DieCast: Testing Distributed Systems with an Accurate Scale Model

Diwaker Gupta, Kashi Vishwanath, and Amin Vahdat
University of California, San Diego
{dgupta,kvishwanath,vahdat}@cs.ucsd.edu

Abstract

Large-scale network services can consist of tens of thousands of machines running thousands of unique software configurations spread across hundreds of physical networks. Testing such services for complex performance problems, configuration errors, and fault tolerance remains a difficult problem. Existing testing techniques, for example through simulation or running smaller instances of a service, have limitations in predicting overall service behavior.

Although technically and economically infeasible at this time, testing should ideally be performed at the same scale and with the same configuration as the deployed service. We present DieCast, an approach to scaling network services; we multiplex all of the nodes in a given service configuration as virtual machines (VM) spread across a much smaller number of physical machines in a test harness. CPU, network, and disk are then accurately scaled to provide the illusion that each VM matches a machine from the original service in terms of both available computing resources and communication behavior to remote service nodes. We present the architecture and evaluation of a system to support such experimentation and discuss its limitations. We show that for a variety of services, including a high-performance, cluster-based file system, and resource utilization levels, DieCast matches the behavior of the original service while using a fraction of the physical resources.

1 Introduction

Today, more and more services are being delivered by complex systems consisting of large ensembles of machines spread across multiple physical networks and geographic regions. Economies of scale, incremental scalability, and good fault isolation properties have made clusters the preferred architecture for building planetary-scale services. A single logical request may touch dozens of machines on multiple networks, all providing instances of services transparently replicated across multiple machines. Services consisting of tens of thousands machines are commonplace [12].

Economic considerations have pushed service providers to a regime where individual service machines must be made from commodity components—saving an extra \$500 per node in a 100,000-node service is critical. Similarly, nodes run commodity operating systems, with only moderate levels of reliability, and custom-written applications that are often rushed to production because of the pressures of "Internet Time." In this environment, failure is common [25] and it becomes the responsibility of higher-level software architectures, usually employing custom monitoring infrastructures and significant service and data replication, to mask individual, correlated, and cascading failures from end clients.

One of the primary challenges facing designers of modern network services is testing their dynamically evolving system architecture. In addition to the sheer scale of the target systems, challenges include: heterogeneous hardware and software, dynamically changing request patterns, complex component interactions, failure conditions that only manifest under high load [22], the effects of correlated failures [20], and bottlenecks arising from complex network topologies. Before upgrading any aspect of a networked service—the load balancing/replication scheme, individual software components, the network topology—architects would ideally create an exact copy of the system, modify the single component to be upgraded, and then subject the entire system to both historical and worst-case workloads. Such testing must include subjecting the system to a variety of controlled failure and attack scenarios since problems with a particular upgrade will often only be revealed under certain specific conditions.

Of course, creating an exact copy of a modern networked service for testing is both technically challenging and economically infeasible. The architecture of many large-scale networked services can be characterized as "controlled chaos," where it is often impossible to know exactly what the hardware, software, and network topology of the system looks like at any given time. Even when the precise hardware, software and network configuration of the system is known, the resources to replicate the production environment might simply be unavailable, particularly for large services. And yet, reliable, low overhead, and economically feasible testing of network services remains critical to delivering robust higher-level services. As one motivating example, consider that the

Nikkei Stock Exchange recently shut down for a day [6] while the New York Stock Exchange indicated an inaccurate precipitous price drop (dropping 200 points almost instantly) [2] as a result of, in both cases, unusually high trading volumes. Today, testing Internet services is relegated to small-scale deployments on hardware, software, and interconnects that only approximate the target architecture.

The goal of this work is to develop a testing methodology and architecture that can accurately predict the behavior of modern network services while employing an order of magnitude less hardware resources. For example, consider a service consisting of 10,000 heterogeneous machines, 100 switches, and hundreds of individual software configurations. We aim to configure a smaller number of machines (e.g., 100-1000 depending on service characteristics) to emulate as closely as possible the original configuration and to subject the test infrastructure to the same (unscaled) workload and failure conditions as the original service. The performance and failure response of the test system should closely approximate the real behavior of the target system. Of course, these goals are infeasible a priori without giving something up: if it were possible to capture the complex behavior and overall performance of a 10,000 node system on 1,000 nodes, then the original system should likely run on 1,000 nodes.

A key insight behind our work is that we can trade time for system capacity while accurately scaling individual system components to match the behavior of the target infrastructure. We employ *time dilation* to accurately scale the capacity of individual systems by a configurable factor. Time dilation fully encapsulates operating systems and applications such that the rate at which time passes can be modified by a constant factor. A time dilation factor (TDF) of 10 means that for every second of real time, all software in a dilated frame believes that time has advanced by only 100 ms. By not changing the rate of I/O, the system then appears to have substantially higher processing power, network and disk I/O at the cost of time itself. If we wish to subject a target system to a one-hour workload when scaling the system by a factor of 10, the test would take 10 hours of real time. For many testing environments, this is an appropriate tradeoff.

In this paper, we present DieCast, a complete environment for building accurate models of network services (Section 2). Critically, we run the actual operating system and application software of some target environment on a fraction of the hardware in the target environment. This work makes the following contributions. First, we extend our original implementation of time dilation [19] to support fully virtualized as well as paravirtualized hosts. To support complete system evaluations, our second contribution shows how to extend dilation to disk and CPU (Section 3). In particular, we integrate a full disk simulator into the VMM to consider a range of possible disk architectures. Finally, we conduct a detailed system evaluation, quantifying DieCast's accuracy for a range of services, including a commercial storage system (Section 4). The goals of this work are ambitious and we cannot claim to have addressed all of the myriad challenges associated with large-scale testing, Section 6 summarizes some outstanding issues.

2 System Architecture

We begin by providing an overview of our approach to scaling a network service down to a target test harness. We then discuss the individual components of our architecture.

2.1 Overview

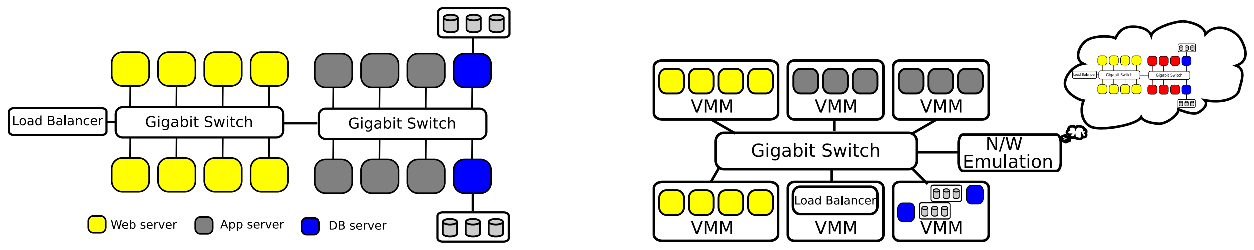
Figure 1 gives an overview of our approach. On the left (Figure 1(a)) is an abstract depiction of a network service. A load balancing switch sits in front of the service and redirects requests among a set of front-end HTTP servers. These requests may in turn travel to a middle tier of application servers who may query a storage tier consisting of databases or network attached storage.

Figure 1(b) shows how a target service can be scaled with DieCast. We encapsulate all nodes from the original service in virtual machines and multiplex several of these VMs onto nodes in the test harness. Critically, we employ time dilation in the VMM running on each physical machine to provide the illusion that each virtual machine has, for example, as much processing power, disk I/O, and network bandwidth as the original configuration. DieCast configures VMs to communicate through a network emulator to reproduce the characteristics of the original system topology. We then initialize the test system using the setup routines of the original system and subject it to appropriate workloads and fault-loads to evaluate system behavior.

2.2 Choosing the Scaling Factor

The first question is the desired scaling factor. One use of DieCast is to reproduce the scale of an original service in a test cluster. Another application is to scale existing test harnesses to achieve significantly more realism than possible from the raw hardware. For instance, if 100 nodes are already available for testing, then DieCast might be employed to scale to a thousand-node system with a more complex communication topology. While the DieCast system may still fall short of the scale of the original service, it can provide more meaningful approximations under more intense workloads and failure conditions than might have otherwise been possible.

Overall, the goal is to pick the smallest scaling factor possible while still obtaining accurate predictions from



(a) Original System (b) Test System

Figure 1: Scaling a network service to the DieCast infrastructure.

experiments in the test system as DieCast predictions will naturally degrade with increasing scaling factor. For instance, while commodity server hardware typically supports timer resolutions of 1 ms, most operating systems only use timer resolutions of 10 ms. Therefore, time dilation can operate with perfect fidelity up to a dilation factor of 10. This degradation depends on the characteristics of the target system (see Section 6). Applications with coarse grained timing requirements may tolerate higher time dilation factors, while time sensitive applications might experience performance degradation.

Note that it is neither necessary nor possible to uniformly scale all aspects of a target service. One feature that we cannot currently scale is capacity, either for main memory or disk. Thus, it may not be possible to scale memory or disk-intensive aspects of the system as aggressively as more processor or I/O bound portions of the system. However, this is not a fundamental limitation. For example, one partial solution is to configure the test system with more memory and storage than the original system. While this will reduce some of the economic benefits of our approach, it will not erase them. For instance, doubling a machine's memory will not typically double its hardware cost. More importantly, it will not substantially increase the typically dominant human cost of administering a given test infrastructure because the number of required administrators for a given test harness usually grows with the number of machines in the system rather than with the total memory of the system.

Looking forward, ongoing research in VMM architectures have the potential to reclaim some of the memory [34, 21] and storage overhead [35] associated with multiplexing multiple virtual machines on a single physical machine. For instance, four nearly identically configured Linux machines running the same web server will overlap significantly in terms of their memory and storage footprints. Similarly, consider an Internet service that replicates content for improved capacity and availability. When scaling the service down, multiple machines from the original configuration may be assigned to a single physical machine. A VMM capable of detecting and exploiting available redundancy could significantly reduce the incremental storage overhead of multiplexing multiple VMs.

In our current implementation, we employ Xen [11] (version 3.0.4). We allocate the CPU among competing virtual machines using Xen's Credit scheduler [1] running in non-work-conserving mode. Briefly, the Credit scheduler is a proportional fair share scheduler that also allows the VMM to upper bound the amount of CPU available to a VM, even if there are idle cycles in the system.

2.3 Cataloging the Original System

The next task is to configure the appropriate virtual machine images onto our test infrastructure. Maintaining a catalog of the hardware and software configuration that comprises an Internet service is challenging in its own right. However, for the purposes of this work, we assume that such a catalog is available. This catalog would consist of all of the hardware making up the service, the network topology, and the software configuration of each node. The software configuration includes operating system, installed packages and applications, and the initialization sequence run on each node after booting.

The original service software may or may not run on top of virtual machines. However, given the increasing benefits of employing virtual machines in data centers for service configuration and management and the popularity of VM-based appliances that are pre-configured to run particular services [7, 3], we assume that the original service is in fact VM-based.This assumption is not critical to our approach but it also partially addresses any baseline performance differential between a node running on bare hardware in the original service and the same node running on a virtual machine in the test system. Tools such as VMWare's P2V Assistant [33] automate the process of converting an existing physical machine to a VM image.

2.4 Configuring the Virtual Machines

With an understanding of appropriate scaling factors and a catalog of the original service configuration, DieCast then configures individual physical machines in the test system with multiple VM images reflecting, ideally, a one-to-one map between physical machines in the original system and virtual machines in the test system. With a scaling factor of 10, each physical node in the target system would host 10 virtual machines. The mapping from physical machines to virtual machines should account for: similarity in software configurations, per-VM memory and disk requirements, the capacity of the hardware in the original and test system, etc. In general, a solver may be employed to determine a near-optimal matching [27]. However, given the VM migration capabilities of modern VMMs and DieCast's controlled network emulation environment, the actual location of a VM is not as significant as in the original system.

DieCast then configures the VMs such that each VM appears to have resources identical to an entire physical machine in the original system. Consider a physical machine hosting 10 VMs. DieCast would run each VM with a scaling factor of 10, but allocate each VM only 10% of the actual physical resource. Suppose a CPU intensive task takes 100 seconds to finish on the original machine. The same task would now take 1000 seconds (of real time) on a dilated VM, since it can only use a tenth of the CPU. However, since the VM is running under time dilation, it only perceives that 100 seconds have passed. Thus in the VMs time frame, resources appear equivalent to the original machine.

2.5 Network Emulation

The final step in the configuration process is to match the network configuration of the original service using network emulation. We configure all VMs in the test system to route all their communication through our emulation environment. Note that DieCast is not tied to any particular emulation technology: we have successfully used DieCast with Dummynet [28], Modelnet [32] and Netem [4] where appropriate.

It is likely that the bisection bandwidth of the original service topology will be larger than that available in the test system. Fortunately, time dilation is of significant value here. Convincing a virtual machine scaled by a factor of 10 that it is receiving data at 1 Gbps only requires forwarding data to it at 100 Mbps. Similarly, it may appear that latencies in an original cluster-based service may be low enough that the additional software forwarding overhead associated with the emulation environment could make it difficult to match the latencies in the original network. To our advantage, maintaining accurate latency with time dilation actually requires *increasing* the real time delay of a given packet, e.g., a 100 μs delay network link in the original network should be delayed by 1 ms when dilating by a factor of 10.

2.6 Workload Generation

Once DieCast has prepared the test system to be *resource equivalent* to the original system, we can subject it to an appropriate workload. These workloads will in general be application-specific. For instance, Monkey [17] shows how to replay a measured TCP request stream sent to a large-scale network service. For this work, we use application-specific workload generators where available and in other cases write our own workload generator that both captures normal behavior as well as stresses the service under extreme conditions.

To maintain a target scaling factor, clients should also ideally run in DieCast-scaled virtual machines. This approach has the added benefit of allowing us to subject a test service to a high level of perceived-load using relatively few resources. Thus, DieCast scales not only the capacity of the test harness but also the workload generation infrastructure.

3 Implementation

We begin this section with a brief overview of network dilation [19] and then describe the new features required to support DieCast.

3.1 Time Dilation

Critical to time dilation is a VMM's ability to modify the perception of time within a guest OS. Fortunately, most VMMs already have this functionality, for example, because a guest OS may develop a backlog of "lost ticks" if it is not scheduled on the physical processor when it is due to receive a timer interrupt. VMMs typically do this by periodically synchronizing the guest OS time with the physical machine's clock. The only requirement for a VMM to support time dilation is this ability to modify the VM's perception of time. In fact, as we demonstrate in Section 5, the concept of time dilation can be ported to other (non-virtualized) environments with ease.

Operating Systems employ a variety of time sources to keep track of time, including: timer interrupts (eg. the Programmable Interrupt Timer or PIT), specialized registers (eg. the TSC on Intel platforms) and external time sources such as NTP (Network Time Protocol). Time dilation works by intercepting the various time sources and scaling them appropriately to fully encapsulate the OS in its own time frame.

3.2 Support for OS diversity

Our original time dilation implementation only worked with paravirtualized machines, with two major drawbacks: it supported only Linux as the guest OS, and the guest kernel required modifications. To be widely applicable, DieCast must support a variety of operating systems. Generalizing to other platforms would have required code modifications to the respective OS.

To address these limitations, we ported time dilation to support *fully virtualized* Xen VMs, enabling DieCast to support unmodified OS images for Windows, FreeBSD, Solaris, etc. While Xen support for fully virtualized VMs differs significantly from the paravirtualized VM support in several key areas such as I/O emulation, access to hardware registers, and time management, the general idea behind the implementation remains the same: we want to intercept all sources of time and scale them.

In particular, our implementation scales the PIT, the TSC register (on x86), the RTC (Real Time Clock) and the ACPI PM Timer. As in the original implementation, we also scale the number of timer interrupts delivered to a fully virtualized guest.

3.3 Scaling Disk I/O and CPU

Our original implementation did not scale disk performance, making it unsuitable for any services that perform significant disk I/O. Ideally, we would scale individual disk requests at the disk controller layer. The complexity of modern drive architectures, particularly the fact that much low level functionality is implemented in disk controller firmware, makes such implementations challenging. Further complicating matters are the different I/O models in Xen: one for paravirtualized (PV) VMs and one for fully virtualized (FV) VMs. DieCast provides mechanisms to scale disk I/O for both models.

Note that simply delaying requests in the disk device driver is not sufficient since disk controllers may re-order and batch requests for efficiency. On the other hand, functionality embedded in hardware or firmware is difficult to instrument and modify. Instead, DieCast integrates a highly accurate and efficient disk system simulator — Disksim [14] — which gives us a good trade-off between realism and accuracy.

Figure 2(a) depicts our integration of DiskSim into the fully virtualized I/O model: for each VM, a dedicated user space process (`ioemu`) in Domain-0 performs I/O emulation by exposing a "virtual disk" to the VM (the guest OS is unaware that a real disk is not present). A special file in Domain-0 serves as the backend storage for the VM's disk. To allow `ioemu` to interact with DiskSim, we wrote a wrapper around the simulator for inter-process communication.

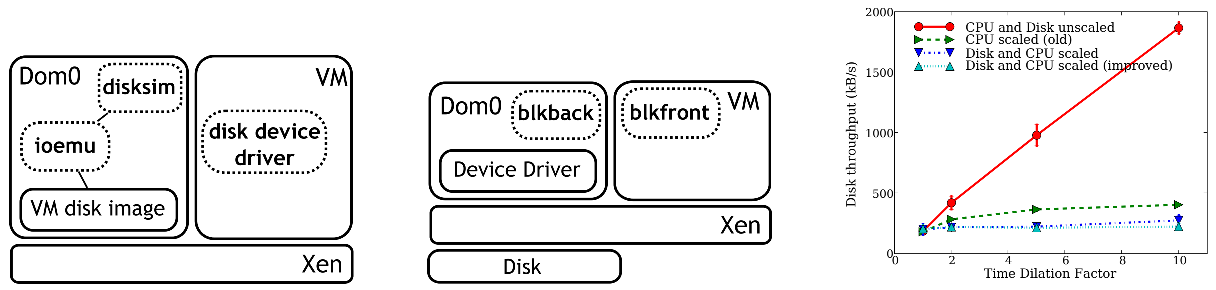
After servicing each request (but before returning), `ioemu` forwards the request to Disksim, which then returns the time, rt, the request would have taken in its simulated disk. Since we are effectively layering a software disk on top of `ioemu`, each request should ideally take exactly time rt in the VM's time frame, or $tdf * rt$ in real time. If $delay$ is the amount by which this request is delayed, the total time spent in `ioemu` becomes $delay + dt + st$, where st is the time taken to *actually* serve the request (Disksim only simulates I/O characteristics, it does not deal with the actual disk content) and dt is the time taken to invoke Disksim itself. The required delay is then $(tdf * rt) - dt - st$.

The architecture of Disksim, however, is not amenable to integration with the PV I/O model (Figure 2(b)). In this "split I/O" model, a front-end driver in the VM (`blkfront`) forwards requests to a back-end driver in Domain-0 (`blkback`), which are then serviced by the real disk device driver. Thus PV I/O is largely a kernel activity, while Disksim runs entirely in user-space. Further, a separate Disksim process would be required for each simulated disk, whereas there is a single back-end driver for all VMs.

For these reasons, for PV VMs, we inject the appropriate delays in the `blkfront` driver. This approach has the additional advantage of containing the side effects of such delays to individual VMs — `blkback` can continue processing other requests as usual. Further, it eliminates the need to modify disk specific drivers in Domain-0. We emphasize that this is functionally equivalent to per-request scaling in Disksim: the key difference is that scaling in Disksim is much closer to the (simulated) hardware. Overall our implementation of disk scaling for PV VM's is simpler though less accurate and somewhat less flexible since it requires the disk subsystem in the testing hardware to match the configuration in the target system.

We have validated both our implementations using several micro-benchmarks. For brevity, we only describe one of them here. We run DBench [30] — a popular hard-drive and file-system benchmark — under different dilation factors and plot the reported throughput. Figure 2(c) shows the results for the FV I/O model (with Disksim). We first run the benchmark without scaling disk I/O or CPU, and we can see that the reported throughput increases almost linearly, an undesirable behavior. Next, we repeat the experiment and this time scale the CPU alone (thus, at TDF 10 the VM only receives 10% of the CPU). While the increase is no longer linear, in the absence of disk dilation it is still significantly higher than the expected value (ideally, the throughput should remain constant). Finally, with disk dilation in place we can see that the throughput tracks the expected value much more closely.

However, as the TDF increases, we start to see some divergence. We find that this deviation is due to the way CPU is scaled. Recall that we scale the CPU by bounding the amount of CPU available to each VM. However, simply scaling the CPU does not govern how those CPU cycles are distributed. To illustrate, consider an application that consumes 8% CPU in real time. If we run the same application under TDF 10 (so it is allocated 10% of the CPU), the *execution pattern* of the application in



(a) I/O Model for FV VMs (b) I/O Model for PV VMs (c) DBench throughput under Disksim

Figure 2: Scaling Disk I/O

the dilated timeframe may be identical to its execution in the real timeframe. Suppose a VM should receive 10 ms every 100 ms. With regular CPU scaling, the VM may consume its 10 ms at any time within that window. However, for some workloads, we may actually wish to enforce that the VM's CPU consumption is spread *uniformly* across those 100 ms.

We modified the Credit CPU scheduler in Xen to support this mode of operation as follows: if a VM runs for the entire duration of its time slice, we make sure that it does *not* get scheduled for the next $(tdf - 1)$ time slices. If a VM voluntarily gives up the CPU or is pre-empted before its time slice expires, it may be re-scheduled in a subsequent time slice. However, when it consumes a cumulative total of a time slice's worth of run time (carried over from the previous time it was descheduled), it will be pre-empted and not allowed to run for another $(tdf - 1)$ time slices.

The final line in figure 2(c) shows the results of the DBench benchmark with disk scaling using this modified scheduler. As we can see, the throughput remains consistent even at higher TDFs. Note that unlike in this benchmark, DieCast typically runs multiple VMs per machine, in which case this "spreading" of CPU cycles occurs naturally as VMs compete for CPU.

Most of our evaluation in Section 4 does not employ disk dilation because of the difficulty involved with building an appropriate DiskSim model for the disk drives in our physical machines. Note that scaling disk I/O becomes less important as network latencies begin to dominate. Fortunately, the workloads were not disk I/O bound and separate experiments (Section **??**) show that we are able to maintain end-to-end accuracy even without accurate disk dilation. The evaluation of a commercial file system in Section 5 clearly requires disk dilation and our evaluation there reveals both its requirement and accuracy.

4 Evaluation

To demonstrate the accuracy of DieCast scaling, we consider three different network services: i) BitTorrent, a popular peer-to-peer file sharing program; ii) RUBiS, an auction service prototyped after eBay; and iii) Isaac, our configurable network three-tier service that allows us to subject DieCast to a range of workload scenarios. We seek to answer the following questions: i) Can we configure a smaller number of physical machines to match the CPU cycles, complex network topology, and I/O rates of a larger service? ii) How well does the performance of a DieCast-scaled service running on fewer resources match the performance of a baseline service running with more resources? iii) What are the limits of DieCast scaling? At what point do our predictions lose so much accuracy that they are no longer valuable?

Configuration	**Baseline**	**Disk not scaled**	**Disk scaled**
LAN setting	47.71 (15.47)	38.67 (8.09)	47.67 (13.68)
WAN setting	74.98 (4.76)	73.03 (4.06)	71.35 (4.68)

Table 1: Disk I/O scaling only matters for systems it is the primary bottleneck. Standard deviations are shown in parenthesis.

4.1 BitTorrent

Our first experiment establishes the need for disk scaling in systems where disk I/O dominates. For the baseline, we configure 10 physical machines hosting a single VM each (TDF 1) to download a 50MB file using BitTorrent. We connect the machines in a fully-connected mesh. Each link is 100 Mbps and has a one way latency of 1 ms. For each VM, Disksim simulates a Seagate ST3217 drive. We next repeat the experiment under a dilation factor of 10: all 10 VMs are running on a single physical machine, with CPU and network resources scaled appropriately. However, we do *not* scale disk I/O requests. Finally, we repeat the experiment with all resources (including disk I/O) scaled appropriately. For each experiment, we measure the mean and standard deviation across the download times of the clients. Table **??** shows that when disk I/O is not scaled, the clients experience a 20% deviation from the baseline.

However, note that despite the lack of disk I/O scaling, the deviations from baseline are modest (compared to the

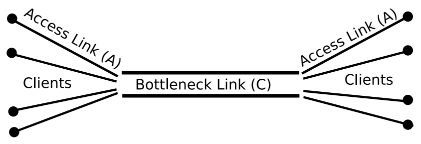


Figure 3: Topology for BitTorrent experiments .

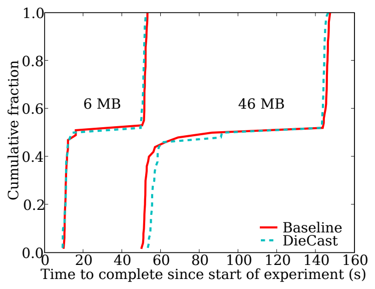


Figure 4: Performance with varying file sizes.

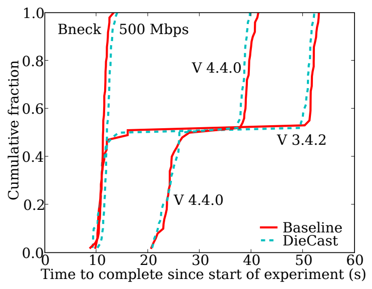


Figure 5: Varying topology and version.

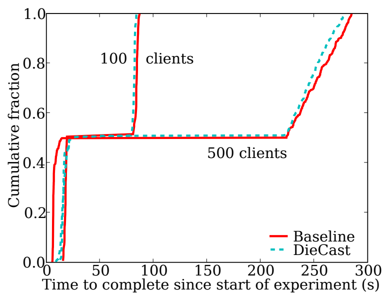


Figure 6: Varying #clients.

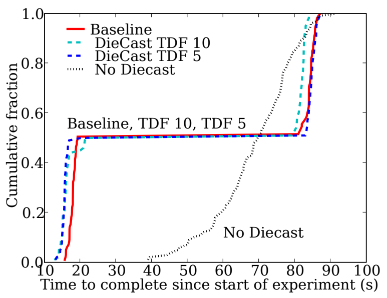


Figure 7: Different configurations.

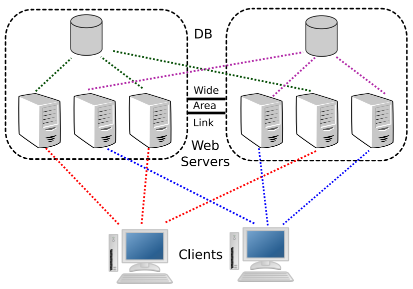


Figure 8: RUBiS Setup.

pure I/O workload from Figure 2(c)). In our experience, systems with wide area latencies are typically unaffected by disk scaling since network latencies are the dominant bottlenecks. Since we are more interested in large, wide area services, for the remaining experiments in the paper, we do not scale disk I/O unless otherwise mentioned.

We now evaluate DieCast's accuracy for more complex scenarios. For our baseline experiments, we run a varying number of BitTorrent clients on a total of 50 physical machines. Each machine is a 2.8GHz Pentium with 1GB RAM running Linux 2.6.10. We configure the machines to communicate across a ModelNet-emulated dumbbell topology (Figure 3), with varying bandwidth and latency values for the access link (A) from each client to the dumbbell and the dumbbell link itself (C). We vary the total number of clients, the file size, the network topology, and the version of the BitTorrent software. Unless stated otherwise, we compare the distribution of file download times across all clients for a baseline with 50 physical machines to set of five dilated physical machines hosting 10 virtual machines each, scaled by a factor of 10 using DieCast. The aim here is to observe how closely DieCast-scaled experiments reproduce behavior of the baseline case for a variety of scenarios.

The first experiment establishes the baseline where we compare different configurations of BitTorrent sharing a 6MB file across a 10Mbps dumbbell link and constrained access links of 10Mbps. All links have a one-way latency of 5ms. We run a total of 50 clients (with half on each side of the dumbbell).

Figure 4 plots the cumulative distribution of transfer times across all clients for different file sizes. We show the baseline case using solid lines and use dashed lines to represent the DieCast-scaled case. With DieCast scaling, the distribution of download times closely matches the behavior of the original system. For instance, well-connected clients on the same side of the dumbbell as the randomly chosen seeder finish more quickly (before 10 seconds) than the clients that must compete for scarce resources across the dumbbell (50 seconds). The results also show that, in this case, there is no significant performance overhead in moving from physical machines to VMs configured with the same software.

Figure 4 also compares baseline and DieCast-scaled experiments with a different file size (46MB) as shown by the right-most pair of curves. The download pattern of clients remain the same although the absolute download times and the gap between the fast and slow clients increase due to the larger file size.

Having established a reasonable baseline, we next consider sensitivity to changing system configurations. We first vary the network topology by leaving the dumbbell link unconstrained (500 Mbps) with results in Figure 5. The graph shows the difference in CDFs when compared to the constrained dumbbell-link case for the 6-MB file (repeated for reference); all clients finish within a small time difference of each other as shown by the leftmost pair of curves.

Next, we consider the relative behavior of two different implementations of BitTorrent, versions 3.4.2 and

4.4.0, and retain the same topology from the baseline experiment (i.e., bottleneck link of 10Mbps capacity). Figure 5 also shows these results. Once again, the DieCast-scaled version of the experiment performs nearly identically to the baseline configuration. Interestingly, this experiment also shows that the newer version of BitTorrent attempts to increase "fairness" across the client population, resulting in a slowdown for the fast clients in version 4.4.0 relative to the 3.4.2 clients. In the newer version, fast clients spend more effort trying to help clients on the other side of the dumbbell. Indeed fast clients now take around 20 seconds to finish their download whereas slow clients, on the other side of the dumbbell, complete their downloads in 40 seconds as compared to 50 seconds for version 3.4.2.

Next, we consider the effect of varying the total number of clients. Using the topology from the baseline experiment we repeat the experiments for 100 and 500 simultaneous BitTorrent clients. Once again the two cases are 50 physical machines vs. 5 machines hosting 50 VMs. Figure 6 shows the results. The curves for the baseline and DieCast-scaled versions completely overlap each other for 100 clients (left pair of curves) and show minor deviation from each other for 500 clients (right pair of curves).

Finally, we consider an experiment that demonstrates the flexibility of DieCast to reproduce system performance under a variety of resource configurations starting with the same baseline. Figure 7 shows that in addition to matching $1:10$ scaling using 5 physical machines hosting 10 VMs each, we can also match an alternate configuration of 10 physical machines, hosting 5 VMs each with a dilation factor of five. This figure demonstrates that even if it is necessary to vary the number of physical machines available for testing it may still be possible to find an appropriate scaling factor to match performance characteristics. Finally, this graph also has a fourth curve corresponding to running the experiment with 50 VMs on five physical machines, each with a dilation factor of 1. This corresponds to the approach of simply multiplexing a number of virtual machines on physical machines without using DieCast. The graph shows that the behavior of the system under such a naive approach varies widely from actual behavior.

4.2 RUBiS

Next, we investigate DieCast's ability to scale a fully functional Internet service. We use RUBiS [29]—an auction site prototype designed to evaluate scalability and application server performance. RUBiS has been used by other researchers to approximate realistic Internet Services [16, 15, 13].

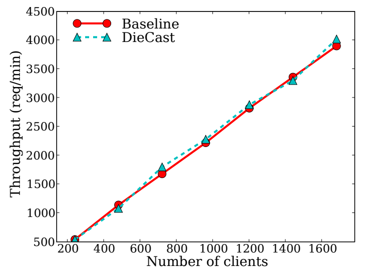
We use the PHP implementation of RUBiS running Apache as the web server and MySQL as the database. For consistent results, we re-create the database and pre-populate it with 100,000 users and items before each experiment. We use the default read-write transaction table for the workload that exercises all aspects of the system — adding new items, placing bids, adding comments, viewing and browsing the database, etc. The RUBiS workload generators warm up for 10 seconds, followed by a session run time of 100 seconds and ramp down for 10 seconds.

We emulate a topology of 10 nodes consisting of two database servers, six web servers and two workload generators as shown in Figure 8. A 100 Mbps network link connects two replicas of the service spread across the wide-area. Within a replica group, 1 Gbps links connect all components. Each system component (servers, workload generators) runs in its own Xen VM.

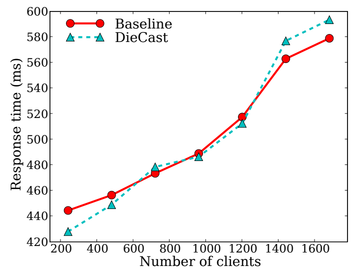
We now evaluate DieCast's ability to scale a larger RUBiS configuration with fewer resources. For the baseline, we run a VM on each of the 10 physical machines. For our DieCast-scaled runs, we multiplex 10 VMs on a single physical machine and allocate 10% of the resources to each VM. Each VM runs with the same amount of memory in both the scaled and baseline experiments. ModelNet emulates identical network characteristics for both cases.

Figures 9(a) and 9(b) compare the baseline performance with the scaled system for overall system throughput and average response time (across all client-webserver combinations) on the y-axis as a function of number of simultaneous clients (offered load) on the x-axis. In both cases, the performance of the scaled service closely tracks that of the baseline. Interestingly, for one of our initial tests, we ran with an unintended misconfiguration of the RUBiS database: the workload had commenting-related operations enabled, but the relevant tables were missing from the database. This led to an approximately 25% error rate with similar timings in the responses to clients in both the baseline and DieCast configurations. These types of configuration errors are one example of the types of testing that we wish to enable with DieCast.

Next, Figures 11(b) and 11(a) compare CPU and memory utilization in each node for both the scaled and unscaled experiments as a function of time for the case of 1200 simultaneous clients generating load. One important question is whether the average performance results in earlier figures hide significant incongruities in per-request performance. Here, we see that resource utilization in the DieCast-scaled experiments closely tracks the utilization in the baseline on a per-node and per-tier (client, web server, database) basis. Similarly, Figure 11(c) compares the network utilization of individual links in the topology for the baseline and DieCast-scaled experiment. This graph demonstrates that DieCast closely



(a) Throughput



(b) Response Time

Figure 9: Application performance: Baseline vs. DieCast.

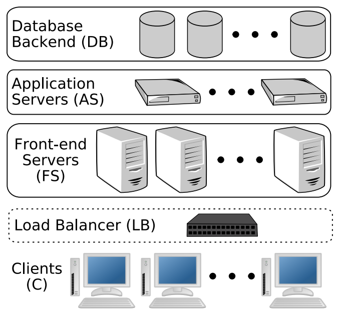
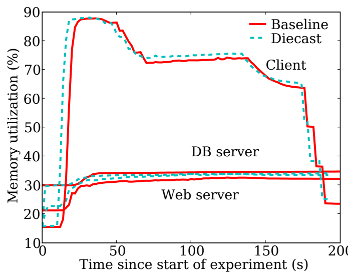
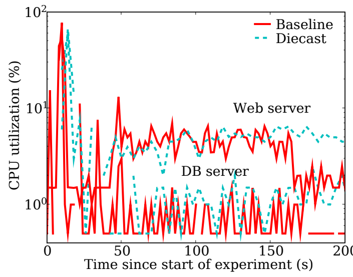


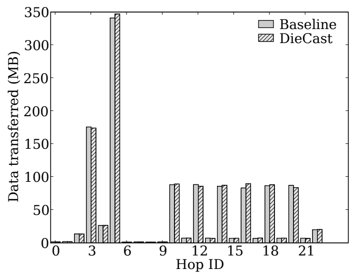
Figure 10: Architecture of Isaac.



(a) Memory profile



(b) CPU profile



(c) Network profile

Figure 11: Scaling with DieCast: Accurate emulation of system behavior with 1/10th of the resources.

tracks and reproduces variability in network utilization for various hops in the topology. For instance, hops 3 and 5 in the Figure correspond to access links of clients and show the maximum utilization, whereas individual access links of Webservers (hops 10, 12, 14, 16, 18 and 20) are moderately loaded.

4.3 Exploring DieCast Accuracy

While we were encouraged by DieCast's ability to scale RUBiS and BitTorrent, they represent only a few points in the large space of possible network service configurations, for instance, in terms of the ratios of computation to network communication to disk I/O. Thus, we built Isaac, a configurable multi-tier network service to stress the DieCast methodology on a range of possible configurations. Figure 10 shows Isaac's architecture. Requests originating from a client (C) travel to a unique front end server (FS) via a load balancer (LB). The FS makes a number of calls to other services through application servers (AS). These application servers in turn may issue read and write calls to a database back end (DB) before building a response and transmitting it back to the front end server, which finally responds to the client.

Isaac is written in Python and allows configuring the service to a given interconnect topology, computation, communication, and I/O pattern. A configuration describes, on a per request class basis, the computation, communication, and I/O characteristics flowing back and forth across multiple service tiers. In this manner, we can configure experiments to stress different aspects of a service and to independently push the system to capacity along multiple dimensions. We use MySQL for the database tier to reflect a realistic transactional storage tier.

For our first experiment, we configure Isaac with six DBs, six ASs, six FSes. and 32 clients. The clients generate requests, wait for responses, and sleep for some time before generating new requests. Each client generates 20 requests and each such request touches five ASes (randomly selected at run time) after going through the FS. Each request from the AS involves 10 reads from and 2 writes to a database each of size 1KB. The database server too is chosen at random at runtime. Upon completing its database queries, each AS computes 500 $SHA1$ hashes of the response before sending it back to the FS. Each FS then collects responses from all five AS's and finally computes 5,000 $SHA1$ hashes on the concatenated results before replying to the client.

We perform this 50-node experiment both with and without DieCast scaling. For brevity, we do not show the results of initial tests validating DieCast accuracy (in all cases, performance matched closely in both the dilated and baseline case). Rather, we run a more complex experiment where a subset of the machines fail and then recover. Our goal is to show that DieCast can accurately match application performance before the failure occurs, during the failure scenario, and the application's recovery behavior. For the baseline, we run 50 physical machines

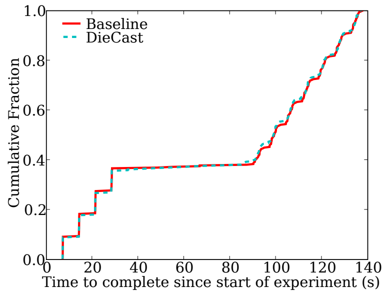


Figure 12: Request completion time.

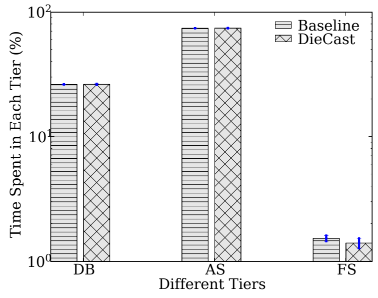


Figure 13: Tier-breakdown.

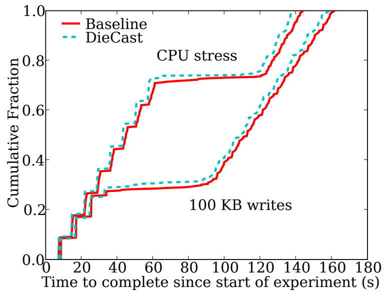


Figure 14: Stressing DB/CPU.

with 180MB of RAM each. For DieCast, we run with 50 VMs on five physical machines with a scaling factor of 10 and as usual, configure each VM to receive 10% of the resources and 180MB RAM. 30 seconds into the experiment, we fail half of the database servers by stopping MySQL servers on the corresponding nodes. As a result, client requests accessing failed databases will not complete, slowing the rate of completed requests. After one minute of downtime, we restart the MySQL server and soon after we expect to see the rate request completion to regain its original value. Figure 12 shows the comparison of completion time of requests across all clients. DieCast closely matches the baseline application behavior with a dilation factor of 10. Before the failure, i.e., until around 30 seconds, time-spaced requests originating from clients are synchronized and due to symmetrical load-distribution, finish in close proximity to each other resulting in a step function. However, once the databases start failing, ASes making requests to database servers that are dead, established connections to dead servers, variability in ASes talking to dead databases, etc., will all leave the system desynchronized and hence, when the database servers eventually heal (90 seconds), the step function smoothes out. We also show the comparison of the time spent in each tier of the service in Figure 13.

Encouraged by the results of the previous experiment, we next attempt to saturate individual components of Isaac to explore the limits of DieCast's accuracy. First, we evaluate DieCast's ability to scale network services when database access becomes the bottleneck. Figure 14 shows the completion time for requests where each service issues a 100KB (rather than 1KB) write to the database with all other parameters remaining the same. This amounts to a total of 1 MB of database writes for every request from a client. Even for such large data volumes DieCast faithfully reproduces system performance. While for this workload, we are able to maintain good accuracy, the evaluation of disk dilation summarized in Figure 2(c) suggests that there will certainly be points where disk dilation inaccuracy will affect overall DieCast accuracy.

Next, we evaluate our ability to perform scaling when one of the components in our architecture saturates the CPU. Specifically, we configure our front-end servers such that prior to sending each response to the client, they compute $SHA1$ hashes of the response 500,000 times to artificially saturate the CPU of this tier. The results of this experiment too are shown in Figure 14. We see that the performance of the scaled system begins to diverge slightly from the baseline. We are encouraged overall as the system does not significantly diverge even to the point of CPU saturation. For instance, the CPU utilization for nodes hosting the FS in this experiment varied from $50 - 80\%$ for the duration of the experiment and even under such conditions DieCast closely matched the baseline system performance.

5 Commercial System Evaluation

While we were encouraged by DieCast's accuracy for the applications we considered in Section 4, all of the experiments were designed by DieCast authors, and were largely academic in nature. To understand the generality of our system, we consider its applicability to a large-scale commercial system.

Panasas [5] builds scalable storage systems targeting Linux cluster computing environments. It has supplied solutions to several Government agencies, Oil and Gas companies, media companies and several commercial HPC enterprises. A core component of Panasas's products is the PanFS parallel file system (henceforth referred to as PanFS): an object-based cluster file system which presents a single, cache coherent unified namespace to clients.

To meet customer requirements, Panasas must ensure its systems can deliver appropriate performance under a range of client access patterns. Unfortunately, it is often impossible to create a test environment that reflects the setup at a customer site. Since Panasas has several customers with very large super-computing clusters and limited test infrastructure at its disposal, its ability to perform testing at scale is severely restricted by hardware availability, exactly the type of situation DieCast targets. For example, the Los Alamos National Lab has deployed PanFS with its Roadrunner peta-scale super computer [8]. The Roadrunner system is designed to deliver a sustained performance level of one petaflop at an estimated cost of $90 million. Because of the tremendous scale and cost, Panasas cannot replicate this computing environment for testing purposes.

Porting Time Dilation. In evaluating our ability to apply DieCast to PanFS , we encountered one primary limitation. PanFS clients use a Linux kernel module to communicate with the PanFS server. The client-side code runs on all recent versions of Xen and hence DieCast supported them with no modifications. However, the PanFS server runs in a custom operating system derived from an older version of FreeBSD that does not support Xen. The significant modifications to the base FreeBSD operating system made it impossible to port PanFS to a more recent version of FreeBSD that does support Xen. Thus, unfortunately we could not easily employ the existing time dilation techniques with PanFS on the server side. However, since we believe DieCast concepts are general and not restricted to Xen, we took this opportunity to explore whether we could modify the PanFS OS to support DieCast, without any virtualization support.

To implement time dilation in the PanFS kernel, we scale the various time sources and consequently the wall clock. The TDF can be specified at boot time as a kernel parameter. As before, we need to scale down resources available to PanFS such that its perceived capacity matches the baseline.

For scaling the network, we use Dummynet [28], which ships as part of the PanFS OS. However, there was no mechanism for limiting the CPU available to the OS, or to slow the disk. For CPU dilation, we had to modify the kernel as follows. The PanFS OS does not support non work-conserving CPU allocation. Further, simply modifying the CPU scheduler for user processes is insufficient because it would not throttle the rate of kernel processing. Thus, we created a CPU-bound task, (`idle`), in the kernel and we statically assigned it the highest scheduling priority. We scale the CPU by maintaining the required ratio between the run times of `idle` task and all remaining tasks. If the idle task consumes sufficient CPU, it is removed from the run queue and the regular CPU scheduler kicks in. If not, the scheduler always picks the idle task because of its priority.

For disk dilation, we were faced by the complication that multiple hardware and software components interact in PanFS to service clients. For performance, there are several parallel data paths and many operations are either asynchronous or cached. Accurately implementing disk dilation would require accounting for all of the possible code paths as well as modeling the disk drives with high fidelity. In an ideal implementation, if the physical service time for a disk request is s and the TDF is t, then the request should be delayed by time $(t-1)s$ such that the total physical service time becomes $t \times s$, which under dilation would be perceived as s as desired.

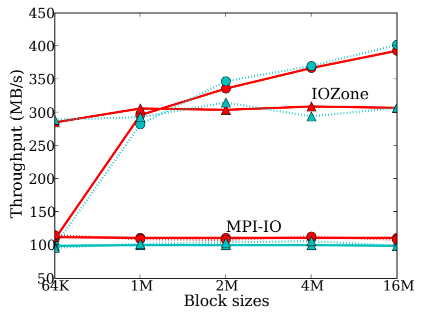


Figure 15: Validating DieCast on PanFS .

Unfortunately, the Panasas operating system only provides coarse-grained kernel timers. Consequently, sleep calls with small durations tend to be inaccurate. Using a number of micro-benchmarks, we determined that the smallest sleep interval that could be accurately implemented in the PanFS operating system was 1 ms.

This limitation affects the way disk dilation can be implemented. For I/O intensive workloads, the rate of disk requests is high. At the same time, the service time of each request is relatively modest. In this case, delaying each request individually is not an option, since the overhead of invoking sleep dominates the injected delay and gives unexpectedly large slowdowns. Thus, we chose to aggregate delays across some number of requests whose service time sums to more than 1 ms and periodically inject delays rather than injecting a delay for each request. Another practical limitation is that it is often difficult to accurately bound the service time of a disk request. This is a result of the various I/O paths that exist: requests can be synchronous or asynchronous, they can be serviced from the cache or not, etc.

While we realize that this implementation is imperfect, it works well in practice and can be automatically tuned for each workload. A perfect implementation would have to accurately model the low level disk behavior and improve the accuracy of the kernel sleep function. Because operating systems and hardware will increasingly support native virtualization, we feel that our simple disk dilation implementation targeting individual PanFS workloads is reasonable in practice to validate our approach.

Validation We first wish to establish DieCast accuracy by running experiments on bare hardware and comparing them against DieCast-scaled virtual machines. We start by setting up a storage system consisting of an PanFS server with 20 disks of capacity 250GB each (5TB total storage). We evaluate two benchmarks from the standard bandwidth test suite used by Panasas. The first benchmark involves 10 clients (each on a separate machine) running IOZone [24]. The second benchmark uses

Aggregate Throughput	Number of clients		
	10	250	1000
Write	370 MB/s	403 MB/s	398 MB/s
Read	402 MB/s	483 MB/s	424 MB/s

Table 2: Aggregate read/write throughputs from the IOZone benchmark with block size 16M. PanFS performance scales gracefully with larger client populations.

the Message Passing Interface (MPI) across 100 clients (again, on separate machines).

For DieCast scaling, we repeat the experiment with our modifications to the PanFS server configured to enforce a dilation factor of 10. Thus, we allocate 10% of the CPU to the server and dilate the network using Dummynet to 10% of the physical bandwidth and 10 times the latency (to preserve the bandwidth-delay product). On the client side, we have all clients running in separate virtual machines (10 VMs per physical machine), each receiving 10% of the CPU with a dilation factor of 10.

Figure 15 plots the aggregate client throughput for both experiments on the y-axis as a function of the data block size on the x-axis. Circles mark the read throughput while triangles mark write throughput. We use solid lines for the baseline and dashed lines for the DieCast-scaled configuration. For both reads and writes, DieCast closely follows baseline performance, never diverging by more than 5% even for unusually large block sizes.

Scaling With sufficient faith in the ability of DieCast to reproduce performance for real-world application workloads we next aim to push the scale of the experiment beyond what Panasas can easily achieve with their existing infrastructure.

We are interested in the scalability of PanFS as we increase the number of clients by two orders of magnitude. We design an experiment similar to the one above, but this time we fix the block size at 16MB and vary the number of clients. We use 10 VMs each on 25 physical machines to support 250 clients to run the IOZone benchmark. We further scale the experiment by using 10 VMs each on 100 physical machines to go up to 1000 clients. In each case, all VMs are running at a TDF of 10. The PanFS server also runs at a TDF of 10 and all resources (CPU, network, disk) are scaled appropriately. Table 2 shows that the performance of PanFS scales to large client populations. Interestingly, we find relatively little increase in throughput as we increase the client population. Upon investigating further, we found that a single PanFS server configuration is limited to 4 Gb/s (500 MB/s) of aggregate bisection bandwidth between the servers and clients (including any IP and filesystem overhead). While our network emulation accurately reflected this bottleneck, we did not catch the bottleneck until we ran our experiments. We leave a performance evaluation when removing this bottleneck to future work.

We would like to emphasize that prior to our experiment, Panasas had been unable to perform experiments at this scale. This is in part due to the fact that such a large number of machines might not be available at any given time for a single experiment. Further, even if machines are available, blocking a large number of machines results in significant resource contention because several other smaller experiments are then blocked on availability of resources. Our experiments demonstrate that DieCast can leverage existing resources to work around these types of problems.

6 DieCast Usage Scenarios

In this section, we discuss DieCast's applicability and limitations for testing large-scale network services in a variety of environments.

DieCast aims to reproduce the performance of an original system configuration, and is well suited for predicting the behavior of the system under a variety of workloads. Further, because the test system can be subject to a variety of realistic and projected client access patterns, DieCast may be employed to verify that the system can maintain the terms of Service Level Agreements (SLA).

It runs in a controlled and partially emulated network environment. Thus, it is relatively straightforward to consider the effects of revamping a service's network topology (e.g., to evaluate whether an upgrade can alleviate a communication bottleneck). DieCast can also systematically subject the system to failure scenarios. For example, system architects may develop a suite of faultloads to determine how well a service maintains response times, data quality, or recovery time metrics. Similarly, because DieCast controls workload generation it is appropriate for considering a variety of attack conditions. For instance, it can be used to subject an Internet service to large-scale Denial-of-Service attacks. DieCast may enable evaluation of various DOS mitigation strategies or software architectures.

Many difficult-to-isolate bugs result from system configuration errors (e.g., at the OS, network, or application level) or inconsistencies that arise from "live upgrades" of a service's software configuration. The resulting faults may only manifest as errors in a small fraction of requests and even then after a specific sequence of operations. Operator errors and mis-configurations [23, 25] are also known to account for a significant fraction of service failures. DieCast makes it possible to capture the effects of mis-configurations and upgrades before a service goes live.

At the same time, DieCast will not be appropriate for certain service configurations. As discussed earlier, DieCast is unable to scale down the memory or storage capacity of a service. Services that rely on multi-terabyte data sets or saturate the physical memories of all of their machines with little to no cross-machine memory/storage redundancy may not be suitable for DieCast testing.

DieCast may change the fine-grained timing of individual events in the test system. Hence, DieCast may not be able to reproduce certain race conditions or timing errors in the original service. Some bugs, such as memory leaks, will only manifest after running for a significant period of time. Given that we inflate the amount of time required to carry out a test, it may take too long to isolate these types of errors using DieCast.

Multiplexing multiple virtual machines onto a single physical machine, running with an emulated network, and dilating time will introduce some error into the projected behavior of target services. This error has been small for the network services and scenarios we evaluate in this paper. In general however, DieCast's accuracy will be service- and deployment-specific.

Some services employ a variety of custom hardware, such as load balancing switches, firewalls, and storage appliances. In general, it may not be possible to scale such hardware in our test environment. Depending on the architecture of the hardware, one approach is to wrap the various operating systems for such cases in scaled virtual machines. Another approach is to run the hardware itself and to build custom wrappers to intercept requests and responses, scaling them appropriately. A final option is to run such hardware unscaled in the test environment, introducing some error in system performance. Our work with PanFS shows that it is feasible to scale unmodified services into the DieCast environment with relatively little work on the part of the developer.

7 Related Work

Our work builds upon previous efforts in a number of areas. We discuss each in turn below.

Testing scaled systems SHRiNK [26] is perhaps most closely related to DieCast in spirit. SHRiNK aims to evaluate the behavior of faster networks by simulating slower ones. For example, their "scaling hypothesis" states that the behavior of 100Mbps flows through a 1Gbps pipe should be similar to 10Mbps through a 100Mbps pipe. When this scaling hypothesis holds, it becomes possible to run simulations more quickly and with a lower memory footprint. Relative to this effort, we show how to scale fully operational computer systems, considering complex interactions among CPU, network, and disk spread across many nodes and topologies.

Testing through Simulation and Emulation One popular approach to testing complex network services is through building a simulation model of system behavior under a variety of access patterns. While such simulations are valuable, we argue that simulation is best suited to understanding coarse-grained performance characteristics of certain configurations. Simulation is less suited to configuration errors or to capturing the effects of unexpected component interactions, failures, etc.

Superficially, emulation techniques (e.g. Emulab [36] or ModelNet [32]), offer a more realistic alternative to simulation because they support running unmodified applications and operating systems. Unfortunately, such emulation is limited by the capacity of the available physical hardware and hence is often best suited to considering wide-area network conditions (with smaller bisection bandwidths) or smaller system configurations. For instance, multiplexing 1000 instances of an overlay across 50 physical machines interconnected by Gigabit Ethernet may be feasible when evaluating a file sharing service on clients with cable modems. However, the same 50 machines will be incapable of emulating the network or CPU characteristics of 1000 machines in a multi-tier network service consisting of dozens of racks and high-speed switches.

Time Dilation DieCast leverages earlier work on Time Dilation [19] to assist with scaling the network configuration of a target service. This earlier work focused on evaluating network protocols on next-generation networking topologies, e.g., the behavior on TCP on 10Gbps Ethernet while running on 1Gbps Ethernet. Relative to this previous work, DieCast improves upon time dilation to scale *down* a particular network configuration. In addition, we demonstrate that it is possible to trade time for compute resources while accurately scaling CPU cycles, complex network topologies, and disk I/O. Finally, we demonstrate the efficacy of our approach end-to-end for complex, multi-tier network services.

Detecting Performance Anomalies There have been a number of recent efforts to debug performance anomalies in network services, including Pinpoint [16], MagPie [10], and Project 5 [9]. Each of these initiatives analyzes the communication and computation across multiple tiers in modern Internet services to locate performance anomalies. These efforts are complementary to ours as they attempt to locate problems in deployed systems. Conversely, the goal of our work is to test particular software configurations at scale to locate errors before they affect a live service.

Modeling Internet Services Finally, there have been many efforts to model the performance of network services to, for example, dynamically provision them in response to changing request patterns [18, 31] or to reroute requests in the face of component failures [13]. Once again, these efforts typically target already running services relative to our goal of testing service configurations. Alternatively, such modeling could be used to feed simulations of system behavior or to verify at a coarse granularity DieCast performance predictions.

8 Conclusion

Testing network services remains difficult because of their scale and complexity. While not technically or economically feasible, a comprehensive evaluation would require running a test system identically configured to and at the same scale as the original system. Such testing should enable finding performance anomalies, failure recovery problems, and configuration errors under a variety of workloads and failure conditions before triggering corresponding errors during live runs.

In this paper, we present a methodology and framework to enable system testing to more closely match both the configuration and scale of the original system. We show how to multiplex multiple virtual machines, each configured identically to a node in the original system, across individual physical machines. We then dilate individual machine resources, including CPU cycles, network communication characteristics, and disk I/O, to provide the illusion that each VM has as much computing power as corresponding physical nodes in the original system. By trading time for resources, we enable more realistic tests involving more hosts and more complex network topologies than would otherwise be possible on the underlying hardware. While our approach does add necessary storage and multiplexing overhead, an evaluation with a range of network services, including a commercial filesystem, demonstrates our accuracy and the potential to significantly increase the scale and realism of testing network services.

References

[1] Credit Based CPU Scheduler. `http://wiki.xensource.com/xenwiki/CreditScheduler`.

[2] Dow jones plunge fueled by overwhelmed computers. `http://slashdot.org/article.pl?sid=07/02/28/1416236`.

[3] Free os zoo. `http://free.oszoo.org/`.

[4] Netem. `http://linux-net.osdl.org/index.php/Netem`.

[5] Panasas. `http://www.panasas.com`.

[6] Tokyo stock exchange stops trading amid wave of selling. `http://www.usatoday.com/money/world/2006-01-18-tokyo-ap_x.htm`.

[7] Vmware appliances. `http://www.vmware.com/vmtn/appliances/`.

[8] Panasas ActiveScale Storage Cluster Will Provide I/O for World's Fastest Computer. `http://panasas.com/press_release_111306.html`, November 2006.

[9] M. K. Aguilera, J. C. Mogul, J. L. Wiener, P. Reynolds, , and A. Muthitacharoen. Performance Debugging for Distributed Systems of Black Boxes. In *Proceedings of the 19th ACM Symposium on Operating System Principles*, 2003.

[10] P. Barham, A. Doelly, R. Isaacs, and R. Mortier. Using Magpie for Request Extraction and Workload Modelling. In *Operating Systems Design and Implementation*, 2004.

[11] P. Barham, B. Dragovic, K. Fraser, S. Hand, T. Harris, A. Ho, R. Neugebauer, I. Pratt, and A. Warfield. Xen and the Art of Virtualization. In *Proceedings of the 19th ACM Symposium on Operating System Principles*, 2003.

[12] L. A. Barroso, J. Dean, and U. Holzle. Web Search for a Planet: The Google Cluster Architecture. *Micro, IEEE*, 2003.

[13] J. M. Blanquer, A. Batchelli, K. Schauser, and R. Wolski. Quorum: Flexible Quality of Service for Internet Services. In *Proceedings of the 3rd Networked Systems Design and Implementation*, 2005.

[14] J. S. Bucy, G. R. Ganger, and Contributors. The DiskSim Simulation Environment. `http://www.pdl.cmu.edu/DiskSim/index.html`.

[15] E. Cecchet, J. Marguerite, and W. Zwaenepoel. Performance and scalability of EJB applications. In *Proceedings of the 17th ACM SIGPLAN conference on Object-oriented programming, systems, languages, and applications*, 2002.

[16] M. Y. Chen, E. Kiciman, E. Fratkin, A. Fox, and E. Brewer. Pinpoint: Problem Determination in Large, Dynamic Internet Services. In *DSN '02: Proceedings of the 2002 International Conference on Dependable Systems and Networks*, 2002.

[17] Y.-C. Cheng, U. Hoelzle, N. Cardwell, S. Savage, and G. M. Voelker. Monkey See, Monkey Do: A Tool for TCP Tracing and Replaying. In *USENIX Technical Conference*, 2004.

[18] R. Doyle, J. Chase, O. Asad, W. Jen, and A. Vahdat. Model-Based Resource Provisioning in a Web Service Utility. In *Proceedings of the USENIX Symposium on Internet Technologies and Systems (USITS)*, March 2003.

[19] D. Gupta, K. Yocum, M. McNett, A. C. Snoeren, G. M. Voelker, and A. Vahdat. To Infinity and Beyond: Time-Warped Network Emulation. In *Proceedings of the 3rd ACM/USENIX Symposium on Networked Systems Design and Implementation*, 2006.

[20] A. Haeberlen, A. Mislove, and P. Druschel. Glacier: Highly durable, decentralized storage despite massive correlated failures. In *Proceedings of the 3rd Symposium on Networked Sytems Design and Implementation (NSDI)*, 2005.

[21] Jacob Faber Kloster and Jesper Kristensen and Arne Mejlholm. On the Feasibility of Memory Sharing in Virtualized Systems. In *Conference on Virtual Execution Environments*, 2007.

[22] J. Mogul. Emergent (Mis)behavior vs. Complex Software Systems. In *Proceedings of EuroSys*, 2006.

[23] K. Nagaraja, F. Oliveira, R. Bianchini, R. P. Martin, and T. D. Nguyen. Understanding and Dealing with Operator Mistakes in Internet Services. In *Proceedings of the 6th*

USENIX Symposium on Operating Systems Design and Implementation (OSDI), 2004.

[24] W. Norcott and D. Capps. IOzone Filesystem Benchmark. `http://www.iozone.org/`.

[25] D. Oppenheimer, A. Ganapathi, and D. Patterson. Why do Internet services fail, and what can be done about it. In *USENIX Symposium on Internet Technologies and Systems (USITS)*, 2003.

[26] R. Pan, B. Prabhakar, K. Psounis, and D. Wischik. SHRINK: A Method for Scalable Performance Prediction and Efficient Network Simulation. In *IEEE INFOCOM*, 2003.

[27] R. Ricci, C. Alfeld, and J. Lepreau. A Solver for the Network Testbed Mapping Problem. In *SIGCOMM Computer Counications Review 33(2)*.

[28] L. Rizzo. Dummynet and Forward Error Correction. In *Proceedings of the USENIX Annual Technical Conference*, 1998.

[29] RUBiS. `http://rubis.objectweb.org`.

[30] A. Tridgell. dbench. `http://samba.org/ftp/tridge/dbench/`.

[31] B. Urgaonkar, P. Shenoy, and T. Roscoe. Resource overbooking and application profiling in shared hosting platforms. In *Proceedings of the 5th symposium on Operating systems design and implementation*, 2002.

[32] A. Vahdat, K. Yocum, K. Walsh, P. Mahadevan, D. Kostić, J. Chase, and D. Becker. Scalability and Accuracy in a Large-Scale Network Emulator. In *Proceedings of the 5th Symposium on Operating Systems Design and Implementation*, 2002.

[33] `http://www.vmware.com`. VMWare.

[34] C. A. Waldspurger. Memory Resource Management in VMware ESX Server. In *Proceedings of the 5th Symposium on Operating Systems Design and Implementation*, 2002.

[35] A. Warfield, R. Ross, K. Fraser, C. Limpach, and H. Steven. Parallax: Managing Storage for a Million Machines. `http://www.usenix.org/events/hotos05/final_papers/warfield.html`.

[36] B. White, J. Lepreau, L. Stoller, R. Ricci, S. Guruprasad, M. Newbold, M. Hibler, C. Barb, and A. Joglekar. An Integrated Experimental Environment for Distributed Systems and Networks. In *Proceedings of the 5th Symposium on Operating Systems Design and Implementation*, 2002.