VM placement with effective energy management in cloud using optimal VM allocation framework (OVAF)

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ABSTRACT
The performance of servers at the data centers is affected when the servers are overloaded. To overcome this problem, the workload at the overloaded servers has to be redistributed to other servers which is possible with live VM migration. Live migration plays a crucial role in handling the overload at the data centers without service interruption. However, live migration also incurs some performance loss and energy overhead. The energy consumption at the data centers is a matter of utmost concern both in terms of economy and ecology. In this paper we are proposing a novel approach to find the most suitable server for VM placement. We have introduced an Optimal VM Allocation Framework (OVAF) in which the hosts at the source requests the destination for their available slots. Based on the response from the available servers, the utilization factor is calculated and the selection of appropriate destination for VM placement is done. Simulations carried out have shown 10% improvement in energy saving.

Keywords:
Energy consumption
Live migration
VM placement

1. INTRODUCTION
In cloud computing the IaaS layer provides high computation speed and large storage capacity for an enterprise. Virtualization in servers helps the data center to function as a sophisticated cloud architecture [1, 2]. A cluster of host forms the core of the datacenters. At the datacenters, the hosts may experience more workload. To maintain the efficiency and performance of hosts, the workload has to be transferred to hosts or datacenters with lesser workload. This is achieved through VM Migration. VM migration requires extensive IO operations which results in high energy consumption. The other factors which contributes to the energy consumption are: an idle server, power consumption by server, data transmission etc. The data center manager aims at the ways to develop VM Placement Policy for energy reduction and maximize resource utilization and return of investment [1–4]. An energy and cost efficient migration can be achieved by properly choosing the VM to be migrated and considering the factors like the destination where the VM has to be copied, bandwidth availability, downtime and migration time [5]. The self-managing techniques implemented at the data centers for dynamic allocation of resources results in reduction of efficiency [6].

Recent studies show that even the idle servers consume 69-97% of the total energy consumed by a fully utilized server [7]. Even the shutting down process of a physical machine for a specified time and restarting it after lapse of the inert period does not significantly contribute towards an acceptable energy saving procedure, as the switch on-switch off cycle leads to several steady state or quiescent state violations calling for enhanced power requirements. In this paper we are concentrating on the energy consumption during live migration. The energy, E can be calculated as,

\[ E = P \times T \]
where P represent the power consumption and T is time taken through the process of live migration.

On an average, the major sections of energy consumption at the data centers are infrastructure, server, cooling etc., as shown in Figure 1 [8, 9].

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Figure 1. Average energy consumption at the data centers

2. RELATED WORK

Various studies have been conducted to estimate and reduce the energy consumption at the data centers during live VM Migration. In [3], the author has developed a model by applying linear regression on the available data. The model helps to estimate the cost of energy consumed during live VM Migration with 90% accuracy. In an incessant VM demand state, static allocation is considered to be the better option whereas for sporadic VM requests, dynamic allocation is more efficient [7]. In [8], the authors have suggested integer quadratic program for power optimization at the data center. This method, however, is not suitable for systems with heavy workload.

Li et al. in [10] have proposed the multi-agent method for VM consolidation to balance the workload at the physical machines by VM allocation. However, the best results of this approach is attributed to the proper VM selection process. The Iterative Weighted Linear Regression method (IWLR) has been used to predict the host utilization and select the most suitable host for migrating the VMs [11].

The traditional resource allocation methods viz, First Fit, Worst Fit and Best fit can be applied to the VM consolidation problem. It can be considered as an online bin packing optimization problem where the randomly arriving VM requests (objects) must be accommodated into the available PMs(bins). The requirement of a new PM arises when the allocation methods fail to find a suitable PM for allocating the VMs [12]. The heuristics-based dynamic approaches does not guarantee optimal performance, especially in the worst cases [13].

In [14, 15], the author has analyzed the dynamic part of power consumption by a physical machine. The difference between the energy consumed before migration and the energy consumed during migration gives the energy overhead incurred during live migration.

\[
\text{Energy overhead} = \text{Energy before mig} - \text{Energy during mig}
\]

In [16], the authors made an observation that approximately 20 seconds are required for the source and destination servers to balance the level of power consumption with the number of allocated VMs. In [17], the authors have suggested Medium Fit method to balance between the overload threshold and underload threshold. The power efficiency of a physical server is calculated as \( \text{Power efficiency} = \frac{\text{CPU total}}{\text{Max power}} \)

In [18], the authors have used the correlation of coefficient to determine the PM that has to be chosen for VM Placement. The PM with value close to -1 is chosen as the appropriate PM. The case of multiple PMs with the same co-efficient is not considered here. In [19, 20], the authors have computed the total energy consumption, TE, in the time duration between \( t_0 \) and \( t_1 \) as follows.

\[
TE = \int_{t_0}^{t_1} Power_{util}(t) dt \tag{1}
\]

The CPU utilization can be enhanced to minimize the energy consumption. In [21], the authors mention power usage effectiveness (PUE) as a factor to measure the energy efficiency.
The lesser the value of PUE, the data center will be more energy efficient.

3. OPTIMAL VM ALLOCATION FRAMEWORK

In [22, 23], the authors have used the following four categories of VM consolidation.

- a) The overloaded host detection.
- b) The Selection of VM to be migrated
- c) The selection of destination for VM Placement
- d) The underloaded host detection.

The VM migration comprise of mainly a preparatory work at the source and the Host Acceptance work at the destination. Once the workload at the source datacenter reaches a threshold, say 80%, the VMs and the workload from the particular datacenter has to be redistributed to another datacenter. The second step is the selection of appropriate VM for migration. The VM that is selected for migration has to be placed at a destination server. The destination is a server with moderate workload, which can accommodate the migrated VM. Not only does the overloaded servers affects the performance, even running the datacenters with very less workload also affects the performance. This the VMs from the underloaded host also need to be migrated so that they can be shut down to save energy.

Load balancing at the IaaS level can be effectively done by predicting the future resource requirements of the new tasks and allocating the resources at the physical machine accordingly [24]. Based on the predicted load the set of physical machines is sorted in descending order. The last PM in the sorted list, say PM, which is the most underloaded server, is chosen. Further in PM, the VMs with the minimum load is selected for migration. Suitable PM is searched from the sorted list which can accommodate VMs. The process is repeated until all the VMs from underloaded servers are migrated to other physical machines [25].

The migration process is based on the three statistics obtained from source and destination servers.

- a) Request statistics from Source (HostRequestStatistics),
- b) Reply statistics from Destination (DestinationReplyStatistics) and
- c) the statistics of Energy Efficiency (EnergyEfficiencyStatistics).

The Minimum Migration Time (MMT) policy for VM Placement is found to be efficient [20, 25]. In MMT, the VM to be migrated, say vm, is selected based on the (16). In the equation $Mem_{util}(vm)$ represents the memory utilization of the VM, vm, selected for migration and $Mem_{util}(q)$ represents the quantity of memory utilization of other VMs on host H. The notation $unusedbw_H$ is used to denote the network bandwidth unused at host H.

$$vm \in H \forall q \in H, \frac{Mem_{util}(vm)}{unusedbw_H} \leq \frac{Mem_{util}(q)}{unusedbw_H}$$

3.1. Migration Request Protocol

The analysis has to be done for the request and reply statistics. The statistics is based on the spatial and temporal conditions. The spatial conditions include the resource listing and capacity of utilization. The temporal conditions are done on the basis of past, present and future migrations (prediction).

For minimizing the energy involved in migration, the number of repetitions, i.e, the transfer attempts have to be minimized. For that solid maximum successful transfer only should take place. The smaller VMs can be offloaded to another server. The total time for setup and data content transfer has to be minimum. In order to save maximum energy, the most effective way is to reduce the number of active servers [26]. The major energy consumption areas are Computation energy, Migration energy, Switching energy and the overhead energy [27].

$$Total_{energy} = Comp_{energy} + Mig_{energy} + Switch_{energy} + Overhead_{energy}$$

The objective is to minimize the number of operational servers (S) with reduced energy usage. For ‘n’ physical machines the sum of energy consumption, $ep_i$ should be minimum. While migrating the resource requirement of virtual machines, $VR_i$, should be less than the physical resources, $PR$, available. The Virtual Machine Placement problem can be formulated as follows.

$$Minimize S = \sum_{i=1}^{n} ep_i$$
Subject to,
\[ \sum_{j=1}^{m} V_j R \leq PR \]

Algorithm 1: OptimalSlotSelectionAlgorithm
Input: H \( \triangleq \{h_1, h_2, h_3, \ldots, h_n\} \) represent n hosts
Output: Allocate the VMs with proper load balancing
1. Track the overloaded hosts.
2. For each host, h_i in the hostList H,
3. Calculate resource utilization
   \[ U_i = \frac{1}{h_i} \sum_{k=1}^{n} R_k(t) \]  \hspace{1cm} (5)
4. if the utilization is above threshold, i.e.,
   \[ U_i > 80\% \] then
5. OverloadHostList.add(h_i)
6. Endif
7. Endfor
8. Get the VM Request Statistics
9. Use the HostRequestStatistics
10. VM, \( \epsilon \) = Select a VM from Overload Host
11. SelectVMLList.add(VM_i)
12. Choose the destination servers for VM allocation.
\[ D = \text{DestinationReplyStatistics}() \]
13. Allocate the tasks to the most suitable destination server, with minimum energy consumption
   using the EnergyEfficientAlgorithm().

Algorithm 2: HostRequestStatistics
Input : OH \( \triangleq \{oh_1, oh_2, oh_3, \ldots, oh_i\} \) represents the Overloaded hosts.
Output: The list of Underloaded Hosts where migrated VMs can be placed.
1. Sort the hosts in descending order based on the CPU utilization.
2. Predict the Host for migration based on Iterative Weighted Linear Regression method.
3. The simple regression line is shown below.
   \[ Y = a + bX \]
   The regression co-efficients a and b are derived using least square method.
4. The tricube weight function can be used to predict the K values of host utilization.
   \[ W = (1 - (p)^3)^3 \]
   where p is the difference between the current and the last observation.
5. If W<1, UH=add the host to underloaded host list
6. Return UH.

Algorithm 3: DestinationReplyStatistics
Input : UH \( \triangleq \{uh_1, uh_2, uh_3, \ldots, uh_v\} \) represents the Overloaded hosts.
Output: Server with correlation co-efficient \( \approx -1 \).
For hosts in the UH list, choose
\[ D \triangleq \{d_1, d_2, d_3, \ldots, d_m\} \] for space allocation.
1. Select the VM with Minimum Migration time.
2. Calculate \( \gamma \), the correlation co-efficient as shown below.
   \[ \gamma = \frac{\sum_{i=1}^{m} (e_i - \bar{e})(r_i - \bar{r})}{\sqrt{\sum_{i=1}^{m} (e_i - \bar{e})^2 \sum_{i=1}^{m} (r_i - \bar{r})^2}} \] \hspace{1cm} (6)
   where, \( \bar{e} \) is the mean of the estimated resource demands and \( \bar{r} \) is the mean of the residual.
3. Choose the servers from \( D \), with \( \gamma \approx -1 \).
4. Return \( D \)
Algorithm 4: EnergyEfficiencyEstimation
Input : Power utilization by various components at the data center.
Output: Server with minimum Energy consumption.
1. Determine the Euclidean distance for the resource request and the resource utilization of the selected servers.
2. Choose the server with maximum distance so that the servers are fully utilized.
3. Obtain the power usage values while the ith server is inactive and also when it is completely utilized.
4. Calculate the power consumption for the migration process with M memory size and the allotted bandwidth B. Assume the migration starts at time t1 and ends at time t2.

\[ Migr_{energy} = \int_{t_1}^{t_2} Power_{src} \cdot \frac{M}{B} + \int_{t_1}^{t_2} Power_{src} \cdot \frac{M}{B} \]  

(7)

5. The maximum power usage by the physical machine and the CPU utilization are the parameters that affects the power consumption at the server [28-30].

\[ Power_{cu} = n \cdot Max_{power} + (1 - n) \cdot Max_{power} \cdot cu \]

\[ = Max_{power} \cdot (0.7 + 0.3 \cdot cu) \]

(8)

Here n represents the fraction of power that the inactive server consumes, cu denotes the CPU utilization. The variations in workload changes the CPU utilization over time, t.
6. The computation energy by servers can be computed as

\[ Comp_{energy} = \sum_{i=0}^{n} Power_{cu} \cdot time \]

(9)

where n denotes the number of servers currently in use.
7. The Overhead energy is the difference between the power consumed during migration and the idle power consumption at the source and target servers.

\[ OH_{energy} = Migr_{energy} - Idle_{energy} \]

(10)
8. Compute the overall energy consumption as the sum of energy computation cost, energy for migration, energy for server switching and the energy overhead as

\[ Total_{energy} = Comp_{energy} + Migr_{energy} + OH_{energy} \]

(11)

4. RESULT AND ANALYSIS
The simulation set up has been done in Cloudsim 3.0.3, by randomly selecting the values for the number of VMs to be migrated with the settings shown in Table 1. The features of the VM is similar to the features of AmazonEC2 instance types, but with single core VM. The Minimum Migration Time (MMT) policy is used in the model which selects the VM with minimum migration time requirement [31].

| Parameters     | Configuration                      |
|----------------|------------------------------------|
| Server Types   | HPProLantML110G4/(2X1800MIPS)      |
| Number of Servers | 800 diverse servers, 400 of each host type |
| Workloads      | PlanetLab (10 days of traces)       |
| Overload decision | Iterative Weighted Local Regression |

The increase in number of VMs increases the computation energy, migration energy and overhead energy. This in turn increases the total energy consumption. Figure 2 shows the variation of energy with the variation in number of VMs.

The energy consumption for a particular run with and without OVAF is shown in the Figure 3. The result of implementation of OVAF has shown an improvement of approximately 10% in energy consumption as shown in Figure 4.
Factors such as hardware, bandwidth etc., affect the premigration and postmigration scenario. Our methodology helps in energy savings to a certain extent which can be complemented by the following methods, but at a certain cost (i) An improved bandwidth of the migration channel which is an important parameter that decides the efficiency of migration process. (ii) Using the finest set of processors, memory and storage for migration activities can also help in energy saving.
5. CONCLUSION

The upsurge in the number of data centers is a major threat to the environment. The energy consumption at the data centers are static and dynamic in nature. Energy is consumed during VM Migration and even while the servers are idle. The energy consumption can be reduced with the proper selection of hosts during migration. The selection of host is done by using the most appropriate methods like Iterative Weighted Local Regression (IWLR) and with the Euclidean methods. Our experiment has shown that with the implementation of our algorithm the energy consumed during VM migration can be brought down to a certain extent.

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