bunny sequence.

b. Star war sequence.

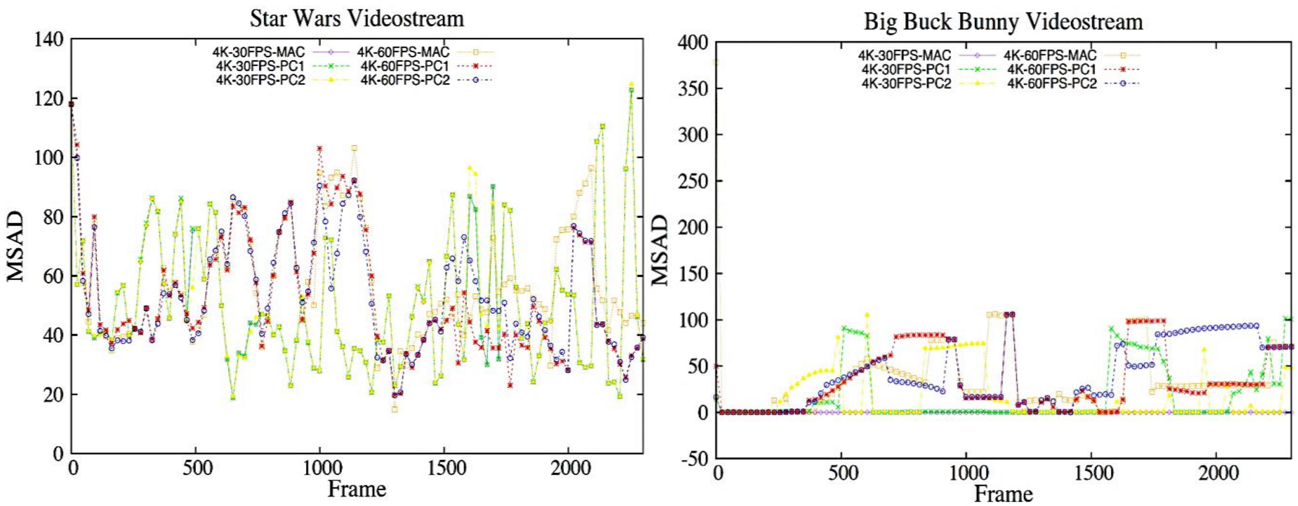
Fig. 4. Observation of objective metrics (APSNR).



a.Big Buck bunny sequence.

b. Star war sequence.

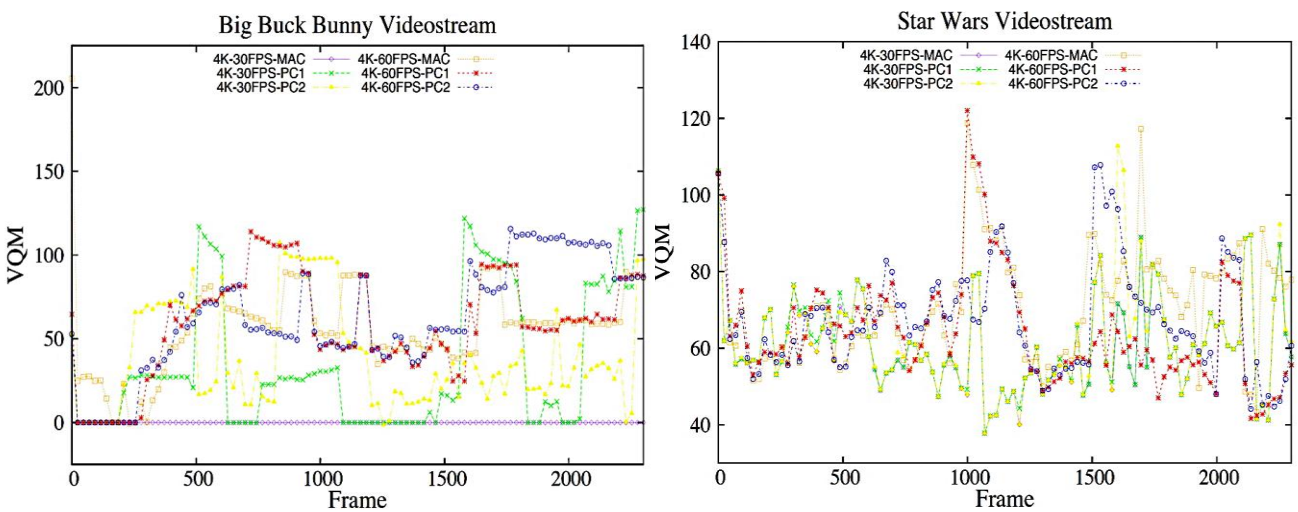
Fig. 5. Observation of objective metrics (SSIM).



a. Big Buck bunny sequence.

b. Star war sequence.

Fig. 6. Observation of objective metrics (MSAD).



a. Big Buck bunny sequence.

b. Star war sequence.

Fig. 7. Observation of objective metrics (VQM).

Fig. 8. Artifact of the videos: first row states low motion and second row states high motion.

For the second test experiment, QoS parameters (throughput, delay, jitter, and packet loss) are shaped to detect the interaction between objective evaluation and network behavior then we find QoE assessment for each end-user. Therefore, in order to evaluate the proposed subjective methodology, we select eighty universities participates. Various male and female genders are selected and their ages started from twenty-one to forty-five years old. To provide an accurate test, inquires forms are papered to all users. The questions are included in the sensing of participants to comfortably give feedback on the watching videos and whether users have the complexity of distinguishing visions between images colors and perceive video degradation.

The MOS measurement score initiates from five to one, while five is indicated excellent satisfaction of the perceptual video quality and one point to very annoying. Therefore, the test has been conducted in a domination environment. The entire tests took eight weeks to complete the accurate subjective test. A particular observation result of this experiment is presented in Table 4. Therefore, the mean average was calculated the for both objective and subjective measurements which is given by

$$\mu = \frac{1}{n}\sum_{i=1}^{n}(xi) \quad (9)$$

The correlation between the restriction values of QoS parameters and the objective and the subjective metrics is revealed in Table 4. The realized tests for the video profile ID_{1} have these characteristics; encode version: X264, encoding quality: 4.1, bit rate control mode: Dynamic, bitrate: variable, resolution: 2k, frame rate: 30, optimal buffer level: 4000, GOP size: 16, internal bit depth: 32 and video motion: low.

The perceived video quality is imperceptible when the delay equals to 100ms. The users are still perceptible for the video when the packet loss is 0.01%, but not annoying. However, 0.01 of the jitters reduced the video quality to a poor level and the users are annoyed. Furthermore, when the characteristic of the video escalates to higher frame rate and higher resolution, the MOS also becomes degraded; however, the profile of ID_{1} for 60 FPS and 100ms delayed is recorded high MOS value.

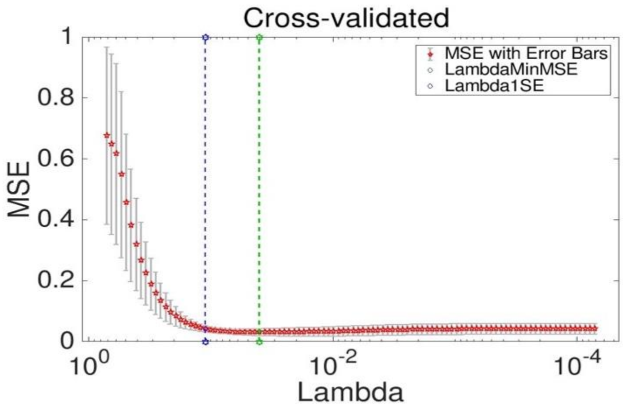
Table 4. Subjective and objective evaluation mapping.

QoS		Assessment Metrics				
Parameters	Values	APSNR (μ)	SSIM(μ)	MSAD(μ)	VQM (μ)	MOS (μ)
Delay On way (msec.)	**100**	**99,910**	**1**	**0,009**	**0,006**	**5**
	250	48,992	0,866	2,008	2,412	2
	500	25,8043	0,722	5,299	4,56	2
	750	19,363	0,605	11,848	7,244	1
	1000	9,4	0,4	17,555	10,01	1
Jitter (msec.)	**0.01**	**26,318**	**0,736**	**7,738**	**6,266**	**2**
	0.05	20,277	0,630	1,659	7,818	1
	0.10	14,555	0,5	14,54	8,65	1
	0.50	8,555	0,38	16,87	10	1
	1	1,789	0,1	20	12	1
Packet loss (%)	**0.01**	**84,704**	**0,987**	**0,111**	**0,403**	**4**
	0.05	45,039	0,896	2,437	2,519	3
	0.10	27,517	0,814	4,631	4,791	2
	0.50	18,470	0,624	6,68	7,681	1
	1	15,322	0,515	8,930	9,386	1

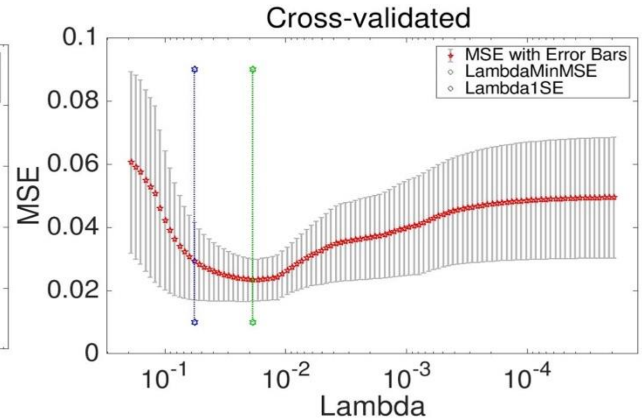
It is important to note that when the jitter and delay approaches to 0.01 250ms respectively, the video quality deteriorates. For both types of measurements subjective/objective metrics the mapping is sketched. This is enabling us to measure the mean square error and then mapping the objective metric into the MOS scale. However, the QoE is highly depends on the delay, jitter and packet loss, therefore, we extract these constrained parameters in the assessment.

5.4 Improving prediction accuracy of QoE via LASSO

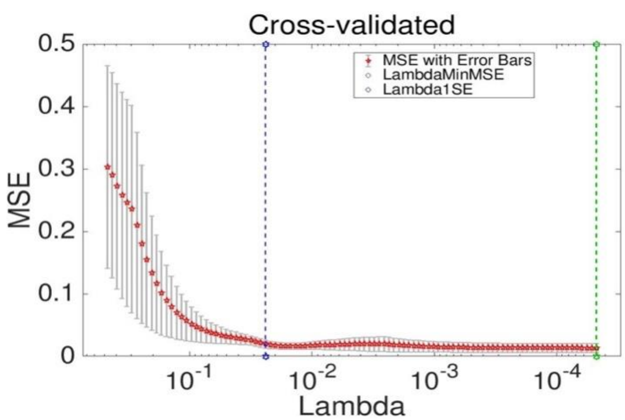
In this paper, the LASSO-regression model based on minimizing Mean Squared Error (MSE) is used to determine the minimum error rate. It can be clearly seen from Figure 9, different objective metrics are used to assess the QoE for the end-users considering different QoS parameters. According to the attained results, the minimum error rate and MSE cross-validated are related. Here, the red dots are representing the MSE and each estimation value is illustrated by the dot stretching error bars which is segmented by the vertical line. In addition, the right lines across the figure are to demonstrate that value which minimizes the MSE cross-validation. On the other hand, the left line is used to distinguish the maximum/ minimum values of the MSE. Figure 9 (a) presented the minimum error rate collected during the system utilizes the essential parameters of the video characteristic, QoS parameters, and characteristics of devices. However, different results can be noticed when each QoS parameter is validated separately by LASSO as demonstrated in Figures 9 (a), 9 (b), and 9 (c). Based on the achieved results from the LASSO regression, for different parameters, the model has the ability to learn from different QoS parameters i.e. bandwidth, delay, packet loss, and jitter. Consequently, they affected the delivery results in terms of QoE evaluation. As indicated in Table 4, each restriction value of QoS has calculated from the LASSO regression. In such a way that the model trains all entry parameters till the MSE of the experiment are reaching 0.0036; but for the case where the QoE being destroyed during the high packet loss, the minimum error is significantly increased, which is approximately equal to 4.7237.



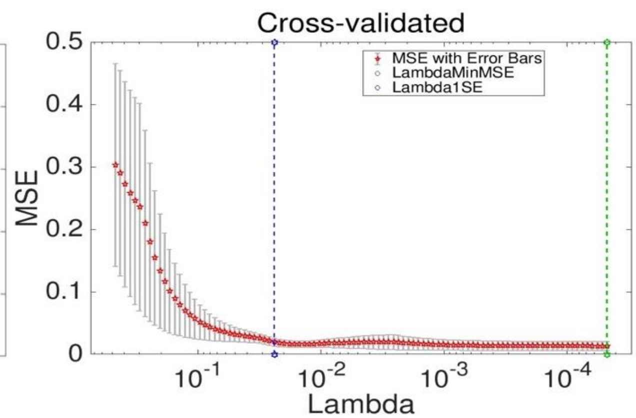
a. All QoS parameters are included.



b. Only Delay is included.



c. Only jitter is included.



d. Only packet loss is included.

Fig. 9. QoE prediction based on LASSO Regression.

Finally, to show the performance of the proposed regression model in this paper, LASSO was compared to other various kinds of regression models (Ridge), Support Vector Regression (SVR), and artificial neural network (ANN) as shown in Table 5. Feature normalization was not needed for the collective approach. Nevertheless, the regression parameters model was pre-processed using two processing (Scaling and mean subtraction) in order to calculate the unit variance. It is important to note that the transformation of features for the data mean and variance are determined by merely utilizing the training data. We determined the best parameters, for each of the regression models; the training set used 10-fold cross-validation.

This procedure is constantly repeated on every valid possible train/test. Therefore, the LASSO Regression is compared to other regression models to show the whole enhancements delivered by the learned regression models; MATLAB is utilized for validated results independently which is revealed in Table 5. In this situation, the LASSO regression accomplished the maximum average performance than other regression models. Table 5 has also shown that SVR achieves better performance over all the other comparison approaches in all the cases. Also, note that the Ridge-regression-based method obtains higher performance than the ANN model. It is obvious from the predicted QoE, the LASSO-based regression method predicts more accurate future QoE with a significant reduction in error rates.

Table 5. Distinguish between LASSO Model and other tools.

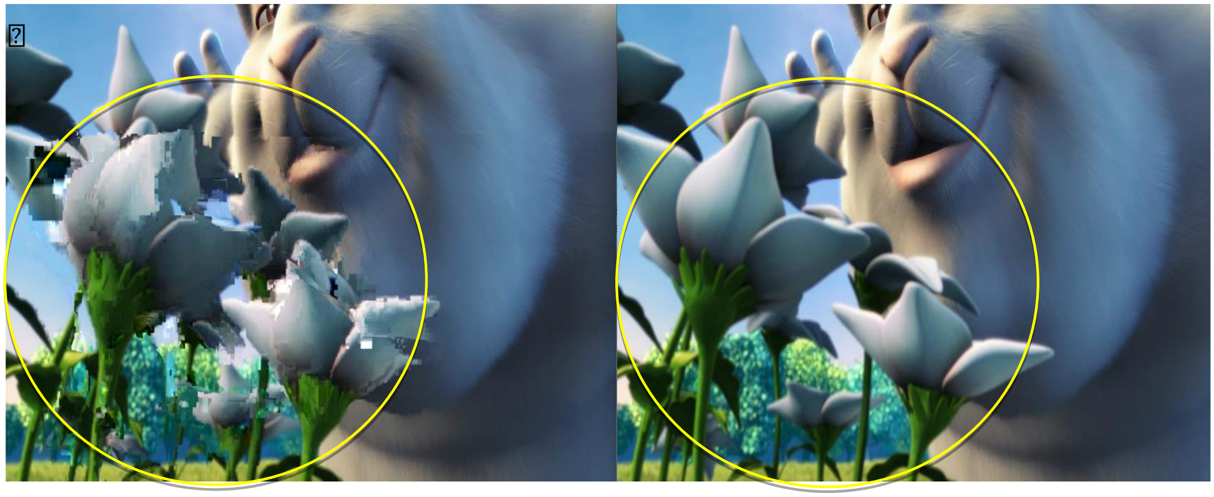
Regression Model	**Min Mean Square Error**	
LASSO	0.0036	
Ridge	0.0098	
ANN	0.3016	
SVR	0.6012	

5.5 Benchmark comparison

In order to assess the performance of the proposed algorithm, a set of test scenarios are performed. The DMOS subjective metric is employed to compare our approach with the state-of-the-art techniques reported in the literature. The methodology evaluation included 10 people; they are not expert with the evaluation of video streaming. To provide higher fidelity of result information, the scenario is chosen based on the eight different characteristics videos as per mentioned previously. The videos were demonstrated to the participants under some particular network circumstance. Table 6 shows summarized of the evaluation results. In contrast to Figure 10 (a) and (b), the characteristic of image qualities is shown for the couple approaches.

Table 6. DMOS comparison between our approach and traditional approach

Genre	**DMOS evaluation for Video streaming based on non-adaptive approach**	**DMOS evaluation for Video streaming based on adaptive approach**
ID_1	2	4
ID_2	2	4
ID_3	2	4
ID_4	1	4
ID_5	1	3
ID_6	1	3
ID_7	1	2
ID_8	1	2



a. Streaming over non-adaptive approach b. Streaming over adaptive (proposed) approach

Fig. 10. Comparison between traditional and adaptation approach.

Similarly and dissimilarity of our approach versus other approaches shown in Table 6, benchmark parameters such as proposed approach, performance, functionality, accuracy decision for QoE assessment and consistency are shown. The comparison shows QoE evaluation and management for a group of users when receiving video streaming over a wireless network. In order to provide the comparison, different metrics are taken in the system such as video codec support, protocols and evaluation, and management parameters.

Table 7 shows that the proposed approach provides better functionary than the state of related approaches, although QoE assessment was based on selecting Full-Reference and No-Reference. The smart learning model is used to estimate QoE for the management of video quality, therefore, the management bases on the adaptive approach; this method selects better bitrate, frame rate and high or low video motion to the end-users. Moreover, the proposed algorithm uses the priority of QoS when users suffer from the adaptation of video coding.

Table 7. Comparison our method with other proposed works.

Items	Ref. [13]	Ref. [16]	Ref. [23]	Our proposal
Transportation protocol support	No specified	RTP	UDP	UDP
QoE evaluation	✓	✓	✓	✓
Management algorithm	✓	✗	✓	✓
Tests based on Network emulation	✗	✗	✓	✓
Subjective Metrics base on DMOS	✗	✓	✓	✓
Objective metric based on Full-Ref.	✗	✓	✓	✓
Objective metric based on No-Ref.	✗	✗	✓	✓
Smart QoE prediction	✗	✗	✓	✓
Wireless network	✓	✓	✗	✓
Initial delay	✗	✗	✗	✓
Frozen frames	✗	✗	✗	✓
Network health monitor	✗	✗	✗	✓
Adaptive transcoding	✓	✓	✓	✗
Adaptive Bitrate	✓	✗	✓	✓
Adaptive Frame rate	✗	✗	✗	✓
Adaptive resolution	✗	✗	✗	✓
Adaptive QoS priority	✓	✗	✗	✓
Heterogeneous end-users’ devices	✗	✗	✗	✓

6. CONCLUSION AND FUTURE WORK

In this paper, we proposed the smart algorithm for assessing and managing the QoE video streaming over wireless networks for multimedia service. We investigated to develop a new algorithm with respect to the correlation between the network parameters, video quality, and the QoE device capacity of end-users. We, therefore, introduced a new model that utilizes the LASSO regression method to predict more accurate QoE assessments. In stark contrast, the proposed predictor model uses the empirical measurement to estimate the objective metrics and the network channel metric values.

In order to achieve the functionality of the algorithm, we stream two kinds of videos. Each of them has a quality of 2610p and display frames at 60fps. The characteristic of the first video is low motion and the second is high motion. To test the algorithm, we provide two phases, in the first phase, both videos are streamed to the group of the end-users and these received videos are saved on the clients’ devices. The second phase, it is included repeating the previous phase with our application by applying the smart prediction.

The model defines how the LASSO works better than the other models by shrinking the coefficients exactly to zero. Therefore, to show the comparison benchmark between the two approaches, we find different mean score meaning (DMOS) by showing the videos with applying the smart algorithm and without applying the smart algorithm. As a result, the proposed algorithm increased the quality of experience and achieved significant bandwidth saving.

The future recommendation would be planning to perform the proposed method on a more sophisticated system such as a mobile video streaming service according to [20] and investigate using deep learning model to train to obtain data of the parameters to evaluate QoE and using different video codecs and services as mentioned in [21, 22, 24, 25], this approach would enhance QoE of mobility devices such as smart devices, mobiles, and tablets.

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CONFLICT OF INTEREST

Authors declare that they have no conflict of interest.

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