Optimal Scheduling of Secondary Content for Aggregation in Video-on-Demand Systems*

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Abstract– Dynamic service aggregation techniques can exploit skewed access popularity patterns to reduce the costs of building interactive VoD systems. These schemes seek to cluster and merge users into single streams by bridging the temporal skew between them, thus improving server and network utilization. Rate adaptation and secondary content insertion are two such schemes.

In this paper, we present and evaluate an optimal scheduling algorithm for inserting secondary content in this scenario. The algorithm runs in polynomial time, and is optimal with respect to the total bandwidth usage over the merging interval. We present constraints on content insertion which make the overall QoS of the delivered stream acceptable, and show how our algorithm can satisfy these constraints. We report simulation results which quantify the excellent gains due to content insertion. We discuss dynamic scenarios with user

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arrivals and interactions, and show that content insertion reduces the channel bandwidth requirement to almost half. We also discuss differentiated service techniques, such as N-VoD and premium no-advertisement service, and show how our algorithm can support these as well.

Keywords: Video-on-demand, service aggregation, secondary content insertion, scheduling

1 Introduction

Non-uniform popularities of movies can result in skewed user access patterns in VoD systems[6] . Several techniques exploit this principle to aggregate individual users and serve them in groups. These resource sharing schemes map multiple "logical" channels onto a smaller number of "physical" channels to perform *service aggregation*. They include batching[6], server caching[12], client caching or bridging[2], chaining[11] (a limited form of distributed caching), rate adaptive merging[7], content insertion[10, 13] and content excision[13].

Stream clustering minimizes end-to-end bandwidth requirements by bridging the temporal skew between streams carrying the same content. This can be done by adaptive piggybacking[7] (we call it rate adaptive merging) and by content insertion[10]. One can view stream clustering as a synchronization problem where the leading and trailing streams are out of "sync" and we can bridge the skew by changing the relative content progression rates, e.g. by slowing the leading stream via insertion of secondary content. Rate adaptive merging of two streams can be achieved by accelerating the trailing stream towards the leading stream by about 7%[1] until both are at the same position in the program[9]. At this time, all users on both streams can be served off the same stream using multicast.

Secondary content insertion is similar to rate adaptation, although at a much coarser granularity. Here, the temporal skew between two streams is bridged by inserting short segments of secondary content into the leading stream, to allow the trailer to catch up. In [10], content insertion is presented in server overload situations and is unconstrained. We propose to use this technique to actively aggregate streams during normal operation of a VoD system. Clearly, indiscriminate insertion of content may cause unacceptable degradation of the viewing experience for some users. We address this problem by introducing a number of QoS constraints which bound the amount of secondary content inserted into streams, and also *shape* the inserted content to make the entire package acceptable. We also discuss techniques to support multiple levels of ad insertion, including the use of N-VoD, and premium subscription with no content insertion.

Secondary content can take the form of advertisements, short news flashes, weather information, stock updates, sports scores, or other items of interest. Advertisements also serve to directly defray the cost of content production and service. We believe that such a scheme would help the VoD service provider in earning extra revenue, and at the same time subsidize the cost of programming to subscribers who are willing to receive QoS-constrained

[1] an acceptable limit according to an empirical study

secondary content. Some subscribers may wish to receive premium service with no advertisements, or receive all the ads at the beginning of the movie (near VoD). Our algorithm supports these cases too, optimally. Furthermore, these techniques are not restricted to the commercial VoD scenario, but can be extended to video-over-IP streaming frameworks as well.

The aggregation process involves two steps:clustering and merging. A clustering algorithm is used to generate *clusters* of streams to be merged [3]. A cluster consists of a number of streams, each serving the same content, but skewed temporally with respect to each other. The channels in a cluster are then merged by selectively inserting secondary content.

In this paper, we deal with stream merging. We discuss *optimal* techniques for scheduling of secondary content under different constraints with the primary goal of minimizing total bandwidth used during merging. We refer to this as the "static snapshot" case because a snapshot of the stream positions is taken at the beginning of the merging period and no user interactions are allowed to take place during this period. We begin with a constrained situation where the inter-stream spacings are multiples of intervals equivalent to a group of ads and present a dynamic programming (DP) algorithm of time complexity $\mathcal{O}(n^3)$ to solve the problem. We then relax the constraint and consider a situation where the inter-stream spacing need not be a multiple of the ad-group interval. Here, unlike the previous case, secondary content need not be inserted in groups of fixed intervals. We adapt our earlier DP algorithm to include this case. We also outline certain heuristics for the harder "dynamic" version of the problem where user arrivals and interactions[2] are allowed to occur during the merging process. Throughout this paper, the terms "advertisement", "ad(s)" and "secondary content" have been used interchangeably, and they refer to the same thing.

With the increasing popularity of streaming media over the Internet, user demand may frequently outstrip the resources available at popular streaming servers. Using secondary content insertion, the server can continue supporting the existing users while merging them dynamically, meanwhile trying to accommodate new users, who would otherwise have been blocked.

The main contribution of this paper is an optimal solution for the QoS-constrained content insertion problem. The use of content insertion for bridging large skews and rate

[2]Fast-Forward, Rewind, Pause, Quit

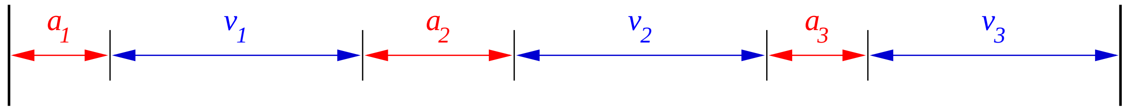


Figure 1: Ad schedule for a single user

adaptation for fine-tuning has been described in [10]. Content insertion and excision have been discussed in conjugation with dynamic buffer management for near-VoD systems by Tsai and Lee [13]. Optimal techniques for performing rate-adaptive merging or adaptive piggybacking have been discussed in [3, 1]. An implementation of dynamic service aggregation using rate-adaptive merging has been described in [4].

Section 2 describes the problem and the constraints in detail; Section 3 discusses a restricted case of the problem and proposes a solution for this case; Section 4 extends this solution to the generalized case; Section 5 touches upon some practical issues which may be encountered during implementation. Section 6 discusses some simulation results for the snapshot case. Section 7 concludes the paper.

2 Problem Formulation

We define an *ad schedule* as a sequence of tuples, of the form $(a_j,\ v_j)$. This represents delivery of advertisements for time a_j, followed by delivery of video content for time v_j. Figure 1 depicts a possible ad schedule for a single user. When generalized to a set of U users, the ad schedule becomes a matrix of tuples $(a_{ij},\ v_{ij})$, where each tuple represents the j^{th} pair of ad and video time given to user i. Typically, the interval a_{ij} will consist of a burst of multiple ads.

If the system could insert ads in an unconstrained manner, the optimal way to merge two users temporally separated by T seconds, is to keep the leader on ads for T seconds, and allow the trailer to catch up in this time period. For large values of T, this unacceptably degrades the viewing experience for the leader. Therefore, aggressive use of advertisement scheduling can succeed only when it is controlled by a set of QoS constraints which ensure that the viewing experience is not intolerably degraded due to advertising: no burst of ads should be excessively long; neither should ad bursts be delivered too close to each other; no user should receive more than a certain amount of ad time over some viewing interval; partial ads cannot be displayed. These constraints can be formally stated as follows:

$$a_{ij} = nA_{min} \qquad n \in \mathcal{Z}^+ \quad \forall_{i,j} \tag{1}$$

$$a_{ij} \leq A_{max} \qquad \forall_{i,j} \tag{2}$$

$$v_{ij} \geq V_{min} \qquad \forall_{i,j} \tag{3}$$

$$\sum_T a_{ij} \leq \alpha \sum_T (a_{ij} + v_{ij}) \quad \forall_{i,j} \tag{4}$$

In this paper, we assume that all advertisements are of the same length, A_{min} which represents the granularity of every a_{ij}. However, this approach can easily be extended to serve ads of different lengths, as long as all the ad-lengths are integer multiples of some base value A_{min}. A_{max} is the maximum length of a single ad burst. Clearly, A_{max} should also be an integer multiple of A_{min}. V_{min} is the minimum video time that has to occur between two ad-bursts. There are two limits on the fraction of viewing time that can be used to display ads. One is the *long-term ad-dosage limit* (α, T), which represents the fraction of viewing time available for ads α, over some time interval T. This is a pinwheel scheduling constraint [8], applicable over any time interval T. The other is the *short-term ad-dosage limit* which represents the maximum rate at which ads can be inserted in video. It is given by

$$\beta = \frac{A_{max}}{A_{max} + V_{min}} \tag{5}$$

It is easy to see that in general, $\alpha \leq \beta$. The problem which we are trying to address in this paper is the following:

> *"For a group of N streams carrying the same content but at different points in time (i.e. if a snapshot of the stream positions is taken at a particular time instant), what is the ad-video schedule that minimizes the total bandwidth while merging them into one stream, at the same time obeying the above QoS constraints?"*

If at the start of the merging cycle, stream i was at position p_i and stream j was at position p_j, then for these two streams to merge, the following should hold:

$$p_i - p_j = nA_{min} \quad n \in \mathcal{Z}^+ \tag{6}$$

This implies that ad scheduling can only be used to bridge skews which are integral multiples of the minimum ad length. In practice, such temporal skews are uncommon, therefore ad insertion must be coupled with another, more fine-grained aggregation technique like rate adaptive merging [7].

3 A Restricted Case

We first consider a restricted scenario, where ad scheduling is constrained by a number of simplifying assumptions. In further sections, we will remove these and discuss a generalized solution to the problem. The simplified problem has the following additional constraints:

$$\alpha = \beta \tag{7}$$

$$a_{ij} = 0 \,|\, A_{max} \qquad \forall_{i,j} \tag{8}$$

$$v_{ij} = V_{min} \qquad \forall_{i,j} \tag{9}$$

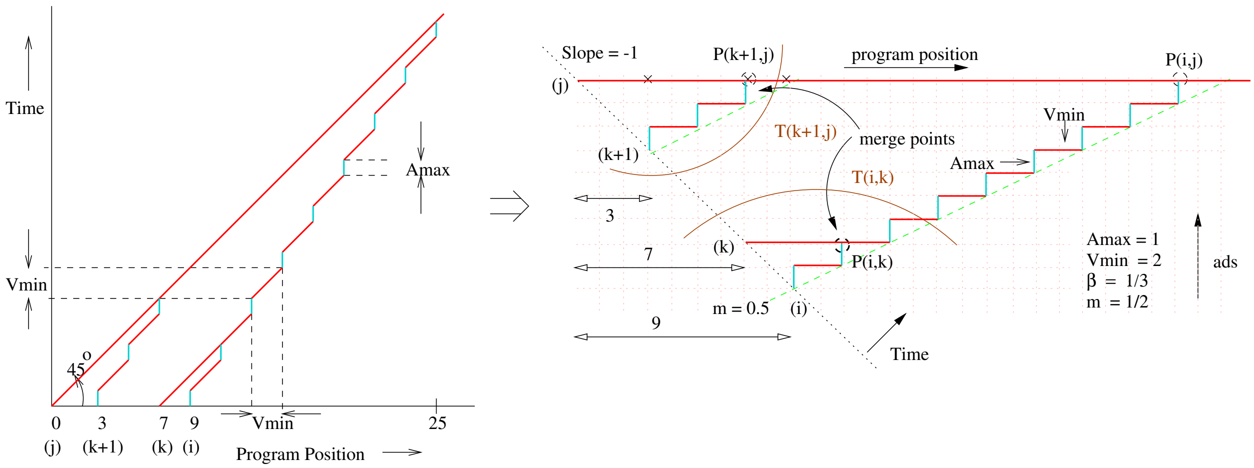
Briefly, we simplify the problem by making the two constraints on ad dosage equal. Also, we constrain the ad dosage to zero, or a fixed value which is the maximum we can give. Inter-ad video dosage is also fixed at the minimum possible limit. It is clear that any solution satisfying these constraints will also satisfy the general constraints presented earlier. As described previously we observe an additional constraint on program positions at the start of the merging cycle:

$$p_i - p_j = nA_{max} \qquad n \in \mathcal{Z}^+ \qquad \forall_{i,j} \tag{10}$$

Hence, the restricted problem can only merge programs whose initial difference is an integral multiple of our ad dosage unit (A_{max} in this case).

3.1 Preliminaries

We first introduce a graphical notation to denote the merge-able streams with different content progression rates on a time scale. On the left in Figure 2 is an intuitive representation of the streams on Cartesian axes; diagonal motion along a line with slope 1 refers to a stream with normal speed and vertical motion refers to a stream in content-insertion state. For simplicity, we use a rectilinear representation of this graph, as shown on the right in Figure 2. The figure has two time axes: horizontal for video time, and vertical for ad time. Units on both these axes are taken to be equal. Note that for two streams with an initial skew Δ to merge, the leading stream must be given ads for Δ time more than the trailing stream. The leading stream is farthest to the right. Other streams are placed along the



(a) Intuitive Representation (b) Rectilinear Representation

Figure 2: Restricted ad schedule grid for multiple users

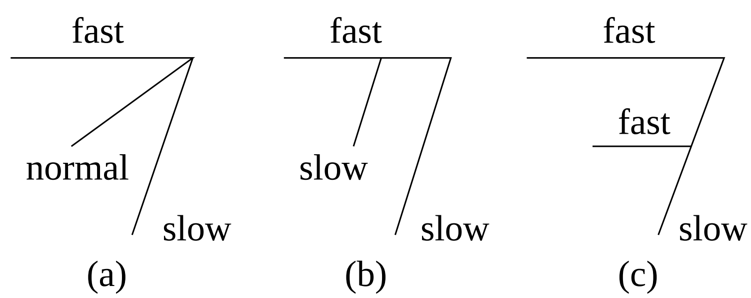


Figure 3: Merging of three streams

horizontal time axis as their skews signify. Then, we can plot a line with slope -1 through the initial point, and project the initial temporal skews from the horizontal (video) time-line onto the diagonal to obtain the initial points on the graph. In this rectilinear grid graph, a horizontal step represents video delivery for time V_{min} on that stream, and a vertical step represents ad delivery for time A_{max}. At any given point in time, a diagonal line with slope -1 gives the locus of all stream positions. We can visualize this diagonal line sweeping towards North-East across the grid as time progresses.

A *merge point* is defined as a point where two or more streams merge into one. A *segment* is a section of a stream between two merge points, or between the start point and the first merge point.

Lemma 3.1 *To achieve optimality, a segment can only be in one of the two states: decelerated and steady. A segment in decelerated state receives the maximum ad-dosage available. A segment in steady state receives no ads.*

Lemma 3.2 *At each merge point, exactly two segments merge into a single segment.*

This can be deduced by noting that a segment lies between merge points, and therefore does not contain any merge points within itself. Therefore, the aim of giving advertisements to a stream can only be to slow it down so that a trailing stream may catch up. Since this state of affairs will not change through the length of the segment, clearly the optimal scheduling policy will decelerate the segment at the maximum possible rate. This is illustrated in Figure 3. It is clear that both case (b) and case (c) have less cost than case (a).

Lemma 3.3 *If advertisements are to be inserted in a segment, it is less costly to give advertisements as early as possible, and video content later.*

If the decelerated stream is not going to merge with any stream within the current ad-video pair, then it does not matter. However, if the decelerated stream is merging with a trailing stream within this ad-video pair, optimal use of bandwidth is achieved by having ads as early as possible. In Figure 4(a), the decelerated stream merges earlier with the trailing stream than in 4(b), because ads are given earlier. This lemma is central to many of the proofs in this paper.

Lemma 3.4 *For a decelerated segment, the optimal ad scheduling technique is to give the maximum possible ad dosage in the beginning, followed by the video complement for this ad dosage. This pattern is repeated periodically throughout the segment.*

This follows from Lemma 3.3 and the pinwheel scheduling constraint in Equation 4. So as not to violate the pinwheel scheduling requirement, we must give a periodic ad-video-pairing, with each period satisfying the scheduling requirement. A notable exception to this lemma occurs when giving ads early violates some other constraint. For example, immediately before a merge point, the decelerated stream receives an ad burst. Therefore, immediately after the merge point, the merged segment must receive a video burst; otherwise, the viewers of the prior decelerated stream receive too many ads.

Lemma 3.5 *The point where all streams finally merge occurs at a time V_{min} before the intersection of a horizontal line drawn from the trailing stream, and a diagonal line of slope $m = \frac{\beta}{1-\beta}$ drawn from the leading stream. All streams are constrained within the envelope formed by these two lines.*

(a) Giving ads early

(b) Giving ads late

Figure 4: Ad dosage earlier vs. later

Streams are constrained within this envelope because these two lines depict the maximum and minimum ad dosage, therefore all streams must receive ad dosage between these. By Lemma 3.4, we observe maximum gains by giving ads as early as possible, and in the case of the final merge point we see that giving ads early leads to the final merge occurring at a time V_{min} before the envelopes intersect. Final merge cannot occur before this. In Figure 2, the ad constraint envelope is shown by a diagonal line of slope m. For convenience, m is shown here to be 1; in practice, m would be considerably less (around $\frac{1}{6}$, which translates to 10 minutes of ads per hour of viewing time).

Theorem 3.1 *The graph with segments formed from a merging schedule for a given scenario is a binary tree where the average slope of each segment is either 0 (no ads) , or* $m = \frac{\beta}{1-\beta} = \frac{A_{max}}{V_{min}}$ *(ad-video bunches). Also, finding the optimal merge pattern is isomorphic to the optimal binary tree finding problem.*

This follows from Lemmas 3.1 and 3.2. See [1, 3] for similar results on rate-adaptive merging.

3.2 Solution to the Restricted Case

The number of possible binary trees with n leaf nodes is $\frac{1}{n}\binom{2n-2}{n-1}$[3], which grows exponentially, so exhaustive search of all possible binary trees is impractical for any significant value of n. However, a dynamic programming approach helps to solve this problem in a reasonable amount of time. We outline the solution below.

We number the streams from 1 to n, with 1 being the leading stream and n being the trailing stream. Let L be the length of the movie (last program position). Consider two streams, i and j, with $i < j$ and $p_i > p_j$. Let $P(i, j)$ denote the optimal program position

[3] $(n-1)^{st}$ Catalan number

where streams i and j would merge, if these were the only two streams under consideration. This is well-defined from Lemma 3.5 as a point which is V_{min} time before the intersection of a horizontal line through j and a line of slope $m = \frac{\beta}{1-\beta}$ through i. If we now consider the streams $i, \ldots, j$, then an optimal merge policy cannot merge these streams earlier than $P(i, j)$. Also, it is easy to see that the existence of other streams in the range $i, \ldots, j$ cannot prevent i and j from merging at $P(i, j)$. Therefore, $P(i, j)$ is the optimal final merge point for streams $i, \ldots, j$ and is given by:

$$
\begin{aligned}
P(i,j) &= p_i, & i = j \quad (11)\\
&= p_j + \frac{p_i - p_j}{\beta} - V_{min}, & i \neq j \quad (12)
\end{aligned}
$$

Let $T(i, j)$ denote an optimal binary tree for merging streams $i, \ldots, j$. Let $C(i, j)$ denotes the cost of this tree. Since this is a binary tree, there exists a point k such that the right subtree contains the nodes $i, \ldots, k$ and the left subtree contains the nodes $k+1, \ldots, j$. From the principle of optimality, if $T(i, j)$ is optimal (has minimum cost) then both the left and right subtrees must be optimal. That is, the right and left subtrees of $T(i, j)$ must be $T(i, k)$ and $T(k + 1, j)$. The cost of this tree is given by

$$
\begin{aligned}
C(i,j) &= L - p_i, \quad i = j & (13)\\
&= C(i,k) + C(k+1,j) - \max(L - P(i,j), 0) + (p_k - p_j), \quad i \neq j & (14)
\end{aligned}
$$

and the optimal policy merges $T(i, k^*)$ and $T(k^* + 1, j)$ into $T(i, j)$, where k^* is given by

$$
k^* = \text{argmin}_{i \leq k < j}\{C(i,k) + C(k+1,j) - \max(L - P(i,j), 0) + (p_k - p_j)\} \quad (15)
$$

Here $C(i, k)$ and $C(k+1, j)$ are the costs of the right and the left subtrees respectively, calculated all the way till the end of the movie. The third term is subtracted to eliminate the cost duplication after the streams i and j merge. The fourth term is added to figure in the ad time after $P(i, k)$ into the cost formulation. This is because, even if a certain stream has been put on ads momentarily, the resources allocated to it in the server and the network (in case of bandwidth reservation) cannot be freed until it actually merges with some other stream. Since the number of ad channels is assumed to be fixed (ideally, one multicast ad channel suffices), the bandwidth costs due to those channels do not feature in Equation 14.

We begin by calculating $T(i,i)$ and $C(i,i)$ for all i. Then, we calculate $T(i,i+1)$ and $C(i,i+1)$, then $T(i,i+2)$ and $C(i,i+2)$ and so on, until we find $T(1,n)$ and $C(1,n)$. This gives us our optimal cost. The algorithm can be summarized as follows:

```
Algorithm DP_Find_Tree
{
  for (i=1 to n)
    initialize P(i,i), C(i,i) and T(i,i) from equations 11 and 13

  for (p=1 to n − 1)
    for (q=1 to n − p)
      Compute P(q,q+p), C(q,q+p) and T(q,q+p) from equations 12, 14 and 15
}
```

There are $\mathcal{O}(n)$ iterations of the outer loop and $\mathcal{O}(n)$ iterations of the inner loop. Additionally, determination of $C(i,j)$ requires $\mathcal{O}(n)$ comparisons in the *argmin* step. Hence, the algorithm DP_Find_Tree has a complexity of $\mathcal{O}(n^3)$. A point to be noted here is that in real systems, n is not likely to be very high, thus making the complexity acceptable. We show later in the simulation section that not much optimality is lost by reducing the size of a snapshot.

4 The General Case

In this section, we attempt to solve the scheduling problem for more general cases by relaxing the constraints imposed in the previous section.

4.1 First-Stage Constraint Relaxation

We begin by relaxing the constraints outlined in Equation 8. Therefore, a_{ij} is now variable, subject to equations 1 and 2. The graphical representation of this case is shown in Figure 5.

From lemma 3.3, the optimal scheduling policy schedules as much ad time as early as possible, and then fills in the video as necessary. We can easily see that the problem

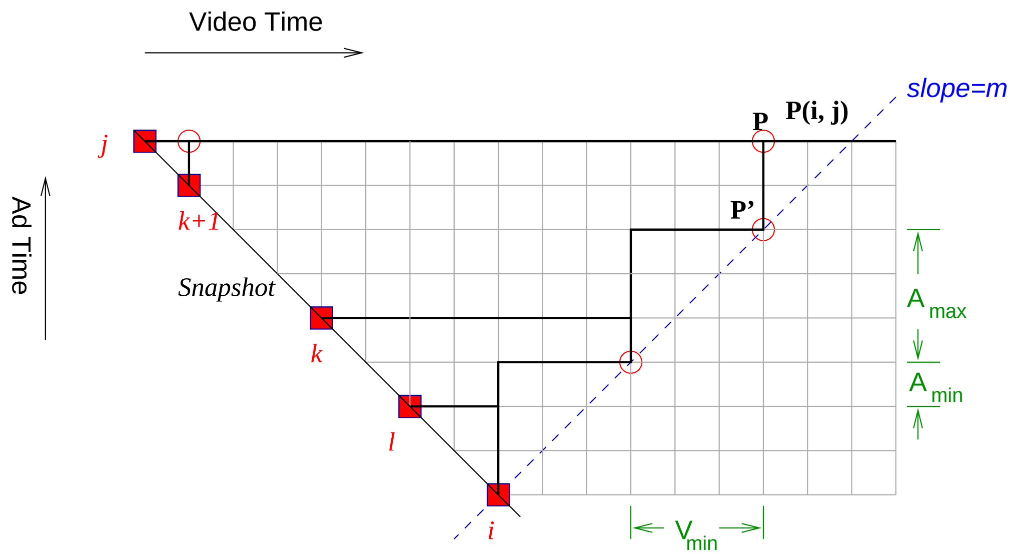


Figure 5: First-stage constraint relaxation

once again reduces to an optimal binary tree problem. In this case, calculation of $P(i,j)$ is different from the previous one since a merge point can occur during an ad-burst. It is given by:

$$P(i,j) = p_i + (\lceil \frac{p_i - p_j}{A_{max}} \rceil - 1) \times V_{min}, \tag{16}$$

where $\lceil \frac{p_i - p_j}{A_{max}} \rceil - 1$ is the number of times ads are given till point P' on the tree. Multiplying this quantity by V_{min} yields the amount of video given till point P, since no video is given between P' and P. To represent the tree $T(i,j)$ completely, we also need to store at each merge point the additional amount of ads that can be given to that stream without violating any constraints. We represent this by SA_{go} and it is given by,

$$SA_{go}(i,j) = A_{max} - (p_i - p_j) \bmod A_{max} \tag{17}$$

Since we can accurately determine $P(i,j)$ for any i, j using Equation 16, we can use algorithm `DP_Find_Tree` to find an optimal tree for this generalized case, substituting equation 16 in place of equation 12. Further, since the complexity of determining $P(i,j)$ is $\mathcal{O}(1)$, the complexity of this algorithm remains $\mathcal{O}(n^3)$.

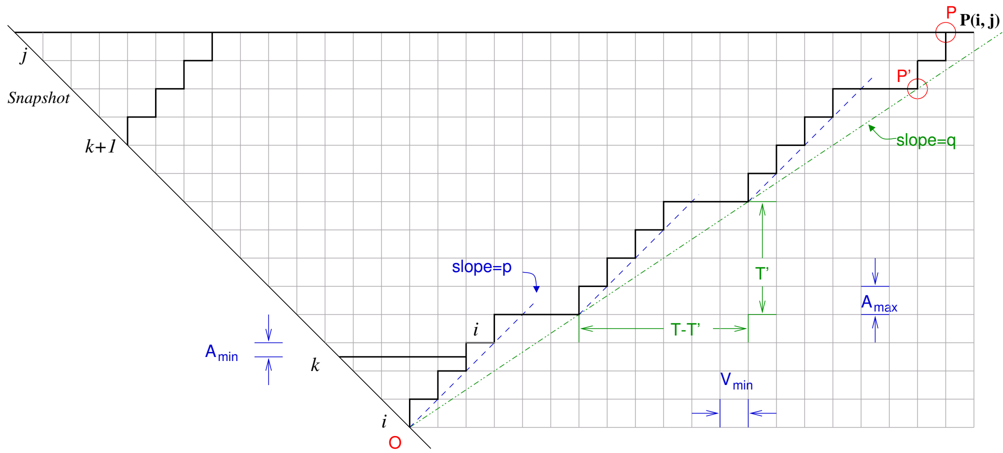


Figure 6: Second-stage constraint relaxation

4.2 Further Relaxation of Constraints

We complete the generalization by relaxing the final artificial constraint, given in equation 7. Now we have to handle two ad constraints, the *short-term* constraint and the *long-term* constraint. The short-term ad constraint, defined in Equation 5, is represented on the grid graph by a line of slope p, where $p = \frac{\beta}{1-\beta}$. The long-term ad constraint (α, T) is represented on the graph by a line of slope q, where $q = \frac{\alpha}{1-\alpha}$.

These constraints are depicted in figure 6 where we attempt to calculate $P(i,j)$ by considering the subtrees $T(i,k)$ and $T(k+1,j)$. Through i, we draw two diagonal lines of slopes p and q. Initially, the decelerated segment follows line p as specified in section 4.1. However, now the long-term constraint is also in force. Therefore, the scheduler must ensure that after time T, segment OP has an average slope q. This can be enforced by the following technique. We know that $T' = \alpha T$ is the maximum ad-dosage possible within time interval T. Therefore, the scheduler keeps track of how much ad-dosage has been given within this long-term interval T. If the ad-dosage given is T', then the scheduler will not give any more ads for the remaining time in interval T. Once time interval T has elapsed, the scheduler once again begins inserting ads at an average rate p.

Again in this case, $P(i,j)$ has to be calculated in a slightly different manner:

$$P(i,j) = p_i + (\lceil \frac{(p_i - p_j)}{T'} \rceil - 1) \times (T - T') + (\lceil \frac{MOD(p_i - p_j, T')}{A_{max}} \rceil - 1) \times V_{min} \quad (18)$$

$$MOD(x,k) = 1 + (x-1) \bmod k \quad (19)$$

The second additive term corresponds to the video given in the segment OP' and the third term amounts to the video given in the segment $P'P$. Each merge point stores SA_{go}, representing the ad-time remaining in the current burst, and LA_{go}, representing the ad-time remaining in this current long-term section. The equations for these quantities can be found out using logic similar to that used in Equations 17 and 18, and have been omitted due to paucity of space. Note that if $p_i - p_j < T'$, then this merge can be scheduled by the rules in section 4.1.

Since we can obtain $P(i,j)$ accurately, once again the algorithm `DP_Find_Tree` can be used to generate the optimal merging schedule. Furthermore, since evaluation of $P(i,j)$ is an $\mathcal{O}(1)$ operation, the complexity of the algorithm remains $\mathcal{O}(n^3)$. This analysis is valid only for *static* snapshots; changing scenarios due to user interactions are discussed in the next section. In the above analysis, we also assume that the counters SA_{go} and LA_{go} have been reset to A_{max} and T' respectively at the beginning of the snapshot. One way to ensure this is to run all the streams at a steady state for some time t, such that the ad-counters are reset. Essentially t will be the maximum of the long-run "to-go" video time over all streams. Clearly $t \leq T'$. But running all the streams at steady state for time t can be a source of suboptimality in dynamic situations, hence we require schemes that do not need the ad-counters to be reset. We discuss one such scheme in the following subsection.

4.3 Optimal Scheduling with Incomplete Initial Ad-Budget

In this case, a starting stream i is characterized by a program position p_i and a triplet $(SA_{go}, LA_{go}, V_{go})$. SA_{go} is the remaining short-term ad budget as described previously, LA_{go} is the long-term ad budget which can be calculated similarly, and V_{go} is the remaining amount of video that has to be given to this stream in the current long-term period. Whenever a stream enters the system or goes through a long-term period of time T, this triplet is set to $(A_{max}, T', T - T')$. In order to calculate the new optimal paths for streams with triplet constraints from a current snapshot, we need to modify the equations 16 and 18. The situation has been represented in Figure 7 at the second snapshot. Stream i has a triplet constraint associated with it. Lemma 3.4 instructs the scheduler to give all the remaining ads (SA_{go}) right-away, followed by periodic ad-video bursts. So essentially the leading stream keeps on running the way it was.

Now, we will derive the modified expressions for $P(i,j)$ for all pairs of streams (i,j) in this scenario. Let p_i, p_j be the positions of the leading and trailing streams respectively,

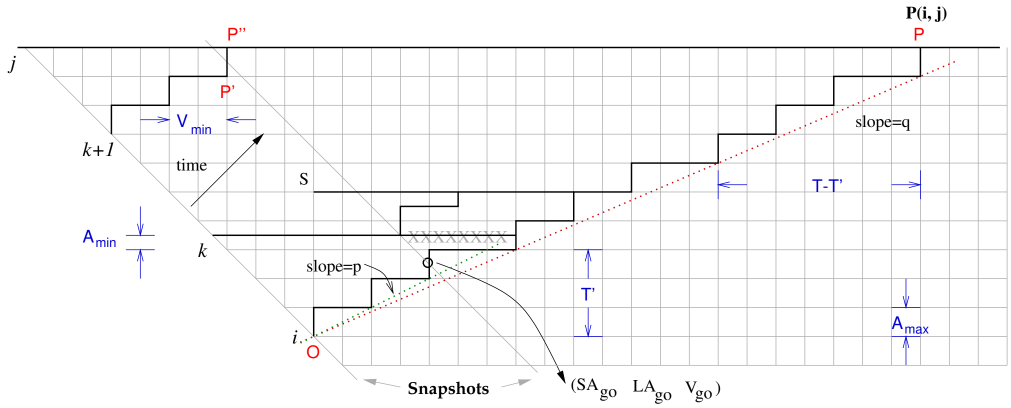


Figure 7: Handling incomplete initial ad-budget

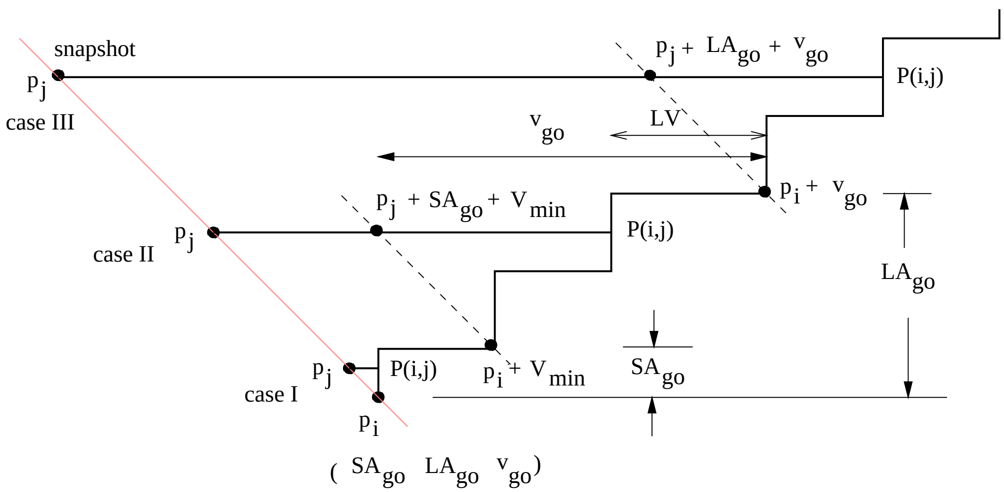


Figure 8: Method for calculation of P(i,j)

at the beginning of the second snapshot. We treat this as three different cases which are demonstrated in Figure 8 and are elaborated below:

Case I $p_i - p_j \leq A_{max}$: Here it is easy to see that $P(i, j) = p_i$

Case II $A_{max} < p_i - p_j \leq T'$: In this case, imagine advancing stream i to point `A` where the program position is $p_i + V'_{go}$, where $V'_{go} = MOD(V_{go} - LV, V_{min})$, and $MOD(\cdot)$ is given by Equation 19. Simultaneously stream j advances to program position $p_j + SA_{go} + V'_{go}$. At this point the situation is same as that in Section 4.1, so we can plug in the new stream positions into Equation 16 to get:

$$P(i, j) = p_i + V'_{go} + (\lceil \frac{p_i - p_j - SA_{go}}{A_{max}} \rceil - 1) \times V_{min}, \qquad (20)$$

Case III $p_i - p_j > T'$: Similar to the previous case, imagine advancing stream i to point `B`. At that instant, the program positions of streams i and j will be $p_i + V_{go}$ and $p_j + LA_{go} + V_{go}$, respectively. The situation then is same as the one discussed in Section 4.2. Hence putting the new stream positions into Equation 18, we get:

$$P(i,j) = p_i + V_{go} + (\lceil \frac{(p_i - p_j - LA_{go})}{T'} \rceil - 1) \times (T - T') + (\lceil \frac{MOD(p_i - p_j - LA_{go}, T')}{A_{max}} \rceil - 1) \times V_{min} \quad (21)$$

5 Practical Issues

In this section, we move from the algorithmic aspects of our solution towards the practical aspects. We briefly discuss some of the issues with supporting interactions into our model and also some techniques for implementing the system.

The algorithms discussed in the previous sections generate optimal schedules only in the static snapshot case. But while designing real VoD systems, one needs to find techniques for handling user interactions without sacrificing optimality. A standard way of achieving this goal is to recompute the optimal schedule by `DP_Find_Tree` periodically. This period can be based on time or the rate of arrivals/interactions. However, if the rate of interactions is high, then the re-computations have to be done very frequently. The other technique that sacrifices some optimality is a *segment fitting* technique, which maintains the original merging schedule and tries to optimally "connect" the (interactive) streams that have cropped up in the interior of the merging tree, to the original tree, if possible. Of course, this technique may lead to highly suboptimal solutions under specific situations and has no good upper bounds on the cost increase. We conduct simulations to observe the effectiveness of this segment fitting heuristic.

In a real implementation of this system, a multicast delivery network is assumed. When the server detects a merge event, it informs all users on the trailing stream to leave their previous multicast groups and join the leader's. The resources pertaining to the trailing streams are subsequently reclaimed by the server. Whenever the server decides to give ads to a certain group of users, they are all asked to join the broadcast channel on which ads are being shown. If all the ads on that channel are of length A_{min} and V_{min} is an integral multiple of A_{min}, then a user will always find a new ad starting when he/she is switched onto the ad channel. Another solution is to push a group of ads to the user as a separate stream in the beginning, allowing the user's client to do the ad insertion under server control. Since ads are often re-broadcast during the same program in current broadcast television, this technique can save network bandwidth by rotating ads in the client.

Personalization and value-added secondary content such as news are important factors in increasing the acceptability of this solution. For example, we may have four multicast ad channels, one multicast news channel, one multicast sports channel, and so on. These channels may show the same content in one-minute bursts, for half an hour. By appropriately switching the leader to different multicast channels, we can improve his overall viewing experience. Further, the ad channels may be personalized to groups of target customers. Preloading ads to the client as discussed above could also be leveraged for personalization.

Another important factor for the success of ad insertion is an appropriate pricing policy. Inserting ads in this manner has the dual benefit of reducing server requirements by aggregating users, and providing a revenue stream to content and service providers. Any pricing structure has to provide enough subsidies to the user to make an ad-inserted package attractive to him/her. On the other hand, users interacting heavily during ads and video should be made to pay the price. Also, uniform ad insertion into a video stream is not always feasible due to the occurrence of "gripping" situations. We propose off-line insertion of certain metadata into the stream which will instruct the server not to attempt any aggregation at that point in time.

6 Simulation Results

In this section, we describe the simulation experiments that we designed for evaluating the gains due to secondary content insertion. We report the results for the snapshot case in the next subsection. The simulation procedure and results for the dynamic case are presented in Section 6.2.

6.1 Snapshot Case Results

In this section we present the simulation results for the most general case of the content insertion algorithm presented in Section 4. We assume a static snapshot of the program positions of all users and try to merge them using our algorithm. Table 1 enlists the various parameters used in the simulations.

For simulating a static snapshot, we generate exponentially distributed program positions separated by mean time interval $\frac{1}{\lambda}$. Then we try to merge the streams using two

Table 1: Snapshot Case: Simulation Parameters

Parameter	Meaning	Value
L	Length of a movie	120 min
A_{min}	Length of one ad	30 sec
A_{max}	Maximum length of an ad-burst	2 min
V_{min}	Minimum video time between ad-bursts	8 min
T	Long term time window	60 min
α	Fraction of ad-time in the long run	$\frac{1}{6}$
N	Number of streams in the snapshot	$50 - 100$
λ_{arr}	Mean inter-arrival rate	$\frac{1}{60} - \frac{1}{15}\,\mathrm{sec}^{-1}$

different variants of our DP algorithm. The first one is the optimal algorithm which tries to merge all the N streams into one cluster. The second algorithm attempts to form multiple sub-clusters till the end of the movie.

The performance measure we are interested in is the *aggregation ratio*, θ which is simply the ratio of the average bandwidth used by a stream with aggregation and that used by a stream without ad insertion, over a merging period which extends till the end of the movie in this case. It quantifies the average "bandwidth compression" obtained over a merging period by using our content insertion algorithm. Note that our algorithm assumes that the initial inter-spacings between successive streams in the snapshot must be an integer multiple of A_{min}. Therefore the streams are batched and grouped till the next A_{min} boundary for this static case simulation. The gain reported however, does not include that due to this initial batching.

Figure 9 shows the variation of θ with N and λ for each of the two different schemes. We observe that a better (lower) aggregation ratio is achieved as the arrival rate increases. This is not far from expected since the streams are closer together for higher values of λ and they merge sooner than for lower values.

We also observe that for a fixed value of λ, θ remains almost constant for different values of N. That essentially means that aggregation gains are more or less independent of the number of streams in a snapshot if the arrival rate is constant. From these results, we can conclude that not much optimality is lost if we divide a snapshot containing 100 streams, for example into four snapshots with 50 streams each. On the other hand, a lot of computing time can be saved with the latter approach, since it will be about $\frac{100\times100\times100}{2\times50\times50\times50} = 4$ times faster.

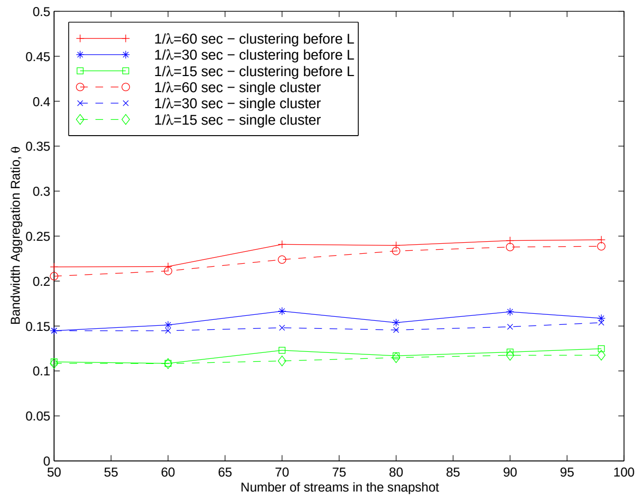


Figure 9: Snapshot Case

In most situations, all the streams cannot be merged into one stream before the movie ends. Then the algorithm can be modified by breaking a cluster into a group of smaller cluster, the streams in each of which will be merged into one stream[4]. This again helps in reducing computational overhead. The solid lines in Figure 9 represent this variant. We can easily see that there is very little difference between the optimal algorithm (dashed lines) and its sub-cluster variant.

6.2 Dynamic Case

Here, we describe the general scenario where the users come into the system, interact with the system and leave. We believe that a near-optimal solution to the dynamic problem will be based on a repeated application of the "optimal" static algorithm which we have presented in Section 4. However, the interesting part of the problem is: when to perform this re-computation? We treat this simulation as a discrete-time control problem. We propose some heuristic approaches which are worthy of experimental evaluation:

- **Period-based:** Periodically take a snapshot of the system and compute the merging schedule by `DP_Find_Tree`. The period is a fixed system parameter determined by experimentation.

- **Event-driven:** The problem with the above technique is that it does not respond to the rate of arrivals/interactions in the system. Therefore, take a snapshot of the

[4] It is easy to verify if $P(i,j) < L$

system whenever the number of new arrivals or interactions exceeds a given threshold. As a refinement the count can be on a per-movie basis, that is, recompute for that movie if the number of arrivals and interactions exceeds a threshold. Recomputing on every event may lead to sub-optimal results. Again, the threshold parameter has to be determined experimentally.

- **Adaptive:** Adapt the re-computation period based on interactivity and the state of the system. For example, for high degrees of interaction, the re-computation period should be small, and vice-versa.
- **Policy iteration:** Based on observed system behavior over a large period of time, compute the best policy for each set of circumstances. Choose the best policy for the current circumstance.
- **Customer Profiling:** Some customers may be highly interactive, whereas others may be relatively passive. If we can trace a customer's profile from the logs, we can decide whether to keep him/her on a separate stream (if he/she interacts often) or to include him/her in a current snapshot. Accurate profiling may result in near-optimal solutions.

The set up consists of two logical modules: a discrete event simulation driver and a content insertion (CI) unit. The simulation driver maintains the state of all streams and generates events for user arrivals, departures and VCR actions (fast-forward, rewind, pause and quit) with inter-event times obeying a given probability distribution. A re-computation period is an interval of time during which a content insertion algorithm attempts to release channels. Once in every re-computation period, the simulation driver conveys the position and status of each stream to the CI unit (which computes the merging schedule) and queries it after every simulation tick to get the status of the streams. It then advances each stream accordingly. For instance, if the clustering unit reports that a particular stream is to remain in the *content insertion* state for a particular amount of time, the simulation driver keeps the stream on secondary content for that time. If any customer interacts, then the simulation driver changes the state of the corresponding stream or allocates a new one if necessary.

This experimental set up will help us evaluate all the control heuristics under different dynamic situations, and will help us verify how much of the gain due to ad insertion in the static case holds for the dynamic case.

In this work, we investigate the period based re-computation strategy, which is the simplest and the easiest to implement. The main performance measure that we are interested

Table 2: Dynamic Case: Additional Simulation Parameters

Parameter	Meaning	Value
M	Number of movies	100
R	Re-computation interval	1200 sec
B	Initial batching interval	$A_{min} = 30\ sec$
λ_{arr}	Mean inter-arrival rate	0.0833 sec^{-1}
λ_{int}	Mean interaction rate	0.07 sec^{-1}
λ_{dur}	Mean interaction duration	5 sec
f	Rate of Rewind/FF	5x

in, in the dynamic scenario is the ratio of the number of running streams to the number of users in the system, which directly quantifies the gains due to secondary content insertion. We outline the dynamic simulation scheme in Figure 10.

R is the re-computation window after which a new snapshot is taken. Initially all streams are run for time R at normal speed and only then the ad-insertion starts. At the beginning of every snapshot, algorithm DP_Find_Tree computes the *optimal* paths for each stream and stores them in local data structures. Until the next snapshot happens, all currently running (non-interacting) streams follow the paths as prescribed by the algorithm. Newly arrived streams, however are allowed to run at normal speed until the next snapshot. One important assumption that we make in the interaction model is that interactions are not allowed during ad-bursts. All interactions that occur during an ad-burst are serviced at the end of the burst. When a user interacts, he/she is allocated a new stream at least for the duration of interaction. But after resuming the user can be merged with any other stream since the ad-budget of that stream is reset after the interaction event. This is to discourage users from interacting for the sole purpose of skipping the ads. However, if a user has premium service, he/she should not be affected by this.

The additional simulation parameters for the dynamic case can be found in Table 2. We simulate the case where the most popular movie has arrivals once every minute which translates to the aggregate arrival rate of $\frac{1}{12} sec^{-1}$ for 100 movies. Figures 11 and 12 show the gains due to ad-insertion in this dynamic interactive scenario. The average number of users in the system U should approximately be $\lambda_{arr} \times L = 600$, in our case. The simulations show a slightly higher value (around 625) since ad-insertion slows users down resulting in more number of users. But, after aggregation, the number of streams in the system is only around 350, which directly translates to a 45% saving in capacity. Therefore secondary content insertion helps us in cutting down the bandwidth requirement to almost half the original

Initialize a subscriber pool, P
$time_{current} = time_{prev} = 0$;
while ($time_{current} < MAXSIMTIME$) {

Generate movie requests from users in P; The movies are selected from a list of M movies according to a Zipfian popularity distribution. The inter-arrival times are exponentially distributed;

Batch the requests till the nearest A_{min} boundary to make the streams fall on the discrete grid;

Generate VCR actions (FF, Rewind, Pause, Quit) and handle them;

if ($time_{current} - time_{prev} == R$)

Call algorithm DP_Find_Tree with the current snapshot of stream positions;
Form multiple sub-clusters keeping in mind the end of the movie.
Advance all streams accordingly;

$time_{prev} = time_{current}$;

else if ($time_{current} < R$)

Advance all streams normally with no ad-insertion;

else /* $time_{current} - time_{prev} < R$ */

Advance all streams as instructed by DP_Find_Tree;

$time_{current} + +$;

}

Figure 10: Simulation Algorithm

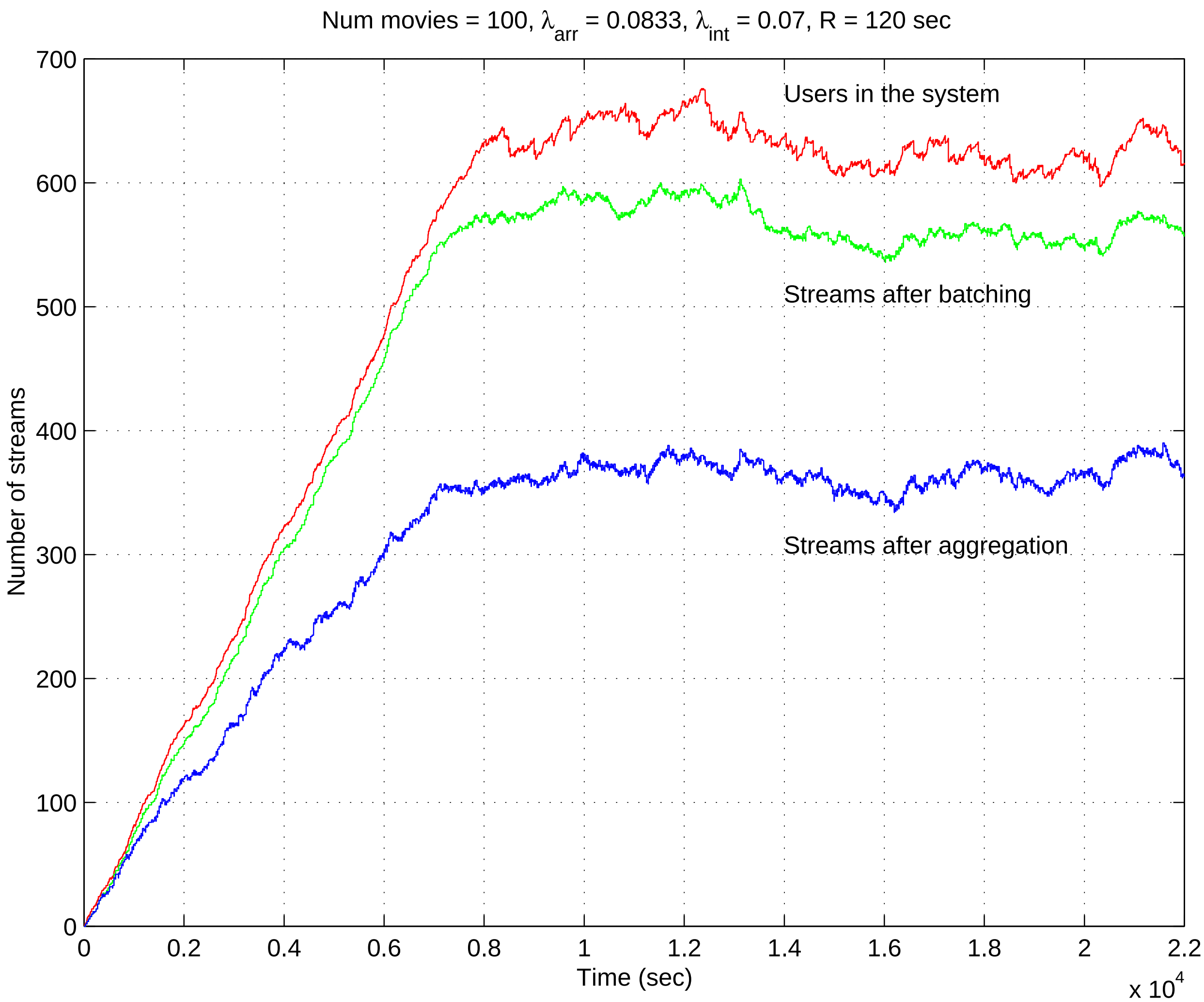


Figure 11: Dynamic Case with Arrivals and Interactions, R = 120 sec

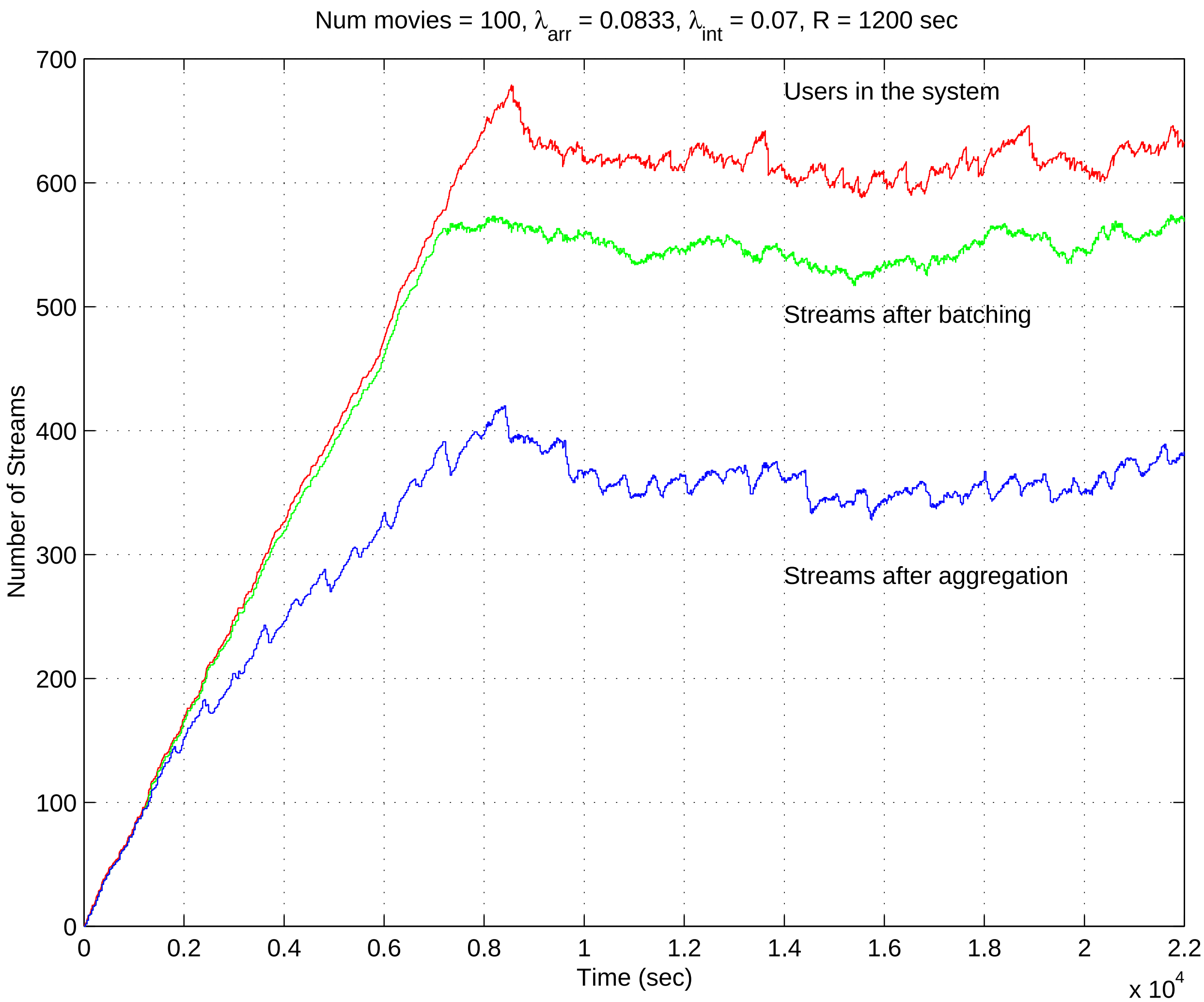


Figure 12: Dynamic Case with Arrivals and Interactions, R = 1200 sec

amount; the spare bandwidth, if any can be used to serve a larger number of customers.

Figures 11 and 12 also show the effect of increasing the re-computation interval and using segment fitting heuristics. R was increased from 120 seconds (fig 11) to 1200 seconds (fig 12). We observed no appreciable increase in resource usage. This shows that for low to medium interaction levels, segment fitting heuristics work well and re-computation can be done relatively infrequently. This reduces the computational overhead of the algorithm.

7 Conclusions and Future Work

In this paper, we presented and evaluated an optimal algorithm for scheduling secondary content in video-on-demand systems. We demonstrated that the algorithm runs in $O(n^3)$ time, where n is the number of streams in a cluster. For a static snapshot of $50 - 100$ users separated with a mean inter-spacing of 1 min, we have shown a bandwidth compression by about a factor between 4 and 5. This algorithm is well-suited for performing the merging step in a dynamic service aggregation system. We have also presented the simulation results for a fully interactive scenario where the users are arriving, interacting and leaving the system. For a mean arrival rate of around $\frac{1}{12}\, sec^{-1}$, and a combined interaction rate of around $0.07\, sec^{-1}$, we show almost 50% reduction in the number of channels required.

The general problem of multiple levels of differentiated content insertion needs to be examined. Analysis of the effect of changing access patterns and interaction rates on the performance of our algorithm is currently underway. Finally, a real prototype demonstrating constraint ad-insertion needs to be developed for exploring some systems issues which have been abstracted out in this modeling phase.

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