Post-Streaming Wastage Analysis – A Data Wastage Aware Framework in Mobile Video Streaming

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Abstract—Mobile video streaming is now ubiquitous among mobile users. This work investigates a less studied and yet significant problem in mobile video streaming – data wastage, i.e., some downloaded video data may not be played back but discarded by video players due to early departure or video skip, thus the bandwidth consumed in transferring them is wasted. Our measurements show that data wastage is significant in practice, e.g., 25.2 percent∼51.7 percent of video data downloaded are in fact wasted. Moreover, substantial data wastage exists not only in current commercial streaming platforms, but also in state-of-the-art adaptive streaming systems proposed in the literature. This work develops a new post-streaming wastage analysis (PSWA) framework to tackle this problem by converting existing adaptive streaming algorithms into data wastage aware versions. PSWA enables the streaming vendors to explicitly control the tradeoff between data wastage and quality-of-experience (QoE). Extensive evaluations show that PSWA can reduce data wastage significantly (e.g., 80 percent) without any adverse impact on QoE. Moreover, it has strong robustness to perform consistently across a wide range of networks. PSWA can be readily implemented into current streaming platforms, and thus offers a practical solution to data wastage for mobile streaming services.

Index Terms—Video streaming, mobile network, data wastage, quality-of-experience

1 Introduction

Mobile video streaming has quickly become a key application in the mobile Internet [1]. For many mobile users, watching videos using their smartphone has become a daily activity. With so many sources of videos, it is not surprising that not all the videos are watched from start to finish. In fact, due to common viewing behaviors such as *early departure* and *video skip* (i.e., changing to a different playback point), a significant portion of videos were not watched completely by viewers [2], [3], [4]. For example, Finamore *et al.* [2] measured the video access logs on YouTube and found that 60 percent of videos were watched for no more than 20 percent of their whole duration. A side-effect of early departure and video skip is that some of the downloaded video data are *discarded* and the bandwidth consumed in transferring them is thus wasted. We call this *data wastage* in the rest of the paper.

At first glance, such data wastage may not appear to be a significant issue. However, current on-demand video streaming (VoD) has practically all migrated to some forms of HTTP-based bitrate adaptive transfer protocol (e.g., DASH [5]). Common to these protocols is the use of HTTP over TCP to transfer the video data as fast as TCP allows. Therefore, if the TCP throughput is higher than the selected video bitrate then the client will fetch video data ahead of their playback schedules and store them in the local buffer. This can improve streaming performance significantly, as the buffered data can be used to absorb mobile networks' bandwidth fluctuations to prevent playback rebuffering. However, the same fetch-ahead buffering mechanism could also increase data wastage significantly if the viewer terminates or skips the video playback before all downloaded data are rendered.

Our measurements for existing adaptive streaming algorithms showed that 25.2∼51.7 percent of video data downloaded were wasted. This level of data wastage has two far-reaching consequences. First, today's mobile data services purchased by users generally have a hard data cap, e.g., 10 GB per month [6]. If the data usage exceeds the given data quota, mobile users have to purchase additional data quota at a much higher price. Therefore, given the significant data wastage, a substantial portion of the data quota would be

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wasted in transferring video data which are never watched. Second, data wastage consumes precious bandwidth resources from the streaming vendor's network (e.g., CDN), which are often charged by the volume of data transferred. Given the immense cost of the infrastructure, even a tiny percentage of wasted bandwidth can be financially significant to streaming vendors. For example, Chen *et al.* [7] measured that the cost due to data wastage could be tens to hundreds of millions of dollars each year.

One method to reduce data wastage is to limit the video client buffer size. Taking it to the extreme, if the player buffers no more than one video segment at any time then the worst-case data wastage will only be one segment. However, the client buffer exists for an important reason – to buffer data such that video playback can be sustained during periods of low bandwidth so that playback rebuffering can be avoided. Too small a buffer will likely lead to frequent rebuffering and significant Quality-of-Experience (QoE)[1] degradation, which can be an even bigger problem than data wastage. This is especially important in the mobile network where rapid and substantial bandwidth fluctuations are the norm rather than the exception.

Therefore, the fundamental question is whether a feasible tradeoff between QoE and data wastage exists in today's mobile networks, and if so, how to achieve a desired wastage-QoE tradeoff in a streaming platform. This work provides an answer to these questions by developing a new Post-Streaming Wastage Analysis (PSWA) framework to allow the streaming vendor to explicitly control the tradeoff between data wastage and QoE. Specifically, PSWA introduces two wastage-aware parameters that can be easily incorporated into existing adaptive streaming algorithms so that fine-grained control of wastage-QoE tradeoffs can be enabled. By analyzing the streaming trace data from past video sessions, PSWA automatically optimizes the wastage-aware parameters and then applies them to future video sessions to minimize data wastage while maintaining high QoE.

Extensive evaluations showed that PSWA can reduce data wastage by 31.6∼79.9 percent even without any QoE loss. In addition, it could reduce data wastage even further by a small tradeoff in QoE (e.g., 4 percent drop in QoE improves data wastage reduction to 44.4∼90.2 percent). Moreover, PSWA performs consistently across a wide range of networks. Therefore, it offers an immediate and practical solution to reduce data wastage in current and future streaming platforms.

This work has three major contributions. First, since data wastage and QoE are inherently conflicting objectives, reducing wastage may result in QoE loss. However, QoE is critical to streaming services and the tolerance for QoE loss differs among different streaming vendors. PSWA addresses this challenge by providing the streaming vendors with an interface called acceptable QoE loss ratio to allow them to specify their QoE preference. Specifically, they can set the QoE loss ratio to any values within 0∼100 percent where 0 percent means no QoE loss. PSWA then minimizes data wastage while maintaining the actual QoE degradation according to the ratio specified. To the best of our knowledge, PSWA is the first system that can control data wastage based on the streaming vendor's QoE preference.

Second, PSWA breaks the one-size-fits-all approach commonly adopted by the existing data wastage solutions [7], [8], [9], [10], [11] and optimizes wastage-aware parameters according to the specific network condition a streaming session operates in. This enables PSWA to not only outperform the existing approaches significantly, but also have strong robustness to achieve consistent performance across a wide range of network environments.

Last but not least, PSWA is designed to complement (as opposed to replacing) the existing adaptive streaming algorithms by converting them into wastage-aware versions while keeping their original adaptation logic intact. This offers an immediate and ready solution for the streaming platforms already in service. Although this work focuses on adaptive on-demand streaming, PSWA is a generic framework that can potentially be extended to other streaming services, such as non-adaptive streaming, 360-degree video streaming, live streaming, etc.

The rest of the paper is organized as follows: Section 2 reviews the related work; Section 3 investigates the data wastage problem in mobile video streaming; Section 4 presents the design of the PSWA framework; Section 5 evaluates the performance of PSWA using trace-driven simulations and real experiments, and Section 6 summarizes the study and outlines some future work.

2 Related Work

Much work has been done in video streaming in recent years. A comprehensive review of the area is beyond the scope of this work. We refer interested readers to the studies by Seufert *et al*. [12], Juluri *et al*. [13], Kua *et al*. [14] and Bentaleb *et al*. [15] for survey and comparison of existing streaming algorithms.

Existing studies typically assumed that viewers watch videos continuously from the beginning to the end. However, this is often not the case in practice. For example, Finamore *et al.* [2] analyzed YouTube and found that 60 percent of videos were watched for no more than 20 percent of their whole duration. Chen *et al.* [17] reported that 62.5 percent of video sessions were not played back continuously but have video skips. Dobrian *et al.* [3] found that rebuffering and low bitrate can significantly reduce the viewer engagement time. This was echoed by Li *et al.* [4] who also found that video download speed has a notable impact on viewer engagement time. In another study, Lebreton *et al.* [39] found that the viewer departure rate was significantly higher at points of rebuffering. These studies motivated researchers, e.g., Shafiq *et al.* [40], to develop models to predict viewer engagement time from network dynamics.

Since the existing studies on streaming algorithms typically did not consider these viewing behaviors, it is no surprise that data wastage is often not considered in the design of the streaming algorithms. However, with the almost ubiquitous deployment of HTTP-based video streaming, data

1. *Quality of Experience (QoE) quantifies and measures the goodness of the experience as perceived by the user. Common components of QoE in video streaming include video quality/bitrate, playback rebuffering, quality variations, and so on. In this work, we adopted existing QoE metrics designed for streaming video, i.e., [26], [27], [33] and [34], in the performance evaluations. We refer the interested readers to* Section 3 *and their original studies for more details.*

wastage can no longer be an afterthought. For example, Finamore *et al*. [2] found that data wastage is significant, e.g., during peak hours, 25∼39 percent of bandwidth was wasted by desktop users and 35∼48 percent by mobile users.

In another work, Chen *et al*. [7] looked into the data wastage problem in Tencent Video [16] and found that over 20 percent of bandwidth was wasted due to video data delivered but unwatched. To reduce data wastage, they developed a server-side Behavior-Based (henceforth called BB) streaming strategy. BB was designed for the scenario where the network is already fully utilized. It reduced data wastage through limiting the transmission rate to 1.05 times of the video bitrate (as opposed to as fast as TCP allows) during the viewer browsing phase (this phase generally exists at the beginning of videos with high departure rate [17]). The bandwidth saved in this phase can then be reallocated to other streaming clients to improve their QoE. However, BB was designed only for non-adaptive streaming so it may not be directly applicable to today's adaptive streaming platforms (e.g., DASH [5]).

In a recent study, Yarnagula *et al*. [8] proposed SARA to reduce data wastage for adaptive video streaming. SARA was deployed in the video clients and designed for reducing data wastage through limiting the amount of data in the buffer with a pre-defined buffer threshold (i.e., 20s). Specifically, when the client buffer occupancy reaches the buffer threshold, the request for downloading the next segment will be delayed until the buffer occupancy falls below the threshold. In another study, Chen *et al*. [9] proposed an energy-aware rate adaptation algorithm that controls data wastage in the same way as SARA but sets the buffer threshold to 30s. However, our empirical study (c.f. Section 3.2) showed that merely limiting the buffer size could lead to more rebuffering events, degrading the QoE performance.

In another direction, two studies by Li *et al*. [10] and Huang *et al*. [11] proposed the use of Lyapunov optimization theory to design bandwidth allocation strategies for the base station with the goal to reduce the total data wastage for all mobile users served by the base station. However, their proposed strategies require mobile operators to modify the link-layer implementation of the base stations which is far from simple in today's mobile infrastructures. In comparison, the PSWA framework proposed in this study is designed to work with the current streaming platforms and operate in existing networks so that it can be readily deployed.

In an earlier work [18], we also investigated the challenge of data-wastage. This study extends our earlier work in four significant aspects. First, the earlier work only studied data wastage caused by early departure. In this work, we extended the scope to include data wastage due to both early departure as well as video skip. In fact, our results showed that video skip could cause even more data wastage than early departure (c.f. Section 3). To our knowledge, this is the first work tackling data wastage in both early departure and video skip.

Second, in contrast to our earlier work, PSWA no longer adopts the one-size-fits-all approach. Specifically, our investigation in this work revealed a key insight that led to the design of PSWA – the tradeoff between QoE and data-wastage is not fixed but differs across different network conditions. Hence, a single optimized streaming algorithm such as the one in our earlier work [18], would be sub-optimal. This motivated the development of throughput-level-based PSWA which enables the algorithm to be optimized for different network types/conditions (c.f. Section 4.2). As a result, PSWA not only outperformed our earlier work, but also exhibited significantly more robust performance across a wide range of networks.

Third, the scope of the experiments and performance evaluations has been expanded substantially in this work. While our earlier work primarily employed 3G network trace data for experiments and performance evaluation, this work expanded the scope to include both 4G/LTE as well as Wi-Fi, and trace dataset was captured by us [22] as well as by other researchers [20], [21]. The far broader range of networks enabled us to obtain a better understanding of the behaviors of different algorithms under a wide range of network conditions. Furthermore, we also included two new state-of-the-art adaptive streaming algorithms, i.e., Pensieve [27] and SARA [8], in the performance comparisons (c.f. Section 5.2).

Last but not least, we implemented a prototype of the PSWA framework into dash.js and reported experimental results in Section 5.5. The results verified the feasibility of PSWA for use in today's video streaming platforms and its potential performance gains in practical operational settings.

3 Data Wastage in Mobile Video Streaming

In this section, we measure data wastage in current HTTP-based on-demand streaming (VoD) platforms. We first investigate the two common viewing behaviors (early departure and video skip) and then employ trace-driven simulation to measure data wastage in some state-of-the-art adaptive streaming algorithms.

3.1 Early Departure and Video Skip

We first look into *early departure* through a real-world empirical trace dataset [38]. The notion of data wastage is that some downloaded video data are not watched but discarded. Therefore, data wastage can be derived from the proportion of a video watched as well as downloaded at the time of early departure. In the dataset, for video session i, $0 \leq i < N$, we can obtain the video physical duration, denoted by L_i, the amount/duration of video data downloaded, denoted by D_i, and the viewing duration, denoted by V_i.

To quantify early departure, we define *viewing ratio* $\boldsymbol{\phi}_i$ as the ratio of video played back (in duration) to the video physical duration for video session *i*, i.e.,

$$\phi_i = V_i / L_i. \tag{1}$$

Similarly, we define download ratio θ_i as the ratio of video downloaded (in duration) to the video physical duration, i.e.,

$$\theta_i = D_i / L_i. \tag{2}$$

The left chart in Fig. 1 plots the cumulative distributions of the two ratios from the empirical dataset. It is evident that a significant proportion of video sessions ended early, with an overall average viewing ratio of 42.6 percent. In

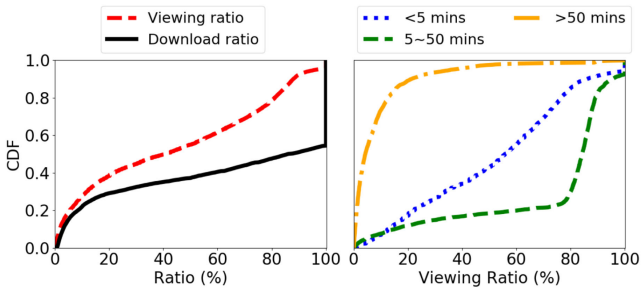

Fig. 1. Statistics for viewing ratio and download ratio.

comparison, the download ratio is substantially higher, with an overall average of 63.1 percent. This suggests that a significant proportion of the video data was downloaded but not played back. We further divided all the video sessions into three subsets based on their video physical duration, i.e., short (<5 mins), medium (5∼50 mins), and long (>50 mins), and then plotted their viewing ratio distributions in the right chart in Fig. 1. We observed that their viewing ratios differ significantly. For example, viewers tend to leave relatively early when watching long-length videos (i.e., >50 minutes), whereas tend to watch completely when watching medium-length videos (i.e., 5∼50 minutes). More detailed analysis for early departure can be found in Appendix A.1, which can be found on the Computer Society Digital Library at http://doi.ieeecomputersociety.org/10.1109/TMC.2021.3069764.

Next, we investigate *video skip* using another empirical model from Chen *et al.* [17]. The left chart in Fig. 2 plots the proportion of the mean skip number in each video session. We can observe that 62.5 percent of video sessions have video skips (i.e., except " $= 0$") and the proportion of skip number "$> = 4$" is significantly higher than others. This is intuitive because if a viewer is not interested in the current video content, the viewer will naturally skip several times to keep looking for the points of interest.

The right graph in Fig. 2 shows the proportion of skip span. The key observation is that nearly 80 percent of the skips are within 5 mins, and the proportion of long skip span (>30 min) is very small. Overall, in addition to early departure, video skip is also a very common viewer behavior that can cause data wastage. Next we apply these viewer behavior models to measure their impact on data wastage.

3.2 Data Wastage Measurement

We employed trace-driven simulations to measure data wastage in realistic network settings where the simulator replicates the bottleneck link by replaying TCP throughput trace data obtained from real production mobile networks.

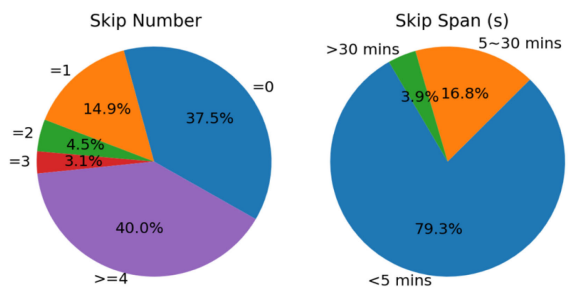

Fig. 2. Statistics for video skip number and skip span.

TABLE 1
Statistics of Seven Throughput Trace Datasets

Characteristics	Dataset #1	#2	#3	#4	#5	#6	#7
Throughput (Mbps)	5.57	4.71	3.29	2.87	1.21	12.1	3.12
Coefficient of Variation	0.44	0.39	0.74	0.53	0.83	0.69	0.59
Network type	3G	3G	3G	3G	3G	LTE	WiFi
Collection location	L1	L1	L2	L3	L4	L5	L6
Service provider	S1	S2	S1	S1	S3	S2	S4

We used a total of 60 weeks of TCP throughput trace data (∼100000 video sessions) covering 3G, 4G/LTE and Wi-Fi networks. The trace data are publicly available [20], [21], [22] and we summarized their key statistics in Table 1. Viewing behavior traces (e.g., early departure, video skip) were derived from the empirical datasets introduced in Section 3.1. The available video bitrates follow the Apple profile [19] augmented by four additional bitrates at 10 Mbps, 12 Mbps, 16 Mbps, and 20 Mbps. The rest of the streaming parameters are summarized in Table 2. Please refer to Appendix A.2, available in the online supplemental material, for more details of the simulation settings.

We implemented seven state-of-the-art streaming algorithms which include two throughput-based bitrate adaptive algorithms – LBG [23] and Stagefright [24], two buffer-based bitrate adaptive algorithms – BBA [25] and SARA [8], two hybrid throughput-buffer-based bitrate adaptive algorithms – RobustMPC (henceforth called MPC) [26] and Pensieve [27], and one non-adaptive algorithm BB [7]. It's worth noting that SARA and BB were both originally designed to control data wastage while all others were non-wastage-aware algorithms.

To quantify data wastage, we define a metric to compute the amount of data wastage in video session i, denoted by W_i, from the difference between video data downloaded and viewed:

$$W_i = \sum_{\forall d_{i,j}>0} d_{i,j} - \sum_{\forall v_{i,j}>0} s_{i,j}\frac{v_{i,j}}{l_{i,j}}, \tag{3}$$

where $d_{i,j}$, $s_{i,j}$, $l_{i,j}$, $v_{i,j}$ are the downloaded data amount, segment size, full segment duration, segment duration viewed for segment j respectively. Similarly, we can compute the ratio of data wastage for session i, denoted by R_i, from

TABLE 2
Evaluation Settings

Parameters	Values
Bitrate profile	{0.2, 0.4, 0.8, 1.2, 2.2, 3.3, 5.0, 6.5, 8.6, 10, 12, 16, 20} Mbps [19]
Segment duration	2s
Video duration	Empirical distribution (30s to 10800s)
Session number	∼ 100000
Initial bitrate	0.2 Mbps

TABLE 3
Evaluation Results of Existing Streaming Algorithms

Streaming algorithm	Buffersize	Wastage ratio (%)	Daily mean wastage amount (Petabyte)	Skip v.s. Departure	Bitrate (Mbps)	Buffer occupancy (s)	Rebuffering duration (s)	Rebuffering frequency	QoE
LBG	184s	51.7	5.75	69% v.s. 31%	1.77	35.9	1.23	1.18	0.92
BBA	240s	50.5	6.17	63% v.s. 37%	1.31	40.7	0.80	1.29	0.94
MPC	30s	28.3	1.19	69% v.s. 31%	2.99	6.70	6.33	7.21	1.55
Stagefright	20MB	39.8	3.01	66% v.s. 34%	1.71	16.7	1.07	1.44	1.11
Pensieve	60s	25.2	1.17	67% v.s. 33%	3.22	5.73	8.94	9.9	1.73
BB	30s	38.5	1.24	51% v.s. 49%	1.32	6.79	9.08	4.54	0.71
SARA	20s	30.3	1.21	65% v.s. 35%	1.23	10.9	3.10	3.41	0.80

$$R_i = 1 - \sum_{\forall v_{i,j}>0} s_{i,j}\frac{v_{i,j}}{l_{i,j}} \Bigg/ \sum_{\forall d_{i,j}>0} d_{i,j}. \tag{4}$$

In addition to data wastage, for video session i, we also measured mean video bitrate – defined as the average bitrate selected, mean buffer occupancy – defined as the average buffer level, rebuffering duration – defined as the total time at which playback is suspended due to client buffer underflow, rebuffering frequency – defined as the total number of rebuffering events, and QoE – calculated by the QoE function proposed by Mao *et al.* [27]:

$$Q_i = \frac{1}{K}\left(\sum_{k=0}^{K-1}\vartheta_{i,k} - \sum_{k=1}^{K-1}\left|\vartheta_{i,k} - \vartheta_{i,k-1}\right| - 2.66 \times Z_i\right), \tag{5}$$

where Z_i is the rebuffering duration, K is the total number of segments in video session i and $\vartheta_{i,k}$ is the video quality calculated by

$$\vartheta_{i,k} = \log\left(r_{i,k}/r_{\min}\right), \tag{6}$$

where $r_{i,k}$ is the bitrate selected for segment k and r_{min} is the lowest available bitrate in the profile. Note that the coefficient of Z_i (i.e., 2.66) follows Mao *et al.* [27].

Table 3 summarizes the simulation results. The first observation is that the overall data wastage ratio across the seven algorithms ranges from 25.2 to 51.7 percent, implying that a quarter to half of the downloaded data is wasted. In addition, daily data wastage on average amount is 1.17∼6.17 Petabyte each day. Using the pricing of Amazon CDN [28], such amounts of data wastage could cost the streaming vendor tens to hundreds of millions of dollars each year.

Second, the "Skip v.s. Departure" column of Table 3 compares the percentage of data wastage caused by video skip versus early departure. We can see that video skip incurs about twice as much data wastage as early departure in almost all the algorithms (except for BB due to its bandwidth-limiting strategy at the beginning of each video session [7]). This is intuitive as viewers can only quit at most once in each video session while on average skip $2 \sim 3$ times in a single session (c.f. Fig. 2).

Third, LBG and BBA both exhibited substantial data wastage (51.7 and 50.5 percent) which is a result of their large buffer size and conservative bitrate adaptation logic (reflected by video bitrate). Consequently, their rebuffering duration and rebuffering frequency are much lower than others, as their higher buffer occupancy can absorb larger throughput fluctuations to prevent playback rebuffering.

In comparison, although Stagefright also has a conservative bitrate adaptation logic, its data wastage (39.8 percent) is much lower than LBG and BBA due to its smaller buffer size (20MB or approximately 90s of video data). SARA has the smallest buffer size (i.e., 20s) among all the evaluated streaming algorithms thus achieved lower data wastage (30.3 percent) than Stagefright. However, such a small buffer led to much more rebuffering events for SARA, thereby decreasing its QoE performance.

Interestingly, although MPC and Pensieve are non-wastage-aware, they can also achieve comparatively lower data wastage (28.3 percent for MPC and 25.2 percent for Pensieve). This is due to their aggressive bitrate adaptation logics, which resulted in relatively low buffer level. In comparison, while BB's strategy (i.e., restricting bandwidth) is also effective in reducing data wastage, it significantly increased the number of rebuffering events (the average rebuffering duration is 9.08, which is the largest among the seven algorithms) and thus lowered the QoE achieved.

Table 4 compares the data wastage ratio/amount for MPC across the throughput trace dataset #1∼#7 (results for other streaming algorithms are similar, see Appendix A.3, available in the online supplemental material, for the full set of results). Interestingly, we found that dataset #1, #2, and #6 exhibited far more data wastage than others. Given the trace data statistics in Table 1, it appears that data wastage is more severe in networks with higher mean throughput. To further investigate this, we divided all video sessions into 10 throughput levels, with level $l = 01,\ldots,8$ collecting sessions with mean throughput within $(l,\ l+1]$ Mbps, plus level 9 with mean throughput $\geq$9Mbps, and then summarized their wastage ratio/amount in Table 5 (the full results are in available Appendix A.3, available in the online supplemental material).

The results strongly suggest that data wastage increases as the throughput level increases. The higher throughput

TABLE 4
Data Wastage of MPC Across Seven Trace Datasets

	Dataset						
Metrics	#1	#2	#3	#4	#5	#6	#7
Wastage Ratio (%)	33.2	32.7	26.3	25.6	22.9	39.5	24.3
Wastage Amount (PB)	2.01	1.95	1.04	1.14	0.78	4.10	1.07

TABLE 5
Data Wastage of MPC Across Ten Throughput Levels

Metrics	Throughput Level 0∼1	2∼3	4∼5	6∼7	8∼9
Wastage Ratio (%)	21.0	26.9	29.9	34.1	41.4
Wastage Amount (PB)	0.71	1.12	2.08	3.02	4.54

not only allows the player to select higher video bitrate, but also to accumulate more video data in the local buffer awaiting playback. As a result, more data will be wasted in case the viewer quits or skips the playback.

3.3 Discussions

We gained two insights from the above results. First, data wastage is directly attributed to the buffered video data, as all the data in the buffer will be discarded upon early departure or video skip. However, video buffering is essential for preventing rebuffering and maintaining high QoE. Therefore, the need for reducing data wastage inherently conflicts with QoE. One potential solution is to investigate whether a feasible tradeoff exists between data wastage and QoE, and if so, how to achieve the desired tradeoff. From Table 3, we found two factors that can impact both data wastage and QoE, namely *buffer size* and *bitrate adaptation aggressiveness*, so exploiting these two factors could offer a solution to achieve the desired wastage-QoE tradeoffs.

Second, Tables 4 and 5 revealed another interesting property – data wastage is not uniform but throughput-dependent. However, existing streaming algorithms were almost all designed to be one-size-fits-all, i.e., using fixed streaming parameter values (e.g., buffer size) irrespective of the network environments (e.g., ranging from 3G networks with a few Mbps mean bandwidth to 4G networks with 100+ Mbps peak bandwidth). Therefore, in this work we propose to optimize the streaming parameters according to the specific network conditions so that the desired wastage-QoE tradeoff can be maintained consistently across a wide range of networks. In next section, we present a new PSWA framework to tackle the above-mentioned challenges.

4 Wastage-Aware Video Streaming

In this section, we present the Post-Streaming Wastage Analysis (PSWA) framework. We first develop wastage-aware parameters to convert existing adaptive streaming algorithms into wastage-aware and then apply post-streaming analysis [31] to optimize the wastage-aware algorithms.

4.1 Data Wastage Awareness

Most of the existing streaming algorithms were not designed to incorporate the impact of data wastage. To this end, we design two generic wastage-aware parameters, namely *buffer limit* β and *adaptation multiplier* γ, to convert them to wastage-aware versions.

Buffer limit β. From Section 3, we found that data wastage is highly correlated with the amount of buffered video data. This suggests that limiting the buffer can control wastage. Most existing streaming algorithm has an internal buffer size setting (c.f. Table 3), denoted by B. As this size is typically fixed for a given algorithm, it cannot adapt to the network conditions, thereby resulting in suboptimal performance (c.f. Section 3.2). Therefore, we propose a dynamic buffering mechanism to address this limitation.

TABLE 6
Internal Metric and Adaptation Multiplier γ of the Existing Streaming Algorithms

Algorithm	Internal metric	Range of γ
LBG [23]	Video segment duration over segment download time	0∼3
Stagefright [24]	The sliding window of throughput measurement	0∼5
BBA [25]	Mapping slope between buffer occupancy and video bitrate	0∼12
MPC [26]	The harmonic mean of past throughput divided by previous estimation error	0∼5
Pensieve [27]	Throughput measurement vector including past 8 video segments	0∼3

Specifically, ignoring network latency, let t_i and f_i be the starting and completion time for transferring video segment i to the client. Let b_i be the buffer occupancy at time f_i. We schedule the starting time to transmit the next video segment at t_{i+1} to limit the buffer occupancy within β:

$$t_{i+1} = \begin{cases} f_i, \text{if} b_i \ < \ \beta \\ f_i + b_i - \beta, \ otherwise \end{cases} \tag{7}$$

where the value of β is no longer fixed, but is to be dynamically tuned within the original buffer size B, i.e., $0<\beta\leq B$, according to the network conditions (c.f. Section 4.2).

Adaptation Multiplier γ. Section 3 shows that bitrate selection aggressiveness also has significant impacts on data wastage. The intuition is that the increase in the video bitrate will increase segment download time, thereby reduce buffer occupancy and consequently data wastage as well. To exploit this, we develop a mechanism to regulate the adaptation algorithm's bitrate selection aggressiveness. Specifically, most of the algorithms *originally* have one or more internal metrics [29], [30] which are the key criterion for them to determine the video bitrate for future video segments (refer to [29] for the notion of "internal metric"). To control it, we introduce an adaptation multiplier γ to multiply the internal metric to indirectly tune its bitrate selection aggressiveness.

It's worth noting that the definition of the internal metric in the existing streaming algorithms depends on the specific design of their adaptation logic, so the definition differs across different algorithms. Table 6 summarizes the description for the internal metric of five existing adaptive streaming algorithms, and we refer the interested readers to their original studies [23], [24], [25], [26], [27] for the detailed definitions.

To illustrate how the adaptation multiplier γ works, we take MPC [26] as an example, of which the definition of the internal metric is reproduced below:

$$D_k = H_k/(1 + e_k), \tag{8}$$

where D_k is the estimated throughput for determining the bitrate of segment k, H_k is the harmonic mean throughput for downloading the past 5 segments (i.e., segment k–6

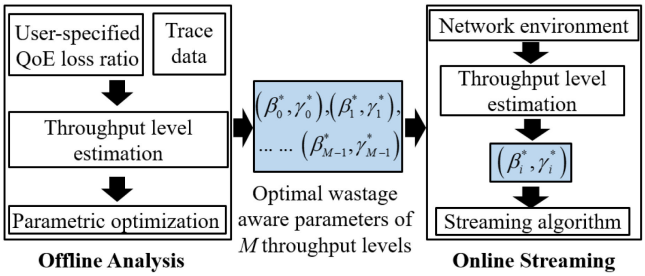

Fig. 3. The architecture of PSWA framework.

$\sim k$–1) and e_k is the previous maximum absolute estimation error. MPC mainly relies on the estimated throughput D_k to determine video bitrate [26], so we can apply the multiplier γ to D_k to control the bitrate selection aggressiveness:

$$D'_k = \gamma \times D_k, \tag{9}$$

where the value of γ can be tuned to change the final output, denoted by D'_k.

Naturally, different streaming algorithms may use different internal metrics (e.g., the throughput measurement vector in Pensieve [27] as opposed to harmonic mean in MPC) but one can apply γ in a similar fashion (see Table 6) to control their bitrate selection aggressiveness.

4.2 Post-Streaming Wastage Analysis (PSWA)

With the two wastage-aware parameters (i.e., β and γ) defined in Section 4.1, the next challenge is to find a way to determine their optimal values to achieve the desired tradeoff between data wastage and QoE.

Although mobile networks are known to have rapid bandwidth fluctuations, they also exhibit consistent properties over longer timescales (e.g., days) so that analysis of the network conditions in past video sessions (e.g., in the past a few days) could inform the optimization of future streaming sessions [31]. Exploiting this, Liu *et al*. [31] proposed Post-Streaming Analysis that can provide predictable streaming performance in adaptive video streaming. The idea is to exploit past streaming trace data captured as a by-product of video sessions to automatically tune streaming parameters in the adaptation logic to achieve the desired streaming performance, e.g., target rebuffering probability, in future video sessions.

Drawing on the Post-Streaming Analysis principle, we developed a novel Post-Streaming Wastage Analysis (PSWA) framework to control data wastage through optimizing the wastage-aware parameters, i.e., buffer limit β, and adaptation multiplier γ. Specifically, PSWA comprises repeating cycles of two phases, namely *offline analysis* and *online streaming*, as depicted in Fig. 3. PSWA executes offline analysis periodically, e.g., daily, to compute the optimal value of β and γ for use in online streaming, e.g., the next 24 hours.

Offline Analysis. One key insight from Section 3 is that the wastage-QoE tradeoff is throughput-dependent. This suggests that a single set of parameters optimized for all kinds of network conditions is likely to be sub-optimal. To tackle this challenge, we segregate network conditions into different classes according to the throughput level (c.f. Section 3) so that the wastage-aware parameters can be optimized separately to match the characteristics of different network classes. However, while the throughput level can be calculated directly in offline analysis, as the throughput trace data are given, it cannot be known before streaming the actual video session in online streaming. Therefore, we need a way to estimate the throughput level for the new video sessions.

Video players typically prefetch a number of video segments before commencing playback. The throughput in downloading the prefetch segments reflects the current network condition and thus can be used to estimate the throughput level for the new video session. Specifically, let α be the pre-configured bitrate for the first m segments during prefetch, i.e.,

$$r_{j,k} = \alpha, k = 0, 1, \ldots m-1, \tag{10}$$

where $r_{j,k}$ denotes the selected video bitrate for the kth segment in session j. After segment m-1 is received, the system can then calculate the mean throughput from

$$V_j = \frac{1}{m}\sum_{k=0}^{m-1}\frac{s_{j,k}}{d_{j,k}}, \tag{11}$$

where $s_{j,k}$, and $d_{j,k}$ are size and download time for segment k in the prefetch phase of session j. We then employ a linear quantization policy to map the throughput level T_j from the mean throughput V_j:

$$T_j = \min\left(\left\lfloor\frac{V_j}{\Delta}\right\rfloor, M-1\right), \tag{12}$$

where Δ is the quantization step size and M is the maximum number of the throughput level. Based on the throughput level T_j, the next step is to divide all video sessions trace data $S_j, j = 01, \ldots, N$, into M network classes:

$$C_p = \{S_j | T_j = \langle p \rangle, \forall j\},\ p = 0, 1, \ldots, M-1, \tag{13}$$

where T_j is the throughput level for video session j.

PSWA then conducts *parametric optimization* to calculate the optimal wastage-aware parameters for each network class separately. Specifically, for throughput level p, PSWA executes trace-driven simulation with streaming trace data C_p to test the effectiveness of different values of wastage-aware parameter, i.e., β_p and γ_p. Note that the trace data has two types, namely *TCP throughput trace* (replicating network condition) and *viewing behavior* trace (replicating early departure and video skip), both of which are captured as a by-product of past video sessions so no extra measurements are needed.

After the simulation, PSWA records the resultant streaming performance metrics including selected bitrates, playback rebuffering, etc., to compute the overall QoE achieved in each network class, denoted by $\{Q(\beta_p, \gamma_p) \,|\, p = 01, \ldots, M-1\}$, where $Q(.)$ is the QoE function adopted, e.g., (5). Concurrently, PSWA also records the data wastage amount, i.e., $W(.)$, in each network class, denoted by $\{W(\beta_p, \gamma_p) \,|\, p = 01, \ldots, M-1\}$. With these two wastage-aware parameters, PSWA quantifies the relationship between QoE and data wastage (see Appendix A.2, available in the online

supplemental material, for more details on the trace-driven simulation).

QoE and data wastage are inherently conflicting metrics so reducing data wastage may impair QoE. However, QoE is critical to streaming services and it is likely application, service, and even user dependent so we need a mechanism for the streaming vendor to control data wastage based on their QoE preference. One possibility is to combine QoE and data wastage into a unified utility function such that the problem becomes a utility-maximization problem. However, such a utility function does not exist in the literature and it is unclear how the utility can be normalized between QoE and data wastage.

Therefore, we adopted a different approach in that the system offers an interface (e.g., a configurable server or video player option) for the streaming vendors to specify an acceptable QoE loss ratio, denoted by δ. The purpose of δ is to allow the streaming vendors to specify their QoE preference, e.g., they can set δ to any values within 0 percent$\sim$100 percent. Note that setting δ to 0 percent indicates no QoE loss, in which case PSWA will maintain the actual QoE at the same level as that achieved by the original streaming algorithms (i.e., the algorithm without wastage-aware parameters).

In the following, we denote the QoE achieved by the original streaming algorithms in throughput level p as U_p, $p = 01, \ldots M-1$. PSWA aims at minimizing the amount of data wastage and at the same time maintaining the QoE loss to within δ, through tuning the two wastage-aware parameters β_p and γ_p, i.e.,

$$\begin{aligned} &\min_{\beta_p,\gamma_p} \; W(\beta_p,\gamma_p) \\ &s.t. \; 1-\tfrac{Q(\beta_p,\gamma_p)}{U_p} \le \delta. \\ &p = 0,1,\ldots,M-1 \end{aligned} \tag{14}$$

After solving the optimization problem, PSWA obtains the optimal wastage-aware parameters for each throughput level, denoted by $\{\beta_p^*, \gamma_p^* | p = 0,1,\ldots M-1\}$.

Online Streaming. After offline analysis, the optimized wastage-aware parameters will be loaded into the video player as part of the streaming metadata (e.g., MPD playlist in DASH [5]). To begin a new video session, the video player first estimates the throughput level from the prefetch process, i.e., (10)$\sim$(12), and then applies the optimal wastage-aware parameters according to the throughput level to the current video session. The rest of the streaming process is unchanged. Overall, the modification needed is very simple so that PSWA can be readily deployed into existing streaming platforms.

4.3 Takeaway and Deployment

Takeaway. PSWA is designed to complement (rather than replace) the underlying streaming algorithms by converting them into wastage-aware versions. Thus it can be applied to the streaming platforms already in service and is compatible with the existing video streaming protocols such as DASH. The insight behind PSWA is that mobile networks exhibit consistent properties over a timescale of days so that one can analyze past video sessions' trace data to achieve predictable performance (data wastage and QoE) for future sessions [31]. Therefore, to capture the properties of the mobile network and keep detecting whether they have evolved, PSWA employs the repeated cycle of the two-phase design (c.f. Section 4.2). This guarantees that 1) the value of the wastage-aware parameters can be continuously updated, thus maintaining consistent wastage-QoE tradeoff performance as the network infrastructure evolves, and 2) the deployed PSWA can automatically adapt to new network developments (e.g., 5G).

Deployment. In applying PSWA to rate-adaptation algorithms, the computation complexity should be low as bitrate decision needs to be performed frequently online. This can be easily achieved by PSWA as most of the computations are consolidated into the offline analysis that is executed on the server-side. For example, the CDN server of the streaming vendors can be easily extended to record the video session's trace data for offline analysis when it delivers the video data to the players over HTTP/TCP. Moreover, the optimal wastage-aware parameters can be embedded into the meta-data file of the streaming protocols (e.g., MPD in DASH) for delivery to the video player. For online streaming, the only computation requirement is the throughput level measurement during prefetch, which is not computationally expensive and is performed only once at the beginning of each video session. To demonstrate PSWA's feasibility, we implemented PSWA into an open-source video player (dash.js [32]) and evaluated its performance in Section 5.5.

5 Performance Evaluation

In this section, we evaluate PSWA's effectiveness in reducing data wastage and analyze the tradeoff between data wastage and QoE.

5.1 Experiment Setup

We employed trace-driven simulations with the same setup as described in Section 3.2. PSWA was applied to optimizing the five non-wastage-aware streaming algorithms, namely LBG [23], Stagefright [24], BBA [25], MPC [26], and Pensieve [27], to turn them into wastage-aware versions. In addition, the two existing wastage-aware algorithms, BB [7] and SARA [8], were evaluated to compare to the performance of PSWA.

We used a total of 60 weeks' trace data ($\sim$100000 video sessions) in the evaluation. PSWA was configured to use the past one day's trace data in offline analysis phase to optimize the two wastage-aware parameters $\{\beta, \gamma\}$, which were then applied to online streaming phase in the next 24 hours. β is tuned within the streaming algorithm's buffer size (c.f. Table 3), and the tuning range of γ is listed in Table 6. For the throughput level, we adopted the linear mapping policy in (12) with quantization step size of $\Delta = 1$ Mbps and $M = 10$. Unless stated otherwise we adopted (5) as the default QoE function. The rest of the parameters are summarized in Table 2.

5.2 Performance Tradeoff

PSWA offers a tool for streaming vendors to explicitly control the tradeoff between data wastage and QoE through specifying QoE loss ratio δ. To evaluate the tradeoff trajectory, we varied δ from 0 percent to 4 percent to evaluate the

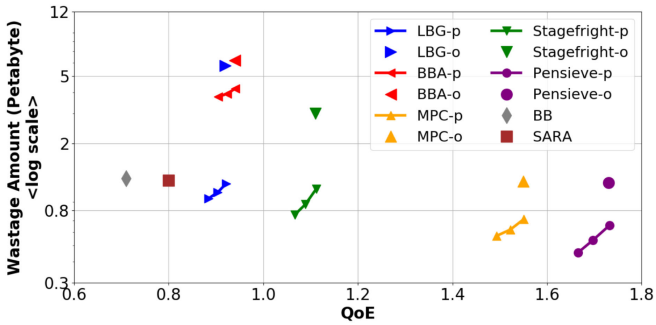

Fig. 4. Comparison of data wastage amount and QoE performance.

tradeoff between QoE and data wastage in Fig. 4, which plots the tradeoff trajectories for all seven streaming algorithms evaluated. The performance of the original algorithms (without applying PSWA) are indicated by the "-o" suffix (e.g., "LBG-o") while PSWA-optimized versions are indicated by the "-p" suffix (e.g., "LBG-p").

We observed that all five non-wastage-aware algorithms optimized by PSWA show a significant reduction in data wastage with little or even no loss of QoE. In all cases, PSWA enables them to achieve a continuous tradeoff trajectory between data wastage and QoE. In comparison, since BB and SARA are wastage-aware algorithms, they did achieve relatively low data wastage. However, due to their one-size-fits-all model, both of them can only achieve one specific point of tradeoff and the resultant QoE is relatively low.

To evaluate PSWA's control on QoE loss, we defined a new metric φ to quantify the actual QoE loss proportion, i.e.,

$$\varphi = \sum_{\forall i} (U_i - Q_i) \Big/ \sum_{\forall i} U_i, \tag{15}$$

where U_i is the QoE achieved by the original algorithm for video session i, Q_i denotes the QoE achieved by the PSWA-optimized algorithms. We then compare φ against the specified QoE loss ratio δ in Table 7. We observe that the five algorithms performed similarly, all of which achieved actual QoE loss proportion lower than but close to δ.

Next, we quantify data wastage reduction using a new metric called data wastage reduction proportion:

$$\varsigma = \sum_{\forall i} (P_i - W_i) \Big/ \sum_{\forall i} P_i, \tag{16}$$

where P_i is data wastage amount produced by the original algorithm for video session i, W_i is the data wastage amount of the PSWA optimized algorithm.

TABLE 7
Actual QoE Loss Proportion φ (%) Versus Specified QoE Loss Ratio δ

	QoE Loss Ratio δ (%)				
Algorithm	0	1	2	3	4
LBG	-0.15	0.96	1.75	2.86	3.93
BBA	-0.09	0.90	1.81	2.77	3.78
MPC	-0.06	0.87	1.79	2.98	3.69
Stagefright	-0.21	0.99	1.89	2.57	3.90
Pensive	-0.10	0.79	1.92	2.49	3.71

TABLE 8
Data Wastage Reduction Proportion ς (%) Versus Specified QoE Loss Ratio δ

	QoE Loss Ratio δ (%)				
Algorithm	0	1	2	3	4
LBG	79.9	83.2	85.4	87.2	90.2
BBA	31.6	35.7	38.2	41.8	44.4
MPC	40.3	45.1	48.7	50.4	52.3
Stagefright	64.2	68.6	71.0	74.3	74.8
Pensive	44.0	48.3	54.2	57.1	61.2

Table 8 summarizes the data wastage reduction proportion versus the specified QoE loss ratio δ. We observed that through PSWA, all five streaming algorithms' data wastage was reduced significantly, i.e., up to 44.4 percent∼90.2 percent wastage reduction within 4 percent QoE loss, where LBG achieved the most substantial result.

Remarkably, PSWA could reduce data wastage even without any QoE loss. From the column with $\delta = 0\%$ in Table 8, PSWA enabled the five algorithms to achieve 31.6 percent to 79.9 percent wastage reduction with no degradation in QoE. This counter-intuitive result is due to PSWA's ability to lift the limitation of the one-size-fits-all model adopted by the existing streaming algorithms.

In particular, the optimal value of a streaming algorithm's internal metric (c.f. Section 4.1) in fact can and does vary with the network condition [29]. However, these existing streaming algorithms were only equipped with a fixed set of internal metrics so were inevitably suboptimal when applied to a wider range of network conditions. By contrast, PSWA tunes γ to optimize the streaming algorithms' internal metrics based on the specific network conditions and thus also improves their QoE performance beyond their original version.

The increased QoE thus provides the QoE margin for PSWA to reduce data wastage such that the overall QoE performance is not degraded (see Appendix A.4, available in the online supplemental material, for more details).

To see if the above observations are consistent across different QoE metrics, we repeated the experiments using three other QoE functions, i.e., $\text{QoE}_2 \sim \text{QoE}_4$ [26], [33], [34] (QoE_1 is defined by (5)). We set QoE loss ratio δ to 0 percent and summarized the resultant data wastage reduction under the four QoE functions in Table 9. We observed very similar patterns across the four QoE functions, where PSWA enables the five streaming algorithms to achieve substantial data wastage reduction without any QoE loss.

TABLE 9
Data Wastage Reduction Proportion ς (%) Across Four QoE Functions ($\delta = 0\%$)

Algorithm	QoE_1	QoE_2	QoE_3	QoE_4
LBG	79.9	73.5	83.3	90.1
BBA	31.6	27.0	39.5	30.5
MPC	40.3	51.7	49.7	41.7
Stagefright	64.2	50.1	66.4	56.6
Pensive	44.0	58.2	66.1	51.2

TABLE 10
Data Wastage of MPC Across Seven Throughput Trace Datasets ($\delta = 2\%$)

Metrics		Wastage Ratio (%)		Wastage Amount (PB)		Data Wastage Reduction ς (%)
Version		MPC-o	MPC-p	MPC-o	MPC-p	
Dataset	#1	33.2	13.9	2.01	0.90	55.1
	#2	32.7	13.6	1.95	0.91	53.2
	#3	26.3	13.4	1.04	0.61	41.3
	#4	25.6	13.1	1.14	0.67	40.7
	#5	22.9	12.9	0.87	0.59	32.3
	#6	39.5	13.1	4.10	0.96	76.9
	#7	24.3	14.0	1.07	0.63	41.1

5.3 Variation Across Network Conditions

In this section, we investigate PSWA's performance across different network conditions. Specifically, we evaluated PSWA's performance over seven throughput trace dataset #1 $\sim$ #7, which were collected from multiple mobile operators and locations (c.f. Table 2). In this experiment, PSWA made use of the past one day's trace data for offline analysis where the trace data are a combination of training data from the dataset #1 $\sim$ #7. The rest of the unseen trace data were then used for performance evaluation. Note that in this section we only show the results of MPC with a setting δ to 2 percent. Results for other streaming algorithms and settings of δ are similar.

Table 10 summarizes PSWA's wastage reduction performance when applied to MPC across the seven trace datasets. It is clear that PSWA consistently enabled MPC to achieve substantial data wastage reduction across all seven datasets, ranging from 32.3 to 77.1 percent.

Moreover, compared to the original MPC (MPC-o), the PSWA-optimized version (MPC-p) achieved more consistent wastage ratio and wastage amount across the datasets. These results suggest that using trace data from a sufficiently wide spectrum of network conditions in the offline analysis phase, PSWA can enable one algorithm to effectively control the data wastage over a broad range of network environments.

To further analyze the results across different levels of throughput, we divided all video sessions into 10 throughput levels, with level $l = 01,\ldots,8$ collecting sessions with average throughput within $(l, l+1]$ Mbps, plus level 9 with average throughput $\geq$9Mbps, and then summarized their respective data wastage performance in Table 11.

We observed that through PSWA's optimization, MPC-p can now consistently control data wastage throughout the throughput levels. The higher data wastage at the high throughput levels is now compensated by PSWA with higher wastage reduction. Consequently, MPC-p's wastage ratio is far more consistent across the 10 levels although its wastage amount still increases with the throughput level. This increase is inevitable as adaptive streaming algorithms will select higher video bitrate at higher throughput levels and hence the larger video segment size would naturally lead to more data wastage. Nevertheless, with PSWA, the rate of increase in the wastage amount of MPC-p is substantially lower than that of MPC-o.

TABLE 11
Data Wastage of MPC Across Ten Throughput Levels ($\delta = 2\%$)

Metrics	Algorithm	Throughput Level 0~1	2~3	4~5	6~7	8~9
Wastage Ratio (%)	MPC-o	21.0	26.9	29.9	34.1	41.4
	MPC-p	13.2	14.3	13.1	13.2	12.8
Wastage Amount (PB)	MPC-o	0.71	1.12	2.08	3.02	4.54
	MPC-p	0.48	0.65	1.05	1.17	1.39
Wastage Reduction ς (%)		32.1	41.9	49.4	61.2	69.2

TABLE 12
Wastage-aware Parameters of MPC-p Across Ten Throughput Levels ($\delta = 2\%$)

Network Characters and Wastage-aware Parameters	Throughput Level 0~1	2~3	4~5	6~7	8~9
Throughput (Mbps)	0~2	2~4	4~6	6~8	≥8
Coefficient of Variation (CoV)	0.84	0.59	0.42	0.32	0.25
Buffer limit β (s)	11.2	10.3	8.8	7.9	6.9
Adaptation multiplier γ	0.8	1.3	1.7	2.1	2.6

To further investigate the dynamics of PSWA with respect to throughput levels, we calculated in Table 12 the mean values of the wastage-aware parameters (i.e., β and γ) of MPC-p across different throughput levels. There are two observations. First, the results clearly show that the optimal wastage-aware parameters vary substantially across throughput levels. This validates PSWA's throughput-level differentiation approach to optimize the parameters. Second, as throughput level increases, the buffer limit β decreases while the adaptation multiplier γ increases.

This indicates that PSWA is able to exploit the (better) network condition at higher throughput levels to increase the algorithm's bitrate selection aggressiveness (via increasing γ) and to reduce the amount of buffered data (via decreasing β) so that data wastage is reduced in case the viewer quits or skips.

Next we study PWSA's behavior over time in Fig. 5, which plots the daily mean values of β and γ in throughput level 5 over a period of 70 days (similar patterns can be observed in other throughput levels). Since the mean throughput at a certain throughput level is limited to a specific range (e.g., 5 Mbps $\sim$ 6 Mbps in throughput level 5), we could ignore the impact of mean throughput and focus on the impact of throughput variations (quantified by throughput Coefficient of Variation (CoV) in Fig. 5). The key observation here is that the two parameters were constantly changing over time as one would expect. More importantly,

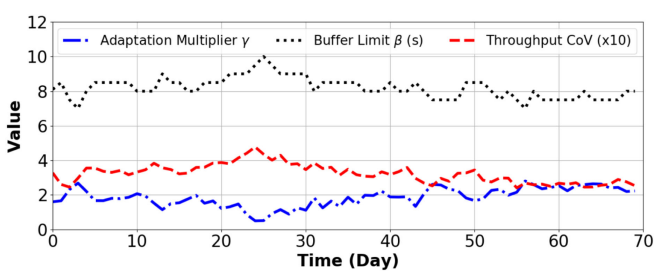

Fig. 5. The evolution of wastage-aware parameters (in throughput level 5) over a period of 70 days.

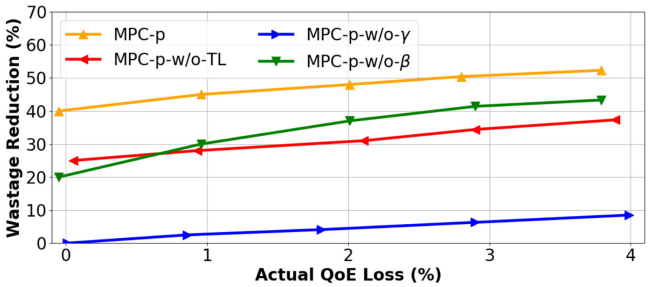

Fig. 6. Performance contributions of PSWA's key components.

their trajectories clearly correlate with the variations in the throughput CoV over the 70 days.

Intuitively, higher throughput CoVs is more likely to cause rebuffering events so the results suggest that PSWA is able to adapt to the long-term (i.e., day) variations in the network behavior (i.e., throughput variations) to optimize the wastage-aware parameter to consistently achieve the desired tradeoff between data wastage and QoE. Interested readers are referred to Appendix A.4, available in the online supplemental material, for a deeper analysis of the two wastage-aware parameters.

5.4 Sensitivity Analysis

In this section, we dissected PSWA by investigating the relative performance contributions by its key components. Specifically, we investigate the significance of: (a) tuning the buffer limit β only while keeping γ to 1; (b) tuning the adaptation multiplier γ only while keeping β to the algorithm's original buffer size; (c) removing the throughput level differentiation.

We compared the performance of the full version PSWA (indicated by the "-p" suffix) to the three handicapped versions, indicated by "-p-w/o-β" (without tuning β), "-p-w/o-γ" (without tuning γ) and "-p-w/o-TL" (without differentiating throughput levels) suffixes respectively. Fig. 6 compares their performances in terms of QoE loss and data wastage reduction. We only showed the results for MPC as the results for other algorithms are similar. It is clear that both the throughput level differentiation and the two wastage-aware parameters are essential to PSWA as the effectiveness of reducing data wastage drops significantly without any one of them. In particular, the performance drops the most without tuning γ (i.e., MPC-p-w/o-γ) where the curve exhibits a more linear pattern passing through the origin.

5.5 Implementation and Real Experiments

In this section, we report results from a prototype implementation of PSWA into the well-known *dash.js* video player (version 3.11) [32] to validate PSWA's practicality and to verify its performance in real-world streaming setups. Specifically, we first modified dash.js to support the five non-wastage-aware streaming algorithms. For Pensieve, dash.js was configured to fetch bitrate selection decisions from a specialized bitrate decision server where Pensieve's neural network is deployed. All other algorithms were embedded into "AbrController.js" of dash.js and executed directly. Next, we specified a 2 percent QoE loss ratio for PSWA's offline analysis and then applied the optimal wastage-aware parameters into the streaming algorithms in dash.js.

TABLE 13
Real Experimental Results ($\delta = 2\%$)

	Actual QoE Loss (%)	Wastage Reduction (%)
LBG	1.74	78.3
BBA	1.91	40.2
MPC	1.87	53.9
Stagefright	1.62	71.5
Pensieve	1.88	56.1

In our setup, the video server host ran Linux with the Apache httpd [35] serving video data over TCP CUBIC [36] and the video client was a Google Chrome browser running in a smartphone with the Android operating system. We used an improved version of DummyNet [37] to emulate the network conditions between the client and server based on our collected TCP throughput trace data [22], along with 80 ms minimal RTT to model propagation delay. Other streaming settings (e.g., video duration, bitrate profile, etc.) were consistent with those in Section 3.2.

We ran each streaming algorithm twice, each streaming 1000 video sessions (the throughput trace data was the same for both runs). Specifically, we ran streaming algorithms with their original settings (i.e., without PSWA) for the first time, and then applied the wastage-aware parameters into the algorithms to run a second time (i.e., with PSWA).

Table 13 summarizes the proportion of actual QoE loss and data wastage reduction for each algorithm. We observed that the actual QoE losses of the five algorithms were all within the specified QoE loss ratio of 2 percent. Meanwhile, the data wastage reduction is significant in all cases, ranging from 40.2 to 78.3 percent. Overall, the experimental results verified PSWA's design goal to achieve the desired tradeoff performance between QoE and data wastage in a real-world streaming implementation. Therefore, PSWA offers an immediate and practical solution to significantly reduce data wastage in current as well as future streaming platforms.

6 Summary and Future Work

This work reveals that current video streaming systems can result in substantial data wastage due to viewer's early departure and video skip behaviors. To tackle this problem, we proposed a novel PSWA framework which can reduce data wastage significantly (e.g., up to 80 percent) with little to no degradation of QoE. PSWA not only can convert existing on-demand adaptive streaming algorithms into wastage-aware versions, but it can also be incorporated into the design of new streaming algorithms so that data wastage becomes an integrated performance metric rather than an afterthought.

This work is only the first step in this direction. There are many opportunities for future research. For example, data wastage is not limited to on-demand streaming. There is a rapid increase in live streaming services in recent years. Although viewers cannot skip ahead in a live stream, their

early departure would certainly result in data wastage. Similarly, the emerging 360-degree video streaming poses an even bigger challenge on data wastage due to its viewport-based streaming approach. More work is thus warranted to investigate these research challenges.

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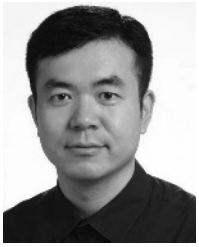

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