Storage Performance—Metrics and Benchmarks

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An ever-widening mismatch between storage and processor performance is causing storage performance evaluation to become increasingly more important. In this paper, we discuss the metrics and benchmarks used in storage performance evaluation. We first highlight the technology trends taking place in storage systems, such as disk and tape evolution, disk arrays, and solid-state disks. We then describe, review, and run today's popular I/O benchmarks on three systems: a DECstation 5000/200 running the Sprite Operating System, a SPARCstation 1+ running SunOS, and an HP Series 700 (Model 730) running HP_UX. We also describe two new approaches to storage benchmarks—LADDIS and A Self-Scaling Benchmark with Predicted Performance.

I. Introduction

In the last decade, innovations in technology have led to extraordinary advances in computer processing speed. These advances have led many of those who evaluate a computer's performance to focus their attention on measuring processor performance to the near exclusion of all other metrics; some have even equated a computer system's performance with how well its CPU performs. This viewpoint, which makes system-wide performance synonymous with CPU speed, is becoming less and less valid. One way to demonstrate this declining validity is illustrated in Fig. 1, where IBM disk performance, represented by the throughput of accessing a random 8-kb block of data, is contrasted with IBM mainframe CPU performance [18]. For the sake of comparison, both CPU and disk performance are normalized to their 1971 levels. As can readily be seen, over the past two decades, IBM mainframe CPU performance has increased more than 30-fold, while IBM disk performance has barely doubled. Microprocessor performance has increased even faster than mainframe performance [12],[41]. If CPU performance continues to improve at its current pace and disk performance continues to obtain more moderate improvements, eventually the performance of all applications that do any input or output (I/O) will be limited by that I/O component—further CPU performance improvements will be wasted [1].

In light of this developing trend toward I/O-limited applications, storage performance and storage architecture

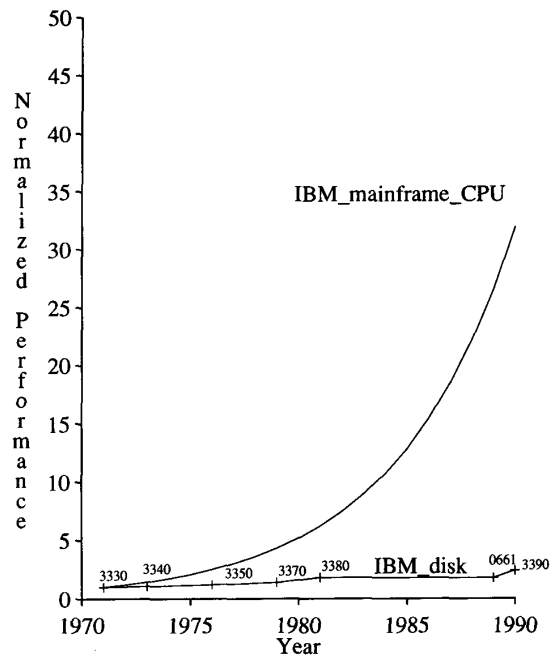

Fig. 1. Contrasting trends of CPU and disk performance improvements. Over the past two decades, CPU performance improvements have far outstripped disk performance improvements. In this graph, CPU performance refers to IBM mainframe performance; disk performance refers to IBM disk (33×0 series) throughput on a random 8-kb access. Both are normalized to their 1971 level. The IBM mainframe performance comes from [18, p. 4, fig.1.1].

become increasingly more crucial to overall system performance. In this paper, we use the terms I/O performance and storage performance interchangeably.

In this paper, we first discuss common metrics used in evaluating storage systems. Next, we highlight several trends in storage systems and how these trends affect storage performance evaluation. After addressing metrics and trends in storage systems, we devote the rest of the paper to discussing benchmarks used in evaluating I/O performance. We list desirable characteristics of an I/O benchmark, survey and run current I/O benchmarks, and discuss two new I/O benchmarks—one an evolutionary step in I/O benchmarks, the other a new approach to I/O benchmarks.

Manuscript received May 13, 1993.

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IEEE Log Number 9211348

0018-9219/93$03.00

II. METRICS

More than other areas of computer performance evaluation, storage evaluation involves many varied types of metrics. In this section, we present an overview of some of the metrics commonly used today in choosing and evaluating storage systems. The value of most metrics depend strongly on the workload used, hence the dual emphasis on metrics and benchmarks in this paper.

The most basic metric for I/O performance is *throughput.* Throughput is a measure of speed—the rate at which the storage system delivers data. Throughput is measured in two ways: I/O rate, measured in *accesses/second*, and data rate, measured in *bytes/second (B/s)* or *megabytes/second (MB/s)*. The I/O rate is generally used for applications where the size of each request is small, such as transaction processing [2]; data rate is generally used for applications where the size of each request is large, such as scientific applications [38].

Response time is the second basic performance metric for storage systems. Response time measures how long a storage system takes to access data. This time can be measured in several ways. For example, one could measure time from the user's perspective, the operating system's perspective, or the disk controller's perspective, depending on what you view as the storage system.

Usefulness for a storage system not only includes *how fast* data can be accessed, but also *how much* data can be stored on the storage system. *Capacity* is not normally applied as a metric to nonstorage components of a computer system, but it is an integral part of evaluating an I/O system. If capacity were ignored as a metric, tape, and disk manufacturers would soon find their customers switching to solid-state (memory-based) storage systems, which offer much higher performance but less capacity per dollar.

Because users store valuable data on I/O systems, they demand a reliability level much higher than for other parts of the computer. If a memory chip develops a parity error, the system will (hopefully) crash and be restarted. If a storage device develops a parity error in a database of bank accounts, however, banks could unwittingly lose billions of dollars. Thus *reliability* is a metric of great importance to storage systems.

Cost, of course, applies to all components in computer systems. Disk subsystems are often the most expensive component in a large computer installation [3]. Cost is usually expressed as a composite metric, such as capacity cost, or throughput cost.

Various combinations of these five metrics in storage system evaluation, throughput, response time, capacity, reliability, and cost, are common. One popular combination is a response time versus throughput graph (Fig. 2). Such graphs vary a parameter, such as the number of users on the system, to display the tradeoff between improving throughput and degrading response time. More users generate higher system utilization and increase throughput. On the other hand, higher utilization leads to slower response times. Because a single performance number is easier to use

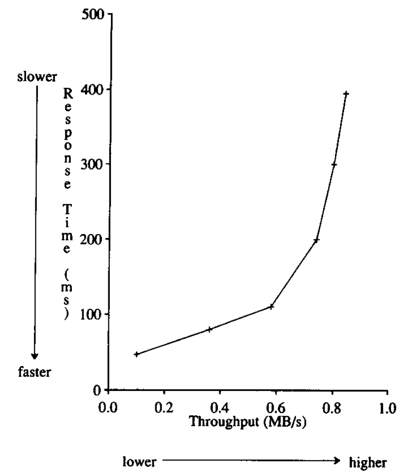


Fig. 2. Example response time versus throughput graph. Increasing the utilization of a system usually leads to higher throughput but slower response time. This figure was adapted from [6].

Metric	IBM 3390	Redundant Disk Array of IBM 0661 disks
Max Read I/O Rate	609 I/O's per second	3889 I/O's per second
Max Read Data Rate	15 MB per second	130 MB per second
Min Response Time	20 ms	20 ms
Capacity	23 GB	22 GB
Mean Time to Data Loss	6-28 years	753 years
Cost (estimated)	$156,000 - $260,000	$67,000 - ?

Fig. 3. Metrics for two storage systems. Here we show the differences in the values of several types of metrics for an IBM 3390 disk system and a redundant disk array made of IBM 0661 3.5 in drives [23]. This table was adapted from [13].

than a full graph, many evaluators combine throughput and response time by reporting throughput at a given response time [2], [6]. For example, the TPC-B benchmark reports maximum throughput with 90% of all requests completed within 2 s [65].

Another composite metric is *data temperature*, defined as I/O rate divided by capacity [26]. Data temperature measures how many I/O's per second a storage system can support for a fixed amount of storage. Users who are limited by I/O rate rather than capacity should buy systems with high data temperature.

A general parameterizable composite metric can be formulated for any combination of the above metrics. For example, one could imagine a system administrator who wanted a system with the highest capacity per dollar, as long as it satisfied minimum reliability, throughput, and response time demands.

Figure 3, adapted from [13] shows the values of the above metrics for two different disk systems.

III. TRENDS IN STORAGE SYSTEMS

In this section we highlight some of the current trends in storage systems. We discuss advances in magnetic disk technology, arrays of disks, file caching and solid-state disks, magnetic tape, and log-structured file systems.

Magnetic disks have long been the mainstay of storage systems. But, since 1970, disk performance has improved

Metric	IBM 3330	IBM 0661	Average Yearly Improvement
Average Seek Time	30 ms	12.5 ms	5%
Average Rotational Delay	8.3 ms	7 ms	1%
Transfer Rate	806 KB/s	1700 KB/s	4%

Fig. 4. Magnetic disk performance improvement over the past eight years. This table shows the slow average improvement in disk performance over the past eight years. The IBM 3330 was introduced in 1981 and has a 14-in diameter; the IBM 0661 was introduced in 1989 and has a 3.5-in diameter [16], [23].

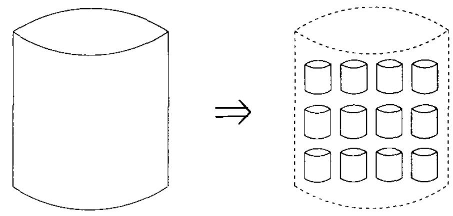


Fig. 5. Combining multiple smaller disks to improve performance. Performance of single disks is not improving rapidly (Fig. 4); however, disks are rapidly becoming physically smaller and cheaper. Disk arrays take advantage of this downsizing to provide higher aggregate throughput by simultaneously operating many small disks.

Device	Total Capacity	Cost/Capacity	Media Capacity	Latency
Magnetic Disk	1 GB	$2,500/GB	1 GB	0.01 sec.
Dilog DAT Stacker	10 GB	$527/GB	1.3 GB	75 sec.
Exabyte 120 Tape Library	500 GB	$80/GB	5 GB	100 sec.
Metrum RSS-600 Tape Library	8700 GB	$62/GB	14.5 GB	50 sec.

Fig. 6. 1992 Storage capacity. This table, adapted from [9] shows the extraordinary capacity of today's tape systems.

only modestly. In Fig. 4 we compare two disks, the IBM 3330, introduced in 1971, and the IBM 0661, introduced in 1989. The average yearly improvement in performance has inched forward at a few percent a year. Cost per capacity, on the other hand, has improved at a much faster pace, averaging a 23% reduction per year from 1977 to 1986 [13]. Disk size has also been gradually decreasing. The most common disk diameter of the 1970's and 1980's was 14 in. Those disks are disappearing and are being replaced with 5.25- and 3.5-in diameter disks. These smaller disks have somewhat better performance than their larger, more expensive predecessors.

The trend toward smaller, less expensive disks creates an opportunity to combine many of these disks into a parallel storage system known as a *disk array*. The concept of constructing an array of multiple disks has been used for many years for special purposes [24] but is only now becoming popular for general use. The list of companies developing or marketing disk arrays is quite long: Array Technology, Auspex, Ciprico, Compaq, Cray, Datamax, Hewlett-Packard, IBM, Imprimis, Intel Scientific, Intellistor, Maximum Strategy, Pacstor, SF2, Storage Concepts, Storage Technology, and Thinking Machines. Some analysts have projected the disk array market to expand to $8 billion market by 1994 [39].

The basic concept behind disk arrays is straightforward—combine many small disks and distribute data among them (Fig. 5). This increases the aggregate throughput available to an application. The array of disks can either service many small accesses in parallel or cooperate to deliver a higher data rate to a single large access [5], [6], [13], [28], [32], [49], [54]. Disk arrays compensate for the lower reliability inherent in using more disks by storing redundant, error-correcting information. Current disk array research is focusing on how to distribute (stripe) data across disks to get optimal performance [5], [29], [30], how to spread redundant information across disks to increase reliability and minimize the effect of disk failures [13], [20], [40], and how to reduce the penalties associated with small writes in certain types of disk arrays [35], [63].

Disk arrays improve throughput by using more disks to service requests. Requests which are serviced by a single disk, however, see the same response time. File caches, disk caches, and solid-state disks use dynamic RAM (random-access memory) to decrease response time. Caches can be placed in a variety of places in the system memory hierarchy [62]. Two common places are the disk controller, as in the IBM 3990 disk cache [34], and main memory, as in the Sprite operating system's file cache [42], [45]. Response times for writes is decreased by writing the data to RAM, acknowledging the request, then transferring the data to disk asynchronously. This technique, called *write-behind*, leaves the data in RAM more vulnerable to system failures until written to disk. Some systems, such as the IBM 3990, mitigate this reliability problem by storing the cached data in nonvolatile memory, which is immune to power failures [34]. As with any cache, read response time is decreased if the requested data are found in cache RAM.

Solid-state disks are similar to caches in that they improve response time by storing requests in RAM rather than on magnetic disks. The principal difference between solid-state disks and caches is that solid-state disks speed up all accesses while caches speed up access only to the most commonly requested data. Solid-state disk is much more expensive than magnetic disk for equal capacity but is dramatically faster. Response times for solid-state disks are commonly less than 3 ms [4], [25], while response times for magnetic disks are approximately 10–30 ms. On the other hand, solid-state disks cost 50–100 times more than magnetic disks for the same capacity [13].

Two storage metrics have been addressed—throughput and response time. Dramatic improvements to capacity per cost have occurred in magnetic tapes (Fig. 6). A new method of reading and writing tapes, helical scan, has increased the capacity of a single tape from 0.1–0.2 GB to 5–20 GB [27], [66], [68]. Tapes are extremely slow, however, with response times of 20 s to a few minutes. Throughput for these devices is less dismaying, ranging from 0.1–2.0 MB/s. Current research related to tape devices addresses the questions of how to migrate data from tape to faster storage [15], [17], [37], [61], [67], how to increase tape throughput using striping [27], and how to decrease response time by prefetching and caching [9], [14].

Reported disk reliability has improved dramatically over the past ten years, though actual reliability has improved more slowly. The most common metric for reliability, *mean-time-to-failure*, has increased from 30 000 to 150 000–200 000 h. This jump in apparent reliability comes mostly from changing the method of computing mean-time-to-failure and is not expected to continue improving as quickly [13].

Innovation is also taking place in the file system. A good example of how file systems have improved I/O system performance is the Log-Structured File System (LFS) [46], [50]. LFS writes data on the disk in the same order that they are written. This leads to highly sequentialized disk writes and thus improves the sustainable disk write throughput.

Although the raw performance in storage technology has improved much slower than processor technology, innovation such as file caches, disk arrays, robot-driven tape systems, and new file systems have helped close the gap.

IV. I/O Benchmarks

These developments in disks, disk array, file caches, solid-state disks, tapes, and file systems create new challenges for storage system evaluation. Benchmarks used in the evaluation process must evolve to comprehensively stress these new I/O systems. For example, disk arrays are able to service many I/O's at the same time; benchmarks therefore need to issue many simultaneous I/O's if they hope to stress a disk array. Caches create distinct performance regions based on the size of the file space touched by a program; benchmarks likewise should measure these different performance regions.

The rest of this paper is devoted to discussing benchmarks used in evaluating I/O performance. We first list standards used to critique I/O benchmarks. We then review, run, and evaluate I/O benchmarks in use today. Last, we discuss two new I/O benchmarks being proposed.

In this paper, we use I/O benchmarks to measure the data I/O performance seen by a program issuing reads and writes. Specifically, we are *not* using I/O benchmarks to measure the performance of file system commands, such as deleting files, making directories, or opening and closing files. While these are perfectly valid and important metrics, they are more a measure of the operating system and processor speed than they are of the storage components.

V. The Ideal I/O Benchmark

In purchasing and evaluating an I/O system, most people unfortunately use trivial benchmarks. These include, for example, the time to write 1 MB to disk, the average disk access time, or the raw disk transfer rate. These metrics are similar to the CPU clock rate in processor performance evaluation; they provide some insight but do not translate easily into performance visible to the end user. In this section we list some desirable characteristics of I/O benchmarks.

First, a benchmark should help system designers and users understand why the system performs as it does. Computer architects and operating system programmers need to have benchmarks to evaluate design changes and isolate reasons for poor performance. Users should be also able to use benchmarks to understand optimal ways to use the machine. For instance, if a user wanted to have his application fit within the file cache, the ideal I/O benchmark should be able to provide information on the file cache size of a machine. This criterion may require reporting results for several different workloads, enabling the user to compare these results. These multiple workloads should require little human interaction to run.

Second, to maintain the focus of measuring and understanding I/O systems, the performance of an I/O benchmark should be limited by the I/O devices. The most intuitive test of being I/O-limited is the following: if the speedup resulting from taking out all I/O from an application is greater than the speedup resulting from taking out all CPU operations (leaving only I/O), then the application is I/O-limited. Unfortunately, this test is quite hard to perform in practice—almost any nontrivial application will not function when its I/O is eliminated. Instead, we test for how I/O-limited an application is by measuring the fraction of time spent in doing data I/O.

Third, the ideal I/O benchmark should scale gracefully over a wide range of current and future machines. Without a well planned-out scaling strategy, I/O benchmarks quickly become obsolete as machines evolve. For instance, *IOStone* tries to exercise the memory hierarchy, but touches only 1 MB of user data. Perhaps at the time IOStone was written, 1 MB was a lot of data, but this is no longer true. Another example of an I/O benchmark's need to scale is provided by disk arrays. As mentioned above, disk arrays allow multiple I/O's to be in progress simultaneously. Most current I/O benchmarks do not scale the number of processes issuing I/O, and hence are unable to properly stress disk arrays. Unfortunately, it is difficult to find widespread agreement on a scaling strategy, especially for benchmarks intended for a wide range of audiences.

Fourth, a good I/O benchmark should allow fair comparisons across machines. This comparison has two aspects. First, a fair comparison across machines should be able to be made for I/O workloads identical to the benchmark. However, users rarely have the same workload as a standard benchmark. Thus the results from a benchmark should predict performance for workloads that differ from the benchmark.

Fifth, the ideal I/O benchmark would be relevant to a wide range of applications. It is certainly easier to target a benchmark to a specific audience, and benchmarks that do a good job representing their target applications are invaluable for those applications. But, it would be even better for a benchmark to be usable by many audiences.

Finally, in order for results to be meaningful, benchmarks must be tightly specified. Results should be reproducible by general users; optimizations which are allowed and disallowed must be explicitly stated; the machine environment on which the benchmarking takes place must be well-defined and reported (CPU type and speed, operating system, compiler, network, disk, other load on the system) the starting state of the system (file cache state, data layout on disk) should be well-defined and consistent, and so on.

System Name	SPARCstation 1+	DECstation 5000/200	HP 730
Year Released	1989	1990	1991
CPU	SPARC	MIPS R3000	PA-RISC
SPECint rating	8.3	19.9	76.8
Disk System	CDC Wren IV	3 disk (Wren) RAID 0	HP 1350SX
I/O Bus	SCSI-I	SCSI-I	Fast SCSI-II
Mem. Peak Speed	80 MB/s	100 MB/s	264 MB/s
Memory Size	28 MB	32 MB	32 MB
Operating System	SunOS 4.1	Sprite LFS	HP/UX 8.07

Fig. 7. System platforms. This table shows the three systems on which we run benchmarks. The DECstation uses a three disk RAID disk array [49] with a 16-kB striping unit [6] and is configured without redundancy. The SPECint rating is a measure of the integer speed of the processor. Ratings are relative to the speed of a VAX 11/780. The full name of the HP 730 is the HP Series 700 Model 730.

System	Copy Phase (% I/O)	Compile Phase (% I/O)	Total (% I/O)
SPARCstation 1+	82 sec. (4%)	137 sec. (7%)	219 sec. (6%)
DECstation 5000	20 sec. (10%)	67 sec. (3%)	87 sec. (4%)
HP 730	17 sec. (27%)	28 sec. (6%)	45 sec. (13%)

Fig. 8. Results from the Andrew benchmark. This table shows results from running the Andrew benchmark. We divide Andrew into two sections: the *copy phase*, consisting of the copy, examination, and reading stages; and the *compile phase*. In each column, we list the percentage of time spent performing reads and writes. Each of these numbers represents the average of three runs; each run starts with an empty file cache. Note the small percentage of time spent in I/O.

In summary, the six characteristics of the ideal I/O benchmark are as follows: it should help in understanding system performance; its performance should be I/O-limited; it should scale gracefully over a wide range of current and future machines; it should allow fair comparisons across machines; it should be relevant to a wide range of applications; it should be tightly specified.

VI. System Platforms

In running benchmarks in this paper, we use three systems. All are high-performance workstations with differing I/O systems. Figure 7 summarizes their characteristics. Note that these computers were introduced in different years—our study is not meant to be a competitive market analysis of the competing products.

In order to better understand these benchmarks, we slightly modified their software. For example, we compiled in special I/O routines which traced I/O activity. Hence, we used publicly available code for as many programs as possible. In general, we used GNU (Gnu's Not Unix) code developed by the Free Software Foundation. To make results directly comparable between machines for benchmarks which used the compiler, we took the same step as Ousterhout [47] in having the GNU C compiler generate code for an experimental CPU called SPUR [19].

VII. Overview of Current I/O Benchmarks

In this section, we describe, critique, and run five common benchmarks used in I/O system evaluation: Andrew, TPC-B, Sdet, Bonnie, and IOStone. Figure 14 contains information for obtaining these benchmarks. We categorize them into two classes: application benchmarks and synthetic benchmarks.

A. Application Benchmarks

Application benchmarks use standard programs, such as compilers, utilities, editors, and databases, in various combinations, to produce a workload. Each benchmark targets a single application area, such as transaction processing or system development. Application benchmarks usually do a good job of accurately representing their target application area. But, as we shall see, they are often not I/O-limited.

1) Andrew: The Andrew benchmark was designed at Carnegie-Mellon University to be a file system benchmark for comparatively evaluating the Andrew File System against other file systems [21]. It was originally meant to be only a convenient yardstick for measuring file systems, not necessarily as a representative workload for benchmarking. Despite this intent, it has become a widely used *de facto* benchmarking standard [47].

Andrew is meant to represent the workload generated by a typical set of software system developers. It copies a file directory hierarchy, examines and reads the new copy, then compiles the copy. The file directory contains 70 files totaling 0.2 MB. CMU's experience in 1987 suggests the load generated roughly equals that generated by five users.

In Fig. 8, we list results from Andrew on our three system platforms. As in [47], we divide Andrew into two sections: the *copy phase*, consisting of the copy, examination, and reading stages; and the *compile phase*. Note that on all machines Andrew spends only 6%–13% actually doing data reads and writes. The HP 730, which has the fastest CPU, spends a higher fraction of time in I/O than the others. This supports our contention that systems with faster and faster CPU's will become more and more I/O-limited.

2) TPC-B: TPC-B measures transaction processing performance for a simple database update [65]. The first version, TP1, first appeared in 1985 [2] and quickly became the *de facto* standard in benchmarking transaction processing systems. TPC-A[1] [64] and TPC-B [65] are more tightly specified versions of TP1 and have replaced TP1 as the standard transaction processing benchmark. As a transaction processing benchmark, TPC-B not only measures the machine supporting the database but also the database software.

TPC-B repeatedly performs *Debit–Credit* transactions, each of which simulates a typical bank account change on a bank database. The database consists of customer accounts, bank branches, and tellers. Using a random customer request, a Debit–Credit transaction reads and updates the necessary account, branch, and teller balances. Requests are generated by a number of simulated customers, each requesting transactions as quickly as possible.

TPC-B's main metric is maximum throughput measured in transactions-per-second, qualified by a response time threshold demanding that 90% of all transactions complete

[1] The main difference between TPC-A and TPC-B is the presence of real terminals. TPC-A demands the test be done with actual terminals providing input at an average rate of one request every 10 s. TPC-B generates requests with internal drivers running as fast as possible. This paper discusses only TPC-B.

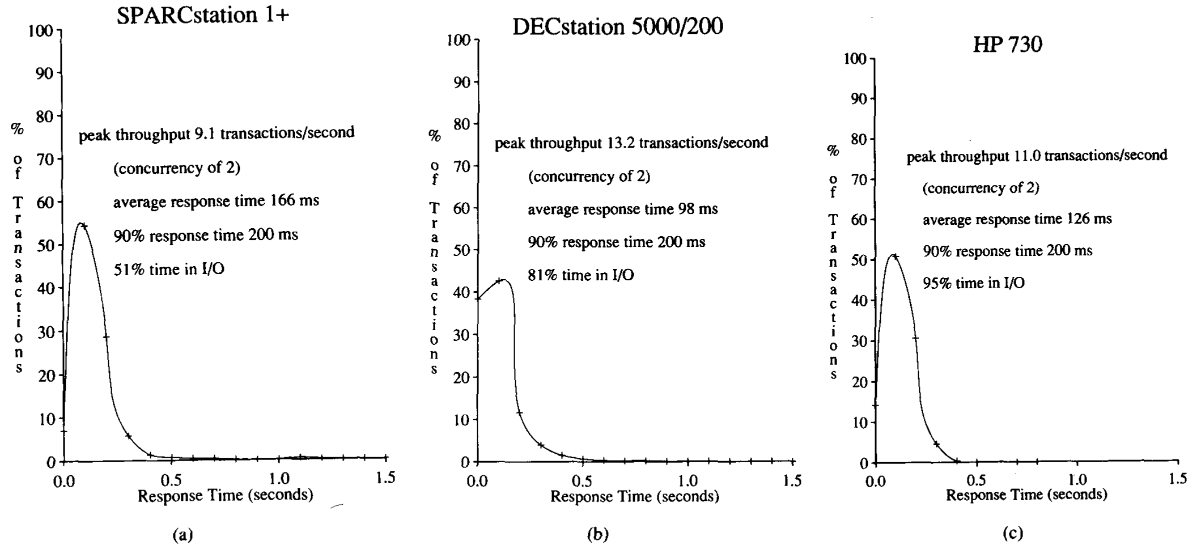


Fig. 9. TPC-B Results. These figures show TPC-B results for our three experimental systems. As a database program, we used Seltzer's simple transaction processing library LIBTP [57]. Due to software limitations, we were unable to run at concurrencies higher than 2, reflected by response times much faster than those required by TPC-B.

within 2 s. TPC-B also reports price for the system and required storage. The number of accounts, branches, and tellers specified by TPC-B is proportional to throughput—for each additional transaction-per-second of performance reported, the test system database must add 10 MB more account information. Using this database size, TPC-B reports a graph of throughput versus the average number of outstanding requests and a histogram of response times for the maximum throughput. In Fig. 9, we show the TPC-B response time characteristic on our three systems, using Seltzer's simple transaction supporting package LIBTP [57].

3) Sdet: The System Performance Evaluation Cooperative (SPEC) was founded in 1988 to establish independent standard benchmarks [56]. Their first set of benchmarks, SPEC Release 1, primarily measures CPU performance. Their second set of benchmarks, System Development Multi-tasking (SDM) Suite, measures overall system performance for software development and research environments. SDM consists of two benchmarks, Sdet [10], [11] and Kenbus1 [33]. Sdet and Kenbus1 are quite similar in benchmarking methodology; their main difference is the specific mix of user commands. We limit our discussion to Sdet, which does more I/O than Kenbus1.

Sdet's workload consists of a number of concurrently running *scripts*. Each script contains a list of user commands in random order. These commands are taken from a typical software development environment and include editing, text formatting, compiling, file creating and deleting, as well as miscellaneous other UNIX utilities [52]. Sdet increases the number of concurrently running scripts until it reaches the system's maximum throughput, measured as the script completion rate (scripts per hour). Sdet reports this maximum rate, along with the graph of throughput versus the script concurrency (Fig. 10). Once again, only a small percentage of time, 10%–22%, is spent in I/O.

B. Synthetic Benchmarks

Synthetic benchmarks exercise an I/O system by directly issuing read and write commands. In contrast, application benchmarks use standard programs, which in turn issue I/O. By issuing reads and writes directly, synthetic benchmarks are able to generate more I/O intensive workloads. But, synthetic benchmarks often yield less convincing results because they, unlike application benchmarks, do not perform useful work. We review three synthetic benchmarks here. Two popular benchmarks are Bonnie and IOStone; we also create a third synthetic benchmark to demonstrate a typical scientific I/O workload.

1) Bonnie: Bonnie measures I/O performance on a single file for a variety of simple workloads. One workload sequentially reads the entire file a character at a time; another writes the file a character at a time. Other workloads exercise block-sized sequential reads, writes, or reads followed by writes (rewrite). The final workload uses three processes to simultaneously issue random I/O's. The size of the file is set by the evaluator and should be several times larger than the system's file cache size, thus preventing the entire file from fitting in the cache. For each workload, Bonnie reports throughput, measured in kilobytes per second or I/O's per second, and CPU utilization. We show results for the three systems in Fig. 11. Most of Bonnie's workloads are I/O-limited, however, the character reads and writes are CPU-limited.

2) IOStone: IOStone is a synthetic I/O benchmark [48] based on system traces of Unix minicomputers and workstations [22], [44] and IBM mainframes [59], [60]. Using 400 files totaling 1 MB, IOStone reads and writes data in

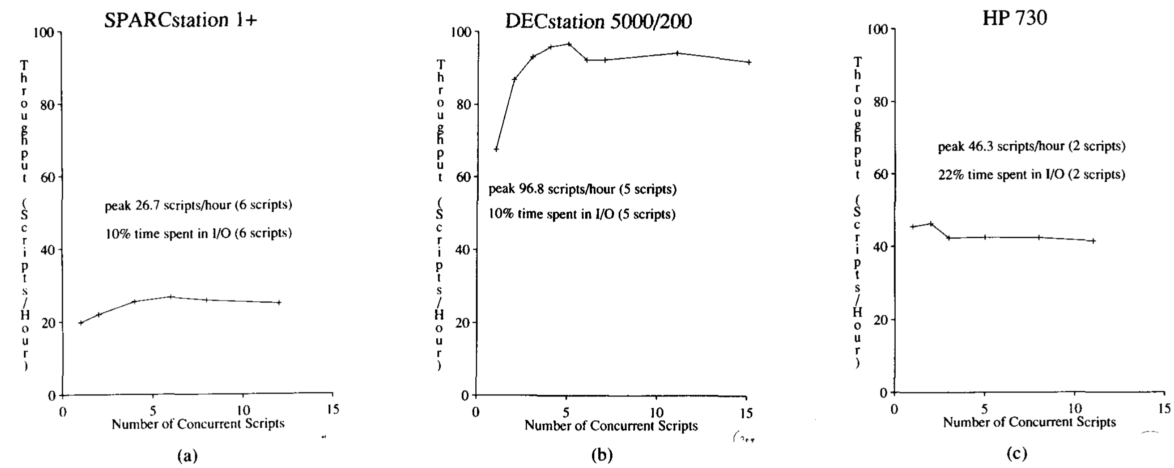


Fig. 10. Sdet results. These figures show results from the SPEC SDM benchmark Sdet.

System	Sequential Char Write KB/s (% CPU)	Sequential Block Write KB/s (% CPU)	Sequential Block Rewrite KB/s (% CPU)	Sequential Char Read KB/s (% CPU)	Sequential Block Read KB/s (% CPU)	Random Block Read IO/s (% CPU)
SPARCstation 1+	229 (99%)	558 (37%)	230 (26%)	193 (98%)	625 (37%)	31 (22%)
DECstation 5000	300 (77%)	663 (14%)	297 (14%)	253 (60%)	781 (18%)	32 (14%)
HP 730	1285 (98%)	1777 (16%)	604 (13%)	995 (85%)	2023 (13%)	39 (5%)

Fig. 11. Results from Bonnie. This table shows results from running Bonnie. For all runs, we used a 100-MB file.

System	IOStones/second	Percent Time Spent in I/O
SPARCstation 1+	11002	61%
DECstation 5000	50905	26%
HP 730	20409	81%

Fig. 12. Results from IOStone. This table shows results from running IOStone. The Sprite DECstation's file cache is large enough to contain the entire data space; hence its performance is 2–4 times better than the other systems.

System	Large File Reads (MB/s)	Large File Writes (MB/s)
SPARCstation 1+	.64 MB/s	.64 MB/s
DECstation 5000	.82 MB/s	1.28 MB/s
HP 730	1.98 MB/s	1.86 MB/s

Fig. 13. Results from two sample scientific workloads. This table shows results from running two simple workloads typical of scientific applications. *Large File Reads* consists of sequentially reading a 100-MB file in 128-kB units. *Large File Write* consists of sequentially writing a 100-MB file in 128-kB units.

patterns which approximate the locality found in [44]. One process performs all the accesses—no I/O parallelism is present. IOStone reports a single throughput result, IOStones per second (Fig.12). IOStone runs much faster when the system's file cache is large enough to contain the small data space of the benchmark. Thus the Sprite DECstation, with a maximum file cache of 25 MB, runs IOStone 2–4 times faster than the SPARCstation or the HP 730.

3) Scientific: Andrew, SDM, IOStone, and Bonnie all target system development or workstation environments. Other application areas, such as scientific or supercomputing code, have substantially different workload characteristics [38]. Typical scientific applications generally touch much more data and use much larger request sizes than workstation applications. To illustrate I/O performance for a supercomputing environment, we define two simple workloads: a large file read, in which we read a 100-MB file in 128-kB units, and a large file write, in which we write a 100-MB file in 128-kB units. In Fig. 13, we show results for our three system platforms.

VIII. Critique of Current Benchmarks

In applying our list of benchmark goals from Section V to current I/O benchmarks, we see that there is much

Benchmark	Contact	E-mail address
SPEC SDM	National Computer Graphics Corp.	spec-ncga@cup.portal.com
TPC	Shanley Public Relations	shanley@cup.portal.com
Bonnie	Tim Bray	tbray@watsol.Waterloo.EDU
IOStone	Jeffrey Becker	becker@iris.ucdavis.EDU
LADDIS	Bruce Keith	spec-preladdis-beta-test@riscee.pko.dec.com
Self-Scaling Benchmark	Peter Chen	anonymous ftp @ ftp.cs.Berkeley.EDU /ucb/benchmarks/pmchen/benchmark.tar.Z

Fig. 14. List of contacts for various benchmarks.

room for improvement. We show a qualitative evaluation of today's I/O benchmarks in Fig. 15 and make the following observations:

- *Many I/O benchmarks are not I/O-limited.* On the DECstation 5000/200, Andrew, Sdet,[2], and IOStone spend 25% or less of their time doing I/O. Further, many of the benchmarks touch very little data. IOStone touches only 1 MB of user data; Andrew touches only 4.5 MB. The best of the group is Bonnie, but even Bonnie had some tests which were CPU-bound.
- *Today's I/O benchmarks do not help in understanding system performance.* Andrew and IOStone give only a single bottom-line performance result. TPC-B and Sdet

[2]This refers to Sdet running at the peak throughput concurrency level of 5.

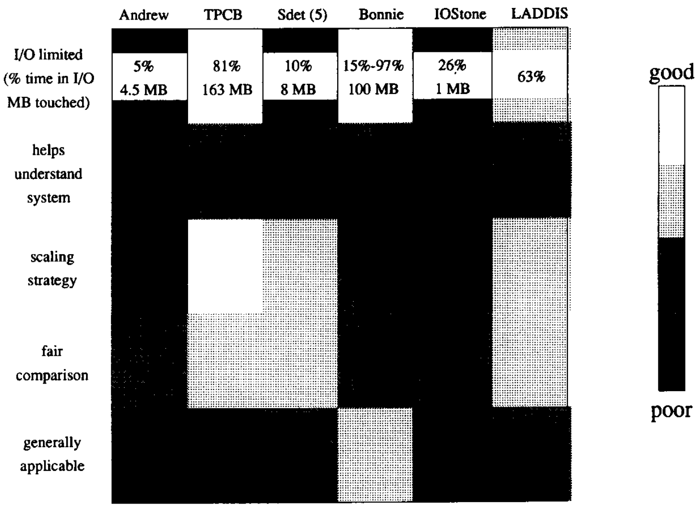


Fig. 15. Current state of I/O benchmarks. In this figure, we show a qualitative evaluation of benchmarks used today to evaluate I/O systems. We see that several are not I/O-bound and that most do not provide understanding of the system, lack a well-defined scaling strategy, and are not generally applicable. The percent time spent in I/O was measured on the DECstation 5000/200 of Fig. 7.

fare somewhat better by helping the user understand system response under various loads. Bonnie begins to help the user understand performance by running six workloads. These workloads show the performance differences between reads versus writes and block versus character I/O, but do not vary other aspects of the workload, such as the number of I/O's occurring in parallel.

- *Many of today's I/O benchmarks have no scaling strategy.* Several made no provision for adjusting the workload to stress machines with larger file caches, for example. Without a well-defined scaling strategy, I/O benchmarks quickly grow obsolete. Two exceptions are notable. TPC-B has an extremely well-defined scaling strategy, made possible by TPC-B's narrow focus on debit–credit style transaction processing and the widespread agreement on how databases change with increasing database throughput. Sdet also has a superior scaling strategy, varying the number of simultaneously active scripts until the peak performance is achieved. This idea of scaling aspects of the workload automatically is a major improvement over single workload benchmarks. However, Sdet does not scale any other aspects of the benchmark, such as request size or read/write ratio.
- *Today's I/O benchmarks make fair comparisons for workloads identical to the benchmark, but do not help in drawing conclusions about the relative performance of machines for other workloads.* It would be ideal if results from the benchmark could be applied to a wider range of workloads.
- *Today's I/O benchmarks focus on a narrow application range.* For example, TPC-B is intended solely for benchmarking debit–credit transaction processing systems.

The general poor state of I/O benchmarks suggests the need for new benchmarks.

IX. Emerging I/O Benchmarks

In this section, we review two emerging benchmarks. *LADDIS* is an evolutionary step beyond current benchmarks; *A Self-Scaling Benchmark with Predicted Performance* is a research idea being developed by this paper's authors at the University of California at Berkeley in the context of the RAID (Redundant Arrays of Inexpensive Disks) project [49].

A. LADDIS

Network file systems provide file service to a set of *client* computers, connected by a network. The computer providing this file service is called the *server*. One popular protocol for network file service is Sun Microsystem's NFS [55]. In 1989, Shein, Callahan, and Woodbury created NFSStone, a synthetic benchmark to measure NFS performance [58]. NFSStone generated a series of NFS file requests from a single client to stress and measure server performance. These operations included reads, writes, and various other file operations such as examining a file. The exact mix of operations was patterned after a study done by Sun [55]; the file sizes were patterned after the study done in [44]. Later, Legato Systems refined NFSStone, dubbing it NHFSStone. NFSStone and NHFSStone had several problems: one client could not always fully stress a file server; different versions of the benchmarks abounded; file and block sizes were not realistic; and only SunOS clients could run them.

In 1990, seven companies joined forces to create an NFS benchmark capable of stressing even the most powerful file servers. The result was *LADDIS*, named after the seven companies (Legato, Auspex, Digital Equipment Corporation, Data General, Interphase, and Sun). LADDIS is based on NHFSStone but, unlike NHFSStone, runs on multiple, possibly heterogeneous, clients and networks [31], [43]. Like NHFSStone, LADDIS is a synthetic benchmark with a certain mix of operations. LADDIS is highly parameterized—besides the percentage of each operation in the workload, LADDIS gives an evaluator the ability to change the number of clients issuing requests to the server, the rate at which each client issues requests, the total size of all files, the block size of I/O requests, and the percentage of write requests that append to an existing file. LADDIS defines default values for all tunable parameters to make benchmark results standard and comparable. For example, by default, half of all I/O requests are done in 8-kB blocks and half are done in fragments of 1, 2, or 4 kB.

LADDIS is quite similar to TPC-B in reporting philosophy. The preferred metric is a throughput (NFS operations per second) versus response time graph. As a more compact form, users may report the maximum throughput subject to an average response time constraint of 50 ms. Like TPC-B, LADDIS scales according to the reported throughput—for every 100 NFS operations per second of reported throughput, capacity must increase by 540 MB. LADDIS was released by SPEC in March of 1993 as the first part of the SPEC-SFS (System Level File Server) Suite of benchmarks.

B. A Self-Scaling Benchmark with Predicted Performance

In this section, we describe two new ideas in I/O benchmarks, proposed in more detail by this paper's authors in [7]. First, we describe a *Self-Scaling Benchmark* that automatically scales its workload depending on the performance of the system being measured. During evaluation, the benchmark automatically explores the workload space, searching for a relevant workload on which to base performance graphs.

Because the base workload resulting from the Self-Scaling Benchmark depends on the characteristics of each system, we lose the ability to directly compare performance results for multiple systems. We describe how to use *predicted performance* to restore this ability. *Predicted performance* uses the results of the Self-Scaling Benchmark to estimate performance for unmeasured workloads. The ability to accurately estimate performance for arbitrary workloads yields several benefits. First, it allows fairer comparisons to be drawn between machines for their intended use—today, users are forced to apply the relative performance from benchmarks that may be quite different from their actual workload. Second, the results can be applied to a much wider range of applications than today's benchmarks. Of course, the accuracy of the prediction determines how effectively prediction can be used to compare systems. We discuss the method and accuracy of prediction in Section IX-B2.

1) A Self-Scaling Benchmark: The workload that the Self-Scaling Benchmark uses is characterized by five parameters. These parameters lead to the first-order performance effects in I/O systems. See Fig.17 for examples of each parameter.

- **uniqueBytes**—the number of unique data bytes read or written in a workload; essentially the total size of the data.
- **sizeMean**—the average size of an I/O request. We choose sizes from a normal Bernoulli distribution[3] with a coefficient of variation equal to 1.
- **readFrac**—the fraction of reads; the fraction of writes is $1-readFrac$.
- **seqFrac**—the fraction of requests that sequentially follow the prior request. For workloads with multiple processes, each process is given its own thread of addresses.
- **processNum**—the concurrency in the workload, that is, the number of processes simultaneously issuing I/O.

In this paper, a *workload* refers to a user-level program with parameter values for each of the above five parameters. This program spawns and controls several processes if necessary.

The most important question in developing a synthetic workload is the question of representativeness [8]. A synthetic workload should have enough parameters such that its performance is close to that of an application with the same set of parameter values.[4] On the other hand, when workload models become too complex, users lose the ability to easily estimate the parameter values for their workload. Our five parameter workload model attempts to make a reasonable compromise between these two conflicting goals of simplicity and generality. Reference [7] gives a first-order verification that this synthetic workload model is general enough to capture the performance of interesting applications.

a) Single-parameter graphs: Most current benchmarks report the performance for only a single workload. The better benchmarks report performance for multiple workloads, usually in the form of a graph. TPC-B and Sdet, for example, report how performance varies with load. But even these better benchmarks do not show in general how performance depends on parameters such as request size or the mix of reads and writes.

The main output of the Self-Scaling Benchmark is a set of performance graphs, one for each parameter (uniqueBytes, sizeMean, readFrac, processNum, and seqFrac) as in Fig. 17. While graphing one parameter, all other parameters remain fixed. The value at which a parameter is fixed while graphing other parameters is called the *focal point* for that parameter. The vector of all focal points is called the *focal vector*. In Fig. 17, for example, the focal vector is {uniqueBytes = 12 and 42 MB, sizeMean = 20 kB, readFrac = 0.5, processNum = 1, seqFrac = 0.5}. Hence, in Fig. 17(e), uniqueBytes is varied while the sizeMean = 20 kB, readFrac = 0.5, processNum = 1, and seqFrac = 0.5.

[3]This distribution of sizes can be particularly useful in representing multiple applications running simultaneously.

[4]Given the uncertain path of future computer development, it is impossible to determine *a priori* all the possible parameters necessary to ensure representativeness. Even for current systems, it is possible to imagine I/O workloads that interact with the system in such a way that no synthetic workload (short of a full trace) could duplicate that I/O workload's performance.

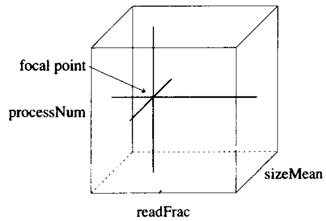


Fig. 16. Workloads reported by a set of single parameter graphs. This figure illustrates the range of workloads reported by a set of single parameter graphs for a workload of three parameters.

Fig. 16 illustrates the workloads reported by one set of such graphs for a three-parameter workload space. Although these graphs show much more of the entire workload space than current benchmarks, they still show only single-parameter performance variations; they do not display dependencies between parameters. Unfortunately, completely exploring the entire five-dimensional workload space requires far too much time. For example, an orthogonal sampling of six points per dimension requires 6^5, almost 8000, points. On the Sprite DECstation, each workload takes approximately 10 min. to measure, thus 8000 points would take almost 2 months to gather! In contrast, measuring six points for each graph of the five parameters requires only 30 points and 5 h. The usefulness of these single-parameter graphs depends entirely on how accurately they characterize the performance of the entire workload space. In the section on predicted performance we shall see that, for a wide range of I/O systems, the *shapes* of these performance curves are relatively independent of the specific values of the other parameters.

The Self-Scaling Benchmark scales by choosing different focal points for different systems. Two factors influence the choice of focal points. First, the benchmark should display a range of relevant workloads. Relevancy in turn involves two factors: the workloads must perform reasonably well, and the workloads must be practical. Second, the benchmark should adequately characterize the entire workload space with only a few graphs. Reference [7] gives more details as to how the benchmark chooses the focal points and the ranges of the graphs.

b) Examples: This section contains results from running the Self-Scaling Benchmark on the SPARCstation 1+ and a DECStation 5000/200 described in Fig. 7.

Figure 17 shows results from the Self-Scaling Benchmark on a SPARCstation 1+. The uniqueBytes values that characterized the two performance regions are 12 and 42 MB. Graphs (a)–(d) show the file cache performance region, measured with uniqueBytes = 12 MB. Graphs (f)–(i) show the disk performance region, measured with uniqueBytes = 42 MB. We learn the following from the Self-Scaling Benchmark:

- The effective file cache size is 21 MB. Applications that have a working set larger than 21 MB will go to disk frequently.
- Larger request sizes yield higher performance. This effect is more pronounced in the disk region than in the file cache region.
- Reads are faster than writes, even when all the data fit in the file cache (Fig. 17(b)). Although the data fit in the file cache, writes still cause i-node changes to be written to disk periodically for reliability in case of a system crash. This additional overhead for writing causes writes to be slower than reads.
- Increasing concurrency does not improve performance. As expected, without parallelism in the disk system, workload parallelism is of little value.
- Sequentiality offers no benefit in the file cache region (Fig. 17(b)) but offers substantial benefit in the disk region (Fig. 17(a)).

Figure 18 shows self-scaling benchmark results for the DECstation 5000/200. The uniqueBytes graph (Fig. 18(a)) shows three performance plateaus, uniqueBytes = 0 to 5 MB, uniqueBytes = 5 to 20 MB, and uniqueBytes > 20 MB. Thus the self-scaling benchmark gathers three sets of measurements: at uniqueBytes 2, 15, and 36 MB. The most interesting phenomenon involves readFrac (Fig. 18(b)).

In the first performance level (uniqueBytes = 2 MB), reads and writes are the same speed. At the next performance level (uniqueBytes = 15 MB), reads are much faster than writes. This is due to the effective write cache of Sprite's LFS being much smaller than the read cache, so reads are cached in this performance region while writes are not. The write cache of LFS is smaller because LFS limits the number of dirty cache blocks to avoid deadlock during cleaning. The effective file cache size for writes is only 5–8 MB, while for reads it is 20 MB [51].[5] In contrast, when uniqueBytes is large enough to exercise the disk for both reads and writes, writes are faster than reads. This phenomenon is due to Sprite's LFS, which improves write performance by grouping multiple small writes into fewer large writes.

2) Predicted Performance: The Self-Scaling Benchmark increases our understanding of a system and scales the workload to remain relevant. However, it complicates the task of comparing results from two systems. The problem is the benchmark may choose different workloads on which to measure each system. Also, though the output graphs from the Self-Scaling Benchmark apply to a wider range of applications than today's I/O benchmarks, they stop short of applying to all workloads. In this section, we show how predicted performance solves these problems by enabling us to accurately estimate the I/O performance for arbitrary workloads based on the performance of a small set of measured workloads (that is, those measured by the Self-Scaling Benchmark).

A straightforward approach for estimating performance for all possible workloads is to measure a comprehensive set of workloads. However, measuring all possible workloads is not feasible within reasonable time constraints. A more attractive approach is to use the graphs output by the Self-Scaling Benchmark (such as Fig. 17) to estimate

[5] The default limit was tuned for a machine with 128 MB of memory; in production use, this limit would be changed for the 32-MB system being tested.

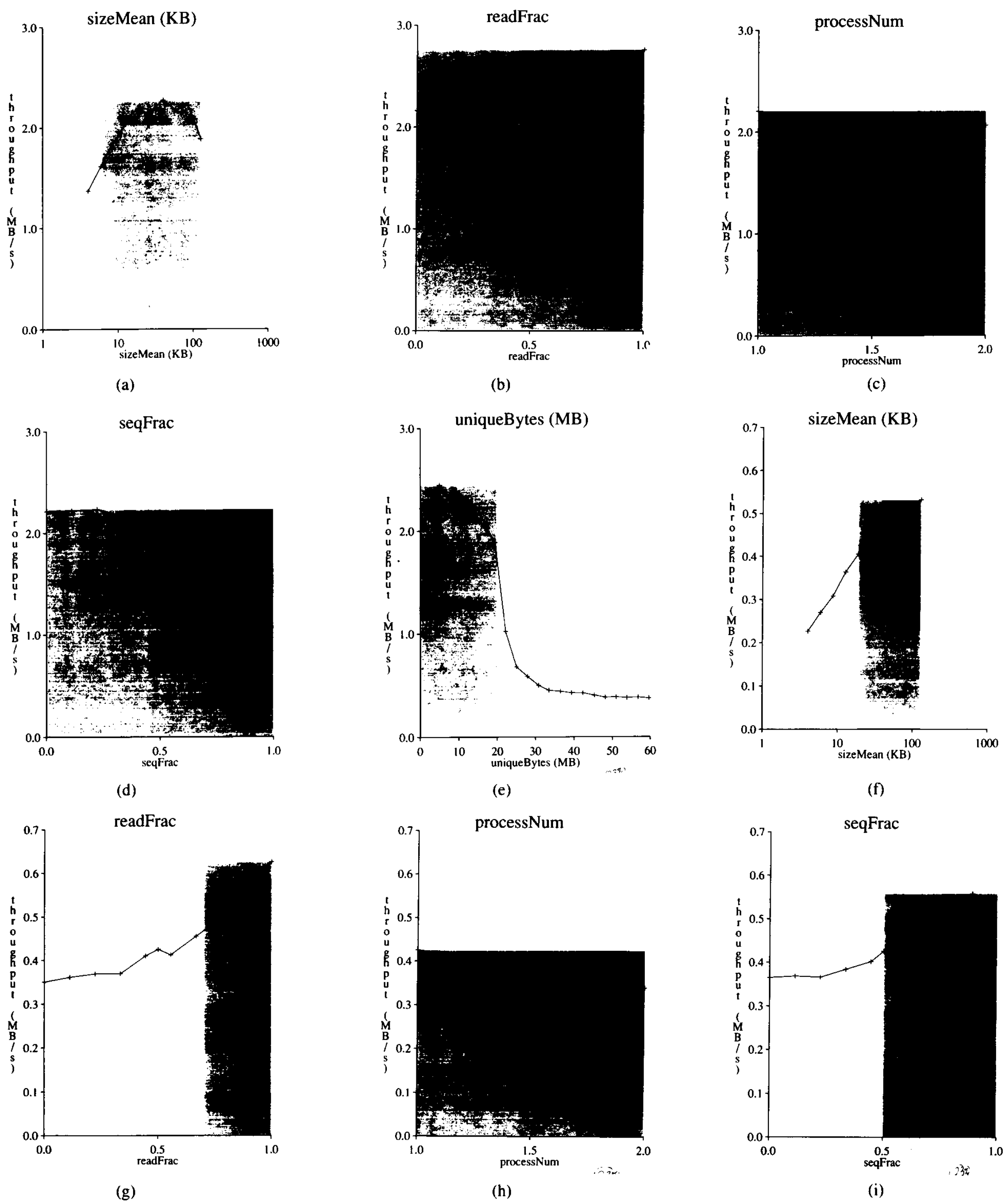
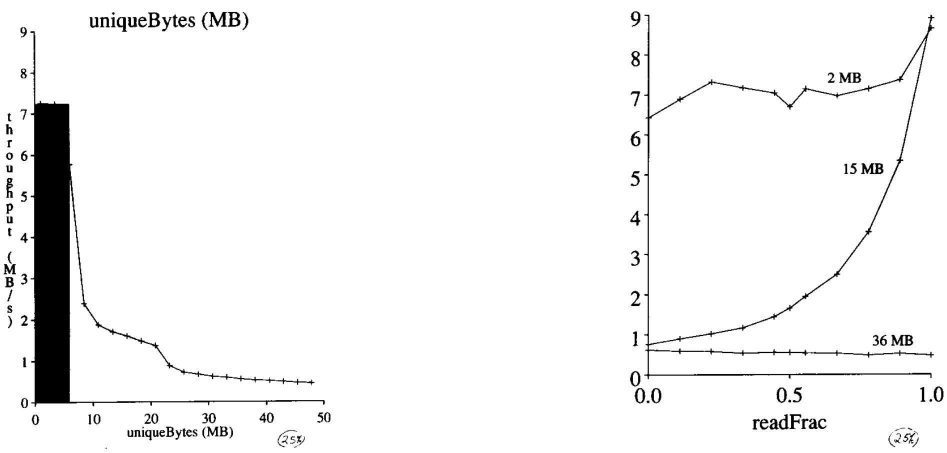


Fig. 17. Results from a self-scaling benchmark when run on a SPARCstation 1+. This figure shows results from the Self-Scaling Benchmark when run on a SPARCstation 1+. The focal point for uniqueBytes is 12 MB in graphs (a)–(d) and 42 MB in graphs (f)–(i). For all graphs, the focal points for the other parameters is sizeMean = 20 kB, readFrac = 0.5, processNum = 1, seqFrac = 0.5. Increasing sizes improve performance, more so for disk accesses than file cache accesses (parts (a) and (f)). Reads are faster than writes, even when data are in the file cache. This is because inodes must still go to disk. Sequentiality increases performance only for the disk region (part (i)).

performance for unmeasured workloads. This is similar in concept to work done by Saavedra-Barrera, who predicts CPU performance by measuring the performance for a small set of FORTRAN operations [53].

We estimate performance for unmeasured workloads by assuming the *shape* of a performance curve for one parameter is independent of the values of the other parameters. This assumption leads to an overall



(a) (b)

Fig. 18. Selected results from Self-Scaling Benchmark when run on a DECstation 5000/200. In this figure, we show selected results from the Self-Scaling Benchmark when run on a DECstation 5000/200. Graph (a) shows three plateaus in uniqueBytes, due to the different effective file cache sizes for reads and writes. The focal points chosen for uniqueBytes are 2, 15, and 36 MB. The focal points for the other parameters is sizeMean = 40 kB, readFrac = 0.5, processNum = 1, seqFrac = 0.5. Note in graph (b) how reads are much faster than writes at uniqueBytes 15 MB, slightly slower than writes at uniqueBytes 36 MB, and approximately the same speed at uniqueBytes 2 MB. These results helped us understand that, due to the default limit on the number of dirty file cache blocks allowed, the effective file cache size for writes was much smaller than the file cache size for reads.

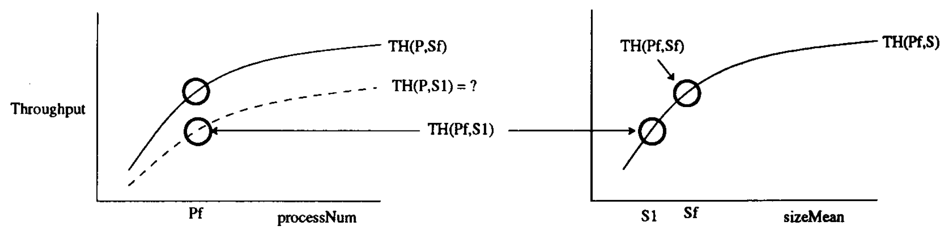


Fig. 19. Predicting performance of unmeasured workloads. In this figure, we show how to predict performance with a workload of two parameters, processNum and sizeMean. The solid lines represent workloads that have been measured; the dashed line represent workloads that are being predicted. The left graph shows throughput graphed against processNum with sizeMean fixed at $sizeMean_f$. The right graph shows throughput versus sizeMean with processNum fixed at $processNum_f$. We predict the throughput curve versus processNum with sizeMean fixed at $sizeMean_1$ by assuming that $Throughput(processNum, sizeMean_f)$ / $Throughput(processNum, sizeMean_1)$ is constant (independent of processNum) and fixed at $Throughput(processNum_f, sizeMean_f)$ / $Throughput(processNum_f, sizeMean_1)$.

performance equation of *Throughput* $(X, Y, Z...) = f_X(X) \times f_Y(Y) \times f_Z(Z)\ldots$, where X, Y, Z, ... are the parameters. Pictorially, our approach to estimating performance for unmeasured workloads is shown for a two parameter workload in Fig. 19. In the Self-Scaling Benchmark, we measure workloads with all but one parameter fixed at the focal point. In Fig. 19, these are shown as the solid line throughput curves *Throughput* $(processNum, sizeMean_f)$ and *Throughput* $(processNum_f, sizeMean)$, where $processNum_f$ is processNum's focal point and $sizeMean_f$ is sizeMean's focal point. Using these measured workloads, we estimate performance for unmeasured workloads *Throughput* $(processNum, sizeMean_1)$ by assuming a constant ratio between *Throughput* $(processNum, sizeMean_f)$ and *Throughput* $(processNum, sizeMean_1)$. This ratio is known at $processNum = processNum_f$ to be

$$\frac{Throughput(processNum_f, sizeMean_f)}{Throughput(processNum_f, sizeMean_1)}$$

. To measure how accurately this approximates actual performance, we measured 100 workloads, randomly selected over the entire workload space (the range of each parameter is shown in Fig. 17).

Fig. 20 shows the prediction accuracy of this simple product-of-single-variable-functions approach. We see that, over a wide range of performance (0.2 to 3.0 MB/s), the predicted performance values match extremely well to the measured results. 50% of all workloads have a prediction error of 10% or less; 75% of all workloads had a prediction error of 15% or less. In contrast, any single-point I/O benchmark would predict all workloads to yield the

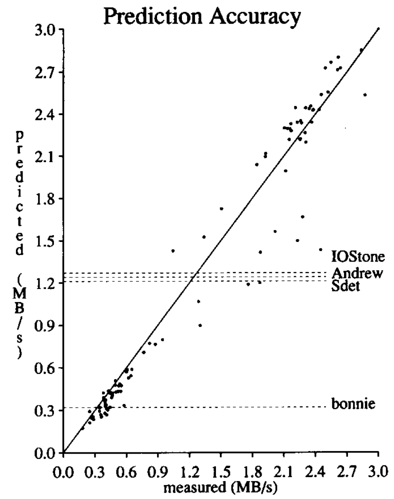


Fig. 20. Evaluation of prediction accuracy for SPARCstation 1+ with 1 disk. This figure graphs the predicted performance against the actual (measured) performance for the SPARCstation in Fig. 17. Each point represents a single workload, with each parameter value randomly chosen from its entire range shown in Fig. 17. The closer the points lie to the solid line, the better the prediction accuracy. Median error is 10%. Performance for each workload ranges from 0.2 to 3.0 MB/s. For comparison, we show the single-performance point predicted by Andrew, IOStone, and Bonnie (sequential block write), and Sdet as horizontal dashed lines. Clearly these single point benchmarks do not predict the performance of many workloads.

same performance. For example, Andrew's workload and IOStone's workload both yield performance of 1.25 MB/s, leading to a median prediction error of 50%. Bonnie's sequential block write yields a performance of 0.32 MB/s, for a median prediction error of 65%. These are shown by the dashed lines in Fig. 20.

The accuracy of our predictions has two important ramifications. First, it renders the graphs from the Self-Scaling Benchmark much more useful, since they can be used to estimate performance for other workloads. Second, it supports the assumption of shape independence; the shape of each graph in Fig. 17 is approximately independent of the values of the other parameters.

X. Summary

I/O performance, long neglected by computer architects and evaluators [18], is rapidly becoming an area of important research activity. As CPU and memory speed increases continue to outstrip I/O speed increases, this trend will continue and accelerate. I/O performance evaluation differs from other types of computer performance evaluation in several key ways:

- The main metric in processor evaluation is speed, or its reciprocal, time. In contrast, I/O evaluation considers many more factors—capacity, reliability, and several composite metrics such as throughput-response time graphs.
- Researchers have been developing CPU benchmarks for many years. In contrast, I/O benchmarks have only recently begun to be of wider interest. As a result, I/O benchmarks are not as mature as CPU benchmarks.
- I/O performance, even more than CPU performance, depends critically on what workload is applied. Hence, the benchmarks evaluators use in measuring I/O performance is of primary importance.
- I/O benchmarks must scale in order to remain relevant. Benchmarks generally require several years to become accepted. By this time, nonscaling benchmarks have been made nearly obsolete by the rapid increases in I/O system capacity or other developments. Of the benchmarks described in this paper, TPC-B, Sdet, and LADDIS have the greatest chance of remaining relevant for many years due to how they scale the size of the benchmark according to the performance of the system.

System	Median Error	Enhanced Error	Repeatability Error
SPARCstation 1+	10%	7%	2%
DECstation 5000/200	12%	10%	3%
HP 730	13%	8%	3%
Convex C240	14%	8%	5%

Fig. 21. Summary of median prediction errors. This table summarizes the prediction errors on all systems. "Enhanced Error" on all machines but the Convex refers to the prediction error on the sample of workloads not in the thrashing region between the file cache and disk locality regions. For the Convex, prediction error was most closely correlated with sizeMean, so enhanced error refers to points with sizes smaller than 300 kB. The last column in the table lists the inherent measurement error, which was measured by running the same set of random workloads twice and using one run to "predict" performance of the other run.

Storage systems are improving rapidly in some areas. Disks and tape systems are improving in capacity/cost; disk arrays are improving the available data and I/O throughput; file caching and solid-state disks are improving response times for cacheable data. Overall, however, further innovation is needed to keep up with the incredible gains made in CPU performance.

We have described a new approach to I/O performance evaluation—the Self-Scaling Benchmark with Predicted Performance. The Self-Scaling Benchmark scales automatically to current and future systems by scaling the workload to the system under test. It also gives insight on a machine's performance characteristic by revealing its performance dependencies for each of five workload parameters.

Predicted performance restores the ability to compare two machines on the same workload lost in the Self-Scaling Benchmark. Further, it extends this ability to workloads that have not been measured by estimating performance based on the graphs from the Self-Scaling Benchmark. We have shown that this prediction is far more accurate over a wide range of workloads than any single point benchmark.

We hope this approach will help I/O architects understand I/O systems and will help direct their efforts in developing the next generation of storage systems.

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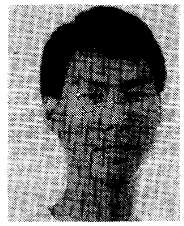

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