Workload Flurries

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Abstract

The performance of computer systems depends, among other things, on the workload. Performance evaluations are therefore often done using logs of workloads on current productions systems, under the assumption that such real workloads are representative and reliable; likewise, workload modeling is typically based on real workloads. However, real workloads may also contain anomalies that make them non-representative and unreliable. A previously unrecognized type of anomaly is workload flurries: surges of activity with a repetitive nature, caused by a single user, that dominate the workload for a relatively short period. Under suitable conditions, such flurries can have a decisive effect on performance evaluation results. The problem is that workloads containing such a flurry are not representative of normal usage. Moreover, creating a statistical model based on such a workload or using it directly is also not representative of flurries in general. This motivates the approach of identifying and removing the flurries, so as to allow for an evaluation under normal conditions. We demonstrate this for several evaluations of parallel systems, showing that the anomalies in the workload as embodied by flurries carry over to anomalies in the evaluation results, which disappear when the flurries are removed. Such an evaluation can then be augmented by a separate evaluation of the deviation caused by the flurry.

Categories and subject descriptors: C.4 [Performance of Systems], K.6.2 [Installation Management]: Performance and usage measurement.

General terms: Experimentation, Measurement, Performance.

Additional Key Words and Phrases: Computer workload, User behavior, Abnormal workload, Representative workload, Data sanitation.

1 Introduction

The performance of a computer system depends not only on its design and implementation, but also on the workload to which it is subjected [11]. Different workloads may lead to different absolute performance numbers, and in some cases to different relative ranking of systems or designs. Using representative workloads is therefore crucial in order to obtain reliable performance evaluation results.

One way to obtain representative workloads is to use real workloads from productions systems. If a current system is available that has a similar functionality to the system being evaluated, one can assume that the same workload may apply. One can then record the workload on the current system, and play back the recording to drive a simulation of the new system. Alternatively, the recorded workload can be used as the basis for constructing a workload model (e.g. [17, 9, 22]). This has the benefit of allowing for more flexible usage, e.g. by modifying model parameters so as to adapt it to different system configurations.

However, using recorded workloads also has its problems. It is well known that workloads at different installations differ, and that workloads evolve with time as users learn to better use the system [16]. This paper deals with a different type of drawback: real workloads may contain abnormal behaviors that, though they do in fact occur on rare occasions, are not representative in general. Workload flurries are such events. They consist of huge surges of activity by single users that dominate the workload for a limited time.

Workload flurries have two types of effects on performance evaluation. One is in the context of workload modeling, and specifically the fitting of statistical distributions to workload data. The existence of a flurry may alter workload statistics, leading to the use of un-representative values by an unwary analyst. The other is an effect on performance evaluation results when using a workload trace to drive a simulation. Flurries may be very sensitive to the details of the system's behavior, so extremely small modifications may lead to large effects that are not reliable predictors of real performance. We demonstrate both effects in the context of workloads on parallel supercomputers.

The contributions of this paper are the following:

- The identification of workload flurries as an important phenomenon, independent of other workload features that have been recognized in the past (Sections 3 and 4).
- Showing that the existence of workload flurries can taint workload modeling, leading to models that are actually non-representative and overly complex. For example, distributions of workload parameters that seem different in successive years actually only differ due to the flurries that are included (Section 5).
- Showing that workload flurries may cause system evaluations to be extremely sensitive to minor details, because the whole flurry reacts to a change *en masse* and thereby amplifies its effect. Section 6 relates an example where changing the runtime of one job in 67,667 by 30 seconds (relative to a total runtime of 18 hours) caused the average bounded slowdown of *all* the jobs to change by about 8%, because of its effect on a subsequent 375-job flurry.
- Showing that noisy or inconsistent evaluation results can be traced to the effect of flurries (several examples are given in Section 7).
- Suggesting that the best way to deal with flurries is to carefully identify and remove them (Section 8). This allows for a more reliable evaluation of normal, non-flurry conditions; a separate evaluation can then be performed to assess the potential impact of flurries. While such data sanitation has been done in the past (e.g. [9]), understanding the characteristics and behavior of flurries will make it easier to apply.

2 Data Sanitation

The need to use representative workloads for system evaluations has long been recognized, and has led to the practice of monitoring existing systems and characterizing their workloads for this purpose [15, 1]. But using workload traces "as is" is a risky business, as they may include various sorts of anomalous behavior. Previous work has focused on analyzing the workload as a whole, and trying to determine whether it is stationary and representative. We suggest a complementary approach in which the data is "cleaned up" by removing the non-representative parts, and only the remaining data is used in the evaluation.

One striking example was reported in the analysis of the workload on the NASA Ames iPSC/860 hypercube [12]. The histogram of job sizes on that 128-node machine indicated that more than half of the jobs were serial; moreover, most of the serial jobs were flagged as being run by the system support staff (Fig. 1). This was a result of an ad-hoc method used to verify that the system was operational and responsive by running the Unix pwd command on a single node. Overall, a full 56.8% of the trace (24025 jobs) were such check-runs. It is quite obvious that these jobs should be removed if the trace is used to analyze parallel workloads or to evaluate parallel job schedulers.

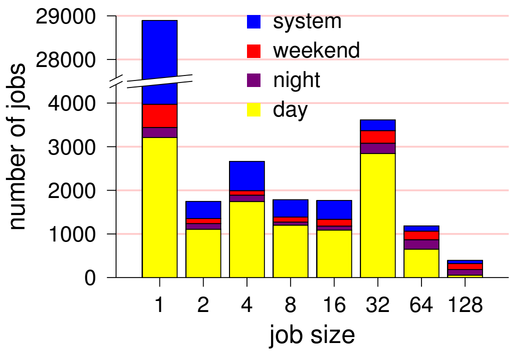


Figure 1: *Histogram of job sizes from the NASA Ames iPSC/860, showing abnormally many single-node system jobs.*

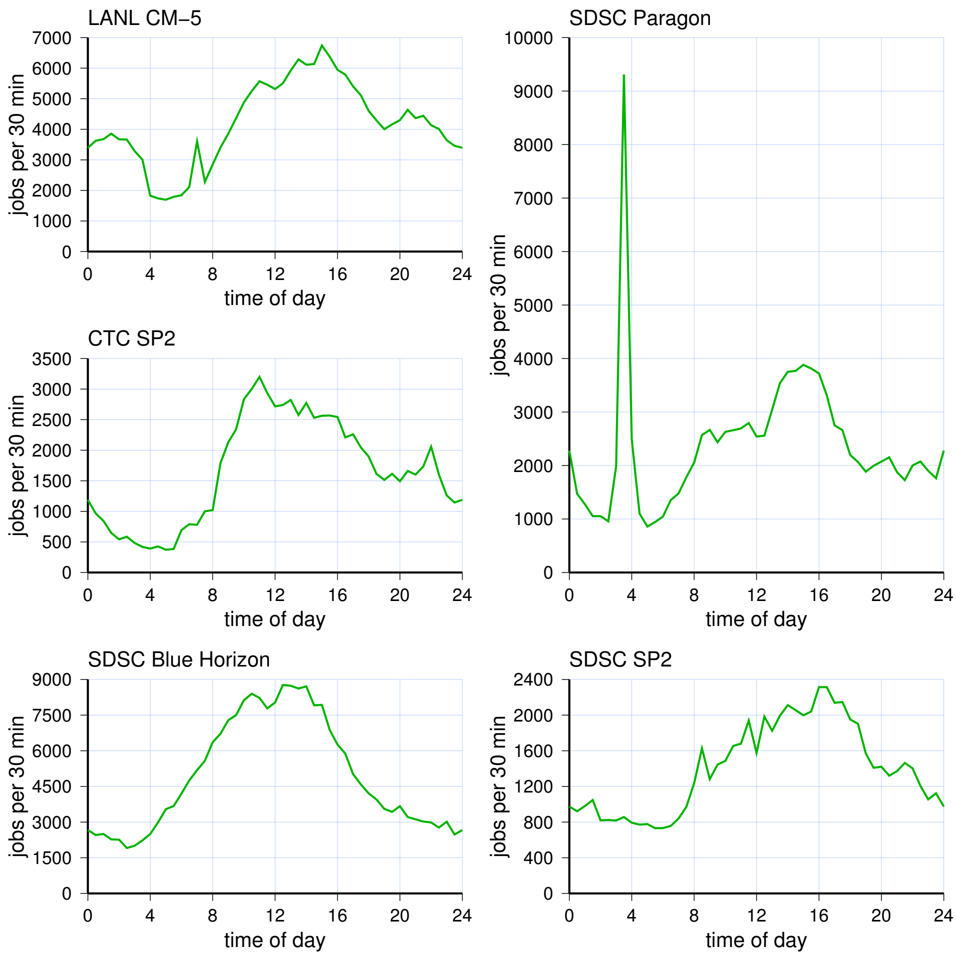


Figure 2: *Daily arrival pattern on 5 parallel supercomputers, showing abnormal spike at 3:30 AM on the SDSC Paragon.*

Another example is shown in Fig. 2. This compares the daily arrival cycle on 5 different parallel supercomputers. All display the expected periodic behavior, with load peaking during work hours and lower loads at night. But the SDSC Paragon machine has an additional and much higher peak between 3:30 and 4:00 AM. Upon investigation, it turned out that a set of 16 jobs with an distinct profile was executed during this time slice every day. While specific information is not available, it is reasonable to assume that these jobs served some system administration function and were executed automatically. It is again obvious that they should be removed when using the log for evaluations, so as to reduce the danger of optimizing for this abnormal behavior.

The above two examples were identified by manual inspection of the workload traces. Obviously, it is desirable to be able to perform data sanitation automatically. There seems to have been very little work on this in the past. One example is the proposal by Cirne and Berman [9]. They noticed that workload logs sometimes contain periods that are highly abnormal, and suggested that such periods should be deleted. Their methodology was to partition the log into days, and characterize each day's workload by a vector of length n (specifically, this was applied to the modeling of the daily arrival cycle, and the vector contained the coefficients of a polynomial describing it). The days are then clustered into two clusters in R^n. If one of the clusters turned out to contain a single day, that day was deleted, and the process was repeated. However, this approach would not catch the two examples cited above, which occur across the whole log.

Workload flurries, to be defined and exemplified in the next section, are also candidates for data sanitation. However, this is much less obvious than for the examples cited above.

3 The Phenomenon of Workload Flurries

We define a workload flurry to be a pattern of activity with the following characteristics:

1. It causes a level of activity that is significantly higher than usual, thus dominating the workload
2. It exists for a limited period of time
3. It significantly changes the distributions of workload attributes
4. It is caused by a single user.

The name "workload flurry" derives from the first and second attributes, and from the fact that the items constituting the flurry are typically lightweight, because otherwise the system would be overwhelmed by their numbers.

3.1 Observation of Flurries on Parallel Supercomputers

The above definition is derived from observations of such phenomena in the long-term workloads experienced by large-scale production parallel supercomputers. While most of the following demonstrations and discussion are in the context of parallel systems, we believe that the phenomenon of workload flurries is much more wide spread, and provide some additional examples and generalizations in Section 8.1.

Workload data from several large-scale parallel supercomputers is available in the Parallel Workloads Archive [25]. We use data (including job arrivals, runtimes, sizes, etc.) from five different installations, and from different times, as summarized in Table 1. Dozens of research papers have used these and a few other logs as the basis of their evaluations of scheduling mechanisms, oblivious to the fact they contain flurries that might significantly distort the results.

Fig. 3 shows the job load (the number of jobs submitted) as a function of time, at the granularity of weeks. In all five logs, large flurries are observed. They range in size from double the average activity to 10 times the average activity, are typically caused by a single user, and extend from a few days to several weeks.

Installation	Machine	Duration	Proc's	Jobs
Los Alamos National Lab (LANL)	TMC CM-5	10/1994 – 9/1996	1024	201387
San Diego Supercomputer Ctr (SDSC)	Intel Paragon	1/1995 – 12/1996	400	115595
Cornell Theory Center (CTC)	IBM SP2	7/1996 – 5/1997	512	79302
San Diego Supercomputer Ctr (SDSC)	IBM SP2	5/1998 – 4/2000	128	73496
San Diego Supercomputer Ctr (SDSC)	Blue Horizon	4/2000 – 12/2002	1152	250440

Table 1: *Job logs used in the study.*

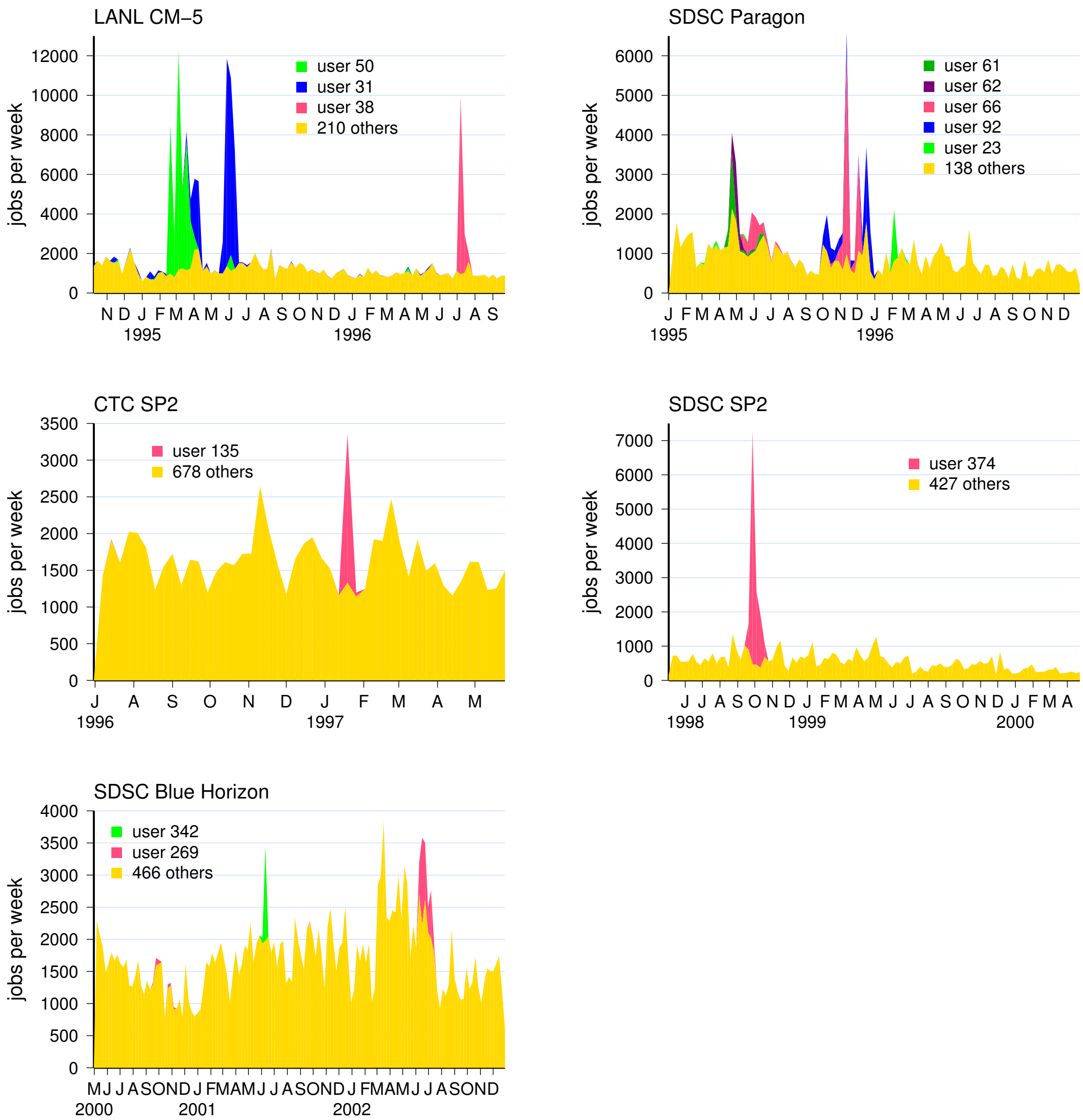


Figure 3: *Job arrivals per week on five large-scale parallel machines. All exhibit flurries of activity due to single users.*

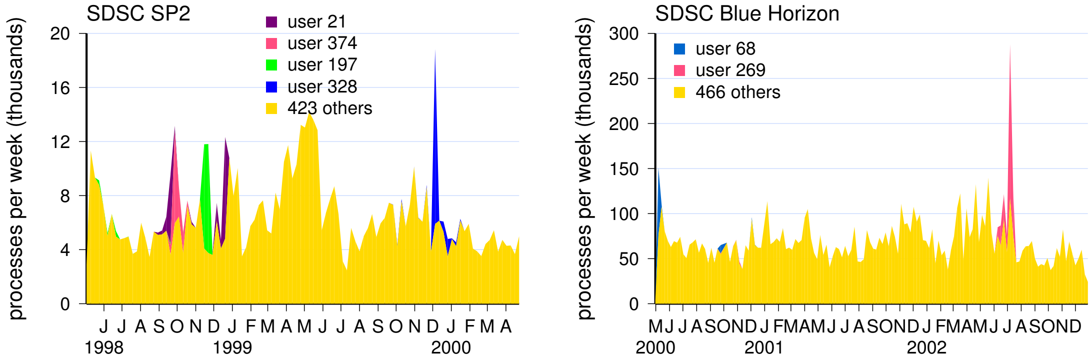


Figure 4: *Process arrivals per week also display flurries, which may be different from the job-arrival flurries.*

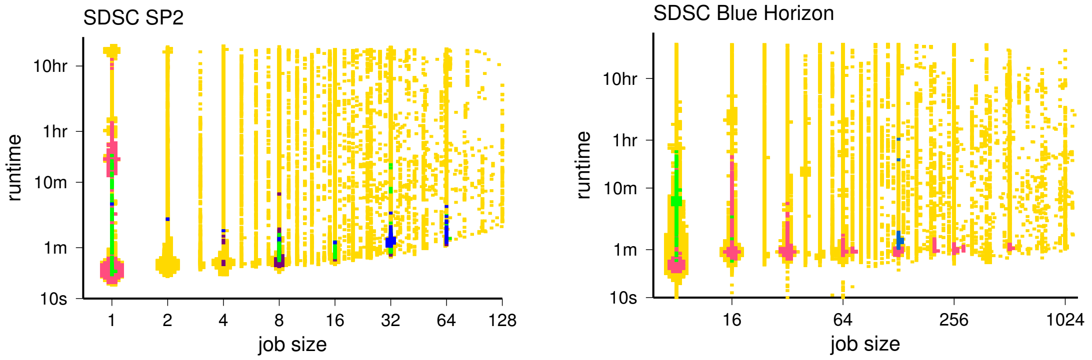


Figure 5: *Scatter plot showing joint distribution of job size and runtime. The single-user flurries typically have rather unique characteristics. Color-coding corresponds to flurries shown in Figs. 3 and 4.*

The flurries in the CTC log and the Blue Horizon log seem similar to normal fluctuations, but nevertheless turn out to have an important effect (at least for CTC), as shown in Section 7.

It should be noted that this dataset includes all the long logs in the Parallel Workloads Archive. Flurries were not observed in the shorter logs, including the NASA Ames iPSC/860 (3 months), the KTH SP2 (11 months), the LLNL T3D (4 months), and the LANL Origin 2000 Cluster (5 months). Indeed, periods several months long with no flurry occur also in the five logs that do include flurries.

Fig. 4 illustrates the process load on two of the machines, showing that job flurries do not necessarily correspond to process flurries (on parallel supercomputers a job can be composed of dozens of processes). In the Blue Horizon log, the largest process flurry is even much more distinctive than any job flurry. In fact, what exactly constitutes a flurry depends on the context in which the question is asked. “High load” can also be defined in terms of memory usage, disk operations, or network bandwidth consumed. But here we focus only on job and process flurries, for which data is available, and which can be identified unequivocally. A listing is given in the appendix.

The statistical nature of these flurries is explored in Fig. 5 (this is representative for other logs as well). This shows the joint distribution of two major attributes of parallel jobs: the number of processors they use, and their runtime. The flurries tend to correspond to specific locations in these scatter plots, indicating that they are largely composed of jobs with fixed characteristics. In particular, the jobs composing the flurries identified here tend to be small, using few processors and/or running for a relatively short time, as witnessed

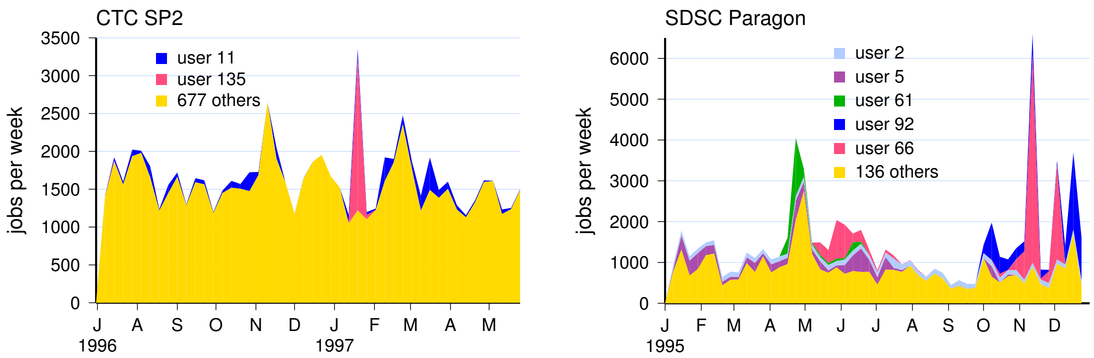


Figure 6: *Active users who spread their work over time do not create flurries.*

by the fact that they concentrate near the axes. Note that both axes use a logarithmic scale.

3.2 Towards Automatic Identification of Flurries

It is well-known that many computer workloads are bursty. Flurries are not just bursts of higher load. They are much larger than "normal" bursts, and they are caused by a single user. These characteristics enable a simple identification procedure.

The approach is based on graphs such as those shown in Figs. 3 and 4. To create such graphs automatically, the workload log is scanned at weekly granularity. For each week, the total activity is tabulated, as well as the activity of individual users. The weeks are then sorted in decreasing levels of activity, in order to identify weeks with abnormally high activity levels. Within each such week, the users are sorted in decreasing levels of activity. These lists of users are then merged to identify users who are very active in any high-load week. This is used to create color-coded graphs like those shown. Flurries caused by single users immediately stand out. In nearly all cases, these correspond to the first users in the list.

However, there are also smaller peaks of activity that are caused by single users; how do we decide when they qualify as a "flurry"? For the time being we note that flurries such as those that occurred on the SDSC SP2 and the LANL CM-5 machines, as shown in Fig. 3, are quite obviously highly abnormal events. The issue of identifying smaller flurries is discussed in Section 4 and in the conclusions.

It should be emphasized that flurries are not defined only by a high level of activity, but also that this activity is concentrated within a relatively short time. Comparing the temporal spread of activity of very active users, we often see that very active users do not create flurries. For example, on the CTC machine user 11 was actually much more active than user 135 (2,930 jobs as opposed to only 2,103 jobs), but this activity was spread across the whole log; therefore it does not constitute a flurry (Fig. 6). Likewise, on the SDSC Paragon machine, users 5 (6,203 jobs) and 2 (5,986 jobs) were more active than user 61 (who, at 2,465 jobs, is only the 7th most active user), but again this was spread out across the log.

Note also that, while some users who create flurries hardly generate any other non-flurry load, this is not necessarily part of the definition. Users who create flurries may also be generally active over long periods of time. The flurries are identified as being excessively large and of limited duration.

Finally, it should be emphasized that flurries do not necessarily correspond to excessive use of resources. Creating graphs similar to those shown in Fig. 3, in which node-seconds are counted instead of jobs, shows that the users who use the most resources tend to do so on a continuous basis, and do not create flurries that are concentrated in a specific time period.

3.3 Related Work

Workload characterization and modeling have been advocated and practiced for many years [15, 7]. This is typically done by collecting workload traces, and creating a statistical model based on fitting the distributions of workload attributes [19]. But such an approach is questionable if the data is not stationary, as seems to be the case in the context of parallel supercomputers. For example, Chiang et al. analyze six non-consecutive months of data from the NCSA Origin 2000 machine, and find that the workloads in different months may be quite different from each other [8]. We identify flurries as a specific type of deviations from stationarity that have to be taken into account when creating a workload model.

Our notion of abnormal activity embodied by flurries seems complimentary to other work which had the opposite goal: to identify representative slices of the workload, in order to enable shorter but nevertheless reliable simulations. For example, in the context of evaluating computer architectures and cache designs, Lafage and Seznec suggest using short slices of applications [18], and Sherwood et al. suggest using basic blocks [29]. In both cases these are then clustered to find a small number of repeated segments that can represent the whole application. This approach works due to the high regularity exhibited by typical computer programs, which iterate among a limited number of computational phases.

In job-level workloads, on the other hand, the variability is much greater. As a result such clustering cannot be fruitfully applied to the whole workload, but rather only to the activity of each user, leading to the construction of a user behavior graph [14, 6]. While this can be used to construct a workload model that reflects the variability introduced by different users, it cannot be used directly to identify abnormal behavior. However, it may be possible to use a *second level* of clustering, applied to the user behavior graphs, for this purpose. At present we leave this idea for future work.

4 Flurries and Self-Similarity

Self similarity is the property of looking the same at different scales. In the context of workloads this typically refers to different time scales, and implies that the workload is bursty at all granularities: it displays small bursts of activity at short time scales, and large swells of activity at long time scales. Such phenomena have been seen in a wide variety of workloads, especially related to network traffic (see, e.g., [26]). It is therefore natural to ask whether flurries are just the largest in a whole spectrum of bursts of activity.

A well-known characteristic of self similarity is that the burstiness is retained when the process is aggregated, and viewed at a coarser time scale (this is in contradistinction from Poisson processes, where the fluctuations average out). The graphs shown in Figs. 3 and 4 are at the rather coarse granularity of a week. Indeed, they show a large degree of burstiness at this granularity. And importantly, this remains the case if the flurries are removed.

Self-similarity is quantified by the Hurst parameter H, which can be measured using Pox plots of the R/s (rescaled range) metric. Starting with a time series X_i specifying the number of arrivals in the ith time unit, this is defined as [23, 27]

$$\left(\frac{R}{s}\right)_n = \frac{\max_{j=1\ldots n} \sum_{i=1}^{j}(X_i - \bar{X}) - \min_{j=1\ldots n} \sum_{i=1}^{j}(X_i - \bar{X})}{\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(X_i - \bar{X})^2}}$$

The numerator measures the range of cumulative deviations from the mean, and the denominator rescales this range by the standard deviation. To create a Pox plot, this is repeated for subsequences of different lengths n, and moreover different subsequences for each n (that is, not only the first n, but also the subsequence from $n + 1$ to $2n$, etc.), and the results plotted in a scatter plot on log-log axes. Self similarity is manifested by a linear relationship, with the slope of the regression line giving the Hurst parameter, which should lie in the range $\frac{1}{2} < H < 1$.

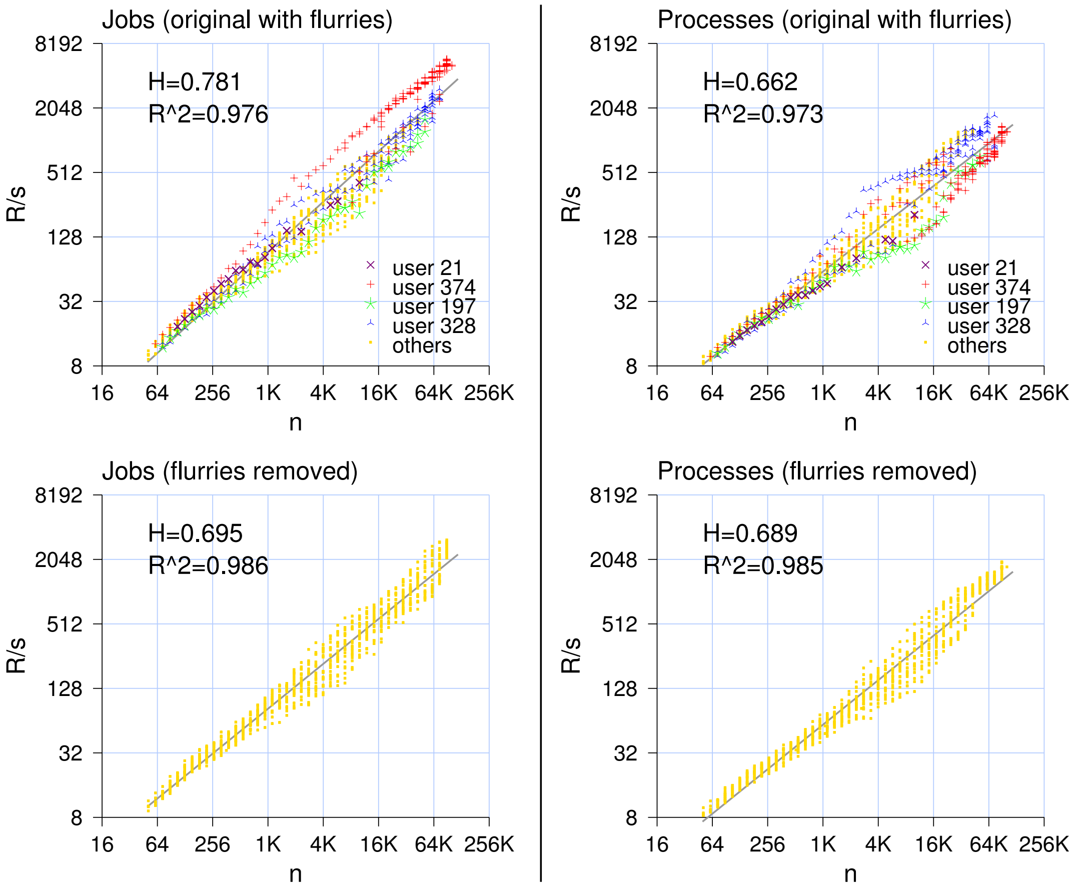


Figure 7: *Pox plots of job and process arrivals on the SDSC SP2.*

To generate the Pox plots in Fig. 7 and the results in Table 2, we used the following settings. The basic time unit was 10 minutes. n ranged from 4 to the size of the dataset, using logarithmic intervals with a multiplier of 1.2. For each value of n, 20 values of R/s were computed. For large n (more than one twentieth of the dataset) these are 20 equally spaced but overlapping subsequences of the data. For smaller n we divide the whole dataset into 20 non-overlapping parts, and in each one produce the average of however many non-overlapping subsequences of size n fit in. Ranges in which all data were zeros were dropped.

The example in Fig. 7 is for the SDSC SP2 trace, and shows Pox plots for both job and process arrivals, with and without flurries. In the plots of the original trace (with flurries, top of figure), points corresponding to a span of data containing a flurry are color-coded with the same colors as in Figs. 3 and 4. For both jobs and processes, we see that the data is closer to a linear relationship after the flurries are removed, and this is also reflected in the R^2 values of the regression (bottom of figure).

In the job data we see that the large flurry due to user 374 in the SDSC SP2 data of Fig. 3 creates a distinct set of points that lie a certain distance above the points for the rest of the data. In the process data we see a similar but less pronounced effect for n near 4K, which is due to the large flurry of activity by user 328 in the SDSC SP2 data of Fig. 4. In other traces flurries did not produce such independent streaks in the Pox plots, but they did cause the cloud of points be to wider and more diffuse than when they were removed.

Comparing all the traces in Table 2, we find that in nearly all cases the Hurst parameter is reduced when flurries are removed. Moreover, the higher values are reduced more than the lower ones, leading to a

	jobs		*processes*	
trace	*original*	*cleaned*	*original*	*cleaned*
LANL CM-5	0.844 (0.969)	0.771 (0.975)	0.832 (0.969)	0.740 (0.973)
SDSC Paragon	0.822 (0.981)	0.764 (0.986)	0.742 (0.980)	0.673 (0.982)
CTC SP2	0.657 (0.981)	0.646 (0.980)	0.653 (0.991)	0.656 (0.991)
SDSC SP2	0.781 (0.976)	0.695 (0.986)	0.662 (0.973)	0.689 (0.985)
SDSC Blue H.	0.781 (0.986)	0.765 (0.986)	0.716 (0.985)	0.694 (0.988)

Table 2: *Changes to the Hurst parameter of job and process arrivals to supercomputers when the flurries are removed. Note that the range of values observed in different logs is reduced, leading to greater consistency.* R^2 *values are given in parentheses; they also tend to improve when flurries are removed.*

concentration of the different values in a somewhat narrower range. In addition, the R^2 values either stay the same or are improved when flurries are removed. Nevertheless, removing the flurries does not cause a significant qualitative difference to the Pox plots or H values.

Thus, while flurries make a certain contribution to the detection and quantification of self similarity, they are not crucial for it. Moreover, flurries are different from self-similarity in two ways. First, some of the flurries are large bursts of activity that occur over short time scales, on a background of relatively stable normal activity. Indeed, the activity graphs shown in Fig. 3, while showing bursts of activity, are quite different from the graphs showing bursts at different time scales typically used to illustrate self similarity (e.g. [20, 31]). Second, in the context of network traffic, self-similarity only refers to the arrival process, i.e. to the temporal structure of the workload. In flurries we also include the repetitive nature of the jobs (size, runtimes, etc.), which leads to modal distributions of workload parameters as demonstrated below.

In interpreting these results, it is important to note that many users commonly display activity patterns in which a lot of repetitive work is concentrated in a short time span. These bursts of activity cover a whole spectrum of sizes, from very small to rather significant. The question is then whether flurries are just the largest in a continuum of effects. In our opinion, the large job flurries like those observed on the LANL CM5 and the SDSC SP2 machines are truly exceptional, and are so much larger than any other event that they certainly qualify as a distinct type of phenomenon. But the job flurries on the CTC SP2 and SDSC Blue Horizon, and most of the process flurries on the SDSC SP2, may be just the largest of a continuum. Nevertheless, they may still have an uncomfortably large impact on modeling and evaluation results, as shown in the following sections. This justifies the idea of separate evaluations, with the flurries and without them.

5 The Effect of Flurries on Workload Modeling

Workload modeling attempts to generalize from specific workloads by finding invariants that are common to workloads from similar settings [4]. Workload flurries interfere with this endeavor by their obvious effect on workload statistics. By definition, a flurry involves a large number of similar jobs. The combined weight of these jobs can cause significant modifications to the distributions of various workload parameters relative to the background load in which no flurries are present.

An early example of this effect was provided by the analysis of memory usage on the LANL CM-5 parallel supercomputer [10]. Here we extend this analysis to other workload attributes, initially focusing on the later part of the log, starting from January 1996 . Such an analysis is greatly influenced by the flurry of activity by user 38 seen in Fig. 3. This is shown in Fig. 8, which compares the distributions of job sizes, runtimes, memory usage, and interarrival times, for the raw workload and after removing the activity of user 38. The flurry consisted of jobs that were about 10 seconds long, arrived about 12 seconds apart, ran on 128

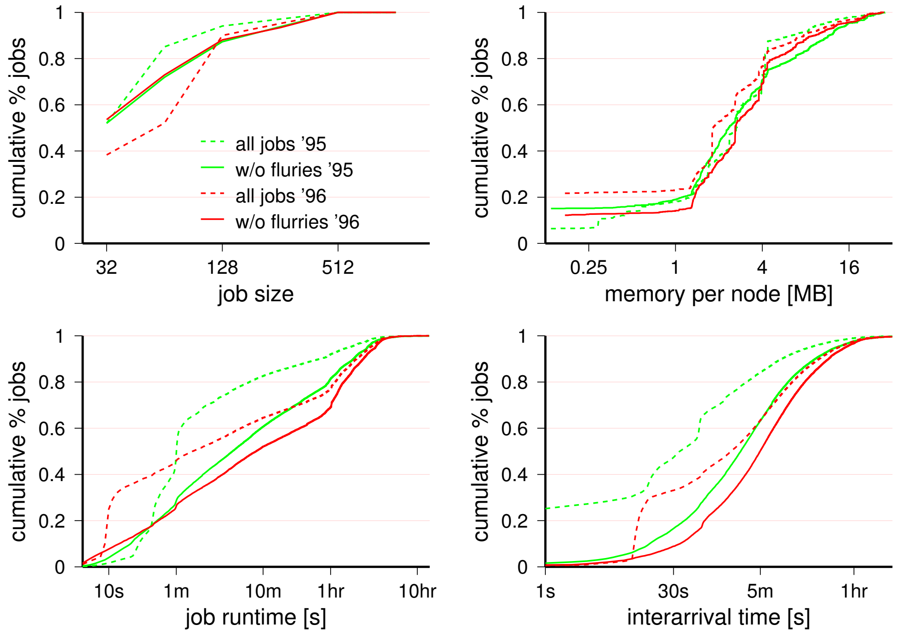


Figure 8: *Changes to the distributions of workload attributes when flurries are removed from the LANL CM-5 log. Most differences between 1995 and 1996 may be attributed to the different flurries.*

nodes, and used either very little memory or about 1.84 MB per node. This accounted for 12,344 (29%) of the total of 42,702 jobs in this part of the log.

For comparison, we repeated this exercise using the 1995 portion of the log, which contains two flurries by users 31 and 50. There were a total of 123,058 jobs in that year, of which an amazing 71,161 (58%) belonged to the two rather large flurries. Fig. 8 also shows the 1995 results. It immediately shows that the distributions of the cleaned logs in the two years are pretty similar to each other (solid lines), whereas the distributions of the raw logs are quite distinct (dashed lines), due to the modifications caused by the different flurries. This is an extremely important result, as it implies that the base workload (without the flurries) is actually quite consistent across a long period of time, suggesting that the data is stationary. The major differences between 1995 and 1996 are actually the result of flurries introduced by 3 users out of a total population of 213. As may be expected, the modifications caused by the flurries are both qualitative and quantitative: the distributions become more modal, and emphasize shorter runtimes and interarrival times.

Indeed, flurries tend not only to modify the workload distributions but also to make them more complex, by making their shapes more jagged and by adding modes. Focusing on the LANL CM-5 interarrival times as an example, we find that the distribution for the whole log is distinctly modal, with several values that are extremely common and each come from a different flurry (appearing on the left in Fig. 9). After the flurry-related data is removed, the underlying distribution can easily be characterized as lognormal.

It is important to note that using the distributions measured from the whole log, including the flurries, leads to a lose-lose situation. On one hand, it is not representative because it is influenced by the flurries, and does not reflect normal usage. On the other hand it also does not reflect flurries, because flurries have a specific temporal structure: they are concentrated within a limited span of time. Sampling from a distribution that includes a flurry does not produce a flurry; rather, it spreads the flurry evenly over the whole duration of the generated workload. Moreover, any specific flurry is not representative of flurries in general.

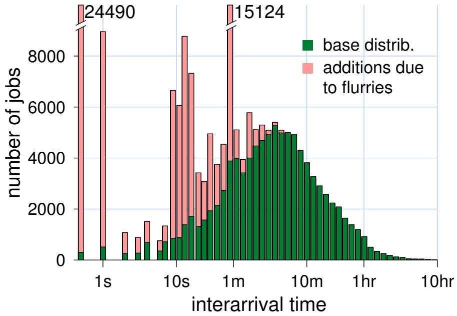


Figure 9: *Flurries turn the lognormal distribution of interarrival times into a noisy and modal distribution. Data from LANL CM-5.*

6 The Effect of Flurries on Performance Evaluation: A Case Study of Instability

Apart from the effect flurries have on workload statistics, and through them on workload modeling, they also may have a significant effect on performance evaluation results. In this section we will present a case study showing how the presence of a flurry leads to unstable results: very small changes to the workload are amplified by the flurry and lead to an unexpectedly large change in the results. The next section will further demonstrate that such effects indeed cause problems in practice.

6.1 Background: EASY Scheduling and Bounded Slowdown

The case study involves the popular EASY backfilling scheme for batch parallel job scheduling [21], used by the SP2 machines that generated the logs mentioned above. Parallel jobs can be seen as rectangles in processor-time space: each job needs a certain number of processors for a certain time. The basic scheduling scheme is first-come first-serve: jobs are kept in a queue in order of arrival, and whenever there are enough free processors for the first queued job, it is allocated the processors and executed. The problem is that this may lead to fragmentation. If the first queued job requires many processors, it may have to wait a long time until enough processors are freed. During this time, processors are left idle as they accumulate.

Backfilling is an optimization whereby small jobs may skip ahead in order to fill in holes in the schedule and utilize such waiting processors (Fig. 10). However, this may lead to starvation if small jobs continuously move forward and the first queued job never gets to run. The solution adopted by the EASY scheduler is to first make a reservation for the first queued job, and allow later jobs to move forward only if they do not violate this reservation [21]. But in order to do so, the scheduler must know how long each job will run. Users are therefore required to provide an estimate (or rather, an upper bound) on the run time of each submitted job. Jobs are killed if they exceed this estimate.

One of the most useful metrics used to evaluate job schedulers is the average bounded slowdown. Slowdown is response time normalized by running time. Bounded slowdown eliminates the emphasis on very short jobs due to having the running time in the denominator [13]; a threshold of 10 seconds is commonly used in the context of parallel job scheduling. The definition is

$$bsld = \frac{T_w + T_r}{\max\{T_r, 10\}}$$

where T_r is the job's runtime on a dedicated system, and T_w is the job's waiting time.

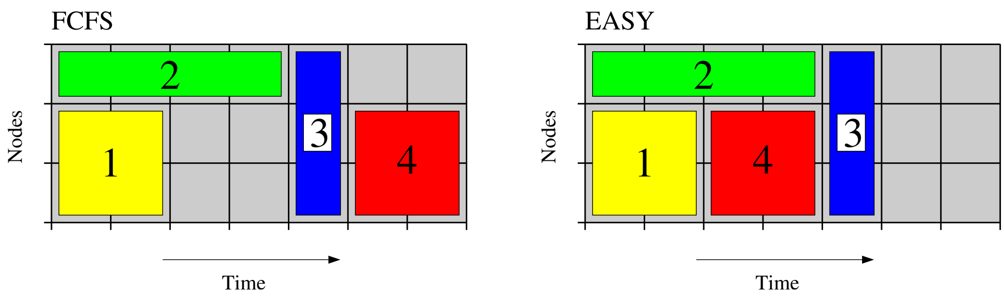


Figure 10: *Left: FCFS scheduling (jobs numbered in order of arrival). Right: FCFS with backfilling. Note that it would be impossible to backfill job 4 had its length been more than 2, as the reservation for job 3 would have been violated.*

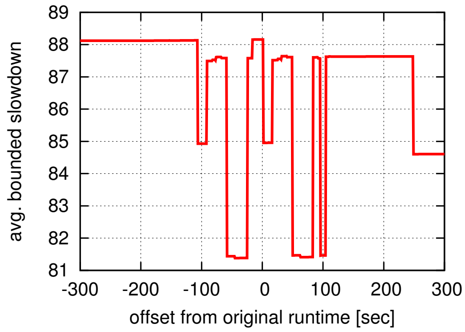


Figure 11: *Average bounded slowdown obtained by the EASY scheduler on the SDSC trace, as a function of changing the runtime of job 59,210.*

6.2 Example of a Butterfly Effect

update number of jobs, 59210, etc.

The largest user runtime-estimate appearing in the SDSC SP2 trace is 18 hours. This is a limit imposed by the site administrators (different sites may have different limits). Consequently, the longest jobs in this trace are limited to 18 hours (since a job that exceeds its runtime-estimate is killed by the system). However, in a real system, it takes some time to propagate the instruction to kill a job to all the nodes[1]. Therefore the trace indicates that some jobs run for a bit more than 18 hours. Of the 67,667 jobs in the trace, only 619 (less than 1%) have runtimes longer than 18 hours. In a simulation it is possible to change the irregular runtimes to be *exactly* 18 hours.

What we found is that the average bounded slowdown is extremely sensitive to such a change. The following is a cool example that demonstrates this phenomenon: Job 59,210 was submitted on the 551st day of the log (which spans over 728 days), it required 9 nodes (out of 128 available), was estimated to run for 18 hours, and ran for 18 hours and 30 seconds. Note that this is one job out of a total of 67,667 (0.0000148%). In our simulation, we truncated this job's runtime by a mere 30 seconds, and set it to exactly 18 hours (a modification of 0.0000154%). As a result, the average bounded slowdown of *all the jobs in the trace* changed from 88.16 to 81.38 — that is, by about 8%! Moreover, the effect depends on exactly how much the runtime of this job is changed. Fig. 11 shows the effect of different changes to the runtime of job 59,210 on the overall average. Note that counter intuitively, the average may change by roughly the same amount both by enlarging and by reducing the runtime of the job.

[1]In a simulation this is of course not the case. To maintain the logged runtimes we therefore increase the estimates given in the log to match the actual runtimes.

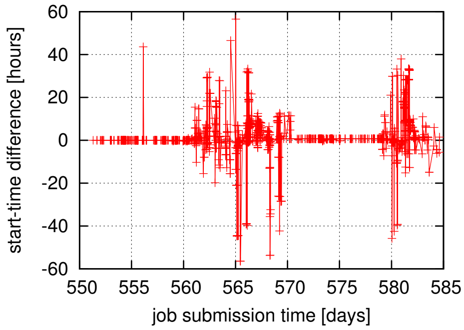


Figure 12: *Shortening job 59,210 by 30 seconds had an effect for more than a (simulated) month, causing subsequent jobs to start earlier or later by up to nearly 60 hours (positive values indicate jobs that started earlier due to the truncation).*

6.3 The Role of a Flurry in Causing the Effect

In a nutshell, the mechanism leading to the above effect has two components. First, the backfilling algorithm propagates the small modification to a single job and influences many other jobs. Second, a whole flurry of similar jobs are affected *en masse*, and their combined weight leads to the observed change in the global average.

In a batch system, a reduction of 30 seconds in the runtime of a job has the obvious immediate (minor) effect of allowing other waiting jobs to obtain the required resources sooner, possibly allowing them to start earlier by up to 30 seconds. But in the context of a backfilling scheduler, a more important effect is that a modification of 30 seconds is enough to make the difference regarding a backfilling decision: by terminating 30 seconds earlier, a slightly larger window is opened, and a job that was previously considered too big may now fit into the available space. This causes a modification of the schedule down the road. Such a chain of modifications allows the effect of one truncated job to accumulate. In our simulation, 2024 jobs were affected by the truncation of job 59,210 in terms of changed start-time. Each such job is represented by a single point in Fig. 12. The rest of the schedule was left unchanged.

According to the figure, the start time of most affected jobs was made earlier by 30 seconds, because processors became available 30 seconds earlier. The bigger differences between the original and modified schedules are focused in two areas: between days 560-570 (10 days after job 59,210), and between days 580-585 (a month after), and reflect changes in backfilling decisions. But the 8% change in the average bounded slowdown actually stems from start-time differences associated with a group of jobs submitted at the 581st day. This can be seen in Fig. 13, that compares between the running averages of the bounded slowdowns obtained by the two schedules. The running average bounded slowdown at time T is defined to be the average of bounded slowdowns experienced by jobs that were submitted prior to T. From this figure it is evident that all the changes in days 560–570 had a negligible affect on the overall bounded slowdown, and that the major change occurs around the 581st day.

A closer inspection of the data revels that the perceived change is due to a flurry composed of 375 similar jobs that were submitted sequentially over a period of about 10 hours in the 581st day (exactly one month after the truncated job was submitted). All these jobs were submitted by user 319, required 32 nodes, were estimated to run five minutes, and ran for about one to two minutes; this is the biggest flurry shown in the left of Fig. 4[2]. The running average bounded slowdown of the original and the "truncated" runs were quite

[2] In the figure the flurry is attributed to user 328. This is an unfortunate result of a new conversion of the log in the parallel workloads archive. The results in this section were derived before this change, and use the original log.

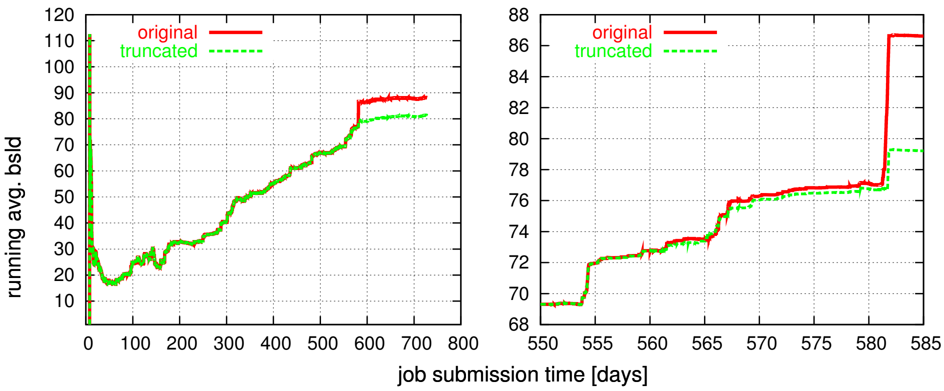


Figure 13: *Running average of the bounded slowdown obtained by the EASY scheduler on the SDSC SP2 trace with/without the 30-second truncation of job 59,210. Left: full trace. Right: zoom in on the part where start-time differences occur.*

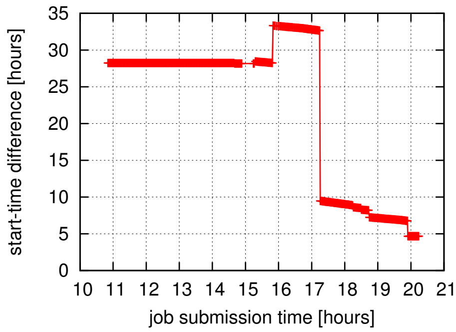


Figure 14: *Start-time differences of the 375 jobs submitted by user 319 on the 581st day (X-axis denotes hours on that day).*

similar when the first job of this flurry was submitted (about 1% difference). By the time the last job of the flurry was submitted, the difference was as high as 9%.

Fig. 14 shows the start-time differences associated with the jobs of the flurry (this is a subset of the data displayed in Fig. 12). The jobs' profile similarity along with the fact that they were submitted sequentially, explains their tendency to be effected in the same way by changes to the schedule (in terms of wait time). Note that the effect of shortening the wait time of a job with runtime of around one minute by 30 hours is a reduction of 1800 in its bounded slowdown. This is a huge figure compared to the average bounded slowdown of the entire trace (less than 90), a fact that explains the considerable difference between the slowdown averages of the truncated and original runs.

6.4 Explaining the Sensitivity

Truncating the runtime of job 59,210 is only one of many trivial modifications we have identified that resulted in a significant change in the average bounded slowdown. These modifications may involve more than one job, they may be applied on jobs with different runtimes, different runtime estimates, and different sizes. However, all these modifications have an effect only when the flurry identified above is scheduled. No other flurry in this log displayed this type of sensitivity. In particular, similar modifications in the neighborhood of the huge flurry identified at the beginning of the log (see Fig. 3) didn't produce similar

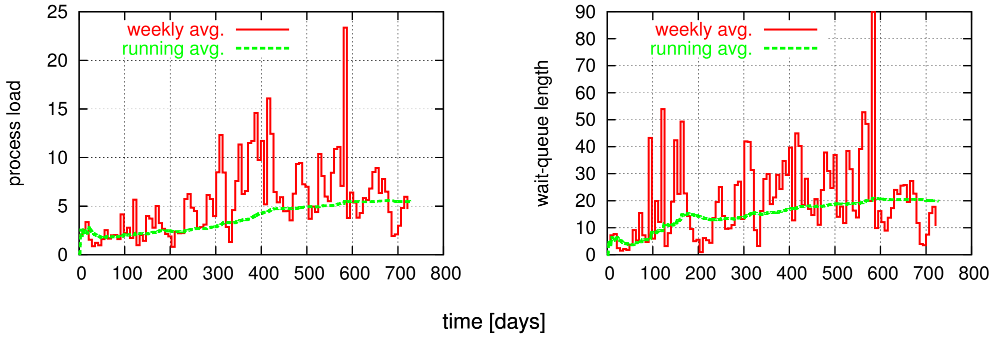


Figure 15: *Evolution of the SDSC SP2 process load and the waiting-queue length when simulating EASY on the original trace.*

effects, even though the earlier flurry is an order of magnitude bigger than the later one (in terms of the number of jobs composing it).

The reason that the 375-job flurry is so sensitive is that it induces a very high process-load on the system. The process load at time T is defined to be the total number of running or waiting processes (not jobs) that are present in the system at that time instant, divided by the size of the machine. For example, if a machine with 10 nodes is currently running 8 processes (leaving 2 nodes idle), while two jobs of size 6 are waiting in the queue, then its process load is $(8 + 6 + 6) / 10 = 2$. The left of Fig. 15 displays the evolution of the process load associated with the SDSC SP2 trace. The unequivocal peak in the weekly-average line occurs in the week that contains the 581st day. The right of Fig. 15 shows that this is also reflected in the state of the waiting-queue.

We note in passing that the long-term average process load grows continuously across the trace. This explains the growth trend of the average bounded slowdown (as seen in the left of Fig. 13). It is tolerated by the users because the majority of the jobs still enjoy a fairly reasonable quality of service, as indicated by the bounded slowdown median of the SDSC SP2 trace which is 1.8.

Finally, it should be noted that the effect described above depends on the existence of the flurry, but not only on it. It also depends on the metric being used. When measuring the actual response time, the difference caused by the flurry jobs is not significant enough to change the overall average, because the average response time is dominated by long jobs. [11]. By contrast, the average slowdown is dominated by short jobs (that typically have higher slowdowns), so a flurry of short jobs may have a large effect.

7 The Impact of Flurries on System Evaluation

As we saw, simulations of parallel job scheduling can be extremely sensitive to the exact workload conditions. This may also happen in normal evaluations, without any targeted modifications.

An example is given in Fig. 16, using the CTC workload trace. This is again a simulation of the performance of EASY backfilling, this time showing how it depends on the system's offered load (i.e. the fraction of the machine's capacity that is used). The way to create different offered load conditions is to multiply the job interarrival times by a constant. For example, if the original offered load is ρ, multiplying all arrival times by a factor of $\rho/0.8$ will change the offered load to 0.8. Naturally, this causes the produced schedule to change, as the space available for backfilling is changed. As Fig. 16 shows, such changes to the schedule cause large fluctuations in the bounded slowdown results. It would be ludicrous to take such effects at face value, and claim that, say, the expected performance at a load of 0.77 is much better than at a load of 0.76. In fact, these fluctuations are again examples of amplifications by a flurry. If the 2000-job flurry of activity

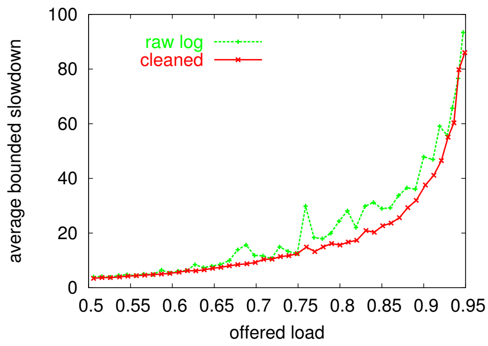


Figure 16: *Simulation of EASY backfilling on the CTC log. Flurries tend to be sensitive to exact simulation conditions, leading to instabilities. Simulations using a cleaned log are smoother.*

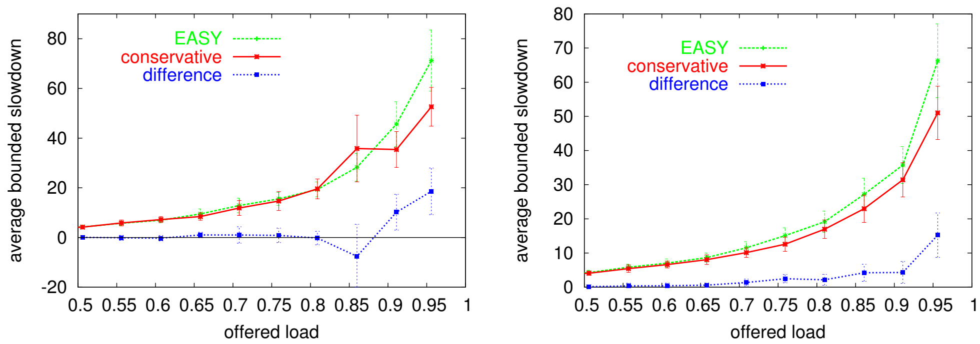


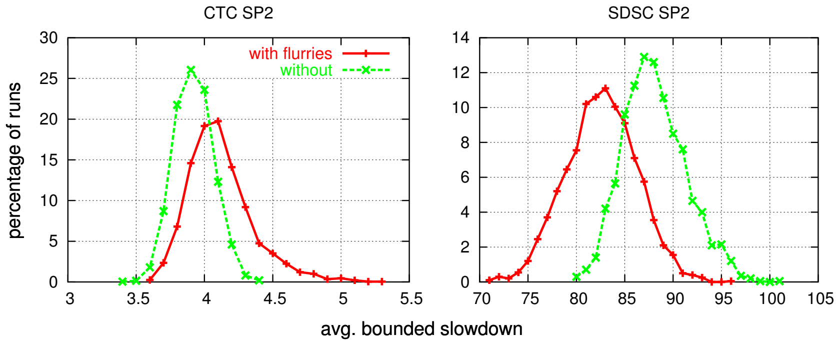
Figure 17: *Comparison of EASY and conservative backfilling, using the CTC log and accurate user runtime estimates. Left: using the complete log leads to inconsistent results. Right: removing the user 135 flurry leads to consistent results.*

by user 135 is removed (this is 2.5% of the total of 78,500 jobs in the log) the result becomes a smooth curve similar to those produced in queueing analysis.

Given that results such as these are hard to predict and correlate with the modifications used to change the offered load, they can also sway the results of evaluations. An example is given in Fig. 17. This shows a study comparing EASY backfilling with conservative backfilling (a version in which reservations are made for all skipped jobs, rather than only for the first one [24]). The study in question dealt with the effect that the accuracy of user runtime estimates have on the performance of the two backfilling schemes [11]. The results shown on the left of Fig. 17 were obtained when simulating the CTC workload using accurate runtime estimates, rather than the real user estimates as they appear in the log. The results were inconsistent, showing that conservative backfilling produced higher slowdown values for an offered load of 0.85 but lower values for 0.9 and 0.95. This inconsistency was traced to the same flurry identified above: rerunning the simulations on a modified workload where the flurry was removed led to the cleaner results shown on the right.

However, the results still seem not to be statistically significant as the 90% confidence intervals (computed using the batch means approach) still overlap. We therefore performed a more sophisticated analysis of these results, using the common random numbers[3] variance reduction technique [19]. In this analysis, we first compute the difference in slowdowns between the two schedulers on a per-job basis, which is possible

[3]The name is somewhat of a misnomer in this case, as we are using a logged workload rather than generating it using a random number generator.



stddev	CTC	SDSC
all jobs	0.236	3.616
w/o flurry	0.140	3.235
change	-40.7%	-10.5%

Figure 18: *With randomization, simulation results become non-deterministic. Flurries make them spread out more, reducing the accuracy with which results can be reported.*

because we are using the same workload trace. We then compute confidence intervals on these differences using the batch means approach. This shows that the flurry indeed makes a big difference in the quality of the results. When it is present, we cannot say anything definite for most offered loads. When it is removed, the advantage of conservative over EASY is clear across the whole range of offered loads.

A final example is given in Fig. 18. This is again part of the study of the effect of user runtime estimates, this time by randomly shuffling the estimates in the log among the jobs. As a result, the average bounded slowdown is different in each run. The figure shows the distribution of these averages over 2000 runs. When flurries are present, the standard deviation is larger, thereby enlarging the confidence intervals characterizing the result.

8 Discussion and Conclusions

Workload flurries are a newly identified type of workload phenomenon. They are related to the burstiness of self-similarity and to the high levels of activity exhibited by certain users. But they are also different, mainly by being unique events of limited duration. The novelty of flurries is at least in part just giving them a name, as singular workload events have been identified in the past, especially in the context of world-wide web traffic. Part of our contribution is therefore the realization that this type of phenomenon is much more widely spread.

The essence of flurries is a huge surge of activity, due to a single user, which dominates and changes the workload for a limited period of time. It is dangerous to use logs with unknown flurries, because this may significantly reduce the reliability of the results. Specifically,

- Flurries cause the workload to be non-representative, as they modify the characteristics of the usual workload. In addition, individual flurries can be quite different from each other. So evaluations using a workload with flurries only reflect that specific combination, and do not reflect the performance of normal workload or of other flurries.
- Likewise, statistical modeling using such a workload leads to a model that is not representative of normal behavior, and also not of flurries. It does not even reflect the flurry that appeared in the original workload, because the repeated appearance of similar items during a short period is lost when sampling from a distribution.
- Flurries may amplify performance effects, thereby causing the evaluation to be very sensitive to fine details of the input, to the point of obscuring the effects related to the system issues being studied.

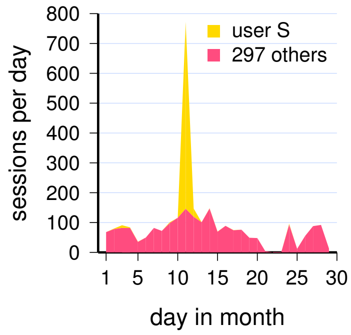


Figure 19: *A flurry in the sessions on a Unix server.*

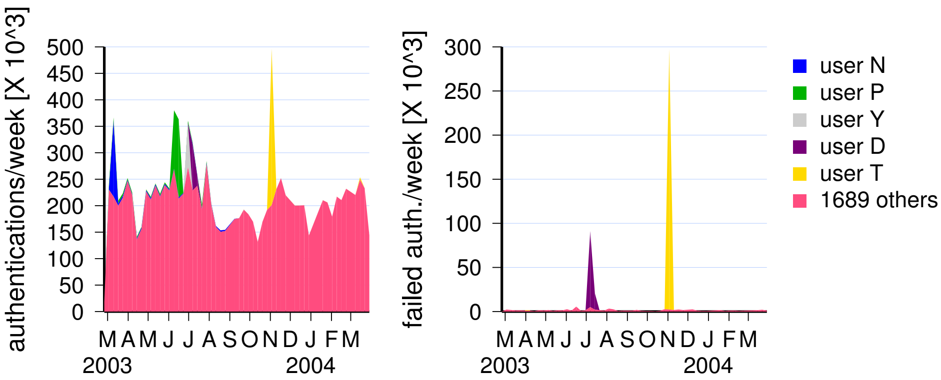


Figure 20: *Flurries of activity on an authentication server. Note that the normal level of about 2000 failed authentications a week is completely swamped by rare flurries caused by automatic retries that refuse to give up.*

8.1 Futher Examples and Generalization of Workload Flurries

While the present study has focused on the workload on parallel supercomputers, flurries can be found in other workloads as well. For example, we have observed a case where 539,253 of 661,452 jobs (82%) submitted to a departmental server over a 30 hour period in March 2003 were all invocations of the Unix ps command by the same user. This turned out to be the result of a bug in implementing an exercise in the operating systems course[4]. A large flurry was also observed in the session log for March 2004 of a Unix server used by students (Fig. 19). In this case it turned out to be the result of ftp'ing a large directory structure by a certain student one afternoon; the implementation automatically opened a new ftp session for each directory. Obviously, this data does not represent normal user sessions, and would cause misleading results if used as the basis of a model of interactive user sessions. A third example is the activity on our authentication server (Fig. 20). In this case data covering a long period was available, and several distinct flurries were observed. This dataset is especially interesting in that if we are interested in failed authentications (rather than the full activity) the flurries become much more pronounced. In particular, the flurry attributed to user T was traced to a bug in Windows, where an authentication failure led to an infinite loop of retries.

[4]Indeed, it is possible that some of the flurries on supercomputers are also the result of runaway scripts rather than being intentional. However, this does not detract from the importance of the phenomenon. On the contrary, situations in which flurries are unintentional add motivation to the need to identify them before using the workload as representative of normal work.

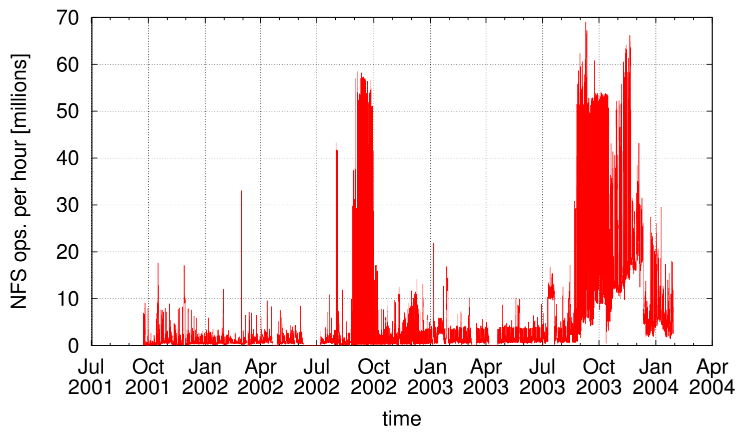


Figure 21: *Activity on a departmental filer over a year exhibits two unique high-load events.*

An important generalization of flurries replaces the source component of their definition: instead of being work generated by a single user, we can consider work generated by a singular event. A couple of examples are shown in the file server data of Fig. 21. The first high-load event, in September 2002, is attributed to a massive copying due to a hardware upgrade. The second, during September to December 2003, is attributed to a bug in a new release of the GNU C library[5] [30]. Installing the new version is the event that triggered this flurry of activity, and fixing it ended the flurry.

There are many accounts of flurry-like events on the Internet, provided we generalize the notion of source from a single user to some singular event that attracts many users (but still a small subset of all Internet users, and for a limited time). For example, new releases of software by Microsoft have caused the so called "midnight madness" phenomenon, where users flocking to download the new version (typically released at midnight) saturate the network and overwhelm the servers [28]. Other examples include the surge of activity on CNN's servers on September 11, 2001, and the usage of sites set up especially to cover sporting events such as the Olympic games or the World Cup finals [3]. All of these events are singular, and lead to unique traffic patterns. We claim that it would be wrong to use workload data including such singular events to analyze the performance of web servers under normal conditions, just as it would be wrong to use normal data for an evaluation of how systems would behave under unique conditions. Of course, in these particular cases the unique high-load conditions may be more important and meaningful than the normal conditions; if this is the case, they should be the focus of study rather than being eliminated as suggested below. For example, Ari et al. model such activity, which they call "flash crowds", with the aim of evaluating schemes to survive them [2].

Targeted attacks on specific servers also qualify as flurries. In many cases, the nature of the attack is to flood the server and overwhelm it with a load that is much higher than its capacity. This load is generated by a small group of machines (relative to the whole Internet), and lasts for a limited, well-defined time. In this case, an analysis of the attack workload patterns is not only useful for evaluation of servers, but also as a tool in identifying such attacks [5].

[5]The bug is actually that the d_off field in the dirent structure is not maintained correctly by the auto-mount daemon. Specifically, the 64-bit offset is either 0 or a garbage value. When using a 32-bit file system interface (like the libc readdir routine), getdents verifies that only 32 bits are actually used, and therefore fails if the garbage contains more bits. In trying to handle this error it attempts to seek to the beginning of the erroneous entry, identified using the offset of the previous one. But this is also a garbage value. And if it is 0, we end up with an endless loop of repeatedly reading the first entry, which is what caused the surge of activity seen in Fig. 21.

8.2 Dealing with Flurries

We suggest that the phenomenon of flurries cannot be ignored, as they may lead to large effects on workload modeling and on performance evaluations using real workloads. Instead, the workload needs to be separated into "normal" workload and flurries. Modeling and evaluation of normal workloads can then be performed using current methodologies. This may be expected to lead to reliable and consistent results that are applicable most of the time — that is, all the time during which flurries are not present. Comparing evaluation results using the cleaned log with results based on the original log will identify whether the removed flurries actually have a significant effect in the specific case being studied.

Removing the flurries is especially justifiable in those cases where the flurries are actually unintentional, and arise due to runaway scripts or other bugs in the workload creation process. But it is also justifiable if the flurries represent real work. The heart of the matter is that flurries are rare and unique. Using a workload with a flurry in effect emphasizes the rare and unique event at the expense of the normal conditions. Thus *leaving the flurry in* is actually the unjustifiable approach. To argue for evaluations based on workloads with flurries, one must argue that the activity of a specific user during a short time should indeed dominate the evaluation results. Also, one must be satisfied with results that may change considerably if the span of time covered by the evaluation is shifted such that the flurry happens to be excluded.

The question is then how to identify and remove the flurries. The methodology we have used is to plot activity levels as a function of time. In the case of parallel jobs, this means job arrivals per unit time, and process arrivals per unit time. In other contexts, other workload attributes would be appropriate. For example, when analyzing Internet traffic one can tabulate packets and flows; for storage systems, one can look at I/O operations and at bytes transferred.

Once a period of time with exceptionally heavy load is identified, this load should be checked for uniformity and source. The flurries we have identified were all composed of numerous repetitions of the same type of work. Identifying this is the key for removing the flurry from the workload, as the combination of the time frame and the flurry's specific attributes often provide an effective filter. As finding flurries is not trivial, this information should be shared together with the original data. In other words, when workload data is made available, it should be accompanied by all the accumulated knowledge regarding problems with its use, and specifically, with information regarding flurries that occur in it. As a first step, we have added our data to the parallel workloads archive [25], from which our original data comes, and which is used by many researchers for numerous studies of parallel job scheduling.

A similar approach to data sanitation has been proposed in the past by Cirne and Berman [9]. They too noticed that workload logs sometimes contain periods that are highly abnormal, and suggested that such periods should be deleted. Their methodology was to partition the log into days, and delete days that are identified as unique using a clustering analysis. Based on the characterization of flurries, we can suggest two refinements to this procedure. First, flurries can be longer than a day. Hence if the clustering identifies a sequence of consecutive days as being highly abnormal, this should be removed as well. Second, it may be beneficial to inspect the abnormal days, and attempt to remove only the flurries, rather than deleting these days completely.

Of course, just eliminating flurries is also not a good solution, as flurries do in fact occur. An open question is how to model or evaluate the effect of the flurries on a system designed and optimized for the more common non-flurry workload. An obvious first step is to use specific flurries that occur in recorded workloads and study their effect. But it is doubtful whether this can predict the effect of other potential flurries. Important future work is therefore to develop methods to extend and generalize the results obtained with specific flurries, and try to derive bounds on the effects of other potential flurries.

To summarize, it is extremely important to use real data regarding the workload on computer systems. But it is equally important to ensure that this is high-quality and representative data. Using measured workloads indiscriminantly risks the introduction of unknown anomalies that may lead to unknown effects. Workload flurries are such an anomaly, and should be handled with care.

Acknowledgment

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A Listing of Identified Flurries

The following table lists the job and process flurries we have identified in the parallel supercomputer workloads. The traces in the parallel workloads archive are given in Standard Workload Format, which includes a sequential numbering of all jobs. Each flurry is defined as the activity of a certain user within a certain range of jobs.

Trace	User	From	To	type	jobs
LANL CM-5	50	24439	64542	job	33452
	31	83739	115040	job	34307
	38	178585	192710	job	11570
SDSC Paragon	61	17496	25397	job+proc	2005
	62	17442	26320	job	2139
	66	55420	69427	job+proc	8678
	92	69857	76814	job+proc	3476
	23	79908	81548	job	1283
CTC SP2	135	47421	50307	job	2080
SDSC SP2	21	13717	16207	proc	944
	374	14969	28552	job+proc	11740
	197	31767	33202	proc	635
	328	66553	68106	proc	452
SDSC Blue H.	68	58	564	proc	477
	342	88202	91148	job	1468
	269	200425	217010	job+proc	5181