Effects and Implications of File Size/Service Time Correlation on Web Server Scheduling Policies

Dong Lu* † Peter Dinda* Yi Qiao* Huanyuan Sheng*
{donglu,pdinda,y-qiao3,h-sheng}@northwestern.edu
*Northwestern University
†Ask Jeeves, Inc.

Abstract

Recently, size-based policies such as SRPT and FSP have been proposed for scheduling requests in web servers. SRPT and FSP are superior to policies that ignore request size, such as PS, in both efficiency and fairness, given heavy-tailed service times. However, a central assumption that is usually made in implementing size-based policies in a web server is that the service time of a request is strongly correlated with the size of the file it serves. By collecting web server trace data taken from the logs of modified Apache web servers, this paper reveals that the correlation between service time and file size can be quite low, and shows how the performance of SRPT and FSP can be dramatically affected by the weak correlation via trace-driven simulations. In response, we propose and evaluate domain-based scheduling, a simple technique that better estimates connection times by making use of the source IP address of the request. Domain-based scheduling improves SRPT and FSP performance on web servers, bringing the performance benefits of these scheduling polices even to those regimes where the correlation between file size and service time is low.

1 Introduction

In a web server, requests continuously arrive to be serviced. A request requires a certain service time to be completed, a time whose components include the CPU, the disk, and the network path. A request is queued when it arrives and remains in the system until it is complete, the total time from arrival to completion being the sojourn time or response time. Scheduling policies determine which requests in the queue are serviced at any point in time, how much time is spent on each, and what happens when a new request arrives. Common goals of the scheduling policy are to minimize the mean sojourn time (response time of the request), the average slowdown (the ratio of its response time to its size), and to behave fairly to all requests.

Many policies are possible. First Come First Served (FCFS) is a non-preemptive policy in which the requests are run to completion in the order in which they were received. A more common policy is Processor Sharing (PS), which is preemptive. In PS all requests in the queue are given an equal share of the web server's attention. Generalized Processor Sharing (GPS) generalizes PS with priorities. Often, FCFS can be combined with PS or GPS, with FCFS dispatching of requests from the queue to a pool of processes or threads that are collectively scheduled using PS or GPS. These polices ignore the service time of the request.

Recently, size-based scheduling policies, those that incorporate the service time of the request into their decisions, have been proposed for use in web servers. Harchol-Balter, et al, have proposed the use of the Shortest Remaining Processing Time (SRPT) scheduling policy in web servers [8, 18], showed how to incorporate it into actual implementations [18], and proved that the performance gains of SRPT usually do not come at the expense of large jobs [8]. In other words, SRPT is fair with heavy-tailed job size distributions. Gong, et al further investigated the fairness issues of SRPT through simulation [16] and proposed two hybrid SRPT scheduling policies [17] to trade off the fairness with performance. The Fair Sojourn Protocol (FSP) is a modified version of SRPT that has been proven to be more efficient and fair than PS given any arrival sequence and service time distribution [14].

In the *implementation* of size-based polices such as SRPT and FSP on a web server, the service time of the request is needed. The common assumption is that the service time is the size of the file being served, as this

Effort sponsored by the National Science Foundation under Grants ANI-0093221, ACI-0112891, ANI-0301108, EIA-0130869, and EIA-0224449. Any opinions, findings and conclusions or recommendations expressed in this material are those of the author and do not necessarily reflect the views of the National Science Foundation (NSF).

is very easy to discover when the request enters the system. More broadly, the assumption is that the service time is strongly correlated to the file size. In this paper, we examine the validity of this assumption, and the impact that the degree of correlation between file size and service time has on the performance of SRPT and FSP.

To evaluate this impact, we developed a simulator that can support PS, SRPT, and FSP in both M/G/1/m and G/G/n/m. The simulator operates on a trace of request arrivals, which can come either from an augmented Apache [1] web server log, or from a trace generator. The trace contains the request arrivals, the file sizes, and the actual service times in microseconds. We use traces that we have captured on our department-level web server, and traces captured by others on web caches.

In our earlier work [20], we showed that for the metrics of mean response time and slowdown, the performance of SRPT and FSP are highly dependent on the correlation (Pearson's R [6]) between estimated and actual job size, and can fall well below that of PS for low R values. Effective job size estimators are critical to applying size-based scheduling policies. This paper focuses on applying size-based scheduling in web servers when the correlation R between file size and service time is low. We first study how the performance of the file size-based policies (SRPT-FS, FSP-FS) diverges from their ideal versions (SRPT, FSP) as we increase the load on the web server. We then propose a better estimator and evaluate it via trace-driven simulations.

We study G/G/n/m in addition to M/G/1/m because previous research [12, 26] has shown that HTTP arrivals do not form a Poisson process. HTTP document transmissions are not entirely initiated by the user: the HTTP client will automatically generate a series of additional requests to download embedded files, thus resulting in a more bursty process. Previous work [12] pointed out that the aggregated interarrival times of HTTP requests can be modeled with a heavy-tailed Weibull distribution.

There has been significant work on the G/G/n queuing model. However, we are aware of no analytical results on G/G/n/m for SRPT or FSP scheduling in regimes where interarrival times and service times are heavy-tailed. Therefore, the work we describe in this paper is based on measurement and simulation.

Using our infrastructure, and measured and synthesized trace data, we address the following questions:

1 What is the actual degree of correlation between file size and service time in practice? (Section 2)

2 What is the performance of SRPT, FSP and PS under typical real workloads? (Section 3)

3 Is there a simple and low-overhead estimator for service time that would make SRPT and FSP on M/G/1/m and G/G/n/m perform better? (Section 4)

Policy	Description
PS	Processor Sharing
FSP	Ideal Fair Sojourn Protocol (exact service times)
SRPT	Ideal Shortest Remaining Processing Time (exact service times)
FSP-FS	File size-based FSP (file size as service time)
SRPT-FS	File size-based SRPT (file size as service time)
FSP-D	Domain-based FSP (domain-estimated service times)
SRPT-D	Domain-based SRPT (domain-estimated service times)

Figure 1. Scheduling policies.

It is important to point out that our results in addressing questions 2 and 3 are largely independent of our results for question 1, and the algorithm we develop in response to question 3 provides benefits to SRPT and FSP over a wide range of possible answers to question 1.

Our definition of service time is the time needed to send all of requested data in the absence of other requests in the system. Our measurements show that the assumption that file size and service time are strongly correlated is unwarranted—the correlation is, in fact, often rather weak. We believe that the reason for this phenomenon is *path diversity* to different clients. Even if for every specific request, the service time $t_s = L + N/B$, where N is the number of bytes in the transfer and L and B are the latency and bandwidth of the path, every path will likely have a different L and B. In aggregate, this will mean that t_s will be weakly correlated with N. Notice that this explanation does not require that the bottleneck for file transfer be the network. Path diversity is simply a fact of life of a large network.

Our trace-driven simulations show that the performance of file size-based SRPT and FSP is strongly affected by the weak correlation between file size and service time reflected in our web server traces. In fact, R is indeed low enough that both file-size based SRPT and FSP perform worse than PS. The job size distribution, arrival process and load decide the threshold value of R that SRPT and FSP need to outperform PS.

These results led us to believe that a better estimator for service time was needed. We refer to our estimator as a domain estimator, and the use of our domain-based estimator with a size-based scheduling policy such as SRPT or FSP as *domain-based scheduling*. The basic idea is to use the high order k bits of the source IP ad-

Model	Description
$M/G/1/\mathrm{m}$	Poisson arrival process; Single server; General service time distribution; Limited queue capacity m.
$G/G/\mathrm{n}/\mathrm{m}$	General arrival process (Pareto and Weibull); General service time distribution; n servers ; Limited queue capacity m

Figure 2. Queuing models.

dress to assign the request to one of 2^k domains. For each domain, we estimate the service rate (file size divided by service time) based on all previous completed transfers to the domain. The service rate is then used to estimate the service time of a new request based on its file's size. Based on our traces, there is a strong correlation between these estimates and the actual service times that grows with the number of bits k used. In short, by choosing k appropriately, we can create enough correlation to make SRPT and FSP perform well. Surprisingly, k can be kept relatively small, making the implementation of domain-based scheduling feasible and fast. Throughout the paper, we refer to the scheduling policies as listed in Figure 1, and refer to the queuing models used as listed in Figure 2.

2 File size and service time

Size-based SRPT scheduling appeared in digital communication networks research in 1983 [10]. In this context, the service time was taken to be equal to the transmission time of a message, which is proportional to the length of the message stored in the node buffers. A web server serving static requests appears superficially similar in that it transmits files to the client. However, there are differences. First, in the digital communication network context, the work represented by the service time is pushing the bits of the message onto the wire, while for the web server context, the work involves end-to-end cooperation along an entire shared heterogeneous path. Although most transfers are likely to be dominated by the bottleneck bandwidth in the path and the latency of the path, there are multiple possible bottlenecks along the path and they can vary with time due to packet losses and congestion. Second, the disk(s), memory system(s), and CPU(s) of the web server and the client are also potential bottlenecks. These complexities suggest that the service time of a request may not be proportional or even well correlated with the size of the file it serves.

There are several possible definitions for service time in the web server context. For example, we could focus on a bottleneck resource on the server, such as the CPU, and define the service time as the total CPU time needed to execute the request. Alternatively, we could treat the CPU, disk, and network link of the server as a single resource and consider the total non-blocked time of a request on it. We could also take a holistic view and consider it the time spent on the bottleneck resource on the path from server to client. We take the position that the service time of a request is the time that the combination of server, client, and network would take to finish the request given no other requests in the whole end-to-end system (no load on any server resource). In the following sections, we use this definition and argue that our measurement methodology measures it by verifying that the loads on the resources of the end-to-end system that we measure are miniscule.

To measure correlation between file size and service time we use the correlation coefficient (Pearson's R) [6]. To answer the question posed by this section, we examine R values for a large trace acquired by us from a typical web server, as well as 70 traces collected from web cache servers. The main conclusion is that R can vary considerably from server to server, and can be quite small. $R = 0.14$ for our web server trace, while the web caches have R evenly distributed in the range $[0.12, 0.61]$. In subsequent sections, we use our web server trace to drive our simulation. However, we also use synthetically generated traces in which we can control R directly. While many web server traces are available, none that we could find record the actual service time of the request and thus are not useful for the purposes of our study.

2.1 Measurement on a typical web server

We modified the code of the Apache log module so that it records the *response time* of each request with microsecond granularity (using the IA32 cycle counter to measure time). Under extremely low load conditions, as we document below, this time is *equivalent* to the service time according to our definition above.

We deployed the module on our department-level web site. We collected data from September 15, 2003 to October 19, 2003. This trace includes approximately 1.5 million HTTP requests, among which less than 2% are dynamic PHP requests that collectively took less than 1% of the total service time recorded. $> 98\%$ of our requests and $> 99\%$ of the service time in the trace are for static pages. Hence, our web server is dominated by static web content. our results are comparable to previous work [21, 19, 18] that claims static content dominates web traffic. The requests originated from 110 "/8"

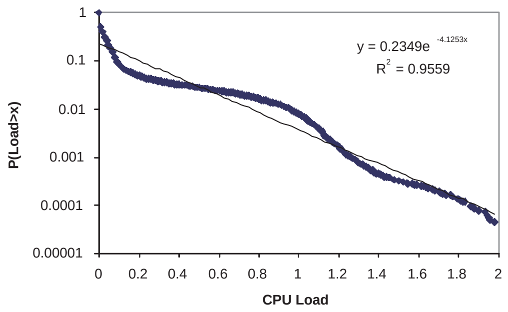


Figure 3. CCDF of CPU load.

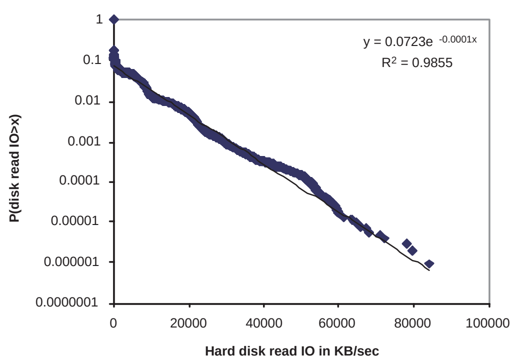


Figure 4. CCDF of storage read I/O.

IP networks, 7220 "/16" IP networks and 31250 "/24" IP networks spread over the world. We claim that this server is typical. However, the conclusions of this paper are also supported by other measured traces and generated traces.

The bottleneck resource of a request in this trace is hardly ever the CPU of the server. The web server is a dual processor Pentium IV Xeon machine running Red Hat Linux 7.3. CPU load is defined as the exponentially averaged number of jobs in the run queue of the OS kernel scheduler (the Unix load average), The machine can serve two CPU intensive applications with full CPU cycles. Figure 3 plots the complementary distribution of the CPU load during the period of trace collection. This distribution can be modeled with a exponential distribution with $R^2 \approx 0.96$. Figure 3 shows that the probability $P[CPUload > 2]$ is minuscule. The memory system is also clearly not a bottleneck based on these results as significant cache stalls would show up as increased load.

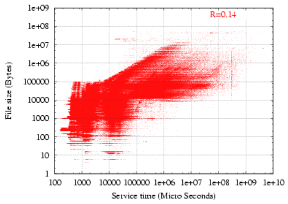
The bottleneck resource of a request in this trace is hardly ever the disk system of the server. The machine's file systems reside on a NFS-mounted (over private gigabit Ethernet SAN) RAID 5 storage server. Figure 4 shows the complementary distribution of the storage system reads during the period of the trace. The distribution can be modeled with a exponential distribution with R^2 close to 0.99.

Read			Write	
Char	Block	WebRead	Char	Block
23604	1399254	29879	16777	50355

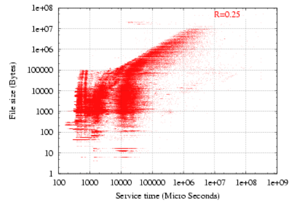
Figure 5. Storage bandwidth, KB/sec.

We benchmarked the storage system using Bonnie, which is a widely used utility that measures the performance of Unix file system operations that an application sees [2]. Bonnie reads and writes a 100 MB file (marked uncacheable) by character or by block. Both sequential and random access are tested. Random block and character throughput give us upper and lower bounds on the performance of file system I/O that Apache sees. We also wrote our own benchmark (WebRead) to get a sense of the typical read performance that Apache sees. WebRead simply reads the files in our access log, in order, as fast as possible. Not surprisingly, the WebRead performance is in between the character read and block read benchmark given by Bonnie. Bonnie and WebRead measurements are shown in Figure 5. From Figures 4 and 5, it is clear that in our trace encountering a read throughput exceeding the WebRead throughput < 0.001. No recorded read throughput was larger than Bonnie's block read benchmark. Notice also that the highest throughputs seen are lower than the 125 MB/s throughput limit of the Ethernet SAN, hence the SAN is also not a bottleneck.

As it is clear that the CPU, memory, and disk systems are not bottlenecks, if there is any bottleneck it is in the network or the client. Based on many earlier measurements of load behavior on clients that indicate their resources spend much of their time idle [22, 13], it is extremely unlikely for a client to be the bottleneck. If there is any bottleneck, it is in the network path to the client, which agrees with earlier work [24, 18] that showed that the network is the bottleneck for the web servers serving mainly static content. Given the low rate of requests, it is highly likely that a single request would perform similarly to the requests in our trace. Hence, the high-resolution response time that we record in the Apache log is a close approximation of the service time as defined above. Obviously, there are situations where CPU or disk can become bottlenecks, such as in virtual server configuration in which one physical server hosts several



(a) R=0.14



(b) R=0.25

Figure 6. File size versus service time: (a) whole trace, (b) selected /16 network.

web sites, or on a web server that hosts database-based dynamic web content.

Given the provenance of the trace, we can now use it to answer our question. Figure 6 (a) is a log-log scatter plot of file size versus service time. Visually, we can see hardly any correlation between file size and service time. File transfer times vary over several orders of magnitude with same file size. *Over the entire 1.5 million requests in the trace, we find that R is a very weak 0.14.*

Within a domain, R is larger. We define precisely what we mean by a domain and connect it with CIDR in Section 4. Here, simply consider it as a single network that may be recursively decomposed into subnetworks. For example, Figure 6 (b) is a log-log scatter plot of file size versus service time for requests originating with a single "/16" IP network, where the network address is 16 bits. $R = 0.25$ for this situation. As the domain grows smaller (has fewer IP addresses, or more bits representing its network address), R grows larger. For example, if we focus on a particular "/24" LAN subnet (24 bit network address) that is contained within the previous network, $R = 0.39$.

We speculate that the reason for this behavior is that network bandwidth heterogeneity from the server to the clients of a domain decreases as the size of the domain decreases. This provides a different, but compatible, explanation for earlier findings [8] that file size-based SRPT scheduling can decrease mean sojourn time by a factor of 3-8 over PS in a LAN for load higher than 0.5, but can only decrease the mean sojourn time by 25% on the WAN.

We are actively acquiring additional traces, but this is difficult because web server modifications are necessary to acquire fine grain service times. Many available traces, such as those from the Internet Traffic Archive [3], our institution's other web servers, and others provide only file size, not service time and thus are unsuitable for our work. We have, however, acquired many traces from web caches, described next, and built a trace generator that allows us to control R as well as the distributions of service time and interarrival time, described later.

2.2 Measurement on web caches

We examined 70 sanitized access logs from Squid web caches, made available through the ircache site [4]. These traces contain actual fine grain service times (not response times) in addition to file sizes. Internet object caching stores frequently requested Internet objects (i.e., pages, images, and other data) on caches closer to the requester than to the source. Clients can then use a local cache as an HTTP proxy, reducing access time as well as bandwidth consumption.

Squid is a high-performance proxy caching server for web clients. Unlike traditional caching software, Squid handles all requests in a single, non-blocking, I/O-driven process [5], making it very easy to determine the service time of a request. Squid is similar to a web server in that it also accepts HTTP requests and sends back requested files, but it is different in that the Squid servers form a overlay network that uses the Internet Cache Protocol (ICP) to perform server selection for web clients and load balancing among the cache servers [28]. A client sees that it typically receives a reply from the nearest cache server, while from the Squid cache servers' points of view, the Internet is divided into several regions with each cache server serving requests for a region.

Because a single Squid cache serves clients largely from one region of the Internet, the bandwidth heterogeneity to the clients is likely to be less than that seen by a web server, which services clients regardless of region. This, we believe, should lead to larger R being measured on Squid caches than on web servers. The partitioning of the network as seen from the web server into domains that we describe in Section 4 builds on this observation.

While we cannot (and do not) use web cache traces as proxies for web server traces, it is instructive that R on the caches is also rather weak. Figure 7 shows a complementary distribution plot of the R values in the 70 traces. The traces were collected from 10 squid web cache servers over 7 days Each trace contains from 0.1 to 1.1 million requests. The smallest $R = 0.12$, while the largest $R = 0.61$. The mean is 0.34 with standard deviation 0.13. Given that we expect that R for web servers will be lower than R for web caches by the reasoning in the previous paragraph, that measured Rs on web caches are low suggests that R on web servers is likely to be low as well.

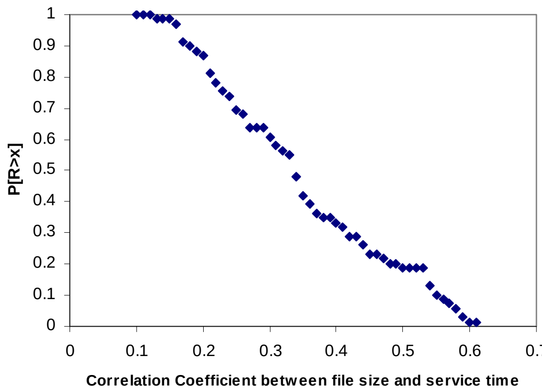


Figure 7. CCDF of R in web cache traces.

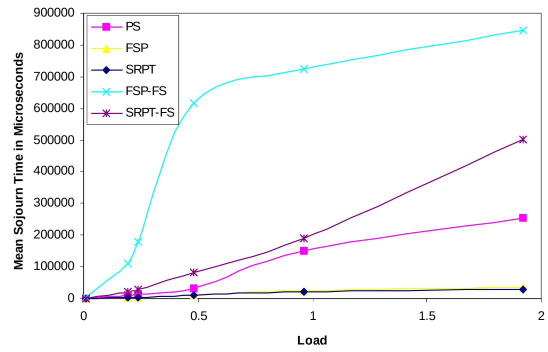


Figure 8. Mean sojourn time versus load, G/G/1/m, Pareto arrivals, web server trace.

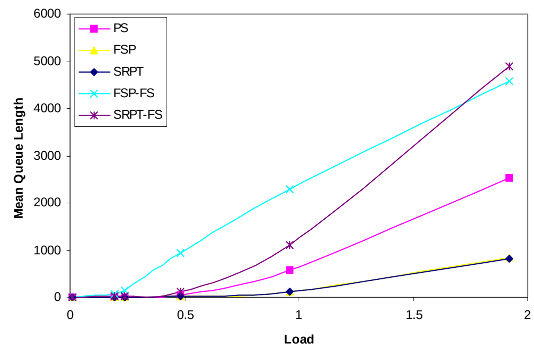


Figure 9. Mean queue length versus load, G/G/1/m, Pareto arrivals, web server trace.

In combination with the low R seen on our web server trace, we believe that we can now answer the question posed by this section in the negative: *The correlation between request file size and service time on web servers is weak.*

3 Correlation and performance

We have seen that request service time on web servers and caches is not strongly correlated with request file size. Here, we investigate, via simulation, how this weak correlation (R) affects the performance of size-based scheduling policies (SRPT and FSP, where actual service time is known a priori, and SRPT-FS and FSP-FS, where the file size is used as the service time) and compare with a size-oblivious policy (PS). Our metrics are the mean sojourn time (response time) and mean queue length. In our earlier work [20], we found that for these metrics the performance of non-ideal SRPT and FSP (SRPT-FS and FSP-FS here) is dramatically affected by R, falling below that of PS for low R values, such as we encountered in the previous section. Here, we show how the performance of SRPT-FS and FSP-FS diverge from the ideal as a function of the load on the web server.

3.1 Simulator

Our simulator supports both M/G/1/m and G/G/n/m queuing systems. It is driven by a trace in which each request contains the arrival time, file size, and service time. In addition to the web server trace described in the previous section, our simulator can also support synthetic traces with many interarrival time and file size / service time distributions. The correlation between file size and service time in a synthetic trace can also be directly controlled. More detail is available [20].

3.2 Simulation with web server trace

Here we consider the performance of SRPT, SRPT-FS, FSP, FSP-FS, and PS on the web server trace ($R = 0.14$) described in Section 2.1. The mean service time is 1250 microseconds. The scheduling policies are described in Figure 1. Note that although our web server trace represents very low load, here we vary the load in the system by controlling the arrival process of the requests represented in the trace. We make use of Poisson arrivals, Pareto arrivals, and Weibull arrivals and control their mean rate in order to control the load. Load control is important, because, as we discussed in Section 2.1, the load captured in the trace is rather low. The time units are microseconds throughout the rest of the paper. Each simulation is repeated 20 times.

First, we consider G/G/1/m (Job interarrival has a heavy-tailed Pareto distribution, file sizes and service times as in the trace). Figure 8 shows the mean sojourn times of different scheduling policies with increasing load, while Figure 9 shows the mean queue length of different scheduling policies with increasing load on the queue. In both figures, ideal SRPT and FSP perform very well and almost identically. However, SRPT-FS and FSP-FS both perform quite poorly, and their performance diverges dramatically from their ideal performance with increasing load. SRPT-FS and FSP-FS perform worse than SRPT and FSP in all our simulations.

For a queue with unlimited queue capacity, the mean sojourn time and queue length tend to be infinity if the load is over unity, and therefore it is meaningless to present mean sojourn time and queue length. Our simulator uses a finite queue capacity to better match implementations. The server will begin to reject jobs when it is overloaded for some period of time (when the queue is full). Hence, both mean sojourn time and mean queue length are meaningful; they represent the behavior of the server under transient overload.

We have also investigated a Weibull arrival process and Poisson arrival process, where the interarrival times of requests in the trace are drawn from a Weibull distribution and exponential distribution respectively. The results are similar to those for the Pareto arrival process shown earlier.

Our simulations show that the performance of SRPT-FS and FSP-FS, SRPT and FSP where request file size is used as request service time, is largely affected by the weak correlation R between file size and service time. With such weak correlations as in our web server trace and some of our web cache traces, PS can actually be preferable to size-based policies. However, our previous work [20] demonstrates that even small increases in R can dramatically increase the performance of non-ideal SRPT and FSP. Hence, we turned to developing a better estimator of service time.

4 Domain-based scheduling

We have found that request file size and service time are weakly correlated and that the performance of size-based scheduling policies are strongly dependent on the degree of this correlation. Given these results, a natural question is whether there is a better service time estimator than file size, one whose estimates are more strongly correlated with actual service time. Such an estimator must also be lightweight, requiring little work per request. For this reason, we cannot use active probing techniques. Instead, we explore the web logs and use past web requests as our probes.

4.1 Statistical stability of the Internet

Domain-based scheduling relies on the Internet being statistically stable over periods of time, particularly from the point of view of the web server. Fortunately, there is significant evidence that this is the case.

Routing stability: Paxson [25] proposed two metrics for route stability, prevalence and persistency. Prevalence, which is of particular interest to us here, is the probability of observing a given route over time. If a route is prevalent, then the observation of it allows us to predict that it will be used again. Persistency is the frequency of route changes. The two metrics are not closely correlated. Paxson's conclusions are that Internet paths are heavily dominated by a single route, but that the time periods over which routes persist show wide variation, ranging from seconds to days. However, 2/3 of the Internet paths Paxson studied had routes that persisted for days to weeks. Chinoy found that route changes tend to concentrate at the edges of the network, not in its "backbone" [11]. Barford, et al measured the web performance in the wide area network and found that the routes from/to the client to/from a web servers was asymmetric, but very stable [9].

Spatial and temporal locality of end-to-end TCP throughput: Balakrishnan, et al analyzed statistical models for the observed end-to-end network performance based on extensive packet-level traces collected from the primary web site for the Atlanta Summer Olympic Games in 1996. They concluded that nearby Internet hosts often have almost identical distributions of observed throughput. Although the size of the clusters for which the performance is identical varies as a function of their location on the Internet, cluster sizes in the range of 2 to 4 hops work well for many regions. They also found that end-to-end throughput to hosts often varied by less than a factor of two over timescales on the order of many tens of minutes, and that the throughput was piecewise stationary over timescales of similar magnitude [7]. Seshan, et al applied these findings in the development of the Shared Passive Network Performance Discovery (SPAND) system [27]. Myers, et al examined performance from a wide range of clients to a wide range of servers and found that bandwidth to the servers and server rankings from the point of view of a client were remarkably stable over time [23]. Yin Zhang, et al [29] found that three Internet path properties, loss rate, delay and TCP throughput show various degrees of constancy and concluded that one can generally count on constancy on the time scale of minutes.

4.2 Algorithm

Although the Internet, web servers, and clients form a highly dynamic system, the stability we pointed out in the previous section suggests that previous web requests (the web server's access log) are a rich history which can be used to better estimate the service time of a new request. We assume that after processing a request we know (1) its file size, (2) the actual service time, and (3) the IP address of the client. Collecting this information is simple and efficient. Our goal is to develop an efficient estimator that uses a history of such requests, combined with the file size and IP address of the current request to determine the likely service time of the current request. The correlation R between the estimated service time and the actual service time should be higher than the correlation between file size and actual service time. R must exceed a threshold in order for SRPT to perform better than PS, and as R increases, the performance of SRPT increases.

Classless Inter Domain Routing (CIDR) [15] was proposed in 1993 as "a strategy for address assignment of the existing IP address space with a view to conserve the address space and stem the explosive growth of routing tables in default-route-free routers". The CIDR strategy has been widely deployed since 1993. "One major goal of the CIDR addressing plan is to allocate Internet address space in such a manner as to allow aggregation of routing information along topological lines". Consider a *domain*, a neighborhood in the network topology. The broad use of CIDR implies that routes from machines in the domain to a server outside the domain will share many hops. Similarly, the routes from the server to different machines in the domain will also have considerable overlap. This also means that the routes will be likely to share the same bottleneck network link and therefore have similar throughput to/from the server. The smaller the domain, the more the sharing.

The aggregation of CIDR is along a hierarchy of increasingly larger networks and is reflected in IP addresses. The first k bits of an IP address gives the network of which the address is a part, the first $k-1$ bits give the broader network that contains the first network, and so on. We exploit this hierarchy in domain-based scheduling, the algorithm of which is given below.

1 Use the high order k bits of the client IP address to classify the clients into 2^k domains, where the k bits are treated as the domain address.

2 Aggregate past requests to estimate the service rate (or representative bandwidth) for each domain. This can be done with several estimators, but our experiments show that the estimator $S_R = \frac{F_s}{S_t}$ performs the best. Here S_R is the representative service rate, F_s is the sum of the requested file sizes from the domain, and S_t is the sum of the service times for these requests. Notice that updating this estimate after a request has been processed is trivial: simply add the request's file size and service time to F_s and S_t, respectively (two reads, two adds, two writes). For each domain, we store F_s and S_t. An array of these pairs is kept, indexed by the domain address. The total state size is 2^{k+1} floating point numbers.

3 For each incoming client request, the web server first extracts the domain address, indexes the array and computes S_R for the domain. It then estimates the request's service time as $T_{estimate} = \frac{f_s}{S_R}$, where f_s is the request file size. The estimator requires a logical shift, two reads, a division, and a multiply. For a request from a heretofore unobserved domain, which occurs exactly once per domain, we simply use file size as the estimate.

4 Apply a size-based scheduling policy such as SRPT using the estimated service times. We suffix the scheduling policy with "-D": SRPT-D, FSP-D.

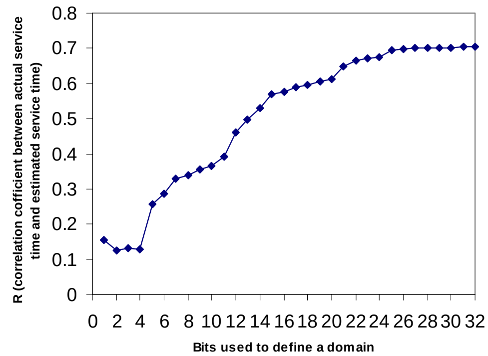


Figure 10. R versus bits k defining domain.

As we might expect, as domains become smaller (k gets larger), predictive performance increases, at the cost of memory to store the state. Figure 10 shows the relationship between k, the number of bits used to define a domain and the correlation R between the actual service time and estimated service time. The figure is derived from our web server trace. R jumps to 0.26 with $k = 5$ bits, beyond the threshold at which SRPT begins to perform better than PS. Notice that this is a mere 32 domains (state size of 256 bytes with 4 byte floats). After $k = 24$ bits, there are only very small increases of R, probably because at this point we have divided the Internet into LANs, where each machine on a LAN shares a common route to every other machine in the Internet, and thus shares the same bottlenecks. The maximum R

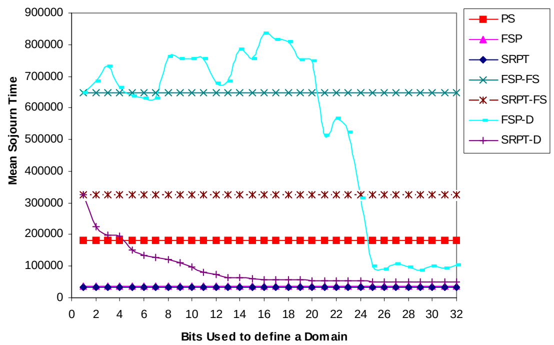


Figure 11. Mean sojourn time versus k for web trace, G/G/1/m, Pareto arrivals with $\alpha = 1.32$ and bounds $[84, 5 \times 10^5]$, load 0.88.

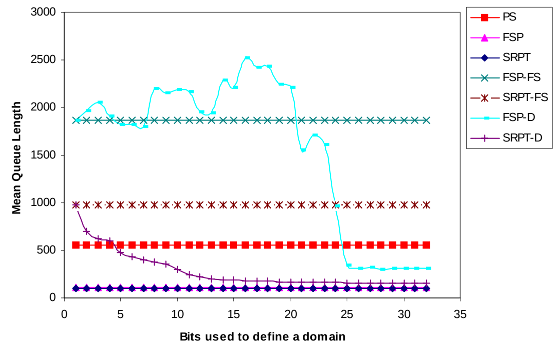


Figure 12. Mean queue length versus k for web trace, G/G/1/m, Pareto arrivals with $\alpha = 1.32$ and bounds $[84, 5 \times 10^5]$, load 0.88.

we were able to achieve was 0.704.

4.3 Performance evaluation

To evaluate domain-based scheduling (SRPT-D and FSP-D, also see Figure 1), we use the methodology of Section 3.2. We replay our web trace with Poisson, Pareto, and Weibull arrivals to control load. We vary k, the number of high-order bits we use to define a domain.

Figures 11 and 12 show the mean sojourn time and mean queue length of all the scheduling policies with heavy-tailed Pareto arrivals as a function of k. Notice that PS, FSP, SRPT, FSP-FS, and SRPT-FS are flat lines. PS ignores service time. FSP and SRPT have exact knowledge of the service times (they represent the ideal performance of these policies). FSP-FS and SRPT-FS use file size as a proxy for service time (representing current practice). Notice that as we increase the number of bits k used to define a domain, the performance of SRPT-D and FSP-D first exceeds that of PS and finally converges to near the ideal performance.

While SRPT-D's performance increases continuously, with diminishing returns, with increasing k, FSP-D is rather insensitive until $k = 16$ to 24 bits, at which point its performance jumps dramatically and comes very close to SRPT-D's. Since R doesn't increase much beyond $k = 24$ bits, as we might expect, the performance of SRPT-D and FSP-D plateaus. Similar conclusions can be drown for Poisson arrivals and Heavy-tailed Weibull arrivals.

Our performance evaluation of SRPT-D and FSP-D demonstrates that better, practical estimators of service time are possible and that they can dramatically improve the performance of size-based scheduling policies on web servers.

5 Conclusions and future work

This paper has made the following contributions. First, we have (1) demonstrated that the assumption that file size is a good indicator of service time for web servers is unwarranted. File size and service time are only weakly correlated. The implication is that size-based scheduling policies that use file size, such as SRPT-FS and FSP-FS are likely to perform worse than expected. Next, using simulations driven by our web server trace, we have (2) evaluated the performance of SRPT-FS and FSP-FS and found that their performance does indeed degrade dramatically due to the weak correlation reflected in the trace. In response, we (3) proposed, implemented, and evaluated a better service time estimator that makes use of the hierarchical nature of routing on the Internet and the history of past requests available on the web server. We refer to SRPT and FSP augmented with our domain-based estimator as SRPT-D and FSP-D. The state size of our estimator is a parameter. Finally, we (4) found that, with a small state size, SRPT-D can outperform PS, and with a practical state size, SRPT-D can exhibit close to ideal performance. FSP-D requires a significantly larger state size to perform close to its ideal. SRPT reacts very quickly to increasingly accurate service time estimates.

Because the TCP connection (and disk) that a request uses can block, implementations of size-based scheduling in web servers often use what we call *back-filling*. An executing request that becomes blocked is preempted in favor of a request with a larger number of bytes remaining to be handled—it is the non-blocked request of smallest remaining size that is run, not the smallest request. Our simulations do not model such a system. However, as far as we are aware, there are no analytical results for size-based scheduling with blocking behavior either, making it quite difficult to validate a simulator.

References

[1] The apache software foundation. http://www.apache.org/.

[2] Bonnie, a unix file system benchmark. http://www.textuality.com/bonnie/.

[3] The internet traffic archive. http://ita.ee.lbl.gov/.

[4] The ircache project. http://www.ircache.net/.

[5] The squid web proxy cache project. http://www.squid-cache.org/.

[6] ALLEN, A. O. *Probability, statistics, and queueing theory with computer science applications*. Academic press, Inc., 1990.

[7] BALAKRISHNAN, H., SESHAN, S., STEMM, M., AND KATZ, R. H. Analyzing Stability in Wide-Area Network Performance. In *Proceedings of ACM SIGMETRICS* (June 1997), pp. 2–12.

[8] BANSAL, N., AND HARCHOL-BALTER, M. Analysis of SRPT scheduling: investigating unfairness. In *Proceedings of SIGMETRICS/Performance* (2001), pp. 279–290.

[9] BARFORD, P., AND CROVELLA, M. Measuring web performance in the wide area. *Performance Evaluation Review 27*, 2 (1999), 37–48.

[10] BUX, W. Analysis of a local-area bus system with controlled access. *IEEE Transactions on Computers 32*, 8 (1983), 760–763.

[11] CHINOY, B. Dynamics of internet routing information. In *Proceedings of SIGCOMM* (1993), pp. 45–52.

[12] DENG, S. Empirical model of WWW document arivals at access links. In *Proceedings of the IEEE International Conference on Communication* (June 1996), pp. 1797–1802.

[13] DINDA, P., AND O'HALLARON, D. An evaluation of linear models for host load prediction. In *8th IEEE International Symposium on High Performance Distributed Computing (HPDC-8)* (1999), pp. 87–96.

[14] FRIEDMAN, E. J., AND HENDERSON, S. G. Fairness and efficiency in web server protocols. In *Proceedings of SIGMETRICS/Performance* (2003), pp. 229–237.

[15] FULLER, V., LI, T., YU, J., AND VARADHAN, K. (rfc1519) Classless Inter-Domain Routing (CIDR): an address assignment and aggregation strategy, September 1993.

[16] GONG, M., AND WILLIAMSON, C. Quantifying the properties of srpt scheduling. In *Proceedings of IEEE MASCOTS* (2003), pp. 126–135.

[17] GONG, M., AND WILLIAMSON, C. Simulation evaluation of hybrid srpt scheduling policies. In *Proceedings of IEEE MASCOTS* (2004), pp. 355–363.

[18] HARCHOL-BALTER, M., SCHROEDER, B., BANSAL, N., AND AGRAWAL, M. Size-based scheduling to improve web performance. *ACM Transactions on Computer Systems (TOCS) 21*, 2 (May 2003), 207–233.

[19] KRISHNAMURTHY, B., AND REXFORD, J. *Web Protocols and Practice: HTTP1.1, Networking Protocols, Caching, and Traffic Measurements*. Addison-Wesley, 2001.

[20] LU, D., SHENG, H., AND DINDA, P. Size-based scheduling policies with inaccurate scheduling information. In *Proceedings of IEEE MASCOTS* (2004), pp. 31–38.

[21] MANLEY, S., AND SELTZER, M. Web Facts and Fantasy. In *Proceedings of the 1997 Usenix Symposium on Internet Technologies and Systems (USITS97)* (Monterey, CA, 1997), pp. 125–134.

[22] MUTKA, M. W., AND LIVNY, M. The available capacity of a privately owned workstation environment. *Performance Evaluation 12*, 4 (July 1991), 269–284.

[23] MYERS, A., DINDA, P. A., AND ZHANG, H. Performance characteristics of mirror servers on the internet. In *Proceedings of IEEE INFOCOM* (1999), pp. 304–312.

[24] PADMANABHAN, V. N., AND SRIPANIDKULCHAI, K. The case for cooperative networking. In *IPTPS* (2002), pp. 178–190.

[25] PAXSON, V. End-to-end routing behavior in the Internet. In *Proceedings of the ACM SIGCOMM* (New York, August 1996), ACM Press, pp. 25–38.

[26] PAXSON, V., AND FLOYD, S. Wide area traffic: the failure of Poisson modeling. *IEEE/ACM Transactions on Networking 3*, 3 (1995), 226–244.

[27] SESHAN, S., STEMM, M., AND KATZ, R. H. SPAND: Shared passive network performance discovery. In *Proceedings of the USENIX Symposium on Internet Technologies and Systems* (1997), pp. 135–146.

[28] WESSELS, D., AND CLAFFY, K. ICP and the Squid Web cache. *IEEE Journal on Selected Areas in Communication 16*, 3 (1998), 345–357.

[29] ZHANG, Y., DU, N., PAXSON, V., AND SHENKER, S. On the constancy of internet path properties. In *Proceedings of the ACM SIGCOMM Internet Measurement Workshop* (2001), pp. 197–211.