Revisiting Size-Based Scheduling with Estimated Job Sizes

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***Abstract*—We study size-based schedulers, and focus on the impact of inaccurate job size information on response time and fairness. Our intent is to revisit previous results, which allude to performance degradation for even small errors on job size estimates, thus limiting the applicability of size-based schedulers.**

We show that scheduling performance is tightly connected to workload characteristics: in the absence of large skew in the job size distribution, even extremely imprecise estimates suffice to outperform size-oblivious disciplines. Instead, when job sizes are heavily skewed, known size-based disciplines suffer.

In this context, we show – for the first time – the dichotomy of over-estimation versus under-estimation. The former is, in general, less problematic than the latter, as its effects are localized to individual jobs. Instead, under-estimation leads to severe problems that may affect a large number of jobs.

We present an approach to mitigate these problems: our technique requires no complex modifications to original scheduling policies and performs very well. To support our claim, we proceed with a simulation-based evaluation that covers an unprecedented large parameter space, which takes into account a variety of synthetic and real workloads.

As a consequence, we show that size-based scheduling is practical and outperforms alternatives in a wide array of use-cases, even in presence of inaccurate size information.

I. Introduction

Size-based scheduling protocols, which prioritize jobs that are closest to completion, are well known to have very desirable properties: the shortest remaining processing time policy (SRPT) provides optimal mean response time [1], while the fair sojourn protocol (FSP) [2] provides similar efficiency while guaranteeing strong fairness properties at the same time.

Despite these characteristics, however, scheduling policies similar to SRPT or FSP are very rarely deployed in production: a key reason is that, in real systems, job size is almost never known *a priori*. It is, instead, often possible to provide *estimations* of job size, which may vary in precision depending on the use case: however, the impact of errors due to these estimations in realistic scenarios is not yet well understood.

Perhaps surprisingly, very few works tackled the problem of size-based scheduling with inaccurate job size information: as we discuss more in depth in Section II, the existing literature gives somewhat pessimistic results, suggesting that size-based scheduling is effective only when the error on size estimation is small; known analytical results depend on restrictive assumptions on size estimations, while simulation-based analyses only cover a limited family of workloads. More importantly, no study we are aware of tackled the design of size-based scheduling techniques that are *explicitly designed with the goal of coping with errors* in job size information.

In Section III, we provide a qualitative analysis of the impact of size estimation errors on the behavior of scheduling: we show that, for heavy-tailed job size distributions, both FSP and SRPT behave problematically when large jobs are under-estimated; fortunately, it is possible to modify scheduling protocols to solve this problem. The solution we propose is incarnated in FSPE+PS, a simple modification to FSP. Analogous solutions can be applied to protocols such as SRPT.

We developed a simulator, described in Section IV, to study the behavior of FSP, SRPT, and FSPE+PS in a wide variety of scenarios. Our simulator allows both replaying real traces and generating synthetic ones varying system load, job size distribution and inter-arrival time distribution; for both synthetic and real workloads, scheduling protocols are evaluated on errors that range between relatively small quantities and others that may vary even by orders of magnitude.

From the experimental results of Section V, we highlight the following ones, validated both on synthetic and real traces:

1) When job size is not heavily skewed, SRPT and FSP outperform size-oblivious disciplines even when job size estimation is very imprecise and past work would hint towards important performance degradation; on the other hand, when the job size distribution is heavy-tailed, performance degrades noticeably;
2) FSPE+PS does not suffer from the performance issues of FSP and SRPT; it provides good performance for a large part of the parameter space that we explore, being outperformed by a processor sharing strategy only when *both* the job size distribution is heavily skewed *and* size estimations are very inaccurate;
3) FSPE+PS behaves fairly, guaranteeing that most jobs complete in an amount of time that is not disproportionate to their size.

As we discuss in Section VI, we conclude that our work highlights and solves a key weakness of size-based scheduling protocols when size estimation errors are present; the fact that FSPE+PS consistently performs close to optimally highlights that size-based schedulers are more viable in real systems than what was known from the state of the art; we believe that our work can help inspiring both the design of new size-based schedulers for real systems and analytic research that can provide better insight on scheduling when errors are present.

II. Related Work

We discuss two main areas of related work: first, results for size-based scheduling on M/G/1 queuing models; second, practical approaches devoted to the estimation of job sizes.

A. M/G/1 Queues

Performance evaluation of scheduling policies in M/G/1 queues has been the subject of many studies of the last 40 years, from both theoretical and experimental perspectives. Among all the policies, it has been shown that those that take into account the size of the submitted job obtain the smallest mean response time. Unfortunately, job sizes can often be only known approximatedly, rather than exactly. Since in our paper we consider this case, we review the literature that targets this problem.

Perhaps surprisingly, not much work considers the effect of inexact job size information on size-based scheduling policies. Lu *et al.* [3] have been the first to consider this problem, showing that size-based scheduling is useful only when job size evaluations are reasonably good (high correlation, greater than 0.75, between the real job size and its estimate). Their evaluation focuses on a single heavy-tailed job size distribution, and does not explain the causes of the observed results. Instead, we show the effect of different job size distributions (heavy-tailed, memoryless and light-tailed), and we show how to modify the size-based scheduling policies to make them robust to job estimation errors.

Wierman and Nuyens [4] provide analytical results for a class of size-based policies, but consider an impractical assumption: results depend on a bound on estimation error. In the common case where most estimations are close to the real value but there are outliers, bounds need to be set according to outliers, leading to pessimistic predictions on performance. In our work, instead, we do not impose any bound on the error.

To the best of our knowledge, these are the only works targeting job size estimation errors for the M/G/1 queue. We remark that, by using an experimental approach and replaying traces, we can take into account phenomena that are not represented in M/G/1 or G/G/1 queues, such as periodic temporal patterns or correlations between job size and submission time.

B. Job Size Estimation

In the context of distributed computational systems, FLEX [5] and HFSP [6] proved that size-based scheduling can perform well in practical scenarios. In both cases, job size estimation is performed with very simple means (*i.e.*, by sampling the execution time of a part of the job): such rough estimations are sufficient to provide good performance, and our results provide an explanation to this.

In several practical contexts, rough job size estimations are easy to perform. For instance, web servers can use the size of files to serve as an estimator of job size [7], and the variability of the end-to-end transmission bandwidth will determine the variability of the estimation error. More elaborate job size estimation means are in several cases already available, since estimating job size is not only interesting for the scheduler; relevant examples are approaches that deal with predicting the size of MapReduce jobs [8]–[10] and of database queries [11]. The estimation error can be always evaluated *a posteriori*, and this evaluation can be used to decide if the size-based scheduling works better than policies blind to size.

III. Scheduling Based on Estimated Sizes

We now introduce formally the SRPT and FSP size-based scheduling protocols, and describe the effects that estimation errors have on their behavior, focusing on the difference between over- and under-estimation. We notice that under-estimation triggers a behavior which is problematic in particular for heavy-tailed job size distributions, and we propose a solution to handle it.

A. SRPT and FSP

The SRPT policy gives priority to the job with smallest remaining processing time. SRPT is *preemptive*: a new job with size smaller than the remaining processing time of the running one will preempt (*i.e.*, interrupt) the currently running one. When the scheduler has access to exact job sizes, SRPT has optimal mean sojourn time (MST) [1] – *sojourn time*, or *response time*, is the time that passes between a job's submission and its completion.

SRPT may however cause *starvation* (*i.e.*, never providing access to resources): for example, if small jobs are constantly submitted, large jobs may never get served. FSP (also known in literature as *fair queuing* [12] and *Vifi* [13]) is a policy that doesn't suffer from starvation by virtue of *job aging*, *i.e.* gradually increasing the priority of jobs that are not scheduled. More precisely, FSP serves the job that would complete earlier in a *virtual* emulated system running a processor sharing (PS) discipline: since all jobs eventually complete in the virtual system, they will also eventually be scheduled in the real one.

In the absence of errors, a policy such as FSP is particularly desirable because it obtains a value of MST which is close to what is provided by SRPT while guaranteeing a strong notion of fairness in the sense that FSP *dominates* PS: no jobs complete later in FSP than in PS [2]. When errors are present, such a property cannot be guaranteed; however, as our experimental results in Section V show, FSP still preserves better fairness than SRPT even when errors are present.

B. Dealing With Errors: SRPTE and FSPE

We now consider the behavior of SRPT and FSP when the scheduler has access to *estimated* job sizes rather than exact ones. For clarity, we will refer hereinafter to *SRPTE* and *FSPE* in this case.

In Figure 1 on the following page, we provide an illustrative example where a single job size is over- or under-estimated while the others are estimated correctly, focusing (because of its simplicity) on the behavior of SRPTE; job sojourn times are represented by the horizontal arrows. The left column of Figure 1 illustrates the effect of over-estimation. In the top, we show how the scheduler behaves without errors, while in the bottom we show what happens when the size of job $J1$ is

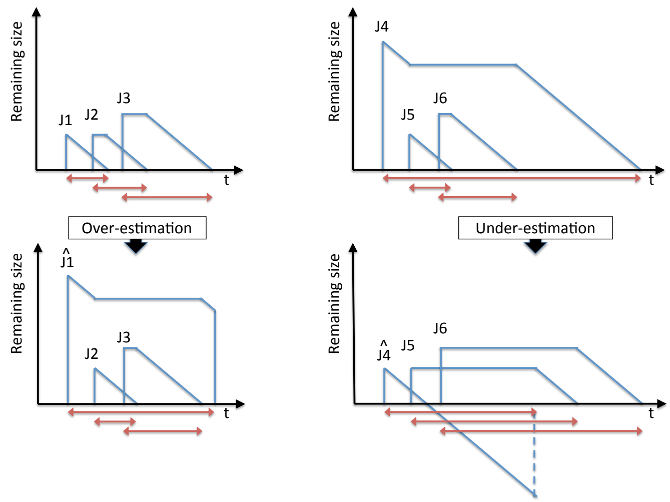


Fig. 1. Examples for job under- and over-estimation.

over-estimated. The graphs shows the remaining (estimated) processing time of the jobs over time (assuming a normalized service rate of 1). Without errors, jobs $J2$ does not preempt $J1$, and $J3$ does not preempt $J2$. Instead, when the size of $J1$ is over-estimated, both $J2$ and $J3$ preempt $J1$. Therefore, the only job suffering (*i.e.*, experiencing higher sojourn time) is the one that has been over-estimated. Jobs with smaller sizes are always able to preempt an over-estimated job, therefore the basic property of SRPT (favoring small jobs) is not significantly compromised.

The right column of Figure 1 illustrates the effect of under-estimation. With no estimation errors (top), a large job, $J4$, is preempted by small ones ($J5$ and $J6$). If the size of the large job is under-estimated (bottom), its estimated remaining processing time eventually reaches zero: we call *late* a job with zero or negative estimated remaining processing time. *A late job cannot be preempted* by newly arrived jobs, since their size estimation will always be larger than zero. In practice, since preemption is inhibited, the under-estimated job *blocks the system* until the end of its service, with a negative impact on multiple waiting jobs.

This phenomenon is particularly harmful when job sizes are heavily skewed: if the workload has few very large jobs and many small ones, a single late large job can significantly delay several small ones, which will need to wait for the late job to complete before having an opportunity of being served.

Even if the impact of under-estimation seems straightforward to understand, surprisingly *no work in the literature has ever discussed it*. To the best of our knowledge, we are the first to identify this problem, which significantly influences scheduling policies dealing with inaccurate job size.

In FSPE, the phenomena we observe are analogous: job size over-estimation delays only the over-estimated job; under-estimation can result in jobs terminating in the virtual PS queue before than in the real system; this is impossible in absence of errors due to the dominance result introduced in Section III-A. We therefore define *late* jobs in FSPE as those whose execution is completed in the virtual system but not yet in the real one and we notice that, analogously to SRPTE, also in FSPE late jobs can never be preempted by new ones, and they block the system until they are all completed.

C. Our Solution

Now that we have identified the issue with existing size-based scheduling policies, we propose our countermeasure. Several alternatives are envisionable, including for example updating job size estimations if new information becomes available as work progresses: such a solution may not however be always feasible, due to limitations in terms of information or computational resources available to the scheduler.

We propose, instead, a simple solution that requires no additional job size estimation, based on the simple idea that *late jobs should not prevent executing other ones*. This goal is achievable by performing simple modifications to preemptive size-based scheduling disciplines such as SRPT and FSP. The key property is that the scheduler takes corrective actions when one or more jobs are *late*, guaranteeing that – even when very large late jobs are being executed – newly arrived small jobs will get executed soon.

We show here *FSPE+PS*, which is a modification to FSPE: the only difference is that, when one or more jobs are late, (*i.e.*, they have completed in the emulated virtual system and not in the real one), *all late jobs are scheduled concurrently in a PS fashion*. FSPE+PS inherits from FSP and FSPE the guarantee that starvation is absent, it is essentially as complex to implement as FSP is and, as we show in Section V, it performs close to optimally in most experimental settings we observe. Due to the dominance of FSP with respect to PS, if there are no size estimation errors no jobs can ever become late: therefore, with no error FSPE+PS is equivalent to FSP.

Several alternatives to FSPE+PS are possible: we experimented for example with similar policies that are based on SRPT rather than on FSP, that use a least-attained-service policy rather than a PS one for late jobs, and/or that schedule aggressively jobs that are not late yet as soon as at least one reaches the "late" stage. With respect to the metrics we use in this work, their behavior is very similar to the one of FSPE+PS, and for reasons of conciseness we do not report about them here. We however encourage the interested reader to examine their implementation at bit.ly/schedulers. In practice, most of the performance gain is due to the *explicit management of the late jobs*, and how late jobs are handled has no significant impact on such a gain.

Algorithm 1 on the next page presents our implementation of FSPE+PS, which is based on Friedman and Henderson's original description of FSP [2, Section 4.4]. System state is kept in three variables: the virtual PS queue state is kept in a list $\mathcal{O}$, containing (j_i, w_i, c_i) tuples and ordered by the w_i values: each such tuple represents a job j_i having remaining processing time w_i in the virtual system, while the c_i boolean flag is set to True if j_i is running in the real system; late jobs

```
def NextVirtualCompletionTime:
    if |O| = 0: return ∅
    else: return t + w_0 * |O|
def ProcessJob:
    if |L| ≠ 0: return {(l_i, 1/|L|) | l_i ∈ L}
    elif |O| = 0: return ∅
    else:
        k ← min{i | c_i}
        return {(j_k, 1)}
def UpdateVirtualTime(s):
    for (_, w_i, _) ∈ O:  w_i ← w_i − (s − t)/|O|
    t ← s
def VirtualJobCompletion(s):
    UpdateVirtualTime(O, t, s)
    if c_0: add j_0 to L
    remove the first element from O
def RealJobCompletion(j):
    find i such that j_i = j
    c_i ← False
def JobArrival(s, j, w):
    UpdateVirtualTime(O, t, s)
    insert (j, w, True) in O maintaining ordering
```

Algorithm 1: FSPE+PS.

are stored in a $\mathcal{L}$ set; the variable t stores the last time at which the information in $\mathcal{O}$ had been updated.

Computation is triggered by three events: if a job j of estimated size w arrives at time s, JobArrival(s, j, w) is called; when a job j completes, RealJobCompletion(j) is called; finally, when a job completes in the virtual system at time s, UpdateVirtualTime(s) is called (NextVirtualCompletionTime is used to discover when to call VirtualJobCompletion). After each event, the ProcessJob procedure is called to determine the new set of scheduled jobs: its output is a set of (j, s) pairs where j is the job identifier and s is the fraction of system resources allocated to it.

IV. Evaluation Methodology

Understanding size-based scheduling systems when there are estimation errors is not a simple task. The complexity of the system makes an analytical study feasible only if strong assumptions, such as a bounded error [4], are imposed. Moreover, to the best of our knowledge, no analytical model for FSP (without estimation error) is available, making an analytical evaluation of FSPE and FSPE+PS even more difficult.

For these reasons, we evaluate our proposed scheduling policies through simulation. The simulative approach is extremely flexible, allowing to take into account several parameters – distribution of the arrival times, of the job sizes, of the errors. Previous simulative studies (*e.g.*, [3]) have focused on a subset of these parameters, and in some cases they have used real traces. In our work, we developed a tool that is able to both reproduce real traces and generate synthetic ones. Moreover, thanks to the efficiency of the implementation, we were able to run an extensive evaluation campaign, exploring a large parameter space. For these reasons, we are able to provide a broad view of the applicability of size-based scheduling policies, and show the benefits and the robustness of our solution with respect to the existing ones.

A. Scheduling Policies Under Evaluation

In this work, we take into account different scheduling policies, both size-based and blind to size. For the size-based disciplines, we consider SRPT as a reference for its optimality with respect to the MST. When introducing the errors, we evaluate SRPTE, FSPE and our proposal, FSPE+PS, described in Section III.

For the scheduling policies blind to size, we have implemented the *First In, First Out* (FIFO) and *Processor Sharing* (PS) disciplines. These policies are the default disciplines used in many scheduling systems – *e.g.*, the default scheduler in Hadoop [14] implements a FIFO policy, while Hadoop's FAIR scheduler is inspired by PS; the Apache web server delegates scheduling to the Linux kernel, which in turn implements a PS-like strategy [7]. Since PS scheduling divides evenly the resources among running jobs, it is generally considered as a reference for its fairness (see the next section on the performance metrics). Finally, we consider also the *Least Attained Service* (LAS) [15] policy. LAS scheduling, also known in the literature as *Foreground-Background* (FB) [16] and *Shortest Elapsed Time* (SET) [17], is a preemptive policy that gives service to the job that has received the least service, sharing it equally in a PS mode in case of ties. LAS scheduling has been designed considering the case of heavy-tailed job size distributions, where a large percentage of the total work performed in the system is due to few very large jobs, since it gives more priority to small jobs than what PS would do.

B. Performance Metrics

We evaluate scheduling policies according to two main aspects: *mean sojourn time* (MST) and *fairness*. MST is the time that passes between the moment a job is submitted and when it completes; such a metric is widely used in the scheduling literature.

The definition of fairness is more elusive: in his survey on the topic, Wierman affirms that *"fairness is an amorphous concept that is nearly impossible to define in a universal way"* [18]. A common approach is to consider *slowdown*, *i.e.* the ratio between a job's sojourn time and its size, according to the intuition that the waiting time for a job should be somewhat proportional to its size. In this work we focus on the per-job slowdown, based on the intuition that as few jobs as possible should experience "unfair" very high slowdown values; moreover, in accordance with the definition by Wierman [19], we also verify whether jobs having a given size experience an "unfair" high expected slowdown value.

C. Parameter Settings

Our goal is to empirically evaluate scheduling policies in a wide spectrum of cases. Table I on the following page

TABLE I
SIMULATION PARAMETERS.

Parameter	Explanation	Default
sigma	σ in the log-normal error distribution	0.5
shape	shape for Weibull job size distribution	0.25
timeshape	shape for Weibull inter-arrival time	1
njobs	number of jobs in a workload	10,000
load	system load	0.9

synthetize the parameters that our simulator can accept as inputs; they are explained in detail in the following.

Job Size Distribution: Job sizes are generated according to a Weibull distribution, which allows us to evaluate both heavy-tailed and light-tailed job size distributions. Indeed, the ***shape*** parameter allows to interpolate between heavy-tailed distributions (shape < 1), the exponential distribution (shape$= 1$), the Raleigh distribution ($\mathrm{shape} = 2$) and bell-shaped distributions centered around the '1' value ($\mathrm{shape} > 2$). We set the *scale* parameter of the distribution to ensure that its mean is 1.

Since scheduling problems have been generally analyzed on heavy-tailed workloads with job sizes using distributions such as Pareto, we consider a default heavy-tailed case of $\mathrm{shape} = 0.25$. In our experiments, we vary the shape parameter between a very skewed distribution with $\mathrm{shape} = 0.125$ and a bell-shaped distribution with $\mathrm{shape} = 4$.

Size Error Distribution: We consider log-normally distributed error values. A job having size s will be estimated as $\hat{s} = sX$, where X is a random variable with distribution

$$\text{Log-}\mathcal{N}(0, \sigma^2). \quad (1)$$

This choice satisfies two properties: first, since error is multiplicative, the absolute error $\hat{s} - s$ is proportional to the job size s; second, under-estimation and over-estimation are equally likely, and for any σ and any factor $k > 1$ the (non-zero) probability of under-estimating $\hat{s} \leq \frac{s}{k}$ is the same of over-estimating $\hat{s} \geq ks$. This choice also is substanciated by empirical results: in our implementation of the HFSP scheduler for Hadoop [6], we found that the empirical error distribution was indeed fitting a log-normal distribution.

The ***sigma*** parameter controls σ in Equation 1, with a default – used if no other information is given – of 0.5; with this value, the median factor k reflecting relative error is 1.40. In our experiments, we let sigma vary between 0.125 (median k is 1.088) and 4 (median k is 14.85).

It is possible to compute the correlation between the estimated and real size as σ varies. In particular, when sigma is equal to 0.5, 1.0, 2.0 and 4.0, the correlation coefficient is equal to 0.9, 0.6, 0.15 and 0.05 respectively.

The mean of this distribution is always larger than 1, and growing as sigma grows: the system is biased towards overestimating the aggregate size of several jobs, limiting the underestimation problems that FSPE+PS is designed to solve. Even in this setting, the results in Section V show that the improvements obtained by using FSPE+PS are still significant.

Job Arrival Time Distribution: For the job inter-arrival time distribution, we use a Weibull distribution for its flexibility to model heavy-tailed, memoryless and light-tailed distributions. We set the default of its shape parameter (***timeshape***) to 1, corresponding to "standard" exponentially distributed arrivals. Also here, timeshape varies between 0.125 (very bursty arrivals separated by long intervals) and 4 (regular arrivals).

Other Parameters: The ***load*** parameter is the mean arrival rate divided by the mean service rate. As default value, we use the same value of 0.9 used by Lu *et al.* [3]; in our experiments we let the load parameter vary between 0.5 and 0.999.

The number of jobs (***njobs***) in each simulation round is 10,000 (in additional experiments – not shown for space reasons – we varied this parameter, without obtaining significant differences). For each experiment, we perform at least 30 repetitions, and we compute the confidence interval for a confidence level of 95%. For very heavy-tailed job size distributions ($\mathrm{shape} \leq 0.25$), results are very variable and therefore, in order to obtain stable averages, we performed hundreds and/or thousands of experiment runs, until the confidence levels have reached the 5% of the estimated values.

D. Simulator Implementation Details

Our simulator is available under the Apache V2 license at https://bitbucket.org/bigfootproject/schedsim. It has been conceived with ease of prototyping in mind: for example, our implementation of FSPE as described in Section III requires 53 lines of code. Workloads can be both replayed from real traces and generated synthetically.

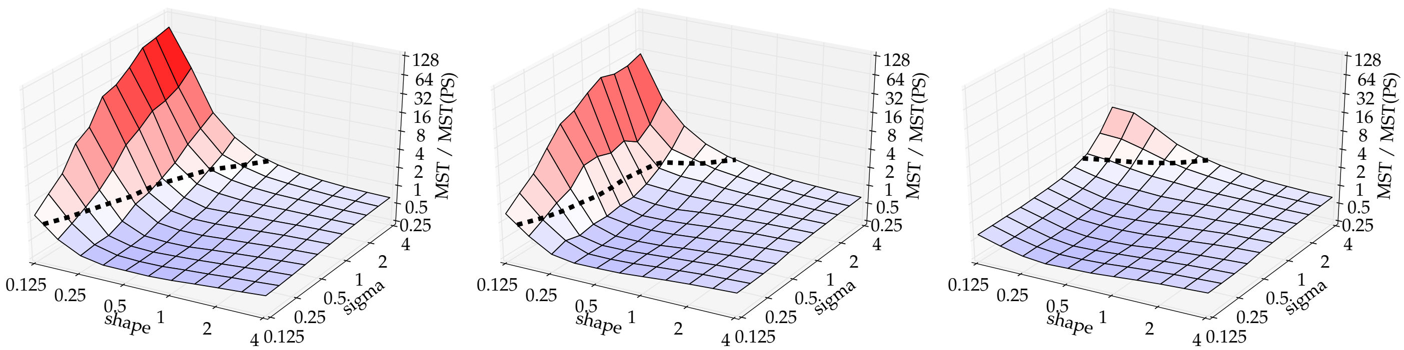
The simulator has been written with a focus on computational efficiency. It is implemented using an event-based paradigm, and we used efficient data structures based on B-trees (stutzbachenterprises.com/blist/). As a result of these choices, a "default" workload of 10,000 jobs is simulated in around half a second, while using a single core in our machine with an Intel T7700 CPU. We use IEEE 754 double-precision floating point values to represent time and job sizes.

V. EXPERIMENTAL RESULTS

We now present our experimental findings. For all the results shown in the following, the parameters whose values are not explicitly stated take the default values shown in Table I. For the readability of the figures, we do not show the confidence intervals: for all the points, in fact, we have performed a number of runs sufficiently high to obtain a confidence interval smaller than 5% of the estimated value. We first present our results on synthetic workloads generated according to the methodology of Section IV-C; we then show the results by replaying two real-world traces from workloads of Hadoop and of a Web cache.

A. Synthetic Workloads

Mean Sojourn Time Against PS: We begin our analysis by comparing the three size-based scheduling policies, using PS as a baseline because PS and its variants are the most widely used set of scheduling policies in real systems. In Figure 2



(a) SRPTE. (b) FSPE. (c) FSPE+PS.

Fig. 2. Mean sojourn time against PS.

we plot the value of the MST obtained using respectively SRPTE, FSPE and FSPE+PS, normalizing it against the MST of PS. We vary the sigma and shape parameters influencing respectively job size distribution and error rate; we will see that these two parameters are the ones that influence performance the most. Values lower than one (below the dashed line in the plot) represent regions where size-based schedulers perform better than PS.

In accordance with intuition and to what is known from the literature, we observe that the performance of size-based scheduling policies depends on the accuracy of job size estimation: as sigma grows, performance suffers. From Figures 2a and 2b, we however observe a new phenomenon: *job size distribution impacts performance even more than size estimation error.* On the one hand, we notice that large areas of the plots (shape > 0.5) are almost insensitive to estimation errors; on the other hand, we see that MST becomes very large as job size skew grows (shape < 0.25). We attribute this latter phenomenon to the fact that, as we highlight in Section III, late jobs whose estimated remaining (virtual) size reaches zero are never preempted. If a large job is under-estimated and becomes *late* with respect to its estimation, small jobs will have to wait for it to finish in order to be served.

As we see with Figure 2c, *FSPE+PS outperforms PS in a large class of heavy-tailed workloads* where SRPTE and FSPE suffer. The net result is that a size-based policy such as FSPE+PS is outperformed by PS only in extreme cases where *both* the job size distribution is extremely skewed *and* job size estimation is very imprecise.

It may appear surprising that, when job size skew is not extreme, size-based scheduling can outperform PS even when size estimation is very imprecise: even a small correlation between job size and its estimation can direct the scheduler towards choices that are beneficial on aggregate. In fact, as we see more in detail in the following, sub-optimal scheduling choices become less penalized as the job size skew diminishes.

Impact of shape: We now delve into details and examine how schedulers perform when compared to the optimal MST that SRPT obtains. In the following Figures, we show the ratio between the MST obtained with the scheduling policies we implemented and the optimal one of SRPT.

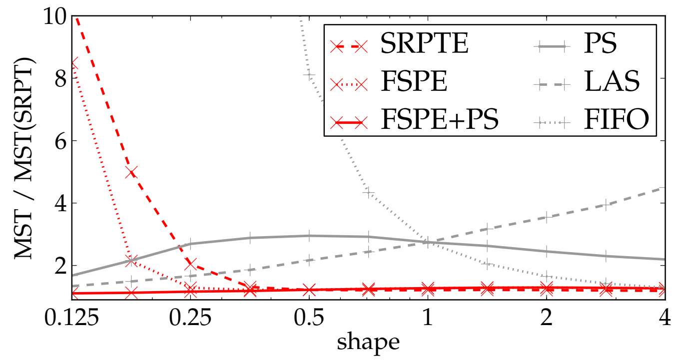
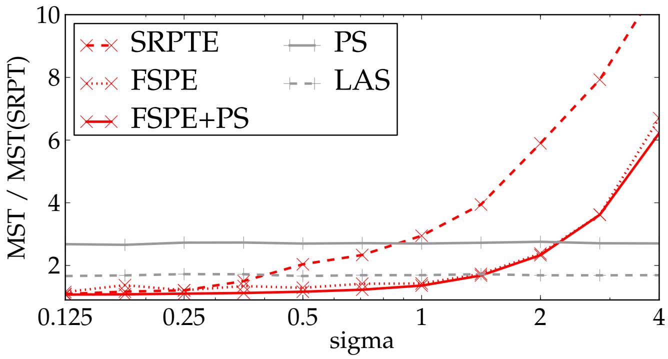


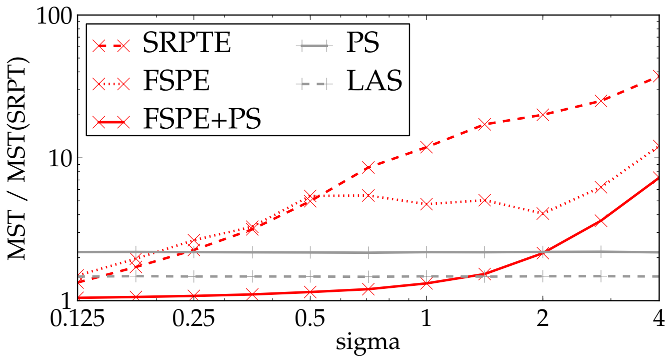
Fig. 3. Impact of shape.

From Figure 3, we see that the shape parameter is fundamental for evaluating scheduler performance. We notice that FSPE+PS has *almost optimal performance for all shape values considered* with the default sigma=0.5, which corresponds to a correlation coefficient between job size and it estimate of 0.9, while SRPTE and FSPE perform poorly for highly skewed workloads. Regarding non size-based policies, PS is outperformed by LAS for heavy-tailed workloads (shape < 1) and by FIFO for light-tailed ones having shape > 1 ; PS provides a reasonable trade-off when the job size distribution is unknown. When the job size distribution is exponential (shape $= 1$), non size-based scheduling policies perform analogously; this is a result which has been proven analytically (see *e.g.* the work by Harchol-Balter [20] and the references therein). It is interesting to consider the case of FIFO: in it, jobs are scheduled in series, and the priority between jobs is not correlated with job size: indeed, the MST of FIFO is equivalent to the one of a random scheduler executing jobs in series [21]. FIFO can be therefore seen as the limit case for a size-based scheduler such as FSPE or SRPTE when estimations carry no information at all about job sizes; the fact that errors become less critical as skew diminishes can be therefore explained with the similar patterns observed for FIFO.

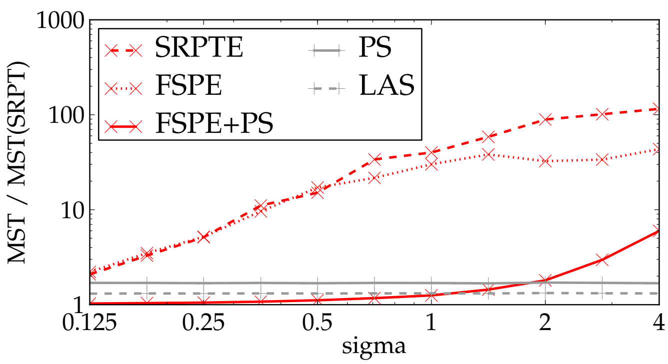
Impact of sigma: The shape of the job size distribution



(a) shape=0.25



(b) shape=0.177

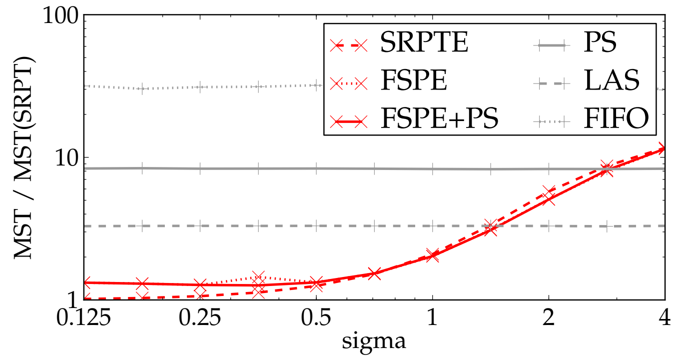


(c) shape=0.125

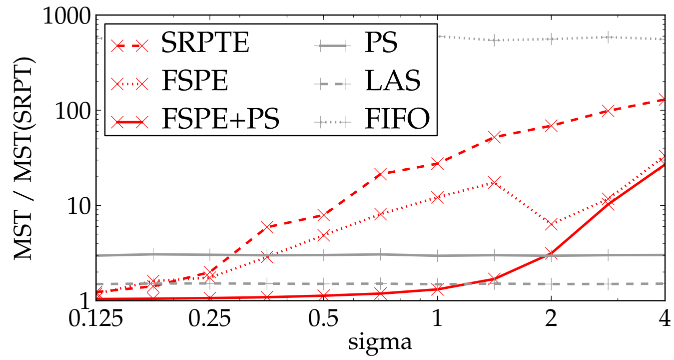
Fig. 4. Impact of error on heavy-tailed workloads, sorted by growing skew.

is fundamental in determining the behavior of scheduling algorithms, and heavy-tailed job size distributions are those in which the behavior of size-based scheduling differs noticeably. Because of this, and since heavy-tailed workloads are central in the literature on scheduling, we focus on those.

In Figure 4, we show the impact of the sigma parameter representing error for three heavily skewed workloads. In all three plots, the values for FIFO fall outside of the plot. These plots demonstrate that FSPE+PS is robust with respect to errors in all the three cases we consider, while SRPTE and FSPE suffer as the skew between job sizes grows. In all three cases, FSPE+PS performs better than PS as long as sigma is lower than 2: this corresponds to lax bounds on size estimation quality, requiring a correlation coefficient between job size and its estimate of 0.15 or more.



(a) $\alpha = 2$



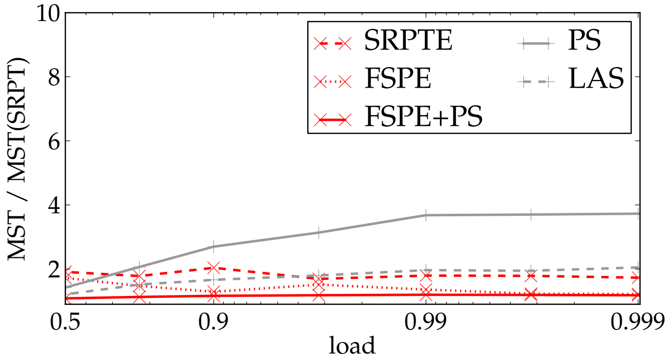
(b) $\alpha = 1$

Fig. 5. Pareto job size distributions, sorted by growing skew.

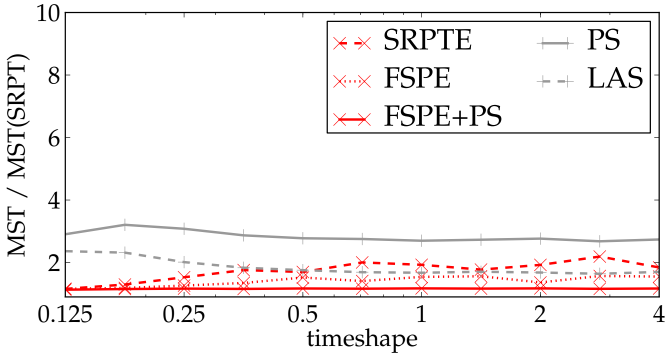
In all three plots, FSPE+PS performs better than SRPTE; the difference between FSPE+PS and FSPE, instead, becomes discernible only for shape < 0.25. We explain this difference by noting that, when several jobs are in the queue, size reduction in the virtual queue of FSPE is slow: this leads to less jobs being late and therefore non preemptable. As the distribution becomes more heavy-tailed, more jobs become late in FSPE and differences between FSPE and FSPE+PS become significant, reaching differences of even around one order of magnitude.

In particular in Figure 4b, there are areas ($0.5 < \text{sigma} < 2$) in which increasing errors decreases (slightly) the MST of FSPE. This counterintuitive phenomenon is explained by the characteristics of the error distribution: the mean of the log-normal distribution grows as sigma grows, therefore the aggregate amount of work for a set of several jobs is more likely to be over-estimated; this reduces the likelihood that several jobs at once become late and therefore non-preemptable. In other words, FSPE works better with estimation means that tend to over-estimate job size; it is however always better to use FSPE+PS, which provides a more reliable and performant solution to the same problem.

Pareto Job Size Distribution: In the literature, workloads are often generated using the Pareto distribution. To help comparing our results to the literature, in Figure 5 we show results for job sizes having a Pareto distribution, using $x_m = 0$ and $\alpha = \{1, 2\}$. The results we observe for the Weibull distribution



(a) Varying load.



(b) Varying timeshape.

Fig. 6. Impact of load and timeshape.

are still qualitatively valid for the Pareto distribution; the value of $\alpha = 1$ is roughly comparable to a shape of 0.15 for the Weibull distribution, while $\alpha = 2$ is comparable to a shape of around 0.5, where the three size-based disciplines we take into account still have similar performance.

Impact of Other Parameters: In Figure 6, we show the impact of varying the load and timeshape parameters, while keeping sigma and shape at their default values.

Figure 6a shows that performance of size-based scheduling protocols is not heavily impacted by load, as the ratio between the MST obtained and the optimal one remains roughly constant (note that the graph shows a ratio, not the absolute values, that increase as the load increases); conversely, non size-based schedulers such as PS and LAS deviate more from optimal as the load grows.

Figure 6b shows the impact of changing the timeshape parameter: with low values of timeshape, job submissions are bursty and separated by long pauses; with high values job submissions are evenly spaced. We note that size-based scheduling policies respond very well to bursty submissions where several jobs are submitted at once: in this case, adopting a size-based policy that focuses all the system resources on the smallest jobs pays best; as the intervals between jobs become more regular, SRPTE and FSPE become slightly less performant; FSPE+PS remains close to optimal.

Conditional Slowdown: We now consider the topic of fairness, intending here – as discussed in Section IV-B – that jobs'

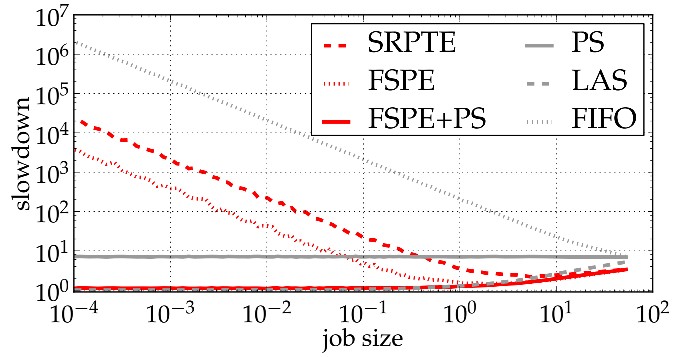


Fig. 7. Mean conditional slowdown.

running time should be proportional to their size, and therefore not experience large slowdowns.

To better understand the reason for the unfairness of FIFO, SRPTE and FSPE, in Figure 7 we evaluate *mean conditional slowdown*, comparing job size with the average slowdown (job sojourn time divided by job size) obtained at that size using our default simulation parameters. The figure has been obtained by sorting jobs by size and binning them in 100 equally sized classes of jobs with similar size; points plotted are obtained by averaging job size and slowdown in each of the 100 class.

The almost parallel lines of FIFO, SRPTE and FSPE for smaller jobs are explained by the fact that, below a certain size, *job sojourn time is essentially independent from job size*: indeed, it depends on the total size of older (for FIFO) or late (for SRPTE and FSPE) jobs at submission time.

We confirm experimentally the fact that the expected slowdown in PS is constant, irrespectively of job size [19]; FSPE+PS and LAS, on the other hand, have close to optimal slowdown for small jobs. The better MST of FSPE+PS is instead due to better performance for larger jobs, which are more penalized in LAS.

Per-Job Slowdown: The results we have shown testify that, for FSPE+PS and similarly to LAS, slowdown values are homogeneous across classes of job sizes: neither small nor big jobs are penalized when using FSPE+PS. This is a desirable result, but the reported results are still averages: in order to ensure that sojourn time is commensurate to size *for all jobs*, we need to investigate the *per-job* slowdown distribution.

In Figure 8 on the following page, we plot the CDF of per-job slowdown for our default simulator parameters. By serving efficiently smaller jobs, all size-based scheduling techniques and LAS manage to obtain an optimal slowdown of 1 for the majority of jobs. However, some jobs experience very high slowdown values: jobs with a slowdown larger than 100 are around 1% for FSPE and around 8% for SRPTE.

PS, LAS, and FSPE+PS perform well in terms of fairness, with no jobs experiencing slowdown higher than 100 in our experiment runs.[1] While PS is generally considered the refer-

[1] Figure 8 plots the results of 121 experiment runs, representing therefore 1,210,000 jobs in this simulation.

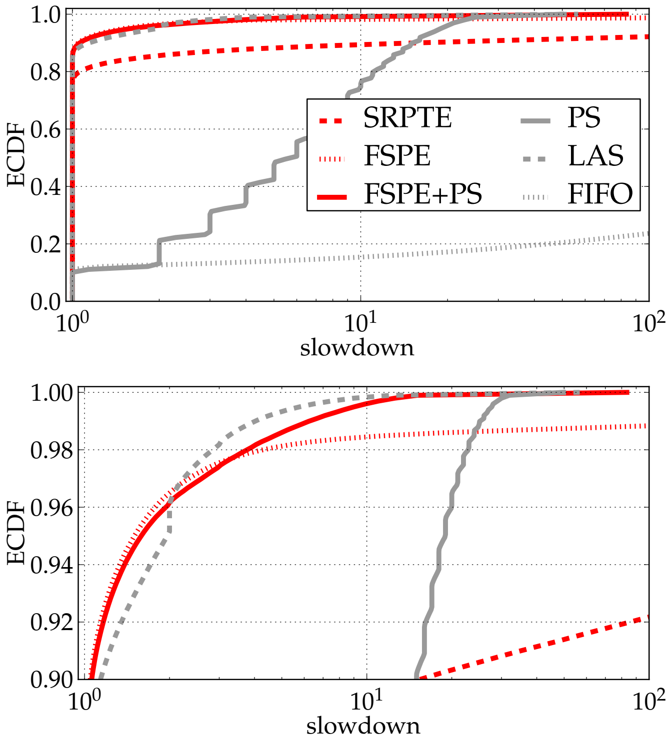


Fig. 8. Per-job slowdown: full CDF (top) and zoom on the 10% more critical cases (bottom).

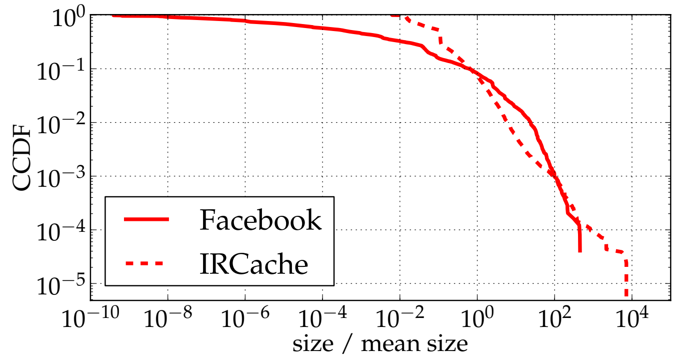


Fig. 9. CCDF for the real workloads.

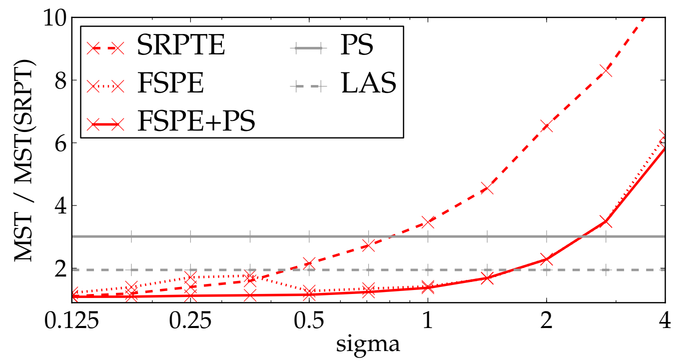


Fig. 10. MST of the Facebook workload.

ence for a "fair" scheduler, it obtains slightly better slowdown than LAS and FSPE+PS only for the most extreme cases, while being outperformed for a large majority of the jobs. We remark that slowdown values for PS are clustered around integer values, because they are obtained in the common case where a small job is submitted when n larger ones are running.

B. Real Workloads

We now consider two real workloads in order to confirm that the phenomena we observed in our experiments are not an artifact of the synthetic traces that we generated, and that they indeed apply in realistic cases. From the traces we obtain two data points per job: submission time and job size. In this way, we move away from the assumptions of the $G/G/1$ model, and we provide results that can account for more general cases where periodic patterns and correlation between job size and submission times are present.

Hadoop at Facebook: We consider a trace from a Facebook Hadoop cluster in 2010, covering one day of job submissions. The trace has been collected and analized by Chen *et al.* [22]; it is comprised of 24,443 jobs and it is available online.[2] For the purposes of this work, we consider the job size as the number of bytes handled by each job (summing input, intermediate output and final output): the mean size is 76.1 GiB, and the largest job processes 85.2 TiB. To understand the shape of the tail for the job size distribution, in Figure 9 we plot the complementary CDF (CCDF) of job sizes (normalized against the mean); the distribution is heavy-tailed and the largest jobs are around 3 orders of magnitude larger than the average size. For homogeneity with the results of Section V-A, we set the processing speed of the simulated system (in bytes per second) in order to obtain a load (total size of the submitted jobs divided by total length of the submission schedule) of 0.9.

In Figure 10, we show MST, normalized against optimal MST, while varying the error rate. We remark that these results are very similar to those that we observe from Figure 4 on page 7: also in this case, FSPE and FSPE+PS perform well even when job size estimation errors are far from negligible. We do not plot the slowdown CDF for space limitations: results are analogous to those observed in Figure 8. These results show that this workload is well represented by our synthetic workloads, when shape is around 0.25.

We performed more experiments on these traces; extensive results are available in a technical report [23].

Web Cache: IRCache (ircache.net) is a research project for web caching; traces from the caches are freely available. We performed our experiments on a one-day trace of a server from 2007 totaling 206,914 requests;[3] the mean request size in the traces is 14.6KiB, while the maximum request size is 174 MiB. In Figure 9 we show the CCDF of job size; as compared to the Facebook trace analyzed previously, the

[2] https://github.com/SWIMProjectUCB/SWIM/blob/master/workloadSuite/FB-2010_samples_24_times_1hr_0.tsv

[3] ftp://ftp.ircache.net/Traces/DITL-2007-01-09/pa.sanitized-access.20070109.gz.

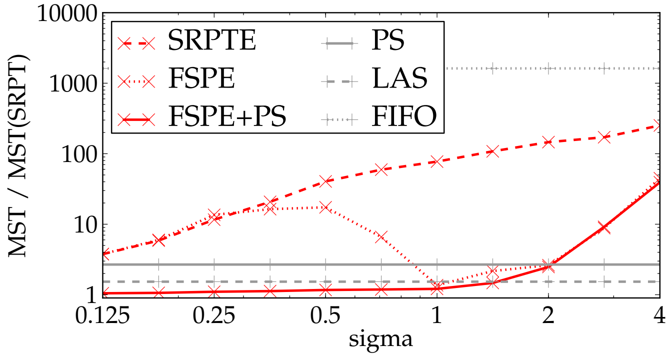


Fig. 11. MST of the IRCache workload.

workload is more heavily tailed: the biggest requests are four orders of magnitude larger than the mean. As before, we set the simulated system processing speed in bytes per second to obtain a load of 0.9.

In Figure 11 we plot the evolution of MST as the sigma parameter controlling error grows. Since the job size distribution is more heavily tailed, sojourn times are more influenced by job size estimation errors (notice the logarithmic scale on the y axis), confirming the results we have from Figure 2 on page 6. The performance of FSPE does not worsen monotonically as error grows, but rather becomes better for $0.5 < \text{sigma} < 1$; this is a phenomenon that we also observe – albeit to a lesser extent – for synthetic workloads in Figure 4b on page 7 and for the Facebook workload in Figure 10 on the previous page. The explanation that we provided in Section V-A applies: since the mean of the log-normal distribution grows as sigma grows, the aggregate amount of work for a given set of jobs is likely to be over-estimated in total, reducing the likelihood that several jobs at once become late and therefore non-preemptable. Also in this case, we still remark that FSPE+PS consistently outperforms FSPE. Once again, the results for the slowdown distribution – not reported for space limitations – are qualitatively analogous to those reported in Section V-A.

VI. Conclusion

This work shows that size-based scheduling is an applicable and performant solution in a wide variety of situations where job size is known approximately rather than exactly. The limitations shown by previous work are, in a large part, solved by the approach we took in FSPE+PS, which is a simple modification to FSP; analogous measures can be taken in other preemtpive size-based scheduling disciplines.

FSPE+PS also solves a fairness problem: while FSPE and SRPTE penalize small jobs and results in slowdown values which are not proportionate to their size, FSPE+PS has constant and optimal slowdown for most small jobs. Our work suggests that, if even rough estimates can be produced to estimate job sizes, it is worthy to try size-based scheduling: our proposal, FSPE+PS, is essentially as complex to implement as FSP is, and provides close to optimal response times and good fairness in all but the most extreme of cases.

We released our simulator as free software: it can be reused for *1)* reproducing our experimental results; *2)* prototype new scheduling algorithms; *3)* predict system behavior in particular cases, by replaying traces.

We are currently evaluating other scheduling variants, going beyond FSPE+PS with the goal of having a scheduler that adapts dynamically to the characteristics of job size and error distribution, striving to *always* be at least as performant as non size-based scheduling policies such as LAS.

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