RELIABLE PERFORMANCE DATA COLLECTION FOR STREAMING MEDIA SERVICES

Beomjoo Seo
University of Southern California
Los Angeles, CA

Michelle Covell, Mirjana Spasojevic, Sumit Roy
Hewlett–Packard Laboratories
Palo Alto, CA

Roger Zimmermann
University of Southern California
Los Angeles, CA

Leonidas Kontothanassis, Nina Bhatti
Hewlett–Packard Laboratories
Palo Alto, CA

Keywords: Media servers, workload modeling, performance characterization.

Abstract: The recent proliferation of streaming media systems in both wired and wireless networks challenges the network operators to provide cost-effective streaming solutions that maximize the usage of their infrastructure while maintaining adequate service quality. Some of these goals conflict and motivate the development of precise and accurate models that predict the system states under extremely diverse workloads on-the-fly. However, many earlier studies have derived models and subsequent simulations that are well-suited only for a controlled environment, and hence explain a limited sets of behavioral singularities observed from software component profiles. In this study, we describe a systematic performance evaluation methodology for streaming media systems that starts with the reliable collection of performance data, presents a mechanism to calibrate the data for later use during the modeling phase, and finally examines the prediction power and the limitations of the calibrated data itself. We validate our method with two widely used streaming media systems and the results indicate an excellent match of the modelled data with the actual system measurements.

1 INTRODUCTION

The recent developments in media compression technologies such as MPEG-4 and the tremendous growth in available end-user network bandwidth in combination with infrastructure-level services such as Content Delivery Networks (CDN) has made streaming media an ubiquitous web application. As streaming media becomes an increasingly important part of the data traffic, there is a growing need to characterize server behavior and to understand the end-user experience in order to minimize costs and make the best use of the server infrastructure.

Traditionally, server performance has been observed by examining simple metrics such as CPU, disk, and network utilization. However, such singular metrics do not capture the complex interdependence of resources and may result in either under- or over-provisioning of the infrastructure. In this study, we propose a systematic and exhaustive methodology for evaluating the performance of streaming media servers, utilizing both server and client-side measurements under a wide range of workloads. Figure 1 illustrates our multi-stage streaming server characterization process that aims to predict the current server load on-the-fly.

The characterization process consists of three main phases with a total of seven sub-steps. The goal of the *data collection* (Fig. 1 A.) phase is to collect meaningful, usable performance data. It consists of three procedural steps: 1. identifying a set of disjoint workloads (we call these *pure workloads*), 2. measuring the server capacity for each pure workload, and 3. calibrating the performance statistics. The first step – the *workload selection* (Fig. 1 A.1.) – is a design process to define a set of disjoint workloads with precise properties aimed at providing a significant sampling of the workload space. The proper choice of

Timmerman M. (2006).
BUSINESS PROCESS EMBEDDED INFORMATION SYSTEMS - For Flexibility and Adaptability.
In *Proceedings of the Eighth International Conference on Enterprise Information Systems - DISI*, pages 124-129
DOI: 10.5220/0002462601240129

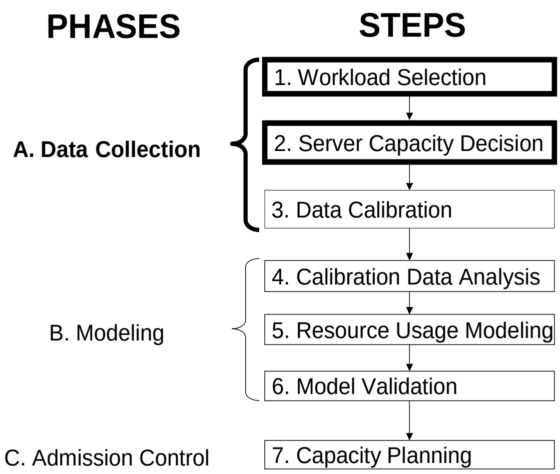


Figure 1: Procedural methodology to characterize streaming media servers.

non-overlapping workloads provides relevant result information while reducing the scope of the extensive experiments and their evaluations during the second step. The second step, the *server capacity decision* (Fig. 1 A.2.), is crucial in that it defines the maximum number of concurrent streaming sessions that can be admitted to the system with acceptable service quality. We term this maximum the *server capacity* or *saturation point*. The complex interactions of the components and resources in a large streaming media system introduce statistical variations that result in non-deterministic service failures near the saturation point. Hence, we adopt a rigorous saturation decision model that iterates until the experimental results provide a reproducible decision for each pure workload. Given the server capacity decisions, the last step, the *data calibration* (Fig. 1 A.3.), collects resource usage profiles, associating the measurement data and the different loads.

After the data collection phase, a careful analysis of the calibrated data identifies which client and server resources are the dominating factors that contribute to the measured system saturation (Fig. 1 B.). In a final phase, the resource usage model may provide the basis for off–line capacity planning or even for online admission control (Fig. 1 C.). Although we do not present the modeling aspects of our work here due to space limitations, our mathematical model that combines a large number of measurements predicts the server saturation state very accurately, thus being capable of playing an important role as a server capacity planning tool in server-clustered networks where multiple streaming servers cooperate to support a massive number of concurrent users. A more detailed description of this model is contained in (Covell et al., 2005).

In this paper, we focus on the evaluation methodology of the first phase and its two steps: workload selection and server capacity decision. The rest of this paper is organized as follows. Section 2 describes our performance data evaluation methodology. In Section 3 we validate our methodology by extensively measuring the performance of an industry standard server with the proposed comprehensive workload evaluation matrix. Section 4 presents the related work. Finally, we conclude and present ideas for future work in Section 5.

Table 1: Pure workload matrix and its naming convention.

	Popular		Unpopular	
	High Rate	Low Rate	High Rate	Low Rate
VoD	VPH	VPL	VUH	VUL
Live	LPH	LPL	LUH	LUL

2 METHODOLOGY

This section presents the evaluation methodology used in our data collection phase. Section 2.1 describes the types of client workloads on which we calibrate. In Section 2.2, we define the notion of service failures and explain the decision criteria for server saturation.

2.1 Workload Selection

Our approach for choosing a set of workloads for our benchmark experiments and evaluations is to represent the complex and large streaming workload space with a number of non-overlapping sets, so-called *pure workloads*. To narrow the evaluation scope to a practical number of experiments and still maintain the rich expressiveness of a general workload, we classify the pure workloads along three dimensions: (1) the source location of requested content, (2) the access popularity, and (3) the content encoding rate. Details of each dimension are described in (Spasojevic et al., 2005). The two selections along each of the three workload dimension produces a total of $2^3 = 8$ pure workloads. Table 1 summarizes these conventions.

2.2 Server Capacity Decision

When approaching overload, a server might start to perform erratically. Such failures are, however, apt to occur even at lower loads before entering the overload region due to random operational spikes. Thus, a consistent and reproducible determination of the maximum number of concurrent streaming sessions (the *server capacity* for short) per pure workload becomes very challenging from observing the server statistics. For the server capacity decision, we examine the performance data collected from the server and the clients.

2.2.1 Client Logging

We have developed a light–weight client application that requests an RTP (Schulzrinne et al., 1996) stream from a media server, accepts RTP packets, and records session-level statistics. In addition, it can record a trace of every RTP/RTCP packet (packet arrival time, size, sequence number, and the media decode time).

Every experiment runs two types of client applications: *loading clients* and *probing clients*. A loading client is a long-lived session that exercises the server at the level of concurrent requests. To support a large number of simultaneous loading clients, it only records session-level statistics. The probing client is a short-lived session that is issued consecutively to collect detailed session statistics after an experiment launches all the loading clients and reaches steady state. It records both session-level statistics and a trace of the delivered data packets.

From the trace, we can also derive the number of rebuffering events, which is the number of late-arriving packets observed from the probing session. Late-arriving packets are computed from the packet-arrival offset, the difference between each packet delivery time and its deadline. The detection of rebuffering events was, however, often problematic due to increasingly bursty packet transmissions as the server workload increased. The timing of these bursts was such that, on occasion one or two packets would be delayed beyond their delivery deadline. This small amount of over-delayed data resulted in rebuffering violations on those experiments, even when the server was otherwise not saturated. We found that, by re-categorizing these few packets as being lost data (instead of late data), we could avoid a rebuffering violation without inducing a size violation. This greatly improved the reliability and reproducibility of our decision surface.

2.2.2 Session Failure and Server Capacity Decision

If the server system is overloaded, a newly delivered streaming request may be either rejected or admitted but experience degraded session quality. Among session failures, some can be detected from error log files easily (hard failure), while others need further processing (soft failure). Admission rejection and explicit session termination in the middle are hard failures.

Soft failure is a general term that describes an unacceptable user streaming experience of a session. Duration violations, size violations, and rebuffering violations belong to this category. These are defined as follows:

- **Duration Violation:** Any session that satisfies the following inequality condition $|\frac{T(s)}{T_s} - 1| > \rho_T$ is considered to violate the duration requirement. T_s is the expected duration of session s, $T(s)$ is its measured duration, and $\rho_T (0 < \rho_T < 1)$ is the acceptable range of the duration.
- **Size Violation:** Any session that satisfies that following inequality condition $1 - \frac{B(s)}{B_s} > \rho_B$, where $B(s) < B_s$, is considered to violate the session length requirement. B_s is the expected amount of data bytes received at the client side for session s, $B(s)$ is its measured size, and $\rho_B (0 < \rho_B < 1)$ is the acceptable range of the bitstream length.
- **Rebuffering Violation:** Any experiment which has N number of individual probing statistics and satisfies following inequality condition $\frac{\sum_s^N \{I(s)+P\cdot R(s)\}}{\sum_s^N T_s} > \rho_Q$ is considered to violate the desired service quality. $I(s)$ is the start-up delay of the measured session s, $R(s)$ is the sum of time periods when the session s was in a rebuffering state, P is the penalty constant assigned per rebuffering event, and $\rho_Q (0 < \rho_Q < 1)$ is the acceptable range of the service quality.

Duration and size violations are obtainable from session-level statistics, while rebuffering violations are computed from data packet traces available at client log statistics. Our failure model excludes the condition $B(s) > B_s$ where the test session receives more packets than expected, which is caused by packet retransmission.

To evaluate the user's experience, we may directly measure the quality of voice samples and the quality of video images received at the client side (P.862, 2001; Wolf, 2001) or indirectly estimate a user's frustration rate. We prefer the less accurate but real–time quality evaluation method. Otherwise, the server capacity decision would take a tremendous amount of time to finalize due to its stepwise nature. For this reason, we chose Keynote's indirect method (Keynote Inc., 2003). The frustration rate proposed by Keynote Inc. is a well-established methodology to quantify a user's streaming experience. This measure computes the waiting time spent at startup, the initial buffering, and rebuffering events of the measured session. To minimize false negatives caused by statistically generated spikes during the experiments, our methodology extends Keynote's rating system by collecting and analyzing multiple probing sessions.

If any session failures are seen at any time during the experimental epoch, the streaming server is labelled as being saturated for the full experimental epoch. Each experimental epoch used to determine the saturation point consists of five 20-minute measurement sets at a possible saturating workload. This repetition ensures a reproducible, internally consistent categorization of the server.

3 EVALUATION RESULTS

Throughout this section, we discuss the results that we observed when calibrating the Apple *Darwin Streaming Server (Apple, 2003)* and the RealNetworks *Helix Universal servers (RealNetworks,)*. While sharing a similar core architecture, they use very different internal policies, leading to different performances with the same hardware.

We use box–and–whiskers plots: the horizontal line in the middle of the box is the median value; the lower and upper lines of the box are the 25th and 75th percentile of the sample data.

3.1 Experimental Setup

Our experiments run on three distinct sets of machines: the streaming-server machine that is being calibrated or tested; up to four live-source machines; and up to six client machines. The server machine is a dual 1.4GHz Pentium III PC with 1GB memory, running SuSE 8.2 (kernel version 2.4.20). The other machines are selected to have sufficient computation and I/O capacity[1]. All the machines were connected to a switched Gigabit network, isolated to avoid uncontrolled network interference.

To avoid performance variations, we used multiple distinct copies of the same material for Live and VoD tests. For our Live tests, the material was stored on the live-source machines and was relayed through the streaming server under test using the *Darwin Playlist-Broadcaster* (Apple, 2003).

Each experimental period has three distinct phases: ramping up, steady-state, and termination. During the first phase, loading clients are added at 500 ms intervals, which avoids start-up failures purely due to transient effects. The loading clients are used to induce a particular type of workload on the server. After reaching the steady-state period, we collect measurements from the streaming server machine. We also sequentially launch 20 probing clients, which run for non-overlapping 1 minute periods.

3.2 Maximum Server Capacity

Tables 2 shows the results of the final server capacities measured with three different experimental setups. The first set (1) Darwin was performed in the Darwin environment without any systematic decision model. The server saturation is determined by an expert's intuition. This approach detects some failures that we later refined in our failure model: hard failures, duration violations, and size violations. The second and the third sets were executed with the Darwin and the Helix experimental setup, respectively, using our proposed methodology. In our decision model, we use 0.03 for ρ_T, ρ_B, ρ_Q, or 3% allowances.

With the (2)Darwin experiments, several pure workloads exhibited a different failure reason for the server to saturate. For example, the failure type of the VPH workload that was determined due to hard failure on the (1)Darwin set later turned out to be a rebuffering violation. This inconsistency is caused by the existence of a rebuffering violation which occurred before the system experienced a hard failure. The dramatic server capacity change on the Darwin server sets (52% difference for the VUL experiments) is largely due to improper handling of temporary performance spikes.

When comparing different servers, we found that the Helix server achieved higher system throughput than the Darwin server for the CPU–intensive workloads such as VPx and LPx. For I/O intensive workloads, the Darwin server reported a slightly improved throughput for VUL and LUH.

3.3 Server-side Observations

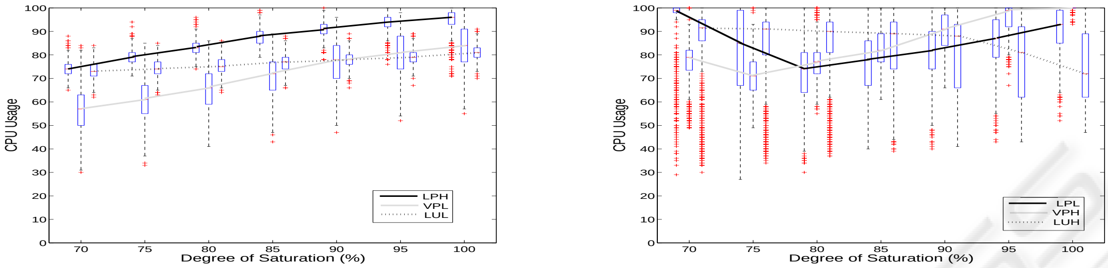
Server side performance metrics are by far the easiest to identify and understand. CPU, disk, network, and memory identify the critical resources of any modern computer system. Each of those metrics can reach the saturation region independently. CPU utilization indicates whether the server processor can keep up with the tasks associated with serving the streams. Disk and network utilization indicate how much of the available bandwidth from these two subcomponents is being used by a particular workload. Memory exhaustion in streaming workloads is an unlikely problem in modern systems. However, if the main memory of the server is exhausted, and the system starts paging, performance deteriorates rapidly and CPU utilization spikes. It is possible to saturate either one of those resources before CPU utilization reaches 100%, and thus they must be monitored independently rather than be proxied by the CPU utilization of the server.

In this section, we focus on discussing the statistics of CPU usages. Figure 2 plots the summary statistics of CPU usages for the CPU–intensive pure workloads. They do not show statistically significant trends over the workload ranges of interest. The linear trend with increasing load on the Darwin server is attributable to the initial load offset, which is incremented as an experiment progresses (Figure 3(a)). Such a sawtoothed temporal dependency of the load usage makes it hard to estimate the current server state from the performance data collected during a randomly chosen short time interval if the initial load off-

[1] In our test-bed, the live–source and client machines have 1.0 - 2.4 GHz Pentium III processors with 256 MB - 1GB memory.

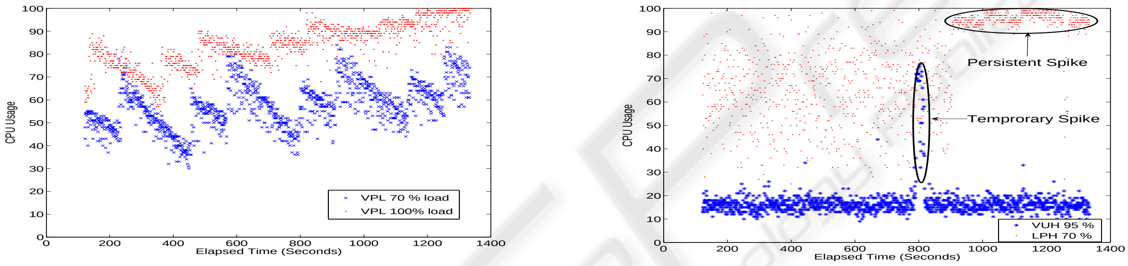
Table 2: Different sets of experimental setups and their server capacity.

	VPH	VPL	VUH	VUL	LPH	LPL	LUH	LUL
(1)Darwin	438	780	36	170	996	-	-	405
(2)Darwin	425	726	33	259	1158	1976	405	405
(3)Helix	590	1220	91	228	1460	2870	396	492



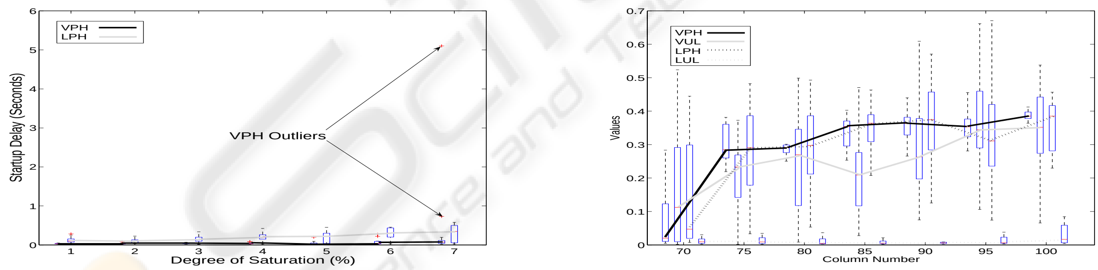
(a) Darwin (b) Helix

Figure 2: CPU usage as a function of the degree of saturation.



(a) Darwin: Sawtoothed temporal dependency (b) Helix: Persistent load spike vs. temporary load spike

Figure 3: Abnormal behaviors of CPU utilization.



(a) Darwin (b) Helix

Figure 4: Startup Delay.

set is unknown. On the Helix server, the median CPU measurements for LUx workloads (Figure 2) shows a slightly negative trend with increasing load. Furthermore, the CPU usage for the popular workloads (LPx and VPx) is non-monotonic with changing load. The Helix experiments tend to have more load spikes (Figure 3(b)) than the Darwin experiments. While the temporarily imposed load spike (VUH measurements in the Figure) disappears quickly, a persistent spike lasts for a long time and the system stays heavily loaded, shown as a '+' symbol in Figure 2(b). Of course, the non-monotonic nature of the Helix server is a side-effect of such persistent spikes.

3.4 Client-side Observations

We expect that there are good indicators for the server saturation at the client-side. Depending on the server policy, an overload may result in increased startup latency or a number of late packets, or both. Specifically, we present saturation behaviors of the startup delay. Increased startup latency indicates that the server is falling behind in processing new requests.

In Figure 4(a), the Darwin server shows a number of outliers from the startup delays when approaching the saturated region for VPx workloads. When the Darwin server is fully loaded with the VPH workload, startup delays begin to show extremely large outliers (5 seconds and 0.8 seconds in Figure 4(a)), while their median value is very small. We cannot observe such large outliers when the server runs in the unsaturated region. Thus, any occurrence of intolerable startup delay for the VPx workload on the Darwin server would quickly indicate that the server system enters the saturated region. Figure 4(b) shows that the median values of the startup delays over various workloads on the Helix server seems to converge quickly when the load approaches 75% of the saturation level. Thus, any median values (more than 300 milli-seconds) collected for a short-period of time indicates that the server experiences more than 70% of the saturating load. However, the wide variability and the negative trends of the Helix startup delay above the 75% load-percentile inevitably prevent any predictions.

4 RELATED WORK

Cherkasova *et al.* (Cherkasova and Staley, 2003; Cherkasova et al., 2005) provided one of the first comprehensive performance analysis of media servers under video-on-demand workloads with both popular and unpopular content. The authors identified important client side performance metrics, namely jitter and rebuffering. The paper also recognized the need to measure the basic capacity of the server under different workloads. Our work extends both the workload space by examining live streams in addition to video on demand (as well as considering their mix), and the client metrics space by looking into failures, startup latency, and thinning.

Independent monitoring and verification of performance is provided by several commercial services such as Keynote[2], Streamcheck[3] and Broadstream[4]. They also provide a weighted score that summarizes in a single number the overall the performance derived from low level metrics.

5 CONCLUSIONS

In this paper we have presented a systematic performance evaluation methodology to measure the capacity of streaming media systems consistently and reliably. We then validated our methodology with a case study of two commercial streaming servers.

Compared with our earlier approach that primarily relied on expert's intuition, our new method correctly predicts a 52% higher server capacity for the *Darwin* VUL workload while confirming the other workload decisions. We have demonstrated that the performance metrics at the server-side such as CPU load and at the client-side such as startup delay are affected by the system load in different ways, and that each by itself cannot be a good classifier to differentiate workload types and to estimate the system load accurately.

The lessons we learnt through the extensive measurements of two commercial streaming servers are directly applicable to the management of multiple servers (e.g., in a cluster configuration). We conclude that better throughput can be achieved by assigning requests and content so that the popularity of clips is maximized, by separating requests for on-demand and live streams to different servers and by converting on-demand requests to live streams whenever possible.

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

[3]http://www.streamcheck.com

[4]http://www.broadstream.com

REFERENCES

Apple (2003). Darwin Streaming Server 4.1.3. http://developer.apple.com/darwin/projects/streaming/.

Cherkasova, L. and Staley, L. (2003). Building a performance model of streaming media application in utility data center environment. In *3rd IEEE/ACM International Symp. on Cluster Computing and the Grid*, Tokoyo, Japan.

Cherkasova, L., Tang, W., and Vahdat, A. (2005). Mediaguard: a model–based framework for building streaming media services. In *Proc. of the SPIE Conf. on Multi–Media Computing and Networking*.

Covell, M., Roy, S., and Seo, B. (2005). Predictive modeling of streaming servers. *SIGMETRICS Perform. Eval. Rev.*, 33(2):33–35.

Keynote Inc. (2003). *Measurement and Monitoring: Streaming Perspective*. http://www.keynote.com/-downloads/datasheets/streaming_0104.pdf.

P.862, I.-T. R. (2001). Perceptual evaluation of speech quality (PESQ), an objective method for end-to-end speech quality assessment of narrowband telephone networks and speech codecs.

RealNetworks. Helix Universal Server. http://www.-realnetworks.com/products/media_delivery.html.

Schulzrinne, H., Casner, S., Frederick, R., and Jacobson, V. (1996). RTP: A Transport Protocol for Real-Time Applications. RFC 1889.

Spasojevic, M., Bhatti, N., Kontothanassis, L., and Roy, S. (2005). Undestanding the impact of diverse streaming workloads on end–user quality of service. In *10th International Workshop on Web Caching and Content Distribution (WCW)*.

Wolf, S. (2001). Draft technical report for 'objective video quality measurement using a peak-signal-to-noise-ratio (PSNR) full reference technique'. T1A1.1/2001-026R1.