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Review of methods evaluating video quality in adaptive streaming

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***Abstract*—The video streaming industry is growing. There is demand for high quality videos. These videos are stream to the consumers with a promising quality and low latency. There are various methods to measure the video quality of experience (QoE) in a streaming environment. The main goal of this paper is to provide an overview of methods and techniques to measure the QoE in adaptive streaming domain. This paper provide overview of metrics and QoE models which asses the video quality in streaming. This paper also discusses the dataset exist in video streaming. This paper highlights the challenges and future strategies that should be considered building models for assessing the video quality in adaptive streaming.**

***Keywords*—video streaming; QoE; ABR algorithm; latency**

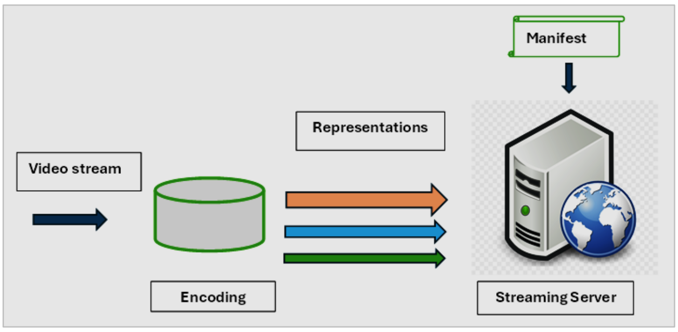

Fig. 1. DASH Network Environment

I. INTRODUCTION

THE is exponential growth in the use of video streaming services. This trend likely continue to grow in the future. A statistical trend [1] show that by year 2026 77 % of the streaming applications will be video centric. The HTTP Adaptive Streaming (HAS) is the popular industry for the delivery of video in streaming environment [2] [3]. There are two media delivery format, one is HTTP Live streaming (HAS) and the second is Dynamic adaptive streaming over HTTP (MPEG-DASH). In HAS media [4] delivery standard video is encoded into the segments. The segment duration varies from 2 seconds to 15 seconds. The segments are encoded using various bitrates and resolutions. These segments are stored on a streaming server as shown in (Fig. 1). The client access the video segments through adaptive bitrate (ABR) algorithm. These ABR algorithm consider technical factors before downloading the segments. These are network bandwidth, buffer size and latency [5] .

The video streaming industry is growing which increases the demand for video on demand (VOD) and Live streaming [6]. This trend also made service providers competition with each other, The service providers promised to deliver high quality services to the consumer and fulfill their expectations. The service providers want o provide services for better quality of experience (QoE). Measuring quality of experience is very crucial. There is a requirement to build QoE models which are based on network factors and asses the user QoE [5][7].

In Live streaming the video content is effected by latency. It take time to record the content using camera and deliver it to the consumer. This delay have potential impact on the user viewing experience. In Live streaming environment it is very challenging to design ABR algorithms and other techniques to minimize the latency [8][4][5]. The buffer capacity also important factor to minimize latency. The buffer at client side should be minimized which results lower latency. The ABR algorithms should perform efficiently and adopt the network conditions in efficient manner.

The article focuses on the overview of experimental procedure measuring the video quality in adaptive streaming domain. Moreover, the paper explains the cutting-edge methods and evaluation strategies. In this work various methods will be reviewed and analysed for the aptness of full high-definition (FHD) and 4K video resolutions. The study responds on the following research questions.

1) *What are the strategies for setting the experiment in adaptive streaming domain?*
2) *What methods are used to evaluate the video quality in adaptive streaming?*

The rest of the article is organized as follows. Section II describes the basics concepts of adaptive streaming. Section III mention the QoE models in adaptive streaming domain. Section IV provides the details about ABR algorithms and its utilization in adaptive streaming. Section V demonstrate the metrics used to calculate the QoE in adaptive streaming. Section VI is dedicated to the datasets developed specifically for adaptive streaming. Section VII summarize the paper, identifies the research gaps, and proposes future research work in the adaptive streaming domain.

The presented research results come from a research and development project entitled ,,Technology for Secure and Reliable Delivery of Professional Audio/Video Contribution Live Transmissions with the Lowest Possible Latency." The project was carried out under Sub-measure 1.1.1 of the Intelligent Development Operational Program 2014–2020 and co-financed from the Polish National Center for Research and Development. It was implemented as part of the National Center for Research and Development's Fast Path competition.

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II. BACKGROUND

In this section, we will discuss the background information on the methods evaluating the video quality in adaptive streaming.

A. *Adaptive Streaming Technology*

In adaptive streaming [5][2][9] the video sequence is encoded at various quality levels and then further divided into segments. The segments can be 2, 4, 8 or 10 seconds long in duration. These segments are stored on the streaming server. The information about the video content such as codec, bandwidth and downloaded URLs, is provided in a file called media presentation description (MDP). The client send request to the server to download a video segment, and the request depends on the bandwidth of the network.

B. *QoE factors*

There are some factors which potentially impact the video quality in streaming [10]. The previous research studies highlighted on rebuffering which caused inconvenience to the user and impact the positive viewing experience [11]. The buffer duration and the frequency are the two vital aspects of the video streaming. The buffer duration and frequency should be minimized by the adaptive streaming algorithms. The switching quality is also important factor that impacts the video quality. The amplitude of the switching quality seems affects the video quality of experience (QoE) [12][13][14].

C. *Measuring quality in adaptive streaming*

The video quality alters after encoding and streaming to the client. It is important to evaluate the video quality in streaming in order to provide positive user experience [15][16]. There are some metrics which can be used to measure video quality. These metrics are grouped into subjective and objective [17]. Both subjective and evaluation methods have pros and cons. The subjective method is significant in assessing video quality. The issue is subjective method is time consuming and expensive. On the other hand, objective evaluation is fast and can be deployed swiftly [18].

III. ADAPTIVE STREAMING QOE MODELS

There are different QoE models which are parametric, bitstream based and hybrid based models. Here the bitstream model will be explained in detail [19][20].

A research article by [21] proposed a QoE model which is based on video segment quality, switching quality and streaming rebuffering instances. The results demonstrate that the model have low complexity and better performance.

A research work [22] demonstrates the quality assessment by combining median with minimum quality in linear representation.

$$Q_{\mathrm{Overall}} = \alpha\, Q_{\mathrm{medium}} + \beta\, Q_{\mathrm{min}} \tag{1}$$

where α and β are constant values and the Q_{medium} and Q_{min} are the median and minimum of the average obtained quality. This model is tested, and the results illustrate the quality of composing frequency of the non-periodic QP change video session utilized in order to assess the video quality.

The research [23] presented QoE model by considering the encoded video quality and the variation in the quality. The quality is modelled as under.

$$Q_{\mathrm{Overall}} = \sum_{n=1}^{N_{SQ}} \alpha_n FQ_n + \sum_{m=-M}^{1} \beta_m F_{\nabla Q_m} \tag{2}$$

where α_n and β_m are the input parameters in the model given by equation (2) and N_{SQ} , F_{Qn} and $F_{\nabla Qm}$ represents segment quality bins, frequency of segment quality bins and frequency of quality gradient bin in the model.

The model is tested against the standard parameters. The result validates that the model is significant. The testing observation shows that the switching has an impact on the QoE.

The model is extended and presented [24], the initial quality, loading delay and rebuffer events taken into consideration. The following equation derived which estimate the QoE:

$$\mathrm{QoE}_{\mathrm{Overall}} = I_{QS} - I_{RB} - I_{ILD} \tag{3}$$

In above equation I_{QS} is the impairment factor which altered due to the switching amplitude and the initial quality value. The I_{RB} is the factor when rebuffer event occurred and I_{ILD} is the factor inherited due to initial delay. The model is tested and results demonstrate that the switching amplitude depends on the starting quality. The other important factor is the rebuffer event which also have any impact on the overall QoE.

A model proposed by [25] includes media quality (Q_{LT}) and quality degradation caused by loading delay (I_{ILD}) and rebuffer (I_{RB}). The combination of all above parameters calculates:

$$\mathrm{MOSAVF_{inal}} = Q_{LT} - (I_{ILD} + I_{RB}) \tag{4}$$

A study carried out by [cumulative video 2019], proposes a model that asses the cumulative video quality in adaptive streaming. The model is tested against the defined parameters. The result shows that the minimum window quality, last window quality and the average window quality are the three significant components of the cumulative quality model. This model can be deployed in a real time environment. The model can be calculated as follows:

$$\mathrm{CQM} = w_1.\mathrm{WQ}_{mi} + w_2.\mathrm{WQ}_{l} + w_3.\mathrm{WQ}_{av} \tag{5}$$

where w_1 , w_2 and w_3 represent the weights of WQ_{mi}, WQ_{l} , and WQ_{av}.

A model presented by [2], is based on stalling and switching quality parameters. This model can be utilized as a foundation for improving the ABR algorithms in the adaptive streaming environment.

$$\mathrm{QoE} = 5.67 \times \frac{\bar{q}}{q_{max}} - 6.72 \times \frac{\hat{q}}{q_{max}} + 0.17 - 4.95 \times F \tag{6}$$

$$\mathrm{F} = \frac{7}{8} \times \max\left(\frac{\ln(\phi)}{6} + 1.0\right) + \frac{1}{8} \times \left(\frac{\min(\psi, 15)}{15}\right) \tag{7}$$

IV. ABR ALGORITHMS AND QOE

In adaptive streaming ABR algorithms are responsible to adjust the video bitrate based on the available network bandwidth. The aim of the ABR algorithms are maximize the video quality and provide better QoE.

A study is carried out [25] considering quality adaptation strategies. The video segments are tested having various frame rate, resolution and compression levels. The results demonstrate that quality adaptation impact the user persuasion and potentially influence the QoE.

In a research work [26] framework is developed in order to achieve a optimum quality while optimizing the bitrate and encoding complexity. It is evident from the results that the file size can be minimized, and the quality level maintained.

A model [27] is presented based on the heuristics ABR algorithm. For validation both subjective and objective evaluation performed.

The work presented in the [28] demonstrate DashReStreamer, which creates adaptive streaming video in a real network. A dataset is created and tested. In the dataset video clips created based on video logs. These video logs gathered from the mobile and wireless networks. The videos in the dataset can be utilized in subjective evaluation.

The framework [29] based on the quality switching, loading delay and stalls. A set of evaluation carried out to test the framework specifically in adaptive streaming.

The author [5] develop model which can be used to evaluate low- latency in the streaming. A variety of test cases created for evaluation. These tests are performed using network traces, media players and ABR algorithms. The test results reveal that that LLL framework perform better as compared to earlier ABR algorithms and maintaining high QoE.

The author [7] presented a model which can be utilized to evaluate the latency and its impact on the QoE. The analysis is carried out by evaluating ABR algorithms and its relation with latency. In this work Dynamic algorithm perform well and achieve the best QoE. The other algorithms also better performed but caused stalling. The low latency algorithm L2A-LLperform poor as demonstrated by the results.

The work [5] reported the evaluation of ABR algorithm Llama and see the suitability of this algorithm in low streaming. The Llama algorithm is evaluated against the low-latency algorithms. The results demonstrated that Llama achieved the lowest live Latency by some margin. The Llama also achieved improved MOS which shows the Quality of experience.

V. QOE METRICS IN ADAPTIVE STREAMING

There are various metrics [5][7][30] used to measure video quality of experience. The details are provided as follows.

Playback delay: As the video stream starts, the time between first frame loading and displaying at the client end is called playback delay. The more time it take to load the initial frame its frustrating for the viewers.

Loss rate: In video streaming video packets could lost in the network. The packets may loose in the buffering event. The packet loss cause distortion and negatively impact the user experience.

Buffer underflow: The situation when client request for video frames and the buffer is empty this is called buffer underflow. When buffer underflow occurs, it impact the video quality. The rate of buffer underflow is crucial metric for assessing the video quality in streaming domain. The ratio of underflow duration and playback time is called the underflow time ratio.

Playout rate: The playout rate should be above threshold so it impact the user experience positively. The playout rate is also an important metric to be measured.

Video Quality: This is significant metric to calculate the objective video quality. This metric is calculated as the arithmetic means of the indices ranges from 0 to 4, of the segments quality.

Average Live Latency: This metric is calculated as a average time between segment generation and the segment is displayed at client device.

VI. DATASETS IN ADAPTIVE STREAMING

This section provides details about the datasets specifically designed for adaptive streaming. The author [31] presented dataset for simulation and real-time assessment of DASH network. This dataset provides sequences encoded by H.264 and H.265 encoders.

The dataset modeled in [32] provides the complex distorted sequences which are generated using mobile phones. The dataset contains 208 video sequences recorded using smart phones. The subjective evaluation is carried out in this experiment and the dataset is evaluated by using several IQA and VQA algorithms.

A dataset is developed by [33] that consists of 20 RAW high-definition (HD) source video sequences. The database includes 450 video sequences generated in streaming environment. The streaming sessions are created through the ABR algorithms and presented based on heuristics ABR algorithms. For the sake of validation both subjective and objective evaluation were executed.

The study in [34] demonstrated the dataset based on AVC, HEVC, VP9, and AV1 codecs. This multi-codec dataset is tested with different network profiles. The evaluation is performed to measure the encoding efficiency in the DASH streaming.

The research in [35] presents the high-definition video dataset contains 32 source videos and 384 distorted version. The dataset is based on High Efficiency Video Coding (HEVC). The subjective and objective evaluation are performed for validation.

The author [36] created mobile video quality database containing 174 video sequences. The stalling events generated, and subjective evaluation is performed on distorted video sequences. The results presented showing the impact of factors on the video quality of experience.

A database [37] presents the Ultra High Definition (UHD) video sequences. The encoding was performed using H.264, HEVC and VP9. Both subjective and objective evaluation is carried on video sequences. The results analyzed to find the tradeoff between bitrate, resolution, framerate and content.

The video dataset [38] developed contains high-definition sequences. This dataset consists of 12 source video clips and 96 processed (PVSs) sequences. The subjective assessment is performed to measure the quality of distorted videos.

The 4K resolutions dataset [39] presented encoded using AVC, HEVC, VP9, AVS2 and AV1 codecs. The subjective method is used to perform the evaluation on video sequences. Several objective models are evaluated and results presented.

The open Ultra Video Group [40] developed a database containing 4K resolution video sequences. These video sequences are stored in RAW YUV format. This dataset is based on HEVC and VVC encoding. The objective and subjective evaluation is performed for video sequences.

An MPEG-DASH dataset [41] developed containing 8K video content. The video content is encoded using AVC, HEVC, AV1 and VVC codecs. The sequence is 322 seconds long and each segment is 4 seconds and 8 seconds in duration.

The dataset [42] created from 4065 video segments of 2 seconds duration. The resolution of the dataset is up to 4K (UHD). The dataset is based on various metrics acquired from the segments encoded with varying compression. The dataset extract characteristics to color, space and time from the video segments. The dataset contains sequences with 240, 360, 480, 720, 1080, 1440 and 4K resolutions.

VII. OPEN CHALLENGES

In this paper, we presented an overview of methods to evaluate the video quality in adaptive streaming environment. The assessment methods are analyzed comprehensively. The existing QoE assessment models are reviewed and summarized. The limitations of these models are also discussed in the sequel. The quality switching, stalling and playback rebuffering impact the video quality and user experience. A research investigates an intelligent DASH approach for the H.264 coding and proposes a heuristic QoE-aware adaptation scheme. There is a requirement to investigate the impact of content, spatial and temporal characteristics on the user's QoE. The Table I, shows the existing studies in video streaming domain.

The work carried out by [43][4][36] analyzed the impact of stalling and quality switching on the user quality of experience. As evident from the results the models need to be extended incorporating additional parameters, video sequences and switching patterns.

The research work in [44][45][12][5][7] measuring the impact of low-latency ABR algorithms on the user quality of experience. The research has limitations and there is a need to carry it out for further evaluation by considering the ABR algorithms and incorporate the QoE metrics. In the low-latency streaming domain further investigation is required to improve the ABR algorithms. This study extendable to find the optimum latency measurement.

There are articles by [36][43][14], [45][11] on switching quality, rebuffering and playback interruptions and its impact on the user quality of experience. Further analysis are required by considering long and short stalls and the frequency of stalling event in a streaming session. The impact of playback interruption on the user perception also needs to be investigated in detail. The ABR algorithms should be modified to minimize stalling and balance latency and quality. Strategies should be developed to investigate the impact of buffering on QoE in various network conditions.

The work presented in [5][7][30] mention the video quality metrics to measure the video quality of experience. Research is needed that build models by combining the contextual and subjective factors. The methods require to be developed in order to assess QoE in live streaming environment. The existing subjective assessment method should be improved to effectively collect the data in streaming network. The model can be developed to quantify QoE of stalling, switching, starting delay and playback interruption.

The datasets developed and presented [31][36][33][34][41] specifically for streaming domain. The existing datasets have limitations in term of content, resolution and segments duration. Various segments are needed. The different encoding are also required.

The scalable video coding of H.264 and H.265 to be created. The QoE models can be created and tested using the existing datasets. The existing datasets can be extended to incorporate the latest codecs such as AV2 and LCEVC codecs. The HDR and higher frame rates (60FPS) should be incorporated in existing datasets. As there is high demand for ultra-low-latency streaming, existing datasets lacks metrics relevant to low-latency streaming.

Table I
VIDEO STREAMING STUDIES

Reference	QoE parameter	Subjective/objective Methodology	Metrics	Resolutions	Focus of the study
[46]	Adaptation frequence, stalling	Subjective, crowdsource	Bitrate, MOS	720p	The paper focuses on quality adaptations and strategies.
[47]	Quality switch, stalling	Subjective	MOS	Up to 720p	This work focuses on assessing impact of adaptation on the QoE
[48]	Bitrate switching, stalling	Subjective	MOS	Up to 1080p	The research focuses on impairment functions and its impact on QoE
[49]	Stalling Switching	Subjective	MOS	Up to 1080p	This paper presents evaluation of trade-off between stalling and initial video quality.
[50]	Buffering, switching, interruption	Subjective objective	Bitrate, MOS	480P	This work present video quality metric for DASH streaming.
[51]	Quality switching, initial delay, Interruption	Subjective objective	MOS	720p	This research shown a QoE model for HTTP adaptive streaming. The QoE model is based on initial delay, quality switching and interruptions.
[52]	Quality switching Resolution	Subjective	MOS	Up to 1080p	This work focuses on resolution switching and its impact on the QoE. This study presents that video content and resolution have an impact on the user perception.
[53]	Stalling	Subjective, Crowdsource	MOS	720p	The study focuses on the subjective video quality assessment. In this work the crowdsource subjective studies are described
[54]	Quality Switching	Subjective	MOS	Up to 1080p	This research work compares the constant bitrate (CBR) and Constrained Constant Rate Factor (CRF) strategies. This work assesses the impact of CBR and CRF on the video resolution.
[55]	Buffering	Subjective	MOS	720p	This work investigates the impact of synchronization and buffering under a specific bandwidth profile.

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