



What Size Should your Buffers to Disks be?

Guillaume Aupy, Olivier Beaumont, Lionel Eyraud-Dubois

► **To cite this version:**

Guillaume Aupy, Olivier Beaumont, Lionel Eyraud-Dubois. What Size Should your Buffers to Disks be?. International Parallel and Distributed Processing Symposium (IPDPS), May 2018, Vancouver, Canada. 10.1109/IPDPS.2018.00075 . hal-01623846v2

HAL Id: hal-01623846

<https://hal.inria.fr/hal-01623846v2>

Submitted on 13 Jul 2018

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

What Size Should your Buffers to Disks be?

Guillaume Aupy*, Olivier Beaumont* and Lionel Eyraud-Dubois*

*Inria, LaBRI, Univ. Bordeaux, CNRS, Bordeaux-INP, France

guillaume.aupy@inria.fr, olivier.beaumont@inria.fr, lionel.eyraud-dubois@inria.fr

Abstract—Burst-Buffers are high throughput, small size intermediate storage systems typically based on SSDs or NVRAM that are designed to be used as a potential buffer between the computing nodes of a supercomputer and its main storage system consisting of hard drives. Their purpose is to absorb the bursts of I/O that many HPC applications experience (for example for saving checkpoints or data from intermediate results). In this paper, we propose a probabilistic model for evaluating the performance of Burst-Buffers. From a model of application and a data management strategy, we build a Markov-chain-based model of the system, that allows us to quickly answer issues about dimensioning of the system: for a given set of applications, and for a given Burst-Buffer size and bandwidth, how often does the buffer overflow? We also provide extensive simulation results to validate our modeling approach.

I. INTRODUCTION

Solving the bottleneck of I/O is a major point in current HPC systems. This point is especially striking when observing their recent evolution. For instance, when Los Alamos National Laboratory moved from Cielo to Trinity, the peak performance moved from 1.4 Petaflops to 40 Petaflops ($\times 28$) while the I/O bandwidth moved to 160 GB/s to 1.45TB/s (only $\times 9$) [1]. The same kind of results can be observed at Argonne National Laboratory when moving from Intrepid (0.6 PF, 88 GB/s) to Mira (10PF, 240 GB/s) and to Aurora (expected 180PF and 1TB/s) [2]. Indeed, the main storage technology is still based on hard drive, that have shown a better capacity to scale up in terms of storage capacity than speed.

On the other hand, the usage of HPC systems makes I/O more and more important. First, in the framework on the convergence between HPC and BigData [3], HPC systems are more and more used to run BigData applications, that require much more I/O bandwidth than traditional HPC applications. The main characteristic of BigData workload is that they are dominated by read operations. Second, the MTBF (Mean Time Between Failures) of HPC systems is decreasing [4], [5] and Checkpoint/Restart strategies are used to ensure the reliability of computations over a failure prone system. Contrarily to BigData applications, Checkpoint/Restart strategies consume a lot of I/O bandwidth for storing checkpoints, and are dominated by write operations. An important feature of checkpoints is that in general, each new checkpoint for an application can erase the previous one, so that not all checkpoints have to be ultimately saved to the slow disk. Third, HPC applications themselves consume a lot of I/O bandwidth (see Section II-C). They typically follow a quasi-periodic pattern, with an alternance of compute and I/O phases, that cannot be overlapped. As in the case of checkpointing,

such HPC applications mostly write data to the disk, and due to their bursty nature, they are known to generate interference and idle times at the I/O level [6] when several applications attempt to store their results simultaneously.

In order to cope with the limited I/O bandwidth of HPC system, Burst-Buffers have emerged as promising solution [7], [8], [9]. On the technological side, the use of NVRAM or SSDs makes it possible to achieve much higher bandwidth than hard disks. Due to their high cost and limited capacity, Burst-Buffers are not expected to replace hard-drives, but rather act like a potential intermediate storage layer between the computing nodes and the hard drive storage. Such a layer can be used both to increase data locality and to cope with I/O bursts, using their higher I/O bandwidth to avoid interferences and slowdowns.

There is still no clear consensus on Burst-Buffer architecture (see Section II-A) to know whether they should be centralized or distributed over the platform, and whether they should act as a cache between the computing nodes and the storage system or if they could be bypassed by the applications. In this paper, we consider the simplest model where the Burst-Buffer acts as a potential intermediate centralized layer, with a higher I/O bandwidth but a smaller capacity than the hard disk storage system.

Our goal is to propose a probabilistic model for applications, that is amenable to theoretical analysis based on Markov chains and that provides an estimation of the I/O contention as a function of the size of the Burst-Buffer at a very reasonable cost. The rest of this paper is organized as follows. In Section II, we present the related work on Burst-Buffer architecture, bandwidth allocation and HPC applications models. Then, we present in Section III the probabilistic model that will be used throughout the paper. In Section IV, we propose two methods to evaluate I/O bandwidth overflows respectively based on the use of (weighted) Chernoff bounds and on an ad-hoc algorithm. Then, we prove in Section V that a simple Markov chain can be used to evaluate the idle time induced by Burst-Buffer overflow and we provide simulation results to study the important parameters of the Burst-Buffers. In Section VI, we validate the probabilistic model introduced in Section III by comparing the results of the Markov chain approach with those of a discrete event simulator based on a more sophisticated applications model. At last, we prove in Section VII that the Markov chain approach can be used to evaluate other Burst-Buffer management strategies, such as those recently introduced to limit transfers between the Burst-Buffer and the storage system. We give a complete

summary of assumptions and results in Section VIII and we propose concluding remarks in Section IX. Note that all our results are validated through thorough evaluation. The code source and scripts for those evaluations are available at <https://gitlab.inria.fr/orodo-bdx/io-peak>.

II. RELATED WORK

A. Burst-Buffer Architectures and models

There are many implementations of Burst-Buffers. The two most studied characteristics are the location of the buffers and whether the buffers are shared between multiple applications.

Typically, Burst-Buffers can be located between the compute nodes and the Parallel File System (PFS). This is the case of DDN IME [7], [10] and Cray DataWarp [8], [11], [9]. In this *pseudo-centralized* architecture, the Burst-Buffers are often colocated with the I/O nodes. The management strategy can then differ. Mubarak et al. [11] study the case where the buffers are shared between the different applications on the platform and used to accelerate transfers and to prevent I/O congestion. On the contrary, in Schenck et al. [10] and Daley et al. [9], applications decide the size of the buffer that should be dedicated to them.

Another solution is a *distributed* version of Burst-Buffers where the buffers are allocated close to the compute nodes [12], [13], [14]. A solution consists in allocating the distributed buffers to the applications using the compute nodes close to buffers [15]. However, other strategies focus on how to share them between the different applications [11], [12], [13]. This is particularly true in the context of fault-tolerance, where using a buffer on a different node can allow the implementation of hierarchical checkpointing strategies that provide more resilience than in-node buffer strategies [13]. Furthermore, in the case where, because of their costs, the number of buffers in the machine has to be limited, one must choose on which node they should be deployed and between which subset of applications they should be shared.

In this paper, we focus on the *pseudo-centralized* model, where Burst-Buffers are shared between applications. We use a model of architecture similar to the one shown by Schenck et al. [10]. We consider that applications are running on *Compute Nodes*. They use or generate data (also called I/O in this work) that has to be sent to the *Parallel File System*. This is done by sending their data to the I/O nodes where Burst-Buffers are located.

More precisely, the architecture we consider is depicted in Figure 1.

- The I/O nodes communicate with the PFS using a maximum bandwidth B .
- The Burst-Buffers are located next to the I/O nodes, their total size is denoted by S (in GB) and they communicate with the I/O nodes with a bandwidth B_{BB} .

B. Algorithms to deal with Burst-Buffers

When it comes to using Burst-Buffers, several solutions have been proposed. We present and discuss the most common ones.

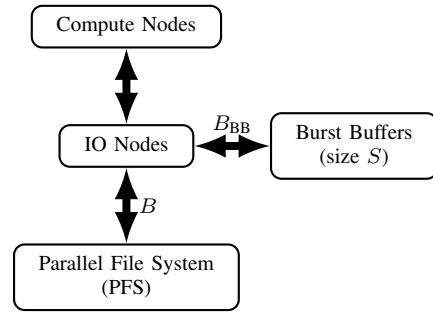


Figure 1: Modeling of the pseudo-centralized platform.

A natural idea is to use Burst-Buffers as a cache to improve the I/O-performance of applications [10]. For instance, DDN [7] announces bandwidth performance 10-fold that of PFS using their Burst-Buffers. The idea is to move the I/O to the Burst-Buffer as a temporary stage between compute nodes and the Parallel File System (whether the data is incoming or outgoing). Thanks to the higher bandwidth of the Burst-Buffers, this has the advantage of improving the I/O transfer time while pipelining the (slowest) phase of sending/receiving data from the PFS with the compute phase of the application. However, as was noted by Han et al. [16], this idea is not viable, (i) Burst-Buffers are based on technologies that are extremely expensive with respect to hard drives, (ii) they are currently based on SSD technology, that is known to have a limited rewrite lifespan [16]. Thus, the large number of I/O operations in HPC applications would decrease their lifespan too fast. This is why we do not consider this solution in this work.

The second natural idea proposed in the literature is to use Burst-Buffers to prevent I/O congestion [17], [18] while maintaining their lifespan. To achieve this goal, the applications use the direct link to the PFS (see Figure 1) when its bandwidth B is not exceeded. When the bandwidth is exceeded by the set of transfers, then the higher bandwidth of the Burst-Buffer is used to complement the bandwidth of the PFS. This is one of the solutions advocated by DDN in [7]. The intuition behind this strategy is that the average use of PFS bandwidth is usually small enough, but that Burst-Buffers are crucial to deal with applications' (simultaneous) bursts. This corresponds to the model depicted in Figure 1 that will be used throughout this paper.

Finally, a large part of the literature on Burst-Buffers shows how to use them with a specific application workflow [9], [10]. Specifically, they consider systems where applications have dedicated and pre-allocated Burst-Buffers, and where the application can explicitly control its data transfers and the use of the Burst-Buffer. This must to be done for each application and is very platform dependent. In practice, only few applications have the human-power to implement this. By opposition, our work is only architecture dependent and does not require any additional work from applications developers. However, we believe our results can also be used by applications developers if they want to estimate the size of Burst-Buffers that they

would need based on their application characteristics.

C. Application Model

Many recent HPC studies have independently observed patterns in the I/O behavior of HPC applications. The quasi-periodicity of HPC applications has been well documented [19], [20]. HPC applications alternate between computation and I/O transfer phases, this pattern being repeated almost identically over time.

Hu et al. [21] summarized the four key characteristics of HPC applications observed in the literature.

- 1) *Periodicity*: Applications alternate between compute phases and I/O phases. Furthermore they do so in a quasi periodic fashion.
- 2) *Burstiness*: In addition to the observed periodicity, sometimes, short I/O bursts occur.
- 3) *Synchronization*: I/O transfers of an application are performed in a synchronized way between the different parallel processes.
- 4) *Repeatability*: The same jobs are often run many times with different inputs, hence their compute-I/O pattern of an application can be reasonably predicted before execution.

When modeling applications, most Burst-Buffer related work use workload models based on these patterns [18], [16], [11]. In addition to this, Mubarak et al. [11] introduce a random background traffic representing HPC workloads such as graph computations and linear algebra solvers, based on the work of Yuan et al. [22].

III. MODEL

We consider a large computing platform, and we focus on modeling and analyzing the behavior of the storage system. We will thus ignore the computing nodes of the platform, and simply consider that we have a (fixed) set of n applications \mathcal{A}_i currently executing on the platform. We model the long-term storage system as a single file server with input bandwidth B (in a real system with several file servers, B would represent their aggregate bandwidth). In addition to this file server, the platform contains a Burst-Buffer, whose input bandwidth is significantly larger, and whose size is S . Figure 1 provides a schematic view of the model we consider.

Following the related work discussed in Section II-C, application \mathcal{A}_i alternates computation and I/O phases. When it performs computations it does not induce any load on the storage system. When it sends intermediate results to the disks, it does so with a fixed bandwidth denoted by b_i . We do not assume that the applications follow a perfect periodic pattern. In the simulations proposed in Section VI, we add a certain amount of noise to model pseudo periodicity: for a phase of expected duration T_i , we actually set its duration to a value chosen uniformly at random in $[(1 - \epsilon)T_i, (1 + \epsilon)T_i]$. Finally, we denote the quasi-period of application \mathcal{A}_i by d_i , and the proportion of time spent doing data transfers by p_i , so that the expected duration of a data transfer for application \mathcal{A}_i is $p_i d_i$ (and the phases where only computation happens have an

Table I: Characteristics of the APEX applications data set.

Workflow	EAP	LAP	Silverton	VPIC
Number of Instances	13	4	2	1
b_i (GB/s)	160	80	160	160
d_i Period (s)	5671	12682	15005	4483
Checkpoint time (s)	20	25	280	23,4
$p_i (\times 10^{-3})$	3.51	1.97	18.7	5.11

expected duration of $(1 - p_i)d_i$). Note that we do not specify whether an application overlaps the communication with some computation or not.

To obtain realistic values, we concentrate on the workflows described in the APEX report [23]. At LANL, most of the load comes from 4 applications, whose characteristics are given in Table I. To obtain the checkpointing period (not provided in [23]), we rely on theoretical works [24] to determine the optimal checkpointing period from the MTBF and the checkpointing time.

In order to obtain theoretical results, we model application data transfers with a random process. To achieve this, we omit the quasi-period d_i in the model. More specifically, we consider discretized time units and we assume that during each of these time units, application \mathcal{A}_i sends data with probability p_i (with bandwidth b_i). In order to have a time unit corresponding to the characteristic size of the system, we set it as the average value of the data transfer times ($p_i d_i$) in what follows.

Therefore, in our model, all applications share a common time unit, and there is no correlation (no memory) between what happens at time step t and $t + 1$. This assumption is of course crucial to build a Markov chain model. However, if the length of a data transfer for \mathcal{A}_i is much longer than the time unit, the fact that \mathcal{A}_i is involved in a communication at time t strongly influences the probability that it is involved in the same communication at time $t + 1$. On the other hand, if the period of the pattern for \mathcal{A}_j is much shorter than the time unit, then the I/O bandwidth consumed during one time unit with our model is very imprecise, since it is either sending or not sending during the whole time unit, whereas such an \mathcal{A}_j actually performs several communication and computation phases. For this reason, we assume in this work that all applications share a similar characteristic time.

In order to validate the ability of the model to predict the load of the Burst-Buffer, we rely on simulations based on a discrete event simulator based on the actual characteristics of the applications, both on synthetic data and on the trace based on [23]. In this trace, the time period varies in a ratio of about 3. In Section VI, we consider time periods that vary in a ratio of 10 and show that this assumption is valid to predict Burst-Buffer needs, which validates the prediction capacity of the Markov-based model.

An important quantity in our model is the expected load EXPECTEDLOAD, defined by $\text{EXPECTEDLOAD} = \sum_i p_i b_i$. It represents the average bandwidth requirement over a long period of time. If many applications send data at the same

time and exceed the bandwidth B to the PFS, the excess can be sent to the Burst-Buffer, and later on sent back to the disk when some bandwidth is available. If the Burst-Buffer is full, this will induce some sort of contention and idle time, which is what we try to avoid. Section V presents a model of the system behavior to analyze the waste implied by these overflow events.

IV. INSTANTANEOUS LOAD ESTIMATION

With the model of Section III, since the expected load EXPECTEDLOAD is given by $\text{EXPECTEDLOAD} = \sum_i p_i b_i$ and the available bandwidth is given by B , we can immediately notice that if $\text{EXPECTEDLOAD} > B$, the I/O bandwidth will not be able to cope with all the demands and the Burst-Buffer, whatever its size, will eventually be saturated. To cope with this situation, we will introduce in Section V a delay mechanism where the applications freeze and stop sending data to the Burst-Buffer during one time unit so as to avoid Burst-Buffer overflow.

In this section, we are rather interested in estimating the probability distribution of the INSTANTLOAD of I/Os, where $\text{INSTANTLOAD} = \sum_{i \in \mathcal{A}(t)} b_i$ denotes the bandwidth required by the set $\mathcal{A}(t)$ of applications involved in a transfer at instant t . We discretize the possible values of the bandwidth with respect to B . More precisely, let us set $B = 100$ and let us assume that all b_i values are integer values. This corresponds to rounding the value b_i to the closest integer and induces a loss of precision of at most 1%. Given the difficulty to precisely estimate the I/O bandwidth required by an application \mathcal{A}_i when transferring data to the disk, we consider that this approximation is smaller than the noise of the measurements.

Our goal is in particular to detect when it exceeds the capacity of I/O bandwidth to the Burst-Buffer B_{BB} . We propose two different approaches to achieve this goal. We rely in Section IV-A on generalizations of Chernoff bounds to the case of a weighted sum of independent variables, and we propose in Section IV-B an ad-hoc strategy to estimate precisely the discretized probability distribution, and we compare both strategies in Section IV-C.

A. Chernoff based bounds

In order to analyze the probability distribution of INSTANTLOAD, let us denote by X_i the random variable indicating whether \mathcal{A}_i is sending I/Os. We assume that X_i s are independent random variables, what is in general the case if workflows and coupled codes are considered as distinct applications. Using the model described in Section III, we have $Pr(X_i = 1) = p_i$ and $Pr(X_i = 0) = (1 - p_i)$ and the random variable X which represents the instant load is given by $X = \sum_i b_i X_i$ and its expected value is $E(X) = \sum_i b_i p_i$. We cannot apply directly Chernoff bounds since X is a weighted sum, but several extensions have been proposed in the literature to deal with weighted sums (see [25], [26], [27], [28]). Theorem 1 provides a way to estimate the probability that the instant load differs by an additive value λ from its expected value.

Theorem 1 ([26]). *Let X_1, \dots, X_n be independent random variables such that $Pr(X_i = 1) = p_i$ and $Pr(X_i = 0) = (1 - p_i)$ and let $X = \sum_i b_i X_i$. Let us set $\nu = \sum_i b_i^2 p_i$ and $b = \max\{b_1, \dots, b_n\}$. Then,*

$$Pr(X \leq E(X) - \lambda) \leq \exp\left(-\frac{\lambda^2}{2\nu}\right) \text{ and}$$

$$Pr(X > E(X) + \lambda) \leq \exp\left(-\frac{\lambda^2}{2(\nu + b\lambda/3)}\right).$$

B. Ad-Hoc Estimation

Chernoff bounds are known to model well the asymptotic behaviors, but due to their simplicity and generality, they fail to provide useful estimations in practical cases as they overestimate the probability that X differs from its expected value. Therefore, we propose in this section an ad-hoc way to estimate the probability distribution of X .

We describe in Algorithm 1 the code used to compute the probability distribution DIST of $X = \sum_i b_i X_i$, where $\text{DIST}(k)$ is the probability that $\mathcal{A}_1, \dots, \mathcal{A}_n$ contribute to exactly k . To compute DIST , we add applications \mathcal{A}_i one after the other and we update at step i the probability distribution using only applications $\mathcal{A}_1, \dots, \mathcal{A}_i$. The size of vector DIST is $\sum_i b_i$, i.e. the maximal possible instant value which is upper bounded by $nB = 100n$, such that the overall complexity of Algorithm 1 is $100n^2$, where n denote the number of applications and is therefore expected to be very small ($n = 20$ is already large in practical settings), so that computing DIST is immediate.

Algorithm 1: FINDDISTRIBUTION($\mathcal{A}_1, \dots, \mathcal{A}_n$)

Input: The characteristics of $\mathcal{A}_1, \dots, \mathcal{A}_n$
Output: DIST , such that $\text{DIST}(k) = Pr(\sum b_i X_i = k)$
1 DIST is initialized with zeros and its size is $\sum b_i$;
2 **foreach** \mathcal{A}_i **do**
3 **foreach** k **do**
4 $\text{DIST}(k) = (1 - p_i)\text{DIST}(k) + p_i\text{DIST}(k - b_i)$ if
 $k \geq b_i$;
5 $\text{DIST}(k) = (1 - p_i)\text{DIST}(k)$ if $k < b_i$;
6 **end**
7 **end**
8 **return** DIST

C. Estimating the distribution

We can use the Chernoff bounds proposed in Section IV-A to estimate the distribution of the instantaneous load. Indeed, let us set

- $f_u(x) = \exp\left(-\frac{(\sum b_i p_i - x)^2}{2\nu}\right)$ if $x \leq \sum b_i p_i$ and $f_u(x) = 1$ otherwise ;
- $f_l(x) = \exp\left(-\frac{(x - \sum b_i p_i)^2}{2(\nu + b(x - \sum b_i p_i)/3)}\right)$ if $x \geq \sum b_i p_i$ and $f_l(x) = 0$ otherwise.

$$\text{Then, } \forall x, \quad f_l(x) \leq Pr(X \leq x) \leq f_u(x).$$

To estimate the precision of these inequalities, we have compared them to the result provided by Algorithm 1 on some randomly generated set of applications. We target an expected

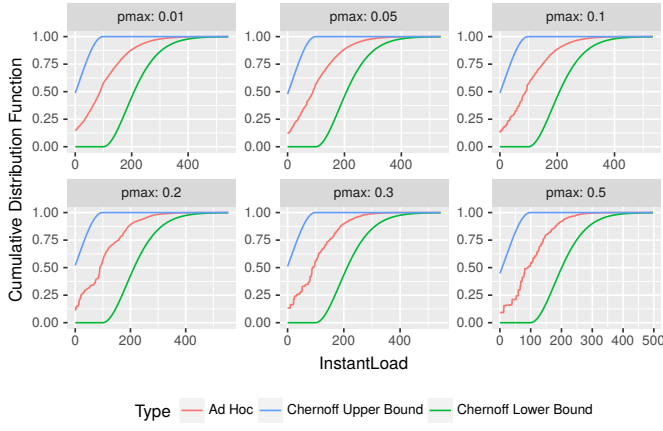


Figure 2: Comparison of distribution estimations for different values of p_{\max} , EXPECTEDLOAD = 100.

load of $M = 100 (= B)$ and we generate applications in the following way. We add applications one by one by generating the values p_i uniformly between 0 and p_{\max} and the values b_i values uniformly between 0 and 1 until the expected load is reached. Then, we rescale the p_i s so as to achieve exactly $M = 100 (= B)$. Figure 2 provides the comparison of the obtained distribution estimations for different values of p_{\max} . We can see that the Chernoff bounds are always correct, but very imprecise. Since computing the exact distribution with Algorithm 1 is in practice very fast, we will rely on this algorithm in the rest of the paper.

V. BURST-BUFFER LOAD ESTIMATION

In Section IV-B, we proposed Algorithm 1 to compute the probability $\text{DIST}(k)$ of having $\text{INSTANTLOAD} = k \ \forall 0 \leq k \leq \sum b_i$. As shown in Section IV-C, $\text{DIST}(k)$ can be used directly to evaluate the probability of exceeding the I/O bandwidth to the disk. In Section V-A, we use DIST in order to evaluate the probability of exceeding the capacity of the Burst-Buffer, using a Markov Chain to model the load of Burst-Buffer.

A. Markov Chain Model

In this section, we propose to model the occupation of the Burst-Buffer when using Algorithm 2.

Following the model described in Section II-B, Algorithm 2 transfers as much data as possible to the disk. If $\text{INSTANTLOAD} \leq B$, then the Burst-Buffer is emptied as fast as possible, provided that the I/O bandwidth to the disk B is not exceeded (see Section III and Figure 1). If $\text{INSTANTLOAD} > B$, then the occupation of the Burst-Buffer increases. If the capacity of the Burst-Buffer is exceeded, then all transfers are stopped for one time unit so as to empty the Burst-Buffer at rate B .

The occupation of the Burst-Buffer when using Algorithm 2 can be easily modeled by a Markov Chain [29]. Let us denote by $Y_j, 0 \leq j \leq S$ the “normal” state of the chain when the size of Burst-Buffer is exactly j and let us define $\sum_i b_i$ additional

Algorithm 2: ALLOCATETRANSFERS

Input: The set of active applications $\mathcal{A}_{k_1}, \dots, \mathcal{A}_{k_l}$, the load of the Burst-Buffer LOAD

Output: The set of transfers to the disk and to the Burst-Buffer

```

1 if  $\sum_1^l b_{k_i} \leq B$  then
2   Transfer  $\sum_1^l b_{k_i}$  from the computing nodes to the disk ;
3   Transfer  $\min(\text{LOAD}, (B - \sum_1^l b_{k_i}))$  from the
   Burst-Buffer to the disk ;
4 end
5 else
6   Transfer  $B$  from the computing nodes to the disk ;
7   if  $\text{LOAD} + \sum_1^l b_{k_i} - B \leq S$  then
8     Transfer  $\sum_1^l b_{k_i} - B$  from the computing nodes to
     the Burst-Buffer;
9   end
10 else
11   Transfer  $S - \text{LOAD}$  from the computing nodes to
   the Burst-Buffer;
12   Stop all applications until the transfer is over ;
13   During each time unit, transfer  $B$  from the
   computing nodes to the disk ;
14   Complete with Burst-Buffer data at the end ;
15 end
16 end

```

“overflow” states $Y_j, S+1 \leq j \leq S + \sum_i b_i$ that correspond to the states where the capacity of the Burst-Buffer is exceeded.

Using DIST , we can compute the probability to move from State Y_j to State $Y_l, \forall 0 \leq j, l \leq S + \sum_i b_i$.

When in normal state $Y_i, i \leq S$, if $\text{INSTANTLOAD} = k$, then

- If $i + k \leq B$, then the Burst-Buffer becomes empty and we jump to state Y_0 .
- If $i + k - B \leq S$, then we jump to normal state Y_{i+k-B} .
- If $i + k - B > S$, then we jump to overflow state Y_{i+k-B} .

When the chain is in an overflow state $Y_i, i \geq S$, then applications are kept idle for one time unit and the Burst-Buffer is emptied at maximal rate, so that we jump to (normal or overflow) state Y_{i-B} . Therefore, the probability $P_{j,l}$ of transition between state Y_j and state Y_l is defined as follows:

- If $0 \leq j \leq S$ and $1 \leq l \leq S + \sum_i b_i$, then $P_{j,l} = \text{DIST}(l - j + B)$.
- If $0 \leq j \leq B$, then $P_{j,0} = \sum_{k=0}^{B-j} \text{DIST}(k)$.
- If $S + 1 \leq j \leq S + \sum_i b_i$, then $P_{j,j-B} = 1$.

B. Steady State Load Estimation

The Markov chain Y introduced in Section V-A can be used to estimate the idle time induced by Algorithm 2. Let us first prove with Theorem 2 that Y has a stationary probability π .

Theorem 2. *There exists a unique stationary distribution π for the Markov chain Y .*

Proof. Since $p_i < 1$ for all i , we have $\text{DIST}(0) > 0$. This implies that each state Y_i has a non-zero probability to jump to state $Y_{\max(i-B,0)}$, and thus that state 0 is accessible from any state Y_i . The Markov chain thus has only one final class

(the one containing state 0). This implies that Y has one and only one stationary distribution. Additionally, since $P_{0,0} > 0$, this class is aperiodic and this distribution can be obtained as the limit of $\pi^l = P^l \pi^0$, independently of π^0 . \square

The size of the transition matrix P is $S + \sum b_i \times S + \sum b_i$ and π is the solution of the linear system $\pi = \pi * P$. In all the experiments that follow, since we set $B = 100$ in Section IV-B, the size of P is therefore of a few hundreds. Moreover, in all our experiments, we use an iterative algorithm $\pi^l = \pi^{l-1} P$ that always converged in less than 10 iterations. Therefore, the computation of the stationary distribution is extremely fast.

Theorem 3. *The idle time induced by Algorithm 2 is given by $\sum_{k>S} \pi(k)$.*

Proof. $\pi(k)$ represents the probability of being in state Y_k . For $k \leq S$, the load of the Burst-Buffer is smaller than its size S , and no idle time is induced. On the other hand, states Y_k , $k > S$ correspond to an overflow of the buffer. In this case, Algorithm 2 stops all transfers from the applications with probability 1 in order to empty the Burst-Buffer for one time-unit. Therefore, the fraction of idle time corresponds to the probability of being in a state Y_k , $k > S$ and is therefore given by $\sum_{k>S} \pi(k)$. \square

C. Idle Time Prediction

This section presents the results obtained with the Markov chain model presented above. We generate applications in the same way as in Section IV-C and we observe the resulting stationary distribution. We fix the bandwidth B of the disk to 100, and we vary the expected load M of the system, by considering different values of $\alpha = \frac{M}{B}$. As a reminder, once M is fixed, we add applications by picking uniformly at random $p_i \in [0, p_{\max}]$ and $b_i \in [0, B]$ until $\sum_i b_i p_i \geq M$ and then we rescale the p_i s so that $\sum_i b_i p_i = M = \alpha B$. Small values of α result in an underloaded system in which the buffer does not fill very often. On the other hand, values of α larger than one mean that idle times are required even in presence of a very large buffer in order to allow enough time to write to the disks.

Figure 3 shows the resulting proportion of idle time (see Theorem 3) for different values of p_{\max} and α . We can observe that obtained results do not strongly depend on p_{\max} and that, as expected, the idle time decreases with the buffer size, converging to 0 for values of α below 1, and to a positive value for α above 1.

VI. MODEL VALIDATION AND SIMULATIONS

A. Comments on the probabilistic model

In this section, we aim at evaluating the influence of the application model described in Section III on the quality of the prediction of the idle time induced by Algorithm 2. Indeed, we have proved in Section V that this model is theoretically and numerically tractable since a simple Markov chain enables to compute the idle time at low computational cost. Nevertheless, the model of Section III is not strictly equivalent to the models

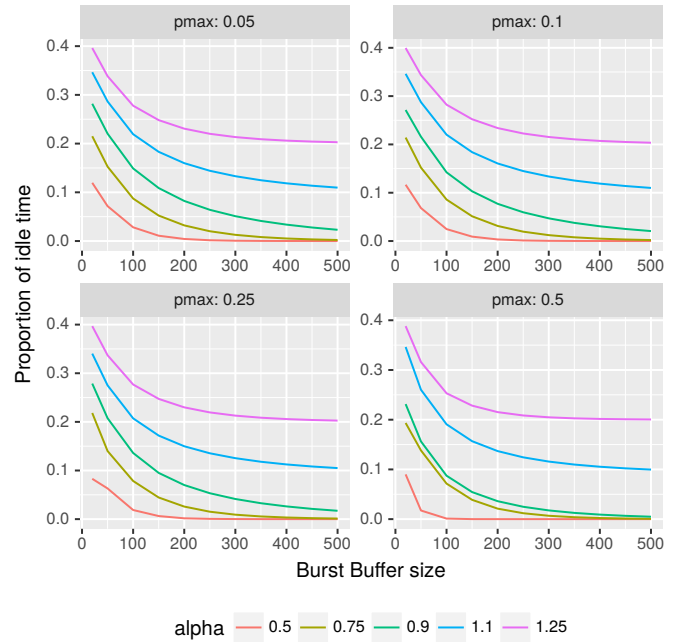


Figure 3: Proportion of idle time as a function of buffer size, for different values of p_{\max} and α .

proposed in Section II-C. Indeed, it is generally assumed that HPC applications follow a quasi periodic pattern alternating compute and communication phases and that the rate of emission is proportional to the number of I/O nodes and is therefore constant over time. Our model captures several crucial characteristics of the quasi periodic model, (i) alternating communication and computation phases, (ii) the quasi periodic pattern modeled by p_i probability of I/O communication (iii) the constant bandwidth b_i used by a given application \mathcal{A}_i when performing I/Os. Nevertheless, as underlined in Section III, the Markov-based model requires a common time unit for all applications and induces more randomness, which may induce modeling errors. It is therefore crucial to validate our probabilistic model against a more realistic (but theoretically intractable) model using a discrete event simulator that will be presented in Section VI-B.

B. Discrete Event Simulator

In order to validate the ability of the application model presented in Section III to predict the idle time, we build a discrete event simulator. The platform model is the same as the one introduced in [10] and described in Figure 1, and is characterized by the I/O bandwidth B between the processing nodes and the disks, that is shared by the transfers between the Burst-Buffer and the disk, so that the overall bandwidth to the disk is bounded by B .

On the application side, simulations rely on a more sophisticated model. Each application is characterized by a time period d_i , a probability of sending I/Os p_i and a used bandwidth b_i , and we add another parameter u that will be used to add noise

to the pattern of \mathcal{A}_i . More precisely, a pattern for \mathcal{A}_i is built as follows

- \mathcal{A}_i computes during $(1 - p_i)d_i x$ where x is chosen uniformly at random in $[1 - u, 1 + u]$ at each computing burst,
- \mathcal{A}_i sends data at rate b_i during $p_i d_i x$ where x is chosen uniformly at random in $[1 - u, 1 + u]$ at each burst of I/Os.

Using above model, we generate a pattern that is almost periodic (exactly periodic if $u = 0$), and the quasi-period of \mathcal{A}_i is different for each application, so that the model is close to what has been observed in HPC systems (see Section II-C and references therein).

Our discrete event simulator is described in Algorithm 3. $comp_i$ is a boolean value that indicates whether the next burst for \mathcal{A}_i is a I/O ($comp_i = 0$) or a compute ($comp_i = 1$) burst.

Algorithm 3: Discrete Event Simulator

Input: The set of active applications $\mathcal{A}_{k_1}, \dots, \mathcal{A}_{k_l}$, with their characteristics p_i, b_i and d_i and their random starting times t_i
a large time bound T_{\max} , the regularity of bursts length u
Output: The total idle time IDLETIME

```

1  $\forall i, comp_i = 1$  NEXTEVENT =  $\min(t_1, \dots, t_n)$  ;
2 while NEXTEVENT  $\leq T_{\max}$  do
3    $i = \text{argmin}(t_1, \dots, t_n)$  ;
4   Choose  $x$  uniformly at random in  $[1 - u, 1 + u]$  ;
5   if  $comp_i == 1$  then
6      $t_i = \text{NEXTEVENT} + (1 - p_i)d_i x$ ;
7      $comp_i = 1 - comp_i$ ;
8   end
9   else
10     $t_i = \text{NEXTEVENT} + p_i d_i x$ ;
11     $comp_i = 1 - comp_i$ ;
12  end
13  Update Burst-Buffer occupation at time  $t_i$ 
14  while Burst-Buffer occupation at time  $t_i \geq S$  do
15    Stop all transfers for one time unit;
16    Increase IDLETIME;
17  end
18 end
19 return IDLETIME

```

C. Model Validation

a) *On synthetic data:* In order to compare the results obtained with the Markov chain model to those of the discrete event simulator, we once again generate applications for different values of p_{\max} and α as was done in Section V-C. In addition to p_i and b_i values, we also generate the values d_i uniformly at random between some value d_{\min} and βd_{\min} , where $\beta = 1, 2, 5, 10$. $\beta = 1$ corresponds to the case where all applications share the same period, whereas $\beta = 10$ models applications with different dynamics. The value of d_{\min} is chosen in each case so that the expected value of d_i is 10. The results are depicted on Figure 4. For each scenario, we run Algorithm 3 10 times up to $T_{\max} = 1000$, and we show on the plots the confidence intervals for the mean idle time with a filled ribbon. We can see that our

model is able to predict the behavior of the Idle Time induced by limited size of the Burst-Buffer, even for large β values. The Markovian model tends to overestimate the Idle time, especially in the case when $\alpha = 1$, *i.e.* when the load of the system actually corresponds, on average, to the capacity of the storage system. This validates the ability of the Markov-based model introduced in Section III to predict the load of the b .

b) *On the APEX trace:* We performed simulations using data presented in [23] for LANL and described in Section III. Using APEX trace, the expected load is small with respect to the bandwidth of the system (it corresponds to a value $\alpha = 9\%$). In order to validate the model into a more stressed context, we also scaled p_i values so as to obtain $\alpha = 0.75, 1$ and 1.25 . The results are depicted on Figure 5. Again, the idle time predicted by the Markovian model has the correct behavior, but slightly overestimates the idle time, especially when $\alpha = 1$.

VII. LAZY EMPTYING

A. Algorithm

To prevent from the phenomena of *Write Amplification* [30], Han et al. [16] consider lazy strategies for emptying the Burst-Buffer. In particular, they propose to empty the Burst-Buffer only when its load reaches a certain level. The rationale behind this is that performing a transfer between the Burst-Buffer and the disk has a fixed cost that does not only depend on the transferred data. Therefore, there is a clear interest in keeping the Burst-Buffer to disk link quiet as often as possible. Algorithm 4 is based on this idea. If the load of the Burst-Buffer is smaller than a given $\text{THRESHOLD} < S$, the Burst-Buffer is not emptied, even if some bandwidth remains available once the transfers between the computing nodes and the disk have been allocated.

In this context, we have two conflicting objectives. Indeed, we are interested in both maximizing the quiet time of the Burst-Buffer (denoted by QUIET) and to minimize the idle time induced by Burst-Buffer overflow (denoted by IDLETIME). Clearly, a high value of THRESHOLD is expected to make QUIET larger (since we keep the lazy strategy longer), but also to make IDLETIME larger (since we take more risks by not emptying the buffer). The details of the algorithm are presented in Algorithm 4. In order to enforce the properties of the associated Markov chain (see Section VII-B and Theorem 4), we keep a (very small probability) of emptying the Burst-Buffer, even if $\text{THRESHOLD} < S$.

B. Markov Chain associated to Algorithm 4

Similarly to what has been proposed in V-A, it is easy to associate a Markov chain to Algorithm 4, where state Y_j^{LAZY} corresponds to a load j of the Burst-Buffer and whose transition matrix P^{LAZY} is defined as follows

- If $\text{THRESHOLD} \leq j \leq S$ and $1 \leq l \leq S + \sum_i b_i$, then $P_{j,l}^{\text{LAZY}} = \text{DIST}(l - j + B)$.
- If $0 \leq j < \text{THRESHOLD}$:
 - if $0 \leq l < j$ then $P_{j,l}^{\text{LAZY}} = 0.01 \times \text{DIST}(l - j + B)$;

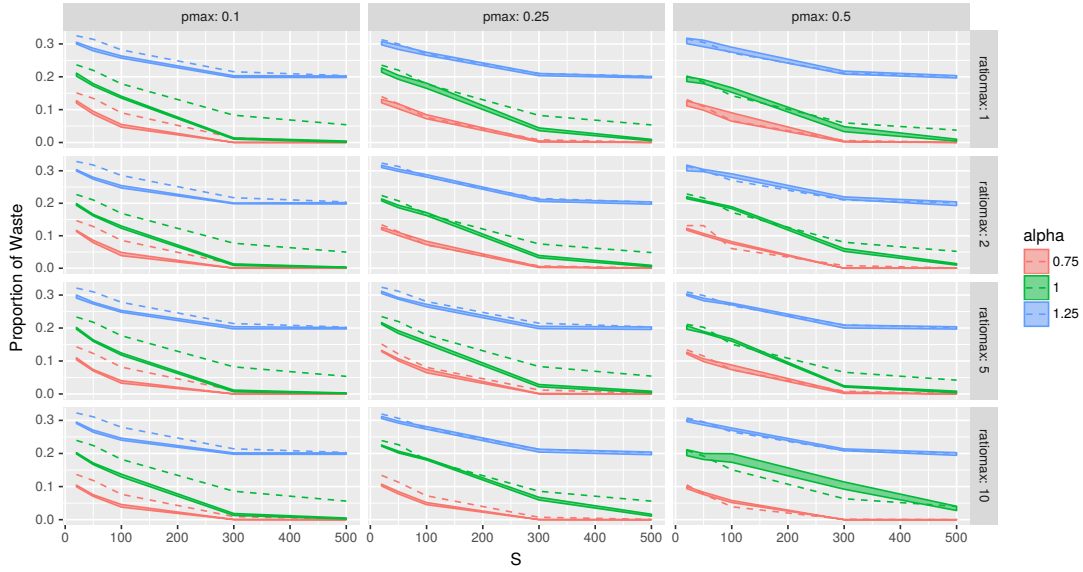


Figure 4: Comparison of predicted idle times between Markov chain (dashed lines) and discrete event simulator – Synthetic Data (full lines). $ratiomax$ is the ratio between the bounds of the interval in which the different d_i are chosen in each simulated set.

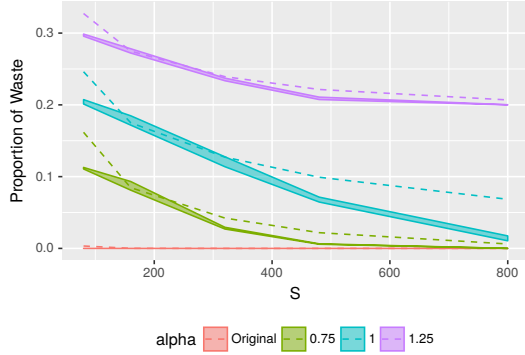


Figure 5: Comparison of predicted idle times between Markov chain (dashed lines) and discrete event simulator – APEX data (full lines)

- $P_{j,j} = 0.99 \times \sum_{l=0}^{B-1} \text{DIST}(l-j+B) + \text{DIST}(B)$;
- if $j < l \leq S + \sum_i b_i$, then $P_{j,l}^{\text{LAZY}} = \text{DIST}(l-j+B)$.
- If $S+1 \leq j \leq S + \sum_i b_i$, then $P_{j,j-B}^{\text{LAZY}} = 1$.

With above definition, we can easily prove Theorem 4 and Theorem 5.

Theorem 4. *There exists a unique stationary distribution π^{LAZY} for the Markov chain Y^{LAZY} .*

Proof. The difference between Y and Y_j^{LAZY} lies in the weights only, and not in the structure of the transitions. Therefore, the proof of Theorem 2 directly applies to Theorem 4 if we define π^{LAZY} as the solution of the linear system $\pi^{\text{LAZY}} = \pi^{\text{LAZY}} \times P^{\text{LAZY}}$. \square

Algorithm 4: Lazy ALLOCATETRANSFERS

Input: The set of active applications $\mathcal{A}_{k_1}, \dots, \mathcal{A}_{k_l}$, the load of the Burst-Buffer LOAD

```

1 if  $\sum_1^l b_{k_i} \leq B$  then
2   Transfer  $\sum_1^l b_{k_i}$  from the applications to the disk ;
3   if  $\text{LOAD} \geq \text{THRESHOLD}$  then
4     Transfer  $\min(\text{LOAD}, (B - \sum_1^l b_{k_i}))$  from the
      Burst-Buffer to the disk ;
5   end
6 else
7   With probability 0.01, transfer
       $\max(\text{LOAD} - (B - \sum_1^l b_{k_i}), 0)$  from the
      Burst-Buffer to the disk ;
8 end
9 end
10 else
11   Transfer  $B$  from the computing nodes to the disk ;
12   if  $\text{LOAD} + \sum_1^l b_{k_i} - B \leq S$  then
13     Transfer  $\sum_1^l b_{k_i} - B$  from the computing nodes to
      the Burst-Buffer;
14   end
15 else
16   Transfer  $S - \text{LOAD}$  from the computing nodes to
      the Burst-Buffer;
17   Stop all applications until the transfer is over ;
18   During each time unit, transfer  $B$  from the
      computing nodes to the disk ;
19   Complete with Burst-Buffer data at the end ;
20 end
21 end

```

Theorem 5. *The idle time induced by Algorithm 4 is given by $\text{IDLETIME} = \sum_{k>S} \pi^{\text{LAZY}}(k)$ and the quiet time induced by Algorithm 4 is given by $\text{QUIET} =$*

$$\sum_{k=0}^S \left(\pi^{\text{LAZY}}(k) \times \sum_{l \geq k} P^{\text{LAZY}}(k, l) \right).$$

Proof. The states Y_k^{LAZY} with $k > S$ correspond to overflow states and systematically induce one time unit of idle time. To estimate QUIET, we sum, for all possible “normal” states Y_k^{LAZY} , $k \leq S$, the probability to not decrease the load of the Burst-Buffer, *i.e.* to jump to a state Y_l^{LAZY} , $l \geq k$. \square

C. IDLETIME and QUIET times induced by Algorithm 4

To study the effect of the threshold value on the performance of the Burst-Buffer, we analyze the results obtained using the Markov chain model. We generate applications like previously, and we consider varying values for α , p_{\max} , and for the threshold ratio (*i.e.*, the ratio between the THRESHOLD value and the buffer size S). A threshold ratio of 0 is equivalent to the basic case, and a threshold value of 1 means that the burst buffer is only emptied when it is full. Results for IDLETIME time are shown in Figure 6. In addition, we also measure QUIET time during which the burst buffer is not emptied (*i.e.*, its occupation either increases or stays the same). This is shown on Figure 7.

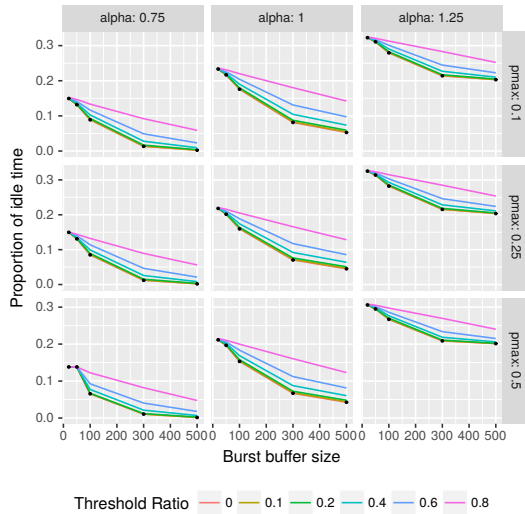


Figure 6: IDLETIME times for different THRESHOLD values. Black dots represent the basic case, with threshold 0.

We can see that in most cases, even a small positive value of THRESHOLD allows to improve the QUIET, except when the load is high and p_{\max} is also high. In those cases, the Burst-Buffer is almost continuously kept full due to the constant arrival of application data, and both strategies behave similarly. In all other cases, the buffer has a non-zero probability of having a small enough load for the threshold to be useful. In many cases however, a too high value of THRESHOLD (above 20 or 40% of the Burst-Buffer size) induces significant cost on IDLETIME time. Since even a small THRESHOLD brings a benefit on the QUIET times (and for low load, increasing THRESHOLD further does not degrade IDLETIME time), we can see that this lazy strategy indeed has the potential to

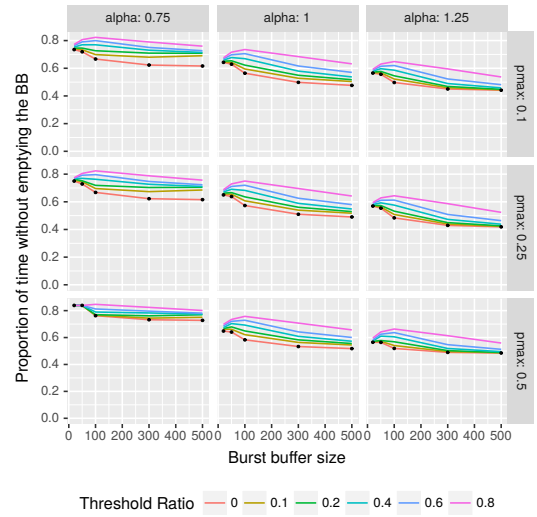


Figure 7: QUIET times for different THRESHOLD values. Black dots represent the basic case, with threshold 0.

increase the performance of the Burst-Buffer. It is important to correctly dimension the THRESHOLD value, however a 20% value appears to be a good safe guess.

VIII. SUMMARY OF RESULTS AND RECOMMENDATIONS

In this section, we provide (i) a summary of the assumptions underlying the Markovian model and (ii) a summary of the results and findings that we obtained using it.

In this paper, we focus on using Burst-Buffers solely as a temporary storage unit for data destined to go on the PFS. The Burst-Buffer is not used as a cache for the PFS, but as a buffer when the bandwidth to PFS is saturated. In particular, we leave for future work the ability to store intermediate data on the Burst-Buffer, that may or may not be committed to the PFS. We assume that this is a system-wide process, and that there is no application-specific strategy to use the Burst-Buffer.

As far as applications are concerned, we assume that their I/O behavior is (quasi-)periodic (most of the I/O within an application happens in chunks) and rather predictable, in terms of quantity of data sent and of frequency of sending periods. In the Markovian model, however we assume that these sending periods happen at random times. We also assume that they all share a similar characteristic time, which is often almost the case when the sending pattern comes from checkpointing.

To validate the Markovian model, we compared its results for Idle Time prediction against an ad-hoc discrete event simulator. We performed the comparison both on synthetic data covering a wide range of parameters and on an actual workload trace from LANL.

We prove in this paper that the Markovian model is tractable and can be used to predict with a very low computing cost the instantaneous load distribution and the idle time. It can also be augmented to analyze more sophisticated management strategies for the Burst-Buffer, like lazy emptying strategies.

In the crucial context of Idle Time prediction, the comparison with simulations show that the Markovian model, despite its bursty nature, is in fact able to predict the behavior of the load of the Burst-Buffer. It therefore provides a low-cost algorithm to dimension the Burst-Buffer characteristics (size, strategy, ...) on HPC systems.

IX. CONCLUSION

In this paper, we propose a probabilistic model for the use of Burst-Buffers in the context of organizing the transfers of a set of HPC quasi-periodic applications. We prove that this model enables to estimate at low computational cost the load of the Burst-Buffer under several classical management strategies. Present work opens several perspectives. First, it would be of great interest to include in the probabilistic model the specific characteristics of BigData workload (*i.e.* the ability to prefetch data) and checkpointing strategies (*i.e.* the ability of removing old checkpoints without writing them eventually to the disk), that can improve the performance of the Burst-Buffer. Then, this work makes it possible to evaluate complex Burst-Buffer management strategies where the Burst-Buffer is used differently by the different applications. At last, extending this model to more distributed Burst-Buffer architectures is also an interesting perspective.

ACKNOWLEDGEMENTS

This work was supported in part by the ANR Dash project (ANR-17-CE25-0004). The authors would like to thank Jean-Thomas Acquaviva for insightful discussions and the reviewers for useful comments.

REFERENCES

- [1] "The trinity project," <http://www.lanl.gov/projects/trinity/>, online; accessed 21 October 2017.
- [2] "I/o at argonne national laboratory," https://wr.informatik.uni-hamburg.de/_media/events/2015/2015-iodc-argonne-isaila.pdf, online; accessed 21 October 2017.
- [3] D. A. Reed and J. Dongarra, "Exascale computing and big data," *Communications of the ACM*, vol. 58, no. 7, pp. 56–68, 2015.
- [4] F. Cappelletto, A. Geist, W. Gropp, S. Kale, B. Kramer, and M. Snir, "Toward exascale resilience: 2014 update," *Supercomputing frontiers and innovations*, vol. 1, no. 1, pp. 5–28, 2014.
- [5] G. Bosilca, A. Bouteiller, E. Brunet, F. Cappelletto, J. Dongarra, A. Guermouche, T. Herault, Y. Robert, F. Vivien, and D. Zaidouni, "Unified model for assessing checkpointing protocols at extreme-scale," *Concurrency and Computation: Practice and Experience*, vol. 26, no. 17, pp. 2772–2791, 2014.
- [6] O. Yildiz, M. Dorier, S. Ibrahim, R. Ross, and G. Antoniu, "On the root causes of cross-application i/o interference in hpc storage systems," in *IPDPS'16*. IEEE, 2016, pp. 750–759.
- [7] DDN Storage, "BURST BUFFER & BEYOND, I/O & Application Acceleration Technology," https://www.ddn.com/download/resource_library/brochures/technology/IME_FAQ.pdf, 2014, online; accessed 20 October 2017.
- [8] D. Henseler, B. Landsteiner, D. Petesch, C. Wright, and N. J. Wright, "Architecture and design of cray datawarp," *Cray User Group CUG*, 2016.
- [9] C. S. Daley, D. Ghoshal, G. K. Lockwood, S. S. Dosanjh, L. Ramakrishnan, and N. J. Wright, "Performance characterization of scientific workflows for the optimal use of burst buffers," in *WORKS@ SC*, 2016, pp. 69–73.
- [10] W. Schenck, S. El Sayed, M. Foszczynski, W. Homberg, and D. Pleiter, "Evaluation and performance modeling of a burst buffer solution," *ACM SIGOPS Operating Systems Review*, vol. 50, no. 1, pp. 12–26, 2017.
- [11] M. Mubarak, P. Carns, J. Jenkins, J. K. Li, N. Jain, S. Snyder, R. Ross, C. D. Carothers, A. Bhatele, and K.-L. Ma, "Quantifying i/o and communication traffic interference on dragonfly networks equipped with burst buffers," in *Cluster Computing (CLUSTER), 2017 IEEE International Conference on*. IEEE, 2017, pp. 204–215.
- [12] D. Kimpe, K. Mohror, A. Moody, B. Van Essen, M. Gokhale, R. Ross, and B. R. De Supinski, "Integrated in-system storage architecture for high performance computing," in *Proceedings of the 2nd International Workshop on Runtime and Operating Systems for Supercomputers*. ACM, 2012, p. 4.
- [13] L. Bautista-Gomez, S. Tsuboi, D. Komatitsch, F. Cappelletto, N. Maruyama, and S. Matsuoka, "Fti: high performance fault tolerance interface for hybrid systems," in *Proceedings of 2011 international conference for high performance computing, networking, storage and analysis*. ACM, 2011, p. 32.
- [14] K. Tang, P. Huang, X. He, T. Lu, S. S. Vazhkudai, and D. Tiwari, "Toward managing hpc burst buffers effectively: Draining strategy to regulate bursty i/o behavior," in *2017 IEEE 25th International Symposium on Modeling, Analysis, and Simulation of Computer and Telecommunication Systems (MASCOTS)*. IEEE, 2017, pp. 87–98.
- [15] L. Cao, B. W. Settlemyer, and J. Bent, "To share or not to share: comparing burst buffer architectures," in *Proceedings of the 25th High Performance Computing Symposium*. Society for Computer Simulation International, 2017, p. 4.
- [16] J. Han, D. Koo, G. K. Lockwood, J. Lee, H. Eom, and S. Hwang, "Accelerating a burst buffer via user-level i/o isolation," in *Cluster Computing (CLUSTER), 2017 IEEE International Conference on*. IEEE, 2017, pp. 245–255.
- [17] N. Liu, J. Cope, P. Carns, C. Carothers, R. Ross, G. Grider, A. Crume, and C. Maltzahn, "On the role of burst buffers in leadership-class storage systems," in *Mass Storage Systems and Technologies (MSST), 2012 IEEE 28th Symposium on*. IEEE, 2012, pp. 1–11.
- [18] S. Herbein, D. H. Ahn, D. Lipari, T. R. Scogland, M. Stearman, M. Grondona, J. Garlick, B. Springmeyer, and M. Taufer, "Scalable i/o-aware job scheduling for burst buffer enabled hpc clusters," in *Proceedings of the 25th ACM International Symposium on High-Performance Parallel and Distributed Computing*. ACM, 2016, pp. 69–80.
- [19] Carns *et al.*, "2A7 characterization of petascale I/O workloads," in *Proceedings of CLUSTER09*. IEEE, 2009, pp. 1–10.
- [20] G. Aupy, A. Gainaru, and V. L. Fèvre, "Periodic i/o scheduling for super-computers," in *International Workshop on Performance Modeling, Benchmarking and Simulation of High Performance Computer Systems*. Springer, Cham, 2017.
- [21] W. Hu, G.-m. Liu, Q. Li, Y.-h. Jiang, and G.-l. Cai, "Storage wall for exascale supercomputing," *Journal of Zhejiang University-SCIENCE*, vol. 2016, pp. 10–25, 2016.
- [22] X. Yuan, S. Mahapatra, W. Nienaber, S. Pakin, and M. Lang, "A new routing scheme for jellyfish and its performance with hpc workloads," in *Proceedings of the International Conference on High Performance Computing, Networking, Storage and Analysis*. ACM, 2013, p. 36.
- [23] S. LANL, NERSC, "Apex workflows," <https://www.nersc.gov/assets/apex-workflows-v2.pdf>, Technical report, LANL, NERSC, SNL, Tech. Rep., 2016.
- [24] G. Aupy, Y. Robert, F. Vivien, and D. Zaidouni, "Checkpointing algorithms and fault prediction," *Journal of Parallel and Distributed Computing*, vol. 74, no. 2, pp. 2048–2064, 2014.
- [25] F. Chung and L. Lu, "Connected components in random graphs with given expected degree sequences," *Annals of combinatorics*, vol. 6, no. 2, pp. 125–145, 2002.
- [26] —, "Concentration inequalities and martingale inequalities: a survey," *Internet Mathematics*, vol. 3, no. 1, pp. 79–127, 2006.
- [27] M. Habib, C. McDiarmid, J. Ramirez-Alfonsin, and B. Reed, *Probabilistic methods for algorithmic discrete mathematics*. Springer Science & Business Media, 2013, vol. 16.
- [28] B. Vöcking, "Selfish load balancing," *Algorithmic game theory*, vol. 20, pp. 517–542, 2007.
- [29] W. J. Stewart, *Introduction to the numerical solutions of Markov chains*. Princeton Univ. Press, 1994.
- [30] X.-Y. Hu, E. Eleftheriou, R. Haas, I. Iliadis, and R. Pletka, "Write amplification analysis in flash-based solid state drives," in *Proceedings of SYSTOR 2009: The Israeli Experimental Systems Conference*. ACM, 2009, p. 10.