Failure Data Analysis of HPC Systems *

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Abstract

Continuous availability of HPC systems built from commodity components have become a primary concern as system size grows to thousands of processors. In this paper, we present the analysis of 8-24 months of real failure data collected from three HPC systems at the National Center for Supercomputing Applications (NCSA). The results show that the availability is 98.7-99.8% and most outages are due to software halts. On the other hand, the downtime are mostly contributed by hardware halts or scheduled maintenance. We also used failure clustering analysis to identify several correlated failures.

1. Introduction

Continuous availability of high performance computing (HPC) systems built from commodity components have become a primary concern as system size grows to thousands of processors. To design more reliable systems, a solid understanding of failure behavior of current systems is in need. Therefore, we believe failure data analysis of HPC systems can serve three purposes. First, it highlights dependability bottlenecks and serves as a guideline for designing more reliable systems. Second, real data can be used to drive numerical evaluation of performability models and simulations, which are an essential part of reliability engineering. Third, it can be applied to predict node availability, which is useful for resource characterization and scheduling [1].

In this paper, we studied 8-24 months of real failure data collected from three HPC systems at the National Center for Supercomputing Applications (NCSA). The remainder of this paper is organized as follows. In §2 we described the systems characteristics and failure data collection. We present preliminary analysis of failure data in §3 followed by failure distribution and correlation analysis in §4 and §5. We summarize related work in §6 and conclude our study in §7.

2. The Systems and Measurements

The three HPC systems we studied are quite different architecturally. The first is an array of SGI Origin 2000 (O2K) machines. SGI Origin 2000 is a cc-NUMA distributed shared memory supercomputer. An O2K can have up to 512 CPUs and 1 TB of memory, all under control of one single-system-image IRIX operating system. The configuration at NCSA is an array of twelve O2K’s (total 1520 CPUs) connected by proprietary, high-speed HIPPI switches. Table I lists its detailed specification. The machines A, B, E, F, and N are equipped with 250 MHz MIPS R10000 processors, and the rest with 195 MHz MIPS R10000 processors. M4 accepts interactive access, while the others machines only service batch jobs. Peak performance of NCSA O2K is 328 gigaflops.

The second and the third systems are Beowulf-style PC clusters. “Platinum” cluster has 520 two-way SMP 1 GHz Pentium-III nodes (1040 CPUs), 512 of which are compute nodes (2 GB memory), and the rest are storage nodes and interactive access nodes (1.5 GB memory). “Titan” cluster consists of 162 two-way SMP 800 MHz Itanium-1 nodes (324 CPUs), 160 of which are compute nodes (1.5 GB memory) and 2 are for interactive access. Both clusters use Myrinet 2000 and Gigabit Ethernet as system interconnect. Myrinet is faster and for node communications, whereas the Gigabit Ethernet is slower and serves I/O traffic. Both clusters have one teraflop of peak performance.

All three HPC systems use batch job control software to manage workload. O2K runs LSF (Load Sharing Facility) queueing system. Each job on O2K have resource limits of 50 hours of run-time and 256 CPUs. Platinum and Titan employ Portable Batch System with the Maui Scheduler, and the job limits are 352 and 128 nodes for 24 hours, respectively.

According to a user survey [8], the NCSA HPC systems are devoted to multiple disciplinary sciences research: physics (20%), engineering (16%), chemistry (14%), biology (13%), astronomy (13%), and material science (12%).
Seventy percent of users write programs in Fortran (F90 and F77) or mix of Fortran and C/C++. Sixty-five percent users use MPI or OpenMP as the parallel programming model. In terms of job sizes, 22% users typically allocate 9-16 CPUs. About equally many users (14-15%) allocate 2-4, 5-8, 17-32, or 33-64 CPUs.

The failure log was collected in the form of monthly or quarterly reliability reports. At the end of a month or quarter, a report for each node/machine is created. A report records outage date (but no outage time), type, and duration. There are five outage types defined by NCSA system administrator: Software Halt (SW), Hardware Halt (HW), Scheduled Maintenance (M), Network Outages, and Air Conditioning or Power Halts (PWR). The cause of an outage is determined as follows: a program runs at machine boot time prompts the administrator to enter the reason for the outage. If nothing is entered after two minutes, the program defaults to recording a Software Halt.

The data collection period was two years (April 2000 to March 2002) for O2K and eight months (January 2003 to August 2003) for Platinum and Titan. In this set of failure log, there is no occurrence of Network Outage, so we exclude it from the rest of analysis.

3. Preliminary Results

Before describing the failure data, we would like to clarify some terminology. Time to Failure (TTF) is the interval between the end of last failure and the beginning of next failure. Time between Failures (TBF) is the interval between the beginnings of two consecutive failures. Time to Repair (TTR) is synonymous with Downtime. Figure 1 illustrates the differences. Because the failure log does not include the start and end times of outages, we can only calculate TBFs in terms of days.

![Figure 1. TBF, TTF, and TTR](image)

Table 1 and 2 and Figure 2 summarize the failure data for the three HPC systems. There are two kind of availability measures. The usual availability is computed as

$$1 - \frac{\sum (# \text{Down CPU} \times \text{Downtime})}{\# \text{Total CPU} \times \text{Total time}}$$

The scheduled availability (S Avail) removes the Scheduled Maintenance downtime from consideration and only counts scheduled uptime as total time, so it is computed as

$$1 - \frac{\sum (# \text{Down CPU} \times \text{Unsched. Downtime})}{\# \text{Total CPU} \times \text{Sched. time}}$$

Note that in O2K’s case, the twelve machines have different number of CPUs, so “# Down CPU” is the number of CPUs on the failed machine. In Platinum and Titan’s case, the “# Down CPU” is 2.

For the whole system of O2K, the TBF reported in Table 1 is actually TBF, and the downtime is the weighted average of individual machine downtimes:

$$\frac{\sum (# \text{Down CPU} \times \text{Downtime})}{\# \text{Total CPU}}$$

From the data it is obvious that software halts account for most outages (59-83%), but the average downtime (i.e. MTTR) is only 0.6-1.5 hours. On the other hand, although the fraction of hardware outages is meager (1-13%), average hardware downtime is the greatest among all unscheduled outage types (6.3-100.7 hours). This is reasonable because hardware problems usually requires ordering and replacing parts and performing tests, while many software problems can be fixed by reboot.

We contacted the NCSA staff about the hardware failure causes of PC clusters. We were told that there were two or three cases where power supplies needed to be replaced; otherwise, the main cause of hardware outages is the Myrinet, including network cards, cables, and switch cards. A network card resides at a host PC and is connected by cables to the Myrinet switch enclosure. A Myrinet switch enclosure stacks many Myrinet M3-SPINE switch cards. The usual symptom that prompts a network card or switch card replacement is there are excessive CRC check errors. Sometimes the self-testing in a switch card may fail and lead to replacement. Cable replacements also occurred because the “ping” query packets cannot get through.

The availability is lower for O2K because when one of its machine is down, as much as one-sixth of the overall system capacity could disappear (e.g. machine B, which has 256 CPUs.) This is unlike PC clusters in which each node usually contains no more than 8 CPUs, so the availability could degrade more gracefully, assuming the outage is not catastrophic such as a power failure or network partitioning. Although monolithic single-system-image machines benefit from ease of administration, a unified view of process space, and extremely fast interprocess communication, it seems large systems composed of finer-grained management units are more favorable in terms of availability.

For O2K, the machine-wise TBFs and TTRs are skewed toward small values. Eleven of twelve machines have MTBF greater than 8 days, but the medians of TBF are mostly smaller than 4 days. For TTR, nine machines’ MTTR are greater than 2.5 hours, yet the medians are 0.3-0.9 hours. The same phenomenon also occurs on Platinum.
| All | A    | B    | E    | F    | H1   | H    | J    | M    | M2   | M4   | N    | S    |
|-----|------|------|------|------|------|------|------|------|------|------|------|------|
| CPUs | 1520 | 128  | 256  | 128  | 128  | 128  | 128  | 64   | 48   | 128  | 128  |      |
| Mem (GB) | 618  | 64   | 128  | 64   | 76   | 64   | 32   | 32   | 16   | 14   | 64   | 32   |
| Outages | | 687  | 87   | 182  | 40   | 81   | 42   | 25   | 32   | 24   | 41   | 59   | 37   | 37   |
| SW (%) | 59   | 74   | 68   | 53   | 63   | 57   | 60   | 59   | 42   | 44   | 39   | 49   | 46   |      |
| HW (%) | 13   | 8    | 19   | 13   | 9    | 21   | 8    | 3    | 17   | 10   | 5    | 5    | 32   |      |
| M (%) | 21   | 11   | 12   | 28   | 20   | 12   | 24   | 19   | 29   | 32   | 49   | 38   | 14   |      |
| PWR (%) | 7    | 7    | 2    | 8    | 9    | 10   | 8    | 19   | 13   | 15   | 7    | 8    | 8    |      |
| Downtime (day) | | 9.5  | 8.7  | 19.2 | 15.3 | 5.9  | 13.8 | 6.2  | 3.6  | 4.8  | 7.5  | 4.5  | 5.5  | 5.0  |
| SW (%) | 27   | 32   | 49   | 11   | 36   | 9    | 5    | 25   | 15   | 27   | 12   | 6    | 16   |      |
| HW (%) | 28   | 35   | 29   | 1    | 10   | 67   | 49   | <1   | 22   | 12   | 4    | 28   | 22   |      |
| M (%) | 41   | 28   | 20   | 85   | 44   | 22   | 45   | 66   | 58   | 52   | 75   | 62   | 58   |      |
| PWR (%) | 4    | 4    | 2    | 3    | 9    | 2    | 2    | 9    | 4    | 9    | 10   | 4    | 4    |      |
| Avail (%) | | 98.3 | 98.8 | 97.4 | 97.9 | 99.2 | 98.1 | 99.2 | 99.5 | 99.3 | 99.0 | 99.4 | 99.2 | 99.3 |
| S Avail (%) | | 99.2 | 99.1 | 97.9 | 99.7 | 99.6 | 98.3 | 99.5 | 99.8 | 99.7 | 99.5 | 99.8 | 99.7 | 99.7 |
| MTBF (day) | | 1.0  | 8.1  | 4.0  | 15.9 | 8.6  | 14.7 | 29.5 | 22.5 | 30.3 | 17.4 | 12.3 | 18.6 | 18.5 |
| StdDev | 2.1  | 14.5 | 5.8  | 28.5 | 14.7 | 20.9 | 36.9 | 33.4 | 48.3 | 31.7 | 18.7 | 34.3 | 22.9 |      |
| Median | 0.9  | 1.7  | 2.1  | 1.7  | 2.5  | 3.5  | 25.0 | 1.0  | 4.0  | 1.6  | 5.7  | 1.0  | 11.0 |      |
| MTTR (hr) | | 3.5  | 2.4  | 2.5  | 9.2  | 1.7  | 7.9  | 6.0  | 2.7  | 4.8  | 4.4  | 1.9  | 3.6  | 3.2  |
| StdDev | 13.1 | 7.8  | 5.2  | 29.9 | 5.1  | 33.2 | 15.6 | 7.5  | 9.3  | 7.7  | 8.1  | 8.8  | 7.2  |      |
| Median | 0.5  | 0.4  | 0.9  | 0.43 | 0.4  | 0.5  | 0.5  | 0.3  | 0.5  | 0.7  | 0.4  | 0.4  | 0.5  |      |
| MTTR SW | 1.5  | 1.1  | 1.8  | 1.9  | 1.0  | 1.3  | 0.5  | 1.1  | 1.7  | 2.7  | 0.6  | 0.4  | 1.1  |      |
| MTTR HW | 6.3  | 10.5 | 3.9  | 0.6  | 2.0  | 24.7 | 36.3 | 0.4  | 6.4  | 5.4  | 1.3  | 18.6 | 2.2  |      |
| MTTR M | 8.0  | 5.8  | 4.3  | 28.6 | 3.9  | 14.6 | 11.2 | 9.6  | 9.6  | 7.1  | 2.8  | 5.9  | 13.8 |      |
| MTTR PWR | 2.1  | 1.5  | 3.4  | 3.8  | 1.0  | 1.5  | 1.3  | 1.2  | 1.7  | 2.8  | 2.6  | 1.7  | 1.7  |      |

Table 1. O2K Failure Data Summary

| Platinum | Titan |
|----------|------|
| Outages  | 7279 | 947  |
| Outage/Node | 14.00 | 5.85 |
| SW (%) | 84   | 80   |
| HW (%) | < 0.1 | 5    |
| M (%) | 16   | 1    |
| PWR (%) | 0    | 34   |
| Downtime/Node (hr) | 12.16 | 12.55 |
| SW (%) | 69   | 18   |
| HW (%) | 10   | 18   |
| M (%) | 21   | < 1  |
| PWR (%) | 0    | 64   |
| Avail (%) | 99.79 | 99.78 |
| S Avail (%) | 99.83 | 99.79 |

Table 2. Platinum and Titan Failure Data Summary
Figure 2. The rows from top to bottom depict weekly Availability, Outages, Downtime, and Failure Clustering (see §5), respectively. The X axis in all plots is week. The Y axis in Downtime row is CPU-hours and in Failure Clustering row, the number of machines/nodes involved.
and Titan’s node TTR. These prompt us to study examine closely the distributions of TBF and TTR, which we documented our findings in the next section.

4. Failure Distribution

In analytical modeling, the distributions of TBF and TTR are key components for obtaining precise results [12] because distributions of the same mean and variance can still yield very different outcomes. In this section, we investigate the distributions of TBF and TTR with the assumption that failures and repairs are all independent.

We first choose a set of distributions as our parametric probability models and seek the parameters that best fit the data to these models. An open-source statistical package called WAFO [2] is used to find parameters. Then we apply chi-square test as goodness-of-fit test to pick the best-fit distribution.

Our selection of probability models includes exponential, gamma distribution and a family of heavy-tail distributions (Weibull, Truncated Weibull, Log-normal, Inverse normal, and Pareto [4]). Heavy-tail means the complementary cumulative distribution function $1 - F(x)$ decays more slowly than exponentially. Heavy-tail distributions are chosen because many failure data studies (e.g. [10, 3]) have shown that they are actually more prevalent than exponential distribution, which is commonly assumed in probability models to make analysis tractable.

For each system, we conglomerate TBF and TTR data of all machines/nodes and present their distributions and fitting functions in Figure 3. For O2K, the TTR is fit by Inverse normal $f(x) = 1.87(2\pi x^3)^{-0.5}\exp(-12.76(x-0.37)^2/x)$ and TBF by Weibull $F(x) = 1 - \exp(-5.61x^{0.5})$. For Platinum, the TTR is fit by Truncated Weibull $F(x) = 1 - \exp(-0.79(x + 0.14)^{0.15} + 5.07)$ and TBF by Exponential $F(x) = 1 - e^{-0.07x}$. For Titan, the TTR is fit by Gamma $f(x) = 0.27x^{-0.51}e^{-0.23x}$ and TTR by Exponential $F(x) = 1 - e^{-0.037x}$.

The distributions of Titan’s failure data have staircase-like shapes unfound in other two systems’. For example, there are two sudden shoot-ups at 1.4 hour and 6.8 hour in Titan’s TTR distribution. The shoot-ups mean that there were massive nodes down for about the same period of time, which implies a possibility of correlated failure. To understand this anomaly, we perform a failure correlation analysis, as described in the next section.

5. Failure Correlation

In the last section we assumed the failures are independent and derived the failure distribution. Failure independence is a common assumption in reliability engineering to
simplify analysis and system design. However, many statistical tests and log analyses showed that real-world distributed computing environments do exhibit correlated failures.

In this section, we investigate how outages of different machines relate to each other by clustering approach [13]. Roughly speaking, this approach groups failures which are close either in space or in time. It should be emphasized that the correlation resulted from clustering is purely statistical and does not imply the failures really have cause-and-effect (causal) relationship. Since our collection of failure log lacks error details, we can only rely on statistics to find correlation.

To not confuse with the word “cluster” in “PC clusters,” we will refer to a failure cluster as a “batch.” We define a batch to be a time period \([T_1, T_2]\) in which every day there is at least one outage (regardless of type), and no outages occur on day \(T_1 - 1\) or \(T_2 + 1\). Put another way, we coalesce into a batch the failures of different machines/nodes that occur in consecutive days. The bottom row of Figure 2 illustrates the results. The width and height of a rectangle indicate the duration and the machine/node count of that batch, respectively.

Using this method, we found there are 79 batches for O2K, accounting for 55 percent of all outages. Eight-five percent of batches last for no more than three days, and 89 percent of batches involve no more than four machines. There are four batches that involve all twelve machines. In week 31, the failure was caused by power or air conditioning problem and was followed a two-day maintenance. In week 35, there was a system-wide maintenance on the first day, but some machines experienced hardware halts and all were again taken offline for maintenance on the second day, and all machines had short software problems on the last day. In week 78, a system maintenance occurred and lasted 37-91 hours. The last catastrophic outage occurred on week 97 due to power problems. Note that the massive outages in week 31, 35, and 78 are also reflected as spikes in Availability, Outages, and Downtime plots.

The failure clustering plot also reveals some possible failure correlation in Platinum and Titan systems. Statistically speaking, the chance of a batch having a great deal of outages in a short time (e.g. the razor-thin rectangles in the bottom row of Figure 2) is close to zero. Thus, a reasonable explanation for such an occurrence is failure correlation. To justify this claim, we take Platinum system as an example. There is a batch in week 4 which contains 501 nodes in one day. If we assumes failures are independent and TBF has exponential distribution, then the number of failures in a given duration follows Poisson distribution. So the chance of at least 501 outages in one day is

\[
\sum_{n=501}^{\infty} \left( e^{-30}30^n/n! \right) = 6.3 \times 10^{-14}
\]

where 30 is the average number of outages per day of Platinum system. After checking the log, it shows that particular outage is Software Halt and gives 5-15 minutes downtime.

Titan system’s failure correlation is even more conspicuous. The three peaks represent massive outages at week 10, due to a 9 minute software halt followed by 6.8 hours of hardware halt, at week 14, due to 1.4 hours of power failure, and at week 21, due to 6.8 hours of power failure. The 1.4 and 6.8 hours of downtime explains the two sudden rises in Titan’s TTR distribution in Figure 3 as most nodes experienced them. The three staircases in Titan’s TBF distribution reflect the intervals among the three massive outages, which are 64, 29, and 48 days. As in O2K’s case, the three outages of Titan are also mirrored in Availability, Outages, and Downtime plots.

6. Related Work

Field failure data analysis of very large HPC systems is usually for internal circulation and is almost never published in detail. Nevertheless, there are several talks and reports that shed light on the administration experience of some of the world’s most powerful supercomputers.

Koch [5] reported the situation of ASCI White. A whole-system reboot of ASCI White takes 4 hours and preventive maintenance is performed weekly, with separate periods for software and hardware. Machine problems occurred in every aspect of the system. Transient CPU faults generated invalid floating-point numbers, and it took great effort to spot these corrupted nodes because they passed standard diagnostic tests and only failed in real programs. Bad optical interconnects led to non-repeatable link errors which corrupted the computation because these errors could sneak through network host firmware without being detected. The storage system was not 100% dependable either. The parallel file-system sometimes failed to return I/O error to the user program when the program was dumping restart files. In addition, the archival subsystem’s buggy firmware corrupted restart files and made the user program fail to launch.

Seager [11] showed that the reliability of the ASCI White improved over time as MTBF increased steadily from as short as 5 hours in January 2001 to 40 hours in February 2003. Except uncategorized failures, the storage system (both local disks and IBM Serial Disk System) is the main source of hardware problems. Next to disks is CPU and third-party hardware troubles. For software, communication libraries and operating systems contributed the most interruptions.

Morrison [9] reported operations of the ASCI Q during June 2002 thru February 2003. The MTBI (mean time between interruption) is 6.5 hours, and on the average there were 114 unplanned outages per month. Putting storage subsystem aside, hardware problems account for 73.6% of
node outages, with CPU and memory modules being responsible for over 96% of all hardware faults (CPU is 62.5% and memory is 33.6%). Network adaptors or system boards seldom fail.

Levine [7] described the failure statistics of Pittsburgh Supercomputing Center’s supercomputer Lemieux: MTBI during April 2002 to February 2003 is 9.7 hours, shorter than predicted 12 hours. The availability is 98.33% during mid-November 2002 to early February 2003.

The National Energy Research Scientific Computing Center (NERSC) houses several supercomputers and their operations are summarized in NERSC’s annual self-evaluation reports [6]. During August 2002 to July 2003, their largest supercomputer Seaborg reached 98.74% scheduled availability, 14 days MTBI, and 3.3 hours MTTR. Storage and file servers had similar availability. Two-thirds of Seaborg’s outages and over 85% of storage system’s outages are due to software.

7. Conclusions

In this paper we reported the failure data analysis of three NCSA HPC systems, one of which is an array of distributed shared memory mainframes and the rest are PC clusters. The results show that the availability is 98.7-99.8%. Most outages are due to software halts, but the downtime per outage is highest due to hardware halts or scheduled maintenance. We also sought the distributions of time-between-failures and time-to-repairs and found some of them exhibit heavy-tail distributions instead of exponential. Finally, we applied failure clustering analysis and identified several correlated failures. Because failure data analysis of HPC system is scarce, we believe this paper provides very valuable information for researchers and practitioners working on reliability modeling and engineering.

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