Cloud simulation

December 22, 2017

Abstract

Simulating the cloud from the client point of view.
Assessment of the impact of different metrics.
Recommendations for using cloud simulators.
WARNING: figures in text might not be up to date.

1 Introduction

The problem of allocating cloud resources in performant, robust and energy-efficient ways is of paramount importance in today's usage of computing infrastructures. Cloud resources proposed to clients as Infrastructure as a Service (IaaS) open a large field of investigation regarding how automatic tools can hepl users to better provision the resources and schedule their computation or storage tasks with regard to the trade-off between rental cost and performance. Indeed it rapidly becomes very difficult for users to manually handle the provisionning and scheduling decisions when the workloads involve numerous tasks, which are potentially dependent on others – and such complex workloads are the focus in this paper. In the last decade a number of research papers have contributed new allocation techniques to address this issue. A pitfall of research on IaaS lies in the validation of the models and algorithms proposed, as validation on actual clouds requires infrastructures that are difficult to set up for individual researchers. As a consequence, many researchers evaluate their work through simulation. A number of simulators have been developed for that purpose as reviewed in the related work section hereafter. They are typically based on discrete-event simulation, using models for each elementary component of the infrastructure, which are then composed to simulate the whole system and applications running on it.

However, such an *ab initio* construction poses a significant problem regarding the calibration and validation of the composed model against real-world measurements. We show in this paper that a precise modeling of each component may not be sufficient to yield accurate predictions of the whole system's behavior. Yet, from the client-side (or equivalently, from the application perspective), the validaty of the simulation is evaluated against macros-metrics, such as the makespan and the rental cost of the application executions. It means that the interactions betweens all components must be taken into account in the simulation, including the lower level components such as the network sharing or the higher level components such as the scheduler. For instance, a decision which starts simultaneously a large number of Virtual Machines (VMs) may result in trashing [12] affecting the expected performance.

This work's objective is to study how an actual cloud setup behavior can be predicted through simulation on practical use-cases. Our approach is original in that we have co-developed a client-side cloud broker, called Schlouder [13], and a simulation software called SimSchlouder, whose aim is to predict Schlouder's behavior. Schlouder implements here the automated process making the provisioning and scheduling decisions on behalf the user on the real infrastructure. The comparison between the observations of actual executions and the simulation results has allowed us to tune the simulator, especially for higher level components such as the modeling of VM boot times and the scheduling policies. At the lower level, we rely on the discrete event simulation toolkit SimGrid [4] for which validation results regarding accuracy have been published (e.g [16, 17]). To build SimSchlouder, we have added to SimGrid a new interface which enables to express IaaS operations. Thus, this work is not restricted to the simulation of Schlouder but can be extended to the simulation of any application making use of IaaS clouds.

This paper's contributions is therefor twofold. First, we propose a new simulation tool extending SimGrid with an interface capable of modeling of IaaS clouds by providing a new interface for that field. This interface is publicly available as open-source software. Above this interface, we also developed SimSchlouder to demonstrate how a client-side cloud broker can be modeled using this interface. Secondly, as we advocate that a precise assessment of simulation should be carried out against real execution figures to better understand the limits of simulation applicability, we make an in-depth analysis of the factors that impact the simulation accuracy, and in this regard go further than the related works. We analyze the sensitivity of several parameters, among which the impact of the job submission management overheads, the effect of inaccuracies in the job execution times specified by the user, or the boot time of VMs. The study is carried out on several use cases which comprise two different types of applications (workflow and bag-of-tasks), with several size instances for each of them, and each application operated on two different types of infrastructure (private and public).

The paper is organized as follows. We first present the related work regarding simulation in Section 2. The next part describes the system we seek to simulate (Section 3), which includes the cloud management system, the real platforms on which experiments are run, and the applications that serve as test-cases. The following part presents our contribution to the simulation of clouds, with our extension of SimGrid to model IaaS clouds, and its application to the simulation of Schlouder. The last part is an evaluation of the accuracy of the simulation against real observations.

2 Related Work

In the past decade, a number of research works have proposed simulation tools for clouds. Some of them have a longer history as they build upon the experience of researchers in the simulation of computing grids. Most cloud simulators are based on discrete event simulation (DES). In discrete event simulations the simulation is a serie of events changing the state of the simulated system. For instance, events can be the start (or end) of computations or of communications. The simulator will jump from one event to the next, updating the times of upcoming events to reflect the state change in the simulation. Such DES-based simulators require at least a platform specification and an application description. The platform specification describes both the physical nature of the cloud, e.g. machines and networks, and the management rules, e.g. VM placement and availability. Depending on the simulator, the platform specification can be done through user code, as in CloudSim [2] for example, or through platform description files, as is mostly the case in SimGrid [3]. The application description consists in a set of computing and communicating jobs, often described as an amount of computation or communication to perform. The simulator computes their duration based on the platform specification, and its CPU and network models. An alternative approach is to directly input the job durations extrapolated from actual execution traces.

The available cloud DESs can be divided in two categories. In the first category are the simulators dedicated to study the clouds from the provider point-of-view, whose purpose is to help evaluating the design decisions of the datacenter. Examples of such simulators are MDCSim [11], which offers specific and precise models for low-level components including network (e.g InfiniBand or Gigabit ethernet), operating system kernel and disks. It also offers a model for energy consumption. However, the cloud client activity that can be modeled is restricted to web-servers, application-servers or data-base applications. GreenCloud [9] follows the same purpose with a string focus on energy consumption of cloud's network apparatus using a packet-level simulation for network communications (NS2). In the second category are the simulators targeting the whole cloud ecosystem, including client activity. In this category, CloudSim [2] (originally stemming from GridSim) is the most broadly used simulator in academic research. It offers simplified models regarding network communications, CPU or disks. However, it is easily extensible and serves as the underlying simulation engine in a number of projects (e.g [1], see section **??**). Simgrid [3] is the other long-standing project, which when used in conjunction with the SchIaaS cloud interface provides similar functionnalities as CloudSim. Among the other related projects, are iCanCloud [14] proposed to address scalability issues encountered with CloudSim (written in Java) for the simulation of large use-cases. Most recently, PICS [8] has been proposed to specifically evaluate simulation of public clouds. The configuration of the simulator uses only parameters that can be measured by the cloud client, namely inbound and outbound network bandwidths, average CPU power, VM boot times, and scale-in/scale-out policies. The data center is therefore seen as a black box, for which no detailed description of the hardware setting is required. The validation study of PICS under a variety of use cases has nonetheless shown accurate predictions.

At the core of DES is the solver. The solver considers the states of the system generated by the platform and previous events to compute the timing of the future events. In most cases, simulators have a *bottom-up* approach: the modeling concerns low-level components (machines, networks, storage devices), and from their interactions emerge the high-level behaviours. Working on disjoint low level components make it easier to tune the precision of the model to the wanted accuracy or speed trade-off.

FIXME: next paragraph to be adapted depending on wether stochastic simulation is mentioned. However, when the simulated system is subject to variability, it is difficult to establish the validity of simulation results formally. Indeed, given some defined inputs, a DES outputs a single deterministic result,

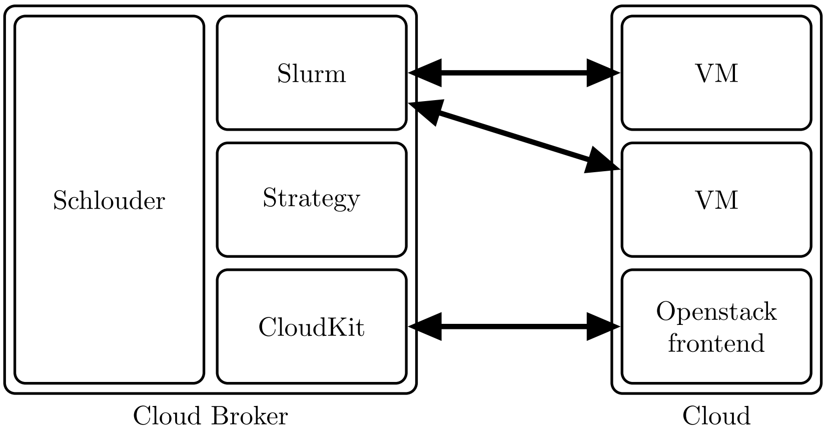


Figure 1: The Schlouder cloud broker and its components relating to an Openstack cloud.

while a real system will output slightly different results at each repeated execution. Hence, in practice the simulation is informally regarded as valid if its results are "close" to one or some of the real observations. Notice however that in the field of grid or cloud computing, published results in terms of validation against real settings are scarce relatively to the number of projects.

3 Context and Setup

In the first part of this article

As mentioned in introduction, complex workloads require scheduling and provisionning tools, and we present in this section the cloud management system together with the actual hardware setup we run to handle these experiments.

3.1 Schlouder

Every experiment log in the archive was generated by running a scientific workflow through a client-side cloud resource broker named *Schlouder* [13]. *Schlouder* automates the provisioning of resources needed to execute a workflow, the scheduling of tasks to the provisioned resources and, monitors the proper execution of tasks. Provisioning is done through a cloud kit interface that allows Schlouder to communicate with different clouds in order to start and stops the necessary VMs to execute the workload. To account for the pricing of commercial IaaS, Schlouder views provisioning in fixed increments of time, referred to as billing time unit (BTU), machines idle when arriving at the end of their time will be automatically shut off. Tasks execution is monitored using SLURM [18] which connects to the available VMs, send the jobs, and monitors their executions.

A strategy controls provisioning and scheduling decisions, it determines when VM provisioned and to which VM each task is assigned. Schlouder provides a few basic strategies and new ones can be added trivially. Strategies can affect the workload's *makespan*, the VMs usage rate, and the number of opened BTUs (i.e. the price of the experiment on a commercial cloud). The experiments in our archive mainly use two strategies, *as soon as possible* (ASAP) and *as full as possible* (AFAP)

ASAP will attempt to execute tasks as early as possible by booting a new VM unless a VM is already idle or one is predicted to become idle faster than a VM can boot.

AFAP will favor scheduling tasks on already opened VM unless doing is predicted extend the VM runtime by an additional BTU, in which case it will boot a new VM.

Predicted tasks runtimes, as well as tasks dependencies, are user-provided. Scheduling is done dynamically, as soon as tasks are submitted and all their dependencies have been completed. Once assigned to a designated VM jobs are not rescheduled. However, if a VM fails to boot Schlouder will provision a new one to replace it.

3.2 Hardware Setup

Evaluation of simulation is done by comparing simulation logs, against logs generated by running actual scientific workflows on multiple platforms. During this study we gathered traces for 274 experimental executions on two significantly different environments that are described hereafter.

Private Cloud Our private cloud is based on two local nodes sporting dual $2.64GHz$ Intel Xeon processors (X5650), for a total of 96 cores. Nodes operated on Ubuntu 12.04 distributions and virtualisation is achieved using KVM. Openstack 2012.1.3 was used as a cloud interface. This cloud was build on perfectly homogeneous nodes and devoid of other users. For data storage these experiments rely on a Network File-System (NFS). Special attention was taken to not overbook VMs by caping the number of single core VMs to 25. Due to the experimental nature of this cloud configurations have change overtime. Table 1 regroups configurations of all cloud versions. We will referrer to this cloud as `openstack-icps.`*version*.

Public Cloud BonFire [7] is a public multi-cloud distributed all over Europe. Our experiments were run over three sites of BonFire: de-hlrs based in Stuttgart, uk-epcc in Edinburgh, and fr-inria in Rennes. BonFIRE clouds were accessed through an OCCI based API and the clouds were controlled throught software derived from OpenNebula 3.6. Each site provided different hardware[1].Resource quotas limited most experiment 20 VMs, not far from the limits generally imposed on public clouds. Centralized storage was provided through a NFS based on the be-ibbt site in Ghent. Due to network acces restriction the Schlouder server was brought in the BonFIRE WAN through a VPN. Due to the experimental nature of this cloud configurations have change overtime. Table 1 regroups configurations of all cloud versions. In this article we refer to experiment run on the BonFire clouds by the name of the cloud site followed by the version number.

[1] Comprehensive information available at `http://www.bonfire-project.eu/infrastructure/testbeds`

Cloud	#cores	Hypervisor	Network	version	#VM	Storage
openstack-icps	48	KVM	100mb	1-3	25	NFS
			1Gb	4-5	10	NFS
de-hlrs	344	Xen 3.1.2	n/a	v1-3	20	NFS
fr-inria	96	Xen 3.2	n/a	v1-3	20	NFS
uk-epcc	176	Xen 3.0.3	n/a	v1-2	20	NFS

Table 1: Characteristics of our cloud testbeds, version numbers also account for changes in measured boot times not presented in this table.

3.3 Use cases: Applications characteristics

Our study is based on the experimentation with two test-case applications that cover a variety of application profiles in terms of computation intensity, data load, and task dependency.

3.3.1 OMSSA

The Open Mass-Spectrometry Search Algorithm (OMSSA) [5] comes from the field of biology, it is used in tandem mass spectrometry analysis (also known as MS/MS analysis) to identify peptides from the mass and fragment ions obtained by a mass spectrometer. OMSSA matches measurements from the mass spectrometer, called spectra, to a protein database.

The OMSSA workload features fully independent tasks, making it Bag of Tasks (BoT), since every spectra within a set can be submitted independently to OMSSA. With a *communication-to-computation* ratio comprised between 20% and % OMSSA is considered an CPU-intensive workload.

This application was run with 4 different workload covering 2 different mass spectrometer resolutions of two different protein solutions, denoted *brs*,*hrs*,*brt* and *hrt*.

3.3.2 Montage

The Montage Astronomical Image Mosaic Engine [6] is designed to gather astronomical images into a mosaic. This application is a workflow designed to reproject, normalize, and collate source images into a single output image. The montage workflow is presented figure 2. Working on images Montage is an extremely data intensive workflow with a *communication-to-computation* ratio superior to 90%. This application was run on images of the *Pleiade* star cluster at 3 different output sizes, 1X1, 2X2 and 3X3.

4 Simulation

SimGrid was originally developped 20 years ago to evaluate scheduling algorithms in distributed computing environments such as grids. Since then, it has been largely extended and has become a framework able to tackle new fields of distributed computing. Its layered design, depicted on Figure 3, offers three interfaces to access the simulation layer (SIMIX on figure) which in turn relies on the simulation core engine (SURF). Each interface implements a different concurrent programming model: MSG offers a CSP **??**-like programming model,

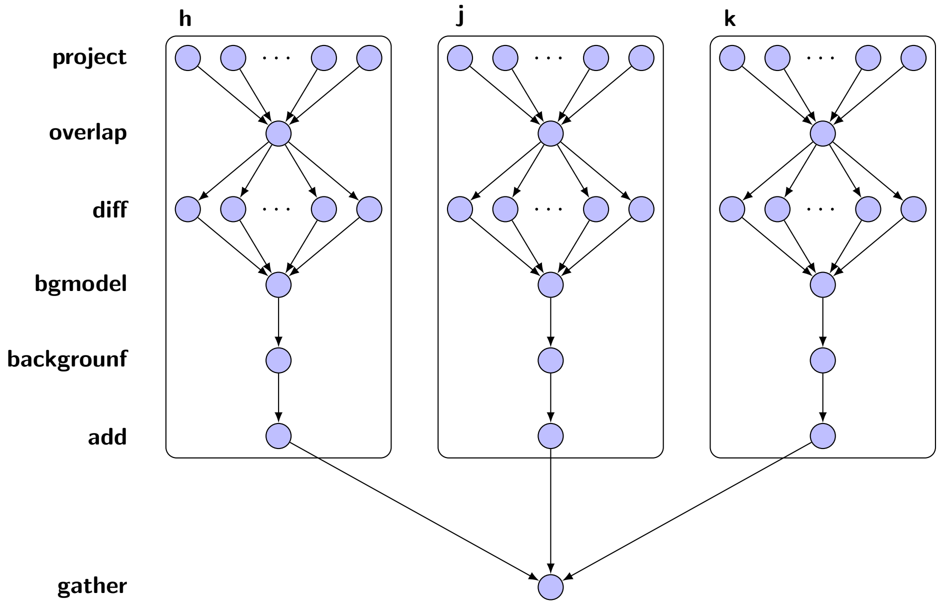


Figure 2: Illustration of the Montage workflow. Each node represents a tasks and each arc represents a data dependency between two tasks. Every task on a specific row run the Montage command indicated on the left hand side of the graph.

SMPI enables MPI programs, and SimDag is best suited to represent graphs of dependent tasks. User code may built directly upon one of these interfaces to model a field of interest, e.g peer-to-peer systems [15] or MapReduce applications [10]. For our study, we developped a new interface upon MSG, called SchIaaS and dedicated to model IaaS operations. While SimGrid implements hypervisor level functionalities such as starting or stoping a VM, SchIaaS implements cloud level functionalities. We call *instance* the virtual machine when seen from the client side –this terminology has been popularized by AWS. The main operations provided by SchIaaS are the one ususally provided by public cloud providers: run, terminate, suspend, resume and describe instances and operations regarding cloud storage. For sake of modeling a cloud, SchIaaS also allows the user to describe the available resources, the image and instance types management, the VM placement policy on the clusters and operating-system levels parameters such as boot and other VM life-cycle processes.

4.1 Simulator

Architecture de SchIaaS les moteurs à instancier etc. Intérêts.

SimSchlouder/SCHIaaS/Simgrid

SimSchlouder reproducing Schlouder runs. Same input/output file.

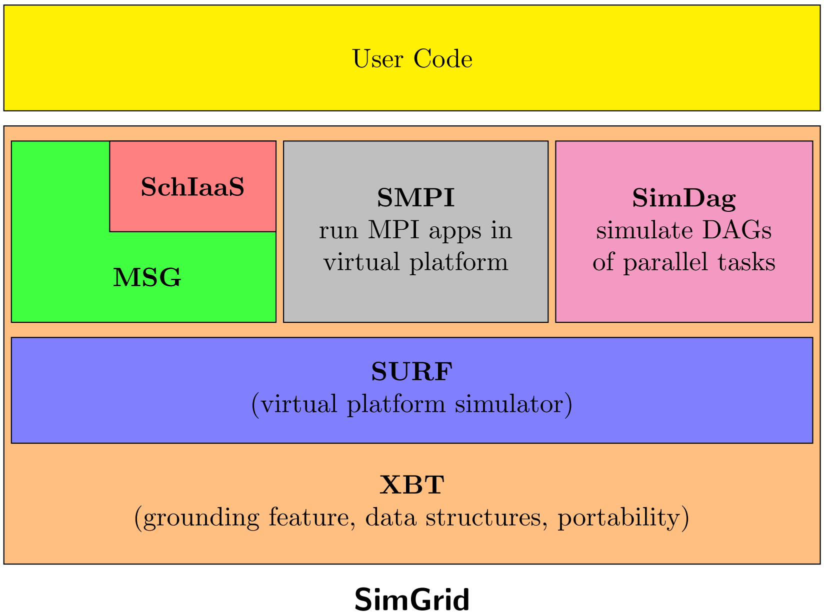


Figure 3: The layered architecture of SimGrid, with the additionnal SchIaaS interface

5 Evaluation

5.1 Simulations

5.1.1 Lab

éléments concrets pour le lab (c.f Renpar).

Le lab est un ensemble de scripts permettant d'automatiser l'exécution des simulations, la collecte des observations, ainsi que leur analyse. Il permet donc d'exécuter de bout-en-bout l'étude par simulation, de la définition des différentes simulations, à la production des graphiques.

Au delà de l'aspect pratique et du gain de temps de mise en œuvre de l'étude, le lab a pour vocation de "standardiser" l'étude. Cette standardisation assure sa reproductibilité, ainsi qu'une comparaison équitable entre solutions à un même problème.

Mais le lab permet également une approche systématique permettant à l'expérimentateur de ne pas rater de phénomène. En effet, il est fréquent de faire un grand lot de simulations, puis d'observer plus finement celles qui présentent des particularités. Ce faisant, l'expérimentateur exclu les autres simulation de ces observations plus précises, à moins de les refaire entièrement. En rendant plus pratique la définition des observations directement au niveau du *workflow* de simulations, le lab assure que tous les cas seront observés de la même manière, ce qui évite de rater un phénomène, ou de différencier le traitement des simulations au risque d'arriver à des conclusions abusives.

5.1.2 Procedural Analysis

Démarche expérimentale de validation du simulateur.

Process de simulation : choisir l'application, définir les métriques, executer

Voici la procédure expérimentale que nous avons employé: Sur ce type d'application nous avons besoin des informations

1. Real executions (xp) to test Schlouder and provisioning/scheduling strategies. Schlouder/SimSchlouder input:
   - Nodes: boottime prediction, amount of instances limit, standard power
   - Tasks: walltime prediction
2. Normalization of xp traces (4 versions of schlouder, missing data)
3. Extraction of information about each xp:
   - Instance: provisioning date, start date, end date, boottimes, instance type
   - Tasks: submission date, scheduling date, start date, end date, walltime, input time and size, runtime, output time and size, management time
4. Simulation of each xp, injecting different information from real xps
5. Comparison of Schlouder and SimSchlouder outputs (python)
6. Statistical analysis of all traces (R) : distribution de l'erreur
7. Close analysis of each outlier to understand the differences.

5.1.3 life-cycles and observed times

- Execution: $e \in E$
- Node of execution e: $n \in N_e$
- Task of execution e: $t \in T_e$
- Task handled by node n: $t \in T_n$
- The node running the task t is denoted $n_t \in N$
- v^R denotes the value v in the rality
- v^S denotes the value v in the simulation
-

During the execution, the node are in the following states:
The observed times are:

- $uptime(n) = terminated_n - booting_n$
- $boottime(n) = idle_n - booting_n$

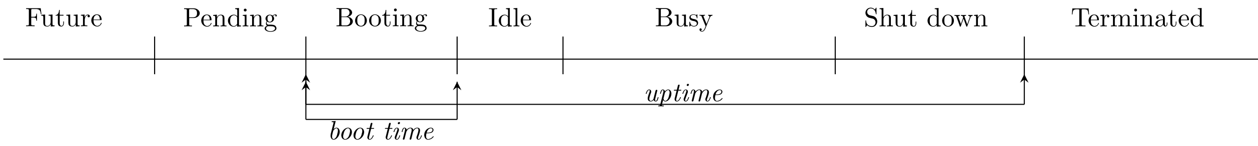


Figure 4: Nodes' states

During the execution, the task are in the following states, each corresponding to one date:

1. Pending: Once they are subitted to the system;
2. Scheduled: Once the system decided on which node the taks should be executed;
3. Submitted: Once the task is sent to the worker node;
4. Inputting: Once the task begin to download its data;
5. Running: Once the task begin to computed;
6. Outputting: Once the task begin to upload its result;
7. Finished: Once the task is finished;
8. Complete: Once the system aknowledge the completion of the task.;

The observed times are:

- $walltime(t) = complete_t - submitted_t$
- $inputtime(t) = running_t - inputting_t$
- $runtime(t) = outputting_t - running_t$
- $outputtime(t) = finished_t - outputting_t$
- $managementtime(t) = walltime_t - (inputtime_t + runtime_t + outputtime_t)$
- or $managementtime(t) = (inputting_t - submitted_t) + (complete_t - finished_t)$

5.2 Discussion of Results

5.3 Definitions

4 metrics $m \in M$ for each execution $e \in E$:

- uptime: amount of rented resources, cost

$$uptime(e) = \sum_{n \in N_e} uptime_n$$

- makespan: duration of the xp from the submission of the first task to the end of the last task, user experience

$$makespan(e) = max_{t \in T_e} complete_t$$

- usage: runtime / uptime, efficiency of the provisioning

$$usage(e) = \frac{\sum_{t \in T_e} walltime_t}{\sum_{n \in N_e} uptime_n}$$

- schederror: number of tasks that are not assigned to the same node in the simulation compared to the reality, accuracy of the scheduling decisions

$$schederror(e) = |t \forall t \in T / t_n^R \neq t_n^S|$$

Absolute errors are computed for each metric $m \in M$:

$$m.ae(e) = \frac{|m^S(e) - m^R(e)|}{m^R(e)}$$

Results are shown as frequencies and statistics (stat = min, mean, median, max) of absolute errors occurrences. Frequencies are weighted so that the two applications weigth the same, and the two platforms weigth alos the same (i.e. each couple application $\times$ platform represents 1/4th of the frequencies).

To compare absolute errors between set of simulations S and S' S being the reference:

- $\delta stat(m.ae(E)) = stat_{e \in E}(m.ae^{S'}(e)) - stat_{e \in E}(m.ae^S(e))$
- $\Delta stat(m.ae(E)) = stat_{e \in E}(m.ae^{S'}(e) - m.ae^S(e))$

5.4 Simulator accuracy

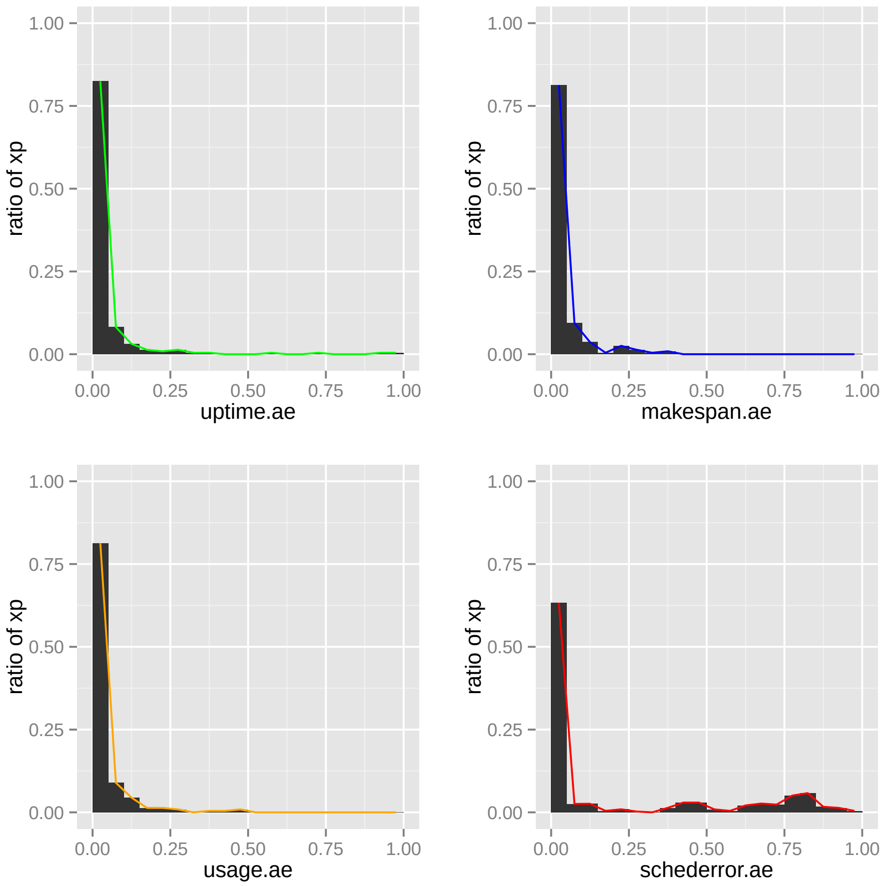
Best simulation we can do.

Assess the raw simulator accuracy, injecting all real-life hazards that can be captured : boottimes, walltimes and scheduling dates.

Scheduling dates allow to simulate some internal threaded mechanisms of Schlouder. Schlouder uses two threads: the node manager and the task manager. At settled intervals, the node manager interrupts the task manager to start and stop new nodes. This changes the state of nodes, which influence provisioning and scheduling decisions. However, simulating the exact moment of this interruption is utterly difficult, leading to differences between simulation and reality.

- uptime: 86% show less than 0.05 of absolute error, 92% less than 0.10, 2 simulations exceed 0.30, ranging from 0.00 to 0.50, for a mean of 0.025 and a median of 0.001

- makespan: 76% show less than 0.05 of absolute error, 90% less than 0.10, 0 simulations exceed 0.30, ranging from 0.00 to 0.62, for a mean of 0.042 and a median of 0.018



	uptime.ae	makespan.ae	usage.ae	schederror.ae
min	0.000	0.000	0.000	0.000
mean	0.023	0.017	0.019	0.124
median	0.001	0.000	0.001	0.000
max	0.995	0.375	0.500	0.961

Figure 5: Frequencies and statistics about absolute error of best simulations (274 xp)

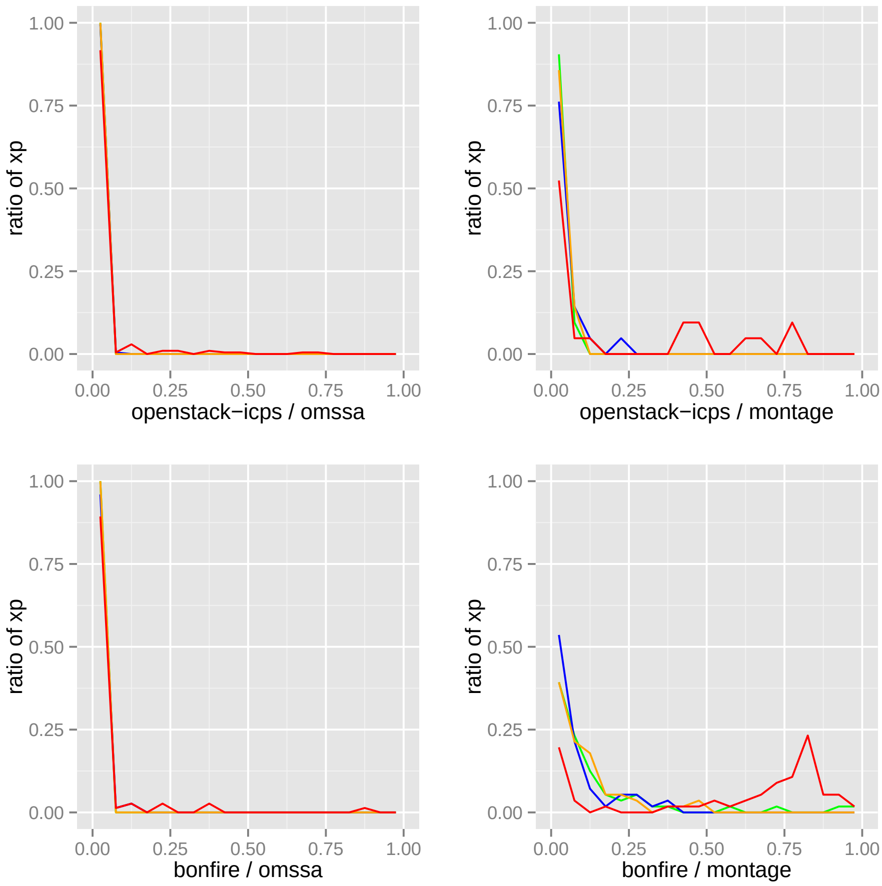


Figure 6: Absolute error frequencies of best simulations according to platforms and applications

- usage: 59% show less than 0.05 of absolute error, 91% less than 0.10, 2 simulations exceed 0.30, ranging from 0.00 to 0.60, for a mean of 0.043 and a median of 0.002
- schederror: 70% show less than 0.05 of absolute error, 72% less than 0.10, 59 simulations exceed 0.30, ranging from 0.00 to 0.965, for a mean of 0.155 and a median of 0.000

If global metrics are quite accurately assessed by the simulator, the scheduling decisions can be very different between simulation and reality. One part of the explanation is that scheduling decisions are interdependent: any error leads to several others.

5.5 Simulator accuracy according to platforms and applications

- openstack-icps / omssa (107 xp):

	uptime.ae	makespan.ae	usage.ae	schederror.ae
min	0.000	0.000	0.000	0.000
mean	0.001	0.001	0.001	0.024
median	0.000	0.000	0.001	0.000
max	0.029	0.079	0.029	0.749

All metrics are almost perfectly assessed (mean AR from 0.001 to 0.002) except scheduling error (mean 0.04 and max 0.75, 13% of xp show at least one error), leading to small makespan and usage errors.

We looked at each single case of scheduling error and all those errors comes from ambiguities in the scheduling algorithms.

This is a first limitation of simulation: Whenever heuristics lead to several equivalent solutions, the decision is made by the implementation and relies on data structures (e.g. selection of the first encountered suitable solution) or clocks (e.g. the solution differs from a second to the next, which depends on threads activations and timers). While we made sure to use the same structures and timers, some clocks-related events can not be captured nor simulated: Processing the nodes and tasks queues for scheduling and provisioning decisions take time. Consequently, if those decisions rely on clock, they change during the decision process in reality, as clocks advance by itself, but not in simulation, as clocks advance only explicitly.

Thus, the simulation is not mistaken, but only different from reality. Actually, the decisions made by the simulator are exactly those that one can expect, while the decisions made by the real scheduler are sometimes difficult to understand.

Filtering the xps showing clocks-related issues (16 xps), the results are perfect: all metrics present a mean ae of at most 0.001.

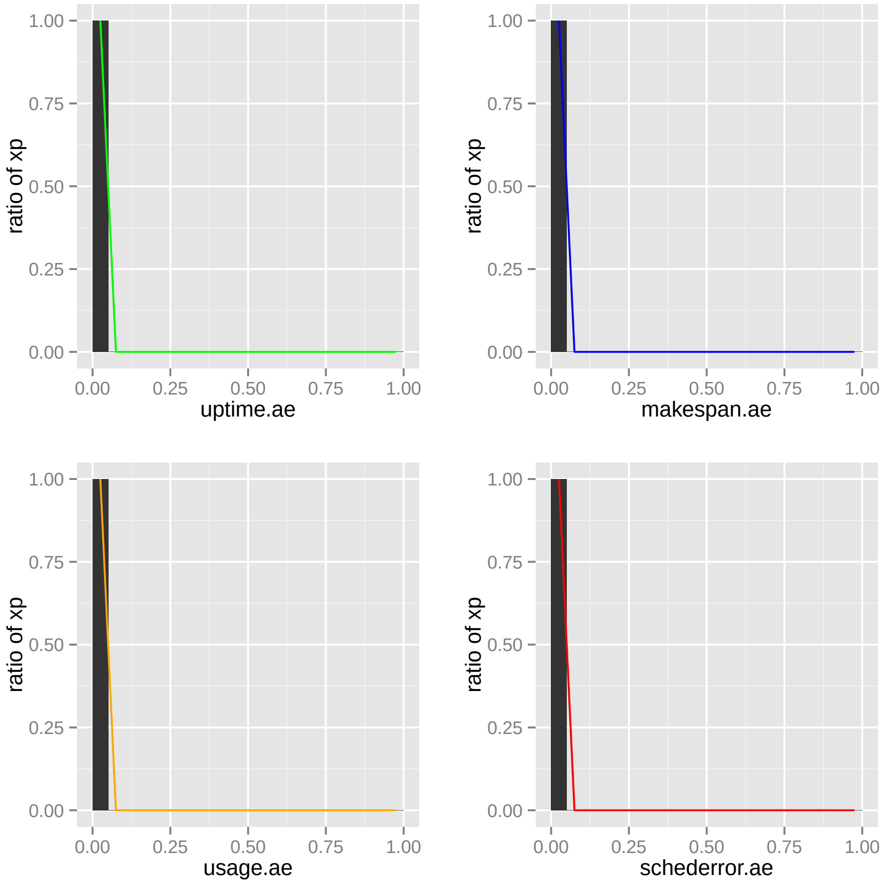
The less accurate simulation shows a makespan absolute error of 0.010. Actually, the makespan of the simulation is $94s$, whereas it is $95s$ in reality. This small difference is due to one lag between two consecutive tasks in the middle of the simulation. Such lags are not injected in our simulations.

This shows that, providing that one can inject the right information, the only limitation of our simulator are micro clock-related hazards.

- openstack-icps / montage (36 xps):

	uptime.ae	makespan.ae	usage.ae	schederror.ae
min	0.000	0.000	0.000	0.000
mean	0.010	0.033	0.018	0.231
median	0.000	0.001	0.002	0.000
max	0.086	0.221	0.079	0.790

	uptime.ae	$\delta_{uptime.ae}$	makespan.ae	$\delta_{makespan.ae}$	usage.ae	$\delta_{usage.ae}$	schederror.ae	$\delta_{schederror.ae}$
min	0.000	+0.000	0.000	+0.000	0.000	+0.000	0.000	0.000
mean	0.010	+0.009	0.033	+0.032	0.018	+0.017	0.231	+0.207
median	0.000	+0.000	0.001	+0.001	0.002	+0.001	0.000	0.000
max	0.086	+0.056	0.221	+0.141	0.079	+0.050	0.790	+0.041



	uptime.ae	makespan.ae	usage.ae	schederror.ae
min	0.000	0.000	0.000	0.000
mean	0.001	0.000	0.001	0.000
median	0.000	0.000	0.001	0.000
max	0.003	0.010	0.011	0.000

	uptime.ae	$\delta_{uptime.ae}$	makespan.ae	$\delta_{makespan.ae}$	usage.ae	$\delta_{usage.ae}$	schederror.ae	$\delta_{schederror.ae}$
min	0.000	+0.000	0.000	0.000	0.000	+0.000	0.000	0.000
mean	0.001	−0.000	0.000	−0.001	0.001	−0.000	0.000	−0.024
median	0.000	+0.000	0.000	+0.000	0.001	+0.000	0.000	0.000
max	0.003	−0.027	0.010	−0.069	0.011	−0.018	0.000	−0.749

Figure 7: Frequencies and statistics about absolute error of best simulations for openstack-icps / ommssa, without scheduling error cases (91 xps)

With a work-flow, scheduling errors are more numerous (ae mean of 0.24 for a max of 0.79), leading to less accurate assessments of uptime, makespan and usage (mean ae of 0.01, 0.05, and 0.01), that is ten times more than with a BoT.

First, montage has much more tasks (from 43 to 1672) than omssa (from 33 to 223). Consequently, queues are much longer, which increases the clock-related issues.

Second, BoT scheduling are actually made offline (i.e. scheduling decisions are taken before any actual execution), while WF scheduling implies decisions during the execution, every time dependencies are satisfied. Those decisions rely on the system state (predicted end date of nodes for instance). Consequently, divergences between simulation and reality have more important impacts with WF than with BoTs.

For instance, the worst case shows a very large amount of scheduling errors (0.954). A close examination of this case shown that the simulation behave as expected : After the first dependencies were satisfied, three newly ready tasks $t1$, $t2$, and $t3$ were scheduled on the node n. However in reality, scheduling takes time. During this time, the last task scheduled to node n was completed between the scheduling of $t2$ and $t3$, but before $t1$ were actually submitted to n. This lead to mistakingly set the state of node n to idle, impacting the scheduling decision of $t3$.

Those kind of complex and unforeseeable events are actually frequent when confronted to reality. However, they are utterly difficult to detect (1672 jobs were scheduled for the presented case). Comparing real execution with simulation allow the detection of such case, without having to look at each scheduling decision.

the last task assigned to node n was completed during the scheduling of the tasks which dependencies were satisfied first. But those tasks were intended to This completion lead Schlouder to mistake the state of the

- bonfire / omssa (75 xp):

	uptime.ae	makespan.ae	usage.ae	schederror.ae
min	0.000	0.000	0.000	0.000
mean	0.002	0.009	0.005	0.032
median	0.001	0.004	0.004	0.000
max	0.044	0.134	0.045	0.857

	uptime.ae	$\delta_{uptime.ae}$	makespan.ae	$\delta_{makespan.ae}$	usage.ae	$\delta_{usage.ae}$	schederror.ae	$\delta_{schederror.ae}$
min	0.000	+0.000	0.000	+0.000	0.000	+0.000	0.000	0.000
mean	0.002	+0.002	0.009	+0.008	0.005	+0.003	0.032	+0.008
median	0.001	+0.001	0.004	+0.004	0.004	+0.003	0.000	0.000
max	0.044	+0.015	0.134	+0.054	0.045	+0.016	0.857	+0.108

On a public shared heterogeneous cloud, scheduling errors are more numerous (AR mean of 0.03 for a max of 0.86), leading to less accurate assessments of uptime, makespan and usage (mean AR of 0.005, 0.045, and 0.053).

More interesting, usage are never perfectly assessed: 16% of xp show less than 0.05 of AR, while 86% show an AR between 0.05 and 0.10

This show the impacts of public heterogeneous platforms on simulation accuracy: It is not possible to precisely simulate the vm-to-pm scheduling algorithm of public cloud, as they are generally not public, and their decisions impacts performances, as one can not predict the power of the VM one get.

- bonfire / montage (56 xp):

	uptime.ae	makespan.ae	usage.ae	schederror.ae
min	0.000	0.001	0.001	0.000
mean	0.138	0.082	0.104	0.572
median	0.081	0.048	0.082	0.742
max	0.995	0.375	0.500	0.961

	uptime.ae	$\delta_{uptime.ae}$	makespan.ae	$\delta_{makespan.ae}$	usage.ae	$\delta_{usage.ae}$	schederror.ae	$\delta_{schederror.ae}$
min	0.000	+0.000	0.000	+0.000	0.000	+0.000	0.000	0.000
mean	0.002	+0.002	0.009	+0.008	0.005	+0.003	0.032	+0.008
median	0.001	+0.001	0.004	+0.004	0.004	+0.003	0.000	0.000
max	0.044	+0.015	0.134	+0.054	0.045	+0.016	0.857	+0.108

On a public shared heterogeneous cloud, scheduling errors are even more numerous (AR mean of 0.48 for a max of 0.96), leading to less accurate assessments of uptime, makespan and usage (mean AR of 0.10, 0.115, and 0.48).

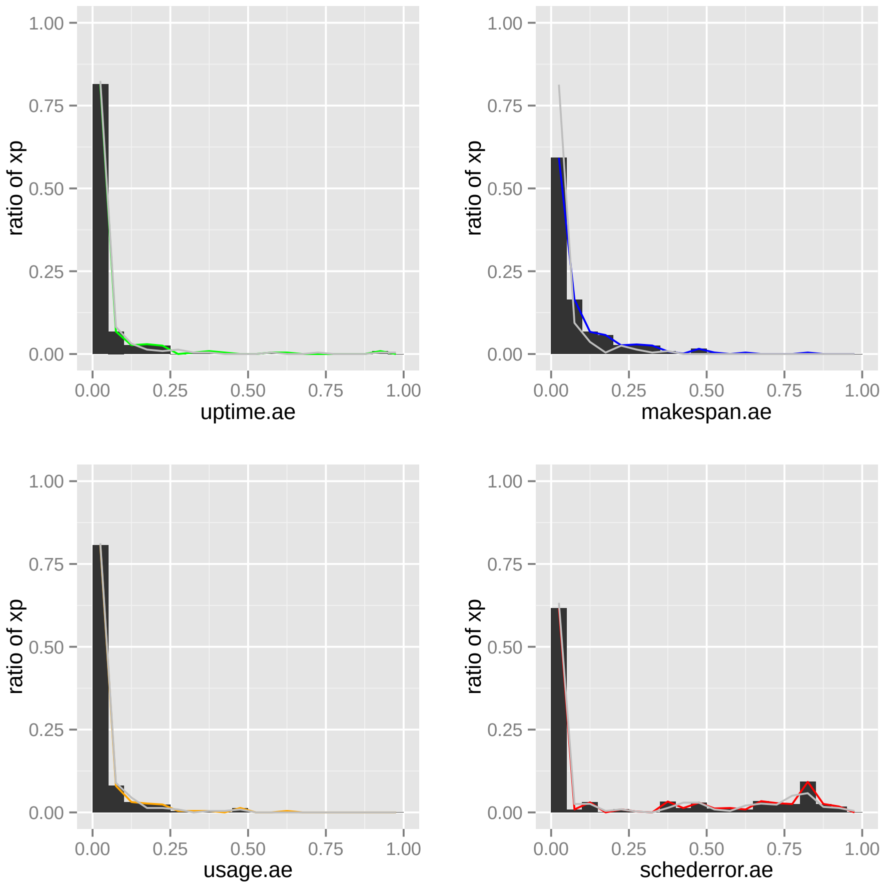
This is simply explained by the cumulation of inaccuracies from both platform and applications.

5.6 Boottime impacts

Assessing the impact of efficient boottimes simulation.

Same simulations, without injecting the boottimes observations. Thus, boottimes are only predictions, based on linear regressions of previously observed boottimes.

The worst case show a makespan ae of 0.816 (3141s instead of 17076s). This is due to boottimes on BonFire that were completely of charts: 5 boots were normal (ranging from 232s to 311s), the 17 others ranged from 3281s to 11084s. Whereas BonFire were intended to deliver 22 simultaneous VMs, only 5 were available at the time of the experiment. Instead of refusing the following 17 VMs, the provisioning system of BonFire put them in pending state, waiting for the delivered ones to stop. The VMs being provisioned for one hour, following the 5 normal boots, 5 boots took approximatively 1 hour, then 5 other boots took



	uptime.ae	makespan.ae	usage.ae	schederror.ae
min	0.000	0.000	0.000	0.000
mean	0.026	0.059	0.028	0.134
median	0.001	0.008	0.002	0.000
max	0.918	0.815	1.711	0.949

	uptime.ae	$\delta_{uptime.ae}$	makespan.ae	$\delta_{makespan.ae}$	usage.ae	$\delta_{usage.ae}$	schederror.ae	$\delta_{schederror.ae}$
min	0.000	+0.000	0.000	+0.000	0.000	+0.000	0.000	0.000
mean	0.026	+0.003	0.059	+0.042	0.028	+0.009	0.134	+0.010
median	0.001	+0.000	0.008	+0.007	0.002	+0.000	0.000	0.000
max	0.918	−0.077	0.815	+0.440	1.711	+1.211	0.949	−0.012

	$\Delta_{uptime.ae}$	$\Delta_{makespan.ae}$	$\Delta_{usage.ae}$	$\Delta_{schederror.ae}$
min	−0.373	−0.164	−0.249	−0.288
mean	+0.003	+0.042	+0.009	+0.010
median	0.000	+0.004	0.000	0.000
max	+0.412	+0.807	+1.528	+0.583

Figure 8: Frequencies, statistics, and comparison with best of simulations with no real boot times injection

2 hours, and 5 another more took 3 hours. Finally, 2 boots took 1 hour after the last dependencies were satsified.

This illustrates that defective clouds can not be efficiently simulated without proper information capture. However, once captured, this kind of defection is perfectly simulated by SchIaaS. Consequently, it can be used to assess behavior and robustness of solutions facing these defections.

Some case are surprisingly improved without the real boot times injection: For instance, one xp shows a real makespan of 25788s, for 35106s with boot times injection and 24266s without.

5.6.1 No-threads

Injection of: real boot times and some times due to Schlouder internal threads, such as lapses after a node become ready and the start of the first job.

Assess the impact of efficient internal threads simulation

5.6.2 Communications

Injection of: real boot times, some times due to Schlouder internal threads, such as lapses after a node become ready and the start of the first job, and, real runtimes and real data size for jobs input and output communications.

Assess the impact of efficient communications

5.6.3 Prediction

Injection of nothing from the real xp, except the xp description as submitted to schlouder.

Assess the efficiency of using a simulator as a predictor of a cloud.

6 Open-science

```
git clone https://git.unistra.fr/gossa/schlouder-traces.git
git clone https://scm.gforge.inria.fr/anonscm/git/schiaas/schiaas.git
cd schiaas
cmake .
make
cd lab
./lap.py -p2 setup/simschlouder/validation.cfg
cd setup/simschlouder/validation-results
ls
```

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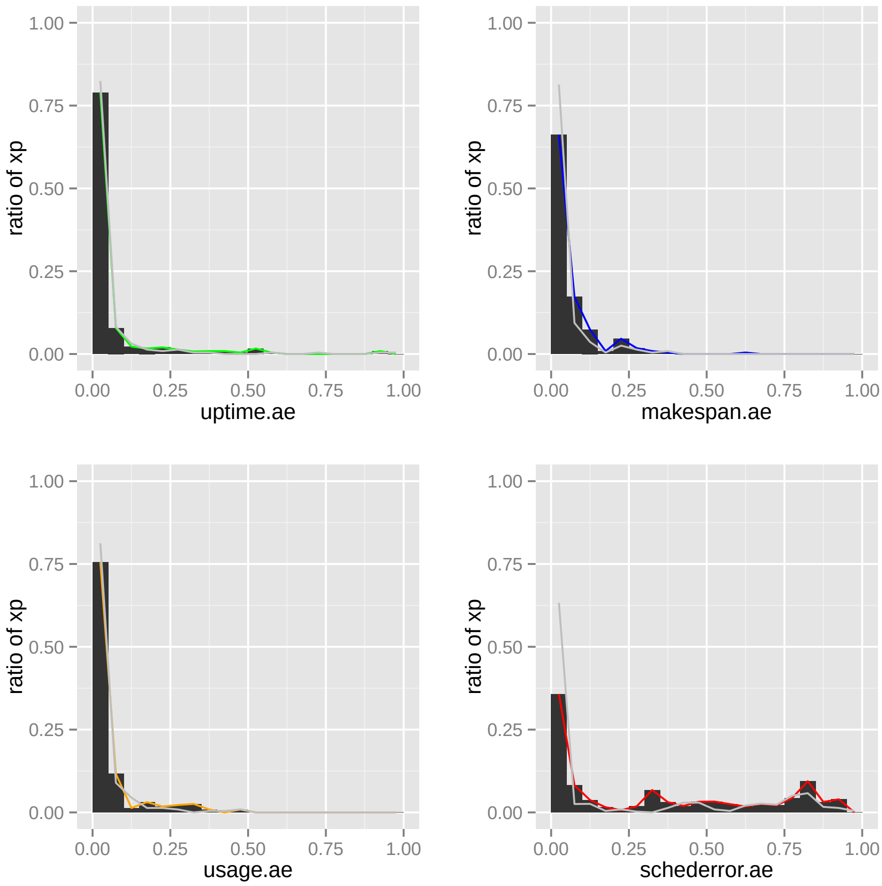
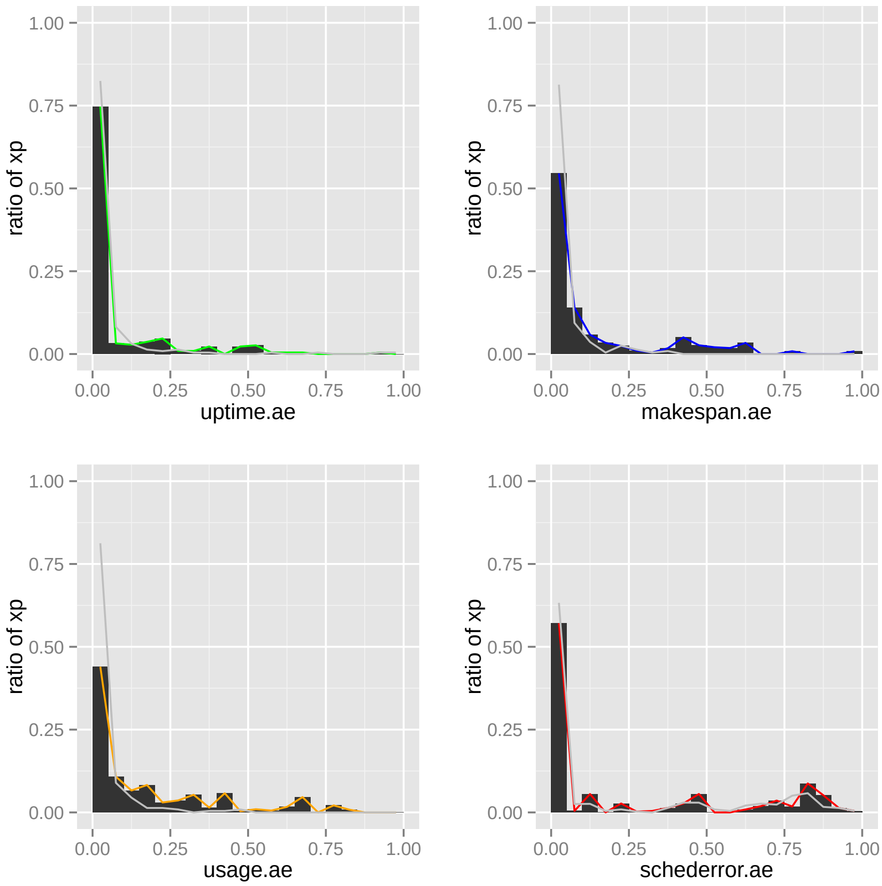


	uptime.ae	makespan.ae	usage.ae	schederror.ae
min	0.000	0.000	0.000	0.000
mean	0.033	0.038	0.029	0.261
median	0.001	0.013	0.002	0.092
max	0.918	0.607	0.479	0.944

	uptime.ae	$\delta_{uptime.ae}$	makespan.ae	$\delta_{makespan.ae}$	usage.ae	$\delta_{usage.ae}$	schederror.ae	$\delta_{schederror.ae}$
min	0.000	−0.000	0.000	+0.000	0.000	+0.000	0.000	0.000
mean	0.033	+0.009	0.038	+0.021	0.029	+0.010	0.261	+0.137
median	0.001	+0.000	0.013	+0.013	0.002	+0.000	0.092	+0.092
max	0.918	−0.077	0.607	+0.231	0.479	−0.020	0.944	−0.017

	$\Delta_{uptime.ae}$	$\Delta_{makespan.ae}$	$\Delta_{usage.ae}$	$\Delta_{schederror.ae}$
min	−0.251	−0.181	−0.143	−0.601
mean	+0.007	+0.020	+0.007	+0.138
median	0.000	+0.003	−0.000	+0.046
max	+0.403	+0.554	+0.288	+0.870

Figure 9: Frequencies, statistics, and comparison with best of simulations with no real thread times injection



	uptime.ae	makespan.ae	usage.ae	schederror.ae
min	-1.000	0.000	-26175.045	0.000
mean	0.063	0.078	-104.675	0.143
median	0.001	0.012	0.026	0.000
max	2.068	1.109	0.824	0.961

	uptime.ae	$\delta_{uptime.ae}$	makespan.ae	$\delta_{makespan.ae}$	usage.ae	$\delta_{usage.ae}$	schederror.ae	$\delta_{schederror.ae}$
min	-1.000	-1.000	0.000	$+0.000$	-26175.045	-26175.045	0.000	0.000
mean	0.063	$+0.039$	0.078	$+0.061$	-104.675	-104.694	0.143	$+0.019$
median	0.001	$+0.000$	0.012	$+0.012$	0.026	$+0.025$	0.000	0.000
max	2.068	$+1.073$	1.109	$+0.734$	0.824	$+0.325$	0.961	0.000

	$\Delta_{uptime.ae}$	$\Delta_{makespan.ae}$	$\Delta_{usage.ae}$	$\Delta_{schederror.ae}$
min	-0.141	-0.211	-0.294	-0.426
mean	$+0.044$	$+0.047$	$+0.073$	$+0.017$
median	0.000	$+0.003$	$+0.010$	0.000
max	$+2.015$	$+0.642$	$+0.761$	$+0.751$

Figure 10: Frequencies, statistics, and comparison with best of simulations with simulation of communications

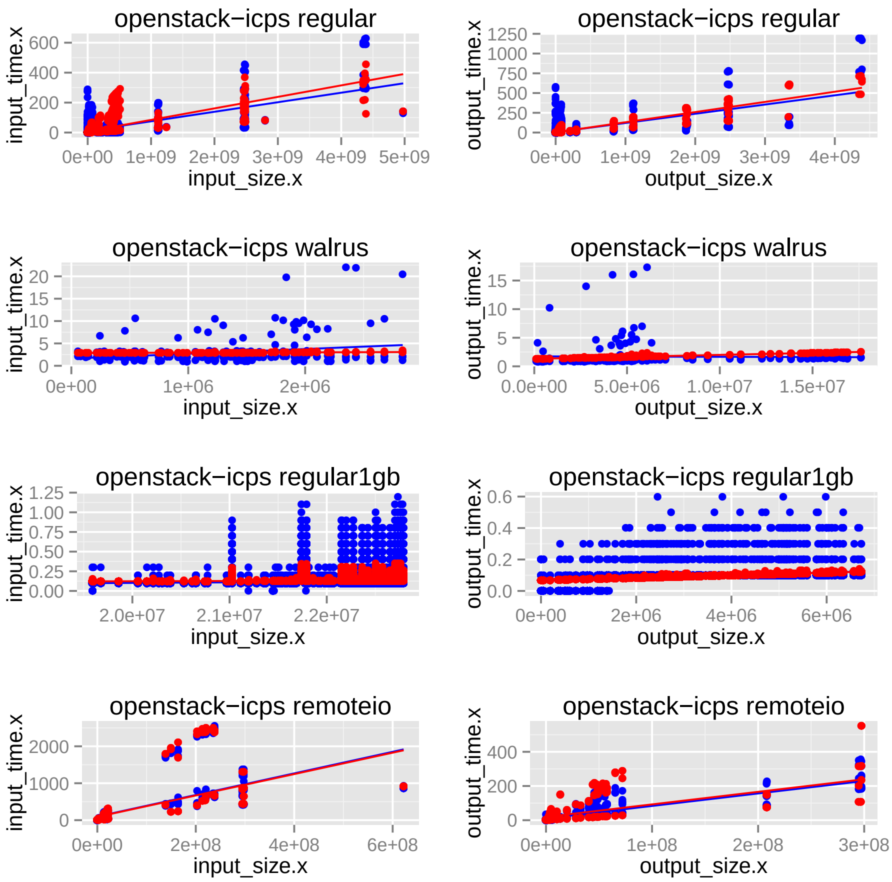


Figure 11: Linear regressions of communication times vs. data size, according to platform, storage, and communication direction on openstack-icps

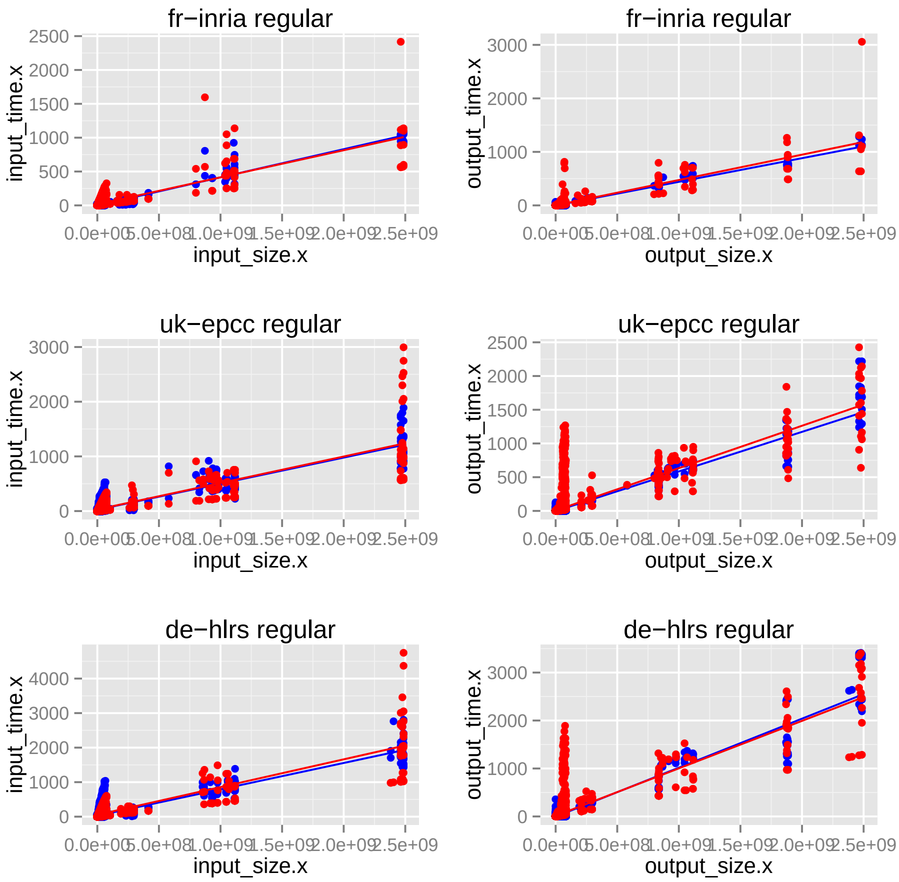
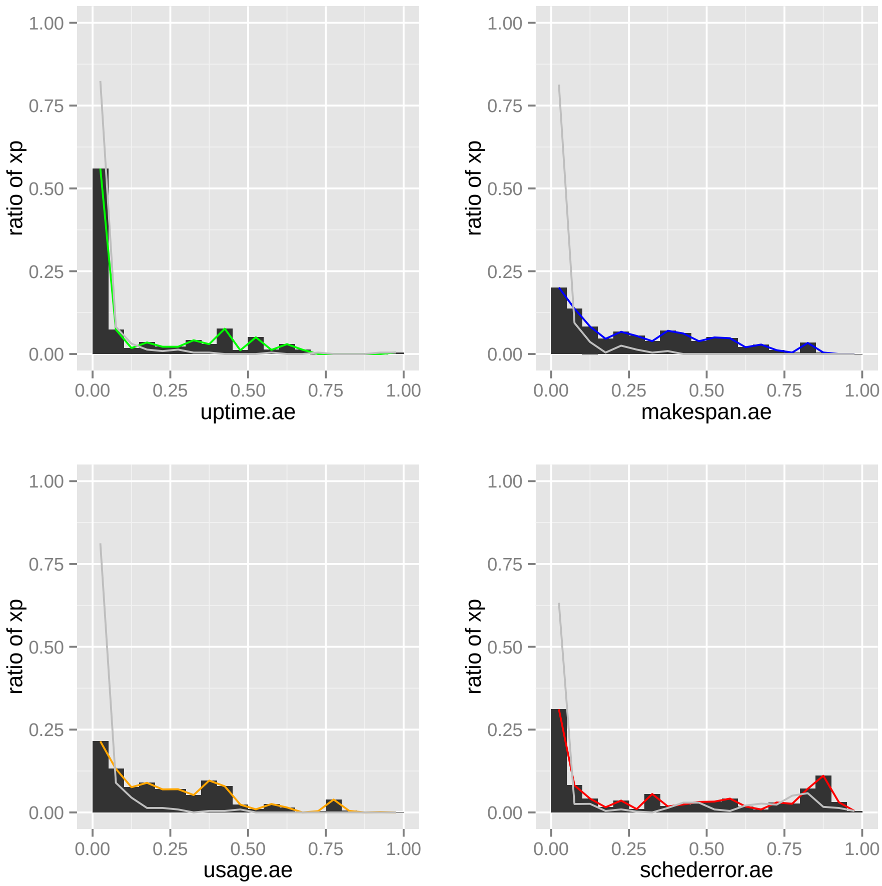


Figure 12: Linear regressions of communication times vs. data size, according to platform, storage, and communication direction on BonFire



	uptime.ae	makespan.ae	usage.ae	schederror.ae
min	-1.000	0.006	-27953.710	0.000
mean	0.119	0.212	-110.118	0.274
median	0.003	0.115	0.142	0.108
max	1.601	1.772	2.911	0.965

	uptime.ae	$\delta_{uptime.ae}$	makespan.ae	$\delta_{makespan.ae}$	usage.ae	$\delta_{usage.ae}$	schederror.ae	$\delta_{schederror.ae}$
min	-1.000	-1.000	0.006	$+0.006$	-27953.710	-27953.710	0.000	0.000
mean	0.119	$+0.096$	0.212	$+0.195$	-110.118	-110.137	0.274	$+0.150$
median	0.003	$+0.002$	0.115	$+0.115$	0.142	$+0.141$	0.108	$+0.108$
max	1.601	$+0.606$	1.772	$+1.396$	2.911	$+2.411$	0.965	$+0.004$

	$\Delta_{uptime.ae}$	$\Delta_{makespan.ae}$	$\Delta_{usage.ae}$	$\Delta_{schederror.ae}$
min	-0.141	-0.211	-0.294	-0.426
mean	$+0.044$	$+0.047$	$+0.073$	$+0.017$
median	0.000	$+0.003$	$+0.010$	0.000
max	$+2.015$	$+0.642$	$+0.761$	$+0.751$

Figure 13: Frequencies, statistics, and comparison with best of simulations with no injection

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