Perceptual QoE-Optimal Resource Allocation for Adaptive Video Streaming

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***Abstract*—Video streaming in mobile environments has always been challenging due to various factors. The time-varying wireless channel, limited and shared transmission resources, fluctuating network conditions between the video server and the end user etc. greatly affect the timely delivery of videos. Given these factors, it is important that the wireless networks perform optimal allocation of resources and cater to the demands of the video streaming users without degrading their quality-of-experience (QoE). Modeling streaming QoE as perceived subjectively by the users is non-trivial, and in general a complex task, as it is continuous, dynamic, and time-varying in nature. The continuous perceptual QoE degradation due to network induced artifacts such as time-varying video quality and rebuffering events has not been considered in the literature for resource allocation (RA). In this paper, we propose Video Quality Aware Resource Allocation (ViQARA), a perceptual QoE based RA algorithm for video streaming in cellular networks. ViQARA leverages the strength of the latest continuous QoE models and integrates it with the generalized α-fair strategy for RA. Through extensive simulations, we demonstrate that ViQARA can provide significant improvement in the users perceptual QoE as well as a remarkable reduction in the number of rebufferings when compared to existing throughput based RA methods. The proposed algorithm is also shown to provide better QoE optimization of the available resources in general, and especially so when the cellular network is resource constrained and/or experiences large packet delays.**

***Index Terms*—α-fairness, DASH, machine learning, NARX, QoE, rebuffering, resource allocation, SVR, time-varying quality, video streaming.**

I. Introduction

DUE TO the proliferation of mobile devices, mobile data traffic has grown exponentially over the last few years. According to Cisco's Visual Networking Index [1], the global mobile traffic accounted for 63% of the total data traffic in 2016. Of this, videos constituted 60% of the traffic and it is estimated that more than three-fourth of the world's mobile data traffic will be constituted by videos by 2021. Such a dramatic increase in the video traffic will cause a bottleneck for content delivery networks, especially in the last hop of mobile data networks where the users are connected via wireless links.

Unlike data transmission such as file transfer, video streaming is a delay-sensitive application. Video streaming in wireless networks is challenging due to the time-varying nature of the wireless channel. This is further fueled by the increasing number of users in the network as well as the limited resources that are to be shared amongst these users. Resource sharing is a critical task when a large number of video users demanding higher data rates need to be served using limited network resources. In addition, congested traffic conditions in the network between the video server and the base station termed as eNodeB in case of Long Term Evolution (LTE) networks can result in delayed packet arrivals for the video users, thereby affecting their playback conditions. In order to alleviate these problems, Hypertext Transfer Protocol (HTTP) based adaptive streaming frameworks such as Dynamic Adaptive Streaming over HTTP (DASH) provide flexibility by allowing their clients to adapt across different video bitrates based on the time-varying network and channel conditions [2]. Though this rate adaptation tries to achieve seamless streaming with uninterrupted playback, it often results in a video quality that keeps varying with time [3], [4]. Furthermore, the delay in the video packet arrival causes the playback to stall resulting in rebuffering events. Time-varying video quality and rebuffering events significantly affect the playback conditions in adaptive streaming leading to a degradation in the user's quality-of-experience (QoE) [4], [5].

Understanding the QoE dynamics is important in order to minimize the factors causing QoE degradations. Most QoE models existing in the literature rely on the network-level heuristics based on throughput, buffer-level etc. to quantify the QoE [6]. A few other QoE models that predict the mean opinion scores (MOS), do so at the end of the video session and not in a continuous time fashion [3], [7]. Such prediction models are not useful for real time QoE monitoring and optimization of resources in cellular networks. The continuous QoE prediction of video users in real time could be helpful in minimizing playback interruptions and facilitate optimized resource management for enhanced video delivery. Due to this, continuous QoE assessment as perceived subjectively by the

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video users (perceptual QoE) has gained a lot of attention in recent times. However, the continuous QoE assessment in response to the dynamically occurring QoE influencing events is a challenging problem. The problem has been addressed in some of the recent works such as [4], [8], [9], and is currently an active topic of research. Works such as [10], [11] have studied the problem of understanding the relationship between the continuous QoE and their influencing factors. Specifically, they consider the joint modeling of QoE with two major influencing factors: 1) rebuffering (playback stalls) and 2) time-varying quality. Given that the relationship between the users' QoE and their influencing factors is complex [12], QoE predictive models based on machine learning (ML) techniques have been proposed in [10] and [11]. Specifically, in [10], a QoE prediction model based on a nonlinear autoregressive neural network (NARX-QoE) has been proposed. NARX-QoE uses a neural network for predicting the QoE in a continuous manner in response to the influencing events captured through carefully selected features. Similarly, in [11], SVR-QoE, a support vector regression (SVR) based system for QoE prediction has been presented. It has been demonstrated through an evaluation over continuous QoE databases that these ML models are capable of effectively capturing the complex relationships involved in the QoE, and hence, can provide effective objective evaluation of the continuous QoE [10], [11].

Using continuous QoE predictive models, it is possible to optimize the allocation of network resources such that the video users' QoE is optimized despite network fluctuations. Such a carefully designed resource allocation algorithm will be helpful in enhancing the QoE levels of the video streaming users in real time. In this regard, we make the following contributions in the paper:

1. We investigate the utility of ML based perceptual QoE models for monitoring the continuous QoE of the video streaming users in cellular networks. We rely on the DASH based server-client streaming model.
2. We propose Video Quality-of-experience Aware Resource Allocation (ViQARA), a novel QoE based resource allocation algorithm for performing the optimal utilization of OFDM resource blocks (subchannels) in cellular networks. We employ two QoE prediction models for ViQARA, namely, NARX-QoE [10] and SVR-QoE [11] and perform an extensive evaluation of the proposed algorithm.
3. We consider the generalized α-fairness in the proposed algorithm for allocating resources to the users [13], [14]. We evaluate the allocation under various fairness criteria and discuss its utility in each case. We show that the proposed QoE aware resource allocation (RA) algorithm can provide a significant improvement in the overall QoE of the users in the network in comparison with the conventional throughput based α-fair RA strategies, particularly under resource-constrained settings. To the best of our knowledge, this is the first work that explicitly studies continuous perceptual QoE models for resource allocation in cellular networks for providing QoE optimized video streaming.

The rest of the paper is organized as follows. Section II gives a brief overview of the existing continuous QoE modeling approaches. The DASH streaming setup in cellular network and the continuous QoE model employed for performing QoE based resource allocation is discussed in Section III. Section IV presents the proposed resource allocation algorithm ViQARA. Performance evaluation and analysis of the proposed method is detailed in Section V. Finally, Section VI provides the concluding remarks.

II. Related Work

Enhancing the user's QoE has gained a lot of attention in a variety of over-the-top (OTT) multimedia services in the recent times. This is primarily because higher user QoEs have been shown to translate to better revenues for service providers [15]. Maintaining an 'acceptable' user QoE is of paramount importance for content providers such as Netflix, YouTube, Hulu etc. However, providing higher QoE and maintaining it throughout the streaming session is challenging as the end-to-end network conditions are time-varying. Hence, there is a need for QoE based service provisioning and network design for video delivery [6]. Several works propose methodologies and provide guidelines for the QoE based design of networks for multimedia streaming and services [6], [16]–[22]. However, most of these works employ network-level quality-of-service (QoS) metrics such as average throughput, average packet delay etc. for quantifying the QoE. Based on the IQX hypothesis [23], the QoE is calculated in terms of QoS parameters using a model that describes an exponential relation between the QoS and the QoE. The work in [7] provides a nonlinear formula to map the QoS metrics such as bitrate, frame rate, and packet loss rate to estimate MOS (QoE). A survey of QoE considerations for adaptive streaming and guidelines for rate adaptation based on prior works is presented in [24]. In [25], a subjective study has been conducted to identify the impact of adaptation parameters on QoE. QDASH, a QoE-aware DASH system has been proposed in [26] to improve the user-perceived video quality and highlight that the users prefer gradual quality changes over abrupt switchings. In [27], an adaptive Q-Learning based streaming client that dynamically learns the optimal behavior has been proposed. Using the perceived quality model in [27], a rate adaptation solution using stochastic dynamic programming has been proposed in [28]. In [29], a QoE based rate adaptation solution for variable bitrate videos has been proposed by exploiting the bitrates of segments in the future time instants. In all of these works, the measurement of QoE relies on the client-level quality-of-service (QoS) attributes such as the bitrate, frame freezes, and representation switches. However, the user perceived QoE has not been considered in any of these works.

Content agnostic video delivery has been shown to provide sub-optimal performance both in terms of the user QoE as well as resource utilization in wireless networks [18]. Network controllers such as eNodeB in cellular networks can provide enhanced video delivery for its DASH users, as it has better knowledge of the load and radio conditions in the cell as well as the QoE information of its users. In [18], a QoE based video rate adaptation method has also been proposed using a proxy at the base station. It has been shown that additional gains in the perceived video quality can be obtained

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using the QoE based proxy approach for redirecting the HTTP client requests. In [19], a framework for QoE provisioning in wireless networks has been presented using network utility maximization. In this framework, the utility based QoS mechanisms are extended to incorporate the QoE, wherein, the users are allowed to dynamically express their satisfaction with respect to their service quality. In [20], a QoE evaluation methodology that involves the notion of rebuffering outage capacity to quantify the video service quality has been considered and subsequently resource management for enhancing the QoE has been performed. Several QoE-centric adaptive bitrate algorithms have been proposed in the literature [30]–[39]. However, these algorithms suffer from limited dynamic range, i.e., they do not perform uniformly well across the range of network conditions seen in practice [39]. Although these algorithms aim at maximizing the QoE by reducing the QoE degrading influences such as low average bitrate, rate of occurrence of rebuffering events, rapid bitrate switchings, startup delay etc., they do not incorporate the perceptual aspects involved in the QoE process such as the video quality and memory effects. Relying on such non-perceptual QoE based measures have been shown to be sub-optimal in various subjective studies [4], [8], [11], [40]. For instance, it is shown in [4] that modeling the time-varying quality (TVQ) resulting from rate adaptation involves incorporating cognitive aspects of the human visual perception such as hysteresis effects, memory etc. and therefore, the TVQ cannot be measured using any of the network-level heuristics and QoS based metrics.

In [41], a QoE prediction model for multipath video streaming over heterogeneous wireless access networks has been presented and subsequently, rate allocation has been performed. However, this work does not consider the case of adaptive streaming where playback stalls constitute a major QoE influencing factor. A comparison of HTTP based progressive download and adaptive streaming with potential metrics for QoE evaluation in HTTP adaptive streaming has been provided in [6]. However, these metrics are based on the client/network level parameters such as throughput and buffer status. None of these metrics consider the QoE as perceived subjectively by the video users. The problem of optimal content cache management for HTTP adaptive streaming has been investigated in [22] and a logarithmic model for computing the QoE from the streaming rates has been employed. The QoE in this model is determined by two parameters: the required playback video rate and the actual playback rate. However, the impact of other QoE influencing factors such as playback stalls (rebuffering) have not been considered.

A QoE based optimization framework for resource allocation in LTE has been proposed in [42]. The method in [42] involves maximizing the user-perceived quality based on MOS. However, MOS is insufficient for measuring continuous QoE which is dynamic in nature. Moreover, MOS is measured using the Video Structural Similarity (VSSIM) Index [43], which is essentially a video quality assessment (VQA) metric. VQA metrics have been shown to be inefficient and suboptimal for quantifying the QoE in several works [4], [8], [11]. In [44], a quality-fair adaptive streaming solution has been proposed to deliver fair video quality. The proposed solution is shown to optimize shared resources in a LTE network according to video content characteristics, playout-buffer, and channel conditions. It has also been shown to achieve asymptotically fair playout buffer levels among DASH clients with the help of an additional media aware network element. D-DASH, a framework that combines deep learning and reinforcement learning techniques for optimizing the QoE in DASH has been designed in [45]. However, in both [44] and [45], Structural Similarity (SSIM) Index [46], an image quality assessment (IQA) metric is considered for quantifying the QoE. While the IQA metrics measure the video's spatial quality, they are inadequate for evaluating the spatio-temporal quality of the videos [47].

In summary, we identify the following limitations in the prior works:

1. Most QoE based video delivery solutions still rely on the network-level QoS parameters such as delay, throughput, or client-level parameters such as video bitrate, buffer status as proxies for QoE. It has been reported in subjective studies [4], [8], [48] that the QoE predictions based on QoS attributes do not correlate well with the human visual perception. Moreover, the subjective QoE involves memory effects that cannot be captured using any of these QoS measures. None of the solutions so far have addressed this limitation.
2. Although a few QoE models consider MOS as a proxy for QoE, they evaluate the overall QoE rather than the continuous and time-varying QoE. A single QoE score at the end of a video session does not help in the real time QoE optimization of the users. Rather, a continuous QoE evaluation will be useful for real-time monitoring and resource optimization as the QoE in DASH is time-varying in nature.
3. The video-aware delivery solutions proposed so far do not consider the perceptual QoE. The QoE measurements considered so far have employed metrics such as peak signal-to-noise ratio, SSIM [46] and so on. However, these metrics are basically either IQA or VQA metrics, and can measure only the instantaneous spatial quality or short-term spatio-temporal quality of the video that is currently being rendered to the user. They are not capable of capturing the memory effects involved in the user QoE, and hence, cannot estimate the time-varying perceptual QoE [4], [8]. Therefore, there is a need for video delivery solutions that rely on continuous perceptual QoE evaluation models.

These limitations motivate us to investigate the utility and effectiveness of continuous perceptual QoE models for video streaming in cellular networks and perform QoE based resource optimization for the users. To the best of our knowledge, there are no solutions in the literature that incorporate the continuous time perceptual QoE for video delivery. Therefore, in this work, we propose Video Quality-of-experience Aware Resource Allocation (ViQARA), a QoE based resource allocation algorithm using the continuous QoE models presented in [10] and [11]. We investigate the performance of the proposed algorithm and demonstrate its effectiveness in comparison with the throughput based resource allocation

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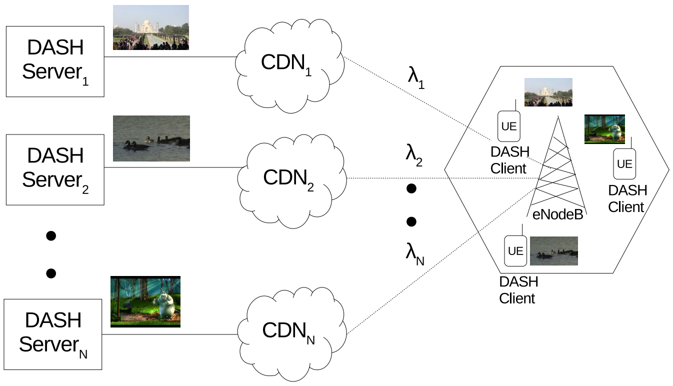

Fig. 1. DASH system for video transmission in a cellular network.

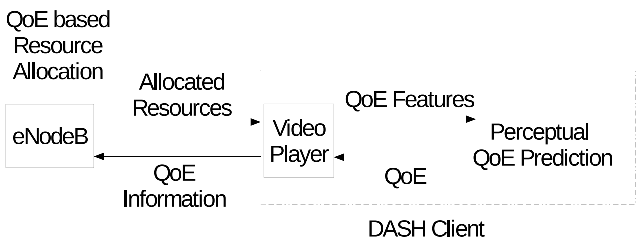

Fig. 2. QoE based resource allocation for DASH clients in a cellular network.

algorithms. We show that the QoE-optimal resource allocation can provide significant improvements in the QoE, particularly under resource constrained settings. In the next section, we describe the cellular network setup and the QoE evaluation models for video streaming.

III. System Model and Evaluation

We consider DASH based video streaming setup in a cellular network as depicted in Fig. 1 for evaluating the proposed QoE based resource allocation (RA) algorithm. We consider an OFDMA based network with a macro eNodeB serving multiple DASH clients (video users) in the downlink. We assume that the video users are distributed randomly in the coverage area of the eNodeB. The video from the server is delivered to the user through the content delivery networks (CDNs). We model the packet arrival at eNodeB as a Poisson point process [49], [50]. Thus, the inter-arrival times between the video packet arrivals at eNodeB follows the exponential distribution [51].

Fig. 2 shows the system for performing QoE prediction and facilitate resource allocation. We assume that the QoE prediction system is embedded in the DASH client for QoE computation. The prediction system extracts the necessary QoE features based on the client's playback status and evaluates the QoE. We also assume that the evaluated QoE information is periodically shared with the eNodeB via uplink for facilitating QoE based resource allocation. In this work, we consider two learning based continuous perceptual QoE models for performing QoE based resource allocation, namely SVR-QoE [11] and NARX-QoE [10]. We use these models for resource allocation given their excellent QoE prediction performance. Further, they are capable of providing dynamic QoE prediction continuously in real time throughout the streaming session of the user. The QoE information at eNodeB allows the resource allocator to monitor and facilitate QoE optimization for all the video users in its network.

In the DASH framework, the videos are encoded at different bitrates and resolutions that constitute multiple representations at the server [2]. Videos in each representation are broken down into small duration chunks called segments. Video segmentation provides the flexibility to the client to adapt across different representations in accordance with the changing channel conditions. However, rate adaptation results in time-varying video quality (TVQ) affecting the perceptual QoE [4]. In order to evaluate the QoE degradation due to TVQ, it is required to measure the instantaneous quality of the video segments, referred to as short time subjective quality (STSQ) [4]. STSQs can be computed using any of the video quality assessment (VQA) methods such as STRRED [47], MS-SSIM [52], VMAF [53] etc. The STSQs can be computed offline and can be supplied through the media presentation document of DASH to facilitate QoE computation at the client. Further, in HTTP streaming, the media segments are carried over CDNs through Transmission Control Protocol/Internet Protocol (TCP/IP). Since TCP is a reliable transmission protocol, the packets are re-transmitted whenever they are not delivered to the client due to packet loss or packet drop. These re-transmissions coupled with jitter in the network can result in delayed packet arrivals leading to rebuffering events at the client. The rebuffering events cause severe degradation in the QoE by distorting the temporal structure of the video [5], [8], [11]. Hence, in the proposed RA algorithm, we evaluate the effects of both TVQ as well as rebuffering, jointly, on QoE degradation using the perceptual QoE prediction system. In the next subsection, we discuss the significance of various VQA algorithms for measuring the STSQ.

A. Video Quality Assessment (VQA)

Video quality plays a crucial role in QoE estimation. We employ VQA metrics for evaluating the STSQ of the video segments in DASH. The video quality, in general, is determined by various factors such as resolution, amount of motion, content type etc. of the video. VQA is classified into three categories depending on the availability of the reference video: 1) full-reference (FR), 2) reduced-reference (RR), and 3) no-reference (NR). In this work, we employ STRRED [47], a reduced-reference VQA metric for STSQ evaluation as it is widely used for evaluations in previous works and is shown to provide excellent VQA prediction performance [54]. Any other efficient VQA metric (irrespective of FR/RR/NR) can also be employed for STSQ computation. In the context of video streaming, the STSQ is predominantly determined by the encoding rate as encoding artifacts is the key factor affecting the video quality [4].

Let $f^{VQ}(\cdot)$ represent the function that computes the quality of the video segments, i.e., $f^{VQ}(\cdot)$ takes the video frames constituting a video segment as the input and estimates the video segment quality (STSQ). Let the video to be streamed

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be encoded at J different bitrates, leading to J video representations. Let each representation (rep) be denoted by the index $j = 1, 2, \ldots, J$. Let $V^r_{j,k}$ denote the bitrate of the j^{th} rep and the k^{th} segment in terms of kilo-bits-per-second (kbps). Since the STSQ of the segments is determined primarily by their encoding bitrates, we have STSQ as a function of the bitrates. Thus, $STSQ_{j,k}$ is related to $V^r_{j,k}$ through the function $f^{VQ}(\cdot)$ as follows:

$$q_{j,k} = STSQ_{j,k} = f^{VQ}\left(V^r_{j,k}\right),$$

where, $q_{j,k}$ represents the STSQ of the k^{th} segment in the j^{th} video representation.

B. QoE Estimation

Given that the continuous QoE is determined by the time-varying quality and rebuffering, we employ a set of QoE features that capture the influences of these events on the QoE. Let $\mathbf{Q}_f$ represent the QoE input feature vector and $f^{QoE}(\cdot)$ represent the continuous QoE prediction function that maps $\mathbf{Q}_f$ to the QoE Q. Next, we setup the notations for the two continuous QoE prediction models employed in the proposed RA algorithm: 1) SVR-QoE [11] and 2) NARX-QoE [10] in the following subsections.

C. SVR-QoE

In the SVR-QoE model, the QoE is modeled in two states, namely the playback state and the rebuffering state. Let $\mathbf{Q}_f$ be constituted by two sets: $\mathbf{Q}^{pb}_f$, the set of QoE input features for prediction in the playback state and $\mathbf{Q}^{rebuf}_f$, the set of QoE input features for prediction in the rebuffering state. At any given time instant t, $\mathbf{Q}^{pb}_f(t)$ includes the current STSQ and the previous QoE as the QoE input features, i.e., $STSQ\ (t)$ and $Q(t{-}1)$.

In the playback state, the continuous QoE of the users is observed to be a smoother process when compared to the variations in the channel and the STSQ [4], [11]. The user QoE is observed to vary relatively slower despite rapid bitrate switchings due to rate adaptation. The QoE prediction during the playback state in the SVR-QoE model is performed using a support vector regression (SVR) function denoted by $f^{QoE}_{SVR}(\cdot)$, which is trained on the subjective QoE data in the LFOVIA QoE Database [11]. The predicted QoE in the playback state at any time instant t denoted by $Q^{pb}(t)$, can be written as follows:

$$Q^{pb}(t) = f^{QoE}\left(\mathbf{Q}^{pb}_f(t)\right) = f^{QoE}_{SVR}(STSQ(t), Q(t-1)). \quad (1)$$

In the rebuffering state, the QoE input feature set $\mathbf{Q}^{rebuf}_f(t)$ at time t includes the pre-rebuffering QoE denoted by Q_{PrB}. Using Q_{PrB}, the QoE prediction is performed using an exponential QoE depreciation (EQD) function denoted by $f^{QoE}_{EQD}(\cdot)$, as follows:

$$Q^{rebuf}(t) = f^{QoE}_{EQD}\left(Q_{PrB}, t_{rebuf}\right) = e^{-\gamma t_{rebuf}} Q_{PrB}, \quad (2)$$

where, t_{rebuf} is the rebuffering time tracker that keeps track of the time elapsed since the last rebuffering event. The QoE depreciation factor γ is determined using the input feature Q_{PrB} based on a linear relation as described in [11]. Further, it is observed that a higher pre-rebuffering QoE results in a higher γ, and hence, greater depreciation in the QoE [11]. This is because whenever there is a rebuffering event with a high pre-rebuffering QoE, it implies that the QoE expectations of the users are higher and therefore, it results in greater dissatisfaction as compared to the case where the pre-rebuffering QoE is lower.

Based on (1) and (2), we now comprehensively represent the predicted QoE $Q(t)$ combining the prediction in both the states as follows:

$$Q(t) = PI \cdot Q^{pb}(t) + (1 - PI) \cdot Q^{rebuf}(t), \quad (3)$$

where, PI is the playback indicator variable which takes a value of 1 in the playback state and 0 otherwise. It should be noted in (3) that while the QoE computation appears to be independent across the two states, they are in fact dependent. The QoE computation in the rebuffering state depends on Q_{PrB} of the playback state prior to rebuffering. Similarly, the QoE in the playback state after a rebuffering event depends on the last depreciated QoE in the rebuffering state. Hence, the QoE predictions in the two states are interdependent. We next discuss the NARX-QoE model presented in [10].

D. NARX-QoE Model

We also investigate the efficacy of the NARX-QoE model proposed in [10] for evaluating the performance of ViQARA. The QoE estimation in the NARX-QoE model uses the following three features: 1) STSQ, 2) Rebuffering Indicator (RI), and 3) Time elapsed since last impairment (TSL). RI is a continuous binary variable which indicates whether the client is currently experiencing rebuffering or not. TSL tracks the bitrate changes and the occurrence of rebuffering events. The QoE at time instant t, $Q(t)$ is computed as,

$$\begin{aligned} Q(t) = f^{QoE}_{NARX}\big(&\mathbf{Q}_f(t), \mathbf{Q}_f(t-1), \mathbf{Q}_f(t-2), \ldots, \mathbf{Q}_f\left(t-d_f\right), \\ &\times Q(t-1), Q(t-2), \ldots, Q\left(t-d_q\right)\big), \end{aligned}$$

where, $f^{QoE}_{NARX}(\cdot)$ is the nonlinear autoregressive neural network function for QoE prediction [10], $\mathbf{Q}_f(t)$ is given by $[STSQ(t), RI(t), TSL(t))]$. The quantities d_f and d_q represent the number of lags in the input and the external variables, respectively. We set $d_f = d_q = 15$ as employed in [10]. The parameters used in the function $f^{QoE}_{NARX}(\cdot)$ are based on training a neural network on the subjective QoE data in the LFOVIA QoE Database [11].

It should be noted that the functions $f^{QoE}_{SVR}(\cdot)$ and $f^{QoE}_{NARX}(\cdot)$ are obtained through an offline training procedure over the subjective QoE data as explained in [11] and [10], respectively. The training process could be computationally intensive, and hence, it is performed offline. However, once the model is trained, the QoE prediction is computationally simple and inexpensive given the available hardware resources in mobile devices, thus making it suitable for deployment in practice. Therefore, the QoE models can be conveniently integrated into the DASH client as illustrated in Fig. 2, enabling QoE computation in real time.

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In the next section, we present the proposed resource allocation algorithm.

IV. The Proposed Algorithm – ViQARA

In this section, we present the QoE based resource allocation algorithm for DASH clients. We define the following quantities to help formulate the QoE optimization:

1. *Cumulative Average QoE* ($\overline{Q}(t)$) at any time instant t is computed as

$$\overline{Q}(t) = \frac{1}{t}\sum_{\tau=1}^{t} Q(\tau). \tag{4}$$

   Here, $\overline{Q}(t)$ refers to the cumulative mean of the QoE scores until time t and $Q(\tau)$ is the QoE at time τ. The continuous QoE computation begins as soon as the playback is started.

2. *Average Throughput* ($\overline{R}(t)$) at any time instant t is defined as

$$\overline{R}(t) = \frac{1}{W}\sum_{\tau=t-W+1}^{t} R(\tau), \tag{5}$$

   where, $R(\tau)$ refers to the data rate at time instant τ. $\overline{R}(t)$ essentially refers to the download rates averaged over past W time slots [55], [56].

3. We also define *per-subchannel throughput* denoted by $r^{th}(t)$ as

$$r^{th}(t) = \frac{1}{W}\sum_{\tau=t-W+1}^{t} \frac{R(\tau)}{\overline{s}(t)},$$

   where, $\overline{s}(t)$ refers to the average number of allocated resources (subchannels) in the past W time slots prior to the current time slot t. It is given by

$$\overline{s}(t) = \frac{1}{W}\sum_{\tau=t-W+1}^{t} s(\tau),$$

   where, $s(\tau)$ is the number of allocated resources at time τ.

We next explain the α-fair resource allocation strategy.

A. Resource Allocation (RA)

We consider the resource allocation performed by eNodeB in a centralized manner in an OFDM-based macro cell. The resources are available in the form of OFDM resource blocks, which we refer to as subchannels. The eNodeB serves its users by allocating these subchannels in a dynamic fashion. Broadly, most approaches address the problem of RA in wireless networks by considering the user data rate requirements as well as the fairness between the users. Hence, in this work, we employ the generalized α-fairness for allocating resources to the video users [14], [57].

Let S represent the number of subchannels available for allocation to N video users in the macro cell. Let $U_\alpha(q)$ represent a class of functions as defined in the following.

$$U_\alpha(q) = \begin{cases} \frac{h(q)^{1-\alpha}}{1-\alpha}; & \text{if } \alpha \neq 1 \\ \log\, h(q); & \text{if } \alpha = 1. \end{cases}$$

where, $h(q)$ is a concave function in q in the range $[0, \infty)$ [57]. As a result, $U_\alpha(q)$ is also a concave function in q. We investigate the α-fair resource allocation method based on the user throughput as defined in (5), referred to as throughput-RA. Using the function $U_\alpha(q)$, we also propose ViQARA, a QoE based RA for video users. Since the RA is based on α-fairness, we have the following RA strategies:

1. *α-fair throughput:* We define the α-fair throughput objective function $U_\alpha(r_i^{th}) = h^{th}(r_i^{th})$ corresponding to the i^{th} user as a function of the per-subchannel throughput r_i^{th}. The α-fair throughput based optimization for resource allocation is performed every time slot t and is stated as follows:

$$\begin{aligned} \underset{s_i, \forall i}{\text{maximize}} \quad & \sum_{i=1}^{N} \frac{h^{th}\big(r_i^{th}(t)\big)^{1-\alpha}}{1-\alpha} \\ \text{subject to} \quad & \sum_{i=1}^{N} s_i(t) \leq S, \\ & s_i(t) \geq 0 \text{ integer.} \end{aligned} \tag{6}$$

   Here, the optimization is performed over the subchannels $s_i, \forall i = 1, 2, \ldots, N$. The constraints indicate that the allocated subchannels are non-negative integers and the sum total of allocated subchannels is less than or equal to the total available subchannels S. Further, we investigate an objective function for $h^{th}(\cdot)$ such that the subchannels $s_i(t)$ allocated to the user i at time t constitute the weights of the per-subchannel throughput $r_i^{th}(t)$ as follows:

$$h^{th}\Big(r_i^{th}(t)\Big) = r_i^{th}(t) s_i(t). \tag{7}$$

2. *α-fair QoE:* We propose ViQARA, an α-fair QoE based resource allocation method for video users. We define α-fair QoE objective function $U_\alpha(Q_i) = h^{QoE}(Q_i)$ corresponding to the i^{th} user for allocating the resources as a function of the QoE Q_i. The α-fair QoE based optimization for resource allocation is formulated as follows:

$$\begin{aligned} \underset{s_i, \forall i}{\text{maximize}} \quad & \sum_{i=1}^{N} \frac{h^{QoE}(Q_i(t))^{1-\alpha}}{1-\alpha} \\ \text{subject to} \quad & \sum_{i=1}^{N} s_i(t) \leq S, \\ & s_i(t) \geq 0 \text{ integer.} \end{aligned} \tag{8}$$

   Here, $Q_i(t)$ refers to the QoE of the user i at time t. It should be noted that the constraints in (8) are the same as those in (6). Similar to (7), we define the α-fair QoE objective function $h^{QoE}(\cdot)$ as follows:

$$h^{QoE}(Q_i(t)) = Q_i(t) s_i(t). \tag{9}$$

   The solution $s_i(t)$ allocated to the user i at time t, $\forall i = 1, 2, \ldots, N$ constitutes the weight vector for the current QoE $Q_i(t)$ in the objective function.

Note that the optimizations defined in (6) and (8) are online in nature, and hence, are computed dynamically at every time slot t. Further, we would like to note that the generalized

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α-fairness based objective functions employed in both these methods encompass a variety of fairness criteria for resource allocation among the users. For instance, while the allocation with $\alpha = 1$ corresponds to proportional fairness, $\alpha = 2$ corresponds to minimum delay potential fairness. $\alpha = \infty$ results in max-min fair allocation [13], [58]. Thus, this gives the flexibility to the network operator to choose an appropriate value of α of choice for different objective functions.

The resource allocation is performed dynamically by solving the optimizations in (6) and (8) corresponding to the methods throughput-RA and ViQARA, respectively. The data rate seen by the user i in the time slot t will be $s_i(t)r_i(t)$, where $s_i(t)$ is the number of subchannels allocated to the i^{th} user. Note that the optimizations in (6) and (8) are essentially integer programming problems due to the discrete nature of the variables s_i, $\forall i = 1, 2, \ldots, N$. However, in order to find the optimal allocation analytically, we relax the integer constraint and let the optimization variable s_i to take continuous values in the range [0, S]. Then, the optimal $s_i, \forall i$ can be obtained using the result as stated in the following Lemma [57]:

Lemma 1: For the generalized α-fair resource allocation method as defined in (6) and (8), if the function $h(x_i)$ is a linear function of x_i for user i, i.e., $h(x_i) = s_i \cdot x_i$, with x_i weighted by the optimization variable s_i as defined in (7) and (9), then the optimal allocation $s_i^*, \forall i$ is given by $s_i^* = \frac{x_i^{\frac{1-\alpha}{\alpha}}}{\sum_{i=1}^{N} x_i^{\frac{1-\alpha}{\alpha}}}$.

Proof: See the Appendix. ■

Since the optimal subchannel allocation s_i^* is continuous, we apply the floor operation on $s_i^*, \ \forall i = 1, 2, \ldots, N$ to map it back to the discrete integer space. Any residual subchannels after mapping is allocated to the user having the least playback buffer content. This strategy is employed in order to minimize the occurrence of rebuffering for the most rebuffering-vulnerable user so that the network-level QoE degradation is minimized.

We next explain the rate adaptation strategy employed at the DASH client.

B. Rate Adaptation

Rate adaptation can be classified into two types: 1) upward rate adaptation and 2) downward rate adaptation [11]. The rate adaptation is performed at the client side (users) in compliance with the DASH standard without any collaboration with the eNodeB. We employ a conservative model for both the adaptation strategies. The occurrence of a rebuffering event is an indicator of bad channel/network conditions. Therefore, in order to minimize the ill-effects of these events on the QoE degradation, the segment corresponding to the lowest representation is fetched in order to resume the playback as quickly as possible. When the playback is resumed following a rebuffering event, the upward rate adaptation is performed steadily with the representations (bitrates) switched up conservatively. Specifically, the segments corresponding to the same video representation are fetched for a period of T_{URA} seconds before switching up the bitrate [11]. A time period of T_{URA} is chosen so as to allow the playback to buffer sufficient video content ahead of time. This upward rate adaptation strategy is employed in order to avoid frequent occurrence of rebuffering events.

TABLE I
SYSTEM MODEL PARAMETERS

Channel bandwidth	180 kHz	Transmit power	46 dBm
Penetration loss	20 dBm	W	5
Carrier frequency	2 GHz	t^r	100 ms
S	8	N	8
α	1/11, 1/2, 1, 2, ∞	ISD	500 m
λ	{0-5}	t^q	1 s
Pathloss (d in m) = 128 + 37.6 $\log_{10}(d/1000)$, $d \geq 35$ m			

Let D_i represent the sequence of video representations (segments) fetched by the user i. Let $d_{j,k}^i \in D_i$ represent the k^{th} segment fetched from the j^{th} rep for the i^{th} user. In the playback state, the next segment k+1 is fetched based on the following criterion:

$$d_{j,k+1}^i = \underset{\forall j=1,\ldots,|J|}{\operatorname{argmax}} \ V_{j,k+1}^r$$
$$\text{such that } d_{j,k+1}^i \leq \overline{R}_i(t),$$

where, $|J|$ represents the number of video representations. This means that the segment with the video bitrate that best matches the current average throughput is fetched. This strategy is applicable for both upward and downward rate adaptation as long as the DASH client is in the playback state. Next, we present the performance evaluation and analysis of the proposed RA algorithm.

V. PERFORMANCE EVALUATION AND ANALYSIS

In this section, we investigate the performance of the proposed ViQARA and compare with that of the benchmark throughput-RA algorithm. We consider a scenario where an eNodeB is serving video users in its coverage area as illustrated in Fig. 1. We consider path loss, shadowing, thermal noise, penetration loss, cable loss, and other transmission parameters according to the specification in LTE-A Release 9 for an urban macro cell environment [14] implemented in MATLAB. We assume that all the subchannels undergo frequency flat fading. We perform resource allocation at a granularity of $t^r = 100$ milli-seconds [14]. Table I summarizes the system parameters used in the MATLAB simulation setup for evaluation. For a fair investigation and evaluation of the proposed method, we assume that all users are streamed the same video from the video server in the downlink. We assume that the backhaul between the eNodeB and the video server is a finite capacity link carrying video packets from the server to the eNodeB through CDNs as depicted in Fig. 1. We model the video packet arrival as Poisson point process with parameter λ. This implies that the packet inter-arrival times are exponentially distributed [59].

We arbitrarily choose a pristine video sequence from the LFOVIA QoE Database for streaming. The chosen video has a resolution of ultra-HD (4K) at a frame rate of 30 fps and has a duration of 120 seconds. A duration of 120 seconds is chosen as it is shown to be sufficiently long for QoE analysis [11].

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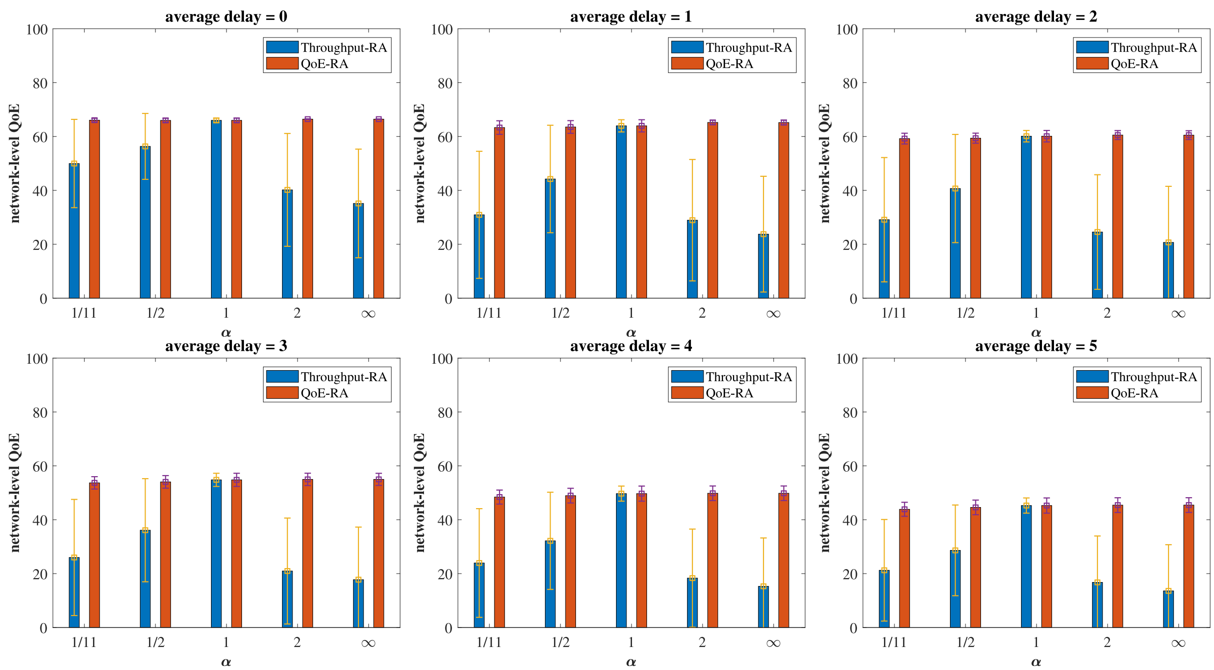

Fig. 3. Network-level QoE performance with $N = 8$ video users and $S = 8$ subchannels for varying α and for different delays under the throughput-RA and the proposed ViQARA with SVR-QoE methods. Vertical lines on the bar plot indicate the 95% CI around the mean value.

TABLE II
RATE TO RESOLUTION MAPPING FOR RATE ADAPTATION

Encoding Rate (kbps)	Resolution (pixels)
100	640×360 (240p)
300	640×360 (360p)
600	1280×720 (360p)
1200	1280×720 (720p)
3000	1920×1080 (1080p)
5000	3840×2160 (2160p)

Different video representations are created by encoding the video at constant bitrates ranging from a few kbps to several Mbps for rate adaptation. The videos are encoded using FFmpeg [60]. Table II shows the mapping between the encoding rates and the spatial resolution. We employ this mapping in order to minimize the distortions introduced by the artifacts when encoded at low resolutions. The segmentation of encoded videos is performed at a granularity of 1 second. This implies that the users have the flexibility to adapt video rates over an interval as low as 1 second. Thus, we have the QoE computation granularity denoted by $t^q = 1$ second. The computed QoE values lie in the range [0, 100]. Further, we employ the upward rate adaptation interval T_{URA} for playback periods following a rebuffering event equal to 3 seconds [11].

We examine the resource allocation for five values of α, namely, $\alpha = 1/11, 1/2, 1, 2,$ and ∞. In our work, the case of $\alpha = 1$, i.e., the proportionally fair allocation corresponds to the equal resource allocation. We consider the setting where there are 8 video users in the network, i.e., $N = 8$, that are uniformly distributed in the macro cell. The users are allowed to have a startup delay of 3 seconds. This is to ensure there is sufficient content in the playback buffer before the playback starts. Since eNodeB is the central resource allocator, it is assumed that it collects the necessary QoE information periodically from all of its video users in order to perform QoE based RA as depicted in Fig. 2. This is a reasonable assumption as the QoE computation is performed at a much larger time granularity of $t^q = 1$ second, as compared to the time granularity of resource allocation $t^r = 100$ ms. We compare the performances of ViQARA and throughput-RA methods in terms of their network-level QoE. The network-level QoE is computed as the mean overall QoE of the users, i.e.,

$$QoE_{netw} = \frac{1}{N}\sum_{i=1}^{N} QoE_i^{overall},$$

where, $QoE_i^{overall}$ represents the overall QoE of the user i at the end of the video session. $QoE_i^{overall}$ is computed as the average QoE of user i penalized by its variability [61], i.e.,

$$QoE_i^{overall}(T_i') = \overline{Q_i}(T_i') - \sqrt{\frac{1}{T_i'}\sum_{\tau=1}^{T_i'}\left(Q_i(\tau) - \overline{Q_i}(T_i')\right)^2},$$

where, T_i' represents the total playback duration (including rebuffering durations if any) and $\overline{Q_i}$ represents the average QoE of the i^{th} user as defined in (4).

A. Results with SVR-QoE as the QoE Model

In this subsection, we present the results of the proposed ViQARA algorithm with SVR-QoE [11] as the QoE prediction model. Fig. 3 shows the average performance of ViQARA in comparison with that of throughput-RA in terms of the network-level QoE (QoE_{netw}) across 100 realizations of random deployment of video users in the network. The network-level QoE variability with 95% Confidence Interval (CI) is

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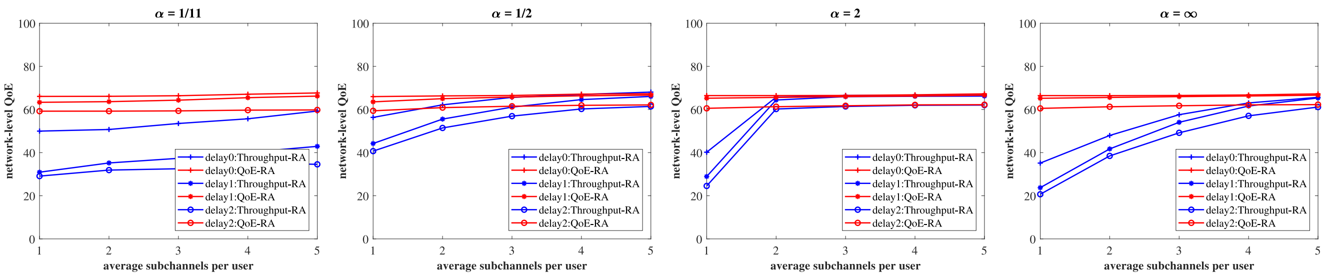

Fig. 4. Network-level QoE performance for $N = 8$ video users with increased availability of subchannels under the throughput-RA and the proposed ViQARA with SVR-QoE methods.

TABLE III
PERCENTAGE IMPROVEMENT IN THE NETWORK-LEVEL QOE PERFORMANCE OF THE PROPOSED VIQARA WITH SVR-QOE OVER THROUGHPUT-RA WITH $N = 8$ VIDEO USERS AND $S = 8$ SUBCHANNELS

α	λ = 0	λ = 1	λ = 2	λ = 3	λ = 4	λ = 5
1/11	32.1846	104.7482	103.4161	106.6111	102.2597	106.5881
1/2	17.1299	43.6561	45.9328	49.6683	52.1209	55.7185
2	65.3310	125.4354	146.6106	162.2752	171.7944	171.2492
∞	89.0270	174.4566	192.4674	209.6804	225.8444	234.4671

TABLE IV
PERCENTAGE REDUCTION IN THE AVERAGE REBUFFERING TIME USING THE PROPOSED VIQARA WITH SVR-QOE OVER THROUGHPUT-RA WITH $N = 8$ VIDEO USERS AND $S = 8$ SUBCHANNELS

α	λ = 0	λ = 1	λ = 2	λ = 3	λ = 4	λ = 5
1/11	1911.8	697.2944	223.3123	135.3465	101.2039	85.6094
1/2	887.1795	224.4248	78.6468	53.0324	43.7781	41.6577
2	11249	801.2482	207.8604	128.0247	101.6600	88.0039
∞	15109	963.5140	249.8138	150.9961	123.5719	109.6057

also illustrated in Fig. 3 Further, the plots show the performances for $N = 8$ video users with $S = 8$ subchannels and for different average delays of packet arrivals at eNodeB. It is observed that the proposed QoE-RA method provides consistently higher performance as compared to the throughput-RA method across all values of α. This allows the network service provider to operate at the desired level of α-fairness, while providing improved network-level QoE. Table V shows the variability between the overall QoE of the video users using standard deviation. A significantly lower standard deviation in the network-level QoE for ViQARA when compared to that of throughput-RA suggests that the users consistently enjoy better QoE in the ViQARA framework. It is also observed that for higher values of α, the proposed method yields significant improvement in the network-level QoE. Table III shows the percentage improvement in the network-level QoE performance of the proposed method as compared to the throughput-RA method for various network delays. It can be noticed that for any given α-fairness, the proposed method provides better performance as the network delay increases. Further, it is seen that as the delay in the network increases, the QoE suffers under both the methods as the network delay leads to the occurrences of rebuffering events. However, the reduction in the network-level QoE performance of the proposed method is far lower compared to that of the throughput-RA method. In other words, whenever the network experiences larger delays, the QoE awareness brought by ViQARA is more pronounced leading to better RA strategies and hence, resulting in an improvement in the network-level QoE.

TABLE V
STANDARD DEVIATION BETWEEN THE OVERALL QOE OF $N = 8$ VIDEO USERS WITH $S = 8$ SUBCHANNELS. THE BEST PERFORMING RESULTS ARE INDICATED IN BOLD

average delay	**Method**	α **1/11**	**0.5**	**2**	∞
0	Throughput-RA	19.5960	14.6338	25.0460	24.1184
	ViQARA	**0.8530**	**0.9614**	**0.1717**	**0.1256**
1	Throughput-RA	28.2117	23.8668	26.9589	25.6951
	ViQARA	**3.0126**	**2.8183**	**1.0098**	**1.1018**
2	Throughput-RA	27.5959	24.0221	25.4426	24.8977
	ViQARA	**2.3972**	**2.2286**	**1.9913**	**1.9644**
3	Throughput-RA	25.7857	22.8947	23.5217	23.3475
	ViQARA	**2.7398**	**2.7945**	**2.7442**	**2.6849**
4	Throughput-RA	24.1284	21.5689	21.7732	21.4740
	ViQARA	**3.1205**	**3.2557**	**3.2444**	**3.2452**
5	Throughput-RA	22.5485	20.1483	20.6127	20.5089
	ViQARA	**3.1118**	**3.2495**	**3.2693**	**3.2685**

Since rebufferings are observed to be highly annoying and degrade the user QoE severely, we investigated the amount of time spent by the users in rebuffering during the entire video session. Table IV shows the percentage reduction in the average rebuffering time of the users with the proposed method over the throughput-RA method for different network delays. A significant reduction in the rebuffering times can be noted using ViQARA for different α-fair strategies.

We also investigated the performance of the two RA strategies with the availability of more subchannels in the network. Fig. 4 shows the performance of the proposed method and throughput-RA in terms of the network-level QoE for different network delays. It is interesting to note that with the

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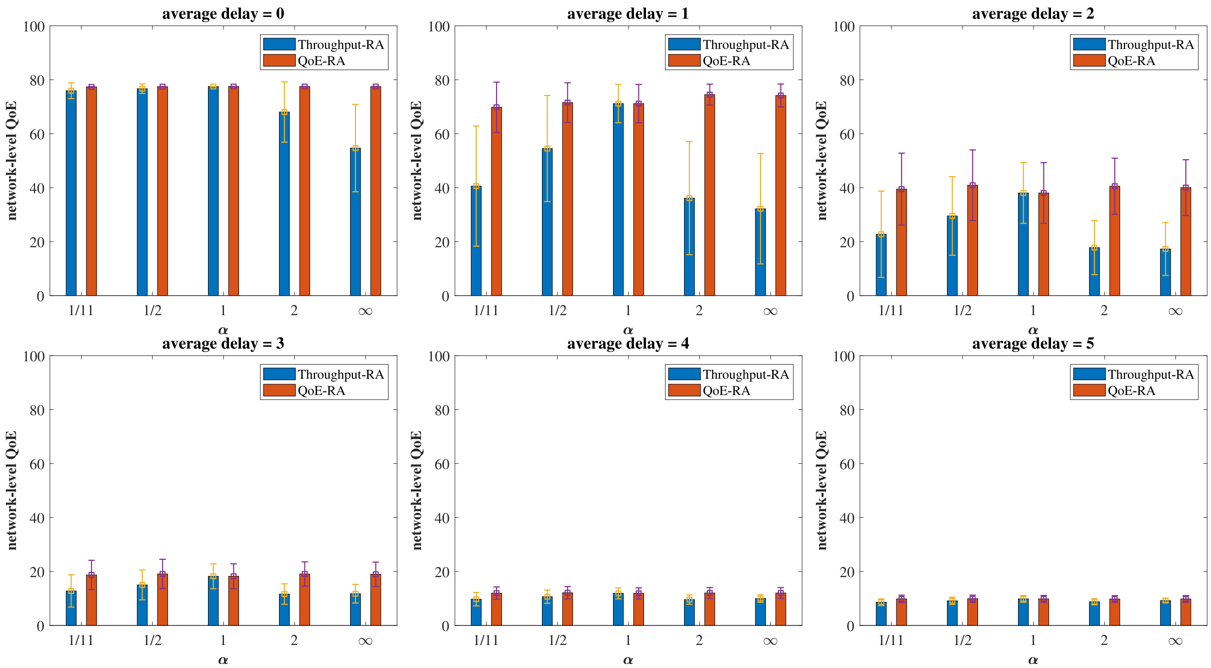

Fig. 5. Network-level QoE performance with $N = 8$ video users and $S = 8$ subchannels for varying α and for different delays under the throughput-RA and the proposed ViQARA with NARX-QoE methods. Vertical lines on the bar plot indicate the 95% CI around the mean value.

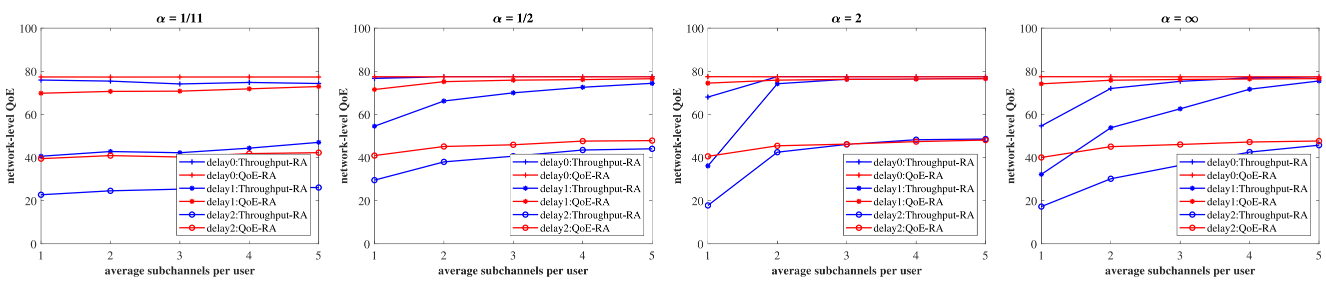

Fig. 6. Network-level QoE performance for $N = 8$ video users with increased availability of subchannels under the throughput-RA and the proposed ViQARA with NARX-QoE methods.

availability of more resources in the network, the performance of the throughput-RA approaches ViQARA's performance. This is because, with more resources, the eNodeB can allocate more resources to its video users thereby allowing them to meet their video bitrate requirements. With this, the occurrences of rebuffering events are reduced, and thus, the throughput based strategy optimizes for the user's QoE as well.

B. Results with NARX-QoE as the QoE Model

We next investigate the utility of the ViQARA algorithm with NARX-QoE as the QoE model. Fig. 5 shows the average network-level QoE performance along with 95% CI across 100 random deployment of video users in the network for different values of α. Fig. 6 shows the network-level QoE performance with the increase in the number of subchannels in the network. Table VI shows the percentage improvement in the network-level QoE of the proposed method and Table VII shows the reduction in the rebuffering time achieved with the proposed method. A value of ∞ in Table VII indicates that the users experienced zero rebuffering with the ViQARA method. From these results, it is observed that the performances obtained with NARX-QoE resonates with those of SVR-QoE based ViQARA method.

Thus, based on the evaluations with two perceptual QoE models for ViQARA, we conclude that QoE-optimal resource allocation strategies can provide a significant improvement in the QoE performance together with consistency for video streaming users compared to the conventional throughput based RA strategies. The proposed method ViQARA is highly effective in the scenarios where the network is congested due to heavy traffic and/or the resources in the wireless network are limited/constrained. Further, the proposed RA algorithm can be easily integrated with the current operational mobile networks; the only requirement being the periodic transmission of user QoE information to the eNodeB which can be readily handled in the uplink similar to Channel Quality Information (CQI) sharing. The QoE information of the video users which is monitored in a continuous manner can help in minimizing the influences of the QoE degrading factors and in optimizing the resources to achieve QoE maximization. QoE awareness provided by the perceptual QoE models is very useful in such scenarios.

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TABLE VI
PERCENTAGE IMPROVEMENT IN THE NETWORK-LEVEL QOE PERFORMANCE OF THE PROPOSED VIQARA WITH NARX-QOE OVER THROUGHPUT-RA WITH $N = 8$ VIDEO USERS AND $S = 8$ SUBCHANNELS

α	$\lambda = 0$	$\lambda = 1$	$\lambda = 2$	$\lambda = 3$	$\lambda = 4$	$\lambda = 5$
1/11	1.8915	71.9790	73.6427	46.4908	23.0548	14.2902
1/2	0.9889	31.2205	38.5870	27.1348	13.7749	8.4970
2	13.8776	106.2507	127.9334	63.8866	25.4676	11.6705
∞	41.7226	130.4126	131.9565	61.3179	20.4536	6.3471

TABLE VII
PERCENTAGE REDUCTION IN THE AVERAGE REBUFFERING TIME USING THE PROPOSED VIQARA WITH NARX-QOE OVER THROUGHPUT-RA WITH $N = 8$ VIDEO USERS AND $S = 8$ SUBCHANNELS

α	$\lambda = 0$	$\lambda = 1$	$\lambda = 2$	$\lambda = 3$	$\lambda = 4$	$\lambda = 5$
1/11	9700	2358.3	360.0778	180.7306	124.1975	117.8098
1/2	∞	1105.1	163.5095	80.9980	60.1107	54.6962
2	∞	14282	395.0283	169.9075	120.7607	104.7934
∞	∞	14155	430.8770	202.0759	143.4630	121.1698

VI. CONCLUSION AND FUTURE WORK

In this paper, we proposed ViQARA, a QoE based algorithm for resource allocation in cellular networks for adaptive video streaming. The proposed algorithm exploits the strength of continuous perceptual QoE prediction models for performing optimal allocation of resources in the network. The proposed method is compared with the existing throughput based RA solutions. Based on an extensive evaluation using two perceptual continuous QoE models, it is observed that ViQARA enhances the QoE for various cases of α. The average rebuffering time using the proposed method is significantly reduced owing to the availability of the user's perceptual QoE information at the eNodeB, the central resource allocator. The proposed method is shown to provide QoE optimization of the resources yielding a significantly better QoE performance for the video users, especially in the scenarios where the wireless network is resource constrained and/or the CDN is overloaded resulting in large packet delays. Further, we found that with the availability of more resources in the network for allocation, the performance of the throughput-RA strategy converges to that of the proposed ViQARA algorithm. Although the performance of the proposed algorithm is demonstrated over the LTE network, it is equally applicable in other networks where the resources are shared and constrained.

In future, we plan to investigate the performance of QoE based RA methods on a real-time LTE test-bed for DASH video streaming. It would also be interesting to investigate the performance of these RA methods with other VQA metrics upon the videos having a wide variety of content, as different videos involve different spatio-temporal complexity. Given the effectiveness of content-specific encoding of videos in such a context, it would be worthwhile to explore content-adaptive encoding for creating video representations. Since the efficacy of perceptual optimization of network resources heavily relies on the employed QoE model, the development of more robust models that takes into account parameters such as screen resolution of the user device, viewing conditions of the users etc. would be another interesting direction to explore.

APPENDIX
PROOF OF LEMMA 1

We have,

$$\begin{aligned} \underset{s_i,\forall i}{\text{maximize}} \quad & \sum_{i=1}^{N} \frac{(s_i x_i)^{1-\alpha}}{1-\alpha} \\ \text{subject to} \quad & \sum_{i=1}^{N} s_i \leq S, \\ & s_i \geq 0. \end{aligned}$$

The Lagrangian $L(s, \lambda)$ is given by

$$L(s, \lambda) = \sum_{i=1}^{N} \frac{(s_i x_i)^{1-\alpha}}{1-\alpha} + \lambda\left(\sum_{i=1}^{N} s_i - S\right).$$

Differentiating L with respect to s_i and equating to zero, we get

$$\frac{\partial L}{\partial s_i} = x_i^{1-\alpha} s_i^{-\alpha} - \lambda = 0,$$

$$\Rightarrow \lambda = \frac{x_i^{1-\alpha}}{s_i^{\alpha}}, \tag{10}$$

$$\Rightarrow s_i = \left(\frac{x_i^{1-\alpha}}{\lambda}\right)^{\frac{1}{\alpha}}, \forall i = 1, 2, \ldots, N. \tag{11}$$

Using complementary slackness condition, we get

$$\sum_{i=1}^{N} s_i - S = 0. \tag{12}$$

Substituting for s_i from (11) in (12), we get

$$\sum_{i=1}^{N} \left(\frac{x_i^{1-\alpha}}{\lambda}\right)^{\frac{1}{\alpha}} = S,$$

$$\Rightarrow \frac{1}{S} \sum_{i=1}^{N} x_i^{\frac{1-\alpha}{\alpha}} = \lambda^{\frac{1}{\alpha}}.$$

Substituting for λ from (10), we get

$$\frac{1}{S} \sum_{i=1}^{N} x_i^{\frac{1-\alpha}{\alpha}} = \frac{x_i^{\frac{1-\alpha}{\alpha}}}{s_i}.$$

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Solving for s_i, we obtain the optimal s_i^*

$$s_i^* = \left(\frac{x_i^{\frac{1-\alpha}{\alpha}}}{\sum_{i=1}^{N} x_i^{\frac{1-\alpha}{\alpha}}} \right) S.$$

This completes the proof of *Lemma 1*.

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