Effective Resource Management of Cloud Data Center

Hu XUE, Jian-ping LUO*, Xiong-wen HUANG and Yun YANG

College of Information Engineering, Shenzhen University, Shenzhen, China
Guangdong Key Laboratory of Intelligent Information Processing and Shenzhen Key Laboratory of Media Security, Shenzhen, China

*Corresponding author

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Abstract. Cloud computing is playing an increasingly important role in modern life, especially in the information age. What followed is a growing number of large-scale data centers were established around the world. It is conceivable that so many data centers must consume huge amounts of electrical energy. A considerable part of the consumption of these electrical energy is due to the irrational use of resources. In this study, the proposed adaptive heuristics for dynamic consolidation of VMs is based on an analysis of hybrid historical data from the resource usage by VMs, which significantly reduce energy consumption, while guaranteeing a high level of Service Level Agreements (SLA). Through simulations we validate that our approach reduces power consumption and ensures SLA compared to other algorithms using PlanetLab workload traces.

Introduction

The cloud computing as a new computing model for the purpose of providing customers with more convenient and high-quality network services in 2006, once raised has aroused widespread concern. It can be considered as a computing model which exists a number of characters like elastic scaling, on-demand computing resources, minimizing costs of operation and maintenance, and building a pay-as-you-go business paradigm [1]. Due to these features there is a highly increasing number of clients and their demands, it is obligatory for a cloud service provider to ensure that they can meet various consumer requirements [2]. However, the increase of application of cloud computing consumes large amounts of electricity, it can lead to high operating costs and carbon dioxide emissions. It is calculated that the energy consumption in data centers approximately equaled 1.3% of the world energy consumption in 2010 [3]. Moreover, it is predicted that the world electricity demand for data centers would face a 66% rise during 2011 to 2035 [4].

In data centers, the utilization of resource at the server is a significant factor for performance and energy consumption [5]. Studies indicate that resource utilization at the server is 10% to 50% in average [6]. The reason for high energy consumption is not only the power inefficiency of hardware, but also rest with the inefficient usage of these resources. Therefore, it is imperative to take action for an optimal management of data centers [7].

Using virtual machines (VMs) is one of the effective approaches to enhance efficiency in cloud data centers [8].

Making use of the virtualization technology makes it possible to activate several VMs on a physical machine (PM) in a way that each VM responds to the demand of several users [9]. Through live migrating [10], the VMs can be migrated from one physical machine to another. When a physical machine is empty, it can be switched into sleep or hibernation modes that can achieve the purpose of reducing energy consumption. However, when an application suffers an increasing demand giving rise to an unexpected rise of the resource usage, overbearing consolidation of VMs may bring about performance degradation [11]. Therefore, it is essential for cloud computing environments to guarantee dependable Quality of Service (QoS) defined via Service Level Agreements (SLAs) established between cloud providers and their customers [11].

At present, considering that there is a relationship between the power consumption and CPU utilization of hosts, most of researches migrate VMs based on CPU utilization [12]. Models based
on CPU utilization can offer accurate predictions for CPU-intensive applications, but for other types of application such as networks, I/O and memory-intensive application, they are often inaccurate [13]. In this work, an integrated live dynamic VM consolidation policy is presented for data centers in cloud computing environment. The proposed strategy can not only enables the minimization of energy but can also satisfy SLA. The main contribution of this work is:

1) Propose a novel adaptive heuristics for the problem of energy and performance efficient dynamic consolidation of VMs.

2) Develop the Multiple Factors Detection (MFD) method based on an analysis of historical data for overload hosts.

3) Present the Maximum Utilization (MU) VMs selection strategy and the modification of the Best Fit Decreasing (BFD) algorithm denoted CPU Aware Best Fit Decreasing (CABFD).

4) Carry out a simulation-based evaluation and performance analysis of the proposed policy and compare of different VMs consolidation policies.

The paper is organized as follows: Section 2 discusses the related work. Section 3 presents the adaptive heuristics policy for dynamic VMs consolidation. Section 4 gives the simulation results and analysis. Finally, the conclusion and future work is discussed in Section 5.

Adaptive Heuristics Policy for Dynamic Vms Consolidation

The problem of dynamic VMs consolidation is split into four portion: (1) determining when a host is overloaded; (2) judging when a host is underloaded and then migrating all VMs from the host and switch it to the sleep mode; (3) selecting one or more VMs that should be migrated from overloaded hosts; (4) searching new hosts for VMs that selected for migration from overloaded and underloaded hosts.

Host Overloading Detection

In this study, we use the upper utilization threshold detecting when a host is overloaded. In descriptive statistics, the interquartile range (IQR), is a measure of statistical dispersion, being equal to the difference between the third and first quartiles, which reflects the dispersion degree of the middle 50% of the data. In contrast to the total range, the interquartile range is a robust statistic with a 25% breakdown point and is therefore usually better than the total range. In this work, we use the formula developed in [11] to calculate the upper utilization threshold of different resources (CPU, RAM and BW). The formula as shown in Eq. (1):

$$ T_{u(CPU, RAM, BW)} = 1 - s \times Utl_{IQR(CPU, RAM, BW)} $$

Where is a parameter of the method that defines how aggressively the system consolidates VMs. is the interquartile range of the utilization of CPU, RAM and BW.

In a real physical machine, CPU, memory, network bandwidth, storage are necessary resources to host VMs. It is distinct that different goals (CPU, RAM and BW) may have different measures. So in this paper we use a metric that synthesizes the CPU, RAM and BW to detect the utilization of a host. The predicted utilization of a host can be formed as shown in Eq. (2):

$$ PreUtil = w_1 \times T_{u(CPU)} + w_2 \times T_{u(RAM)} + w_3 \times T_{u(BW)} $$

Where is the weight of different resources, furthermore, , and are the upper utilization of CPU, RAM and BW of the host calculated by Eq. (1) respectively. When the utilization of the host greater than or equal that is calculated by Eq. (2) then the host is confirmed to be overload.

VM Selection

Once a host is detected to be overload, the next step is to select specific VMs to migrate from this host. In this section we propose a novel policy- Maximum Utilization (MU) policy for VM selection. The MU policy migrates a VM that has the maximum utilization relatively to the other VMs
allocated to the host. This policy differs from the literature [2] where the VM are always selected based on the maximum energy saving strategy for the overload hosts. This policy can effectively decrease the number of VMs need to be migrated, which is beneficial to reduce energy consumption and ensure the service quality. The proposed policy is applied iteratively. The host is examined again for being overload after a selected VM to be migrated. The MU policy will be applied again to select another VM if the host is still considered as being overload. This process will be repeated until the host is considered as being not overload. The algorithm is shown in Algorithm 2.

![Algorithm 1. Dynamic scheduling of VMs](image)

1. foreach host in hostList do
2. Use Multiple Factors Detection (MFD) method;
3. If host is overloaded
4. Use Maximum Utilization (MU) VMs selection strategy;
5. Use CPU underloading detection method
6. If host is underloaded
7. Use Maximum Utilization (MU) VMs selection strategy;
8. Use CPU Aware Best Fit Decreasing (CABFD)

![Algorithm 2. Maximum utilization (MU) VM selection](image)

Input: power host  Output: the VM that selected to be migrated
1. migratableVmList = getMigratableVms(host);
2. tempMigratableVmList = NULL;
3. vmToMigrate = NULL;
4. if migratableVmList = NULL then
5. return NULL;
6. foreach vm in migratableVmList do
7. if vm is in migration then
8. continue;
9. else tempMigratableVmList.add(vm);
10. vmToMigrate = tempMigratableVmList.getMaximumUtilizationVm;
11. return vmToMigrate;

![Algorithm 3. CPU Aware Best Fit Decreasing (CABFD)](image)

Input: hostList, vmList  Output: allocation of VMs
1. vmList.sortDecreasingUtilization();
2. foreach vm in vmList do
3. minUtilization = MAX;
4. allocatedHost = NULL;
5. foreach host in hostList do
6. //Apply the multiple factors detection method to judge whether the host will be overload after allocating the VM to it.
7. if isHostOverUtilizedAfterAllocation(host, vm) then
8. continue;
9. if host has enough resources for vm then
10. utilization = getMaxUtilizationAfterAllocation(host, vm)
11. allocatedHost = host;
12. minUtilization = utilization;
13. if allocatedHost NULL then
14. allocation.add(vm, allocatedHost);
15. return allocation;

**VM Placement**

The problem of VM placement can be considered as a bin packing problem. Because the bin packing is NP-hard, to solve it we apply a modified Best Fit Decreasing (BFD) algorithm that is verified to use no more than $11/9\text{OPT} + 1$ bins (where OPT is the number of bins provided by the optimal solution).

In this study, the modified BFD algorithm is denoted CPU Aware Best Fit Decreasing (CABFD). In this algorithm, all VMs are sorted in the decreasing order according to their current CPU
utilization, and then each VM is allocated to a host that provides the least increase of the utilization caused by the allocation. This not only ensures that the increased energy consumption is minimal, but also makes full use of the heterogeneity of the nodes by first selecting the nodes with the highest utilization. The pseudocode for the algorithm is presented in Algorithm 3. The complexity of the algorithm is, where \( n \) is the number of hosts and \( m \) is the number of VMs.

**Host Underloading Detection**

It is important to reduce total energy consumption by converting a host that is below the utilization thresholds into an energy saving state. For determining underloaded hosts we come up with a simple method. This method uses different lower thresholds utilization to maximize the requirements of different users. In this work we set five different thresholds that is from 0.1 to 0.5.

**Performance Evaluation**

In this section, we discuss a performance analysis of the adaptive heuristics policy for dynamic VMs consolidation presented in Section 3. We choose CloudSim toolkit [19] to perform simulation experiments. CloudSim is a cloud computing simulation platform launched by Grid Laboratory of the University of Melbourne and the Gridbus project in 2009. Compared with other simulation toolkits (e.g. SimGrid, GangSim), it provides data center-based virtualization technology, virtual cloud modeling and simulation function, furthermore, it supports the energy aware simulated experience of hosts.

The workload data of the VMs were obtained from the CoMon Project, which is one of the monitoring facilities of PlanetLab [22]. The data includes CPU utilization of more than 1,000 VMs in 500 different regions around the world tested every 5 minutes.

**Power Model**

In the cloud data center, energy consumption is mostly caused by the CPU, memory, disk and refrigeration systems, and other hardware modules [20]. The modern multi-core CPUs energy consumption modeling is very difficult, which makes the establishment of accurate mathematical model has become a complex research problem. Therefore, we do not use the server's power analysis model, but rather use the actual data provided by the SPECpower benchmark [21].

Two server configurations with dual-core CPUs published in February 2011 was selected: HP ProLiant ML110 G4 (Intel Xeon 3040, 2 cores * 1860 MHz, 4 GB), and HP ProLiant ML110 G5 (Intel Xeon 3075, (2 cores * 2660 MHz, 4 GB). The power consumption characteristics of the selected servers are shown. Multi-core servers have little impact on simulating a large number of servers to evaluate VM consolidation, therefore the dual-core CPU is adequate to analyze the resource management algorithms.

**Performance Metrics**

In order to compare the efficiency of the algorithms, we use three metrics to evaluate their performance. The following metrics are used: (1) Total energy consumption is defined as the sum of energy consumed by the data center which is calculated according to the model defined in section 4.1. (2) Number of VM migrations: This metric is initiated by the VM manager during the adaptation of the VM placement. (3) SLA violations: It is defined as the percentage of SLA violation events relatively to the total number of the processed time frames. An SLA violation occurs when a given VM cannot get the amount of Million Instructions Per Second (MIPS) that are requested.

**Simulation Results and Analysis**

Using the selected workload data (p1, p5 and p7) described in Section 4, we have compared the results of the simulation of several combinations of five host overloading detection algorithms (THR, IQR, MAD, LR, and LRR), three VM selection algorithms (MMT, RS and MC) with Power Aware Best Fit Decreasing (PABFD) VM placement algorithm to our algorithm (MFD-MU
CABFD) in different lower utilization thresholds (LUT). The parameters of the algorithm: IQR-MC-PABFD, LR-MC-PABFD, LRR-MMT-PABFD, MAD-RS-PABFD, THR-MMT-PABFD and MFD-MU-CABFD are 1.5, 1.2, 1.2, 2.5, 0.7 and 1.5 respectively. The weight of different resources, and are 0.5, 0.3 and 0.2 respectively.

Figure 1 shows the simulation results of energy consumption, VM migrations and SLA respectively proposed in Section 4.2 for different algorithms. From the results, we can see the energy consumption of the data center decreases sharply with the increase of LUT of a host and then increases gradually after the utilization rate exceeds 0.3, the number of VM migrations and SLA has been increasing with the increase of LUT. But the SLA of our algorithm is always in a very low range. The reason why our algorithms perform better than other algorithms is to consider the multiple resources required for VM migration and to minimize the impact on CPU when allocating VMs and to choose as few VMs as possible. Comprehensive view of all the performance metrics, we can conclude that our policy (MFD-MU-CABFD) has obvious advantages over other policies.

![Figure 1. Energy consumption of different policies for different lut and instances (p1, p5 and p7).](image)

**Conclusion**

Dynamic consolidation of VMs is one of the resource management methods to reduce energy consumption in the cloud computing data centers. However, such consolidation can lead to violations of the SLA. In this paper we have presented a complete consolidation program for VMs which including robust overload detection for hosts, VMs selection, VMs placement and underload
detection. Comparing to other algorithms presented in the CloudSim toolkit, our algorithm perform
much better. In other words, our algorithm can minimize the energy consumption as well as keep up
with SLA in data centers.

In our future work, we plan to obtain a lower utilization threshold that can be dynamically
adjusted based on historical data of different resources. In addition, we will focus on designing a
VMs management method that integrates more system resources such as storage and network
topology.

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