Improving Fairness, Efficiency, and Stability in HTTP-based Adaptive Video Streaming with FESTIVE

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June 14, 2012
CMU-CS-12-128

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This research was funded in part by the National Science Foundation under award number CNS-1040801.

Keywords: Internet video, network measurement

Abstract

Many commercial video players rely on some underlying bitrate adaptation logic to adapt the bitrate in response to changing network conditions. Past measurement studies have identified issues with today's commercial players with respect to three key metrics—efficiency, fairness, and stability—when multiple bitrate-adaptive players share a bottleneck link. Unfortunately, our current understanding of why these effects occur and how they can be mitigated is quite limited. In this paper, we present a principled understanding of bitrate adaptation and analyze several commercial players through the lens of an abstract player model. This helps us identify the root cause of several undesirable interactions that arise as a consequence of overlaying the video bitrate adaptation over HTTP and lead to poor efficiency, fairness, and stability. Building on these insights, we develop a set of techniques that can systematically guide the tradeoffs between stability, fairness and efficiency and thus lead to a general framework for robust video adaptation. We pick one concrete instance from this design space and demonstrate that it significantly outperforms all commercial players on all three key metrics across a range of experimental scenarios.

1 Introduction

Video traffic is becoming the dominant share of Internet traffic today [5]. This growth in video is accompanied, and in large part driven, by a key technology trend: the shift from connection-oriented video transport protocols (e.g., RTMP [9]) to HTTP-based adaptive streaming protocols (e.g., [1, 10, 12, 35]). With a HTTP-based adaptive streaming protocol, a video player can dynamically (at the granularity of seconds) adjust the video bitrate based on the available network bandwidth. As video traffic is expected to dominate Internet traffic [5], the design of robust adaptive HTTP streaming algorithms is important not only for the performance of video applications, but also the performance of the Internet as a whole. Drawing an analogy to the early days of the Internet, a robust TCP was critical to prevent "congestion collapse" [25]; we are potentially at a similar juncture today with respect to HTTP streaming protocols.

Building on this analogy, the design of a robust adaptive video algorithm must naturally move beyond a single-player view to account for the interactions across *multiple* adaptive streaming players [13, 20, 41] that compete at bottleneck links. In this respect, there are three (potentially conflicting) goals that a robust video adaptive streaming algorithm must try to achieve:

- *Fairness:* Multiple competing players sharing a bottleneck link should be able to converge to an equitable allocation of the network.
- *Stability:* A player should avoid needless bitrate switches as this can adversely affect the user experience.
- *Efficiency:* A group of players must choose the highest feasible set of bitrates to maximize the user experience.

Recent work shows that two widely used commercial players fail to achieve one or more of these properties when two players compete at a bottleneck link [13, 24]. We extend these experiments (§2) and confirm that the problems manifest across many state-of-art HTTP adaptive streaming protocols: SmoothStreaming [11], Netflix [8], Adobe OSMF [2], and Akamai HD [3]. Furthermore, these problems worsen as the number of competing players increases.

While such measurements are valuable in identifying the shortcomings of today's players, our understanding of the root causes of these problems is limited. To this end, we provide a systematic study of these problems through the lens of an abstract video player that needs to implement three key components: (1) scheduling a specific video "chunk" to be downloaded (see §2), (2) selecting the bitrate for each chunk, and (3) estimating the bandwidth.

At a high-level, the aforementioned problems arise as a result of *overlaying* the adaptation logic on top of several logical layers that may hide the true network state. Consequently, the "feedback" signal that the player receives from the network is not a true reflection of the network state and can be biased by the decisions the player makes! Specifically, we observe that periodic chunk scheduling used in conjunction with stateless bitrate selection used by players today can lead to undesirable feedback loops with bandwidth estimation and cause unnecessary bitrate switches and unfairness in the choice of bitrates.

Our goal is to design a *fair*, *efficient*, and *stable* video viewing experience. In doing so, we want to retain the characteristics that have fundamentally contributed to the rapid growth of Internet video—using HTTP, no modifications to end-host stacks, and little modification to network, CDN,

and server infrastructure. Working within these constraints, we leverage measurement-driven insights to design robust mechanisms for the three player components that help overcome the biases that arise as a result of implementing the adaptation logic at the application layer.

Our specific recommendations are (we elaborate on these in §3): (1) *randomized chunk scheduling* to avoid synchronization biases in sampling the network state, (2) a *stateful bitrate selection* that compensates for the biased interaction between bitrate and estimated bandwidth, (3) a *delayed update* approach to tradeoff stability and efficiency, and (4) a bandwidth estimator that uses the *harmonic* mean of download speed over recent chunks to be robust to outliers. Taken together, these approaches define a family of adaptation algorithms that vary in the tradeoff across fairness, efficiency, and stability. As a concrete instance, we also show how to pick a sweet spot in this tradeoff space called the FESTIVE algorithm.[1]

We evaluate FESTIVE against several (emulated) commercial players across a range of scenarios that vary the overall bandwidth and number of users. Compared to the closest alternative, FESTIVE improves fairness by 40%, stability by 50% and efficiency by at least 10%. Furthermore, FESTIVE is robust to the number of players sharing a bottleneck, bandwidth variability increases, and to the available set of bitrates.

In summary, this paper makes the following contributions:

- We systematically explore the design space of adaptive video algorithms with the multiple goals of being fair, stable, and efficient.
- We identify the main factors in bitrate selection and chunk scheduling employed in state-of-art players today that lead to undesirable feedback loops and instability.
- We design robust mechanisms for chunk scheduling, bandwidth estimation, and bitrate selection that inform the design of a suite of adaptation algorithms that vary in the tradeoff between stability, fairness and efficiency.
- We identify one concrete design from this family of algorithms as a reasonable point in this tradeoff space and show that it consistently outperforms state-of-art players.

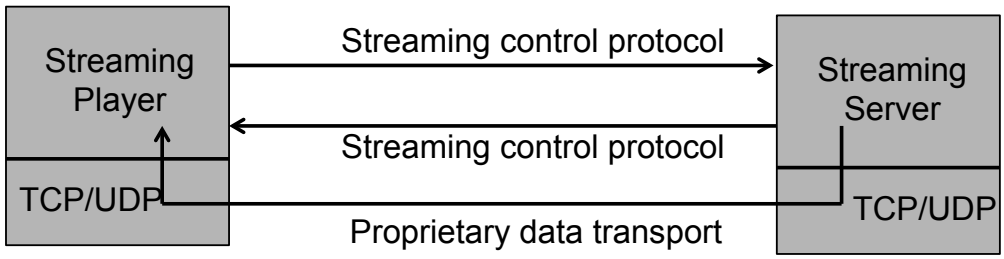
2 Background

2.1 HTTP Adaptive Video Streaming

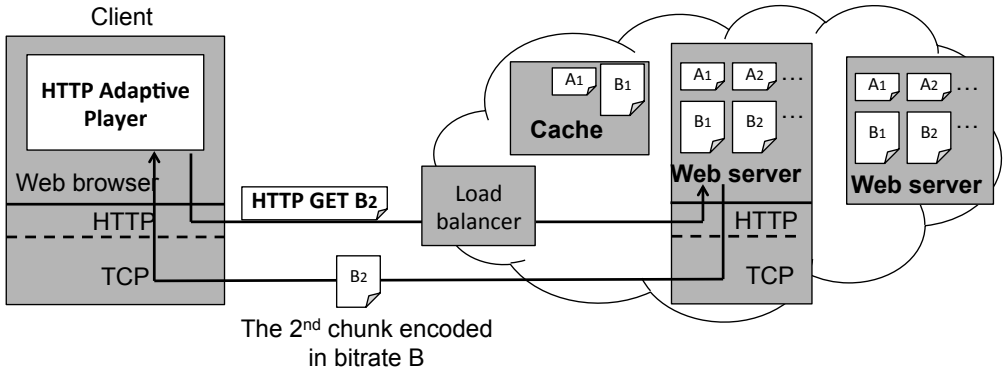
Early Internet video technologies (e.g., Apple QuickTime [4], Adobe Flash RTMP [9]) were based on connection-oriented video transport protocols. As shown in Figure 1(a), these protocols have a session abstraction between the client and the server, that both maintain per-session state and a (proprietary) stateful control protocol is used to manage the data delivery. The new generation of Internet video technologies such as Microsoft SmoothStreaming [11], Apple's HLS [35], and Adobe's HDS [1], however, are HTTP-based adaptive streaming protocols.

In HTTP adaptive streaming, a video is encoded with multiple *discrete* bitrates and each bitrate stream is broken into multiple 1-5 seconds segments or "chunks". The i^{th} chunk from one bitrate stream is aligned in the video time line to the i^{th} chunk from another bitrate stream so that a video

[1]The name FESTIVE refers to a **F**air, **E**fficient, and **S**table adap**TIVE** algorithm.



(a) Connection-oriented streaming



(b) HTTP adaptive streaming

Figure 1: Difference between connection-oriented and HTTP adaptive streaming protocol.

player can smoothly switch to a different bitrate at each chunk boundary. As shown in Figure 1(b), HTTP-based adaptive streaming protocols differ from the traditional connection-oriented video transport protocols in several important aspects. First, clients use standard HTTP protocol which provides more ubiquitous reach and support as this traffic can traverse NATs and firewalls [36]. Second, the servers are Web servers or caches; this use of existing CDN and server technology has been a key driver for rapid growth and low costs. Third, the use of HTTP implies caches deployed by enterprise and service providers automatically improve the performance and reduce network load. Finally, a client fetches each chunk *independently* and maintains the playback session state while servers do not. This makes it possible for the client to receive chunks from multiple servers: enabling load-balancing and fault tolerance on both CDN side (among multiple servers) and client side (among multiple CDNs) [30, 31].

The client side video player usually runs in a constrained sandbox environment such as Flash or Silverlight and implements the adaptive logic. The adaptive part arises because the player uses the throughput observed for each chunk and the chunk size to estimate the available network bandwidth. These estimates are used to choose a suitable bitrate for the next chunk to be downloaded. The player tries to maintain an adequate video playback buffer to minimize rebuffering which can adversely impact user engagement [19]. Our focus in this paper is on this adaptive logic in the video player on top of a HTTP-streaming protocol.

At first glance, this logic appears analogous to TCP congestion control. There are, however, key architectural differences between HTTP video adaptive streaming and TCP. First, the two control algorithms operate at different levels in the protocol stack. For example, video players

can only access coarse information as they run in an application-level sandbox. Second, TCP is a connection-oriented protocol with control logic implemented at the sender-side while video adaptation is a connectionless protocol with receiver-side control. Third, the granularity of data and time are very different. TCP operates at the packet level ($\sim$1KB), has multiple packets in transit, and the control loop acts on the timescale of milliseconds. Video adaptation operates at the chunk level ($\sim$ hundreds of kilobytes), has only one chunk in transit, and the control loop runs at the timescale of seconds (i.e., chunk fetch delay). Last, due to the video-specific requirement that playout buffer cannot be empty, the control actions are very different; a TCP sender delays packet transmission under congestion whereas the receiver in a video adaptation algorithm requests a lower bitrate chunk. Taken together, these factors mean that the rich literature and and experience in designing TCP is not directly applicable here.

2.2 Desired properties

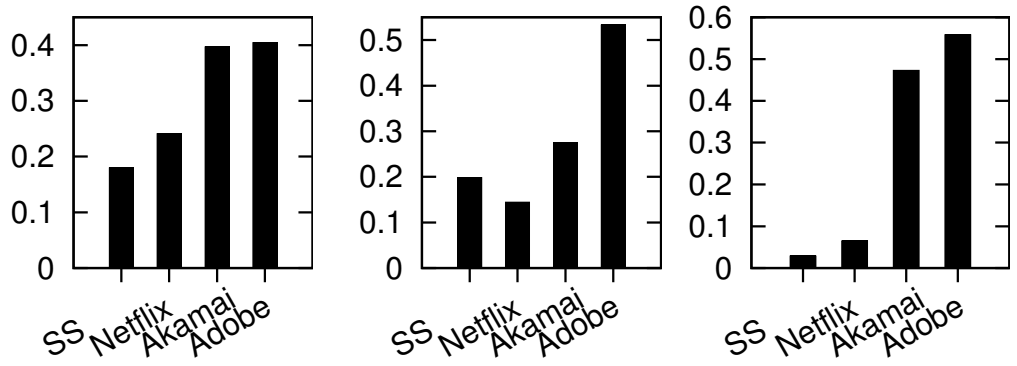
We are interested in a *multi-player* setting when multiple video players may be sharing a bottleneck link [13, 24, 41]. We generalize the metrics defined by Akhshabi et al in the context of two video players to multiple players [13]. To formally define the metrics, we consider a setting with N players sharing a bottleneck link with bandwidth W, with each player x playing bitrate $b_{x,t}$ at time t.

- *Inefficiency:* The inefficiency at time t is $\frac{|\sum_x b_{x,t} - W|}{W}$. A value close to zero implies that the players in aggregate are using as high an average bitrate as possible which improves user experience [19].
- *Unfairness:* Now, some players could see a low bitrate while other players may see high quality. Akhshabi et al., use the difference between bitrates in a two-player setting to compute the unfairness [13]. We generalize this to multiple players as $\sqrt{1 - JainFair}$, where $JainFair$ is the Jain fairness index [37] of $b_{x,t}$ over all player x, because we want to quantify unfairness. A lower value of the metric implies a more fair allocation.
- *Instability:* Studies suggest users are likely to be sensitive to frequent and significant bitrate switches [16, 33]. We define the instability metric as $\frac{\sum_{d=0}^{k-1} |b_{x,t-d} - b_{x,t-d-1}| \cdot w(d)}{\sum_{d=1}^{k} b_{x,t-d} \cdot w(d)}$, which is the weighted summation of all switch steps observed within the last $k = 20$ seconds divided by the weighted summation of bitrate in the last $k = 20$ seconds. We use the weight function $w(d) = k - d$ to add linear penalty to more recent bitrate switch.

2.3 Today's solutions

Next, we analyze how today's commercial solutions—SmoothStreaming [10], Akamai HD [3], Netflix [8], Adobe OSMF [2]—perform w.r.t the above metrics. In doing so, we generalize the measurements from previous work that study 1 or 2 of these players in isolation and demonstrate that these problems are more widespread.

We consider a setup with three players sharing a bottleneck link with a stable bandwidth of 3 Mbps with default player settings. Each player runs in a separate Windows machine running



(a) Unfairness (b) Inefficiency (c) Instability

Figure 2: Performance of today's commercial players (SS stands for SmoothStreaming).

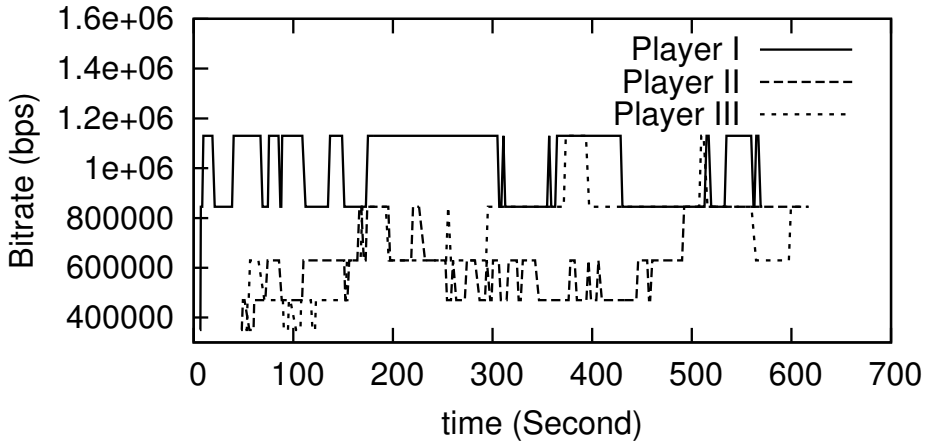


Figure 3: Visualizing unfairness and instability in SmoothStreaming

on a 2.8 Ghz desktop and accesses the respective demo website. Figure 2 shows the unfairness, inefficiency, and instability. We see that the Akamai and Adobe players are very unstable, while all of them are quite unfair. To give some context for what this unfairness index means, Figure 3 shows a timeseries of the bitrates of the three SmoothStreaming players which visually confirms that the allocation is quite unfair even for the best player in the above result. (In this case, the optimal allocation would be for all players to pick the same bitrate at all times.) Furthermore, Table 1 shows that the problems become worse as the number of players competing for the bottleneck link increases. Here, with a N player setup, we assume a stable bottleneck of $N \times 1$ Mbps. For brevity, we only show the result SmoothStreaming because this was the best overall player across all three metrics in our earlier experiment.

3 Design

As the previous section showed, today's state-of-art players do not satisfy the goals of fairness, efficiency, and stability. In this section, we describe how we design a adaptive streaming player

# players	BW (bps)	Unfairness	Inefficiency	Instability
5	5M	0.140	0.184	0.0537
11	11M	0.180	0.230	0.0648
19	19M	0.235	0.343	0.0909

Table 1: The performance of SmoothStreaming worsens as the number of players increases. We see similar trends with other players too (not shown for brevity).

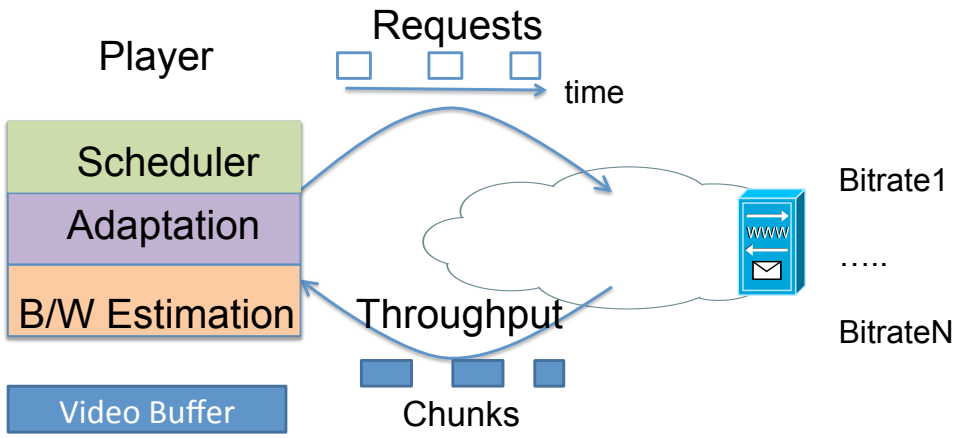


Figure 4: General framework of HTTP adaptive video streaming. The server supports multiple bitrate encodings, each a separate logically chunked file. The player issues GET requests for each chunk at a specific bitrate and adapts the bitrate based on the observed throughput.

that satisfies these properties. As the high-level model from Figure 4 shows, an adaptive streaming player involves three components to:

1. Schedule when the next chunk will be downloaded.
2. Select a suitable bitrate for the next chunk.
3. Estimate the network bandwidth.

In designing each component, we make a conscious decision to be compatible with today's deployments and end-host stacks and do not require modifications to end-hosts' operating system stacks or CDN servers. For each component, we use measurement-driven insights to analyze problems with today's players to arrive at a suitable design. We validate each component in §5.2 and their interaction in §5.3.

3.1 Chunk Scheduling

The feedback that a player gets from the network is the observed throughput for each chunk. However, the discrete nature of the chunk download implies that the throughput a player observes is coupled to the time when the player "occupies" the link. This is in contrast to a long-running TCP flow that will observe its true share. Thus, we need a careful chunk scheduling approach to avoid biases in observing the network state.

We begin by considering two strawman options: (1) download the next chunk *immediately* after the previous chunk has been downloaded and (2) download chunks *periodically* so that the

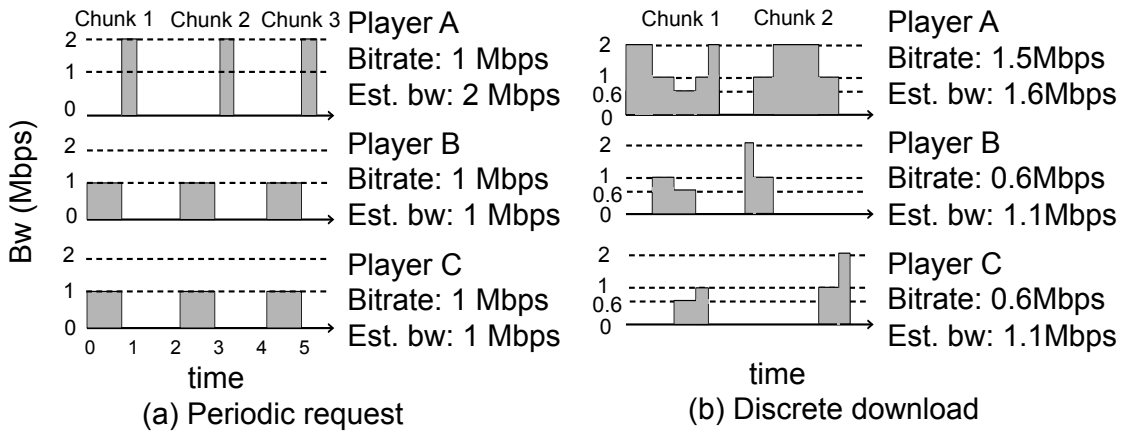


Figure 5: Two sources of bias with today's players: periodic request intervals and higher bitrates lead to higher bandwidth estimates

player buffer is sufficiently full. For example, SmoothStreaming uses the periodic strategy [13]. However, there are subtle issues with both approaches that we highlight next.

Immediate download: This greedily builds up the player buffer to avoid future buffering events. This approach, however, can be suboptimal for the following reasons. First, greedily downloading at the highest bitrate may needlessly increase the server's bandwidth costs, especially if users leave prematurely [21]. Second, greedily downloading low bitrate chunks may preclude the option of switching to a higher quality in case the network conditions improve which will increase user engagement [6, 19, 43]. Furthermore, in the case of live content, future chunks may not even be available and thus this approach is not a viable option. While this greedy download option might be useful in the initial ramp-up phase for a player, the above reasons make it unsuitable in the steady state.

Periodic download: The periodic request strategy tries to maintain a *constant* playback buffer to minimize rebuffering [13]. This target buffer size is usually a fixed number of chunks; e.g., SmoothStreaming uses a 2-second chunk and a target playback buffer of 30 seconds (i.e., 15 chunks). This approach works as follows. Let t_i^{start} be the time when the i^{th} chunk is requested, t_i^{end} be the time that it is downloaded, and Δ denote the length of each chunk (in seconds). Suppose $buffer_i$ is length of the playback buffer (in seconds) at t_i^{end} and $targetbuf$ is the target buffer size (e.g., 30s). Then, the time to request the next chunk t_{i+1}^{start} can be written as:[2]

$$t_{i+1}^{start} = \begin{cases} t_i^{end}, \text{if } \ buffer_i < targetbuf \\ t_i^{end} + buffer_i - targetbuf, \text{otherwise.} \end{cases} \quad (1)$$

While this avoids wasting network bandwidth and prematurely committing to low quality, it suffers a different issue – players may see a biased view of the network state. Specifically, with the periodic download, the players' initial conditions may cause it to get stuck in suboptimal allocations. Figure 5(a) illustrates this problem. Suppose the players use a fixed request period of 2 seconds and the total bandwidth is 2 Mbps. Players A and B always request the next chunk at

[2]We can prove that this downloads one chunk every Δ seconds at steady state; we do not show this for brevity.

even seconds (i.e., 0,2,4,, ...), while player C requests it at odd seconds (i.e., 1,3,5, ...). The throughput observed by A and B will be 1 Mbps (half the bandwidth) whereas C estimates it to be 2 Mbps (whole bandwidth). In other words, the initial conditions can lead to unfairness in bandwidth allocation.

Randomized scheduling: In order to avoid this bias introduced by the initial conditions, we introduce a *randomized* scheduler that extends the periodic strategy. As before, we want to maintain a reasonable playback buffer. Instead of requiring a constant $targetbuf$, however, we treat it as an *expected* value. Specifically, for each chunk i we choose a target buffer size $randbuf_i$ uniformly at random from the range $(targetbuf - \delta, targetbuf + \delta]$. In particular, we choose $\delta = \Delta$ which is driven by the analysis from §4. Then, the time to request the next chunk is:

$$t_{i+1}^{start} = \begin{cases} t_i^{end}, \text{ if } buffer_i < randbuf_i \\ t_i^{end} + buffer_i - randbuf_i, \text{ otherwise.} \end{cases} \quad (2)$$

At steady state, the chunks will be downloaded roughly periodically, but with some jitter as we randomize the target buffer size. We show via analysis in §4 and measurements in §5, that this strategy ensures that the time to request each chunk, and consequently the estimated bandwidth, is independent of a player's start time.

3.2 Bitrate Selection

Having chosen a chunk scheduling strategy that ensures that each player is not biased by its start time, we move to bitrate selection. Our high-level goal here is to ensure that the players will eventually *converge* to a fair allocation irrespective of their current bitrates.

Bias with stateless selection: A natural strategy is to choose the highest available bitrate lower than the estimated bandwidth. We refer to this as a class of *stateless* approaches as it only considers the estimated bandwidth; e.g., not taking into account current bitrate or whether it is ramping up or ramping down its bitrate. For example, if the available bitrates are 00, 600, and 800 Kbps and the estimated bandwidth is 750 Kbps, the player chooses 600 Kbps.

While this stateless approach seems appealing, it can result in an unfair allocation of a bottleneck link. To understand why this happens, let us look at an example in Figure 5(b) with three players A, B and C sharing a bottleneck link with an available bandwidth of 2Mbps, using the randomized scheduler. There are three bitrates available: 600, 1200, and 1500Kbps. Suppose Player A is currently using a bitrate of 1500 Kbps and Player B and C are currently using bitrate 600 Kbps. As shown in Figure 5(b), because Player A uses a higher bitrate, its "wire occupancy" is higher than Player B and C. This implies that there are points in time where Player A is occupying the bottleneck link alone and thus Player A's estimated bandwidth will be higher than Player B and C. In other words, the discrete download process introduces a natural bias: *players with a higher bitrate observe a higher bandwidth*. We formally derive the relationship between estimated bandwidth and bitrates in §4.

Now, because there are only a discrete set of available bitrates (e.g., 4-5 encodings), players sharing a bottleneck link can often converge to an equilibrium state that is inherently unfair; e.g.,

Round	Bitrates (Kbps)	→	Estimated bw. (Kbps) (network feedbacks)
1	[350,350,1520]	→	[730,730,1356]
2	[470,470,1130]	→	[717,717,1146]
3	[470,470,1130]	→	[717,717,1146]
...	...	...	...

Table 2: Example of unfairness with stateless bitrate selection. The bitrate levels are {350,470,730,845,1130,1520}Kbps and the total bandwidth is 2Mbps.

in Figure 5(b), Player B and C will never increase their bitrate. This scenario is not merely hypothetical. For example, Table 2 shows an actual run using our setup (described in detail in §5), where the players converge to an equilibrium state that is inherently unfair.

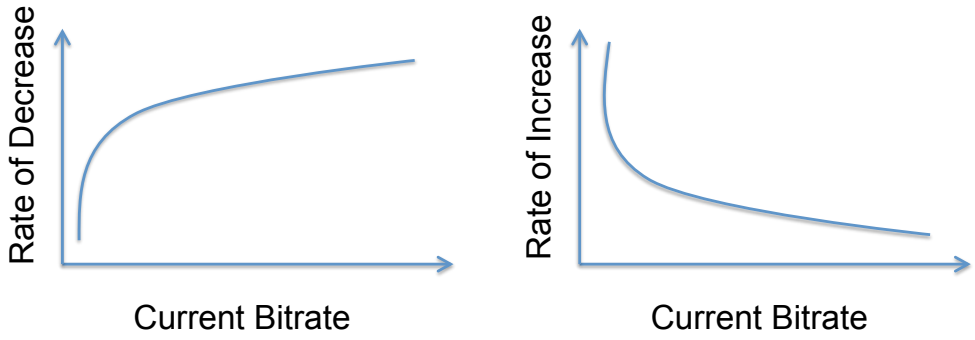


Figure 6: Intuition behind stateful selection: we want players with lower bitrate to ramp up aggressively or players with higher bitrate to ramp down aggressively.

Our approach: At a high-level, we need to compensate for the aforementioned bias so that the players can converge to a fair allocation irrespective of their current bitrates. We can achieve this in one of two ways as shown in Figure 6: (1) the rate of bitrate increase is a monotonically decreasing function of the bitrate or (2) the rate of decrease is a monotonically increasing function of the bitrate. Intuitively, we are making the player *stateful* by accounting for its current bitrate.[3] Our current design chooses option (1) and we simply keep the rate of decrease a constant function. In the example in Table 2, this approach causes the players starting at 350 Kbps to more aggressively ramp up their bitrates so that they will observe the true network state after 2-3 switches.

This stateful strategy can be realized either by allowing *multi-level* bitrate switches (e.g., from 350 to 1130 and skipping intermediate levels) or by altering the *rate* of switching the bitrates (e.g., once per chunk at 350 but once every 5 chunks at 1130). While we do not conclusively know if users are more sensitive to multi-level switches or the number of switches [16], recent work suggests that changing quality levels gradually is preferable [33]. Thus, we choose a *gradual* switching strategy where the player only switches to the next highest level and uses a lower rate of upward switches at higher bitrates. We discuss our specific approach in §3.5. We do, however, note that the property achieved by a stateful approach is agnostic to how specific players implement the mechanism from Figure 6.

[3]We can show that this approach is sufficient; we do not know or claim that this is necessary.

3.3 Delayed Update

While the previous discussion provides guidelines for choosing the bitrate to converge to a fair allocation, it does not consider the issue of *stability*. Switching too frequently is likely to annoy users (e.g., [16]) and thus in this section, we focus on balancing these two potentially conflicting goals: efficiency and fairness on one hand vs. stability on the other.

To this end, we introduce a notion of *delayed update*. We treat the bitrate from the previous section only as a *reference* bitrate and defer the actual switch based on a measured tradeoff between efficiency/fairness and stability. Specifically, we compute how close to the efficient or stable allocation the current (b_{cur}) and the reference bitrate computed from the previous discussion (b_{ref}) are.

The *efficiency cost* for bitrate b is:

$$score_{efficiency}(b) = \left| \frac{b}{\min(w, b_{ref})} - 1 \right|$$

Here, w is the estimated bandwidth and b_{ref} is the reference bitrate from the previous section. Intuitively, the score is the best and equal to zero when $b = b_{ref}$. (The "min" in the denominator corrects for the fact that the reference bitrate may be underutilizing or overutilizing the bottleneck link.)

The *stability cost* for a given bitrate b is a function of the number of bitrate switches the player has undergone recently. Let n denote the number of bitrate switches in the last $k = 20$ seconds. Then the stability metric is,

$$score_{stability}(b) = \begin{cases} 2^n + 1 & \text{if } b = b_{ref} \\ 2^n & \text{if } b = b_{cur} \end{cases}$$

The reason to use exponential function of n as stability score is that $score_{stability}(b_{ref}) - score_{stability}(b_{cur})$ is monotonically increasing with n, which adds more penalty of adding a new switch if there have already been many switches in recent history.

The combined score is simply the weighted average:

$$score_{stability}(b) + \alpha \times score_{efficiency}(b)$$

The player computes this combined score for both the current and reference bitrates, and picks the bitrate with the lower combined score. The factor α here provides a tunable knob to control the tradeoff between efficiency/fairness and stability. We provide empirical guidelines on selecting a suitable value for α in §5.2.

3.4 Bandwidth Estimation

As we saw in the previous discussions, the throughput observed by a player for each chunk is not a reliable estimate of the available capacity. We suggest two guidelines to build a more robust bandwidth estimator. First, instead of using the instantaneous throughput, we use a "smoothed" metric

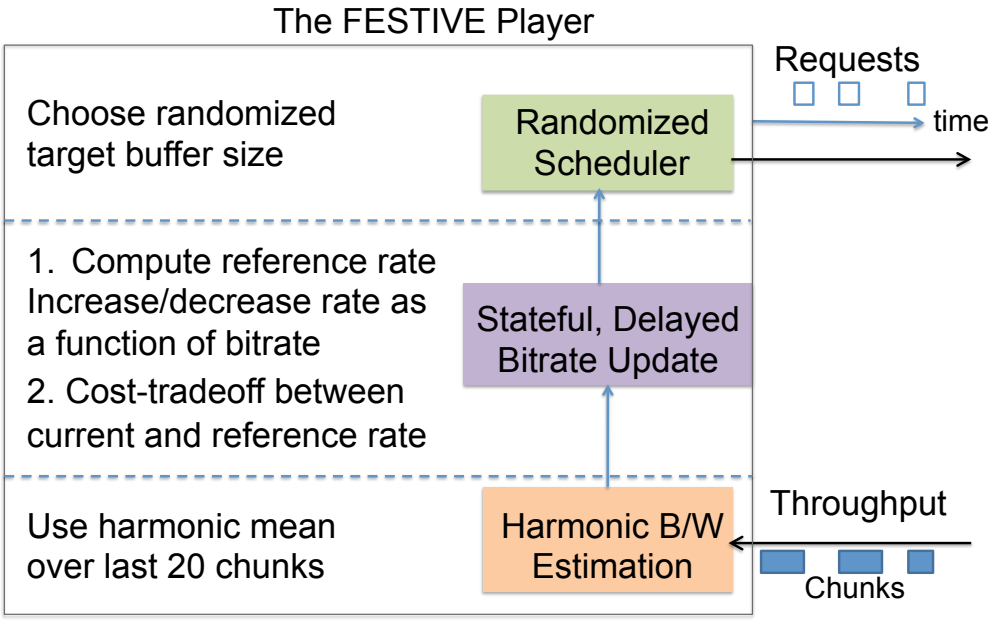


Figure 7: Overview of the FESTIVE adaptive video player.

computed over the last several chunks. In our current prototype, we use the last 20 samples. (We do not claim smoothing is new; commercial players likely already implement some smoothing.) Second, we want this smoothing to be *robust* to outliers. For example, using the arithmetic *mean* is biased by outliers if one chunk sees a very high or low throughput. To this end, we use the *harmonic mean* over the last 20 samples. The reason for using this approach is two-fold. First, the harmonic mean is more appropriate when we want to compute the average of "rates" as is the case with such throughput estimation. Second, it is also more robust to larger outliers [7]. This is particularly relevant in the context of our randomized scheduler. We are especially concerned about larger outliers; i.e., there are few competitors. (If there are more competitors, then each player is more likely to observe a bandwidth close to its fair share.) With a randomized scheduler, however, if there are fewer competitors for a certain chunk, the throughput will be larger. In such cases, the harmonic mean minimizes the impact of outliers.

3.5 The FESTIVE Algorithm

We now proceed to put the different design components together to describe the FESTIVE (Fair, Efficient, Stable, adaptIVE) algorithm. Figure 7 shows a high-level overview of FESTIVE. FESTIVE retains the same external-facing interface as today's HTTP video streaming players. That is, FESTIVE selects the bitrate for each chunk and decides when to schedule the request and the input to FESTIVE is the throughput observed per-chunk.

In describing FESTIVE, we only focus on the steady-state behavior. The ramp up behavior of FESTIVE can be identical to today's players; e.g., aggressively download chunks potentially at a low rate to start playing the video as soon as possible. As discussed in the previous sections, FESTIVE has three key components:

1. The *harmonic bandwidth estimator* computes the harmonic mean of the last $k = 20$ throughput estimates. This provides *reliable* bandwidth estimates on which future bitrate update decisions can be made. In the initial phase before we have sufficient samples, FESTIVE does not employ any rate switches because its bandwidth estimate will be unreliable.
2. The *stateful and delayed bitrate update* module receives throughput estimates from the bandwidth estimator and computes a reference bitrate. As a specific implementation of Figure 6, we use a gradual switching strategy; i.e., each switch is only to the next higher/lower level. Here, we increase the reference bitrate at bitrate level k only after k chunks, but decrease the bitrate level after every chunk if a decrease is necessary. This ensures that the bitrates eventually *converge* to a fair allocation despite the biased bitrate-to-bandwidth relationship. To decide if we need to decrease, we compare the current bitrate with $p = 0.85\times$ the estimated bandwidth. The parameter p helps tolerate the buffer fluctuation caused by variability in chunk sizes [41]. For the delayed update, we use a value of the tradeoff factor $\alpha = 12$ (see §5.2).
3. The *randomized scheduler* works as shown in Eq(2). It schedules the next chunk to be downloaded immediately if its playback buffer is less than the target buffer size. Otherwise, the next chunk is scheduled with a random delay by selecting a randomized target buffer size. This ensures there are no *start time biases*.

4 Analysis of FESTIVE

In this section, we analytically show that:

- The randomized scheduler in FESTIVE ensures that the request time of a player is independent of its start time.
- The stateful bitrate selection in FESTIVE ensures that bitrates will eventually converge to a fair allocation.

Together these ensure that the network state observed by competing players will not be biased either by when they arrive or the initial bitrates of other players.

Notation: We use i, k to denote chunk indices, j for a specific epoch, and x, y, z to denote players. Let n be the number of players and m be the number of chunks and let the bottleneck bandwidth be W. We use Δ to denote the length (in time) of each chunk.

Model: Our focus here is on the steady state behavior and not the initial ramp up phase. To make the analysis tractable, we make four simplifying assumptions. First, we assume the bottleneck bandwidth is stable. Second, this bandwidth is not saturated by the summation of bitrate, and each player's bitrate is less than its allocated bandwidth. As a result, for each chunk, a player will complete the download before the "deadline", so the $buffer_i > randbuf_i$ will hold for most chunks. Third, if n players are simultaneously downloading over a bottleneck of bandwidth W, we assume that each player will get a bandwidth share of $\frac{W}{n}$. Last, we consider an *epoch-based* model, where players synchronously choose a new bitrate at the start of each epoch and estimate the bandwidth at the end of each epoch.[4]

[4]Each epoch can consist of multiple chunks.

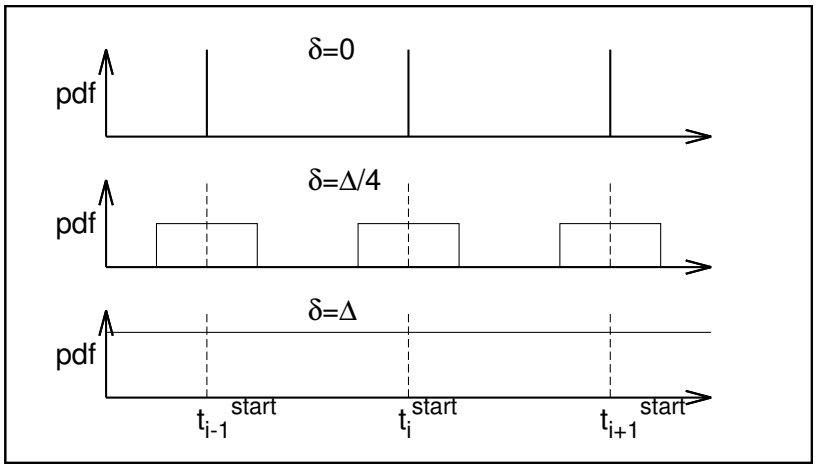


Figure 8: Intuition for Theorem 1.

4.1 Randomized scheduler

The goal of the randomized scheduler is to ensure the request time is independent of a player's start time. Formally, we want to show that:

Theorem 1 *If a player uses* $randbuf_i$ *drawn uniformly at random between* $(targetbuf-\Delta, targetbuf+\Delta]$ *and* $buffer_i > randbuf_i$ *for each chunk* i *(*$i = 1, \ldots, m$*), then the probability distribution of chunk request times does not depend on the start time* t_0^{start}.

Proof 1 *The buffer length at time* t_{i-1}^{end}*, when chunk* $i-1$ *has been downloaded is* $buffer_{i-1} = (i-1)\Delta - (t_{i-1}^{end} - t_0^{start})$ *where* $(i-1)\Delta$ *is the length of content downloaded so far and* $t_{i-1}^{end} - t_0^{start}$ *is the amount of video played. If* $buffer_{i-1} > randbuf_{i-1}$*, then by Eq* (2)*, the time to request the next chunk:*

$$\begin{aligned} &t_i^{start} = t_{i-1}^{end} + buffer_{i-1} - randbuf_{i-1} = \\ &t_{i-1}^{end} + (i-1)\Delta - (t_{i-1}^{end} - t_0^{start}) - randbuf_{i-1} \\ &= t_0^{start} + (i-1)\Delta - randbuf_{i-1} \end{aligned}$$

Because each $randbuf_{i-1}$ *is a uniform random variable in the range* $(targetbuf-\Delta, targetbuf+\Delta]$*, this means that for a given* i*,* t_i^{start} *is a uniform random variable in the range* $(t_0^{start} + (i-1)\Delta - targetbuf - \Delta, t_0^{start} + (i-1)\Delta - targetbuf + \Delta]$*. Let* T *denote a random variable representing the request time. Then* $T = t$ *can occur for exactly there are exactly two intervals* i^* *and* i^*+1 *(with* $i^* = \frac{1}{\Delta}(t + targetbuf - t_0^{start})$ *) as shown in Figure 8. Thus,* $f(T=t) = f(t_{i^*}^{start} = t \text{ or } t_{i^*+1}^{start} = t) = 2 * \frac{1}{2\Delta} = \frac{1}{\Delta}$ *which is independent of* t_0^{start}.

Notice that for other $\delta \neq \Delta$, if $randbuf_i$ is at random in range $(targetbuf - \delta, targetbuf + \delta]$, then the same argument of Theorem 1 does not hold. For example, if $\delta = \frac{1}{r}\Delta$ where $r > 2$, then the ranges of t_i^{start} for different i will not overlap (see Figure 8). Consequently, for any t, there will be at most one t_i^{start} whose range covers t. That is, $f(T=t)$ will be $\frac{1}{2\delta}$ for exactly one k such that

$t_0^{start} + k\Delta - targetbuf - \delta < t \leq t_0^{start} + k\Delta - targetbuf + \delta$ and 0 otherwise. In other words, the request time distribution depends on the start time t_0^{start}. The periodic scheduler is an extreme case with $r \to \infty$.

4.2 Stateful bitrate selection

We begin by deriving the relationship between estimated bandwidth and bitrate in Lemma 1 which shows that a player with higher bitrate will see relatively higher bandwidth.

Lemma 1 *For two players, x and y, let w_x and w_y be the harmonic mean of the throughput seen by them and b_x, b_y be their bitrates. Then, $\frac{w_x}{w_y} = \frac{b_x+W}{b_y+W}$.*

Proof 2 *Since we are using random scheduler, each player will join the link randomly. Let n_{ix} be the number of competitors when player x downloads chunk i, then the bandwidth allocation of chunk i is $\frac{W}{n_{ix}+1}$. Thus, the download time for chunk i is $d_{ix} = \frac{b_x\Delta(n_{ix}+1)}{W}$ where $b_x\Delta$ is the chunk size. The total download time is $\sum_{i=1}^{m} d_{ix}$, and the fraction of time when player x is downloading is:*

$$q_x = \frac{1}{m\Delta}\sum_{i=1}^{m} d_{ix} = \frac{1}{m\Delta}\sum_{i=1}^{m} \frac{b_x\Delta(n_{ix}+1)}{W}$$
$$= \frac{b_x}{W}\sum_{i=1}^{m} \frac{(1+n_{ix})}{m} = \frac{b_x}{W}N_x$$

where $N_x = 1 + E(n_{ix})$ is the expected number of competitors for x. When each chunk length is small, the probability that player i is competing for the bandwidth is simply the fraction of time spent downloading, q_x. Thus, we have $N_x = 1 + E(n_{ix}) = 1 + \sum_{z\neq x} q_z$.[5] Thus, we have

$$\frac{q_x W}{b_x} + q_x = 1 + \sum_z q_z = \frac{q_y W}{b_y} + q_y \Rightarrow \frac{b_x + W}{b_y + W} = \frac{\frac{b_x}{q_x}}{\frac{b_y}{q_y}}$$

On the other hand, the harmonic mean of bandwidth:

$$w_x = \frac{m}{\sum_{i=1}^{m}\frac{1}{w_{ix}}} = \frac{W}{\frac{1}{m}\sum_{i=1}^{m}(1+n_{ix})} = \frac{W}{N_x} = \frac{b_x}{q_x}$$

Thus, we have $\frac{b_x+W}{b_y+W} = \frac{w_x}{w_y}$

Notice that w_x is a harmonic mean, rather than expectation, of the bandwidth the player sees, which is consistent with how bandwidth is estimated in FESTIVE.

Based on this, we have the following theorem which proves bitrate convergence. Recall from §3.5 that if bitrate $b_x > pw_x$ where w_x is the harmonic mean of bandwidth of the epoch and p is a real value parameter, then the player x will decrease bitrate in the next epoch. Otherwise, it will increase in a rate which depends on the bitrate level.

[5]This is by linearity of expectation

Theorem 2 *Let l_x^j and l_y^j be the bitrate levels of players x and y in j^{th} epoch with $l_y^j - l_x^j \geq 2$. Then the gap will eventually converge to be at most one level, i.e., $\exists j' > j$, where $|l_x^{j'} - l_y^{j'}| \leq 1$*

Proof 3 *Given $l_y^j - l_x^j \geq 2$, we show that $l_y^j - l_x^j$ monotonically decreases as a function of j until $|l_y^j - l_x^j| = 1$. Let b_x^j, b_y^j denote the bitrates and w_x^j, w_y^j be the bandwidth in epoch j. By Lemma 1, there is no p for which $pw_x < b_x^j$ and $b_y^j < pw_y$. (Otherwise, $\frac{w_x^j}{w_y^j} < \frac{b_x^j}{b_y^j} < \frac{b_x^j+W}{b_y^j+W}$, which contradicts Lemma 1.) Therefore, there are only three cases for the estimated bandwidths w_x^j, w_y^j, (i) $pw_x^j > b_x^j, pw_y^j < b_y^j$, (ii) $pw_x^j < b_x^j, pw_y^j < b_y^j$, and (iii) $pw_x^j > b_x^j, pw_y^j > b_y^j$. For (i), b_y^j will decrease, and b_x^j will not decrease, therefore, $l_y^{j+1} - l_x^{j+1} \leq l_y^j - l_x^j - 1$. For (iii), before switching to (i) or (ii), x will increase earlier than y according to the stateful bitrate update (Figure 6), so $l_y^j - l_x^j$ will decrease. For (ii), since the two players cannot always decrease bitrate in (ii), so eventually, they will enter (iii) or (i). As a result, in each epoch, $l_x^j - l_y^j$ cannot increase and it will not always remain constant.*

5 Evaluation

We divide our evaluation into four high-level sections:

1. We compare the performance of FESTIVE against (emulated) commercial players (§5.1).
2. We validate each component—randomized chunk scheduling, stateful and delayed bitrate selection, and harmonic bandwidth estimation (§5.2).
3. We evaluate how critical each component is to the overall performance of FESTIVE (§5.3).
4. Finally, we evaluate the robustness of FESTIVE as a function of bandwidth variability, number of players, and the set of available bitrates (§5.4).

Emulation platform: We implemented an emulation platform that allows us to flexibly evaluate different algorithms for chunk scheduling, bitrate selection, and bandwidth estimation. Our setup consists of client players, video servers, and a bottleneck link. Both client and server side mechanisms are implemented as Java modules (about 1000 lines each) that run on different machines within a local network. The client player decides the bitrate for the next chunk and when to issue the request. Once the video server receives the request which explicitly encodes the bitrate, it generates a file with size dependent on the bitrate. The client downloads this "chunk" over a regular TCP socket. All traffic between clients and servers goes through the bottleneck which uses Dummynet [40] to control the total bandwidth and delay. Unless specified otherwise, we emulate a ten-minute long video with eight bitrate levels from 350Kbps to 2750Kbps and using 2 second chunks. (This is based on the parameters we observe in the demo website [10]). We use chunk sizes of an encoded video for each bitrate by analyzing real traces of commercial players.

5.1 Comparison with Commercial Players

Emulating commercial players: Our goal is to evaluate the underlying *adaptation logic* of different adaptive players. However, the proprietary nature of the client/server code for these players makes it difficult to do a head-to-head comparison because using the commercial players conflates

external effects: network (e.g., wide-area bottlenecks) and server-side (e.g., CDN load) effects, issues w.r.t video encoding/decoding, and player plugin performance. To do a fair comparison, we heuristically create *emulated* clones that closely mimic each commercial player. In each case, we verified over a range of settings that our emulated clone is a *conservative* approximation of the commercial player; i.e., the unfairness, inefficiency, and instability with the emulated clone are strict *lower bounds* for the actual player.

Our heuristic approach works as follows. We start with a basic algorithm that uses the periodic scheduler and the harmonic bandwidth estimation algorithms. Based on trace-driven analysis, we observed that most commercial players appear to employ a *stateless* bitrate selection algorithm that can be modeled as a linear function of the throughput estimated for the previous chunk(s). We use linear regression to find the best fit for each commercial player separately. For example, the SmoothStreaming player appears to pick the highest available bitrate below $0.85\times$ the estimated bandwidth. We do not claim that these are the exact algorithms; our goal is to use these as *conservative approximations* of the players to do a fair comparison with FESTIVE.

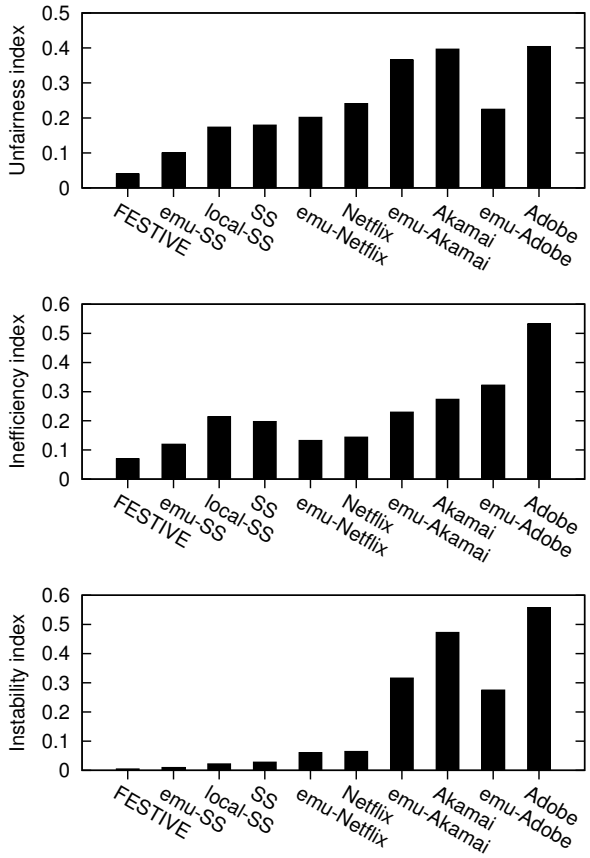


Figure 9: Comparison between FESTIVE, emulated commercial players, and the actual commercial players with 3 players sharing a bottleneck link of 3 Mbps. Here, SS stands for SmoothStreaming; "emu-X" stands for our conservative emulation of the "X" commercial player; and local-SS is running a local SmoothStreaming server.

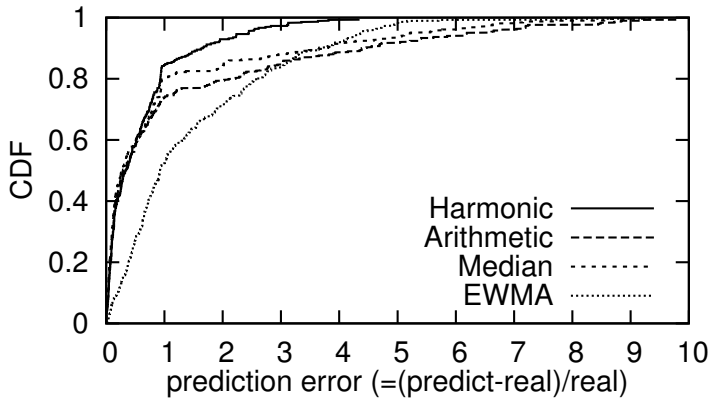


Figure 10: Prediction error in bandwidth estimation.

Result: We consider a setup with three players that share a bottleneck link of 3 Mbps. Figure 9 compares the performance of FESTIVE to the emulated commercial players using the median value over 15 runs. In each case, a lower value of the performance metric is better. For reference, we also show the performance of the commercial players with an equivalent three player setup (using respective demo sites). For SmoothStreaming, we also have access to the server implementation. Thus, we also evaluate a local setup with the real players and server. For each commercial player, we confirm that the emulated version is a *conservative* approximation. We see that FESTIVE outperforms the next best solution (SmoothStreaming) by at least $2\times$ in all three metrics, and is much better than the other solutions. We also observed that FESTIVE provides higher benefits as we increase the number of players (not shown).

5.2 Component-wise Validation

Next, we examine whether each component achieves the properties outlined in §3. As a *baseline* point of reference, we use the emulated SmoothStreaming player and evaluate the effect of incrementally adding each component.

Bandwidth estimator: We begin by comparing the accuracy of four bandwidth estimation strategies: arithmetic mean, median, EWMA,[6] and harmonic mean. Each method computes the estimated bandwidth using the observed throughput of the $k = 20$ previous chunks.[7] For this analysis, we extract the observed chunk throughputs from the real SmoothStreaming setup from §2 with 19 competing players and emulate each estimation algorithm. We report the CDF of the prediction error $\frac{|PredictedBW - ActualBW|}{ActualBW}$ in Figure 10. The result shows that the harmonic mean outperforms the other methods. (The large prediction errors in the tail appear because the observed bandwidth for each chunk depends on the number of competing players that chunk sees which is highly variable.) We also manually confirmed that the harmonic mean is effective when a new observed throughput is an outlier. Thus, for the rest of this section, we consider the baseline algorithm with a harmonic bandwidth estimator.

[6]Using the update function $bw_{next} = 0.9bw_{prev} + 0.1bw_{cur}$

[7]We observe similar trends for most $k > 5$

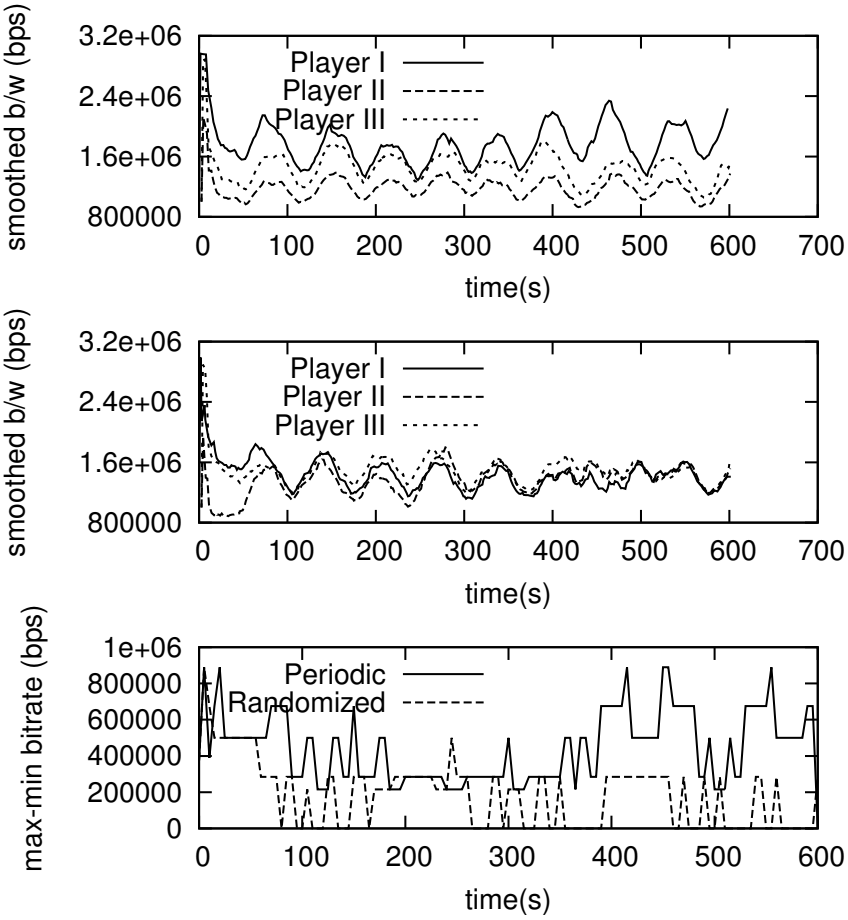


Figure 11: Randomized scheduling avoids start-time biases and ensures a fair allocation of bandwidth

Chunk scheduling: Here, the baseline player uses stateless bitrate selection, instant update, harmonic bandwidth estimation, and the *periodic chunk scheduling* discussed in §3. We consider a modified baseline that uses the *randomized scheduling* instead but retains the other components. Figure 11 shows the perceived bandwidth for the three players over time for one run. (The results are consistent across runs, we do not show them for brevity.) We can visually confirm that the periodic scheduler leads to large bias in the estimated bandwidth, while the randomized scheduler ensures a more equitable bandwidth share. The result also shows the difference between maximum and minimum bitrate to confirm that this bias in observed bandwidth also translates into unfairness in bitrate selection.

Stateful bitrate selection: The goal of the stateful bitrate selection approach is to ensure that different players will eventually converge to a fair allocation. To validate this, we consider ten players sharing a bottleneck link of 10 Mbps. Each player picks a start time uniformly at random in the interval of $[0, 30]$ seconds.

Figure 12 compares the efficiency and fairness achieved by three player settings: (1) fixed scheduler with stateless selection (baseline), (2) randomized scheduler with stateless selection, and (3) randomized scheduler with stateful selection. (We disable delayed update and use harmonic

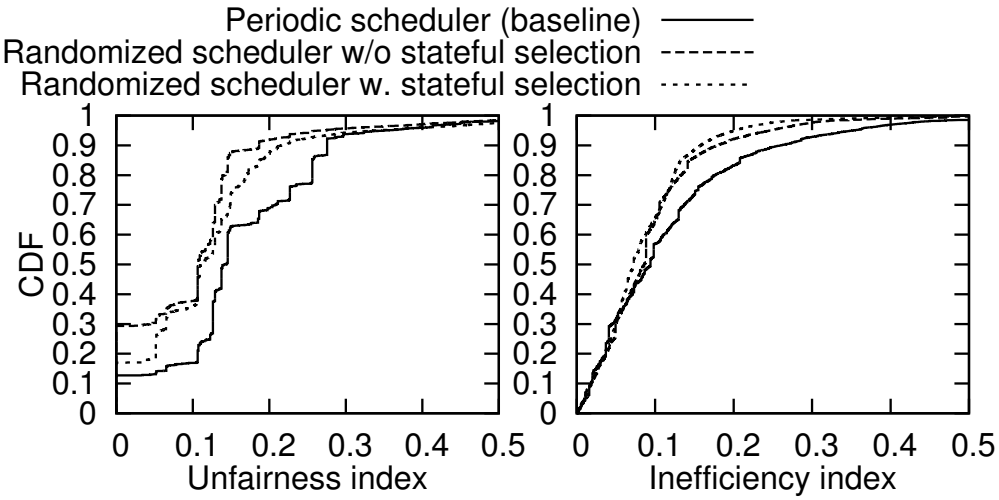


Figure 12: Stateful bitrate selection improves fairness with minimal impact on efficiency.

mean estimator for all three.) We see that stateful selection works well in conjunction with randomized scheduling and further improves the fairness. One concern with stateful bitrate selection is that players may increase/decrease bitrate synchronously and lead to over/under utilization (low efficiency). The result also shows that the efficiency is almost unaffected and may even be better than the stateless approach. The reason is that once the players converge to a fair allocation, all subsequent switches are only between two consecutive levels, which keeps the inefficiency small.

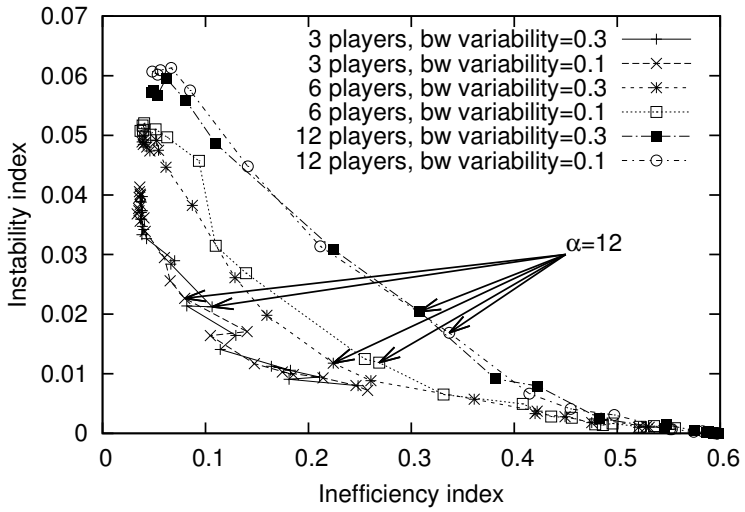


Figure 13: Tradeoff of delayed update between efficiency and stability: 'knee' points using $\alpha = 12$.

Delayed Update: The parameter α provides a way to tune the tradeoff between efficiency and stability. We examine this tradeoff with different number of players and bandwidth variability in Figure 13. (We discuss the exact variability model in §5.4). From the bottom-right to top-left, α increases from 5 to 30; larger α provides higher efficiency at the cost of stability (§3). We suggest a guideline of picking the α that is close to the "knee" of the curve or the point closest to the origin.

Across most scenarios, we find this roughly corresponds to $\alpha = 12$; we use this value for FESTIVE.

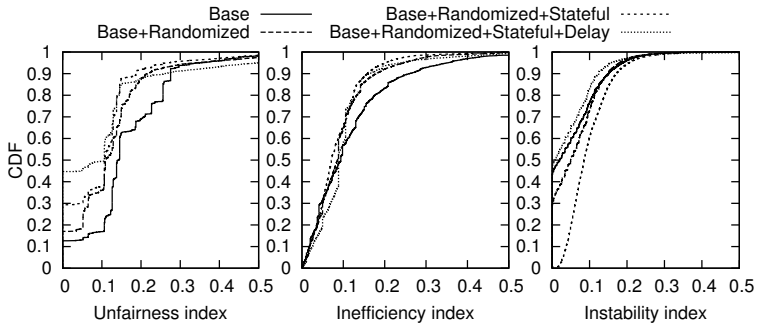


Figure 14: Break-down evaluation of FESTIVE.

5.3 How critical is each component?

To see the effect of each component in FESTIVE, Figure 14 shows the effect of incrementally adding the randomized scheduler, stateful bitrate selection, delayed update to the baseline. For this result, we consider the scenario with 10 players competing for a 10 Mbps bottleneck link. First, we see that the randomized scheduler improves the fairness and efficiency over the baseline (by avoiding bias of starting time), and stateful bitrate selection further improves these (by avoiding bias of initial bitrates). However, these components are likely to increase the instability relative to the baseline. The delayed update then helps control this tradeoff between efficiency and stability; it reduces the efficiency slightly but improves stability significantly.

5.4 Robustness

Last, we investigate FESTIVE's performance in the presence of varying number of concurrent players, bandwidth variability and available bitrate sets.

Number of concurrent players: We fix the total bandwidth at 10Mbps and vary the number of concurrent players from 2 to 30. In each run, the players arrive randomly within the first 30 seconds after the first player starts. For each setting, we report the median and error bars over 15 runs for both baseline and FESTIVE in Figure 15. First, we see that FESTIVE outperforms the baseline across all settings and that the performance variability of FESTIVE is much smaller. Second, we see that unfairness and instability issues are lower when there are too few or too many players. In the former case, all player can sustain the highest bitrate and in the latter case the only feasible solution is for all players to choose the lowest bitrate (350 Kbps). Finally, we see an interesting effect where the metrics are not "monotone" in the number of players. Specifically, the case of 12 and 20 players are much better than their nearby points. This is essentially an effect of the discreteness of the bitrate levels. For example, when 12 players share a 10Mbps bottleneck, each player is very likely to stay at 845Kbps and saturate the link. However, at 10 players or 14 players, the player will try lower or higher bitrate because there is no optimal "saturation" bitrate.

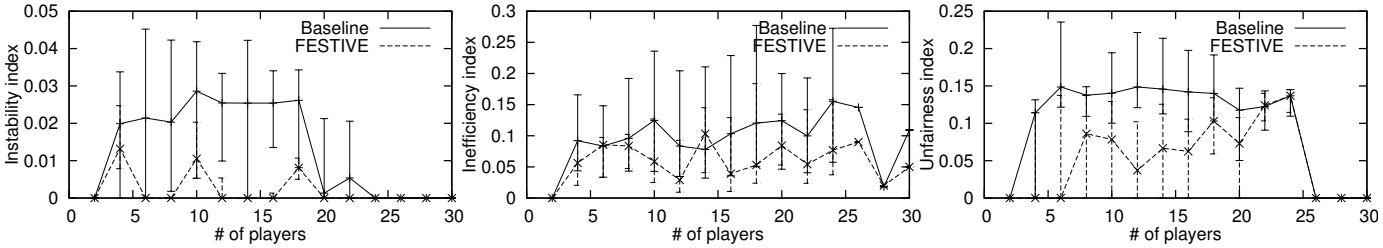


Figure 15: Performance of FESTIVE and the baseline player as a function of the number of concurrent players. Here, we assume the players are sharing a 10 Mbps bottleneck link.

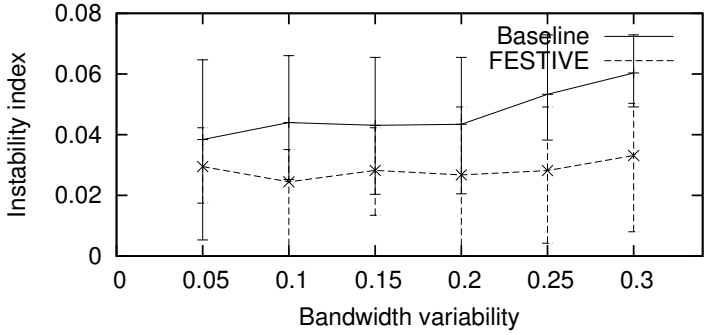


Figure 16: Instability vs. bandwidth variability when 10 players compete for a 10Mbps (expected) link

Bandwidth variability: We focus on the 10 player scenario with an *expected* bottleneck bandwidth of 10 Mbps. All players arrive within the first 30 seconds and we report the results from 15 runs per parameter. This bottleneck bandwidth is an expected value, because we vary the bandwidth every 20 second by picking a value uniformly at random $[BW \times (1-\epsilon), BW \times (1+\epsilon)]$. Figure 16 plots the performance of baseline and FESTIVE as a function of this parameter ϵ. We see that FESTIVE is more robust to the bandwidth variability (from $\epsilon = 0.05$ to $\epsilon = 0.3$) and in fact the improvement with FESTIVE increases with higher variability.

	Unfairness		Instability		Inefficiency	
g	Base.	FESTIVE	Base.	FESTIVE	Base.	FESTIVE
1.2	0.128	0.071	0.052	0.039	0.111	0.126
1.4	0.154	0.061	0.049	0.005	0.125	0.095
1.6	0.172	0.076	0.002	0.0	0.104	0.117
1.8	0.184	0.051	0.040	0.0	0.133	0.121

Table 3: Performance metrics vs. bitrate gaps when 10 players compete a bottleneck of 10Mbps

Available bitrates: Last, we test robustness to the set of available bitrate levels. We create a set of 10 available bitrate levels by $\{b_i = g^i \cdot 350Kbps\}_{i=0,\ldots 9}$, where g controls the gap between the bitrates, i.e., how "discrete" the bitrate levels are. A value of g close to 1 means that the gaps between consecutive levels are small and vice versa for larger g. Table 3 compares the performance of baseline and FESTIVE under g. FESTIVE consistently outperforms the baseline. The baseline becomes more unfair as g increases while FESTIVE works robust against higher g.

5.5 Summary of main results

In summary, our evaluation shows

- FESTIVE outperforms existing solutions in terms of fairness by $\geq$40%, stability by $\geq$50%, and efficiency by $\geq$10%.
- Each component of FESTIVE works as predicted by our analysis and is necessary as they complement each other.
- FESTIVE is robust against various number of players, bandwidth variability, and different available bitrate set.

6 Discussion

Heterogeneous algorithms: Studying the interaction between multiple heterogeneous players is an interesting direction of future work. We believe the space of designs defined by the guidelines in §3 is broad and can accommodate many player designs that meet our high-level requirements.

Interaction with non-video traffic: Another natural question is how video adaptation logic interacts with non-video traffic (e.g., short Web transfers) [27]. Because FESTIVE retains the single-connection HTTP-based interface, it retains TCP-level friendliness per chunk. Thus, we expect the impact of FESTIVE on background traffic to be minimal.

Decoupling bandwidth estimation: One of the main problems we saw is that discrete chunk downloads may lead to biased bandwidth estimates. This raises the question of whether we should decouple these altogether. One challenge is that the player running in a browser sandbox may not have access to packet-level information to get accurate estimates (e.g., packet pair). Second, this potentially increases the network overhead if we need frequent re-estimation.

Wide-area effects: Another interesting direction of future work is to see if and how the problems w.r.t efficiency, fairness, and stability manifest in the wide area. For example, there is more traffic aggregation, less synchronization but many more players, multiple bottlenecks, interaction with router buffer sizing, among other factors.

7 Related Work

Measurements of commercial players: Early studies focused on the bitrate switching behavior of a single player in response to bandwidth variation (e.g., [18, 34, 38, 41]). More recent work analyzes fairness, efficiency, and stability when two players share a bottleneck link [13, 15, 24]). These have identified the periodic behavior as a potential problem similar to §3. We confirm these problems on a broader set of commercial players and extend these beyond the two-player setting. More importantly, we provide a detailed understanding of the causes and present a concrete design to address these shortcomings.

Quality metrics: A key aspect in video delivery is the need to optimize user-perceived "quality of experience". There is evidence that users are sensitive to frequent switches (e.g., [16]), sudden changes in bitrate (e.g., [33]), and buffering (e.g., [19]). The design of a good QoE metric (e.g.,

[42]) is still an active area of research. As our understanding of video QoE matures, we can extend FESTIVE to be QoE-aware.

Player optimizations: The use of multiple connections or multipath solutions can improve throughput and reduce the bandwidth variability (e.g., [17, 23, 26, 28]). However, these require changes to the application stack and/or server-side support. Furthermore, they may not be "friendly" to background traffic. In contrast, FESTIVE retains the same single TCP connection interface and requires no modifications to the server infrastructure or the end-host stack. Other approaches use better bandwidth prediction and stability techniques (e.g., [29, 32, 34]). Our framework can leverage such estimation techniques as well and performs well in multiple-player scenarios.

Server and network-level solutions: This includes the use of server-side bitrate switching (e.g., [27]), TCP changes to avoid bursts (e.g., [22]), and in-network bandwidth management and caching (e.g., [24, 34, 39]). Our focus is on client-side mechanisms without requiring changes to the network or servers. While these approaches will further improve the performance, we believe that a client-side solution is fundamentally necessary for two reasons. First, the client is in the best position to detect and respond to dynamics. Second, recent work suggest the need for cross-CDN optimizations that imply the need for keeping minimal state in the network or servers [30, 31].

Video Coding: Layered or multiple description coding offer more graceful degradation of video quality (e.g., [14]). However, they impose higher overhead on content providers and the delivery infrastructure and thus we do not consider this class of solutions.

8 Conclusions

The dominance of video streaming traffic running on top of HTTP necessitates the design of robust video bitrate adaptation algorithms. We provide a principled understanding of problems that lead to inefficiency, unfairness, and instability when multiple players compete for a bottleneck link. Building on these insights, we provide guidelines on designing better scheduling and bitrate selection techniques to overcome these problems. In doing so, we retain the properties that enabled the rise of Internet video—using existing HTTP techniques, no modifications to end-host stacks, and no modification to network, CDN, and server infrastructure. Using these guidelines, we demonstrate one concrete design that significantly outperforms existing solutions.

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