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PROACTIVE AND REACTIVE THERMAL AWARE OPTIMIZATION TECHNIQUES TO MINIMIZE THE ENVIRONMENTAL IMPACT OF DATA CENTERS

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Ph.D. Thesis

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A mis padres.
Y a Félix.

Dolça Catalunya,
pàtria del meu cor,
quan de tu un s'allunya
d'enyorança es mor.

— Jacint Verdaguer, *L'emigrant*

"I remember my youth and the feeling that will never come back any more. The feeling that I could last for ever, outlast the sea the earth, and all men."

— Joseph Conrad

Saeta que voladora
cruza, arrojada al azar,
y que no sabe dónde
temblando se clavará;
...
eso soy yo, que al acaso
cruzo el mundo sin pensar
de dónde vengo ni a dónde
mis pasos mi llevarán

— Gustavo A. Becquer *Rima II (Rimas y Leyendas)*

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"And if I ever lose my eyes, if my colors all run dry. Yes if I ever lose my eyes. Oh if... I won't have to cry no more."

— Cat Stevens, *Moonshadow*

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Y a los que me habéis hecho más fuerte.

Muchas gracias a todos.

Abstract

"Learn from yesterday, live for today, hope for tomorrow. The important thing is to not stop questioning."

— Albert Einstein

Data centers are easily found in every sector of the worldwide economy. They consist of tens of thousands of servers, serving millions of users globally and 24-7. In the last years, e-Science applications such e-Health or Smart Cities have experienced a significant development. The need to deal efficiently with the computational needs of next-generation applications together with the increasing demand for higher resources in traditional applications has facilitated the rapid proliferation and growing of data centers. A drawback to this capacity growth has been the rapid increase of the energy consumption of these facilities. In 2010, data center electricity represented 1.3% of all the electricity use in the world. In year 2012 alone, global data center power demand grew 63% to 38GW. A further rise of 17% to 43GW was estimated in 2013. Moreover, data centers are responsible for more than 2% of total carbon dioxide emissions.

This PhD Thesis addresses the energy challenge by proposing proactive and reactive thermal and energy-aware optimization techniques that contribute to place data centers on a more scalable curve. This work develops energy models and uses the knowledge about the energy demand of the workload to be executed and the computational and cooling resources available at data center to optimize energy consumption. Moreover, data centers are considered as a crucial element within their application framework, optimizing not only the energy consumption of the facility, but the global energy consumption of the application.

The main contributors to the energy consumption in a data center are the computing power drawn by IT equipment and the cooling power needed to keep the servers within a certain temperature range that ensures safe operation. Because of the cubic relation of fan power with fan speed, solutions based on over-provisioning cold air into the server usually lead to inefficiencies. On the other hand, higher chip temperatures lead to higher leakage power because of the exponential dependence of leakage on temperature. Moreover, workload characteristics as well as allocation policies also have an important impact on the leakage-cooling tradeoffs. The first key contribution of this work is the development of power and temperature models that accurately describe the leakage-cooling tradeoffs at the server level, and the proposal of strategies to minimize server energy via joint cooling and workload management from a multivariate perspective.

When scaling to the data center level, a similar behavior in terms of leakage-temperature tradeoffs can be observed. As room temperature raises, the efficiency of data room cooling units improves. However, as we increase room temperature, CPU temperature raises and so does leakage power. Moreover, the thermal dynamics of a data room exhibit unbalanced patterns due to both the workload allocation and the heterogeneity of computing equipment. The second main contribution is the proposal of thermal- and heterogeneity-aware workload management techniques that jointly optimize the allocation of computation and cooling to servers. These strategies need to be backed up by flexible room level models, able to work on runtime, that describe the system from a high level perspective.

Within the framework of next-generation applications, decisions taken at this scope can have a dramatical impact on the energy consumption of lower abstraction levels, i.e. the data center facility. It is important to consider the relationships between all the computational agents involved in the problem, so that they can cooperate to achieve the common goal of reducing energy in the overall system. The third main contribution is the energy optimization of the overall application by evaluating the energy costs of performing part of the processing in any of the different abstraction layers, from the node to the data center, via workload management and off-loading techniques.

In summary, the work presented in this PhD Thesis, makes contributions on leakage and cooling aware server modeling and optimization, data center thermal modeling and heterogeneity-aware data center resource allocation, and develops mechanisms for the energy optimization for next-generation applications from a multi-layer perspective.

Keywords — Energy, Energy-efficiency, Data Centers, Green Computing, Power modeling, Temperature prediction, Cooling, Resource management, Optimization

Resumen

"Si buscas resultados distintos, no hagas siempre lo mismo."

— Albert Einstein

Los Centros de Datos se encuentran actualmente en cualquier sector de la economía mundial. Están computestos por miles de servidores, dando servicio a los usuarios de forma global, las 24 horas del día y los 365 días del año. Durante los últimos años, las aplicaciones del ámbito de la e-Ciencia, como la e-Salud o las Ciudades Inteligentes han experimentado un desarollo muy significativo. La necesidad de manejar de forma eficiente las necesidades de cómputo de aplicaciones de nueva generación, junto con la creciente demanda de recursos en aplicaciones tradicionales, han facilitado el rápido crecimiento y la proliferación de los Centros de Datos. El principal inconveniente de este aumento de capacidad ha sido el rápido y dramático incremento del consumo energético de estas infraestructuras. En 2010, la factura eléctrica de los Centros de Datos representaba el 1.3% del consumo eléctrico mundial. Sólo en el año 2012, el consumo de potencia de los Centros de Datos creció un 63%, alcanzando los 38GW. En 2013 se estimó un crecimiento de otro 17%, hasta llegar a los 43GW. Además, los Centros de Datos son responsables de más del 2% del total de emisiones de dióxido de carbono a la atmósfera.

Esta tesis doctoral se enfrenta al problema energético proponiendo técnicas proactivas y reactivas conscientes de la temperatura y de la energía, que contribuyen a tener Centros de Datos más eficientes. Este trabajo desarrolla modelos de energía y utiliza el conocimiento sobre la demanda energética de la carga de trabajo a ejecutar y de los recursos de computación y refrigeración del Centro de Datos para optimizar el consumo. Además, los Centros de Datos son considerados como un elemento crucial dentro del marco de la aplicación ejecutada, optimizando no sólo el consumo del Centro de Datos sino el consumo energético global de la aplicación.

Los principales componentes del consumo en los Centros de Datos son la potencia de computación utilizada por los equipos de IT, y la refrigeración necesaria para mantener los servidores dentre de un rango de temperatura de trabajo que asegure su correcto funcionamiento. Debido a la relación cúbica entre la velocidad de los ventiladores y el consumo de los mismos, las soluciones basadas en el sobre-aprovisionamiento de aire frío al servidor generalmente tienen como resultado ineficiencias energéticas. Por otro lado, temperaturas más elevadas en el procesador llevan a un consumo de fugas mayor, debido a la relación exponencial del consumo de fugas con la temperatura. Además, las características de la carga de trabajo y las políticas de asignación de recursos tienen un impacto importante en los balances entre corriente de fugas y consumo de refrigeración. La primera gran contribución de este trabajo es el desarrollo de modelos de potencia y temperatura que permiten describes estos balances entre corriente de fugas y refrigeración; así como la propuesta de estrategias para minimizar el consumo del servidor por medio de la asignación conjunta de refrigeración y carga desde una perspectiva multivariable.

Cuando escalamos a nivel del Centro de Datos, observamos un comportamiento similar en términos del balance entre corrientes de fugas y refrigeración. Conforme aumenta la temperatura de la sala, mejora la eficiencia de la refrigeración. Sin embargo, este incremente de la temperatura de sala provoca un aumento en la temperatura de la CPU y, por tanto, también del consumo de fugas. Además, la dinámica de la sala tiene un comportamiento muy desigual, no equilibrado, debido a la asignación de carga y a la heterogeneidad en el equipamiento de

IT. La segunda contribución de esta tesis es la propuesta de técnicas de asigación conscientes de la temperatura y heterogeneidad que permiten optimizar conjuntamente la asignación de tareas y refrigeración a los servidores. Estas estrategias necesitan estar respaldadas por modelos flexibles, que puedan trabajar en tiempo real, para describir el sistema desde un nivel de abstracción alto.

Dentro del ámbito de las aplicaciones de nueva generación, las decisiones tomadas en el nivel de aplicación pueden tener un impacto dramático en el consumo energético de niveles de abstracción menores, como por ejemplo, en el Centro de Datos. Es importante considerar las relaciones entre todos los agentes computacionales implicados en el problema, de forma que puedan cooperar para conseguir el objetivo común de reducir el coste energético global del sistema. La tercera contribución de esta tesis es el desarrollo de optimizaciones energéticas para la aplicación global por medio de la evaluación de los costes de ejecutar parte del procesado necesario en otros niveles de abstracción, que van desde los nodos hasta el Centro de Datos, por medio de técnicas de balanceo de carga.

Como resumen, el trabajo presentado en esta tesis lleva a cabo contribuciones en el modelado y optimización consciente del consumo por fugas y la refrigeración de servidores; el modelado de los Centros de Datos y el desarrollo de políticas de asignación conscientes de la heterogeneidad; y desarrolla mecanismos para la optimización energética de aplicaciones de nueva generación desde varios niveles de abstracción.

Contents

List of Tables

List of Figures

1. Introduction

Yo sé un himno gigante y extraño
que anuncia en la noche del alma una aurora,
y estas páginas son de ese himno
cadencias que el aire dilata en las sombras.

— Gustavo A. Bécquer, *Rima I (Rimas y Leyendas)*

This introductory Chapter presents the motivation, problem context and a brief state of the art on the work presented in this Ph.D. Thesis. Besides, the main contributions of this work are highlighted and an overview of the structure of this Ph.D. Thesis is also provided.

1.1 Motivation and Context

Data centers often comprise thousands of enterprise servers that typically serve millions of users globally in a 24-7 fashion. The increasing demand for computing resources has recently facilitated the rapid proliferation and growth of data center facilities. Nowadays, these infrastructures can be found in every sector of the economy. They provide the required infrastructure for the execution of a wide range of applications and services including social and business networking, Webmail, Web search, electronic banking, Internet marketing, distributed storage, High Performance Computing (HPC), etc. In the last years, population monitoring applications (such as e-Health applications or Ambient Intelligence), E-science and applications for Smart Cities have experienced a significant development, mainly because of the advances in the miniaturization of processors and the proliferation of embedded systems in many different objects and applications. Next-generation systems are composed by a large set of nodes, distributed among the population. Data obtained by these sensor nodes are communicated to the embedded processing elements by means of wireless connections. Huge sets of data must be processed, stored and analyzed. The need to deal efficiently with such computing-intensive tasks, and the increasing demand for higher computer resources has facilitated the rapid proliferation and growth of data center facilities.

For decades, data centers have focused on performance, defined only as raw speed. Examples include the TOP500 list of the world's fastest supercomputers[1], which calculates the speed metric as floating-point operations per second (flops), and the annual Gordon Bell Awards for Performance and Price/Performance at the Supercomputing Conference[2]. However, raw speed has increased tremendously over the past decade without relative and proportional energy efficiency. In 2007, although there had been a 10.000-fold increase in speed since 1992, performance per watt was only improved 300-fold and performance per square foot only 65-fold. This huge performance improvement is mainly due to increases in three different dimensions: the number of transistors per processor, each processors operating frequency, and the number of processors in the system. Collectively, these factors yield an exponential increase in power needs of data centers that is not sustainable. The focus on just speed has let other evaluation metrics go unchecked. Data centers consume a huge amount of electrical power and generate a tremendous amount of heat.

[1]http://www.top500.org
[2]http://www.sc-conference.org

During 2008 world power consumption exceeded US $30 billion [136] when an average data center consumed as much energy as 25,000 households [85]. About 15% of this costs are due to removing the heat generated throughout the infrastructure [19]. The situation is critical since the numbers are growing. Only in 2010, worldwide data center consumption reached 1.5% of global energy, having increased by 56% since 2005, and reaching a density of 60 kW/m^2 [87]. In year 2012, global data center power consumption increased by 43% to 38GW. A further rise of 17% to 43GW was estimated in 2013 [158].

When data centers are placed in urban areas, they face problems related to the insufficient energy provided by the grid. Raskino *et al.* [99] estimate that at least a 50% of urban Data Centers have achieved the maximum capacity of the grid. Major players in the data center and high-end computing markets often negotiate energy deals with electricity suppliers to build or upgrade power substations, near or immediately next to their computing facilities. Alternatively, when not enough power infrastructures can be built at or near computing facilities, many companies move their computing facilities to the power source, *e.g.,*Google [3], [101] and Microsoft [156].

In addition to the economic impact of excessive energy consumption, the environmental impact has also affected the data center community. The heat and the carbon footprint emanated from cooling systems are dramatically harming the environment. According to Mullins [115], U.S. data centers use about 59 billion kWh of electricity, exceeding US $4.1 billion and generating 864 million metric tons of CO2 emissions released into the atmosphere, roughly a 2% of total worldwide emissions.

Both research and industry have recently proposed several approaches to tackle the power consumption issue in data center facilities. Industry has begun to shift their goal from performance to energy, reporting not only FLOPS, but FLOPS per watt and measuring the average power consumption when executing the LINPACK (HPL) benchmark [95]. This benchmark is used to elaborate the Green500 list [3], which ranks computers from the TOP500 list of supercomputers in terms of energy efficiency. Cooling is one of the major contributors to overall data center power consumption, representing from 30% to 50% of the total cost. According to Amazon data centers estimations [70], expenses related to operational costs of the servers reach 53% of the budget, while energy costs add up to 42%, which are broken down into cooling (19%) and power consumption of the infrastructure (23%).

Reference companies around the world such as Google, IBM or Amazon are implementing measures to make their data centers more efficient, and begin to measure the Power Usage Effectiveness (PUE) of their facilities. PUE is one of the most representative metrics, and consists in the facility's total power consumption divided by the computational power used only by servers, storage systems and network gear. A PUE close to 1 means that the data center is using most of the power for the computing infrastructure instead of being lost or devoted to cooling devices.

According to a report by the Uptime Institute, average PUE improved from 2.5 in 2007 to 1.89 in 2012, reaching 1.65 in 2013 [102]. This average PUE values are still far from the 1.1 to 1.3 obtained in data centers using the most efficient free cooling techniques [37], that allow to reach values as low as the 1.13 achieved by Google Data Centers [66]. Moreover, according to Koomey [87], PUE in year 2011 ranged from 1.36 to 3.6, implying there were still a very large number of data centers using inefficient cooling mechanisms.

The current energy and environmental cost trends of data centers are thus unsustainable, and affect both the computing power used by IT equipment and the associated data room cooling costs. It is critically important to develop data center-wide power and thermal software management solutions that improve the energy efficiency of data centers to place them on a more scalable curve. In the next subsections, we present an analysis on the current trends in trying to reduce power consumption at the server and the data center level.

This PhD Thesis proposes the development of proactive and reactive thermal and energy-aware optimization techniques to leverage energy efficiency in Data Centers. This work develops energy models and uses the knowledge about the energy demand of the workload

[3]http://www.green500.org

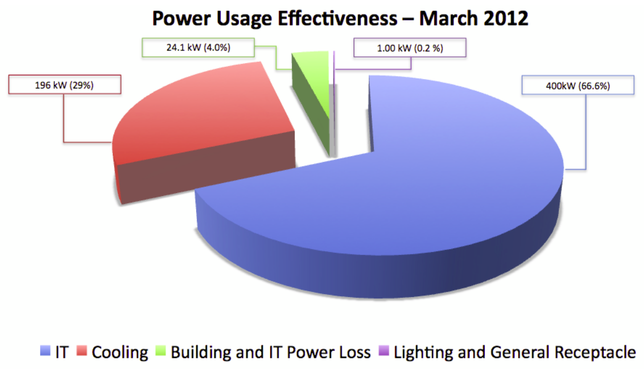


Figure 1.1: Power consumption distribution in a typical data center. Taken from [159]

and the computational and cooling resources available at the Data Center to optimize energy consumption. Moreover, the data center is considered as another element in its environment, optimizing not only the energy consumption of the facility, but the global energy consumption of the application framework. We envision the proposal of solutions under the new computational paradigms for next-generation applications, proposing solutions from a global, multi-layer perspective. To conclude, it is important to note that, to all intents and purposes, this thesis will try to offer a useful and applicable knowledge in real-life environments, filling the gap between academy and industry when it comes to the usage of real-life algorithms and solutions.

1.2 Overview of the State-of-the-Art

In this section we provide more details on the State-of-the-Art of the main topics related to this Ph.D. thesis. We start by briefly highlighting the energy consumption breakdown in today's data centers. Then, we present the approaches taken by industry to reduce data center power, also presenting the current situation of data centers. Finally, we describe the main trends proposed by academia in both energy efficient computing and cooling.

1.2.1 Energy consumption breakdown

The main contributors to the energy consumption in a data center are the computing power (also known as IT power) which is the power drawn by servers and other IT equipment, and the cooling power needed to keep the servers within a certain temperature range that ensures safe operation. Together, both factors account for more than 85% of the total power consumption of the data center, being the other 15% the power consumption due to lightning, generators, UPS (Uninterrupted Power Supply) systems and PDUs (power distribution units) [87]. Figure 1.1 shows the power consumption distribution in the Berkeley lab of the US Department of Energy.

IT power in the data center, specially in High-Performance Computing (HPC), facilities is dominated by the power consumption of the enterprise servers, with storage and network equipment still representing less than 15% of overall IT power [56]. The power consumption of an enterprise server can be further divided into three different contributors: (i) the dynamic or active power, (ii) the static or leakage power and (iii) the cooling power, due to the server fans. Dynamic power is due to the switching of the transistors in electronic devices, i.e. it is the power used to perform calculations. Leakage power is the unwanted result of subthreshold current in the transistors and does not contribute to the microcontroller function. When integration technology scales below the 100nm boundary, static consumption becomes very significant, being around 30-50% of the total power under nominal conditions [117]. This issue is intensified by the influence of temperature on the leakage current behavior. Each passing day fan power is becoming a more important contributor to overall server power, accounting for up to 14% of overall data center power [80].

1.2.2 Industry approaches to energy efficiency

Both research and industry have recently proposed several approaches to tackle the power consumption issue in data center facilities. However, their approaches have been very different. For instance, industry has focused in the reduction of the cooling costs of the data center, diminishing the PUE value of this facilities. Traditionally, cooling costs accounted for 30% to 50% of overall data center power; nowadays, we can find data centers with PUE values as low as 1.02 or 1.03 [66]. This efficiency values are achieved by improving cooling performance via hot or cold aisle containment and closed-coupled cooling. These techniques minimize air recirculation in the data center by placing cooling units as close as possible to the IT load they intend to cool, and containing the heat exhaust so that heated air cannot recirculate to the inlet of servers. Almost a 20% of large scale data centers are nowadays implementing this kind of solutions, i.e. in-row or in-rack cooling techniques that cool IT equipment to increase efficiency [102]. In all previous cases, cooling is performed by means of the heat exchange between air and liquid (water or a refrigerant). Thus, an important percentage of overall cooling energy is devoted to the chillers and towers that extract heat from the refrigerant. Because of this, to reduce the power consumption needed to extract the heat there is a generalized tendency to build data centers in cold areas of the world (Greenland, Finland, Sweden, etc.) in order to be able to apply free cooling techniques and reduce the power consumption due to water chilling [82].

Because the previous approaches rely on renewing the cooling equipment, rising capital expenses in the data center, another very common technique consists on using higher data room ambient temperatures [102]. The performance of cooling subsystems increases in tandem with room temperature and heat exhaust, improving cooling efficiency.

However, higher server inlet temperature has some drawbacks, the most important being: i) the possible harmful effects on reliability, ii) the reduction on the safety margins of servers and iii) the potential increase in IT power consumption.

There is much literature on the reliability effects of increased temperature at the server and data center level. Solutions to the energy problem must not suppose a decrease in the lifetime of servers or in their Mean Time To Failure (MTTF). A report by the Uptime Institute[150] showed that for every 10°C degrees of temperature in excess of 21°C in the inlet temperature of servers, long-term reliability could be reduced by 50%. Recent research by El-Sayed *et al.* [54] shows that the effect of high data center temperatures on reliability is smaller than what has been assumed. However, high temperatures at the chip level have irreversible adverse effects on the chips, such as electromigration that reduce the lifetime of the chip [14]. To prevent harmful effects over servers due to high temperatures, enterprise servers are configured with CPU critical temperature thresholds, so that the whole server shuts down when there is a CPU thermal redlining.

Moreover, as the ambient temperature of the data center and CPU temperature increase, the safety margin for the server thermal shutdown is decreased. Data room modeling is still an open issue, as the only feasible ways to model the thermal behavior of the data room and be able to predict the inlet temperature of the servers are: i) by deploying temperature sensors in the data room that take measurements, or ii) by performing very time consuming and expensive Computational Fluid Dynamics (CFD) simulations. CFD software, such as Mentor Graphics Flovent [61] (see Figure 1.2), is the most common technique and uses numerical methods to analyze the data room and model its behavior. However these simulations do not often match the real environments and must be re-run every time the data center topology changes.

The urge for reducing PUE, even by increasing room temperatures, has let other metrics go unchecked. Lower PUE values imply an increase in cooling efficiency; however, PUE is only a metric of cooling efficiency, not of overall data center efficiency. As such, it does not account for the aggregate fan power and CPU leakage power that exhibit a significant increase

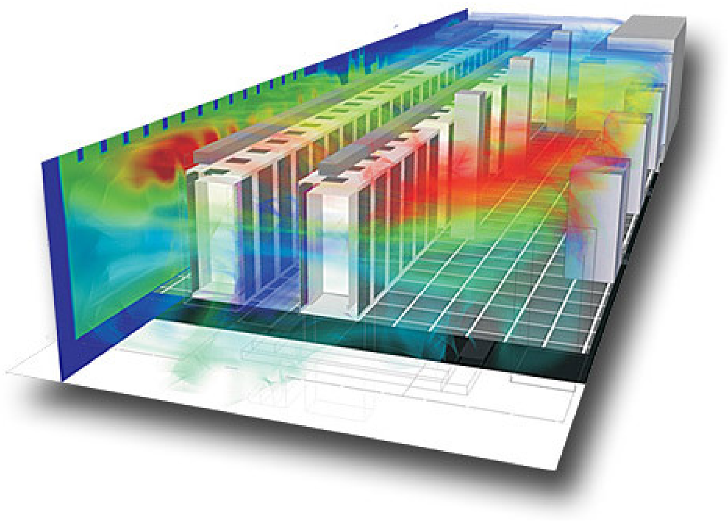


Figure 1.2: Flovent software screenshot showing air distribution between hot and cold aisles

when room temperature rises. Moreover, PUE is a very sensitive metric to parameters such as the climate and latitude at which the data center is located. Hence, the reliability of PUE as an energy-efficiency metric decreases as the leakage and fan power continue to increase in next-generation servers.

In summary, there exists a wide heterogeneity in terms of infrastructure in current data centers. The vast majority of small- and medium-scale data centers hosts volume servers, achieving medium-low power densities (i.e. around 5kW per rack), and, thus, use traditional cooling techniques based on air-cooled raise-floor data rooms without hot-cold aisle containment. These facilities usually have PUE values above 1.8. On the other hand, high density data centers hosting power-hungry equipments have already migrated to more efficient cooling techniques, obtaining high efficiency in the cooling subsystem.

1.2.3 Energy-efficient computing

In academia, there is a number of different techniques to reduce the energy cost and power density of IT equipment at different scopes: (i) hardware (ii) server and (iii) data center level. Optimizations within these scopes can be further divided into different abstractions levels as shown on Figure 1.3.

Hardware scope

The main achievements in energy-efficiency at the technology level mainly focus on technology scaling, voltage reduction, chip layout optimization and capacitance minimization [52]. Duarte *et al.* [30] showed that scaling down technology reduces energy consumption considerably. The reduction to $0.07\mu m$, $0.05\mu m$ and $0.035\mu m$ yielded savings of 8%, 16% and 23% respectively. Other techniques such as timing speculation have increased energy efficiency by 13% for high-performance low-power CMOS and by 32% using ultra-low power CMOS technology [88].

Logic-level design strategies focus on optimizing switching activity, minimizing switching capacitance [22]; via improving clock management and accurately modeling delay [120] or via power gating techniques [6]. The PowerNap mechanism [103], featuring per-core power gating, has shown the reduction of server idle power decreasing power requirements by about 20% when the processor is halted.

At the circuit-level, several techniques propose a more energy-efficient use of pipelines [144], or the reduction of logic depth between registers to increase pipeline stages [81]. Other ap-

HARDWARE SCOPE	SERVER SCOPE	DATA CENTER SCOPE
RM & Scheduling	RM & Scheduling	**RM & Scheduling**
Application	Application	**Application**
Middleware	Middleware	**Middleware**
Run-time system	**Run-time system**	Run-time system
Compiler	**Compiler**	Compiler
Architectural	**Architectural**	Architectural
Circuit	Circuit	Circuit
Logic	Logic	Logic
Technology	Technology	Technology

Figure 1.3: Main abstraction levels highlighted by hardware, server and data center scope

proaches aim at the reduction of energy consumption in the system bus. Research by Brahmbhatt *et al.* [31] proposes an adaptive bus encoding algorithm to improve energy savings by around 24%.

Server scope

From the server scope, we find optimization proposals at three different levels: i) architecture, ii) compiler and iii) run-time. Most of these techniques are inherited from the embedded system and MPSoCs world, and only very recently have started to be applied to tackle the problem of energy consumption in enterprise servers.

Power savings are typically achieved at the architectural-level by optimizing the balance of the system components to avoid wasting power. Compared to other resources, CPU is the main contributor to power consumption [110], and, significant research focuses on increasing CPU energy efficiency. However, the power consumption breakdown of recent enteprise servers shows that the impact of memory power, disk and fans is not negligible, and that no single component dominates the total power consumption of the server [103]. To this end, some authors have tried to dynamically regulate CPU power and frequency to optimize power consumption [29], [92]. Deng *et al.* [49] apply DVFS to memory management achieving 14% of energy savings. Pinheiro *et al.* [35] suggest the use of multi-speed disks, so that disks could be slowed down to reach lower energy consumption during low-load periods. As reported in the research by Heo *et al.* [76], the usage of DVFS combined with Feedback On/Off techniques can yield total power savings that reach 84% in low-load systems and 55% when workload is the highest possible.

The goal of compiler-level optimizations is to generate code that reduces the energy consumption of the processor with or without a penalty in performance. In general, these approaches rely on code transformation and optimization, profiling and annotation [59]. Work by Simunic *et al.* [83], [163] optimizes the implementation of an MP3 audio decoder for embedded systems, obtaining an energy consumption decrease of 77% over the original audio decoding.

Several techniques can be used to reduce energy efficiency during the execution of the workload, i.e. at runtime. In the field of Multiprocessor System on Chip (MPSoC) significant improvements have been reached at run-time by proposing energy-aware workload scheduling policies [167]. Several works use statistical models that allow run-time system-wide prediction of server power consumption [50], [93]. A prediction-based scheme for run-time adaptation is presented by Curtis-Maury *et al.* [47] improving both performance and energy savings by up to a 40%.

Data center scope

Optimization within the data center scope can also be further divided into three different abstraction levels: i) middleware, ii) application and iii) resource management.

One of the major sources of inefficiency in data centers comes from the lack of proportionality in server energy consumption. Recent studies show that tipically, an idle server consumes up to 66% of the total power consumption [39]. Thus, maximizing resource utilization results in energy savings due to the high power consumption for idle and underutilized servers. At the middleware level, the usage of virtualization and consolidation techniques increase the overall utilization of servers and achieving up to 23% energy savings [41], [154]. Together with machine turn-off policies, dynamic consolidation techniques can achieve up to 45% energy savings for cloud computing workloads without SLA violations [21]. However, the specific demands of HPC clusters, where performance is a key aspect, often mismatch the assumptions of virtualization. Virtualization techniques introduce an overhead, implying a certain performance degradation. Virtualization for HPC clusters is still a very new area of research, but work so far highlights the possible future benefits of virtualization in HPC [106]. Handling the operating server set can be useful when considering the inherent periodic behavior of workloads through time, and is a common technique used in several data centers. In that sense, the totality of the resources might only be used at concrete time periods or at certain times of the day [24]. In HPC facilities, such as CeSViMa data center, it is common to turn off unused server during low utilization periods. A periodic workload behavior is usually observed in HPC clusters, as can be seen when observing workloads from the Parallel Workloads Archive [4].

Optimizations at the application level aim to use the knowledge about the particular applications that compose the workload of the data center to optimize energy efficiency. For instance, PowerPack [63] uses circuit-level application profiling to determine how and where power is consumed. In grid computing, approaches have also been made to efficiently distribute compute-intensive parallel applications [62].

Resource management is a well known concept in the data center world and refers to the efficient and effective deployment of computational resources of the facility where they are needed. Several algorithms and methodologies can be found in the literature to minimize energy consumption via allocation and scheduling techniques based on: i) load-balancing [34], [51], ii) linear programming techniques [183], iii) controller-based approaches [64], iv) greedy algorithms [118] or v) other heuristics [182].

In general, the previous approaches do not consider an accurate power modeling of the computing resources, and results are tested in simulation space, not in real-life environments or with real production tools. Moreover, these solutions focus on minimizing IT power, but disregard the data center cooling and the data room environment.

1.2.4 Energy-efficient cooling

Energy-efficient cooling strategies try to minimize the cooling costs, either by means of i) thermal-aware or ii) cooling-aware workload scheduling.

Thermal-aware workload scheduling aims at the reduction of hot-spots in servers, and particularly in their CPU's) and data centers, thus lowering the cooling effort and increasing energy efficiency. This is the case for research on temperature-aware floor-planning of cores in MPSoCs [72], [78], which is devoted to getting the optimum floorplan that reduces the maximum temperature of the chip. Hot-spots can also be reduced by means of temperature-aware

[4]http://www.cs.huji.ac.il/labs/parallel/workload/

task allocation and scheduling algorithms [166] at the CPU level, at the operating-system level [42], and even at the cluster level [27].

The goal of cooling-aware workload scheduling is to be able to reduce the cooling costs of the data center via scheduling techniques, allowing to increase the air supply temperature of CRAC units and, thus, saving energy in the cooling subsystem. In traditional air-cooled raised-floor data centers, energy efficiency from the cooling perspective can exploit two different facts: (i) placing the workload in areas that are more efficient to cool [114] or areas that need less cooling [165], also taking into account temperature imbalances [112]; or (ii) maximizing cooling efficiency by increasing CRAC air supply temperature [152] or minimizing heat recirculation [151].

These approaches try to maximize the air supply temperature of CRAC units. For that purpose, they generally use CFD software to model the inlet temperature of servers in an homogeneous data center or use simple linear models to describe heat interference across servers. However, the goal of these policies is not to reduce overall energy consumption of the data center (i.e. cooling and IT power) but to minimize cooling power only. Moreover, they base their optimizations on inlet temperature, disregarding CPU temperature and its effect on leakage power and fan power consumption.

1.2.5 Joint strategies for IT and cooling

At the server level, joint workload and cooling strategies consider fan control together with scheduling in a multi-objective optimization approach [16]. Work by Chan *et al.* [38] makes use of a joint energy, thermal and cooling management technique to reduce the server cooling and memory energy costs. However, these contributions are not able to split the contributions of leakage and cooling power, so their minimization strategy is unaware of the leakage-cooling tradeoffs.

At the data center level, research by Gutpa *et al.* [2] presents the data center as a distributed Cyber-Physical System (CPS) in which both computational and physical parameters can be measured with the goal of minimizing energy consumption. However, the validation of these works is kept in the simulation space, and solutions so far are not applied in real data center scenarios.

1.2.6 Trends and open issues

The impact of energy optimization in an environment that handles so impressively high figures in both energy and economic costs as data centers, has motivated many researchers to focus their academic work on proposing solutions to this challenge.

A great body of research has been devoted to addressing energy efficiency at different abstraction levels. We observe that the benefits in terms of energy savings raise for higher abstraction levels. However, there are still open challenges at the server and data center abstraction level that need further effort. Today's data centers exhibit many degrees of heterogeneity in their resources. The high costs of IT equipment promote the co-existence of different generations of servers in data center rooms and thus, the heterogeneity in terms of hardware. However, current research at the resource management level does not accurately tackle resource heterogeneity, which continues to be an open issue.

Workload management in the state-of-art lacks of accurate, flexible and scalable power and energy models that support the proposed optimizations. These models need to be able to explain the effect of temperature on power, as well as the leakage-cooling tradeoffs at the server level, and the impact at the room level. Current data room models are based on time costly CFD simulation techniques or on unrealistic static linear models, that often do not match the real dynamics of the data room and are not robust to changes. Most contributions lack a validation in presently-shipping enterprise servers or data center scenarios.

There exists a lack of high-level orthogonal optimization techniques that can be applied together to minimize overall energy consumption. Joint workload and cooling resource allocation (i.e. proactively and jointly optimizing the cooling and computational resources of the

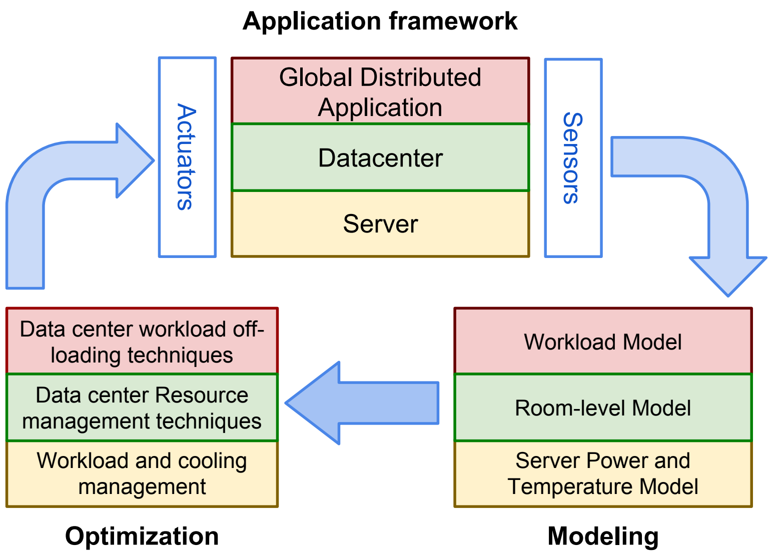

Application framework
Global Distributed Application
Datacenter
Server
Actuators
Sensors
Data center workload off-loading techniques
Data center Resource management techniques
Workload and cooling management
Optimization
Workload Model
Room-level Model
Server Power and Temperature Model
Modeling

Figure 1.4: Overview of the proposed analysis and optimization system.

data center) is still an open issue. Regulation over CRAC units and energy-efficient allocation, have not yet been integrated in the control loop of real data centers.

Moreover, solutions to the energy challenge have focused on minimizing power consumption at the data center, disregarding its environment, the global framework where the workload is generated and the particular application. However, next-generation e-science applications such as the ones found in Smart Cities, e-Health, Ambient Intelligence or any kind of population monitoring applications, require constantly increasing high computational demands to capture, process, aggregate and analyze data and offer services to users. Research has traditionally paid much attention to the energy consumption of the sensor deployments that support this kind of applications. However, computing facilities are the ones presenting a higher economic and environmental impact due to their very high power consumption.

To tackle energy consumption of computing facilities, the energy cost of performing part of the processing in any of the different abstraction layers, from the node to the data center (i.e. data center off-loading), should be evaluated.

Finally, it has to be taken into account that local optimization in one of the abstraction layers (i.e. in the data center) can have a large negative impact on the others, so that the global energy of the system is increased. In this way, the relationships between all the computational agents have to be taken into account. All the agents involved in the problem need to cooperate to achieve the common goal of reducing energy in the overall system.

1.3 Problem formulation and optimization paradigm

The work developed in this Ph.D. Thesis proposes a global solution based on the energy analysis and optimization for next-generation applications from a multi-layer perspective. The envisioned modeling and optimization paradigm is summarized in Figure 1.4. This framework takes as input all the information gathered from the application to be optimized, at all possible abstraction layers (i.e. server, application and data center), via sensor measurements of both physical and computational magnitudes. Data is stored to generate models, also at different abstraction levels. The models obtained enable the design of multi-layer optimization strategies. Results of these optimizations are evaluated by a decision-making system, which is beyond the scope of this Ph.D. Thesis, whose mission is to integrate the decisions taken.

The scenario chosen for the development of this PhD thesis, is a global distributed application framework for next-generation E-science applications such as the ones found in Smart Cities, e-Health or Ambient Intelligence. These applications require constantly increasing high computational demands in order to capture, process, aggregate and analyze data and offer services to users. Next-generation systems are composed by a large set of nodes, distributed among the population. Data obtained by these sensor nodes are communicated to the embedded processing elements by means of wireless connections. Huge sets of data must be processed, stored and analyzed. In order to deal efficiently with such computationally intensive tasks, the use of data centers is devised.

To this end, the scenario chosen for the development of energy-aware techniques at the data center level is a dedicated, non-virtualized, High-Performance Computing (HPC) data center. We assume this data center may be composed of different generations of servers, i.e. it has a certain degree of heterogeneity in the IT equipment. We assume a traditional hot-cold aisle data center layout with CRAC-based cooling. In particular, at the data center level we consider a raised-floor air-cooled data center where cold air is supplied via the floor plenum and extracted in the ceiling.

Without loss of generality, we propose the *"Centro de Supercomputación y Visualización de Madrid" (CeSViMa)* [5] data center as a case study scenario for this PhD Thesis. *CeSViMa* is an institution belonging to Universidad PolitÃ©cnica de Madrid that hosts the Magerit supercomputer, a cluster composed of Intel Xeon and Power7 processors holding a total amount of 3920 processor and 7840GB of RAM. The data room is composed of 10 racks distributed in a hot/cold aisle scheme with raised-floor air-cooling. CeSViMa uses an open-source resource management software tool (SLURM) used to allocate the incoming workload to the computing nodes. The applications run in CeSViMa are, in general, CPU and memory intensive analysis and optimization applications performed by researchers.

However, the validation of the models and optimizations proposed in this PhD thesis are not limited to the CeSViMa case study scenario. Several server architectures are tested by means of the monitoring and modeling of various presently-shipping enterprise servers. Also, at the data center scope other reduced scenarios are used to test the proposed optimization policies.

1.4 Contributions of this Ph.D. Thesis

The main goal of this Ph.D. Thesis is the development of proactive and reactive thermal-aware optimization techniques to improve the energy efficiency and minimize the environmental impact of data centers. This research proposes the development of orthogonal modeling and optimization techniques to be applied at different abstraction levels: server, data center and the global distributed application framework. These techniques are applied from a holistic perspective taking into account the knowledge of the applications to be executed and both the cooling and computing resources at the Data Center.

Particularly, the main contributions of this PhD thesis can be described as follows:

- Modeling and optimization at the server level:
  - The design of empirical models to estimate various power components in enterprise servers (e.g static and dynamic power, CPU and memory power), validated in presently-shipping servers. The methodology proposed enables the extension of these models to various heterogeneous architectures. Moreover, because of their low computational overhead, the models can be scaled to describe the room-level behavior.
  - The analysis of the leakage vs. cooling power tradeoffs, showing the importance of temperature-dependent leakage in server energy consumption. This Ph.D. Thesis also studies the relationship among power, temperature, application characteristics and workload allocation.

[5]http://www.cesvima.upm.es

  - The proposal of optimization techniques that aim to jointly reduce the computing and cooling energy of the servers in a data center, by managing the server fans and the workload scheduling. These optimizations are faced from two perspectives: (i) a reactive approach, based on exploiting dynamic workload profiling mechanisms, and (ii) a proactive perspective that exploits the energy models.

- Modeling and optimization at the data center level:
  - The development of data center room level models, based on Machine Learning techniques, able to work on runtime with low computational overhead, to describe the system from a high level of abstraction, as opposed to other techniques such as CFD. The proposed models are flexible, and incorporate a variable number of power consumption sources from IT and cooling equipment. These models are trained and tested with traces from a real data center scenario at the Centro de Supercomputación y Visualización de Madrid (CeSViMa).
  - The design of heterogeneity-aware proactive and reactive optimizations that aim to reduce the computing power of the data center by properly assigning workload to computational resources. The techniques proposed rely on the knowledge of the applications to be executed and on the computational resources available. The optimization problem is solved by using Mixed Integer Linear Programming, and has low performance overhead to work on runtime.
  - This work proposes optimizations to reduce the cooling power of the data center. These techniques aim to provide energy savings by making the servers work on safe thermal regions (from the reliability perspective) that allow to reduce the cooling costs at the room level.
  - The development of joint computational and cooling optimizations, that come from an efficient combination of the above mentioned techniques. The joint approach combines the modeling and optimization techniques at both the server and room-level, and provides energy savings to a greater extent, increasing the savings that come from applying either computational or cooling optimizations independently.

- Global distributed application framework optimization: one of the main objectives of this Ph.D. Thesis is the development of global energy optimization policies that take into account the energy relationship between different abstraction layers. By managing orthogonal optimization techniques applied at the server, data center and the global distributed framework of a particular application, we obtain the maximum benefit of energy-aware policies. In particular, we leverage the usage of data center off-loading techniques in a case study for e-Health scenarios and show the benefits of integration all optimizations in a multi-layer approach.

1.5 Structure of this Ph.D. Thesis

The rest of the document of this Ph.D. thesis is organized as follows:

- Chapter 2 presents the techniques developed to model the different contributors to the power consumption of enterprise servers (*i.e.,*static, dynamic and cooling power) and the estimation of server CPU temperature. Modeling results are shown for a presently-shipping enterprise server.

- Chapter 3 proposes joint cooling and workload management strategies to minimize energy consumption at the server level. Experimental results are carried out in the same systems where modeling was performed.

- Chapter 4 raises the level of abstraction to the data center level, developing automatic room modeling techniques based on metaheuristics to predict the parameters of the data room that have an impact on cooling energy and control.

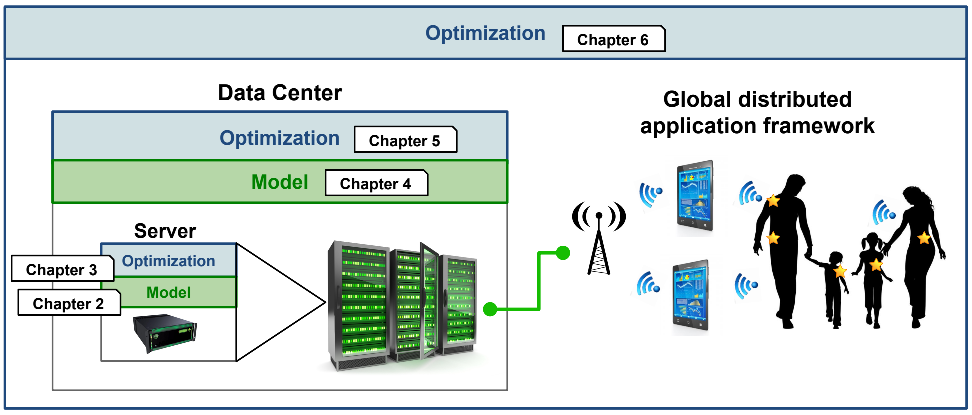


Figure 1.5: Overview of the Ph.D. Thesis structure and chapter organization

- Chapter 5 describes resource management optimization techniques based on application and heterogeneity awareness to reduce the energy consumption at the data center.
- Chapter 6 shows how the developed models and optimization strategies can be applied in the framework of an e-Health application, and how our multi-layer approach yields important benefits to the energy minimization of the overall application.
- Chapter 7 summarizes the conclusions derived from the research that is presented in this Ph.D. thesis, as well as the contributions to the state-of-the-art on energy efficiency in data centers. The Chapter also includes a summary on future research directions.

Figure 1.5 provides the reader with an overview of the structure of this Ph.D. thesis and how the Chapters are organized. As can be seen, Chapters are arranged from lower to higher abstraction level, and describe the different modeling and optimization techniques developed in this work.

1.6 Publications

The results of this PhD Thesis, together with other related research have been published in international conferences and journals. In this section we briefly present these publications and highlight the chapter in which the specific contributions can be found.

1.6.1 Journal papers

In terms of scientific publications, this Ph.D. thesis has generated the following articles in international journals:

- M. Zapater *et al.*, "Ommited for blind review", *IEEE Transactions on Evolutionary Computation (TEVC)*, [Submitted, under review] [JCR Q1 IF=5.545] *(Chapter 4 of this Ph.D. Thesis)*
- M. Zapater, O. Tuncer, J. L. Ayala, *et al.*, "Leakage-aware cooling management for improving server energy efficiency", *IEEE Transactions on Parallel and Distributed Systems (TPDS)*, 2014, ISSN: 1045-9219. DOI: `10.1109/TPDS.2014.2361519` [JCR Q1 IF=2.173] *(Chapters 2 and 3 of this Ph.D. Thesis)*
- M. Zapater, P. Arroba, J. L. Ayala, *et al.*, "A novel energy-driven computing paradigm for e-health scenarios", *Future Generation Computer Systems*, vol. 34, pp. 138–154, 2014, ISSN: 0167-739X [JCR Q1 IF=1.864] *(Chapters 1 (paradigm) and 6 of this Ph.D. Thesis)*

- M. Zapater, C. Sanchez, J. L. Ayala, *et al.*, “Ubiquitous green computing techniques for high demand applications in smart environments”, *Sensors*, vol. 12, no. 8, pp. 10 659–10 677, 2012, ISSN: 1424-8220 [JCR Q1 IF=1.953] *(Chapter 6 of this Ph.D. Thesis)*

- M. Zapater, P. Arroba, J. M. Moya, *et al.*, “A State-of-the-Art on energy efficiency in today’s datacentres: researcher’s contributions and practical approaches”, *Green ICT: Trends and Challenges*, vol. 12, no. 4, pp. 67–74, 2011, [Awarded best paper of the year 2011.], ISSN: 1684-5285

1.6.2 Conference papers

Also, this Ph.D. thesis has generated the following articles in international peer-reviewed conferences:

- M. Zapater, J. L. Ayala, and J. M. Moya, “Proactive and reactive thermal aware optimization techniques to minimize the environmental impact of data centers”, in *Design Automation Conference*, ser. DAC’14, [PhD Forum], 2014 [Core A conference]

- M. Zapater, J. L. Ayala, J. M. Moya, *et al.*, “Leakage and temperature aware server control for improving energy efficiency in data centers”, in *DATE’13*, 2013 [Core B conference] *(Chapters 2 and 3 of this Ph.D. Thesis)*

- M. Zapater, J. L. Ayala, and J. M. Moya, “Leveraging heterogeneity for energy minimization in data centers”, in *CCGRID’12*, 2012 [Core A conference] *(Chapter 5 of this Ph.D. Thesis)*

- M. Zapater, J.-M. de Goyeneche, J. M. Moya, *et al.*, “Thermal-Aware optimization of heterogeneous systems”, in *26th Conference on Design of Circuits and Integrated Systems*, ser. DCIS’11, Nov. 2011 *(Chapter 5 of this Ph.D. Thesis)*

- M. Zapater, J. L. Risco, J. L. Ayala, *et al.*, “Combined Dynamic-Static approach for Thermal-Awareness in heterogeneous data centers”, in *Innovative Architecture for Future Generation High Performance (IWIA), 2010 International Workshop on*, ser. IWIA’10. 2010, pp. 75–82 *(Chapter 5 of this Ph.D. Thesis)*

1.6.3 Book chapters

This Ph.D. thesis has generated the following book chapters:

- M. Zapater, J. L. Ayala, and J. M. Moya, “Energy-aware policies in ubiquitous computing facilities”, in *Cloud Computing with e-Science Applications*, O. Terzo and L. Mossuca, Eds., CRC Taylor & Francis, 2014, pp. 265–284

- M. Zapater, J. L. Ayala, and J. Moya, “GreenDisc: a HW/SW energy optimization framework in globally distributed computation”, in *Ubiquitous Computing and Ambient Intelligence*, ser. Lecture Notes in Computer Science, J. Bravo, D. López-de Ipiña, and F. Moya, Eds., Springer Berlin Heidelberg, 2012, pp. 1–8 *[Chapters 1 (paradigm) and 6 of this Ph.D. Thesis]*

1.6.4 Other publications

Finally, the author has also contributed in the following articles in international peer-reviewed conferences and journals, not specifically related to the contents of this Ph.D. Thesis:

- M. Zapater, D. Fraga, P. Malagon, *et al.*, “Self-organizing maps versus growing neural gas in detecting anomalies in data centers”, *Logic Journal of the IGPL*, 2015, [In Press. To appear in 2015] [JCR Q1 IF=1.136]

- J. M. Colmenar, A. Cuesta, Z. Bankovic, *et al.*, "Comparative study of meta-heuristic 3D floorplanning algorithms", *Neurocomputing*, 2014, [In Press. To appear in 2014] [JCR Q1 IF=2.005]

- P. Arroba, J. L. Risco-Martín, M. Zapater, *et al.*, "Evolutionary power modeling for high-end servers in cloud data centers", in *Mathematical Modelling in Engineering & Human Behaviour*, 2014

- P. Arroba, J. L. Risco-Martín, M. Zapater, *et al.*, "Server power modeling for Run-Time energy optimization of cloud computing facilities", in *International Conference on Sustainability in Energy and Buildings*, ser. SEB'14, 2014

- P. Arroba, M. Zapater, J. L. Ayala, *et al.*, "On the leakage-power modeling for optimal server operation", in *IWIA*, 2014

- J. Pagán, M. Zapater, O. Cubo, *et al.*, "A Cyber-Physical approach to combined HW-SW monitoring for improving energy efficiency in data centers", in *Conference on Design of Circuits and Integrated Systems*, ser. DCIS'13, [This publication is a result of the MSc. Thesis developed by J. Pagán under the supervision of the author.], 2013, pp. 140–145, ISBN: 978-84-8081-401-0

1.7 Research Projects and Grants

This author of this work has been awarded the following research grants:

- Pre-doctoral fellowship of the *International Programme for Talent Recruitment (PICATA)* of the Moncloa Campus of International Excellence, for the development of a Ph.D. Thesis coordinated by the Universidad Complutense de Madrid (UCM) and the Universidad Politécnica de Madrid (UPM), in the cluster of Global Change and New Energies *[71,850€ awarded on a competitive basis, March 2011].*

- Mobility Grant from the Moncloa Campus of International Excellence, for a 3-month research stay at the Performance and Energy-Aware Computing Lab. (PeacLab) at Boston University (Boston, MA, USA) *[4,900€ awarded, July 2012].*

- Mobility Grant from the European Network of Excellence on High Performance and Embedded Architecture and Compilation (HiPEAC), for a 3-month research stay at the Performance and Energy-Aware Computing Lab. (PeacLab) at Boston University (Boston, MA, USA) *[5,000€ awarded on a competitive basis, September 2014]*

Moreover, during the development of the Ph.D. Thesis the author has participated in the following R&D projects and industrial contracts:

- CALEO project: Thermal-aware workload distribution to optimize the energy consumption of data centres. Funded by the Centro para el Desarrollo Tecnológico e Industrial (CDTI) of Spain. *[September 2012]*

- GreenDISC project: development of HW/SW Technologies for Energy Efficiency in Distributed Computing Systems. The project proposes several research lines that target the power optimization in computing systems. Funded by the National Programme for Fundamental Research Projects (MINECO) of the Spanish Ministry of Economy and Competitiveness. *[September 2013]*

- LPCloud project: This project focuses on the optimum management of low-power modes for cloud computing. Funded by the National Programme for Public-Private Cooperation, INNPACTO (MINECO) of the Spanish Ministry of Economy and Competitiveness. *[September 2013]*

- Industrial contract with Oracle, Inc. and Decision Detective Corporation (SBIR): Participation in these industry contracts during both research stays at Boston University.
- GreenStack project: This project focuses on the development of energy optimization policies in OpenStack, providing it with awareness of the behavior of the data center to accurately anticipate actual needs. Funded by the National R&D&i Programme for Societal Challenges, RETOS-COLABORACION (MINECO) of the Spanish Ministry of Economy and Competitiveness. *[September 2014]*

In the next chapter...

the reader will find a description of the temperature, power and energy models developed at the server level.

2. Server power and temperature modeling

En els teus fills i els teus nets, tu els hi has d'ensenyar, les quatre regles primeres per ser un bon catala: Que s'ha d'estimar la llengua, que s'ha d'estimar la llar, que s'ha d'estimar la terra, que s'ha d'estimar la mar.

— Joan Anton Carrau, *La meva avia – Havanera*

The work presented in this chapter develops a methodology to accurately model the main contributors to power consumption in enteprise servers. We design empirical models to estimate static and dynamic CPU power, memory power, and CPU temperature. This chapter also analyzes the leakage vs. cooling power tradeoffs at the server level, showing the importance of temperature-dependent leakage in server energy consumption. We also study the relationship among power, temperature, application characteristics and workload allocation.

The models are developed and validated on a presently shipping, highly multithreaded SPARC server. Moreover, we also show how our methodology can be applied to the modeling of an Intel Sandybridge-EP server belonging to the Open Compute Project.

2.1 Introduction

Each data center houses thousands of enterprise servers that need to run 24/7. The computation requirements of these facilities make them power hungry. The power drawn by servers and other IT equipment accounts for around 60% of the total energy budget in traditional data centers. Another 30% of the electricity bill is needed to cool down the servers, keeping them within reliable thermal operating conditions [33]. In the last years, a significant effort has been devoted to decrease the cooling power. When changing cooling equipment is not an option due to the high capital expenses, raising the inlet temperature is one of the most common strategies to increase efficiency [102]. The increase in room ambient temperature, however, also increases the fan speed of servers to keep all components below critical thermal thresholds. As fan power is a cubic function of fan speed, using high fan speeds leads to a high cumulative server fan power. Fans have become an important contributor to power consumption, reaching up to 14% of the overall cooling power consumption [80].

Higher room temperatures also imply increasing the chip temperatures, which are already high due to the rapid increment in CMOS power density [166]. This may cause potential reliability problems as well as increased leakage power because of the exponential dependence of leakage on temperature.

Even though dynamic power has historically dominated the power budget, leakage power is becoming a more important contributor as CPU technology continues to shrink. Prior work analyzing the effect of leakage on servers highlights that reducing cooling power by allowing higher room temperatures may or may not be efficient depending on the specific data center configuration [129].

The power drawn by servers and other IT equipment are the highest contributor to power consumption. To develop data center energy efficiency strategies we first need to understand how power is being used by servers, and, moreover, we need to be able to predict the power consumption of servers under different conditions.

This chapter focuses on the development of server-level models that will be used to develop server and data center optimization strategies (see Chapters 3 and 5 respectively). In particular, the main contributions presented in this chapter are as follows:

- We design empirical models to estimate and separately quantify the static and dynamic power of a server, and the cooling power.
- We develop a CPU temperature model that allows to predict the temperature that a certain workload attains.
- We analyze leakage vs. cooling power tradeoffs at the server level, and show the importance of temperature-dependent leakage in server energy consumption. We also study the relationship among power, temperature, application characteristics and workload allocation.
- We validate our models and methodology using a wide range of applications running on a presently-shipping highly multi-threaded SPARC enterprise server. Moreover, we show how our methodology is applied to the modeling of an Intel Sandybridge-EP server.

The remainder of this chapter starts by describing the related work in the area (Section 2.2). Section 2.3 describes the experimental framework. In Sections 2.4 and 2.5 we develop and validate the proposed models, whereas in Section 2.6 we show how our methodology can be extended to other setups. In Section 2.7 we summarize the methodology and results. Finally, Section 2.8 draws the most important conclusions.

2.2 Background on server modeling

Prior work on server power modeling usually focuses on estimating the dynamic power consumed by servers. The major contributors to dynamic power consumed by servers are the CPU and memory subsystems, followed by the power consumption of disk and network, which are substantially lower, as shown in a report by Intel [110]. Based on this observation, Lewis et al. [93] develop a linear regression model based on performance counters to provide run-time system-wide power prediction. Other models formulate server power as a quadratic function of CPU usage [57]. The power modeling technique vMeter [28], observes a correlation between the total system power consumption and component utilization, and creates a linear total server power model. Cochran et al. [43] determine the relevant workload metrics for energy minimization and manage tradeoffs between energy and delay. Arjona*et al.* [7] use real measurements to split the contributors to power of the CPU, disk and network subsystems. All previous approaches in server power modeling assume that leakage has minimal impact and disregard cooling power.

However, even though dynamic power has traditionally dominated the power budget, when scaling technology below the $100nm$ boundary, static consumption becomes much more significant, being around 30-50% [117] of the total power under nominal conditions. This issue is intensified by the influence of temperature on the leakage current behavior. With increasing temperature the on-current of a transistor is reduced slightly. However, the reduction of the threshold voltage is not sufficient to compensate for the decreased carrier mobility that has a strong exponential impact on leakage current.

The current generated in a MOS device due to leakage is the one shown in equation 2.1:

$$I_{leak} = I_s \cdot e^{\frac{V_{GS}-V_{TH}}{nkT/q}} \cdot (1 - e^{\frac{V_{ds}}{kT/q}}) \tag{2.1}$$

Research by Rabaey [135] shows that if $V_{DS} > 100mV$ the contribution of the second exponential is negligible, so the previous formula can be rewritten as in Equation 2.2:

$$I_{leak} = I_s \cdot e^{\frac{V_{GS}-V_{TH}}{nkT/q}} \tag{2.2}$$

where technology-dependent parameters can be grouped together in a constant B to obtain the formula in Equation 2.3:

$$I_{leak} = B \cdot T^2 \cdot e^{\frac{V_{GS}-V_{TH}}{nkT/q}} \tag{2.3}$$

Among the enterprise server components, CPUs exhibit the majority of the temperature-dependent leakage power [129], as the DRAM leakage does not significantly depend on temperature [67]. The power consumption of the state-of-the-art DRAMs is also temperature-dependent only if the DIMMs support temperature-aware dynamic frequency settings [67]. Most DIMMs in presently shipping enterprise servers (including the ones in our experimental framework), do not support this feature. For this reason, as shown in Section 2.5, our work focuses on the CPU while modeling temperature dependency.

Another major factor that affects temperature in servers is the workload dynamics. Different workload allocation schemes change the temperature balance across the chip and thus, the leakage power [46]. Our work, presents an accurate model for leakage power consumption and shows its impact on total power consumption, and is robust to changes in the workload allocation policy.

2.3 Experimental framework

The purpose of our experimental framework is to develop models for the various contributors to power consumption in the server. In this section we provide an insight on the workloads used for modeling, the servers and we provide an insight via experimental exploration on the leakage-temperature trade-offs at the server level. This way we justify the need to isolate and control the cooling subsystem of the server, as well as to gather workload and sensor data from the server for the purpose of modeling.

2.3.1 Workload

To develop server-level models we run a comprehensive set of workloads to train and test our models. For model training, we use synthetic workloads that allow to stress different components of the system:

- *LoadGen* is a customized load-synthesis tool that brings two advantages for energy and thermal characterization: (i) it uses a core algorithm that maximally stuffs the instruction pipes for multi-thread CPUs, obtains the highest possible gate switching in the chips; and (ii) allows and provides customized dynamic profiles that meet any desired utilization level through duty-cycling with any desired cycling frequency.
- *RandMem* is a synthetic benchmark that accesses random memory regions of a given size with a given access pattern. The original benchmark [97] is modified to stress the large DRAMs in our system. The benchmark also allows us to configure the size of the memory blocks to be accessed and the access pattern, making *RandMem* a suitable benchmark to explore memory power consumption. The current version of this benchmark is published open source [1].

To validate the developed models, we use the following benchmarks as test set:

- SPEC Power_ssj2008 [149], a benchmark that evaluates the power and performance characteristics of volume class servers
- A subset of integer and floating point (FP) workloads from the CPU-intensive SPEC CPU 2006 [148] benchmark that exhibit a distinctive set of characteristics according to the work by Phansalkar et.al. [132]
- The PARSEC multi-threaded benchmark suite [25] that assesses the performance of multiprocessor systems.

[1]https://github.com/greenlsi/randmem

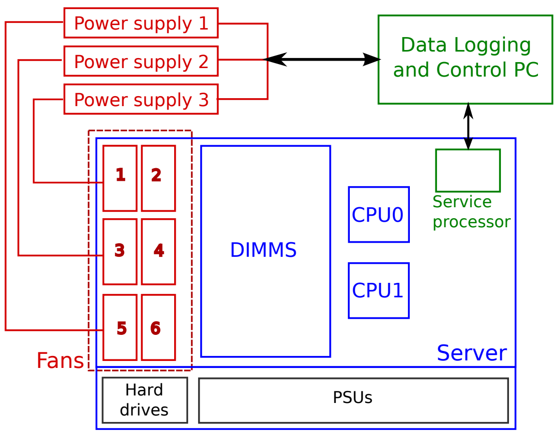


Figure 2.1: Experimental setup and internal diagram of SPARC T3 server.

2.3.2 Experimental set-up

Oracle SPARC T3 Server

Experiments are carried out on a presently shipping enterprise server which contains two SPARC T3 processors [146] in 2 sockets that provide a total of 256 hardware threads, 32 8GB memory DIMMs, and 2 hard drives. Each processor has 16 cores, and each core has 8 hardware threads, providing a total number of 256 hardware threads on the server. The machine is cooled by 6 fans (distributed in 3 columns of 2), which blow air through the memory modules (DIMMs) to the processors. The Power Supply Units (PSUs) and hard disks are located on one side of the server. The server internals are shown in Figure 2.1. We enable characterization experiments to be performed through customized fan control by replacing the original fans with new ones of the same manufacturer and model, and setting the fan currents through external Agilent E3644A power supplies.

We map the input current values to fan speeds, which are inferred with very high accuracy by taking the FFT of vibration sensors. Using this setup, we are able to accurately measure and isolate the cooling power of the server. In our work, we use a minimum fan speed of 1800RPM, and a maximum of 4200RPM. 1800RPM is sufficiently low to observe how leakage becomes dominant over fan power in our system. This will be shown later on Section 3.3. Moreover, fan speeds lower than 1800RPM lead to unstable fan behavior. On the other hand, 4200RPM overcools the server under our experimental conditions, and is above the maximum server default fan speed.

The fan speed can be remotely adjusted by software scripts in the Data Logging and Control PC (DLC-PC), which also collects server sensor data through the Continuous System Telemetry Harness (CSTH) [69]. CSTH runs in the service processor of the enterprise server as a part of the existing system software stack; therefore, no overhead is introduced by the sensor data processing. For our experiments, we collect the following sensor data: (i) CPU and memory temperature, (ii) per-CPU voltage and current, (iii) total server power. We poll the sensors every second to observe the power and thermal behavior with sufficient granularity.

We use Solaris 10 OS tools (*sar*, *cpustat*, *busstat* and *iostat*) to poll the hardware counters for workload characterization. Hardware counters are a set of special-purpose registers built into modern CPUs to store the counts of hardware-related events. Because they are integrated into the architecture, polling these counters has a negligible overhead in the performance of the workload being profiled. Modern servers come with a high number of performance counters that can be polled.

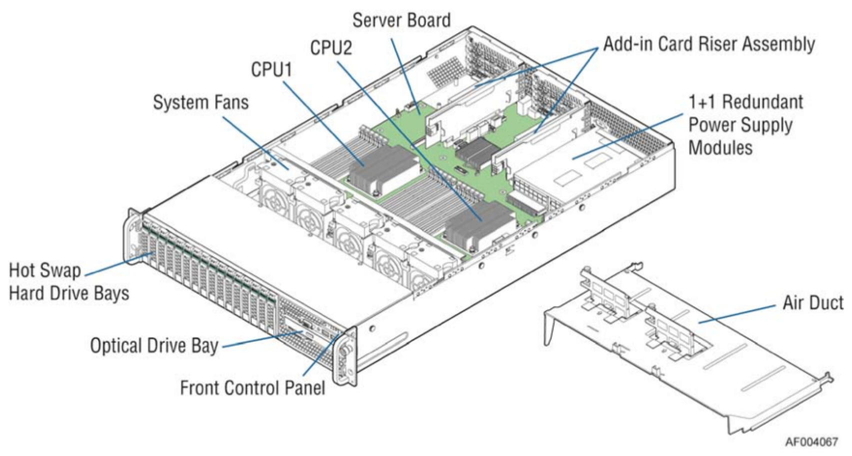


Figure 2.2: Decathlete server internal diagram. Taken from [79]

Intel SandyBridge-EP OCP Server

We use an Intel SandyBridge-EP server belonging to the Open Compute Project (OCP) [2] to validate our methodology in a different server and provide heterogeneous architectures for optimization purposes.

The idea behind choosing an OCP server is to exploit the benefits of flexibility and scalability brought by open-hardware designs, allowing us to extend our customized monitoring, modeling and optimization setup easily to other platforms. The creation of the OCP initiative, led by Facebook Inc., brought a new dimension to data center management. The aim of this project is to bring together a community of engineers from around the globe whose mission is to develop the most efficient data center hardware.

The server chosen is an Intel S2600GZ, whose design is based on an Intel OCP v2.0 Decathlete board. The board has two sockets, each can be equipped with a 6-core Intel SandyBridge-EP processor providing up to 12 hardware threads. The server is equipped with 8 4GB memory DIMMs, 4 1TB hard drives, 2 PSUs and 5 fans. Figure 2.2 shows a diagram of the server internals.

The server runs a CentOS 6.5 Linux operating system. We use IPMI to poll the available server sensors: i) CPU temperature, ii) fan speed and iii) overall server power consumption. Fan speed in this server can be controlled by setting different PWM values to the fan controllers via the BIOS [79]. We use the *oprofile* tool to poll the server hardware counters during runtime [3].

However, the original server monitoring via IPMI did not provide values for neither the CPU power nor the fan power. In order to apply our modeling methodology we need to split and quantify both fan power and CPU power. To this end, we deploy intrusive current measurement sensors in the critical board components: i) fans, ii) memory DIMMs and iii) hard disk drives. This way we are able to split the contribution from cooling power, memory and disk from that of CPU power.

To measure power consumption, we use the commercial chip from Texas Instruments INA219. This chip uses an integrated power measurement circuit that measures the voltage drop in a *shunt* resistor placed in series with the power supply of the device to be measured. This setup allows us to measure the power drawn by a memory DIMM, a fan, and the disks. To obtain the highest accuracy possible we need to select the highest resistance that ensures a voltage drop in the resistance that is low enought to keep the devices working.

Because fans and disks are powered directly via the PSU of the system, we can insert our sensor in between the power supply wires. However, because the memory DIMMs are powered via the motherboard, we need to insert a memory expander that incorporates the shunt

[2]http://www.opencompute.org
[3]http://oprofile.sourceforge.net/news/

resistors to enable power measurement.

The INA219 current measurement chip has an I2C interface that we connect to a wireless sensor node that retrieves all the information from the chip and sends it wirelessly to a gateway node [124]. The wireless node can be placed either inside or top of the server, allowing us to place the server inside a rack.

For more information on the monitoring setup the reader is referred to [143].

2.3.3 Experimental exploration

Leakage-temperature tradeoffs can have a high impact on the energy efficiency of enterprise servers. To evaluate them, we first perform a series of experiments using the SPARC server.

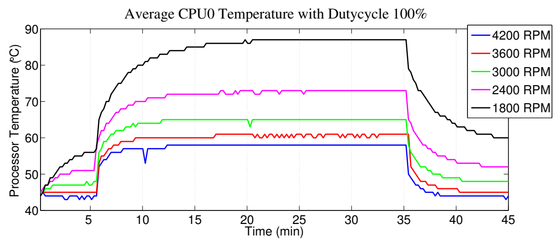
All experiments take place under the same conditions as follows: (i) the server is in an isolated environment at an ambient temperature of 24°C ; (ii) the machine always starts execution from a cold state that has been previously forced by at least 10 minutes of idle execution with fans rotating at 3600RPM; (iii) at the beginning of the execution (i.e., t = 0), fan speed is set to the appropriate value, and the machine is idle for another 5 minutes to allow temperature stabilization; (iv) the last 10 minutes of the experiments are always conducted with the CPUs idle, to let temperature drop to a steady state. These conditions are selected so that experiments reflect realistic working conditions and isolate the thermal-energy issues that we want to study. We first perform experiments to gather data at varying utilization levels and fan speeds.

To explore the system dynamics, we run *LoadGen* for 30 minutes at various utilization levels (10%, 25%, 40%, 50%, 60%, 75%, 90% and 100%) with different fan speeds (1800RPM, 2400RPM, 3000RPM, 3600RPM and 4200RPM) at the highest CPU frequency. In this case, we set the same fan speed for all three pairs of fans. Figure 2.3(a) shows CPU0 temperature under 100% utilization and all the fan speeds. These experiments show interesting results for both the transient and the steady state. We observe significantly different time constants depending on the fan speed. For 1800RPM the steady state is reached after 15 minutes of execution, whereas for the 4200RPM case, steady state is achieved after only 5 minutes. The magnitude of the thermal time constant is important for designing control mechanisms. The lower the fan speed, the slower the temperature reaction, which leaves more time for control decisions. In addition, the considerable change in thermal time constants indicate that thermal models/predictors based on chip thermal modeling would need to take fan speeds into account to ensure accuracy in real-life settings. Again, this effect can be observed in Figure 2.3(a), where we see how temperature for a fan speed of 4200RPM stabilizes around 57°C in less than 5 minutes, whereas it takes almost 15 minutes for temperature under 1800RPM to stabilize around 87°C.

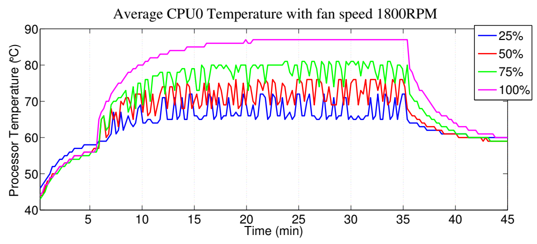
Figure 2.3(b) shows the temperature at different workload utilization levels using a fan speed of 1800RPM. Thermal oscillations occur as *LoadGen* uses PWM to achieve a desired level of utilization. This plot shows the two transient temperature trends: a fast trend that raises the CPU temperature by 5°C to 8° in less than 30 seconds due to workload changes (from idle to high utilization), and the slow temperature increase taking up to 15 minutes due to the time constants.

The variation in CPU temperature attained by the same workload running under different fan speed values lead to differences in terms of the overall power consumption due to leakage. This effect can be observed in Figure 2.4, where we show how the sum of fan power and leakage power describe a convex-like curve that reaches a minimum around 70°C, which corresponds to a fan speed of 2400RPM, when we set *LoadGen* to 100% utilization. A similar trend is observed for other utilization level, but the fan speed that yields the minimum power varies.

To motivate our work, it is interesting to discuss here the potential benefits of a predictive fan speed controller for this kind of application. At first sight, savings can be achieved by appropriately setting server cooling during runtime. It would seem convenient to propose a predictive controller that predicts power consumption under a certain workload, and follows the trend of temperature to predict future temperature and leakage values and set fan speed accordingly. However, the results previously shown in Figure 2.3(a) indicate that a prediction



(a) Temperature for 100% utilization for varying fan speeds



(b) Temperature for varying utilization levels at 1800RPM

Figure 2.3: Processor temperature with different fan speed and utilization

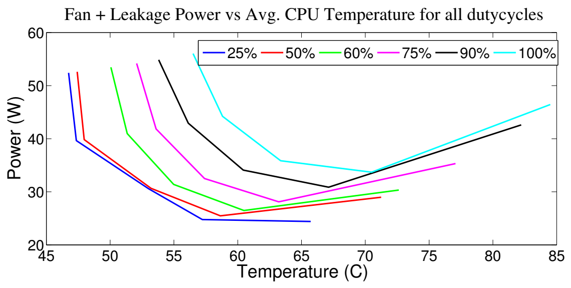


Figure 2.4: Fan and leakage power for *LoadGen* running at 100% utilization

based on current temperature would not be sufficient. The fan speed completely changes the dynamics of the system, achieving a certain temperature with different time constants. In order to develop a proactive model, a prediction based on both temperature and fan speed is needed.

2.4 Server Power Modeling

This section presents the server power modeling methodology needed and the experimental framework used to enable proactive cooling management. First, we model the temperature-dependent power consumption in the server. This way, we separate static CPU power from dynamic power. Changing the workload allocation to the processor cores has an impact on both temperature and energy, affecting the power consumption of both CPU and memory. In order to reliably evaluate the impact of different allocation schemes, we also model the memory power and validate that memory power does not depend on temperature.

Finally, in the next section 2.5, we develop a CPU temperature model which enables to estimate the temperature attained by a certain workload and to proactively set the fan speed to the optimum cooling conditions.

2.4.1 Overview

The power consumption of a server can be split into three different contributors: (i) the dynamic or active power, (ii) the static power, and (iii) the cooling power due to the server fans:

$$P_{server} = P_{static} + P_{dynamic} + P_{fan} \tag{2.4}$$

Static power consumption refers to the cumulative idle server power of all the server components and the temperature-dependent leakage power, whereas dynamic power is inherent to the execution of a certain workload. In our system, CSTH provides the overall power consumption (P_{server}) using sensor measurements, whereas the cooling power (P_{fan}) is isolated and can be measured independently.

We further divide P_{static} into two components as $P_{static} = P_{idle} + P_{leakT}$, where P_{idle} represents the idle power of all components when leakage is minimum, i.e., at the maximum server fan speed (4200RPM in our experimental setup), and P_{leakT} is the temperature-dependent leakage power due to the increase in temperature during workload execution.

Similarly, we divide the workload-induced dynamic power into its sub-components as follows:

$$P_{dynamic} = P_{CPU,dyn} + P_{mem,dyn} + P_{other,dyn} \tag{2.5}$$

where $P_{CPU,dyn}$ is the dynamic CPU power, $P_{mem,dyn}$ is the dynamic memory power, and P_{other} is the contribution of other components. This last component is mainly composed of disk and network activity. Although its absolute value can be significant in some workloads, P_{other} has negligible dependence on workload allocation and temperature for the workloads we run.

To find the optimum cooling conditions at runtime, we need to model the temperature-dependent leakage power P_{leakT}. Additionally, to analyze the impact of workload allocation, we need to derive a model for memory power. In the next subsections, we provide a detailed explanation on these models.

2.4.2 CPU power

As the temperature-dependent leakage is mainly due to CPU leakage, we develop an empirical CPU power model, and validate our assumption by observing that overall server leakage can be expressed by the CPU leakage with sufficient accuracy.

Equation 2.6 shows how CPU power can be further divided into $P_{CPU,idle}$, which contains a temperature-independent leakage plus the power consumption due to the OS running, a temperature-dependent leakage component ($P_{CPU,leakT}$), and the dynamic power due to workload execution ($P_{CPU,dyn}$):

$$P_{CPU} = P_{CPU,idle} + P_{CPU,leakT} + P_{CPU,dyn} \tag{2.6}$$

As CSTH provides P_{CPU} and $P_{CPU,idle}$ using voltage/current sensor readings, we only need to model $P_{CPU,leakT}$ and $P_{CPU,dyn}$. We start by modeling the temperature-dependent leakage power, $P_{CPU,leakT}$.

2.4.3 Temperature-dependent CPU leakage

To train this model, we use *LoadGen* synthetic workload with full utilization. We run the same workload under different fan speeds ranging from 1800RPM to 4200RPM, and measure CPU power and temperature from the two CPUs of the system. Because the workload is constant in all experiments and the only control knob is fan speed, power consumption can only change due to the temperature-dependent leakage. As leakage power depends exponentially on temperature, we use the measured CPU temperature and power to regress the Taylor series expansion of an exponential:

$$P_{leak} = \alpha_0 + \alpha_1 \cdot T_{CPU} + \alpha_2 \cdot T_{CPU}^2 \tag{2.7}$$

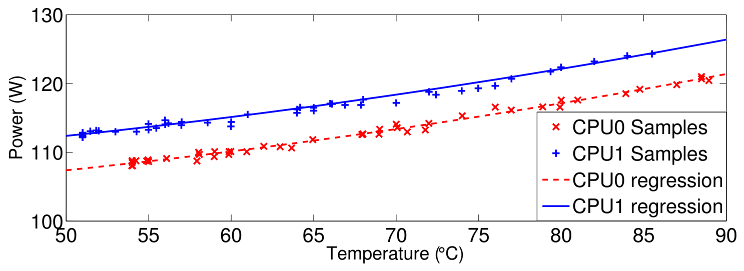


Figure 2.5: Temperature-dependent CPU leakage model regression for both CPUs in the system.

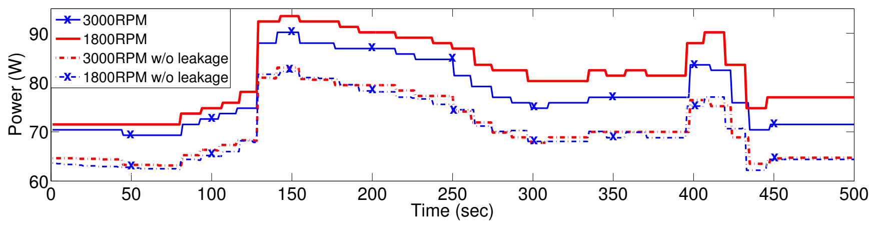


Figure 2.6: Temperature-dependent CPU leakage model validation for 128 copies of mcf running on CPU0.

where α_i's are regression coefficients, and T_{CPU} is the CPU temperature in Celsius. We derive the above model for each of the two CPUs in our system. We see that for both models, the constants α_1, α_2 are the same, but α_0 differs by an offset value of ˜5W, which is potentially caused by the temperature difference due to the asymmetric location of the CPU sockets in the server.

Figure 2.5 shows the data regression against the measured samples of the training set. The model exhibits a Root-Mean-Square Error (RMSE) of 0.39W and 0.45W for CPU0 and CPU1, respectively, for the training set.

To validate our model, we run our test workloads under different fan speeds, and subtract $P_{CPU,leakT}$ from the power traces. Because the executions of a given workload only differ in fan speed, the remaining power ($P_{CPU,idle} + P_{CPU,dyn}$) should be the same. Figure 2.6 shows two example traces of our validation using two different fan speeds. The difference between the curves once leakage has been subtracted is called the residual function, and it is a direct analytical estimate of the error of our model. We apply the aforementioned methodology to all the SPEC CPU and PARSEC workloads in our test set (*mcf, sjeng, libquantum, cactusADM, zeusmp, lbm, calculix* from SPEC CPU 2006, and *fluidanimate, canneal, bodytrack, streamcluster, ferret, facesim* from PARSEC) when running with 64, 128 and 192 threads, (i.e., 25%, 50% and 75% utilization), and compute the difference between the resultant curves. The average error in the test set is only 0.67W, which shows very high accuracy.

Finally, we apply the same methodology using the server power instead of CPU power. All the test workloads result in RMSE below 10W, which is also the error margin of the sensor measuring P_{server}. Hence, we conclude that the temperature-dependent leakage power is mostly explained by the CPU leakage, agreeing with prior work [129].

2.4.4 Dynamic CPU power

Finally, to model the dynamic CPU power, prior work suggests using utilization [134] or number of retired instructions per cycle (IPC) [15]. However, Figure 2.7 clearly shows that the utilization is not a reliable metric for modeling power in our hyper-threaded multi-core processor, as the same utilization value can correspond to important differences in dynamic CPU power. Similarly, as can be observed in Figure 2.8, IPC is also an inaccurate power metric as

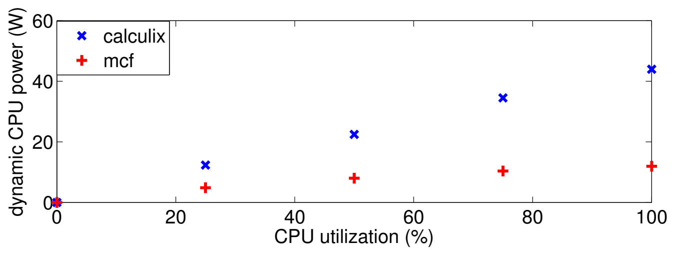


Figure 2.7: Dynamic CPU power vs. utilization for selected SPEC CPU workloads.

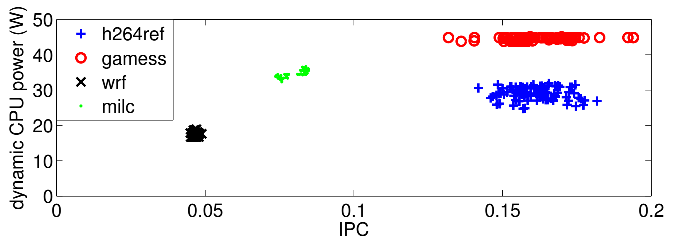


Figure 2.8: Dynamic CPU power vs. IPC for 128 concurrent copies of selected SPEC CPU workloads.

the same IPC value can correspond to different dynamic CPU power levels. Because of these outcomes, our dynamic power prediction is based on our leakage model. We directly subtract the estimated leakage power and idle power from the measured CPU power to obtain the dynamic power using Equation 2.6.

2.4.5 Memory power

This section presents our memory power model, which is used both to confirm that the memory power does not depend on temperature and to explain the impact of workload allocation on server power.

We use a modified version of the synthetic benchmark *RandMem* to train our memory model. *RandMem* stresses the memory with desired number of read-write accesses. We generate random read-write accesses using a memory space from 512Mb to 64GB and gather power consumption via CSTH and information on the number of per-bank read-write accesses per second to the bus via the Solaris *busstat* tool. In particular we collect the following performance counters: i) per-bank read-write accesses per second and ii) per bank bank-busy stalls. We sum read-write per-bank accesses to obtain overall memory accesses, and use them to derive memory power.

In our system, we have two available power measurements: CPU voltage/current sensors that allow measuring P_{CPU}, and power sensors that measure P_{server}. As the benchmark *RandMem* has negligible disk and network number of accesses, we directly use the power difference $P_{server} - P_{CPU}$ to train the model.

To check that our claim is correct and disk power is not having an impact in our modeling methodology, we monitor the amount of disk accesses that take place during the execution of *RandMem* stressing 64GB of memory with the *iostat* tool. We compare the results to the disk accesses when the system is idle and find the disk activity of *RandMem* to be negligible.

Figure 2.9 shows how memory power grows linearly with the number of memory accesses per second. We experiment with three different fan speeds to test whether the memory power depends on temperature. As seen in the figure, samples representing different fan speeds are distributed along the plot, indicating that there is no significant dependence between memory power and temperature. Hence, we conclude that the temperature-dependent leakage power is mostly explained by the CPU leakage, agreeing with prior work [129]. Based on this obser-

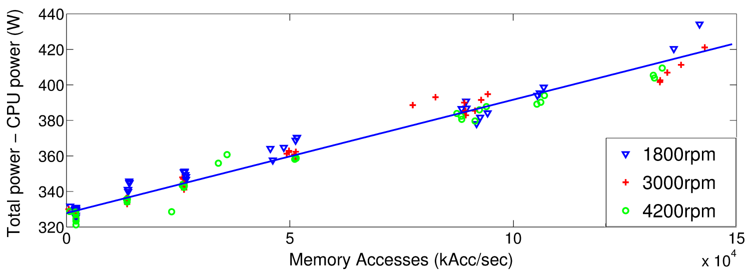


Figure 2.9: Server power vs. number of memory accesses for RandMem workload under different fan speeds

vation, we use Equation (2.8) to model memory power consumption:

$$P_{mem,dyn} = \beta_0 + \beta_1 \cdot RW_{acc/sec} \tag{2.8}$$

where $RW_{acc/sec}$ represents the amount of accesses per second and β_0, β_1 are the regression coefficients.

We use both memory- and CPU-bounded SPEC CPU workloads, SPEC Power and *streamcluster* from PARSEC to test our model, using two of the lowest fan speeds (i.e. 1800RPM and 2400RPM). As these benchmarks do not stress the memory alone, the residual function, i.e. the difference between model prediction and measured power, also reflects the power contribution of the other components of the server ($P_{other,dyn}$) besides the model error. All the test workloads result in RMSE below 10W, which is the error margin of the server power sensor. Therefore, our results have acceptable accuracy. The small error also shows that the remaining power sources $P_{other,dyn}$ have negligible contribution on the server power for the workloads we use.

2.5 CPU temperature estimation

Using the previous models, we can obtain the server leakage power at a given temperature with sufficient accuracy. To adjust fan speed at runtime and minimize the energy consumption, we also need to predict the future temperature to compensate for the thermal delays associated with the processor. For this purpose, we propose a model which first predicts the steady-state temperature based on power measurements and fan speed, and then estimates the transient behavior.

2.5.1 Steady-state estimation

The steady-state temperature of a processor running a constant workload is strongly correlated with dynamic power; i.e. each dynamic power level has a corresponding steady-state CPU temperature.Hence, we need an estimation of the dynamic power to predict the processor temperature. To this end, we use our dynamic CPU power model derived in Section 2.4.2.

In our experiments, we observe a linear relationship between the steady-state maximum chip temperature and the dynamic power consumption for each fan speed as demonstrated in Figure 2.10. To train our model, we launch *LoadGen* with different duty cycles to vary the average dynamic power, and record the steady-state temperature. We repeat the procedure for each available fan speed and derive models in the following form:

$$T_{CPU,ss} = k_0 + k_1 \cdot P_{CPU,dyn} \tag{2.9}$$

where $T_{CPU,ss}$ is the steady-state CPU temperature, and k_0, k_1 are the model coefficients. We also observe an offset difference between the models of the two CPUs, potentially caused by

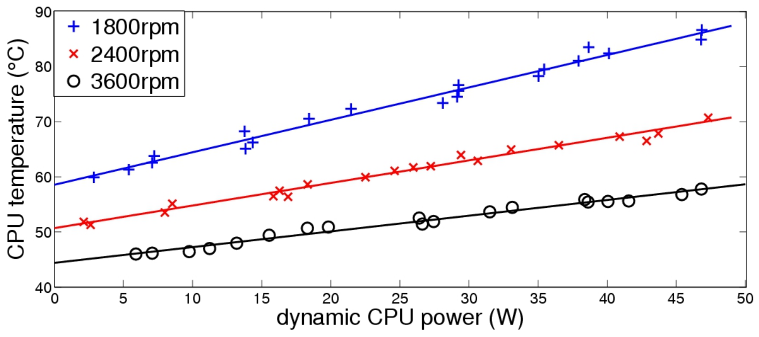


Figure 2.10: Steady-state temperature model and measured samples for three different fan speeds.

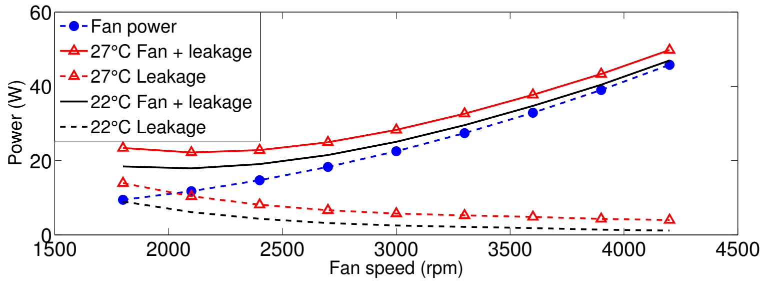


Figure 2.11: Effect of ambient temperature on the *leakage power plus fan power* curve of mcf.

the asymmetric location of the CPU sockets. We put the model coefficients for all the available fan speeds and CPUs in a Look-Up Table (LUT).

We derive our model using an ambient temperature of 22°C. However, as shown in Figure 2.11, ambient temperature affects the optimum fan speed, and including it in the model is necessary for robustness. To consider different ambient temperatures, we use the known linear relationship between the local ambient and the chip temperature [130]. We experimentally observe that if we add the difference in ambient temperature to our temperature estimation as an offset, the RMSE and maximum error do not increase. This approach ensures the robustness of the model while keeping its simplicity.

We validate our model by running a set of SPEC CPU2006 workloads at two different ambient temperatures, 22°C and 27°C, where we obtain a maximum error of 6.6°C and RMSE below 2.1°C. This accuracy is sufficient for our purposes.

2.5.2 Transient state modeling

In our work, we are interested in the thermal behavior that is affected by the fan speed, where the temperature changes slowly due to the large thermal time constants introduced by the die, the heat spreader and the heat sink.

When processor power varies, temperature changes exponentially with a time constant. We compute the thermal time constant of each fan speed by fitting exponential curves to the temperature measurements obtained while running *LoadGen* after the idle steady-state. As seen in Figure 2.12, the time constants, maximum observable temperatures and temperature range decrease as the fan speed increases. As the small changes in temperature do not affect the leakage power significantly, we only need to detect the large changes with time constants in the order of minutes. With such long time constants, we predict the temperature only during the next minute. A more fine-grained temperature prediction will lead to better approximations to the optimal fan speed by capturing small changes in the temperature; however, it will

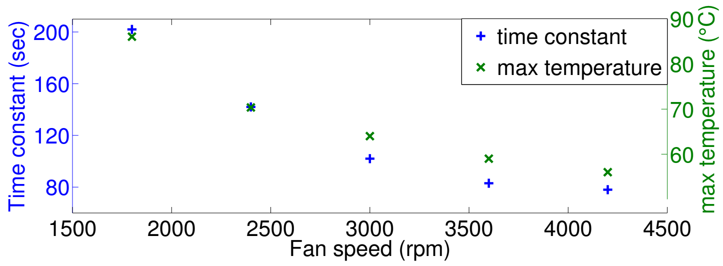


Figure 2.12: Thermal time constant and maximum observed temperature under various fan speeds

also induce unnecessary changes in fan speed and decrease the lifetime of the fans. The duration of the temperature prediction should be selected considering this trade-off. We select this duration heuristically both to capture the large changes in temperature and to approximate the optimal fan speed selection while avoiding.

2.6 Applying methodology to other servers

The goal of this section is to show how our modeling methodology is extended to other server setups, to enable the modeling and optimization of heterogeneous data center setups. The procedure to extend the methodology to other servers is equivalent.

2.6.1 Extension to Intel OCP server

As a case study, we use the Intel Sandybridge-EP OCP server previously presented in Section 2.3. In a similar way than for the SPARC server, in the Intel SandyBridge-EP server, we have isolated the different contributors to power consumption.

We model the system following the same procedure than for the SPARC server, and assuming again that Equations 2.4 and 2.5 stand true:

1. *Leakage power modeling:* We use the synthetic benchmark Lookbusy [4], to stress the CPU to its highest utilization possible, and change the default server fan speed in the BIOS, generating various temperatures in the CPU and, thus, different leakage values. We derive the leakage model by fitting the Taylor series expansion of an exponential (see Equation 2.7). Once we derive leakage power, we are able to subtract it from CPU power and obtain dynamic CPU power.

2. *Memory power modeling:* We use our modified version of Randmem to stress the memory with different utilization patterns, and collect power and performance counter values to generate the memory power model (Equation 2.8).

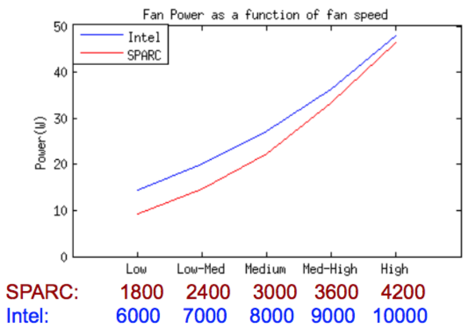
3. *CPU temperature modeling:* We use dynamic CPU power measurements and CPU temperature measurements to derive several linear curves that describe the CPU temperature under different fan speed values (Equation 2.9).

2.6.2 Power consumption comparison

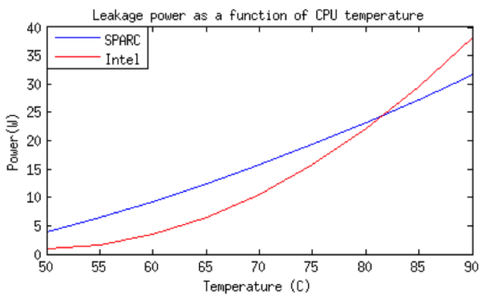
Once we have developed the aforementioned models, we can perform some comparisons between both architectures. This comparison is needed to provide an insight on the performance in terms of energy when executing various workloads.

Figure 2.13(a) shows a comparison between the fan power drawn by the SPARC and the Decathlete server. Because fan speed is highly dependant on the physical fan parameters

[4]http://www.devin.com/lookbusy/

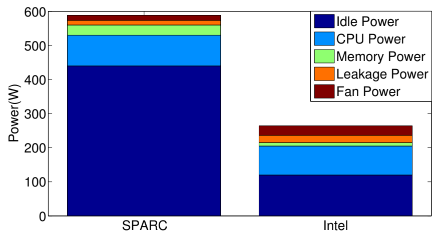


(a) Servers fan power for various fan speeds

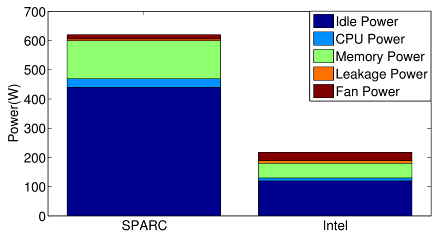


(b) CPU leakage power for various temperatures

Figure 2.13: Leakage and fan speed power comparison between Intel and SPARC architectures.



(a) Server power for CPU-intensive workload



(b) Server power for memory-intensive workload

Figure 2.14: Power consumption breakdown for SPARC and Intel server under various workloads and Low-Med fanspeed.

(i.e. fan size and number of fans) in the x-axis we compare fan speeds that result in similar server airflow. In this sense, 2400rpm in the SPARC server is equivalent in terms of airflow to 7000rpm in the Decathlete server. As can be seen, in both cases the trend is similar.

Figure 2.13(b) compares the leakage power consumption in the CPUs of both servers as temperature increases. As can be seen, the Decathlete server exhibits similar leakage values than the SPARC. However, because overall power consumption of the SPARC server is much higher than the Intel server (i.e. 750W maximum power vs 250W), the impact of leakage is much higher in the Intel server.

For instance, in Figures 2.14(a) and 2.14(b) we can observe the overall power consumption for a CPU-intensive and a memory-intensive workload respectively in the SPARC and Intel servers. The Intel server is more energy-proportional than the SPARC server. The CPU power consumption in both servers is similar, however, the SPARC is shipped with 16-core CPUs (up to 128 hardware threads per CPU) whereas the Intel has 6-core CPUs (up to 12 threads per CPU).

As for the memory subsystem, the DIMMs consume a similar amount of power, i.e. the SPARC server has twice as many DIMMs as the Intel and, thus, consumes twice as much.

2.7 Models Summary

Here we summarize the work presented in the previous section and provide some hints on how these models are used in the next chapter to enable server optimization.

- We have been able to isolate the static and dynamic power of enterprise servers, providing a methodology to split the contributors to power in enterprise servers, and a model for leakage power.

- We have modeled the contributors to power consumption that are affected by leakage power and workload allocation, i.e. CPU and memory power.
- We have estimated the steady-state and the transient CPU temperature.
- We have shown how our methodology can be extended to other servers, to enable optimization in heterogeneous data center setups.

Given a certain workload, the models allow us (i) to separate the contribution of dynamic power from that of leakage, (ii) to predict CPU temperature and thus leakage power for each available cooling setup (i.e. fan speed) in the serve and (iii) to select the fan speed that minimizes the *leakage plus fan* power. Moreover, the models enables us to evaluate the impact of workload allocation in the next Chapter 3.

2.8 Conclusions

The computational and cooling power demands of enterprise servers are increasing at an unsustainable rate. Higher chip power densities brought by new process technologies cause temperatures to rise, which in turn, increases leakage power. Moreover, as data center cooling becomes more efficient, the contribution of leakage and server fans become more significant.

Understanding the relationship between computational power, temperature, leakage, and cooling power is crucial to enable energy-efficient operation at the server and data center levels. This chapter has focused on the development of empirical models to estimate the contributions of static and dynamic power consumption in enterprise servers for a wide range of workloads, and analyzes the interactions between temperature, leakage, and cooling power for various workload allocation policies. Moreover, we have shown how our proposed methodology can be extended to other enteprise servers, which is particularly useful to minimize energy in heterogeneous data centers.

Our models allow us to split and separately quantify the different contributors to power, advancing the state-of-the-art by developing highly-accurate leakage and cooling-aware models for arbitrary workload. Our solution enables the usage of proactive optimization strategies both at server and at data center levels.

In the next chapter...

the reader will find how the described server modeling is used to optimize energy at the server level via power- and thermal-aware proactive cooling and workload management strategies.

3. Leakage and temperature aware workload and cooling management at the server level

C'était l'automne, un automne où il faisait beau.
Une saison qui n'existe que dans le Nord de l'Amérique.
Là-bas on l'appelle l'été indien.

— Joe Dassin, *L'été indien*

Backed up by the models developed in the previous chapter, here we propose leakage-, power- and temperature-aware cooling management techniques that minimize server energy consumption by setting the optimum fan speed during runtime, in a way that is robust to workload allocation.

In particular, this chapter analyzes previous cooling management strategies in the state-of-the-art, and proposes two policies: i) a first version based on a Look-Up-Table (LUT) approach that is unaware of the workload dynamics, which we use to motivate the need of server modeling and workload-awareness; and ii) an improved version that works for arbitrary workloads and allocation schemes.

Our experimental results on a presently shipping enterprise server demonstrate that including leakage awareness in workload and cooling management provides additional energy savings without any impact on performance.

3.1 Introduction

Reducing the energy consumption for computation and cooling in servers is a major challenge considering the data center energy costs today. Server power consumption depends on the characteristics of the running workload and the allocation policy [44]. And, as shown in the previous chapter, the impact of leakage and fan power is not negligible, specially in data centers where cooling power is optimized. Nowadays, apart from dynamic server power, both static and fan power need to be taken into account when designing energy optimization strategies at the server level.

However, state-of-the-art techniques are either focused at the CPU level, or, if scaled to the server level, they tackle fan control, leakage power reduction, and temperature-aware workload allocation problems separately [71]. Yet, server temperature and energy depend on decisions in all these domains. In order to obtain the highest possible energy savings in the overall server power consumption, the dependencies between these domains need to be considered, motivating the design of a comprehensive multivariate control strategy.

This chapter proposes a strategy to reduce server energy consumption, in a way that is aware of the interactions among power, temperature, leakage, and workload dynamics. Our specific contributions are as follows:

- Based on our previous modeling, we develop a control strategy that proactively sets the optimum cooling on runtime for arbitrary workloads.
- We study the relationship among power, temperature, application characteristics and workload allocation when designing cooling strategies, and show the importance of

modeling to tackle arbitrary workloads.

- We test our policy on a commercial server, obtaining reductions on *leakage plus fan* energy of up to 6% compared to existing policies, and more than 9% compared to the default server control policy, without imposing any performance penalty.
- We analyze the impact of workload allocation, showing how choosing the best-EDP allocation for a given load along with our proactive policy yields savings up to 15%.
- We apply our policy to a broader data center scenario, and demonstrate that by applying our policies we can reduce the CPU power consumption of the whole cluster by 2.5% compared to other techniques. Moreover, we show how the impact of our policy increases as data room temperature raises.

The rest of the chapter is organized as follows. Section 3.2 describes the related work in the area. Section 3.3 shows the experimental framework used to develop and validate our strategies. Section 3.4 describes the proposed policies, whereas Section 3.5 shows the tradeoffs in terms of allocation. Section 3.6 and 3.7 present the results and discussion respectively, whereas Section 3.8 concludes the chapter.

3.2 Related Work

This section describes the related work in the area of cooling management techniques to increase the energy efficiency of servers, focusing on fan control strategies and workload allocation policies.

3.2.1 Fan control

In the area of server energy efficiency, several works tackle fan control to reduce cooling costs. Xuefei et al. [71] propose a runtime fan controller based on offline thermal modeling validated via simulation. Wang et.al [164] propose an optimal fan speed control for thermal management of servers and tackle the problem of over-cooling. However, they disregard the leakage contributions and its effects on power consumption. Shin et al. [145] use Dynamic Voltage-Frequency Scaling (DVFS) together with fan control to minimize cooling and CPU power in a desktop computer by using RC-based thermal models. Chan et al. [38] approach the fan control problem both from the energy minimization and fan-induced vibration perspective. Their solution jointly minimizes the disk access errors caused by vibrations and the cooling power consumption. Even though our work could be combined with DVFS, our goal is to minimize overall server energy without relying on this technique as it introduces penalties in execution time, potentially increasing energy consumption. Moreover, the research described in this chapter minimizes leakage and cooling power by proactively setting the optimum fan speed before a thermal event occurs, and is validated on a presently-shipping enterprise server.

Other approaches that take into account the leakage-cooling tradeoffs do not include a setup that enables fan speed control. These approaches control the fan speed indirectly by setting a critical threshold to CPU temperature. Because leakage plus cooling power describe a convex curve, policies such as TAPO-server, proposed by Huang et al. [77], indirectly vary fan speed by controlling the processor thermal threshold at runtime to reactively find the optimum fan speed. TAPO is effective only with constant workloads as it waits for the thermal steady-state to control the fan speed. Similarly, recent work by Pradelle et.al. [134] uses a hill-climbing optimization technique that optimizes the leakage-cooling tradeoffs. This technique relies on utilization as a proxy variable for the estimation of heat dissipation which, as we show in this work, is not sufficient to select the optimum cooling for an arbitrary workload. In this work, we have direct control over the cooling subsystem of the server. Moreover, to enable proactiveness, we develop power and thermal models of the server to predict the leakage and cooling power for arbitrary workloads.

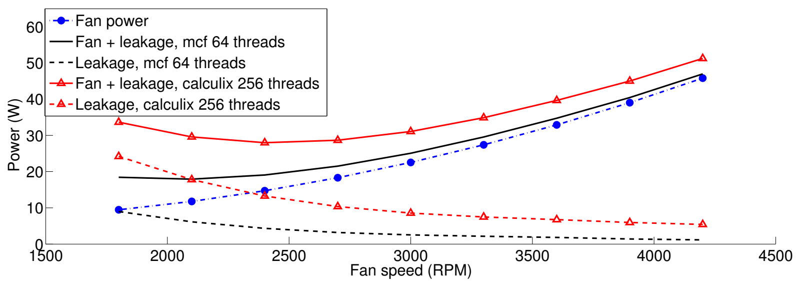


Figure 3.1: Fan and leakage power for various workloads.

3.2.2 Workload allocation

There are some recent techniques that consider fan control together with scheduling for multi-objective optimization [16], [38]. These approaches make use of a joint energy, thermal and cooling management technique to reduce the server cooling and memory energy costs. They propose a thermal model that uses electrical analogies to represent the thermal coupling between the server components and the effect of fan speed on heat dissipation. Our work, on the contrary, is able to split and separately quantify the contributions of cooling power from those of leakage and total system power.

To the best of our knowledge, our approach is the first to present a leakage-aware multivariate cooling management strategy that is robust to arbitrary workloads and allocation policies running on a presently-shipping enterprise server.

3.3 Experimental methodology

In this section we describe the motivation and experimental methodology followed to develop the proactive fan control policies. The goal of this work is to reduce the energy consumption in enterprise servers found in energy-hungry data centers.

The main purposes of the server fans are to remove the heat produced and to prevent the overheating of the hottest components such as CPUs and memories. The fan speed should be carefully selected to avoid overcooling, which implies high cooling costs, and also overheating, which results in shorter component lifetimes and higher leakage power. To clarify this point, Figure 3.1 shows the cubic increase in fan power with fan speed as well as the exponential increase in leakage power when fan speed decreases for two particular workloads running on the SPARC server described in Section 2.3: (i) a memory intensive workload utilizing 25% of the server (64 copies of *mcf*) and (ii) a CPU intensive workload fully utilizing the server (256 copies of *calculix*). We observe that different RPM settings minimize the total fan plus leakage power for the two workload scenarios.

We propose a proactive fan speed policy that sets the optimum cooling in a way that is aware of the leakage-cooling tradeoffs at the server, and yet robust to different workload allocation policies. To build this proactive policy, we use the models developed in the previous chapter, using as experimental setup the SPARC server described.

3.4 Cooling management policies

In this Section we describe the two proposed cooling management policies: i) a first approach based on Look-Up-Table (LUT) fan control policy, and ii) a proactive fan control policy that works for arbitrary workloads, and that constitutes the main contribution of this work.

As shown next, the LUT based policy is derived for a particular workload and, thus, is unaware of workload characteristics and allocation. As we show in the results Section 3.6, to leverage energy efficiency, we need a policy that works for arbitrary workloads and allocation policies. To this end, we propose the proactive fan control policy in subsection 3.4.2.

3.4.1 Look-Up-Table based policy

Theoretical background

The LUT-based policy uses the observations on leakage power shown in the previous chapter 2.4 but, instead of using the proposed models, it simply generates a LUT based on the power-utilization values provided by the workload of the training set *LoadGen*.

As *LoadGen* stresses the system at different levels of utilization (U), we can describe active power as a function of U. Leakage has an exponential dependence on temperature T as shown in Eqn.(3.1), where C is a constant. Using all the measurements of power and temperature at a set of utilization values, we apply model fitting techniques to derive the constant values k_1, k_2, k_3.

$$P_{leak} = k_1 \cdot U \quad and \quad P_{leak} = C + k_2 \cdot e^{k_3 \cdot T} \tag{3.1}$$

For the equations above, we obtain the following parameters from the fitting: $k1 = 0.4452$, $k2 = 0.3231$, $k3 = 0.04749$, with a fitting error $2.243W$ and an accuracy of 98%. This fitting gives an analytical model that is valid across all utilization values for the *LoadGen* workload.

Based on the model fitting results we generate a Lookup Table (LUT) that holds the optimum fan speed values for each utilization level. This fan control policy aims at setting the optimum fan speed at runtime based on workload utilization. The main benefit of this technique is that it is based solely on utilization, making it simple and fast due to its low overhead.

If CPU power was accurately represented by utilization for arbitrary workloads, this policy would yield the maximum energy savings. However, in the previous chapter, we showed that, in general, utilization is not a good proxy for CPU power. Thus, even though this policy works for *LoadGen*, we expect a worse performance for arbitrary workloads.

Implementation

The LUT-based policy periodically monitors server load by polling utilization through the *sar* and *mpstat* Solaris utilities. Given utilization, and based on the LUT output, we set fan speed to the appropriate value by increasing or decreasing the current of the power supplies. Utilization is polled every second to be able to respond to sudden utilization spikes. Polling the utilization does not introduce any noticeable overhead on the CPUs. The controller makes decisions based on changes in the load utilization rather than reacting to temperature changes, which allows the system to proactively set the optimum fan speed before a thermal event occurs.

In order to ensure the stability of the controller and to prevent fan reliability issues in the case of unstable workloads, we set a maximum frequency for the fan speed changes. This condition is important for the case of very fast changing or unstable workloads. We allow the controller to react fast (i.e., change fan speed as soon as a spike is detected); however, we do not allow RPM changes for 1 minute after each RPM update. This 1-minute value is a tradeoff between the maximum number of fan changes allowed during the execution of a highly variable workload and the maximum temperature overshoot we want to tolerate in our system. Note that 1-minute is a safe choice for our system considering the large thermal time constants.

3.4.2 Proactive fan control policy

This fan control policy uses temperature and power measurements to proactively determine the fan speed that minimizes the *fan plus leakage* power. This policy uses the models in Chapter 2.4 to isolate the different contributors to power and, thus, as opposed to the previous policy, does not assume any particular workload characterstics.

We first describe how our policy works when setting fan speed for workloads that have achieved a steady-state. Then, we improve our algorithm to tackle transients. Finally, we discuss the applicability and overhead of our policy.

Figure 3.2 shows the fan speed selection procedure for steady-state. As discussed in Chapter 2.4, the dynamic power of a constant workload can be estimated by subtracting temperature-dependent leakage and idle power from the CPU power. Using dynamic power, we predict the steady-state processor temperature under each available fan speed setting using our temperature model given in Section 2.5.1. Then, we calculate the expected steady-state leakage and fan power for every fan speed. Finally, we set the fan speed to the value that provides the minimum *leakage plus fan* power.

The workloads we use exhibit small fluctuations in power consumption that do not affect temperature significantly. To avoid inaccuracies caused by these fluctuations, we average dynamic power over a period significantly smaller than the thermal time constants. In our case, we choose an 8-second averaging that captures the large changes in power that govern temperature while smoothing out the power trace.

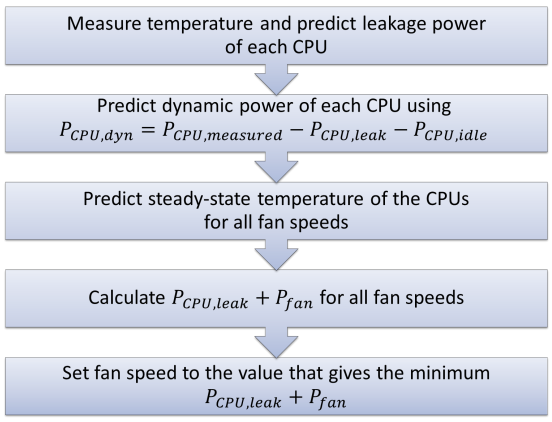

Measure temperature and predict leakage power of each CPU
Predict dynamic power of each CPU using $P_{CPU,dyn} = P_{CPU,measured} - P_{CPU,leak} - P_{CPU,idle}$
Predict steady-state temperature of the CPUs for all fan speeds
Calculate $P_{CPU,leak} + P_{fan}$ for all fan speeds
Set fan speed to the value that gives the minimum $P_{CPU,leak} + P_{fan}$

Figure 3.2: Fan speed selection procedure for steady-state.

The main shortcoming of a steady-state approach is that it ignores the thermal transients. As the thermal time constants are large, the processor temperature can differ from its steady-state value by several degrees, especially for highly variable workloads, and energy can be saved during transients. We consider the transient behavior by proposing the run-time policy given in Algorithm 1, where f represents a function and f^{-1} its inverse.

The policy first calculates the expected steady-state temperature T_{ss} for each CPU (lines 2-3). Then, it computes the average temperature T_{pred} over the next τ_{wait} period, using a closed form integration of the transient temperature prediction (line 4). As temperature changes slowly, we find a dynamic power corresponding to T_{pred} using our steady-state temperature model inversely, obtaining dynamic power (line 5).

We use dynamic power $P_{dyn,pred}$ to predict the expected temperature T_{exp} under each fan speed (line 7). Next, the expected leakage power $P_{leakT,exp}$ under various fan speeds are calculated using the leakage model. We prevent the selection of fan speeds that result in temperatures above the critical value $T_{critical}$, by setting the corresponding leakage power to a very high value.

All predictions until this point are done separately for each CPU. Finally, total server leakage plus fan power consumption $P_{leakT+fan}$ is computed for all available fan speeds. The policy selects the fan speed that provides the minimum $P_{leakT+fan}$ and waits τ_{wait} seconds while monitoring the system for a workload change. If dynamic CPU power changes significantly, this interval is interrupted and the optimum fan speed is re-calculated. For our scenario the dynamic CPU power change threshold is heuristically selected as $5W$. The waiting time ensures the stability of the controller and prevents the fan reliability issues that could arise with very frequent fan speed changes (i.e. in the order of seconds). For our system, we choose

Grammar 1 Policy

```
1:  for each CPU p do
2:      $P^p_{dyn} = P^p_{meas} - P^p_{idle} - f_{leakage\_model}(T^p_{meas})$
3:      $T^p_{ss} = f_{temperature\_model}(P^p_{dyn})$
4:      $T^p_{pred} = f_{transient\_model}(T^p_{ss}, T^p_{meas})$
5:      $P^p_{dyn,pred} = f^{-1}_{temperature\_model}(T^p_{pred})$
6:      for each fan speed s do
7:          $T^{p,s}_{exp} = f_{temperature\_model}(P^p_{dyn,pred})$
8:          if $T^{p,s}_{exp} \geq T_{critical}$ then
9:              $P^{p,s}_{leakT,exp} = \infty$
10:         else
11:             $P^{p,s}_{leakT,exp} = f_{leakage\_model}(T^{p,s}_{exp})$
12:         end if
13:     end for
14: end for
15: for each fan speed s do
16:     $P^s_{leakT+fan} = P^s_{fan} + \sum_p P^{p,s}_{leakT,exp}$
17: end for
18: Set fan speed to $\underset{s}{\operatorname{argmin}}(P^s_{leakT+fan})$
19: Wait $\tau_{wait}$ while monitoring $P_{dyn}$
```

a τ_{wait} value of 1 minute, which is a safe choice considering the large thermal time constants.

We use a 300RPM resolution for the fan speed selection in our policy, which is a heuristically selected value. This resolution is selected such that the available fan speeds lead to a sufficient approximation to the optimal cooling conditions. Selecting an unnecessarily fine resolution will increase the computational overhead of the policy.

Applicability

Our models and the fan speed algorithm are based solely on power and temperature measurements. Thus, they are agnostic to workload characteristics, and can be derived using any constant stress workload with controllable utilization. Even if sensor data rate is limited by measurement delay, the performance of our policy is not significantly affected as the thermal time constants are in the order of minutes, which is much slower than the policy response time. Even though our policy does not consider hot spots on the chip, the operating points are well below the critical thresholds.

Overhead

The fan speed control policy is run by the DLC-PC in our implementation. On the DLC-PC, the policy measures and averages power every second, and decides on the fan speed every 60 seconds using LUTs and polynomials. The leakage and temperature prediction is computed only for 9 different fan speeds that cover the entire fan speed range (from 1800 to 4200RPM) with a resolution of 300RPM. As these are very simple operations with long periods, the policy has negligible overhead and can be easily implemented in the service processor.

3.5 Impact of workload allocation

This section describes the impact of workload allocation on the leakage-cooling and energy-performance tradeoffs at the server level.

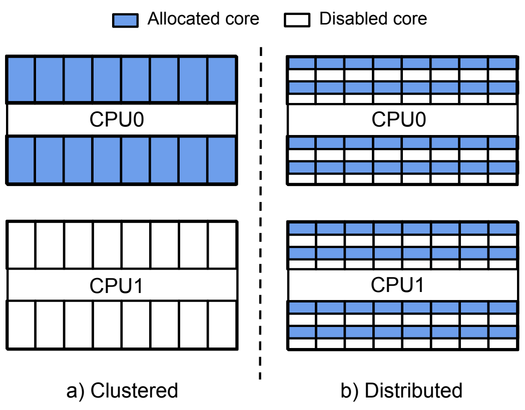


Figure 3.3: Clustered vs distributed allocation schemes for 128 active threads.

3.5.1 Allocation schemes

We experiment with two different allocation schemes: *clustered* and *distributed*. Clustered allocation packs all the threads together into the first N cores of the server, maximally utilizing all the available hardware threads in a core. Distributed allocation spreads the workload as much as possible into all available cores. Figure 3.3 shows a diagram of the clustered and distributed allocation for an application with 128 threads, i.e., 50% utilization. Each box in the figure represents a core, each with 8 hardware threads that can be individually enabled or disabled. In the case of single-threaded benchmarks, we launch multiple copies to get various utilization values.

Distributing the workload activates more cores and increases the number of available FP units and integer pipelines, as well as the amount of cache and memory bandwidth. On the other hand, clustering the workload reduces the amount of active cores in the server, decreasing the power consumption. Recent enterprise servers come with core-disabling capabilities that allow setting idle cores in deep sleep mode when all their hardware threads are disabled, saving up to 60% power [146].

3.5.2 Leakage-cooling tradeoffs

From the leakage-cooling perspective, distributed allocation reduces the CPU temperature by balancing the workload across all cores. This generates similar temperatures in both CPUs, and thus, similar leakage power. However, clustering the workload stresses CPU0 more than CPU1, and generates temperature and leakage imbalance between the CPUs. Thus, the same workload can yield different optimum fan speed values depending on the allocation scheme. Table 3.1 shows the impact of allocation for four workloads with different characteristics from our test set with 75% utilization, all running under the same fan speed. As can be seen, the temperature imbalance between the CPUs depends on the workload, and leads to different optimum fan speeds. For example, the optimum fan speed for *Bodytrack* is 1800RPM when the clustered allocation is selected, but 2400RPM if we select the distributed scheme.

As workload allocation changes the leakage and cooling tradeoffs, fan speed policies that do not take into account temperature and power imbalances cannot fully exploit the advantage of energy efficient dynamic fan control. Our proactive policy, on the contrary, is robust to workload imbalances across the CPUs as it predicts the leakage for both CPUs separately and computes the optimum fan speed. Therefore, the policy finds the optimum regardless of how the workload is allocated.

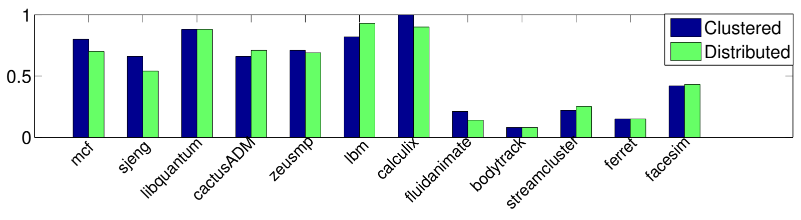
Task	Allocation	$P_{CPU,dyn}$	P_{mem}	T_{CPU0}	T_{CPU1}
		(W)	(W)	(2400rpm,$^\circ C$)	
sjeng	Distributed	55.2	32	57.4	55.4
192 threads	Clustered	47.4	31	59.4	52.9
mcf	Distributed	14.9	95	54.3	51.5
192	Clustered	14.2	98	56.5	51.4
calculix	Distributed	75.1	114	63.4	60.7
192	Clustered	65.1	99	66.4	55.6
bodytrack	Distributed	30.0	16	55.2	53.1
192	Clustered	26.3	18	54.7	50.6

Table 3.1: Summary of dynamic power and CPU temperature at 2400RPM for selected PARSEC and SPEC benchmarks running with 192 threads

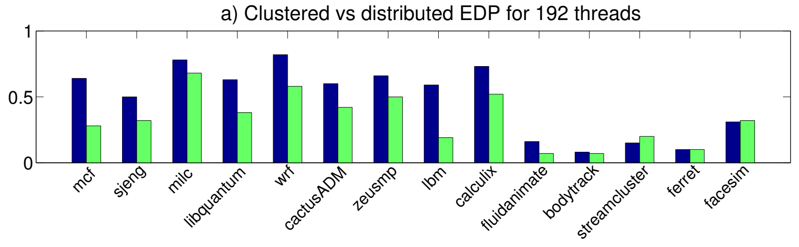
3.5.3 Energy-performance tradeoffs

Interesting tradeoffs exist in terms of performance and energy when clustering/distributing workloads. Distributed allocation leads to a flatter thermal profile and maximally utilizes pipelines, whereas clustering reduces the communication distance between threads, potentially increasing the performance of parallel applications with data sharing.

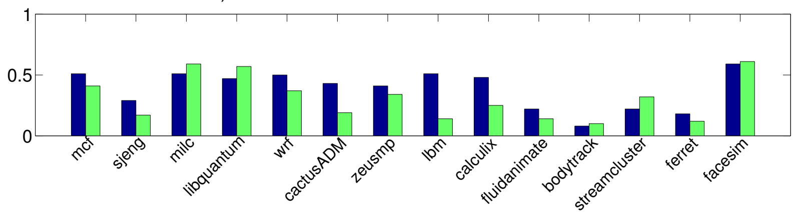
We use the Energy-Delay Product (EDP) metric, which weighs power against the square of execution time, for the joint evaluation of performance and energy. EDP is calculated considering the total CPU power (P_{CPU}) and memory power ($P_{mem,dyn}$), as those are the two main factors affected by the workload allocation. We assume that when all the hardware threads in a core are disabled, the core goes into deep sleep mode and its idle power $P_{CPU,idle}$ is reduced.



a) Clustered vs distributed EDP for 192 threads



b) Clustered vs distributed EDP for 128 threads



c) Clustered vs distributed EDP for 64 threads

Figure 3.4: Normalized EDP in clustered and distributed allocation schemes for SPEC CPU and PARSEC benchmarks under various number of threads.

Figure 3.4 presents the EDP comparison between the two allocation schemes for the benchmarks in our test set under various utilization values. The plot is normalized to the highest

Type	Workload	Perf. counters for distributed			
		IPC	Mem Acc.	FP Instr	L1 acc
High IPC	sjeng	1.0	0.01	0.0	0.3
Mem. intensive	mcf	0.1	0.9	0.0	0.8
High FP Instr.	calculix	0.7	0.1	0.6	0.7
Low L1 & L2 misses	bodytrack	0.3	0.0	0.4	0.1

Table 3.2: Summary of performance counters (normalized to the highest value across benchmarks) of selected PARSEC and SPEC benchmarks with 192 threads.

Metric	Benchmark
High IPC	sjeng, fluidanimate, calculix, ferret
High FP Instr.	lbm, zeusmp, cactusADM, calculix, wrf
Memory intensive	lbm, mcf, libquantum, milc
Low L1 & L2 misses	bodytrack, fluidanimate, canneal

Table 3.3: Summary of relevant characteristics for SPEC and PARSEC benchmarks. For each parameter, benchmarks are ordered from high-to-low.

EDP value across experiments. We see that distributing is better for most cases, as the workloads benefit from a larger number of available computational units. As expected, results for clustering and distributing converge as the number of threads increase. Note that for the cases where EDP are similar (e.g., *libquantum* with 192 threads), leakage-cooling tradeoffs should be considered when determining the most efficient allocation.

Because the results are highly dependent on the workload characteristics, we gather relevant performance counters to explain the differences in EDP between the two allocation schemes. First, we perform a correlation test over the performance counters when running the distributed allocation scheme. We obtain a cross-correlation matrix between all performance counters and EDP values, finding the following metrics to have high correlation with EDP: *active thread count, Instructions Per Cycle (IPC), L1 data cache misses, Floating Point (FP) instructions, store instructions and number of read-write memory accesses*. All metrics except *active thread count* and *IPC* are computed per instruction, and normalized to the highest observed value. Table 3.2 summarizes the most relevant features for some workloads. Table 3.3 groups together the benchmarks that exhibit similar characteristics in terms of their performance counters, and thus, exhibit similar tradeoffs in EDP.

Putting together the experimental results of Figure 3.4, Table 3.2, and Table 3.3, we see that high-IPC CPU-bounded workloads such as *sjeng*, *fluidanimate* or *calculix* always benefit more from distributing, regardless of utilization. *zeusmp* and *cactusADM* do not have the highest IPC values, but they are FP-intensive. Because each core shares one FP unit among all threads, as utilization decreases, these benchmarks benefit more from being distributed. Benchmarks such as *streamcluster* have a high amount of synchronization locks between threads, so they do not benefit from a higher number of available pipelines, and are better clustered for all utilization cases. The performance of memory-intensive applications, such as *mcf*, *lbm*, *libquantum*, *milc* depends on the tradeoff between available memory bandwidth (decreases with higher utilization) and contention (increases with higher utilization).

In a more general way, we can highlight the following results regarding task classification according to EDP:

- High-IPC and high-FP non-memory-intensive workloads achieve lower EDP when they are distributed for all utilization values. However, benefits are higher as utilization decreases.

- Low-IPC non-memory-intensive tasks (i.e., tasks with many synchronization locks) have lower EDP when they are clustered for all utilization levels.
- Memory-intensive benchmarks benefit more from distributing, especially for medium utilization values, because of the tradeoffs between available memory bandwidth and contention.

3.6 Results

In this section, we present several state-of-the-art policies and compare their performance against our proposed fan control strategies. First, we show the performance of the LUT policy when we use a synthetic workload pattern that stresses the system to different utilization values using *LoadGen*. Then, we extend our results to the usage of arbitrary workloads from SPEC CPU 2006 and PARSEC, presenting the benefits of the proactive fan control strategy based on our previous modeling.

We also show the tradeoffs in terms of energy and performance when using different allocation schemes and how our proactive fan control policy is robust to power and temperature imbalances.

3.6.1 Baseline policies

Best fixed fan speed

The default server fan policy sets a fixed fan speed that ensures the server reliability for a worst-case scenario for each ambient temperature. The default fan speed for our server is of 3000RPM, which leads to significant overcooling when the ambient temperature is low.

To ensure a fair comparison, apart from 3000RPM, we use the fan speed that minimizes *leakage plus fan* power for the majority of the workloads as a baseline to evaluate the benefits of dynamic fan speed selection. After running all workloads under all fan speeds, we find that the best fixed fan speed in our system is 2400RPM for 22°C ambient temperature. Fan speed is increased to 4200RPM if the CPU temperature reaches 87°C to ensure safe operation.

Note that this policy does not predict leakage or temperature of the server at runtime, it only uses the results of an off-line profiling to decide the best fixed fan speed. This profiling consists of running all workloads under all fan speeds, and selecting the fan speed that minimizes power for the majority of workloads at a particular ambient temperature.

TAPO

The TAPO server fan control policy introduced by Huang et al. [77] changes the thermal set point T_{sp} of the processor to indirectly control the fan speed. Assuming the workload is constant, once the thermal steady-state is reached, the policy changes T_{sp}. Then, it observes the change in the processor temperature and power processor to decide whether to increase or decrease the setpoint to achieve lower power. We implement the T_{sp} selection mechanism on our SPARC server.

TAPO assumes an underlying fan controller that keeps the maximum processor temperature at T_{sp}. In our TAPO implementation, we write a bang-bang fan speed control script that checks CPU temperature every Δt minutes and changes the fan speed if the temperature is out of the range $T_{sp} \pm \Delta T$. ΔT and Δt are heuristically chosen as 5°C and 2 minutes, respectively, to avoid fan speed oscillations. The fan speed resolution is 300RPM as in our proactive policy.

Bang-bang controller

The bang-bang controller tracks CPU temperature and tries to maintain the temperature within a desirable range by means of a multi-threshold controller. Our implementation tries to keep temperature within the 65$°C$-75$°C$, thus: (i) if maximum temperature T_{max} goes below 60$°C$, fan speed is set to 1800RPM (lowest); (ii) if T_{max} is in between 60$°C$ to 65 $°C$, fan speed is

	λ, μ	Workload sequence (benchmark and number of threads)									
		1	2	3	4	5	6	7	8	9	10
1	25 , 20	ferret 128	libquan. 192	zeusmp 128	wrf 128	calculix 128	fluid. 192	sjeng 128	cactus 128	facesim 128	zeusmp 128
2	25 , 20	zeusmp 192	milc 128	wrf 128	sjeng 128	mcf 128	cactus 128	calculix 64	lbm 128	canneal 64	zeusmp 192
3	15 , 10	sjeng 192	mcf 128	sjeng 128	sjeng 128	calculix 192	facesim 192	facesim 128	facesim 128	ferret 128	facesim 128
4	15 , 10	fluid. 192	canneal 128	stream. 64	stream. 64	canneal 128	calculix 128	canneal 64	canneal 64	lbm 192	bodytrack 192

Table 3.4: Summary of main characteristics for workload profiles. The profiles 1 and 3 have a $p(high)$ of 0.8, and the profiles 2 and 4 have a $p(high)$ of 0.2. Arrival (λ) and service (μ) times are given in minutes.

lowered by 600RPM; (iii) if T_{max} is between 65 to 75 degrees, no action is taken; (iv) if T_{max} rises above 75$°C$, fan speed is increased by 600RPM; and, (v) if T_{max} is above 80$°C$, fan speed is increased to 4200RPM.

Smaller target temperature ranges (e.g., 70$°C$-75$°C$) increase fan speed change frequency whereas larger ranges (e.g., 60$°C$-75$°C$) create higher temperature overshoots and undershoots, which lead to higher fan speeds and larger thermal cycles. The threshold values are heuristically chosen to optimize this tradeoff, ensuring the stability of the controller while keeping temperature in a range that ensures high reliability and low leakage.

3.6.2 Workloads used

Synthetic *LoadGen* tests

To test the benefits of the LUT-based controller we use *LoagGen* to generate different synthetic profiles of 80 minutes of total duration: (i) Test-1 ramps up and down from 0% to 100% utilization to test how controller reacts to gradual changes in utilization; (ii) Test-2 generates different periods (5, 10 and 15 minutes) between high and low utilization values to test controller reaction against sudden changes; (iii) Test-3 changes utilization values every 5 minutes to test reaction against sudden and frequent changes in utilization; and (iv) in Test-4 utilization value follows a statistical distribution of Poisson arrival times and exponential service times that emulates a shell workload as described in prior work [104].

Arbitrary workload profiles

We generate 4 different workload profiles that exhibit a wide range of behaviors from a statistical perspective to evaluate our policies agains existing methods. Each workload profile consists of 10 tasks of the test set used for modeling and described in Chapter 2.3 (i.e., the workloads from SPEC or PARSEC launched with certain number of copies as described in Sections 2.4 and 3.5), generated with a Poisson statistical distribution of arrival (λ) and service (μ) times. To generate profiles with variable stress in terms of power consumption, all benchmarks from SPEC and PARSEC with 25%, 50% and 75% utilization are arranged into two classes: high power consumption and low power consumption. For each profile, we vary the probability of choosing benchmarks from the high power class ($p(high)$). Within each class, benchmarks are chosen randomly.

Table 3.4 summarizes the main parameters of each profile, and describes the sequence of benchmarks.

3.6.3 Cooling management under synthetic workloads

First, we compare the performance of the default server fan speed policy (i.e. 3000 rpm) with that of the most common policy, i.e. the bang-bang controller, and our LUT-based approach, under the synthetic tests.

Test	Control scheme	Energy (kWh)	Net Savings (kWh)	Peak Pwr (W)	Max. Temp (°C)	#fan change	Avg RPM
1	Default	0.6695	–	710	61	0	3300
	Bang	0.6570	6.8%	715	75	6	2089
	LUT	0.6556	7.7%	705	73	6	2117
2	Default	0.6857	–	720	61	0	3300
	Bang	0.6856	0.05%	722	76	10	2173
	LUT	0.6685	8.7%	705	75	8	2181
3	Default	0.6284	–	720	60	0	3300
	Bang	0.6253	2.0%	722	77	14	2042
	LUT	0.6226	3.9%	710	69	12	2161
4	Default	0.6160	–	720	62	0	3300
	Bang	0.6101	4.7%	722	76	10	1936
	LUT	0.6071	6.9%	710	74	12	1968

Table 3.5: Summary of controller properties

When implementing all fan control policies we take into consideration the following constraints that ensure fan reliability: (i) the available fan speeds in the system range from a minimum of 1800 rpm to a maximum of 4200 rpm, that can be selected in steps of 300 rpm; and (ii) fan speed maximum change frequency is set to 1 minute, except when there is a rise in either CPU temperature or dynamic power consumption.

Table 3.5 summarizes the results for the three controllers for all the tests. We use the default behavior of the server as the baseline for comparison. The default server fan speed leads to very low temperatures and to overcooling of the system. Note that setting a high minimum fan speed is common in commercial servers to ensure reliable operation under a wider range of ambient and altitude settings. Both bang-bang and LUT controller provide energy savings in comparison to the original fan control scheme. However, in some cases such as Test-2, the improvement of bang-bang controller is very limited. This is because the controller reacts after a thermal event occurs, leading to high average temperatures for the case of spiky loads, increasing leakage power. LUT-based controller reacts rapidly to workload changes and keeps average temperature lower, resulting in the lowest energy across the tests.

Net energy savings are computed by subtracting the total server idle energy from the energy values (3^{rd} column) and comparing each of our controllers against the baseline. We discard the idle server power as that part of the consumption is dependent on the server hardware configuration and cannot be influenced by fan control. The LUT-based controller achieves up to 8.7% energy savings and 25W peak power reduction compared to the baseline. It also keeps temperature under 75°C using a low number of fan speed changes.

Figure 3.5 compares the runtime behavior of the three controllers for Test-3. We have chosen this test as it is the one with the highest load variability and thus, the one that might be most similar to a real-workload scenario. As expected, the default fan controller keeps temperature very low with a fan speed of 3000 rpm. The bang-bang controller addresses the over-cooling in the baseline case by letting the temperature rise but keeping it in between the 55°-75°range. The bang-bang controller is similar to existing fan controllers in commercial servers but it allows higher temperatures. As a result, bang-bang controller generates temperature spikes and higher oscillations. LUT controller changes fan speed according to utilization to minimize power. Even though it does not monitor temperature, the runtime temperature values are lower and more steady, so leakage is always kept low. In this test, LUT controller only needs to change the RPM between two different fan speeds because the machine is in a colder environment compared to the ambient of a data center.

One of the main properties of the LUT controller is its rapid reaction upon load spikes. This significantly reduces the temperature overshoot and undershoot that can be observed with both the original fans and the bang-bang controller. This phenomena occurs when fan speeds are changed as a reaction to a sudden increase-decrease in temperature, i.e., after a

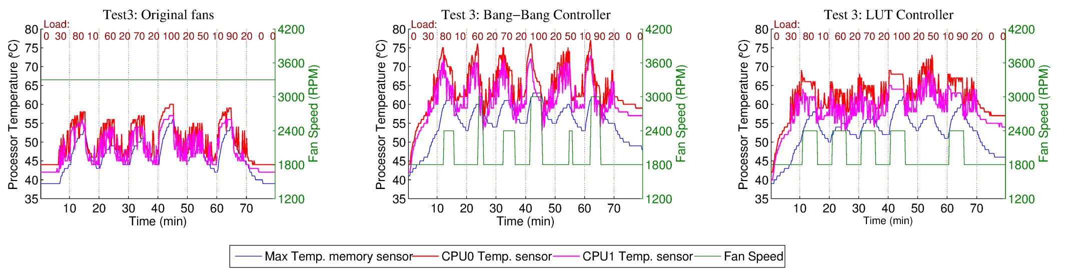


Figure 3.5: Temperature sensor readings in Test-3 for the three different controllers.

thermal event has occurred. This effect generates spikes in the temperature of the processor and thus should be avoided. As the system has some thermal inertia and the thermal effects of workload change are slower than the load monitoring frequency, the LUT controller decisions are taking effect before any thermal event has occurred. On the other hand, the frequency limitation ensures that the controller will not oscillate and, as it is setting the fan speed with respect to the leakage-cooling tradeoffs studied before, the controller obtains the best energy results.

3.6.4 Joint workload and cooling management

In this section we implement and test all fan control policies described in Section 3.6.1 plus the proactive policy, and test them for every workload profile described in Section 3.6.2, under different allocation policies: (i) a clustered allocation scheme without core sleep states, (ii) a clustered allocation scheme with core sleep states, (iii) a distributed allocation scheme, and (iv) a best-case allocation that selects the lowest EDP allocation for each benchmark, as in Figure 3.4.

Table 3.6 shows the results of all the controllers for the clustered (without core sleep states) and the distributed allocation schemes. The energy metric (column 4) is computed with total CPU power minus CPU idle power plus fan power (i.e., $P_{CPU+fan} = P_{CPU} - P_{CPU,idle} + P_{fan}$), and the savings (column 5) represent the % reduction of leakage and fan energy achieved by our policy compared to other policies. It has to be taken into account that the fixed fan speed policy shown in Table 3.6 has been selected considering the leakage-cooling tradeoffs (see Section 3.6.1). This policy is already reducing the CPU energy of workload profile 1 by 8.3% when compared to the server default fan control policy.

The performance of the fan control policies depend both on the workload profile and on the allocation. As the fixed fan speed policy uses 2400RPM, its performance mainly depends on the number of the benchmark-allocation pairs, that have 2400RPM as their best fan speed. For instance, the fixed fan policy performs better with the clustered allocation than the distributed allocation while running workload profile 3, because most of the applications in profile 3 have lower energy consumption when clustered. The fixed fan speed policy outperforms the dynamic baseline policies in some cases, as temperature-driven controllers (i.e., TAPO and Bang-Bang) use the maximum temperature across two CPUs to set the fan speed. As they do not consider the temperature imbalance between CPUs, their performance depends on how well the total leakage depends directly on the maximum temperature. Therefore, they waste energy especially when the workload is clustered in one of the CPUs. On the other hand, the LUT controller uses utilization to set the fan speed. As utilization is not an accurate metric for power modeling, it does not perform well with arbitrary workloads. Our proactive policy computes the fan speed that minimizes the sum of the cooling power and the leakage power of both CPUs, and thus, it yields the most efficient results regardless of the workload and the allocation.

Figure 3.6 shows the fan speed and the processor temperature trends of the fixed fan speed

Profile, Allocation	Fan policy	Fan Energy (Wh)	CPU Energy (Wh)	Leak+Fan Savings (%)	Avg RPM
1, Clustered	Fixed	64.2	243.9	2.3	2400
	TAPO	42.4	243.8	2.2	1848
	Bang	44.1	241.2	0.2	1888
	LUT	43.9	245.4	3.4	1883
	Proactive	49.8	240.9	-	2047
1, Distributed	Fixed	64.2	241.2	1.3	2400
	TAPO	41.6	241.5	1.6	1821
	Bang	41.4	243.0	2.7	1819
	LUT	43.9	243.6	3.2	1883
	Proactive	57.3	239.5	-	2236
2, Clustered	Fixed	62.3	217.7	3.1	2400
	TAPO	42.1	216.2	1.9	1874
	Bang	43.8	216.4	2.0	1915
	LUT	44.1	217.6	3.0	1921
	Proactive	55.3	213.9	-	2226
2, Distributed	Fixed	62.3	219.4	2.5	2400
	TAPO	40.2	219.6	2.6	1821
	Bang	40.4	218.1	1.5	1825
	LUT	43.5	219.4	2.5	1906
	Proactive	54.6	216.3	-	2210
3, Clustered	Fixed	33.1	137.8	0.8	2400
	TAPO	22.7	137.7	0.6	1887
	Bang	22.9	138.3	1.5	1896
	LUT	26.6	138.1	1.2	2079
	Proactive	30.9	137.3	-	2297
3, Distributed	Fixed	33.1	143.0	6.4	2400
	TAPO	22.7	140.1	2.4	1887
	Bang	22.4	140.5	3.0	1872
	LUT	25.8	139.6	1.7	2039
	Proactive	28.2	138.5	-	2171
4, Clustered	Fixed	58.5	163.1	2.7	2400
	TAPO	38.2	161.7	1.5	1843
	Bang	38.0	161.9	1.7	1837
	LUT	41.8	162.0	1.7	1927
	Proactive	47.9	160.1	-	2120
4, Distributed	Fixed	58.0	164.8	3.7	2400
	TAPO	37.7	162.5	1.6	1830
	Bang	38.0	162.3	1.5	1837
	LUT	36.9	163.4	2.5	1806
	Proactive	47.8	160.7	-	2118

Table 3.6: Summary of fan control results for all workloads under different allocation schemes.

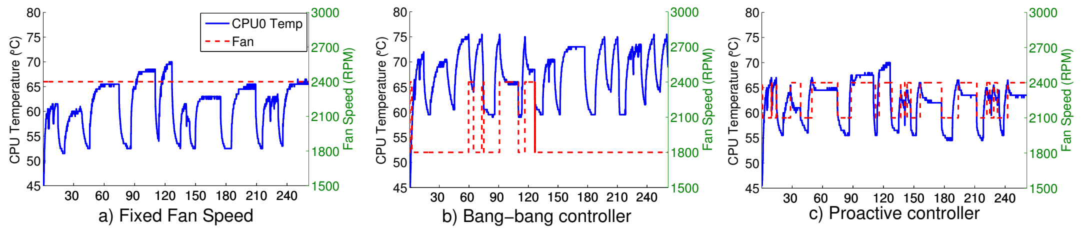


Figure 3.6: Fixed speed, bang-bang, and proactive controller temperature and RPM traces for workload profile 1.

Profile, Allocation	EDP (kWh^2)	Energy (Wh)	Exec.Time (min)	$T_{CPU_{max}}$ (°C)
1, Clustered (w/o sleep)	2.63	823.8	192	71
Clustered (w/sleep)	2.33	731.6	192	71
Distributed	1.83	712.4	154	67
Best-case	1.82	697.6	157	67.5
2, Clustered (w/o sleep)	2.87	818.0	210	68
Clustered (w/sleep)	2.48	707.9	210	68
Distributed	1.84	697.6	158	66
Best-case	1.86	684.5	163	65
3, Clustered (w/o sleep)	0.74	428.1	104	71.5
Clustered (w/sleep)	0.67	383.7	104	71.5
Distributed	0.55	384.4	85	68.5
Best-case	0.55	368.5	89	67.5
4, Clustered (w/o sleep)	2.1	634.3	196	71
Clustered (w/sleep)	1.7	525.7	196	71
Distributed	1.9	617.5	182	64
Best-case	1.7	538.8	191	64.5

Table 3.7: EDP, Energy and performance for various allocation policies with proactive policy.

policy, the bang-bang policy, and the proactive policy running workload profile 1 under clustered allocation scheme. We observe that the proactive policy reduces oscillations in temperature when compared to the bang-bang controller, as it maintains temperature within the range that minimizes the leakage plus fan power curve.

Finally, we compare the energy consumed by the workload profiles under different allocation schemes. Even though the SPARC T3 cores support core-level deep sleep modes, the current software on our server does not support direct control over this feature. To overcome this limitation, we use the reported sleep power values [146], and compute EDP for the scenarios including sleep periods accordingly. We apply this computation adjustment to the real data obtained in our system.

Table 3.7 shows a summary of EDP, energy, power and performance metrics for different allocation policies under the proactive fan control policy. The energy results for columns 3 and 4 are computed by summing up memory power and total CPU power. Column 5 reports workload execution time without considering the idle server time between workload arrivals. The best-case allocation shows the lowest energy consumption in most of the cases, resulting in up to 12.7% improvement when compared to a distributed allocation and up to 15% when compared to a clustered allocation scheme. Even though the execution time of the best-case allocation is longer than the distributed scheme in all cases, it results in better EDP by saving more energy. Moreover, the best-case allocation reduces the maximum CPU temperature when compared to the clustered allocation, and increases only by a maximum of $1°C$ when compared to the distributed allocation.

The tradeoffs in power, energy, temperature and performance need to be jointly handled in order to improve the energy efficiency at the server level. Our proactive cooling control strategy is aware of these tradeoffs, and thus, able to improve over the other state-of-the-art controllers on a wide range of workloads and different allocation schemes. Moreover, both the fan control strategy and the optimum workload allocation exhibit higher benefits for highly-variable workloads (i.e. workload profiles 3 and 4) which are the ones more likely to be observed in real data center environments.

3.7 Discussion on the impact at the data center

In this section, we present a case study to discuss and evaluate the impact of our server-level policies with a data center scope. To this end, we gather server power traces of a high-performance computing cluster consisting of 260 computer nodes in 9 racks at the Madrid

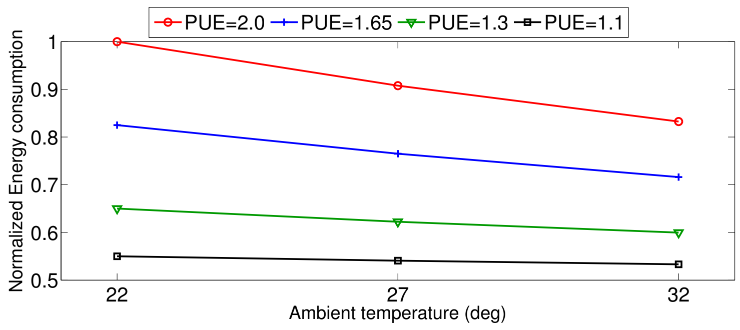


Figure 3.7: Normalized CeSViMa cooling plus IT power for the workload execution under various PUE scenarios

Supercomputing and Visualization Center (CeSViMa). By using the telemetry deployed in CeSViMa, we gather 3 hours of server power traces for 256 servers. We use these power traces to simulate our proactive policy in a larger-scale scenario with a realistic workload profile.

We compute the energy savings that our policy would achieve when compared to the fixed fan speed policy (see Section 3.6.1). We calculate the savings for the whole cluster under different room ambient temperatures that are within the allowable range published by ASHRAE (i.e., 15°C to 32°C for class A1 enterprise servers). We perform this analysis offline in simulation space, applying our models and policy to the gathered power traces and computing the energy savings. We analyze the effect of different ambient temperatures based on data by Miller et al., in which each degree of increase in room temperature yields 4% energy savings in the cooling subsystem [109].

As room temperature raises, the fan speed needed to keep servers within safe environmental conditions also increases. Hence, in our case study, we use a fixed fan speed of 2400RPM, 2700RPM, and 3000RPM as a baseline for comparison under 22°C, 27°C, and 32°C ambient temperature, respectively. Our proactive policy outperforms both the fixed and the default server fan policies for all power traces and under every ambient temperature scenario. The savings obtained are 1.9% at 22°C ambient temperature, 5.5% at 27°C, and 10.3% at 32°C for the whole cluster in *leakage plus fan* power. This is translated into a reduction of 2.5% in the total CPU energy consumption of the cluster at 27°C ambient.

The impact of the leakage-temperature tradeoffs in the overall power consumption of the data center increases as the data room cooling becomes more efficient, i.e., as PUE decreases. Figure 3.7 shows the total energy consumption in our simulations for different PUE scenarios. As we can see, for a PUE of 2.0, energy consumption significantly depends on the room temperature, whereas for PUE of 1.1, increasing temperature does not save energy. This is because leakage and fan power increase by 20% when room temperature raises from 22°C to 32°C. This observation is in accordance with prior work [129]. Note that the exact values are highly dependent on the cooling equipment as well as on the climate and altitude at which the data center is located.

Lower PUE values imply an increase in cooling efficiency; however, PUE does not account for the aggregate fan power, which climbs with the cubic power of fan RPMs, and CPU leakage power (exponential with temperature). Hence, the reliability of PUE as an energy efficiency metric decreases as the leakage and fan power continue to increase in next-generation servers. As the server-level leakage-cooling tradeoffs become more significant in modern data centers, the impact of our policy is expected to be even higher.

3.8 Conclusions

Using the models developed in the previous chapter, we have proposed a leakage-aware cooling control policy that minimizes the energy consumption. Our policy is able to work with arbitrary workloads, and it is robust to variations in workload allocation. Our results on a commercial server show that our policy reduces the *leakage plus fan* energy by up to a 6% compared to existing policies and the CPU energy consumption by more than 9% compared to the default server control policy, without imposing any performance penalty. We have also analyzed the impact of workload allocation, and have shown that by choosing the best-EDP allocation for a given load along with using our proactive cooling control policy, we can obtain energy savings by up to 15%.

The devised policy has also been applied in a broader distributed scenario with real data center traces, optimizing CPU power consumption by 2.5% for the whole cluster, and showing how the impact of our policy raises as data room temperature increases.

In the next chapter...

we scale to a higher abstraction level, i.e. the data center, following our previous modeling-optimization methodology. The reader will find an unsupervised methodology for the development of overall server room modeling techniques to enable data center proactive optimization strategies.

4. Data center room-level modeling using gramatical evolution techniques

A structure this beautiful just had to exist
— James Watson, *talking about the DNA double helix*

In this chapter we present an unsupervised methodology based on Gramatical Evolution techniques to model the inlet and CPU temperature of enteprise servers in a data room. We train and test our models with real traces from enteprise servers, and show how our solution can be applied to the temperature prediction in a production data center. As a case study, we show how our methodology works for temperature prediction in CeSViMa data center, a research cluster that belongs to Universidad Politécnica de Madrid.

4.1 Introduction

The cooling needed to keep the servers within reliable thermal operating conditions is one of the major contributors to data center power consumption, and accounts for over 30% of the electricity bill [33] in traditional air-cooled infrastructures. In the last years, both industry and academia have devoted significant effort to decrease the cooling power, increasing data center Power Usage Effectiveness (PUE), defined as the ratio between total facility power and IT power. According to a report by the Uptime Institute, average PUE improved from 2.5 in 2007 to 1.89 in 2012, reaching 1.65 in 2013 [102]. Apart from using more efficient cooling systems, raising data room ambient temperature is one of the most common strategies to increase efficiency [102]. Some authors estimate that increasing the setpoint temperature by just one degree can reduce energy consumption by 2 to 5 percent [32]. Microsoft reports that raising the temperature from two to four degrees in one of its Silicon Valley data centers saved $250,000 in annual energy costs [107].

However, increased ambient temperatures reduce the safety margins to CPU thermal redlining and may cause potential reliability problems. To avoid server shutdown, the maximum CPU temperature limits the minimum cooling. The key question of how to set the supply temperature of the cooling system to ensure the worst-case scenario, is still to be clearly answered [54]. Most data centers typically operate with server inlet temperatures ranging between 18°C and 24°C, but we can find some of them as cold as 13°C degrees [32], [102], and others as hot as 35°C [108]. These values are often chosen based on conservative suggestions provided by the manufacturers of the equipment, and should always ensure inlet temperatures within the allowable range published by ASHRAE (i.e., 5°C to 45°C for class A4 volume servers, and 15°C to 32°C for class A1 enterprise servers [13]).

Data center designers have collided with the lack of accurate models for the energy-efficient real-time management of computing facilities. Nowadays, to simulate the inlet temperature of servers under certain cooling conditions, designers rely on time costly and very expensive Computational Fluid Dynamics (CFD) simulation. These techniques use numerical methods to solve the differential equations that drive the thermal dynamics of the data room. They need to consider a comprehensive number of parameters both from the server and the data room (i.e. specific characteristics of servers such as airflow rates, model, data room dimensions and setup). Moreover, they are not robust to changes in the data center (i.e. rack placement and layout changes, server turn-off, inclusion of new servers, etc.). If the simulation fails to properly incorporate a relevant parameter, or if there is a deviation between the theoretical and the real values, the simulation becomes inaccurate.

To minimize cooling costs, the development of models that accurately predict the CPU temperature of the servers under variable environmental conditions is a major challenge. These models need to work on runtime, adapting to the changing conditions of the data room, and enabling data center operators to increase room temperature safely.

The nature of the problem suggests the usage of meta-heuristics instead of analytical solutions. Meta-heuristics make few assumptions about the problem, providing good solutions even when they have fragmented information. Some meta-heuristics such as Genetic Programming (GP) perform Feature Engineering (FE), a particularly useful technique to select the set of features and combination of variables that best describe a model. Grammatical Evolution (GE) is an evolutionary computation technique based on GP used to perform symbolic regression [141]. This technique is particularly useful to provide solutions that include non-linear terms offering Feature Engineering capabilities and removing analytical modeling barriers. Also, designer's expertise is not required to process a high volume of data as GE is an automatic method. However, GE provides a vast space of solutions that may need to be bounded to achieve algorithm efficiency.

This work develops a data center room thermal modeling methodology based on GE to predict on runtime and with sufficient anticipation the critical variables that drive reliability and cooling power consumption in data centers. Particularly, the main contributions of our work are the following:

- The development of multi-variable models that incorporate time dependence based on Grammatical Evolution to predict CPU and inlet temperature to the servers in a data room during runtime. Due to the feature engineering and symbolic regression performed by GE, our models incorporate the optimum selection of representative features that best describe thermal behavior.

- The usa of a reduced experimental setup, consisting of real measurements taken from a single server isolated in a fully sensorized data room to tune the models, selecting the optimum parameters and fitness function. We prevent premature convergence by means of Social Disaster Techniques and Random Off-Spring Generation, dramatically reducing the number of generations needed to obtain accurate solutions.

- We offer a comparison with other techniques commonly used in literature to solve temperature modeling problems, such as autoregressive moving average (ARMA) models and linear model identification methods (N4SID).

- The proposal of an unsupervised automatic data room thermal modeling methodology that scales our solution to a realistic Data Center scenario. As a case study, we model CPU and inlet temperatures using real traces from a production data center.

Our work makes contributions in the area of data room thermal modeling, allowing the unsupervised generation of accurate temperature models able to work on runtime and adapt to the ever changing conditions of these scenarios.

The remainder of this Chapter is organized as follows: Section 4.2 accurately describes the modeling problem, whereas Section 4.3 provides an overview of current state-of-the-art solutions. Section 4.4 describes our proposed solution. Section 4.6 shows the experimental results obtained, whereas Section 4.7 discusses these results. Finally, Section 4.8 concludes the chapter.

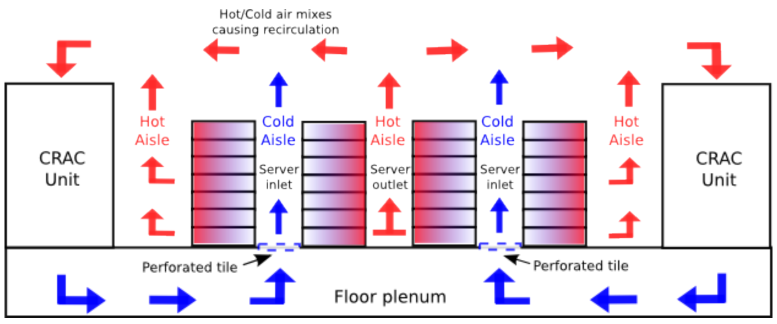


Figure 4.1: Typical raised-floor air-cooled data center layout

4.2 Problem description

4.2.1 Data room thermal dynamics

To ensure the safe operation of a traditional raised-floor air-cooled data center, data rooms are equipped with chilled-water Computer Room Air Conditioning (CRAC) units that use conventional air-cooling methods. Servers are mounted in racks on a raised floor. Racks are arranged in alternating cold/hot aisles, with the server inlets facing cold air and the outlets creating hot aisles. The CRAC units supply air at a certain temperature and air flow rate to the data center through the floor plenum. The floor has some perforated tiles through which the blown air comes out. Cold air refrigerates servers and heated exhaust air is returned to the CRAC units via the ceiling, as shown in Figure 4.1.

Even though this solution is very inefficient in terms of energy consumption, the majority of the data centers in the world use this mechanism. In fact, despite the recent advances in high-density cooling techniques, according to a survey by the Uptime Institute, in 2012 only 19% of large scale data centers had incorporated new cooling mechanisms [102].

In some scenarios, the control knob of the cooling subsystem is the cold air supply temperature, whereas in others, it is the return temperature, i.e. the temperature of the heated exhaust air returning to the CRAC unit.

The maximum IT power density that can be deployed in the data center is limited by the perforated tile airflow. Because the plenum is usually obstructed (e.g. blocked with cables in some areas), a non-uniform airflow distribution is generated and each tile exhibits a different pressure drop. Moreover, in data centers where the hot and cold aisles are not isolated (i.e. the most common scenario, and the case of CeSViMa data center) the heated exhaust air sometimes recirculates to the cold aisle, mixing with the cold air.

4.2.2 Temperature-energy tradeoffs

The factor that limits the minimum data room cooling is the maximum server CPU temperature. Temperatures higher than 85°C can cause permanent reliability failures [14]. At temperatures above 95°C, servers usually turn off to prevent thermal redlining. Server CPU temperature directly depends on: i) power consumption, which is dependant on workload execution, ii) fan speed, which changes the cooling capacity of the server, and iii) server cold air supply (inlet temperature).

Thus, to keep all the equipment under normal operation, the CRAC units have to supply the air at an adequately low temperature to ensure all CPU's are below the critical threshold. ASHRAE's Guidelines [13] use inlet temperature as a proxy to CPU temperature and recommend using inlet temperatures of servers below 35°C to ensure safe operation under a worst case scenario. However, inlet temperature is also not uniform across servers. The cold air temperature at the server inlet depends on several parameters: i) the CRAC cold air supply temperature, ii) the airflow rate through the perforated tiles, and iii) the outlet temperature of adjacent servers, mainly due to airflow recirculation.

Setting the cooling air supply temperature to a low value (or, if not available, the hot air return), even though ensures safety operation, implies increased power consumption due to an larger burden on the chiller system. The goal of energy-efficient cooling strategies is to reduce the cold air supply temperature without reaching thermal redlining. Due to the non-linear efficiency of cooling systems, lowering air supply temperature can yield important energy savings. A metric widely used is that each degree of increase in air supply temperature yields 4% energy savings in the cooling subsystem [109].

To increase air supply temperature safely, however, we need to be able to predict not only the inlet temperature to the servers, but also the CPU temperature that each server attains under the current workload.

Due to the temperature gradients between hot and cold aisles, the air inside a data center performs like a turbulent fluid. Thus, obtaining an analytical relation between cool air supply and server inlet temperature is not trivial, making inlet and CPU temperature prediction a challenging problem. Besides, data centers are composed of thousands of CPU cores, whose temperatures need to be modelled independently. This prevents the usage of classical regression techniques that need human interaction to train and validate the models.

4.3 Related work

Data center room thermal modeling is a topic that arises much interest in literature as it enables both thermal emergency management and energy optimization and enhances reliability. Because of the non-linear behavior of the air and thermal dynamics in the data center room, Computational Fluid Dynamics (CFD) simulation has traditionally been the most commonly used solution in both industry and research [96], [127], [147]. These works use CFD to model the inlet and outlet temperature of servers given the cooling air supply temperature and airflow, a certain room layout, server configuration and data center utilization to either calculate and optimize cooling costs or to detect hot spots in servers [1], [112].

CFD solvers perform a three-dimensional numerical analysis of the physical thermodynamic equations that govern the data room. They use discretization techniques to transform differential equation into their algebraic non-linear form and iterate over them until they reach a suitable convergence, thus providing very accurate results. The main drawback of this solution is that CFD is computationally costly both in the modeling stage (i.e modeling a small-sized data room can take from hours to days) and in the evaluation phase, preventing their online usage. Moreover, CFD simulation is not robust to changes in the layout of the data center, i.e. changes in the rack or server placement, open rack doors, open tiles, etc. Also, changes on the utilization of the data center, the number of servers running or intentional variation to the cooling would require new simulations.

To solve these issues, recent research by Phan et.al. [131] proposes the usage of Building Energy Simulation (BES) Programs and by means of a multi-zone modeling obtain a quicker insight on the data room behavior with less accuracy and, thus, computational costs, than CFD. Other approaches propose the usage of CFD together with sensor information to calibrate the simulation and reduce computational complexity. The solution by Chen et.al. [40] achieves a prediction error below 2°C when predicting temperature 10 minutes into the future. In fact, in the last years industry has started to agree upon the importance of environmental room monitoring [20] to improve energy efficiency. Several works [2], [152] present the data center as a distributed Cyber-Physical System (CPS) in which both computational and physical parameters can be measured with the goal of minimizing energy consumption.

Our work leverages the concept of Cyber-Physical systems by using a monitoring system developed in our previous work [124] capable of collecting both environmental (i.e. cold air supply temperature, inlet and outlet temperature, and airflow through tiles, etc.) and server data (i.e. CPU temperature, server power, fan speed, etc.) from a real data center scenario.

A common alternative to CFD modeling is the proposal of abstract heat flow models. These linear models characterize the steady state of hot air recirculation inside the data center, i.e. they assume that each inlet temperature rises above the supply temperature due to heat from recirculation. Recirculation can be described by a cross-interference coefficient matrix which denotes how much of its outlet heat each node contributes to the inlet of every other node. This matrix is obtained in an offline profiling stage that usually simulates the inlet and outlet temperatures attained under certain cooling and workload conditions with CFD [157]. Even though the profiling is still costly, the evaluation stage can be performed online.

Machine learning techniques have also been used in data center modeling. The Weatherman [111] tool uses neural networks to predict the inlet temperature of servers given the data center utilization and cooling setup, obtaining prediction errors below 1°C in over 90% of their traces. However, they use simulation traces obtained with CFD simulation for their training and test sets, instead of using data from a real data center. This approach disregards CPU temperature and uses utilization to model power.

The main issues in all previous approaches are: i) they monitor and predict server inlet temperature instead of CPU temperature, ii) they do so for only certain data center cooling, server and workload configurations, iii) they use CPU utilization as a proxy for server power consumption, iv) they assume homogeneous data centers in which all servers are equal, v) assume that the fan speed of servers is always constant (something that is not true for current enterprise servers) and vi) they do not validate results with traces from real data center scenarios.

Our work, on the contrary, first predicts inlet temperature and then uses this result to predict CPU temperature, as this is the factor that limits cooling and drives server thermal shutdown. Both in our training and test sets, we use real traces obtained from enterprise servers in a data center. Moreover, as shown in previous work [177], in highly multi-threaded servers such as the ones found in data centers, utilization is not linear with power for arbitrary workloads, and this can only be claimed for certain CPU-intensive workloads. Our solution can be applied to heterogeneous data centers running arbitrary workloads, as it uses power instead of utilization to predict temperature.

Enterprise servers come with automatic temperature-driven variable fan control policies. When fan speed changes, so does the airflow and the server cooling capacity. Moreover, fan power has a cubic dependence with fan speed. Work by Patterson et.al. [129] presents some conservative numbers for fan current consumption on Intel platforms, showing how 1U server fans can draw from 40 watts at peak load to 8 watts at the lowest speed. Our previous work in this area also shows how server fans are an important contributor to server power consumption that should not be disregarded [176]. All previous policies assume that servers have a constant airflow, disregarding the effects of automatic server fan control. Our work, on the contrary, also considers the contribution of variable fan speed when modeling temperature.

At the server level, Heather et.al. [74] proposes a server temperature prediction model based on simplified thermodynamic equations, trading accuracy for execution time, obtaining results within 1°C of accuracy for CPU temperature. C-Oracle [137] is a software infrastructure that uses the previous model to predict the temperature several minutes into the future for efficient thermal emergency management. Even though this approach predicts CPU temperature and takes into account inlet temperature, it does not predict the inlet and thus, is unaware of the thermal dynamics of the data room. Moreover, their solution needs specific knowledge about several server parameters, such as the mass and specific heat capacity of the server hardware components, airflow and heat flow.

Our approach only uses information from the sensors deployed in the server and data room. Thus, it does not need any specific information on the server hardware dimensions, airflow or mass, making it suitable to model heterogeneous servers in all scenarios.

A very common approach to CPU temperature modeling is the usage of autoregressive moving average (ARMA) modeling to estimate future temperature accurately based on previous measurements [46]. Their main drawback is that, because they only use past temperature samples, the prediction horizon is usually below the second. Moreover, they do not provide a physical model, disregarding the effect of power or airflow, and need to be retrained often.

Our work, on the contrary achieves prediction horizons of 1 minute for CPU temperature and 10 minutes for inlet temperature with high accuracy. This enables data center operations to take action before thermal events occur, by changing either workload or data room cooling.

4.4 Modeling via Gramatical Evolution techniques

Evolutionary algorithms use the principles of evolution, mainly the survival of the fittest and natural selection, to turn one population of solutions into another, by means of selection, crossover and mutation. Among them, Genetic Programming (GP) has proven to be effective in a number of Symbolic Regression (SR) problems [162]. However, GP presents some limitations like bloating of the evolution (excessive growth of memory computer structures), often produced in the phenotype of the individual. In the last years, variants to GP like Grammatical Evolution (GE) appeared as a simpler optimization process [121]. GE is inspired in the biological process of generating a protein given the genetic material (DNA) of an organism. GE evolves computer programs given a set of rules, adopting a bio-inspired genotype-phenotype mapping process.

In this section, we describe how we perform feature selection, provide a brief insight on the grammars and mapping process, as well as on several model parameters.

4.4.1 Feature selection and model definition

As mentioned previously, in this work we use Feature Engineering (FE) and Grammatical Evolution to obtain a mathematical expression that models CPU temperature and server inlet temperature. This expression is derived from experimental measurements in real server and data room scenarios, gathering data that has an impact on temperature, according to previous work in the area [124], [177]. For instance, to predict CPU temperature, we gather server power, server fan speed, inlet temperature and previous CPU temperature measurements. For inlet temperature, we gather the CRAC air supply and return temperature, humidity, airflow through perforated tiles and previous inlet temperature measurements. Our goal is to predict temperature a certain time (samples) into the future, by using past data of the available magnitudes within a window. Moreover, in this prediction we may need to use past samples from the magnitude we need to predict, or even previously predicted data.

For illustration purposes, in Figure 4.2 we show a diagram in which CPU temperature is predicted 1 minute into the future given: i) 20 minutes of past measurements (data window) for fan speed, power, inlet and CPU temperature and, ii) the previous CPU temperature predictions (prediction window).

Formally, we claim that CPU temperature prediction for a certain time instant α samples into the future is a function of past data measurements within a window of size $i = \{0..W_{cpu}\}$, and previous prediction values within a window of size $j = \{1..\alpha\}$ as expressed in Equation 4.1:

$$\widehat{T}_{CPU}(k+\alpha) = f\big(T_{inlet}(k-i), FS(k-i), P(k-i), T_{CPU}(k-i), \widehat{T}_{CPU}(k+j)\big) \qquad (4.1)$$

where T_{CPU}, T_{inlet}, FS and P are past CPU temperature, inlet temperature, fan speed and power consumption values respectively, and $\widehat{T}_{CPU}$ are previous temperature predictions.

In the case of inlet temperature, our claim is that inlet temperature T_{inlet} of a certain server is driven by the room thermal dynamics and can be expressed as a function of the cold air supply temperature (or CRAC return temperature, if the previous is not available), T_{CRAC}, the airflow through the perforated tiles γ and data room humidity h, as in Equation 4.2:

$$\widehat{T}_{inlet}(k+\beta) = f\big(T_{CRAC}(k-i), \gamma(k-i), h(k-i), FS_{p-m}(k-i), \widehat{T}_{inlet}(k+j)\big) \qquad (4.2)$$

where the data window can be defined in the range $i = \{0..W_{inlet}\}$ and the prediction window is $j = \{1..\beta\}$

Note that, in general, α and β are not equal, as the room dynamics are much slower than the CPU temperature dynamics of the servers, i.e. in a real data room we might need hours to appreciate substantial differences in ambient temperature, whereas CPU temperature changes within seconds.

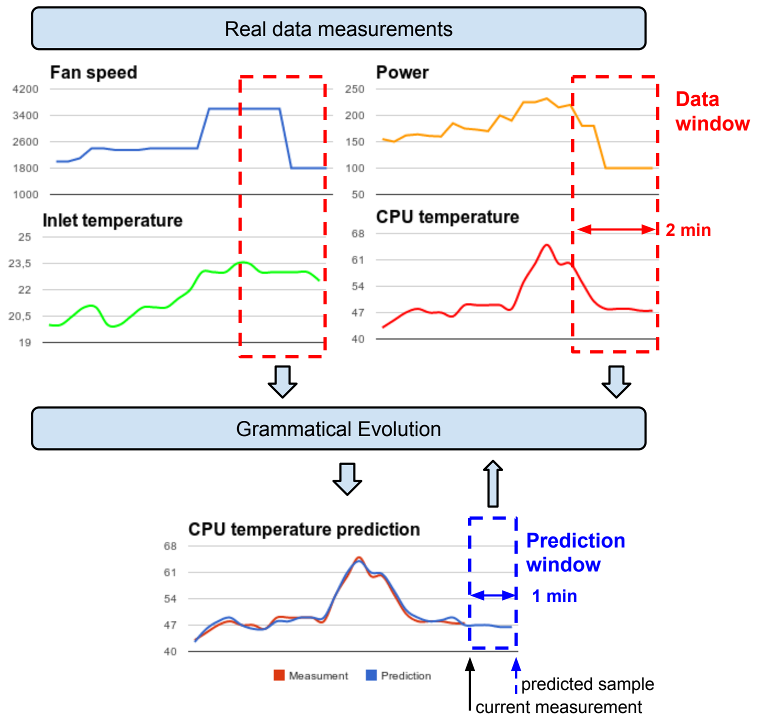


Figure 4.2: CPU temperature prediction diagram. CPU temperature is predicted given past data measurements of various magnitudes (data window) and past CPU temperature predictions.

Among all data measurements within their window, to select the relevant features we deal with a Symbolic Regression (SR) problem. SR tries to simultaneously obtain a mathematical expression while including the relevant features to reproduce a set of discrete data. In our approach, GE allows the generation of mathematical models applying SR.

Regarding both the structure and the internal operators, GE works like a classic Genetic Algorithm [17]. GE evolves a population formed by a set of individuals, each one constituted by a chromosome and a fitness value. In SR, the fitness value is usually a regression metric like Root Mean Square Deviation (RMSD), Coefficient of Variation (CV), Mean Squared Error (MSE), etc. In GE, a chromosome is a string of integers. In the optimization process, GA operators, (i.e. selection, crossover and mutation [65]) are iteratively applied to improve the fitness value of each individual. In order to compute the fitness function for every iteration and extract the mathematical expression given by an individual (phenotype), a mapping process is applied to the chromosome (genotype). This mapping process is achieved by defining a set of rules to obtain the mathematical expression, using grammars in Backus Naur Form (BNF) [121].

The process does not only perform parameter identification like in a classical regression method. In conjunction with a well-defined fitness function, the evolutionary algorithm is also computing mathematical expressions with the set of features that best fit the target system. Thus, GE is also defining the optimal set of features that derive into the most accurate power model.

Moreover, this methodology can be used to predict magnitudes with memory, such as temperature, where the current observation depends on past values. To incorporate time dependence, data used for model creation needs to be a timeseries. In addition, we need to tune our grammars so that they can produce models where past temperature values can be used to predict temperature a certain number of samples into the future. Grammar 2 shows an example where variable x may take values in the current time step k, i.e., $x[k-0]$ or in previous samples like $x[k-1]$ or $x[k-2]$. Moreover, a new variable $xpred[k-idx]$ can be included, that accounts for previously predicted values of variable x.

Including time dependence into a grammar has some drawbacks that need to be taken into account when generating the models. First, we are substantially increasing the search space of our algorithms, as now the GE needs to search for the best solution among all variables within the specified window. As a consequence, the number of generations needed to obtain a good fitness increases. Second, as we show in the results section, depending on the prediction horizon (i.e. the number of samples ahead we want to predict) the models tend to fall into a local optimum, in which the best phenotype is the last available observation of the variable to be predicted.

Grammar 2 Example of a grammar in BNF format that generates phenotypes with time dependence

$$\langle expr \rangle ::= \langle expr \rangle \langle op \rangle \langle expr \rangle \mid \langle preop \rangle (\langle expr \rangle) \mid \langle var \rangle \tag{I}$$

$$\langle op \rangle ::= + \mid - \mid * \mid / \tag{II}$$

$$\langle preop \rangle ::= \text{sin} \mid \text{cos} \mid \text{log} \tag{III}$$

$$\langle var \rangle ::= \text{x[k-}\langle idx \rangle\text{]} \mid \text{xpred[k-}\langle idx \rangle\text{]} \mid \text{y} \mid \text{z} \mid \langle num \rangle \tag{IV}$$

$$\langle num \rangle ::= \langle dig \rangle . \langle dig \rangle \mid \langle dig \rangle \tag{V}$$

$$\langle dig \rangle ::= 0 \mid 1 \mid 2 \mid 3 \mid 4 \mid 5 \tag{VI}$$

$$\langle idx \rangle ::= 0 \mid 1 \mid 2 \tag{VII}$$

For a more detailed explanation on the principles of the mapping process, and how the BNF grammars are used to incorporate time dependence, the reader is referred to Appendix A.3.1.

4.4.2 Preventing premature convergence

Premature convergence of a genetic algorithm arises when the chromosomes of some high rated individuals quickly dominate the population, constraining it to converge to a local optimum. The premature convergence is generally due to the loss of diversity within the population, and is one of the major shortcomings when trying to model low variability magnitudes by using GE techniques, as we show in Section 4.6.

To overcome the lack of variety in the population, work by Kureichick et.al. [105] proposes the usage of Social Disaster Techniques (SDT). This technique is based on monitoring the population to find local optima (i.e. a loss of diversity, usually diagnosed by a lack of improvement in the fitness function), and apply one of these two operators:

1. *Packing*, in which all individuals having the same fitness value except one are fully randomized.

2. *Judgment day*, in which only the fittest individual survives while the remaining are fully randomized.

Work by Rocha et.al. [140] proposes the usage of Random Off-spring Generation (ROG) to prevent the crossover of two individuals with equal genotype, as this would result in the off-spring being equal to the parents. To this end, individuals are tested before crossover and, if equal, then one off-spring (1-RO) or both of them (2-RO) are randomly generated.

Both previous solutions have shown important benefits in classical Genetic Algorithms problems. In our work, we use these techniques to improve the convergence time of our solutions, as we show in Section 4.6.

4.4.3 Fitness and problem constraints

The goal of using GE for data room thermal modeling is to obtain accurate models, able to predict future samples of a certain magnitude. Thus, our fitness function needs to express the error resulting in the estimation process. To measure the accuracy in our prediction, we would preferably use the Mean Absolute Error (MAE). However, because temperature is a magnitude that varies slowly and might remain constant during large time intervals, we need to give higher weight to large errors. To this end, we select the Root Mean Square Error (RMSE) as a fitness function.

As we are modeling the behavior of physical magnitudes, (i.e., temperature), for optimization purposes, it is desirable to obtain a solution with physical meaning. To this end, we can constrain the model generation in several ways that are next presented:

- Constraining the grammar to obtain a limited number of functions that match the physical world. E.g. including the exponential function when modeling temperature.

- Biasing fitness to force the appearance of some parameters that we know drive the variables being modelled. E.g. giving worse fitness to expressions that do not include power consumption when modeling temperature.

- Use of real vs. mixed models. Purely real cannot use future predictions of the variable, whereas purely predictive models do not used previous temperature data measurements, but may use previous predictions. Adding the predicted samples as a variable to our grammars increases the size of the search space and, thus, we expect longer convergence time. However, it may deliver more accurate results.

In the results Section 4.6 we evaluate the impact of these constraints in the model generation stage. Further explanation on the fitness and problem constraints is provided in Appendix A.3.1.

4.5 Experimental methodology

In this section we describe the experimental methodology followed in this paper to model server and environmental parameters in Data Centers.

First, we describe the experimental setup of a reduced scenario consisting only in the temperature prediction of one server in a small air-cooled data room. We use this scenario to tune the model parameters, testing those that generate better models and studying the convergence of the solutions. Once we have tested that our solution works in the reduced scenario, we apply the best algorithm configuration to a real data center. As a case study, we use the real traces of CeSViMa data center, a High Performance Computing cluster at Universidad Politécnica de Madrid.

4.5.1 Reduced scenario

Our reduced scenario consists on an Intel Xeon RX-300 S6 server equipped with 1 quad-core CPU and 16GB of RAM. The server is installed in a rack with another 4 servers, 2 switches and 2 UPS units, in an air-cooled data room of approximately 30 square meters, with the rack inlet facing the cold air supply and the outlet facing the heat exhaust. The air conditioning unit mounted in the data room is a Daikin FTXS30 split, used to cool all the servers in the data room. In this reduced scenario, the split unit is mounted on the ceiling of the data room, and there is no floor plenum. The cold air supply ranges from between 16°C to 26°C. Both the servers and the environment of the reduced scenario are fully monitored, and we have control over both the environmental parameters (i.e. we can change the data room cooling at will) and the server parameters (i.e. we control the workload being executed).

Monitoring

Both the server and the data room are fully monitored using the internal server sensors and a wireless sensor network, as described in [124]. In particular, server CPU temperature and fan speed values are obtained via the server internal sensors, collected through the Intelligent Platform Management Interface (IPMI) tool [1]. IPMI allows to poll the internal sensors of the enterprise server with negligible overhead. Because the server is not shipped with power consumption sensors, we use non-intrusive current clamps connected to the power cord of the server to gather total server power consumption. Wireless nodes monitor the inlet temperature of the server, the cold air supply temperature of the split unit and data room humidity. All data is sent to the monitoring server where it is stored and measurements are aligned to ensure a common timestamp.

Training and test set generation

We generate a training and a test set by assigning a wide variety of workloads that exhibit different stress levels in both the CPU and memory subsystems of the server while we modify the cold air supply temperature of the split in a range from 16°C to 26°C.

The workloads used are the following: i) *Lookbusy*[2], a synthetic workload that stresses the CPU to a customizable utilization value, avoiding the stress of memory and disk; ii) a modified version of the synthetic benchmark *RandMem*[3], that allows us to stress random memory regions of a given size with a given access pattern, and iii) HPC workloads belonging to the SPEC CPU 2006 benchmark suite [148].

During the training set, we launch *Lookbusy* and *Randmem* at different utilization values, plus a subset of the SPEC CPU 2006 benchmarks that exhibit a distinctive set of characteristics according to Phansalkar et.al. [132]. Both the idle time between tasks and the duration of each task are randomly selected. During execution, the cold air supply temperature is also randomly changed.

For the test set, we randomly launch any SPEC CPU benchmark, with also random waiting intervals and randomly changing cold air supply temperature.

Our monitoring system collects all data with a 10 second sampling interval for a total time of 5 hours for the training and 10 hours for the test set. Figure 4.3 shows part of the training set used for modeling.

4.5.2 Case study: CeSViMa data center

To show how our solution can be applied to a real data center scenario, this paper presents a case study for a real High-Performance Computing data center at the Madrid Supercomputing and Visualization Center (CeSViMa)[4]. CeSViMa hosts the *Magerit* Supercomputer, a cluster consisting of 286 computer nodes in 11 racks, providing 4,160 processors and nearly 200 TB of storage. 245 of the 286 nodes are IBM PS702 2S with 2 Power7 CPU's blade servers, each with 8 cores running at 3.3GHz and 32GB of RAM. The other 41 nodes are HS22 2U servers with 2 Intel Xeon processors of 8 cores each at 2.5GHz (10.2GFlops) and 64GB RAM. *Magerit* executes High-Performance jobs on demand with a maximum node reservation for high priority jobs of 1024 processors during 72 hours. The remaining infrastructure in CeSViMa hosts a Private Cloud and storage units.

CeSViMa data room has a cold-hot aisle layout and is cooled by means of 6 CRAC units arranged in the walls that impulse air through the floor plenum. To control data room cooling, the air return temperature of each CRAC unit can be set independently. The room has a total size of 190 square meters. Figure 4.4a shows the layout of the data center. Rack 0 is a control rack that runs no HPC computation. Racks 1-9 are filled with Power7 nodes, whereas rack 10 contains Intel Xeon servers. Each Power 7 node (i.e. each blade server) is installed in a

[1]http://ipmitool.sourceforge.net/
[2]http://www.devin.com/lookbusy/
[3]http://www.roylongbottom.org.uk
[4]http://www.cesvima.upm.es/

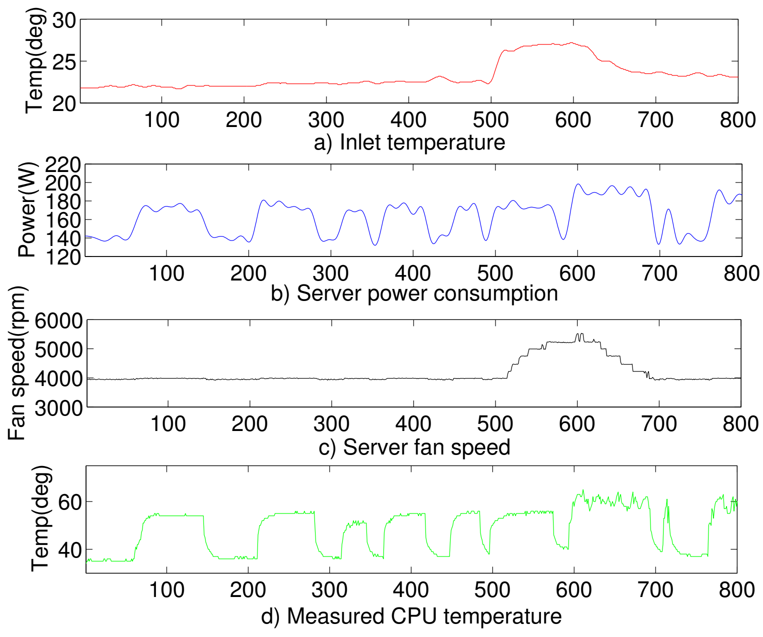


Figure 4.3: Training samples used for CPU temperature modeling

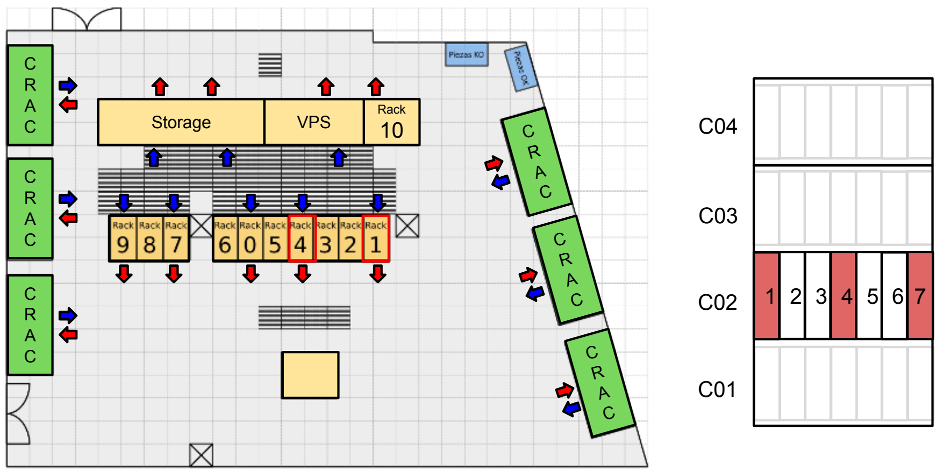
blade center (i.e. a chassis). Each blade center contains up to 7 blades, and each rack contains 4 chassis (C01 to C04), as shown in Figure 4.4b. To run our models, we have deployed the same sensor network that in the reduced scenario. In particular, to model inlet temperature we gather inlet temperature, humidity, CRAC air return temperature and differential pressure through the floor plenum. Because we have placed pressure sensors in the tiles in front of racks 1 and 4, we model the Power7 nodes in these racks. Moreover, data from all servers are gathered also via IPMI. To model CPU temperature, apart from the previous metrics we also collect temperature and fan speed. CeSViMa Power7 chassis do not have per-server current sensors to measure the power consumption drawn and because each server is installed in a chassis, we are not able to deploy current clamps. Thus, we use per-server utilization as a proxy for the power consumption of the node. As stated before, utilization is not an accurate metric for arbitrary workloads. However, because of the nature of the workloads in CeSViMa and only for thermal modeling purposes, utilization can be used as a proxy variable to power consumption, as we show in Section 4.6.

In this work we show the results for the modeling of the servers highlighted in red in Figure 4.4, i.e. nodes 1,4,7 at chassis c02 of both rack 1 and 4. These nodes are the ones that exhibit the most variable workload and the most extreme temperature conditions and, thus, the worst-case scenario for modeling purposes.

4.5.3 Modeling framework

Because of the large number of servers in CeSViMa, to enable cooling optimization we need a framework that allows us to automatically model and predict the CPU and inlet temperature to all servers. Even though CeSViMa is a small-sized data room, it has a very high density in terms of IT equipment. For instance, the amount of data gathered that needs to be processed to enable full environmental modeling and prediction, for a period of 1 year, is above 100GB. Thus, modeling the whole data center with traditional approaches that require human interaction is not feasible.

Our work uses the proposed Grammatical Evolution techniques to automatically model all the parameters involved in data center optimization in an unsupervised way, by automatically running the training of the algorithms and testing them during runtime.



a) CeSViMa Data Center room layout b) Power7 rack front view

Figure 4.4: CeSViMa data room layout. Models are developed for Power7 nodes 1,4 and 7 at high c02 in racks 1 and 4.

4.6 Results

In this section we present the experimental results obtained when applying Grammatical Evolution to model CPU and inlet temperature. First, we show the results for the reduced scenario, describing the best algorithm configuration, and compare our solution with other state-of-the art solutions. Then, we apply the best configuration to train and test the models in a real data center scenario, in which we predict both CPU and inlet temperature in an automatic way.

4.6.1 Algorithm setup and performance

First, we use GE to obtain a set of candidate solutions with low error when compared to the temperature measurements in our reduced experimental setup, under different constraints.

After evaluating the performance of our model with several setups, we select the following one for all models in this chapter:

- Population size: 200 individuals
- Chromosome length: 100 codons
- Mutation probability: inversely proportional to the number of rules.
- Crossover probability: 0.9
- Maximum wraps: 3
- Codon size: 8 bits (values from 0 to 255)
- Tournament size: 2 (binary)

For CPU temperature prediction, we use a data window of $W_{cpu} = 20$ samples, and a prediction window of $\alpha = 6$. As we have a 10-second sampling rate, we are able to predict CPU temperature 1 minute into the future. Both values are heuristically chosen based on experimental observations. On the one hand, the prediction window is chosen given the physical constraints of the problem: 1-minute prediction is long enough to change the workload assignment of a server and, thus, change energy consumption or avoid thermal redlining. On the other hand, the window size W_{cpu} has been chosen with respect to the largest temperature transient observed.

For inlet temperature prediction, we also use a data window of $W_{inlet} = 20$ samples but a prediction window of $\beta = 5$ samples. Inlet temperature dynamics are much slower than CPU temperature. Because of this, a sampling rate of 2 minutes over inlet temperature is sufficient to get accurate results. Given the size of the prediction window, we are able to obtain inlet temperature samples 10 minutes into the future, which is sufficient time to act upon data room cooling.

Next, we present the comparison among several configurations in terms of grammar expressions and rules, premature convergence prevention and fitness biasing. We detail our results for CPU temperature modeling. The procedure to tune inlet temperature models is completely equivalent.

Data preprocessing and model simplification

Because the power measurements of the Intel Xeon server are taken with a current clamp, the power values obtained exhibit some noise. We preprocess the data to eliminate the high-frequency noise, smoothing the power consumption trace by means of a low pass filter. The remaining traces did not exhibit noise, so no preprocessing was needed.

Moreover, we perform variable standardization for every feature (in the range $[1, 2]$) to assure the same probability of appearance for all the variables and to enhance the GE symbolic regression.

Grammars used

To model CPU temperature we have tested three different grammars:

- The first one is shown in Grammar 3 and contains a wide set of operands and preoperands (rules II and III), that do not necessarily result into models with a physical meaning.
- The second grammar is a variation of Grammar 3 in which the number of preoperands (rule III) is reduced to exponentials only, i.e. $\langle preop \rangle ::= exp$
- The last grammar is the one presented in Grammar 4 and also reduces the set of possible expressions (rule I).

Grammar 3 Grammar used for CPU temperature modeling in BNF format, that uses inlet temperature (TIN), fan speed (FS), power consumption (PS), past CPU temperature (TS) and past predicted CPU temperature (TpS)

$\langle expr \rangle$ ::= $\langle expr \rangle \langle op \rangle \langle expr \rangle$|($\langle expr \rangle \langle op \rangle \langle expr \rangle$)| $\langle preop \rangle$($\langle expr \rangle$)|$\langle var \rangle$|$\langle cte \rangle$ (I)

$\langle op \rangle$ ::= +|-|*|/ (II)

$\langle preop \rangle$ ::= exp | sin | cos | tan (III)

$\langle var \rangle$ ::= TS[k-$\langle idx \rangle$]|TIN[k-$\langle idx \rangle$]|PS[k-$\langle idx \rangle$]|FS[k-$\langle idx \rangle$] (IV)

$\langle idx \rangle$ ::= $\langle dgt2 \rangle \langle dgt \rangle$ (V)

$\langle cte \rangle$ ::= $\langle dgt \rangle$.$\langle dgt \rangle$ (VI)

$\langle dgt \rangle$ ::= 0|1|2|3|4|5|6|7|8|9 (VII)

$\langle dgt2 \rangle$ ::= 0|1 (VIII)

From the previous three grammars the one that has faster convergence time to achieve a low error, is Grammar 4. Constraining the grammar increases convergence time and provides phenotypes that have physical meaning, without an increase in the modeling error obtained. Thus, for the remaining of the chapter we work with the simplied Grammar 4 when modeling CPU temperature.

We test two variations of this grammar: i) one that searches for a mixed model (i.e. uses past temperature predictions, and is the one shown in Grammar 4), and ii) the one that provides a real model (i.e. only uses CPU temperature measurements). The only difference between the mixed and the real grammars, is the presence of the parameter TpS.

Grammar 4 Simplified grammar in BNF format used for CPU temperature modeling

$\langle expr\rangle$ ::= $\langle expr\rangle\langle op\rangle\langle expr\rangle$|($\langle expr\rangle\langle op\rangle\langle expr\rangle$)|$\langle preop\rangle$($\langle exponent\rangle$)|$\langle var\rangle$|$\langle cte\rangle$ (I)

$\langle op\rangle$ ::= +|-|*|/ (II)

$\langle preop\rangle$ ::= exp (III)

$\langle exponent\rangle$ ::= $\langle sign\rangle\langle cte\rangle$*$\langle var\rangle$|$\langle sign\rangle\langle cte\rangle$*($\langle var\rangle\langle op\rangle\langle var\rangle$) (IV)

$\langle sign\rangle$ ::= +|- (V)

$\langle var\rangle$ ::= TpS[k-$\langle idx\rangle$]|TS[k-$\langle idx\rangle$]|TIN[k-$\langle idx\rangle$]|PS[k-$\langle idx\rangle$]|FS[k-$\langle idx\rangle$] (VI)

$\langle idx\rangle$ ::= $\langle dgt\rangle$ (VII)

$\langle cte\rangle$ ::= $\langle dgt2\rangle$.$\langle dgt2\rangle$ (VIII)

$\langle dgt\rangle$ ::= 1|2|3|4|5|6|7|8|9|10|11|12|13|14|15|16|17|18|19|20 (IX)

$\langle dgt2\rangle$ ::= 0|1|2|3|4|5|6|7|8|9 (X)

Tested configurations

With respect to premature convergence, we test three different techniques:

- No premature convergence technique applied
- Random Off-Spring Generation (2-RO) plus Packing, keeping no more that a 5% of the population with equal phenotype.
- Random Off-Spring Generation (2-RO) plus Packing, leaving no more than 1 individual with equal phenotype.

For each of the above mentioned configurations, we run both real and mixed models, with the goal of comparing the converge time and the fitness evolution of each configuration in our particular problem. Because the evolution random, to compare different configurations, we run the same model training 5 times and average the RMSE obtained for different number of generations.

Figure 4.5 shows the RMSE evolution for the three techniques applied to tackle premature convergence, with both real and mixed models. When we do not apply any premature convergence technique, error decay is much slower, as population loses diversity and improves only due to mutation in the individuals. This fact is more dramatic for the mixed models, where search space is larger. When we apply ROG and SDT techniques, we need less generations to obtain good fitness values. However, keeping only 1 individual with the same phenotype and randomizing the remaining population is too aggressive, while keeping a higher percentage of equal individuals, i.e. a 5%, yields better results. As can be seen, using 30,000 generations is enough to obtain low RMSE values.

Regarding fitness biasing, we test the results of giving a higher weight to the fitness of phenotypes in which desired all parameters are present. Figure 4.6 shows the differences in

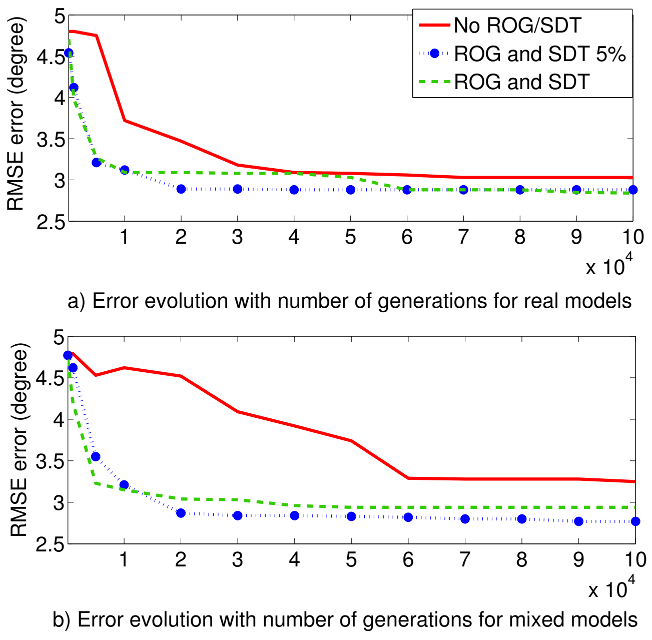


Figure 4.5: CPU temperature error evolution for real and mixed models under different premature convergence prevention techniques: i) no technique applied, ii) ROG + SDT keeping 5% of equal individuals and iii) ROG + SDT randomizing all equal individuals.

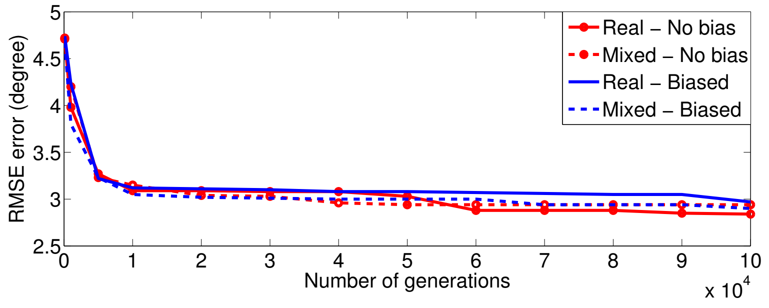


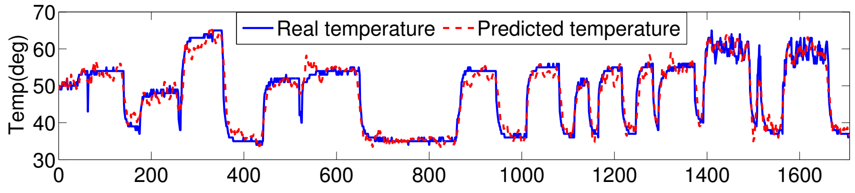
Figure 4.6: CPU temperature error evolution for real and mixed models under ROG + SDT 5% when fitness is biased vs. not biased.

terms of RMSE for different number of generations for real and mixed models when we bias the fitness to force all parameters and when we do not bias the fitness. As can be seen, the convergence is similar, being slightly better that of the non-biased models. In fact, all variables in the grammar tend to appear in non-biased models, thus backing up the hypothesis that all those magnitudes have an importance in the modeling of temperature.

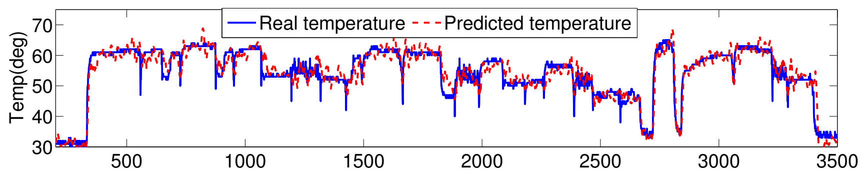
Finally, we show results for both the training and test set when modeling CPU temperature with the best configuration, i.e. a mixed model obtained with Grammar 4, using ROG and Packing techniques leaving 5% of equal individuals, and not biasing the fitness. Table 4.1 shows the 5 better phenotypes obtained for this model and their corresponding RMSE and MAE values for the test set after simplification. In order to avoid overfitting, we use the five best models to compute the samples of the test set, i.e., we predict the next temperature sample with all five equations, obtaining 5 different results, and we average them to obtain the prediction value. By applying this methodology we obtain a RMSE of 2.48°C and a MAE of 1.77°C. Because CPU temperature sensors usually have a resolution of 1°C we consider these results to be accurate enough for our purposes. Figure 4.7 shows the real CPU temperature

Phenotype	RMSE	MAE
$TS[k-3]+PS[k-1]-PS[k-4]+1.1\cdot TIN[k-7]/(e^{(-0.1\cdot(TpS[k-8]-TS[k-3]))}$ $\cdot(PS[k-20]/9.9)+9.9)-(e^{(-4.5\cdot(TpS[k-5]/TS[k-19]))}\cdot TS[k-7])-9.6$	2.8	2.08
$TS[k-5]+PS[k-1])-PS[k-5]+(TS[k-5]/5.7-e^{(-1.3\cdot(TS[k-5]/TIN[k-12]))}$ $\cdot TS[k-5])+PS[k-11]/(3.7-TS[k-5]\cdot(e^{(-0.3\cdot(PS[k-18]+FS[k-7]))}$ $-e^{(-4.9\cdot(PS[k-12]/PS[k-16]))}))-9.8$	2.59	1.86
$TS[k-5]+PS[k-1]-PS[k-4]+e^{(+6.1\cdot(TIN[k-10]/TS[k-5]))}-5.2)$ $-TIN[k-14]\cdot(0.06\cdot(TIN[k-7]/TS[k-5]))+(PS[k-1]/3.1\cdot TIN[k-7])$ $\cdot TS[k-5]-(PS[k-20]/TIN[k-7])\cdot e^{(-6.4\cdot(TIN[k-15]/TS[k-11]))}-8.0$	2.77	2.01
$TS[k-3]+PS[k-1]-PS[k-4]-e^{(-4.1\cdot(TpS[k-5]/TIN[k-19]))}/TS[k-3]$ $+(TpS[k-1]/(e^{(-0.1\cdot(TpS[k-8]-TS[k-3]))}\cdot(PS[k-20]/9.9)+9.2))/1.6-9.6$	2.55	1.77
$TS[k-1]+0.73\cdot(PS[k-1]\cdot 4.4-PS[k-2]\cdot 4.4-TS[k-1]+TpS[k-8]$ $+e^{(-0.2\cdot TIN[k-8])}+(e^{(-3.4\cdot(PS[k-20]/PS[k-10]))}-$ $e^{(-4.0\cdot(PS[k-6]/PS[k-19]))})\cdot TpS[k-12]/9.0-0.9)$	2.5	1.75

Table 4.1: Phenotype, RMSE and MAE for the test set in the CPU temperature modeling reduced scenario



(a) 1-minute training set prediction for mixed model



(b) 1-minute test set prediction for mixed model

Figure 4.7: Training and test set CPU temperature prediction vs. real measurements

trace and its prediction, for both the training and the test set. As can be seen, the prediction accurately matches the measured values in both the training and test sets.

4.6.2 Comparison to other approaches

We compare our results with two common techniques for CPU temperature modeling in the state-of-the-art: autoregressive moving average models and linear subspace identification techniques. We first briefly describe both modeling techniques and then we show the results obtained and compare them with our proposed technique. For further information on the working principles of ARMA and N4SID, the reader is referred to Appendix B.2.

ARMA and N4SID models

ARMA models are mathematical models of autocorrelation in a time series, that use past values alone to forecast future values of a magnitude. The ARMA modeling methodology consists on two steps: i) identification and ii) estimation. During the identification phase, the model order is computed, i.e, we find the optimum values for p and q of the $ARMA(p,q)$ process, where p and q are the orders of the autoregressive (AR) and the moving average (MA) parts of the model, respectively. To perform model identification we use an automated strategy, that computes the goodness of fit for a range of p and q values, starting by the simplest

Model	Training set		Test set	
	RMSE	MAE	RMSE	MAE
$ARMA(1,4)(p<5, q<5)$	4.28	2.18		
$ARMA(9,8)(p<10, q<10)$	4.18	2.5		
$N4sid[6,20,20]$	2.67	1.79	6.27	5.96
GE	2.39	1.7	2.48	1.77

Table 4.2: RMSE and MAE in CPU temperature prediction for each model (Grammatical evolution - GE, ARMA and N4sid)

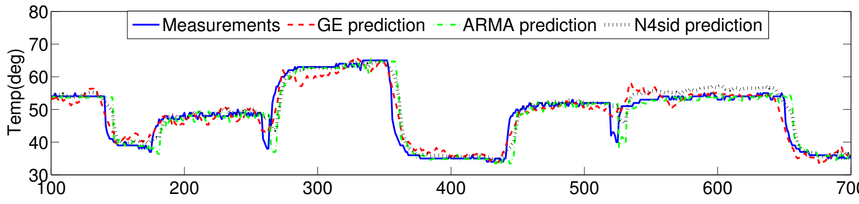


Figure 4.8: Zoomed-in CPU temperature modeling comparison between Grammatical Evolution (GE), ARMA(1,4) and N4sid models

model (i.e., an ARMA(1,0)). The goodness of fit is computed using the Final Prediction Error (FPE), and the best model is the one with lowest FPE value. For a fair comparison with our proposed methodology, the model obtained needs to forecast $\alpha = 6$ samples into the future.

N4SID is a subspace identification method that estimates an n order state-space model using measured input-output data. The approach consists on identifying a parametrization of the model, and then determine the parameters so that the measurements explain the model in the most accurate possible way. To be constructed, certain parameters need to be fed into the model, such as the number of forward predictions (r), the number of past inputs (s_u), and the number of past outputs(s_y). Again, for a fair comparison with our proposed methodology, we need a model in the form $N4SID[r, s_u, s_y]$ where $r = 6$, $s_u = 20$ and $s_y = 20$.

Model comparison

Finally, we compare the results for CPU temperature modeling between our proposed approach, ARMA and N4SID models, all of them with a prediction window of 6 samples (1 minute) into the future.

Table 4.2 shows the RMSE and MAE errors obtained for our proposed modeling technique based on GE, ARMA and N4sid models.

Figure 4.8 shows a zoom-in into the CPU temperature curve for the real measurements and the prediction with all three models for our test set. As can be seen, GE models are the ones with both lower RMSE and MAE. Moreover, the CPU temperature trend is accurately predicted. This does not happen for ARMA models that, even though keep the maximum error low, provide values that are always behind the real trend, yielding poor forecasting capabilities. This issue cannot be solved by increasing the model order, as shown in Table 4.2. N4sid models, even though they are very accurate in the training test, perform poorly in the test set and have an important bias error. Even if the bias error is corrected (which has been done in Figure 4.8) the prediction is still behind the measurements and the system is unable to capture the system dynamics. The GE prediction, even though has more oscillations (due to the smoothed noise of the power consumption signal) is the only one that captures the temperature trend, advancing the real measurements.

4.6.3 Inlet temperature modeling

For inlet temperature modeling we perform the same study than for CPU temperature in terms of grammars, premature convergence and fitness biasing. As expected, the results in terms of

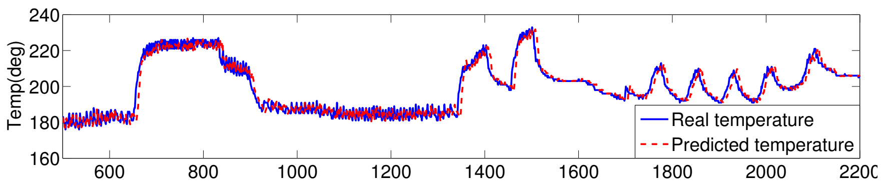


Figure 4.9: 10-minute inlet temperature prediction in the reduced scenario for a mixed model with SDT Packing 5% and simplified grammar

the best model configuration yield very similar results. Thus, for inlet temperature modeling, we use the same configuration: i) a mixed model using a simplied version of the grammar that only allows exponentials, ii) SDT with 5% packing and iii) RMSE fitness function without biasing.

The BNF grammar used is very similar to Grammar 4, where instead of rule VI, we use the following rule:

$\langle var\rangle$ ::= TIN[k-$\langle idx\rangle$] | TpIN[k-$\langle idx\rangle$]|TSUP[k-$\langle idx\rangle$]|HUM[k-$\langle idx\rangle$]

where TSUP is cold air supply temperature, HUM is humidity, TIN are past inlet temperatures and TpIN are past inlet temperature predictions. Figure 4.9 shows the prediction for the test set. The RMSE of the prediction is of 0.33°C and MAE is 0.27°C for a prediction window of 10 minutes into the future and for the test set. Again, the model includes all the available variables, i.e., TSUP, TIN and HUM appear in the final model.

4.6.4 Data center modeling

We use the previous model with the same configuration to predict the CPU and inlet temperature of the blade servers at CeSViMa data center. Because CeSViMa is a production environment, when it comes to server data, we are subject to the data sampling rates provided by the data center. CeSViMa collects all data from servers every 2 minutes, and environmental data (i.e. from coolers) every 15min. Thus, for both CPU and inlet temperatures, we need to change our prediction windows. For CPU temperature we use a prediction window $\alpha' = 1$, which means that we predict CPU temperature two minutes into the future. For inlet temperature we use a prediction window $\beta' = 1$ samples, i.e. we predict temperature 15min into the future.

Because in CeSViMa we cannot control the workload being executed, nor we can modify the cooling to vary data room temperature, we need to select longer training and tests sets to ensure that they exhibit high varibility on the magnitudes of interest. For CPU temperature, we select 2 days of execution for the training set, and 4 days for the test set. For inlet temperature, which varies very slowly in a real data center setup we use 14 days of execution for both the training and the test set.

Figure 4.10 shows a zoomed-in plot of the measured and predicted inlet temperature to the chassis c02 of racks 1 and 4 in CeSViMa data center for a period of 8 days. Figure 4.11 shows the measured and predicted CPU temperature traces for blades b01, b04 and b07 in chassis c02 of both racks, for the first two days of the same period. To generate this last models, instead of using the real inlet temperature measuments, we use predicted inlet temperature. This way, we are able to accurately predict all variables needed for optimization.

Table 4.3 shows the phenotypes obtained for CPU and temperature modeling of the different servers in CeSViMa data center. We also report the MAE for both the training and the test set. We can observe that all phenotypes that model CPU temperature incorporate the parameters of interest (inlet temperature, power and fan speed), and we obtain errors below 1°C in all cases. The average RMSE accross models are 1.52 °C and 1.57°C for the training and test set respectively. As for inlet temperature, the phenotypes incorporate both differential pressure, and CRAC return temperature. Moreover, depending on the rack placement, the influence of

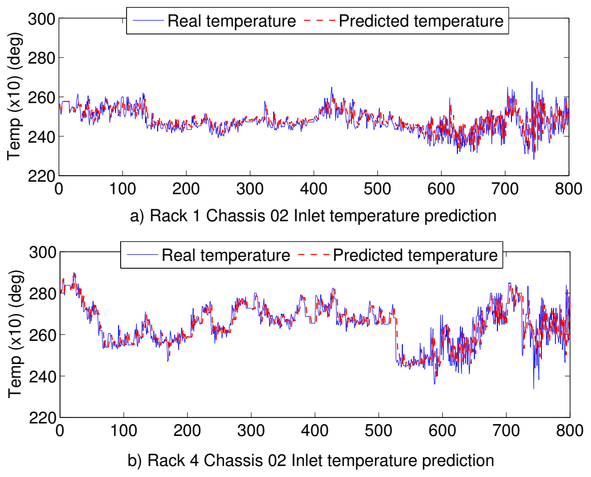


Figure 4.10: Data center inlet temperature modeling for various racks

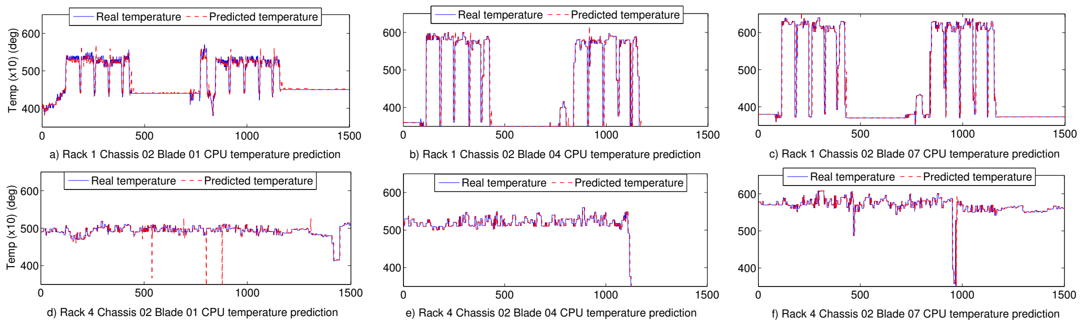


Figure 4.11: Data center CPU temperature modeling for various servers in different racks

the CRAC units vary. Here we can observe the benefits of the feature selection performed by GE. Rack1, which is the leftmost rack in the data center, is affected only by CRAC2; whereas Rack4, situated in the middle of the row, is affected both by CRAC2 and CRAC3. The model automatically incorporates the most relevant features, discarding the irrelevant ones. For inlet temperature prediction, our error is below 0.5°C, which is enough for our purposes and below other state-of-the-art approaches.

4.7 Discussion

In this section we briefly discuss the applicability of our models, i.e. how they can be applied to reduce energy consumption in data centers. We also show the computational effort needed to model a full data center scenario, and the feasibility of our approach.

4.7.1 Applicability

The main purpose of our modeling approach is the development of a methodology to predict server CPU temperature under variable cooling setups, so that cooling-associated costs can be reduced without incurring on reliability issues. To this end, we first predict the inlet temperature of servers given the data room conditions and cooling setup, and use this result to predict server temperature.

Model	Phenotype	Train.	Test
Inlet Rack1	$TIN[k-1] + e^{(-4.3\cdot(TRET2[k-3]/TRET2[k-11]))}/TIN[k-1]\cdot (e^{(+1.5\cdot TIN[k-5])} - e^{(-3.8\cdot(PDIF[k-20]-TIN[k-1]))})$	0.32	0.4
Inlet Rack4	$TIN[k-1] + 3.1/e^{(+5.0\cdot TIN[k-1])}\cdot e^{(+2.2\cdot TIN[k-2])} -e^{(-2.9\cdot TpIN[k-3])}\cdot TRET3[k-12]\cdot (TRET3[k-5] + e^{(-4.9\cdot(HUM[k-6]/TRET2[k-1]))}/ TIN[k-2]/e^{(+7.2\cdot(PDIF[k-20]-TIN[k-1]))})$	0.18	0.44
CPU Rack1, C02, B01	$TS[k-1] + (PS[k-20]\cdot FS[k-1] - 9.4\cdot(TpS[k-5]\cdot TpS[k-2]))/(e^{(+2.0\cdot FS[k-7])}/ e^{(-4.1\cdot TpS[k-5])}/(2.3 + e^{(+1.7\cdot(TpS[k-10]\cdot TpS[k-10]))} +e^{(+1.5\cdot FS[k-1])} - e^{(+1.6\cdot PS[k-7])}))$	0.68	0.76
CPU Rack1, C02, B04	$TS[k-1] + e^{(-7.2\cdot(TS[k-6]/PS[k-1]))}/(e^{(-6.1\cdot(TS[k-10]-PS[k-15]))} /5.6/FS[k-20] - 1.7 + TpS[k-20] - e^{(-3.0\cdot(TIN[k-4]/TS[k-15]))})$	0.51	0.85
CPU Rack1, C02, B07	$TS[k-1] + e^{(-6.2\cdot(TS[k-2]\cdot TIN[k-11]))}/((e^{(-9.8\cdot TS[k-8])} +e^{(-5.2*(TS[k-9]*PS[k-19]))})\cdot e^{(+5.8*FS[k-9])})$	0.55	0.75
CPU Rack4, C02, B01	$TS[k-1] + e^{(-3.1\cdot TS[k-2])}/(((TS[k-3]/PS[k-3]) + (FS[k-18] -FS[k-8])/e^{(-9.4\cdot(FS[k-1]-TpS[k-9]))}) - TpS[k-4] +(TpS[k-6] + TS[k-3]) - (TIN[k-3]/TpS[k-9]))$	0.29	0.46
CPU Rack4, C02, B04	$TS[k-1] + e^{(-5.7\cdot(TpS[k-6]*TpS[k-10]))}/e^{(+9.9\cdot(TpS[k-9]-TIN[k-10]))}$	0.26	0.73
CPU Rack4, C02, B07	$TS[k-1] + TIN[k-11]\cdot e^{(-9.5\cdot(TpS[k-10]/TIN[k-5]))}/ e^{(-9.9\cdot(TIN[k-10]-TS[k-5]))}$	0.43	0.87

Table 4.3: Phenotype and average error (in Celsius) in training and test set for CPU and inlet temperature modeling in a production data center

For a data center with the dimensions of CeSViMa (i.e. two rows of racks), and having analyzed the variability of inlet temperature traces in the data center, we need to predict inlet temperature at 3 different heights (at the bottom, middle and top of the rack), in one out of two racks. This results in having to generate 30 inlet temperature models. Because the maximum CPU temperature in the data center is the one limiting the cooling, we need to predict the CPU temperature of each server in the data room, i.e. we need as many models as servers in the data center.

These models allow us to predict the maximum server temperature attained in the data center and, thus, detect any potential thermal redlining and act before it occurs.

4.7.2 Computational effort

Our approach is computationally intensive in the model training stage. According to our results, our GE model needs to evolve a random initial population for 30,000 generations to obtain accurate results. In our experiments, running 30,000 generations of 4 different models in parallel takes 28h in a computer equipeed with a QuadCore Intel i7 CPU @3.4GHz and 8GB of RAM.

However, because the models obtained for several homogeneous servers are very similar, it is possible to reduce the training overhead by using already evolved populations to fine-tune the models instead of using the a new random population every time. This way, we can reduce the training time.

As for the model testing, in the worst case scenario, the model needs to be tested every 10 seconds. The overhead to test one model is found to be negligible. In this sense, it is feasible to compute all temperatures to find the maximum CPU temperature, i.e. the one that limits the cooling of the data room.

4.8 Conclusions

In this paper we have presented a methodology for the unsupervised generation of models to predict on runtime the thermal behaviour of production data centers running arbitrary workloads and equipped with heterogeneous servers.

Our approach leverages the usage of Gramatical Evolution techniques to automatically generate models of the data room by using real data center traces. Our solution allows us to predict the CPU temperature and the inlet temperature of servers, with an average error below 2°C and 0.5°C respectively. This errors are within the margin obtained by other approaches in the state-of-the art. Our solution, however, can be used on runtime, and does not require the usage of CFD software. Moreover, our models are trained and tested in two realistic scenario, a small-scale data room with one rack, and at a larger scale in the CeSViMa data center.

This work makes substantial contributions in the area of room temperature modeling, and advances the state-of-the-art by proposing the full temperature forecasting of a data center using evolutionary techniques, allowing the model generation in an unsupervised way, and generating predictions on runtime. Full temperature forecasting enables the development of room-wide cooling management strategies, based on the reduction of cooling power without hitting thermal redlining.

In the next chapter...

the reader will find the optimizations developed at the data center level, that allow us to save energy by taking into account the heterogeneity in terms of resources and applications in the data center. Moreover, we show the benefits obtained when using joint workload and cooling management strategies.

5. Data center heterogeneity and application-aware workload and cooling management

Mientras la ciencia a descubrir no alcance
las fuentes de la vida,
y en el mar o en el cielo haya un abismo
que al cálculo resista,
mientras la humanidad siempre avanzando
no sepa a dó camina,
mientras haya un misterio para el hombre,
¡habrá poesía!

— Gustavo A. Bécquer – *Rima IV (Rimas y Leyendas)*

In this chapter we propose a data center optimization strategy that takes advantage of the heterogeneity in terms of computational resources at the data center, to develop resource management techniques that minimize energy consumption.

In particular, we develop a MILP-based approach to first decide on the operating server set, i.e. to select the number of servers of each type used for a particular workload. Then, we allocate incoming tasks to the heterogeneous servers to minimize energy in a runtime fashion. Our experiments first focus on the reduction of IT power among three different server architectures (SPARC, Intel and AMD).

Then, we extend our results to a small air-cooled data center room where we have control over the cooling setup, and show how important benefits can be achieved by jointly optimizing cooling and computational power.

5.1 Introduction

Resource management is a well known concept in the data center world and refers to the efficient and effective deployment of computational resources of the facility where they are needed. Resource management techniques are used to allocate in a spatio-temporal way the workload to be executed in the data center, optimizing a particular goal. Traditionally, these techniques have focused on maximizing performance by assigning tasks to computational resources in the most efficient way. However, the increasing energy demand of data center facilities has shifted the optimization goals towards maximizing energy efficiency. Our work leverages this concept by proposing energy-aware resource management techniques that take into account the heterogeneity in terms of computational resources and applications. Moreover, we consider the impact of cooling power in our setups, and show how overall power consumption can be reduced by taking into account leakage and temperature.

There are a number of different techniques in the state of the art to reduce the energy cost and power density in data centers in different levels of granularity: chip-level, server level, rack level, data center level, etc. In the last years, several authors have addressed this problem by the well-known technique of Dynamic Voltage and Frequency Scaling (DVFS), where the hardware components are switched from high-power states to low-power states whenever performance allows. DVFS techniques usually apply run-time measurement and control of the desired application characteristics in terms of frequency and voltage power supply. While these approaches can effectively reduce the dynamic power of the system, they fail on exploiting the heterogeneity of the data center and they cannot minimize the system leakage power with an appropriate assignment of workloads.

The authors of [152] introduce three heuristic approaches to minimize the total power of a data center. They perform task scheduling to have a uniform outlet temperature profile, minimum server power dissipation, or a uniform workload distribution, respectively. Although these approaches try to minimize the data center power consumption, they do not provide a precise objective function and/or accurate mathematical formulation of the optimization problem that can be used for the validation of the optimal solution. Moreover, the heterogeneity of the data center is not considered and this mechanism of thermal optimization is not exploited by the authors. On the other hand, recent works like [182] do consider heterogeneous data centers and formulate a detailed mathematical model to perform an efficient energy-aware task scheduling. However, the authors do not propose a methodology to solve this optimization problem in an efficient way to drive the selection of processors in an heterogeneous data center under different workloads.

The work proposed in this chapter outperforms previous approaches in the field of energy-aware task assignment for green data centers by targeting the following goals:

- The usage of heterogeneity to minimize the energy consumption in data centers, by using a mixed static/dynamic approach to the problem and by characterizing real workloads in terms of energy.
- The static optimization aims to find which is the best configuration of the data center given a set of heterogeneous machines. We prove that the best combination is an heterogeneous data center.
- The dynamic optimization shows that the energy can be reduced significantly by optimizing the task allocation and distribution algorithm of the resource manager.
- We show how, by using our previous temperature and leakage models, we can reduce data room cooling power while predicting CPU temperature and leakage. This way, we can prevent server thermal redlining, and ensure that overall power does not increase due to server leakage.

This chapter is organized as follows: Section 5.2 describes the related work in the area. Section 5.3 describes our proposed solution, whereas Section 5.4 describes the optimization strategy. Section 5.5 describes the results obtained. Finally, Section 5.6 draws the most important conclusions.

5.2 Related Work

During the last years, several approaches have targeted the problem of energy efficiency in data centers by proposing different techniques to optimize the energy-efficiency metrics. In [29], [92] the authors have tried to identify workload time series to dynamically regulate CPU power and frequency to optimize power consumption. Other works that apply voltage scaling, like [133] and [55], also manage the concepts of (i) monitoring and estimating the load, (ii) switching incoming traffic to the selected server in a transparent way for the services and (iii) managing a pool of generic and interchangeable resources. Besides that, Heo et al. [76] developed a power optimization algorithm using DVFS and shutting down unused servers for large-scale applications spanning several non-virtualized servers with a load balancer. These works have proposed interesting approaches for the run-time management of the workload in homogeneous data centers; however, our research presents how the heterogeneity in the selection of the processors that compose the data center leads to higher energy savings.

Other authors consider the distributed problem as opposed to the previous centralized approaches. For example, the work done by Khargharia et al. in [86] presents a theoretical framework that optimizes both power and performance for data centers at runtime. Also, Bennani and Menasce [116] present a similar hierarchical approach addressing the problem of dynamically redeploying servers in a continuously varying workload scenario.

Load balancing [34], [51] which is a data center level approach can be used to distribute the total workload of the data center among different servers in order to balance the per-server workload (and hence achieve uniform power density). In this topic, dynamic resource provisioning has also been accomplished driven by the thermal response of the server to the running application, and some approaches have tried to predict the incoming workload in terms of requests per second [125]. As opposed to our work, the previous run-time techniques do not consider an off-line analysis for the energy-efficient design of the data center.

Virtualization technology has provided a promising way to manage application performance by dynamically reallocating resources to VMs. Several management algorithms have been proposed to control the application performance for virtualized servers [90], [123]. Several recent studies propose to solve the VM-server mapping problem for power savings [136], [160].

The closest works to ours are [182] and [18]. While the first one is focused on cloud servers and the second one applies control theory, both of them lack of a serious and accurate energy model that supports the proposed optimizations. Moreover, as opposed to us, they tend to consider data centers with a low workload or the absence of any initial workload before the management takes place.

In this chapter, we present a mixed static/dynamic approach for the energy-efficient management and configuration of an HPC data center. While previous techniques have not considered the impact of the proper selection of processors in the design of the data center, our research firstly proposes an heterogeneous design of the system based on an accurate energy model. After that, our optimization problem solved in run-time, will also exploit this heterogeneity to further reduce the energy consumption of the system, outperforming previous approaches. Finally, we show how using cooling management in conjunction with workload management yields increased energy savings.

5.3 Heterogeneity-aware resource management

5.3.1 Computing power reduction

In this section we propose a workload assignment policy that distributes the computation at run-time inside the data center, taking advantage of (i) the knowledge about the energy behavior of the applications to execute, and (ii) the resource heterogeneity of the data center.

To do so, we first propose a static optimization that selects the most appropriate resources of the data center, i.e. the best machines, to execute the workload. Secondly, we perform a run-time allocation that minimizes the energy consumption of the data center facility. Finally, backed up by the server and room-level modeling methodology develop in previous chapters, we set the data room cooling that ensures no server reaches thermal redlining while reducing overall energy consumption.

Our proposed approach mainly targets specific-purpose data centers. We assume a periodic utilization behavior, with periodic that can be easily characterized. This assumption is realistic, as can be seen when examining the workloads published by several HPC data centers in the Parallel Workloads Archive [1] Therefore, we can assume that the workload exhibited during a period of time (i.e: one day) is representative of the workload that the data center will have in any other period of time (i.e: the next day).

The traditional functional system found in today's data centers comprises: i) a workload, which is a set of different tasks entering the system; ii) a task scheduler, which queues the tasks in time, deciding their priority of execution; and, iii) a resource allocator, which has the knowledge of the available resources of the system and decides where each task is going to be

[1] http://www.cs.huji.ac.il/labs/parallel/workload/

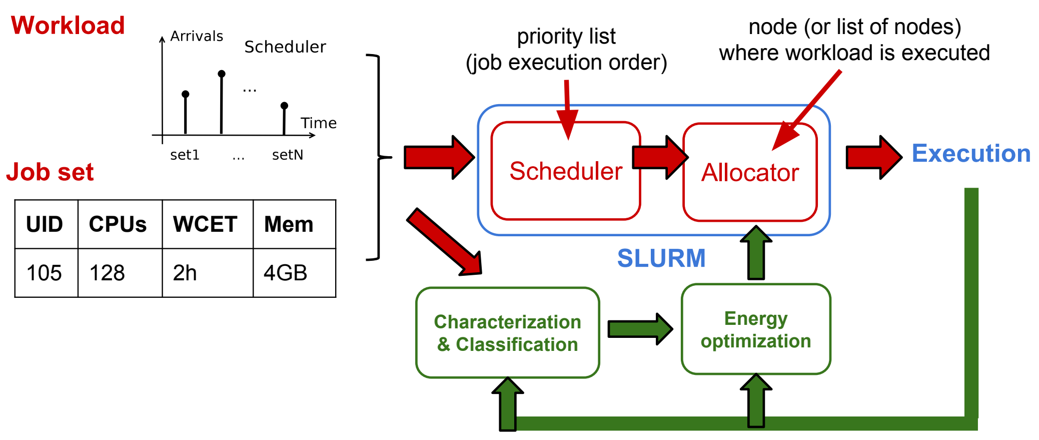


Figure 5.1: Diagram of data center resource management principles

executed (see Figure 5.1). In our work, to simulate workload allocation we use the resource manager SLURM [168].

By default, SLURM uses a round-robin policy to assign tasks to nodes. We use an open source SLURM simulator [98] developed by the Barcelona Supercomputing Centre to simulate the workload assignment with SLURM default allocation policy and our algorithm.

Our optimization assumes that the workload entering the system is scheduled by SLURM using a FIFO policy without backfilling (i.e. tasks are executing according to arrival priority), and we have developed our own allocation plugin to modify workload allocation of tasks to servers as needed.

By workload we understand a collection of job sets randomly distributed in time. Each job set has a random number of tasks; however, the number of different tasks is fixed for all workloads. Each task will be characterized for every machine (resources) of the system in order to obtain its profiling information. This characterization phase obtains the energy consumed by a specific machine or processor (in KWh) when a task is allocated and executed on it, by making real measures. The workload characterization phase obtains the energy consumption of every task in a particular processor. This information is used to make an efficient optimization of the data center in two different ways: static and dynamic.

The static optimization approach performs an off-line configuration of the data center to obtain the most suitable energy-efficient set-up. This approach will find the most appropriate combination of resources (server architectures) from a set of available ones, that will be needed to provide the required energy efficiency and still satisfy the performance constraints. We will show that the result of the optimization is a heterogeneous data center, which performs better than any of the homogeneous data centers.

The dynamic optimization works after the static one has been applied and performs a run-time optimization to allocate and distribute the tasks of the workload between the computing resources. This approach shows that different allocations of tasks lead to different energy consumption values. This means that we can create run-time optimizations in terms of energy that feed information back to the resource manager and exploit the availability of heterogeneous resources.

5.3.2 Cooling power reduction

Finally, we can use our previous server and room modeling methodology to reduce data room cooling power without an increase in leakage power or hitting any CPU thermal threshold.

In a typical air-cooled data center room, the air conditioning units pump cold air into the data room and extract the generated heat. The efficiency of this cycle is generally measured by the *Coefficient of Performance* (COP). The COP is a dimensionless value defined as the ratio between the cooling energy produced by the air-conditioning units (i.e. the amount of heat removed) and the energy consumed by the cooling units (i.e. the amount of work to remove that heat), as shown in Equation 5.1.

$$COP_{MAX} = \frac{\text{output cooling energy}}{\text{input electrical energy}} \tag{5.1}$$

Higher values of the COP indicate a higher efficiency. The maximum theoretical COP for an air conditioning system is described by Carnot's theorem as in Equation 5.2:

$$COP_{MAX} = \frac{T_C}{T_H - T_C} \tag{5.2}$$

where T_C is the cold temperature, i.e. the temperature of the indoor space to be cooled and T_H is the hot temperature, i.e. the outdoor temperature (both temperatures in Celsius). As the difference between hot and cold air increases, the COP decreases, meaning that the air-conditioning is more efficient (consumes less power), when the temperature difference between the room and the outside is smaller.

According to this, one of the techniques to reduce the cooling power is to increase the COP by increasing the data room temperature. However, as we increase room temperature, CPU temperature increases and so does leakage power. Therefore, there is a trade-off between the reduction in cooling power and the increament in server leakage power.

We use the previously developed models to decrease the power wasted on the cooling system to a minimum, while still satisfying the safety requirements of the data center operation, and keeping leakage temperature low so that it does not dominate total power.

5.4 Energy optimization algorithms

In the previous chapters, we focused our work on the development of models for servers and data centers. Once the characterization of the power consumed by the tasks is performed, we use the obtained information to generate a set of optimizations that improve the energy efficiency of a data center. In this sense, we can think of three different scenarios:

- The definition of a data center which has the optimum number of machines, given a limited budget and a limited space, to run the workload. In this work we want to show that the optimum data center, in terms of energy costs, is an heterogeneous data center.
- The upgrade of an existing data center with new machines. We want to show that the optimum resulting data center is heterogeneous and the selected machines for upgrade are selected based on a criteria for energy-optimality.
- The execution of the workloads in an already-existing data center. This refers to applying different and new resource managing techniques that exploit the machine heterogeneity.

These three case studies can really be combined into two: (i) a static and off-line approach, which includes the creation and extension of a data center; and (ii) a dynamic run-time approach, that tackles with the resource managing of the tasks to be executed.

The following subsections will explain further these approaches.

5.4.1 Static off-line data center server selection

The static off-line approach tries to find the suitable number and combination of server machines from a set of architectures, under a certain workload. The maximum number of different architectures to be used is given by the user. Each task of the workload has a different energy profiling in every processor, as characterized in the profiling phase.

The optimization phase is defined as follows. Let us denote by M a set of machines, by P a set of processors and by T a set of tasks that must be executed. Each machine m has a price of ψ_m, consumes power in idle state π_m and occupies a certain space α_m (understood as the number of U's in a rack). Each processor p belongs to one machine m, denoted as p_m. Every task t has a duration and consumes a certain amount of energy depending on the target processor, σ_{tp} and e_{tp} respectively. The problem consists on finding a subset of M that is able to execute the required tasks T minimizing the energy consumption:

$$\text{Minimize} \left\{ \sum_{t \in T, p \in P} k_{tp} \cdot e_{tp} + \sum_{m \in M} \pi_m \cdot \tau^{max} \right\} \tag{5.3}$$

where k_{tp} is a binary variable that is set to 1 if the task t is executed in processor p and k_m is a binary variable that is set to 1 if the machine m is used. τ^{max} is the time instant at which all the tasks have been executed. The set of constraints that the proposed model must fulfill are the following:

$$\sum_{t \in T} k_{tp_m} \cdot \sigma_{tp_m} \leq \tau_m^{max}, \qquad \left\{ \begin{array}{l} m = 1, \ldots M, \\ p_m = 1, \ldots P_m \end{array} \right. \tag{5.4}$$

$$\tau_m^{max} \leq \tau^{max}, \qquad m = 1, \ldots M \tag{5.5}$$

$$\tau_m^{max} \leq K \cdot k_m, \qquad m = 1, \ldots M \tag{5.6}$$

$$\sum_{p \in P} k_{tp} = 1, \qquad t = 1, \ldots T \tag{5.7}$$

$$\sum_{m \in M} k_m \cdot \psi_m \leq \Psi, \qquad \sum_{m \in M} k_m \cdot \alpha_m \leq A \tag{5.8}$$

These constraints 5.4–5.8 ensure that all tasks are executed within a maximum time, that all tasks will be executed once in a processor, and that both the price of the data center and the space used by it will not exceed certain values.

As a result, we will have the suitable number of machines of each type needed to build our data center with energy-performance constraints.

5.4.2 Dynamic run-time allocation

In this case we suppose that we already have an heterogeneous data center with a fixed number $m = 1, \ldots, M$ of machines (i.e.: the heterogeneous data center found with the static optimization) that can be of different types. The dynamic run-time allocation of the tasks, which will be performed by the resource manager, aims at minimizing the energy consumption of the assignment by placing each task where it consumes the minimum energy.

The minimization function is the same than the previous one 5.3. However, a new constraint is added in order to express the needs of the dynamic task allocation 5.9:

$$\sum_{t \in T} k_{tp_m} \cdot \sigma_{tp_m} + \gamma_{pm} \leq \tau_m^{max} \qquad \left\{ \begin{array}{l} m = 1, \ldots M \\ p_m = 1, \ldots P_m \end{array} \right. \tag{5.9}$$

Let us denote by M a set of machines, by P a set of processors and by T a set of tasks that must be executed. Each machine m has a price of ψ_m, consumes power in idle state π_m and occupies a certain space α_m (understood as the number of U's in a rack). Each processor p belongs to one machine m, denoted as p_m. Every task t has a duration and consumes a certain amount of energy depending on the target processor, σ_{tp} and e_{tp} respectively.

This time the problem consists on finding the most appropriate allocation of tasks t into processors p, that is, finding the optimum k_{tp} that minimizes the energy consumption. The new factor γ_{pm} indicates whether a processor $p = 1, \ldots, P$ is free or not when the optimization begins, so that the system can take into account the initial usage of processors.

Server Model	Processor	#Cores	Year	Price	Size
Fujitsu RX-220	AMD Opteron64 @2GHz	2	2005	$2000	2U
Fujitsu PrimePower450	Sparc64V @1.1GHz	4	2004	$1000	4U
Fujitsu RX-300 S6	IntelXeon @2.4GHz	8	2010	$3500	2U

Table 5.1: Server parameters for *Setup A: 3-architecture, IT control only*

The aforementioned constraints ensure that each task will only be allocated into one processor, try to find a compromise between energy minimization and execution time and allow to distribute tasks into an already-occupied system by setting γ_{pm} to an appropriate value.

As a result, the algorithm gives the allocation of each of the tasks in the workload to the specific machine. Because the workload is divided in job sets, the algorithm is executed each time a new set of tasks arrives. Because our problem tackles HPC data centers, we do not consider task reallocation.

5.5 Results

In this section we present the results obtained when applying resource allocation optimization techniques described in Section 5.4.

Through this section, we show results for two diffent setups:

- *Setup A: 3-architectures, IT control only*: In the first setup, we show the energy minimization obtained by applying our optimization in a cluster composed of three different server architectures: i) AMD RX220, ii) an IntelXeon RX330 server, and a SPARC PrimePower450. In this setup we have no control over the cooling subsystem, so we show savings only for IT power.

- *Setup B: 2-architectures, IT + cooling control*: A second setup in which we apply our policy to a cluster with two different server architectures: i) AMD Sunfire v20z servers and ii) IntelXeon RX330. In this cluster we are able to control cooling, and, hence we show the results when applying both IT and cooling control management. This setup is also the one we use for our case study on an e-Health scenario, shown in the next Chapter 6.

For each of the setups we characterize the workload being run, then we apply the static optimization and next the dynamic optimization. Finally, for *Setup B*, we also show the benefits when applying data room cooling control.

5.5.1 Workload characterization and server parameters

Setup A: 3-architectures, IT control only

The workload generated in this setup is composed of 12 different tasks of the SPEC CPU 2006 benchmark. Because we need to execute the benchmark in different architectures, to mitigate the effect of performance due to compilation, we compile all benchmarks with the same compiler tool (gcc-4.3) and with the most similar optimization flags. We generate a random workload of 2000 tasks randomly split in different job sets of 150, 200, 250 or 300 tasks, and with random arrival times of 10, 20 or 30 minutes.

The data used to characterize the workload for this setup has been taken from the commercial servers showed in Table 5.1 while executing the different tasks. The parameters needed to obtain the energy values (i.e: temperature, fan speed, etc.) have been obtained via *snmp*, *ipmitool* and the proprietary tools of Fujitsu. As can be seen in the table, the selected machines present a high level of heterogeneity: they have different processor architectures, different number of cores and hardware configuration and, while the Sparc and AMD machines are quite old, the Intel machine is a presently shipping server and, thus, is expected to outperform the other two servers.

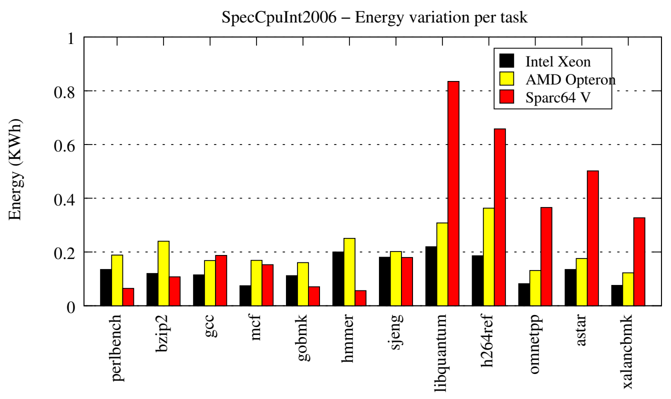


Figure 5.2: Energy Characterization of the tasks for *Setup A: 3-architectures, IT control only*

Server Model	Processor	#Cores	Memory	Idle Power	Max. Power
Sunfire v20z	AMD Opteron @2GHz	2	4GB	122W	220W
Fujitsu RX-300 S6	IntelXeon @2.4GHz	4	16GB	140W	2U

Table 5.2: Server parameters for *Setup B: 2-architectures, IT + cooling control*

We have executed the complete benchmark for all three different servers, measuring the ambient, motherboard and CPU temperature, and fan speed. For all three executions, both the ambient temperature and the fan speed have been approximately constant (i.e: variations in ambient temperature are less than 0.5°C). Figure 5.2 shows the energy consumed by each server when executing each of the tasks of the workload.

At a first glance, we can see that there is margin for improvement. For example, even though the Intel server should outperform the older ones, we find that there are some tasks in which the Sparc servers consume less energy than the Intel. On the other hand, the Sparc server behaves much worse with some other tasks.

Intuitively, this experiment lets us see that with the proper usage of heterogeneity and a good optimization algorithm we could obtain really good results in terms of energy by allocating tasks to those servers where they have a lower energy consumption.

Setup B: 2-architectures, IT + cooling control

In this setup, instead of using only SPEC CPU tasks, we also use some tasks that belong to statistical analysis algorithms, such as the ones used for bio-medical applications. In particular, we choose six applications from IBM SPSS statistical software used to extract information from the data obtained by bio-medical sensor nodes, such as correlation analysis, data regressions, estimation of data parameters and statistical classification.

These applications are characterized in an heterogeneous cluster composed of the two servers shown in Table 5.2. Again, these servers have different architectures, hardware configurations and the AMD Sunfire server is older than the Intel Xeon.

Figure 5.3 shows the energy consumption of each server when executing one instance of SPSS and SPEC CPU integer benchmarks. As can be seen, the most modern server (Intel Xeon server) outperforms the AMD Sunfire in all SPEC CPU 2006 benchmarks. In this sense, this second setup is less benefitial than *Setup A* to perform heterogeneous workload assigment. Still, not all tasks perform better in the Intel server. That does not happen for the SPSS benchmarks, where *boostrapping*, *bayes* and *bankloan* have a lower energy consumption in the AMD server. Moreover, depending on the SPEC benchmark, the differences in terms of energy consumption between AMD and Intel are smaller or larger, leaving room for improvement.

For this setup we generate three different workload profiles: (i) heavy, (ii) reference and (iii) light workload depending on the amount of tasks and their arrival rate. These profiles

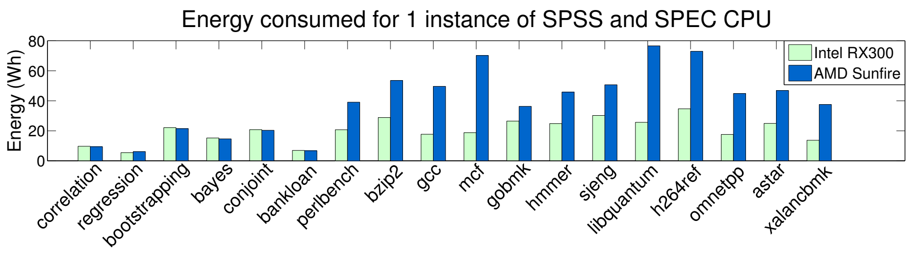


Figure 5.3: Energy for SPEC CPU 2006 benchmarks and SPSS in the servers of *Setup B: 2-architectures, IT + cooling control*

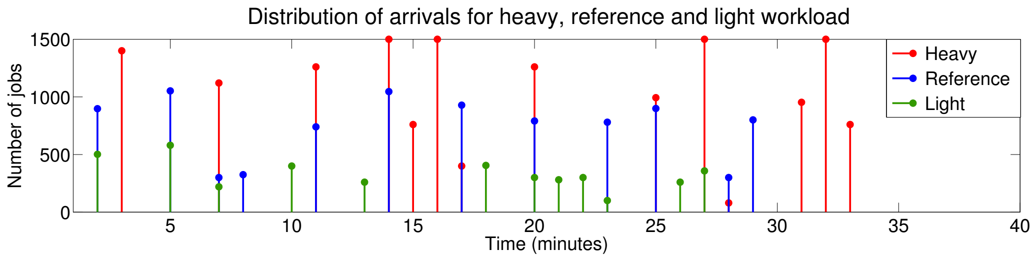


Figure 5.4: Distribution of arrivals for high, medium and low loads for *Setup B: 2-architectures, IT + cooling control*

emulate the typical distributions for workloads that arrive to a computing facility [104], in which the workload might show different temporal patterns of utilization at concrete periods or at certain hours of the day [24]. All three workloads are organized in 10 different job sets that arrive following a Poisson distribution with an average of 30 minutes. Each job set consists of a burst of tasks to be executed. The amount of tasks per job set follows a uniform distribution that depends on the workload profile: 1,000 to 1,500 tasks for the heavy workload profile, 500 to 1200 tasks for the reference workload and 300 to 700 tasks for the light workload profile. The arrival rate for the three workloads is the one presented in Figure 5.4.

5.5.2 Data center server selection results

As shown in Section 5.4.1, this experiment consists on the selection of the optimum heterogeneous data center, i.e., finding the number of servers of each type that minimize energy while keeping appropriate parameters of execution time, space and budget. All the algorithms presented for both this scenario and the next have been programmed using ILOG CPLEX optimization suite. The reason for choosing CPLEX is that provides optimization libraries to solve Mixed Integer Linear Programming (MILP) problems together with a very complete API for Java, C++, Python and .NET that eases the integration with other tools. We feed the algorithms with one job set of the workloads to be executed, and the algorithm solves which is the optimum number of servers to be used, and provides an optimum assignment for that job set.

Setup A, static optimization

In *Setup A*, as we are working with three machines that have completely different architecture, we show results for two scenarios. First we try to find the optimum data center configuration with the selection of cores from the group of the two oldest machines (the Sparc and the AMD architecture). Next, select the best server setup among all three architectures. We compare the results of the heterogeneous data center with the corresponding homogeneous data center, contraining either: (i) the total budget and space, or (ii) the total number cores (i.e. selecting clusters with the same computing capacity).

Configuration	Budget($)	#Cores	Time (hours)	Energy (kWh)
Heterogeneous (AMD & Sparc)	94000	214	118	2761
AMD only (budget limit)	94000	188	276	3472
Sparc only (budget limit)	94000	188	269	2913
AMD only (computation limit)	214000	214	249	3540
Sparc only (computation limit)	54000	214	243	2942

Table 5.3: Data center server selection comparison for *Setup A*

Workload profile	Server selection
Heavy	35 Intel + 5 AMD
Reference	35 Intel + 5 AMD
Light	35 Intel + 5 AMD

Table 5.4: Selected heterogeneous cluster configuration for each workload profile in *Setup B*, with a computation limit of 160 cores

AMD Opteron vs Sparc 64V: In this case, we give the optimizer a pull of 100 Sparc and 100 AMD machines, and a job set of 200 tasks to be allocated. The optimizer tries to minimize space, price and total execution time. Note that we do not feed the optimizer with the complete workload, but with one of the worksets instead. This way, we can optimize the data center configuration for an occupancy similar to the worksets of the workload. This will allow us to minimize the total computation time (and thus, the total idle power).

The optimum data center configuration found by the optimizer is composed of 27 AMD and 40 Sparc servers. The total time to compute the solution with the CPLEX library tools is 20 minutes. The amount of time spent to find a candidate solution is not relevant as this is an off-line optimization carried out just once, when the data center is going to be designed or extended. If we simulate the task allocation of the whole workload using Slurm for both this configuration and for the two equivalent homogeneous data centers, given the budget and the computational capacity limitation, we obtain the results shown in Table 5.3.

As can be seen, the heterogeneous data center outperforms the homogeneous ones both when homogeneous distributions with the same budget limitation are chosen or when the same computational capacity is selected. The savings in terms of energy range from a 5% in the worst case (homogeneous SPARC with budget limit) to 22% (homogeneous AMD with budget limit). In terms of time, the heterogeneous solution is also faster than the homogeneous one, with speed-ups in the range of 27-35%.

IntelXeon vs AMD Opteron vs Sparc 64V: In this case, we repeat the experiment for a pool of 70 Intel, 70 AMD and 70 Sparc, with the same job set of 200 tasks. It must be noted that this scenario is different from the previous one in the sense that it is clear that the Intel machines outperform the other two. The optimizer chooses as the best data center, however, an heterogeneous one comprised of 5 Sparc and 24 Intel machines. In this sense, the optimization system admits that there are some tasks that perform better in Sparc processors, and uses them to minimize energy. The improvement margin is, however, smaller. The heterogeneous solution obviously outperforms any Sparc homogeneous data center. When compared to the homogeneous Intel setup, however, the heterogeneous data center does not outperform the homogeneous Intel for the same budget limitation. However, for the same computation capacity (number of cores), the heterogeneous solution decreases energy by 6% and execution time by 7%.

Setup B, static optimization

Table 5.4 summarizes the results for static optimization in *Setup B*, for each of the three workload profiles (heavy, reference and light workload) when we limit total computation to a maximum of 160 cores for execution.

As can be seen, in this case the optimizer always chooses an heterogeneous data center

Configuration	Time (h)	Energy variation (kWh)
Heterogeneous AMD & Sparc	112	151
AMD only (budget limit)	248	218
Sparc only (budget limit)	261	290
Heterogeneous Intel & Sparc	90	101
Intel only (comp. limit)	100	134
Sparc only (comp. limit)	103	301

Table 5.5: Energy savings and performance for dynamic workload allocation of *Setup A*

containing a small amount of AMD servers that are used to perform the tasks in which they outperform the Intel servers in terms of energy efficiency. Those tasks are the ones previously shown in Figure 5.3. All the combinations use 160 cores and the amount of required AMD servers is highly dependant on the workload to be executed, as well on the duration of the execution, as the AMD servers present a lower static power than the Intel servers.

5.5.3 Runtime workload allocation results

The dynamic allocation of tasks aims at minimizing the energy consumption of the assignment by placing each task where it wastes the minimum energy in a spatio-temporal way. The input to our system is the same than in the previous scenario (i.e., an already scheduled workload). However, instead of allocating a particular job set, we allocate the whole workload.

This case is different from the previous one in the sense that the algorithms must be ready to work during run-time, in parallel with the execution of the workload. This can be accomplished by implementing a new Slurm plug-in that uses the CPLEX library tools for the task distribution and allocation. The optimization runs each time that a new job set (defined as a pack of random tasks) arrives at the resource manager, for a limited period of time, in order to assign tasks to processors. Note that the optimizer assumes all servers selected in the static optimization are turned on (no sleep modes are assumed), and focuses on improving total dynamic energy, i.e., the energy that the system uses for executing the workload. The goal of the optimization is not really to reduce drastically the total execution time (as this time is inherently reduced by the static optimization), but just to ensure that performance is not degraded.

Setup A, dynamic optimization

Table 5.5 shows the results of the dynamic optimization in *Setup A*, performed both for the homogeneous data centers and the heterogeneous ones and after the execution of the optimization algorithms with the whole workload. As can be seen, energy savings are obtained for all the data center setups, but specially for the heterogeneous ones, that outperform the homogeneous configurations in all cases. Even though the improvements are again higher for the AMD and Sparc combination, there are also savings in the Intel and Sparc case. This savings range from 24% to 47% without degradation on execution time.

Finally, it must be noted that the execution of this run-time optimization is completely feasible. As the algorithm does only have to work with the current job set, the optimization is fast: it only needs from 30s to 1min of time to find results with good error margins. As the execution time of a task ranges from 10 minutes to hours, the time overhead introduced by the optimization is negligible.

Setup B, dynamic optimization

For this setup, we provice an insight on the trade-offs of our solution when using different workload profiles, for the heterogeneous clusters selected in the previous section.

Figure 5.5 provides an insight on the workload coming into the data center for the three different workload scenarios when jobs are scheduled by SLURM default round-robin policy

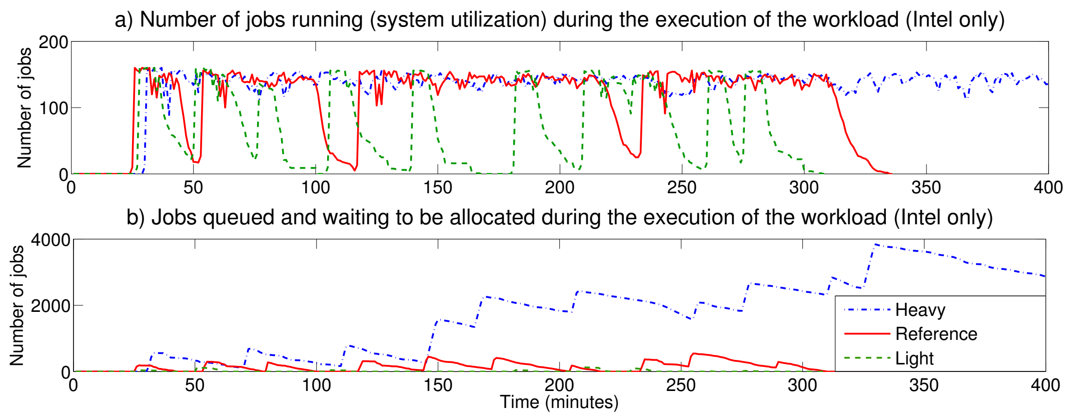


Figure 5.5: Running and waiting jobs in Intel only scenario for various loads with different number of coordinator nodes

Workload profile	Number of tasks	Energy consumption (kWh)			Execution time(h)		
		AMD	Intel	Intel + AMD	AMD	Intel	Intel + AMD
Heavy	8559	127.1	67.46	63.21	16.3	9.23	8.7
Reference	3765	61.7	34.12	31.89	7.8	4.7	4.5
Light	1961	37.31	28.02	27.6	4.8	4.3	4.3

Table 5.6: Energy consumption and execution time comparison between SLURM and optimized allocation for heavy, reference and light workload in *Setup B*

in an Intel 160-core homogeneous cluster. As can be seen, under the heavy workload profile, the number of jobs running is always close to the maximum amount of cores, i.e. the system occupancy is very high. Also, there is a huge number of jobs waiting to be scheduled. However, for the light workload profile with the system has a low occupancy for long periods of time.

Table 5.6 shows the comparison in energy and execution time for the execution of the three workloads, between the AMD homogeneous data center, the Intel homogeneous data center, and the Intel + AMD heterogeneous solution. As can be seen, the heterogeneous solution again clearly outperforms the homogeneous AMD data center. However, our purpose is not to outperform the AMD homogeneous scenario, as those servers are clearly older. Our goal is to prove how by means of application-awareness, i.e. knowing the energy profile of our workload, we can save energy. Moreover, our solution always saves energy without performance degradation when compared to the Intel cluster. This is accomplished not only because of the usage of a heterogeneous data center, but also because we schedule the workload in an optimum way thanks to the a priori knowledge of its behaviour in terms of energy and execution time. The energy savings obtained range from 1.4% for the light workload case to a 7.5% for a reference workload.

5.5.4 Cooling power reduction

In *Setup B* we have control over the cooling subsystem of the data room where the servers are placed. The data room considered is equipped with a Daikin FTXS30 unit, with a nominal cooling capacity of 8.8kW and a nominal power consumption of 2.8KW. For an outdoor temperature of 35°C the theoretical COP curve obtained by using the manufacturer's technical datasheet [48] is shown in Figure 5.6.

This figure shows how as the room temperature and the heat exhaust temperature raise, approaching the outdoor temperature, the COP increases and, thus, cooling efficiency improves. However, as we increase room temperature, CPU temperature increases and so does

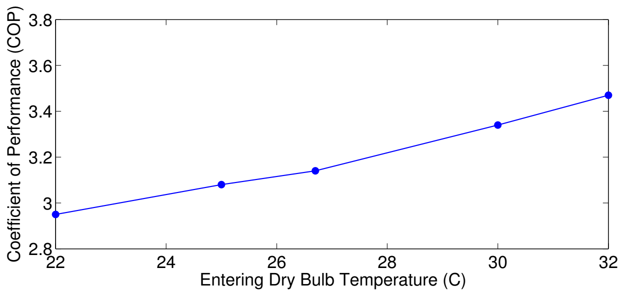


Figure 5.6: Evolution of the air-conditioning COP with room temperature

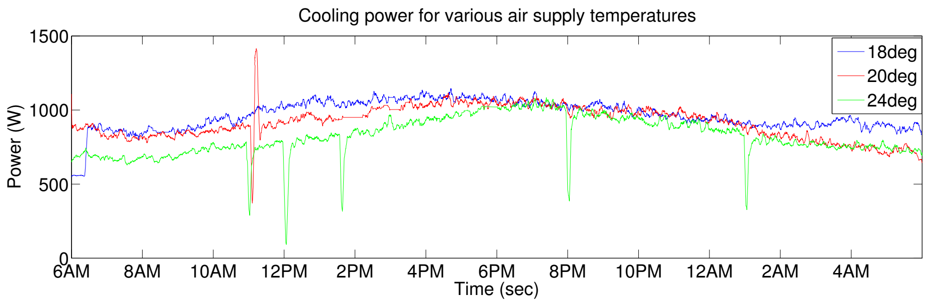


Figure 5.7: Cooling power for different air supply temperatures

leakage power. Therefore, there is a tradeoff between the reduction in cooling power and the increment in server leakage power. In our setup, we deploy sensors to measure the cooling power of the Daikin air conditioning unit, plus environmental sensors to measure the cold air supply temperature.

Moreover, given our previously developed models and the server monitoring deployed in the room, we are able to test the impact of server CPU leakage as room temperature raises.

Figure 5.7 shows the power consumption for different air supply temperatures. Data is gathered for a whole day, as the power consumption exhibits a periodic behavior dependant on the outdoor temperature. The power consumption decreases from 23.17kWh per day at 18°C to 19.65kWh when set to 24°C, yielding a 15% in energy savings.

For the same period of time, we gather server power consumption and CPU temperature when all servers in the data room are fully utilized running tasks of the SPEC CPU 2006 benchmark. Figure 5.8a shows the IT power consumption for the Sunfire V20z server and the IntelXeon that exhibit the higher CPU temperatures in our data room. These servers are the ones limiting the air-supply temperature, as we must ensure their safety operation and, we need to keep leakage from dominating power. Figure 5.8b shows how the server power consumption is almost stable, meaning that for these CPU temperatures we are working in the region where temperature-dependant leakage power is almost negligible.

For temperatures above 24°C, however, the contribution of leakage power starts to be of importance, thus, we set cooling supply temperature to 24°C. Table 5.7 shows the overall data center power consumption (IT and cooling power) when using the default SLURM allocation policy (first row), when only applying cooling control (second row) and when using joint IT and cooling control strategies (third row). As can be seen, we can obtain energy savings that range from 6.5% to 11% in total data center power, which is a very significant value. For the reference workload profile, if we analyze the impact of these savings in the electricity bill, and scale our results to the execution of 1 year of traces, for an energy cost of 0.1€/kWh, we obtain savings of 1,200€ per rack and year.

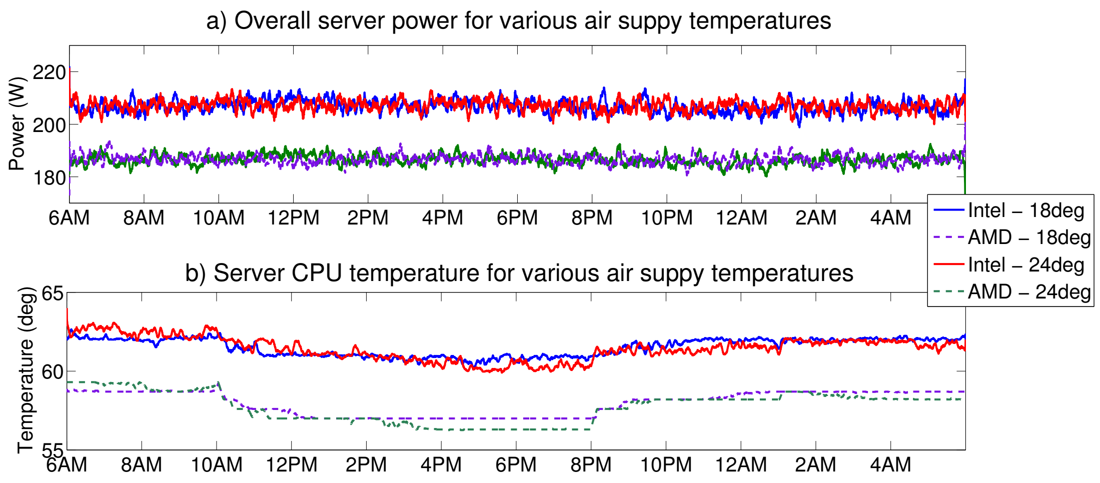


Figure 5.8: IT power and CPU temperature for fully utilized server at various air supply temperatures

	Heavy	Reference	Light
Default Slurm allocation	103.1	52.5	44.6
Default Slurm allocation + cooling control	97.7	49.7	42.1
Optimized allocation + cooling control	91.8	46.6	41.7

Table 5.7: Comparison in energy consumption (KWh) for heavy, reference and light workload when using Slurm default allocation, optimized allocation and cooling control for *Setup B*

5.6 Conclusions

This chapter proposes a mixed static/dynamic energy minimization strategy for data centers. The solution is especially aimed for specific-purpose HPC data centers, which exhibit high occupancies and where the workload can be adequately characterized. The proposed static approach shows how the proper selection of the heterogeneity of the data center design can achieve a notorious energy minimization during the design phase of the system. This energy optimization can be extended to more than a 20% with low execution time overhead when combined with the proposed dynamic load assignment mechanism. Moreover, if we combine the static/dynamic IT optimization with a data room cooling control mechanism, we can achieve energy savings that range from 6% to 11% in overall data center energy savings.

The conducted experimental work in this chapter has tackled realistic workloads and machine architectures, showing results for two different experimental setups. Moreover, the runtime optimization can be easily implemented in the resource manager as an Slurm node selection plugin, which allows integration with actual commercial data centers.

In the next chapter...

the reader will find the optimization of a global distributed application. In particular, we focus our work on the allocation of tasks between distributed nodes and the data center, and show how we can save energy to a greater extent by applying optimizations at different abstraction layers.

6. Global optimization of the distributed application framework. A case study for e-Health scenarios

Astros, fuentes y flores no murmuréis de mis sueños, Sin ellos, cómo admiraros, ni cómo vivir sin ellos?
— Rosalía de Castro, *Astros, fuentes y flores*

Next-generation applications such the ones found in smart cities, e-health, or ambient intelligence, require constantly increasing high computational demands to capture, process, aggregate, and analyze data and offer services to users. Research has traditionally paid much attention to the energy consumption of the sensor deployments that support this kind of application. However, computing facilities are the ones presenting a higher economic and environmental impact due to their very high power consumption.

In this chapter, we propose the use of a global optimization framework to reduce the energy consumption of next-generation applications, focusing on a case study for e-Health scenarios. e-Health systems save lifes, provide better patient care, allow useful epidemiologic analysis and save money. However, there are seveleral concerns about the costs and complexities associated with e-Health implementation, and the need to solve issues about the energy footprint of the high-demanding computing facilities.

This chapter proposes a novel and evolved computing paradigm that: (i) provides the required computing and sensing resources; (ii) allows the population-wide diffusion of e-Health solutions; (iii) exploits the storage, communication and computing services provided by data centers; (iv) tackles the energy-optimization issue as a first-class requirement, taking it into account during the whole development cycle. The novel computing concept and the multi-layer top-down energy-optimization methodology obtain promising results in a realistic scenario for cardiovascular tracking and analysis.

6.1 Introduction

e-Health is a new concept of health management that produces several benefits. First, it reduces sanitary costs by prevention of potential diseases. Besides, it empowers the patients with a new generation of non-invasive, wearable personalized devices to make them more independent, and to provide early signals of health decline and advice for appropriate actions in daily life. Finally, analysis of the obtained data greatly improves prevention by detecting early patterns of potential diseases; it allows to evaluate the efficacy of treatments, to understand (through complex processing) the evolution of diseases and the factors that influence them. Biomedical engineers envision "a new system of distributed computing tools that will collect authorized medical data about people and store it securely within a network designed to help deliver quick and efficient care" [119].

In order to obtain such benefits, the target population has to be monitorized 24 hours a day, and a Wireless Body Sensor Network (WBSN) is deployed. Thus, the system is composed by a large set of nodes, distributed among the population. Such nodes are non intrusive and portable, which imposes constraints on their energy consumption. Data obtained by the sensors are communicated to the embedded processing elements (PDAs, smartphones, etc.) by means of wireless connections.

Then, the huge set of data must be analyzed with the aim of performing the epidemiologic assessment. Also, diagnosis algorithms have to be implemented to allow early detection of pathologies and to learn the evolution of patients.

Since the target population is large, so it is the number of sensing nodes, and the amount of data to be managed is huge. In order to deal efficiently with such computationally intensive tasks, the use of data centers is devised. Thus, the WBSNs will be connected not only at the node level, but also through the PDA, Smartphone, etc. to data centers. Part of the data processing and storage will be local to the node, while another part will be communicated and processed in data centers, depending on the application, the state of the batteries and on security or privacy requirements of the information. The availability of the aforementioned technologies and the need of a continuous, portable, and non-invasive monitoring of the health information has led us to envision and design a real-time health monitoring and analysis framework capable of aiding health-care professionals. According to [60], one of the main questions to be answered is how computation can be offloaded and distributed from mobile devices to the data center efficiently. The reasons for sharing/offloading work from a mobile device would be: limited computational capability, limited battery power, limited connectivity and to make use of idling processing power.

The focus of this work is proposing a novel multi-layered approach for the energy optimization of the overall application framework, and the validation with a case of study devoted to health monitoring and analysis applications.

This chapter makes the following contributions:

- we define a realistic and current application scenario where the computing and energy saving challenges are exposed;
- we propose a new highly-efficient computational paradigm;
- we demonstrate that the application characteristics must be considered in the computational paradigm since the very beginning of the design process;
- we propose a global strategy for energy efficiency in the computational architecture.

The remainder of this chapter is organized as follows: Section 6.2 describes the related work on the area. Section 6.3 shows the proposed energy optimization paradigm, whereas Section 6.4 describes the case study of this work. Section 6.5 briefly describes the models used, whereas Section 6.6 develops a global resource management optimization, which consitutes one of the main contributions of this chapter. In Section 6.7 we show how all the proposed optimizations can be integrated from a multi-layer perspective. To end the Chapter, Section 6.8 summarizes the main challenges and Section 6.9 draws the most important conclusions.

6.2 Related work

The use of MCC environments for the automation of personal health-care systems has been recently related in literature [4], [84], [126]; however, none of these works have approached the energy efficiency these kind of architectures.

Energy consumption is one of the major concerns for the adoption of population-wide health monitoring systems, but energy efficiency cannot be added as an afterthought. Truly energy-efficient monitoring can only be achieved by considering energy as a first-class requirement, taking it into account during the whole development cycle, from design to implementation. Thus, we propose an architecture driven by energy concerns and aimed at optimizing energy consumption globally.

In literature, we can find several energy optimization techniques that target the different abstraction levels of the MCC architecture.

At the distributed computing level, the design of WBSN nodes is mainly focused on maximizing the lifetime of the node by reducing the energy consumption, although other performance requirements such as the delay and quality of the delivered data must be kept into account [23]. Energy efficiency in WBSNs has been tackled by proposing efficient MAC layer alternatives [122], providing stochastic approaches for traffic handling [58] or enabling compressed sensing signal acquisition/compression algorithms [100].

At the server level, throughout this Ph.D. thesis we have cited several sources that support the claim that one of the main problems to be solved in order to achieve the performance goal is the so called *power-wall* [18]. Thus, power consumption limits the advances in computer technology and is becoming a relevant part on the budget of present data centers.

As shown in previous chapters, researchers have done a massive amount of work to provide an energy-aware high performance computing environment. In these works, different scheduling, resource allocation and work assignment mechanisms are studied to improve the energy profile. Multi-layered approaches like ours, that targets both the node and server levels, are still missing. Some energy optimization policies have been detected but not successfully proposed mainly due to the fact that they do not consider the global power consumption. In particular, they do not take into account the following:

1. that the agents involved in the problem (wireless nodes, embedded processors, network interfaces, high-performance servers, etc.) are very heterogeneous from the energy point of view. Therefore, the energy cost of performing part of the processing in any of the different abstraction layers, from the node to the data center, should be evaluated;

2. a local optimization in one of the abstraction layers can have a bigger negative impact on the others, so that the global energy of the system is increased. In this way, the relationships between all the computational agents have to be taken into account.

Our proposal develops global energy optimization policies that start from the design of the architecture of the system and take into account the energy relationship between the different abstraction layers.

In our work, we manage the whole set of abstraction levels in MCC to obtain the maximum benefit of the energy-aware policies. Among others, we consider computation offloading from the data center to the wireless nodes (and viceversa) as an effective mechanism for energy optimization. Computation offloading in MCC scenarios has been proposed by Kumar and Lu [89] and has proved to provide high benefits. However, the authors have not considered realistic scenarios like e-Health and have not proposed a multi-layered optimization approach that combines this technique with other optimization mechanisms.

Some authors have recently followed a similar approach to our multi-layered proposal. For example, Greene [68] described a research work on how to reduce GPS power consumption by offloading certain calculations onto the data center. However, to the best of our knowledge, this is the first time that a work targets for energy optimization purposes the several constituent layers that enable MCC in e-Health scenarios. Our work provides horizontal and vertical approaches to extend the energy savings that these environments require.

6.3 Devised computer paradigm

As previously described, our envisioned MCC e-Health system is composed of a number of body sensors, wirelessly connected to the Internet through a mobile processing device (as illustrated in Figure 6.1). The distributed system spans a network comprised of individual health monitoring systems that connect through to data center facilities.

To provide adequate energy management, this heterogeneous distributed computing system for health monitoring is tightly coupled with an energy analysis and optimization system, which continuously adapts the amount of processing that is performed in the different layers of the distributed system, and the resources assigned to each task.

It is important to stress the need for a top-down approach, driven by the application context and the energy constraints, in order to reach an optimum solution globally.

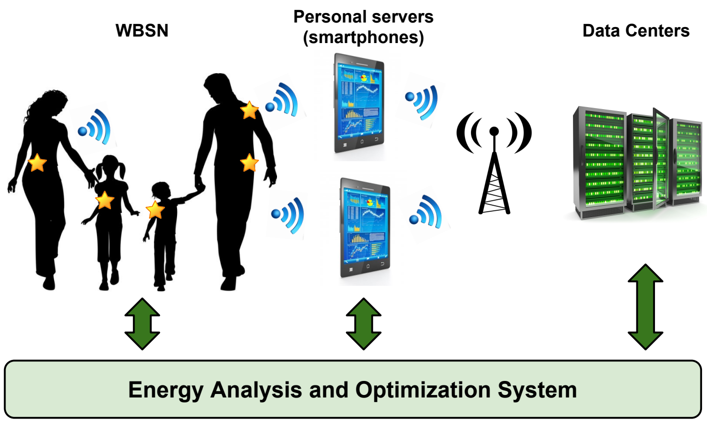

WBSN
Personal servers (smartphones)
Data Centers
Energy Analysis and Optimization System

Figure 6.1: Overview of the proposed architecture for energy optimization in e-Health scenarios

6.3.1 Energy optimization system

The energy optimization system proposed in this chapter follows the architecture proposed in the introductory chapter of the Ph.D. Thesis (see Section 1.3, Figure 1.4), in which we proposed a global optimization paradigm based on monitoring to acquire data, modeling and optimization in several layers of abstraction. Figure 6.2 provides higher detail on the specific system targetting our case study.

Detailed functions of constituents in the system are summarized as follows:

- Application support network: Population analysis applications require an heterogeneous network comprised of sensor nodes, data centers, and some kind of interconnection network. Each node has different computation capacity, functional requirements, communication capacity, battery capacity, power consumption characteristics, etc.
- Sensing infrastructure: Global energy optimization requires a clear understanding of the current state of the network, the characteristics of the different resources and of the analysis to be performed. Therefore, additional HW and/or SW sensors should be added to the system to get an insight.
- Data analysis and sensor configuration: Not every sensor has the same importance to understand the power consumption characteristics of the different components. After a careful analysis, the sensing infrastructure is configured to provide only the relevant data at the required rate for the power model to be useful, and also to minimize the energy overhead of the energy optimization system.
- Storage and inference system: Data provided by the sensing infrastructure has to be stored and statistically analyzed in search of recurrent behaviors that could lead to simple but accurate power models to be used for proactive optimizations. Although the data provided by the sensors is very low-level, simple inference techniques can be used to raise the level of abstraction, for example, to understand the characteristics of energy demand by the different applications.
- Power model: Complex power models are not adequate for online optimization, as different alternatives should be quickly evaluated against the power model to proactively configure the whole system for minimum energy consumption. These power models can be trained with actual data from sensors in order to improve the quality and also to adapt to variations in the heterogeneous application support network.
- Optimization: Based on the current state of the system, the historic data, and the energy characteristics of application and resources, many optimization algorithms can be

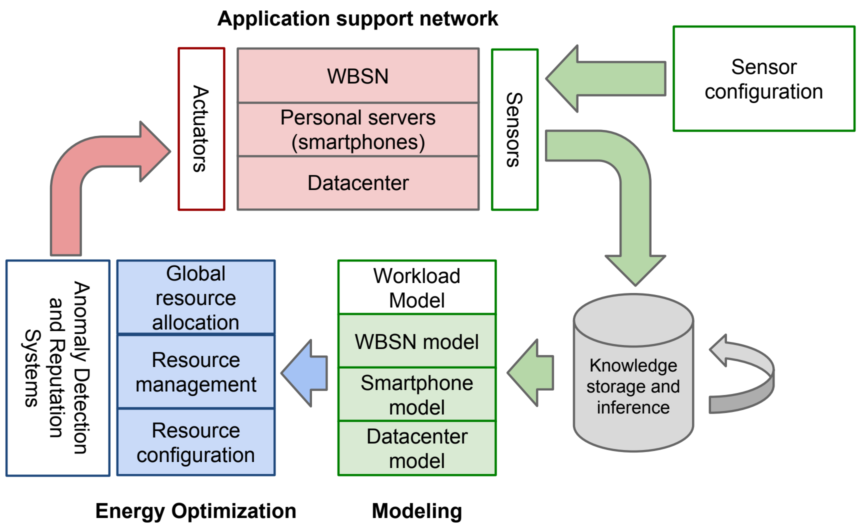


Figure 6.2: Overview of the proposed energy analysis and optimization system for population analysis applications

	Node	Coordinator	Data Center
Resource allocation		*Global resource allocation*	
Resource Management & Configuration	WBSN adaptation [155]	Virtual architecture [5]	*Data center RM* *Cooling control*
Application/Compiler	ECG algorithms [100] [138]	Compiler and app.-level tools [153] [94]	Virtualization
Architecture	Loop buffering [11] [161] IMO [12]	RAM optimizations and PCM [53]	DVFS [91]

Table 6.1: Summary of optimizations for different elements of the architecture and abstraction levels

executed to enhance one or more aspects of the population monitoring system. Heterogeneity can be analysed to always assign tasks to the most adequate resources; resources not being used can be turned off and cooling energy can be taken into account when assigning tasks to resources.

- Decision making system: All the different partial optimizations obtained in the system should be integrated in order to obtain the overall energy savings of the architecture.
- Actuation support: Finally, decisions should be executed. Software agents in the body sensors, personal servers (smartphones or PDAs), and data centers are in charge of reconfiguring their behavior whenever an optimization decision is made.

The energy optimizations that could be applied at the different elements of the architecture and at different levels of abstraction for the particular case of applications for ECG population analysis are summarized in Table 6.1. Research has paid attention to some of the above mentioned aspects, however, there are still some areas where contributions are needed. Moreover, these different contributions need to be integrated in a top-down fashion that ensures the global energy minimization.

Our work makes contributions in the areas not covered by other authors, emphasized in the table, as well as on the integration of all these optimizations. The goal is to perform a multi-objective energy-optimization in all the abstraction levels of design (vertical integration) as well as in all the components of the architecture (horizontal integration). The results of these optimizations are globally evaluated to obtain the energy savings for the whole architecture and observe the impact of each optimization.

Component	Model	Processor	#Cores	Memory	Idle Power	Max. Power
Node	Shimmer	MSP430 @8MHz	1	10KB	6.6mW	85mW
Coordinator	Samsung Galaxy SII	ARM Cortex-A9 @1.2GHz	2	1GB	0.5W	2.5W
Rack Server	SunFire v20z	2x AMD Opteron @2GHz	2	4GB	122W	220W
Rack Server	RX-300 S6	Intel Xeon @2.4GHz	8	16GB	140W	200W

Table 6.2: Summary of properties for all architecture components in the e-Health application

6.4 Case study

In this section we describe a particular case study for ECG monitoring applications that we use throughout the chapter to apply all energy models and optimizations, and that is evaluated from a multi-layer perspective (Sections 6.5, 6.6 and 6.7). The architecture previously mentioned for MCC technologies includes 4 types of elements: (i) sensors, (ii) nodes, (iii) coordinators and (iv) a data center facility. In our case study:

- Sensor: ECG sensors placed on the chest of the subject to record the signals of interest.
- Node: Shimmer platform. Composed of a Texas Instruments MSP430, a low power IEEE 802.15.4-compliant radio (CC2420) and Bluetooth radio (not used due to high power consumption). HW characteristics: CPU 8MHz, 10KB RAM, 48KB Flash. The Shimmer platform is placed near the sensors and connected to them with wires. This node can perform some conditioning on the signals received and sends them to the coordinator via radio. If more than one ECG sensor is used, they are connected to the coordinator describing a star topology.
- Coordinator: Android-based smartphone. HW characteristics: CPU 1GHz, 1GB of RAM, 16GB of Flash Memory and a battery of 2000mAh. The coordinator is usually placed at the waist of the subject and receives information from all the nodes that the person is wearing. It can perform some computations on the received signals (see Section 6.6) and it forwards data to the cloud computing facility via a 3G or WiFi network.
- Data center facility: Modern data centers are equipped with a large number of enterprise servers. Because of budget limits when renewing the equipment, in these facilities we usually find different generations of machines, often from even different manufacturers. For this case study we assume a heterogeneous cloud computing facility with two different servers (Intel and AMD) from different generations, exactly as in *Setup B* in the previous Chapter 5.

Table 6.2 summarizes the properties of the different components of the architecture. Note that maximum power for rack mounted servers indicates the maximum power measured when fully utilizing the system, not the maximum power that can be drawn by the power supply. Thus, this power is dependant on the particular hardware configuration of our servers

This case study considers a deployment consisting on 300 Shimmer nodes, 300 coordinators (smartphones) and a data center where a total amount of 160 cores, belonging to 40 Intel or AMD machines, are dedicated to our computational needs and placed in an air-cooled data room.

We define three different workload profiles: (i) heavy, (ii) reference and (iii) light workload depending on the amount of tasks and their arrival rate, as in the previous chapter (Section 5.5.1, *Setup B*).

The different tasks of the workload are representative of the computation that has to be performed for e-Health monitoring applications and information extraction in data centers. Particularly, we use the following benchmarks and algorithms:

	Tasks	Execution Time	Instructions per Cycle
Low demanding	6 (regression)	<360sec	<1.3
Medium demanding	6 (gcc, mcf)	360-600sec	<1.3
High demanding	6 (bzip2, hmmer)	460-800sec	>1.3

Table 6.3: Classification and main parameters for the tasks of the workload

- Customized state-of-the-art ECG acquisition, compression and delineation algorithms, such as Compressed Sensing or Digital Wavelet Transform, as well as encryption and decryption algorithms (e.g. AES) for secure data transmission.
- Statistical analysis algorithms, obtained from the IBM SPSS Statistics software. We choose six applications commonly used to extract information from the data obtained by biomedical sensor nodes, such as correlation analysis, data regressions, estimation of data parameters and statistical classification.
- CPU-intensive tasks, obtained from the SPEC CPU 2006 benchmark suite [148], representing algorithms of a higher abstraction level for the complex analysis and representation performed over data that has already gone through a data analysis and conditioning step. We choose the 12 tasks of the integer benchmark, among which we find data interpreters, decompression algorithms, combinatorial optimizations, database searching algorithms or event simulations.

This workload must be known and profiled in advance for our experimental study. Data centers usually execute the same set of applications, what facilitates this knowledge extraction. Moreover, modern supercomputing infrastructures like CeSViMa provide a mechanism for fast application profiling before the actual execution.

For our purpose, we suppose that each job set is split in two different levels: (i) a Data-Dependant layer, in which most of the algorithms and computation are dependant on the data generated by the Shimmer nodes; and (ii) an Application-dependant layer, in which algorithms operate over data generated in the previous layer, and computation depends on the particular goal that has to be achieved. Because of the number of nodes deployed, we assume that in our workload, a 60% of tasks belong to the Data-Dependant layer and the other 40% to the Application-dependant layer.

Moreover, because of the different nature of the algorithms to be executed, we assume that the tasks of the workload can be split into different classes according to the computing resources needed for execution. We define three different classes: (i) high-demanding applications, (ii) medium-demanding applications and (iii) low-demanding applications. Tasks are classified into a particular category attending to their computational demand by means of the *k-means* clustering technique presented in Section 6.6. Table 6.3 shows the amount of tasks per category, example tasks for each category as well as two of the most important parameters for classification criteria (execution time and instructions per cycle).

Finally, each of the two layers contains a different percentage of each of these tasks. The Data Dependant layer contains a 70% of low-demanding tasks, a 25% of medium-demanding and a 5% of high-demanding tasks. The Application-dependant layer contains a 70% of high-demanding tasks, a 25% of medium-demanding tasks and a 5% of low-demanding tasks. Figure 6.3 summarizes the main parameters of the workload and its structure.

6.5 Power models used

In order to optimize energy consumption of the overal MCC environment, we first need to understand which are the different main contributors to the overall power consumption. Then, we use several models both from literature and from our previous work to describe the behavior of the different elements of our architecture. Therefore, in this section we present the power

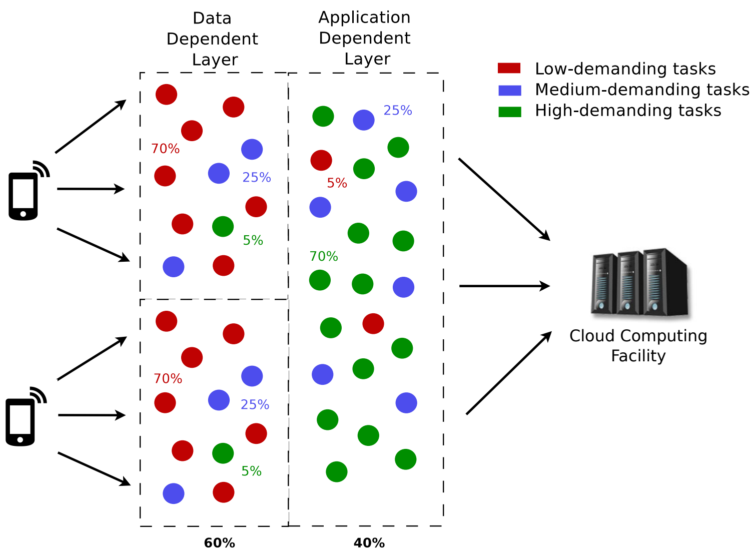


Figure 6.3: Workload structure for the Data Dependant layer and the Application Dependant layer

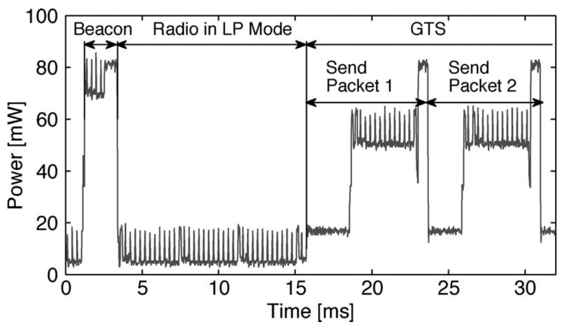


Figure 6.4: Power dissipated in Shimmer during sampling, processing and transmission [100]

modeling for the nodes, coordinators and the data center infrastructure that are managed by the optimization algorithms presented in Sections 6.6 and 6.7.

6.5.1 Node model

The main contributors to the energy consumption at the node level are the sensors themselves (signal transducing and analog-to-digital conversion), the microcontroller (because of the calculations performed), the memory and the radio interface. The energy of the node (E_{node}) can thus be described as the sum of those terms:

$$E_{node} \approx E_{sensor} + E_{\mu C} + E_{mem} + E_{radio} \tag{6.1}$$

Figure 6.4 shows the power consumption trace of the Shimmer node running a simple ECG streaming application. The Shimmer platform implements a reduced version of the beacon-enabled mode of the IEEE 802.15.4 protocol that uses guaranteed time slots (GTS). The transmission consists of three phases: (i) the beacon reception, in which the radio is receiving and the microcontroller is idle, (ii) Low-Power mode until the start of the assigned GTS, and (iii) transmission of the ECG signal to the coordinator during the GTS. During these phases, microcontroller and radio go through different power states [100].

From the energy perspective, there is a trade-off between the amount of information sent through the radio link and the signal processing performed at the microcontroller. In ECG

	ECG Streaming	CS	Single lead	2-lead Morph.	2-lead spline
Packed ready every... (ms)	304	605.9	2250	2250	2250
Energy Consumption (mJ)	7.70	7.29	7.42	8.68	10.12
Lifetime (h)	134.6	142.1	139.6	119.3	102.4

Table 6.4: Node lifetime for the different algorithms

applications, there are several frequently used algorithms for signal compression and reconstruction that are performed at the node level. The most common are: (i) Compressed Sensing (CS), (ii) Digital Wavelet Transform (DWT) and (iii) Multi-lead DWT.

Works by Mamaghanian [100] and Rincon [138] show the energy differences when implementing these algorithms in the Shimmer platform. Table 6.4 summarizes the different node battery lifetime encountered depending on the algorithms and transmission strategies performed.

Results show that total energy consumption increases with the computational burden of the algorithms and, thus, battery life is reduced. However, the radio interface is not always the responsible for most of the energy consumption.

The previous energy results for different ECG algorithms are used in the optimizations in Sections 6.6 and 6.7 to optimize the overall consumption by properly balancing the power consumption of the node elements and the coordinators.

6.5.2 Coordinator energy modeling

Our efforts in the energy modeling of the coordinator nodes (i.e. smartphones) focus on being able to describe the impact of running the MCC algorithms on the smartphone battery life.

The main contributors to the power consumption in todays smartphones are the communications (GSM, Wifi, etc.), graphics and the CPU when the system is suspended (i.e. most of the time) and also the display when the system is idle [36]:

Because the Shimmer nodes are responsible for the wireless transmissions, the Shimmer attached to the smartphone is responsible for the radio reception instead of the smartphone itself, meaning that the ECG algorithms are a computational burden that has an impact mainly on the microcontroller power consumption.

Because of that, we consider that the energy consumed by the coordinator (E_{coord}) can be described as in Equation 6.2:

$$E_{coord} \approx E_{comm,idle} + E_{graphics,idle} + E_{\mu C} \tag{6.2}$$

where $E_{comm,idle}$ and $E_{graphics,idle}$ are the idle power for communications and graphics and $E_{\mu C}$ is the power consumption for the microcontroller, which varies depending on the algorithm executed. In order to characterize the power consumption of the microcontroller we use the *Lookbusy* synthetic workload to stress the system during monitored periods of time. *Lookbusy* can stress all the hardware threads to a fixed CPU utilization percentage without memory or disk usage. The usage of a synthetic workload to derive the CPU model has many advantages, the most important of which is that CPU power can be described as linearly dependent with CPU utilization (u_c) and Instructions Per Cycle (IPC), as seen in Equation 6.3:

$$E_{\mu C,coord} = A_c \cdot u_c + K_c \tag{6.3}$$

where A_c is a constant. Our coordinator nodes (Samsung Galaxy SII smartphones) are equipped with an ARM Cortex-A9 processor at 1GHz. This processor is commonly found in many embedded system devices, such as the Panda board [1]. To ease the profiling process, we characterize the ARM Cortex-A9 processor in the Panda board by measuring the energy consumption

[1]http://pandaboard.org/content/resources/references

with a Fluke 80i-110s AC/DC current clamp when running *Lookbusy* at different utilization values. We then fit this data by means of a MATLAB regression to obtain constants A_c and K_c.

6.5.3 Data Center power modeling

The data center power models used are the ones developed in the previous chapters of this PhD. Thesis. In particular, we use the server, data center and cooling models developed for the particular scenario of *SetupB: 2-architectures, IT + cooling control*, shown in Chapter 5.5.

6.6 Global Resource Allocation techniques

In several traditional distributed Mobile Cloud Computing solutions, the sensor and coordinator nodes of the architecture either perform as much computation as possible (with the inherent penalty in battery lifetime) or forward all computation to the computer facility, even though coordinator nodes have enough computational capabilities to perform other tasks. These strategies do not consider the benefits in terms of energy savings that an efficient allocation of workload can provide.

Our global resource allocation proposes a coarse-grain workload assignment technique that aims to reduce the overall energy consumption of the architecture by optimizing the tradeoff between offloading computation to the data center facility and executing the calculation in the nodes. To do so, low-demanding tasks of the Data Dependant layer are executed in the coordinator nodes, instead of forwarding all the tasks to the data center, while medium and high demanding tasks are offloaded to the data center infrastructure. We leverage the concepts of our previous work on heterogeneous resource management by improving the state-of-the-art allocation algorithms and refining the modelling and assignment for nodes with lower resources. The goal of the allocation policy is to provide energy savings in three different ways: (i) reducing the power consumption of the overall network by executing tasks in low-power nodes instead of in a cloud computing facility (ii), increasing throughput and overall performance by parallelly executing tasks in both data center and coordinator nodes, and (iii) reducing the energy consumption due to communication by decreasing the amount of data transmitted over the network.

The coarse-grain resource assignment allocates tasks between coordinators (smartphones in our case) and data center. Shimmer nodes are not considered in this assignment because they have very low resources and the executed applications are particularly optimized for the Shimmer architecture.

We propose a two-step methodology for our global resource management policy: (i) classifying tasks of the workload according to their computational demand in the three different classes previously presented in Section 6.4, and (ii) running a run-time distributed coarse-grain allocation algorithm to decide whether each task should be executed at the coordinator or forwarded to the data center to maximize energy efficiency across the network.

6.6.1 Task classification

In order to classify the tasks of the workload to be executed, the first time that a task appears in a job set, it is profiled during its execution in the data center. Task profiling is done without performance degradation by gathering information of performance counters and execution time of the application.

Our coarse-grain assignment policy does not need a really accurate metric for the absolute value of the dynamic power consumption of a task. Instead, we aim to obtain a good metric of the energy-performance tradeoff of executing a particular task in a particular type of node (i.e., server or coordinator) that allows us to classify that task. Previous work on this topic [73] shows that IPC and CPU utilization (or the combination of both) is usually a good predictor for power efficiency. However, this approach disregards the memory consumption, which is important in enterprise servers, and can be predicted via the Last Level Cache misses (LLC) [26].

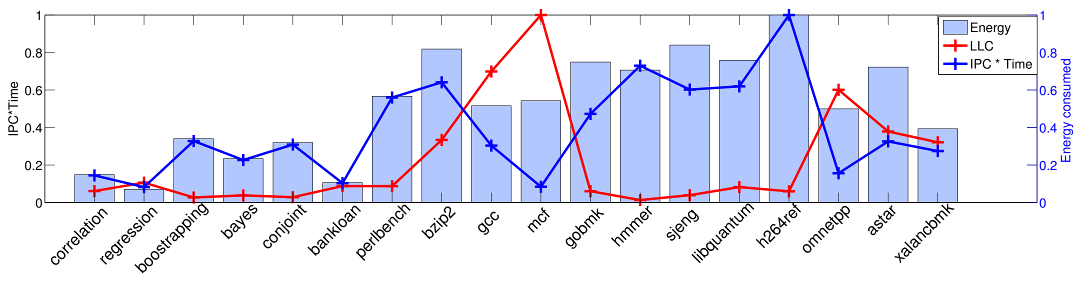


Figure 6.5: Correlation between $IPC * Time$ and LLC metric (left axis, lines) and Energy (right axis, bars)

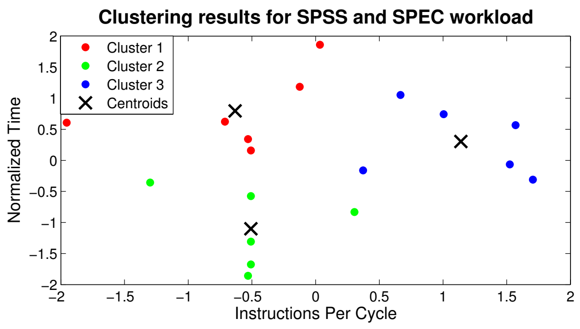


Figure 6.6: Clusters obtained in k-means classification for SPSS and SPEC

We execute all the different tasks of the workload (i.e. the SPSS and SPEC tasks presented on Section 6.4) in one of the servers of the data center, the Intel Xeon RX300, and use PAPI [113] to collect performance counters. We also measure the overall energy consumption of the server when executing each task by polling the power sensors integrated in the server via IPMI. We only perform the profiling in the most modern server of the data center, as our goal is just to get a first rough idea of the computational demand of the tasks.

Figure 6.5 shows the correlation between energy and the $IPC * Time$ and LLC metrics. As can be seen, $IPC * Time$ metric follows the trend of energy consumption, except for some benchmarks such as *gcc*, *omnetpp* or *astar* where the $IPC * Time$ metric underestimates energy consumption. In these benchmarks, LLC is particularly high, meaning that they have a higher amount of memory accesses that have an impact in energy consumption. In this case, as we search for an overall server energy predictor, we propose the usage of the metric $IPC * Time$.

Based on these results, we use IPC and execution time values to classify the different tasks of the workload using a k-means clustering. K-means algorithms need to know a-priori the number of clusters for classification. We use $k = 3$ number of clusters, and compare results with $k = 2$ and $k = 4$, getting the best results for $k = 3$. Figure 6.6 shows the clusters obtained whereas Table 6.5 details the task classification. We validate the clustering by checking whether low, medium and high energy consumption tasks are properly assigned to low, medium and high demand clusters. Our validation shows good results for the k-means clustering.

Cluster	Tasks
Low demanding	correlation, regression, bayes, bankloan,omnetpp,xalancbmk
Medium demanding	bootstrapping, conjoint, gcc mcf, astar, gobmk
High demanding	perlbench, bzip2, hmmer sjeng, libquantum, h264ref

Table 6.5: Task classification for SPSS and SPEC tasks

With these results for the task characterization, we can move on to the proposal of the run-time allocation algorithm.

6.6.2 Run-time allocation algorithm

The run-time allocation algorithm proposes to execute some of the low and medium-demanding tasks of the workload presented in Section 6.4 in the coordinator nodes instead of forwarding all computation to the data center. Each coordinator acts as a concentrator of the information sent by Shimmer nodes and thus, has all the data needed for the computation. If coordinators perform part of the tasks of the Data Dependent layer, the amount of computation in the data center is reduced and, thus, the facility consumes less energy. Moreover, if computations are performed at the coordinators, the amount of data to transmit to the data center is reduced, saving energy in the communication process. Here, we do not aim to estimate the energy consumption of the coordinator to data center communication. Instead, we focus on the benefits on the overall network that come from the reduction in energy due to computation.

When a new job set arrives each coordinator needs to compute whether that task should be executed or forwarded with its data dependencies to the data center. This means that the run-time allocation algorithm must run in a distributed way, i.e. each coordinator launches the algorithm for its particular task, but using the information provided by the data center. As these nodes are battery-operated, it would not be wise to waste their energy calculating the optimum assignment. Instead, we propose the usage of a fast and lightweight distributed allocation algorithm based on Satisfiability Modulo Theory (SMT) formulas.

SMT solvers are fast solvers that determine whether a certain formula is satisfied. In our case, when a certain amount of low- and medium-demanding tasks arrive to a coordinator, it uses an SMT solver to compute which tasks of the workload satisfy certain conditions and the amount of tasks that can be executed. Let us denote by $T_{node_i,j}$ the low and medium demanding Data Dependent tasks of a particular job set j that can be executed in a certain node; by $T_{data,j}$ all the Data Dependent tasks in a job set j and by N_{cores} the overall amount of computational cores available at the data center.

Each task t has a duration and consumes a certain amount of energy depending on whether it is executed at the data center or coordinator, noted by σ_{tp} and e_{tp} respectively. As this optimization does not manage the idle power consumption of the elements of the architecture with turn off policies, we assume that both coordinators and servers are always turned on. Because of this, we aim to optimize the energy variation for executing a certain task. For this reason, e_{tp} does not consider the idle power for neither coordinators or servers, i.e., it considers only the amount of energy spent over idle state. The conditions that the workload have to satisfy in order to be executed are proposed next:

$$\left(\sum_{t\in T_{node_i,j}} e_{tp}\cdot\sigma_{tp}\right)_{coord} \leq 0.1\cdot\left(\sum_{t\in T_{data,j}} e_{tp}\cdot\sigma_{tp}\right)_{datacenter} \tag{6.4}$$

$$\left(\sum_{t\in T_{node_i,j}} \sigma_{tp}\right)_{coord} \leq \alpha\cdot\left(\frac{\sum_{t\in T_{data,j}}\sigma_{tp}}{N_{cores}}\right)_{datacenter} \tag{6.5}$$

$$\left(\sum_{t\in T_{node_i,j}} e_{tp}\right)_{coord} \leq \beta_{max} \tag{6.6}$$

$$\tag{6.7}$$

Equation 6.4 states that the Energy Delay Product (EDP) of the tasks executed in the coordinators must be at least an order of magnitude less than the EDP product for those same tasks if executed in the data center. EDP weights power against the square of execution time, and is a common metric to compare energy efficiency optimizations from both the data center level and the architectural point of view [139]. Equation 6.5 constraints the maximum time taken

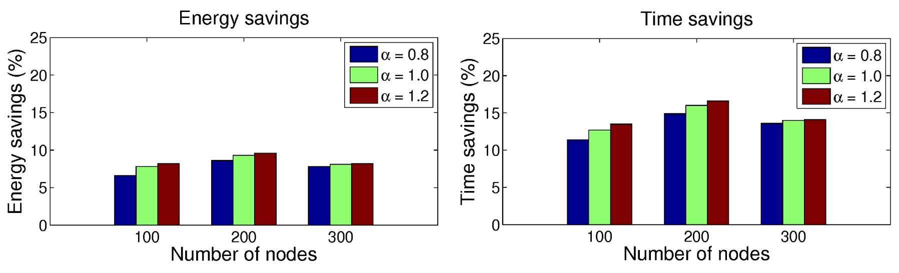


Figure 6.7: Percentage of energy and time savings for each number of nodes and $\alpha = \{0.8, 1.0, 1.2\}$ under the reference workload

for the tasks to be executed to the overall time that it would take to execute data dependent tasks at the data center, i.e. it ensures a certain Quality of Service (QoS). This constraint can be adjusted through the parameter $\alpha = [0 \dots 1]$. Finally, Equation 6.6 constraints the maximum amount of battery used per job set in each coordinator to a maximum energy β_{max}.

In order to perform the run-time allocation, our SMT solver algorithm needs to know an estimation of the energy e_{tp} and duration σ_{tp} of each task t to be executed for each processor p. For this purpose we use the energy profiling results for the Intel Xeon machine and the Samsung Galaxy S2 coordinator of Section 6.5.

Each job set in our workload contains a 60% of tasks belonging to the Data Dependent layer which, in its turn, has a 70% of low-demanding tasks and a 30% of medium demanding tasks. We assume that each coordinators in the architecture generates the same amount of data in average, so that tasks are uniformly split between nodes. We also assume that not all coordinators might be available at all times for computation purposes, so we might have a different amount of coordinators (from 100 to 300). Depending on the workload profile (heavy, reference or light workload) and the amount of coordinators available, each coordinator executes a different amount of tasks.

Our SMT algorithm is implemented using the Yices SMT solver [2] that runs with negligible performance and energy overhead in the coordinator node, obtaining a solution in less than 1 second for each node. If the conditions to execute a task are satisfied, then the task is executed in the coordinator node. If not, it is off-loaded to the cloud infrastructure. For our case study we use a fixed value of $\beta_{max} = 300mWh$, which represents a 30% of the energy resources of the coordinator node Samsung Galaxy SII. We execute the workload for different parameters of $\alpha = \{0.8, 1, 1.2\}$ and calculate the average amount of tasks executed by the coordinator, the energy consumed by each coordinator in the system, and the energy saved at the data center. We use as a baseline for comparison the execution of all the workload in a data center with 160 cores (40 servers) of the Intel Xeon machine of the case study, without using any coordinator. We run the algorithm for the three different workload profiles with three different number of coordinators (100, 200 and 300) to compare performance. Figure 6.7 shows the percentage of dynamic energy and time savings compared to the execution of the reference workload in data center facility in 160 Intel cores.

The allocation of the whole workload at the data center facility (no coordinator nodes) consumes around 24kWh plus the idle energy of the servers, and the execution takes around 13h to complete. These 24kWh are the energy variation due to the workload execution. By using coordinators to execute part of the workload, we can obtain up to a 10% savings in energy variation and a 16% savings in execution time for the reference workload; while up to 24% energy savings for the heavy workload by using 300 coordinators can be achieved. The energy savings do not consider the savings obtained in idle power, which come from the reduction in execution time or occupancy that could lead to server turn-off policies specific to the data centers. The absolute energy values for each workload profile and coordinator are summarized in Table 6.7 in Section 6.7.

[2]http://yices.csl.sri.com

Workload profile	Coordinators	Server selection
Heavy	100	35 Intel + 5 AMD
	200	36 Intel + 4 AMD
	300	37 Intel + 3 AMD
Reference	100	36 Intel + 4 AMD
	200	35 Intel + 5 AMD
	300	36 Intel + 4 AMD
Light	100	31 Intel + 9 AMD
	200	31 Intel + 9 AMD
	300	35 Intel + 5 AMD

Table 6.6: Selected heterogeneous cluster configuration for each workload

6.7 Multi-layer integration

In this section we show how the optimizations developed in the previous chapter can be integrated with the global resource management techniques shown in the previous section (6.6). Moreover, we show the overall energy savings that can be obtained by jointly applying these optimizations in various abstraction layers.

6.7.1 Integration with horizontal optimizations

In this Chapter, for the purpose of global resource management techniques, we had supposed that all computations at the data center were performed in a homogeneous cluster with 160 cores belonging to Intel Xeon machines. However, even though the Intel servers are the most modern ones, on Chapter 5.5 we showed that for some tasks, the AMD server outperforms the Intel in terms of energy efficiency. Moreover, we showed how heterogeneous setups could outperform homogeneous setups when executing the workload.

We re-run the data center server selection static optimization in order to find the optimum number of servers that can be used depending on the number of coordinator nodes deployed in our system, and for each workload profile (light, reference and heavy). Table 6.6 summarizes the results for the static optimization. As can be seen, for all experimental scenarios, the optimizer picks up an heterogeneous data center composed of a majority of Intel and a few AMD nodes.

On top of the previous static optimization, we can run the dynamic run-time allocation of tasks, in order to minimize the energy consumption of the assignment. The dynamic run-time allocation of the tasks, performed by the resource manager, aims at minimizing the energy consumption of the assignment by placing each task where it wastes the minimum energy in a spatio-temporal way.

6.7.2 Overall energy savings

The goal of this section is to provide an insight on how the models and optimizations developed can be vertically integrated and applied together from a multi-layer perspective.

To accomplish this objective we first present a summary of the energy savings obtained for the global resource allocation technique developed in Section 6.6 and the data center resource management policies presented in the previous Chapter 5.5, for each of the workload profiles and for a different amount of coordinators. In Table 6.7 Global resource allocation savings are referred to savings on the dynamic energy consumption only of the data center, whereas the DC policies offer the amount of savings for the data center only. In order to obtain an estimation of the impact of each optimization on the overall energy savings, we must first obtain the baseline energy consumption for each kind of workload without any optimization, and then apply the optimizations one after the other.

Table 6.8 shows the total energy consumption in kWh for the baseline case of not applying any optimization (first row of the table, i.e. the "No optimization" row) and when applying

	High workload			*Medium workload*			*Low workload*		
	100	200	300	100	200	300	100	200	300
Global	7.8%	9.3%	8.1%	4.9%	3.4%	6.4%	3.6%	11.6%	24.0%
DC policies	6.3%	6.0%	5.7%	7.5%	6.5%	5.2%	3.1%	2.3%	1.4%

Table 6.7: Summary of savings for each optimization

	Heavy workload			*Reference workload*			*Light workload*		
	100	200	300	100	200	300	100	200	300
No optimization	153.6	153.6	153.6	101.0	101.0	101.0	49.0	49.0	49.0
Global allocation	103.1	95.3	93.0	53.4	52.5	51.3	45.2	47.7	44.6
	(32.8%)	(37.9%)	(39.4%)	(47.1%)	(48.0%)	(49.2%)	(7.7%)	(2.6%)	(9.3%)
Cooling	97.7	90.2	88.1	50.6	49.7	48.5	42.7	42.2	42.1
	(36.4%)	(41.2%)	(42.6%)	(49.9%)	(50.7%)	(51.9%)	(12.8%)	(13.9%)	(14.1%)
DC Allocation	91.8	84.9	83.0	46.9	46.6	46.1	41.9	41.7	41.7
	(40.2%)	(44.7%)	(45.9%)	(53.6%)	(53.9%)	(54.3%)	(14.5%)	(14.9%)	(14.9%)

Table 6.8: Overall energy savings (in kWh and percentage) for the whole architecture when integrating all optimizations

each optimization on top of the previous one. These values show the energy consumed for the whole architecture, i.e. coordinator nodes plus data center IT power plus data center cooling power. Percentages show the amount of energy savings when compared to the baseline case. These data has been obtained by simulating all the workload profiles by means of the SLURM simulator.

The second row of the table calculates the impact of offloading computation to the coordinator nodes. In Section 6.6 we were presenting the dynamic power savings at the data center level. Here we use SLURM simulator to re-run the workload arriving to the data center for a different amount of coordinators, so that we can see the impact in execution time and static energy consumption. As can be seen, the impact of offloading techniques is huge, and is highly dependant on the workload profile. The third row adds the impact of increasing the air-supply temperature of the cooling system from 18°C to 24°C in the four air conditioning units needed to cool the 40 machines of the experimental set-up. Finally, the fourth row adds the impact of the data center resource selection and optimum workload assignment policies.

6.8 New challenges

The research work presented in this chapter has open new challenges, profusely explored, that represent a novel and evolved conception of the distributed and high-performance computing paradigm. In this chapter, we have tackled the following topics:

- the concept of *heterogeneity* has been considered at different abstraction levels (horizontal heterogeneity among the server architectures of the data center, and vertical heterogeneity between the node-level and the data center-level architectures). This concept has been proved to provide further opportunities for energy-optimization (thanks to the workload distribution mechanisms), but it also encourages the seeking of global-optimization techniques that consider the heterogeneity of the system since the application conception.
- the conceived optimization techniques take into account the *dynamism of the scenario*, where variable workloads and tasks arrive to the computing platform and a varying number of processing nodes can be available for processing or ready to feed new data.
- the constraints imposed by the *Ubiquitous Computing* model have been exposed to be determinant on the architecture of the computing paradigm. Not only a set-up of wearable processing and sensing nodes is required, but also an all-over access to the computing services provided by data centers.

- the need of efficient energy-saving techniques in e-Health application scenarios has driven the conception of a new computing paradigm where the design of the architecture is pushed by the energy consumption of such application. Only with such *application-driven* design style, the energy footprint of the whole computing scheme can be reduced, while the reliability and performance requirements are still satisfied.

6.9 Conclusions

Home assisted living reduces sanitary costs by prevention of potential diseases, provides early signals of health decline and advices for appropriate actions in daily life, and allows complex epidemiologic analysis that improve prevention and efficacy of treatments. However, energy consumption is one of the major concerns for the adoption of population-wide health monitoring systems, but energy efficiency cannot be added as an afterthought.

In this chapter, we have presented a novel concept of the computing paradigm that combines the deployment of population-wide Wireless Body Sensor Networks, wearable computing devices and high-performance computing data-centers. Moreover, we propose an architecture driven by energy concerns and aimed at optimizing energy consumption globally.

This work considers, for the first time, energy as a first-class requirement, taking it into account during the whole development cycle, from design to implementation. The novel strategies presented in the experimental work focus on every abstraction layer, and obtain promising results for a realistic scenario that depicts the cardiovascular tracking and analysis of a broad population.

We believe that the computing paradigm presented in this work, as well as the evolved methodology for energy reduction, deals successfully with many and important challenges, often forgotten in the current related literature.

In the next chapter...

the reader will find a synthesis of the conclusions that are derived from the research that is presented in this Ph.D. thesis, a summary of the major contributions and future research directions.

7. Conclusions and Future Work

The future belongs to those who believe in the beauty of their dreams

— Eleanor Roosevelt

This Ph.D. Thesis has addressed the energy challenge by proposing proactive and reactive thermal and energy-aware optimization techniques that contribute to place High Performance Computing data centers on a more scalable curve. In this Chapter, a synthesis of the conclusions derived from the research undertaken in this Ph.D. thesis is presented, highlighting the contributions of this dissertation to the state-of-the-art. Moreover, we also highlight the open research lines and future research directions derived from this work.

7.1 Summary

As described in the motivation of this Ph.D. thesis (Chapter 1.1), the energy costs and the environmental impact of data centers today represent a huge challenge for both industry and academia. The need to deal efficiently with the computational needs of next-generation applications (such as e-Health or Smart Cities) together with the increasing demand for higher resources in traditional applications has facilitated the rapid proliferation and growth of data center facilities. Since 2010, when data center electricity represented 1.3% of all the electricity use in the world and more than 2% of total carbon dioxide emissions, the energy consumption of these facilities has kept on growing at an unsustained rate. In year 2012 alone, global data center power demand grep 63% to 38GW. A further rise of 17% to 43GW was estimated in 2013.

Previous research, as shown in Chapter 1.2, lacks accurate server and data center power models that enable the development of proactive optimization policies. Moreover, previous approaches tackle cooling and computation optimization separately, instead of jointly managing computation and cooling to minimize overall data center power consumption. Finally, current solutions do not tackle energy as a first-class requirement, and do not focus on reducing the overall energy consumption of applications from a multi-layer integrated perspective.

As summarized in Figure 1.4 in Chapter 1.3, our work proposes a global solution based on the energy analysis and optimization for next-generation applications from multiple abstraction layers. We develop energy models and use the knowledge about the energy demand of the workload to be executed and the computational and cooling resources available at data center to optimize energy consumption. Moreover, data centers are considered as a crucial element within their application framework, optimizing not only the energy consumption of the facility, but the global energy consumption of the application. This Ph.D. thesis proposes solutions to place data centers on a more scalable curve. This work makes contributions in a complex and multidisciplinary area, of high economic and social impact.

Reviewing the objectives presented in Chapter 1.4, this Ph.D. thesis has achieved the following results:

- We have developed empirical models at the server level that are able to isolate and accurately quantify the different contributors to power consumption, predicting power and temperature with high accuracy. These models are flexible, can work during runtime and have been extensively validated in various presently shipping enterprise servers of different architectures. These contribution have been presented in Chapter 2.

- We propose leakage-aware cooling control and workload management strategies to minimize server energy consumption. Experimental results on a presently shipping enterprise server demonstrate energy savings of up to 9% and 30W reduction in peak power when compared to the default cooling control scheme. By adding workload management along with cooling control, we obtain energy savings of up to 15%. This work has been presented in Chapter 3.
- This Ph.D. thesis has developed an unsupervised data room modeling methodology based on Grammatical Evolution techniques able to predict the inlet and CPU temperature of servers. Our models work during runtime and achieve average errors below 0.5°C and 2°C in inlet and CPU temperature respectively. For the first time in literature, we present an accurate unsupervised modeling methodology that has been tuned in a small scenario, and tested with real traces of a production data center. Chapter 4 presents these results.
- We propose a Mixed Integer Linear Programming (MILP) optimization to minimize the energy needed to execute a certain workload in the data center. The proposed approach exploits the heterogeneity of the system from a mixed static/dynamic perspective, and combines the proper selection of cores with the information retrieved during a workload characterization phase. Validation has been performed in two different heterogeneous setups, with real measurements in commercial enterprise servers, obtaining from 7.5% to 24% energy savings when compared to the default allocation of the production-ready tool SLURM. The joint optimization of cooling and computing costs yield savings of up to 1,200€ per rack per year. The previous contributions have been described in Chapter 5.
- Finally, we have shown a case study for e-Health scenarios where energy optimization techniques are applied at various abstraction layers, with the goal of reducing the overall energy consumption of the application. In Chapter 6, we have shown how data center off-loading techniques based on SMT solvers allow to distribute computation between nodes and data center in a distributed applications, reducing energy consumption from 10% to 24% in the overall framework. This energy savings are translated into a reduction of almost 70 tons of CO2 annually for the proposed e-Health scenario. Moreover, by applying our optimizations in several abstraction layers we obtain dramatic energy savings in the execution of the application, ranging from 15% to 50% depending on the workload and the available resources.

The work developed in this Ph.D. Thesis has enabled a very close collaboration between the ArTECS group at Universidad Complutense de Madrid and the LSI group at Universidad Politécnica de Madrid. Moreover, a stable collaboration has been established with the Performance and Energy Aware Computing Lab. at Boston University. So far, this collaboration has resulted into two 3-month research stays of the author at Boston University, one conference and one journal paper co-authored by Boston University and Oracle, Inc., and another conference paper that has been submitted and is currently under review.

The work developed in this Ph.D. thesis had developed realistic models and optimizations that used in real data center scenarios, yielding significant savings. For instance, all models and optimizations proposed in this work have been developed and tested in real scenarios. Server models and optimizations have been validated in presently-shipping enterprise servers, belonging to Boston University, Universidad Politécnica de Madrid and Universidad Complutense de Madrid. For data center room modeling this work has used real traces collected from a small scale data room at the Electronic Engineering Department at Universidad Politécnica de Madrid, as well as from CeSViMa data center. Finally, data center optimizations have been tested and compared against a production-ready resource management tool, the SLURM resource manager. Thus, the work presented has a high applicability, is of high interest to both industry and academic and can potentially obtain important savings in real environments.

7.2 Future Research Directions

The research developed in this Ph.D. thesis has addressed the development of models and optimization techniques at different abstraction layers: from server and data center to the overall application framework. The techniques proposed have tackled heterogeneous computing resources and are aware of the tradeoffs between temperature and cooling. However, some interesting points of future research have emerged during the evolution of this work. The following paragraphs propose future research directions and improvements of the work presented in this dissertation:

- This work has focused on the optimization of traditional raised-floor air-cooled data centers. These facilities are not very efficient in terms of cooling, i.e. their PUE is generally high. The analysis of cooling-optimized highly-efficient data centers would yield different tradeoffs worth exploring. Moreover, the usage of free cooling techniques proposes an interesting field of study to further increase energy efficiency.
- Furthermore, next-generation cooling techniques, such as two-phase immersion cooling need to be investigated. This technique is based on placing server in a container filled with a fluid, e.g. Novec, that dissipates heat by changing phase. This changes completely the thermal behavior of servers, where new trade-offs need to be investigated.
- Even though our work has considered the overall application framework, we have not tackled federated networks of data centers. This field opens a wide area of study from the workload allocation perspective, as data centers in a federated network can collaborate to reduce overall power consumption by adequately migrating workload across facilities. Due to the heterogeneous and distributed nature of the problem, resource management across federated networks of data centers represents an interesting challenge.
- To drastically reduce energy-related costs in data center facilities, another major challenge is the participation of data centers in the Smart Grid. Data centers are very important actors in the power market due to their high power consumption. The participation of data centers demand-response programs, opens a new opportunity to minimize energy costs by dynamically adapting the power consumption of the facility to the power grid needs.
- This work has focused on the development of models for the CPU and memory subsystems of enterprise servers. However, there is still a need to create accurate models to predict data center workload. Therefore, we also need to forecast the performance of applications before they are scheduled and allocated. This can be done via static and dynamic analysis of applications in order to predict power and performance and, thus, data center workload.
- This dissertation has focused on the modeling and optimization of CPU and memory intensive HPC applications. This work needs to be extended to other subsystems in order to predict power and performance of disk and network. Moreover, highly parallel jobs need to be considered if targeting HPC applications, where disk and network can be a bottleneck and have an impact on overall energy consumption.

Appendix A
Mapping process and relevant parameters in Gramatical Evolution

We used to think our fate was in our stars. Now we know, in large measure, our fate is in our genes.

— James Watson

In this appendix we describe with further detail the mapping process in Gramatical Evolution, and how our models incorporate time dependence. Moreover, we provide information on some parameters relevant to our models (such as fitness and problem constraints) and how we have selected them for the purpose of the temperature modeling presented in Chapter 4.

For a more detailed explanation on the principles of Gramatical Evolution, the reader is referred to [142].

A.1 Mapping process

In Gramatical Evolution (GE), in order to extract the mathematical expression given by an individual (phenotype), a mapping process is applied. The mapping process consists on defining a set of rules to obtain the mathematical expressions, by using grammars expressed in Backus Naur Form (BNF) [121]. Generally speaking, a BNF specification is a set of derivation rules, expressed in the form:

$\langle symbol \rangle$ ::= $\langle expression \rangle$

The rules are composed of sequences of terminals, which are items that can appear in the language, and non-terminals, which can be expanded into one or more terminals and non-terminals. Symbols that appear at the left are non-terminals while terminals never appear on the left side.

A grammar is represented by the tuple N, T, P, S, being N the non-terminal set, T is the terminal set, P the production rules for the assignment of elements on N and T, and S is a start symbol that should appear in N. The options within a production rule are separated by a "|" symbol.

Grammar 5 represents an example grammar in BNF format. The final expression consists of elements of the set of terminals T, which have been combined with the rules of the grammar.

The chromosome (or genotype) is used to map the start symbol onto terminals by reading genes (or codons) of 8 bits to generate a corresponding integer value, from which a production rule is selected by using the following mapping function (the modulus operator):

$$\text{Rule} = \text{Codon Value } \% \text{ Number of Rule Choices} \tag{A.1}$$

Example: In the following example, we explain the mapping process performed in GE to obtain a phenotype (mathematical function) given a genotype (chromosome), as it shows how better features are automatically selected. Let us suppose we have the BNF grammar provided in Figure 5 and the following 7-gene chromosome:

Grammar 5 Example of a grammar in BNF format designed for symbolic regression

N = {expr, op, preop, var, num, dig}
T = {+, -, *, /, sin, cos, exp, x, y, z, 0, 1, 2, 3, 4, 5, (,), .}
S = {expr}
P = {I, II, III, IV, V, VI}

$$\langle expr\rangle ::= \langle expr\rangle\langle op\rangle\langle expr\rangle \mid \langle preop\rangle(\langle expr\rangle) \mid \langle var\rangle \tag{I}$$

$$\langle op\rangle ::= +|-|*|/ \tag{II}$$

$$\langle preop\rangle ::= \mathrm{sin}|\mathrm{cos}|\mathrm{log} \tag{III}$$

$$\langle var\rangle ::= \mathrm{x}|\mathrm{y}|\mathrm{z}|\langle num\rangle \tag{IV}$$

$$\langle num\rangle ::= \langle dig\rangle.\langle dig\rangle \mid \langle dig\rangle \tag{V}$$

$$\langle dig\rangle ::= 0 \mid 1 \mid 2 \mid 3 \mid 4 \mid 5 \tag{VI}$$

```
21-64-17-62-38-254-2
```

According to Figure 5, the start symbol is $S = \langle expr\rangle$, hence the decoded expression will begin with the non-terminal:

$$Solution = \langle expr\rangle$$

Now, we use the first gene of the chromosome (equal to 21 in the example) in rule `I` of the grammar. The number of choices in that rule is 3. Hence, the mapping function is applied: `21 MOD 3 = 0` and the first option is selected $\langle expr\rangle\langle op\rangle\langle expr\rangle$. The selected option substitutes the decoded non-terminal. As a consequence, the current expression is the following:

$$Solution = \langle expr\rangle\langle op\rangle\langle expr\rangle$$

The process continues with the codon 64, used to decode the first non-terminal of the current expression, $\langle expr\rangle$. Again, the mapping function is applied to the rule: `64 MOD 3 = 1` and the second option $\langle preop\rangle(\langle expr\rangle)$ is selected. So far, the current expression is:

$$Solution = \langle prep\rangle(\langle expr\rangle)\langle op\rangle\langle expr\rangle$$

The next gene, 17, is now taken for decoding. At this point, the first non-terminal in the current expression is $\langle preop\rangle$, we apply the mapping function and the third option is selected, obtaining expression:

$$Solution = exp(\langle expr\rangle)\langle op\rangle\langle expr\rangle$$

The next codons (62, 38, 256 and 2) are decoded in the same way. After codon 2 has been decoded, the expression is:

$$Solution = exp(x) * \langle var\rangle$$

At this point, the decoding process has run out of codons. That is, we have not reached an expression with terminals in all its components. In GE, the solution consists on reusing codons starting from the first one. In fact, it is possible to reuse the codons more than once. This technique is known as wrapping and mimics the gene-overlapping phenomenon in many organisms [75]. Thus, applying wrapping to our example, the process goes back to the first gene, 21, which is used to decode $\langle VAR\rangle$ with rule `IV`. This result selects the first option, non-terminal y, giving the final expression of the phenotype

$$Solution = exp(x) * y$$

Adding time dependence: So far, previously shown grammars allowed us to obtain phenotypes that were mathematical functions dependent on a certain number of variables (i.e.

x, y, z in our previous example). In this sense, we could use the previous method to predict variables that depend only on the current observation of other magnitudes. For instance, Grammatical Evolution has been used in literature in this way to predict power consumption of servers as a function of utilization, fan speed and other variables [128].

The models created this way can be used to predict magnitudes that do not have memory and the data used for model creation consists on samples. Temperature, however, is a magnitude that has memory, i.e. the current temperature depends on past temperature values. Thus, the data used for model creation needs to be a timeseries. By properly tuning our grammars, we can add time dependence to the variables in the phenotype, so that past variable values (i.e. past temperatures) can be used to predict the variable a certain number of samples ahead into the future.

A.2 Fitness

The selected fitness function needs to express the error resulting in the estimation process. To measure the accuracy in our prediction, we would preferably use the Mean Absolute Error (MAE). However, because temperature is a magnitude that varies slowly and that might remain constant during large time intervals, we need to give higher weight to large errors. To this end, the fitness function f presented in Equation A.2 tries to reduce the variance of the model, leading the evolution to obtain solutions that minimize the the Root Mean Square Error (RMSE or RMSD):

$$f = \sqrt{\frac{1}{N} \cdot \sum_{n} {e_{\mathrm{n}}}^2} \tag{A.2}$$

$$e_{\mathrm{n}} = |T(n) - \widehat{T}(n)|, \qquad 1 \leq n \leq N \tag{A.3}$$

where the estimation error e_{n} represents the deviation between the real temperature samples (both for CPU and inlet temperature modeling) obtained by the monitoring system T, and the estimation obtained by the model $\widehat{T}$. n represents each sample of the entire set of N samples used to train the algorithms.

A.3 Problem constraints

A.3.1 Problem constraints

As we are modeling the behavior of physical magnitudes, (i.e., temperature), for optimization purposes, it is desirable to obtain a solution with physical meaning. To this end, we can constrain the model generation in several ways that are next presented. In the results Section 4.6 we evaluate the impact of these constraints in the model generation stage.

Constraining the grammar

The mathematical expressions of the grammar can be constrained to obtain a limited number of functions that match the physical world. For instance, because temperature exhibits exponential transients, we can include the exponential function in our grammar, whereas we do not find physical fundamentals to include other mathematical functions such as sines or cosines.

Fitness biasing

Based on the laws of physics, we know that there are certain parameters that drive the variables being modeled. For instance, power consumption drives CPU temperature and, thus, this magnitude should be present in the final model if it has physical meaning. We can force the appearance of some parameters by biasing the fitness values, giving higher weights (i.e. worse fitness) to expressions where certain parameters are not present. By biasing fitness we speed-up convergence, however, we may obtain less accurate results.

Real vs. mixed models

Purely real models only uses real temperature data measurements to predict future temperature samples. Purely predictive models do not used previous temperature data measurements, but may use previous predictions. Mixed models may used both real and predicted data. Adding the predicted samples as a variable to our grammars increases the size of the search space and, thus, we expect longer convergence time. However, it may deliver more accurate results.

Appendix B
Classical modeling techniques

Qué es la vida? Un frenesí. Qué es la vida? Una ilusión,
una sombra, una ficción; y el mayor bien es pequeño;
que toda la vida es sueño, y los sueños, sueños son.
— Calderón de la Barca

In this appendix we describe with further detail two classical modeling techniques that we to compare against our proposed models in Chapter 4. These modeling techniques are ARMA and N4SID.

B.1 ARMA models

ARMA models are mathematical models of autocorrelation in a time series, that use past values alone to forecast future values of a magnitude. ARMA models assume the underlying model is stationary and that there is a serial correlation with the data, something that temperature modeling accomplishes. In a general way, an ARMA model can be described as in Equation B.1:

$$y_t = \sum_{i=1}^{p}(a_i \cdot y_{t-i}) = e_t + \sum_{j=1}^{q}(c_j \cdot e_{t-j}) \tag{B.1}$$

where y_t is the value of the time series (CPU temperature in our case) at time t, a_i's are the lag-i autoregressive coefficients, c_i's are the moving average coefficient and e_t is the error. The error is assumed to be random and normally distributed. p and q are the orders of the autoregressive (AR) and the moving average (MA) parts of the model, respectively.

The ARMA modeling methodology consists on two different steps: i) identification and ii) estimation. In our work we use an automated methodology similar to the one proposed by Coskun et.al. [46]. During the identification phase, the model order is computed, i.e, we find the optimum values for p and q of the $ARMA(p, q)$ process. To perform model identification we use an automated strategy, that computes the goodness of fit for a range of p and q values, starting by the simplest model (i.e., an ARMA(1,0)). The goodness of fit is computed using the Final Prediction Error (FPE), and the best model is the one with lowest FPE value, given by Equation B.2:

$$FPE = \frac{1 + n/N}{1 - n/N} \cdot V \tag{B.2}$$

where $n = p + q$, N is the length of the time series and V is the variance of the model residuals. For a fair comparison with our proposed methodology, the model obtained needs to forecast $\alpha = 6$ samples into the future.

B.2 N4SID

N4SID is a subspace identification method that estimates an n order state-space model using measured input-output data, to obtain a model that represents the following system:

$$\dot{x}(t) = Ax(t) + Bu(t) + Ke(t) \tag{B.3}$$

$$y(t) = Cx(t) + Du(t) + e(t) \tag{B.4}$$

where A,B,C and D are state-space matrices, K is the disturbance matrix, $u(t)$ is the input, $y(t)$ is the output, $x(t)$ is the vector of n states and $e(t)$ is the disturbance.

State-space models are models that use state variable observations to describe a system by a set of first-order differential equations, using a black-box approach. The approach consists on identifying a parametrization of the model, and then determine the parameters so that the measurements explain the model in the most accurate possible way. They have been very successful for the identification of linear multivariable dynamic systems.

To be constructed, certain parameters need to be fed into the model, such as the number of forward predictions (r), the number of past inputs (s_u), and the number of past outputs(s_y). Again, for a fair comparison with our proposed methodology, we need a model in the form $N4sid[r, s_u, s_y]$ where $r = 6, s_u = 20$ and $s_y = 20$.

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Todo pasa y todo queda,
pero lo nuestro es pasar,
pasar haciendo caminos,
caminos sobre el mar.
...
Caminante son tus huellas
el camino y nada más;
caminante no hay camino,
se hace camino al andar.

— Antonio Machado, *Caminante no hay camino*

"So long, and thanks for all the fish."

— Douglas Adams, *The Hitchhiker's Guide to the Galaxy*