Cloud simulation

January 21, 2019

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 [13] 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. To that end, we propose a simulation framework called SCHiaaS[1] which specializes in IaaS clouds modeling. This is an extension to the SimGrid simulation toolkit [4], which provides in particular the discrete event simulator engine and the operating-system level operations (e.g messaging, virtual machines management). Using SCHIaaS, we focus in this article on the modeling of a cloud-brokering system. This client-side broker, on behalf on its users, makes scheduling and provisioning decisions, and automates jobs' execution on the real infrastructure. We have used this brokering system to experiment the impact of scheduling and provisioning policies when running two scientific applications using cloud computing resources. The exact setting for this experiment is described in Section 4. The question that this article addresses is: can this brokering system be modeled and predicted accurately through simulation? We have collected numerous execution logs traces when running these scientific applications through the broker, and these provide us with a valuable basis to validate our candidate simulation model.

The broker, called *Schlouder* [14], has been developped by our team, and our effort to build a simulator of it is called *SimSchlouder*. This co-development approach makes this study original as allmost all the previous cloud simulation software proposed have put forward first the design of their software library, leaving the precise validation to fure experiments. By contrast, we have been able to add all the necessary instrumentation in the broker and in the simulator to help us understand how accurate were the predictions for indivual simulated components, especially for higher level components such as the modeling of VM boot times and the scheduling policies. This continuous analysis has allowed us to fine tune the simulation software.

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. Section 3 presents the design of SCHIaaS. Section 4 describes the system we seek to simulate), which includes the cloud management system Schlouder, the real platforms on which experiments are run, and the applications that serve as test-cases. The last section presents the simulation. It first sketches the main design issues for modeling Schlouder. The second part

[1] SCHIaaS stands for *Simulation of Cloud, Hypervisor and IaaS.*

is a thorough evaluation of the simulation accuracy against real observations on the applications test-cases presented earlier.

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 [12], 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 [10] 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 [15] proposed to address scalability issues encountered with CloudSim (written in Java) for the simulation of large use-cases. Most recently, PICS [9] 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, 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 SCHIaaS

3.1 Overview

The first contribution of this paper is the simulation framework called SCHIaaS, that we propose as an extension to SimGrid to model IaaS clouds. 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 1, 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 [6], 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 [16] or MapReduce applications [11].

In this general picture, SCHIaaS is a new interface upon MSG. SCHIaaS entities use MSG to communicate with the core functions of SimGrid, which handles the operating system level objects, such as network communications, running processes, and virtual machines. SCHIaaS entities are mainly *instances*. We use the term *instance*, as popularized by AWS, to designate the virtual machine when seen from the client side. Accordingly, the SchIaaS API offers cloud level functionalities, that is the operations usually 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. By constrast, SimGrid implements hypervisor level functionalities such as starting or stoping

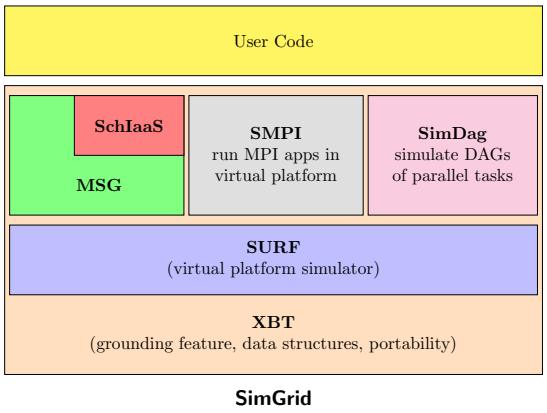

Figure 1: The layered architecture of SimGrid, with the additionnal SchIaaS interface

a VM.

3.2 SCHIaaS's design

Developped in Java, SCHIaaS has been designed as a modular and extensible framework, allowing modelers to plugin their own code in all the key components which model the cloud or application behavior under study. Figure 2 zooms in the SCHIaaS box of Figure 1. It shows the components making up SCHIaaS (in the red box). The boxes with dashed frames indicate that these can be replaced with user-provided code.

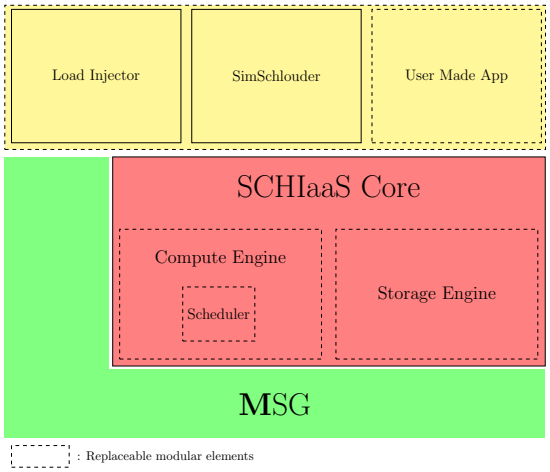

Figure 2: Zoom on the SCHIaaS framework

SCHIaaS Core contains all the management code necessary to set up the data structures corresponding of the cloud described in the configuration file,

and to reflect the effects on the data structures of all the operations triggered though the Compute and Storage engines.

The Compute Engine provides an interface for the management of VMs. It expects an implementation of the way the cloud controller controls the instances, through the definition of start, shutdown, suspend, resume and reboot commands. It also expects an implementation of the scheduling policies used to map instances onto physical machines.

The Storage Engine offers an interface for the management of block storage, through the definition of put, get, delete, and list operations.

In order to model a system SimGrid requires two configuration files:

- a *plaform* file describing the available hardware, including hosts capabilities (e.g number of cores, CPU power) and a description of the network (e.g interconnection topology and network link performances),
- a *deployment* file which maps the applicative processes to some of the hosts described in the platform.

SCHIaaS adds to these a third configuration file to describe one or several clouds. An example configuration is shown in Figure 3, in which the default implementations that come with the SCHIaaS distribution are used. The *storage* and *compute* sections correspond to the storage and compute engines listed above. Each of these component are handled by a *controller* bound to some host in the SimGrid platform file. Implementations of the controller's behavior, that is the storage and compute engine instanciations, appear line 2 and 6. For the compute engine, the specific scheduling policy which computes how VMs are mapped to PMs is implemented in the attached scheduler module line 10. Note that each request that the controller sends to the cluster nodes, be it a simple command or a data transfer, generates network communications that are simulated by SimGrid.

4 Case Study

As mentioned in introduction, handling complex workloads on a distributed computing infrastructure requires scheduling and provisionning tools. In this section, we present the following use case: two scientific applications (one is a bag-of-tasks and the other a workflow) are run on different clouds, and the executions is controlled by a resource management system in charge of resource provisionning and scheduling. This section details this experimental setting, which we have used to collect real execution traces. The paper's goal is to show that we can model this experimental setting and produce accurate simulations of the observed behavior. The way the simulator is build and the evaluation of the simulation is the object of the next section (Section 5).

4.1 Schlouder

The resource management system used, developed by our team, is called *Schlouder* [14]. It is a client-side cloud resource broker which automates the provisioning

```
<cloud id="myCloud">
  <storage id="myStorage" engine="org.simgrid.schiaas.engine.storage.rise.Rise">
    <config controller="controller"/>
  </storage>

  <compute engine="org.simgrid.schiaas.engine.compute.rice.Rice">
    <config controller="controller" image_storage="myStorage"
          image_caching="PRE" inter_boot_delay="10"/>

    <scheduler name="org.simgrid.schiaas.engine.compute.scheduler.SimpleScheduler"
             type="consolidator"
             controller="controller"
             delay="1"/>

    <instance_type id="small" core="1" memory="1000" disk="1690" />
    <instance_type id="medium" core="2" memory="1000" disk="1690"/>
    <instance_type id="large" core="4" memory="1000" disk="1690"/>

    <image id="myImage" size="1073741824"/>
    <cluster id="my_cluster" prefix="node-" suffix=".me" radical="1-"/>
   </compute>
</cloud>
```

Figure 3: An example `cloud.xml` file describing the environment of a given cloud, including the custom java classes used to implement the cloud controller behavior.

of resources needed to execute a workflow, the scheduling of tasks to the provisioned resources and monitors the proper execution of tasks. Schlouder was chosen because we have a deep knowledge of its internals, and hence the capability to finely monitor the execution events, which is a key issue when tracking down the discrepancies between reality and simulation.

Schlouder is actually a frontend which orchestrates the real resource management system of the targeted cloud, sometimes referred to as *cloud kit*, including OpenStack or Eucalyptus, as depicted on Figure 4. Schlouder can be interfaced with all cloud kits accepting the EC2 API. While the cloud kit is in charge of starting or stopping the VMs on the physical machines, tasks execution is monitored using SLURM [17] which connects to the available VMs, sends the jobs, and monitors job's states. 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 a time increment being automatically shut off. While classical scheduling algorithm have long mainly considered the *makespan* minimization as sole objective, Cloud computing adds to the client-side problem statement the economic *cost* of renting the resources as another objective. Hence, provisionning and scheduling is a bi-objective optimization problem. Schlouder makes its decisions based on the workload submitted and some *strategy* specified by the user. A strategy is defined by a provisioning (how much instances to start or stop) and scheduling (when and where assign the tasks) algorithm, and a goal reagarding the cost and makespan objectives. Schlouder provides a few basic strategies and new ones can be trivially added. 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,

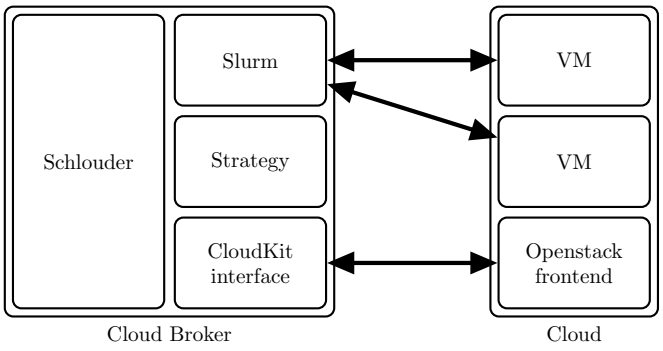

Figure 4: The Schlouder cloud broker and its components relating to an Openstack cloud.

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.

To compute the schedule, 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.

4.2 Hardware Setup

Our case study encompasses both a private cloud with no perturbation from other users and a public cloud which is multi-tenant.

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, two configurations were used overtime. Table 1 regroups configurations of all cloud versions. We will referrer to this cloud as `openstack-icps.`*version*.

Public Cloud BonFire [8] is a public multi-cloud distributed all over Europe. Our experiments were run over three sites of BonFire: de-hlrs based in Stuttgart,

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.

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[2].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.

4.3 The Applications

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.

4.3.1 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 a 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*.

4.3.2 Montage

The Montage Astronomical Image Mosaic Engine [7] 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 5. Working on images Montage is an

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

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.

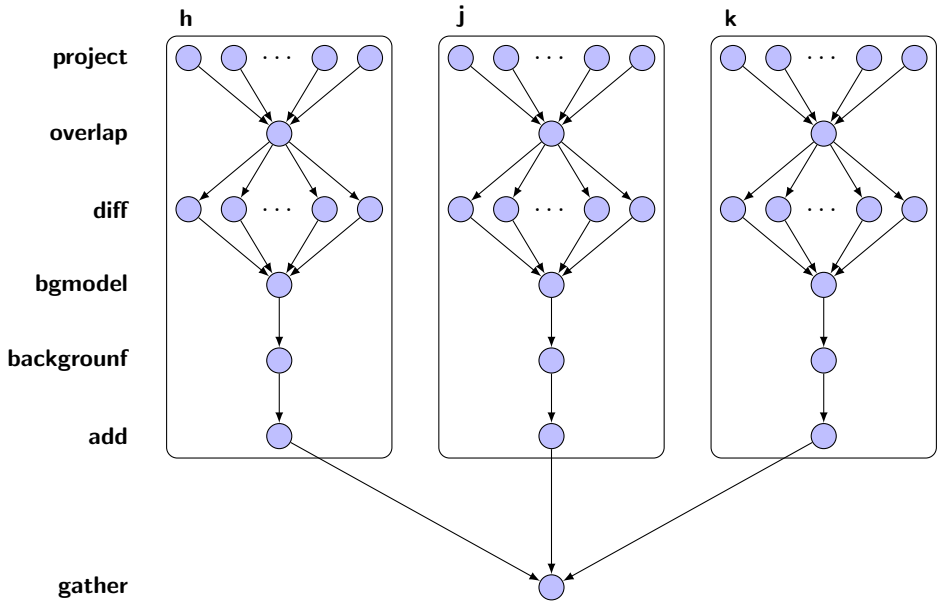

Figure 5: Illustration of the Montage workflow. Each node represents a tasks and each arc represents a data dependency between two tasks. Every task on a specific row run the Montage command indicated on the left hand side of the graph.

5 Simulation

5.1 Using SCHIaaS to simulate Schlouder

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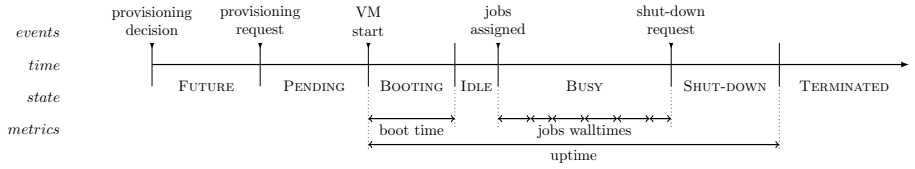


Figure 6: Nodes' states

The actual behavior of a ressource management system in a distributed environment is much more complex than the description sketched in Section 4.1 and on Figure 4. In a real setting, a number of idle periods appear, which can be communications between the controler and the nodes or system delays due

to incoming requests processing. Figures 6 and 7 below show the possible states of nodes and tasks respectively.

For instance regarding the nodes' state, we can evidence from the observations a FUTURE state which is the time between the provisioning decision is computed and the time the controler actually sends the request to the node, this last action being managed in a separate execution thread. Another example is the PENDING state, which is the time between the controler request the node to start a VM and the time the VM actually starts booting on the node. Similarly, a submitted task goes through several steps until it can actually be run on a node: once received by the controler it stays PENDING until it is SCHEDULED on a node, to which is SUBMITTED (involving communication) and evenutally starts on the compute node.

A key question is then: which of those details can be abstracted from our modeling, reflected by the simulator we build, while keeping an acceptable accuracy of the simulation?

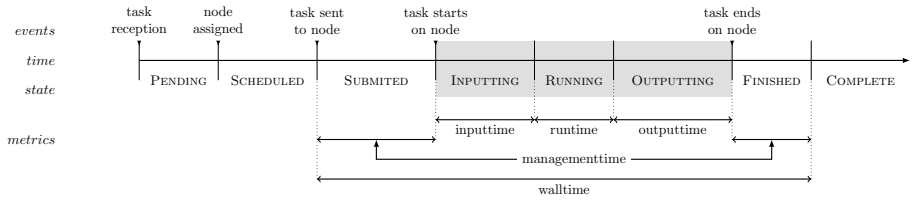


Figure 7: Tasks' states

5.2 Evaluation

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.

The evaluation of the simulation accuracy of such a system is both a complex and tedious task. It is complex because the simple comparison of the observed and predicted walltimes is not sufficient for the experimenter to be aware of which parts of the execution are correctly or wrongly simulated and how much each part impacts the whole simulation. During the process of comparison, the experimenter often has to add extra watch points into the application and re-run the experiment to eventually obtain the relevant measurements. This is a tedious back and forward process which generally increases the number of observed parameters and makes execution log traces heterogeneous over time.

5.2.1 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.

5.2.2 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.

5.2.3 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
-

5.3 Discussion of Results

5.4 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:

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

5.5 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
- 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.

5.6 Simulator accuracy according to platforms and applications

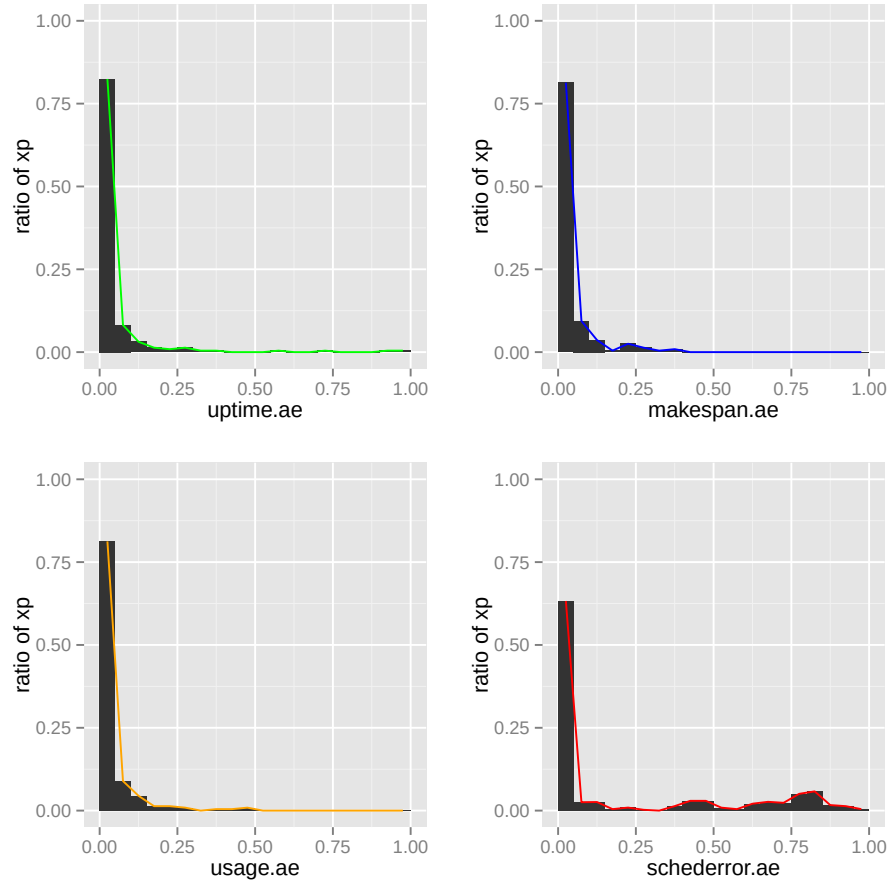
- openstack-icps / omssa (107 xp):

	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



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

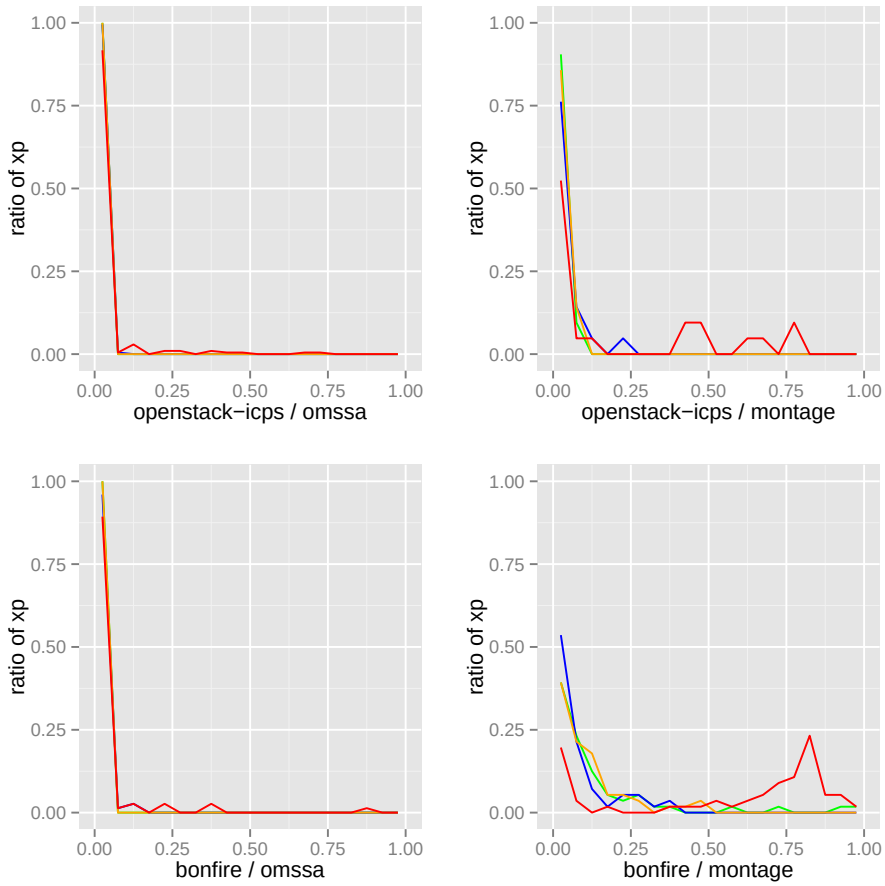


Figure 9: Absolute error frequencies of best simulations according to platforms and applications

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):

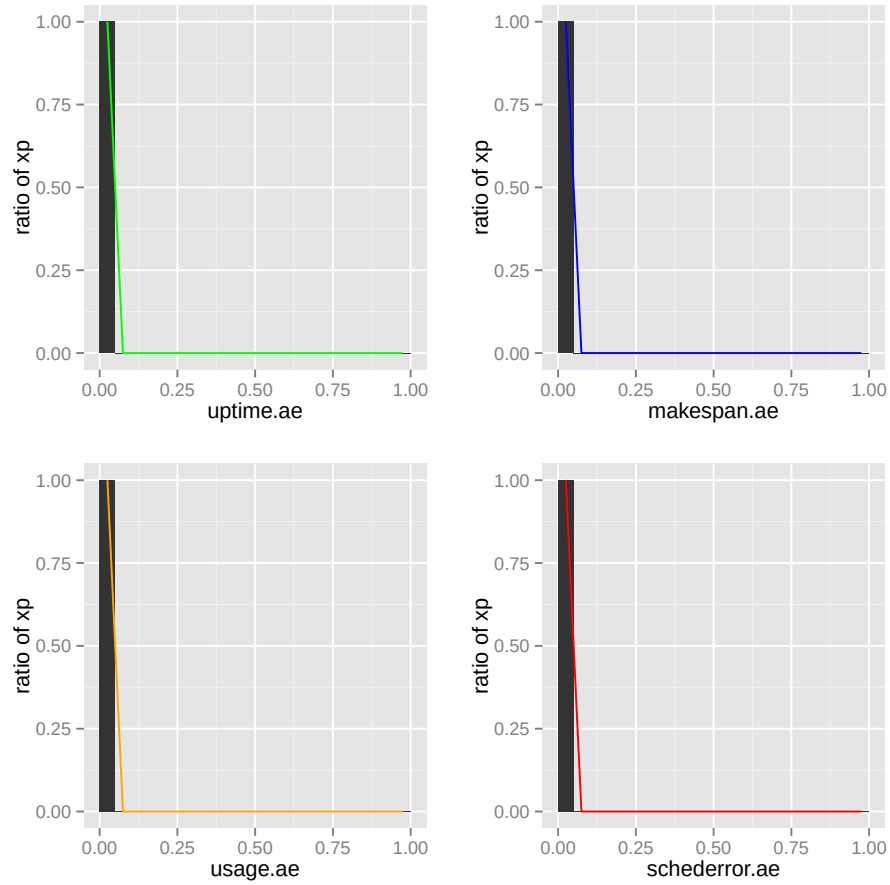
	uptime.ae	makespan.ae	usage.ae	schederror.ae
min	0.000	0.000	0.000	0.000
mean	0.010	0.033	0.018	0.231
median	0.000	0.001	0.002	0.000
max	0.086	0.221	0.079	0.790

	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

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



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

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.

5.7 Boottime impacts

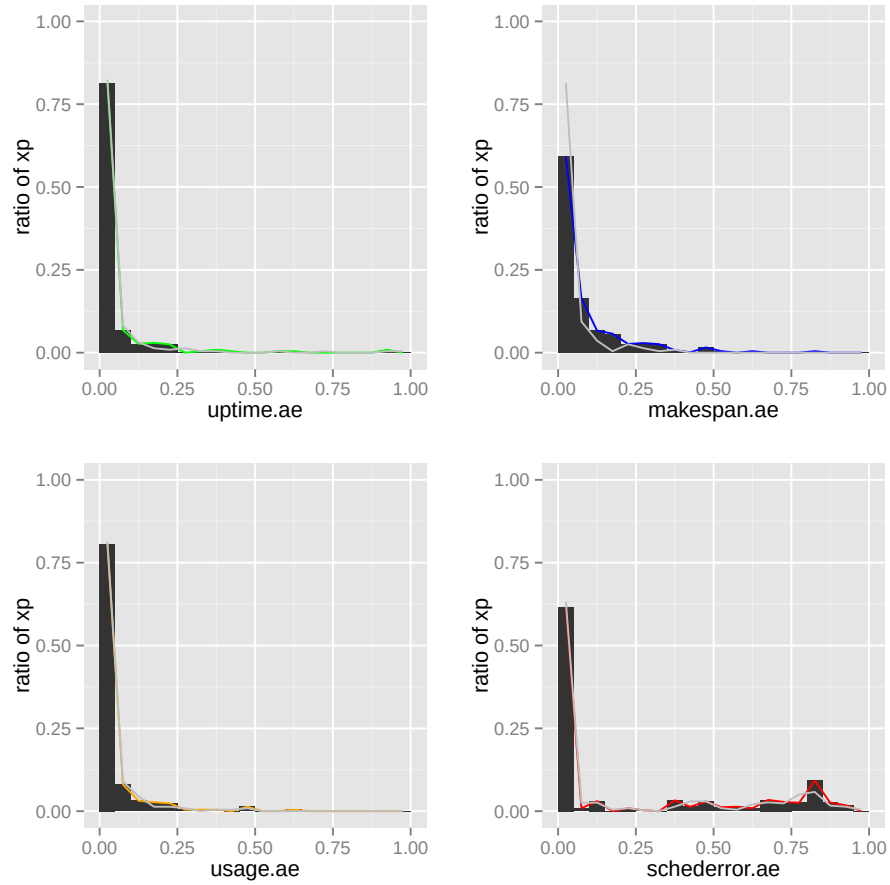
Assessing the impact of efficient boottimes simulation.

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 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.



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

5.7.1 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

5.7.2 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

5.7.3 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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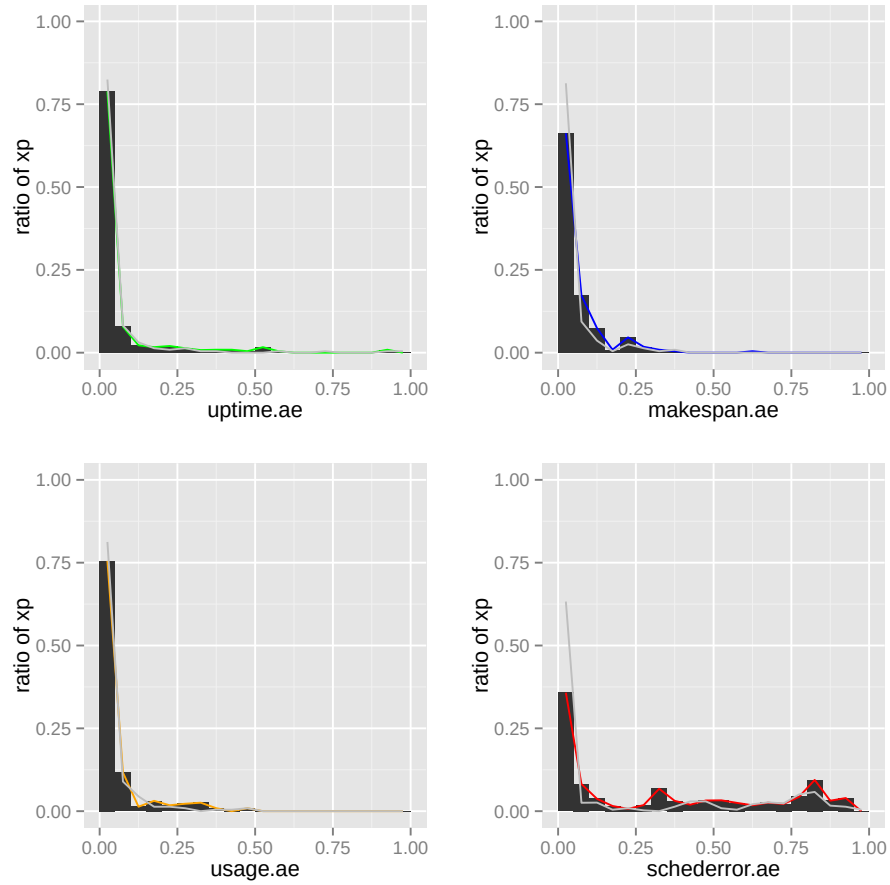
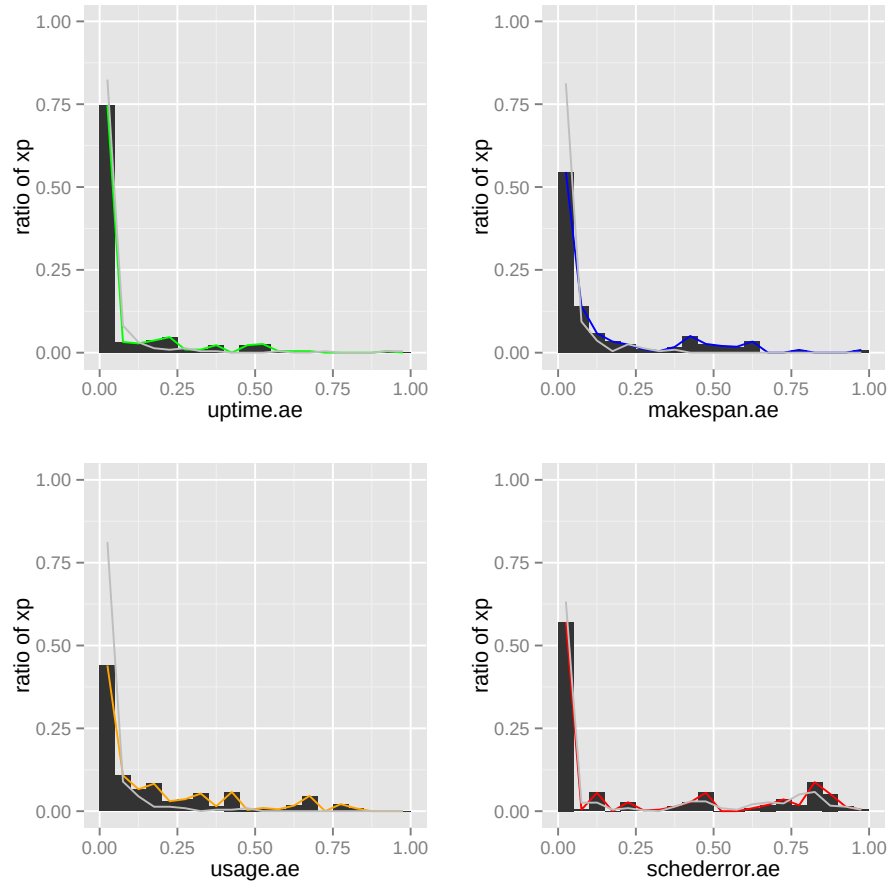


	uptime.ae	makespan.ae	usage.ae	schederror.ae
min	0.000	0.000	0.000	0.000
mean	0.033	0.038	0.029	0.261
median	0.001	0.013	0.002	0.092
max	0.918	0.607	0.479	0.944

	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 12: 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 13: Frequencies, statistics, and comparison with best of simulations with simulation of communications

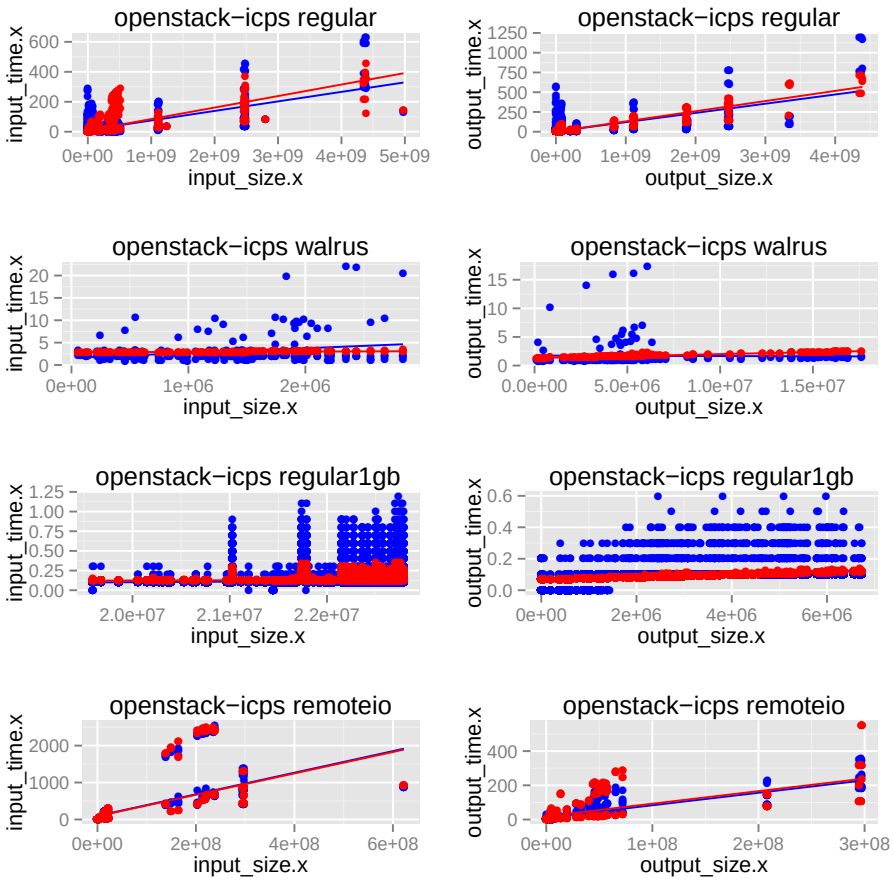


Figure 14: Linear regressions of communication times vs. data size, according to platform, storage, and communication direction on openstack-icps

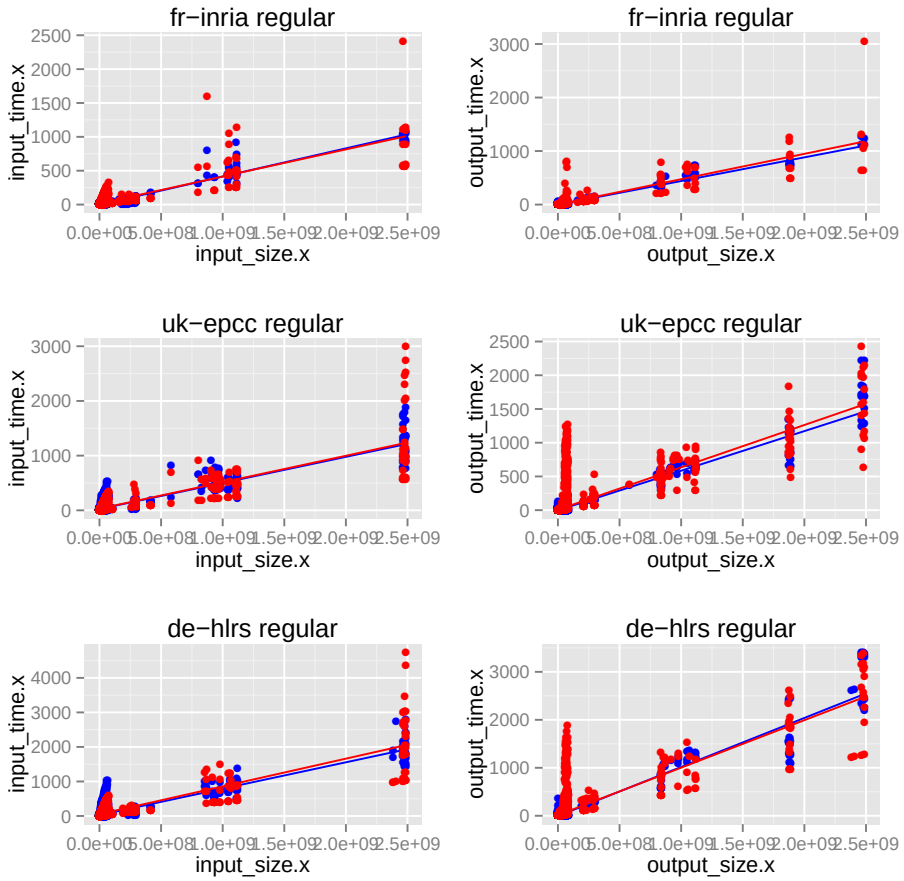
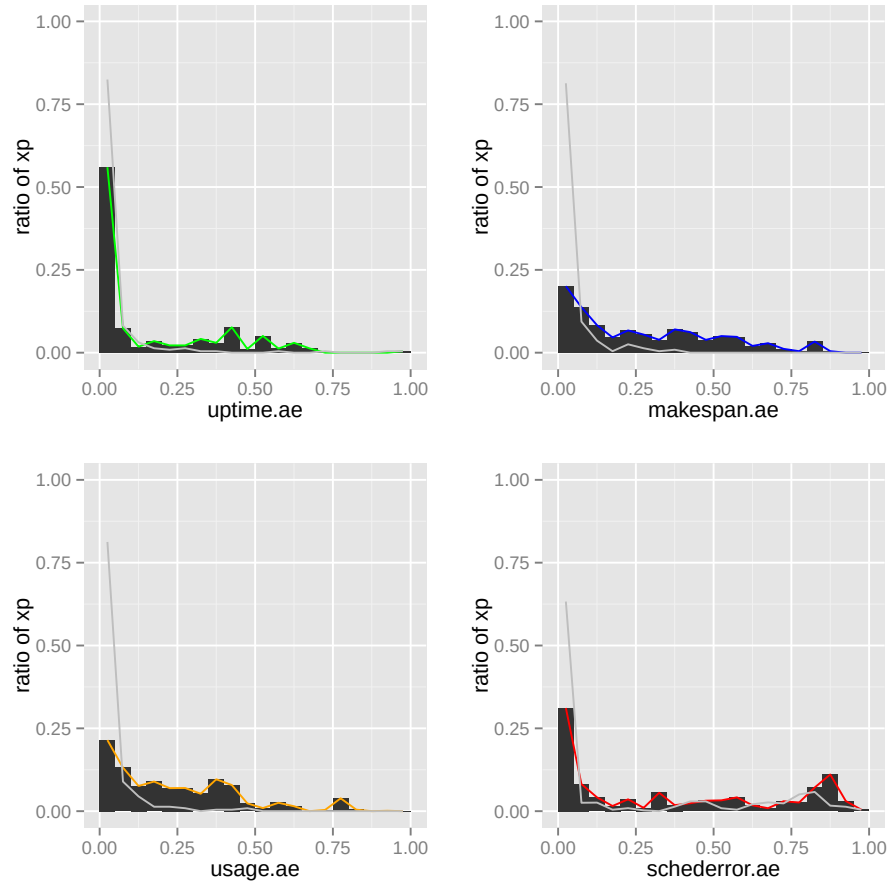


Figure 15: Linear regressions of communication times vs. data size, according to platform, storage, and communication direction on BonFire



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

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