Green Task Allocation: Taking into Account the Ecological Impact of Task Allocation in Clusters and Clouds

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Abstract
The amount of energy needed to operate data centers increases regularly since some years at a high pace. The computer science community concentrates its efforts towards reducing these electricity costs, while keeping performances at high level. After summarizing quickly some of the approaches actually followed in particular within the European COST IC0804 Action on “Energy Efficiency in Large Scale Distributed Systems”, we will demonstrate here that these works do not address exactly the problem of energy savings and consider mainly electricity reduction. We argue in this paper that the ecological footprint is not only related to the raw energy consumption but also depends on the production means of the electricity, some being obviously greener than others and that the full life-cycle of IT equipments should also be considered. We present in this paper proposals to include additional parameters when deciding upon the allocation of tasks to the system.

Keywords: task allocation, cloud, clusters, ecological impact.

1 Introduction
While a major topic since several years in embedded systems with battery operated devices, energy awareness raised interest since only a few years for large-scale systems like super-computers, clusters, grids and clouds. For
a long time, energy consumption has simply been ignored in the performance evaluation in parallel architectures, parallel programming, and lately grid computing. The last years witnessed the rise in interest for energy aware infrastructures and computing in large-scale systems. What appeared at its beginning as a hype is slowly taking more importance in the everyday life when operating large-scale systems. Beside the ecological view coming from the carbon-related global warming concern, attraction is also garnered by several other actors: CEOs and system administrators handling large IT infrastructures caring for their electrical budget or their electricity cap, electricity providers who needs to serve optimally a growing demand, and finally computer and mathematical scientists who see an opportunity to explore a new scientific field.

The demand in research in energy-efficiency in large-scale systems is supported by several incentives [23, 5, 28], including financial incentives by government or institutions for energy efficient industries/companies [22]. Indeed, studies [2] report that the IT consumption accounts between 5 to 10% of the global growing electricity demand, and for a mere 2% of the energy. Data centers hosting web services or cloud computing gather thousands of nodes and every single watt saved on each machine every second is making a real difference. Pickavet et al. [25] estimated the global consumption for data centers at 29 GW in 2008, growing by 12% per year, expected to reach 113 GW by 2020.

Most of the works are driving research for reducing electricity demands in terms of watts. Together with better energy efficient hardware at all levels of the architecture (power supply, CPU/GPU, disks, motherboard, memory, etc.), software, middleware and applications are also being transformed to derive a better energy efficiency. Study about thermal parameters and dispersion of the heat in cluster rooms, low energy consuming air-conditionning systems (water cooling, outside air) are other means to reduce the ecological bill of the global infrastructure.

In the European COST Action IC0804 [23], researchers from 25 countries gather to explore the performance/energy tradeoff to achieve reduction of the energy consumption of servers, clusters, networks and so on, at the middleware, software and networks levels. Most of the existing works are indeed realizing some energy reduction without big losses of performances and with minimal human intervention. The approaches more or less follow all the same paradigms: process less, i.e. optimize algorithms and processing; turn off unused equipments, i.e. try to maximize the utilization of a minimal set of equipments; slow down the equipments so that they consume less.
Mathematical modeling and actual experiments show that time to results of scientific applications are comparable with or without taking into account the energy and the quality of service delivered by service oriented applications can still be acceptable according to Service Level Agreements, by adapting dynamically the physical resources being used (by using hardware mitigation such as CPU DVFS, on/off models; tasks migration; virtualization; etc.). For further reading, the COST IC0804 Proceedings [19] provide good insights.

The metric being used is quite simple in most of the studies: the first immediate metric that has been used coming from Flops is Flops/Watt. The idea is to measure the number of flops that can be achieved using one watt. Simplistic enough, this metric has the merit to be easily understandable and related to its ancestor in Top500. It is used by the Green500 listing (see [7]). A problem mentioned with this metric is that it measures the power, but not the energy spent. The power view is instantaneous while energy $E$ relates to power $P$ over a period of time $t$: $E = P \times t$.

Hence, two obvious way can be used to reduce energy consumption: either by reducing power consumption of the computers, or by reducing time to produce the result. When an infrastructure is always on with the same power consumption factor in average, the time is not an issue. In this situations the Flops/Watt metric makes sense. Less related to the number of flops, a metric considers the number of operations (not only flops) per watt. Conversely, another approach is to measure the average power the infrastructure needs to achieve a given operation. The Spec-power and TPC-Energy benchmarks (see [27, 10]) are using these metrics, respectively.

When computing $E$, do the maximum power or the average power have to be taken into account? Nowadays, many components have internal or software means to reduce the power consumption (see [6]) hence the course of power consumption over time can have big variations. Some infrastructures even rely on unused nodes switch-off to zero power consumption of a set of nodes.

Another metric used is the energy itself when accounting for the energy of finite applications. The idea is to measure the Time To Solution and the consumed (max, average) power. The result of the multiplication is expressed in Joules (Watts·s) or Watt-hour.

A common office computer consumes between 120 and 200 Watts while high end servers consume between 80 to 300 Watts. Several studies [11, 21] split the share of the energy consumption in a computer as: CPU accounts for 37% of energy consumption, memory is 17%, PCI slots are 23%, motherboard is 12%, while disk at 6% and fans with 5% are closing the list. Note
here that this does not include the power supply (which is accounting for more or less 20% loss), the networking infrastructure and all the cooling infrastructure. In data centers for instance the cooling can consume as much electricity than the computers themselves. The GreenGrid Alliance proposes to use the PUE for data centres infrastructures [29, 14]. The PUE (Power usage effectiveness) is computed by dividing the amount of power entering a data center by the power used to run the computer infrastructure within it. Therefore it encompasses all the surrounding of the infrastructure, including power supplies, chillers, air conditioning. For instance best practices data centres can reach a PUE down to 1.1 while the average data centers have a PUE of about 1.9.

Finally, one can either optimize the total energy used, or the energy cap. This latter is related to the maximum power consumption over a small period of time. In all infrastructures, the electricity provided by the energy providers is limited, due to physical constraints of the power (electricity) distribution network. Therefore a metric is to measure the maximum electricity that can be used in the infrastructure, in case of high workload and extreme situations (for instance when cooling is used at its maximum during hot periods).

To the best of our knowledge, only few works takes into account the quality of the energy being used to achieve the tasks [26] or the CO₂ emissions when choosing sites to allocate the tasks to clusters [12]. Also, few works integrate the global environmental cost of the computation (including the lyfe-cycle of the equipments) [31]. But it is obvious that not every Watts has the same ecological impact, depending upon the manufacturing unit producing the equipment, the power plant producing it, and the recycling policies.

2 Additional Parameters to Consider

2.1 On the Quality of the Energy

The International Energy Agency (IEA)¹ publishes regular statistics about the energy production and usage in the world, aggregating by countries or regions in the world. Thus depending on the area of production of the electricity, the ecological impact can be drastically different. For example, France generates electricity altogether about 85% from nuclear plants and about 10% from hydroelectricity, while in Austria this is 60% from hydroelectricity and 10%

¹ www.iea.org
from gas, and in China it is 85% from coal and 10% from hydroelectricity. Thus, having this information helps to head for greener infrastructures in locations with the lowest ecological impact. These numbers reflect directly on CO₂ emissions: while at the global level the CO₂/kWh is averaged at 500 g per kWh, in Iceland it is roughly 0, in France about 90 g and as much as more than 1 kg in China.

But the knowledge about the electricity generation means in the country where an infrastructure is located is not enough, and this for four main reasons, as identified in [26].

(R1) First, in a large-scale distributed systems, it is difficult to know all the equipments and their shares that were used in order to deliver a result. For instance, when a task is sent to a remote site for execution and its data are downloaded from a third party, a number of distributed equipments are involved like the computing resource, the data storage, the routers and switches along the way, without taking into account other hidden services like DNS servers, resource allocation services, middleware for orchestrating the different tasks, etc. All these equipments or services are difficult to account for a single use as they are shared by a number of executions, and institutions. Some may argue that, whatever the usage, the equipments would be present and consume anyway some electricity. But we believe that the share of each equipment, service or application involved must be carefully monitored in terms of energy consumption since it would be then possible to optimize the usage of the equipments, for instance using virtualization.

(R2) Second, the share of electricity means of production changes within a time frame. For instance, the demand in electricity in a day varies greatly, the peak being in Europe at the early evening. Hence, while sufficient energy can be produced with one kind of fuel during full night, there might be the need to push on some others when the demand increases. This also applies between months and seasons, full summer or full winter (for air conditioning and heating, respectively) do not exhibit the same schema. Moreover, countries buy and sell electricity within partners, due to local and global conditions on a global market, and not only due to demands: It is happening that one country buys electricity, even if it has some, in order to sell its own at an other price (higher or lower) to respect some negotiated contracts. Therefore a dynamic parameter reflecting these fluctuations must be included in a model to optimize the ecological impact.

(R3) Third, to make the model more complex, it is possible for a company or organization to actively promote green energy. The organization can follow two ways: (i) The first one consists in constructing a green-infrastructure,
producing by solar plant or wind wheel its own electricity to power its equipments. Although this requires some investment, many companies are advertising this technology to catch new customers. (ii) The second one consists in purchasing certificates that proves the use of green energy and his supported by governments (in Europe, the Renewable Energy Certificate System guarantees such certificates\(^2\)). Of course, no-one can really certify where the electricity flow is going to or coming from, but these certificates show the money flow between the providers and it is a reliable source of information. In both cases, the related information can be retrieved and used in a model.

(R4) Moreover, it is difficult to know the precise electricity consumption and energy generation, since it is a strategic information for many parties. Governments have some reluctance to disclose which electricity means are precisely used in the country (not to show their dependence or their polluting behavior). Enterprises, especially the ones advertising green behavior, do not want to give hints about their energy consumption that could reflect somehow their activity and help the concurrency. The uncertainty about the gathered information has thus to be part of the model.

To these reasons, we can add the following, related to the distribution network quality:

(R5) Energy loss during power transportation and electricity distribution: To transform primary energy to electricity, a factor of 40% loss of energy is largely admitted: 1 Watt in electricity needs the equivalent of 2.1 Watts in primary sources \(^1\). But it depends largely of the production plants, this number being an average at the world level.

Then, when electricity is produced, it must be transported up to the location of usage: It involves loss during the transportation in the high voltage grids and distribution nearby the customers. Factors include technologies used during transportation (mainly voltage and wired sections since the loss is a factor of \(I^2 \times R\), with \(I\) in Ampere and \(R\) in Ohms) and distance (while distance implies voltage levels to limit losses). In the US, the losses for transportation and distribution is about 6.5\(^3\)% and about 5.3% in France\(^4\).

Finally, at the end-user place, the electrical current have to be converted to low current: typically from hundreds of volts (110, 220) to volts (3.5, 5). The power supply units (PSU) are doing the job, with their own efficiency. The

\(^1\) http://www.aib-net.org
\(^2\) http://www.aib-net.org
\(^3\) http://tonto.eia.doc.gov/ask/electricity_faqs.asp
\(^4\) http://www.see.asso.fr/bulletin/actu/2006/1206.htm
80plus initiative\(^5\) that ensures this efficiency to be at least 80% is now widely accepted, but still a huge difference exist between 80 or 90% of efficiency for long-term running clusters.

2.2 On the Life-Cycle Assessments

While the above reasons relates to the production and distribution of the electricity at the time of the usage of the infrastructure, the life cycle of the equipments must also be taken into considerations.

(R6) From [16] we learn that the environmental costs coming from the usage of the computers (4 years) is only twice the costs for manufacturing the equipments: 1000 kg CO\(_2\) equivalent for usage against 500 kg CO\(_2\) for manufacturing. Transport accounts for less than 50 kg CO\(_2\) and recycling produce a benefit of less than 100 kg CO\(_2\). From these numbers, it is clear that from a global point of view, the type of equipments and their place of production should also be considered since these actual costs depends obviously on the technology to produce the equipments, the distance to their usage site, etc.

When considering a large-scale system like a Grid or a Cloud, several equipments bought by different entities (at least in Grids) are participating to the whole infrastructure. Each of these has a different usage/(manufacturing + transport + recycling) ratio. When choosing where to place a task, this factor should be included in the model.

3 The Rebound Effect

First introduced long ago [20] and re-emerged in the 1990s [15] with the climate change question, the rebound effect cannot be ignored here. The idea behind it is that the more energy reductions are possible thanks to technological means, the more global energy consumption will increase due to the then possible access to technologies.

When applied to task allocation in data centers and clouds, this implies that any reduction in the energy waste (for instance in the number of hosts switched on, in the low-power components used) involves more new comers and services: Indeed services becoming cheaper (the OPEX is decreasing thanks to the energy costs reduction), new customers will enter the market. To keep the quality of services high, the provider will arrange new facilities, raising globally the energy and environmental costs.

\(^5\) http://www.80plus.org/
As proposed by Brookes [4], a way to circumvent this trend is to make the price of using new technologies higher. In our case for task allocation in clouds and cluster, it means to include in the prices to use them the total environmental costs of constructing, recycling, transporting and using actually them, for instance with the Carbon Tax.

Since the 1990s, environmental taxes have been developed in several countries. Although not being generalized and still having some issues (like the trade between pollutant countries and under-development countries or the real impact on the global CO₂ emission), it can represent a good metric to measure the ecological impact of human or computer activities, including the manufacturing of the equipments. Unfortunately it is far from being developed: nothing exists to calculate the carbon tax associated with computer equipments, without mentioning their execution impact.

Introducing a parameter about carbon taxes in the allocation algorithm would not be a big deal. It would lead to have a multiplicative factor to estimate the environmental impact of the hosts, when choosing where to allocate tasks.

4 Towards Solutions and Adequate Metrics

5 Current Possibilities and Difficulties

We will in this section go through several possibilities to handle the above considerations.

Regarding the first point R1 (i.e. share of energy consumptions), research is on the move to evaluate through measurements and experiments on a large set of distributed systems the energy consumption induced by the equipments’ activities. In [17] Hlavacs et al. derive energy consumption of switches as a function of network traffic while Otoo et al. [24] analyze the energy consumption of various storage systems. Ge et al. [13] propose analytical models to approximate performance and energy cost for scientific workloads on multicore based power aware systems and Vasić et al. [30] evaluate the performances of cluster based applications when energy is taken into account. Hlavacs et al. [18] present an analytical study of the energy cost for transferring data in P2P applications, while Da Costa et al. [9] collect measurements over the Grid’5000 platform. Da Costa and Hlavacs [8] analytically derive the energy consumption of applications from collected system data. All these studies tend to prove that it is possible to evaluate at more or less coarse grain the energy consumption of applications and their impact on the several
elements of a hardware infrastructure, making it realistic, in a near future to precisely evaluate a priori (for optimization purpose) and afterwards (for billing and accounting) the share of electricity used by each service. There is a need for integration of the different works in order to have a global model taking into account the numerous aspects of the problem. There is also a need for deciding about the policy for distributing the costs of the shared services (like the resource management service or the job scheduler) among their users.

The second point R2 (i.e. evaluation of the dynamic share of electricity generation means) needs some interoperation with the energy suppliers and the energy market. An integrated information system should exist to cope with the dynamic of the market, linked with long-term statistics to hide the micro-fluctuations. Hence this will give a clear view on what type of energy was used during the life of a task. In a first step, long-term statistics at the scale of a region or a country, available online in databases (for instance at the IEA for international data, or based by country like the Energy Information Administration\(^6\) in US) can be sufficient to approximate the shares. A problem resides in the fact that either this information is not free (for instance, 550 euros for one user access to statistics) at the IEA, or is not served as data base services (rather in downloadable files, like at the EIA), raising the question of building a dynamic database or better a data warehouse prior to their exploitation. Another major issue is the periodicity of updates of the data, which is far from real time (4 times a year at IEA, monthly at EIA for instance), and no real time information is available.

For the third point R3-(i), the information of the green-ness of an organization is usually available and it is possible to know if an organization is consuming or producing electricity, and to which amount. Indeed, several constructors of clusters are advertising nowadays energy-positive infrastructure for at least part of it. The company itself that is building/having a distributed infrastructure knows the information: It can easily meter globally its energy balance and include this parameter. For the second R3-(ii), an organization knows obviously if it trades some energy certificates and their nature. These information can be easily integrated in the information system.

Regarding R5-(i) (i.e. transportation and distribution of electricity), the developments of a global information system about the electricity flows with the Smart Grids will be a key issue. Electricity providers tend to develop smart grids for their infrastructures. First, they deploy smart meters at end-

\(^6\) http://www.eia.doe.gov
users places and they smartly direct the flows of electricity according to the demand and the supply, switching on and off on-demand transforming units. They favor free electricity whenever possible (sun, wind, etc.) and activate fossil energy plants when the demands rise. Unfortunately this concept is far from being in operation while the interoperation with the underlying information system would allow for having a balancing factor in the decision algorithms. Hence it is impossible to assess currently the distance between the electricity providers and the electricity users, allowing for a careful computation of electricity loss during transportation and distribution.

For R5-(ii) (i.e. power supply performances), the information is static and can be retrieved from data sheets when the PSU are known. Hence integrating these in the model can be straightforward.

Concerning R6, the integration could be easy if the individual environmental footprints of the equipments could be retrieved. Until more strict regulations concerning the origin and material usage and the development of carbon taxes at large scale, this factor and the underlying ratio will be difficult to integrate on a model.

For R4 (i.e. on accuracy), the difficulty comes in large-scale distributed systems like Grids where several organization or companies are participating in the infrastructure. In that case the shared information system must contain these data but unfortunately these data can represent valuable information for potential concurrent on the market. Therefore, its truth or accuracy is a matter and the quality of the information cannot be guaranteed in general.

6 Taking an Example for Task Allocation

As for an example in task allocation algorithm, we introduced in [3] an energy-aware algorithm to allocate tasks in a cluster infrastructure. Without entering in details, our work is based on the idea of maximizing the minimum yield of the jobs: Jobs require resources (CPU and memory), and we allocate them on a set of machines that tends to optimize the energy consumption while maximizing the satisfaction of the jobs, i.e. minimizing the difference between the amount of CPU resources allocated to the jobs and the resources required. The approach is:

1. aggregating jobs on a reduced number of hosts in order to shut down unused ones;
2. placing jobs on energy efficient hosts;
3. taking into consideration the quality of service of the jobs.
Up to now, this algorithm is not handling R2–R6 developed before, and only partially R1, since we capture the part of CPU resources that a job is using and its energy consumption.

For R1, we believe that two possibilities can be investigated. One is to include a global estimate of the resource consumption induced by the placement of job $j$ on host $h$, meaning capturing also the network activity or disk IOs. Many works on energy savings (mainly when doing server consolidation like in cloud computing) are using virtual machines to easily migrate tasks in the physical infrastructure. Also, current developments in estimating the energy consumption of jobs on hosts will allow for a better accuracy. A rough estimate is to consider the overhead of the presence of job $j$ is a linear function of the CPU load, but non-linear dependence on disks, networks, memory, and other components are expected.

Concerning R2 and R3 we propose to adapt the algorithm in order to attract jobs based on the location of the hosts and the energy market. In previous works, we investigated only values related to the hosts themselves (their energy consumption when idle, when fully loaded, on average, etc.). A multiplying factor reflecting the differences in the electricity providers of the hosts can be integrated easily. In point 1 of the algorithm, it means to aggregate jobs on such hosts that are powered by more environmentally friendly electricity (ideally renewable sources). FTSFTW (Follow the sun, follow the wind) solutions can be integrated, migrating task (in virtual machines) depending on the day and atmospheric conditions. Nevertheless, deriving a factor from the different information can be tricky, because of the different nature of these information and for the integration with other factors of the algorithm not related to location and energy market. Hence the challenge is the construction of an interoperable long-term data warehouse handling such information about the ecological impact of each electricity market provider along the time. This data warehouse would give the opportunity to derive appropriate statistics and prediction models to cope with the energy shares during the lifetime of allocated jobs and the dynamic of the system.

With R5, the idea is to interoperate in the long term with smart metering and smart grids. Meanwhile taking an average does not make much sense since it would be the same for all potential hosts, and would not influence the placement. In a simulator, the parameter can be approximate using the distance to the energy provider, with a higher distance reflecting in higher losses. The aggregation of jobs on a reduced number of hosts (point 1 of the algorithm) would favor hosts closer to production site in order to reduce the
losses. Point 2 would integrate the PSU effectiveness of hosts when choosing the most energy efficient ones.

The same problem arises with R6. Until the full environmental costs are given for every equipments, only simulations can be included in the model in order to favor the most ecological equipments. This leads to change the algorithm in point 2, placing jobs not only to energy efficient hosts but also to environmentally friendly ones.

R4 is concerned with decision making in the presence of uncertainty. Introducing this parameter in the algorithm will certainly give way to different possible sub-optimal allocations. The problem then will be to decide upon which one is the best (average yield, maximum resulting yield: optimistic view, minimum resulting yield: pessimistic view). Metaheuristics like genetic algorithm able to find several candidates when perturbing the initial problem statement allows for the construction of families of potential allocation solutions. Note that R6 is independent and can be studied on its own (i.e. the impact of uncertainty on the allocation results), but makes more sense when R2 and R3 are considered since in these cases the accuracy is difficult to cope with and its range probably higher. Altogether we believe that a threshold can be exhibited below which an error in accuracy has low impact on the allocation, hence on the energy savings.

Finally, it should be noted that most of the considerations detailed hereby can be useful for other task allocation strategies based on characteristics of jobs, hosts, energy market and profiles.

7 Conclusion

We have presented in this article why the true ecological impact of the decision in task allocation in clusters and grid are missing some important factors: the energy production, the electricity transportation, distribution and usage are not integrating in the today job managers. We have outlined some important steps to be taken and we explored possible ways to actually improve the situation.

Nevertheless, several hypothesis are driving this work and could lead to its impossible implementation, or non-realistic results in terms of ecological impact. First, as discussed in this article, it is difficult to have enough accurate and up-to-date information about the energy market and energy generation means. Moreover, if such information are available in some countries, they still remain unknown for many and their accuracy is doubtful. At a large scale, with Grids gathering together resources from tens of countries (for instance
55 countries participate in the EGEE infrastructure\(^7\), with data centers being operated by worldwide companies having servers all around the world (see Google, Microsoft, Intel, Akama and others), this problem is increasing.

Second, large consumers like US, China, India are not at all leading the CO\(_2\) reduction initiatives and the information about their energy share and energy generation means is obviously not a priority. The path to real time information for these large consumers is still long. It would be arguable (and probably useless) to derive a solution in which the major consumers are not taking a part.

In an optimistic view, it can be argued that the missing information, or the imprecise collected and available data is not really a problem when seen at a large scale. Two factors lead this idea. First, large-scale systems tend to attenuate the impact of wrong local values; indeed the number of sites or the number of jobs will actually smooth down the error in decision taken by the system. For instance, a large-scale grid like EGEE is hosting more than 150,000 cores in 260 institutions and process 300,000 jobs per day: if some jobs are non-optimally allocated, the impact may be negligible for the whole system.

Second, small time variations that cannot be captured on the energy market at large are smoothed down by the long-term lifetime of the distributed infrastructure. Indeed, long-term available statistics reflect the trends in behavior of the energy markets and can be used as good approximate as long as the infrastructure and the running jobs last long enough.

The Kyoto agreement entered into force in February 2005. It pushes towards reducing the carbon footprint and promote renewable energy. In Europe, the european commission agreed to reach a share of 20% of renewable energy and some countries pushes further (23% in France for instance). This objective will certainly reduce the impact of non-optimal decisions since more and more energy will go greener.

Finally, we will witness in the future the emergence of a carbon tax, taking into consideration not only the usage but also the full life cycle of computer equipments. Introducing these in our algorithms will be straightforward, given the information available and reliable.

\(^7\) As of 16 November 2009, http://project.eu-egee.org/
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References

143 Green Task Allocation


**Biography**

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His researches focus on trust and reputation systems, cache and replica management, and energy aware distributed systems (in particular sensing, job placement and scheduling, green networking, autonomic computing, mathematical modeling). He is chairing the EU funded COST IC804 Action on “Energy Efficiency in Large Scale Distributed Systems”.

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