Accessing commercial cloud resources within the European Helix Nebula cloud marketplace

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Abstract. Helix Nebula – the Science Cloud Initiative – is a public-private partnership between Europe’s leading scientific research organisations and European IT cloud providers. CERN contributed to this initiative by providing a flagship use case: the workloads from the ATLAS experiment. Aiming to gain experience in managing and monitoring large-scale deployments, as well as in benchmarking the cloud resources, a sizable Monte Carlo production was performed using the Helix Nebula platform. This contribution describes the Helix Nebula initiative and summarizes the experience and the lessons learned from deploying ATLAS experiment application within large cloud setups involving several commercial providers.

1. Introduction
Helix Nebula – the Science Cloud Initiative – is a public-private partnership between Europe’s leading scientific research organisations (CERN, EMBL and ESA) and European IT cloud providers, that aims to establish a cloud computing platform for data intensive science within Europe. Over the past three years, the Helix Nebula initiative has built a federated cloud framework – the Helix Nebula Marketplace (HNX) [1] – to provision cloud services from a range of commercial cloud providers and public e-infrastructures, such as EGI [2] and GÉANT [3]. HNX delivers access to cloud resources through a broker technology deployed by the Helix Nebula initiative. In addition it aims to comply with EU regulations and legislation to provide trusted cloud services.

CERN contributed to this initiative by providing a flagship use case: integration of Helix Nebula cloud resources within the workload management system of the ATLAS experiment. Aiming to gain experience in managing and monitoring large-scale deployments, as well as in benchmarking the cloud resources, a sizable Monte Carlo production was performed using the Helix Nebula platform. Thousands of concurrent virtual machines (VM) were run for four weeks in order to be comparable with the capacity supplied by a typical WLCG Tier-2 site.

2. Cloud resource provisioning
Figure 1 shows the architecture of the set-up used to provision resources within HNX, to steer ATLAS experiment workflows to the running VMs and to monitor the VM status and usage accounting. For the specific purpose of processing ATLAS Monte Carlo simulation events, the
computing resource required are single core VMs with 2 GB of RAM, 20 GB of free disk space and a public IP address. A worker node image was built and adapted to provision VMs, starting from a native CentOS-6 [5] image that was available in each cloud infrastructure. A minimal amount of packages were installed in order to include repositories and basic services such as CVMFS [6], the XRootD [7] client, the Ganglia [8] monitoring daemon. The experiment related libraries and configuration data are accessed by the applications at runtime through the HTTP-based CVMFS read-only file system. The CERN EOS [9] data storage system was used to access input files and to store output files, exploiting remote data access across the WAN using the XRootD protocol.

The standard ATLAS workload management system was used to run jobs inside VMs. At runtime the provisioned VMs join the HTCondor pool of the Atlas Pilot Factory (APF) [10] and are assigned to a dedicated PanDA [11] resource by means of the ATLAS Grid Information System (AGIS) [12], as all other WLCG resources. Jobs were then submitted to the running VMs by the ATLAS PanDA system.

Within HNX the IaaS of each cloud provider is accessed and managed using the SlipStream API [13] and the related BlueBox Web user interface. SlipStream is a multycloud application management platform that abstracts the difference between cloud service providers such as incompatible APIs and diverse configuration procedures. This approach has been selected by the Helix Nebula initiative to hide cloud IaaS differences and to provide a hybrid cloud model where private and public commercial cloud resources can be accessed seamlessly.

![Figure 1. Architecture of the set-up used to provision resources within HNX, to steer ATLAS experiment workflows to the running VMs and to monitor the VM status and usage accounting.](image-url)
VMs were instantiated and terminated within the cloud IaaSs using the SlipStream abstraction layer. Building on the experience of several existing provisioning mechanisms such as VCycle [14], a dedicated resource manager has been developed in order to interact with SlipStream APIs and automatically deploy, scale up/down, and generally manage the VMs. A system of heartbeats and sensors deployed inside each VM constantly communicates to the resource manager the status of the running services. The information is retrieved from SlipStream leveraging the embedded messaging system between the VMs and SlipStream server. A set of configuration parameters – such as the maximum capacity, the rate of deployed VMs per cycle, provisioning timeouts and heartbeat checks – allow efficiently managing the IaaS resources. The system has proved to be able to handle a load of 3000 concurrently running VMs.

The Ganglia open-source distributed monitoring system has been used to check the status of the VMs at runtime, to detect anomalies and raise alarms about misbehaving VMs. In addition, Ganglia data is a useful source of information for resource profiling and accounting. By design the Ganglia Round Robin Database (RRD) is designed and optimised for real-time monitoring. The stored data retain the highest resolution (15 seconds in this case) only for a short time period (1 hour in this case), after which averages aggregated on longer time windows start to replace the high-resolution data. This approach does not allow storing metrics with the highest resolution for the full period of operation in order to permit a-posteriori accurate data analysis on the information collected. The approach adopted in this investigation consists in periodically extracting the high-resolution data from Ganglia, using the rrdtool library [15] and to store them into a time series database InfluxDB [16]. In addition, a daily backup of the extracted data is pushed into the EOS data storage using structured CSV files.

3. Procurement action

In order to identify the potential contractor able to support the ATLAS Monte Carlo physics simulation jobs at the cheapest price, several HNX cloud providers were considered by means of a price enquiry launched by CERN in December 2014. To establish a comparative cost per event of the Monte Carlo production and to evaluate whether the cloud providers were compliant with the procurement technical specifications, a set of performance tests were conducted during the tender procedure, including the processing of ATLAS benchmark workflows using the Kit Validation (KV) [18] tool. The outcome of the price enquiry was the identification of a single contractor, Atos Canopy cloud [19], leasing up to 3000 VMs as described in the technical specifications reported above.

4. Monte Carlo physics simulation

The Monte Carlo physics simulation is best suited for running in a cloud set-up as it is characterised by a CPU intensive processes, with high CPU over wall-clock time ratio and low I/O from files accessed through WAN (see figure 1). The Geant4 [20] simulation of the particle propagation through the ATLAS detector best fits those requirements. Monte Carlo events simulating LHC proton-proton collisions with t\bar{t} pairs in the final state were used. Those events are characterised by a large multiplicity of particles in the final state and, as a consequence, a long processing time per event due to the large number of particles to be propagated through the detector.

The Monte Carlo production was running during the month of March 2015, with a peak capacity of 3000 concurrent running jobs, one for each provisioned VM. Figure 2 shows a plot of the average number of running VMs per hour. Ramping up and down was performed several

1 For more details about the Ganglia monitoring of cloud resources refer to document [17] in this Journal of Physics: Conference Series volume.
5. Resource profiling

Performance measurements and monitoring are essential for the efficient use of computing resources as they allow selecting and validating the most effective resources for a given processing
workflow. In a commercial cloud environment an exhaustive resource profiling has additional benefits due to the intrinsic variability of a virtualised environment where clients just see the performance of the delivered VMs but may lack information about the overall status of the underlying infrastructure such as the hypervisor, storage or network. Resource profiling via initial benchmarking quickly allows to identify issues and mitigate them. Ultimately it can provide additional information for disputes between provider and client regarding the presumed performance of invoiced resources and the actual performance of delivered.

During the ATLAS computing activity on Atos Canopy cloud resources, all provisioned VMs were benchmarked during their start-up as a precondition for the further running of production jobs. The ATLAS KV engine was adopted for this task. It offers several advantages: it allows running a simulation workflow similar to the production workflow as well as using the same detector geometry and software packages. Through the proper choice of the events to simulate, the overall benchmark processing time can be kept short (few minutes) compared to the lifetime of a VM (days). A sequence of 100 single-muon events has been generated and propagated through the ATLAS geometry. By means of a fixed random seed all benchmark processes run exactly the same sequence of events, reducing the measurement uncertainty due to statistical fluctuations seen using different sequences of events if the total amount of events is small. In addition the collected performance metrics separate the contribution of the first processed event from the other events, removing the influence of the initialisation overhead that, for a small number of events, can be sizable. Finally, the Kit Validation offers an easy installation procedure via CVMFS that simplifies the contextualisation and running in a generic cloud provider.

Around 25,000 benchmark measurements were collected and analysed. As the simulation workloads are mainly CPU intensive, the benchmark analysis has been focussed on the CPU performance in terms of the average CPU time needed to process single-muon event. Figure 5 shows the distribution of the average CPU time per event spent running the KV benchmark in each provisioned VM. The CPU time performance is consistent within a spread of 15%. The benchmark profile appears stable over time apart from few anomalous values measured in the last days of operations. (figure 5(b)).

The resource profiling based on a benchmark has been compared with the effective performance of the VMs in running the \( t\bar{t} \) Monte Carlo simulation jobs. The average CPU time per event spent for each job has been collected from job monitoring Dashboard [21]. Figure 6 shows the average CPU time per event, which peaked at 342 seconds, with a RMS of 34 seconds. In addition the average CPU time per event as a function of the job termination time is also
Figure 5. Distribution (a) of the average CPU time per event spent in running the KV benchmark in each provisioned VM. Uniformity of KV metric for the provisioned VMs as a function of the VM creation time is also reported (b) using a boxplot to highlight the main distribution quartiles and outliers.

Figure 6. Distribution (a) of the average CPU time per event spent in running a Monte Carlo simulation job in each provisioned VM. Uniformity of the average CPU time per event as a function of the job termination time is also reported (b) using a boxplot to highlight the main distribution quartiles and outliers.

By connecting the benchmark measurement for a given VM with the CPU time of each job running on the same VM, it is possible to extract quantitative evidence of correlation between those two independent measurements (see figure 7). The scatter plot and the overlaid profile show the degree of linear correlation between KV benchmark and job CPU time. In figure 7 outliers are also reported. Those data points are related to 48 VMs running in three hypervisors that for a few days were performing abnormally. The outliers are clustered in a separate region of the graph, maintaining some degree of correlation between the two measurements, being roughly 2.7 times larger than the average of each 1-dimensional distribution. The prompt benchmarking of resources therefore provides an advantage with respect to anomaly detection as it can identify abnormal VM performance within a shorter time period than standard jobs. In the example
shown, the anomalous VMs that were performing three times worse than the average behaviour can be identified after around 5 minutes of benchmark testing with respect to the 25 hours for a production jobs.

![Figure 7](image)

Figure 7. A scatter plot of the average CPU time per event spent running a $\bar{t}t$ Monte Carlo simulation job (y-axis) versus the average CPU time per event spent in running the KV benchmark (x-axis). The correlation of the two metrics, with linear fit and fit values, is also shown.

6. Conclusions
During the month of March 2015, a sizable Monte Carlo production of LHC events was successfully performed using the Helix Nebula platform on a commercial cloud provider. Over 3,000 single-core VMs were deployed concurrently and connected to the computing infrastructure of the ATLAS experiment, running simulation jobs for approximately 1 million CPU hours, with a job efficiency of 97%. Around 9 million events were processed. The performance of each individual VM was measured for its lifetime and the results show extremely good stability and agreement with the requested specifications, a part few rare exceptions. Client-side benchmarking and monitoring of the cloud resources proved to be essential for real-time monitoring, alarming, accounting and performance validation. This large-scale production activity demonstrated the usability of commercial cloud providers for the simulation workloads, by integrating components of the WLCG and cloud infrastructures.

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