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QABR: A QoE-Based Approach to Adaptive Bitrate Selection in Video Streaming Services

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ABSTRACT

HTTP Adaptive Streaming (HAS) has recently become the de facto choice of today's streaming providers to perform a smooth video content delivery to the end users. The key technology behind HAS is the adaptive bitrate selection (ABR) algorithm that adaptively selects the best suitable video bitrate based on either throughput or buffer monitoring techniques. In order to fulfill user's satisfaction, ABRs must be designed to accurately reflect the perceived quality of experience (QoE), which is influenced by the perceptual and technical factors. However, both throughput and buffer only account for the technical factors, leading to the insufficiency of today's ABRs in demonstrating human perception. Moreover, existing throughput and buffer-based algorithms are slow-responsive to significant network changes and unstable in terms of video quality, as found by recent research efforts. For those reasons, QABR – a novel QoE-based bitrate selection algorithm – is proposed in this paper that combines the underlying network parameters and user's instantaneous QoE (in accordance with perceptual factors). Experimental results demonstrate that QABR outperforms the referenced baseline algorithm in various evaluation criteria.

Key words: HTTP adaptive streaming, adaptive bitrate selection, quality of experience, throughput, buffer

1. INTRODUCTION

Video streaming services have been facing huge demands lately due to the exponential growth of portable devices and innovations in communication technologies, which addresses a problem of utilizing network traffic for large number of users. Over the last decade, several researches have been conducted to this manner, of which the most popular that has been used widely is the HTTP Adaptive Streaming (HAS) technology. In HAS, video content is stored in multiple small segments available in multiple quality levels in terms of bitrates. At the client side, HAS players usually request suitable quality levels, of which the decisions are made by their adaptation or adaptive bitrate selection (ABR) algorithms. Besides, HAS's adaptation algorithms are usually driven by throughput or buffer monitoring methods, where HAS players continuously monitor their throughput or buffer in order to select the video bitrate that aligns well with current network condition. However, throughput-based methods require a sufficient number of probes to obtain reliable throughput measurements, which adapts slowly to abrupt changes of the network [1], [2]. On the other hand, buffer-based approaches usually lack the stability due to high switching frequency, causing negative effects to users [3], [4]. In addition, throughput and buffer do not efficiently reflect the user's quality of experience (QoE) [3].

Recently, a great deal of research has focused on modelling and predicting QoE over video streaming services. The QoE level reflects the user's perception to the service quality in accordance with his/her expectations during a streaming session. In fact, instantaneous QoE can reveal recent network condition since it reacts sensitively to negative events (e.g., rebuffering, bitrate switch) [5]. This shows the potential of applying QoE to adjusting streaming video bitrate. The idea was applied in [6] and [7] with reinforcement learning-based approaches. However, these works only considered single user scenarios, though having shown promising performances. To the best of our knowledge, there is no study that directly utilizes QoE as a main factor for bitrate selection within a multi-user scenario.

In this paper, a QoE-based adaptive bitrate selection algorithm, namely QABR – is proposed. QABR assesses user's instantaneous QoE level, with weighted value that represents current network condition in terms of instantaneous throughput and buffer, to decide the next video bitrate to be requested. Through simulation, we show that our proposal outperforms the referenced method in both users' perception and QoS criteria. Our study is distinguished with existing works by its main contributions as follows:

- We propose QABR – an adaptive bitrate selection algorithm that combines and utilizes instantaneous QoE and underlying network parameters.
- We define the dynamic weighted value α that takes into account the immediate throughput and buffer level of the HAS player.

The rest of this paper is organized as follows: Section 2 provides the research's background and an overview of existing works related to our approach. The proposed QABR is introduced in Section 3. Section 4 presents and discusses evaluation results of QABR, in comparison with the referenced FESTIVE algorithm. Section 5 concludes this paper.

2. RELATED WORK

QoE plays a critical role in the assessment of HAS service, since it is directly connected to user engagement. Thereby, several research efforts on ABR have been carried out to deliver the highest possible perceived quality to users, including the throughput-based and buffer-based approaches.

Throughput-based algorithms estimate the network throughput by several smoothing techniques to decide the next video bitrate. This method has been widely applied to many commercial products (e.g., Microsoft Smooth Streaming [8], Netflix player [9]) providing baselines for various follow-up studies. FESTIVE, proposed by Jiang et al. [10], was one of the first opensource algorithms that utilized this approach to target the bottleneck link competition among players. The study based on the harmonic mean to perform smooth throughput estimation and achieved remarkable optimization in terms of fairness, efficiency and stability.

The smoothing techniques in throughput-based methods are crucial as they prevent the variability in video quality due to the discrete nature of throughput. However, they tend to inhibit the responsiveness of bitrate selection algorithms, causing late reaction to significant throughput decrease [1]. Therefore, like many other throughput-based solutions, the FESTIVE algorithm still struggles with significant throughput variation, causing rebuffering events due to the depletion of play-out buffer. Such events drastically downgrade QoE perceived by the users [3].

Another widely-used approach to bitrate adaptation is the buffer-based algorithms. These methods attempt to maintain the play-out buffer at a certain level, avoiding rebuffering event caused by buffer depletion. Buffer-based algorithm (BBA) [11] is a very well-known algorithm that uses several buffer thresholds to determine whenever a bitrate change is needed, while buffer occupancy based Lyapunov algorithm (BOLA) [12] utilized Lyapunov optimization to indicate bitrate at each chunk. Despite having shown high adaptability, this approach lacks of stability due to high switching frequency of video quality [13] also caused by the discrete characteristic of buffer monitoring method, dealing negative impacts on the user's perception [4].

It should be noticed that throughput and buffer-based ABRs are only resources estimation-based algorithms and do not sufficiently reflect human's perception. According to Seufert et al., the influence factors of QoE are categorized in technical and perceptual factors [3]. Technical factors are related to the underlying technologies of streaming services, in which throughput and buffer estimation capture most attention as discussed above. Whereas, the perceptual factors account for visual entities and events that are directly perceived at the client side including video quality, stalling or re-buffering events, number of quality switches, etc. Therefore, in order to accurately meet with user's expectation, both perceptual and technical factors should be concurrently considered.

The idea has been fulfilled by recent researches by applying the reinforcement learning method, showing superior performances over the above approaches. Claeys et al. [6] defined a reward function utilizing an objective QoE value, which is then used as a feedback input of the learning model, in addition to the discrete throughput and buffer. A similar approach was employed by Liu et al. [7] with the use of subjective QoE and improvements on network structures and learning mechanisms. However, these works only considered single-user scenarios where the bottleneck competition of bandwidth dealt little influence. To this end, our work sets light to QoE-based approaches to ABR under a multi-user scenario.

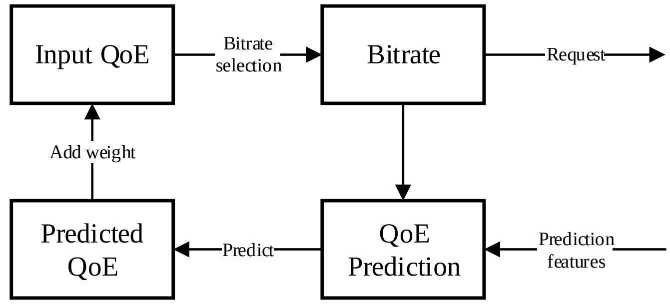

Figure 1: High-level overview of QABR

3. THE QABR ALGORITHM

As stated in section 2, throughput-based adaptive bitrate selection algorithms adapt poorly to network variability that causes rebuffering events, while buffer-based approach suffers from maintaining a stable visual quality. In this section, the design of the proposed QABR algorithm is presented in order to deal with these problems, along with optimizing delivered video bitrate in order to maximize user's perceived quality.

Figure 1 depicts a high-level overview of the proposal. In general, our bitrate selection strategy can be described as follows:

- The client's player starts its session at the buffering state by downloading video chunk at the lowest bitrate. As soon as the first chunk is successfully downloaded, the QoE prediction model starts to monitor its client's instantaneous QoE, producing the ***Predicted QoE***.
- The ***Predicted QoE*** is then recalculated by adding weighted value representing the instantaneous throughput and buffer condition, providing the ***Input QoE***.
- The ***Input QoE*** is then utilized for choosing a suitable bitrate to be requested.

3.1 Predicted QoE

In our model, an instantaneous QoE is considered which accurately represents the instantaneous perception of the user at certain moment during the streaming session. As discussed in Section 2, continuous QoE can reveal network conditions since it interacts with visual quality of delivered video chunks and reacts sensitively to rebuffering events. In other words, by predicting user's QoE, the current network and its affection can be traced and used to decide a suitable bitrate.

This work utilizes the Long Short-term Memory (LSTM) based QoE prediction model proposed in [14] to monitor QoE continuously. The study has proven the effectiveness of applying the LSTM to modelling the complex long/short-term dependencies of continuous QoE. Therefore, the prediction results have shown superior performance in terms of accuracy compared to other approaches. The model relies on three features as follows:

- ***Peak Signal-to-Noise Ratio (PSNR):*** PSNR is a video quality assessment (VQA) metric that refers to the perceived visual quality of the current segment delivered to user.
- ***Rebuffering (R):*** R is a binary indicator specifying the current playback status: 1 for rebuffering and 0 for normal playback.
- ***Time elapsed since last rebuffering events (TR):*** TR is responsible for keeping track of the time elapsed since the latest occurrence of rebuffering event.

3.2 Input QoE

Although the *Predicted QoE* can also reveal the occurrence of rebuffering event, which is the result of severe network condition, our goal is to prevent such events so that user can experience the streaming session at the highest possible quality. Thus, the information of underlying network such as throughput and buffer need to be considered in accordance with predicted QoE. To this manner, we propose a dynamic weighted value by considering the current throughput and buffer level of the user as follows:

$$\alpha = \left[\frac{\left(1 - \frac{bitrate}{throughput}\right) + \frac{current\ buffer}{buffer\ threshold}}{2}\right]^{+} \tag{1}$$

where $[A]+$ denotes the maximum of A and 0. Currently, the buffer threshold is set to 2/3 of the maximum buffer level since we observe stronger correlations. The optimal buffer threshold will be investigated in future works.

The weighted value α is responsible for combining and balancing the discrete characteristic of network metrics used in HAS systems (e.g., throughput and buffer monitoring) and the continuous nature of user's QoE. This will minimize the switching frequency of bitrate during the streaming session. Moreover, by taking into account the immediate network condition, the Input QoE also represents the service's ability and availability to adapt to user's expectation (e.g., increase user's satisfaction thanks to high network performance or recover it after undesirable events).

3.3 Bitrate Selection Algorithm

In this proposal, we apply *gradual* and *stateful* bitrate switching method [10], in which HAS player only switches up to the closest higher bitrate b_{k+1} after k chunks, but switches down to the closest lower bitrate b_{k-1} after every chunk if a decrease is necessary. According to [15], this approach can be more preferable when it comes to an extreme network condition that needs downgrading video bitrate, although abruptly switching up may result in better QoE. The selection for the next bitrate B_{i+1} is decided as follows:

$$B_{i+1} = \begin{cases} b_{k+1}, & if\ Q_{in} * p > Q_l \\ b_{k-1}, & if\ Q_{in} < Q_l * p \\ b_k, & otherwise \end{cases} \tag{2}$$

where b_k represents the current bitrate level, Q_{in} is the current *Input QoE* level, while Q_l denotes the *Predicted QoE* level at the latest bitrate switch. The parameter p is accounted for the trade-off among fairness, efficiency and stability. Through experiments, we defined the optimal value of p as 0.82 in this proposal.

After a certain number of chunks with unchanged bitrate levels, Q_l is updated to the latest *Predicted QoE* until a bitrate switch is decided. This ensures that the algorithm will be able to recover user QoE after the occurrences of undesirable events. In this work, Q_l is reassigned after 5 unchanged bitrate decisions.

QABR Algorithm

Input: $Q_p(PSNR,R,T_R)$: Predicted QoE
Q_l: Q_p of the last bitrate change
Output: B_i: Bitrate at i^{th} chunks

```
if i = 1 then
    B_i ← b_0
    Q_l ← Q_p
    return B_i
end if
Q_in ← Q_p * α
if Q_in < Q_l * p and B_{i–1} > b_0 then
    B_i ← b_{k–1}
    Q_l ← Q_p
else if Q_in * p < Q_l and count_of(b_k) > k then
    B_i ← b_{k+1}
    Q_l ← Q_p
else if count_since(Q_p) > 5 then
    Q_l ← Q_p
end if
```

4. PERFORMANCE EVALUATION

In this section, the performance of QABR will be evaluated and discussed in comparison to the baseline approach namely FESTIVE [10]. The evaluation was assessed from the simulation results conducted by NS-3, based on the criteria described in the following subsection.

4.1 Evaluation Criteria

In order to evaluate and understand the proposal in many different aspects, we defined a variety of evaluation criteria categorized in perceptual and QoS criteria.

A. Perceptual Criteria

Perception criteria show the performance that can be observed and perceived from the client side.

- ***Average Bitrate selection:*** Bitrate represents the visual quality of the streaming session, which is one of the main factors that affect user's QoE. Higher bitrate results in higher visual perception and also higher network consumption. This criterion is obtained by averaging bitrates delivered to all users within the whole streaming session.
- ***Number of rebuffering events:*** Rebuffering or stalling events deal a huge negative impact on user's perception. The study in [16] shows that more rebuffering events can lead to exponential degradation of satisfaction. It is also found in [17] that bitrate drops are more preferable than rebuffering. For this reason, it is crucial to reduce rebuffering events in order to maintain better QoE.
- ***Final QoE level:*** QoE level, ranging from 1 to 5, concludes

the impact of the above criteria on user's perception. It also shows the trade-off between preventing rebuffering events and maintaining the highest possible visual quality. Therefore, we assess the average value of all users' final QoE in order to how the quality of the streaming sessions is perceived eventually.

B. QoS Criteria

QoS criteria [10] account for the interactions among multiple players, also between them and the streaming server. A value closer to 0 indicates a higher performance. To formally describe the metrics, we denote $b_{x,i}$ as the bitrate of player x at chunk i, C is the maximum number of video chunks to be requested by a user and W is the bottleneck bandwidth shared for N players.

- ***Inefficiency:*** The inefficiency of the session is calculated as the average difference between the sum of bitrates delivered to all users and the maximum bandwidth of the server. This metric shows how the available bandwidth is utilized and whether users are experiencing the highest possible bitrates.

$$\frac{1}{C}\sum_{i=1}^{C}\frac{|\sum_x b_{x,i} - W|}{W} \quad (3)$$

- ***Unfairness:*** Unfairness accounts for the fair distribution of bitrates over all users. We define unfairness by the Jain fairness index [18] of bitrates selected for all user at each chunk.

$$\frac{1}{C}\sum_{i=1}^{C}\sqrt{1-\frac{\left(\sum_x^N b_{x,i}\right)^2}{N * \sum_x^N {b_{x,i}}^2}} \quad (4)$$

- ***Instability:*** Bitrate fluctuations or instability may be considered annoying to users, which has been investigated in many studies such as [3] and [15]. In this work, the instability metric is defined as the weighted sum of all bitrate changes within the last k = 20 chunks divided by the weighted sum of bitrates in the last k chunks.

$$\frac{1}{C}\sum_{i=1}^{C}\frac{\sum_{j=0}^{k-1}\left[\left|b_{x,i-j} - b_{x,i-j-1}\right| * (k-j)\right]}{\sum_{j=1}^{k}\left[b_{x,i-j} * (k-j)\right]} \quad (5)$$

4.2 Experimental Setup

To evaluate the proposed algorithm, a Dynamic Adaptive Streaming over HTTP (DASH) simulation was set up, along with a QoE prediction model to simulate a complete streaming system. The simulation was conducted with QABR and FESTIVE in different scenarios, whose results were then compared in order to assess the performance of the proposal.

4.2.1 QoE prediction

A QoE prediction model was deployed at each client for estimating the instantaneous QoE, which was then used for the proposed QABR and also a criterion for evaluation. The prediction model for this experiment was trained using an 80/20 split of the LIVE Netflix Video QoE database [19] with 500 epochs. The training results achieved the Linear Correlation Coefficient (LCC) of 0.878 and Spearman's Correlation (SROCC) of 0.828. Figure 2 illustrates a visual result that confirms the accuracy of the model.

4.2.2 Video Streaming Simulation

To create a lab-environment experiment, a video streaming simulation was created based on the existing DASH-NS3 project presented in [20] with trace-based data from [21]. Streaming clients continuously requested and played out 200 video segments from a DASH server, each of which the duration was 2 seconds. Video segments stored at the server were split into 10 chunks with different bitrates, denoted as representation levels ranging from 0 to 9 as shown in Table 1.

Table 1: Video bitrate denotation

Representation level	Bitrate (Kbps)
0	239
1	381
2	570
3	763
4	1069
5	1782
6	2394
7	3054
8	3916
9	4313

The simulation was set up within an Ubuntu virtual machine, with 4GB of RAM and 2 processor cores, run on a Core i7 physical machine with 8GB of RAM. Additionally, the simulation was conducted in different scenarios, shown in Table 2, in order to assess the performance of the proposal in a robust manner. Figure 3 depicts the network topology used in this simulation.

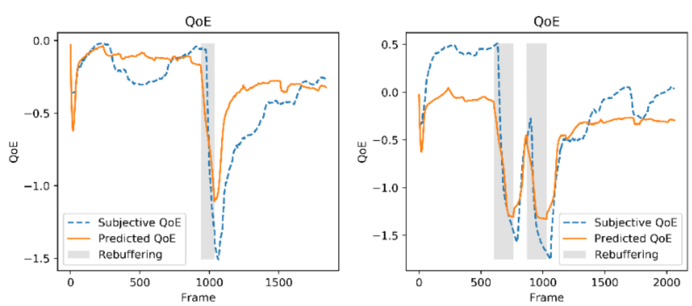

Figure 2: QoE prediction performance over the LIVE Netflix dataset within different scenarios (number of rebuffering events, rebuffering duration)

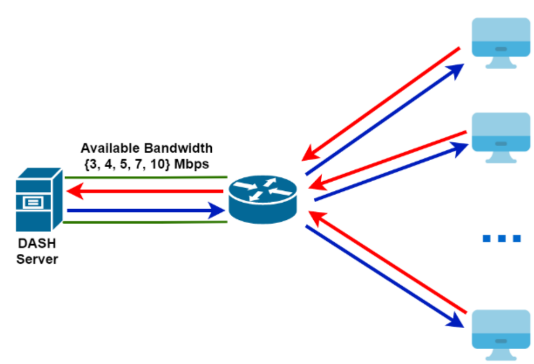

Figure 3: Simulation topology

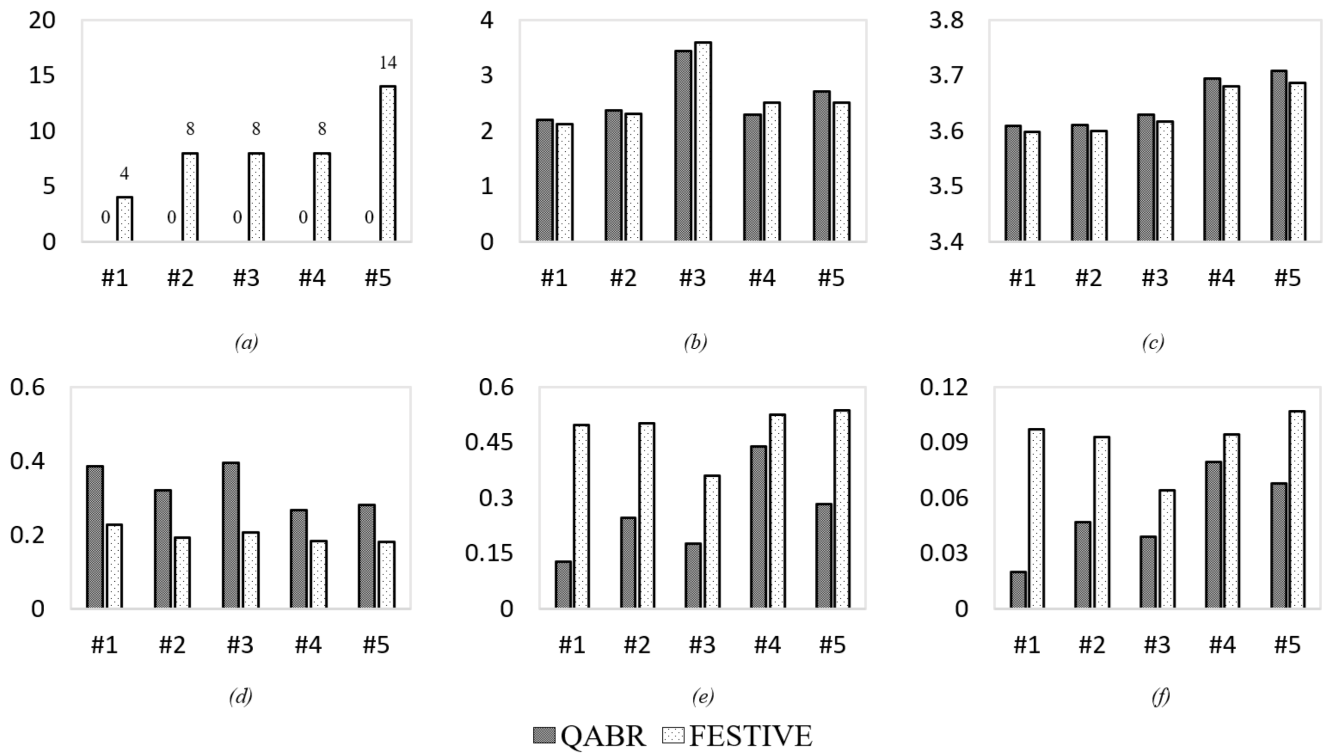

Figure 4: Comparison of overall simulation results between QABR and FESTIVE (*(a)* Number of rebuffering events; *(b)* Final QoE; *(c)* Bitrate selection; *(d)* Inefficiency; *(e)* Unfairness; *(f)* Instability)

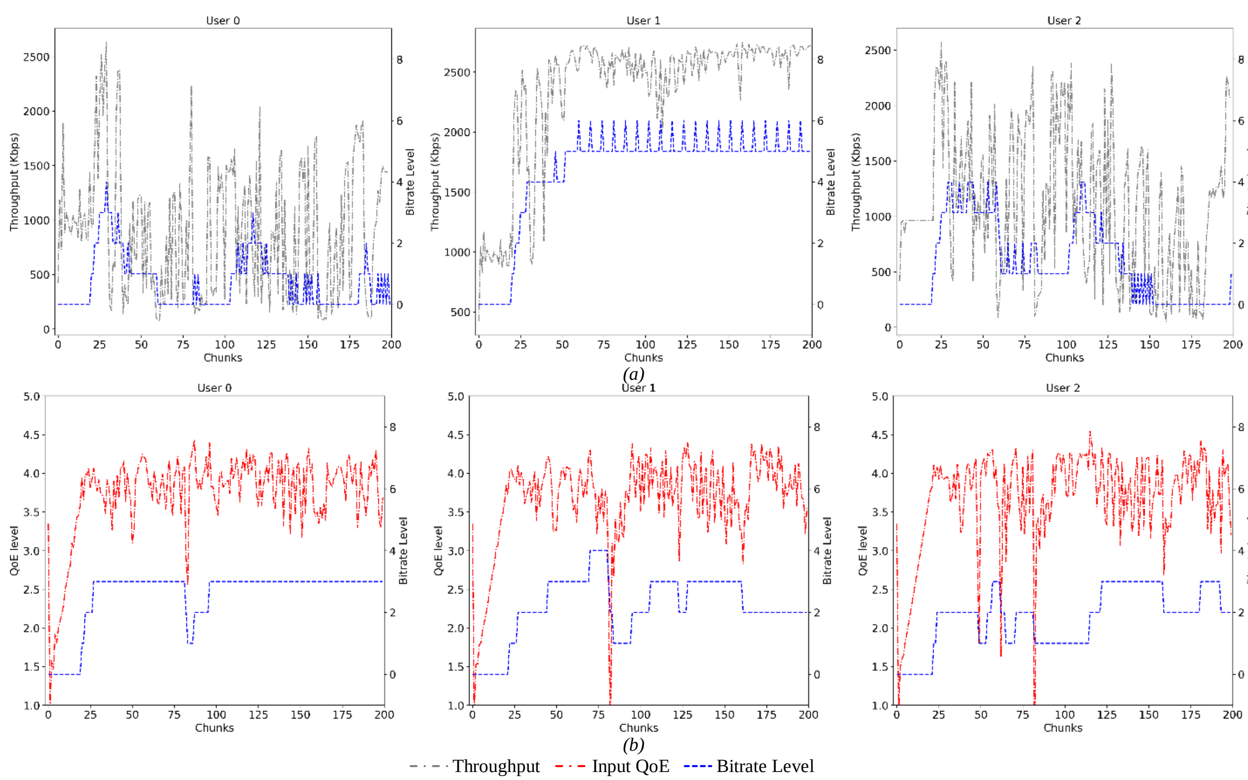

Figure 5: Time-varying bitrate selection visuallization of scenario #1(*(a*)FESTIVE; *(b)* QABR)

Table 2: Experiment scenarios

Scenario	**#1**	**#2**	**#3**	**#4**	**#5**
Bandwidth (Mbps)	3	4	5	7	10
Number of clients	3	4	3	7	10

4.3 Results and Discussion

This subsection discusses the results assessed from the above simulation. The overall results of the simulation are depicted in

Fig. 4, while Fig. 5 shows a time series comparison between bitrates chosen by the two algorithms in scenario #1.

According to Fig. 4a, there is no rebuffering events occurred across all scenarios when using QABR, implying that our proposal is far responsive to network condition in comparison with FESTIVE. This make sense intuitively since our weighted value α takes into account the immediate throughput and buffer condition, rather than the smoothed value of throughput within the last 20-downloaded chunks as in FESTIVE. Therefore, the proposed algorithm can perform earlier decisions to avoid such undesirable events happening.

The weighted value, along with the use of QoE, also contributes to the improvement of visual quality. Bitrates chosen by our proposal are also higher in most scenarios as shown in Fig. 4b. FESTIVE only monitors client's throughput to decide bitrates. In such situations where throughput fluctuates strongly, its smoothing function is too conservative in maintaining stability that it refuses to switch to a higher quality. In contrast, α effectively balances the discrete nature of the underlying network status and the instantaneous perception of users. For that reason, QABR is more decisive to quality switches.

As a result, the overall final QoE of QABR's users outperforms the baseline method (Fig. 4c). The obtained results will be further analyzed and discussed in accordance with inefficiency, fairness and instability within the rest parts of this section.

Despite the ability to delivered higher average bitrate level, Fig. 4d shows that QABR does not effectively utilize the network bandwidth; users are able to request higher bitrates. We speculate this as the trade-off for maintaining a fair, uninterrupted streaming session with high visual quality and perception. The solution to a more efficient utilization of bottleneck bandwidth will be considered in future works.

The results in Fig. 4e also show that, across all scenarios, QABR is able to deliver contents in a fairer manner than FESTIVE. The time-varying graphs in Fig. 5 visually confirms this improvement. It can be seen in Fig. 5a that, when using FESTIVE, user 1 repeatedly consumes a high allocation of the bottleneck bandwidth. On contrary, QABR (Fig. 5b) distributes video bitrates more evenly and users could experience the streaming service with approximately equal qualities.

Additionally, the switching frequency of bitrate is reduced by QABR, providing a more stable streaming session compared to FESTIVE. This has repeatedly proven the effectiveness of our dynamic weighted value in combining and balancing the continuous characteristics of QoE and the discrete nature of HAS systems.

5. CONCLUSION

In this paper, a QoE-based adaptive bitrate selection algorithm – the QABR – is proposed. QABR takes a step forward for utilizing instantaneous subjective QoE for bitrate selection under a multi-user scenario. The algorithm effectively combines and balances the continuous characteristics of QoE and the discrete nature of underlying network parameters by the weighted value α. Therefore, the slow-responsiveness and the high frequency of quality switches in throughput and buffer-based approaches are overcomes. Through the evaluation, it was revealed that QABR outperformed the referenced FESTIVE algorithm by effectively prevented re-buffering events and maintained higher delivered video bitrates, leading to higher user's QoE. Moreover, the proposal also succeeded in delivering contents in a more fair and stable manner. This has repeatedly confirmed the superior performance of QABR, proving that QoE-based approach to ABR is feasible and necessary for future innovations of video streaming technologies. However, at the current state of our work, QABR is deployed at the client side, which is inappropriate since the training for QoE prediction requires huge computational power. Future research can utilize this approach at the server side for a more efficient power consumption.

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