ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 9, September 2017

Dynamic Virtual Machine Consolidation in Cloud Data Centers: A Study

Talvinder Singh[1], Varun Jain[2], Satish Babu G[3], Amit Kumar[3]

Project Associate, Centre for Development of Advanced Computing, Noida, India[1]

Joint Director, Centre for Development of Advanced Computing, Noida, India[2]

Principal Technical Officer, Centre for Development of Advanced Computing, Noida, India [3]

ABSTRACT: With adaption of Cloud computing the demand for computational power has increased rapidly. Cloud data center consume massive amount of electrical energy for IT as well as not-IT purposes. To design an energy-efficient dynamic Cloud resource management system, virtual machine (VM) consolidation is the key mechanism. It is based on the assertion that migrating VMs into fewer number of physical machines would lead to achieve increased utilization of resources and in turn results into less energy consumption in Data Center. In this paper we have presented a study of dynamic virtual machine consolidation for energy & network efficiency as well as to meet other objectives such as SLA violation aware approaches in Cloud Data Centers.

KEYWORDS: Virtual machine consolidation, Cloud data centers, Energy efficient data centers, Cloud resource management.

I. INTRODUCTION

Cloud computing, a very recent exemplar shift in IT industry, is growing rapidly with the goal of providing virtually infinite amount of computing, storage, and communication resources where customers are provisioned these resources according to their demands as a pay-per-use business model [1].

To meet the rapid growth of customer demands for computing power, cloud providers such as Amazon and Google are deploying large number of planet-scale power-hungry data centers across the world, even comprising more than 1 million servers [2]. Reports show that energy is one of the critical TCO (Total Cost of Ownership) variables in managing a data center, and servers and data equipment account for 55% of energy used by data centers [3]. Large data centers also have enormous effects on the environment: higher energy consumption consequently drive in more carbon emission. Furthermore, inefficient use is one of the key factors for the extremely high energy consumption: in traditional data centers, on average servers operate only at 10-15% of their full capacity most of the time, leading to expenses on over-provisioning of resources [4].

VM Consolidation (VMC) is one such technique incorporated in cloud resource management to increase the energy-efficiency of Cloud. VM machine migration has been there since virtualization was introduced. Hardware failure of existing Physical Machines (PMs) and addition of new PMs are continuous events and often occur in data center. Besides, resource requirement to accomplish the remaining tasks of existing service requests evolves with the course of time. Hence, as time progresses, it is necessary to optimize the usage of cloud resources and remap the remaining workload to available resources. The VM consolidation technique is applied to remap the remaining workloads to currently available resources which ultimately choose to migrate VMs into lesser number of active PMs, so that the PMs which would have no VM can be kept into sleep state. Energy consumption by a PM in sleep state is far lower than those in active state which ultimately minimizes the average energy consumption in data center.

As shown in Fig. 1, before VMC is applied, VMs are hosted in different PMs. To utilize resource of a particular PM, VMC migrate the VM onto single PM. The state of vacated PMs can be changed from active to sleep. Thereby, increase the resource utilization and also decrease the overall energy consumption.

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 9, September 2017

II. RELATED WORK

VM consolidation techniques have been very attractive to decrease energy costs and increase resource utilization in virtualized data centers. A good quantity of research works have been done in this area which varies in respect of modelling techniques used and their ultimate objective. Most of the works that apply greedy heuristics mainly model VM consolidation as variants of the bin packing problem and propose modification of simple greedy algorithms such as First Fit Decreasing (FFD) [7], Best Fit [6], Best Fit Decreasing [8], and so on [9, 10]. However, as VM consolidation is a NP-hard problem, greedy approaches are not guaranteed to generate near optimal solutions. Moreover, most of the approaches use mean estimators that fail to capture the multi-dimensional aspect of server resource utilization [6].
Using constraint programming (CP) model, Van et al. [11] proposed VM provisioning and placement techniques to achieve high VM packing efficiency in cloud data centers. The use of CP the proposed frameworks effectively restrict the domain of the total number of servers and VMs in data center, and thus limit the search space.

III. VIRTUAL MACHINE CONSOLIDATION

Most of the popular public or private cloud providers offer different categories of VMs for different purposes with specification for each type of resource. These specifications are mainly based on the physical resource capacity and purpose that user is going to use for. Some VMs could have higher capacity in terms of space and others could have high compute power. Moreover, cloud VM instances host various types of applications and active VMs exhibit dynamic resource demands in run-time that can be captured and used to perform workload prediction and estimation [17]. The resource demand graph in cloud data centers may be stable or it could be spooky at time. The overall prediction of resource demand is another topic of research. VM consolidation addresses the demand of multi-dimensional resource usage with objective of maximization of resource usage and minimization of energy usage.
Compacting more number of VMs into fewer number of PMs, resource utilization ratio of PM PMi, Rpi would become higher. In turn increase mean resource utilization ratio *Rmean* of data center.

$$Rpi = \text{Utilized Amount of Resource of PM}i \,/\, \text{Total Amount of Resource of PM}i \quad \ldots(1)$$
$$Rmean = 1/N \sum Rpi \quad \ldots(2)$$

If more VMs are placed in a single PM, resource contention may arise which would lead towards poor Quality of Service (QoS). Given the problem of maximization of resource usage and minimization of energy usage, it is extremely challenging to design VM consolidation algorithm. In this paper, we have presented detail discussion on a wide range of Dynamic VMC algorithms which caters the aspects of resource utilization maximization and energy consumption minimization.

3.1 VMC COMPONENTS

VMC algorithm has three core components [4, 21] which are as follows:
– ***Source Host Selection:*** First, among all the PMs, a set of PMs are selected from where VMs are migrated out. The Source Host Selection component takes all the PMs and VMs as input and selects one or more PMs as source PM(s) from where VMs would be migrated out.
– ***VM Selection:*** Secondly, one or more VM(s) are selected for migration from a source PM. The VM Selection component takes the PM as input which has been selected by Source Host Selection component and selects one or more VMs from that source PM for migration into a different PM.
– ***Destination Host Selection/VM Placement:*** Finally, the Destination Host Selection/VM Placement component selects a PM for each of the migrating VM which was selected by VM Selection component.

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 9, September 2017

3.2 CLASSIFICATION OF VMC ALGORITHMS

VMC algorithms can be broadly classified in two groups: –

A. ***Dynamic VMC (DVMC) Algorithm:*** The workload received in Cloud is dynamic in nature. Also, removal of some PM due to hardware failure or for maintenance purpose and addition of new hardware in data centre also takes place. In DVMC algorithm, present VM to server assignment is taken into consideration. The workload or resource requirement of any VM ad its location in PM can be dynamic. The algorithm consolidates the VMs considering their dynamic nature of workload and location. Majorly, it focuses on migrating the VMs in lesser number of PMs so as to minimize the active number of PM.

B. ***Static VMC (SVMC) Algorithm:*** Static VMC (SVMC) algorithms, also referred to as consolidated VM placement algorithms do not consider the current VM-to-Server assignment while choosing a new destination PM for any VM. SVMC provides solution for initial VM placement in minimum possible PMs so as to minimize the energy consumption in cloud data center (CDC). In [22], the authors have mentioned that static VMC algorithms work with a set of fully empty PMs and a set of VMs with specific resource requirement. But, do not talk about the reallocation of VMs on to different PMs as workload dynamically changes. Only initial workload requirement is taken into consideration therefore, it is called as SVMC algorithm. [23-26] are examples of SVMC algorithm.

SVMC may cause problems when workload of VMs increase on particular PM, it may also cause degradation of performance. The VM to Server assignment is not taken into consideration in SVMC. They may be useful for initial placement of VMs or migrating VMs from one DC to another DC. As the time progresses, both of workload and resource availability changes in CDC. Therefore, apart from the initial consolidated VM placement, DVMC is one of the key techniques that uphold the energy-efficiency, resource usage optimization and profit maximization of CSPs. As such, in this paper we have focused on DVMC algorithms. In the following section the classification of the DVMC algorithms has been presented.

3.3 DVMC ALGORITHMS

DVMC problem focuses on run-time environments where VMs are active and already hosted by servers in the data center. Consolidation of such VMs are achieved by the VM live migration operations, where a running VM is relocated from its current host to another server while it is still running and providing service to its consumers [27]. DVMC algorithms can be classified into two groups:

– Centralized DVMC Algorithm: As proposed in [28-30], in centralized architecture, a single controller has the information about current resource availability of all the PMs in cluster. The controller runs the Centralized VMC Algorithm which selects a destination PM for a migrating a VM on basis of availability of resource.

– Distributed DVMC Algorithm: In this case there is no single controller, but PMs exchange information related to their current available resource with their neighbor PMs. Distributed DVMS decision is based upon the consensus amongst the PMs. Example of distributed DVMC algorithms are [31, 32].

In section 2, we have mentioned the first task of DVMC algorithm is to select the source PM. A DVMC can randomly choose the source PM or on the basis of under or over resource utilization. In the following section we have discussed about the types of DVMC algorithms based on the way source PMs are selected.

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 9, September 2017

3.3.1 CLASSIFICATION BASED ON THE WAY SOURCE PMs ARE SELECTED

DVMC algorithms can be classified into two groups:

A. ***Threshold-Based DVMC Algorithm:*** Upper and lower threshold values are used to identify a PM as under-loaded or over loaded. Resource utilization ration R*pi* is compared against threshold value. If R*pi* is greater than the threshold, PM*i* is considered as over loaded and vice-versa. High value of R*pi* is strong indicator for degradation of QoS.

B. ***Threshold-Free DVMC Algorithm:*** Unlike threshold-based DVMC algorithms, in threshold-free DVMC algorithms, resource utilization ratio of the PM P*i*, R*pi* is not compared against any threshold value to identify the PM as overloaded or underloaded. Instead, the source PMs are selected either randomly [34] or some functions are applied to favour PMs having either higher or lower Rpi compare to those of other PMs. Examples of threshold free DVMC algorithms are [25, 34, 35].

It is clear from the above definitions that in contrast to threshold-based, threshold-free will select the PMs irrespective of resource usage or in other words, randomly. Threshold-free would consider the global picture of increase of workload in all PMs in combination. As opposed to random source PM selection, the heuristic approach to always select the source PM with highest or lowest resource utilization ratio, may not ensure the achieving of global best solution. Since, there is no random source PM selection policy in threshold-based DVMC algorithm, therefore, it may not provide the global best solution. Furthermore, compare to threshold-free approach, the number of VM migrations may become higher in threshold-based approach. To illustrate more, assume that overall workload in the CDC has become high. PMs would then experience high utilization as per threshold-based approach and would start migrating out their VMs. However, VMC is a combinatorial optimization problem.

3.3.2 CLASSIFICATION OF DVMC ALGORITHMS BASED ON VM SELECTION POLICY

After source PMs are selected, the next step of VMC is to select one or more VMs that need to migrate out from source PM. Based on the different VM selection policies used in different DVMC algorithms, The DVMC algorithms can be largely classified into two groups:

A. ***Clustered VM Selection (CVS):*** In cloud, where multi-layered architecture is deployed to run an application that comprises of application server(s), load balancer, database server(s), these may be hosted separately in different VMs. For such architecture, where frequent communication among the servers is required, it may hamper the performance if these VMs are not hosted in nearby PMs in CDC. Instead of migrating a single VM, a group or cluster of VMs of an application is considered as potential candidate for migration. Prominent examples of such clustered VM selection algorithms are [24, 39].

B. ***Single VM Selection (SVS):*** In contrast to CVS, SVS algorithms select a single VM to migrate out. Various single VM selection strategies as found in the literature are mentioned in the following:

– *Random Choice (RC):* Among all the VMs residing in the source PMs, a VM is randomly selected [33, 40]. Random VM Selection can select a VM in *O*(1) time which is fastest than rest of the approaches.

– *Minimization of VM Migration (MVM):* Minimum number of VMs are migrated to make the current resource utilization of a PM lower than the upper utilization threshold. MVM algorithm as proposed by [33], the VM with the highest utilization is selected and the process is repeated until the new utilization becomes lower than the upper utilization threshold.

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 9, September 2017

– *High Potential Growth (HPG):* The VM with lowest ratio of actual resource usage to its initial claimed resource demand is selected [33]. Asymptotic running time of the algorithm is *O*(n).

– *Minimization of Migration Time (MMT):* In MMT, the VM which takes minimum time for migration is selected. The migration time is calculated as the ratio of RAM utilized by VM to the spare network bandwidth [21]. Asymptotic running time of the algorithm is *O*(n).

– *Maximum Correlation (MC):* VM that has the highest correlation of the resource utilization with other VMs are selected [4]. Multiple Correlation Coefficient as proposed by [41], is used to determine the correlation between the resource utilization of VMs.

The RC has the fastest run time. It may help to find the globally optimal solution, if source PM is selected randomly using threshold-free approach as discussed earlier in section 3.3.1. If source PM is selected using heuristic approach such as choosing PM with highest or lowest resource utilization would be source PM and then VM is randomly chosen for that PM, then RC will not yield global optimal solution. In contrast to that, after selecting source PM, rest of the algorithms such as MVM, HPG, MMT and MC are more likely to decrease the energy consumption as compared to RC. Heuristics like MVM, HPG, MMT and MC certainly provide the local best solution, whereas RC probabilistically chooses a solution which may not be locally optimal. To illustrate more, VMs experience degraded QoS during the period of migration. Therefore, selecting the VM which would take the least migration time (i.e., MMT) would certainly assist in keeping the SLA violation lower [42]. In contrast, RC may choose a VM with higher migration time. Consequently, SLA violation rate would be higher for RC.

3.3.3 CLASSIFICATION OF DVMC ALGORITHMS ON BASIS OF ESTIMATED FUTURE RESOURCE

Future resource estimation may create substantial difference on performance of VMC algorithm in comparison to those which consider current resource utilization. Hence, in this section, we have reviewed both types of VMC algorithms from that perspective.

Non-Predictive Dynamic VMC Algorithm (NPDVMC): NPDVMC algorithms consider the current aggregated resource demand of VMs. VM migration decisions are taken when the current resource utilization of the PM PM*i*, R*pi* becomes very high or very low so that SLA violation can be avoided or energy consumption can be minimized. Projecting nonpredictive VMC algorithms are [24, 25, 28-30, 34, 45].

Predictive Dynamic VMC Algorithm (PDVMC): PDVMC algorithms take the decision to migrate VMs from one PM to another PM considering the estimated future resource demand of VMs instead of current resource demand. Examples of PDVMC algorithms are [36, 46]. Linear regression [38] is used to generate an estimated future resource utilization of a PM from analyzing its past resource utilization statistics.

PDVMC algorithm is more proactive than NPDVMC as VMs are migrated out from the source PMs on basis of prediction of workload in future. PDVMC has displayed lower SLA violation because being a proactive approach if migrate VMs out prior to QoS degradation and shows improvement in reducing resource contention.

One of the core components of DVMC algorithms is destination PM selection where migrating VMs are placed. This is also referred as VM placement problem. In the following section, we have discussed approaches to select destination PMs for migrating VMs as incorporated in different DVMC algorithm.

3.3.4 CLASSIFICATION OF DVMC ALGORITHMS BASED ON DESTINATION PM SELECTION STRATEGIES

After VMs from source PM are selected, they needs to be place in destination PM, that gives rise to new problem of selecting destination PM which is known as VM placement. The goal is to find destination PM in such a way that minimizes the total number of active PMs. Destination PM selection is itself is a NP-Hard problem and hence a number

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 9, September 2017

of heuristic as well as meta-heuristic algorithms have been proposed in the literature. Based on different destination PM selection strategies DVMC algorithms can be classified into three groups:

Random PM Selection (RPS): As proposed in [24], the destination PM is randomly selected from the appropriate PMs for a given VM.

Greedy Heuristic: Greedy Heuristic algorithms are most pervasive in the literature to select the destination PM for migrating VMs. Several popular heuristic based algorithms are as follows:

– *Random Choice (RC):* As discussed in [47], RC algorithm randomly chooses a destination PM for a migrating VM which is already active.
– *First Fit (FF):* In FF [47], PMs are ordered in a sequence and for each VM, the first available PM from the ordered list of PMs is selected. The asymptotic running time of First Fit is O(n), where n is the total number of VMs.

– *First Fit Decreasing (FFD):* FFD is same as FF, except the VMs are sorted in the decreasing order of their resource demand. Then the destination PM for the first VM with highest resource demand is first searched using FF algorithm, as the searching continues for the VM with second highest resource demand and so on. The asymptotic running time of FF is O(n log n + nm) where n is the total number of VMs and m denotes the total number of PMs.

– *Next Fit (NF)/ Round Robin (RR)*: Like FF, NF also performs a sequential search, except it starts from the last server selected in the previous placement [39]. NF is also referred to as Round Robin (RR). The asymptotic running time of NF is same as FF.

– *Best Fit (BF):* In BF, the PM with the minimum residual resource is selected as its destination PM [46]. The residual resource of the PM is the difference between the total resource capacity of that PM and the aggregated resource demand of the hosted VMs in it along with the resource demand of the target VM for which destination PM is under search.

– *Best Fit Decreasing (BFD):* VMs are first sorted in the decreasing order based on their resource demand.
– *Power Aware Best Fit Decreasing (PABFD):* PABFD proposed by [33], is a modified version of BFD, as the VMs are first sorted in decreasing order based on their CPU demand and then the destination PM is selected with the least power increase compare to all the suitable PMs which could host the target VM.

3.3.5 CLASSIFICATION OF DVMC ALGORITHMS BASED ON DIFFERENT OBJECTIVES

Minimization in energy consumption is one important factor among other that VMC concentrate upon by placing the VMs in minimal number of PMs. Simply putting higher number of VMs in single PM may minimize energy consumption but may probably cause performance degradation and hence SLA violation. Therefore, minimization of energy consumption and minimization of SLA violation are two confronting goals. While most researchers have focused to maintain a balance between minimization of PMs' energy consumption and SLA violation, some researchers have considered other aspects too, such as energy consumption by network, network throughput, security and so forth.

A. ***SLA Violation Aware:*** VMs hosted on a PM shares its resources such as CPU, RAM and network bandwidth and so forth, therefore as number of VMs running on a PM increases, it also increase the waiting time for the VM to utilize PM's underlying resource. VM migration also temporarily suspend the service that it is providing to the user. Hence, VMC causes SLA violation. [24] is an example of SLA Violation aware VMC algorithms

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 9, September 2017

B. ***Network Efficiency Aware:*** Such algorithms, for instance, [45] aim to uphold the network efficiency through considering different network related aspects, such as minimization of network energy consumption, reduction of network congestion and so forth. [45, 48] are examples of network efficiency aware VMC algorithm.

C. ***Data Center Energy Aware:*** As resource demand in cloud increases, it directly increases the energy consumption of a data center. Minimization of IT and non-IT energy consumption is one big challenging aspect of any data center. It is crucial for any data center to fully utilize the resource and minimize the energy consumption right from the VM level. Therefore, researchers have presented VMC algorithms which consolidate VMs in such a way that energy spending after cooling the data center can be minimized. [34] is an example of such VMC algorithm which minimizes the energy related to data center cooling.

TABLE 1. DETAILED ANALYSIS OF DYNAMIC VMC ALGORITHMS

VMC Decision Process	**Resource Considered**	**Source PM Selection Strategy**	**Destination PM selection**	**Application of Prediction Strategy**	**VM Selection Criteria**	**Objective**	**Project / Research**
Centralized	CPU	Static and Adaptive Threshold based	Greedy Heuristic	Non Predictive	RC, MMT, MC, HPG	Security Aware	Security Aware and Energy Efficient Virtual Machine Consolidation in Cloud computing systems [28]
Centralized	CPU	Adaptive Threshold based	Greedy Heuristic	Non Predictive	RC, MMT, MC, HPG	Network Efficiency Aware	Dynamic Virtual machine consolidation for improving energy efficiency in cloud data centers [29]
Centralized	Single resource type presented by value	Adaptive Threshold based	Greedy Heuristic	Non Predictive	RC, MMT, MC, HPG	Minimization of Inter cluster VM migration	Hierarchical Portfolio Theory Based Virtual Machine Consolidation in Compute Cloud [24]
Centralized	CPU	Threshold free approach	Meta Heuristic	Non predictive	RC	Minimization of PM and network related energy	Thermal Aware workload consolidation in cloud data centers [34]
Centralized	CPU, Memory and Storage		Mathematical method proposed	Non Predictive		SLA Violation Aware	Optimizing Virtual Machine Consolidation in Virtualized Data centers using Resource sensitivity [25]
Centralized	CPU, Memory and	Static and Adaptive approach	Greedy Heuristic	Predictive	VM with highest resource	SLA Violation Aware	Virtual Machine Consolidation with Multiple

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 9, September 2017

	Network bandwidth				demand		Usage Prediction for Energy efficient data centers [50]
Centralized	CPU	Adaptive Threshold	Greedy Heuristic	Non Predictive	RC, MMT, HPG, MC	SLA Violation Aware	An efficient resource utilization technique for consolidation of virtual machines in cloud computing environment [40]
Centralized	CPU	Over utilized and under utilized PM	Greedy Heuristics	Non predictive	MMT	SLA Violation Aware	Improved Virtual machine migration approaches in cloud environment [22]
Centralized	CPU and Memory	Adaptive Threshold based	Greedy Heuristic	Non predictive	MMT	SLA Violation Aware	Self-Adaptive Resource Management System in IaaS clouds [37]
Distributed	CPU	Adaptive Threshold	Greedy Heuristic	Non predictive		SLA Violation Aware	A Gossip Based Dynamic Virtual Machine Consolidation Strategy for Large Scale Cloud data centers [31]
Centralized	CPU	Static Threshold	Greedy Heuristic	Non predictive	RC, MMT, MC, MVM	Minimize active PMs and SLA Violations while limiting VM migration	An energy aware heuristic framework for virtual machine consolidation in cloud computing [41]
Centralized	CPU	Static Threshold	Meta Heuristic	Predictive	VM from under utilized PMs	Minimization on active servers and maximize resource utilization	Dynamic Virtual Machine Consolidation for energy efficient cloud data centers [42]
Distributed	CPU	Adaptive Threshold	Greedy Heuristic	Non predictive	Fuzzy VM selection	SLA Violation Aware	VM consolidation approach based in heuristics, fuzzy logic and migration control [34]

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 9, September 2017

Centralized	CPU	Static threshold	Heuristic	Non predictive	MMT	SLA Violation Aware	Server Consolidation with minimal SLA violations [45]

IV. CONCLUSION AND FUTURE SCOPE

CDC consumes large amount of energy. State of the art VMC algorithms have developed to tackle multitude of problems of managing resources in CDC. A review of a study of DVMC algorithms have been presented in the paper. We have put forth our viewpoints and highlighted the major differences between various DVMS algorithms.

- Distributed DVMC are more robust and reliable, it eliminates the single point of failure that is the case in centralized DVMC.
- SVMC can be considered as first stage of limiting energy consumption, DVMC further minimize while increasing the resource utilization.
- Threshold based DVMC approach is time efficient, but it may stuck in local minima or maxima, instead of finding globally optimal solution.
- DVMC may cause aggressive consolidations which in turn give rise to SLA violations. Adaptive Threshold-based DVMC algorithms may limit SLA violations but may be less efficient in minimization of energy consumption.
- MMT is most popular VM selection strategy. It is SLA violation aware by selection the VMs in such a way it decreases the migration time.
- Predictive DVMC cause more number of VM migrations but at the same time minimize the SLA violations that may arise due to resource contention in case of increasing demand of workload.
- In contrast to meta-heuristic, greedy heuristic algorithms may stuck in local minima or maxima, but yet give sub-optimal solution quickly.

Existing predictive DVMC algorithms apply common prediction technique for all PMs. The resource usage pattern of different co-hosted VMs in single PM may vary. There could be possibility of wrong prediction because of mismatch in past and present resource utilization. This could be addressed in future works of PDVMC. Moreover, except for MMT, selecting a VM for migration wholly based on CPU demand may cause underutilization of other resources of a PM. To come up with strategy that takes into consideration the multitude nature of VM consolidation id challenging which opens gate for future scope.

REFERENCES

1. Kleinrock L. *A vision for the Internet.* ST Journal of Research. 2005; 2(1):4-5
2. Buyya R, Yeo CS, Venugopal S, Broberg J, Brandic I. *Cloud computing and emerging IT platforms: Vision, hype, and reality for delivering computing as the 5th utility.* Future Generation computer systems. 2009; 25(6):599-616.
3. Kaplan JM, Forrest W, Kindler N. *Revolutionizing data center energy efficiency.* Technical report, McKinsey & Company; 2008.
4. Beloglazov A. *Energy-efficient management of virtual machines in data centers for cloud computing* [dissertation]. Melbourne, AU: The University of Melbourne; 2013.
5. Koomey J. Growth in data center electricity use 2005 to 2010. A report by Analytical Press, completed at the request of The New York Times. 2011; 9.
6. Gartner Estimates I. Industry Accounts for 2 Percent of Global CO2 Emissions. press release. 2007.
7. Buyya R, Beloglazov A, Abawajy J. *Energy-efficient management of data center resources for cloud computing: A vision, architectural elements, and open challenges.* arXiv preprint arXiv:10060308. 2010.
8. Koomey JG. *Estimating total power consumption by servers in the US and the world.* February; 2007.
9. Hopkin J. VMware ESX Server [Image on internet]. OStatic; © 2015.Available from: http://ostatic.com/vmware-esx-server/screenshot/1.
10. Mann ZÁ. *Allocation of virtual machines in cloud data centers—a survey of problem models and optimization algorithms.* ACM Computing Surveys (CSUR). 2015; 48(1):11.

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 9, September 2017

11. Pietri I, Sakellariou R. *Mapping virtual machines onto physical machines in cloud computing: A survey*. ACM Computing Surveys (CSUR). 2016; 49(3):49.
12. Kaur S, Bawa S, *A review on energy aware VM placement and consolidation techniques.* Inventive Computation Technologies (ICICT), International Conference on; 2016:IEEE.
13. Madhan ES, Srinivasan S. *Energy aware data center using dynamic consolidation techniques: A survey*. Proceedings of IEEE International Conference on Computer Communication and Systems ICCCS14; 2014 20-21 Feb. 2014.
14. Pires FL, Barán B, *A Virtual Machine Placement Taxonomy.* 2015 15th IEEE/ACM International Symposium on Cluster, Cloud and Grid Computing; 2015 4-7 May 2015.
15. Ranjana R, Raja J, *A survey on power aware virtual machine placement strategies in a cloud data center.* Green Computing, Communication and Conservation of Energy (ICGCE), 2013 International Conference on; 2013: IEEE.
16. [16]. Varasteh A, Goudarzi M. *Server consolidation techniques in virtualized data centers*: *A survey*. IEEE Systems Journal. 2015.
17. Ahmad RW, Gani A, Hamid SHA, Shiraz M, Yousafzai A, Xia F. *A survey on virtual machine migration and server consolidation frameworks for cloud data centers*. Journal of Network and Computer Applications. 2015; 52:11-25.
18. Choudhary A, Rana S, Matahai KJ. *A Critical Analysis of Energy Efficient Virtual Machine Placement Techniques and its Optimization in a Cloud Computing Environment.* ProcediaComputer Science. 2016; 78:132-8.
19. Masdari M, Nabavi SS, Ahmadi V. *An overview of virtual machine placement schemes in cloud computing*. Journal of Network and Computer Applications. 2016; 66:106-27.
20. Usmani Z, Singh S. *A Survey of Virtual Machine Placement Techniques in a Cloud Data Center.* Procedia Computer Science. 2016; 78:491-8.
21. Beloglazov A, Buyya R. *Optimal online deterministic algorithms and adaptive heuristics for energy and performance efficient dynamic consolidation of virtual machines in cloud data centers.* Concurrency and Computation: Practice and Experience. 2012; 24(13):1397-420.
22. Ferdaus MH, Murshed M. *Energy-aware virtual machine consolidation in IaaS cloud computing*. Cloud Computing: Springer; 2014. p. 179-208.
23. Jersak LC, Ferreto T. *Performance-aware server consolidation with adjustable interference levels.* Proceedings of the 31st Annual ACM Symposium on Applied Computing; Pisa, Italy. 2851625: ACM; 2016. p. 420-5.
24. Pedram M. Hierarchical, *Portfolio Theory-Based Virtual Machine Consolidation in a Compute Cloud.* IEEE Transactions on Services Computing. 2016; PP(99).
25. Nasim R, Taheri J, Kassler AJ, *Optimizing Virtual Machine Consolidation in Virtualized Datacenters Using Resource Sensitivity.* 2016 IEEE International Conference on
26. Cloud Computing Technology and Science (CloudCom); 2016 12-15 Dec. 2016.
27. Chen L, Shen H, Platt S, *Cache contention aware Virtual Machine placement and migration in cloud datacenters*. Network Protocols (ICNP), 2016 IEEE 24th International Conference on; 2016: IEEE.
28. Ferdaus MH. *Multi-objective Virtual Machine Management in Cloud Data Centers.* Melbourne, Australia: Monash University; 2016.
29. Ahamed F, Shahrestani S, Javadi B, *Security Aware and Energy-Efficient Virtual Machine Consolidation in Cloud Computing Systems.* 2016 IEEE Trustcom/BigDataSE/ISPA;2016 23-26 Aug. 2016.
30. Deng D, He K, Chen Y, *Dynamic virtual machine consolidation for improving energy efficiency in cloud data centers.* 2016 4th International Conference on Cloud Computing and Intelligence Systems (CCIS); 2016 17-19 Aug. 2016.
31. Fioccola GB, Donadio P, Canonico R, Ventre G, *Dynamic Routing and Virtual Machine Consolidation in Green Clouds*. 2016 IEEE International Conference on Cloud Computing Technology and Science (CloudCom); 2016 12-15 Dec. 2016.
32. Masoumzadeh SS, Hlavacs H. *A Gossip-Based Dynamic Virtual Machine Consolidation Strategy for Large-Scale Cloud Data Centers.* Proceedings of the Third International Workshop on Adaptive Resource Management and Scheduling for Cloud Computing; Chicago, IL, USA. 2962565: ACM; 2016. p. 28-34.
33. Khelghatdoust M, Gramoli V, Sun D, *GLAP: Distributed Dynamic Workload Consolidation through Gossip-Based Learning*. Cluster Computing (CLUSTER), 2016 IEEEInternational Conference on; 2016: IEEE.
34. Beloglazov A, Abawajy J, Buyya R. *Energy-aware resource allocation heuristics for efficient management of data centers for cloud computing*. Future generation computer systems. 2012; 28(5):755-68.
35. Marcel A, Cristian P, Eugen P, Claudia P, Cioara T, Anghel I, et al., *Thermal aware workload consolidation in cloud data centers.* 2016 IEEE 12th International Conference on Intelligent Computer Communication and Processing (ICCP); 2016 8-10 Sept. 2016.
36. Marotta A, Avallone S, *A Simulated Annealing Based Approach for Power Efficient Virtual Machines Consolidation*. 2015 IEEE 8th International Conference on Cloud Computing; 2015 June 27 2015-July 2 2015.
37. Farahnakian F, Ashraf A, Pahikkala T, Liljeberg P, Plosila J, Porres I, et al. *Using ant colony system to consolidate vms for green cloud computing*. IEEE Transactions on ServicesComputing. 2015; 8(2):187-98.
38. Farahnakian F, Bahsoon R, Liljeberg P, Pahikkala T, *Self-Adaptive Resource Management System in IaaS Clouds*. 2016 IEEE 9th International Conference on Cloud Computing (CLOUD); 2016 June 27 2016-July 2 2016.
39. Farahnakian F, Liljeberg P, Plosila J, *LiRCUP: Linear regression based CPU usage prediction algorithm for live migration of virtual machines in data centers.* 2013 39thEuromicro Conference on Software Engineering and Advanced Applications; 2013: IEEE.
40. Pascual JA, Lorido-Botrán T, Miguel-Alonso J, Lozano JA. *Towards a greener cloud infrastructure management using optimized placement policies*. Journal of Grid Computing.2015; 13(3):375-89.
41. Selim GEI, El-Rashidy MA, El-Fishawy NA, *An efficient resource utilization technique for consolidation of virtual machines in cloud computing environments.* 2016 33rdNational Radio Science Conference (NRSC); 2016 22-25 Feb. 2016.
42. Abdi H. *Multiple correlation coefficient.* The University of Texas at Dallas. 2007.
43. Yan C, Li Z, Yu X, Yu N, editors. *Bayesian networks-based selection algorithm for virtual machine to be migrated*. Big Data and Cloud Computing (BDCloud), Social Computing andNetworking (SocialCom), Sustainable Computing and Communications (SustainCom)(BDCloud-SocialCom-SustainCom), 2016 IEEE International Conferences on; 2016: IEEE.

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 9, September 2017

44. Tanenbaum AS. *Distributed operating systems*: Pearson Education India; 1995.
45. Ferdaus MH, Murshed M, Calheiros RN, Buyya R, editors. *Virtual machine consolidation in cloud data centers using ACO metaheuristic*. European Conference on Parallel Processing;2014: Springer.
46. Ma L, Liu H, Leung YW, Chu X, editors. *Joint VM-Switch Consolidation for Energy Efficiency in Data Centers*. 2016 IEEE Global Communications Conference (GLOBECOM);2016 4-8 Dec. 2016.
47. Farahnakian F, Pahikkala T, Liljeberg P, Plosila J, Hieu NT, Tenhunen H. *Energy-aware vm consolidation in cloud data centers using utilization prediction model*. IEEE Transactions on Cloud Computing. 2016.
48. Dabbagh M, Hamdaoui B, Guizani M, Rayes A. *Toward energy-efficient cloud computing: Prediction, consolidation, and overcommitment*. IEEE Network. 2015; 29(2):56-61.
49. Jobava A, Yazidi A, Oommen BJ, Begnum K, editors. *Achieving Intelligent Traffic-Aware Consolidation of Virtual Machines in a Data Center Using Learning Automata. NewTechnologies, Mobility and Security* (NTMS), 2016 8th IFIP International Conference on; 2016: IEEE.

BIOGRAPHY

Talvinder Singh is a Project Associate in the Data Centre, CDAC, Noida. He received Master of Technology in IT from CDAC in 2015. His research interests are Computer Networks, Cloud computing, Databases and Machine Learning and SDN.

Varun Jain is presently a Joint Director and heading DC & IS at CDAC, Noida. More than 15 years of experience in Data Centre networking and related activities.

Satish Babu G is a Principal Technical officer, DC & IS, CDAC Noida. 10 years of experience in IT and Telecommunications industry at BSNL. He is currently managing IT Infrastructure and business development activities in DC.

Amit Kumar is a Principal Technical Officer at DC & IS, CDAC Noida. More than 10 years of experience in Virtualization, networking and databases. His area of interest includes virtualization, Cloud computing and databases.