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Towards Green Big Data at CERN

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HIGHLIGHTS

- We show how energy efficiency is a large challenge in scientific computing at CERN.
- Making energy consumption visible for stakeholders motivates improving energy efficiency.
- Energy efficiency can be improved by applying operations management methodology.

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ABSTRACT

High-energy physics studies collisions of particles traveling near the speed of light. For statistically significant results, physicists need to analyze a huge number of such events. One analysis job can take days and process tens of millions of collisions. Today the experiments of the large hadron collider (LHC) create 10 GB of data per second and a future upgrade will cause a ten-fold increase in data. The data analysis requires not only massive hardware but also a lot of electricity. In this article, we discuss energy efficiency in scientific computing and review a set of intermixed approaches we have developed in our Green Big Data project to improve energy efficiency of CERN computing. These approaches include making energy consumption visible to developers and users, architectural improvements, smarter management of computing jobs, and benefits of cloud technologies. The open and innovative environment at CERN is an excellent playground for different energy efficiency ideas which can later find use in mainstream computing.

1. Introduction

The Large Hadron Collider (LHC), which was used to discover the famous Higgs boson, started to run at CERN in 2010. During the first run, the CERN computing center stored up to 6 GB of data per second. The total need of computing resources was around 200,000 CPUs and 40 PB disk space. The second run of LHC started in June 2015. During this run, data is stored at a maximum rate of 10 GB per second and CERN alone has allocated 140 PB disk space divided between its data centers in Switzerland and Hungary [1]. The required computing resources for LHC data analysis are divided among 11 tier-1 and 155 tier-2 globally distributed computing centers by using the grid computing paradigm [2]. Efficient management of these computing resources is vital for the success of the project, which is foreseen to be active for the next 20 years.

From the physicist point of view computational speed is of prime importance to efficiently analyze the data and to enable progress on particle physics. It is therefore important to consider both user needs and cost-efficient use of resources when managing the computing infrastructure and training and encouraging users.

The energy efficiency of computing is receiving increasing attention (see e.g., [3] for a survey). For example, Van Heddeghem et al. [4] reported that data centers worldwide consumed 270 TWh of energy in 2012 and this consumption had a Compound Annual Growth Rate (CAGR) of 4.4% from 2007 to 2012. Besides the expenses related to the data center energy consumption, environmental aspects are also relevant. Therefore, the reduction of electricity consumption for computing is important both from cost and environmental point of view.

The increased computational speed enabled by Moore's law has for a long time contributed to increased energy efficiency. If the same task can be completed faster and the power consumption remains unchanged, this obviously results into energy savings. However, we are now in a situation where the computational

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speed will no longer increase. While Moore's law still increases the number of transistors on chips, the computational speed of individual cores has stopped growing [5]. As a result developers need to be able to better distribute their workloads to take advantage of the increasing number of cores in networked systems. However, according to Amdahl's law [6] the distribution is not a panacea, because the speed improvement of parallelism is limited by the parts of the software that cannot be parallelized. Normally this has a negative effect on energy efficiency but in some cases, due to the dynamic voltage and frequency scaling (DVFS) [7], increased parallelism can even have a positive effect on energy efficiency [8]. One conclusion of this is that instead of simply trying to make the software run faster, and, as a result, become more energy-efficient, we need to consider other ways to run the software in a more energy-efficient fashion.

In this article, we take a holistic view of energy efficiency by introducing three main roles, which can be recognized in the value-chain of scientific computing: user, software developer, and data center operator. These three groups are connected through the computing system they use/develop/operate even though their aims and goals are often quite different and orthogonal. This also naturally affects energy consumption. Therefore, we look at energy efficiency from these three perspectives and form a holistic view of the scientific computing ecosystem. We do this by combining the roles with a set of intermixed approaches, which we have studied in our Green Big Data project (https://twiki.cern.ch/twiki/bin/view/Main/GreenBigData) to improve the energy efficiency of CERN computing. Philosophically, we can say that our research methodology is based on decomposing the whole system into independent subsystems, which can be optimized separately [9]. The result of optimization is usually Pareto optimal, meaning that improving the system from the view point of one role, would reduce its optimality for another role. For example, allowing longer queueing times can make it possible to improve the energy efficiency of the data center but it also reduces the service level of the user.

The rest of this article is organized as follows: First, we give a review of related work in energy efficiency in Section 2 and then introduce the reader to scientific computing by reviewing the CERN computing problem (Section 3). In Section 4 we introduce the three roles/stakeholder groups in computing and present possible technology solutions to improve energy efficiency related to the functions of these groups. In Section 5, we discuss future possibilities and identify potential targets for future research. Finally, conclusions are given in Section 6.

2. Related work

A large part of research in energy efficiency has focused on cloud data centers. For example, Dayarathna et al. [10] give a large survey of state-of-art techniques in energy consumption modeling and prediction for Internet data centers, and Shuja et al. [11] present several case studies demonstrating methods and techniques for sustainable data centers. Moreover, Mazumdar and Pranzo [12] study server consolidation in cloud data centers by proposing a formal formulation for the server consolidation problem and showing that using a snapshot-based method it is possible to find efficiently near optimal server allocations.

Another significant part of research focuses on hardware. For example Karpowichz et al. [13] study on energy-aware design in hardware, middleware and software layers. They note that to get benefit on hardware development, a holistic view to the whole system must be taken. This includes, for example, developing power consumption models, measuring methods for energy efficiency, modeling computing and network dynamics, multi-level control systems, energy-aware scheduling and software development techniques.

There are also many studies on energy efficiency in high-performance computing. For example, Rong et al. [14] review energy optimization technologies in high-performance computing and propose a set of strategies to maximize the efficiency and minimize the impact for environment. Further, Zakarya and Gilliam [15] focus on energy efficiency on scientific computing systems. They key findings are: (1) using system level technologies may actually increase energy consumption in clusters; (2) optimizing scheduling and resource allocation in clouds can offer better results than consolidation using migrations; and (3) turning off idle resources works well in clusters but may cause performance issues in cloud when demands fluctuates.

There are also many other studies on resource management and scheduling in scientific computing. Uddin et al. [16] evaluate three scheduling algorithms to find the most energy-efficient one. The algorithms were implemented using the CloudSim software to simulate IaaS cloud infrastructure. The results indicates that the two phases power convergence (TPPC) algorithm [17] is the most energy-efficient of the tested algorithms. Zhao et al. [18] propose an energy and deadline aware scheduling method for data intensive applications. The method is based on the idea of modeling data sets as a binary tree based on correlations among them. This helps reducing data transmission. The second step of the method is based on energy-aware scheduling minimizing the number of active servers. Finally, Madni et al. [19] study resource allocation methods in their review article. Their conclusion is that not all important parameters are taken into account in current methods and improvements would be needed.

Energy-aware algorithms have been received a lot of attention during the last years. Many of these algorithms aim at optimizing resource selection or scheduling problems [20–22], while others focus on cloud computing [23–25] or networking [26–28].

Although most of the research on energy efficiency have focused on hardware, infrastructure, or algorithms there are many studies on software development, too. For example, Jagroep et al. [29] study how to make software developers aware on energy efficiency. In their case study they followed two software development projects and gave feed back to the developers on energy and performance issues. The results indicate that increased awareness makes the developers consider more on energy efficiency.

Energy-efficient operation is naturally highly important for major cloud service providers (e.g. [30] for Google,[31] for Facebook). Although there are commonalities, the key difference between big cloud operators and scientific computing community is that in cloud providers are hosting services which often require low latency to keep the interactive users happy. In scientific computing single jobs can run for hours or even days and thus high throughput is often far more important than shorter runtime. Therefore the architectural concepts are not directly transferable between the two camps but a lot of the learnings can still be beneficial for both.

Moreover, scientific computing has been slow in adopting virtualization, containers, and other techniques which form the basis of commercial cloud services. One reason for the slow adoption has been the belief that all kinds of additional layers waste computing resources. However, some studies indicate that the performance difference especially with container technology is not very significant [32]. Moreover, the resource isolation of containers allows new ways to manage the computation and the possibility to store the entire computational environment in the container provides new opportunities for reproducible research [33]. Therefore it is likely that we see increasing adoption of container technologies in the future in scientific computing following the initial steps already taken [34–36].

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