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Research Article

Detailed Performance and Waiting-Time Predictability Analysis of Scheduling Options in On-Demand Video Streaming

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The number of on-demand video streams that can be supported concurrently is highly constrained by the stringent requirements of real-time playback and high transfer rates. To address this problem, stream merging techniques utilize the multicast facility to increase resource sharing. The achieved resource sharing depends greatly on how the waiting requests are scheduled for service. We investigate the effectiveness of the recently proposed cost-based scheduling in detail and analyze opportunities for further tunings and enhancements. In particular, we analyze alternative ways to compute the delivery cost. In addition, we propose a new scheduling policy, called *Predictive Cost-Based Scheduling* (PCS), which applies a prediction algorithm to predict future scheduling decisions and then uses the prediction results to potentially alter its current scheduling decisions. Moreover, we propose an enhancement technique, called *Adaptive Regular Stream Triggering* (ART), which significantly enhances stream merging behavior by selectively delaying the initiation of full-length video streams. We analyze the effectiveness of the proposed strategies in terms of their performance effectiveness and impacts on waiting-time predictability through extensive simulation. The results show that significant performance benefits as well as better waiting-time predictability can be attained.

1. Introduction

The interest in video streaming has grown dramatically across the Internet and wireless networks and continues to evolve rapidly. Unfortunately, the number of on-demand video streams that can be supported concurrently is highly constrained by the stringent requirements of multimedia data, which require high transfer rates and must be presented continuously in time. Stream merging techniques [1–7] address this challenge by aggregating clients into successively larger groups that share the same multicast streams. These techniques include *Patching* [1, 3], *Transition Patching* [8, 9], and *Earliest Reachable Merge Target* (ERMT) [2, 10]. Periodic broadcasting techniques [11–15] also address this challenge but can be used for only popular videos and require the requests to wait until the next broadcast times of the first corresponding segments. This paper considers the stream merging approach.

The achieved resource sharing by stream merging depends greatly on how the waiting requests are scheduled for service. Despite the many proposed stream merging techniques and the numerous possible variations, there has been only a little work on the issue of scheduling in the context of these scalable techniques. The choice of a scheduling policy can be as important as or even more important than the choice of a stream merging technique, especially when the server is loaded. *Minimum Cost First* (MCF) [16] is a cost-based scheduling policy that has recently been proposed for use with stream merging. MCF captures the significant variation in stream lengths caused by stream merging through selecting the requests requiring the least cost (measured in bytes of the delivered video data).

Motivated by the development of cost-based scheduling, we investigate its effectiveness in detail and discuss opportunities for further tunings and enhancements. In particular, we initially seek to answer the following two important questions. First, is it better to consider the stream cost only at the current scheduling time or consider the expected overall cost over a future period of time? Second, should the cost computation consider future stream extensions done by advanced stream merging techniques (such as ERMT) to satisfy the needs of new requests? These questions are

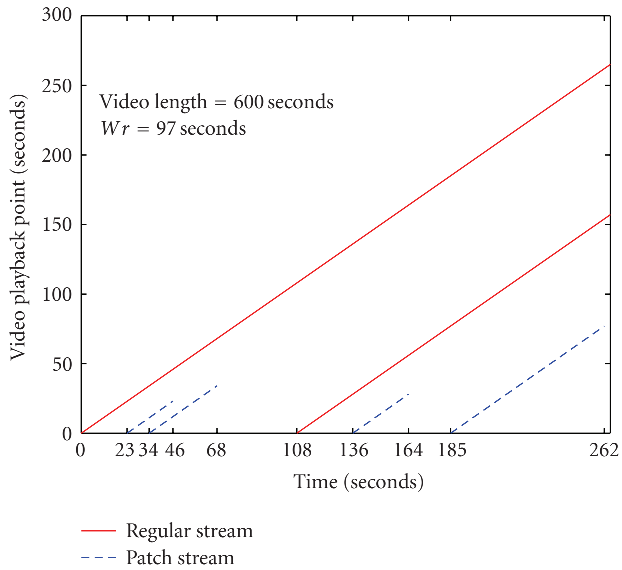


Figure 1: Patching.

important because the current scheduling decision can affect future scheduling decisions, especially when stream merging and cost-based scheduling are used.

Additionally, we analyze the effectiveness of incorporating video prediction results into the scheduling decisions. The prediction of videos to be serviced and the prediction of waiting times for service have recently been proposed in [17]. These prediction results, however, were not used to alter the scheduling decisions. We propose a scheduling policy, called *Predictive Cost-Based Scheduling* (PCS). Like MCF, PCS is cost-based, but it predicts future system state and uses the prediction results to potentially alter the scheduling decisions. It delays servicing requests at the current scheduling time (even when resource are available) if it is expected that shorter streams will be required at the next scheduling time. We present two alternative implementations of PCS.

We also propose an enhancement technique, called *Adaptive Regular Stream Triggering* (ART), which can be applied with any scheduling policy to enhance stream merging. The basic idea of ART is to selectively delay the initiation of full-length video streams.

We study the effectiveness of various strategies and design options through extensive simulation in terms of performance effectiveness as well as waiting-time predictability. The ability to inform users about how long they need to wait for service has become of great importance [17], especially considering the growing interest in human-centered multimedia systems. Today, even for short videos with medium quality, users of online video websites may experience significant delays. Providing users with waiting-time feedback enhances their perceived quality-of-service and encourages them to wait, thereby increasing throughput. The analyzed metrics include customer defection (i.e., turn-away) probability, average waiting time, unfairness against unpopular videos, average cost per request, waiting-time prediction accuracy, and percentage of clients receiving expected waiting times. The waiting-time prediction accuracy is determined by the average deviation between the expected and actual waiting times. We consider the impacts of customer waiting tolerance, server capacity, request arrival rate, number of videos, video length, and skew in video access. We also study the impacts of different request arrival processes and video workloads. Furthermore, in contrast with prior studies, we analyze the impact of flash crowds, whereby the arrival rate experiences sudden spikes.

The results demonstrate that the proposed PCS and ART strategies significantly enhance system throughput and reduce the average waiting time for service, while providing accurate predicted waiting times.

The rest of the paper is organized as follows. Section 2 provides background information on main performance metrics, stream merging, and request scheduling techniques. Section 3 analyzes cost-based scheduling and explores alternative ways to compute the cost. Sections 4 and 5 present the proposed PCS and ART strategies, respectively. Section 6 discusses the performance evaluation methodology and Section 7 presents and analyzes the main results.

2. Background Information

In this section, we discuss the main performance metrics used to evaluate scheduling policies in streaming servers. We then discuss stream merging and request scheduling.

2.1. Main Performance Metrics of Video Streaming Servers. The main performance metrics of video streaming servers are *user defection probability, average waiting time*, and *unfairness*. The defection probability is the probability that a new user leaves the server without being serviced because of a waiting time exceeding the user's tolerance. It is the most important metric, followed by the average waiting time, because it translates directly to the number of users that can be serviced concurrently and to server throughput. Unfairness measures the bias of a scheduling policy against unpopular videos and can be computed as the standard deviation of the defection probability among the videos:

$$\text{Unfairness} = \sqrt{\sum_{i=1}^{n} \frac{\left(d_i - \overline{d}\right)^2}{n-1}}, \tag{1}$$

where d_i is the defection probability for video i, $\overline{d}$ is the mean defection probability across all videos, and n is the number of videos. In this paper, we also consider waiting-time predictability metrics as will be discussed in Section 7.

2.2. Scalable Delivery of Video Streams with Stream Merging. Stream merging techniques aggregate users into larger groups that share the same multicast streams. In this subsection, we discuss three main stream merging techniques: Patching [1, 3, 18], Transition Patching [8, 9], and ERMT [2, 10].

In Patching, a new request joins immediately the latest full-length multicast stream for the video and receives the

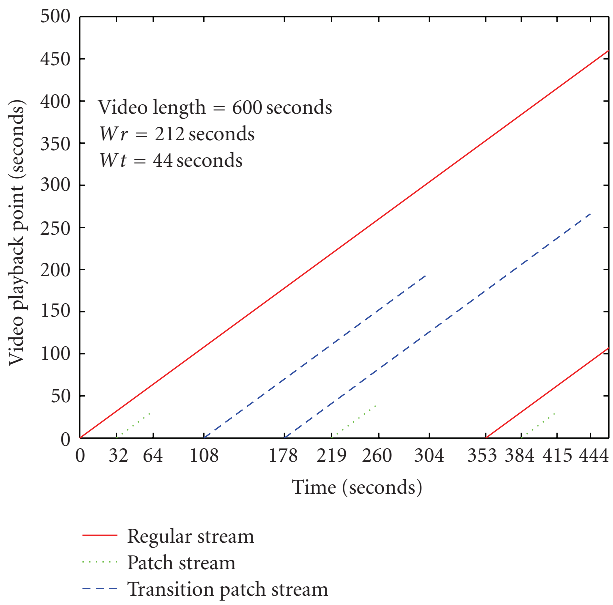


Figure 2: Transition Patching.

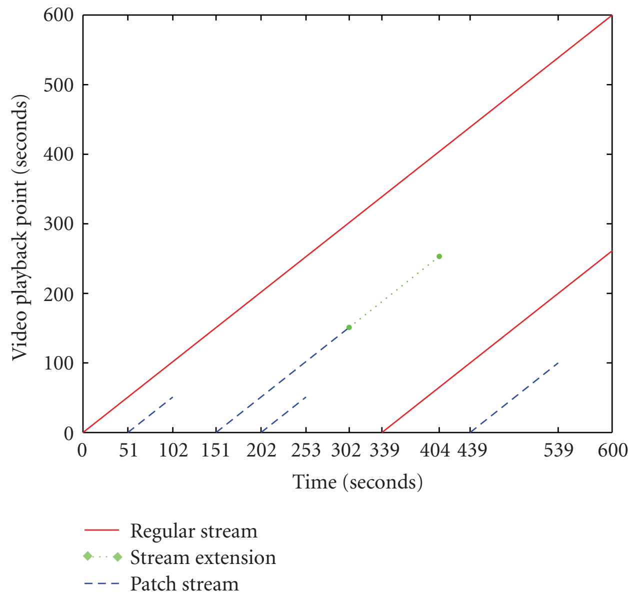


Figure 3: ERMT.

missing portion as a *patch* using a unicast stream. A full-length multicast stream is called *regular stream*. Both the regular and patch streams are delivered at the video playback rate. The length of a patch stream and thus its delivery cost are proportional to the temporal skew from the latest regular stream. The playback starts using the data received from the patch stream, whereas the data received from the regular stream are buffered locally for use upon the completion of the patch stream. Because patch streams are not sharable with later requests and their cost increases with the temporal skew from the latest regular stream, it is cost-effective to start a new regular stream when the patch stream length exceeds a certain value, called *regular window* (Wr). Figure 1 further explains the concept. Initially, one regular stream (first solid line) is delivered, followed by two patch streams (next two dashed lines) to service new requests. Note that the length of the patch stream is the temporal skew to the regular stream. Subsequently, another regular stream (second solid line) is initiated followed by two other patch streams.

Transition Patching allows some patch streams to be sharable by extending their lengths. Specifically, it introduces another multicast stream, called *transition stream*. The threshold to start a regular stream is Wr as in Patching, and the threshold to start a transition stream is called *transition window* (Wt). Figure 2 further illustrates the concept. For example, the client at time 219 seconds starts listening to its own patch stream (second dotted line) and the closest preceding transition patch stream (second dashed line), and when its patch is completed, it starts listening to the closest preceding regular stream (first solid line).

ERMT is a near optimal hierarchical stream merging technique. Whereas a stream can merge at most once in Patching and at most twice in Transition Patching, ERMT allows streams to merge multiple times, thereby leading to a dynamic merge tree. In particular, a new user or a newly merged group of users snoops on the closest stream that it can merge with if no later arrivals preemptively catch them [2]. To satisfy the needs of the new user, the target stream may be extended, and thus its own merging target may change. Figure 3 illustrates the operation through a simple example. We can see that the third stream length got extended after the fourth stream had merged with it. Extensions are shown as dotted lines. ERMT performs better than other hierarchical stream merging alternatives and close to the optimal solution, which assumes that all request arrival times are known in advance [2, 19, 20].

Patching, Transition Patching, and ERMT differ in complexity and performance. Both the implementation complexity and performance increase from Patching to Transition Patching to ERMT. Selecting the most appropriate stream merging technique depends on a tradeoff between the required implementation complexity and the achieved performance.

2.3. Request Scheduling of Waiting Video Requests. A scheduling policy selecting an appropriate video for service whenever it has an available *channel*. A channel is a set of resources (network bandwidth, disk I/O bandwidth, etc.) needed to deliver a multimedia stream. All waiting requests for the selected video can be serviced using only one channel. The number of channels is referred to as *server capacity*.

The main scheduling policies include *First Come First Serve* (FCFS) [21], *Maximum Queue Length* (MQL) [21], *Maximum Factored Queue Length* (MFQL) [22], and *Minimum Cost First* (MCF) [16]. FCFS selects the video with the oldest waiting request, whereas MQL maximizes the number of request that can be serviced at any time by selects the video with the largest number of waiting requests. MFQL attempts to minimize the mean request waiting time by selecting the queue with the *largest factored length*. The factored length of a queue is defined as its length divided by the square root of the relative access frequency of its corresponding video. MCF policy has been recently proposed to exploit the variations in stream lengths caused by stream merging techniques. It gives preference to the videos whose requests require the least cost in terms of the amount of video data (measured in bytes) to be delivered. The length of the stream (in time) is directly proportional to the cost of servicing that stream since the server allocates a channel for the entire time the stream is active. Please note the distinction between video lengths and required stream lengths. Due to stream merging, even the requests for the same video may require different stream lengths. *MCF-P* (P for "Per"), the preferred implementation of MCF, selects the video with the least cost per request. The objective function here is

$$F(i) = \frac{L_i \times R_i}{N_i}, \tag{2}$$

where L_i is the required stream length for the requests in queue i, R_i is the (average) data rate for the requested video, and N_i is the number of waiting requests for video i. To reduce the bias against videos with higher data rates, R_i can be removed from the objective function (as done in this paper). MCF-P has two variants: *Regular as Full* (RAF) and *Regular as Patch* (RAP). RAP treats regular and transition streams as if they where patches, whereas RAF uses their normal costs. MCF-P performs significantly better than all other scheduling policies when stream merging techniques are used. In this paper, we simply refer to MCF-P (RAP) as MCF-P unless the situation calls for specificity.

3. Analysis of Cost-Based Scheduling

We seek to understand the behavior of cost-based scheduling and its interaction with stream merging. Understanding this behavior helps in developing solutions that optimize the overall performance. One of the issues that we explore in this study is determining the duration over which the cost should be computed. In particular, we seek to determine whether the cost should be computed only at the current scheduling time (T_{Now}) or over a future duration of time, called *prediction window* (W_p). In other words, should the system select the video with the least cost per request at time T_{Now} or the least cost per request during W_p. The latter requires prediction of the future system state. We devise and explore two ways to analyze the effectiveness of computing the cost over a period of time: *Lookahead* and *Combinational* scheduling.

3.1. Lookahead Scheduling. In Lookahead Scheduling, the service rate (which is the rate at which a video gets serviced) is computed dynamically for each video that has waiting requests. The total cost for servicing each one of these videos is computed during the time interval W_p. Lookahead Scheduling selects the video j that minimizes the expected cost per request. Thus, the objective function to minimize is

$$F(j) = \frac{\sum_{i=1}^{n} C_i}{\sum_{i=1}^{n} N_i}, \tag{3}$$

where n is the number of expected service times for video j during W_p, C_i is the cost required to service the requests for video j at service time i, and N_i is the number of requests expected to be serviced at service time i. The number of requests at future service times is predicted by dynamically computing the arrival rate for each video. Figure 4 further illustrates the idea. As discussed earlier, ERMT may extend streams to satisfy the needs of new requests. MCF-P, however, does not consider later extensions in computing the cost. In analyzing cost-based scheduling, we also need to consider whether it is worthwhile to predict and consider these later extensions. Hence, we consider a variant of Lookahead Scheduling that considers these extensions. (In Figure 4, the term "virtual time" means the future time imagined or simulated by Lookahead Scheduling, as opposed to the actual system time.)

3.2. Combinational Scheduling. In contrast with Lookahead Scheduling, Combinational Scheduling predicts the best sequence in which various videos should be serviced and performs scheduling based on this sequence. Thus, it considers any correlations on the cost among successive video selections. Figure 5 illustrates the operation of Combinational Scheduling. The best sequence is found by generating all possible sequences for the next n stream completion times during W_p, for only the n-best videos according to the MCF-P objective function. Note that stream completion times indicate when server channels become available for servicing new requests. The objective function of each sequence is then calculated. Consider the sequence $S_j = \{X_1, X_2, X_3, \ldots, X_n\}$, where X_i is the video selected to be serviced at the next ith stream completion time. The objective function for this sequence is

$$F\left(S_j\right) = \frac{\sum_{i=1}^{n} C_{X_i}}{\sum_{i=1}^{n} N_{X_i}}, \tag{4}$$

where C_{X_i} is the cost required to service video X_i, and N_{X_i} is the number of waiting requests for that video. C_{X_i} is determined based on the used MCF-P variant. Combinational Scheduling chooses the sequence that is expected to lead to the least overall cost. Although many optimizations are possible to reduce the implementation complexity, we focus primarily on whether exploiting the correlations between successive video selections is indeed important in practical situations.

4. Proposed Predictive Cost-Based Scheduling

The prediction of videos to be serviced and the prediction of waiting times for service have recently been proposed in [17]. These prediction results, however, were not used to alter the scheduling decisions. In this paper, we analyze the effectiveness of incorporating video prediction results into the scheduling decisions. We propose a scheduling policy, called *Predictive Cost-Based Scheduling* (PCS). PCS is based on MCF, but it predicts future system state and uses this prediction to possibly alter the scheduling decisions. The basic idea can be explained as follows. When a

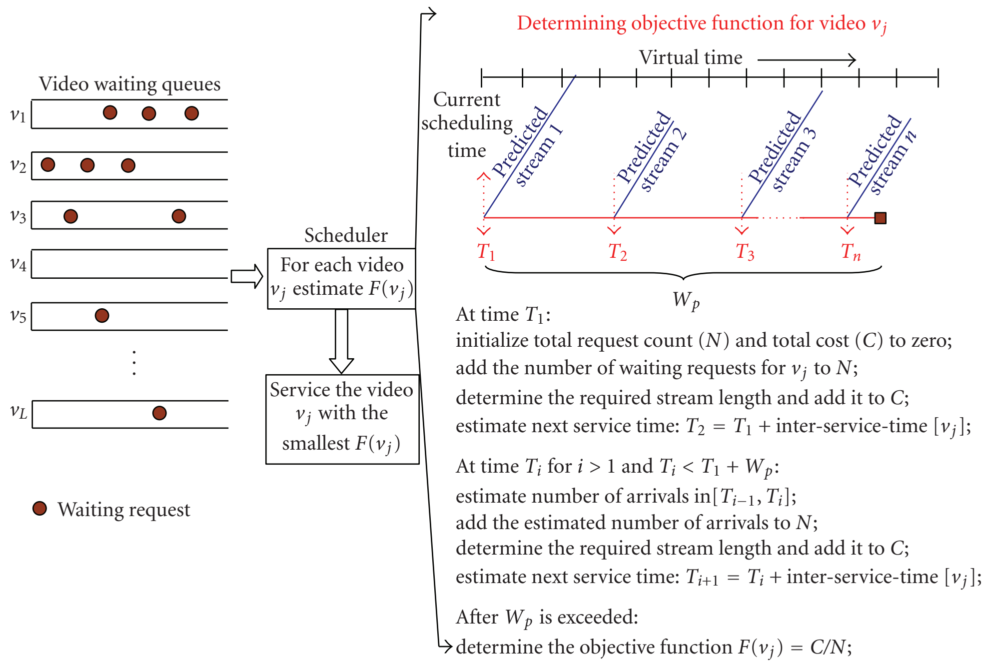


Figure 4: An Illustration of Lookahead Scheduling.

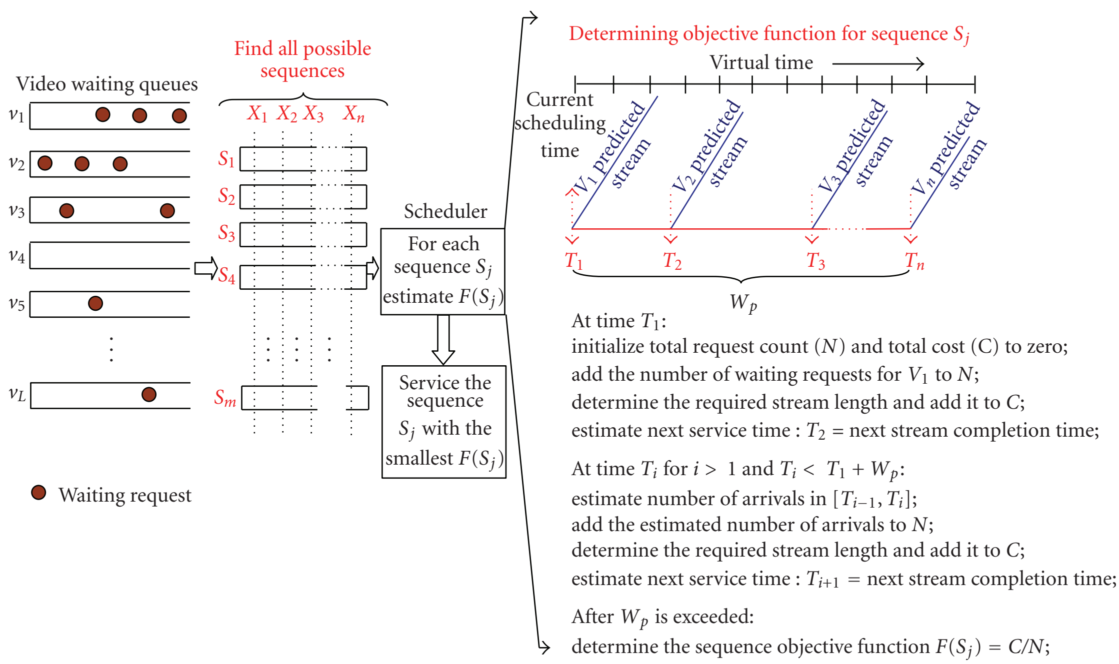


Figure 5: Illustration of Combinational Scheduling.

channel becomes available, PCS determines using the MCF-P objective function the video V_{Now} which is to be serviced tentatively at the current scheduling time (T_{Now}) and its associated delivery cost. To avoid unfairness against videos with high data rates, we use the required stream length for the cost [16]. Before actually servicing that video, PCS predicts the system state at the next scheduling time (T_{Next}) and estimates the delivery cost at that time assuming that video V_{Now} is not serviced at time T_{Now}. PCS does not service any request at time T_{Now} and thus postpones the service of video V_{Now} if the delivery cost at time T_{Next} is lower than that at time T_{Now}. Otherwise, video V_{Now} is serviced immediately.

To reduce possible server underutilization, PCS delays the service of streams only if the number of available server

```
currDefectionRate =defectedCustomers /servedCustomers;
if (currDefectionRate <lasDefectionRate) {
    if (last action was decrement andfreeChannelThresh > 2)
        freeChannelThresh –;
    else if (last action was increment)
        freeChannelThresh ++;
} else if (currDefectionRate >lastDefectionRate) {
    if (last action was increment  andfreeChannelThresh > 2)
        freeChannelThresh –;
    else if (last action was decrement)
        freeChannelThresh + +;
}
lastDefectionRate = currDefectionRate;
```

Algorithm 1: Simplified algorithm for dynamically computing *freeChannelThresh*.

channels (freeChannels) is smaller than a certain threshold (freeChannelThresh). Algorithm 1 shows a proposed algorithm to dynamically find the best value of freeChannelThresh. The algorithm changes the value of the threshold and observes its impact on customer defection probability over a certain time interval. The value of the threshold is then updated based on the trend in defection probability (increase or decrease) and the last action (increase or decrease) performed on the threshold. The algorithm is to be executed periodically but not frequently to ensure stable system behavior.

We present two alternative implementations of PCS: *PCS-V* and *PCS-L*. These two implementations differ in how to compute the delivery cost or required stream length at the next scheduling time. PCS-V predicts the video to be serviced at the next scheduling time and simply uses its required stream length. The video prediction is done by utilizing detailed information about the current state of the server in a manner similar to that of the waiting-time prediction approach in [17]. This information includes the number of waiting requests for each video, the completion times of running streams, and statistics such as the average request arrival rate for each video (which is to be updated periodically). Algorithm 2 shows a simplified algorithm for PCS-V.

In contrast with PCS-V, PCS-L computes the expected required stream length at the next scheduling time based on the lengths of all possible video streams that may be required and their probabilities. A simplified algorithm for PCS-L is shown in Algorithm 3. The probability that a video is selected is equal to the probability that it has at least one waiting request at time T_{Next} times the probability that all video streams with lower cost (i.e., shorter required streams) are not selected. The probability that video v has at least one arrival during duration $T_{\text{Next}} - T_{\text{Now}}$ can be found as one minus the probability of exactly zero arrivals:

$$1 - e^{-\lambda_v \times (T_{\text{Next}} - T_{\text{Now}})}, \tag{5}$$

where λ_i is the request arrival rate for video v and assuming a Poisson arrival process. If the video has already one waiting request, then this probability is 1. Sorting the videos according to the scheduling objective function is required to determine the probability that all videos with lower cost (or higher objective) are not selected.

As can be clearly seen from the algorithms, both PCS-V and PCS-L require a time overhead of $O(N_v)$, where N_v is the number of videos, assuming that a priority queue structure is used to rank the videos according to the objective function.

5. Proposed Adaptive Regular Stream Triggering (ART)

As will be shown later, our analysis reveals a significant interaction between stream merging and scheduling decisions. One of the pertaining issues is how to best handle regular (i.e., full) streams. MCF-P (RAP) considers the cost of a regular stream as a patch and thus treats it in a differentiated manner. The question arises as to whether it is worthwhile, however, to delay regular streams in certain situations. Guided by analysis, we propose a technique, called *Adaptive Regular Stream Triggering* (ART). A possible implementation is shown in Algorithm 4. The basic idea here is to delay regular streams as long as the number of free channels is below a certain threshold, which is to be computed dynamically based on the current workload and system state. ART uses the same algorithm (shown in Algorithm 1) to dynamically find the best value of free Channel Thresh as that of PCS.

To further demonstrate the main idea of ART, Figure 6 plots the ERMT merge tree without and with ART, respectively. The solid lines show the initial stream lengths and the dotted lines show later extensions. The circles identify successive extensions. With ART, there is a gap before a regular stream is initiated because of the postponement. We also observe that ART enhances the stream merging decisions of ERMT. The number of initial regular streams (called *I Streams* in this paper) in the merge tree is relatively much smaller with ART. For example, there is only one *I Stream* in the merge tree with ART while there are many more *I Streams* in the merge tree without ART.

As can be seen form the ART algorithm in Algorithm 4, ART requires a time overhead of $O(1)$ in addition to the time overhead of the base scheduling policy used.

In principle, ART can be used with any scheduling policy, including PCS, although some negative interference happens when it is combined with PCS, as will be shown in Section 7.

6. Evaluation Methodology

We study the effectiveness of the proposed policies through simulation. The simulation, written in *C*, stops after a steady-state analysis with 95% confidence interval is reached.

6.1. Workload Characteristics. Table 1 summarizes the workload characteristics used. Like most prior studies, we generally assume that the arrival of the requests to the server follows a Poisson Process with an average arrival rate λ. We also experiment with the Weibull distribution with two parameters: shape and scale [23]. We analyze the impact

```
V_Now = find the video that will tentatively be serviced at T_Now;
if (freeChannels ≥freeChannelThresh)
    Service the requests for V_Now;
else {
    currStreamLen = find required stream length to service V_Now at T_Now;
    V_Next = find the video that is expected to be serviced at T_Next;
    nextStreamLen = find required stream length to service V_Next at T_Next;
    if (currSreamLen ≤nextStreamLen)
        Service the requests for V_Now;
}
```

Algorithm 2: Simplified algorithm for PCS-V.

```
V_Now = find the video that will tentatively be serviced at T_Now;
if (freeChannels ≥freeChannelThresh)
    Service the requests for V_Now;
else {
    currStreamLen = find required stream length to service V_Now at T_Now;
    Calculate objective function for each video at T_Next;
    Sort videos from best to worst according to objective function;
    expectedStreamLen = 0; // initialization
    // loop to find expected stream length at T_Next
    for (v = 0; v < N_v; v + +){ // for each video
        nextStreamLen = find required stream length to service v at T_Next;
        Prob(video v is selected) = Prob(no other video with better objective is selected)
                *Prob(video v has at least one arrival);
        expectedStreamLen +=Prob(video v is selected) * nextStreamLen;
    }
    if (currSreamLen ≤ expectedStreamLen)
        Service the requests for V_Now;
}
```

Algorithm 3: Simplified algorithm for PCS-L.

of the shape (k), while adjusting the scale so that the desired average request arrival rate is reached. Additionally, we assume that the access to videos is highly localized and follows a Zipf-like distribution. With this distribution, the probability of choosing the nth most popular video is $C/n^{1-\theta}$ with a parameter θ and a normalized constant C. The parameter θ controls the skew of video access. Note that the skew reaches its peak when $\theta = 0$, and that the access becomes uniformly distributed when $\theta = 1$. We analyze the impact of this parameter, but we generally assume a value of 0.271 [24, 25].

We characterize the waiting tolerance of customers by three models. In *Model A*, the waiting tolerance follows an exponential distribution with mean μ_{tol} [24, 25]. In *Model B*, users with expected waiting times less than μ_{tol} will wait and the others will have the same waiting tolerance as Model A [24, 25]. We use *Model C* to capture situations in which users either wait or defect immediately depending on the expected waiting times. The user waits if the expected waiting time is less than μ_{tol} and defects immediately if the waiting time is greater than $2\,\mu_{\text{tol}}$. Otherwise, the defection probability increases linearly from 0 to 1 for the expected waiting times between μ_{tol} and $2\,\mu_{\text{tol}}$ [17].

As in most previous studies, we generally study a server with 120 videos, each of which is 120 minutes long. We examine the server at different loads by fixing the request arrival rate at 40 requests per minute and varying the number of channels (server capacity) generally from 200 to 750. In addition to the fixed-length video workload (in which all videos have the same length), we experiment with a variable-length video workload. Moreover, we study the impacts of arrival rate, user's waiting tolerance, number of videos, and video length (in the fixed-length workload).

Flash crowds workload characteristics were adopted from [26].

6.2. Considered Performance Metrics. To evaluate the effectiveness of the proposed schemes, we consider the main performance metrics discussed in Section 2.1. In addition, we analyze waiting-time predictability by two metrics: waiting-time prediction accuracy and the percentage of clients receiving expected waiting times. The waiting-time prediction accuracy is determined by the average deviation between the expected and actual waiting times. For waiting-time prediction, we use the algorithm in [17]. Note that this algorithm may not provide an expected waiting time to each

```
V_Now = find the video that will be serviced at T_Now;
if (freeChannels ≥ freeChannelThresh)
    Service the requests for V_Now;
else {
    currStreamLen = find the required stream length to serve V_Now at T_Now;
    if (currStreamLen < movieLen) // not a full stream
        Service the requests for V_Now;
    else // full stream
        Postpone the requests for V_Now;
}
```

Algorithm 4: Simplified implementation of ART.

Table 1: Summary of Workload Characteristics.

Parameter	Model/Value(s)
Request Arrival	Poisson Process (default) Weibull Distribution with shape $k = 0.6$ to 0.9
Request Arrival Rate	Variable, Default is 40 Req./min
Server Capacity	200 to 750 channels
Video Access	Zipf-Like
Video Skew (θ)	0.1 to 0.6, Default = 0.271
Number of Videos	Variable, Default is 120
Video Length	Fixed-Length Video Workload (Default) with length of 60 to 180 min (same for all videos), Default = 120 min Variable-Length Video Workload: with lengths randomly in the range: 60 to 180 min
Waiting Tolerance Model	A, B, C, Default is A
Waiting Tolerance Mean (μ_{tol})	Variable, Default is 30 sec
Flash Crowds	The peak arrival rate is 40 times the normal rate for a period of two movie lengths and flash crowds arrival rate is variable. Default: no flash crowds

client because the prediction may not always be performed accurately.

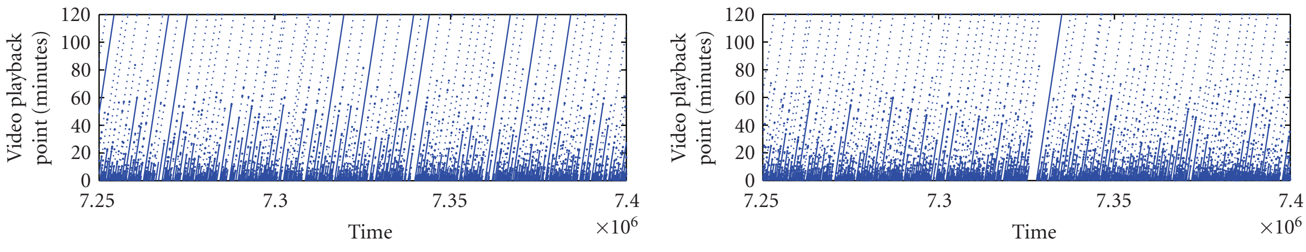
7. Result Presentation and Analysis

7.1. Comparing the Effectiveness of Different Cost-Computation Alternatives. Let us start by studying the effectiveness of Lookahead and Combinational Scheduling. Interestingly, there is no clear benefit for computing the cost over a future period of time. In some cases, as shown in Figure 7, the performance in terms of customer defection and average waiting time may be worse than those when computing the cost at the current scheduling time with MCF-P. The results of Lookahead Scheduling are shown for two different prediction window values. Only the results with future stream extensions are shown. The results without extensions are almost the same.

Although computing the cost over a time interval seems intuitively to be an excellent choice, it interferes negatively with stream merging. Later in this paper, we discuss how the interaction between stream merging and scheduling can be utilized by using the proposed ART technique, which can be used with any scheduling policy. Based on these results, we only consider next computing the cost at the current scheduling time.

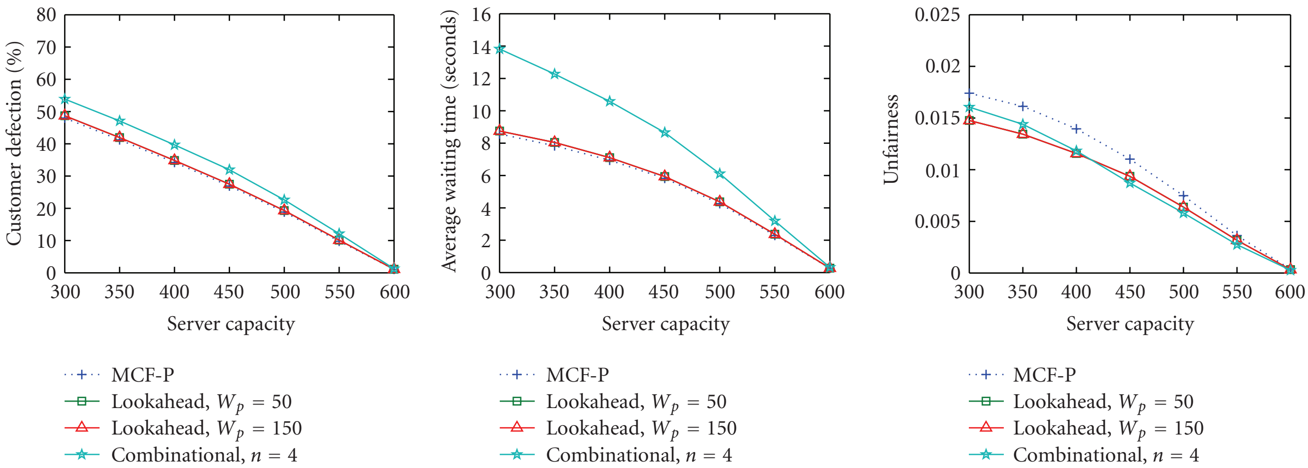
7.2. Effectiveness of the Proposed PCS Policy. Figures 8, 9, and 10 demonstrate the effectiveness of the two implementations of PCS when applied with ERMT, Transition Patching, and Patching, respectively, in terms of the customer defection probability, average waiting time, and unfairness. The figures show that PCS outperforms MCF-P and MQL in terms of both the two most important performance metrics (defection probability and average waiting time), whereas MCF-P is fairer towards unpopular videos. The two implementations of PCS perform nearly the same and thus PCS-V is preferred because of its simplicity. From this point on, we consider only the PCS-V implementation.

7.3. Effectiveness of the Proposed ART Enhancement. Figure 11 shows the effectiveness of the proposed ART technique when ERMT is used. With MCF-P, ART reduces



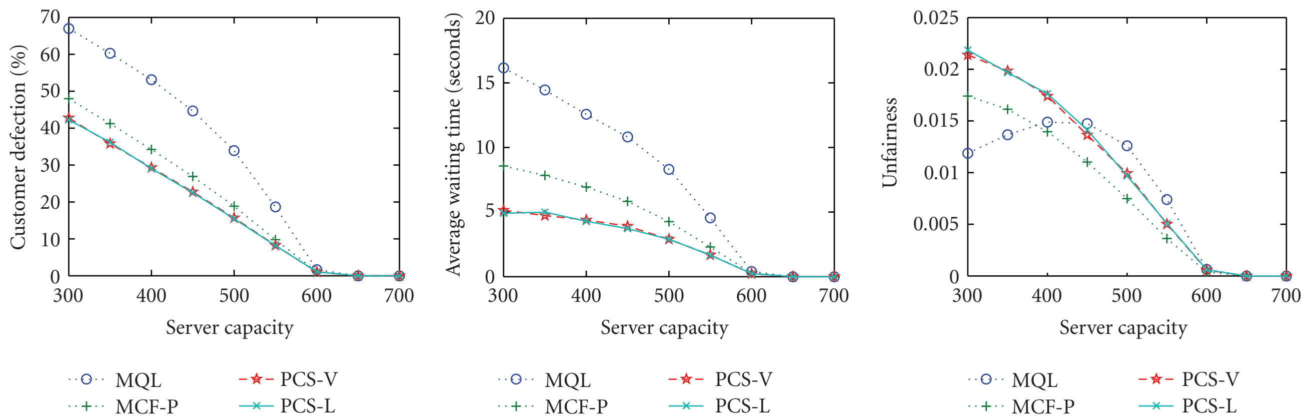
(a) MCF-P without ART (b) MCF-P with ART

Figure 6: Impact of ART on ERMT Stream Merge Tree (*Video 11, MCF-P, Server Capacity* = 450).



(a) Defection rate (b) Average waiting time (c) Unfairness

Figure 7: Effectiveness of Lookahead and Combinational Scheduling (*ERMT*).

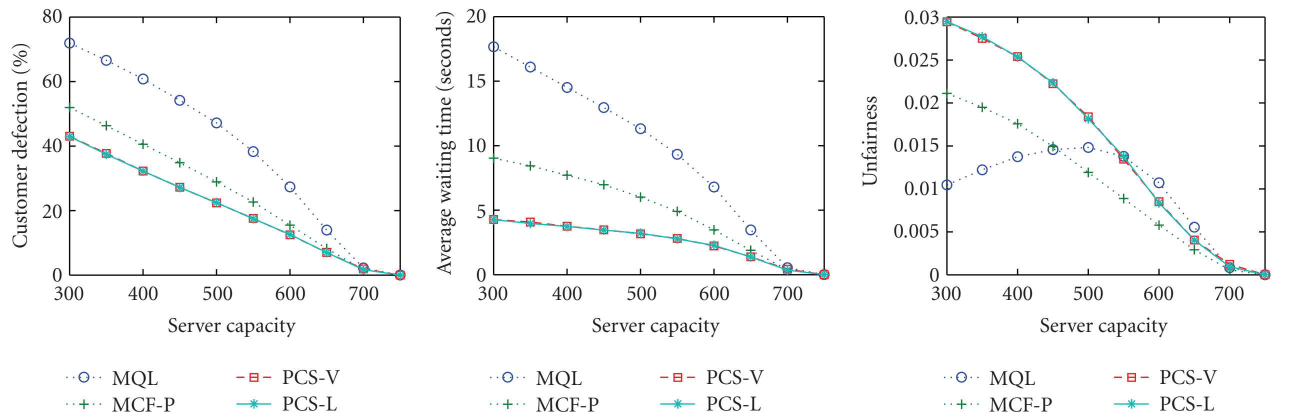


(a) Defection rate (b) Average waiting time (c) Unfairness

Figure 8: Effectiveness of PCS (*ERMT*).

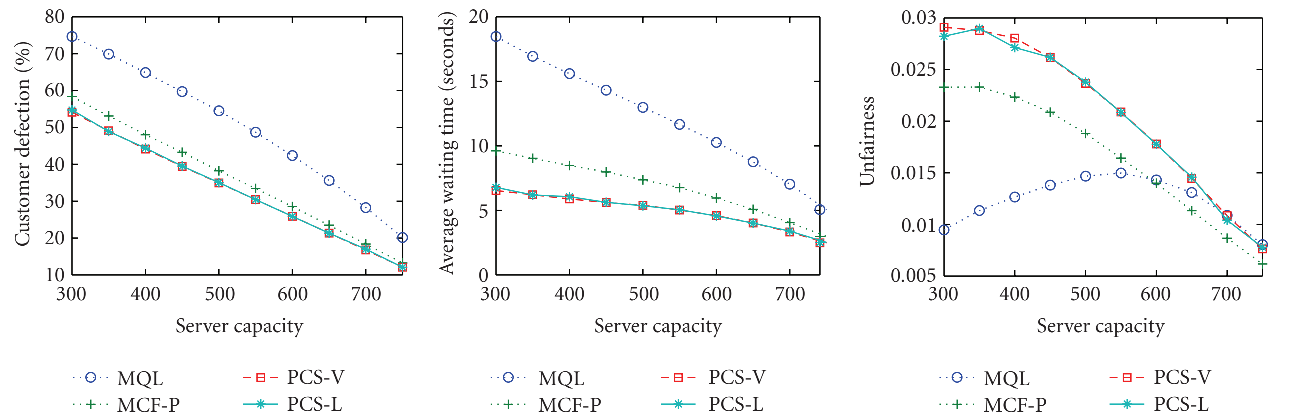
the customer defection probability and average waiting time by up to 25% and 80%, respectively. It also yields significant improvements when used with MQL. Unfairness, the least important metric, is a little larger with ART because of its nature in favoring videos with shorter streams, but it is still acceptable compared with MQL.

Figure 12 depicts the impact of ART on regular streams in ERMT. We observe that when ART postpones regular streams, it forces ERMT to make more merges, which, in turn, increases system utilization. We also observe that the number of regular streams does not decrease significantly despite of postponing these streams. In contrast, Figure 12(a) indicates that the average time between two successive regular streams for popular videos is even smaller with ART than that without it. This is because ERMT keeps extending streams, which eventually become regular streams. Figures 12(b) and 12(c) compare the percentage of initial regular streams (I Streams) and extended regular streams



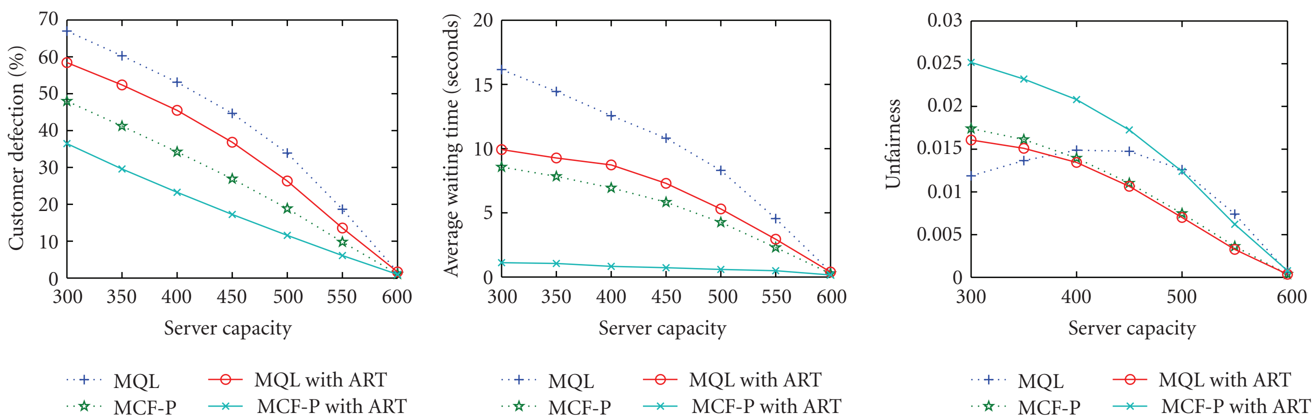
(a) Defection rate (b) Average waiting time (c) Unfairness

Figure 9: Effectiveness of PCS (*Transition Patching*).



(a) Defection rate (b) Average waiting time (c) Unfairness

Figure 10: Effectiveness of PCS (*Patching*).



(a) Defection rate (b) Average waiting time (c) Unfairness

Figure 11: Effectiveness of ART (*ERMT*).

(E Streams) without and with ART, respectively. We can see that the percentage of extended regular streams with ART is much higher. This supports the fact that the number of regular streams is not reduced by postponing. In summary, we can say that ART improves ERMT by replacing many *I Streams* with *E Streams*.

Let us now discuss the impact of ART when Transition Patching and Patching are used. Transition Patching results are presented in Figure 13 and Patching results are presented in Figure 14. As with ERMT, ART reduces significantly the customer defection probability and the average waiting time when it is combined with MCF-P and MQL. Unfairness with ART is a little larger but still acceptable compared with that of MQL for medium and high server capacities.

Interestingly, ART improves Transition Patching and Patching despite that their best scheduling policy, MCF-P (RAP), depends on a conflicting principle. As discussed earlier, MCF-P (RAP) gives preference to regular streams while ART postpones them in certain situations. As illustrated in Figure 15, the main impact of ART is dynamically optimizing Wr, which is larger than that of MCF-P (RAP) and smaller than that of MCF-P (RAF) for popular videos, and even greater than that of MCF-P (RAF) for unpopular videos. The horizontal line in the figure marks the equation-based value of Wr [27]. (Note that the equation does not yield optimum values because it is based on important simplifying assumptions.)

7.4. Comparing the Effectiveness of PCS and ART. Although ART can be applied with any scheduling policy, including PCS, for the time being, we consider it as an alternative to PCS because of negative interference between the two, as will be shown in Section 7.8. In this subsection, we compare the effectiveness of PCS-V and ART in terms of customer defection probability, average waiting time, unfairness against unpopular videos, and cost per request. Figures 16, 17, and 18 show the results of ERMT, Transition Patching, and Patching respectively.

With ERMT, MCF-P when combined with ART performs better than PCS-V in terms of the customer defection probability and average waiting time. The results when Transition Patching and Patching are used exhibit different behavior than those with ERMT. MCF-P combined with ART gives almost the same results as PCS-V in terms of customer defection probability, but it reduces the average waiting time significantly. Unfairness of PCS-V is less than that with ART in all stream merging techniques because ART favors videos with shorter streams more than PCS-V. These results indicate that MCF-P when combined with ART is the best overall performer.

To further support the fact that more customers are served with only one stream when using ART, Figure 19 demonstrates the impact of ART on the cost per request. We can see that the cost per request with ART is the lowest for different server capacities.

7.5. Impact of Workload Parameters on the Effectiveness of PCS and ART. Figures 20, 21, 22, and 23 illustrate the impact of the request arrival rate, customer waiting tolerance, number of videos, and video length on the effectiveness of PCS-V and ART. The results for both Patching and ERMT are shown. The results demonstrate that ART always achieves smaller customer defection probability and average waiting time than PCS-V in the case of ERMT. In Patching, the same trend is observed for the average waiting time, but PCS-V and "MCF-P combined with ART" perform nearly the same in terms of customer defection probability, especially when the server is highly loaded.

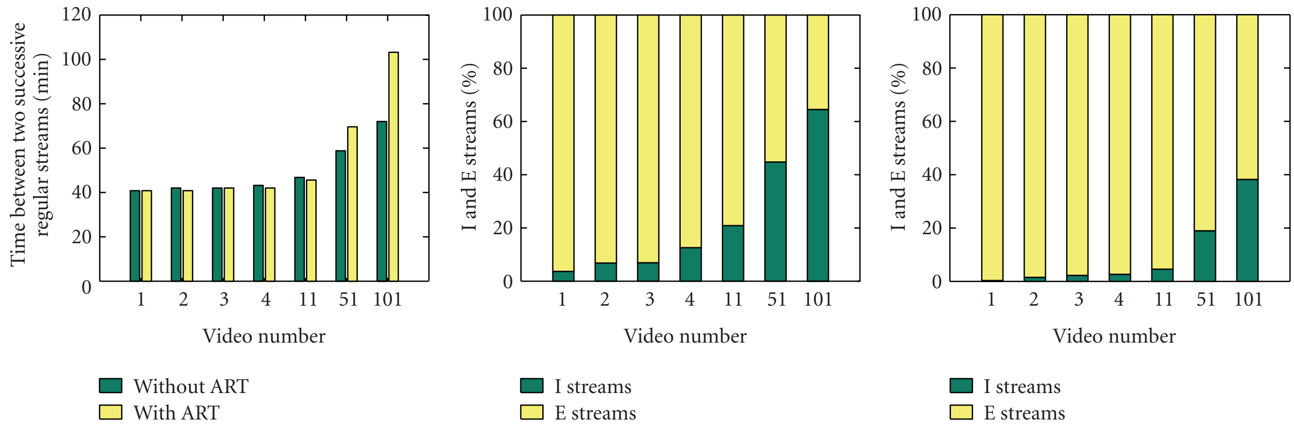
Figure 24 shows that the skew in video access has significant impacts on the customer defection probability, average waiting time, and unfairness. Recall that as θ increases, the skew in video access decreases. Both the defection probability and average waiting time are worsen by the reduction in the skew. This is because cost-based scheduling policies favor popular videos by nature. When θ increases, the deference in video popularity decreases which in turns makes the scheduling decision harder to make. Unfairness decreases by increasing θ which is as expected. Again, "MCF-P combined with ART" is the best policy in terms of all performance metrics, except unfairness.

The results so far are for a video workload of a fixed video length. Figure 25 shows the customer defection probability, average waiting time and unfairness results for a variable-length video workload. The workload is comprised of videos with lengths in the range of 60 to 180 minutes. The length of each video is generated randomly within the specified range. The results for the workload are obtained by averaging the values of four runs. The PCS-V and ART algorithms also work well in this workload. "MCF-P combined with ART" as in most cases performs better than all other policies. Moreover, we can see that the fairness of ART and PCS-V is better than that of MCF-P with variable-length video workload.

The results so far assume a Poisson request arrival process. Let us now examine the behavior under Weibull distribution with different shape (k) values. Figure 26 demonstrates that the shape has a little impact, especially when the server capacity is larger than 500 channels. Figure 27 compares MCF-P, PCS-V, and MCF-P with ART under Weibull Arrival Distribution with the same shape. The results with other shape parameters have the same trend and thus are not shown. We can see clearly that PCS-V and "MCF-P combined with ART" sill perform better than MCF-P. We can see also that MCF-P with ART is the best policy.

7.6. Comparing Waiting-Time Predictability with PCS and ART. Figure 28 compares the predictability of MCF-P, PCS-V, and "MCF-P combined with ART" in terms of the average deviation and percentage of clients receiving expected time of service (PCRE) under waiting tolerance Model B. The results with Model C are similar and thus are not shown. The results demonstrate that ART significantly improves the predictability of MCF-P. PCS-V is also more predictable than MCF-P. In particular, ART reduces the average deviation by up to 30% and 75% for models B and C, respectively. It also increases the number of clients receiving expected times by up to 35%. Moreover, "MCF-P combined with ART" gives more customers expected times than PCS-V with a relatively less significant increase in the average deviation.

7.7. Impact of Flash Crowds on the Effectiveness of PCS and ART. Let us now discuss the impact of flash crowds on the the effectiveness of PCS-V and ART. Figure 29 demonstrates the impact of flash crowds interarrival time on MCF-P, PCS-V, and "MCF-P combined with ART." The results shows that

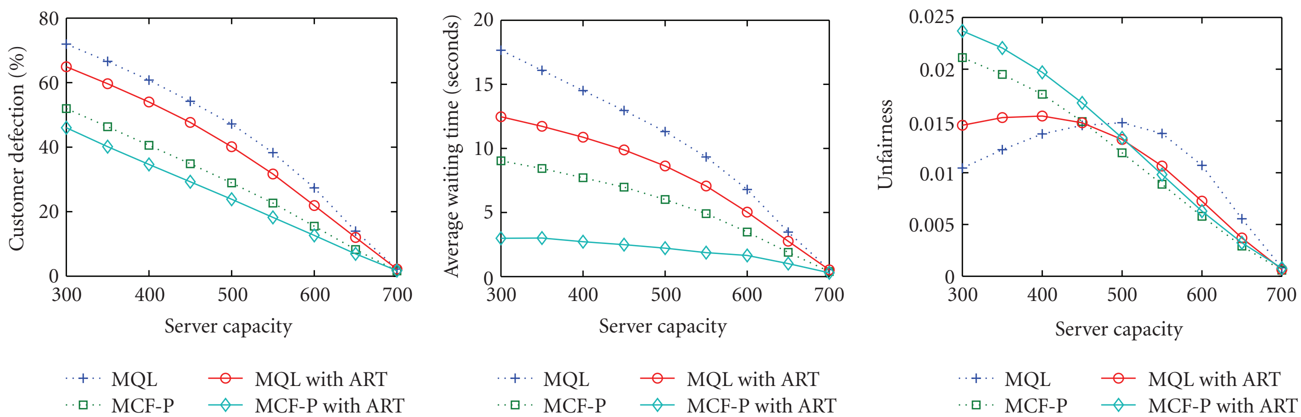


(a) Average time between two regular streams

(b) Initial and extended regular streams without ART

(c) Initial and extended regular streams with ART

Figure 12: Impact of ART on regular streams (*ERMT, MCF-P, Server Capacity* = 450).

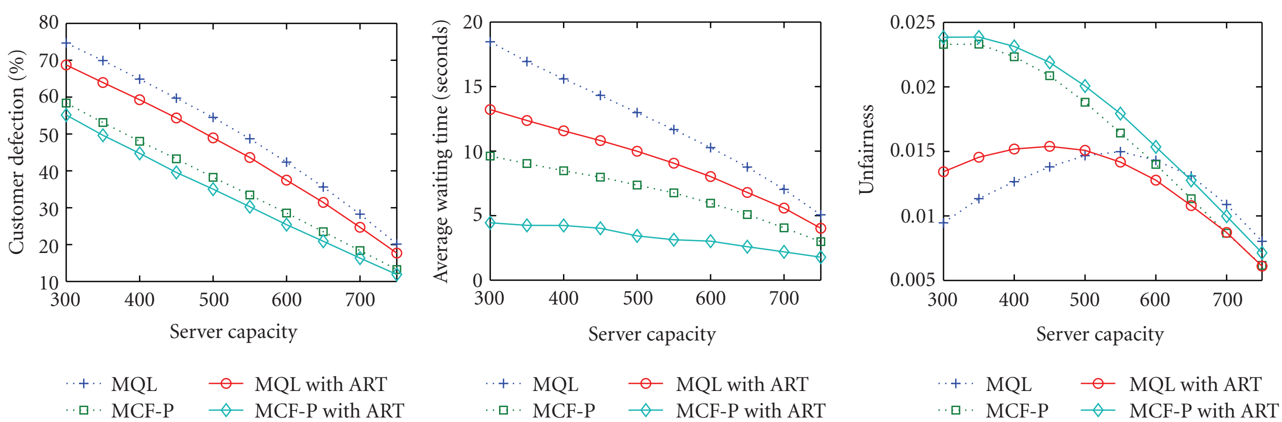


(a) Defection rate

(b) Average waiting time

(c) Unfairness

Figure 13: Effectiveness of ART (*transition patching*).

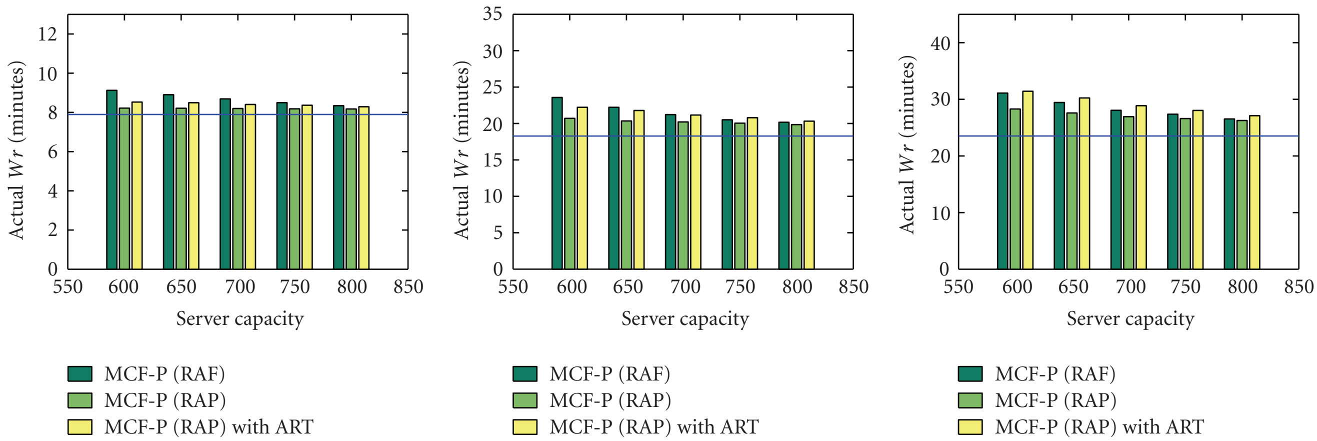


(a) Defection rate

(b) Average waiting time

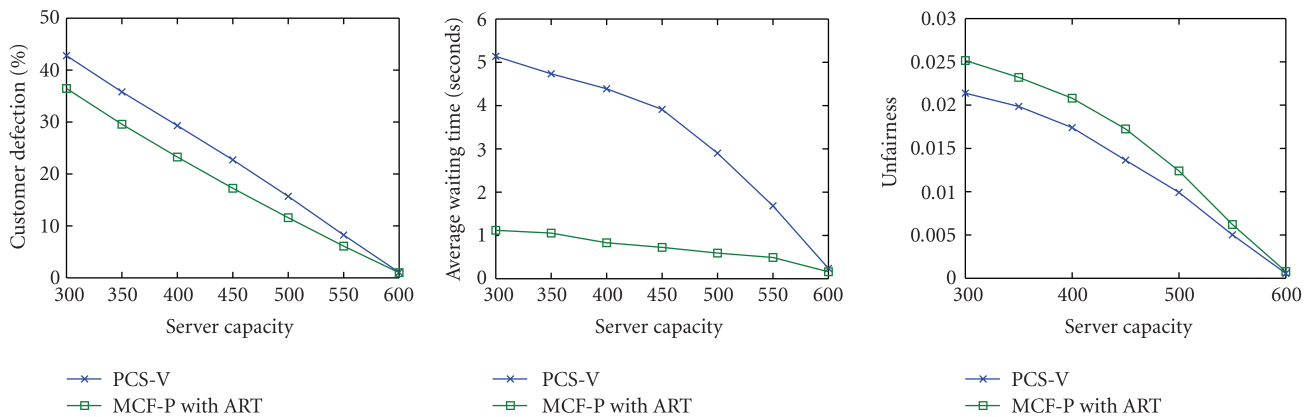
(c) Unfairness

Figure 14: Effectiveness of ART (*patching*).



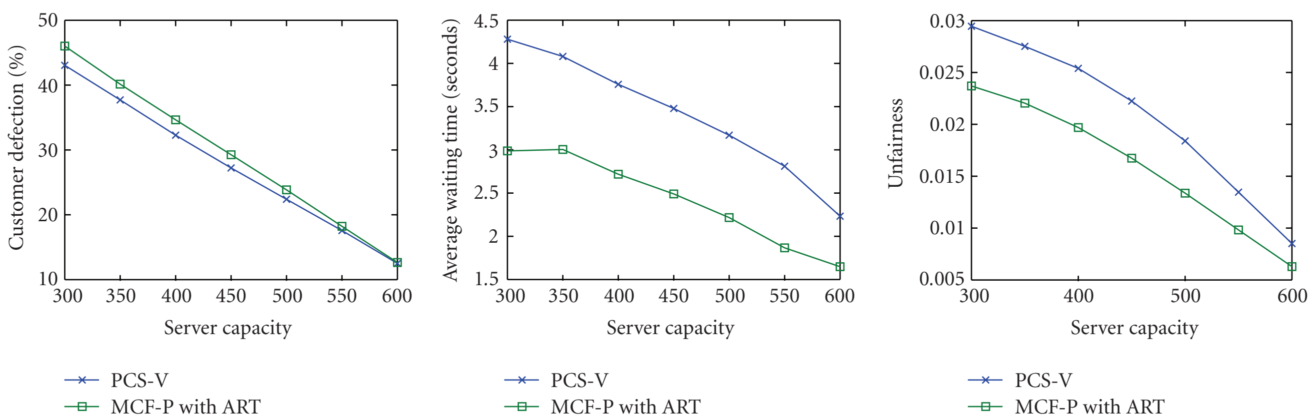
(a) Video 1 (b) Video 10 (c) Video 20

Figure 15: Comparing Actual *Wr* in MCF-P (RAF), MCF-P (RAP), and MCFP(RAP) with ART (*patching*).



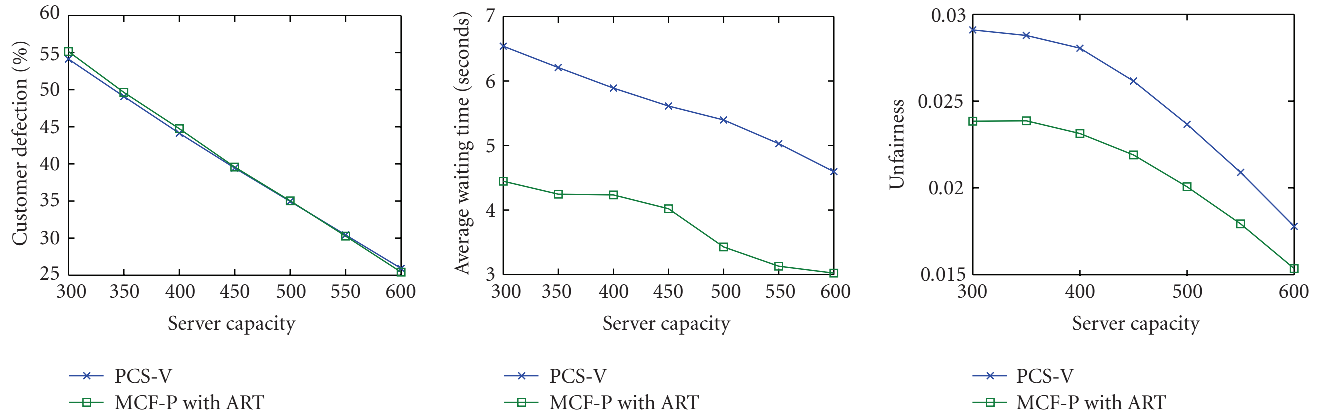
(a) Defection rate (b) Average waiting time (c) Unfairness

Figure 16: Comparing the effectiveness of PCS and ART (*ERMT*).



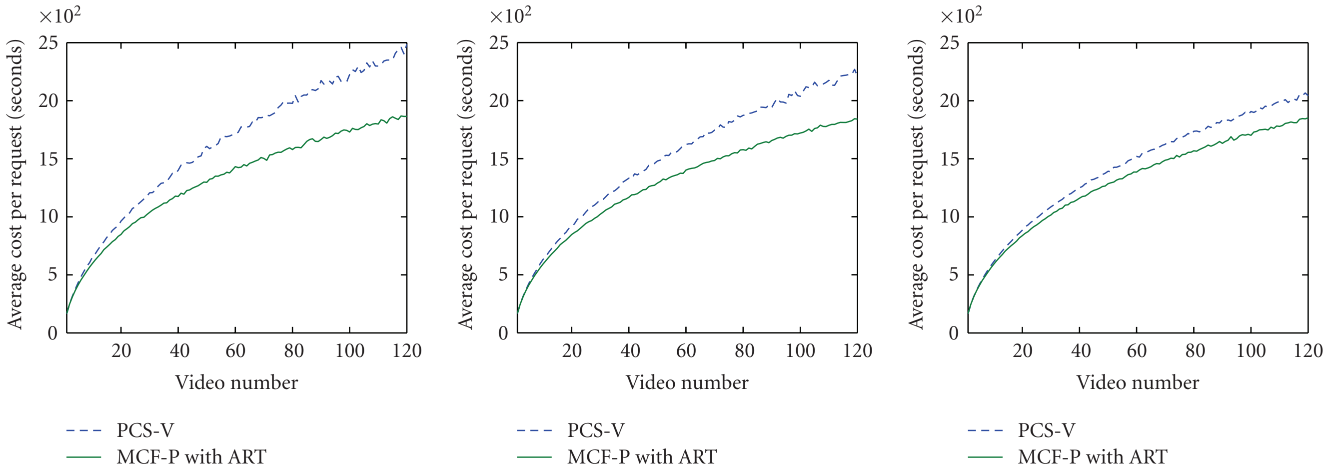
(a) Defection rate (b) Average waiting time (c) Unfairness

Figure 17: Comparing the effectiveness of PCS and ART (*Transition Patching*).



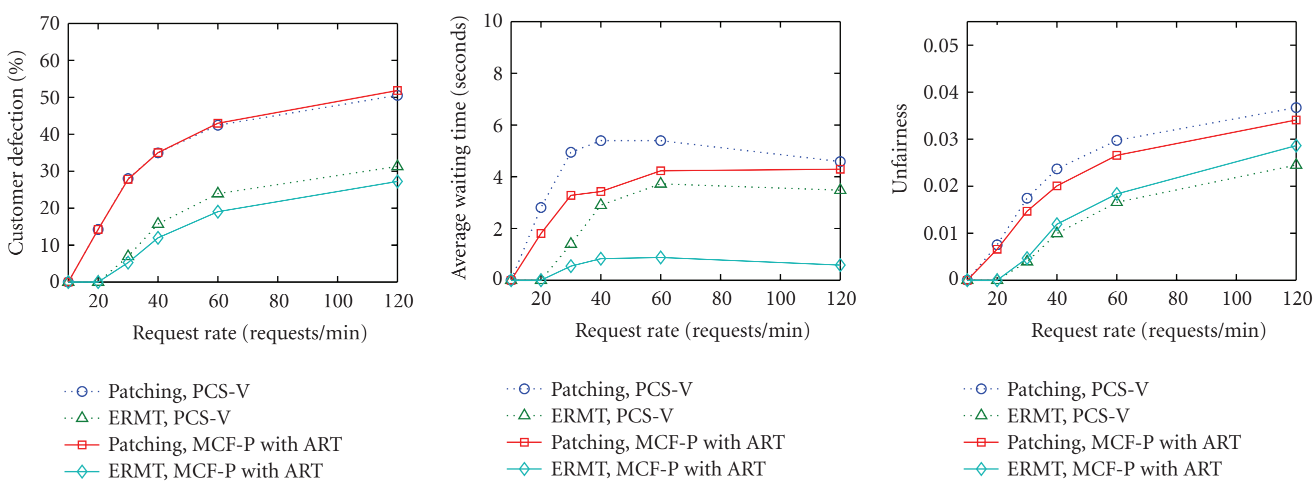
(a) Defection rate (b) Average waiting time (c) Unfairness

FIGURE 18: Comparing the Effectiveness of PCS and ART (*Patching*).



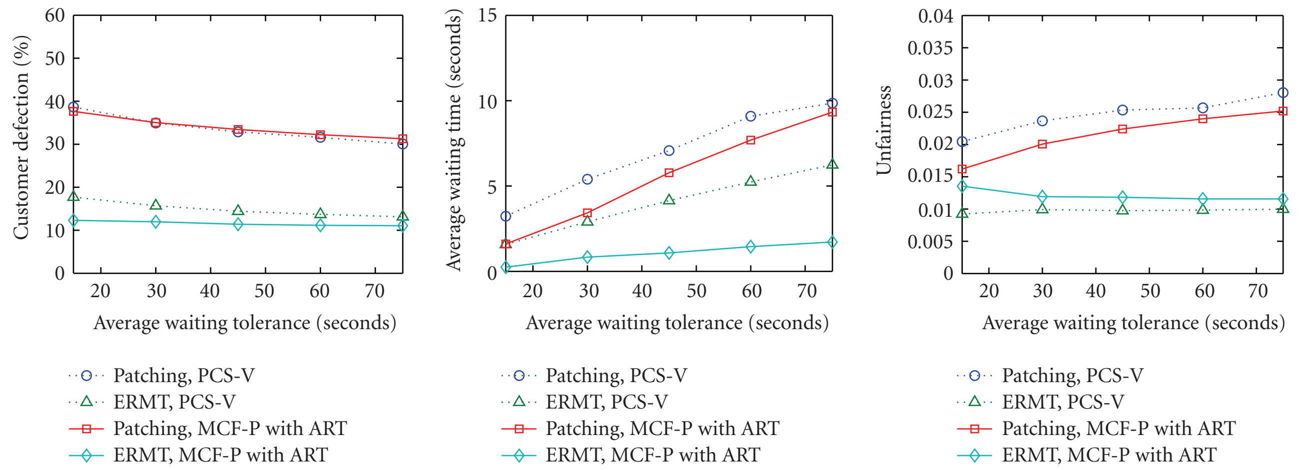
(a) 300 channel (b) 400 channel (c) 500 channel

FIGURE 19: Comparing the Impacts of PCS and ART on Cost per Request (*ERMT, MCF-P*).



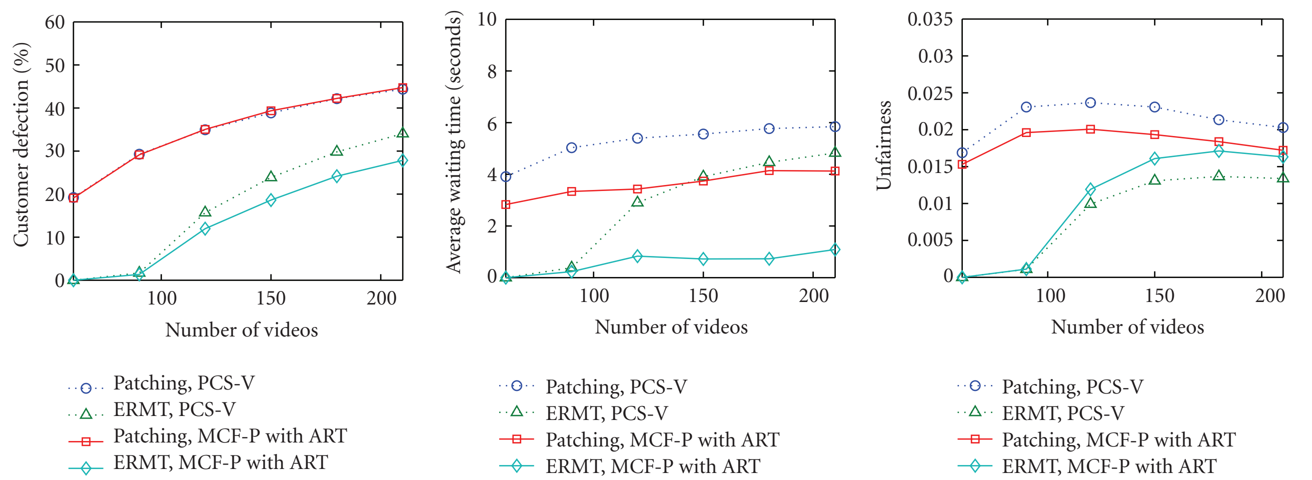
(a) Defection rate (b) Average waiting time (c) Unfairness

FIGURE 20: Impact of Request Arrival Rate (*Server Capacity* = 500).



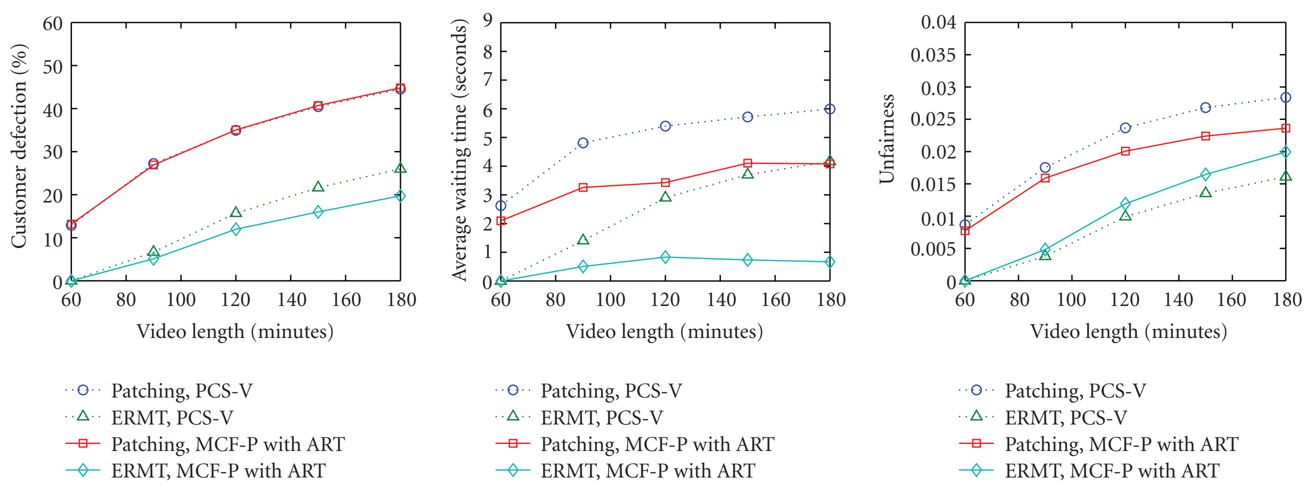
(a) Defection rate (b) Average waiting time (c) Unfairness

FIGURE 21: Impact of Customer Waiting Tolerance (*Server Capacity* = 500).



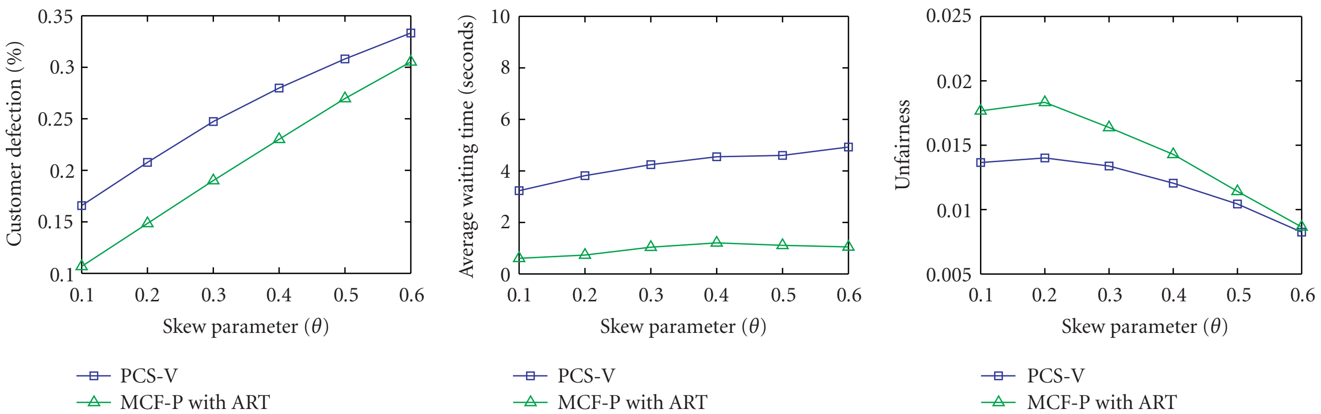
(a) Defection rate (b) Average waiting time (c) Unfairness

FIGURE 22: Impact of Number of Videos (*Server Capacity* = 500).



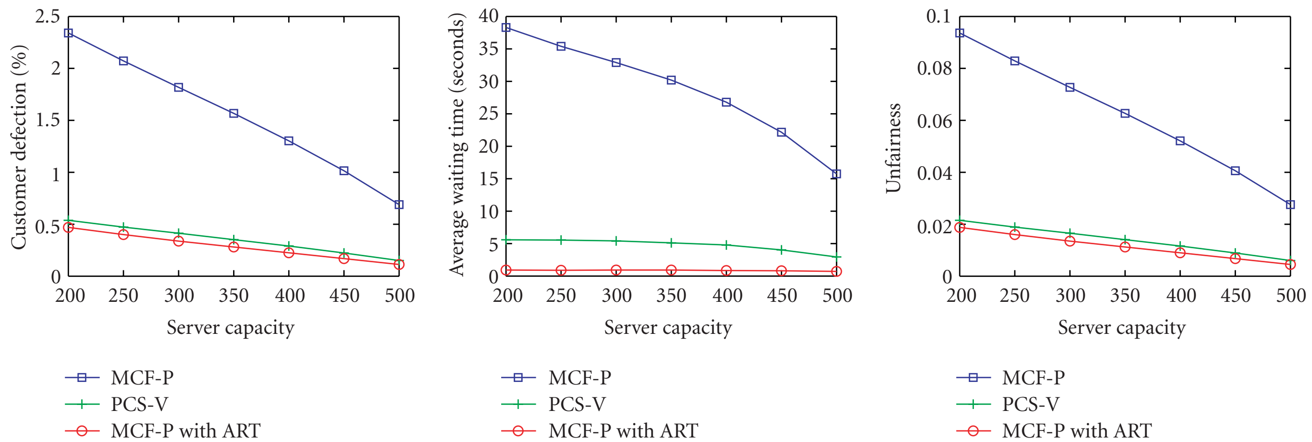
(a) Defection rate (b) Average waiting time (c) Unfairness

FIGURE 23: Impact of Video Length (*Server Capacity* = 500).



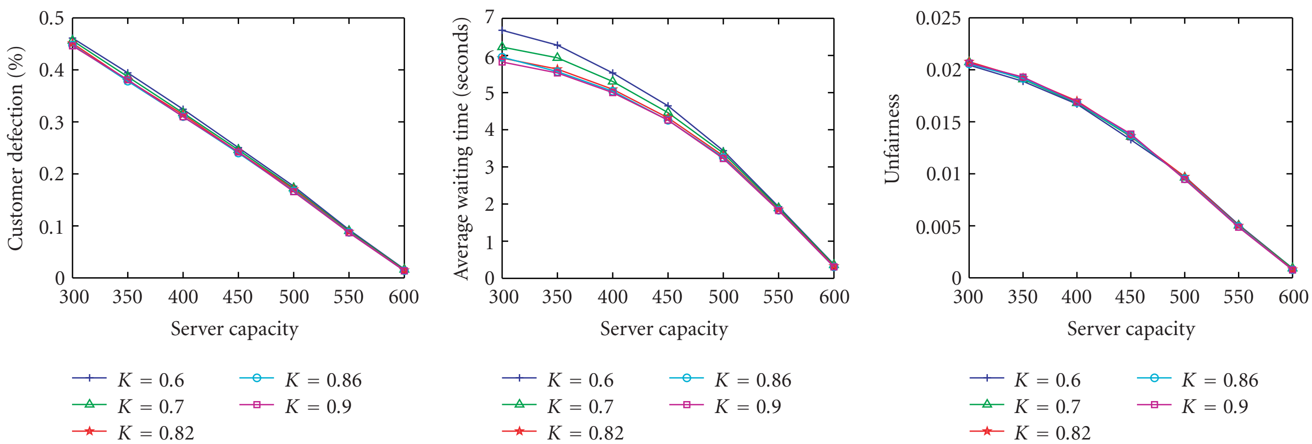
(a) Defection rate (b) Average waiting time (c) Unfairness

Figure 24: Impact of Skew in Video Access (*ERMT, Server Capacity* = 450).



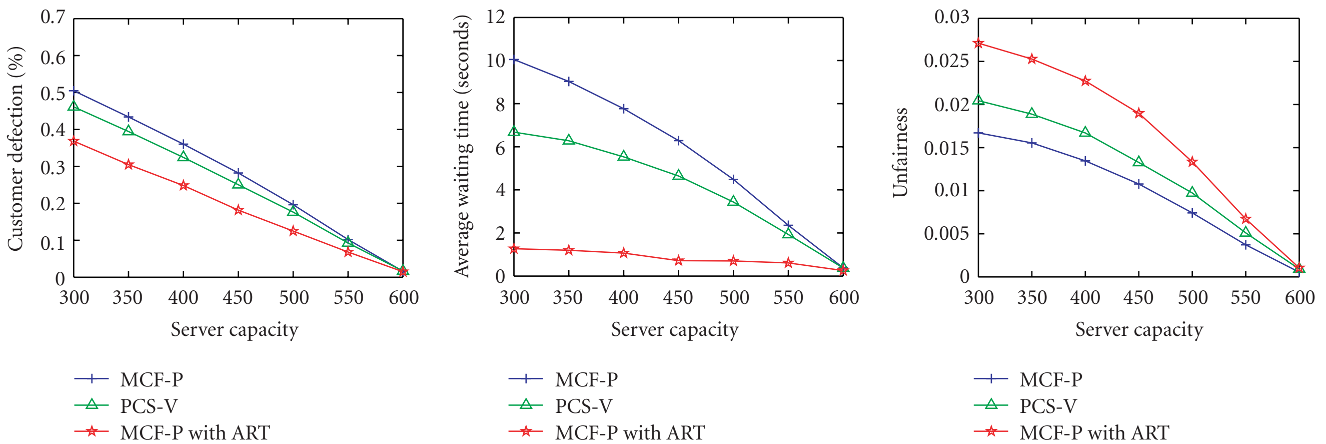
(a) Defection rate (b) Average waiting time (c) Unfairness

Figure 25: Comparing the Effectiveness of MCF-P, PCS, and ART under a Variable-Length Video Workload (*ERMT, 60 to 180 minutes Video Length Range*).



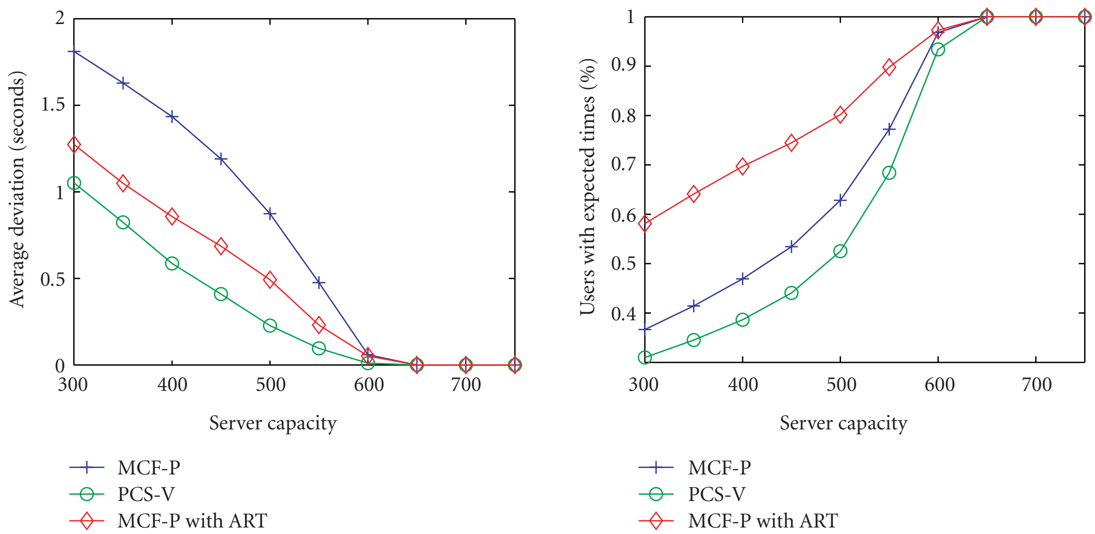
(a) Defection rate (b) Average waiting time (c) Unfairness

Figure 26: Impact of the Shape Parameter of Weibull Arrival Distribution (*ERMT, PCS-V*).



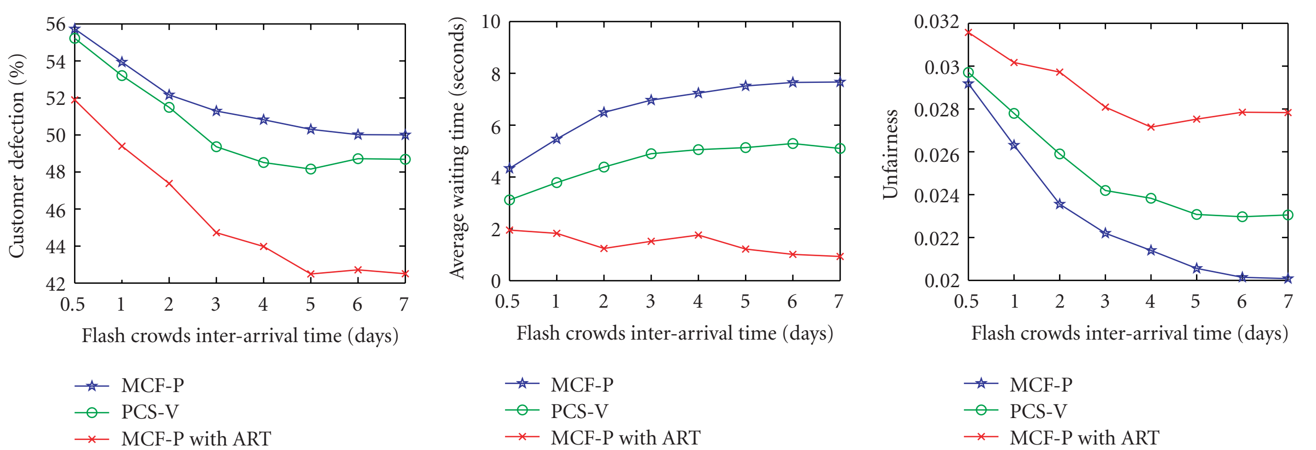
(a) Defection rate (b) Average waiting time (c) Unfairness

Figure 27: Comparing MCF-P, PCS-V, and MCF-P with ART under Weibull Arrival Distribution (*ERMT, K* = 0.6).



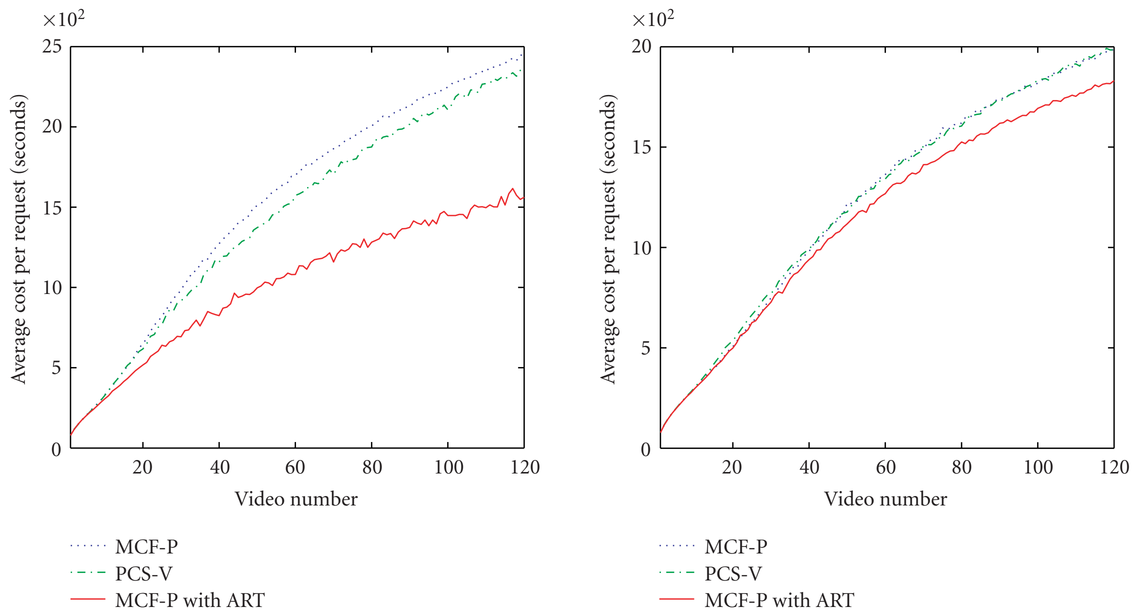
(a) Average deviation (b) Customer with expected time

Figure 28: Waiting-Time Predictability of MCF-P, MCF-P with ART, and PCS-V (*ERMT*, $W_p = 0.5\,\mu_{\text{tol}}$, *Model B*).



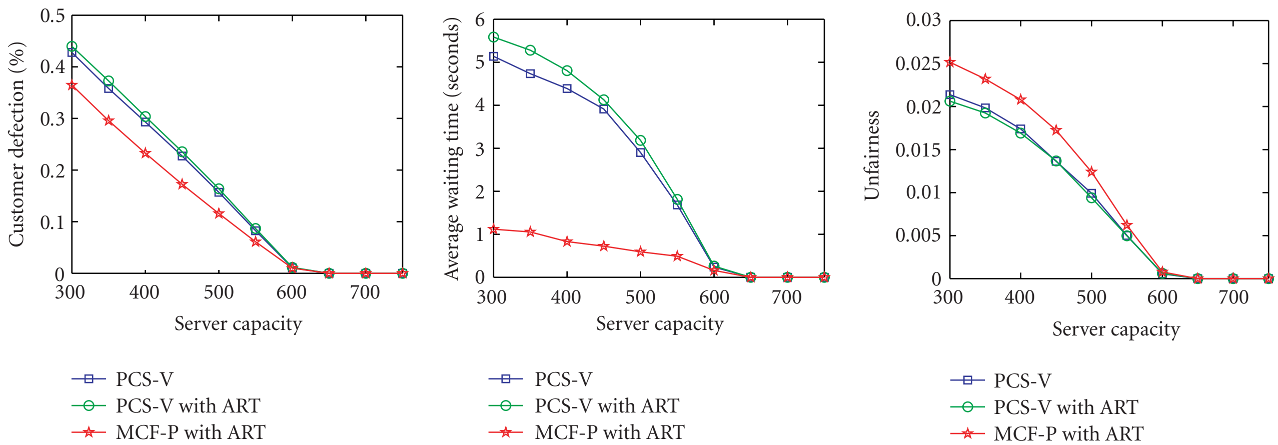
(a) Customer defection (b) Waiting time (c) Unfairness

Figure 29: Impact of Flash Crowds on MCF-P, PCS-V, and ART as a Function of Flash Crowds Iner-arrival Time (*ERMT, Server capacity* = 300).



(a) 300 (b) 500

Figure 30: Comparing MCF-P, PCS-V, and MCF-P with ART with Flash Crowds in Average Cost per Request (*ERMT, Flash Crowds Arrival Rate = 1/day*).



(a) Defection rate (b) Average waiting time (c) Unfairness

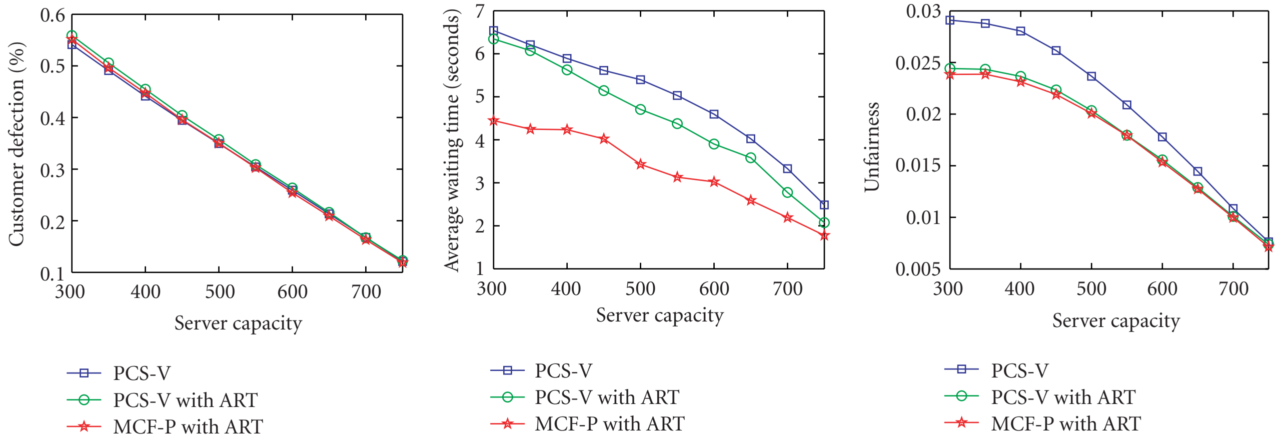
Figure 31: Effectiveness of Combining Art with PCS (*ERMT*).

MCF-P when combined with ART handles the flash crowds more efficiently than the other policies. In particular, it achieves the best customer defection probability and average waiting time under all flash crowds interarrival times. PCS-V achieves better results than MCF-P, but its improvement is less than that of ART. Figure 30 confirms that ART enhances the efficiency of stream handling even with flash crowds. It is clearly evident that "MCF-P combined with ART" achieves the lowest cost per request for all videos.

7.8. Effectiveness of Combining ART with PCS. Let us now look at the results of combining PCS-V with ART. We show the results under ERMT and Patching in Figures 31 and 32, respectively. Transition Patching has the same trend as Patching and therefore its results are not shown. These results indicate that "MCF-P combined with ART" performs the best among all variations, and that PCS-V performs better than "PCS-V with ART." From these figures, we conclude that negative interference occurs when ART is combined with PCS-V. Removing this interference by modifying these two strategies is a challenging task and left for a future study.

8. Conclusions

We have analyzed in detail cost-based scheduling for on-demand video streaming and proposed new strategies:



(a) Defection rate (b) Average waiting time (c) Unfairness

Figure 32: Effectiveness of Combining PCS-V and ART (*Patching*).

Predictive Cost-Based Scheduling (PCS) and *Adaptive Regular Stream Triggering* (ART). The main results can be summarized as follows.

(i) There is no clear advantage of computing the cost over a future time window, compared with computing the cost only at the next scheduling time.

(ii) The proposed PCS scheduling policy outperforms the best existing policy (MCF-P) in terms of customer defection probability and average waiting time. The waiting times can also be predicted more accurately with PCS. The two variations of PCS (PCS-V and PCS-L) perform nearly the same and thus the simpler variant (PCS-V) is preferred because of its lower implementation complexity.

(iii) By enhancing stream merging behavior, the proposed ART technique substantially improves both the customer defection probability and the average waiting time.

(iv) Although ART in principle can be applied with any scheduling policy, including PCS, negative interference exists between ART and PCS, and thus their combination generally achieves worse than any of them applied individually. Removing this interference by modifying these two strategies is a challenging task and left for a future study.

(v) The best overall performer is "MCF-P combined with ART", followed by PCS. With ART, significantly more clients can receive expected waiting times for service than PCS, but at a somewhat lower waiting time accuracy.

Acknowledgments

This paper is a revised and extended version of our paper "Performance and waiting-time predictability analysis of design options in cost-based scheduling for scalable media streaming," which was presented at the International MultiMedia Modeling Conference (MMM 2009), Antipolis, France, January 2009. It also combines the MMM 2009 paper with a short paper "Predictive cost-based scheduling for scalable video streaming," presented at the IEEE International Conference on Multimedia & Expo (ICME 2008), Hannover, Germany, June 2008. This work was supported in part by NSF Grants CNS-0626861 and CNS-0834537.

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