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Virtual Machine Sizing in Virtualized Public Cloud Data Centres

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ABSTRACT

Virtual machine (VM) consolidation in data centres is a technique that is used to ensure minimum use of physical servers (hosts) leading to better utilization of computing resources and energy savings. To achieve these goals, this technique requires that the estimated VM size is on the basis of application workload resource demands so as to maximize resources utilization, not only at host-level but also at VM-level. This is challenging especially in Infrastructure as a Service (IaaS) public clouds where customers select VM sizes set beforehand by the Cloud Service Providers (CSPs) without the knowledge of the amount of resources their applications need. More often, the resources are overprovisioned and thus go to waste, yet these resources consume power and are paid for by the customers. In this paper, we propose a technique for determining fixed VM sizes, which satisfy application workload resource demands. Because of the dynamic nature of cloud workloads, we show that any resource demands that exceed fixed VM resources can be addressed via statistical multiplexing. The proposed technique is evaluated using VM usage data obtained from a production data centre consisting of 49 hosts and 520 VMs. The evaluations show that the proposed technique reduces energy consumption, memory wastage and CPU wastage by at least 40%, 61% and 41% respectively.

Keywords : Virtual Machines Sizing, Virtual Machine Consolidation, Statistical Multiplexing

I. INTRODUCTION

In recent years, the use of cloud computing has increased in organizations in providing infrastructure to process application workloads. This increased appetite can be attributed to its success in delivering service on a pay-as-you-go basis. This has caused services providers to install many data centre across the world to address the demand. Unfortunately, data centres consume a lot of energy and this a concern. According to [1] and [2], power bills has been the largest commodity service expenditure in CSPs. Moreover, data centre electricity usage was about 3% by 2012 and now it is expected to triple by 2020 [1]. The main cause of data centre power wastage is low server utilization, which is caused by inefficient resource utilization leading to use of many physical servers to run application workloads [3] [4].

The main technology that supports cloud computing is virtualization [5]. This technology allows many different applications to be executed independently in shared hardware by sharing resources. This is known as consolidation, which allows packing many VMs in the one physical machine (PM) so that other PMs can be shut down thus achieving energy savings. However, this technique may not be useful in some circumstances. For instance, in Infrastructure as a service (IaaS), which is the most promising cloud model among small organizations [6], [7], customers are allowed to pick VM sizes from CSPs' list of available VM types without the knowledge of the actual amount of resources their applications need [8]. More often, the resources are over-provisioned and thus goes to waste. From this viewpoint, consolidation only helps in host-level resources maximization and not VM-level resources maximization.

To determine the actual resources required by a VM, data on resource usage about a VM have to be analyzed for a given period of time [9]. CSPs can do this to propose the right VM sizes to their clients. In this regard, CSPs have attempted to help their client perform right-sizing such as ParkMyCloud for Windows Azure Cloud, Amazon CloudWatch and Google cloud right-sizing [9] [10]. All the methods provided by Azure, Google and AWS cloud services have to be manually completed by customers and seems to fit customers who already have knowledge in cloud computing. Moreover, the customer has to choose from the VM type preset by the CSP for resizing their VMs. Nevertheless, if the recommendations are applied correctly and consistently, cloud customers can save up to 70% on the monthly bill.

Moreover, there has been a growth of literature touching on efficient use of computing resources with the aim of reducing data centre energy consumption via VM sizing [8], [11], [12]. Different works have used different techniques but there's still room to improve resource utilization for energy savings by utilizing different techniques.

In [13], the authors have proposed a VM sizing technique. A VM sizes (amount of resources allocated to a VM) if given as a function of a VM's own resource requirements, resource requirements of the co-located and the overall effect of VM co-location. Based on the proposed VM size, a VM allocation has been developed to ensure the least resource demands and minimize VM migrations.

In [8] the authors have proposed a VM sizing algorithm that customizes VM sizes to match application workload resource demands in a containerized cloud environment. In this approach, application tasks are clustered using features such as resources usage, task length, and priority and submission rate. The clustered jobs are then mapped to the appropriate VM sizes that meet the resource demands for the applications. In this approach, Google Cluster Trace has been used to evaluate the proposed technique. The authors have reported that the proposed technique achieves efficient utilization of resources leading to energy savings.

In [5] the authors have proposed a VM sizing approach by creating copies of similar VMs in different hosts to reduce the pressure put on particular resources in one host. This technique take advantage of hosting dissimilar workloads in the same host. This way, aggressive consolidation can be achieved without performance degradation caused by homogeneous workloads. A secondary benefit for this technique is reliability brought about by having multiple copies of the same VM for processing workloads.

Finally, in [14] the authors have proposed a VM sizing algorithm, whose aim is to match resources allocated to VMs with the actual application load. This is achieved using time division multiplexing. After a VM is resized, the new changes can be implemented by existing hypervisor capabilities such as CPU-Hotplug and Memory Ballooning.

In this paper, we propose a simple but effective technique for VM right-sizing IaaS multi-tenant public cloud based on historical resource usage. We determine a fixed VM size for a VM and then show that statistical multiplexing can be used to take care of resource demands, which exceed the fixed VM resources. In this paper, statistical multiplexing in VM is used to mean where a busy VM can borrow resources from an idle VM simply because co-located VM do not peak simultaneously. By ensuring that VMs are allocated the resources that are actually demanded by cloud workloads, leads to the use of less physical server and thus saving on energy. The overall benefit is that operating costs for running the data centre on the part of the CSP and running VMs on the part of the client is reduced. The target cloud service and deployment model in this work is IaaS multi-tenant cloud, where cloud users are allowed to determine their application resource demands (VM size), by selecting VM sizes pre-set by CSPs.

The remainder of this paper is organized as follows. Section II discusses the materials and methods used in this paper. Section III presents the results obtained from our procedures. In section IV, we discuss the results obtained from our procedures and the paper is concluded in section V.

II. METHODS

In this section, we describe the materials used and the procedures used to achieve our objective. This section clearly explains five areas, 1) A description of data used to evaluate our technique, 2) Visual analysis of VM resource usage using graphs, 3) How a VM sizing algorithm was designed, 4) How we showed that statistical multiplexing is a viable technique for supporting VM sizing and 5) Evaluation of VM sizing algorithm.

A) A description of the data used to evaluate our technique – GWA-T-13.

This data is obtained from the Grid Workload Archive (GWA). The main goal of GWA is to provide a platform where researchers and practitioners can share grid workloads [15]. Any person wishing to share their grid workload can do so as long as they are in a database format (SQLite) or text format (CSV). GWA has collected over 13 workloads shown on their website, Materna being the latest. Materna consists of three traces from a distributed datacenter, namely Materna-trace-1, Materna-trace-2 and Materna-trace-3 with 520 VMs, 527 VMs and 547 VMs respectively. Materna provides service to different organizations featuring different business lines such as government, digital enterprises, IT factory and SAP business consultancy in Germany. The VMs running in the 3 traces are mostly the same and were collected for a period of 3 months and each of the 3 traces contains information representing one month. The resources usage data of each VM is thus treated as time series data. Because of the difference in the number of VMs in the three traces, it not possible to tell one particular VM in the three traces and hence they cannot be merged. For this reason, one can only work with one trace at a time.

Materna trace is obtained from a VMware ESX environment with 49 Hosts, 69 CPU cores and 6780 GB RAM. The data contains information about 520 VMs in 520 CSV files. The following information about each VM is contained in each CSV file.

- Timestamp – this is the epoch timestamp in milliseconds.
- CPU cores – this is the number of vCPUs provisioned to the VM.
- CPU capacity – this is the vCPU capacity in MHZ. It is given as the product of the number of cores and the speed per core.
- CPU usage (MHZ) – CPU capacity that is actually used by workloads in MHZ.
- CPU usage (%) - CPU capacity that is actually used by workloads in percentage (%).
- Memory provisioned - this is the memory capacity for the VM in KB.
- Memory usage (KB) – this is the actively used memory in KB.
- Memory usage (%) – this is the actively used memory in percentage (%).

- Disk write performance – this is the disk throughput in KB/s.
- Disk size – this is the size of the HDD in GB.
- Network throughput (received) - this is the network performance in terms of KB/s.
- Network throughput (transmitted) - this is the network performance in terms of KB/s.

B) Visual analysis of VM resource usage using graphs

The resource usage of VM is visualized using graphs to show VM's actual resource usage as compared to resources allocated. The aim of this is to visually observe how VM resources are used over time and the dynamic nature of cloud workloads. We also used percentiles to try and determine resource allocations that can process most of the workloads across time.

C) Design of VM sizing algorithm.

The data, whose source and characteristics are presented in part A of this section is the basis of the design of this VM sizing algorithm. A VM size is determined by using resource usage at the 90th percentile. Based on the percentile rank of a VMs CPU usage R_{cpu} is given by,

$$\mathbf{R_{cpu}} = \left\lceil \frac{\mathbf{90}}{\mathbf{100}} * \mathbf{N} \right\rceil, \qquad (1)$$

where N is the total number of observations for CPU usage. The percentile ranking is then used to get the CPU usage value, which is treated as 80% of actual VM size according to Datacenter Maturity Model % [16]. Thus, if a function f(.) gives the CPU values at rank R_{cpu}, then the effective VM CPU size, CPU, is given according to equation 2. Similar calculations apply for VM memory.

$$\mathbf{CPU} = \frac{\mathbf{5}}{\mathbf{4}}\mathbf{f}(\mathbf{R_{cpu}}) \qquad (2)$$

Any resource need that exceeds the fixed CPU size is taken care of by statistical multiplexing. After, VM sizing, we compare the resource required in a data centre before and after VM sizing. Next, we show how we determined the viability of statistical multiplexing.

D) Is statistical multiplexing viable?

To determine if statistical multiplexing is a viable technique, we identified all peak points for each of the 520 VMs (in workload described in part A), their corresponding timestamps and if there are peaks in other VM, which occur at the same time. We define a peak point of a VM as any point whose value is higher than a 90th percentile value. The following steps were used to determine the viability of statistical multiplexing with the 520 VM's resources usage time series data as input.

Step 1: Compute the 90th percentile for resources usage for each VM.

Step 2: For all the VMs, identify peak points together with their corresponding occurrence times (timestamps).

Step 3: Determine the frequency of each repeating peak timestamps and compute the percentage of VMs, which peak at particular peak points (if a timestamp appears multiple times, it means some VMs peak at the same time).

E) Evaluation of VM sizing algorithm

The performance of the VM sizing algorithm is evaluated by scheduling workloads on a simulated data centre on CloudSim Plus cloud simulator. The data centre characteristics used in this evaluation (before VM sizing) are similar to those from which the workload data was obtained from. This is summarized in Table 1. We then compare energy usage by the data centre before and after VM sizing using First Fit (FF), Worst Fit (WF) and Best Fit (BF) VM allocation algorithms in turns. The power model used in energy calculation, P_{total}, is given by,

$$\mathbf{P_{total}} = \sum_{\mathbf{i=1}}^{\mathbf{k}}((\mathbf{P_i'} - \mathbf{P_i}) * \left(\frac{\mathbf{n_i}}{\mathbf{100}}\right) + \mathbf{P_i}, \qquad (3)$$

where k is the number of active hosts at any time, P' is the maximum power consumption of the i^{th} host, P is the power consumed by the host when completely idle and n is the percentage CPU utilization of the host. Energy, E, can be calculated as shown in Equation 4.

$$\mathbf{E = PT} \quad (4)$$

where P is average power consumption (in watts) and T is a time (in seconds) interval.

Table 1: CloudSim Plus Datacenter configurations used for evaluation

Item	Before VM sizing
No. of hosts	49
No. of VMs	520
No. of CPU cores	1298
Memory size (in GB)	6780
Hypervisor	VMware ESX
No. of cores allocated per VM	Varying (1,2,4,6 and 8)
Memory size allocated per host (in GB)	Varying (2,4,8 and 16)
Host static power	60 % of host peak power

III. RESULTS

For visual analysis of resource usage by VMs, Fig. 1 shows CPU usage over time for

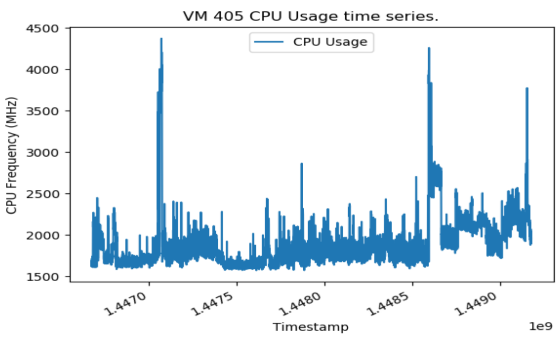

Figure 1: CPU usage time series for VM 405

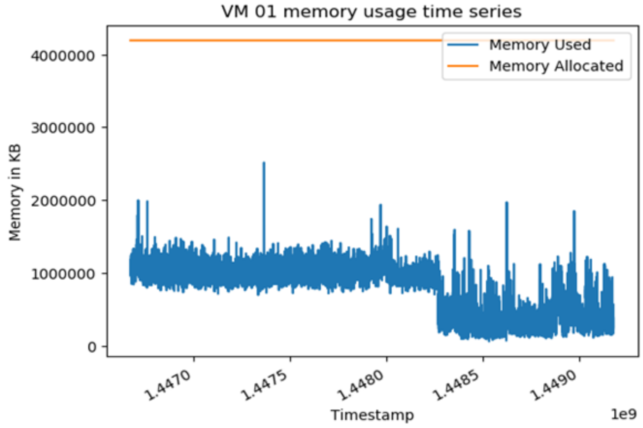

Figure 2: A plot of memory allocated, and memory used for VM 01

VM 405. It shows that CPU requirement by the workloads running the VM is highly dynamic. Fig. 2 shows a graph that compares memory allocated to VM 01 and memory actually used by the VM. It shows that memory allocated is a lot higher that the memory that is actually used. Summarily, the average CPU and memory usage for the 520 VMs was found to be 4.5% and 8.3% respectively. In fact, the percentage of VMs with CPU and memory utilization below 20% is 96.3% and 90.6% respectively. The average highest VM CPU and memory usage stand at 69.3 % and 82.2 % respectively. Moreover, Fig. 3 shows the 90^{th} percentile of CPU usage for VM 467. The figure shows that a 90^{th} percentile resource allocation would cover a good percentage of application workload resource demand not all. If, statistical multiplication has to be used, then co-located VM resource usage should not peak simultaneously. Out of the 520 VMs (with over 4.3 million data points), a memory peak at timestamp 1.447967e+09 happened simultaneously only in 25% of the VMs and it was the highest. For CPU, a peek at timestamp 1.449137e+09 happened simultaneously only in 24% of the VMs and it was the highest. Other peaks for CPU and memory occur simultaneously in less than 24% and 25% respectively.

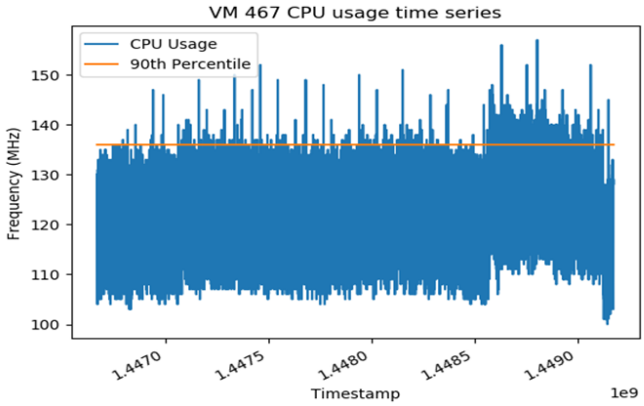

Figure 3: A plot of CPU usage showing 90th percentile for VM 467

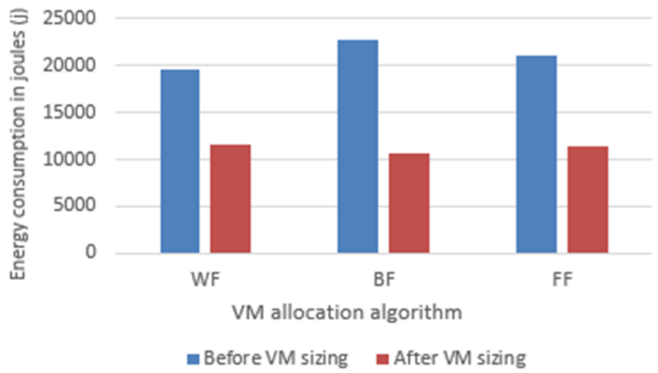

Figure 4: A comparison of energy consumption in datacenter before and after VM sizing using WF, BF and FF VM allocation algorithms

When the technique described in section II (C) above I used to size VMs, CPU cores requirements is reduced from 1298 cores to 535 cores and memory from 6780 GB to 4142 GB for processing workloads for the 520 VMs, which represents 61% and 41% respectively. As a consequent, the number of hosts theoretically reduces from 49 to 28. When the 520 VM application workloads are executed on the simulated data centre before and after VM sizing, there is a considerable energy consumption reduction across the three scheduling algorithm (FF, WF, BF). This is shown in Fig. 4.

IV. DISCUSSION

From the result presented above (Fig. 1 - 3), it is evident that resources demand by VM application workloads is highly dynamic, which explain why it is a challenge to determine a fixed VM resources. Determining VM sizes based on peak resource usage is misleading because it is only a few times when resource usages reach peaks. The fear of compromising performance thus leads to over-provisioning of resources, which go to waste but at the same time consume energy. This is evident from Fig. 2, which indicates that resource usage by VMs is a lot lower than the resources allocated. This is supported by the fact that the average CPU and memory usage for the 520 VMs evaluated was 4.5% and 8.3% respectively. Sometimes, overprovisioning is not intentional but is caused by inexperienced users provisioning resources without knowing how much resources will be demanded by their application workload. Therefore, it makes sense to design techniques for VM right-sizing by analyzing historical resource usage. Instead of basing VM sizes on peak resources usages, using percentiles is a simple but effective technique. Fig. 3 shows 90^{th} percentile of CPU usage for VM 467. This value can be used as the fixed VM size. However, because the 90^{th} percentile does not take care of application workload resources demand for all the time, the rest of the demand (any demand above 90^{th} percentile) can be handled by statistical multiplexing. The results presented above show that statistical multiplexing is a very viable approach to gaining aggressive consolidation because not many VM's resources demand peak at the same time. The process of borrowing of resources from one VM to another can be automated by already hypervisors IaaS space such as Xen and VMware. For the VMs, which peak simultaneously, a VM allocation algorithm should be used to avoid co-locating them thus achieving greater VM consolidation. When the VM sizing algorithm is used to the size, VMs, we noticed a reduced demand in resources to process the same amount of workload. This is because the algorithm tries to allocate an amount of resources that is actually required by a VM. As a result, the number of physical server reduces leading to a reduction in data center energy consumption (Fig. 4).

V. CONCLUSION

In this paper, we have proposed a VM sizing technique that uses percentiles to determine a fixed VM to avoid resource wastage caused by both intentional and unintentional resource overprovisioning. Because of the dynamic nature of cloud workloads, any resource demand above the fixed VM resources is addressed by statistical multiplexing. We have also shown that statistical multiplexing is a viable approach from an analysis of cloud workloads logs (GWA-T-13) obtained from a production data centre. An evaluation of the proposed algorithm on a simulated cloud data center shows that it can achieve efficient resource utilization and as a result reduce the number physical server required to execute the workload. As future research, we plan to propose a VM allocation algorithm that takes into account VM peak resources demand before allocation. This way, VMs which peak simultaneously do not get co-located.

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