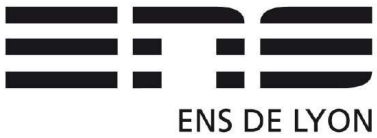
Scheduling on Clouds considering energy consumption and performance trade-offs : from modelization to industrial applications

Daniel Balouek-Thomert

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Ordonnancement sur Clouds avec arbitrage entre la performance et la consommation d'énergie : de la modélisation aux applications industrielles

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A ma mère (et ses bons conseils...)

"Ne reste pas trop longtemps sur l'ordinateur, ce n'est pas bon pour la santé"

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Table of Contents

Abstract

Modern society relies heavily on the use of computational resources. Over the last decades, the number of connected users and devices has dramatically increased, leading to the consideration of decentralized on-demand computing as a utility, commonly named "The Cloud". Numerous fields of application such as High Performance Computing (HPC), medical research, movie rendering, industrial factory processes or smart city management, benefit from recent advances of on-demand computation.

The maturity of Cloud technologies led to a democratization and to an explosion of connected services for companies, researchers, techies and even mere mortals, using those resources in a pay-per-use fashion. In particular, since the Cloud Computing paradigm has since been adopted in companies. A significant reason is that the hardware running the cloud and processing the data does not reside at a company physical site, which means that the company does not have to build computer rooms (known as CAPEX, CAPital EXpenditures) or buy equipment, nor to fill and maintain that equipment over a normal life-cycle (known as OPEX, Operational EXpenditures).

This thesis revolves around the energy efficiency of Cloud platforms by proposing an extensible and multi-criteria framework, which intends to improve the efficiency of heterogeneous platforms from an energy consumption perspective. We propose an approach based on user involvement using the notion of a cursor offering the ability to aggregate cloud operator and end user preferences to establish scheduling policies. The objective is the right sizing of active servers and computing equipments while considering exploitation constraints, thus reducing the environmental impact associated to energy wastage.

This research work has been validated on experiments and simulations on the Grid'5000 platform, the biggest shared network in Europe dedicated to research. It has been integrated to the DIET middleware, and a industrial valorisation has been done in the NUVEA commercial platform, designed during this thesis. This platform constitutes an audit and optimization tool of large scale infrastructures for operators and end users.

Résumé en français

La société moderne s'appuie sur les ressources de calcul de façon intensive. Ces dernières années, le nombre d'utilisateurs et d'appareils connectés a augmenté de façon significative, conduisant à une adoptation de l'informatique décentralisée en tant que commodité, communément appelée "le Cloud".

De nombreux champs d'applications tel que le calcul haute performance (HPC), la recherche médicale, les procédés de fabrication industrielle et les réseaux de capteurs, bénéficient des avancées du calcul à la demande. L'avancement des technologies de Cloud leur a permis de se démocratiser et à conduit à l'explosion de services connectés pour les entreprises, les chercheurs, techniciens et même pour le commun des mortels qui peuvent acheter un accès à ces ressources en fonction de leur usage personnel. Surtout, depuis que le paradigme de Cloud Computing a été adopté par les entreprises. Le matériel qui fait fonctionner le Cloud et qui gère les données ne réside pas physiquement dans l'entreprise qui l'utilise, ce qui évite donc à l'entreprise de dédier ou construire des pièces informatiques, ou même d'avoir à acheter et entretenir des équipements tout au long de leur vie.

Malgré les bénéfices financiers et de fonctionnement, le Cloud peut avoir un impact négatif sur l'environnement en termes de consommation d'énergie. Des résultats récents montrent que la consommation énergétique IT représente 5% de la consommation énergétique mondiale, ce qui soulève des problèmes politiques et environnementaux. L'empreinte carbone générée par l'alimentation et le refroidissement de nombreux équipements tels que des serveurs est prohibitive pour la croissance de cette technologie. A cause de la popularité de cette méthode de stockage, le nombre total de serveurs sur le globe à été multiplié plus de 150 fois en moins de dix ans. D'autres études estiment l'utilisation de ces serveurs à 18% de leur capacité totale, alors que 75% des coûts liés à l'informatique d'une entreprise sont des dépenses énergétiques.

Pour faire face à ce problème d'utilisation abondante d'énergie, il est nécessaire de trouver des ressources informatiques qui prennent en compte l'efficacité énergétique. En particulier, le fait de trop équiper, en prévision des pics de consommation, conduit à la sous-utilisation de ressources le reste du temps, est extrêmement énergivore. Par conséquent, garder des serveurs peu utilisés est un énorme gaspillage en terme de con-

sommation d'énergie. Plusieurs approches peuvent être mises en place afin de résoudre ce problème ; comme par exemple, la conception des installations, l'amélioration des matériels ou encore la gestion des logiciels. Cette thèse propose une approche innovante à ce sujet, en utilisant des trade-offs efficaces du point de vue énergétique sur une plate-forme à large échelle. L'idée clé est de générer un large éventail de solutions et de les utiliser à bon escient afin de satisfaire aussi bien les utilisateurs que les fournisseurs, en fonction des caractéristiques des ressources et des applications. Les évaluations sont faites à partir de simulations mais aussi à partir d'expériences sur des traces d'exploitation réelle de Clouds.

Le focus de cette thèse est le provisionnement efficace des resources et le placement des applications, tout en considérant la volonté des utilisateurs et des fournisseurs de services de réduire leur consommation énergétique. Les travaux de thèse mettent l'accent sur l'implémentation et l'aspect pratique des solutions proposées. La Figure 1 expose une vision simple de ce problème.

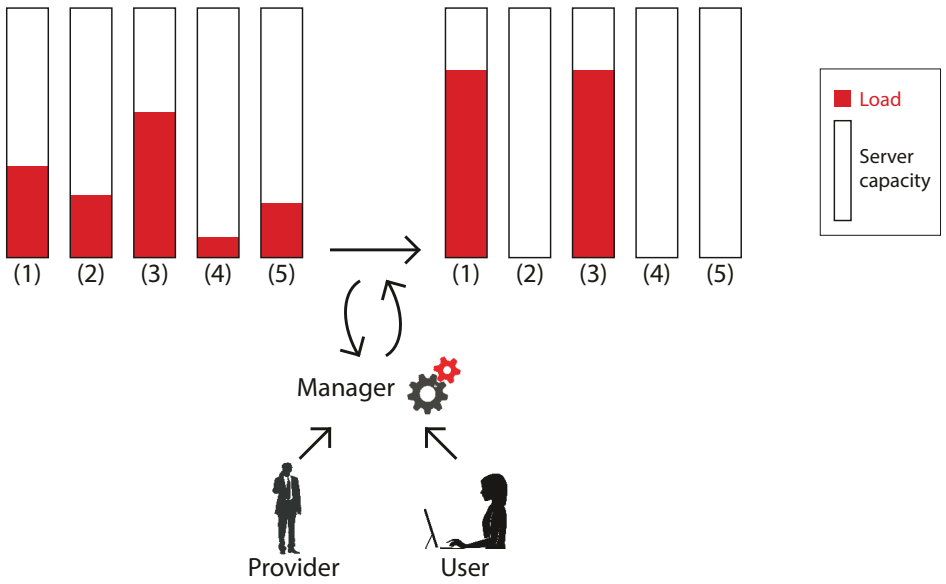

Figure 1: Une schématisation de l'utilisation des serveurs et la visualisation des opérations d'optimisation.

Dans la première configuration, les serveurs sont tous actifs et faiblement utilisés. Dans la seconde configuration, en tirant parti de l'implication des utilisateurs et des fournisseurs, le gestionnaire de cloud execute unepolitique de provisionnement efficace des serveurs dans le but de réduire le nombre de resource active et d'augmenter l'utilisation des serveurs. L'efficacité énergétique de cette petite infrastructure a été amélioré en mettant à disposition les serveurs (2), (3) et (5) pour d'autres usages ou un fonctionnement en basse consommation (veille, extinction).

Cette thèse présente deux applications industrielle des travaux de recherches. Chacune

des applications décrit des contraintes et challengés associés à des cas d'utilisation sur des plateformes Cloud. Un datacenter représente une exploitation intensive de capital pour assurer une continuité de service. Dans ce contexte, la valeur ajoutée de nos travaiux peut-être décrite sur la Figure 2.

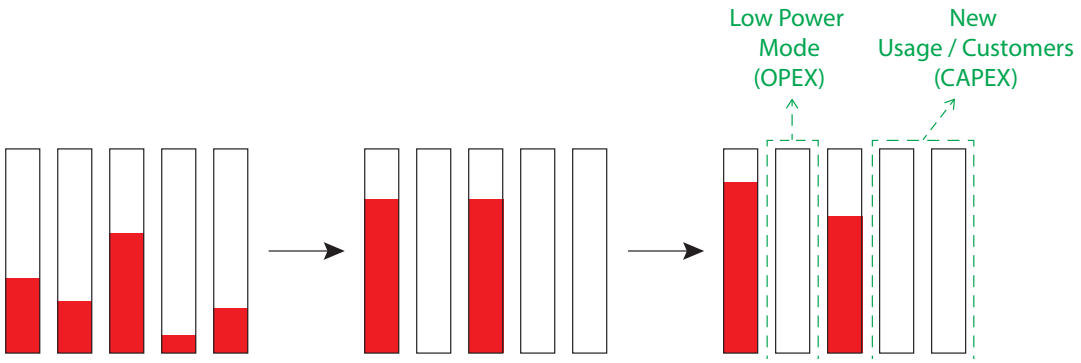

Figure 2: Proposition de valeur ajoutée

Reduction des dépenses d'exploitation (OPEX) Réduire le nombre de serveurs actifs réduit les coûts d'exploitation en influant directement sur la facture énergétique, par la soustraction monétaire des équipements d'alimentation électrique et de refroidissement des serveurs

Réduction du capital d'exploitation (CAPEX) Des serveurs "libres" peuvent être utilisés pour de nouveaux usages clients ou de nouveaux services. Ils peuvent être également utilisés pour des activités internes telles que l'analyse de données et la sauvegarde.

Ethique environemmentale Une utilisation minimale d'énergie promeut à une exploitation responsable, et peut procurer une avantage compétitif

Les chapitres consistuant le coeur de cette thèse sont structurés selon le schéma présenté en Figure 3, et sont principalement issus de publications.

Le Chapitre 2 présente une analyse de la littérature associé aux mesures d'efficacité énergétique et à la gestion de resource dans les Clouds. Cette analyse a permis d'identifier les challenges et verrous technologiques afin de déterminer les directions prises dans la suite du document.

Basé sur cette analyse, le Chapitre 3 décrit la proposition d'une métrique d'évalutation de l'efficacité énergétique d'une resource, indépendamment de toute application. La métrique, GreenPerf, est basé sur la mesure de l'énergie consommé durant la complétion d'un ensemble de service. Cette métrique est extensible en fonction de la quantité d'iinformation disponible. Ces travaux ont été intégrés dans le middleware DIET en

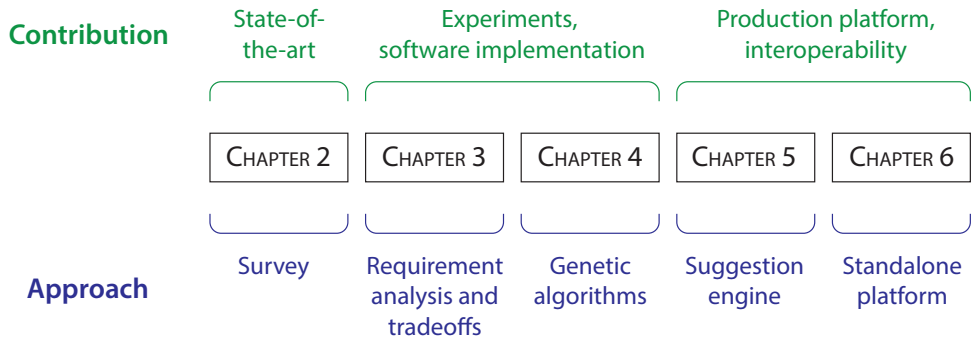

Figure 3: Thesis organisation

tant que GreenDIET, et utilisés pour la création de politique d'ordonnancement basée sur la volonté des utilisateurs et fournisseurs de service d'économiser de l'énergie.

Le Chapitre 4 étant cette approche en utilisant des méta-heuristiques prenant en compte des tâches dépendantes, dit flux de travails (workflows). Nous avons étudiés un alforithme génétique dont la qualité des solutions de placement augemente par itérations successives, mettant en lumière les affinités entre les tâches et les serveurs au regard de la consommation énergétique. La validation de cette proposition a été effectuée sur des traces d'éxécution réelles, avec un réduction signififcative de l'énergie consommé et des améliorations dans la performance globale.

La première application industrielle est décrite dans le Chapitre 5. Le projet nu@ge est motivé par les problèmes de souveraineté des données dans le domaine du Cloud Computing, et preopose l'implémentation d'une fédération de datacenters à taille réduite sur le territoire Français. Notre contribution prend la forme d'un aggrégateur d'information et de contraintes dans le but de sélectionner les meilleurs serveurs de calcul et de placer des machines virtuels à l'échelle nationale.

La plateforme Nuvea constitue la seconde contribution industrielle (Chapitre 6). Cette platforme a été crée selon deux perspectives: une utilisation commerciale au sein de la société NewGeneration-SR en tant que moteur d'optimisation pour la gestion dynamique des infrastuctures de Cloud, et en tant que support de recherche au sein de l'équipe Avalon. Le résultat de ces travaux a été présenté au sein de la communauté scientifique et également intégré à l'offre commerciale.

La gestion des datacenters et des plateformes de Cloud en considérant un arbitrage entre la consommation énégétique et la performance pemettra aux fournisseyrs de proposer des services correctements dimensionner, et ainsi évite une surconsommation énergétique. La recherche dans le domaine de l'efficacité énergétique, telle que présenté dans cette thèse, combiné à des modèles d'exploitation commerciale innovants permettra sans aucun doute des avancées dans le dévellopement responsable des futurs services de calcul.

Chapter 1

Introduction

Modern society relies heavily on the use of computational resources. Over the last decades, the number of connected users and devices has dramatically increased, leading to the consideration of decentralized on-demand computing as a utility, commonly named "The Cloud". Numerous fields of application such as High Performance Computing (HPC), medical research, movie rendering, industrial factory processes or smart city management, benefit from recent advances of on-demand computation.

The maturity of Cloud technologies led to a democratization and to an explosion of connected services for companies, researchers, techies and even mere mortals, using those resources in a pay-per-use fashion. In particular, since the Cloud Computing paradigm has since been adopted in companies. A significant reason is that the hardware running the cloud and processing the data does not reside at a company physical site, which means that the company does not have to build computer rooms (known as CAPEX, CAPital EXpenditures) or buy equipment, nor to fill and maintain that equipment over a normal life-cycle (known as OPEX, Operational EXpenditures).

Despite its financial and operational benefits, the Cloud can have a negative impact on environment in terms of energy consumption [1]. Recent figures calculate IT power consumption as 5% of the global worldwide energy consumption, leading to environmental and political issues [2]. The carbon footprint generated by powering and cooling a large set of servers is prohibitive to the growth of the technology. Following this technology's popularity, the total number of servers on the globe has increased over 150 times in less than a decade [3]. Other studies estimate the average load of these servers to 18% of their capacity, while energy represents around 75% of the total cost of information technologies (IT) infrastructures ownership [4].

To address this concern of high energy usage, it is necessary to deliver computational resources with consideration of energy efficiency. In particular, over-provisioning, caused by dimensioning infrastructures for peak times, leads to underutilized resources the rest of the time, causing an unnecessary consumption of energy. Therefore, keeping servers un-

derutilized is a huge waste from the energy consumption perspective. Several approaches can be considered to solve that matter such as facility design, hardware improvement or software management.

This thesis proposes an innovative approach to this problem by using energy-efficient trade-offs on large scale platform. The key idea is to generate a large spectrum of solutions and use them to involve and satisfy both users and providers, based on the characterization of resources and applications. Evaluations use simulations as well as real experiments on synthetic workloads and real cloud traces. Prototypes were deployed and validated on the Grid'5000 platform. Based on the academic results, production systems have been developed in two industrial projects. This research work takes place in a context of a collaboration between the industrial group NewGeneration-SR[1] and the Avalon research team[2].

1.1 Energy consumption and performance trade-offs on clouds platforms

All Cloud infrastructures offer the same characteristic: they give the possibility to the user to obtain and dispose of the resources on demand and the ability to get access to them from anywhere in the world. Different categories of services exist, based on the model of delivering:

- Software as a Service (SaaS): the Software as Service Cloud enables the duplication of a software, shared by multiple customers. The provider proposes an instance of the code to each user and satisfy requests simultaneously.

- Platform as a Service (PaaS): This type of Cloud offers preconfigured environments to facilitate and minimize the development effort. It advertises scalability and adaptivity compare to traditional application development.

- Infrastructure as a Service (IaaS): IaaS constitutes the basis of Cloud models. One can rent hardware resource without investing in a datacenter and have an infrastructure that fit to their needs and budget. An advantage is the use of up-to-date hardware for the customer without maintenance or renewal concerns.

The proposed work in this manuscript deal with IaaS, where the platform or datacenter presents a pool of remote resources, such as CPUs, GPUs, storage disks, etc. to be booked via a network. It usually involves the following components as shown in Figure 1.1:

[1]NewGeneration-SR is a consulting company oriented on economic development and sustainability.

[2]The INRIA Avalon research team is located in the LIP at the Ecole Normale Supérieure de Lyon. Thematics revolves around Algorithms and Software Architectures for Distributed and HPC Platforms

Users Users can request computational resources as (i) a service (the user will submit data/tasks for a given application), or (ii) a platform (a set of virtual servers or physical servers with minimal installation, mainly for further customization of the software stack)

Access node(s) This is the front-end to the cloud platform, as the recipient of requests. It often exposes an API to demand resource (i.e. the way to formulate requests). Depending of the size and configuration of the cloud, it can be coupled with the manager

Manager The manager operates as the brain of the platform. It contains the information and availability of resources and selects the nodes based on a provisioning policy and/or pricing

Compute nodes These servers read/receive the data, process it and deliver the service. Nodes tend to be grouped in compute farms, and can be virtualized as a "super server" that can be sliced into virtual servers with different specifications of CPUs, memory or internal storage

Storage Cloud storage is always a type of shared storage that can be connected to multiple compute nodes simultaneously. Storage in the cloud can have different features such as redundancy, guaranteed I/O rate or high availability.

In traditional schemes, users request resources based on hardware requirements and specifications. The provider, that owns the resources, put them in place and share information with the manager. Following those, the manager aggregates the designated and available resources and finds the best combination possible to match with the customer needs. From an energy efficiency perspective the appropriate way to perform this mapping is to set a combination of servers that is proportional to the real demand and workload of the application. Methods have been considered to solve that issue. Relying on virtualization technologies, dynamic consolidations allow the live migration of entire systems (packed in virtual machines) from a physical node to another, with the purpose of maximizing the utilization of hosts. Another possibility is brought by the use of hybrid architectures. It implies the use of different hardware devices into one server unit with different ranges of performance and energy consumption along the workload life-cycle. Those techniques are often combined with the transition of unused nodes to low power modes.

However, these approaches are not trivial due to the difficulty of profiling highly variable workload patterns or developed multi-platform applications, and they enable hybrid scheduling, leading to difficulty of adoption among cloud actors. In a context of

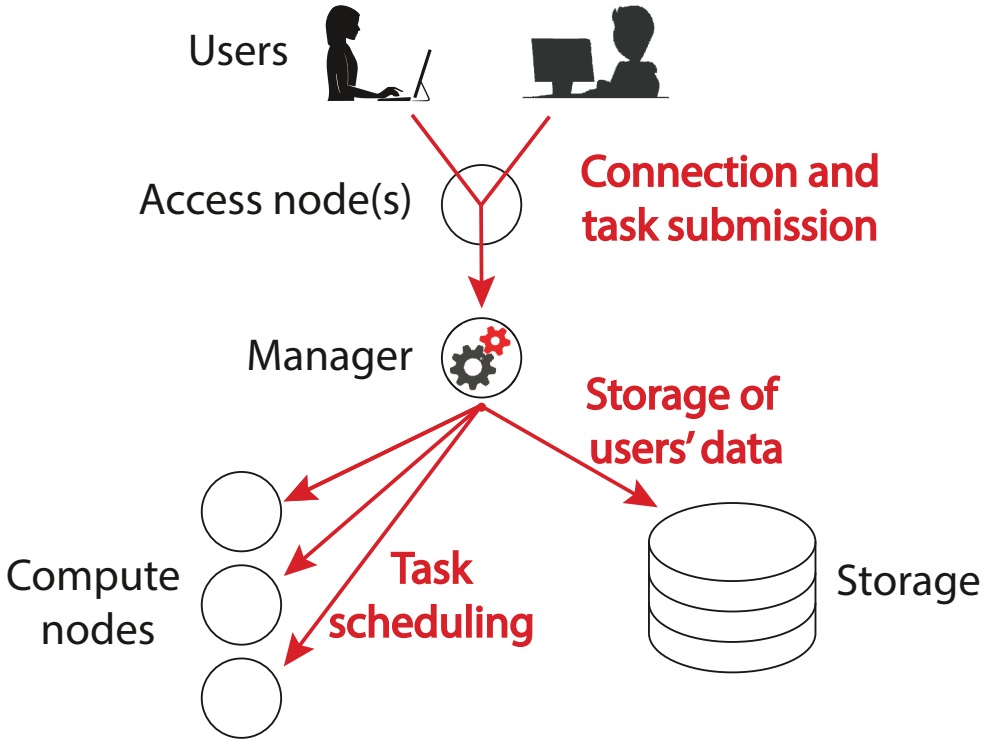

Figure 1.1: User vision of a Cloud platform

on-demand platforms, only a few approaches considers variables related to energy savings into their provisioning schemes.

The scope of this thesis is the efficient provisioning of resources and the mapping of applications while considering users and providers willingness to reduce energy consumption, with an emphasis on the implementation and practicality of the solution. Figure 1.2 expose a simple vision of this problem. On the first configuration, all the servers are active and lightly loaded. On the second configuration, with benefits of user and provider involvement, the manager execute a smarter provisioning scheme to reduce the number of active resource and increase the utilization of servers. The energy efficiency consumption of this small platform has increased as servers (2),(4) and (5) can be used in a better fashion or shutdown. In particular, it is necessary to handle heterogeneous workload since independent users dynamically request resources and execute various types of applications. It means that the resource provider must be application-agnostic.

This thesis focuses on the efficient sizing and provisioning of computational resources with consideration of reducing the target platform's energy consumption and ensuring the performance level requested by customers.

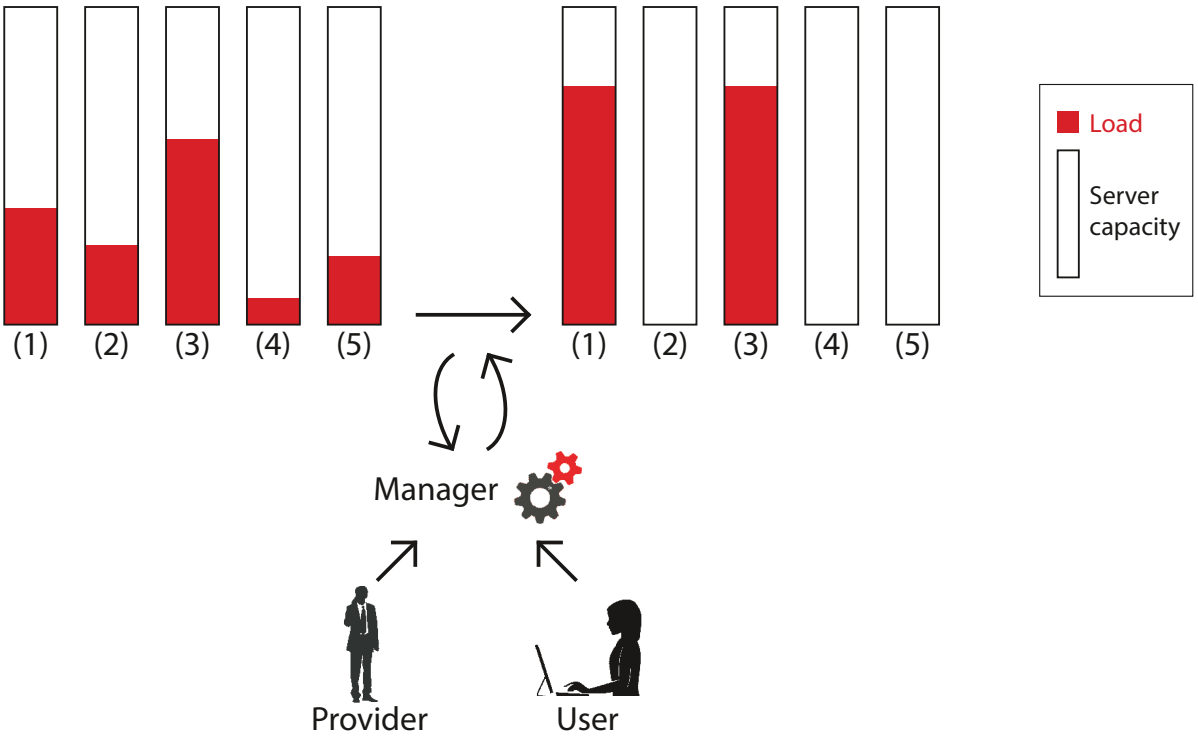

Figure 1.2: A schematization of servers load and visualization of optimization operations

1.2 Industrial impact and strategic stakes

Industrials and companies not only use the cloud technologies for the large amount of resources but, more generally, as a vehicle for growth and transformation.

From the perspective of small businesses, cloud economical models allow to focus on the speed of innovation and compete with larger groups by externalizing the burden of hardware management and maintenance. The reduction of time to market (period of time to propose a commercial offer), reduction of costs and improved collaboration enhanced by connected organization tools are some of the main reasons for a young business to capitalize on a cloud platform. As an example, Netflix is a company offering a subscription service for streaming movies and TV shows. As it needs to support peak demands during the times of highest usage, their Cloud-based model[3] ensure them flexibility on a worldwide pool of customers without the cost of IT ownership.

On the other side, large companies present different needs related to cloud services. They often depends on software solutions and hardware infrastructures that cannot be easily replaced due to past investments and integration into larger organizations. They need to manage the legacy of their strategies while answering the demand of customers and integration of new services.

We can summarize those requirements by a need of consolidation/improvement of ex-

[3]in this specific example, relying on Amazon Web Services

isting infrastructure and a unified access to a distributed infrastructure to start new markets. The critical increase in power consumption of the IT sector is ofter under-considered by the current market situation. The rush for enhanced performance, supported by even more powerful machines, has left many levers for energy management and optimization unexplored. The current market is driven by providers offers but does not allow clients to access to the full premise of cloud computing, therefore, having little knowledge of energy concerns.

The large spectrum of offers and associated vendor locking[4] tends to put customers under a single technology without the ability to reconsider their strategies. In this context, we intend to challenge the existing vendor locking system in the cloud market and ease the adoption of energy efficient software and practices.

In articulation with the research work, we approach this a mult layer problem divided into different ideas:

- Understanding the existing infrastructure and activity of customers
- Creating and offering customizable and non intrusive levers for optimization
- Ease the interoperability to favor market challenges

An emphasis will be put on fast industrial transfer and agile management to enable a circle of innovation close from the reality of market. This strategic vision and the associated objective can be structured under four perspectives, following Kaplan's method [5] presented in Figure 1.3.

The **Learning and Growth** perspective represents the creation of an innovation process. It puts an emphasis on the ability to depict activities and objectives from conception to implementation while building skills and expertise for the team members. The definition of metrics and quality and performance along with the identification of risks allows the fulfillment of business plans and their adaptability to reach the market.

The **Customer** perspective considers the customer needs and their proper characterization. The customer loyalty relies on the success of this process, by understanding and proposing relevant solutions to its business machinery.

The **Internal Business Process** perspective is associated to internal management and collaboration between partners. An efficient organization, in particular between research and industrial partners increase collaboration and feedback, while conceding antagonist goals (academic publication, intellectual property, early communication, etc.).

Finally, the **Financial** perspective takes into account the funding and costs of activities to ensure profitability of the company.

[4]also known as proprietary lock-in or customer lock-in, makes a customer dependent on a vendor for products and services, unable to use another vendor without substantial switching costs.(Wikipedia)

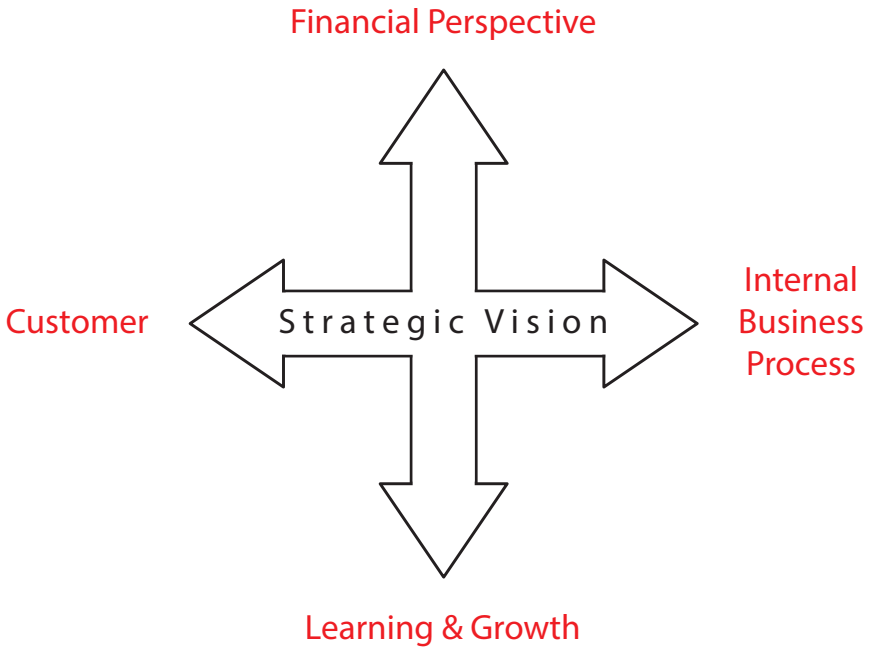

Figure 1.3: Perspectives on the creation of a cloud product following Kaplan's method

This thesis document presents two industrial applications of our research work. Both projects present concerns and challenges related to the existing cloud situations along with management and situations constraints. As a datacenter requires capital-intensive infrastructure to ensure continued operation, the value proposition of this work can be seen as depicted in Figure 1.4):

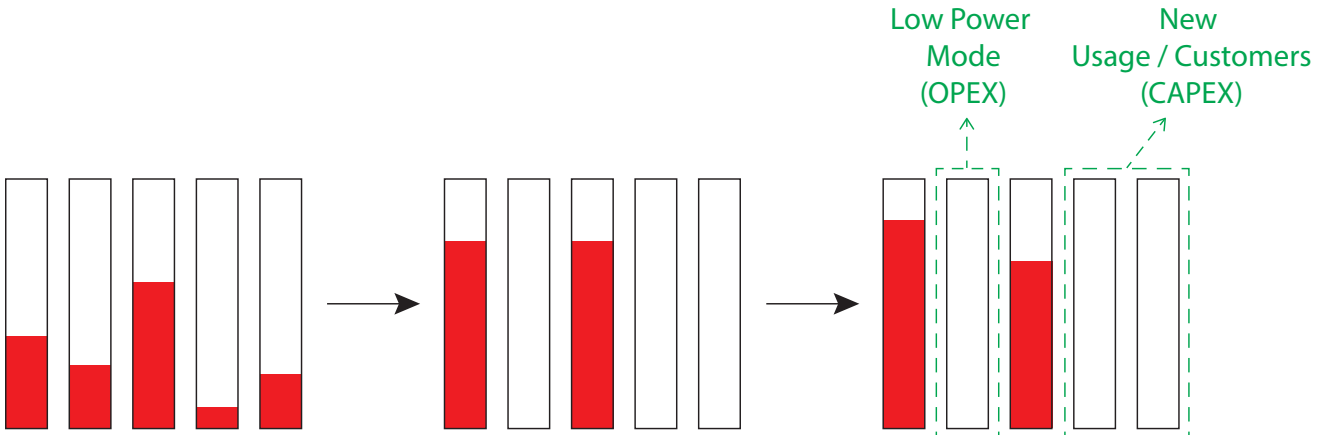

Figure 1.4: Value proposition

Reduction of OPerational EXpenses (OPEX) Reducing the number of active servers saves exploitation costs by cutting on the electricity bill to power servers and cooling systems that remove excess heats from those.

Reduction of CAPital EXpenses (CAPEX) Freed servers can provide extra capacity to sign new customers and develop new services, such as leasing. They can also be used for in-house activities such as backup and data analysis.

Environmental ethic Using as few energy as possible promotes sustainability, and can also create a competitive advantage among the market.

1.3 Problems and objectives

This thesis tackles the research challenges in relation with the energy-efficient scheduling of a set of computing tasks associated to an application or a service on a large scale on-demand platform. In particular, the following research problems are investigated:

How to define an application-independent metric for measuring energy efficiency Applications or services of various types can be executed in the cloud. It is necessary to characterize the behavior of a resource workload execution with an independent metric within a given period.

How to express the willingness of actors to save energy The problem consists in taking into account the context of operation described by the provider (servers availability, energy price, etc.) and the performance level requested by the users to determine an appropriate subset of servers with minimal energy consumption

How to search and express trade-offs in a multi-objective space Balancing actors preferences when scheduling the requests over the physical nodes expresses objectives of contradictory nature. The search and computation of these solutions is a NP-Hard problem, which can be formulated as an optimization problem with multiple contrary objectives: minimizing both energy consumption and completion time.

To deal with the challenges associated with the above research problems, the following objectives have been delineated:

- Explore and analyze the research work in the area of energy-efficient scheduling to understand the current approaches
- Propose a metric to contextualize the behavior of the platform in terms of performance and energy consumption
- Conduct simulations and experimentation using the metric to obtain insights on the design of algorithms for energy-aware resource management

- Implement those mechanisms into an existing middleware for validation with cloud traces and industrialization on production platforms
- Extend the approach to other schemes and the use of third party tools to ease its utilization and adoption in other contexts or within the scientific community.

1.4 Methodology

The research methodology followed in this thesis consists in several consecutive steps summarized below:

1. Conduct theoretical analysis of metrics for energy efficiency;
2. Evaluate the different placement policies in terms of performance loss and energy reduction by executing a synthetic workload;
3. Implement a research prototype based on an existing middleware and the consideration of provider and user preferences;
4. Extend the approach to generate larger spectrum of placement solutions and take into account workloads of mixed demands using a genetic algorithm;
5. Evaluate the prototype with real cloud traces on a testbed;
6. Industrialization on production platforms with an emphasis on open source and interoperable libraries;

1.5 Contributions

The contributions of this thesis can be broadly divided into 3 categories: (i) novel approach for energy and performance trade-offs, (ii) implementation of a framework for multi-objective and under constraints placement, (iii) application to industrial projects and production environments.

1. A state-of-the-art for measurement, evaluation and resource management of energy efficient cloud resources
2. Characterization of resources using an application-independent metric
3. Software implementation of the GreenDIET framework for energy-aware workload placement
4. Novel differential evolution approach for multi-objective scheduling

5. Software implementation of the Nu@ge project scheduler

6. Architecture description and implementation of the Nuvea platform

1.6 Thesis organisation

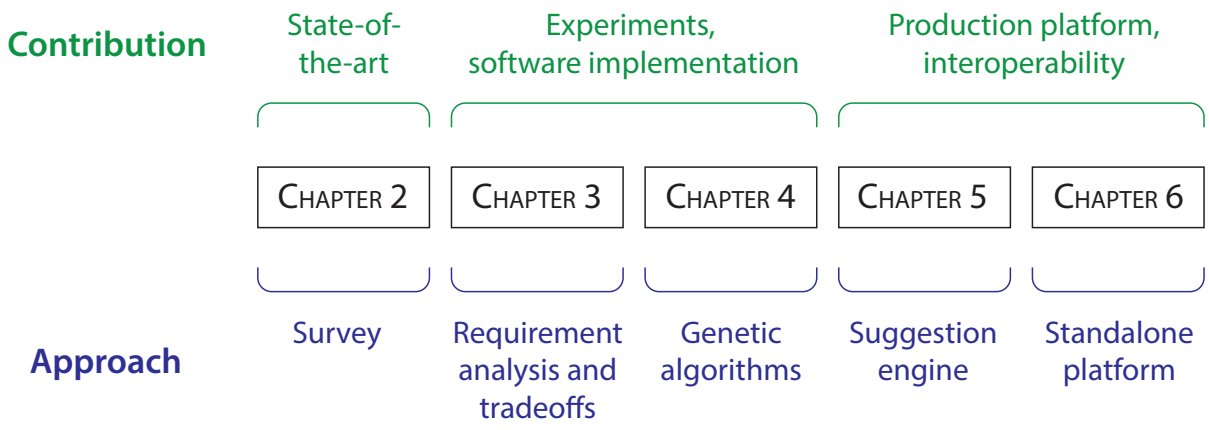

Figure 1.5: Thesis organisation

The core chapters of this thesis are structured as shown in Figure 1.5 and are derived from articles and journals published during the PhD candidature. The remainder of the thesis is organized as follows:

- Chapter 2 gives an overview of the related work for energy efficiency in datacenters.
- Chapter 3 presents the design, implementation and evaluation of GreenDIET, a framework for energy-aware provisioning based on the diet middleware, relying on a metric for energy efficiency.

  Chapter 3 is derived from [6]:

  – Daniel Balouek-Thomert, Eddy Caron, and Laurent Lefevre. Energy-aware server provisioning by introducing middleware-level dynamic green scheduling. In *Workshop HPPAC'15. High-Performance, Power-Aware Computing*, Hyderabad, India, May 2015. In conjunction with IPDPS 2015

- Chapter 4 proposes the use of differential evolution algorithm for a deeper search of trade-offs between energy reduction and performance. This chapter is derived from [7]:

  – Daniel Balouek-Thomert, Arya K. Bhattacharya, Eddy Caron, Gadireddy Karunakar, and Laurent Lefèvre. Parallel differential evolution approach for cloud workflow placements under simultaneous optimization of multiple objectives. In

Congress on Evolutionary Computation (IEEE CEC 2016), Vancouver, Canada, July 2016

- Chapter 5 describes the architecture and implementation of an energy-aware scheduler within the Nu@ge project, a national mesh of container-sized datacenter over the French territory. This chapter is derived from [8] [9]:
  - Daniel Balouek-Thomert, Eddy Caron, Pascal Gallard, and Laurent Lefèvre. Nu@ge: Towards a solidary and responsible cloud computing service. In *CloudTech'2015*, Marrakesh, Morocco, June 2015
  - Daniel Balouek-Thomert, Eddy Caron, Pascal Gallard, and Laurent Lefèvre. Nu@ge : A container-based cloud computing service federation. In *Concurrency and Computation: Practice and Experience (CCPE)*, John Wiley and Sons, Ltd, USA, 2016 (in review)
- Chapter 6 describes the features of the Nuvea platform, dedicated to the evaluation and optimization of cloud platform, along with the technical locks and challenges associated with the projects.
- Chapter 7 concludes the thesis with a summary of main findings, discussion of future research directions, and final remarks.

Part I

Scientific contributions

Chapter 2

Energy efficiency in clouds and large scale platforms

Chapter 1 has presented the scope of this document: we aim at addressing the concern of energy-aware management in a context of resource management and workload placement. This chapter describes existing work from the literature related to this concern.

Datacenters can be seen as complex cyber-physical systems. The on-going activity determine the physical properties such as power consumption and generated heat. Energy efficiency can be considered at different levels: the facility level (physical site or construction that contains the servers) and the server/node level. These two aspects are presented in the first section. We discuss the relevancy of those work and their influence on this thesis orientation.

After discussing the efficiency of resources, we investigate resource management and workload placement. From Grids to Clouds, the placement of services to resources has been well studied. The focus of the study will be put on systems that considers energy consumption when mapping applications to resources.

Finally, we present an overview of the Cloud ecosystem with a list of major providers and their features.

2.1 Measurements and evaluation of energy efficiency

2.1.1 Metrics

The facility represents the datacenter or any room with an aggregation of servers, and often the presence of power supplies and cooling systems. An average data center consumes as much energy as 25,000 households [10].

Several metrics have been proposed and discussed for evaluating the energy efficiency of datacenters [11, 12, 13, 14, 15]. The most influential metrics are presented in the

following section.

PUE Power Usage Effectiveness (PUE) is the most widely used metric nowadays. PUE divides a facility's total power draw by the amount of power used solely by the data center's IT equipment:

$$PUE = \frac{TotalFacilityEnergy}{ITEquipmentEnergy} \tag{2.1}$$

IT Equipment Energy considers the energy consumed by servers, networking devices, storage units and peripheral items. Total Facility Energy includes IT equipment and all data center-related primary electrical systems (power distribution units and electrical switching gear), standby power systems (Uninterruptible Power Sources [UPS]), cooling components, and other infrastructure elements. The closer the value is to 1 (the minimum possible score, all the power provided is used by IT equipment), the more efficient the data center is considered to be: a lower PUE indicates that a greater portion of the power going to a data center is used for its essential tasks and is not going wasted. For example, a PUE of 1.5 means a data center needs half as much additional power as is solely needed for the IT equipment to operate, whereas a PUE of 3.0 means a data center needs twice as much additional power for non-IT elements as it does for IT hardware.

Despite its *de facto* standard in the datacenter industry, one can argue that the PUE has several limitations; namely it can greatly vary depending on:

- IT load: A datacenter might exhibit a lower PUE when under high load, but most of them are not used that way all the time. Plus a high IT load increase power consumption of IT systems but cooling systems do not scale accordingly.
- Different local temperatures outside the DC: The power dedicated to cooling highly systems will depend on location and duration of the tests. A datacenter might exhibit a lower PUE if located in cold areas or if the measure was performed in a specific season.
- Redundancy: High availability can require additional equipments to ensure continuity of service in case of power outages or hardware failures. These equipments would increase the PUE, resulting in an unfair comparison with more simple datacenters.

Hence, PUE needs additional contextual information to perform proper comparison of datacenters [16].

DCIE the Data Center Infrastructure Efficiency (DCIE) is a variant of the PUE as,

where IT equipment power is divided by total facility power:

$$DCIE = \frac{ITEquipmentEnergy}{TotalFacilityEnergy} \tag{2.2}$$

DCIE is expressed as an inverted PUE (Figure 2.1) to obtain a percentage value: For example if a data center's PUE is 1.5, DCIE shows that 2/3 (1/1.5=66 percent) of the data center power is consumed by the IT equipment. DCIE is sometimes preferred to the PUE because increasing values indicate a higher energy efficiency (i.e. higher is better).

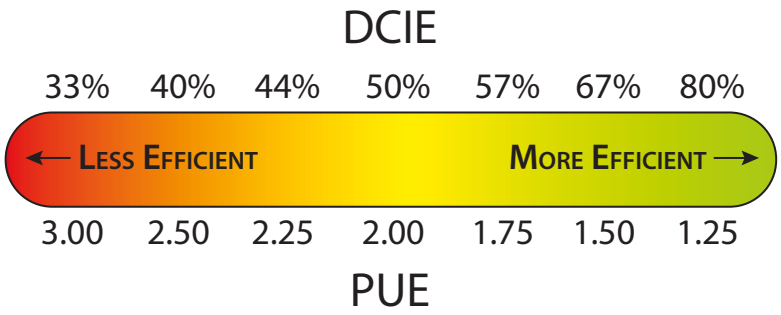

Figure 2.1: Visualization of the PUE and DCIE metrics

DCP Data Center Productivity not only measures the consumption of a data center-related resource, but also quantifies the useful work that a data center produces based on the amount of energy it consumes. In short, DCP tries to define what a data center accomplishes in relation to what it consumes. The formula for DCP is:

$$DCP = \frac{UsefulWorkproducedbydatacenter}{ResourceConsumedproducingthework} \tag{2.3}$$

However, while DCP seems a simple and straightforward metric, it is hard to know what each organization will consider as useful work for a data center, so this makes it a subjective metric, unreliable when comparing different data centers. DCP is more valuable for an operator in order to compare its own lever of optimization or comparing two datacenters executing the same workload.

CADE McKinsey & Co. and the Uptime Institute introduced the Corporate Average Data Center Efficiency (CADE) metric to measure data center performance in a way that encompasses both IT and facilities' technologies. CADE is composed by four elements:

- *Facility energy efficiency:* how much of the power drawn from the electric grid by the data center is being used by IT equipment;

- *Facility asset utilization:* how much of the data center's maximum electrical capacity is in use; IT asset utilization: the average CPU utilization of servers in the data center;
- *IT energy efficiency:* this measurement has not been precisely formulated yet, but is intended to describe how efficiently servers, networking equipment and storage units use the power they are drawing to perform their functions

Combining the first two factors determines the efficiency of the facility; combining the second two determines the efficiency of the IT assets. Each factor is expressed as a percentage and then multiplied by the other:

- FE = Facility Energy Efficiency x Facility Utilization
- AE = IT Energy Efficiency x IT Utilization
- CADE = FE x AE

CADE can be seen as an incentive to increase IT utilization. As the definition of IT energy efficiency has not been precisely formulate yet, it can seems pretty hard to define. We see it as a metric for operational efficiency as removal of unused/old servers or demand management have a direct impact on CADE.

DH-UR Deployed Hardware Utilization Ratio (DH-UR) determines which fraction of IT equipment is not running any application or handling important data. This metric is designed because most IT equipment is always switched on -unless specifically intended not to - regardless whether a given component is doing something important or not. As a result, such 'dormant' equipment can waste significant amount of power during their lifetime. DH-UR can be defined for both servers, as follows:

$$DH\text{-}UR(servers) = \frac{S_{live}}{S_{total}} \tag{2.4}$$

where S live indicates the number of server running live applications and S total indicates total number of deployed servers, or for storage elements as follows:

$$DH\text{-}UR(storage) = \frac{Data_{accessed}}{Data_{total}} \tag{2.5}$$

where $Data_{accessed}$ indicates the number of terabytes of storage holding frequently accessed data and $Data_{total}$ indicates the total terabytes of deployed storage.

DH-UE Deployed Hardware Utilization Efficiency (DH-UE) is a dimensionless ratio that expresses the level of underutilization of servers and storage units. This metric is

designed because, in non-virtualized environments, servers typically run a single application, using only 10-30% of their computing load - a situation commonly known as "server sprawl" [17]. Since servers running at low computation loads often draw nearly as much power as those running at high loads, a large number of such partly loaded servers can quickly consume valuable UPS and HVAC capacity and raise the electricity bill. When the DH-UE is significantly below 1 (the theoretical maximum), implementing virtualization is advised in order to increase the utilization rate. DH-UE for servers is defined as follows:

$$DH\text{-}UE(servers) = \frac{S_{min}}{S_{total}} \tag{2.6}$$

where S_{min} indicates the minimum number of server needed to handle peak computing load and S_{total} indicates total number of deployed servers.

SI-POM The Site Infrastructure Power Overhead Multiplier (SI-POM) determines the amount of overhead a data center consumes to power its critical IT equipment. It is defined as follows:

$$SI\text{-}POM = \frac{P_{DC}}{P_{IT}} \tag{2.7}$$

where P_{DC} expresses the data center consumption at utility meter and P_{IT} expresses the total hardware power consumption at the plug for all IT equipment. SI-POM, proposed by the Uptime Institute, is basically equivalent to the PUE, as it includes all the conversion losses in transformers, UPS, PDU and critical power distribution losses, as well as cooling systems, lights and other minor building loads. The main difference is that SI-POM explicitly mentions "overhead" rather than "efficiency", hence lower values are more intuitively linked to higher efficiency.

H-POM The Hardware Power Overhead Multiplier (H-POM) determines the amount of power wasted in power supply conversion losses or diverted to internal fans, rather than in useful computing power. For a single device, H-POM is defined as follows:

$$H\text{-}POM = \frac{P_{AC}}{P_{DC}} \tag{2.8}$$

where P_{AC} expresses the Alternating Current hardware load at the plug and P_{DC} expresses the Direct Current hardware load before the power supply.

The previously described metric can be generally expressed as a ratio between a useful measure of activity/consumption and its total value. PUE and DCIE are widely popular in the industry. These two metrics are often used as a sales argument when it comes to new facilities. However, their usability and computation is restricted: one need a

fair amount of information that is usually restricted to the manufacturer (equipment specifications, etc.) and the conditions of evaluation (duration, location, effective load) are often hidden. Consequently, in practice, most of the research work focus on the computing units themselves to measure the energy efficiency of an infrastructure.

The second category of metrics focuses on the IT equipment. With regards to the low proportionality of hardware and "server sprawl" concerns, these metrics integrates the utilization rate of resources. Combining DH-UR (portion of active hardware) and DH-UE (portion of hardware necessary to peak periods) promotes good practices in terms of characterization of servers activity regarding the application usage. CADE combines those approaches with the consideration of facility electrical capacity. These metrics do not require additional hardware or software to be computed and data can be fairly easy to come by. It can be possible to compare relative productivity of different datacenter management system using the same application set. The main disadvantage is the relative difficulty to compute them without knowledge of the overlying applications running, in particular, if one has to determine if the cpu utilization of a certain node comes from a dormant usage or a critical operation.

Finally the Power Overhead Multiplier metrics, SI-POM and H-POM, are focused in electric leakages in power distribution and transformers. We consider them manufacturer-oriented as workload placement by software management will have a minimal impact on them.

2.1.2 Node level

Before the raising concerns around energy consumption, the problem of capturing the overall performance of a system has been well studied.

Giladi [18] investigated the FLoating-point Operations Per Second (FLOPS) metric as a measure of computer performance, useful in fields of scientific calculations that make heavy use of floating-point calculations. He used statistical analysis to validate the relevancy of the M(ega)FLOPS metric over different problem sizes and applications. The FLOPS don't consider factors as load (heavy/light load or regular patterns) or the different categories of operations. It is currently use in the HPC field to evaluate supercomputers [19] [20].

Hsu *et al.* compared several metrics in [21] and concluded that the performance-power ratio was appropriate to represent energy efficiency. A metric to aggregate the energy efficiency of all components of a system in a single number has been proposed by Subramaniam et al. [22], using benchmarks which produces different metric as output. Regarding to energy consumption of nodes, several studies indicates that the CPU presents the main consumption of a server [23] [24] [25].

Table 2.1.2 shows the energy consumed by a typical rack server [25].

Component	Peak power	Count	Total	Percentage
CPU	40 W	2	80 W	37.6 %
Memory	9 W	4	36 W	16.9 %
Disk	12 W	1	12 W	5.6 %
PCI slots	25 W	2	50 W	23.5 %
Motherboard	25 W	1	25 W	11.7 %
Fan	10 W	1	10 W	4.7 %
System total		213 W		

Table 2.1: Component peak power breakdown for a typical server

Energy consumption of computing resources can be determined by physical energy sensors (like wattmeters) or estimated by energy models. Deploying energy sensors can present a significant cost and/or encounter space constraints if not done at the time of setting the infrastructure. On the other hand, the use of energy models can ofter interfere with the system they try to estimate [25][26].

A few software utility were developed from the energy consumption perspective. Powertop is a linux tool developed by Intel and whose goal is "find the software component(s) that make a laptop use more power than necessary while it is idle". It uses ACPI[1] and present settings that influence the battery life and discharge rate. Microsoft Joulemeter [27] estimates the power consumption by tracking internal information on different hardware components. The operating system restriction can be prohibitive for customization and experimentation purposes. PowerAPI [28] enables the creation of software defined powermeters through configurable libraries. It requires the knowledge and implementation of energy models by the developer, and is functional for a restrictive set of Intel hardware.

2.2 Resource management

2.2.1 Objectives

In the context of Cloud computing, *resource management* is understood as the process of allocating computing, storage, networking and (indirectly) energy resources to a set of applications [29], in order to jointly meet the performance objectives of applications, infrastructures (i.e., datacenter), providers and users of the cloud resources. An example

[1]ACPI is a standard developed by Hewlett-Packard, Intel, Microsoft, Phoenix Technologies and Toshiba. Its goals are to reduce a computer's power consumption by switching off its components, whereas the operating system manages the power supply of each component.

of typical objective of Cloud providers is the Amazon EC2 service [30], which defines an availability objective of monthly uptime percentage of at least 99,95% for Amazon EC2 within a region.

In addition to management objectives related to satisfying customer Service Level Agreement (SLA), the provider may pursue objectives specifically related to the management of its own datacenter infrastructure. Such objective could, for example, include: *load balancing*, whereby resources should be allocated in a fashion that utilization is balanced across all resources of particular type [31, 32, 33, 34]; *fault tolerance*, whereby resources are allocated in a manner such that the impact of a failure is minimized [35],[36]; or *energy use minimization*, whereby data center resources are allocated in a manner that the amount of energy to execute a given workload is minimized.

This section will focus on techniques that consider *energy use minimization* in the management of the infrastructure.

2.2.2 Virtualization

Virtualization is the most used technique for energy efficiency. A research from Gartner and VMware in 2012 estimates overall adoption rates to be 50-75%. However, despite the wide adaptation of virtualization, the server utilization rate from 2006 to 2012 has remained unchanged between 12 and 18 percent [37] [38].

With virtualization, the computer's physical resources, such as servers, network, memory and storage, are abstractly presented after conversion, so that users can use those resources through customizable virtual machines. Live migration refers to the process of moving a running virtual machine or application between different physical machines without disconnecting the client or application. Memory, storage, and network connectivity of the virtual machine are transferred from the original host machine to the destination.

Early work by Orgerie et al. [39] proposed energy-aware framework using ON/OFF models combined with prediction solutions. The described solution act as an overlay to usual Cloud manager to aggregate resources reservations and apply green policies while avoiding frequent ON/OFF cycles. Stoess et al. [40] proposed a framework for energy management on virtualized servers using power limits dictated by a power generator or thermal constraints. Beloglazov [41] rely on virtualization using a threshold-based approach to perform live migrations as a host gets under/overloaded and consolidate virtual machines on a minimal number of hosts, thus reducing energy by shutting down the others. In [42], authors uses soft scaling and server consolidation to minimize energy under performance constraints. Garg [43] leverages heterogeneity of hardware to minimize CO2 emissions while considering the profit of the provider. While those works are only considering CPU, Kumar et al. [44] take into account CPU, RAM and network to minimize

power under performance and budget constraints based on Dynamic Voltage Frequence Scaling (DVFS). Other works proposes to increase energy proportionality by considering placement on hybrid processors depending on the effective load of applications [45].

2.2.3 Multi-objective optimization

Several approaches using multi-objective optimization to manage workload placement are present in the literature [46, 47]. Objectives refer to load balancing [48], load prediction or platform reconfiguration [49], among others. A Pliant logic approach is used in [50] to improve energy efficiency in simulation based experiments. The authors conclude with the need to find trade-offs between energy consumption and execution time for optimization. Although most of the above works deal with workflow scheduling on Clouds using Multi-Objective Evolutionary algorithms, they have not explored the parallelism potential of the Cloud infrastructure in the scheduling process itself. One of the first developments in that direction is seen in [51], where a Genetic Algorithm is used for optimization and Dynamic Voltage Scaling to minimize energy consumption. A comprehensive review of the state of the field is presented in [52]; work on parallelism of Differential Evolution algorithms in this context is yet to be reported.

In Chapter 4, we propose the design, implementation of a differential evolution algorithm for workflow placement on heterogeneous resources. Evaluation is performed on a real life testbed and considers the CPU, disk and network resources described in a cloud trace. More details about evolutionary heuristics are also presented.

2.3 Cloud Ecosystem

2.3.1 Providers

There exists several surveys on cloud providers [53] [54]. Table I shows a classification of the current major public IaaS providers. The list of providers, extracted from [55], is by no means exhaustive, but it includes current major players in the European and North American markets. Most Cloud providers operate according to their own models and protocols. This problem can lead to vendor lock-in and restrict the transition and interoperability across providers [56]. Furthermore, the headquarters and datacenters location columns show that most providers are based in the USA while only a few are based in Europe.

A means to avoid vendor lock-in is to use open IaaS stack such as OpenStack [2] or VMWare vCloud [57], for creating and managing infrastructure cloud services in private, public, and hybrid clouds.

[2]Openstack, https://www.openstack.org/

2.3.2 Federations

The Cloud federation approach [58] aims to resolve issues of both providing a unified platform for managing resources at different levels and abstracting interaction models of different cloud providers. Several European projects are providing stacks and/or adaptation of cloud-based systems at IaaS levels. Contrail [59], [60] aims at solving the vendor lock-in problem by allowing the seamless switch among cloud providers. InterCloud [58] is a federated cloud computing environment that aims at provisioning application in a scalable computing environment, achieving QoS under variable workload, resource and network conditions. In the Reservoir project [61], the authors propose an architecture for an open federated cloud computing platform. In such architecture, each resource provider is an autonomous entity with its own business goals. Celesti et al. [62], proposes the Dynamic Cloud Collaboration, an approach for setting up highly dynamic cloud federations. A distributed agreement must be reached among the already federated partners to dynamically federate a new provider.

Chapter 5 and 6 presents applications of our research work on industrial use cases.

Provider	Headquarters	Datacenters location
Amazon AWS	USA	USA, Brazil, Ireland, Japan, Singapore, Australia
AT&T Cloud	USA	USA
Google Compute Engine	USA	USA, UK
Hosting.com	USA	USA
GoGrid	USA	USA
Microsoft Windows Azure	USA	USA, Ireland, Netherlands, Hong Kong, Singapore
Rackspace	USA	USA, UK, Hong Kong
OpSource	USA	USA, France, UK
Terramark	USA	USA, Canada, Brazil, Colombia, Dominican Republic, Belgium, France, Germany, Ireland, Italy, Luxembourg, Netherlands, Spain, Sweden, Turkey, UK, China, Japan, Singapore, Australia
Softlayer	USA	USA, Netherlands, Singapore
Aruba Cloud	Italy	Italy
CloudSigma	Switzerland	Switzerland, USA
Gandi	France	France, USA
GreenQloud	Iceland	Iceland
Lunacloud	UK	France, Germany, Latvia, Portugal
CloudWatt	France	France
Numergy	France	France

Table 2.2: Major Cloud providers with location of their infrastructure.

Chapter 3

GreenDIET: A framework for energy-aware scheduling considering providers and users tradeoffs

3.1 Introduction

The chapter proposes a metric for evaluating the energy efficiency of resources by establishing a relationship between the performance of hardware and its energy consumption for a specific application. Next, the expression of user and provider preferences are described. We aim at offer the ability to express levels of performance between energy consumption and performance when allocating resources.

Then, this Chapter presents the design of an energy-aware framework for resource management, that provides control for informed and automated provisioning an the scheduler level. The framework provides developers (administrator or end-user) with an abstract layer to implement aggregation and resource ranking based on contextual information such as infrastructure status, users preferences, and the energy-related external events that can occur over time. The validation is twofold: (i) proving the relevancy of the metric by the means of simulations and (ii) scheduling tasks on a cluster using different scheduling policies to demonstrate the applicability of the solution.

This work differs from the prior literature in the way the system and user involvement are modeled. Rather than implementing a complete manager, we focused on a framework-like approach with an emphasis on the use of customization. The design of the metric and modelization of preferences were project-driven in answer to the problematic of the Nu@ge project, described in Chapter 5. In this context, the framework is at the intersection of highly heterogeneous set of resources: complete datacenters, clusters with restricted-access, cloud front-ends, etc. Therefore, a need for a simple metric is needed to perform global decisions on all resources. This approach can be used within a cluster to determine

the best node or at the federation level to choose the best datacenter and delegate the problem to the local scheduler.

In the definition and analysis of the problem in this Chapter, it is assumed that all resources present a measure or an estimation of energy. Although this assumption may not be satisfied for all types of real-world workload, we assume that the applications are request-based with a sufficient enough number of request to study fluctuations of workload. This hypothesis models a cloud platform where multiple independent users execute identified tasks, and the provider is not necessarily aware of the computational nature of the service.

3.2 GreenPerf

The resources were tasks are computed present a significant impact on the overall energy consumption. Applications can require different demands, often leading to an application-dependent energy efficiency of resources.

Additionally, many works assume that nodes from a homogeneous cluster have the same power consumption. In practice, due to their different uses, fluctuations caused by the external environments or even power leakage , nodes can present different ranges of performance and energy consumption over time compared to their specifications, thus we propose a metric taking into account a dynamic monitoring of resources. In this context, the energy efficiency of a node will be highly dependent on the workload that is submitted.

It appears necessary to base the scheduling of independent tasks of resources on the live behavior of the node and adjust decisions on the fly.

We propose a metric for the sorting of available computing nodes according to a hybrid of their electric consumption and a secondary parameter, the performance of the node.

Following the study in Chapter 2, we observed that most of the metrics require a complete hand on the facility exploitation metrics to be compute. In a project-driven study, where nature of resources are not guaranteed, we need to be able to measure energy efficiency with minimal information.

Assuming that power consumption and performance are able to be gathered at all times, we propose the usage of a ratio reflecting the power effectiveness of a server related to a specific set of requests. GreenPerf is defined as:

$$\frac{\text{PowerConsumption}}{\text{Performance}} \tag{3.1}$$

where $PowerConsumption$ is the measured energy during the completion time of a set r of requests and $Performance$, a unit of completion for an application. We consider

Performance as a number of tasks or requests completed. The lower the value, the more efficient the server is considered to be for that application. Within a comparison, a lower value indicates that a larger amount of work is performed for the same amount of energy consumed. The computation of the metric implies a "bootstrap" phase, where all the servers receive a fix amount of requests. Then, GreenPerf is computed to establish a ranking of nodes and favors energy efficient servers. Table 3.1 describes the behavior of 5 servers offering the same image conversion service within a fixed period of time. Considering only the energy consumption, S4 may be considered the best server of the cluster. If one reports the service completion, S2 appears to be the server according to GreenPerf and the most energy efficient.

Server Name	**Completed requests**	**Energy Consumption**	**GreenPerf**
S1	50	213	4,26
S2	65	118	2,72
S3	50	260	5,2
S4	13	97	7,4
S5	55	190	3,45

Table 3.1: Example of GreenPerf computation with a request-based service executed by 5 servers

The amount of information needed to benchmark the servers and compute the metric can be determined in two ways: (i) time based by re-evaluating the ranking of servers every given unit of time or (ii) request based by considering the re-evaluation every time a server completes a certain number of requests and record that value.

The definition of GreenPerf is inspired from the DCP and the Performance Per Watt metrics. The DCP metric (described in Chapter 2) is expressed as:

$$DCP = \frac{UsefulWorkproducedbydatacenter}{ResourceConsumedproducingthework} \tag{3.2}$$

It is known as a subjective metric in the datacenter community because of the difficulty to quantify useful work in a facility. GreenPerf relies on the notion of requests linked to an application to quantify the amount of work performed. It can be seen as an application of DCP at the server level. However, GreenPerf can also be applied using application that can be quantified in terms of operations, in particular with floating-point operation per second (FLOPS). Using FLOPS as the performance, it becomes a variant of the performance per watt metric. It literally measures the rate of computation that can be delivered for every watt consumed. Other criteria exist in the literature, involving the

consideration of idle consumption [63] or the use rate [64] of the physical nodes.

When discussing GreenPerf, the pros are:

- There is no need of additional software or hardware to compute it under different management systems. It relies straightforwardly on the monitoring of resource. The same scheme can be apply to any kind of devices present in the infrastructure, not only computational servers.

- It can be used to compare the relative productivity of different datacenters with the same application sets.

Green Perf presents disadvantages as it does not comprehend the portion of resources that is not directly tied to the application performing the useful work (i.e. operating systems, management agent, ...). An approach to subtract that cost would be to execute some benchmark on all nodes and measure the idle consumption on each node. The method can induce an extra complexity and is not significant for long period of times. We recommend a more dynamic approach based on the recent behavior of the node.

3.3 Expression of user and provider involvement

Most of the Cloud decisions and optimizations are executed in an automatic fashion, without taking the actors (users and providers) into consideration. By considering that the sizing and selection of resource must balance the actors requirements , we propose an approach that provides users and providers with an easy way to participate in energy-aware decisions. Applications or virtual machines are black boxes from the cloud provider perspective. So, the user is the only one to express its preference related to the behavior of the application. Given that the Cloud provider offers him different types of servers, he could accept to gave slower (less powerful) resources to save energy. This constitutes a lever for energy minimization, and an early step towards a pay-per-energy-consumed cloud. A few energy-aware economical models starts to be proposed to save energy [65] or use renewable sources [66]. This section presents the modelization of providers and users preferences.

3.3.1 Provider Preference

The targeted providers are administrators managing server provisioning in a datacenter. In the context of the Nu@ge project (Chapter 5), administrators of container-sized datacenters have knowledge of electricity price and schedule, as contracted with the electricity provider. Historical data is also often known via logs and monitoring systems.

This can be used to establish resource forecast by identifying usage patterns and ensure the responsiveness of the platform during peak periods.

We use two variables to model the provider preference as a weighted average between resource usage and electricity cost. Other factors can be easily integrated based on the nature of the available data. Equation 3.3 presents the expression of provider preference.

Let $c, u \in [0, 1]$ for each time period:

$$Preference_{provider}(u, c) \rightarrow \alpha(1 - c) + \beta u \tag{3.3}$$

where c is the cost of electricity define as a ratio between the cost for a given period and the theoretical maximum cost. u represents the resource utilization defined as a ratio between the energy consumption over a given period and the total consumed energy. u can be extend (or replaced) by the metrics CADE, DHUE ou DHUR, described in Chapter 2. α and β represent weighting factors as integer values representing the importance of its respective metric compared to another.

We obtain a $Preference_{provider}(u, c) \in [0, 1]$. By adjusting the weighting factors α, β, one can favor a specific metric. The higher the value of $Preference_{provider}(u, c)$, the larger the number of available servers for a time period.

One can also establishes predefined behaviors based on the value of $Preference_{provider}$

3.3.2 User Preference

We offer the user the ability to indicate how his/her application is to be executed. Its interest in the consideration of energy efficiency is defined as $Preference_{user}$. It can be seen as slider (Figure 3.1) between different modes, which is set during request submission as

$$Preference_{user} \begin{cases} -1 & : \text{maximize performance} \\ 0 & : \text{no preference} \\ 1 & : \text{maximize energy efficiency} \end{cases} \tag{3.4}$$

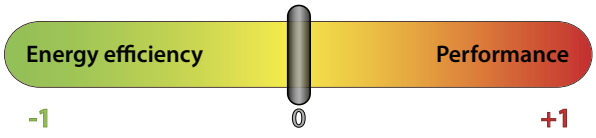

Figure 3.1: Preference of User as the choice between two modes of preference: energy efficiency and performance. The absence of choice leaves it to a neutral mode, without any preference.

Under $Preference_{user} = 1$, a user agrees to an energy efficient mode with resources presenting the lower value of GreenPerf, meaning that servers will present the best

$\frac{\text{PowerConsumption}}{\text{Performance}}$ value. As the metric is dynamically computed over the recent requests, it is guaranteed to be power efficient, not necessarily energy efficient.

Under $Preference_{user} = 0$,the user does not present any influence over the provisioning process.

$Preference_{user} = -1$, the user indicates a preference for the most powerful nodes with no regards of energy consumption.

The remainder of this Chapter presents the DIET middleware, and then describes the integration of the GreenPerf metric in the scheduling engine. Validations are performed by the means of simulations and real task placement.

3.4 The DIET middleware

3.4.1 Overview

The DIET open-source project [67] is focused on the development of a scalable middleware with initial efforts relying on distributing the scheduling problem across a hierarchy of agents. It is implemented in CORBA[1] and benefits from the many standardized, stable services provided by freely-available, high-performance CORBA implementations.

The DIET toolkit present several features:

- Data management
- Task migration
- Cloud capabilities
- Fault tolerance
- Replication of agents
- Workflow execution support

It has been applied validated in different contexts [68], in particular when it comes to scalabilty and ability to be extended. A DIET service consist of the encapsulation of a computing service or program with its input/output parameters and its declaration on an infrastructure to enable remote queries.

The DIET toolkit is composed of several elements, illustrated in Fig. 3.2. The first element is a **Client**, an application that uses the DIET infrastructure to remotely solve problems. The second element is the **SeD** (**Server Daemon**) which acts as the service

[1]The Common Object Request Broker Architecture (CORBA) is a standard defined by the Object Management Group (OMG) designed to facilitate the communication of systems between systems on different operating systems, programming languages, and computing hardware.

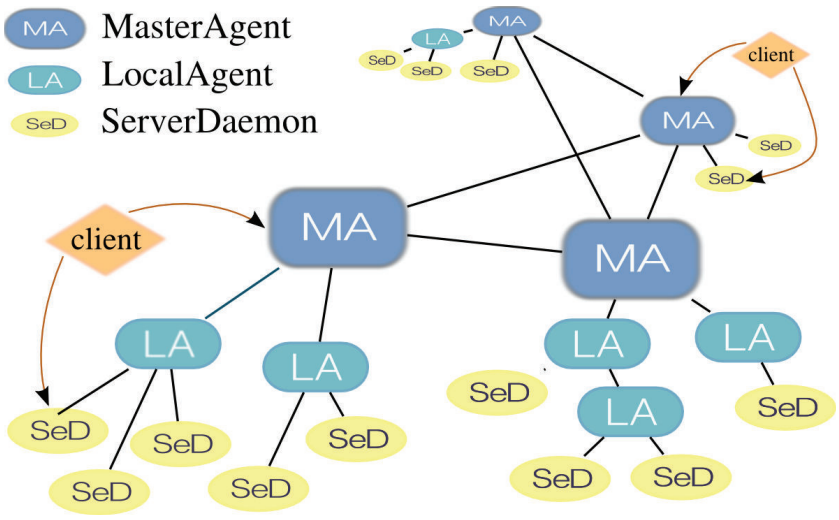

Figure 3.2: A DIET hierarchy.

provider, exposing functionality through a standardized computational service interface; a single SED can offer any number of computational services. The third element of the DIET architecture is the **agent**. Deployed alone or in a hierarchy, the agent facilitates the service location and invocation interactions between clients and SEDs. Collectively, a hierarchy of agents provides higher-level and scalable services such as scheduling and data management. The head of a hierarchy of agents is called a **Master Agent (MA)** while the others are **Local Agents (LA)**.

3.4.2 DIET Plug-in Schedulers

By default, when a user request arrives at a SED, an estimation vector is created via a default estimation function; typically, this function populates the vector with standard values which are identified by system-defined tags. Table 3.2 lists the tags that may be generated by a standard installation.

Consequently, applications targeted for the DIET platform are able to exert a degree of control over the scheduling subsystem via plug-in schedulers. For example, a SED that provides a service to query particular databases may need to include information about which databases are currently resident in its disk cache, so that an appropriate server may be identified for each client request. If the application developer includes a custom **performance estimation function** in the implementation of the SED, the DIET framework will associate the estimation function with the registered service.

Each time a user request is received by a SED associated with such an estimation function, that function, instead of the default estimation procedure, is called to generate the performance estimation values. These features are invoked after a user has submitted a service request to the MA, which broadcasts the request to its agent hierarchy.

As the physical infrastructures that are to be used vary greatly in terms of demands, we used this DIET plug-in scheduler facility at the server level to express contextual information about performance and power consumption, that will taken into account when servers are provisioned. Such vectors are then the basis on which the suitability of different SeDs regarding to energy efficiency is evaluated.

Information tag starts with EST_	**Explanation**
TCOMP	the predicted time to solve a problem
TIMESINCELASTSOLVE	time since last solve has been made (sec)
FREECPU	amount of free CPU between 0 and 1
LOADAVG	CPU load average
FREEMEM	amount of free memory (Mb)
NBCPU	number of available processors
CPUSPEED	frequency of CPUs (MHz)
TOTALMEM	total memory size (Mb)
BOGOMIPS	the BogoMips
CACHECPU	cache size CPUs (Kb)
NETWORKBANDWIDTH	network bandwidth (Mb/sec)
NETWORKLATENCY	network latency (sec)
TOTALSIZEDISK	size of the partition (Mb)
FREESIZEDISK	amount of free place on partition (Mb)
DISKACCESREAD	average time to read from disk (Mb/sec)
DISKACCESWRITE	average time to write to disk (Mb/sec)
ALLINFOS	[empty] fill all possible fields

Table 3.2: Explanation of the standard estimation tags used by the DIET Plug-in scheduler engine.

3.4.3 Adding Green capabilities

Estimation vector

We use this DIET plug-in scheduler facility at the server level to express contextual information about application performance and power consumption. These values are taken into account when servers are processioned. Such vectors are then the basis on which suitability of different SeDs is evaluated. Table 3.3 presents the additional estimation

tags used in the performance estimation vector. The methods of this ranking process comprises an agreggation method, which is simply the logical process by which servers responses are sorted according to the GreenPerf metric.

Information tag starts with EST_	**Explanation**
ENERGYAVG	average energy consumption on solved requests (J)
FLOPS	Node performance (Gflops)

Table 3.3: Explanation of the customized estimation tags added to the DIET Plug-in scheduler engine.

Scheduling process

The first scenario of application of GreenDIET is related to the modelization of preferences described in the previous section.

We couple this preferences with consideration of energy-related events such as fluctuations of energy cost or heat peaks. Energy cost can be seen as an adjustment metric that helps the administrator to define the number of servers/portion of the datacenter to be available. In this context, we consider that a low price is an incentive to use more servers at a given time. Heat peaks and temperature conditions are use to define threshold regarding to normal conditions of exploitation. The knowledge of these information enables the scheduler to check the health of a datacenter before performing provisioning decisions. In Chapter 5, a deeper evaluation of that feature is performed with autonomic decisions and considerations of threshold.

The scheduling process and the role of each DIET agent is described below.

1. The client submits a service request that contains its $Preference_{user}$ in the service parameters
2. Master Agent receives a request describing a task and a value for $Preference_{user}$.
3. A request is propagated and estimation vectors are computed on SeDs retrieved.
4. The scheduler checks the temperature and energy costs thresholds defined by the administrator and adjusts the number of candidate nodes according to $Preference_{provider}(u, c)$.
5. The list of candidates is sorted according to the scheduling criteria (at each level of hierarchy of agents).
6. When the Master Agent is reached, the candidates remaining is returned to the client.

To select the appropriate node based on a client request, we consider the ability to estimate the duration of pending tasks. The following information is assumed to be known for each server at any time:

f_s Number of FLoating-point Operations Per Second (FLOPS) for the server s

c_s Average power consumption when the server s is fully loaded (Watts).

bc_s Consumption during the boot process of server s (Watts).

bt_s Boot time for server s (seconds).

w_s Estimation of tasks waiting queue on server s (seconds).

P $Preference_{user}$

n_i Number of FLOPS to perform the task i.

The knowledge of these variables enables the scheduler to consider inactive nodes in the decision process and thus evaluate the costs of turning servers on if necessary. The execution time of a task i is defined by the number of operations and the performance of server s is $(\frac{n_i}{f_s})$. Both the total computation time and the energy consumed to perform a task depend on the state of the assigned server at the moment of the scheduling decision. The computation time (3.5) and energy consumption (3.6) of a task i on a server s can be divided into two cases, depending on the state of the server.

$$\begin{matrix} computation \\ time \end{matrix} = \begin{cases} w_s + \frac{n_i}{f_s} & \text{active server} \\ bt_s + \frac{n_i}{f_s} & \text{inactive server} \end{cases} \tag{3.5}$$

$$\begin{matrix} energy \\ consumption \end{matrix} = \begin{cases} c_s \times \frac{n_i}{f_s} & \text{active server} \\ bt_s \times bc_s + c_s \times \frac{n_s}{f_s} & \text{inactive server} \end{cases} \tag{3.6}$$

Using these two functions, the scheduler can assign a score Sc to each server and establish a sorting (3.7).

$$Sc : P \rightarrow \left(\begin{matrix} computation \\ time \end{matrix}\right)^{\frac{2}{P+1}-1} \times \left(\begin{matrix} energy \\ consumption \end{matrix}\right) \tag{3.7}$$

This score is coherent with our expectations regarding the previous definitions of $Preference_{user}$ and $Preference_{provider}$ (3.8):

$$Sc : \begin{cases} P \rightarrow -0.9 & \Rightarrow Sc \sim \begin{matrix} computation\ time \end{matrix} \\ P \rightarrow 0 & \Rightarrow Sc \sim \left(\begin{matrix} computation \\ time \end{matrix}\right) \times \left(\begin{matrix} energy \\ consumption \end{matrix}\right) \\ P \rightarrow 0.9 & \Rightarrow Sc \sim \begin{matrix} energy\ consumption \end{matrix} \end{cases} \tag{3.8}$$

When creating a list of candidate nodes, we aim to minimize the total energy consumed by the active servers by maximizing the use of the most energy efficient servers. We do not consider any bound for makespan and assume that servers have steady performance. We use a greedy algorithm for selecting candidate servers with the objective of minimizing the power consumed by servers (Algorithm 1).

Let T be the list of servers sorted according to *GreenPerf*, RES be the result set of servers, P_{Total} be the accumulated power of each server and $P_{required}$ be the required power among the candidate nodes.

Algorithm 1: Selection of candidate servers considering a power consumption cap.

```
1  P_Total ← 0
2  for server ∈ T do
3  |   P_Total+ = server.get_power()
4  end
5  P_required ← Preference_provider × P_Total
6  P ← 0
7  RES ← []
8  while P < P_required do
9  |   P+ = T.get_first_element().get_power()
10 |   RES.add(T.get_first_element())
11 |   T.remove_first_element()
12 end
13 return RES
```

3.5 Validation

3.5.1 Grid'5000: A testbed dedicated to experimental research

Experiments used resources from Grid'5000, a testbed designed to support experiment-driven research in parallel and distributed systems. Located in France, Grid'5000 comprises 29 heterogeneous clusters, with 1,100 nodes, 7,400 CPU cores with various generations of technology spanning 10 physical sites interconnected by a dedicated 10 Gbps backbone network (Figure 3.3). By providing bare-metal resource deployment, Grid'5000 enables users to experiment on all layers of the software stack of distributed infrastructures, including high-performance computing, grids, peer-to-peer, and cloud computing architectures.

The power measurement in the studied clusters is performed with an energy-sensing infrastructure composed of external wattmeters produced by the SME Omegawatt [69]. This energy-sensing infrastructure, also used in previous work [70], collects at every second

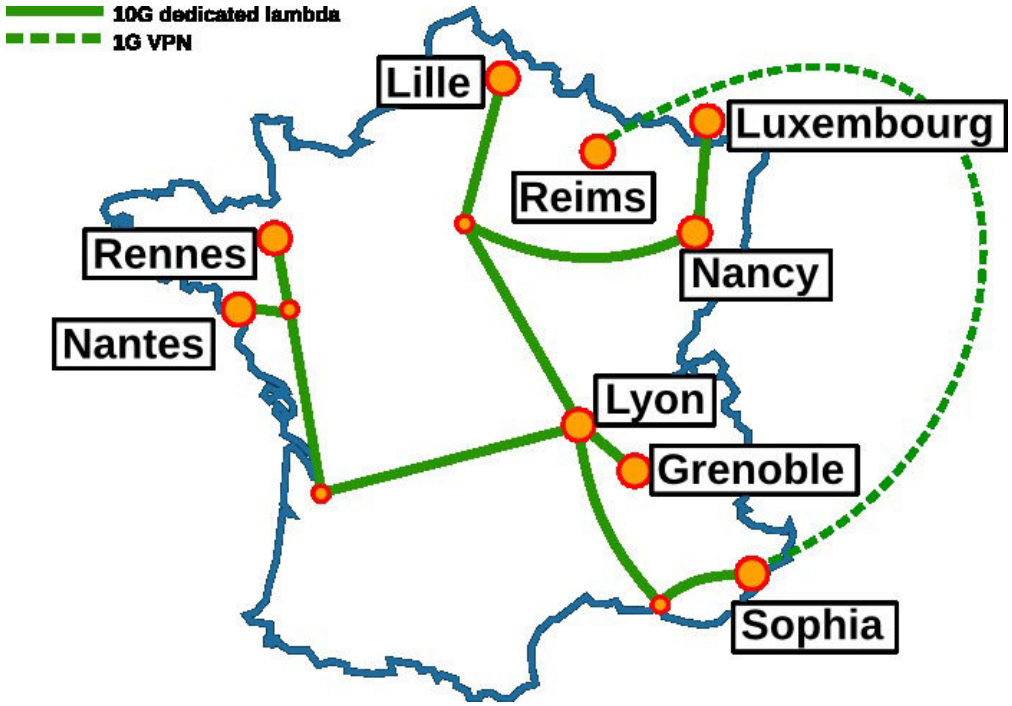

Figure 3.3: Grid'5000

Tool	Description
OAR	Finding and booking avalaible nodes
Kadeploy	Cloning, configuring (post installation) and managingcluster nodes
Execo	Prototyping experiments on distributed systems
Kavlan	Level 2 Network isolation from other experiments
VM5K	Easy and reproducible way to deploy virtual machines
DIET*	Middleware for high-performance computing in distributed environments
Kwapi*	Driver-based energy and network monitoring software
OpenStack*	Control pools of compute, storage and network resources

Table 3.4: Tools used on Grid'5000. The tools designated with (*) are platform-independent tools

the power consumption in watts of each monitored node [71]. A node's consumption is determined by averaging past consumption over more than 3600 measurements per second, whereas its performance is given by the number of FLOPS achieved when using all CPU cores to execute benchmarks are using ATLAS[2], HPL[3] and Open MPI[4].

Additionally, Grid'5000 gives the ease the advantage to ease the separation of the experimental process from metrology concerns. A typical experiment scenario involves:(i) Finding and booking available nodes (ii) Configuring nodes and installing dependencies (iii) Deploying a DIET hierarchy (iv) running an experiment. The monitoring itself is seamlessly performed for the end user. Energy data and logs are available on demand through a web API and can be retrieved in live or post-experiments.

The validation of this framework is performed in two scenario. First, a simulation of placement using the greenperf metric to get an intuition of potential benefits. Next, we performed a real deployment of GreenDIET to evaluate the placement of 1000+ tasks on Grid'5000.

3.5.2 Simulations

Scenario

We evaluate the *GreenPerf* metric as a means to establish the relevancy of the ratio $\frac{\text{Power Consumption}}{\text{Performance}}$ in high and low heterogeneity environments. We use a simulation to manage the level of heterogeneity. After performing an initial benchmark on the physical nodes of Grid'5000, we obtained for each server its mean computation time for a single task along with its peak and idle power consumptions. These values are used to compute the energy consumed by the whole infrastructure during the simulations. Each task is computed with the maximal performance and power of the servers. During the simulation, each server is limited to the computation of one task. Table 3.5 presents the specification of the nodes.

The simulation aims to compare the completion time and energy consumption of a set of task on Grid'5000 considering different variants of the metric, namely PERFORMANCE, POWER, GreenPerf and RANDOM. PERFORMANCE and POWER correspond, respectively, to giving priority to the fastest and to most energy-efficient nodes to hence establishing the bounds of the *GreenPerf* metric. The RANDOM policy selects servers at random. The values presented are the average of 15 consecutive runs.

[2]Automatically Tuned Linear Algebra Software: `http://sourceforge.net/projects/math-atlas/`

[3]Portable Implementation of the High-Performance Linpack Benchmark for Distributed-Memory Computers: `http://www.netlib.org/benchmark/hpl/`

[4]High Performance Message Passing Library: `http://www.open-mpi.org/`

Cluster	Nodes	CPU	Memory
Capricorne	3	2x2cores @2Ghz	2GB
Sagittaire	2	2x1core @2.40Ghz	2GB

Table 3.5: Experimental Infrastructure for the evaluation of GreenPerf (simulations)

Results

Low heterogeneity of hardware

Figure 3.4 shows the comparison of metrics for a low heterogeneity environment. In this scenario, we use 2 different types of servers with similar specifications (Table 3.5). The coordinates of G, GP and P represent the average values obtained of, respectively, the POWER, *GreenPerf* and PERFORMANCE metrics. The shadings represent the area of RANDOM values. One can observe that performance is stable among the different metrics. It is a representation of the completion time of the slowest server to complete its tasks. As the platform only has two different types of hardware, that slowest node appears to always be the same. The range of energy onsumption values for the RANDOM metric illustrates the various combinations of scheduling. Those results are expected: the POWER policy consumes less than GreenPerf, that consumes less than PERFORMANCE but it does not present any tradeoffs between the algorithms.

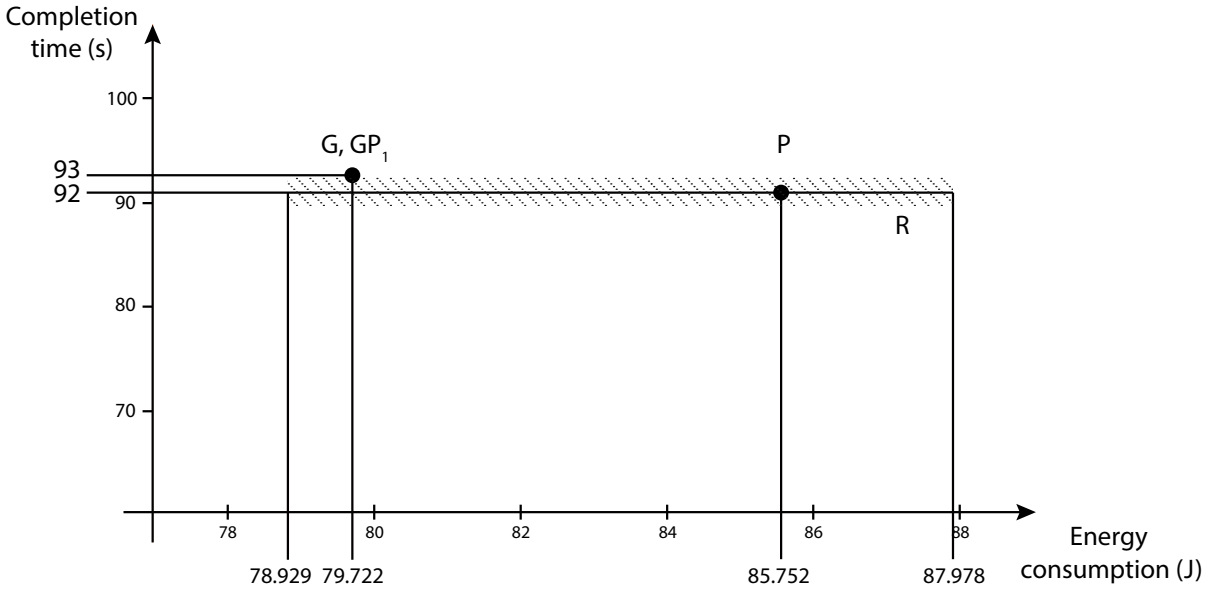

Figure 3.4: Comparison of metrics with 2 different types of servers and 2 clients submitting requests.

High heterogeneity of hardware

In a second scenario, we consider the addition of two simulated clusters to increase the heterogeneity of the platform. Table 4.2 presents the energy consumption of those servers regarding the tasks submitted in the experiment. As a result, Figure 3.5 shows a better tradeoff between POWER and PERFORMANCE, highlighting the need for a sufficient diversity of hardware to efficiently use *GreenPerf* and the benefits of green scheduling through an online decision mechanism.

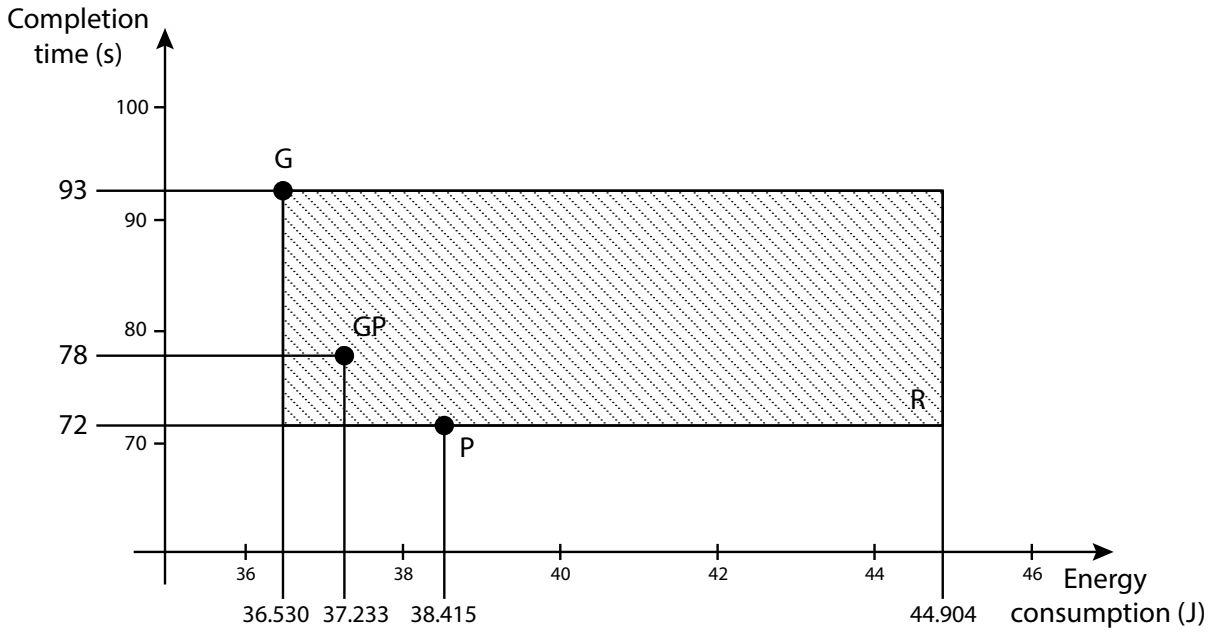

Figure 3.5: Comparison of metrics with 4 different types of servers and 2 clients submitting requests.

Cluster	Idle consumption	Peak consumption
Simulated cluster 1	190	230
Simulated cluster 2	160	190

Table 3.6: Energy consumption of simulated clusters for evaluation of GreenPerf in a highly heterogeneous environment

3.5.3 Experiments

Workload Placement

The evaluation aims to compare the distribution of tasks among nodes on Grid'5000 considering three different policies, namely PERFORMANCE, POWER and RANDOM.

PERFORMANCE and POWER correspond, respectively, to giving priority to the fastest and to most energy-efficient nodes to hence establishing the bounds of the *GreenPerf* metric. The RANDOM policy selects servers at random.

A client submits a set of tasks, wherein a single task is a CPU-bound problem which consists in $1e8$ successive additions, enabling the distinction of nodes in terms of performance. As each task uses a single core, a server cannot execute a number of tasks greater than its number of cores.

Cluster	**Nodes**	**CPU**	**Memory**	**Role**
Orion	4	2x6cores @2.30Ghz	32GB	SeD
Sagittaire	4	2x1core @2.40Ghz	2GB	SeD
Taurus	4	2x6cores @2.30Ghz	32GB	SeD
Sagittaire	1	2x1core @2.40Ghz	2GB	MA
Sagittaire	1	2x1core @2.40Ghz	2GB	Client

Table 3.7: Experimental Infrastructure for the evaluation of GreenPerf (real-life deployments).

The total number of client requests depends on the number of available cores. We consider a number of 10 client requests per available core in this experiment.

The temporal distribution of jobs contains a burst phase, when the client submits r simultaneous requests and a continuous phase when the client submits requests at an arbitrary rate of two requests/second.

We deploy the DIET middleware on 14 physical nodes as follows: 12 dedicated nodes for SeD's, 1 dedicated node for the Master Agent and 1 dedicated node for the Client. The machines are picked among three different clusters as presented in Table 3.7. The nodes are connected to a switch with a bandwidth of 1Gbit/s and run the Debian Wheezy operating system.

Considering that the scheduler does not have specific information on the nodes and does not make assumptions about the hardware, the dynamic information is gathered as tasks are computed by the servers. Figures 3.6, 3.7 and 3.8 show the results of this experiment. The x-axis presents the different nodes available to solve the problem; the y-axis shows the number of tasks executed by the node.

Figure 3.6 shows the distribution according to energy consumption. We observe that most jobs are computed by *Taurus* nodes, which appear to be the most energy-efficient. Execution on *Orion* and *Sagittaire* occurs during the "learning" phase or when *Taurus* nodes are overloaded.

Figure 3.7 shows the distribution of tasks when performance is the criterion for selecting a node. The load balancing of jobs is similar to Figure 3.6, with the majority

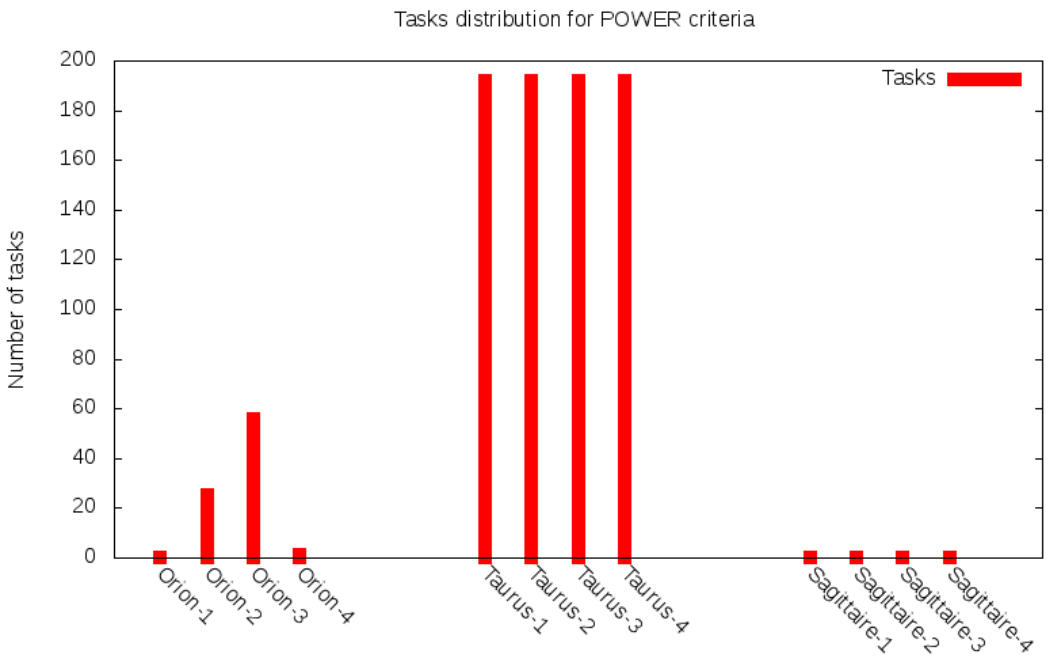

Figure 3.6: Tasks distribution using power consumption as placement criterion.

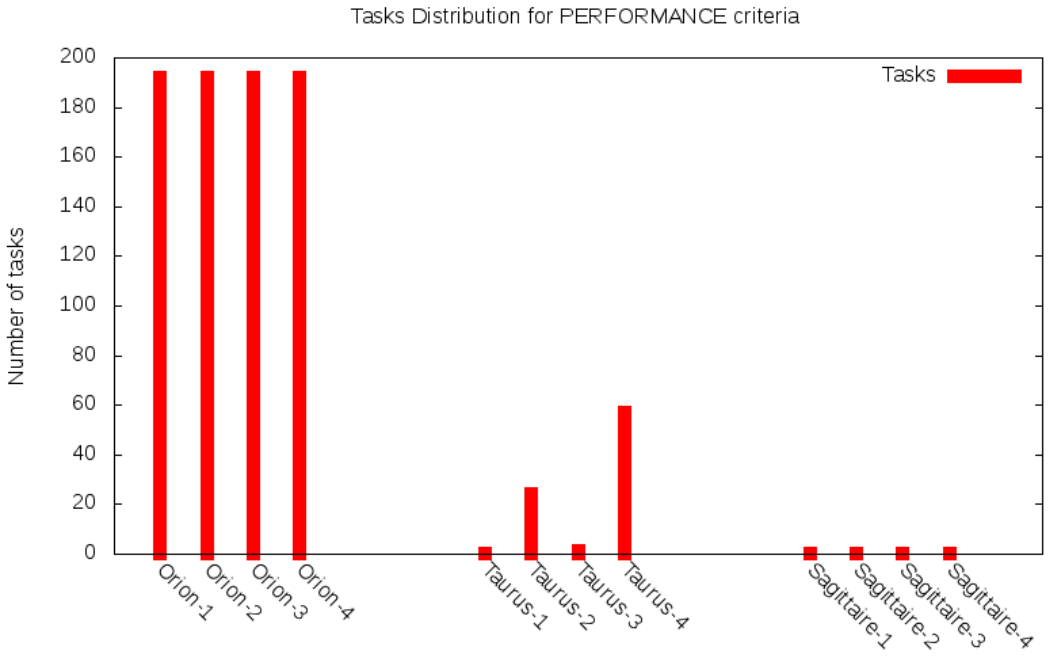

Figure 3.7: Tasks distribution using performance as placement criterion.

of tasks executed on Orion nodes. In Figure 3.8, despite a random distribution of jobs, *Sagittaire* nodes compute less tasks than other nodes. That is explained by the fact that a single task is computed slower on those nodes, thus, they are less frequently available when decisions are made.

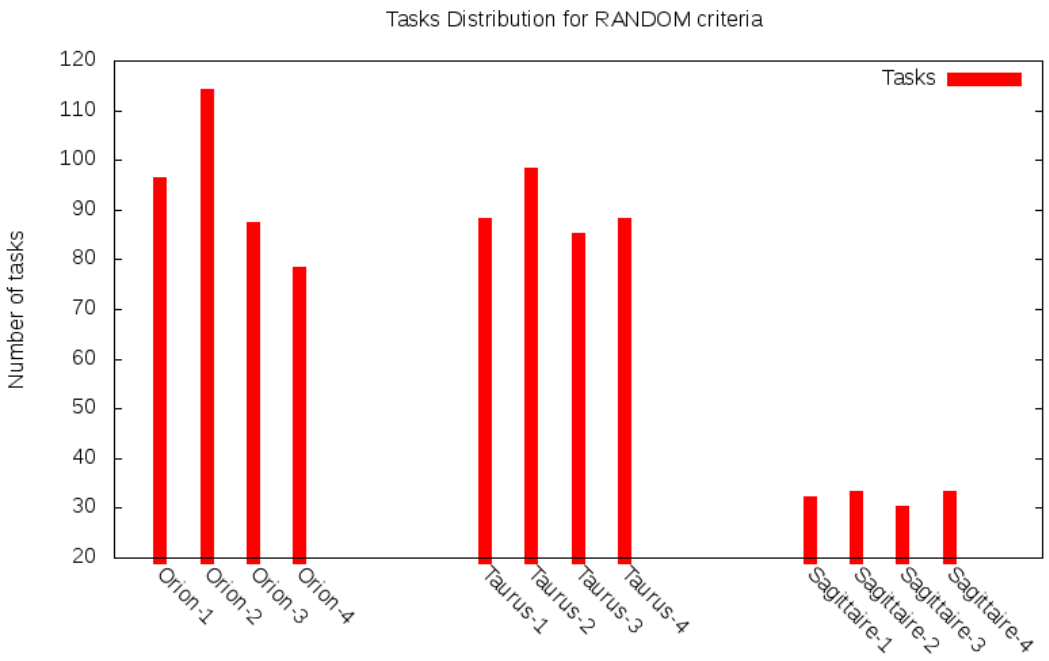

Figure 3.8: Tasks distribution with random placement.

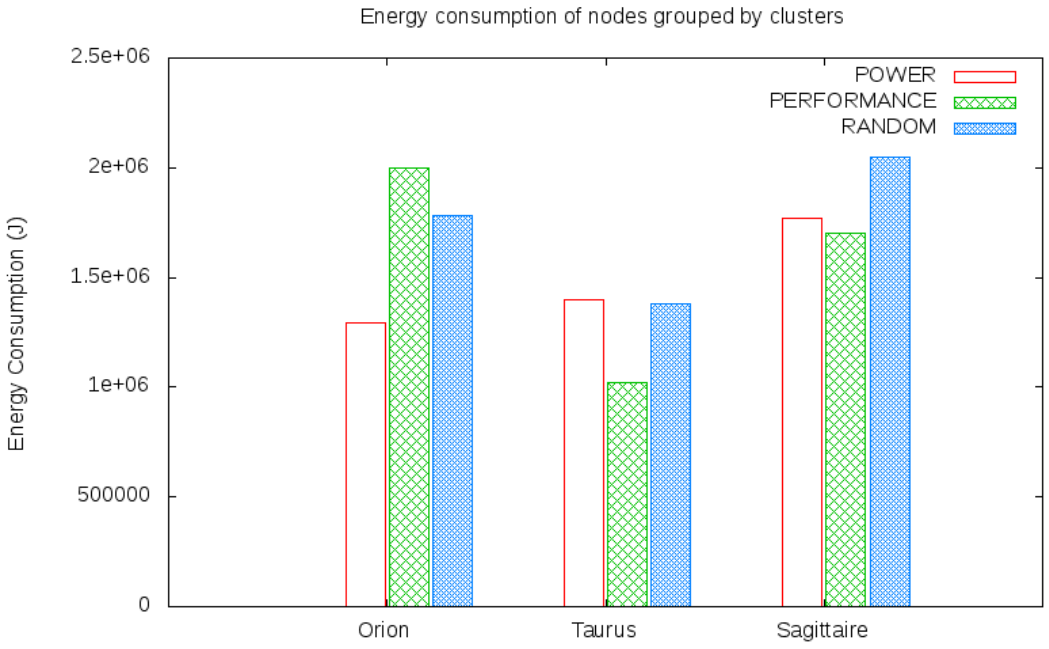

Figure 3.9: Cumulated energy consumption per cluster under POWER, PERFORMANCE and RANDOM scheduling policies.

Figure 3.9 presents the energy consumption of the whole infrastructure grouped by clusters. The energy consumption measured on the DIET agents was constant when executing the three algorithms and does not present any influence on the comparison. We

can observe that distributing the workload using the RANDOM policy is not particularly energy efficient as it guarantees that all the resources are in use during the experiment.

	RANDOM	**POWER**	**PERFORMANCE**
Makespan (s)	2,336	2,321	2,228
Energy (J)	6,041,436	4,528,547	5,618,175

Table 3.8: Experimental Results of POWER, PERFORMANCE and RANDOM scheduling policies

Table 3.8 compares makespan and energy consumption metrics among the scheduling policies. Considering performance, the best case is giving priority to nodes with higher number of FLOPS (PERFORMANCE). Comparing that value with the POWER makespan, we noticed a loss of performance of up to 6%. In terms of energy consumption, POWER presents a gain of 25% when compared to RANDOM, and up to 19% compared to PERFORMANCE.

RANDOM appears, in average, to be the worst case because it ensures that all the nodes are in use, resulting in higher energy consumption. The use of slow nodes is also impacting the performance, but this effect is hidden by the fact that fast nodes will compute more tasks in parallel.

3.6 Conclusion

In this chapter, GreenDIET, a framework for provisioning resources and distributing requests with the objective of meeting performance requirements while reducing energy consumption, was presented. We validated our strategy through experiments using the DIET toolkit and the Grid'5000 experimental testbed. Comparing three different scheduling policies by enabling users and providers to specify trade-offs between performance and energy consumption, results show a reduction of energy consumption of 25% with a minor performance loss (6%).

The effectiveness of this approach strongly relies on the heterogeneity of servers. Results show a reactive scheduling, allowing policy management to be abstracted into a software layer that can be automated and controlled centrally. We expect this approach to be very useful when applied to provisioning servers, using contextual data from third-party predicting or monitoring tools. The motivation to propose the underlying GreenPerf metric was project-driven with often restricted knowledge of a whole datacenter monitoring. Therefore, we rely on a straightforward, yet extensible, metric to be able to characterize all resources.

The following chapters will revolve around a deeper search of workload placement

solutions by considering genetic algorithms and affinities between resources and tasks on real cloud traces. We also describe the application of this framework in industrial use cases.

Chapter 4

Application to multi-criteria and evolutionnary computing

This Chapter presents a joint work with Mahindra Ecole Centrale (Hyderabad, India). The context of this collaboration emerges from the result of Chapter 3 and the evaluation of GreenDIET. Online decisions could benefit from the potential of heuristics to consider affinity between nodes and tasks while searching better solutions of placement.

This research has been supported in part by CEFIPRA (Indo-French Center for promotion of Advanced Research) through its Raman-Charpak Fellowship program, following early discussions at the presentation of [6] at IPDPS 2015 between Avalon and Mahindra Ecole Centrale researchers.

4.1 Introduction

Multiple objective optimization, also known as Pareto optimization is an area of multiple criteria decision making, involving one or more objective functions to be optimized simultaneously. It has been applied in many field of science where optimal decisions need to be taken in the presence of tradeoffs between two or more contradictory objectives. There exists different families of solutions and goals when setting and solving them.

This principles have been investigated using the early results of GreenPerf (Chapter 3). Figure 4.1 presents the simulation results described in the previous chapter. Based on the value of the resulting values of scheduling policies, G (Energy savings), P (Performance), GP (GreenPerf for energy efficiency), one can observe that there is not a single solution that simultaneously minimize the energy consumption and maximize the performance. That range of solution is called Non-dominated or Pareto optimal, as non of the objective function can be improved in value without degrading some of the other objectives.

The curve on Figure 4.1 is a conceptual Pareto front representing the trade-off curve of potential solutions. It informs how one objective is related to the deterioration of the

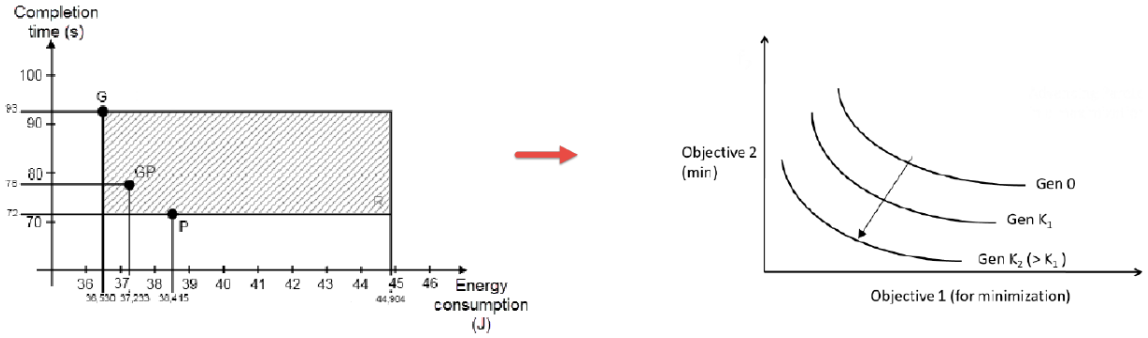

Figure 4.1: A visualisation of the GreenPerf evaluation as a conceptual Pareto optimization where completion time and energy consumption represent objectives to be minimized.

second one. The use of Pareto optimization can enable the full potential of GreenPerf by computing intermediates, yet satisfying, solutions for the user and the provider. Among the family of multi-objective optimization, our work revolves around Evolutionary optimization techniques.

Evolutionary Optimization techniques that from theoretical principles are guaranteed to provide globally optimum solutions, are among the most powerful tools to achieve such optimal placements. Multi-Objective Evolutionary algorithms by design work upon contradictory objectives, gradually evolving across generations towards a converged Pareto front representing optimal decision variables – in this case the mapping of tasks to resources on clusters. However the computation time taken by such algorithms for convergence makes them prohibitive for real time placements because of the adverse impact on makespan. In this work, we have used Non-Dominated Sorting Differential Evolution to obtain the best Pareto front with a spectrum of solutions representing minimum energy at one end of the front and minimum makespan (completion time) at the other.

This chapter introduces several contributions: (i) an evolutionary approach to workflow placement (ii) a choice of solutions to the user based on his priorities, ranging from best-energy to best-performance, and intermediates, (iii) development and launching of a parallel variant of evolutionary optimization on the Grid'5000 testbed using real cloud traces. The solutions under different scheduling policies demonstrate significant reduction in energy consumption with some improvement in performance.

4.2 Genetic metaheuristics

Metaheuristics allows to tackle large-size problems instances by delivering satisfactory solutions in reasonable time [72]. They do not present guarantees to find global optimal solutions or even bounded solutions. Applications of metaheuristics falls into two main families. The first branch includes the single-solution based metaheuristics (S-)

and the second the population-based metaheuristics (P-). Those two families of metaheuristics share several principles but are complementary in their behaviors. While the S-metaheuristics have more a local search based on iterations that help to transform and improve one solution by intensifying the research around its neighborhood, the P-metaheuristics explore a bigger search space by involving the whole set of individuals (population). The individuals evolve together for more diversification in the search space toward better solutions. The rest of this Chapter focuses on the population-based metaheuristics (P-).

The principle of P-metaheuristics mimics the "survival of the fittest". It relies on the evolution of an initial population of solutions through iterations in order to generate a new population that will replace the previous one (Figure 4.2). Among the best known P-metaheuristic algorithms are evolutionary algorithms, scatter search, estimation of distribution algorithms, particle swarm optimization, bee colony. In this Chapter, we deal with evolutionary algorithms, more specifically genetic algorithms. In genetic algorithm, the population contains a number of encoded individuals, where each one represents a potential solution. The first population (initial population) is usually generated randomly. Each iteration of the algorithm is called a generation. During a generation a set of solutions is selected. Those selected solutions are recombined using the evolution operators to provide new solutions. The new solutions replace following a certain policy the worst solutions of the previous population. The algorithm relies on the fitness of the solutions to carry out this operation. The fitness is computed with an evaluation function. This operation is repeated until reaching a termination criterion.

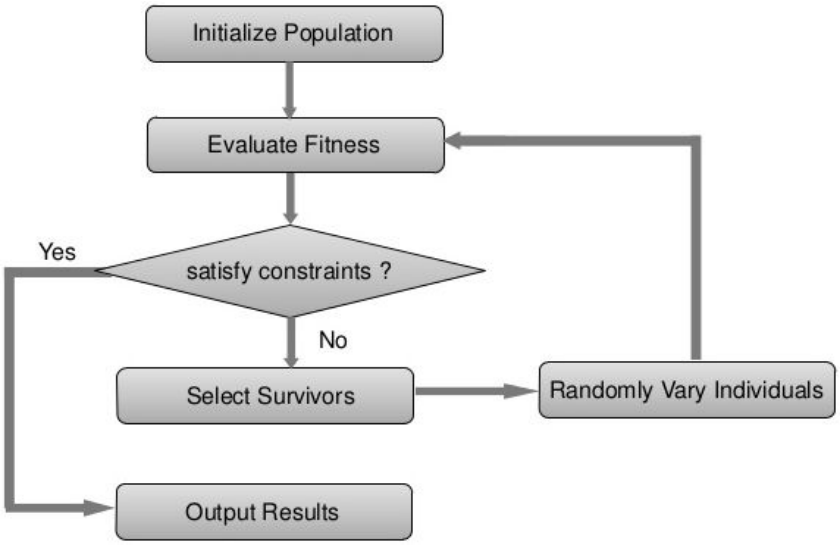

Figure 4.2: Generic flow of operations in a genetic algortihm.

Techniques using evolutionary algorithms, has advanced significantly since the first attempt [73] using Genetic Algorithms, and is widely used today in numerous applica-

tions. Among the most noteworthy developments rank the SPEA2 algorithm by Zitzler *and al.* [74] and NSGA-II algorithm by Deb *and al.* [75].

The developments in Multi-Objective Evolutionary Algorithms referred in the previous paragraph have been along the track of Genetic Algorithm (GA) [76], the baseline Evolutionary optimization approach, applied to the direct multi-objective paradigm. At the basic algorithm level, Differential Evolution (DE) was formulated as an alternate approach to GA by Storn and Price [77]. Bhattacharya *and al.* have applied both GA and DE in a few complex industrial processes [78, 79, 80]; the latter work also provides a comparison in computational efficiency for that industrial process between GA and DE demonstrating that DE comes out favourably. Due to these developments the authors decided to use their version of DE as the baseline algorithm for the current multi-objective problem.

Evolutionary Algorithms that work concurrently on a population of candidate solutions are naturally amenable to parallelization and consequent speedup, because a significant percent of the computations operate on individual candidates independent of the others. There are two broad paradigms for parallelization, the "master-slave" model [81], where the main computation (the master) generates many subproblems, which are fired off to be executed by slave threads/processors and the "island" model [82], where each subpopulation is assigned to a separate processor/thread.

Evolutionary Algorithms have also been successfully parallelized on Cloud frameworks. Lee *and al* [83] implemented a parallel GA-PSO method for inferring gene networks in a Cloud computing environment using the Hadoop MapReduce programming model. Tang and al [84] parallelized the DE algorithm using a resilient distributed datasets model, and compared consequent performance improvements relative to MapReduce on a wide range of benchmark problems. The above examples represent parallelization of single-objective evolutionary algorithms on Cloud clusters to solve specific optimization problems, and not scheduling of actual workflows based on multiple objectives.

We propose a solution based on a parallelized differential evolution algorithm. It brings a contribution to the field by combining an energy aware approach with the scheduling of workflows based on multiple objectives.

4.3 Non Sorting Differential Evolution II (NSDE-II)

Differential Evolution (DE) belongs to the broad class of evolutionary optimization techniques that developed as distinctive variants of classical Genetic Algorithms (GA). DE was selected as the evolutionary method of choice on the basis of the authors' prior studies on the relative efficiency and merits of this against GA, as reported in [78]. The following section presents the concept of differential evolution for a single objective and the key

aspects to adapt it to Multi-Objective Differential Evolution.

This class of features has certains common features with Genetic Algorithm optimisation, namely, they work in parallel on a population of candidate solutions, are stochastic in nature, do not require the objective function to be analytic or even mathematically tractable, and are much less likely to get stuck in local optima as compared to gradient based methods. They differ from one another primarily in the manner in which candidate solutions in a new generation are synthesized from solutions in the current one, which effectively translates into their method of search of the total solution space for a global solution. The fitness of each candidate, as defined by one (or more) objective function(s), plays an important part in the evolution.

The core idea in DE is to superpose the difference between two randomly selected solution vectors (where the elements of a vector correspond to the values in dimensions of the solution space) on a third solution vector with each solution vector being a member of candidate population sets to obtain a new solution. Initially when (and if) the candidate solutions are spread across the solution space, the differences and hence the changes in solution vectors are large, and as the solutions converge to the global optimum, the changes get finer enabling attainment of the optimum faster. This is in contrast to classical GA where the changes on a solution vector are neutral to the level of evolution towards the global optimum.

This section presents the concept of differential evolution for a single objective and the key aspects to adapt it to Multi-Objective Differential Evolution.

4.3.1 Baseline Differential Evolution

Formally, if the dimensionality of the solution space is denoted as D and the number of candidate solutions is N, then the elements of the i^{th} vector of the solution $X_{i,G}$ at generation G may be denoted as

$$X_{i,G} = (X_{1,i,G}, X_{2,i,G}, X_{3,i,G}, ..., X_{D,i,G}) \qquad for \qquad all \qquad i \in \mathbb{N} \tag{4.1}$$

The Differential Evolution (DE) process fundamentally generates new solutions from the current candidate set by adding the weighted difference between two randomly selected candidate solution vectors to a third to generate a mutant vector, and then creating a crossover between an existing vector and the mutant that is called the "trial" vector. The latter is allowed to replace the existing vector only if it is found to be more fit, the complexity of this fitness determination exercise depending entirely upon the nature of the problem under consideration. If $V_{i,G}$ represents the mutant vector, then according to

the baseline DE process called DE/rand/1 [85, 77, 86]

$$V_{i,G} = X_{r1,G} + F \times (X_{r2,G} - X_{r3,G}) \tag{4.2}$$

where $r1$,$r2$ and $r3$ are random integers less than N, different from each other and from i, and F usually lies between 0.5 and 1. There are many variations of this baseline process where two instead of one difference terms are sometimes considered, the best solution in a population is taken into account, etc.; descriptions of alternative schemes may be seen in [87], among others.

Crossover is performed between the mutant vector $V_{i,G}$ and the target vector $X_{i,G}$ to generate a trial vector $Z_{i,G}$ according to

$$z_{j,i,G} = \begin{cases} v_{j,i,G} & if \quad rand_j(0,1) \leq C_r \\ x_{j,i,G} & otherwise \end{cases} \tag{4.3}$$

where $z_{j,i,G}$ is the element j of the trial vector $Z_{i,G}$, $rand_j(0,1)$ denotes a random number between 0 and 1 applied to the element j, C_r is the crossover threshold usually set between 0.4 and 1. Eq. (4.3) simply states that the element j of the trial vector $Z_{i,G}$ is taken from the mutant vector if the corresponding random number generated with seed j is less than C_r, else the original value is left unchanged for that element.

At the final selection step the choice for candidate i in the next generation is made between $Z_{i,G}$ and $X_{i,G}$ on the basis of higher fitness by direct one-to-one comparison.

The present work generates the mutant vector according to the alternate scheme (proposed in [77] and also used by current authors in [78] where it is found to work better than other DE variants)

$$X_{i,G} = X_{r1,G} + R \times (X_{best,G} - X_{r1,G}) + F \times (X_{r2,G} - X_{r3,G}) \tag{4.4}$$

where R is set at 0.5 and F varies randomly between -2 and +2 across generations (and are same for all i within a generation). The crossover probability Cr in eq. 4.3 is set at 0.7.

4.3.2 Multi-Objective Differential Evolution NSDE-II

Compared to single-objective Differential Evolution (DE), the mechanisms for multi-objective DE are radically different. The basis for this difference follows from the altered conditions of selection that relate to this statement in the section above the "choice for candidate i in the next generation is made between $Z_{i,G}$ and $X_{i,G}$ on the basis of higher fitness by direct one-to-one comparison". That works for a single objective which tags a fitness value to both the solutions, enabling comparison. But if there is more than one

objective, it is quite possible that one of them is more fit with respect to one objective, and the second for some other objective. And hence one cannot conclude which solution is more fit, upsetting the basic mechanism of single-objective DE.

This work has adopted the basic multiple-objective selection techniques of NSGA-II [75] while replacing the baseline GA operations to those of the DE variant outlined in Eqs. (4.3) and (4.4) for generation of a trial vector. Hence this is named as NSDE-II. In a problem with K objectives $FF_k, k \in 1...K$, a candidate solution vector X_p is said to dominate another solution X_q if

$$FF_k(X_p) \geqslant FF_k(X_q), k \in 1...K \tag{4.5}$$

and for at least one k, $FF_k(X_p) > FF_k(X_q)$; where $p, q \in 1...N$, N is population size; and in turn X_q is said to be dominated by X_p. This definition is used immediately below.

Now it is apparent that for a population of candidate solutions and with multiple objectives, there will be either one of three types of relations between any pair of candidate solutions. Either one dominates the other according to Eq. (4.5), or one is dominated by the other (i.e. converse to the first relation), or neither dominates or is dominated by the other, i.e. for some objectives one is better and for the balance objectives the other is the better.

This brings us to the NSDE-II selection process from one generation to the next.

Steps of Non-dominated selection:

1. A population of size N, taken for all parent vectors and all trial vectors thus forming a collective pool of size $2N$.

2. To every pool-member i allocate a number n_i and a vector S_i, where the former denotes the number of members that dominate it and the latter contains the identification index of all members that it dominates. This implies that S_i is a set whose size can vary from the null to at most $2N - 1$.

3. Place all members having $n_i = 0$ into a sub-pool called Front $F1$, which is an accumulation of the fittest members (i.e. those not dominated by any others). Thus the original pool is now depleted by the number of members shifted to $F1$.

4. Traversing all i put in F1, go over all the members j that are listed in S_i and reduce the corresponding value of n_j by 1. This implies that once a non-dominated member is shifted out of the pool, each remaining member of the depleted pool who was originally dominated by that removed member, is now dominated by one less member in this pool.

5. Now repeat steps 2-4, with the rider that the new set of $n_i = 0$ members (that

emerge upon reducing the cardinality of domination by one) are put into the second front $F2$, and then $F3$, and so on.

At this point we have segregated the members of pool into a series of fronts with descending degree of non-dominance.

6. If the size of front $F1$ is less than N, select all members of $F1$ into the next generation.

7. Now if the size of front $F2$ is such that $\#(F1 + F2) < N$, then select all members of F2 also into the next generation (symbol # denotes cardinality of a set).

8. In this way move on to $F3$, $F4$ till one comes to some F_q where the size say s_q is larger than the number of unfilled spaces in gen-next, say u_q, i.e.

   $u_q = \left\{N - \sum_{m=1}^{q-1} \#F_m\right\}$, and $s_q > u_q$

9. Use the Crowding Distance Algorithm to select u_q out of s_q.

The core concept of the **Crowding Distance Algorithm** [75] is to select solutions that maximize diversity, i.e. if one solution is in a dense zone with many other solutions around, and another in a relatively sparse zone, then other aspects being equal, the solution from the sparse zone is selected. The algorithm quantifies the density of a point in terms of the distance between its two straddling neighbors in every dimension of the objective space, rather than of the parameter space.

4.4 Problem Formulation

The aim of this work is to improve the energy efficiency of a set of machines while concurrently reducing completion time of a given set of jobs, through optimized workload placement. In most cases, faster machines (low completion time for a task) will have higher energy consumption (demanding hardware), implying that minimizing simultaneously both objectives is strongly contradictory — forming the basis of multi-objective optimization. A server (computing node) is modeled with three resources: CPU, DISK and NETWORK and runs processes which consume these resources. Each task is treated as a design variable to be assigned to a single machine, and cannot be moved from one machine to another.

4.4.1 Decision parameters

Any optimization problem will have design parameters whose best possible values from the viewpoint of the objectives are sought to be attained in the optimization process.

The optimization task here is to map a given set of tasks in a certain sequence onto the available resources.

Suppose there are m number of resources and n tasks. Then, for any resource j, $\forall j \in [1...m]$, all possible permutations of subsets of all sizes of the set of tasks of size n, constitute the total solution space. If we call the size of this solution space as S_j, then

$$S_j = \sum_{k=0}^{n} P(n,k) \qquad where \qquad P(n,k) = \frac{n!}{(n-k)!} \tag{4.6}$$

Since S_j is independent of j, we may write it simply as S. It then follows that the size of the total solution space is m^S.

The information presented in Table 4.1 is assumed to be known for each server s at any time. The knowledge of these variables enables the scheduler to consider the energy efficiency related to the completion of tasks.

Element	**Description**
f_s	Number of FLoating-point Operations Per Second (FLOPS)
dw_s	Disk Writing rate
dr_s	Disk Reading rate
net_s	Available Network bandwidth
c_s	Average power consumption
nf_i	Number of FLOPS to perform the task i
nbw_i	Number of bytes written on disk by the task i.
nbr_i	Number of bytes read on disk by the task i
$nnet_i$	Number of bytes exchanged by the task over the network by the task i.

Table 4.1: Information available for the scheduler related to each task

4.4.2 Objective functions

We have two objective functions:

1. Minimize Makespan (i.e. time taken for completion of all tasks in the workflow)

   The completion time of the workflow is given by

$$T_{mn} = \sum_{s=1}^{m} \sum_{i=1}^{n} T_{is} \tag{4.7}$$

Makespan, defined as the time for completion of the last job on any of the servers, is then expressed as:

$$T_{mn} = \max_{s \in (1..m)} \sum_{i=1}^{n} T_{is} \tag{4.8}$$

2. Minimize Energy consumption (i.e. total energy consumed in a workflow)

   If C_{is} is the energy consumption of the task i per unit time when running on server s, then energy consumption required for the workflow is expressed as

$$W_s = \sum_{i=1}^{n} C_{is} T_{is} \tag{4.9}$$

   and the total energy consumed is

$$W_{mn} = \sum_{s=1}^{m} W_s = \sum_{i=1}^{n} \sum_{s=1}^{m} C_{is} T_{is} \tag{4.10}$$

In most cases, faster machines (low T_i) will have higher energy consumption (high C_s), implying that objectives T_{mn} and W_{mn} are contradictory — forming the basis of multi-objective optimization.

4.5 Implementation

We intend to integrate NSDE-2 as a Multi-Objective Optimization engine within a large scale infrastructure. NSDE-2 would be accessible as a remote service that accepts a workflow as an input and computes a set of placement solution that minimizes energy consumption and makespan as an output. This output is to be placed and executed on the infrastructure using the GreenDIET extension of the DIET Middleware (introduced in Chapter 3), along with ots workflow management capabilities. In this framework, the time spent on NSDE-2 optimization contributes to the makespan, hence this work addresses speedup of NSDE-2 through parallelization. The current version uses only energy and makespan as the objectives for concurrent minimization, the intention is to gradually integrate more independent objectives into the optimization process. The aim of the current framework is twofold: (i) to relieve researchers of the burden of dealing with deployment, resource selection and workload fluctuations when they evaluate new optimization engines and (ii) to offer the possibility to compare them.

4.5.1 Diet Workflow capabilities

The DIET middleware was introduced in Chapter 3. Its plug-in scheduler feature enable the consideration of new metrics, namely energy consumption by the means of the GreenDIET extension. Among other features of the toolkit, DIET presents the ability to workflow execution.

Workflow applications consist of multiple components (tasks) related by precedence constraints that usually follow the data flow between them, i.e., data files generated by one task are needed to start another task. Although this is the most common situation, precedence constraints may exist for other reasons, and be arbitrarily defined by the user.

This kind of application can be modeled as a DAG (Directed Acyclic Graph) where each vertex is a task with given input data and service name, and each edge can either be a data link between two tasks or a basic precedence constraint. The DIET workflow engine can handle that kind of workflow by assigning those tasks to SeDs using one DIET service call. This assignment is made internally and dynamically when the task is ready to be executed (i.e., all predecessors are done) depending on the service performance properties and on available resources on the grid.

A specific agent called the Master Agent DAG (MA) provides DAG workflow scheduling. This agent serves as the entry point to the DIET Hierarchy for a client that wants to submit a workflow.

4.5.2 Optimization sequence

The workflow execution is performed in 3 phases (Figure 4.3): (i) service discovery, (ii) computation of mapping solutions and (iii) workload placement. The service discovery phase corresponds to the search of an optimization engine within the infrastructure by a given client. As multiple engines can be instantiated on the platform, the user can submit its workload to different engines and compare the cost of generated solutions. The computation of mapping solutions is performed by at least one server (multiple servers can be put in cooperation using the same service, based on the engine requirements) with a platform performance description provided by the Master Agent. This description is either based on historical data (past computations) or user-defined benchmarks. Finally, the workload placement is performed and results are returned to the client based on the platform available metrics and monitoring resolution. Mapping solutions are defined as a collection of JSON objects. Each solution contains the mapping between a SeD and a task and an associated cost in terms of workflow completion time and energy consumption.

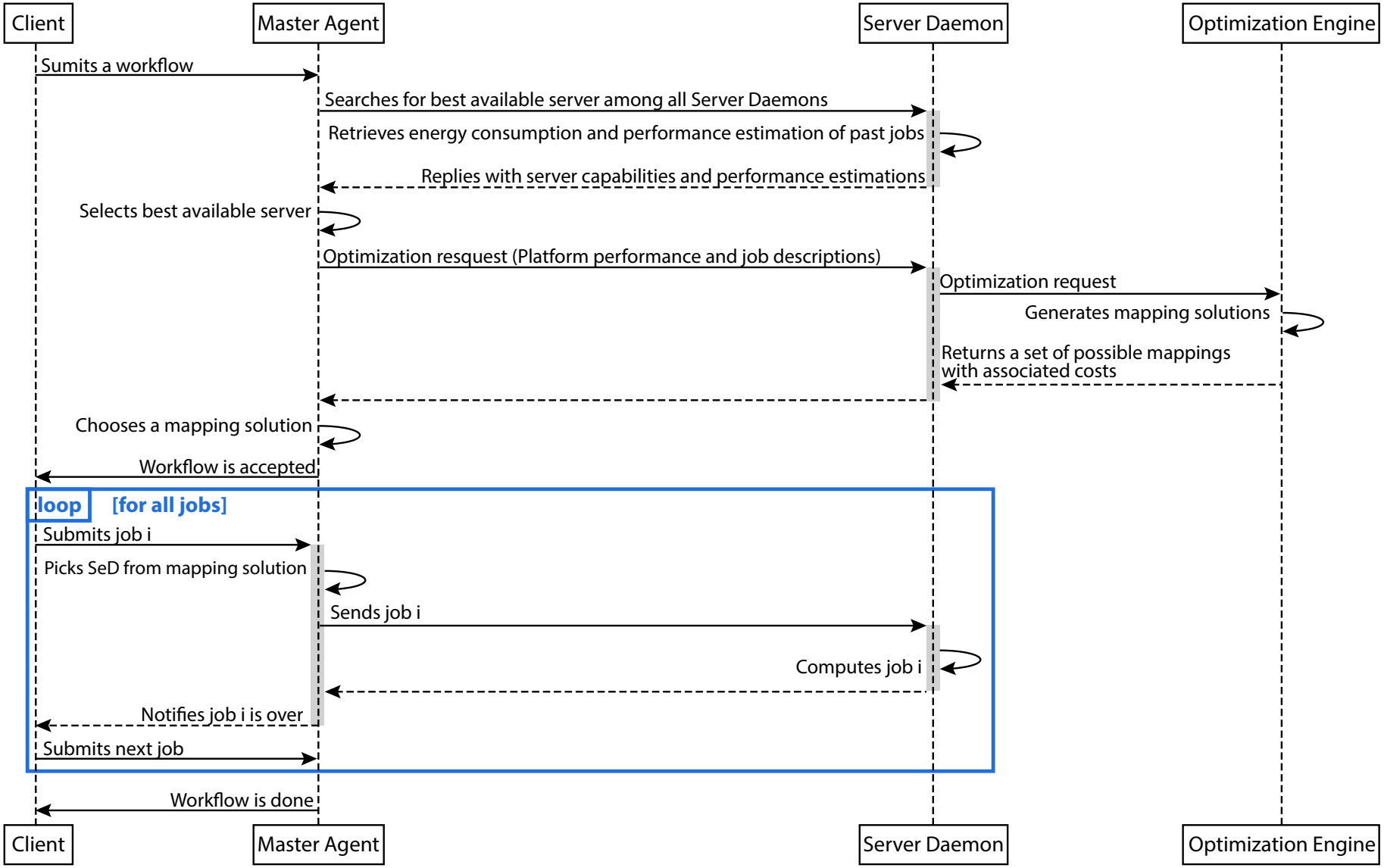

Figure 4.3: Optimisation and workflow execution sequence of DIET and NSDE-2

4.6 Experiments

Two kinds of experiments have been performed to validate this approach. The objective of the first one is to evaluate the computation phase of the engine (i.e., the step where the optimization engine generates a spectrum of solutions) while the second is a comparison of algorithms to evaluate the concrete gain of NSDE-2 compared to an online placement of workload.

4.6.1 Dataset

We have used real-world trace files of an international company called Prezi Inc [1], who offers a presentation editing service, which is available on multiple platforms, therefore they have to convert some of their created media files to other formats before they can display them on all devices. The origin of the Prezi Inc dataset is a competition for engineers to apply their knowledge of control and queueing theories on real-life problems. At the time to evaluate our approach, we searched for original traces that presents:

- Heterogeneous workload
- Frequent arrival of tasks
- Dependencies between tasks

Such datasets appears to be hard to obtain due to privacy issues and relevancy to the evaluations. In general, the difficulty to obtain access or trace logs to real infrastructures prevents a research work close from the concerns and reality of the Cloud market. That quest for logs have been a hard lock within this thesis as they are needed when modeling a problem to gather understanding, but also to evaluate and to validate propositions. Cloud traces present a competitive advantage for research teams and companies, often resulting in non-reproducible techniques and optimizations.

Prezi's conversion processes are carried out on virtual machines: at peak times, they need to launch more instances of these VMs, but over the weekend they can stop most of them. They published log files on their website containing workload traces for two weeks of utilization, which serves as a basis for algorithmic experimentations. They operate three queues in their Cloud system for the jobs participating in the conversion processes:

- export: contains jobs which result in downloadable zipped Prezi files.
- url: these jobs download an image from a URL and insert them into a Prezi file.
- general: all other conversion jobs (audio, video, pdf, ppt, etc.).

[1] http://prezi.com/scale/

The lines of the published workload traces have the following format:

2012-12-14 21:35:12 237 general 9.134963

This means that at the given time, a job enters the general queue with the id 237, and the job will take 9.134963 seconds to run. The available trace files contain more than 2000000 lines, and their submitted (and processed) jobs highly varies over the 14 days.

To represent the job heterogeneity and their hardware requirements, we created a generic multi-thread program in charge of interpreting and executing requests based on a log trace description. Each task is represented by an execution of a bounded number of operations.

An operation is based on the completion of three functions, simultaneously executed by three different threads:

- A CPU-intensive operation consisting in the multiplication of two randomly filled matrices of size 1000x1000 (*cpu*).
- A disk-intensive operation consisting in the writing and reading on disk of a 20MB file (*disk*).
- A network-intensive operation consisting in downloading a 5MB file from a remote server (*net*).

In the context of this experiment, each of the three threads is in charge of the sequential execution of n functions of the same type, n being the weight of each function. Each queue has a weighted sum of functions. We consider the following mapping for each type of job:

export $2 \times cpu + 1 \times disk + 1 \times net$

url $1 \times cpu + 2 \times disk + 3 \times net$

general $3 \times cpu + 1 \times disk + 1 \times net$

As an example, a job with the id 237 from the general queue will be completed after the execution of 10 general operations.

4.6.2 Settings

We consider all the nodes with energy monitoring capabilities of the Grid'5000 platform. We deploy the DIET middleware on 113 physical nodes as follows: 111 dedicated nodes for SED's, 1 dedicated node for the Master Agent and 1 dedicated node for the Client. The machines are picked among six different clusters located on four different geographical sites as presented in Table 4.2.

Cluster	Nodes	CPU	Site	Role
Orion	4	2x6 cores @2.30Ghz	Lyon	SED
Sagittaire	38	2x1 core @2.40Ghz	Lyon	SED
Taurus	10	2x6 cores @2.30Ghz	Lyon	SED
Stremi	38	2x12 cores @1.7Ghz	Reims	SED
Graphite	4	2x6 cores @2.00Ghz	Nancy	SED
Parasilo	17	2x6 cores @2.40Ghz	Rennes	SED
Parasilo	1	2x6 cores @2.40Ghz	Rennes	MA
Parasilo	1	2x6cores @2.40Ghz	Rennes	Client

Table 4.2: Experimental Infrastructure using 113 nodes with energy monitoring capabilities on four different geographical sites from the Grid'5000 platform

4.6.3 Parallelization

Evolutionary Optimization algorithms are naturally amenable to parallelization: In a program, any iterative loop where computations in different passes are independent of consequence of computations in other passes, can be parallelized by distributing the passes across parallel threads In EA's, bulk of computation done on a candidate of population (everything other than the selection process) is independent of all other candidates in a given generation In our NSDE-II program, all the non-parallelizable aspects take about 4.5% of total computation time in a fully sequential run

We first investigate parallelization of the NSDE-2 algorithm on a handy 8-core Intel laptop with chipset i7-4710HQ@2.5Ghz. These are offline simulations using data for a set of 500 tasks to be placed on 85 servers, where task and server data have been extracted from the Grid'5000 testbed. A population size of 200 is considered for all simulations as well as online optimization executions. The master-slave approach is followed in parallelization, using the Open MP Library [88].

In the NSDE program the functions not amenable to parallelization include the selection operations using non-dominated sorting and crowding distance algorithms that take up about 3.3% of runtime, and some I/O operations taking approximately another 1%. It follows from Amdahl's law that the Theoretical Maximum Speedup factor is approximately 22. Table 4.3 shows results obtained using the sequential NSDE-2 program, parallelized NSDE-2 program running on a single core, and on 4 cores.

The data shows computation times and the average values over all candidates for the two objectives, energy and makespan, for a workflow of 500 tasks on 85 servers. The relevance of the average values in these multi-objective simulations is purely to check if the sequential and 1-core-parallel solutions match exactly, which they are observed to

Parallelization	Time for 3000	100 generations		3000 generations	
	generations	Makespan	Energy	Makespan	Energy
Sequential	33:52	39.36	4491.4	37.05	3546.6
1-core	33:49	39.36	4491.4	37.05	3546.6
4-core	14:22	40.46	4874.8	35.85	4061.3

Table 4.3: Evaluation of the parallel variant of the framework on 1-core and 4-core hardware. Time is expressed in minutes, Energy in kJ

do. This, first and foremost, demonstrates the correctness of parallelization. Second, it shows that the speedup factor on 4 cores is 2.36. An interesting observation from Table 4.3 is that the speed of evolution of candidates across generations varies between the parallel solutions and the sequential, reflected in different numerical values of the objectives at the same generation levels. It may be difficult to pinpoint the reasons for this; the evolutionary algorithm being a stochastic process is likely to behave differently when executed concurrently on different numbers of nodes, and these differences are likely to amplify over generations.

Figure 4.4 shows the parallelization speedup factor when running selected sets of 100 and 1000 tasks on 85 servers, real time on the Grid'5000 testbed on a Stremi node (see Table 4.2). It may be noted that in the NSDE solution framework, each task is effectively a decision (design) variable, and obtaining optimized solution with 1000 variables is itself a challenging task.

In fact, this number has been extended to 5000 decision variables on 85 servers launched in parallel on 24 nodes, though comparative sequential runs could not be obtained due to runtime constraints. Figure 4.4 shows that as the size of the workflow increases, the parallelization speedup factor gradually approaches its maximum limit.

4.6.4 Generation of solutions and Pareto fronts

NSDE-2 being an evolutionary multi-objective algorithm works on a population of candidate solutions which improve on all objectives across generations. The solution at any generation is presented in the form of a Pareto front which represents the position of each candidate in the multi-objective reference frame. Here we work on a population of size 200. Figure 4.5 shows the evolution of the Pareto front from an initial stage of 100 generations up to 10000 generations, with minimization of energy consumption and makespan as the objectives. Each dot represents a candidate solution. At any selected generation, at one end of the Pareto front we have the "best energy" solution, and at the other end, the "best makespan" solution.

We can observe that the quality of solutions improves as the number of generations

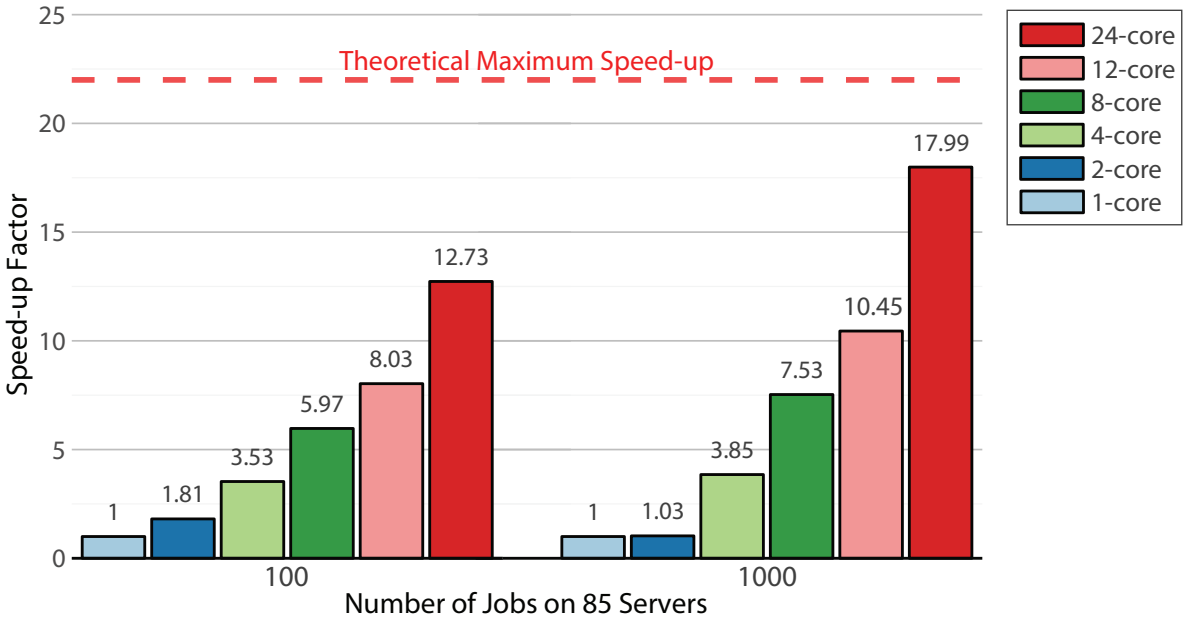

Figure 4.4: Speedup analysis of NSDE-2 on two different size of jobs sets

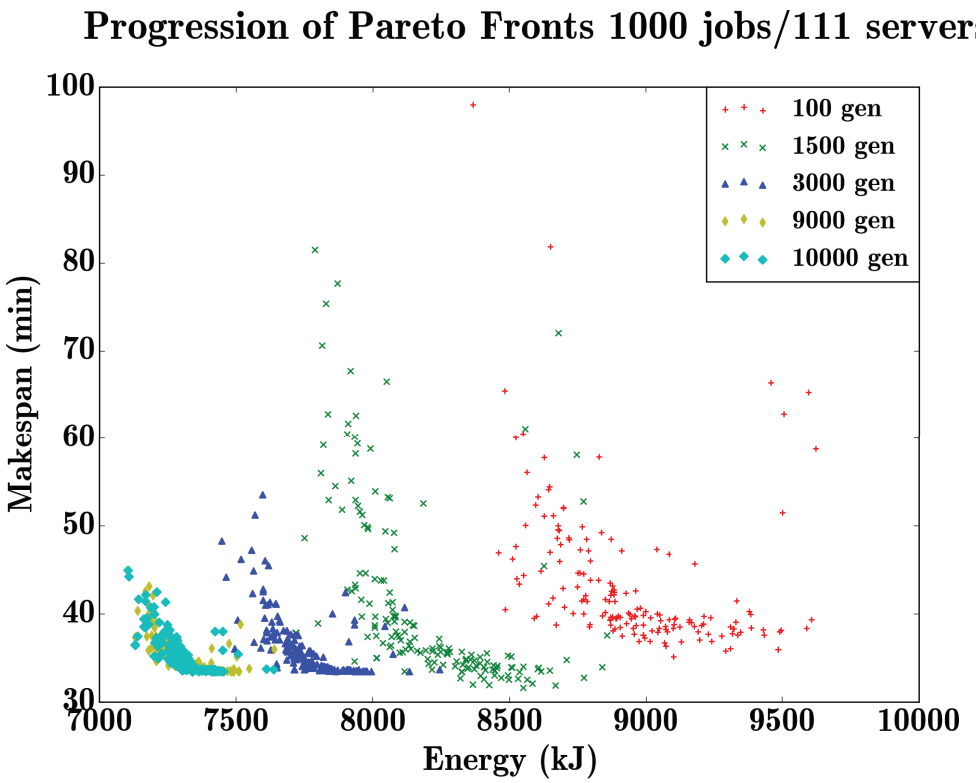

Figure 4.5: Pareto fronts and quality of the solutions generated by NSDE-2 as the number of generations increases. Each dot represents a solution of placement

increases. The computation time increases linearly as the number of generations increase. We choose to retrieve the solution at 3000 generations, after which the improvement of the solution becomes less significant.

It may be noted that if jobs are submitted on the Cloud for execution after prior reservation, then it can be valuable to drive the NSDE-2 to its full potential to obtain the best optimal solution placement.

4.6.5 Scalability and Reactivity

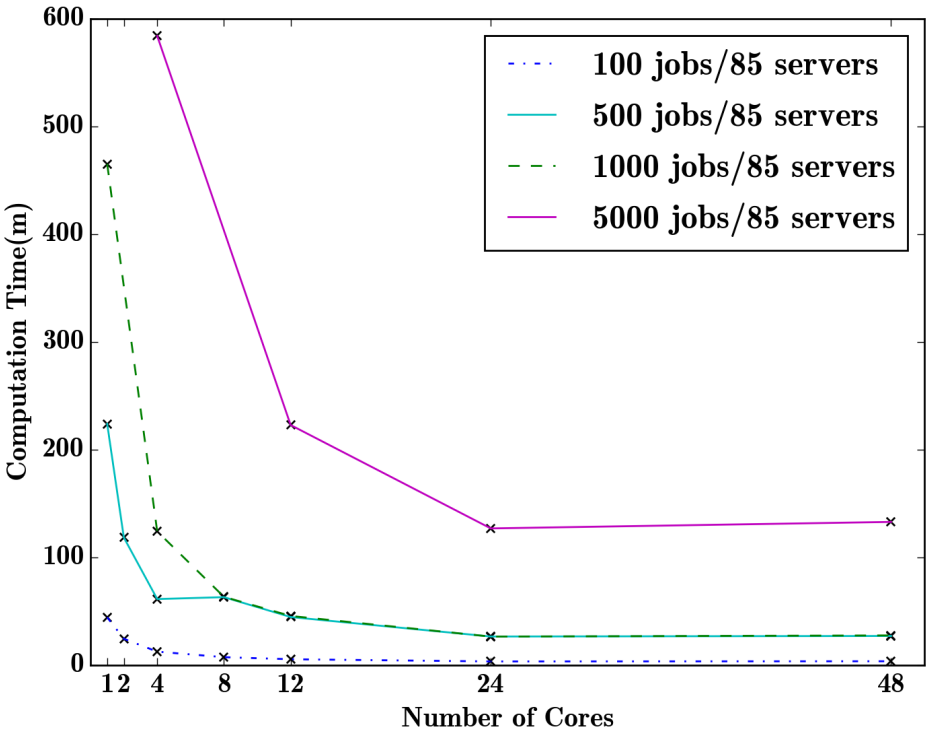

Figure 4.6: NSDE-2 execution time for generating mapping solutions related to 4 datasets and 111 servers

We compared 4 different sizes of the dataset. Due to availability, the experimental servers are a subset of servers presented in Table 4.2. The machine that runs NSDE-2 is a node from the Stremi cluster (Table 4.2) with 24 cores. We can observe a significant improvement in NSDE-2 execution time with increasing parallelization. One can observe that the computation time for 100 jobs and 500 jobs are pretty similar, indicating the importance of disposing enough data to take advantage of parallelization. Plus, increasing the number of threads above the actual number of cores does not impact the performance, independently of the dataset.

4.6.6 Workload placement

This evaluation aims to compare the distribution of tasks among nodes on Grid'5000 considering three different policies, namely NSDE-2 Best Energy, NSDE-2 Best Performance and FIRST FIT. NSDE-2 Best Energy and NSDE-2 Best Performance correspond, respectively, to the smallest energy consumption and the smallest makespan. These solutions establish the bounds of the Pareto Front. The FIRST FIT policy consists in the selection of the first available server in an ordered list accroding to the $GreenPerf$ metric as a non-weighted average ratio between performance and energy consumption for the said type of task.

In each scenario, we consider the first entries of the trace file. For any of considered cases there exists a proper balance between short and long tasks within the dataset. A server is restricted to the execution of, at most, one task at a given time.

Considering that the scheduler does not have specific information on the nodes and does not make assumptions about the hardware, the dynamic information is gathered as a sample of each tasks is computed by the servers prior to the experiment. Figures 4.7, 4.8, 4.9 and 4.10 show the results of this experiment. The x-axis presents the different algorithms used to execute the workflow; the y-left-axis shows the total energy consumption of the solution and the y-right-axis shows the makespan value.

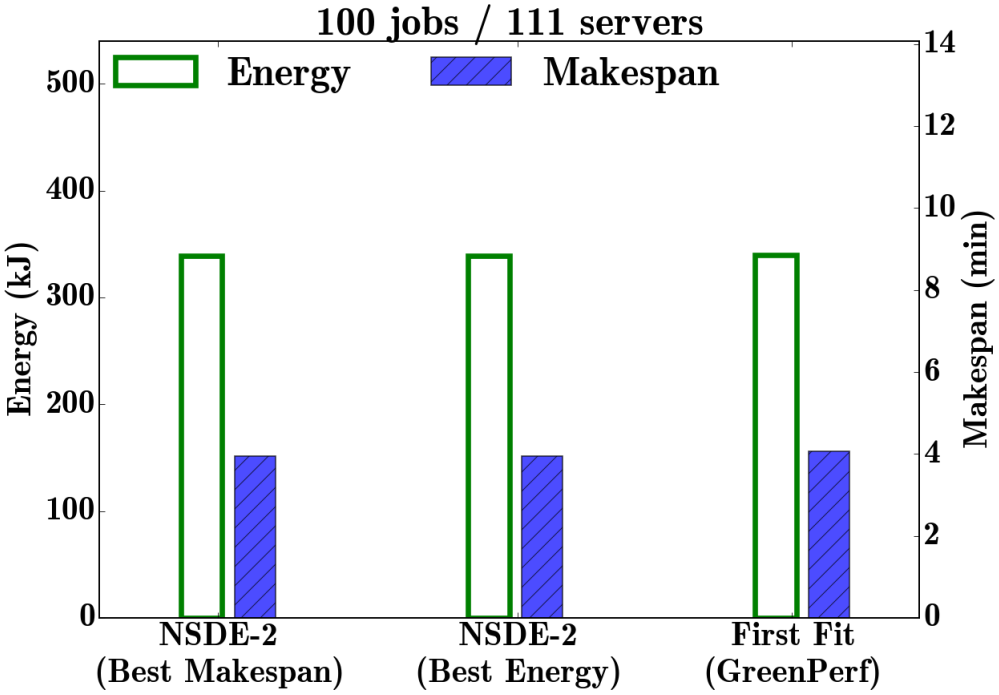

Figure 4.7: Energy and Makespan comparison for 100 jobs and 111 servers

We observe an influence of the ratio jobs/servers on the global results. The larger the dataset (specifically in terms of large tasks), the worst FIRST FIT performs as it

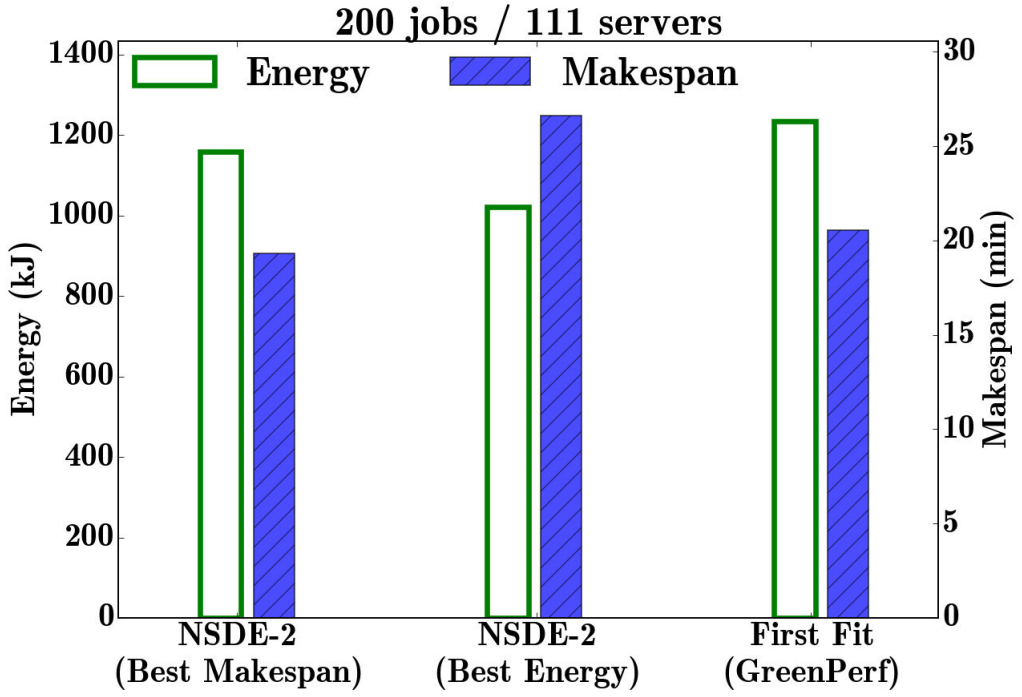

Figure 4.8: Energy and Makespan comparison for 200 jobs and 111 servers

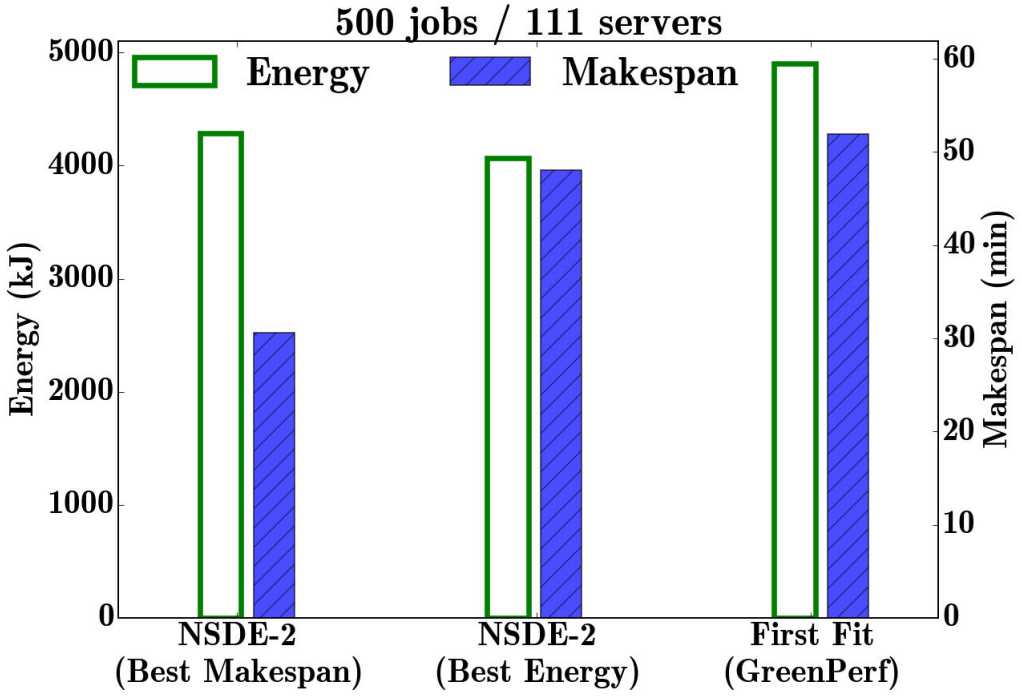

Figure 4.9: Energy and Makespan comparison for 500 jobs and 111 servers

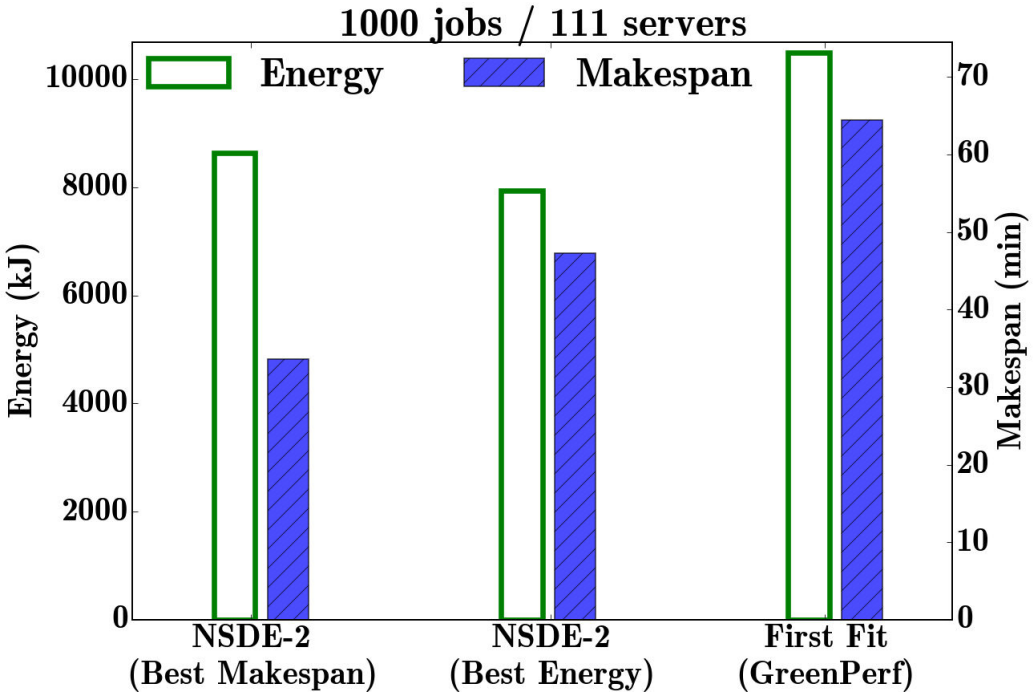

Figure 4.10: Energy and Makespan comparison for 1000 jobs and 111 servers

prevents the packing of tasks on the most energy-efficient nodes, resulting in more uses of least energy-efficient nodes, thus in higher energy consumption. On small dataset, this effect is hidden by the fact that fast nodes will compute more tasks in parallel.

Tables 4.4,4.5,4.6 show actual values obtained in terms of energy and time for the three allocation policies, for the 4 illustrated cases with 111 servers. It may be seen that NSDE-2 improves for any of the scenarios (except in the smallest case (Figure 4.7), and for the larger cases improves makespan as well. The user may choose to select an intermediate solution on the Pareto front that improves both energy and makespan, trading-off between the two objectives. It is worth noting that when the NSDE-2 solution was run up to 10000 generations, it provided a 30% saving in energy with a 50% reduction in makespan. Considering the computation time of the Pareto Front, this can be of value in cases of jobs submitted by prior reservation.

4.7 Conclusion

In this work, we report on design, implementation and evaluation of an energy-efficient resource management system that build upon DIET, an open source middleware and NSDE-II, an Evolutionary Multi-Objective Optimization engine. Our implementation supports an IaaS Cloud and currently provides placement of workflows, considering non-divisble tasks with precedences constraints. Real-life experiment of our approach on

Cases	No of Jobs	NSDE-2 Best Makespan (kJ)	NSDE-2 Best Energy (kJ)	First Fit *GreenPerf* (kJ)
1	100	338.9	338.9	339.8
2	200	1158.1	1020.3	1233.3
3	500	4287.1	4067.7	4901.7
4	1000	8632.5	7943.5	10482

Table 4.4: Energy consumption comparison between NSDE-2 variants and the First Fit algorithms

Cases	No of Jobs	NSDE-2 Best Makespan (m)	NSDE-2 Best Energy (m)	First Fit *GreenPerf* (m)
1	100	3.94	3.94	4.07
2	200	19.33	26.6	20.56
3	500	30.63	48.0	51.89
4	1000	33.64	47.29	64.47

Table 4.5: Makespan comparison between NSDE-2 variants and the First Fit algorithms

Cases	No of jobs	NSDE-2 Computation time of solutions (m)	Makespan NSDE-2 Performance (%)	Makespan NSDE-2 Energy (%)	Energy NSDE-2 Performance (%)	Energy NSDE-2 Energy (%)
1	100	3.46	-82	-82	0	0
2	200	6.0	-23	-59	6.1	17.3
3	500	13.63	15	-19	12.5	17.1
4	1000	26.5	7	-14	17.6	24.3

Table 4.6: Comparative improvements using NSDE-2 in makespan and energy

the Grid'5000 testbed demonstrates the effectiveness of our approach in a dynamic environment. Results shows that our method can provide providers and decision makers an aid to make their decision when conflicting objectives are present or when in search for realistic tradeoff for a given problem.

As future work, it would be valuable to consider (i) multicore integration for the placement of jobs and (ii) platform dynamicity. As Datacenters often present a high rate of hardware issues and availability of servers can rapidly change, the ability to retrieve a server from the population of solution without restarting the generation process would improve the reactivity of the algorithm.

Part II

Transfer of technology

Chapter 5

Towards a national cloud computing service, the Nu@ge project

Cloud computing represents a significant evolution of information and communication technologies, either in terms of usage and organization. This field is an enabler for new markets and is expected to grow up to 29% per year until 2019 [89]. Not all companies apprehends the Cloud in the same way, as discussed in Chapter 1. In particulae, small or recent businesses transition to the cloud for accessing a large amount of resources and setting collaboration between entities, with proportional investments regarding their activity. Despite its benefits to users, Cloud computing raises several concerns of applications, data storage and processing. Cloud providers reveal few information about geographical location and process of data and applications. As information converted and stored in binary digital form is subject to the laws of the country in which it is located, several concerns are raised from a legal standpoint. Third-party entities or governments could take control of sensible data, and legal protections may not apply if one's data is located outside her country. Additionally, data from a company could be physically hosted with data from others. This causes security risks as one company may attempt to access data of another.

The data sovereignty and the lack of major French cloud providers constituted a motivation for the French government to invest in major public cloud projects in 2010, with funding estimated to 150 millions of euros. The ambition was twofold: (i) creating concurrence on the cloud provider market with a french and European alternative (ii) ensuring guarantees from a legal standpoint to the digital data. These projects encountered mixed outcomes but it raised awareness on the topic and opened the door for other national projects. On a different scale, the Nu@ge consortium was gathered with the ambition of creating a federation of small-sized datacenters and resources with the purpose of offering tools to administrators in order to manage their Cloud.

5.1 Consortium

5.1.1 Motivation

The Nu@ge project started in 2012 [1]. The goal of this project is to describe and implement a federated architecture to provision virtual clusters of resources via the network while providing administrators with control over data location and Quality of Service. The proposed solution is based on innovative container-sized datacenters that enables deployment of a cost effective and high performance environment in any location meshing regional company owned datacenters.

5.1.2 Consortium

The Nu@ge consortium comprises 6 SMEs (Small and Medium-sized Entreprise) and 2 research team. Table 5.1 presents each partner and its business activity.

The Nu@ge consortium[2] is composed of the following members:

- NON STOP Systems, secure cloud solutions provider and leading architect of the project
- CELESTE, Internet provider and manufacturer of the StarDC
- Oodrive, online storage specialist
- DotRiver, virtual desktop and environment provider
- Init Sys, private network operator
- New GenerationSR, Green IT consulting
- LIP6, laboratory and its research team REGAL and PHARE of UPMC University, Paris.

5.2 Approach

Nu@ge defines a software stack as a coherent set of tools to homogenize management and exploitation of the resources. This section describes the Nu@ge architecture and its main components.

[1] I joined the project in February 2013.

[2] Nu@ge is a research project funded by the FSN (Fund for the Digital Society, BPI France) as part of the *Investissements d'Avenir* program.

Partner	Activity
	Cloud software Editor
	Storage solutions
	Telecommunication services provider
	Servers hosting and Internet provider for business
	Editor of Virtual Work Environment
	Business consulting
	Computer science research laboratory
	Computer science research laboratory

Table 5.1: Partners involved in the Nu@ge project

5.2.1 Overview

The architecture of the Nu@ge project addresses several system administration concerns, namely providing a single and shared vision of the whole infrastructure; simplifying service implementation; and managing virtual clusters and associated QoS. Nu@ge aims to virtualize any service. This choice breaks the link between logical resources and physical resources. In particular, we consider only the QoS of virtual/logical resources, ignoring the underlying hardware. Nu@ge is modular and favors the autonomy of each component. In this context, a virtual resource can be migrated depending on the following circumstances:

- Hardware failures;
- Performance optimization;

- Energy efficiency improvement; and
- Respect of QoS constraint.

A rack, the unit of administration contains:

- Equipments dedicated to virtualization, called V-nodes;
- Equipments dedicated to storage, called storage nodes;
- Network equipments dedicated to internal communications within the rack;
- Network equipments dedicated to communication with other datacenters; and
- Electrical equipments allowing the supervision and interventions.

The high-level components and their features are described in the following subsections.

5.2.2 V-node

A V-node is a physical node dedicated to the execution of virtual systems. Several infrastructures services are required, including:

- Interconnection between Nu@ge and the various IaaS providers.
- Setting up of network services.
- Piloting process of power supply

The main virtual machines deployed in the system are:

Internet Gateway: Provides Internet access to nodes, physical or virtual, present in the Nu@ge infrastructure. This machine enables the creation of filtering rules (firewall) in order to set a first level of security for network services.

VPN Gateway: Offers a secure access to Nu@ge's internal resources. Identification, authentication and data encryption are performed with digital certificates which are created and managed individually for each Nu@ge user.

IaaS Gateway: This is the component that links Nu@ge to the IaaS platform for the end-user. This virtual equipment is the separation between Nu@ge's area of responsibility and the IaaS administrators.

DNS Service: DNS is a primary service of Internet enabling the resolution of identifiers; required for Internet browsing.

Storage Access Service: Creates storage units dynamically for the IaaS platforms. The storage units are available as file systems or hard drives. This service is linked to an IaaS exposing a dedicated storage zone to the Nu@ge infrastructure.

5.2.3 Storage node

The main objectives of the distributed storage system are availability, traceability, integrity and safety.

For each IaaS hosted in the Nu@ge architecture, a storage cluster is created. The number and the location of hosts depend on the contract established with the IaaS owner.

Storage nodes are machines with significant storage resources. High performance disks allow improved writing/reading operations while traditional disks offer larger storage capacity with greater access time and latency.

Storage nodes are connected using a dedicated subnetwork, as they need to securely exchange user's data. For that purpose, the nodes have two Gbits/Ethernet interfaces and an InfiniBand interface. The QoS is guaranteed, in particular during data replication, to ensure resiliency in case a datacenter is suddenly not available. Additionally, the system keeps a journal of data modifications.

Unlike V-nodes, a storage node provides locally to the nearby V-nodes storage resources. A storage node has a high storage capacity sets of hard drives, each set containing dozens of hard drives.

5.2.4 Network infrastructure

We use two kinds of networks within the Nu@ge architecture: internal, dedicated to the communication between the different IaaS and external, used for the interconnection with end-users.

The internal network allows the creation of private networks between a user's nodes. Private networks require an IP addressing intra and inter-datacenter, in which the flows of information are encapsulated. As the interconnection with end-user is performed via third-party internet providers, it is necessary to have several networks, depending on the segmentation set by the internet providers.

External communication between the datacenters:

A simple method would consist of a star network topology, built around a central site with a full redundancy among the links. In a star topology, every node is connected to a central node called a switch. The switch acts as a server and the peripherals as clients [90]. However, for reasons of cost and architecture consistency, we do not consider this solution.

Ensuring continuity of service, without a star network topology, requires a number of links superior to the number of Nu@ge datacenters. Without any protocol, the interconnection of those links would cause a loop and prevents the delivery of packets.

STP (Spanning Tree Protocol) is a level 2 protocol (Ethernet) allowing the construction of an Ethernet network without loop[3]. STP presents a simple approach of the problem by cutting some links, to obtain a tree architecture. Due to its simple functioning, STP is widely used despite a few limitations such as the poor repartition of flows and a convergence time up to 30 seconds.

While several extensions to STP address those limitations, a new protocol named TRILL is gaining popularity. TRILL (Transparent Interconnection of Lots of Links) is an IETF standard[4]. This protocol presents the avantages of the routers and the network bridges by creating a level 2 network on the different links available.

Then, the protocol sets dynamic routing tables with MAC addresses. Using this level 2 routing, the protocol ensures to always have the shortest path to route packets. In the context of Nu@ge, we use TRILL in order to manage Ethernet segmentation.

Virtual Machine Mobility:

In a context of user mobility and network virtualization, getting a proper identification of an end-user over the network can be a difficult task due to the various possibilities of Internet access. The protocol LISP (Locator/ID Separation Protocol) tackles this problem by enabling migration over network while maintaining the same IP address. LISP is a protocol where IP addresses have two roles, namely localization and identification[5]. LISP aims to solve problems related to the growing size of IPv4 routing tables. Additionally, the protocol enables users to break the link with a single internet access provider (mobile users). LISP addresses this issue by separating the location from the identification. An IP address is used in two ways:

- Identify a machine present in a network
- Locate the identifier of the machine to route the traffic in an IP network

A distributed table of matches allows to find a locator, RLOC (Routing LOCator) from an identifier EID (Endpoint Identifier). LISP is independent of the IP version and can be deployed in an incremental fashion, without the necessity of having the full Internet architecture supporting it.

[3]STP is defined in IEEE 802.1d-2004
[4]TRILL is defined in the RFC 6325
[5]LISP is defined in the RFC 6830

5.3 Related work

5.3.1 Modular datacenters

Clouds depend on datacenters, large facilities used to house computer systems and associated components, such as telecommunications and storage systems. A modular datacenter system is a portable method of deploying data center capacity. As an alternative to the traditional datacenter, a modular datacenter can be placed wherever data capacity is needed.

Modular datacenter systems consist of purpose-engineered modules and components to offer scalable data center capacity with multiple power and cooling options. Numerous manufacturers such as Google, IBM, Sun,Verrari or HP built modular datacenters into standard intermodal containers (shipping containers) with the following key features:

High Density: Maximum accommodation of servers, storage and network equipments within a limited surface.

Cost Reduction: By comparison to the building and exploitation of a traditional raised-floor data center.

Self-contained Cooling: Self-contained cooling technologies, which can enable a cost savings and improve system reliability.

Environmentally Responsible: Minimal carbon footprint.

Disaster Recovery and Security: Characterized by the time of autonomy of the container and the physical equipments dedicated to ensure its integrity.

Fast deployment: Usually expected to be less than 6 months to be put in service after order to the manufacturer.

Industry relies on the TIA-942 specification [91] to classify the minimum requirements for telecommunications infrastructure of data centers and computer rooms into 4 categories, presented in Table 5.2.

5.3.2 Distributed storage

As explained later, the Nu@ge project requires resiliency. In case of the loss of connectivity of a datacenter, the data storage must be distributed among the federation while traceability, integrity and security of data must be ensured. Additionally, the storage system must keep a journal of data modifications to retrieve a coherent state after an incident. The following part evaluates existing distributed storage solutions with the purpose of integrating one suiting Nu@ge needs.

There are two main categories of storage [92][93], Network Attached Storage (NAS) and Storage Area Network (SAN). NAS is file-level computer data storage server con-

	Characteristics of the site infrastructure design topology	Theoretical availability
Tier 1	Single path for power and cooling distribution. No redundant components.	99.671%
Tier 2	Single path for power and cooling distribution. Includes redundant components	99.741%
Tier 3	Multiple power and cooling distribution paths. Only one active path. Includes redundant components. Concurrently maintainable.	99.982%
Tier 4	Multiple power and cooling distribution paths. All paths are active. Includes redundant components. Concurrently maintainable. Fault tolerant.	99.995%

Table 5.2: Characteristics and availability of the TIA-942 Tier system

nected to a computer network providing data access to a heterogeneous group of clients, while SAN is a dedicated network that provides access to consolidated, block level data storage.

Network attached storage:

HDFS [94] is conceived to distribute computations between several nodes. One of the nodes, the *namenode* is a necessary gateway to the system. It constitutes a serious bottleneck and is inappropriate for Nu@ge architecture.

GlusterFS, MooseFS, Pohmelfs and XtreemFS presented various limitations. Unstability issues, troubles with operating system support or lack of contribution support led us to exclude those projects from our choices.

Although the Ceph project [95] is quite close from our requirements, a cluster can only handle one file system, which is a serious technical restriction.

Storage area network:

Despite its lack of journaling support, Ceph project [95] features an extensive block data storage. Nevertheless, Ceph cluster gives no information about data location. In this context, data traceability, one of the main objective of Nu@ge, could be achieved only by creating a Ceph cluster per datacenter. This solution is not worth considering due to the high resource consumption of Ceph. The Sheepdog initative [96] seems relatively inactive and only works with QEMU/KVM virtualization technologies. Some of Sheepdog technical choices would lead to scalability problems in terms of storage or number of

datacenters.

Since no project provided both means to specify data location and journaling support, we decide to initiate a new project over a SAN, as it is less complex to implement. Unlike a NAS that needs the installation of a software on the client desktop, block level data storage can be access through standard protocols (specifically iSCSI [97], supported in a native fashion by numerous operating systems).

5.4 Realizing the architecture with open components

In this section, we describe how we leverage OpenStack and DIET Cloud for realising the Nu@ge federation architecture. As we consider the datacenter as a complete resource (just like memory, storage, cpu or network), its management can be integrated to the conception and exploitation of cloud. We use DIET Cloud, an extension of the DIET middleware to collect information from different IaaS and perform federation-wide decisions.

5.4.1 OpenStack

OpenStack is an open-source cloud computing platform for both private and public clouds. The OpenStack project was announced in July of 2010 by Rackspace and NASA, who made the initial code contributions. The OpenStack software consists of several independently developed components with well-defined APIs. The core component that provides IaaS functionality is OpenStack Compute (also called *Nova*). It handles provisioning and life-cycle management of virtual machines and supports most available hypervisors. *Neutron* is the component for building virtual network topologies that live on top of hardware from different vendors. *Cinder* is the Block Storage, a scalable storage service similar to Amazon S3. *Horizon* is a web-based GUI, primarily for management purposes such as starting/stopping virtual machines and managing user/group configurations. Further components are available such as Image Service and Identity management. The implementation described in this paper is based on the Grizzly release of the OpenStack and it uses Compute, Neutron, Cinder and Horizon which we have extended for our purposes.

In particular, a Block Storage Service was implemented within *Cinder*. Eguan provides a working backend driver for OpenStack's cinder block storage service with High availability, real-time data replication and history features. OpenStack volumes and snapshots can be hosted on one or multiples eguan instances with integrity checks and precise location of the data. The project's source code is available under the Apache 2.0 license. Implementations details are out of the scope of this thesis.

5.4.2 Federation scheduler using DIET Cloud

We rely on DIET [67], an open-source middleware that enables the execution of applications using tasks that are scheduled on distributed resources using a hierarchy of agents for scalability. DIET comprises several elements, including:

- **Client** application that uses the DIET infrastructure for remote problem solving.
- **Server Daemon (SeD)** which acts as a service provider exposing functionality through a standardized computational service interface. A single SeD can offer any number of computational services.
- **Agents**, deployed alone or in a hierarchy, which facilitates service location and interaction between clients and SeDs. Collectively, a hierarchy of agents provides high-level and scalable services such as scheduling and data management. The head of a hierarchy is termed as **Master Agent (MA)** whereas the others are **Local Agents (LA)**.

The steps of the scheduling process are explained below:

1. *Submission of a virtual machine creation request*

   A client issues a request describing a virtual machine template. If none of the datacenter is able to create new instances, a notification is returned to the client.

2. *Propagation of a request*

   The request is propagated through a hierarchy of agents.

3. *Collection of estimation values*

   Each agent computes and gathers its metrics, particularly performance and energy consumption. A reply containing these values is sent back to the scheduler.

4. *Sorting of candidates*

   Once the scheduler retrieves all replies, it proceeds to a sort according to specific criteria. The first ranked node is then elected and notified.

5. *Virtual machine creation*

   The virtual machine is created on the elected node.

DIET [67] implements many prerequisites, such as service calls, scalable scheduling and data management. This allows us to implement a Cloud middleware with minimal effort.

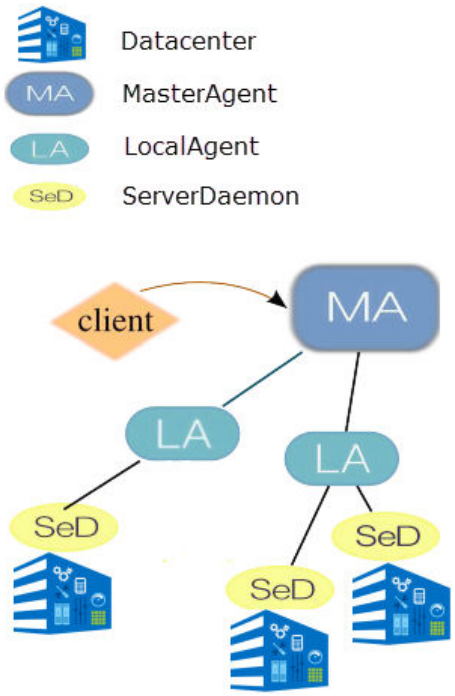

Figure 5.1: Federation scheduling using DIET Cloud

The aim of the DIET Cloud is to provide an architecture that handles a large number of Cloud middleware and Cloud Service Providers. Thus it hides the complexity and heterogeneity of the Cloud API layer, thanks to δ-Cloud [98]. δ-Cloud is a Cloud adapter that provides a library that eases the interfacing with different Clouds. δ-Cloud offers a standardized API definition for IaaS Clouds with drivers for a range of different Clouds. It can be seen as a meta-API. The δ-Cloud API is designed as a RESTful web service and comes with client libraries for all major programming languages.

Using this Cloud extension, DIET can act as a federation scheduler by benefiting from the different IaaS capabilities and manage Virtual Machines. Virtual Machine management decisions will be taken according to the monitor systems from the underlying datacenters.

The federation (See Figure 5.1) establishes relationships between the physical infrastructure and its logical behavior by providing developers (administrator) with an abstract layer to implement aggregation and resource ranking based on contextual information such as infrastructure status, users preferences and requirement, and the energy-related external events that can occur over time.

To perform a placement, information on datacenter health status, energy monitoring and capacity must be obtained.

These metrics are incorporated into DIET SeD to populate its estimation vector using new tags. Every time a client submits a request for a virtual machine, each datacenter retrieves its metrics over the local monitoring tools. Once this information is collected,

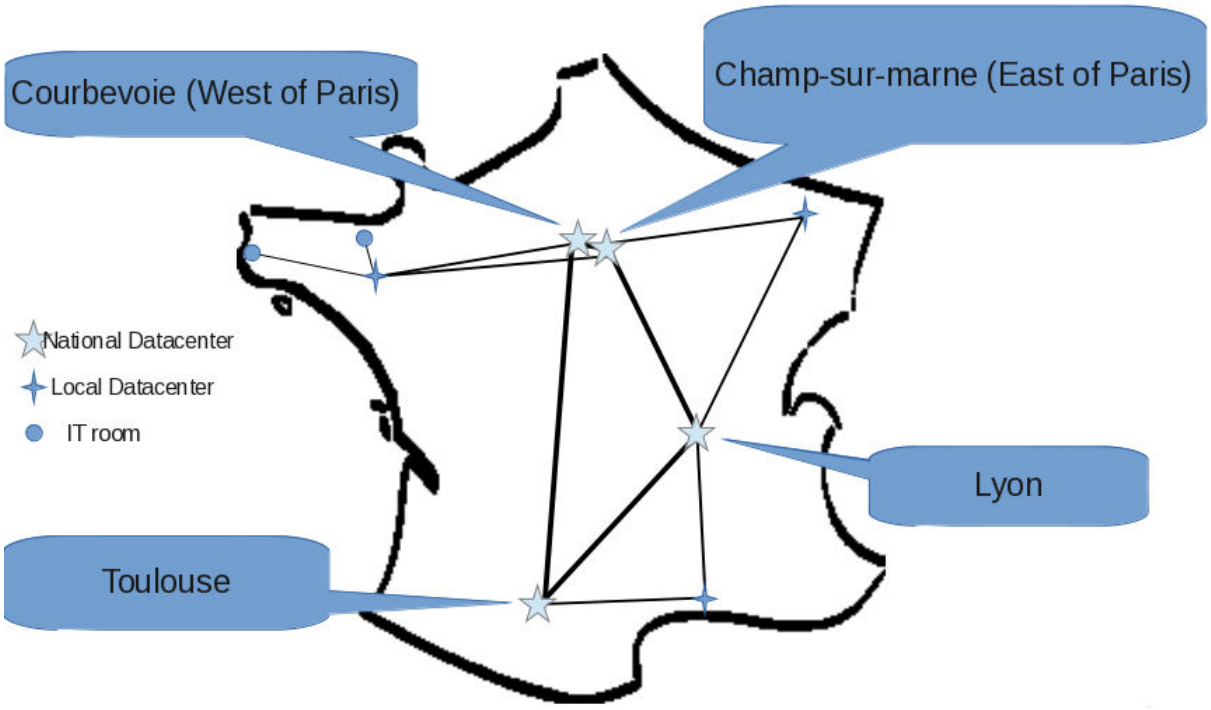

Figure 5.2: Nation-wide deployment over four locations in France

servers are advised to populate and forward an estimation vector to the Master Agent, which in turn uses an **aggregation method** to sort server responses according to the chosen criteria and select the appropriate resource to execute the client request. Each DIET agent of the hierarchy performs the selection following the plug-in scheduler.

5.5 Prototype

This section briefly describes a prototype implementation of the Nu@ge architecture as depicted in Figure 5.4. Such implementation has been used for evaluating the performance and feasibility of the proposed approach. The prototype has been deployed and validated over 4 different geographical locations in France.

5.5.1 StarDC

The *StarDC* (Figure 5.3) features 4 service units of 19 inch racks and can hold up to 168 computing servers. The container provides 15 square meters of floor space, a power capacity of 18 kilowatts and a Power Usage Effectiveness (PUE) of 1.24. The *StarDC* is built within Tier 3 specifications and is the subject of a patent.

Unlike most modular datacenters, the StarDC does not use water cooling. It a broader range of physical locations and an eco-responsible behavior since free cooling is used to cool the container. StarDC uses a mechanism of temperature using outdoor air as a free

Figure 5.3: The public presentation of the StarDC container occured on September 18th 2014 during Nu@ge inauguration in CELESTE headquarters, Marne-la-vallée, France.

cooling source. The purpose is to take advantage of outdoor temperature to naturaly cool of equipments. When the air is injected into machines, its temperature raises by a delta number of 10 ° (common value among commercialized servers). When the outdoor temperature is higher than a threshold, we use air conditioning to cool it.

The Nu@ge customer is in charge of setting up the cold aisle temperature. If he chooses a temperature of 20 ° to have a safety margin, the air conditioning will be active approximately 20% of the year (varies depending on the location). Choosing a temperature value up to 25 ° and more results in less air conditioning and a better ecological impact. We discuss the evaluation of PUE in Section 5.6.

5.5.2 Building of an IaaS

The creation of a new IaaS does not impact the architecture of Nu@ge. The main changes concerns virtual nodes allowing the sharing of physical resources. In particular, the instantiation of a storage access point; an IaaS access point; and a virtual switch interconnecting the IaaS equipments. As a result, several storage nodes and V-nodes can be used by multiple IaaS.

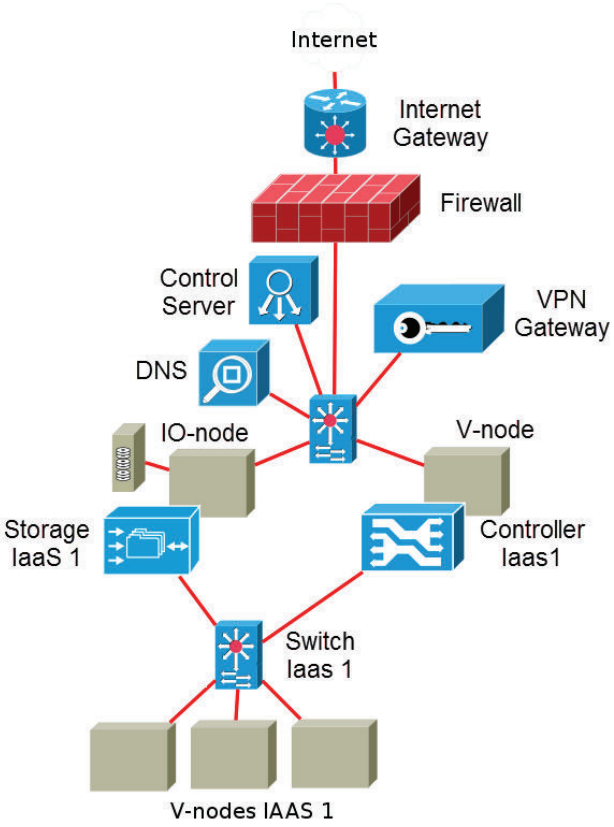

Figure 5.4: Nu@ge architecture including gateways and a IaaS

5.5.3 Storage cluster

Nu@ge racks contains two storage nodes. As storage management can require large computational resources, a storage node features dual-core CPUs for a total of 24 threads and 256 gigabytes of RAM. Deployment of storage nodes is performed via the following steps:

1. Booting via PXE / TFTP protocols.
2. Configuration using Puppet.
3. Creation and configuration of an object storage in RAID1.
4. Creation and configuration of RAID6 objects.
5. Creation of logical volumes.

Once created, the node executes an OpenStack storage service specific to the newly created IaaS, and the storage server. This organization is coherent with Nu@ge objectives of data isolation between IaaS and data traceability for the administrators.

5.5.4 Supervision

An interface has been built to visualize information about datacenters and customers. It provides the visualisation of the dynamic mapping of virtual machine deployment on physical infrastructure along with analysis of performance in terms of user activity and alerts related to usage incidents.

This platform acts as an autonomous webboard displaying information about a local datacenter and to the global federation. It can be used as a complement or integrated into OpenStack's Horizon (Figure 5.5). Logging has been performed using Nagios Core [99] and SNMP, an Internet-standard protocol for managing devices on IP networks, for non-standard devices.

5.6 PUE of Nu@ge

The PUE (Power Usage Effectiveness) is a metric used to evaluate the energy efficiency of a datacenter [100], also detailled in Chpater 2. From a practical point of view, it measures how much energy is used by the computing equipment in comparison to cooling and other overhead. As discussed in Chapter 2, the PUE is expressed by the ratio:

$$PUE = \frac{TotalFacilityPower}{ITEquipementPower} \tag{5.1}$$

Nevertheless, it is very hard to know the real PUE from a company because the area of Equipment Power can be debatable. As an example, for the Google Data center, considering only servers and air conditioning gives a PUE of 1.06. However, if Google includes generators, transformers, site substations and natural gas then the PUE is 1.14.

Green Datacenter from green.ch company (Switzerland) was designed with energy efficiency and reduction consideration. This project is based on energy-optimized data center architecture, latest generation of air conditioners, heat exchangers, waste heat utilization in new office building.

The container-sized datacenter designed by Nu@ge aims at keeping the PUE under the value of 1.30, using two cooling operating modes:

- Total free cooling when the room temperature is within the server specifications. That range is set by the customer resulting in a PUE value of 1.16.
- Air recycling with air conditioning when the temperature is out of range, resulting in a PUE value of 1.55.

Thus, the PUE relies strongly on the climate conditions, and customer-defined rules. In the case of Nu@ge's *StarDC* at Marne-La-Vallée (France), weather forecast indicates that

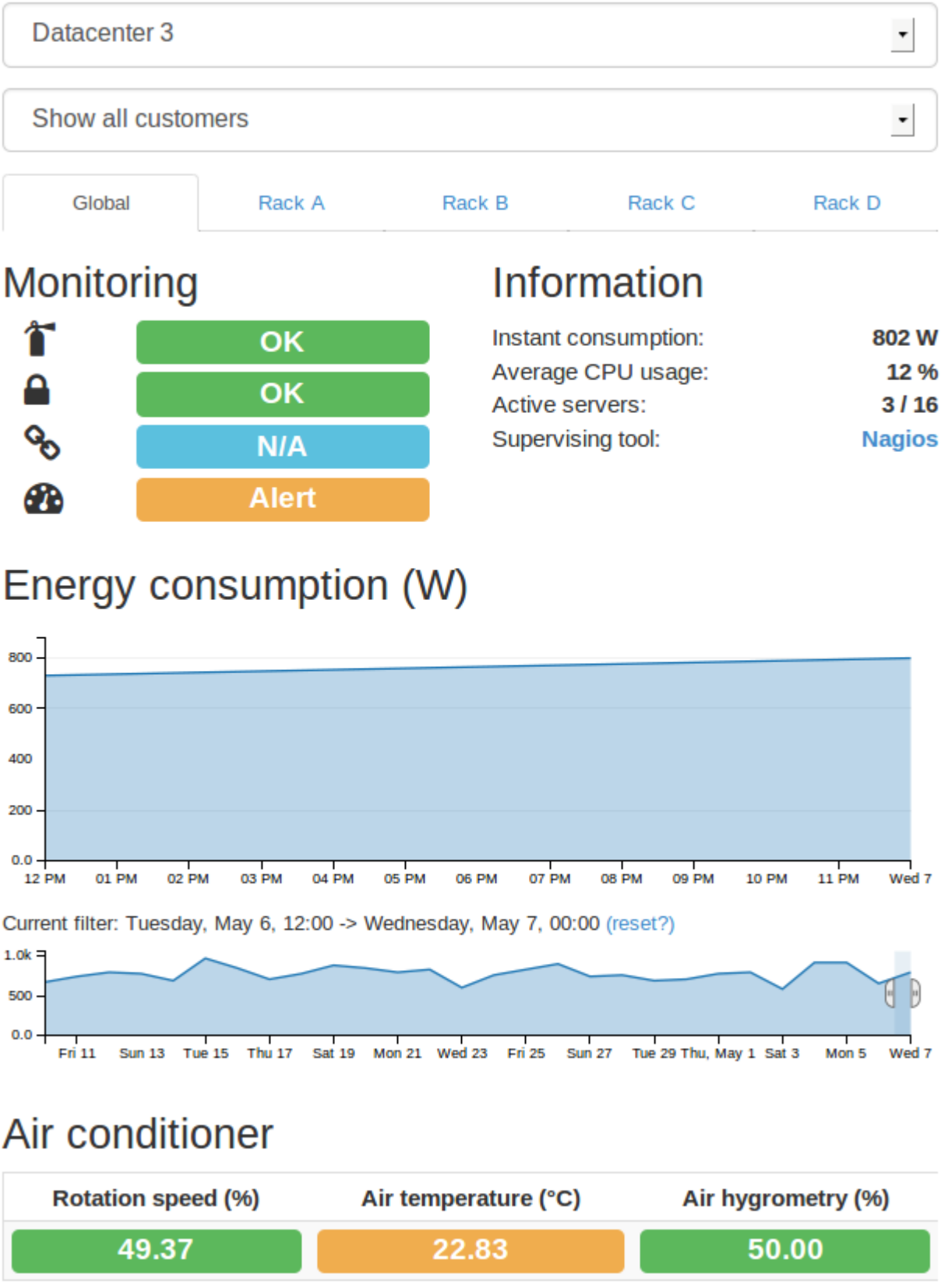

Figure 5.5: Web Interface for the visualisation and management of datacenters

80% of the time, the temperature is below 23 °C. The theoretical maximal value for the PUE is then:

$$PUE_{Nu@ge} = 80\% \times 1.16 + 20\% \times 1.55 = 1.24 \tag{5.2}$$

Data Center	Company	PUE
Prineville DC	Facebook	1.07
Google DC	Google	1.14
StarDC	Nu@ge	1.24
Green Datacenter	grench.ch	1.4

Table 5.3: PUE comparison of different datacenters. Those values are given by each project but no independent evaluation was done.

Among the datacenters in Table 5.3, it is worth noting that StarDC is the only mobile product. Additionally, it can be produced in series and available to third party companies in constrast to more efficient but proprietary datacenters. Recent regulations, in particular Sweden [1], does not allow the construction of datacenter with a PUE above 1.4, putting in perspective the positive PUE value of Nu@ge.

5.7 Energy-aware management

The purpose of the energy-aware management is to evaluate the benefit of green scheduling for reducing electric consumption while matching performance objectives for the virtual machines.

The performance criteria are CPU oriented, and based on a measure of the node performance using all its CPU cores. It produces a value in flops, indicating the number of floating points operations per second. Those benchmarks are based on measurements using ATLAS[6], HPL[7] and Open MPI[8]. Other criteria exist in the literature, involving the consideration of idle consumption [63] or the use rate [64] of the physical nodes.

Regarding the consumption criteria, two approaches are possible. A static way would imply to execute a task on all nodes before starting and measure the power consumption corresponding to the completion time on each node. This method is not significant for long periods because the power consumption of the machine may vary depending on the actual load or external conditions, such as the physical location of the server.

[6]Automatically Tuned Linear Algebra Software.

[7]Portable Implementation of the High-Performance Linpack Benchmark for Distributed-Memory Computers.

[8]High Performance Message Passing Library.

We use a more dynamic approach where the electric consumption metric is based on the number of requests handled by a computational node weighted by the power consumption measured during execution. Every time a client submits a request, a computational node will report its electric consumption and total number of requests.

We coupled the scheduling process to resource provisioning while taking into account energy-related events such as fluctuations of electricity prices or heat peaks. Based on previous work [6] described in Chapter 3, we proposed methods for provisioning resources and distributing requests with the objective of meeting performance requirements while reducing energy consumption. *GreenPerf*, a hybrid metric, was introduced as a ratio of performance and power consumption for energy efficiency. Based on this work, we enable autonomic decisions from the scheduler by checking pre-defined threshold before executing placement/provisioning decisions.

5.7.1 Autonomic and Adaptive Resource Provisioning

We demonstrate the behaviour of the scheduler by considering fluctuations of two metrics over time, namely the cost of electricity and temperature. We inject energy-related events at the scheduler level while a client, aware of the number of available nodes, submits a continuous flow of requests intending to reach the capacity of the infrastructure. Requests are scheduled as they arrive to ensure dynamicity.

The infrastructure is deployed on Grid'5000, on the nodes defined in Table 5.4. The experiment starts with an energy cost of 1.0 and a $Preference_{provider}(u, c)$ giving priority to energy-efficient nodes. The $Preference_{user}$ is not having any influence in the current scenario as the client dynamically adjusts its flow of request to reach the capacity of available nodes. The StarDC was not fully operational, in particular in terms of sensors, at the time of the experiment. Thus, we evaluated this prototype on Grid'5000 with a simulation of energy and temperature parameters.

Cluster	Nodes	CPU	Memory	Role
Orion	4	2x6cores @2.30Ghz	32GB	SeD
Sagittaire	4	2x1core @2.40Ghz	2GB	SeD
Taurus	4	2x6cores @2.30Ghz	32GB	SeD
Sagittaire	1	2x1core @2.40Ghz	2GB	MA
Sagittaire	1	2x1core @2.40Ghz	2GB	Client

Table 5.4: Experimental Infrastructure.

For the sake of simplicity, the cost of energy is defined as a ratio between the cost over a given period and the theoretical maximum cost. Related to the cost of energy, we

defined three states:

- Regular time, when the electricity cost is the highest (1.0).
- Off-peak time 1, when the electricity cost is less expensive than during regular time (0.8).
- Off-peak time 2, when the electricity cost is the least expensive (0.5).

Heat measurements are defined through two states, depending of the temperature of utilization: in-range temperature ($<$ 25 degrees) and out-of-range temperature ($>$ 25 degrees).

The status of the platform corresponds to the value of the exploited metrics at t time. The master agent checks the status of the platform every 10 minutes, with the ability to get information about the scheduled events occurring at $t + 20$. Figure 5.6 presents a sample of provisioning planning, which is a shared XML file using a readers-writers lock that refers to a specific time-stamp. For each sample, we defined three tags, namely *temperature*, *candidates* and *electricity_cost*. At each time interval, the scheduler performs decisions according to the value of the tags. Thus, future information, such as forecasts, can be added to the provisioning planning, ensuring a dynamic behavior regarding to the various contexts. The tags and time interval are customizable variables that can be adjusted to fit specific contexts.

```
<timestamp value="1385896446">
<temperature>23.5</temperature>
<candidates>8</candidates>
<electricity_cost>0.6</electricity_cost>
</timestamp>
```

Figure 5.6: Sample of the server status describing the XML structure.

We set thresholds whose values trigger the execution of actions. Actions can be defined through scripts or commands to be called by the scheduler. In this example, we implemented five behaviors associated with the experiment metrics. Let c be the cost of energy for a given period and T the temperature measured at t.

- if $T > 25$ then candidate_nodes = 20% of all nodes
- if $1.0 \geq c > 0.8$ then candidate_nodes = 40% of all nodes
- if $0.8 \geq c > 0.5$ then candidate_nodes = 70% of all nodes
- if $c < 0.5$ then candidate_nodes = 100% of all nodes

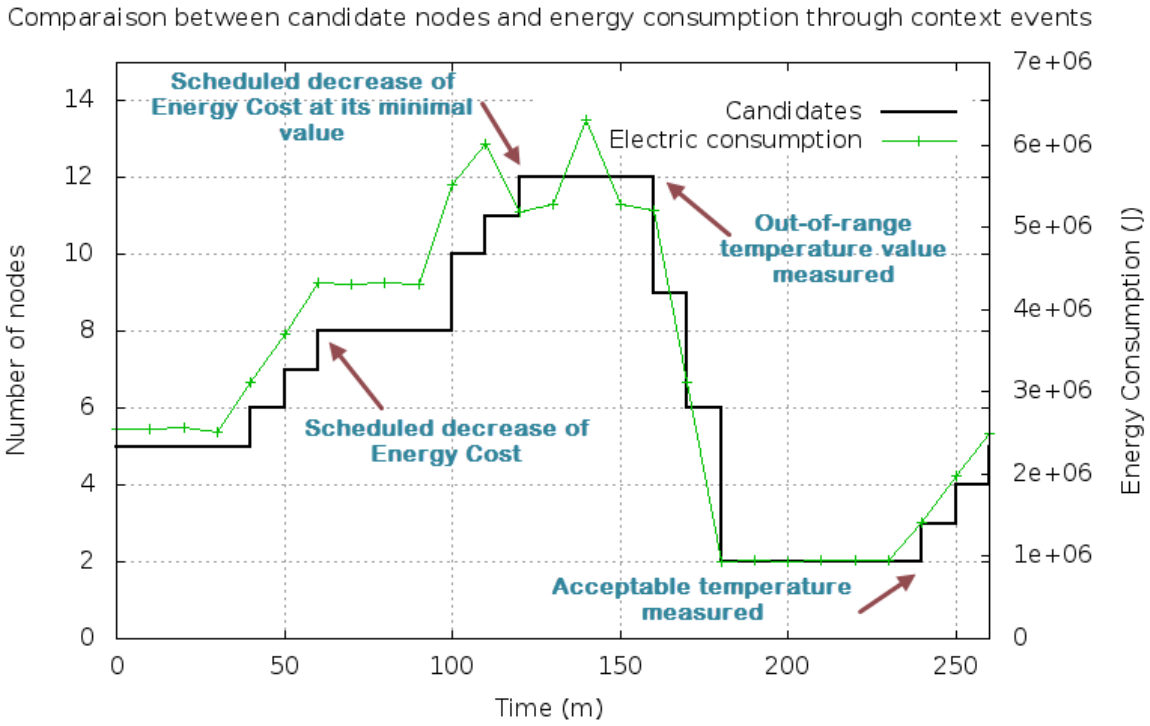

Figure 5.7: Evolution of candidate nodes and power consumption through context and energy related events.

Four different types of events are injected in the provisioning planning made by the scheduler. These events, in turn, fall into two categories, namely scheduled and unexpected. Figure 5.7 presents how the number of candidate nodes and the energy consumption evolve over time. The left y-axis shows the total number of nodes in the infrastructure; The plain line presents the number of candidates during the experiment; The line with crosses is the evolution of the energy consumption, using the right y-axis. Each cross describes an average value of energy consumption measured during the previous 10 minutes. The x-axis represents the time with a total of 260 minutes.

Event 1 (scheduled) is a decrease of the electricity cost occurring at $t + 60$ min. The Master Agent becomes aware of the information at $t + 40$ min. Observing a future cost of 0.8, the agent plans ahead to provide 8 candidates nodes at $t + 60$ min. The set of candidates is incremented slowly to obtain a progressive start, at $t + 50$ min and $t + 60$ min. (It avoids heat peaks due to side effect of simultaneous starts.) We observe a linear increase of electric consumption through the infrastructure. After each request completion, the client is notified of the current amount of candidates nodes, and is free to adjust its request rate.

Event 2 (scheduled), similar to **Event 1**; the electricity cost allows the use of every available node in the architecture. The nodes are added to the set of candidates during the following 20 minutes, resulting in a use of all possible nodes between $t + 120$ and

$t + 160$ min.

Event 3 (unexpected) simulates an instant rise of temperature, detected by the Master Agent at $t + 160$ min. According to administrator rules, the predefined behavior is to reduce the number of candidates nodes to 2. It is performed in 3 steps, in order to cause a drop of heat and energy consumption. We allow tasks in progress to complete, resulting in a delayed drop of energy consumption. The system keeps on working with 2 candidates until an acceptable temperature is measured at $t+240$ min (**Event 4** (unexpected)). The master agent then starts to provision the pool of candidates every 10 minutes to reach again the value of 12.

The scenario of this experiment shows the reactivity of the scheduler and its ability to manage energy-related events by adapting dynamically the number of provisioned resources of the physical infrastructure, therefore the power consumption.

5.8 Conclusion

The Nu@ge project aims at designing and building a network of modular datacenters dedicated to virtualize IT services. This Cloud architecture offers guarantees of Control over the underlying infrastructure, knowledge of data location and control over the different QoS. By using Nu@ge, a final user (i.e. the administrator of an IT system) can focus on the management of a virtual cluster seamlessly spread across a collection of datacenters with support on infrastructure supervision.

The project design and implementation are based upon OpenStack components with an emphasis on extensibility and customization. Administrators are also given a degree of control over the scheduling subsystem using DIET mechanisms (plug-in schedulers) that use information gathered within the federation by the mean of pro-active monitoring.

Our contribution to this project focused on the collection of information from heterogeneous sources in order to specify a model and ensure server provisioning while considering energy related events. Extension of the GreenDIET middleware (described in Chapter 3), interaction with the OpenStack software stack and datacenters supervision engine were developed and integrated to the Nu@ge prototype, later released as commercial offer. Validation was performed on real nodes and showed a reactive provisioning to temperature and energy costs.

Chapter 6

Nuvea: An audit platform for energy-aware virtual machine management

This chapter presents the Nuvea project, a cloud optimization-oriented platform. Cloud computing has evolved from a risky and confusing concept to a strategy that small and large organizations are beginning to adopt as part as their overall computing strategy. Companies are now starting to ask not whether they should think about cloud computing but what types of cloud computing models are best suited to solve their business models. Armed with the experience of previous projects (particularly Nu@ge, described in Chapter 5) and the scientific contributions described in this thesis, the NewGeneration-SR group and the Avalon research team decided to gather their expertise in a standalone product, dedicated to the evaluation and optimization of energy efficiency in IT and Cloud platform. The Nuvea platform ambitions to allow Cloud customers to permanently measure, take over, manage, benchmark and optimize their distributed IT infrastructure in a highly flexible and real time manner. The remainer of this chapter describes the motivation, architecture and current implementation of the Nuvea platform.

6.1 Context

Cloud computing technologies supports the major share of ICT sector, currently identified as the fastest growing sector of the global economy. Worldwide, the cloud computing services market is expected to be worth $127 billions by 2017 [101]. As discussed in previous chapters, the critical increase in power consumption constitutes a negative side effect and the market is inefficient to control it. Computers in datacenters run 24/7 and

consume close to 5% of the global worldwide electricity [10]. As an example, Google[1] is supposedly holding more than 900,000 servers with an estimated consumption of 260MW. US datacenters has an estimated 12 millions servers collectively, with a cost of powering datacenters estimated to exceed 7B per year since 2011 [102]. The reduction of energy consumption represents one of the main objectives of NewGeneration-SR in the IT sector.

Additionally, the IaaS[2] Cloud market present several inefficiencies that could be levered by Nuvea customers. From the perspective of providers, power wastage may represent up to 50% additional cost in what providers bill client for service. This asset-based business models is very sensitive to price, and represents a strong argument to identify and gain clients. From the perspective of customers, the current cloud computing landscape hinders making a straightforward comparison between providers and cloud service offerings. It goes along with negative side effects:

No elasticity Traditional Cloud providers sell fixed-sized virtual machines.

No flexibility Evaluating performance across all of the datacenters of multiple cloud providers is a complicated task. Performance evaluation quickly become out-of-date and tools must be continuously redesigned.

No interoperability Proprietary solutions makes a customer dependent on a vendor for products and services, unable to use another vendor without substantial switching costs (known as *vendor lock-in*).

No transparency Customers have little knowledge and control over the infrastructure hosting their applications. Due to the virtualization of the hardware used in cloud computing, providers may use resource sharing practices that degrade the performance of a cloud application.

In this context, NewGeneration-SR, intends to challenge the existing *vendor lock-in* threat in the cloud infrastructure market.

The ability to manage workload placement with an extendable metric for energy efficiency (Chapter 3), the benefits of state-of-the art heuristics to consider multi-criteria decisions (Chapter 4) constituted the early reflexions of a solution that aims at optimizing the yield of management of datacenters while giving more flexibility to customers.

[1]Google is accountable for several green incentives. https://www.google.com/green/

[2]In an IaaS model, a third-party provider hosts hardware, software, servers, storage and other infrastructure components on behalf of its users.

6.2 Approach

6.2.1 Field survey of practitioners

As we begin the reflexion on a new product, it is important to understand the different types of customers that could benefit our solution and understand the day-to-day reality of their computing strategy. Despite the effort of multiples agencies to address energy efficiency, there is still little knowledge among practitioners on the topic. This section presents an investigation of state-of-the-art practices as an interview of 8 practitioners from companies of different size. We used this survey as a research methodology to explore both the issues to consider for Nuvea as well as the implementation considerations. The following interviews were conducted with industrial partners, potential new customers and early adopters of the Nuvea platform. The following list describes each existing company. For privacy and confidentiality, the name of companies are changed to a single letter.

- Company A: A large size company based in India that develops and provides IT services for others business. The discussion were conducted with the head of Cloud Solutions and an associated engineer.
- Company B: A large size company based in India with an international presence and ownership of datacenters.
- Company C: A large sized company based in France with a business core in sales. They own their IT infrastructure.
- Company D: A small-medium size company based in France. Their core of business in Internet providing and server hosting.
- Company E: A small size company employing approximately 10 employees which provides hosting solutions. Company F owns a datacenter.
- Company G: A small french company employing less than 10 employees which provides hosting solutions. Company H does not own its datacenter but rents space in another one. Discussion was conducted with the CTO who is responsible for the technical, hardware and software implementations.
- Company H: A small french company employing less than 10 employees which provides hosting solutions. Company H does not own its datacenter but rents space in another one.

Table 6.1 depicts the results of the interviews and the practice adoption among companies. Table 6.2 presents the main concerns regarding optimization of their computational infrastructure.

Practices	Company A	Company B	Company C	Company D	Company E	Company F	Company G	Company H
Consolidation			X		X	X	X	
Virtualization	X	X	X		X	X	X	X
Efficient cooling				X				
Energy management systems		X		X				
Monitoring server utilization	X			X	X	X	X	X
Demand management			X		X	X		
Workload estimation	X	X	X	X			X	
Dynamic Power Scaling								
Renewable energy sources				X				
Switch off unused devices								
Energy-efficient hardware				X		X		
Green IT budget	X		X			X		
Dedicated Facilities Manager			X	X	X	X	X	
Hardware upgrades			X	X	X			

Table 6.1: Practice adoption among companies

Company	Core business	Interests in the Nuvea solution	Concerns regarding optimization
A	Cloud services and application hosting	Energy reduction, Cost reduction	Failure to provide the right IT solutions to customers
B	IT Outsourcing	Research and Development collaboration in energy management	Continuous availability, failure to integrate the solution to their existing process, failure of using manpower
C	Sales	Cost reduction	Loss of control over the critical process
D	Internet provider	Energy management, advance monitoring	Loss of performance, extra costs
E	IT Outsourcing and Software Editor	Energy management expertise	Interoperability and integration with existing solutions
F	Server hosting	Meeting environmental regulation and policies, developing energy management	Settings costs, failure to provide quantitative results
G	Server hosting	Cost reduction, space reduction	Integration to production environment
H	Collaborative solution	Energy management	Excessive manpower, extra cost

Table 6.2: Practitioners activities and main concerns

Table 6.2 presents the concerns expressed by the practitioners regarding an optimization of their infrastructure. This short survey is not meant to be exhaustive nor presenting a representative set of practitioners.

Some factors were put in light: the lack of measurements/control over the workload and the difficulty to characterize the target production environment. Very few practitioners described a monitoring system with energy capabilities. They often have the amount of the yearly energy bill but the lack of fine-grained measurement (rack or node level) makes it difficult to characterize any potential gain.

Based on those answers, a partial conclusion is that a key factor of Nuvea's success will rely in an efficient management and monitoring of workload. Management, in this context, refers to how the resources are assigned in order to process workloads. As assignments could be based on resource availability, business priorities, events, geolocation and much more, it makes it difficult to perform any operation without the customer support.

Without careful management and monitoring of current activities, the target organization cannot achieve the right level of performance. The existence or ability to provide a testbed is a key to demonstrate predictable performance while minimizing risk on the target platform. Additionally, it could happen that the customer does not have an accurate expertise of its own infrastructure.

This constitutes one of the early features offered by Nuvea: the ability to audit a target platform, characterize its activity and identify situation-specific levers for performance and energy efficiency. Another important aspect is the importance of APIs. API allows communication to occur between services and specifies the rules and interfaces. In a land of proprietary solutions, it eases the integration on an optimization solution by enabling the pre-development of reference products. In the next phase, they could allow Nuvea to be available as a connected service or as a toolbox for expert users.

6.3 Analysis: A multi-layer solution

The Nuvea platform is composed of a scheduling engine, in a form of a middleware that generates placement or migration decisions on virtual machines. Before discussing the principles and challenges of the solution, we explain the following terms and details their signification in the context of Nuvea.

Task A task is defined as a fixed unit of workload to be executed on a physical machine that produces a result

Virtual Machine (VM) A virtual machine is defined (by analogy with a physical machine) by a certain number of static capacity specifications. These specifications, namely CPU, RAM, Hard Drive (HD) capacity, constitute the template of the vir-

tual machine. Once the VM is started, the monitoring gives report to its dynamic utilization and its operational performance (number of tasks performed in a given time).

Physical Machine (PM) The resources are defined by their location and their capacity (CPU, RAM, HD). They presents different variable of dynamic exploitation such as latency, temperature, energy consumption, etc.

Placement The placement, or mapping, is the action of assigning a VM to a PM. The scheduler determines that placement.

Migration The migration refers to the process of moving a running virtual machines between different physical machines without disconnecting the client or application. Memory, storage, and network connectivity of the virtual machine are transferred from the original PM to the destination.

The main idea behind Nuvea is the ability to get the best applicative performance by affecting the VM to the available PM that fits the most. From an operational point of view, it implies the ability to establish a ranking of resource and the capacity to apply the related placement decisions. This is a pretty straightforward problem if some hypothesis are made on the knowledge of the load (constant and predictable) and status of resources (fixed amount with predictable performance).

These hypotheses can be non-realistic when discussing complex tasks. A simple task can be "anticipated" in terms of completion time or resources demand. A virtual machine hosting several tasks exposes a fluctuating workload during its life-cycle and won't probably used all the resources of its template. The current state of the resources is highly variable. It evolves depending on time, external conditions and hardware failures. The initial state and the succession of decisions is often not enough to determine the current situations.

The placement of virtual machines cannot be considered as independent decisions when it comes to resources demands. If the demand for a shared resource exceeds the supply, known as contention, performance degradation will result. Basically, when several VM are racing to utilize the same resource, one of them will win and the rest will have to wait, with negative impacts on operational performance.

6.3.1 Market situation

The major cloud providers operate exclusively in terms of reservation of capacity: the virtual machine, defined by their template at their creation, are placed by reservation on environments in the limits of their respective host capacity. Two main strategies are employed:

Extensive strategy of isolation by reservation of capacity of physical machines. The virtual machines of a client are placed on a physical machine dedicated to that client, turned on and exclusively booked.

Intensive strategy of saturation of physical resources: virtual machines are affected to a physical machines until it disposes of enough resources.

The extensive strategy is inefficient because it tends to multiply the numbers of active resource with a low utilization. The intensive strategy reaches its limits because it does not address the concerns of colocation side effects such as congestion.

In general, large systems are closed to the customer: he can not expresses specific needs other than templates of virtual machines. The virtual machines placement does not offer guarantees on colocation side effects in a way that a customer can not know the real reasons of performance degradation observed in applications. The reservation of physical capacity is not enough to guarantee all aspects of a Quality of Service.

To our knowledge, current market situation leave unexplored two problematics:

- The negative effects of colocation are not addressed by current schedulers. Most offers relies on templates and uptime guarantees without performance specification.
- The gap between the created/reserved templates and their resource consumption constitutes a wasted of additional value that actual schedulers are not taking advantage of.

6.3.2 Technical locks

The expression of the above problematic raises several locks. With the intent to reduce the time-to-market, an emphasis has been put on practical solutions and fast prototyping.

Definition of criteria related to a Nuvea QoS/SLA Specifications of a Quality of Service that outreach the simple notion of reservation and presents encouraging/-better results that the intensive and extensive strategies. This approach will be done by analyzing existing logs and simulations to evaluate the potential gain between reservations and actual usages.

Observation and characterization of virtual machines The quality of scheduling policies depends on the ability to characterize the effective load and behavior of virtual machines. An environment-independent metric would allow the definition of execution profiles. This work should be done by consideration a non-intrusive observation of the virtual machine (i.e. no software agent running on the virtual machine system would be imposed to the client).

Observation and characterization of resources and physical machines The dynamicity of a set of servers (failures, add/removal of nodes) should be taken into account to perform valid placement. Creating a reconfiguration plan implies to have a time window when decisions are still valid or could be re-adjusted without additional cost.

Generation of placement solution and reconfigurations Once the physical and virtual machines are properly characterized, one must be able to evaluate the optimality of a placement plan, identify better solution and execute them by interacting with hypervisors, operators or middleware.

Learning on colocation side effects The comprehension of colocation side effects, the capacity to perform placement with respect to resources demands (CPU, RAM, HD, network) are necessary to improve the schedulers decisions. These phenomena are well studied in the literature but very few systems implements it in production. The approach to solve those issues is a learning model representing the correlations between decisions and consequences on the resources.

6.4 Project management

The pace of this project constitutes a challenge for the coordination of action between internal teams. With the common ambition of pushing an innovative product that answers customers concern while integrating state-of-the-art technologies, an agile organization was set to coordinate the teams. This section explores the strategy and role of the different teams.

At the start of this project[3], we can identify 3 major entities:

- The research team[4]
- The engineering team[5]
- The marketing team[6]

The agile method describes a set of principles for software development under which requirements and solutions evolves through the collaborative effort of self-organizing teams

[3]The Nuvea project has started in 2014. Initial partners are NewGeneration-SR and the Avalon team from Ecole Normale Superieure de Lyon. I was in charge of coordinating the research and engineering aspects.

[4]Two researchers (Associate professor and permanent researcher)

[5]One employee (CTO)

[6]One employee (CEO)

cross-functional team [103]. In a context of continuous exchanges with potential customers and early adopters, along with tests and prototypes of state-of-the-art technology, agile methods promotes continuous improvement and flexible response to change.

Figure 6.1 presents the application of those concepts to the Nuvea project.

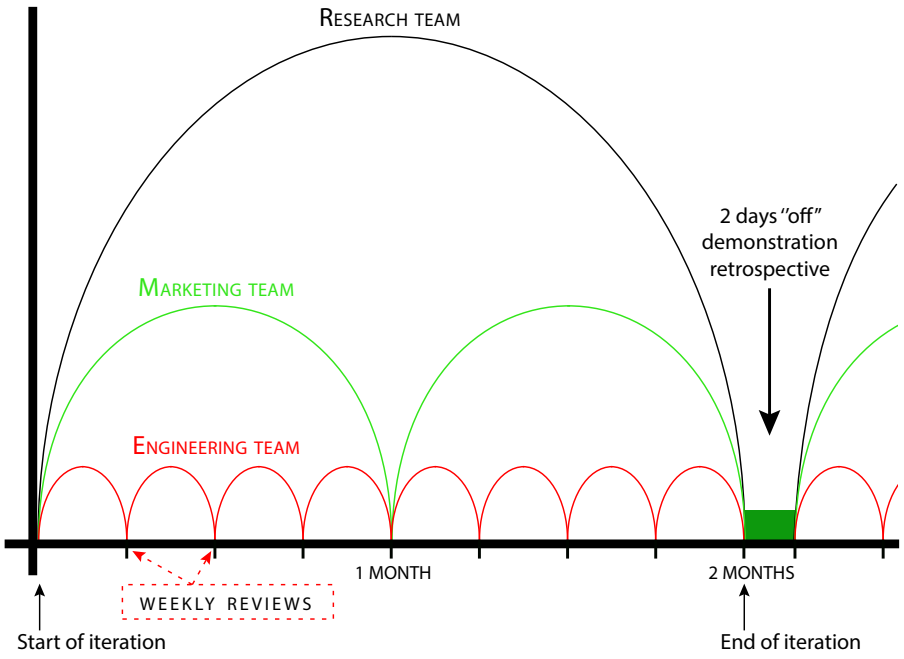

Figure 6.1: Iterative organization of the Nuvea project

The beginning of an iteration constitutes a definition of goals. The engineering team takes into account the suggestions brought by the marketing team and their search of adopters. A major interaction intervenes after one month to discuss progression and early results. The weekly review describes the progression and keeps everyone informed. The research team proceeds to define a research plan based on the technical locks identified as the investigation of new mechanism. The research agenda notably includes communication of scientific results in the community. The marketing team keeps in touch with the project and is devoted to the interactions with investors and customers.

On a 2 month basis, all team gather to present their respective results and sets goals for the next iteration. This organization allows each team to progress at its own pace, independently of other but with frequent synchronization and consideration of the global project roadmap. Through the iteration, an emphasis is put on:

Correctness: maintaining a platform that answers major concerns of customers

Usability: ease of installation, configuration and deployment for the internal teams

Compatibility: the use of loosely coupled patterns to ensure interoperability and integration with new comers and their respective architecture

Modularity: each feature needs to be a separate and independently functional module to ensure the development of experimental/new processes by the research team

The ambition of the Nuvea taskforce is to release a complete solution on the market is 2017. The study related to the impact, market estimation and pricing are available on demand within the current commercial offer[7] but considered out of the scope of this thesis. The remainder of this chapter describes the architecture and current state of the infrastructure.

6.5 Architecture

The major objective of the Nuvea platform is to improve the utilization of physical resources and reduce energy consumption by (re)allocating virtual machines according to their real-time resource demand and transitioning idle hosts to low power mode. For example, assume that two virtual machines are placed on two different hosts, but the combined resource capacity required by the virtual machines to serve the current load can be provided by just one of the hosts. Then, one of the virtual machines can be migrated to the host serving the other virtual machine, and the idle host can be switched to a low power mode to save energy. Another use case is the observation that a virtual machine is using very few resources compare to its template/specification. The manager can restrict this specification to match actual/effective virtual demand.

Apart from virtual machine and consolidation, the system should be able to react to increases in the resource demand and deconsolidate virtual machine to avoid performance degradation.

Figure 6.2 expose the logical components and data stores of the Nuvea Infrastructure. In the following sections, we discuss the design and interaction between modules.

The system is composed of four main modules:

The data collection engine a component that is deployed on the target platform. It is responsible for collecting data about the resource usage of physical machines, virtual machines or the various sensors present in the target infrastructure. It transmits the data in real-time or under a defined periodical interval trough a dedicated bus.

The analysis engine a component that is deployed on the management platform and interprets the collected metrics to raise alerts or identify utilization patterns.

The execution engine a component that is deployed on the management hosts and takes management decisions such as mapping virtual machines on hosts or reduce the template of a virtual machine.

[7] http://www.nuvea.eu

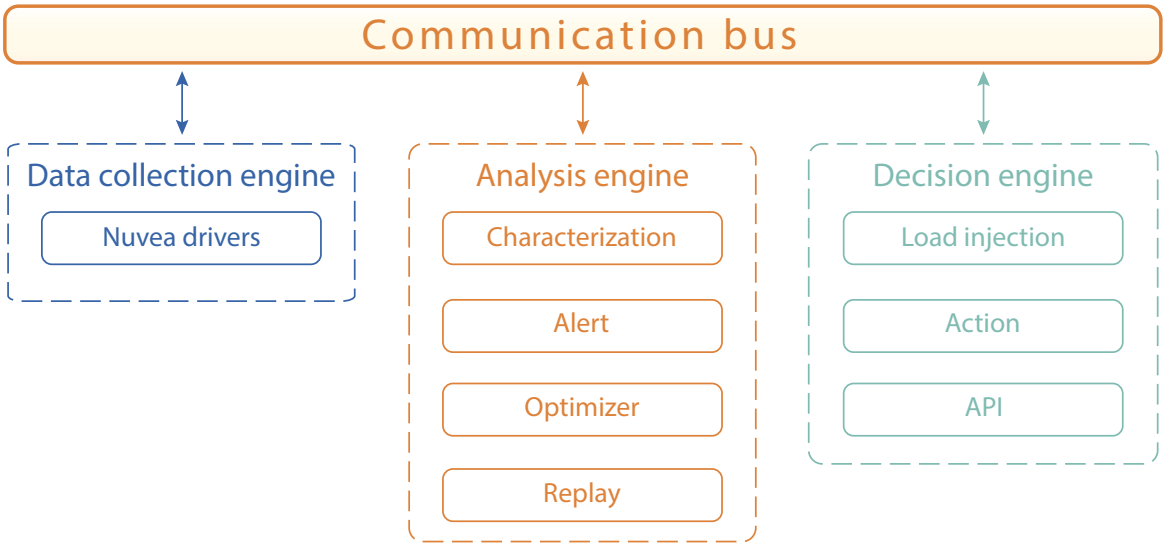

Figure 6.2: Nuvea modules

The visualization engine a component that is deployed on the management hosts and expose a reporting portal for monitoring utilization and services performance.

6.6 Modules

6.6.1 Data collection Engine

The data collection engine is deployed on every infrastructure and is executed periodically to collect utilization, energy and user-defined metrics for any resource. The collected data is the transmitted on a dedicated bus between the target platform and Nuvea servers. The deployment may be adapted depending on the target platform. It is possible to:

- Execute agents on each physical host
- Connect to the hypervisor
- Connect to an existing monitoring system
- Allow the client to report its data

The retrieval of data is managed by the Nuvea drivers, based on the Kwapi monitoring tool [69]. Kwapi is a software toolbox that enables monitoring from different sources with drivers threads. Each thread is associated to a technology or a specific metric and in charge of listening and decoding measured values. In the context of Nuvea, we extend that approach to software source such as systems or user-defined metrics. This approach allows a simple extensibility of the monitoring systems with independent drivers. Nuvea

drivers are instantiated by a driver manager. They send measurements and execute actions. The driver manager loads all drivers according to a configuration file, regularly check that they are alive, and reloads them if they are crashed.

6.6.2 Communication Bus

The communication bus is the interface between Nuvea drivers and other modules, in particular the database of the Analysis engine. Two types of data exchange happen on the bus:

- Metrics issued from the data collection engine
- Actions issued for decisions

6.6.3 Analysis Engine

The analysis engine is deployed on Nuvea servers. It contains the central database that is used for storing monitoring values and the various modules of analysis to extract knowledge and enable decisions on the target platform. The analysis engine exposes a REST API to query to the database. A measurement is timestamped and associated to a metric from a particular machine.

Among other modules, it features four operational engines: *Characterization*, *Optimizer*, *Replay* and *Alert*. Characterization is used to characterize the behavior of an entity regarding to resource demands or pattern of utilization. This information is then used to provide a classification of resource or perform informed decisions.

Optimizer evaluates the cost of placement configurations (i.e. placement of tasks/virtual machines on servers). The evaluation is performed in terms of performance degradation among the virtual machines. It also determines the feasibility of a new configuration based on the number of required migration and the current status of the infrastructure.

Replay allows the study and comparison of algorithms on a given dataset. The task information (size, arrival, deadline, etc.) are read from a trace file and executed on a target platform according developer-defined scheduling policies. At the end of the execution, *Replay* provides statistics such as the energy consumption, time, number of migrations and number of machines used for each policy.

Finally, *Alert* is in charge of settings alarms to receive notifications or take other automated actions when a metric crosses a specific threshold. An alarm watches a single metric over a a defined time period, and performs one or more actions based on the value of the metric relative to a given threshold over a number of time periods.

6.6.4 Decision Engine

The execution engine is deployed on Nuvea servers and communicates with others modules via the communication bus to retrieve information and execute actions related to the target platform. It exposes a REST web API which accepts requests from other modules. The execution engine is in charge of performing placement and interaction with existing schedulers. It is composed of two modules: *load injection* and *actions*. *Load injection* performs the execution of user-defined workload in the virtual machines. This tool enable the study of scheduling policies and the interaction between virtual machines of different types. *Actions* is in charge of executing operations defined by the decision engine. Operations are transmitted via the bus to the corresponding resources in order change their active state (shutdown mechanisms) or limit their resource demands (restriction of bandwidth, disk access rate, etc.).

6.6.5 Reporting Engine

The reporting is essentially a dashboard that provides a monitoring web interface with dynamic graphs generated from the database. This constitutes an evolution from the Nu@ge webboard (see Chapter 5) in terms of features. The Nuvea webboard displays the resource demands of any resource of the system, the possible interactions with the schedulers and the real-time status of resources. As presented in Figure 6.3, it is directed to IT administrators and end users for their respectives actions and must be accessible in a multi-tenant fashion with profiles and permissions. It also constitutes a key element of Nuvea marketing offer as a visual and concrete representation of the product features.

6.7 Implementation

This section describes the current state of implementation of the Nuvea project. It gives insights on the main features.

6.7.1 Nuvea Drivers

Nuvea-drivers, part of the Data Collection engine, are in charge of collecting monitored information on the various source (system, energy sensors, etc.). Table 6.3 presents some of the drivers implemented in the system.

Their execution is based on a configuration file description. It sets the communication bus endpoints (ports that receive/send the information) and the different variables available. The following code section presents the parameters and declaration of a lib-

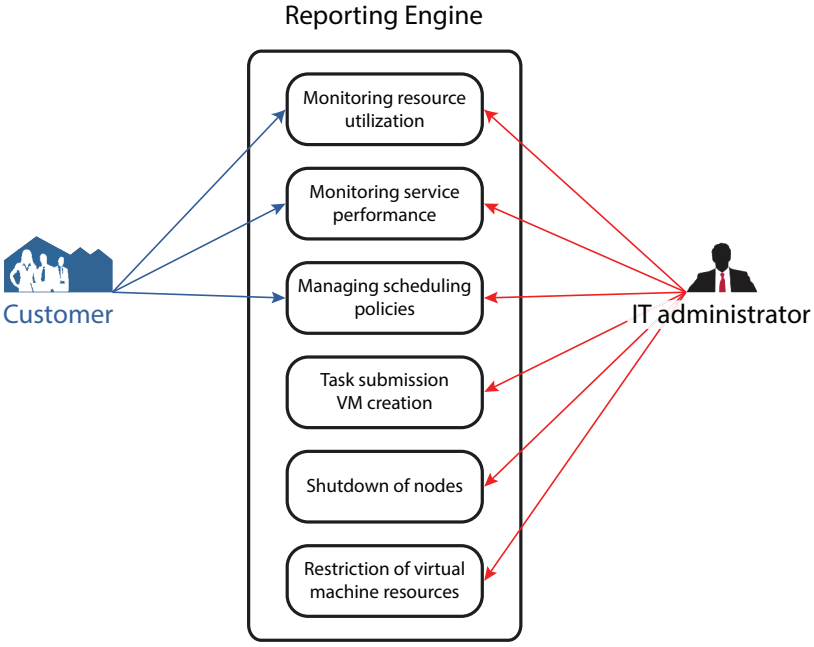

Figure 6.3: Use case diagram of the Reporting engine based on user profile

Drivers	Description
Ipmi	Power management using the Ipmitools suite[8]
JsonUrl	Energy monitoring based on API querying on Grid'5000
QoS	Service performance monitoring
LibvirtInstances	Virtual machines monitoring using the libvirt API
ProxmoxVms	Virtual machines monitoring dedicated to the Proxmox virtualisation solution
SNMP	Physical machines and equipment monitoring using an administration protocol[9]
PowerVM	Virtual machines monitoring dedicated to the PowerVM solution[10]
VMWare	Virtual machines monitoring dedicated to the VMware solution[11]
OpenStack	Infrastructure management using OpenStack public APIs

Table 6.3: Description of nuvea-drivers implemented

virt[12][104] driver, dedicated to the monitoring of virtual machine by direct access to the hypervisor.

```
# Communication
monitoring_endpoint = tcp://0.0.0.0:5010
action_requests_endpoint = tcp://0.0.0.0:5011
action_responses_endpoint = tcp://0.0.0.0:5012

# Log files
log_file = /var/log/nuvea-drivers.log
verbose = true

# Libvirt instances
[libvirt]
driver = LibvirtInstances
hypervisor_uri = qemu+ssh://login@host/system
interval = 5
```

A driver offers the ability to collect metrics and register actions to be triggered. In the context of a libvirt drive, we precise quota actions (restricting resources of a VM at the hypervisor level) and migration capabilities. Those will allow the decision engine to execute these actions.

```
class LibvirtInstances(Driver):
    """Driver for Libvirt"""

    def __init__(self, **kwargs):
        """Initialize the Libvirt driver"""
        Driver.__init__(self, **kwargs)
        self.interval = int(kwargs.get('interval', 5))
        self.register_action(self.cpu_quota)
        self.register_action(self.disk_io_quota)
        self.register_action(self.network_bandwidth_quota)
        self.register_action(self.migration)
        self.conn = None
```

The monitoring an data collection can be performed in different ways based on the access and context of monitoring set on the target infrastructure:

[12]Libvirt interact with the virtualization capabilities of recent versions of Linux and major virtualization software solutions

Single point of collect through ssh This is performed by accessing the hypervisor or cloud operator by using ssh and low level API such as libvirt or the Xen hypervisor. It often requires a root access to the node executing the hypervisor.

Multiple point of collect through drivers The use of the Nuvea driver managers enables a collect from various sources simultaneously. Hypervisor, machines, energy sensors, facility equipment can be monitored by their public API, the administration protocol SNMP or others proprietary protocols.

Hybrid collect with customizable resource collectors The DIET middleware enables the definition of CoRi (Collector of Resource Information). These agents are executed in user mode to retrieve metrics at different level. It can be used to access an operator at the datacenter level (for example, by connecting to OpenStack nova scheduler), at a physical machine level (if executed on the target host) or on any device exposing its metrics or performance level in a parsable format.

6.7.2 Bus

Nuvea architecture uses ZeroMQ[13] to connect the internal modules. ZeroMQ is a distributed messaging software that connect softsware interface in language and platform independent fashion. Relevant features to Nuvea are the implementation of smart patterns like publish-subscribe, push-pull, and router-dealer and the high level of customization and documentation backed by a large and active open source community. Nuvea implements point-to-point security features of authentication and encryption using CurveZMQ[14]. We performed benchmarks in order to determine the necessary bandwidth to ensure the correct transmission of messages.

A metric is represented as follows

```
1 {'virtual_machine': 'Dummy-VM', 'metric_name': 'power', '
    metric_value': 86, 'timestamp': 1465465569, '
    physical_machine': 'Dummy-PM', 'metric_unit': 'W', '
    metric_type': 'Gauge'}
```

This represents 200 bytes (250 bytes with inclusion of encryption overhead and TCP headers). The bandwidth depends on the frequency of metric transmission and the number of monitored nodes. For 100 PM containing each 30 VM, and a frequency of 60 seconds to send 7 metrics, it results in a bandwidth of 700kbits/s. Figure 6.4 exposes some typical bandwidth capacities. The comparison of this results to typical maximum

[13]http://zeromq.org/
[14]http://curvezmq.org/

rates of transmission technologies shows that Nuvea bus can be implemented over standard technologies with competitive performance.

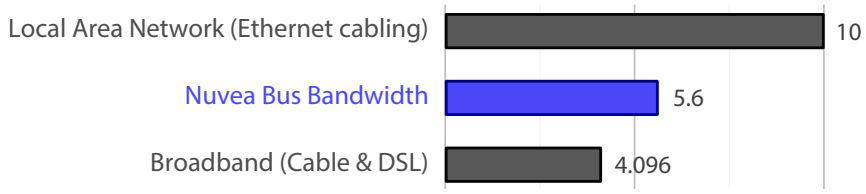

Figure 6.4: Comparison of Nuvea bandwidth requirements to typical bandwidth capacities. Values are expressed in Mbps

6.7.3 Storage

The main database of Nuvea relies on MongoDB. MongoDB belongs to the family of NoSQL database. It avoids traditional table-based relational database structure in favor of JSON-like documents with dynamic schemas. This allows flexibility in the structure of the data collection recordings as some target platforms may produces partial data compared to others ones. The database is populated by the collection engine via the bus. It contains 9 tables:

- customer
- endpoint
- job
- machine
- measurement
- metric
- png
- replay
- rrd
- alarm

The storage configuration accepts 3 modes that can be used simultaneously.

```
#Storage configuration modes
mongo_storage = true
csv_storage = true
rrd_storage = true
```

Originally, recordings of monitoring were stored in the MongoDB according to the *mongo_storage* mode. It describes a collection as presented in Figure 6.5.

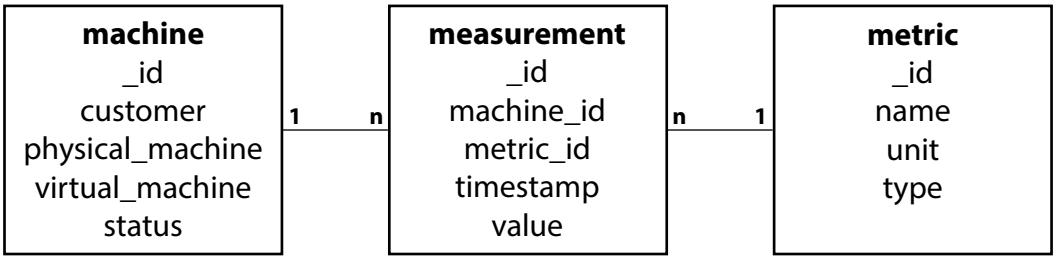

Figure 6.5: Structure of the measurement collection in the mongo database

Benchmarking exposed some limitations in terms of access and writing rates. Table 6.4 presents different situations and their respective performance. Each benchmark represents a sample of 34440 metrics transmitted from the data collection. The benchmarking conditions varies from an non realistic case (Emission without reception) to the real conditions where metrics are received and indexed in the database. We can observe that use of indexes presents serious limitations to the received metric rate. A database index is a data structure that improves the speed of data retrieval operations (queries) on a database table at the cost of additional writes and storage space to maintain the index data structure. This overhead was not acceptable at the time of evaluation by allowing only 180 metrics to be effectively received each second.

To leverage this problem, we considered a raw writing of metrics in plain files. This mechanism can be coupled with a consolidation of metrics (removal of useless information) before a delayed writing in the MongoDB. This alternative approach uses the CSV file format, an open comma-separated representation. Table 6.5 presents the gain of performance between the two approaches. The machine used for this benchmark is a AMD Opteron @1.7 Ghz (cache=512Kb).

Use case

Company C (see Table 6.1) ordered an estimation of necessary storage and described an infrastructure of 40 PM containing each 12 VM and 10 metrics to monitored every 10 seconds. It results in a value of 3444 metrics per second to be transmitted to the storage module. Using the CSV_mode, it would required a 1-CPU machine to collect and store the information.

Benchmarking conditions	Number of metrics received per second
Emission without reception (storage module desactived)	20021
Emission/reception without writings	10976
Emission/Reception without indexes	2163
Emission/Reception with indexes (same metric written in a loop)	1655
Emission/Reception with indexes in real conditions (independant metrics)	180

Table 6.4: Benchmarking of the storage module when using the MongoDB (*mongo_storage* mode)

	Mongo_storage mode	CSV_storage mode
1 CPU	174 metrics per second	7824 metrics per second
4 CPU	410 metrics per second	60244 metrics per second

Table 6.5: Evaluation of performance between storage modes

A CSV recording has the following structure, approximately 100b per measurement. Fields represent the metric identifier, the physical machine name, the metric name, the measured value, the unit and the source.

```
1461593407,stremi-40.reims.grid5000.fr,8ee85c0a-7a78-4a13-8
   f38-7e21bfa9107f,power,94,W,Gauge
```

It would require 30Go of storage per day of analysis for Company C with a total of 1.35To for an analysis of 45 days.

Related work on database performance issues

We identified performance loss and bottleneck when writing data in the MongoDB. This is mainly due to data type conversion cost and indexing mechanism. Those issues are an active research topic within the database community.

Many applications already avoid using database systems, e.g., scientific data analysis and social networks, due to the complexity and the increased data-to-query time. This is often describe as a data deluge where we have much more data than what we can move, store, let alone analyze. A growing part of the database community recognizes this need for significant and fundamental changes to database design, ranging from low-level architectural redesigns to changes in the way users interact with the system [105, 106,

107, 108]

In particular, Alagiannis et al. [109] introduces the NoDB (for No DataBases) philosophy. Authors performed the conversion of a traditional PostGreSQL database (row-like organisation of data) into raw files and discovered that the main bottleneck is the repeated access and parsing of raw files. Their prototype system based on in situ quering (ability to query the data without retructuration or indexing) has been evaluated with different types of files and benchmarks and demonstrates competitive performance with traditional systems. Other research work enables users to write SQL queries directly over structured flat files and gradually transfers data from the files to the DBMS [110]. Abouzied et al. [111] relies on the Hadoop framework to hide the cost of loading information into a database. As MapReduce jobs already performs parsing of data to organize it in tuples, they load the data at that exact time into a database to allow future queries to run faster.

Very large data processing is increasingly becoming a necessity for modern applications in businesses and in sciences. The proposition of an hybrid solution between raw and indexed storage for Nuvea constitutes a future work to ensure the relevance of the platform for the incoming data deluge area.

6.7.4 Load injector

The load injector is in charge of executing a synthetic or a real workload on each deployed virtual machine. This tool has been developed for research and testing purposes in order to recreate virtual machine placement for the evaluation of scheduling policies. It uses a generic multi-thread server (described in details in Chapter 4) that produces a token as the output of the completion of a workflow. The workflow completion is a task that need the execution of 3 steps based on operations using CPU, Network and Disk resources.

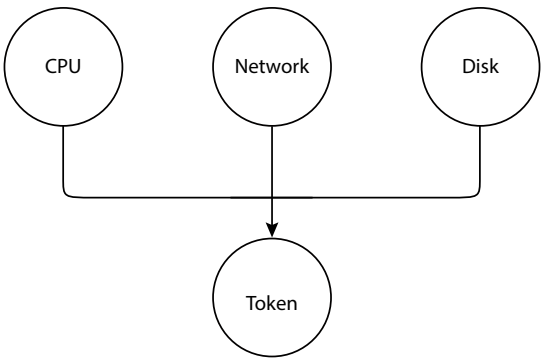

Figure 6.6: Workflow of a token production

A weight factor is defined for each parameter to increase the number of steps to perform the task (i.e. producing the token). The adjustment of this weight can be used

to represent any kind of non-fluctuating workload based on those three resources. The produced token acts as a service. By monitoring the produced tokens rate of a certain set of weights, it is possible to establish Service Level Objectives. The Server Level Objective constitutes the produced token rate for a given configuration. This tool constitutes the base of the analysis of virtual machine placement and the consequences on performance degradation.

We make use of this tool to execute trace on the Nuvea infrastructure and evaluate scheduling policies. Figure 6.7 presents a workflow diagram of trace log execution.

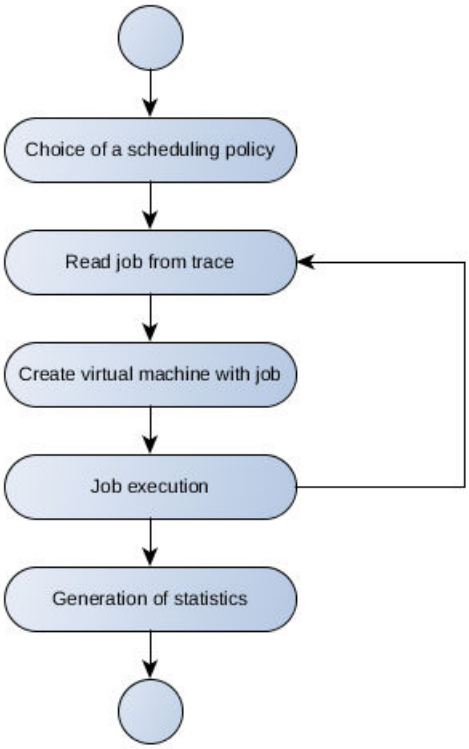

Figure 6.7: Workflow of a trace log replay

The scenario is described with OpenStack installed as the Cloud manager. At the beginning of the trace log replay, a scheduling policy has to be indicated to the manager. The manager reads the trace log as the job inputs to take into account the characteristics of jobs (such as time of arrival, duration, type, dependencies.) It create a script based on the load injector template with appropriate weightings for the token production steps. The script is transmitted to *Cloud init*, a technology that supports automated configuration of instances at boot time. Using the Openstack nova API, a virtual machine is created and executes the script according to the underlying job description of the task. Once all job from the trace logs has been executed, the manager generates statistics associated to the background monitoring of resources to determine the value of number of active servers, energy consumed, etc. related to the trace log replay.

Replays are stored in the replay and job collections (Figure 6.8). They can be analyzed offline post-experiment.

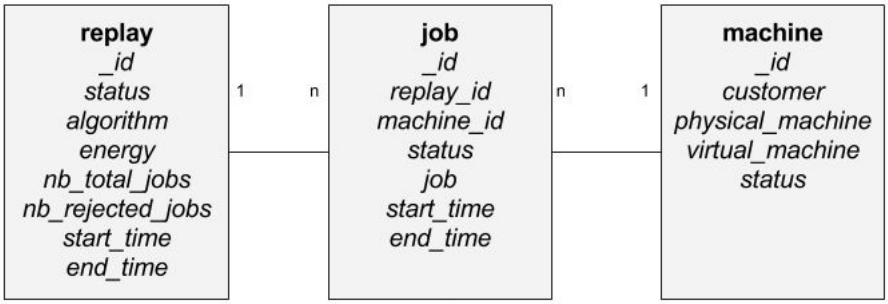

Figure 6.8: Representation of replay collection in the database

6.7.5 Nuvea actions

The Nuvea-actions module is in charge of executing decision on resources by the means of scripts and commands. As part of the decision engine, it transmits orders via the bus to any part of the infrastructure. We use that module to implement energy savings levers. In the current version of Nuvea, two major actions are possible: the transition of resources to low power modes (standby/shutdown) and the limitation of available resource for the virtual machines.

The shutdown lever relies on Intelligent Platform Management Interface (IPMI). IPMI is a standardized management interface, present on most of recent servers, that enables the control of hardware components whether the node is active or not. This is a tool of choice to shutdown servers or start idle nodes. IPMI-enabled devices typically allows the management energy and temperature sensors, cooling systems or servers status (on/off/reset/reboot). The following code section shows the integration of the ipmitool command on Nuvea drivers.

```
    def power(self, physical_machine, value):
        """Set physical machine power status"""
        command = 'ipmitool '
        command += '-I ' + self.interface + ' '
        command += '-H ' + self.host + ' '
        command += '-U ' + self.username + ' '
        command += '-P ' + self.password + ' '
        if value == 'ON':
            command += 'chassis power on'
            #Turn on the server
        else:
```

```
            command += 'chassis power soft'
            #Turn off the server
```

The limitation of virtual machine resource, namely the shrink lever, is the application of quota values for a specific system resource. The hypervisor is the layer between the physical machine and the virtual machine. Using the unique identifier of the virtual machine (UUID), the shrink lever connects to the hypervisor and submits quotas. The following code section presents the limitation of network resource by setting inbound and outbound averages.

```
    def network_bandwidth_quota(self, virtual_machine, quota):
        """Set network quota"""
        domain = self.conn.lookupByUUIDString(virtual_machine)
        for dev in self.getDevices(domain, 'interface'):
            domain.setInterfaceParameters(dev,
                        {'inbound.average': int(quota)})
            domain.setInterfaceParameters(dev,
                        {'outbound.average': int(quota)})
        LOG.info('Network I/O quota for %s is %s' %
                        (virtual_machine, quota))
```

6.7.6 Characterization

The characterization module is in charge of profiling and identifying the resources demands of a virtual machine. The purpose is twofold:

Improving the physical machine utilization Energy wastage is often cause by excessive reservations of capacity due to oversized virtual machines. Besides at peak times, the low utilization on average keeps more active nodes than necessary. By having knowledge of effective virtual machines demands, one could perform consolidation mechanisms limit the number of active resources.

Minimizing the performance degradation between virtual machines. Typically, Cloud systems are dynamic with multiple jobs coming and leaving in an unpredictable fashion, sharing the physical machine capacity. Contention for resources is causing degradation of services performance. By having knowledge of virtual machines demands, one could eliminate excessive share on physical machines and guaranteed Service Level Objectives [112].

The profiling of virtual machines demands is performed while considering the virtual machines as *black boxes*: no software is installed inside the virtual machines so any

observations or monitoring must be performed from external sources. This is highly relevant in terms of non intrusivity regarding the end user applications.

In this context, we rely on the end user to report metrics of activity completion. By analogy with the load injection workflow (Figure 6.6), an application-reported metric can be associated with a Service Level Objective. Application-reported metrics can be any indicator of the applicative workload over a time period: number completed task, number of downloads, number of user connected, etc. We believe these values could be reported without context information to preserve the client privacy.

The key idea of the characterization is to evaluate of a set of system metrics (CPU, network, HD) relates to application-reported variables and establish a correlation analysis to define a virtual machine resource profile. We use Canonical Correlation Analysis (CCA) as the statistical method to obtain workload correlation.

Canonical correlation analysis is used to identify and measure the associations among two sets of variables. Canonical correlation is appropriate in the same situations where multiple regression would be, but where are there are multiple intercorrelated outcome variables. Canonical correlation analysis determines a set of canonical variates, orthogonal linear combinations of the variables within each set that best explain the variability both within and between sets.

Current version of the scheduler shows encouraging results using the CCA approach. Implementation details and evaluation will be released soon by an engineer of NewGeneration-SR.

Related work on correlation-aware techniques

Several research work [113] [114] [115] proposed to estimate historical workload as a static single value to allow VM placement to be abstracted and solved as a single value. It considers the physical servers as bins whose sizes are the capacities of a computing resource such as CPU, memory usage, disk I/O or network bandwidth.

Xiaoqiao et al. demonstrates that summarizing historical workloads with a single value can lose too much information [116]. Their method proposed a correlation-aware VM selection technique that forms pairs of negatively correlated VMs, and placed each negatively correlated on a physical server.

6.7.7 Alert management

The alert module is set to read metrics as they are transmitted to the analysis engine. Any metric present in the database with a unique identifier can be monitored.

The action following the raise of an alarm can be actions from the Nuvea action module (shutdown or shrink of a resource) or notifications sent to a specific modules or

a user. An alarm can have three possible states:

OK The metric is within the defined threshold

ALARM The metric is outside the defined threshold

NONE The metric is not available, or not enough data is available for the metric to determine the alarm state

The following code segment shows the definition of an alarm related to the temperature of a physical machine.

```
class AlertManager(Driver):
    """Management of Alert"""

    def set_alarm(Alert):
        """Initialize the Libvirt driver"""
        Alert.define_resource = resource_id
        Alert.define_metric_id = metric_id
        Alert.define_action = Action.shutdown
        Alert.define_thresold = 28
        Alert.define_thresold_limit = "up"
        Alert.register_period_number = 3
        Alert.register_period_time = 5
```

In this example, if the temperature of the resource is monitored 3 times (3 periods of 5 seconds) over the value 28, the node will be shutdown. It is possible to register a sequence of actions to be performed.

6.7.8 Reporting and visualisation

Nuvea dashboard provides a system-wide visibility into resource utilization, application performance, and operational health. It is implemented as monitoring web interface that enables the creation of dynamic graphs based on any metric monitored. The graphs are generated from RRD files by quering the Nuvea database recordings. The dashboard supports multi-tenant management with profiles and associated permissions. The librairies described in Table 6.6 were used during the development.

The left part of the menu bar shows different metrics: energy, CPU, RAM, disk, network and QoS for a set of resources. On the right side, one can select a different customer, the view mode (PMs or VMs) and the display scale. The following Figures presents screenshots of the web interface. The summary graph shows a stack of all measurements.

Name	Description
Flask	Python framework for web development
Jform	Java based component for generating user input forms
JQuery	JavaScript library for client-side scripting

Table 6.6: Libraries used for the development of the webboard

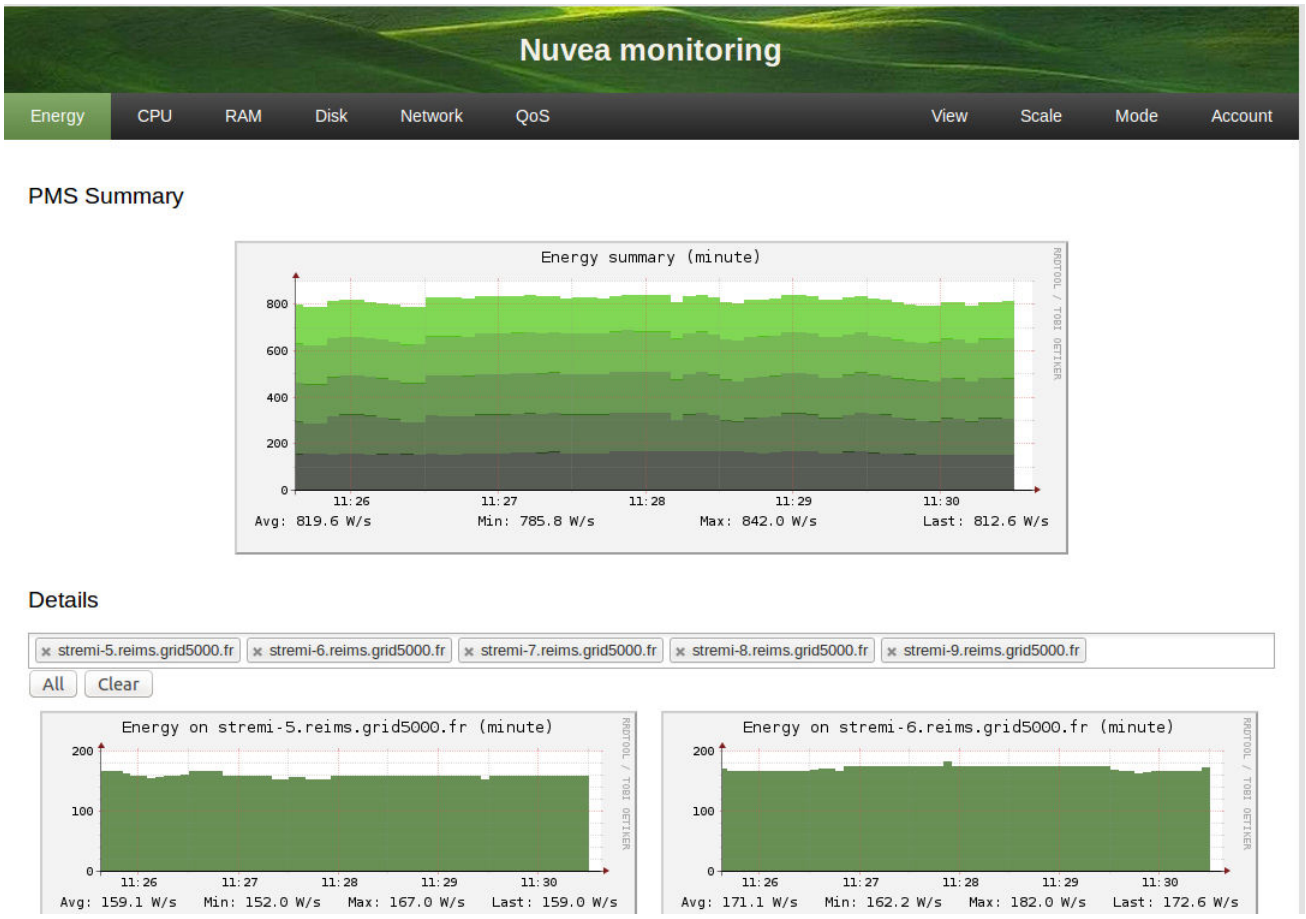

Figure 6.9: Nuvea's dashboard summary

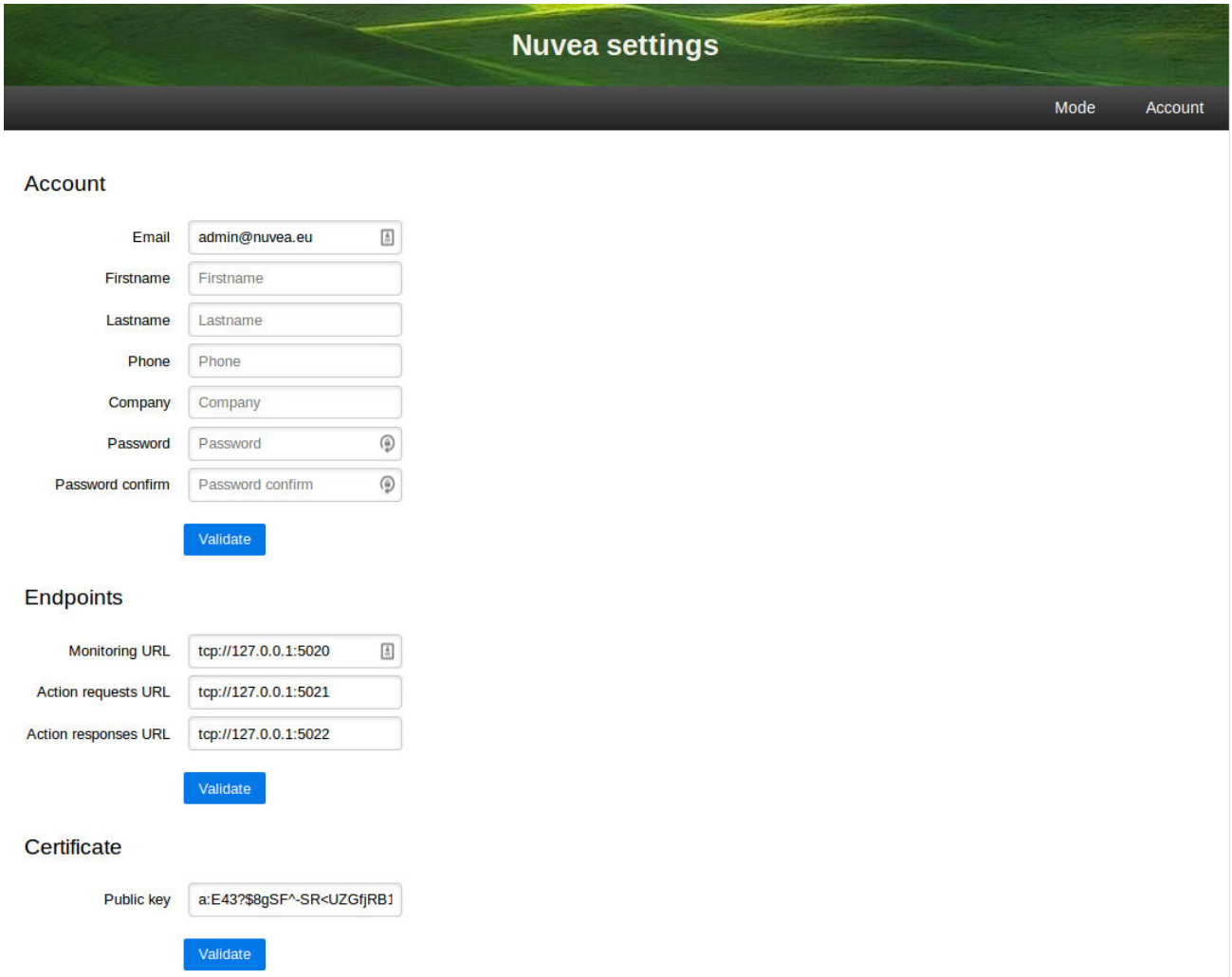

Figure 6.10: Creation of a new administrator account with target endpoints for message exchange and certificate for bus authentication

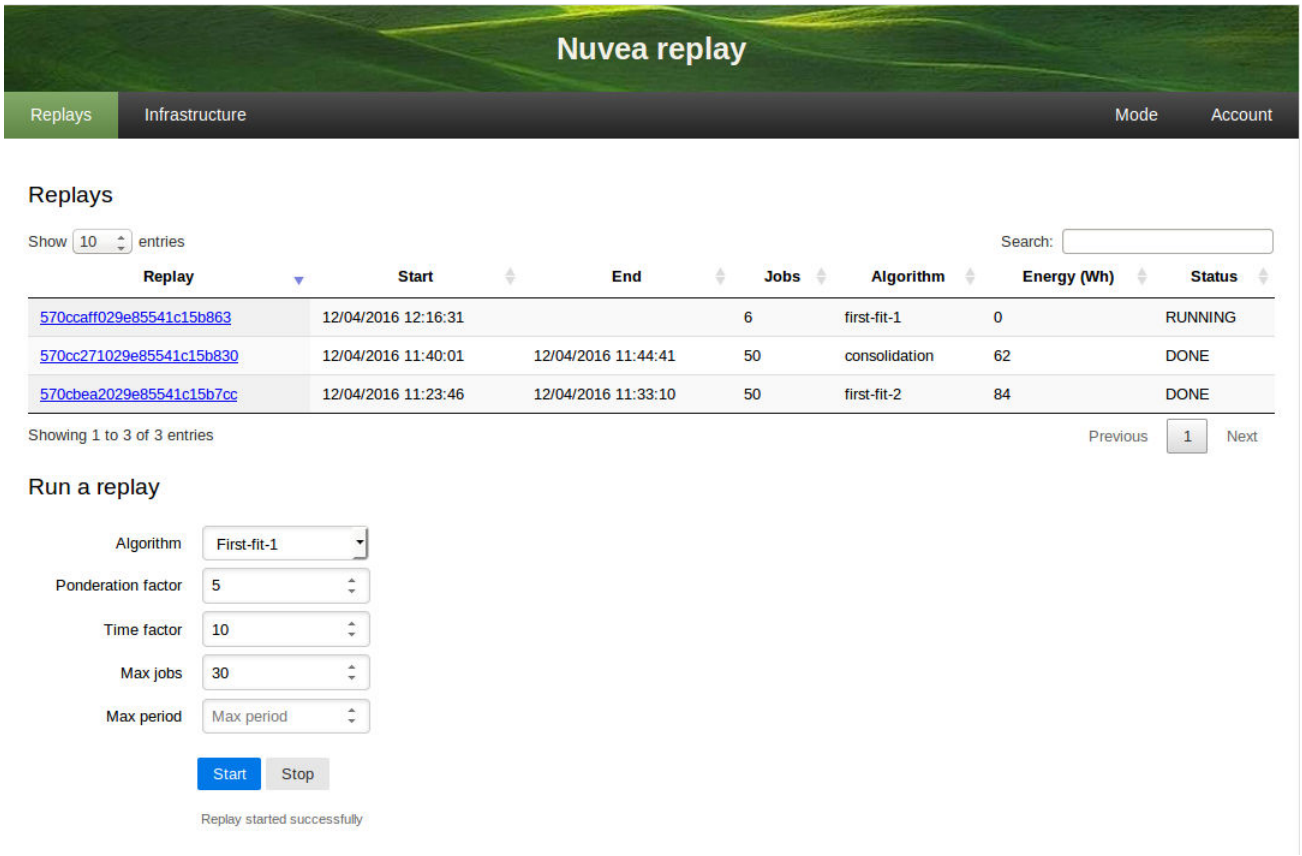

Figure 6.11: Nuvea's replay screen with selection of algorithm to evaluate and statistics of previous executions

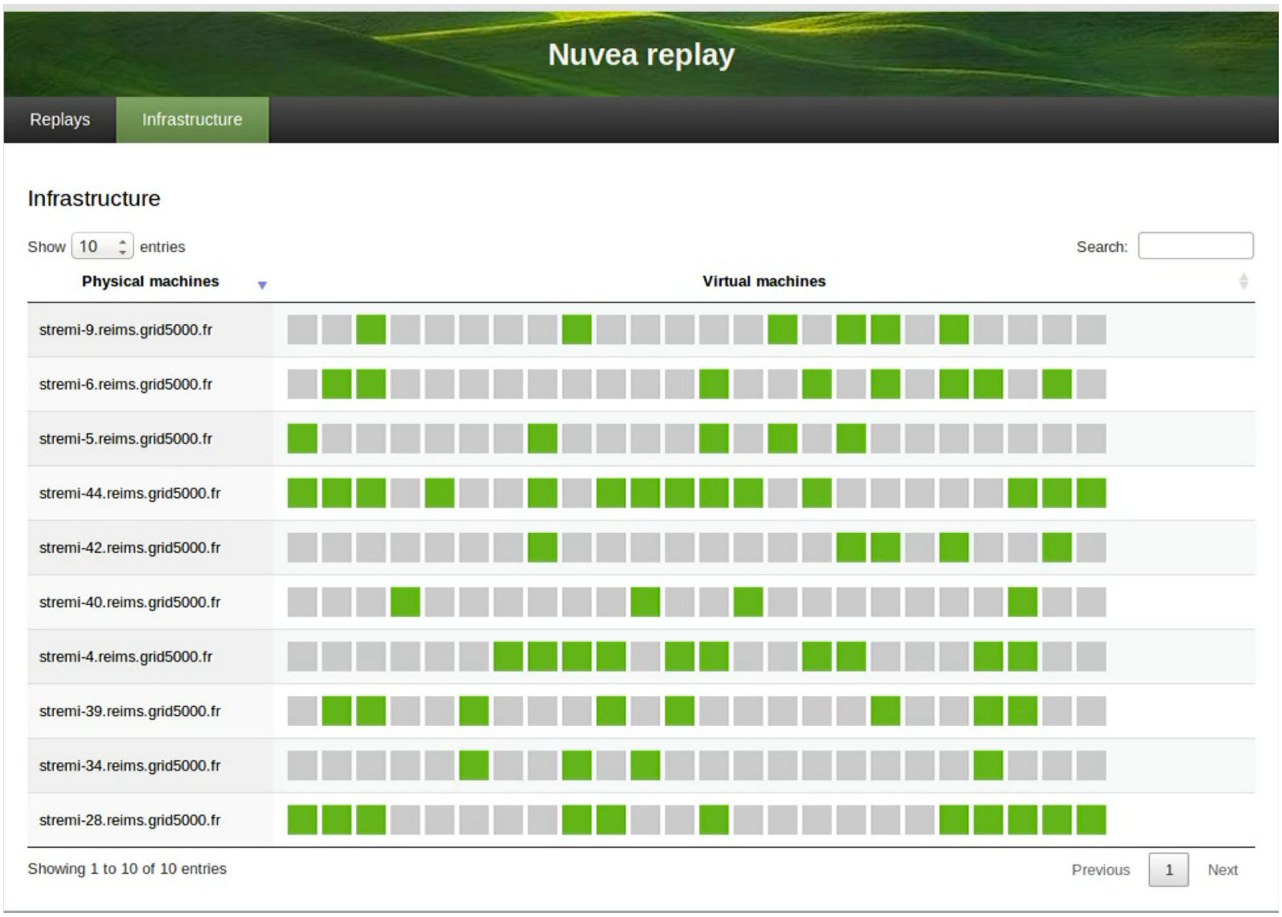

Figure 6.12: Screen of Nuvea replay before an optimization decision. Each line represents a different physical machine. Grey slots represents available resource. Green slots represents active virtual machine. Before optimization, the virtual machines are scattered with a large number of active resources.

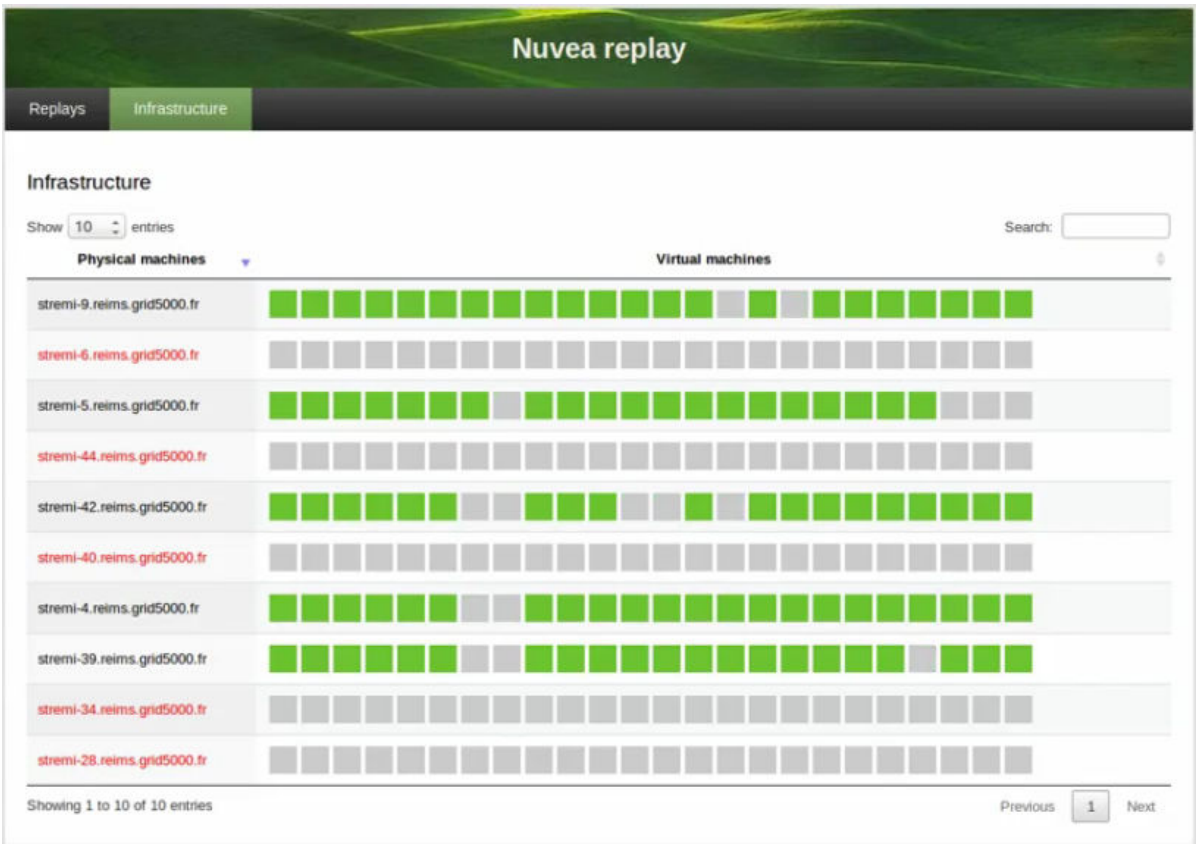

Figure 6.13: Screen of Nuvea replay after an optimization decision. Each line represents a different physical machine. Grey slots represents available resource. Green slots represents active virtual machine. After optimization, the virtual machines are packed on a reduced amount of resources.

6.8 Conclusion

The Nuvea platform is an initiative motivated by the current situation of the Cloud computing market regarding energy wastage and customer access to full premises. The identification of levers related to consolidation of resource according to their effective usage and characterization of resource presents various challenges. From a research perspective, some elements of this topic have been well studied but methods remains hard to implement in real situations. From the industrial perspective, adoption of optimization tools while minimizing risks in production environment limits the adoption state-of-the-art mechanisms. The organization of this project relies on an iterative organization and a coordination between internal teams to maintain a feedback loop according to the customer specifications. Surveys has confirmed the need for such a tool and put in light the lack of control of end users and managers on their own premises.

In this Chapter, the architecture and modules of Nuvea have been proposed and described. Nuvea relies on three engines: (i) the data collection engine that monitors all kind of physical or virtual equipment (ii) the analysis engine that extracts knowledge from real-time situation historical data and (iii) the decision engine that applies levers and interacts with schedulers. The current implementation of the modules has shown promising results and open doors to several contributions from research works and customer use cases.

In 2014 and 2016, Nuvea has been granted by European commission through the selective H2020 ICT Disruptive technologies program[15]. This award highlights our potential to become a major actor in the European Cloud market. The platform has been presented at several scientific and industrial events, in particular at national Inria-Industry Meetings (Paris, France) focused on "Power transition"". A demonstration of live optimization has been performed at Super Computing 2015 in Austin, Texas. Following our collaboration with Mahindra Ecole Centrale (Hyderabad, India), NewGeneration has been invited to take part of the French presidential delegation to visit India and establish partnerships with Indian companies. Recently, Nuvea has received the Award for Energy Transition and Digital Technologies for its energy reduction on datacenters by the *Usine Digitale* [16].

We believe that the next generation of Cloud business models and management systems will need to be adopted *by the practice*. Current offers often advertized encouraging figures of performance and cost reduction but they often neglect the cost of integration within legacy systems. The DevOps profile constitutes a rising trend and is issued from a practice that emphasizes the collaboration and communication of both software devel-

[15] http://cordis.europa.eu/project/rcn/196492_en.html

[16] http://www.usine-digitale.fr/article/nuvea-new-generation-sr-prix-digitalisation-des-trophees-de-la-transition-energetique.N396012 (in french)

opers and other IT professionals while automating the process of software delivery and infrastructure changes [117, 118, 119]. Suggesting innovative tools with consideration of integration, extension and customization will ease the promotion of news practices and their adoption in production environments.

New features, users specification and results from research investigations are continuously integrated into the platform. Figure 6.14 concludes this chapter with a representation of Nuvea's ecosystem.

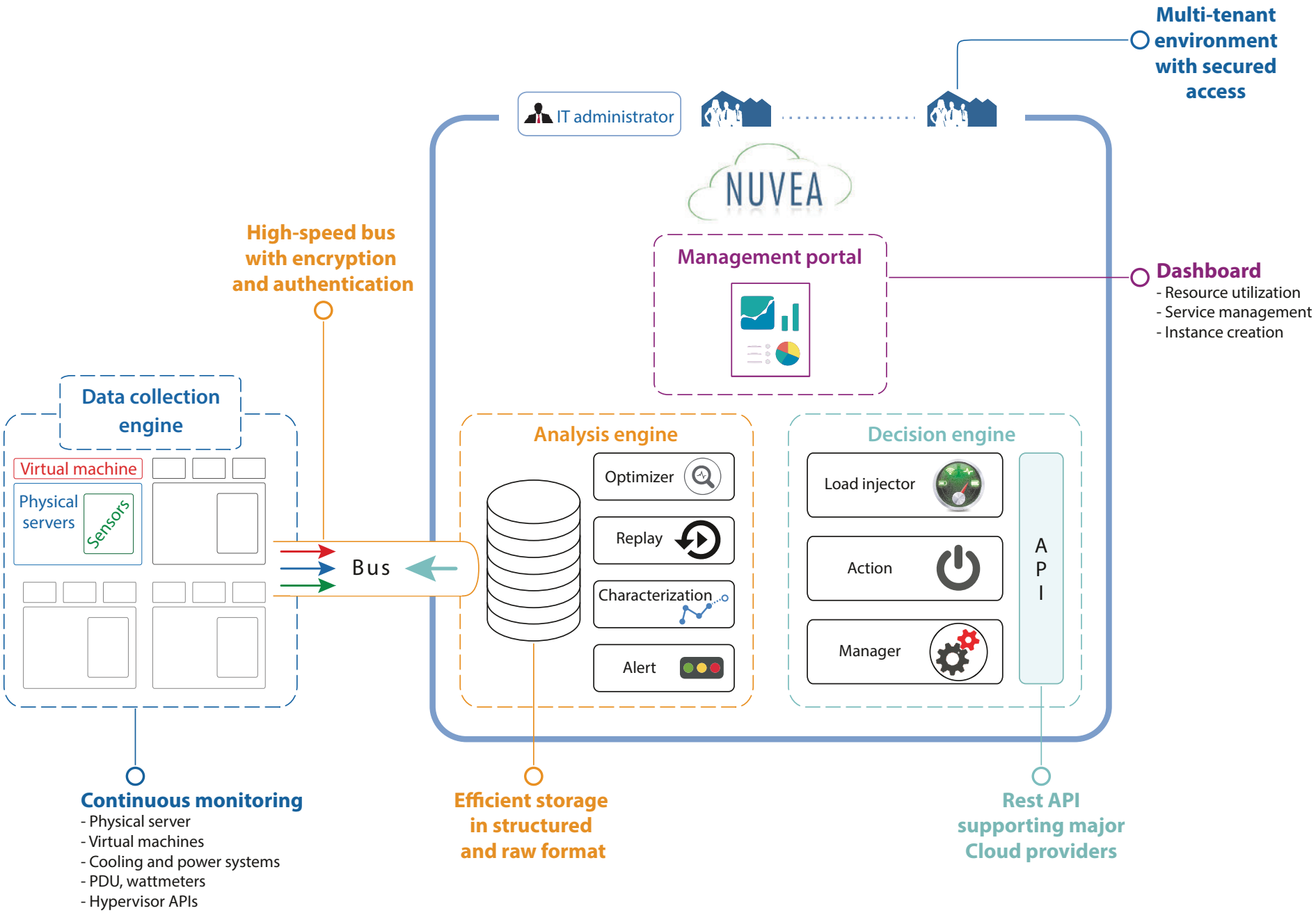

Figure 6.14: Nuvea ecosystem

Chapter 7

Conclusion and Perspectives

7.1 Conclusion

Cloud computing has change the habits of numerical usage. The advances in technology and network access pushes the perception of remote computing resources as a fifth utility [120]. Following this increase of services, users and devices, the number of Cloud datacenters and infrastructures is expected to grow and consume a large portion of the worldwide energy consumption. In this context, an energy-aware management of datacenters is a critical issue in regard to financial and environmental concerns.

This thesis has investigated the problem of scheduling on Clouds by using trade-offs mechanisms between the performance and the energy consumption of resources. These trade-offs enable the involvement of users and providers of Clouds in order to deliver a service that is proportional to the effective demand and eliminate energy wastage often due to over-provisioning.

In addition to the scientific contributions, we took the challenge to apply this techniques on industrial use cases within two major projects. The pace and constraints of the Cloud market imposes a fast transfer of research work to the industry while taking into account operational constraints. To address the formulated issues, this thesis has achieved each of the objectives delineated in Chapter 1.

Chapter 2 presents an analysis of the area of energy-efficiency measurement and resource management in Clouds. The research literature analysis has helped to identify gaps, open challenges and clearly determine the research directions taken in this thesis.

Based on this analysis, Chapter 3 has proposed an application-independent metric that can be used to evaluate the energy-efficiency of a resource. The proposed GreenPerf metric is based on the measurement of energy consumed over the completion of a set of service requests. The metric can easily be extended according to the level of information available. It was integrated in the DIET middleware as GreenDIET, and used to design scheduling policies based on users and providers willingness to save energy.

Chapter 4 has extended the approach by using metaheuristics considering workflow placement. We investigated a genetic algorithm that improves the quality of solutions by the means of successive iterations, highlighting the affinity between tasks and servers from an energy reduction perspective. Evaluation was performed on real Cloud traces with significant reduction in energy consumption and improvements in performance on a large set of solutions, enabling the possibility of trade-offs based on the context of execution.

The first industrial application of this research work is depicted in Chapter 5. The Nu@ge project is motivated by data sovereignty concerns in Cloud Computing, and propose to implement a mesh of container-sized datacenters on the French territory. Our contribution takes places in the aggregation of information and constraints to enable server provisioning and virtual machine placement within a nationwide federation. Apart from the global evaluation of the project, this work resulted in several specifications and improvements of the GreenDIET scheduler by considering energy cost and temperature.

My contribution is the exploitation of those concepts in a standalone platorm, Nuvea, introduced in Chapter 6. The platform has been designed and implemented to both be released as a commercial product dedicated to yield management of datacenters for the NewGeneration-SR start-up and used as a tool in further academic research within the Avalon team. Nuvea constitutes a solution for dynamic virtual machine placement and consolidation based on the collection and analysis of data issued from datacenters and computing resources. Outcomes have been presented within the scientific community and integrated as a commercial product.

Management of datacenters and Cloud resources with the consideration of tradeoffs between energy consumption and performance will enable providers to ensure the delivery of well-dimensioned services with minimal energy wastage. Research in energy-efficient management, such as presented in this thesis, combined with innovative Cloud business models will undoubtedly drive further advances in development and sustainability of next generation computing systems.

7.2 Perspectives

The contributions and investigations presented in this thesis put in light several open research problems that need to be addressed in order to further advance the area.

7.2.1 Exploiting virtual machine dependencies

Virtual machines are requested by end users to provide services. Typical services can express complex patterns of communications between virtual machines (data access, exchange of information, ...). However, due to lack of specifications, non-optimized alloca-

tions or migration operations, communicating virtual machines may end up on distant nodes or locations, resulting in costly network transfers between them.

To reduce that communication cost, it is necessary to take into account the dependencies or the topology of virtual machines. Scheduling policies would benefit from modelization of network equipments to estimate their energy consumption and their influence in the infrastructure. It would ensure that data and virtual machines operation cost does not exceed the benefits of optimization.

7.2.2 Exploiting virtual machine usage patterns

Cloud infrastructures allow end user to deploy any kind of applications and workload. Workload can present fluctuations or present irregular resources utilization in terms of data, network or compute demands. The mutualisation of resources, in particular by the means of virtualization, implies a share of system resources. Applications can be impacted by this co-allocation and suffer performance degradation. Usage patterns, load forecasting or user involvement would lead to a more efficient resource provisioning and increase the guarantee of a satisfying servers use rate.

7.2.3 Integrating thermal-aware scheduling

Datacenters are manufactured with constraints on their efficient use of energy. A significant part of energy is used for the cooling of resource as high temperature of components is known to cause hardware failures and degrade availability. The resource allocation can be combined with the cooling problem by considering heat dissipation and hotspots. With benefits of cross-disciplinary studies in cyber-physical models of datacenters, preserving a safe temperature of resources and specific spatial areas of a datacenter would present additional constraints in regard to a multi-criteria optimization approach (Chapter 4).

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Tables

Figures