Optimal Fairness and Quality in Video Streaming with Multiple Users

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***Abstract*—With the majority of video distribution services relying on the HTTP adaptive streaming paradigm, a great deal of research is geared towards developing algorithms and solutions for improving user perceived quality while making efficient use of available resources. Our goal is to provide the means for benchmarking such solutions in the context of multiple users accessing Video on Demand content while sharing a bottleneck link. For that purpose, we propose a quadratic problem formulation to compute the theoretical optimum in terms of adaptation strategies and corresponding segment downloads across multiple users under given bandwidth constraints. By aiming to maximize both service quality and fairness, we quantify and compare the impact of different fairness objectives (bandwidth fairness, pattern fairness, and session fairness) on resulting quality and achieved QoE fairness. Based on conducted simulations and parameter studies, our results demonstrate the benefits of optimizing for session fairness as compared to other approaches.**

I. Introduction

With the highest share of today's Internet traffic being consumed by video streaming services, both service and network providers face challenges in providing end users with high quality services. The majority of video distribution services have adopted the HTTP Adaptive Streaming (HAS) paradigm, whereby content is stored and delivered in small segments available in multiple quality levels. Decisions related to the quality levels at which to retrieve segments are made by adaptation algorithms run on clients and are driven by bandwidth estimations and/or buffer status.

A great deal of research has focused on the QoE-driven design of adaptation algorithms, with the goal being to deliver video content at high quality levels while avoiding stalling, long initial delays, and frequent quality switches. Faced with the question of how to benchmark the performance of HAS adaptation algorithms compared to a theoretical QoE optimum, the authors in [1] propose problem formulations to compute the theoretical optimum for both single- and multi-user scenarios. Their addressed multi-user scenario assumes users concurrently watching and downloading the same video over a shared bottleneck link.

In this paper, we extend previous work by formulating a QoE optimal download strategy in the case of multiple HAS users accessing Video on Demand (VoD) content via a shared bottleneck link, i.e., users watch different videos at different starting points. A well-known issue linked to such a scenario is that the on/off nature of flows often results in inaccurate client-side bandwidth estimation and leads to potentially unfair resource demands, quality oscillations, and poor bandwidth utilization [2], [3], [4], [5]. While different approaches in literature propose methods to mitigate these problems by employing various monitoring and control solutions at different points along the service delivery path [5], [6], [7], what is missing is a methodology for comparing and benchmarking these different approaches.

We thus propose a quadratic problem formulation to compute the theoretical optimum in terms of adaptation strategies and corresponding segment downloads across multiple users under given bandwidth constraints. We specify the objective as being to maximize average quality, minimize the number of quality switches, and ensure equal utility (QoE) among users while avoiding stalling events. With respect to specifying the optimization objective, previous research has suggested a two-step approach [1], [8]. In a first step, a solution is found that maximizes the sum of overall quality or average quality. In a second step, the number of quality switches is minimized to a number where the maximum quality can still be achieved. However, this constraint does not leave much room to optimize the number of quality switches. An extension to this approach proposed in [9] modifies this constraint by introducing a trade-off parameter α that allows for almost maximum quality, while allowing for much fewer quality switches. In this paper, we combine the aforementioned steps into a weighted linear combination and perform a parameter study to investigate the impact of different assigned weights.

In addition to maximizing quality across multiple users, an inherent question is that of how to address the issue of fairness. There is a clear need to distinguish between QoS fairness (e.g., resulting in equal bitrate allocations) vs. QoE fairness, leading to equal *utility* among users [10]. While client-side bitrate adaptation algorithms may in a best-case scenario achieve flow-based fairness, this will rarely translate to session-level fairness (or QoE level fairness for a given session) [11]. Recent papers have argued that a QoS fair system is not necessarily QoE fair, e.g., [5], [8], given the

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lack of consideration of service QoE models. Such models specify the relationships between user-level QoE and various application-layer performance indicators (e.g., file loading times, video re-buffering) or influence factors such as device capabilities, context of use, network and system requirements, user preferences, etc.

By aiming to maximize both service quality and fairness, we quantify and compare the impact of different fairness objectives (bandwidth fairness, pattern fairness, and session fairness) on resulting quality and achieved QoE fairness. Based on conducted simulations and parameter studies, our results demonstrate the benefits of optimizing for session fairness as compared to other approaches.

The remainder of this paper is structured as follows. Section II further provides background and an overview of related work. Section III introduces the quadratic program and used notation. Simulation results are presented in Section IV, while concluding remarks and outlook are given in Section V.

II. Related Work

A. Fairness

In a shared system where scarce resource must be shared, fairness is always a concern. *Jain's fairness index* is a popular fairness index for QoS [12] that determines the ratio between the square of the mean and the mean of the squares for a set of values. However, it is only suitable for measures on a ratio scales [13], i.e. an interval scale with a true zero point. Resources are allocated according to *max-min fairness* among users if a user only receives more resources when no other user will suffer and obtain less [13]. A rather novel fairness index for QoE has been presented in Hoßfeld et al. [10]. Hoßfeld's fairness index is defined via the ratio between the observed standard deviation of QoE values and the maximal possible standard deviation $F = 1 - \sigma/\sigma_{max}$ which makes it suitable for any interval scales. In Section IV we use this index to quantify fairness from a user-centric point of view for quality layers that serve as QoE indicators. A detailed discussion of QoS and QoE fairness is provided in [13] focusing on the notion of fairness in shared environments and in networking, as well as fairness from the user's perspective.

B. Quality of Experience in Video Streaming

The QoE is "the degree of delight or annoyance of the user of an application or service" [14]. There are many metrics for the QoE of video streaming, which are summarized in [15]. Key performance indicators for QoE include the number of stalling events, the average video quality and the number of quality switches [16]. Some studies claim that switches have no significant impact on the QoE [17], while others include them as key performance indicators [18], [19]. In a recent ITU-T standard from 2017 [20], the number of switches was not included in the QoE model. Nevertheless, we include it since we know from [9] that the number of switches can be reduced drastically at a very low cost in terms of video quality. Furthermore, in the model that we present, a scenario where switches are disregarded can be defined by setting the importance parameter for switches $\beta = 0$. This corresponds to a scenario with $\alpha = 1$ in [9].

Table I
Notations and Variables

$u = 1, 2, 3 \ldots$	index for users (in order of requests)
U	number of users
Y_u	video that is downloaded/watched by user u
T_u	time of request of video Y_u by user u (second)
i	index for segments
n	number of segments
j	index for quality layer
r_{max}	number of quality layers
S_{uij}	size of segment i of video Y_u in quality j (Byte)
D_{ui}	deadline of segment i of video Y_u until which download must be completed (second)
$V(t_1, t_2)$	data that can be downloaded between the points in time t_1 and t_2 (second)
$x_{uij} \in \{0, 1\}$	solution whether segment i of video Y_u is downloaded in quality j or not
w_{uij}	weight for segment i of video Y_u in quality j, e.g. QoE value
F_{ui}	absolute fairness for the quality of segment i between user u and other users
F_u	absolute fairness for the mean quality of all segments between user u and other users
α	relative importance of the average video quality
β	relative importance of quality switches
γ	relative importance of quality fairness
δ	relative importance of upward switches compared to downward switches

Since we know that stalling events have the highest negative impact on QoE, the proposed quadratic program is constrained to completely avoid stalling. The other KPIs have been identified to have some impact, however, the exact degree of the impact is not fully clear. Therefore, we only propose relative importance using a weighting for each of these parameters.

III. Optimization problem

We assume a set of users U. Each user u downloads exactly one video Y_u. Each video is divided into n segments which must be downloaded in exactly one of r_{max} resolutions/layers[1]. The volume of segment i on layer j of video Y_u is defined as S_{uij}. Each segment i of video Y_u must be completely downloaded before its deadline D_{ui} to play the video without stalling. Each user u requests a video at a point in time T_u. We assume that users request videos sequentially, i.e., User 1 requests his video before User 2. The function $V(t_1, t_2)$ describes the data that can be downloaded between the points in time t_1 and t_2. For $V(0, t_1)$ we may use the shortened notation of $V(t_1)$.

The optimization problem that we tackle can be formulated as follows: Optimize the average video quality of all users, while minimizing the number of downward quality switches and maximizing the number of upward switches. Quality switches are weighted with the difference in quality. Further, we minimize the difference between the average quality among users, while avoiding stalling events. The weight of each

[1]If videos may have different numbers of layers or segments, we replace r_{max} with $r_{u,max}$ or n with n_u

$$
\begin{aligned}
\text{maximize} \quad & \alpha \sum_{u=1}^{U} \sum_{i=1}^{n} \sum_{j=1}^{r_{max}} w_{uij} x_{uij} - \beta \sum_{u=1}^{U} \sum_{i=1}^{n} (\sum_{j=2}^{r_{max}} \sum_{k=1}^{j-1} (j-k) x_{uij} x_{u,i+1,k} \\
& - \delta \sum_{j=1}^{r_{max}-1} \sum_{k=j}^{r_{max}} (k-j) x_{uij} x_{u,i+1,k}) - \gamma \frac{1}{nU} \sum_{u=1}^{U} F_u && (1) \\
\text{subject to} \quad & x_{uij} \in \{0,1\} \quad \forall u = 1,...,U, \quad \forall i = 1,...,n, \quad \forall j = 1,...,r_{max} && (2) \\
& \sum_{j=1}^{r_{max}} x_{uij} = 1, \quad \forall u = 1,...,U, \quad \forall i = 1,\dots,n && (3) \\
& \sum_{u=l}^{U} \sum_{i=1}^{k} \sum_{j=1}^{r_{max}} S_{uij} x_{uij} \le V(T_l, D_{uk}), \quad \forall k = 1,\dots,n, \quad \forall l = 1,\dots,U && (4) \\
& F_u \ge \sum_{i=1}^{n} \sum_{j=1}^{r_{max}} w_{uij}((U-1)x_{uij} - \sum_{\tilde{u}=1, \tilde{u} \ne u}^{U} x_{\tilde{u}ij}), \quad \forall u = 1,\dots,U && (5) \\
& F_u \ge - \sum_{i=1}^{n} \sum_{j=1}^{r_{max}} w_{uij}((U-1)x_{uij} - \sum_{\tilde{u}=1, \tilde{u} \ne u}^{U} x_{\tilde{u}ij}), \quad \forall u = 1,\dots,U. && (6)
\end{aligned}
$$

variable that is the subject of the optimization is defined by α for the average quality, β for the number of switches and γ for the fairness in quality among users. Upward switches may have a different impact on the user experience than downward switches. Therefore, we introduce a parameter δ that reflects the relative importance of upward switches compared to downward switches. We arbitrarily chose $\delta = 0.5$ for the remainder of this paper. An overview of all parameters is given in Table I.

Currently QoS fairness is employed via protocols that ensure that users who share the same link may use the same share of resources available. This means, we have fair network QoS. In the following we present two fairness schemes for application layer QoS.

Please note that in the quadratic program we do not use a fairness index such as Jain's or Hoßfeld's QoE fairness metric directly. The optimization problem formulates a theoretical implementation of a QoE management mechanism. Thereby, we rely on a very simple fairness measure for the sake of simplifying the quadratic program. For example, instead of relying on the standard deviation, we use the mean difference, avoiding squares in the formulation. More sophisticated fairness indexes such as the above can be applied to it nevertheless.

A. Session-Fairness

This approach corresponds to how fairness is evaluated over the whole session. Each user u has an average quality QoE_u in which he has viewed the video. The average quality QoE_u of each user should be as similar as possible to achieve high fairness.

The values α, β and γ are normalized so that the minimum and maximum value of their term is 0 and 1. Equation 3 means that each segment of any video of any user must be downloaded in exactly one resolution. Equation 4 means that for each User l, the sizes of all segments, which are downloaded by users who requested a video after User l, may in their sum never exceed the data that can be downloaded since User l joined the system. Equation 5 and 6 are used to implement the absolute value for the difference to the mean. If $T_{\tilde{u}} - T_u < 0$ or $T_{\tilde{u}} - T_u > \max(T)$ then the constraint for this u is omitted. This has been left out of the equations for the sake of clarity. A downside of this approach for fairness is the difficulty of its implementation since do not know if users abandon videos early. A possibility to solve this problem is to implement a history-based fairness system, that considers all segments from the past, and tries to equalize the average quality of users over time. It is also possible to model this problem as a 2-step approach: In the first step, we ignore switches and determine the maximum quality and fairness W that is possible. In the second step, we try to reach at least $W - \epsilon$ and then minimize the number of switches. For the sake of brevity this approach is not presented in further detail.

B. Segment-Fairness

Another way to implement fairness for application layer QoS is to minimize the difference in quality between users for each video segment. This means that the nth segment watched by all users has similar quality, independently of when it is watched, e.g. in the case of maximum quality, the quality pattern in which videos are viewed is the same for each user. If we use segment-fairness (also referred to as pattern fairness), we have the following equations. We replace the last term of Equation 1 with

$$-\gamma \sum_{u=1}^{U} \sum_{i=1}^{n} \frac{1}{nU} F_{ui} \tag{7}$$

and Equations 5 and 6 with

$$F_{ui} \geq \sum_{j=1}^{r_{max}} w_{uij}((U-1)x_{uij} - \sum_{\tilde{u}=1}^{U} x_{\tilde{u},i+\frac{T_{\tilde{u}}-T_u}{\tau},j}), \quad (8)$$

$\forall u = 1,\ldots,U, \quad \forall i = 1,\ldots,n$

$$F_{ui} \geq -\sum_{j=1}^{r_{max}} w_{uij}((U-1)x_{uij} - \sum_{\tilde{u}=1}^{U} x_{\tilde{u},i+\frac{T_{\tilde{u}}-T_u}{\tau},j}), \quad (9)$$

$\forall u = 1,\ldots,U, \quad \forall i = 1,\ldots,n$

IV. Results

In this section, we discuss the results. We first discuss a sample run and then conduct parameter studies, to explain the impact of input values (i.e., scenarios) of the quadratic program.

A. Methodology

The scenario that we investigate in the following section is a low bandwidth scenario. Three users request a YouTube video (ID: CRZbG73SX3s, $\Delta t = 549s$) at different starting points $t_1 = 0s, t_2 = 245s, t_3 = 495$. Videos start playing after an initial delay of 5s. Each video is partitioned into video segments that have an equal duration of $5s$ and are available in four quality levels $(1, 2, 3, 4)$ that differ in average bit rate: 144p (14 kBps), 240p (31 kBps), 360p (68 kBps) and 480p (127 kBps). The users share the same bottlenecked link with a constant effective bandwidth that we vary from 50 kBps to 150 kBps (indicated as 0.5, ...1.5 in the figures).

We used a constant parameter $\alpha = 1$ which indicates that the video quality should always be of high importance. We varied the parameters $\beta, \gamma \in \{0, \ldots 1\}$ to account for scenarios in which the degree of annoyance of quality switches and the degree of importance of fair video quality among users varies. We use $\delta = 0.5$ in every scenario. The quadratic programs were solved in Gurobi[2] with Matlab[3] as an interface. The program was executed on an i7 CPU with four cores with 2.70 GHz and 16 GB RAM. The run time of the program heavily depends on the scenario and the parameters used. The calculation for bandwidth fairness takes 0.2 s for $\beta = 0$ and 0.5 s for $\beta > 0$. The calculation for pattern fairness takes 5 s for $\beta = 0$ and 1700 s for $\beta > 0$. In the latter case we stop the program after 30 s and take non-optimal results to get results within an acceptable time frame. These results are very close to optimal results and do not differ visibly. For session fairness a run takes 0.8 s for $\beta = 0$ and 2 s for $\beta < 0$. The source code of the programs is available online[4]. We invite any scientists to use it for their own research. QoS fairness (also referred to as bandwidth fairness) was modeled by giving each user $\frac{1}{n}$ bandwidth while n users were in the network. Users always fully exhausted their available bandwidth. Then we optimized quality and switches according to α and β for the respective bandwidth pattern using Gurobi, ignoring QoE fairness. In Figure 1 an example of a single run is given in which we see the quality in which segments are watched over time for each user. The three metrics that we investigate are: average video quality, the fairness of the quality among users, and the number of quality switches.

[2]http://www.gurobi.com/

[3]https://www.mathworks.com/products/matlab.html

[4]https://github.com/ChristianMoldovan/Quadratic-Program-for-Optimal-Fairness-and-Quality-in-Video-Streaming-with-Multiple-Users

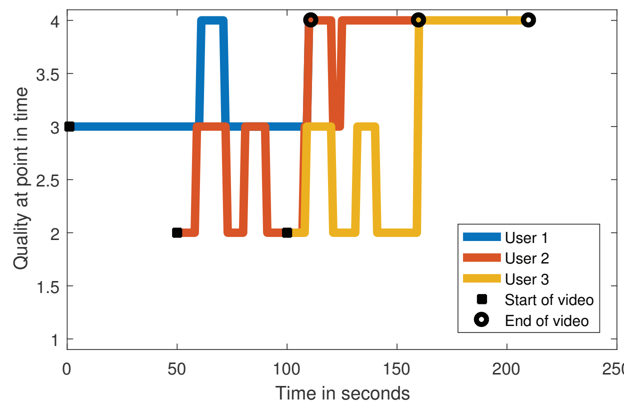

Figure 1. Quality of segments over time for three users watching a video with session-fairness employed and the following parameters: bandwidth = 1.5 Mbit/s, $\alpha = 1, \beta = 1, \gamma = 1$.

B. Trade-off Between Quality, Switches, and Fairness

As can be seen in Figure 2, the quality increases with the bandwidth, the number of switches is reduced with β, and fairness increases with γ. Furthermore, β and γ have no significant impact on the video quality. It is noticeable that the average quality is slightly lower when QoS fairness is enforced since there is less room for optimally scheduling the segment downloads. For example, when the third user joins the system in Figure 1, the user can only use $\frac{1}{3}$ of the available bandwidth since it is fairly shared with the other users. Therefore, User 3 can only download low quality segments. Optimally, when a new user starts a video, the user is given a larger share of the bandwidth initially, so they can start with a higher quality level. Other users may suffer with respect to obtained quality but switching from 240p to 360p is more cost effective as compared to going from 360p to 480p, if we consider the ratio of the bit rate to the quality difference. A detailed analysis of the trade-off between quality and switches has already been conducted in [9].

In Figure 3 we see that a higher bandwidth leads to higher fairness. Furthermore, the fairness parameter γ leads to higher fairness, when approaching 0. In contrast, we can see the trade-off in Figure 4. While higher bandwidth also leads to higher quality, increasing γ leads to an increase in quality.

C. Bandwidth Fairness, Pattern Fairness, Session Fairness

Current systems mostly rely on network QoS fairness, due to its simplicity. Each user receives the same share of resources at any point in time. In the following, we emulate network QoS fairness by reserving $1/n$ of the total bandwidth for each user while n users are watching a video and are in the system.

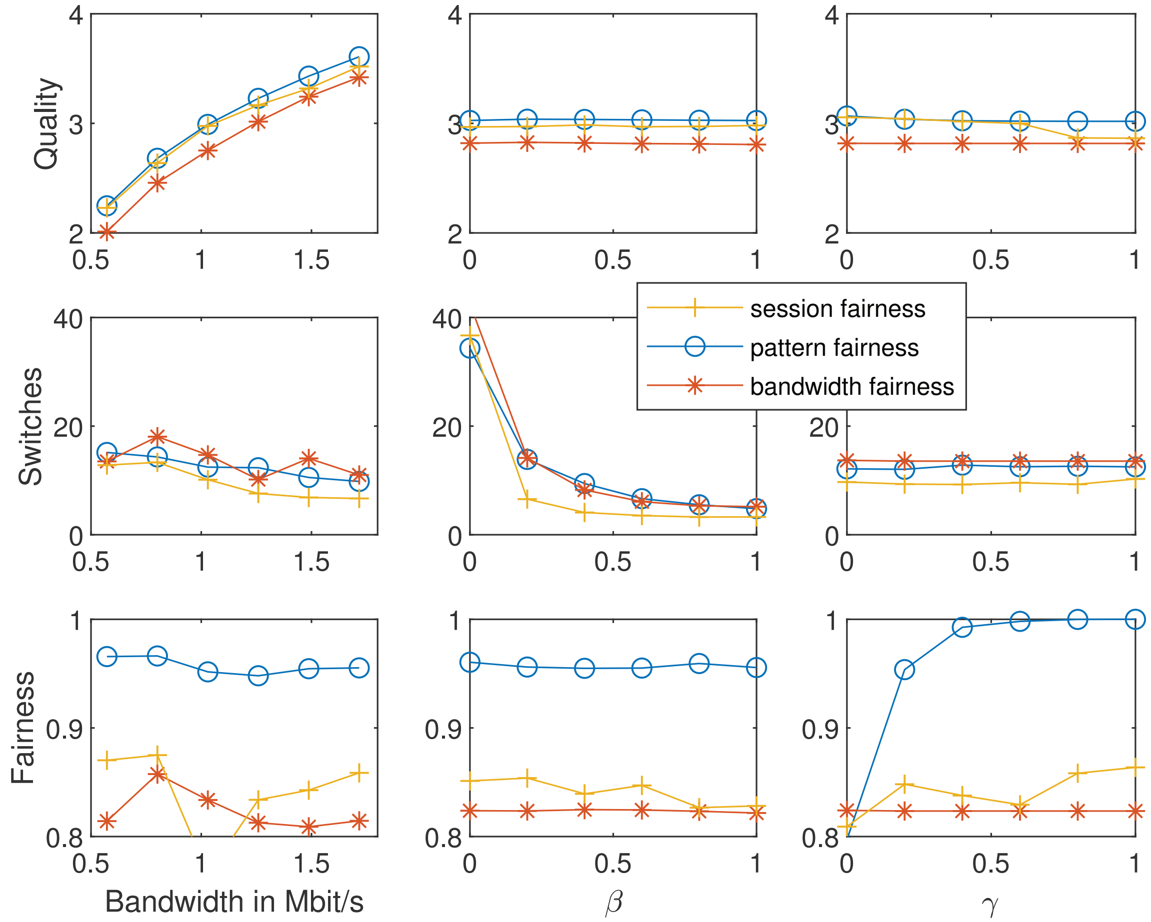

Figure 2. Impact of bandwidth, β and γ on the average video quality, the number of switches and the fairness of the video quality for $\alpha = 1$.

With a network-QoS-fairly shared bandwidth, the average quality is slightly lower, compared to a perfect optimization. Even if perfect session fairness can be guaranteed, the mean quality of every single user is higher than with QoS-fairness. The fairness (in terms of Hoßfeld's fairness index) of the system is not impacted by γ, except for the simple case $\gamma = 0$ in which fairness is not considered in the optimization. This means that optimizing fairness for single segments has no impact on the overall fairness. Rather, it is impacted very much by the bandwidth. In contrast to Figure 3, fairness is always lower compared to optimizing session fairness. In Figure 4 we see that session-fairness leads to the highest quality with an average of 3.03, then segment-fairness with 2.92 and last network QoS fairness with 2.74. This means that the video quality can be increased by 0.29 quality layers in the above scenario on average, while resulting in fairer QoS on the application layer.

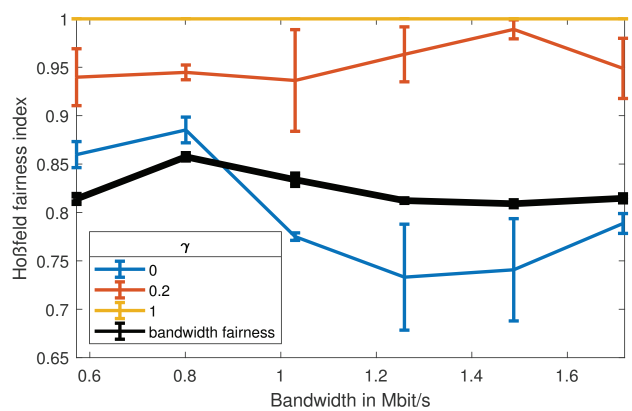

Figure 3. QoS-Fairness: Videotrace number 1585. Impact of bandwidth and gamma on quality with $\beta = 0.4$.

V. Conclusion

Video Streaming is a widespread form of multimedia in the Internet that is consumed by billions of people worldwide. However, from an end user perspective, users care more about QoS on the application layer than on the network layer. Therefore, studies advocate the need to move from solutions

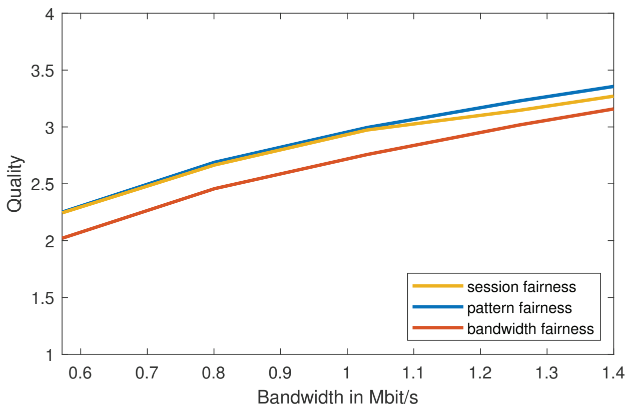

Figure 4. Session-fairness, segment-fairness and network QoS-fairness: impact of bandwidth on the video quality with $\beta = 0.4$. Mean over all γ values.

targeting fair *network QoS* towards those geared towards achieving fair *application QoS*. The first question is whether it is worth taking such a challenging route.

In this paper, we propose a quadratic problem formulation to compute the optimum in terms of quality, quality switches, and fairness among multiple users sharing a bottleneck link, given that we know in advance the bandwidth variations, video request times, and available quality levels. As such, the aim is to provide the means for benchmarking different adaptation algorithms and solutions in the context of multiple users accessing Video on Demand content while sharing a bottleneck link.

We compare the impact of different fairness objectives (QoS fairness, segment fairness and session fairness) on the video quality and QoE fairness. Our results show that ensuring QoS Fairness has no impact on the overall QoE fairness of a session, while on the other hand it can be costly in terms of quality. In contrast, optimizing for session fairness can be realized at a lower cost in terms of quality to give all users the same quality within 0.1 of Hoßfeld's Fairness Index. This demonstrates that it makes sense to look at QoS on application layer, when attempting to distribute resources to users.

In future work, we plan to use the results of this paper to present a decentralized system for video streaming that improves session fairness for users that share a bottleneck link with minimal impact on the average video quality.

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