

Cataclysm: Policing Extreme Overloads in Internet Services

Bhuvan Urgaonkar and Prashant Shenoy
Department of Computer Science,
University of Massachusetts, Amherst MA 01003
 {bhuvan, shenoy}@cs.umass.edu

Abstract—In this paper we present the Cataclysm server platform for handling extreme overloads in hosted Internet applications. The primary contribution of our work is to develop a comprehensive overload control approach that brings together admission control, dynamic provisioning of platform resources, and adaptive degradation of QoS. Cataclysm provides several desirable features under overloads, such as preferential admission of important requests, the ability to handle diverse workloads, and revenue maximization at multiple time-scales via dynamic provisioning and size-based admission control. Cataclysm can transparently tradeoff the accuracy of its decision making with the intensity of the workload allowing it to handle incoming rates of several tens of thousands of requests/second. We implement a prototype Cataclysm hosting platform on a Linux cluster and demonstrate the benefits of our integrated approach using a variety of workloads.

Categories—System Design, Experimentation with real Testbed.

I. INTRODUCTION

During the past decade, there has been a dramatic increase in the popularity of Internet applications such as online news, online auctions and electronic commerce. It is well known that the workload seen by Internet applications varies over multiple time-scales and often in an unpredictable fashion [22]. Certain workload variations such as time-of-day effects are easy to predict and handle by appropriate capacity provisioning [10]. Other variations such as flash crowds are often unpredictable. On September 11th 2001, for instance, the workload on a popular news web site increased by an order of magnitude in thirty minutes, with the workload doubling every seven minutes in that period [22]. Similarly, the load on e-commerce retail web sites can increase dramatically during the final days of the popular holiday season.

In this paper, we focus on handling extreme overloads seen by Internet applications. Informally, an extreme overload is a scenario where the workload unexpectedly increases by up to an order of magnitude in a few tens of

minutes. Our goals are (i) to design a system that remains operational even in the presence of an extreme overload and even when the incoming request rate is several times greater than system capacity, and (ii) to maximize the utility due to the requests serviced by the application during such an overload. We assume that Internet applications or services run on a *hosting platform*—essentially a server cluster that rents its resources to applications. Application providers pay for server resources, and in turn, are provided performance guarantees, expressed in the form of a *service level agreement (SLA)*. A hosting platform can take one or more of three actions during an overload: (i) add capacity to the application by allocating idle or under-used servers, (ii) turn away excess requests and preferentially service only “important” requests, and (iii) degrade the performance of admitted requests in order to service a larger number of aggregate requests.

In this paper, we argue that a comprehensive approach for handling extreme overloads should involve a synergistic combination of all of the above techniques. A hosting platform should, whenever possible, allocate additional capacity to an application in order to handle increased demands. The platform should degrade performance in order to temporarily increase effective capacity during overloads. When no capacity addition is possible or when the SLA does not permit any further performance degradation, the platform should turn away excess requests. While doing so, the platform should preferentially admit important requests and turn away less important requests to maximize overall utility. For instance, small requests may be preferred over large requests, or financial transactions may be preferred over casual browsing requests.

We present the design of the Cataclysm server platform to achieve these goals. Cataclysm is specifically designed to handle extreme overloads in Internet applications and differs from past work in several significant respects.

First, since an extreme overload may involve request rates that are *an order of magnitude greater than the currently allocated capacity*, the admission controller must be able to quickly examine requests and discard a large frac-

tion of these requests, when necessary, with minimal overheads. Thus, the efficiency of the admission controller is important during heavy overloads. To address this issue, we propose very low overhead admission control mechanisms that can scale to very high request rates under overloads. Past work on admission control [5], [8], [24], [27] has focused on the mechanics of policing and did not specifically consider the *scalability* of these mechanisms. In addition to imposing very low overheads, our mechanisms can preferentially admit important requests during overload and transparently tradeoff accuracy of their decision making with the intensity of the workload. The tradeoff between accuracy and efficiency is another contribution of our work and enables our implementation to scale to incoming rates of up to a few tens of thousands of requests/s.

Second, our dynamic provisioning mechanism employs a G/G/1-based queuing model of a replicable application in conjunction with online measurements to dynamically vary the number of servers allocated to each application. A novel feature of our platform is its ability to not only vary the number of servers allocated to an application but also other components such as the admission controller and the load balancing switches. Dynamic provisioning of the latter components has not been considered in prior work.

Last, our work demonstrates that dynamic provisioning and admission control can be coupled in useful ways to enhance the ability of the platform in handling extreme overloads. For instance, the admission controller can proactively invoke dynamic provisioning when the request drop rates exceeds a certain threshold, and the provisioning mechanisms can provide useful information to the admission controller for policing requests. Past work on admission control [5], [8], [24], [27] and dynamic provisioning [3], [21] considered each technique in isolation and did not study the impact of such couplings.

We have implemented a prototype Cataclysm hosting platform on a cluster of twenty Linux servers. We demonstrate the effectiveness of our integrated overload control approach via an experimental evaluation. Our results show that (i) preferentially admitting requests based on importance and size can increase the utility and effective capacity of an application, (ii) our provisioning is both agile and effective at diverting platform resources to where they are needed most, thus improving platform revenue.

The rest of this paper is organized as follows. Section II provides an overview of the proposed system. Sections III and IV describe the mechanisms that constitute our overload management solution. Section V describes the implementation of our prototype. In Section VI we present the results of our experimental evaluation. Section VII

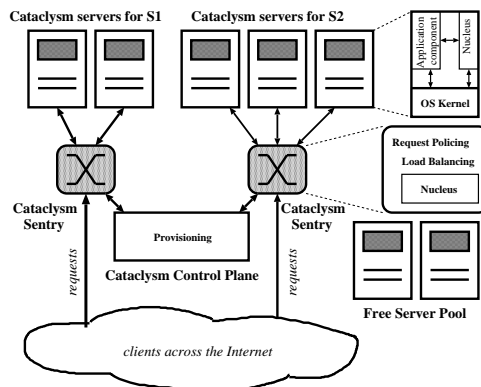


Fig. 1. The Cataclysm Hosting Platform Architecture.

presents related work and Section VIII concludes this paper.

II. SYSTEM OVERVIEW

In this section, we present the system model for our Cataclysm hosting platform and the model assumed for Internet applications running on the platform.

A. Cataclysm Hosting Platform

The Cataclysm hosting platform consists of a cluster of commodity servers interconnected by a modern LAN technology such as gigabit Ethernet. One or more high bandwidth links connect this cluster to the Internet. Each node in the hosting platform can take on one of three roles: cataclysm server, cataclysm sentry, or cataclysm control plane (see Figure 1).

Cataclysm Servers: Cataclysm servers are nodes that run Internet applications. The hosting platform may host multiple applications concurrently. Each application is assumed to run on a subset of the nodes, and a node is assumed to run no more than one application at any given time. A subset of the servers may be unassigned and form the *free server pool*. The number of servers assigned to an application can change over time depending on its workload. Each server also runs the cataclysm nucleus—a software component that performs online measurements of application-specific resource usages, which are then conveyed to the other two components that we describe next.

Cataclysm Sentry: Each application running on the platform is assigned one or more sentries. A sentry guards the servers assigned to an application and is responsible for two tasks. First, the sentry polices all requests to an application’s server pool—incoming requests are subjected to admission control at the sentry to ensure that the contracted performance guarantees are met; excess requests are turned away during overloads. Second, each sentry implements a layer-7 switch that performs load balancing

across servers allocated to an application. Since there has been substantial research on load balancing techniques for clustered Internet applications [19], we do not consider load balancing techniques in this work.

Cataclysm Control Plane: The control plane is responsible for dynamic provisioning of servers and sentries in individual applications. It tracks the resource usages on nodes, as reported by Cataclysm nuclei, and determines the resources (in terms of the number of servers and sentries) to be allocated to each application.

B. Model for Internet Applications

The Internet applications considered in this work are assumed to be inherently replicable. That is, the application is assumed to run on a cluster of servers, and it is assumed that running the application on a larger number of servers results in an effective increase in capacity. Many, but by no means all, Internet applications fall into this category. Vanilla clustered web servers are an example of a replicable application. Multi-tiered Internet applications are partially replicable. A typical multi-tiered application has three components: a front-end HTTP server, a middle-tier application server, and a back-end database server. The front-end HTTP server is easily replicable but is not necessarily the bottleneck. The middle-tier—a frequent bottleneck—can be implemented in different ways. One popular technique is to use server-side scripting such as Apache’s *php* functionality, or to use cgi-bin scripting languages such as *perl*. If the scripts are written carefully to handle concurrency, it is possible to replicate the middle-tier as well. More complex applications use Java application servers to implement the middle-tier. Dynamic replication of Java application servers is more complex and techniques for doing so are beyond the scope of this paper. Dynamic replication of back-end databases is an open research problem. Consequently, most dynamic replication techniques in the literature, including this work, assume that the database is sufficiently well provisioned and does not become a bottleneck even during overloads.

Given a replicable Internet application, we assume that the application specifies the desired performance guarantees in the form of a service level agreement (SLA). An SLA provides a description of the QoS guarantees that the platform will provide to the application. The SLA we consider in our work is defined as follows:

$$\text{Avg resp time } R \text{ of adm req} = \begin{cases} \mathcal{R}_1 & \text{if arrival rate} \in [0, \lambda_1) \\ \mathcal{R}_2 & \text{if arrival rate} \in [\lambda_1, \lambda_2) \\ \dots & \dots \\ \mathcal{R}_k & \text{if arrival rate} \in [\lambda_{k-1}, \infty) \end{cases} \quad (1)$$

Arrival rate	Avg. resp. time for admitted requests
< 1000	1 sec
1000-10000	2 sec
> 10000	3 sec

TABLE I

A SAMPLE SERVICE-LEVEL AGREEMENT.

The SLA specifies the revenue that is generated by each request that meets its response time target. Table I illustrates an example SLA. Additionally, the SLA may also specify a lower bound on the number of servers that an application should be assigned.

Each Internet application consists of $L(L \geq 1)$ request classes: C_1, \dots, C_L . The class of a request determines its importance—requests of class C_1 are treated as most important and those of C_L as the least important. The number of request classes L and the function that maps requests to classes is application-dependent. To illustrate, an online brokerage web site may define three classes and may map financial transactions to C_1 , other types of requests such as balance inquiries to C_2 , and casual browsing requests from non-customers to C_3 .

III. CATACLYSM SENTRY DESIGN

In this section, we describe the design of a Cataclysm sentry whose primary goal is to maximize the application’s revenue. The sentry is responsible for two tasks—request policing and load balancing. As indicated earlier, the load balancing technique used in the sentry is not a focus of this work, and we assume the sentry employs a layer-7 load balancing algorithm such as [19]. The first key issue that drives the design of the request policer is that of providing *class-based differentiation* to the application: a request should not be denied service due to capacity assigned to a request of a less important class. Given our focus on extreme overloads, the design of the policer is also influenced by the second key issue of *scalability*—ensuring very low overhead admission control tests in order to scale to very high request arrival rates seen during overloads. This section elaborates on these two issues.

From a theoretical point of view, the problem of conducting admission control to maximize the number of admitted requests while providing class-based differentiation can be shown to be NP-hard. Due to lack of space we omit the proof here and present it in [23]. With these insights into the properties of the admission control problem, we focus on designing a policer that provides the desired differentiation *with high probability*.

A. Request Policing Basics

The sentry maps each incoming request to one of the classes C_1, \dots, C_L . Each class has a queue associated with it; incoming requests are appended to the corresponding class-specific queue (see Figure 2). Requests within each class can be processed either in FIFO order or in order of their service times. In the former case, all requests within a class are assumed to be equally important, whereas in the latter case smaller requests are given priority over larger requests within each class. Admitted requests are handed to the load balancer, which then forwards them to one of the Cataclysm servers in the application’s server pool.

The policer incorporates the following two features to achieve class-based differentiation.

- (1) The policer introduces *different amounts of delay* in the processing of newly arrived requests belonging to different classes. Specifically, requests of class C_i are processed by the policer once every d_i time units ($d_1 = 0 \leq d_2 \leq \dots \leq d_L$); requests arriving during successive processing instants wait for their turn in their class-specific queues. These delay values, determined periodically, are chosen to reduce the chance of admitting less important requests into the system when they are likely to deny service to more important requests that arrive shortly thereafter. In Section III-E we show how to pick these delay values such that the probability of a less important request being admitted into the system and denying service to a more important request that *arrives later* remains sufficiently small.
- (2) The policer processes queued requests in the decreasing order of importance—requests in C_1 are subjected to the admission control test first, and then those in C_2 and so on. Doing so ensures that requests in class C_i are given higher priority than those in class C_j , $j > i$. The admission control test—which is described in detail in the next section—admits requests so long as the system has sufficient capacity to meet the contracted SLA. Note that, if requests in a certain class C_i fail the admission control test, all queued requests in less important classes can be rejected without any further tests.

Observe that the above admission control strategy meets one of our two goals—it preferentially admits only important requests during an overload and turns away less important requests. However, the strategy needs to invoke the admission control test on each individual request, resulting in a complexity of $O(r)$, where r is the number of queued up requests. Further, when requests within a class are examined in order of service times instead of FIFO, the complexity increases to $O(r \cdot \log(r))$ due to the need to sort requests. Since the incoming request rate can be

substantially higher than capacity during an extreme overload, running the admission control test on every request or sorting requests prior to admission control may be simply infeasible. Consequently, in what follows, we present two strategies for very low overhead admission control that scale well during overloads.

We note that a newly arriving request imposes two types of computational overheads on the policer—(i) protocol processing and (ii) the admission control test itself. Clearly, both these components need to scale for effective handling of overloads. When protocol processing starts becoming bottleneck, we respond by increasing the number of sentries guarding the overloaded application—a technique that we describe in detail in Section IV-C. In this section we present techniques to deal with the scalability of the admission control test.

B. Efficient Batch Processing

One possible approach for reducing the policing overhead is to process requests in *batches*. Request arrivals tend to be very bursty during severe overloads, with a large number of requests arriving in a short duration of time. These requests are queued up in the appropriate class-specific queues at the sentry. Our technique exploits this feature by conducting a single admission control test on an entire batch of requests within a class, instead of doing so for each individual request. Such batch processing can amortize the admission control overhead over a larger number of requests, especially during overloads.

To perform efficient batch-based admission control, we define b buckets within each request class. Each bucket has a range of request service times associated with it. The sentry estimates the service time of a request and then hashes it into the bucket corresponding to that service time. To illustrate, a request with an estimated service time in the range $(0, s_1]$ is hashed to bucket 1, that with service time in the range $(s_1, s_2]$ to bucket 2, and so on. By defining an appropriate hashing function, hashing a request to a bucket can be implemented efficiently as a constant time operation.

Bucket-based hashing is motivated by two reasons. First, it groups request with similar service times and enables the policer to conduct a single admission control test by assuming that all requests in a bucket impose similar service demands. Second, since successive buckets contain requests with progressively larger service times, the technique implicitly gives priority to smaller requests. Moreover, no sorting of requests is necessary—the hashing implicitly “sorts” requests when mapping them into buckets.

When the admission control is invoked on a request class, it considers each non-empty bucket in that class and

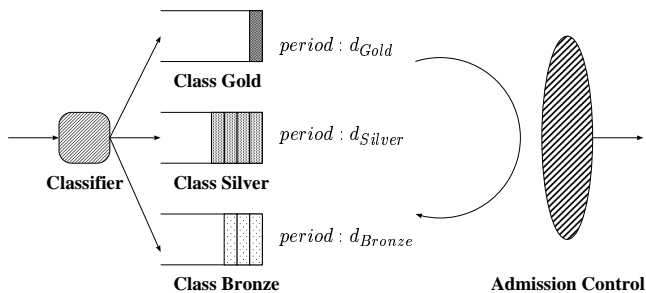


Fig. 2. Class-based differentiation in the Cataclysm sentry.

conducts a single admission control test on all requests in that bucket. (i.e., all requests in a bucket are treated as a batch). Consequently, no more than b admission control tests are needed within each class, one for each bucket. Since there are L request classes, this reduces the admission control overhead to $O(b \cdot L)$, which is substantially smaller than the $O(r)$ overhead for admitting individual requests.

Having provided the intuition behind batch-based admission control, we discuss the hashing process and the admission control test in detail. In order to hash a request into a bucket, the sentry must first estimate the inherent service time of that request. The *inherent service time* of a request is the time needed to service the request on a lightly loaded server (i.e., when the request does not see any queuing delays). The inherent service time of a request \mathcal{R} is defined to be

$$S_{inherent} = \mathcal{R}_{cpu} + \alpha \cdot \mathcal{R}_{data} \quad (2)$$

where \mathcal{R}_{cpu} is the total CPU time needed to service \mathcal{R} , \mathcal{R}_{data} is the IO time of the request (which includes the time to fetch data from disk, the time the request is blocked on a database query, the network transfer time, etc.), and α is an empirically determined constant. The inherent service time is then used to hash the request into an appropriate bucket—the request maps to a bucket i such that $s_i \leq S_{inherent} \leq s_{i+1}$.

The specific admission control test for each batch of requests within a bucket is as follows. Let β denote the batch size (i.e., the number of requests) in a bucket. Let Q denote the estimated queuing delay seen by each request in the batch. The queuing delay is the time the request has to wait at a Cataclysm server before it receives service; the queuing delay is a function of the current load on the server and its estimation is discussed in Section III-D. Let η denote the average number of requests (connections) that are currently being serviced by a server in the application’s server pool. Then the β requests within a batch are admitted if and only if the sum of the queuing delay seen by a request and its actual service time does not exceed the

contracted SLA. That is,

$$Q + \left(\eta + \left\lceil \frac{\beta}{n} \right\rceil \right) \cdot S \leq R_{sla} \quad (3)$$

where S is the average inherent service time of the requests in a batch, n is the number of servers allocated to the application, and R_{sla} is the desired response time. The term $(\eta + \lceil \frac{\beta}{n} \rceil) \cdot S$ is an estimate of the *actual* service time of the *last* request in the batch, and is determined by scaling the inherent service time S by the server load—which is the number of the requests currently in service, i.e., η , plus the number of requests from the batch that might be assigned to the server i.e., $\lceil \frac{\beta}{n} \rceil$. Rather than actually computing the mean inherent service time of the request in a batch, it is approximated as $S = (s_i + s_{i+1})/2$, where $(s_i, s_{i+1}]$ is the service time range associated with the bucket.

As indicated above, the admission control is invoked for each class periodically—once every d_i time units for newly arrived requests of class C_i . The invocation is more frequent for important classes and less frequent for less important classes, that is, $d_1 = 0 \leq d_2 \leq \dots \leq d_L$. Since a request may wait in a bucket for up to d_i time units before admission control is invoked for its batch, the above test is modified as

$$Q + \left(\eta + \left\lceil \frac{\beta}{n} \right\rceil \right) \cdot S \leq R_{sla} - d_i \quad (4)$$

In the event this condition is satisfied, all requests in the batch are admitted into the system. Otherwise requests in the batch are dropped.

C. Scalable Threshold-based Policing

We now present a second approach to further reduce the policing overhead. Our technique trades efficiency of the policer for accuracy and reduces the overhead to a few arithmetic operations per request. The key idea behind this technique is to periodically *pre-compute* the fraction of arriving requests that should be admitted in each class and then simply enforce these limits without conducting any additional per-request tests. Our technique uses estimates of future arrival rates and service demands in each class to compute a *threshold*, which is defined to be the pair (class i , fraction p_{admit}). The threshold indicates that all requests in classes more important than i should be admitted ($p_{admit} = 1$), requests in class i should be admitted with probability p_{admit} , and all requests in classes less important than i should be dropped ($p_{admit} = 0$). We determine these parameters based on observations of arrival rates and service times in each classes over periods of moderate length (we use periods of length 15sec). Denoting the arrival rates to classes $1, \dots, L$ by $\lambda_1, \dots, \lambda_L$

and the observed average service times by s_1, \dots, s_L , the threshold (i, p_{admit}) is computed such that

$$\sum_{j=1}^{j=i} \lambda_j \cdot s_j \geq 1 \text{ and } p_{admit} \cdot \lambda_i \cdot s_i + \sum_{j=1}^{j=i-1} \lambda_j \cdot s_j < 1 \quad (5)$$

Thus, admission control now merely involves applying the inexpensive classification function on a new request to determine its class and then using the equally lightweight thresholding function to decide if it should be admitted.

The threshold-based and the batch-based policing strategies need not be mutually exclusive. The sentry can employ the more accurate batch-based policing so long as the incoming request rate permits one admission control test per batch. If the incoming rate increases significantly, the processing demands of the batch-based policing may saturate the sentry. In such an event, when the load at the sentry exceeds a threshold, the sentry can trade accuracy for efficiency by dynamically switching to a threshold-based policing strategy.

D. Online Parameter Estimation

The batch-based and threshold-based policing algorithms require estimates of a number of system parameters:

- Arrival rate λ_i in each request class.
- Queuing delay Q incurred by a request.
- Number of requests in service η .
- Request service time s .
- The constant α in Equation 2.

These parameters are estimated using online measurements. The nuclei running on the cataclysm servers and sentries collectively gather and maintain various statistics needed by the policer. Due to lack of space, we present the details of how these are measured and how inherent service times of incoming requests are estimated in [23].

E. Analysis of the Policer

In this section we show how the sentry can, under certain assumptions, compute the delay values for various classes based on online observations. The goal is to pick delay values such that the *probability of a newly arrived request being denied service due to an already admitted less important request* is smaller than a desired threshold.

Consider the following simplified version of the admission control algorithm presented in Section III-B: Assume that the application runs on only one server—it is easy to extend the analysis to the case of multiple servers. The admission controller lets in a new request if and only if the total number of requests that have been admitted and are being processed by the application does not exceed a

threshold N . Assume the application consists of L request classes C_1, \dots, C_L in decreasing order of importance. We make the simplifying assumption of Poisson arrivals with rates $\lambda_1, \dots, \lambda_L$, and exponentially distributed service times with means s_1, \dots, s_L respectively. As before, $d_1 = 0$. For simplicity of exposition we assume that the delay for class C_2 is d , and $\forall i > 2, d_{i+1} = k_i \cdot d_i, (k_i \geq 1)$. Denote by A_i the event that a request of class C_i has to be dropped at the processing instant $m \cdot d_i, (m > 0)$ and there is at least one request of a less important class $C_j, (j > i)$ still in service. Clearly,

$$Pr(A_1) = 0 \text{ and } Pr(A_L) = 0.$$

We are interested in ensuring

$$\forall i > 1, Pr(A_i) < \epsilon, 0 < \epsilon < 1. \quad (6)$$

Consider $1 < i < L$. For A_i to occur, all of the following must hold: (1) X_i : at least one request of class C_i arrives during the period $[(m-1) \cdot d_i, m \cdot d_i]$, (2) Y_i : the number of requests in service at time $m \cdot d_i$ is N , (3) Z_i : at least one of the requests being serviced belongs to one of the classes C_{i+1}, \dots, C_L . We have,

$$Pr(A_i) = Pr(X_i \wedge Y_i \wedge Z_i)$$

During overloads, we can assume that the number of requests in service would be N with a high probability p_{drop} . The policer will record p_{drop} over short periods of time. Also, X_i and Z_i are independent. This lets us have

$$Pr(A_i) \approx Pr(X_i) \cdot p_{drop} \cdot Pr(Z_i) \quad (7)$$

$$Pr(X_i) = 1 - e^{-\lambda_i \cdot d_i} \quad (8)$$

Denote by $Z_i^j, (i < j \leq L)$ the event that at least one of the requests being serviced at time $m \cdot d_i$ belongs to the class j . Clearly,

$$Pr(Z_i) = \sum_{j=i+1}^{j=L} Pr(Z_i^j) \quad (9)$$

Let us now focus on the term $Pr(Z_i^j)$. The event Z_i^j is the disjunction of the following events, one for each $l, (l > 0)$: P_j^l : at least one request of class j arrives during the period $[m \cdot d_i - (l+1) \cdot d_j, m \cdot d_i - l \cdot d_j]$ and Q_j^l : at least one request of class j is admitted at the processing instant $m \cdot d_i - l \cdot d_j$ and R_j^l : the service time of at least one admitted request is long enough so that it is still in service at time $m \cdot d_i$. As in Equation (8),

$$Pr(P_j^l) = 1 - e^{-\lambda_j \cdot d_j} \quad (10)$$

Consider R_j^l . During an overload each admitted request competes at the server with $(N-1)$ other requests during

most of its lifetime. A fair approximation then is to assume that a request takes N times its service time to finish. Therefore, we have,

$$Pr(R_j^l) = e^{\frac{-l \cdot d_j}{s_j \cdot N}} \quad (11)$$

We approximate Q_j using the following reasoning. During overloads, a request of class C_j will be admitted at processing instant t only if the number of requests in service at time t is less than N (the probability of this is approximated as $(1 - p_{drop})$) and no request of a more important class C_h arrived during $[t - d_h, t]$. That is,

$$Pr(Q_j) \approx (1 - p_{drop}) \cdot \prod_{h=1}^{h=j-1} e^{-\lambda_h \cdot d_h} \quad (12)$$

Combining Equations (7)-(12), we get the following approximation. $Pr(A_i)$,

$$Pr(A_i) \approx p_{drop} \cdot (1 - p_{drop}) \cdot (1 - e^{-\lambda_i \cdot d_i}) \cdot \sum_{j=i+1}^{j=L} \frac{(1 - e^{-\lambda_j \cdot d_j}) \cdot \prod_{h=1}^{h=j-1} e^{-\lambda_h \cdot d_h}}{e^{\frac{d_j}{s_j \cdot N}} - 1}$$

The above approximation of $Pr(A_i)$ provides a procedure for iteratively computing the d_i values using numerical methods. We pick delay values that make the term on the right hand side smaller than the desired bound ϵ for all i . This in turn guarantees that the inequalities in (6) are satisfied.

IV. PROVISIONING FOR CATACLYSMS

Policing mechanisms may turn away a significant fraction of the requests during overloads. In such a scenario, an increase in the effective application capacity is necessary to reduce the request drop rate. The Cataclysm control plane implements dynamic provisioning to vary the number of allocated servers based on application workloads. The application's server pool is increased during overloads by allocating servers from the free pool or by reassigning under-used servers from other applications. The control plane can also dynamically provision sentry servers when the incoming request rates imposes significant processing demands on the existing sentries. The rest of this section discusses techniques for dynamically provisioning Cataclysm servers and sentries.

A. Queuing-theoretic Model for Replicable Applications

We use queuing theory to model the revenue obtained from assigning a certain number of servers to a replicable application under a given workload. Our model does not make any assumptions about the nature of the request

arrival processes or the service times. Our abstraction of a single replica of a service is a G/G/1 queuing system. The following bound is known for a G/G/1 queuing system [13]:

$$\lambda \geq \left[E[S] + \frac{\sigma_a^2 + \sigma_b^2}{2 \cdot (E[R] - E[S])} \right]^{-1} \quad (13)$$

Here $E[R]$ is the average response time, $E[S]$ is the average service time, λ is the request arrival rate, $\rho = \lambda \cdot E[S]$ is the utilization, and σ_a^2 and σ_b^2 are the variance of inter-arrival time and the variance of service time respectively. It should be pointed out that a number of similar models for simple, replicable applications have been proposed in recent work ([7], [11], [21], [25]) and any of these could potentially be used by our provisioning algorithm. The comparison of our model with these other models is not relevant to our current discussion of overload management and therefore beyond the scope of this work. Modeling of more complex, multi-tiered Internet applications is part of our ongoing research.

Inequality (13) gives a lower bound on the request arrival rate for which one application replica will be able to provide an average response time of $E[R]$. We denote this by λ_{in} henceforth. Let $C(a, n)$ denote the revenue obtained from allocating n servers to application a . Recall from the SLA defined in Section II that to determine this, we need to predict the overall arrival rate to the service during the next provisioning cycle (simply cycle henceforth). Having predicted this rate λ_{pred} , the response time target $E[R]$ is read from the entry in the SLA corresponding to an arrival rate of λ_{pred} . Thus we have

$$C(a, n) = n \cdot \lambda_{in} \cdot r \cdot T_{prov} \quad (14)$$

Here, r is the revenue per admitted request that meets its response time target and T_{prov} is length of a cycle. Due to the lower bound k_{min} on the number of servers assigned to a , we only need to compute $C(a, n)$ for the following values of n :

$$k_{min} \leq n \leq \min \left\{ N, p \geq \frac{\lambda_{pred}}{\lambda_{in}} \right\} \quad (15)$$

N is the total number of cataclysm servers in the cluster. These revenue curves are then used to determine a partitioning of the servers among applications that maximizes the expected revenue over the next cycle. This is achieved by solving the following revenue maximization problem

$$\text{Maximize: } \sum_a C(a, n_a)$$

$$\text{Subject to: } \sum_a n_a \leq N$$

For the replicable applications that we consider in our work (see Section II-B), the revenue curves are linear. A

simple greedy heuristic can be used to solve this problem optimally. This heuristic begins by assigning to each application a number of servers equal to the lower bound guaranteed in its SLA. It then proceeds in steps, each resulting in one additional server being assigned to some application. In each step the heuristic determines the application that would experience the most gain in revenue due to an additional server and that has not yet reached its upper bound on the number of servers. This process continues till (1) all the servers have been assigned or (2) all applications have reached their upper bounds or (3) no application would experience a positive gain in revenue due to an additional server.

B. Predictive and Reactive Provisioning

The dynamic provisioning mechanism normally operates in a *predictive* fashion. It is invoked periodically (once every 30 minutes in our prototype) and uses the workload observations in the previous time period to re-allocate servers to applications if necessary. Since overloads are often unanticipated, a sentry of an overloaded application can dynamically invoke the provisioning mechanism whenever the request drop rate exceeds a certain pre-defined value. In such a scenario, the provisioning mechanism operates in a *reactive* mode to counter the overload. The mechanism uses recent workload measurements for the overloaded application to recompute its revenue curve (unlike the predictive mode where all revenue curves are recomputed, only the curve for the overloaded application is recomputed in the reactive mode). The provisioning mechanism then allocates additional servers to the overloaded application. Undesirable oscillations in such allocations are prevented using two constraints: (i) a limit of Δ is imposed on the number of servers that can be allocated to an application in a single step in the reactive mode and (ii) a delay of δ time units is imposed on the duration between two successive invocations of the provisioning mechanism in the reactive mode (δ is set to 5 minutes in our prototype). Recall that our SLA permits degraded response time targets for higher arrival rates. The provisioning mechanism may *degrade* the response time to the extent permitted by the SLA, add more capacity, or a bit of both. The optimization drives these decisions, and the resulting target response times are conveyed to the request policers. Thus, these interactions enable coupling of policing, provisioning, and adaptive performance degradation. We experimentally demonstrate this coupling in Section VI.

C. Sentry Provisioning

In general, allocation and deallocation of sentries is significantly less frequent than that of Cataclysm servers.

Further, the number of sentries needed by an application is much smaller than the number of servers running it. Consequently, a simple provisioning scheme suffices for dynamically varying the number of sentries assigned to an application. Our scheme uses the CPU utilization of the existing sentry servers as the basis for allocating additional sentries (or deallocating active sentries). If the utilization of a sentry stays in excess of a pre-defined threshold $high_{cpu}$ for a certain period of time, it requests the control plane for an additional sentry server. Upon receiving such requests from one or more sentries of an application, the control plane assigns each an additional sentry. Similarly, if the utilization of a sentry stays below a threshold low_{cpu} , it is returned to the free pool while ensuring that the application has at least one sentry remaining. Whenever the control plane assigns (or removes) a sentry server to an application, it repartitions the application's servers pool equally among the various sentries. The DNS entry for the application is also updated upon each allocation or deallocation; a round-robin DNS scheme is used to loosely partition incoming requests among sentries. Since each sentry manages a mutually exclusive pool of servers, it can independently perform admission control and load balancing on arriving requests; the SLA is collectively maintained by virtue of maintaining it at each sentry.

V. IMPLEMENTATION CONSIDERATIONS

We implemented a prototype Cataclysm hosting platform on a cluster of 20 Pentium machines connected via a 1Gbps ethernet switch and running Linux 2.4.20. Each machine in the cluster runs one of the following entities: (1) an application replica, (2) a cataclysm sentry, (3) the cataclysm provisioning, (4) a workload generator for an application. In this section we discuss our implementation of the cataclysm sentry and provisioning.

Cataclysm Sentry: We used *Kernel TCP Virtual Server* (`ktcpvs`) version 0.0.14 [15] to implement the policing mechanisms described in Section III. `ktcpvs` is an open-source, Layer-7 load balancer implemented as a Linux module. It accepts TCP connections from clients, opens separate connections with servers (one for each client) and transparently relays data between these. We modified `ktcpvs` to implement all the sentry mechanisms described in Sections III and IV. The details of our implementation can be found in [23].

Cataclysm Provisioning: Cataclysm provisioning was implemented as a user-space daemon running on a dedicated machine. At startup, it reads information needed to communicate with the sentries and information about the servers in the cluster from a configuration file. It communicates with the sentries over TCP sockets. The sentries

gather and report various statistics needed by the provisioning algorithm over these sockets. The provisioning algorithm can be invoked in the reactive or predictive modes as discussed in Section IV. After determining a partitioning of the cluster’s servers among the hosted applications, the provisioning daemon remotely logs on to the nodes running the sentries to enforce the partitioning.

VI. EXPERIMENTAL EVALUATION

In this section we present the experimental setup followed by the results of our experimental evaluation.

A. Experimental Setup

The cataclysm sentries were run on dual-processor 1GHz machines with 1GB RAM. The Cataclysm control plane (responsible for provisioning) was run on a dual-processor 450MHz machine with 1GB RAM. The machines used as cataclysm servers had 2.8GHz processors and 512MB RAM. Finally, the workload generators were run on machines with processor speeds varying from 450MHz to 1GHz and with RAM sizes in the range 128MB-512MB. All machines ran Linux 2.4.20. In our experiments we constructed replicable applications using the Apache 1.3.28 web server with PHP support enabled. The file set serviced by these web servers comprised files of size varying from 1kB to 256kB to represent the range from small text files to large image files. In addition, the web servers host PHP scripts with different computational overheads. The dynamic component of our workload consist of requests for these scripts. In all the experiments, the SLA presented in Figure I was used for the applications. Application requests are generated using `httperf`, an open-source web workload generator.

B. Class-based Differentiation

Our first experiment investigates the efficacy of the mechanisms employed by the Cataclysm sentry to provide class-based differentiation to requests. The Cataclysm provisioning was kept turned off in this experiment. We constructed a replicated web server consisting of three Apache servers. This application supported three classes of requests—Gold, Silver and Bronze in decreasing order of significance. The class of a request could be uniquely determined from its URL. The delay values for the three classes were fixed at 0, 50 and 100 msec respectively.

The workload consisted of requests for a set of PHP scripts. The capacity of each Apache server for this workload (i.e., the request arrival rate for which the 95th percentile response time of the requests was below the response time target) was determined offline and was found

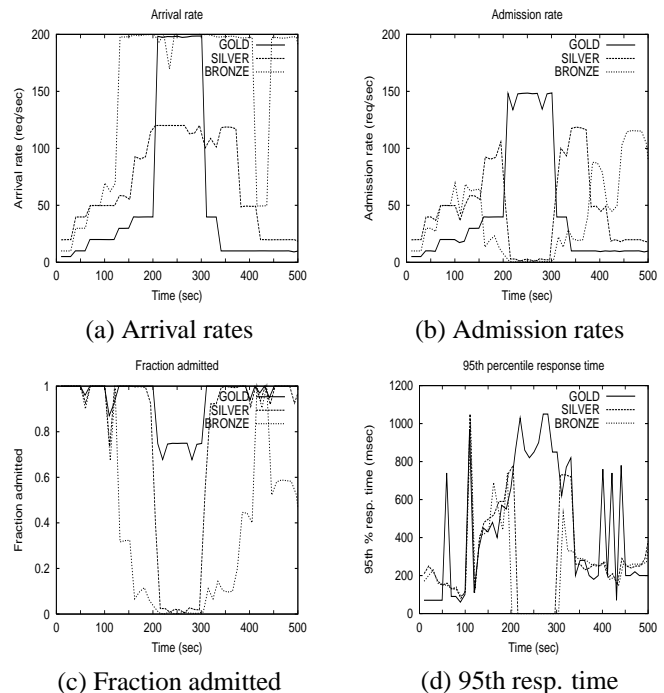


Fig. 3. Demonstration of class-based differentiation achieved by the admission control.

to be nearly 60 requests/sec. Figure 3(a) shows the workload used in this experiment. Nearly all the requests arriving till $t=130$ sec were admitted by the sentry. Between $t=130$ sec and $t=195$ sec, the Bronze requests were dropped almost exclusively. At $t=195$ sec the arrival rate of Silver requests shot up and reached nearly 120 requests/sec. The admission rate of Bronze requests dropped to almost zero to admit as many Silver requests as possible. At $t=210$ sec, the arrival rate of Gold requests shot up to 200 requests/sec. The sentry totally suppressed all arriving Bronze and Silver requests now and let in only Gold requests as long as the increased arrival rate of Gold requests persisted. Figure 3(c) is an alternate representation of the system behavior in this experiment and depicts the variation of the fraction of requests of the three classes that were admitted. Figure 3(d) depicts the performance of admitted requests. We find that the sentry is successful in maintaining the response time below 1000 ms.

C. Scaling to Handle Extreme Overloads

We measured the CPU utilization at the sentry server for different request arrival rates for both the batch-based and the threshold-based admission control. Figure 4 shows our observations of CPU utilization with 95% confidence intervals. Since we were interested only in the overheads of the admission control and not in the data copying overheads inherent in the design of the `ktcpvs` switch, we forced the sentry to drop all requests after conducting the admission control test. We increased the request arrival

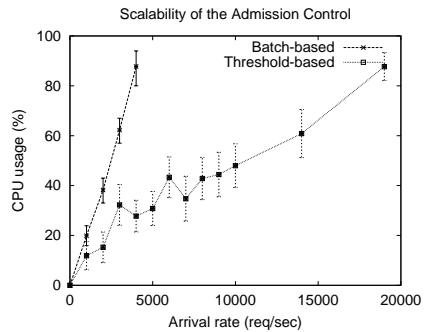


Fig. 4. Scalability of the admission control.

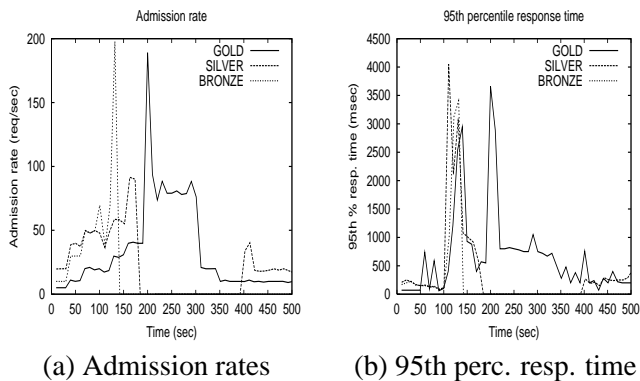


Fig. 5. Performance of the threshold-based admission control. At $t=135$ sec, the threshold was set to reject all Bronze requests; at $t=180$ sec, it was updated to reject all Bronze and Silver requests; at $t=210$ sec it was updated to also reject Gold requests with a probability 0.5; finally, at $t=390$ sec, it was again set to reject only Bronze requests.

rates till the CPU at the sentry server became saturated (nearly 90% utilization). We observe more than a four-fold improvement in the sentry’s scalability—whereas the sentry CPU saturated at 4000 requests/sec with the batch-based admission control, it was able to handle almost 19000 requests/sec with the threshold-based admission control.

A second experiment was conducted to investigate the degradation in the decision making due to the threshold-based admission controller. We repeated the experiment reported in Section VI-B (Figure 3) but forced the sentry to employ the threshold-based admission controller. The thresholds used by the admission control were computed once every 15 sec. Figure 5(a) shows changes in the admission rates for requests of the three classes. The impact of the inaccuracies inherent in the threshold-based admission controller resulted in degraded performance during periods when the threshold chosen was incorrect. We observe two such periods (120-135 sec during which all Bronze requests were dropped and 190-210 sec during which all Bronze and Silver requests were dropped while Gold requests were admitted with probability of 0.5) dur-

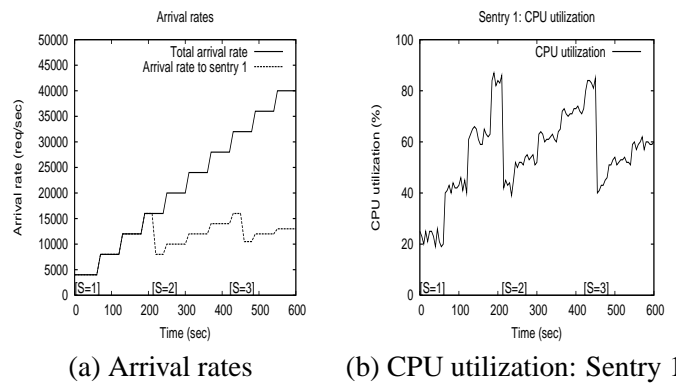


Fig. 6. Dynamic provisioning of sentries. [S= n] means the number of sentries is n now.

ing which the 95th percentile of the response time deteriorated compared to the target of 1000 msec. The response times during the rest of the experiment were kept under control due to the threshold getting updated to a strict enough value.

Finally, we conducted an experiment to demonstrate the ability of the system to dynamically provision additional sentries to a heavily overloaded service. Figure 6 shows the outcome of our experiment. The workload consisted of requests for small static files sent to the sentry starting at 4000 requests/sec and increasing by 4000 requests/sec every minute and is shown in Figure 6(a). If the CPU utilization of the sentry server remained above 80% for more than 30 sec, a request was issued to the control plane for an additional sentry. Figure 6(b) shows the variation of the CPU utilization at the first sentry. At $t=210$ sec, a second sentry was added to the service. Subsequent requests were distributed equally between the two sentries causing the arrival rate and the CPU utilization at the first sentry to drop. A third sentry was added at $t=420$ sec, when the total arrival rate to the service had reached 32000 requests/sec overwhelming both the existing sentries.

D. Cataclysm Provisioning

We conducted an experiment with two web applications hosted on our Cataclysm platform. The total number of cataclysm servers available in this experiment was 11. The SLAs for both the applications were identical and are described in Figure I. Further, the SLAs imposed a lower bound of 3 on the number of servers that each application could be assigned. The default provisioning duration used by the control plane was 30 min.

The workloads for the two applications consisted of requests for an assortment of PHP scripts and files in the size range 1kB-128kB. Requests were sent at a sustainable base rate to the two applications throughout the experiment. Overloads were created by sending increased

number of requests for a small subset of the scripts and static files (to simulate a subset of the content becoming popular). The experiment began with the two applications running on 3 servers each. Sentries invoked the provisioning algorithm when more than 50% of the requests were dropped over a 5 min interval. Figures 7(a) and 7(c) depict the arrival rates to the two applications. The arrival rate for Application 1 was made to increase in a step-like fashion starting from 100 requests/sec, doubling roughly once every 5 min till it reached a peak value of 1600 requests/sec. At this point Application 1 was heavily overloaded with the arrival rate several times higher than system capacity (which was roughly 60 request/sec per server assigned to the service as determined by offline measurements). At $t=910$ sec the sentry, having observed more than 50% of the request being dropped, triggered the provisioning algorithm as described in Section IV. The provisioning algorithm responded by pulling one server from the free pool and adding it to Application 1. At $t=1210$ sec, another server was added to Application 1 from the free pool. Observe in Figure 7(a) the increases in the admission rates corresponding to these additional servers being made available to Application 1. The next interesting event was the default invocation of provisioning at $t=1800$ sec. The provisioning algorithm added all the 3 servers remaining in the free pool to the heavily overloaded Application 1. Also, based on recent observation of arrival rates, it predicted an arrival rate in the range 1000-10000 requests/sec and *degraded the response time target for Application 1* to 2000 msec based on its QoS table (see Figure I). In the latter part of the experiment, the overload of Application 1 subsided and Application 2 got overloaded. The functioning of the provisioning was qualitatively similar to when Service 1 was overloaded. Figures 7(b) and 7(d) show the 95th percentile response times for the two services during the experiment. The control plane was able to predict changes to arrival rates and degrade the response time target according to the SLA resulting in an increased number of requests being admitted. Moreover, the sentries were able to keep the admission rates well below system capacity to achieve response times within the appropriate target with only sporadic violations (which were on fewer than 4% of the occasions).

VII. RELATED WORK

Previous work on overload control in Internet platforms spans several areas. We briefly review prior work that is most relevant to the Cataclysm platform and refer the reader to [23] for a more extensive survey.

Admission Control for Internet Services: Voigt et al. [26] present kernel-based admission control mechanisms to protect web servers against overloads—*SYN*

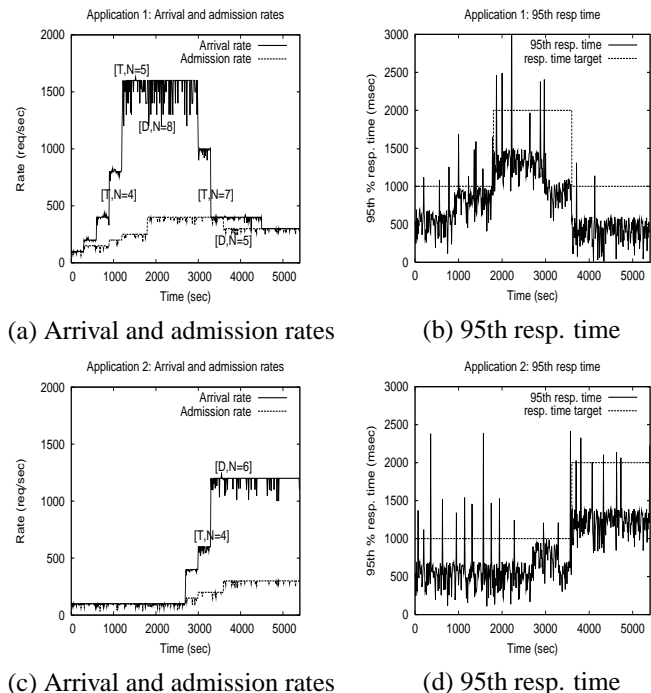


Fig. 7. Dynamic provisioning and admission control: Performance of Applications 1 and 2. D: Default invocation of provisioning, T: Provisioning triggered by excessive drops, [N=n]: size of the server set is n now. Only selected provisioning events are shown.

policing controls the rate and burst at which new connections are accepted, *prioritized listen queue* reorders the listen queue based on pre-defined connection priorities, *HTTP header-based control* enables rate policing based on URL names. Welsh and Culler [27] propose an overload management solution for Internet services built using the SEDA architecture. A salient feature of their solution is feedback-based admission controllers embedded into individual *stages* of the service. In [12], Kanodia and Knightly utilize a modeling technique called *service envelopes* to devise an admission control for web services that attempts to provide different response time targets for multiple classes of requests. Li and Jamin [16] present a measurement-based admission control to distribute bandwidth across clients of unequal requirement. In [8], the authors present an admission control for multi-tier e-commerce sites that externally observes execution costs of requests, distinguishing different requests types. Kamra et al. present a control theoretic approach for admission control in [11].

Dynamic Provisioning in Clusters: The notion of an overflow server pool to handle unexpected surges in workload was proposed by Fox et al. [9]. Several efforts have addressed the problem of provisioning resources at the granularity of individual servers [21], [1]. Muse [3] presents an architecture for resource management in a hosting center. Muse employs an economic model for dynamic provisioning of resources to multiple applications.

Cluster-on-demand provides mechanisms for constructing hierarchical virtual clusters in an on-demand fashion [4]. Doyle et al. [7] present a *model-based* utility resource management focusing on coordinated management of memory and storage. They develop an analytical model for a web service with static content. Ranjan et al. [20] make a case for multiple data centers hosting replicas of an application. In case of one data center becoming overloaded, requests may be diverted over a WAN to others. Our focus in this work was on overload management within a single data center.

In this work, we focus on the efficiency of the policing mechanism—an important issue during overloads—as opposed to prior work that mostly focused on the mechanics of the policing. Further, unlike prior work, our work has considered the tradeoff between accuracy and efficiency of policing to scale to large request rates, as well as techniques to provision sentries. Last, we showed the utility of coupling policing and provisioning, in contrast to prior approaches that considered these techniques in isolation.

VIII. CONCLUSIONS

In this paper we presented *Cataclysm*, a comprehensive approach for handling extreme overloads in a hosting platform running multiple Internet services. The primary contribution of our work was to develop an overload management solution that brought together the techniques of admission control, dynamic provisioning of the platform's resources and adaptive degradation of QoS into one integrated system. *Cataclysm* provides several desirable features under overloads, such as preferential admission of more important requests, the ability to handle diverse workloads and revenue maximization at multiple time-scales via dynamic provisioning of resources and size-based admission control. The *cataclysm* sentry can transparently tradeoff the accuracy of its decision making with the intensity of the workload allowing it to handle incoming rates of up to 19000 requests/second. We implemented a prototype *Cataclysm* hosting platform on a Linux cluster and demonstrated its benefits using a variety of workloads.

REFERENCES

- [1] K. Appleby, S. Fakhouri, L. Fong, M. Goldszmidt, S. Krishnakumar, D. Pazel, J. Pershing and B. Rochwerger. *Oceano - SLA-based Management of a Computing Utility*. In *Proceedings of the IFIP/IEEE Symposium on Integrated Network Management*, May 2001.
- [2] N. Bhatti and R. Friedrich. *Web Server Support for Tiered Services*. In *IEEE Network*, vol. 13, no. 5, pp. 64-71, Sept. 1999.
- [3] J. Chase, D. Anderson, P. Thakar, A. Vahdat, and R. Doyle. *Managing Energy and Server Resources in Hosting Centers*. In *Proceedings of the Eighteenth ACM Symposium on Operating Systems Principles (SOSP)*, pages 103–116, October 2001.
- [4] J. Chase, L. Grit, D. Irwin, J. Moore, and S. Sprenkle. *Dynamic Virtual Clusters in a Grid Site Manager*. In *the Twelfth International Symposium on High Performance Distributed Computing (HPDC-12)*, June 2003.
- [5] L. Cherkasova and P. Phaal. *Session Based Admission Control: a Mechanism for Improving Performance of Commercial Web Sites*. In *Proceedings of Seventh International Workshop on Quality of Service, IEEE/IFIP event*, London, May 31-June 4, 1999.
- [6] M. Crovella and A. Bestavros. *Self-similarity in World Wide Web traffic: evidence and possible causes*. In *Proceedings of the 1996 ACM SIGMETRICS*, Philadelphia, PA, 1996.
- [7] R. Doyle, J. Chase, O. Asad, W. Jin and A. Vahdat. *Model-Based Resource Provisioning in a Web Service Utility*. In *Proceedings of the 4th USENIX Conference on Internet Technologies and Systems (USITS'03)*, March 2003.
- [8] S. Elnikety, E. Nahum, J. Tracey and W. Zwaenepoel. *A Method for Transparent Admission Control and Request Scheduling in E-Commerce Web Sites*. In *Proceedings of International WWW Conference*, New York, USA, 2004.
- [9] A. Fox, S. D. Gribble, Y. Chawathe, E. A. Brewer, and P. Gauthier. *Cluster-based Scalable Network Services*. In *Proceedings of the sixteenth ACM symposium on Operating systems principles (SOSP'97)*, Saint-Malo, France, pages 78–91, December 1997.
- [10] J. Hellerstein, F. Zhang and P. Shahabuddin. *A Statistical Approach to Predictive Detection*. In *Computer Networks*, January 2000.
- [11] A. Kamra, V. Misra and E. Nahum. *Yaksha: A Controller for Managing the Performance of 3-Tiered Websites*. In *Proceedings of the Twelfth IEEE International Workshop on Quality of Service (IWQoS 2004)*, June 7-9, 2004, Montreal, Canada.
- [12] V. Kanodia and E. Knightly. *Multi-class Latency-bounded Web services*. In *Proceedings of IEEE/IFIP IWQoS 2000*, Pittsburgh, PA, June 2000.
- [13] L. Kleinrock. *Queueing Systems, Volume 2: Computer Applications*. *John Wiley and Sons, Inc.*, 1976.
- [14] E. Knightly and N. Shroff. *Admission Control for Statistical QoS: Theory and Practice*. In *IEEE Network*, 13(2):20-29, March/April 1999.
- [15] *Kernel TCP Virtual Server*. <http://www.linuxvirtualserver.org>.
- [16] K. Li and S. Jamin. *A measurement-based admission-controlled web server*. In *Proceedings of INFOCOM 2000*, Tel Aviv, Israel, March 2000.
- [17] J. Moore, D. Irwin, L. Grit, S. Sprenkle, and J. Chase. *Managing Mixed-Use Clusters with Cluster-on-Demand*. *Cluster-on-Demand Draft, Internet Systems and Storage Group*, Duke University, 2002.
- [18] D. Mosberger and T. Jin. *httpperf — A Tool for Measuring Web Server Performance*. In *Proceedings of the SIGMETRICS Workshop on Internet Server Performance*, June 1998.
- [19] V. Pai, M. Aron, G. Banga, M. Svendsen, P. Druschel, W. Zwanepoel and E. Nahum. *Locality-Aware Request Distribution in Cluster-based Network Servers*. In *Proceedings of the Eighth International Conference on Architectural Support for Programming Languages and Operating Systems (ASPLOS-VIII)*, San Jose, California, October 1998.
- [20] S. Ranjan, R. Karrer and E. Knightly. *Wide Area Redirection of Dynamic Content by Internet Data Centers*. In *Proceedings of INFOCOM 2004*, Hong Kong, March 2004.
- [21] S. Ranjan, J. Rolia and E. Knightly. *QoS-Driven Server Migration for Internet Data Centers*. In *Proceedings of IEEE IWQoS 2002*.
- [22] *The Internet Under Crisis Conditions: Learning from September 11*. Committee on the Internet Under Crisis Conditions, NRC, 2002.
- [23] B. Urgaonkar and P. Shenoy. *Cataclysm: Handling Extreme Overloads in Internet Services*. Technical Report TR03-40, Department of Computer Science, University of Massachusetts, MA, December 2003.
- [24] A. Verma and S. Ghosal. *On Admission Control for Profit Maximization of Networked Service Providers*. In *Proc. of 12th Int'l World Wide Web Conf. (WWW2003)*, Budapest, Hungary, May 2003.
- [25] D. Villela, D. Rubenstein and P. Pradhan. *Provisioning Servers in the Application Tier for E-Commerce Systems*. In *Proceedings of the Twelfth IEEE International Workshop on Quality of Service (IWQoS 2004)*, June 7-9, 2004, Montreal, Canada.
- [26] T. Voigt, R. Tewari and D. Freimuth. *Kernel mechanisms for service differentiation in overloaded web servers*. In *Proceedings of the USENIX Annual Technical Conference*, 2001.
- [27] M. Welsh and D. Culler. *Adaptive Overload Control for Busy Internet Servers*. In *Proceedings of the 4th USENIX Conference on Internet Technologies and Systems (USITS'03)*, March 2003.