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Energy-Aware Dynamic Virtual Machine Consolidation for Cloud Datacenters

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ABSTRACT Resource over provisioning in cloud computing consumes energy excessively. Energy-aware dynamic virtual machine consolidation (DVMC) reduces energy consumption without compromising service level agreement. In this paper, we put forward a new framework of DVMC for green cloud computing. In particular, we propose a new virtual machine (VM) placement policy, namely, space aware best fit decreasing (SABFD) and a new migration VM selection policy, namely, high CPU utilization-based migration VM selection (called HS). Thorough simulations are carried out to evaluate the performances of different energy-aware DVMC plans based on real-world workload traces, with DVMC plans as various combinations of host overload detection, migration VM selection, and VM placement policies. The simulation results show that DVMC plans with SABFD policy or with HS policy outperforms alternative DVMC plans. What is more, a DVMC plan with both SABFD and HS policies makes the best performance.

INDEX TERMS Cloud computing, green cloud computing, dynamic virtual machine consolidation, virtual machine placement, cloud datacenter.

I. INTRODUCTION

In a cloud computing environment, the hypervisor creates and sustains multiple virtual machines (VMs) to share the resources of the physical hosts (PHs). To enable the provisioning of computing resources on demand, cloud computing often has to make over-provisioning in order to assure service availability even over peak periods. This results in low resource utilization and excessive energy consumption.

The use of VMs facilitates workload consolidation, resource provisioning on demand, and increases energy-efficiency of computing infrastructures. In dealing with the intricacy among performance, resource utilization and energy consumption, VM consolidation (VMC) tries to pack VMs on as a few physical hosts as possible to reduce energy consumption in cloud computing. This is carried out through finding the best re-placement of VMs onto physical hosts (PHs) under the constraints on VMs and resources provided by PHs, which leads to better resource utilization of the cloud datacenter. VM placement is a NP-hard problem and is difficult to be solved by classic optimization algorithms. There are two types of VM consolidation, namely static and dynamic. Static VM consolidation means resource utilization does not change during execution, and the addition or deletion of VMs only depends on reconfiguration. On the contrary, in dynamic

VM consolidation, VMs can be moved during execution in order to improve the optimality of the placement. Dynamic VM consolidation (DVMC) is particularly useful for cloud computing environment to respond to the bursty nature of VMs workloads, provided that monitoring is in place to avoid any Service-Level Agreements (SLAs) being violated.

VM live migration allows moving a VM from one host to another without rebooting the operating system inside the VM. This is especially usefully for a cloud computing environment in load balancing, fault management, and reduction of system maintenance cost. With the aid of VM migration, it's possible to allocate VMs dynamically, so that workloads of different users can be run on fewer physical machines, with idle servers being suspended or switched off to save energy, while users' performance requirements being still met.

In this paper, we put forward a new framework of dynamic VM consolidation (DVMC) for green cloud computing. In particular, by focusing upon the formation of DVMC plan, we propose a new VM placement policy that reduces energy consumption and suppresses SLA violation to a low level, namely Space Aware Best Fit Decreasing (SABFD), and a new migration VM selection policy, namely high CPU utilization based migration VM selection (called HS). The remainder of this paper is arranged as follows. In Section II,

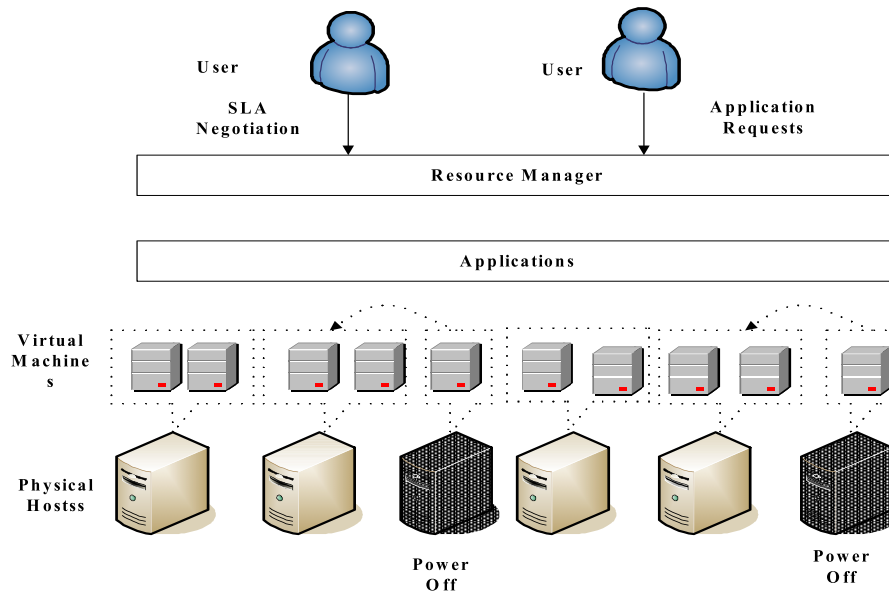


FIGURE 1. System view of green cloud computing.

a literature review on energy-aware DVMC is presented. In Section III, a new energy-aware DVMC plan, comprising VM placement policy and migration VM selection policy, is proposed. In Section IV, simulation evaluations are conducted. Finally, the conclusions are drawn in Section V.

II. LITERATURE REVIEW

In Lin *et al.* [1], two criteria, namely time and load, are used whereby a physical host in cloud computing may be turned off to save energy. A virtual machine will be moved if the remaining working time is longer than a threshold time; and a physical host will be shut down once its load goes under a certain threshold.

In Sharifi *et al.* [2], a metric for virtual machine consolidation is defined using the ratio of performance degradation to energy saved from consolidation. VMs are consolidated based on their processor workloads and disk workloads.

In Murtazaev and Oh [3], the server consolidation algorithm uses CPU and memory to characterize a server and a VM. The VMs on the least loaded server are selected as the candidate for migration and all VMs on one server are migrated or none of them migrated. It's shown that the server consolidation algorithm is suitable for middle size datacenter. However, it is an offline algorithm in that the type of VM must be specified.

In [4] and [5], resource management in cloud computing is undertaken through a global manager role and a local manager role. The global manager resides in a master physical host to optimize VM placement according to the resource utilization of the system, while the local manager resides in each physical host and decides which VMs are selected to move.

In [6]–[10], meta-heuristic optimization algorithms are applied to solve the VM consolidation problem.

Green cloud computing can not only utilize the resources of cloud computing efficiently, but also minimize energy consumption [11]–[13]. In this case, the allocation of cloud resources is undertaken not only to meet the quality of service requirements in SLA, but also to reduce energy consumption by, e.g., suspending or turning off idle physical hosts.

III. FRAMEWORK OF ENERGY-AWARE DYNAMIC VM CONSOLIDATION

Fig. 1 illustrates a system view of green cloud computing environment. The resource manager monitors resource utilization, determines placement of VMs to physical hosts and ensures that no SLA is violated. Fig. 1 also exemplifies a case where two light-loaded physical hosts are turned off so as to save energy.

We put forward a new framework of dynamic VM consolidation (DVMC) for green cloud computing, as illustrated in Fig. 2. The framework of DVMC can be elaborated by a process consisting of four phases, i.e., monitoring, workload analysis, decision and actuation.

In the monitoring phase, information of the system, including workload, resource utilization and energy consumption, etc., is collected and monitored.

In the workload analysis phase, workloads are simulated and estimated, and then hotspots where resource utilization exceeds an upper or lower threshold are detected and overloaded or light-loaded hosts are identified.

In the decision phase, a DVMC plan is formed based on knowledge or information presented from the monitoring phase. A DVMC plan contains decisions on the placement of VMs on physical hosts and the VM live migration strategy. While the migration engine decides which VM is selected to move, the placement engine searches for an optimal

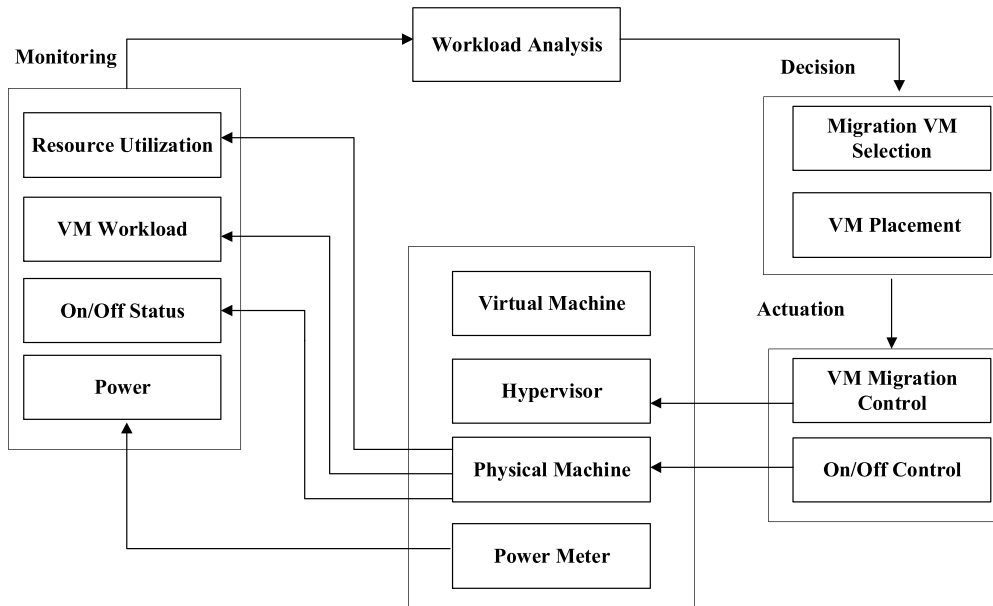


FIGURE 2. Framework of dynamic VM consolidation (DVMC).

placement regarding which physical host for this VM to be moved to.

In the actuation phase, the DVMC plan is executed to carry out the VM migration and the turning on or off of the respective physical host(s).

A. ENERGY MODEL OF DATACENTER

The utilization rate μ_j of the CPU in physical host j is defined as below:

$$\mu_j = P_j^{workload} / P_j^{\max} \quad (1)$$

where $P_j^{workload}$ is the total workload on physical host j ; P_j^{\max} is the CPU capacity of full workload.

Then, the power consumption P_j of physical host j can be represented as follows:

$$P_j = P_{idle} + (P_{\max} - P_{idle})\mu_j(t) \quad (2)$$

where P_{idle} and P_{\max} are the power consumption of the physical host in idle and full workloads, respectively; $\mu_j(t)$ is the CPU utilization rate of the physical host j at time t , $0 \leq \mu_j(t) \leq 1$.

The energy that physical host j consumes in period $[t_0, t_1]$ is defined as below:

$$E_{p_j} = \int_{t_0}^{t_1} P_j(\mu_j(t))dt \quad (3)$$

The energy consumption of VM migration is made from the energy consumption of the physical host and that of the communication.

Let $l(c)$ be the amount of data that will be transferred on the communication c during the VM migration. The energy consumption for transferring $l(c)$ units of data can be calculated

as below

$$E(c) = e_c \cdot l(c) \quad (4)$$

where e_c is defined as energy consumption for a unit of data transfer at different types of communication during VM migration.

The total energy consumption of VM migration can be calculated as below

$$E_M = \sum_{p_j \in P_{\Pi}} E_{p_j} + \sum_{c \in C_{\Gamma}} E(c) \quad (5)$$

where P_{Π} is the set of physical hosts involved in the VM migration; C_{Γ} is the set of different communications.

There are two basic constraints: (i) each VM should only assigned to one physical host, and (ii) the CPU capacity and the memory capacity should never be exceeded.

The placement engine searches for an optimal placement of a VM on to a PH to minimize the total cost which comprises the migration cost and the execution cost.

The cost function needs to balance the total energy savings and the performance of the cloud datacenter. We define the cost function as below:

$$f = C_{Migration} + C_{PM} + C_{Utilization} \quad (6)$$

where $C_{Migration}$ is the cost of live migration, which is the power consumption of the communication, the source PHs and the destination PHs during migration; C_{PM} is the energy consumption of the physical host; $C_{Utilization}$ is the utilization of the physical host. If $C_{Utilization}$ is too high (e.g., above 0.9), which means that this host is too busy, then VM on this host should be migrated to another host to assure the SLA for the users. On the contrary, if $C_{Utilization}$ is too low, which means that this host is light-loaded or idle, then VM should

be migrated to another host so that this host can be turned off to save energy.

B. DYNAMIC VM CONSOLIDATION (DVMC) PLAN

In the case of an overloaded physical host, a DVMC plan will comprise three steps, namely (i) detection of overload in physical hosts, (ii) selection of VMs for migration, and (iii) VM re-placement, while in the case of an underloaded physical host, a DVMC plan will comprise two steps, namely (i) detection of underload in hosts, and (ii) VM re-placement.

The Workload Analysis detects overload in any physical hosts across the cloud datacenter. Then, it obtains a list of overloaded physical hosts. These physical hosts will change to non-overloaded after some VMs running on them are migrated to other physical hosts. A migration VM selection policy must be applied to determine which VMs should be migrated away from the overloaded physical hosts, and then a VM placement policy will determine the destination physical hosts to which the selected VMs should be migrated. This process will continue until all the overloaded physical hosts become non-overloaded. At the same time, the underload in any physical host will be detected as well and all VMs running on them will be migrated to the other physical hosts determined by a VM placement policy. Then, these physical hosts can be changed to sleep mode or switched off to save energy.

The process of formation of a DVMC plan can be formulated as in Algorithm 1. The complexity of forming a DVMC plan is $2N$, where N is the number of physical hosts.

Algorithm 1 Formation of DVMC Plan

Input: PHList **Output:** vmMigrationMap

```

for each PH in PHList do
  if PH overloaded(PH) then
    vmsToMigrate.add(getVmsToMigrate(PH))
    vmMigrationMap.add(getNewPlacement(VmsToMigrate))
  for each PH in PHList do
    if PH underloaded(PH) then
      vmsToMigrate.add(PH.getVmList())
      vmMigrationMap.add(getNewPlacement(VmsToMigrate))
return vmMigrationMap

```

C. HOST OVERLOAD DETECTION AND MIGRATION VM SELECTION

There are several host overload detection policies [14], [15], e.g., adaptive utilization threshold: Interquartile Range (IQR), adaptive utilization threshold: Median Absolute Deviation (MAD), Local Regression (LR), and Robust Local Regression (denoted LRR), etc.

Once a host is deemed overloaded, the next step is to select some VMs to be migrated to other hosts. This can be done by using a migration VM selection policy, e.g., Minimum

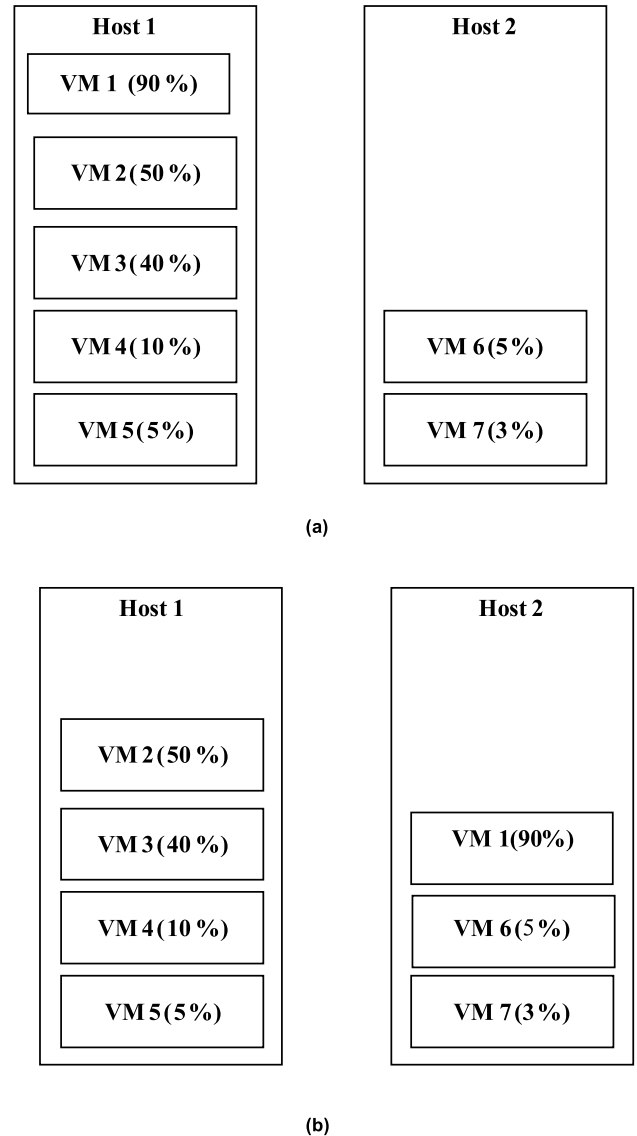


FIGURE 3. High CPU utilization based migration VM selection (called HS) policy. (a) Hosts before VM migration. (b) Hosts after VM migration.

Migration Time (MMT), Random Selection (RS), and Maximum Correlation (MC) [14], [15].

MMT policy selects a VM that takes the shortest possible time to complete the migration. RS policy selects a VM to be migrated based on a uniformly distributed discrete random variable. MC policy selects the VM of the highest correlation of CPU utilization with other VMs to migrate.

For VM migration, we propose a new migration VM selection policy, namely high CPU utilization based migration VM selection (called HS), to select VMs from the overloaded host to migrate. This means that the VM making the highest CPU utilization in the overloaded host will be selected first. If the host is still deemed overloaded after the VM making the highest CPU utilization has been migrated, the VM making the second highest CPU utilization will be selected to migrate. This process repeats until the host becomes non-overloaded.

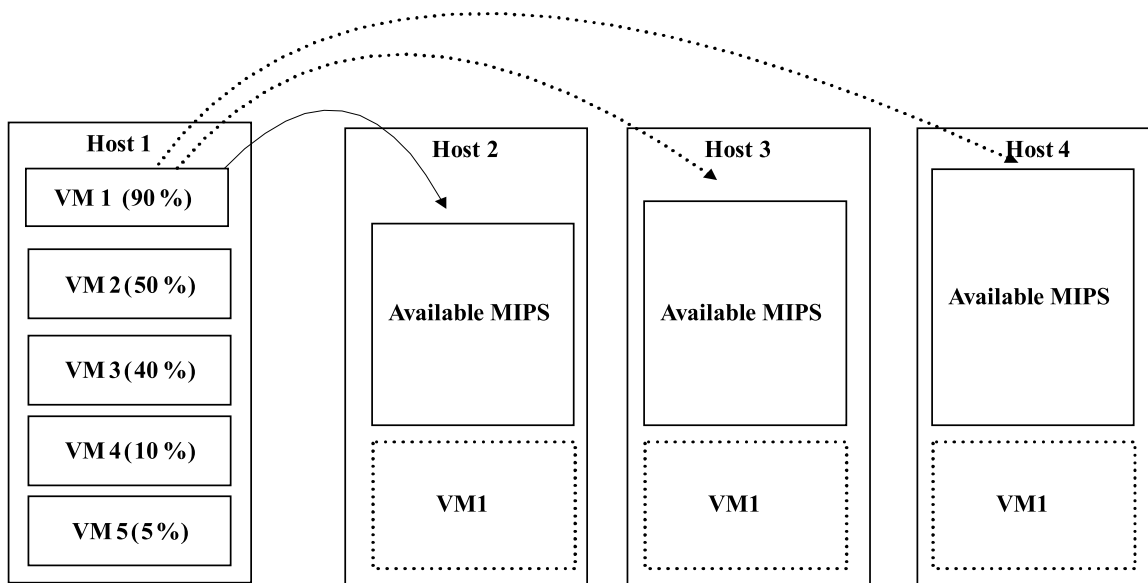


FIGURE 4. VM placement policy - Space Aware Best Fit Decreasing (SABFD).

For example, suppose that the CPU utilization by the VMs on an overloaded host are 90%, 70%, . . . , 10%, 5%, respectively. Then, the VM making 90% CPU utilization will be selected first and then the VM making 70% CPU utilization will be selected, and so on.

The rationale of CPU high utilization is that migrating the VM making high CPU utilization would help decrease the workload of the host quickly and minimize the number of potential migrations needed. Furthermore, the minimum number of migrations helps decrease energy consumption while the SLA of the cloud datacenter is assured.

Fig. 3 illustrates the HS policy for migration VM selection.

D. VM PLACEMENT POLICY

VM placement policy will determine to which host the selected VMs running on an overloaded host should be migrated. VM placement can be seen as a bin packing problem with variable bin sizes and prices. The bins represent the physical hosts and VMs are the items that need to be allocated. Bin’s sizes are the available CPU capacities of the hosts, and the prices are the power consumption by the hosts in the cloud datacenter.

We propose a new VM placement policy, namely Space Aware Best Fit Decreasing (SABFD) as follows. First of all, the VMs selected to migrate are sorted in a decreasing order of CPU utilization. The hosts which have enough resource in MIPS (millions of instructions per second) will be estimated for the first VM. Then, the host with minimum available MIPS after the VM being placed in will be selected to migrate this VM to. This process repeats until all the migration VMs have been migrated. This VM placement policy for migrating VMs to destination hosts helps decrease the number of migrations needed, which leads to saving more energy.

For example, suppose that there are four hosts in a cloud datacenter, as illustrated in Fig. 4. Host1 is overloaded and VM1 is selected to be migrated to another host. There are host2, host3 and host4 to determine to migrate VM1 to. The SABFD policy for VM placement will estimate the available MIPS resource of the hosts after VM1 being allocated to. As host2 has minimum available MIPS among the three potential destination hosts, it is determined that host2 will be the destination host for VM1 to be migrated to.

The SABFD policy for VM placement can be formulated as in Algorithm 2. The complexity of VM placement is nm , where n is the number of hosts and m is the number of VMs that have to be allocated.

Algorithm 2 SABFD Policy for VM Placement

```

Input: PHList.vmList Output: allocation of VMs
MigrationVmList.sortDecreasingUtilization()
for each vm in MigrationVmList do
    minAvailableMips = MAX
    for each PH in PHList do
        if PH has enough resources for vm then
            AvailableMips = estimate mipsAfterAllocation
            if mipsAfterAllocation < minAvailableMips
                minAvailableMips = mipsAfterAllocation
            allocatedHost = PH
    return allocation
    
```

E. HOST UNDERLOAD DETECTION

The Workload Analysis also detects underload in any physical hosts with minimum CPU utilization compared to the other physical hosts. Once all VMs running can be migrated to other hosts, an underloaded host can be turned to sleep

TABLE 1. Dynamic VM consolidation (DVMC) plans.

	DVMC plan	Host overload detection policy	Migration VM selection policy	VM placement policy
1.	NPA	--	--	--
2.	DVFS	--	--	--
3.	IQR_MC_1.5	IQR	MC	PABFD
4.	IQR_MC_1.5_SABFD	IQR	MC	SABFD
5.	IQR_MMT_1.5	IQR	MMT	PABFD
6.	IQR_MMT_1.5_SABFD	IQR	MMT	SABFD
7.	IQR_RS_1.5	IQR	RS	PABFD
8.	IQR_RS_1.5_SABFD	IQR	RS	SABFD
9.	IQR_HS_1.5	IQR	HS	PABFD
10.	IQR_HS_1.5_SABFD	IQR	HS	SABFD
11.	LR_MC_1.2	LR	MC	PABFD
12.	LR_MC_1.2_SABFD	LR	MC	SABFD
13.	LR_MMT_1.2	LR	MMT	PABFD
14.	LR_MMT_1.2_SABFD	LR	MMT	SABFD
15.	LR_RS_1.2	LR	RS	PABFD
16.	LR_RS_1.2_SABFD	LR	RS	SABFD
17.	LR_HS_1.2	LR	HS	PABFD
18.	LR_HS_1.2_SABFD	LR	HS	SABFD
19.	LRR_MC_1.2	LRR	MC	PABFD
20.	LRR_MC_1.2_SABFD	LRR	MC	SABFD
21.	LRR_MMT_1.2	LRR	MMT	PABFD
22.	LRR_MMT_1.2_SABFD	LRR	MMT	SABFD
23.	LRR_RS_1.2	LRR	RS	PABFD
24.	LRR_RS_1.2_SABFD	LRR	RS	SABFD
25.	LRR_HS_1.2	LRR	HS	PABFD
26.	LRR_HS_1.2_SABFD	LRR	HS	SABFD
27.	MAD_MC_2.5	MAD	MC	PABFD
28.	MAD_MC_2.5_SABFD	MAD	MC	SABFD

TABLE 1. (Continued.) Dynamic VM consolidation (DVMC) plans.

29.	MAD_MMT_2.5	MAD	MMT	PABFD
30.	MAD_MMT_2.5_SABFD	MAD	MMT	SABFD
31.	MAD_RS_2.5	MAD	RS	PABFD
32.	MAD_RS_2.5_SABFD	MAD	RS	SABFD
33.	MAD_HS_2.5	MAD	HS	PABFD
34.	MAD_HS_2.5_SABFD	MAD	HS	SABFD
35.	THR_MC_0.8	THR	MC	PABFD
36.	THR_MC_0.8_SABFD	THR	MC	SABFD
37.	THR_MMT_0.8	THR	MMT	PABFD
38.	THR_MMT_0.8_SABFD	THR	MMT	SABFD
39.	THR_RS_0.8	THR	RS	PABFD
40.	THR_RS_0.8_SABFD	THR	RS	SABFD
41.	THR_HS_0.8	THR	HS	PABFD
42.	THR_HS_0.8_SABFD	THR	HS	SABFD

mode or switched off to save energy. Otherwise the under-loaded physical host keeps alive.

IV. PERFORMANCE EVALUATION

A. EXPERIMENT SETUP

Our proposed DVMC plan for green cloud computing will be evaluated via simulations using the CloudSim toolkit [16].

For the simulations, the datacenter comprises of 800 heterogeneous physical hosts, i.e., 400 HP ProLiant ML110G4 servers and 400 HP ProLiant ML110G5 servers.

Each core in HP ProLiant ML110G4 server and in HP ProLiant ML110G5 server is of 1860 MIPS and 2660 MIPS, respectively. The random storage capacity of each server is 4GB. The network bandwidth is 1GB/s. The VMs are single-core. There are four types of VMs. Type #1 VM has a 2500MIPS core and 0.85GB RAM. Type #2 VM has a 2000MIPS core and 3.75GB RAM. Type #3 VM has a 1000MIPS core and 1.7GB RAM. Type #4 VM has a 500MIPS core and 613MB RAM. At the beginning, the VMs are allocated based on the resources requirements defined by the VM types. Then VMs use less resources while the workload is being settled down, which may reach a point where DVMC is triggered.

The workload data used in the simulations comes from the CoMon project [17]. The data of CPU utilization by VMs comes from servers located at more than 500 places around the world. The interval of CPU utilization measurements

is 300 seconds. This study uses the workload data collected on 3 March, 6 March, 9 March, 22 March, 25 March, 3 April, 9 April, 11 April, 12 April, 20 April 2011. At the beginning of the experiment, the average CPU utilization is well below 50%. Each VM is randomly assigned a workload traces from the respective day. The memory constraint is not considered because the simulations are focused on the DVMC plan.

B. PERFORMANCE METRICS

1) ENERGY CONSUMPTION (E)

The total energy consumption by the hosts of a cloud datacenter caused by the application workloads is an important metric to a DVMC system. The energy-aware DVMC plan should reduce the power consumption of cloud datacenter.

2) SERVICE LEVEL AGREEMENT (SLA)

SLA is an important metric to the energy-aware DVMC system. The energy-aware DVMC plan should assure SLA of cloud datacenter to a high level.

SLATAH denotes SLA violation Time per Active Host which is defined as the percentage of time that active hosts have experienced the CPU utilization of 100% during the simulations. SLATAH is calculated as below [14], [15]:

$$SLATAH = \frac{1}{N} \sum_{i=1}^N \frac{T_{sum_i}}{T_{active_i}} \quad (7)$$

TABLE 2. Median values from simulations.

DVMC plan	ESV ($\times 10^{-3}$)	Energy (kWh)	SLAV ($\times 10^{-5}$)	SLATAH	PDM	VM migrations ($\times 103$)	Host shutdowns ($\times 102$)
NPA	0.00	2410.8	0.00	0.00	0.00	0.00	4.62
DVFS	0.00	794.7	0.00	0.00	0.00	0.00	4.62
IQR_MC_1.5	11.94	173.52	6.87	6.89%	0.10%	22.75	55.12
IQR_MC_1.5_SABFD	6.56	117.64	5.24	5.23%	0.10%	17.33	11.37
IQR_MMT_1.5	6.01	183.34	3.00	5.00%	0.06%	25.72	56.53
IQR_MMT_1.5_SABFD	3.60	116.44	2.92	3.68%	0.08%	24.54	11.31
IQR_RS_1.5	12.10	174.38	6.62	6.98%	0.10%	22.89	53.24
IQR_RS_1.5_SABFD	7.34	117.45	5.82	5.42%	0.11%	17.49	11.27
IQR_HS_1.5	15.51	149.06	10.44	6.14%	0.17%	18.16	46.64
IQR_HS_1.5_SABFD	5.15	119.57	4.10	4.10%	0.10%	8.59	13.16
LR_MC_1.2	12.24	158.43	7.11	7.09%	0.10%	23.71	47.41
LR_MC_1.2_SABFD	4.33	117.68	3.42	5.03%	0.07%	11.88	10.05
LR_MMT_1.2	7.19	170.28	3.85	5.42%	0.07%	26.67	53.80
LR_MMT_1.2_SABFD	2.24	123.50	1.79	3.91%	0.05%	16.39	9.79
LR_RS_1.2	12.24	163.59	7.27	7.16%	0.10%	23.54	48.71
LR_RS_1.2_SABFD	4.83	118.26	3.87	5.46%	0.07%	19.09	10.0
LR_HS_1.2	12.39	138.53	8.477	6.06%	0.14%	16.67	36.53
LR_HS_1.2_SABFD	4.18	118.71	3.29	4.06%	0.08%	8.27	11.64
LRR_MC_1.2	12.18	160.81	7.25	7.12%	0.10%	23.61	49.09
LRR_MC_1.2_SABFD	5.71	117.15	4.40	5.70%	0.08%	13.35	10.27
LRR_MMT_1.2	7.07	172.34	3.73	5.33%	0.07%	26.58	52.70
LRR_MMT_1.2_SABFD	2.64	116.45	2.05	4.01%	0.05%	17.08	10.02
LRR_RS_1.2	12.92	171.36	7.58	7.22%	0.11%	24.93	51.38
LRR_RS_1.2_SABFD	5.92	118.01	4.48	5.61%	0.08%	13.36	10.21
LRR_HS_1.2	13.56	140.77	9.35	6.24%	0.15%	17.52	39.38
LRR_HS_1.2_SABFD	4.77	118.67	3.83	4.25%	0.09%	8.62	11.84
MAD_MC_2.5	11.86	176.24	6.95	6.99%	0.10%	22.72	51.99
MAD_MC_2.5_SABFD	7.30	114.90	6.13	5.58%	0.11%	17.46	11.09
MAD_MMT_2.5	5.96	179.20	3.27	5.04%	0.07%	25.45	55.87
MAD_MMT_2.5_SABFD	3.77	114.38	3.08	3.96%	0.08%	24.06	11.04
MAD_RS_2.5	12.07	170.70	7.06	7.09%	0.10%	22.86	52.21
MAD_RS_2.5_SABFD	7.82	115.51	6.31	5.81%	0.11%	17.69	11.11
MAD_HS_2.5	15.27	145.17	10.63	6.26%	0.17%	17.91	45.65
MAD_HS_2.5_SABFD	5.18	116.40	4.25	4.25%	0.10%	8.28	12.63
THR_MC_0.8	12.09	175.72	6.84	6.86%	0.10%	23.33	53.02
THR_MC_0.8_SABFD	6.81	123.67	5.12	5.04%	0.10%	18.06	11.37
THR_MMT_0.8	6.19	184.84	3.46	5.02%	0.07%	25.85	56.83
THR_MMT_0.8_SABFD	3.75	123.30	2.81	3.64%	0.08%	22.33	11.42
THR_RS_0.8	10.62	183.49	6.08	6.99%	0.08%	25.50	55.87
THR_RS_0.8_SABFD	7.53	124.94	5.62	5.27%	0.11%	18.27	11.42
THR_HS_0.8	14.14	151.55	9.43	5.89%	0.16%	17.87	47.07
THR_HS_0.8_SABFD	5.31	121.26	4.71	4.11%	0.10%	8.83	13.11

TABLE 3. Average values from Simulations.

DVMC plan	ESV ($\times 10^{-3}$)	Energy (kWh)	SLAV ($\times 10^{-5}$)	SLATAH	PDM	VM migrations ($\times 10^3$)	Host shutdowns ($\times 10^2$)
NPA	0.00	2410.80	0.00	0.00	0.00	0.00	4.62
DVFS	0.00	829.50	0.00	0.00	0.00	0.00	4.62
IQR_MC_1.5	11.92	178.23	6.76	6.90%	0.10%	23.51	58.51
IQR_MC_1.5_SABFD	6.48	118.80	5.50	5.22%	0.11%	18.21	11.27
IQR_MMT_1.5	6.04	187.53	3.28	5.02%	0.07%	26.50	57.49
IQR_MMT_1.5_SABFD	3.76	117.55	3.13	3.79%	0.08%	26.24	11.22
IQR_RS_1.5	11.98	178.87	6.77	6.97%	0.10%	23.71	53.80
IQR_RS_1.5_SABFD	7.13	119.07	6.06	5.45%	0.11%	18.20	11.24
IQR_HS_1.5	15.60	152.43	10.30	6.13%	0.17%	18.86	47.58
IQR_HS_1.5_SABFD	5.17	120.84	4.32	4.11%	0.11%	8.852	13.12
LR_MC_1.2	12.07	161.77	7.54	7.17%	0.11%	24.65	48.54
LR_MC_1.2_SABFD	4.46	118.86	3.85	5.19%	0.07%	12.58	10.00
LR_MMT_1.2	7.28	164.47	4.51	5.61%	0.08%	27.08	52.51
LR_MMT_1.2_SABFD	2.34	118.92	2.03	4.02%	0.05%	16.46	9.77
LR_RS_1.2	12.33	162.64	7.74	7.20%	0.11%	24.46	48.65
LR_RS_1.2_SABFD	5.09	119.19	4.39	5.63%	0.08%	12.52	9.99
LR_HS_1.2	12.26	140.40	8.79	6.13%	0.14%	17.48	37.10
LR_HS_1.2_SABFD	4.30	120.93	3.62	4.09%	0.09%	8.47	11.63
LRR_MC_1.2	12.32	164.62	7.56	7.19%	0.11%	24.44	49.80
LRR_MC_1.2_SABFD	5.58	118.73	4.80	5.71%	0.08%	14.06	10.22
LRR_MMT_1.2	8.05	173.87	4.71	5.75%	0.08%	26.75	53.76
LRR_MMT_1.2_SABFD	2.80	117.07	2.49	4.26%	0.06%	18.09	9.94
LRR_RS_1.2	12.58	167.09	7.63	7.34%	0.10%	24.68	50.72
LRR_RS_1.2_SABFD	5.90	118.92	5.10	5.96%	0.08%	14.00	10.17
LRR_HS_1.2	13.58	142.49	9.61	6.26%	0.15%	18.24	39.79
LRR_HS_1.2_SABFD	4.93	120.73	4.15	4.34%	0.10%	8.90	11.85
MAD_MC_2.5	12.02	180.38	6.91	6.98%	0.10%	23.54	53.23
MAD_MC_2.5_SABFD	7.02	116.41	6.19	5.56%	0.11%	18.01	11.07
MAD_MMT_2.5	5.96	183.49	3.29	5.05%	0.07%	26.31	56.65
MAD_MMT_2.5_SABFD	3.83	115.12	3.38	3.99%	0.08%	25.32	10.98
MAD_RS_2.5	12.28	174.67	7.08	7.08%	0.10%	23.62	52.94
MAD_RS_2.5_SABFD	7.84	116.81	6.80	5.81%	0.12%	18.06	11.10
MAD_HS_2.5	15.50	148.33	10.53	6.23%	0.17%	18.40	46.46
MAD_HS_2.5_SABFD	5.29	117.63	4.56	4.25%	0.11%	8.53	12.69
THR_MC_0.8	12.22	179.16	6.88	6.88%	0.10%	23.92	53.53
THR_MC_0.8_SABFD	7.02	125.55	5.70	5.19%	0.11%	18.76	11.36
THR_MMT_0.8	6.18	186.31	3.37	5.03%	0.07%	26.30	56.84
THR_MMT_0.8_SABFD	3.68	124.05	3.04	3.69%	0.08%	23.07	11.29
THR_RS_0.8	12.76	180.55	6.43	6.97%	0.10%	24.23	54.10
THR_RS_0.8_SABFD	7.47	126.38	6.03	5.31%	0.11%	19.01	11.39
THR_HS_0.8	15.52	153.80	9.67	5.92%	0.16%	18.15	47.42
THR_HS_0.8_SABFD	5.44	124.54	4.88	4.14%	0.11%	9.29	13.04

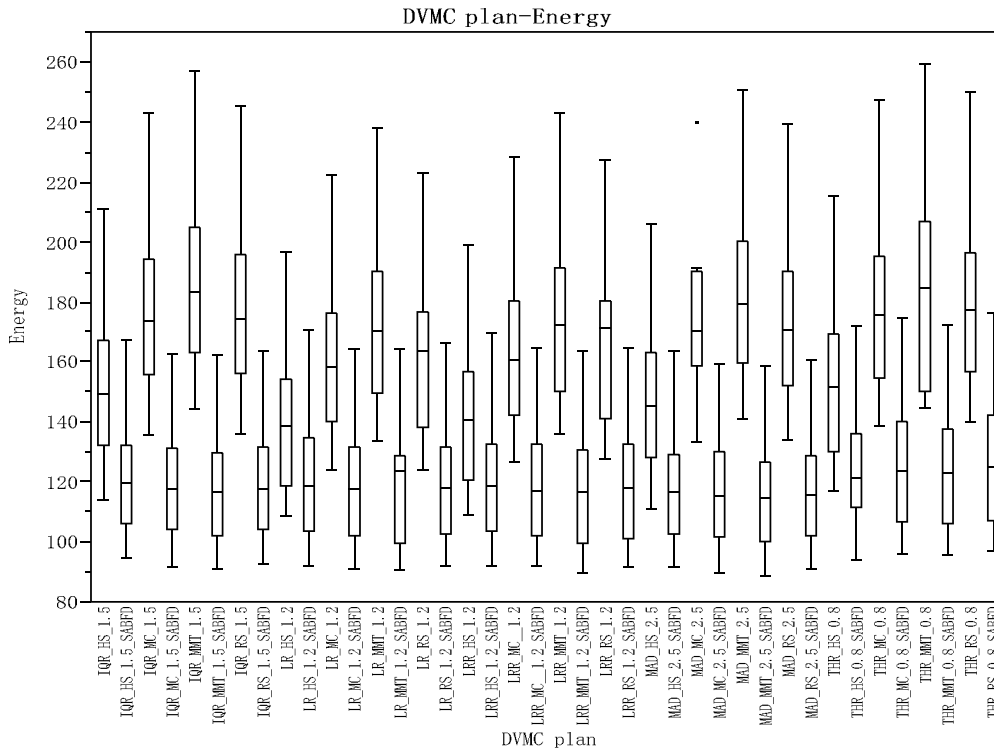


FIGURE 5. Energy consumption vs. DVMC plan.

where N is the number of physical hosts; T_{Sum_i} is the total time during which physical host i has experienced the utilization of 100% leading to an SLA violation. T_{active_i} is physical host i being in the active state.

PDM denotes performance degradation due to migrations which is defined as the overall performance degradation by VMs due to migrations. PDM is calculated as below [14], [15]:

$$PDM = \frac{1}{M} \sum_{j=1}^M \frac{C_{degradation_j}}{C_{request_j}} \tag{8}$$

where M is the number of VMs; $C_{degradation_j}$ is the performance degradation of VM j caused by migrations; $C_{request_j}$ is the total CPU capacity requested by VM j during its lifetime.

SLAV denotes the product of SLATAH and PDM to manifest both performance degradation due to host overloading and VM migrations. SLAV is calculated as below

$$SLAV = SLATAH \cdot PDM \tag{9}$$

ESV denotes the product of energy consumption and SLA violations. The consolidation of hosts in cloud datacenter is to optimize the placement of VMs in order to minimize both the energy consumption and SLA violations. ESV is defined as below:

$$ESV = E \cdot SLAV \tag{10}$$

3) OTHER METRICS

The numbers of VM migrations and host shutdowns during the consolidation will be studied. Furthermore, the time before a host shutdown (switch to sleep) and the time before a VM is migrated from a host will be considered as well.

C. EXPERIMENTAL RESULTS

The simulations compare NPA (non power aware policy), DVFS (Dynamic Voltage and Frequency Scaling) [18], and energy-aware policies. Two VM placement policies are compared in the simulations, that is, one is our proposed Space Aware Best Fit Decreasing (SABFD) policy, and the other is the Power Aware Best Fit Decreasing (PABFD) policy [14], [15], [19]. PABFD sorts all VMs in a descending order of their current CPU utilizations and allocates each VM to the physical host so that VM allocation will cause minimum increase in power consumption.

Five host overload detection polices, i.e., Interquartile Range (IQR), Local Regression (LR), Local Regression Robust (LRR), Median Absolute Deviation (MAD), and four migration VM selection polices, i.e., Minimum Migration Time (MMT), Random Selection (RS), Maximum Correlation (MC) [14], [15], High utilization based migration VM selection (HS) are used in simulations.

The energy-aware DVMC plans in the simulations, along with two defaults with no VMs, are presented in Table 1. The notation of a DVMC plan is formatted of 4 strings. The first two strings denote host overload detection and migration

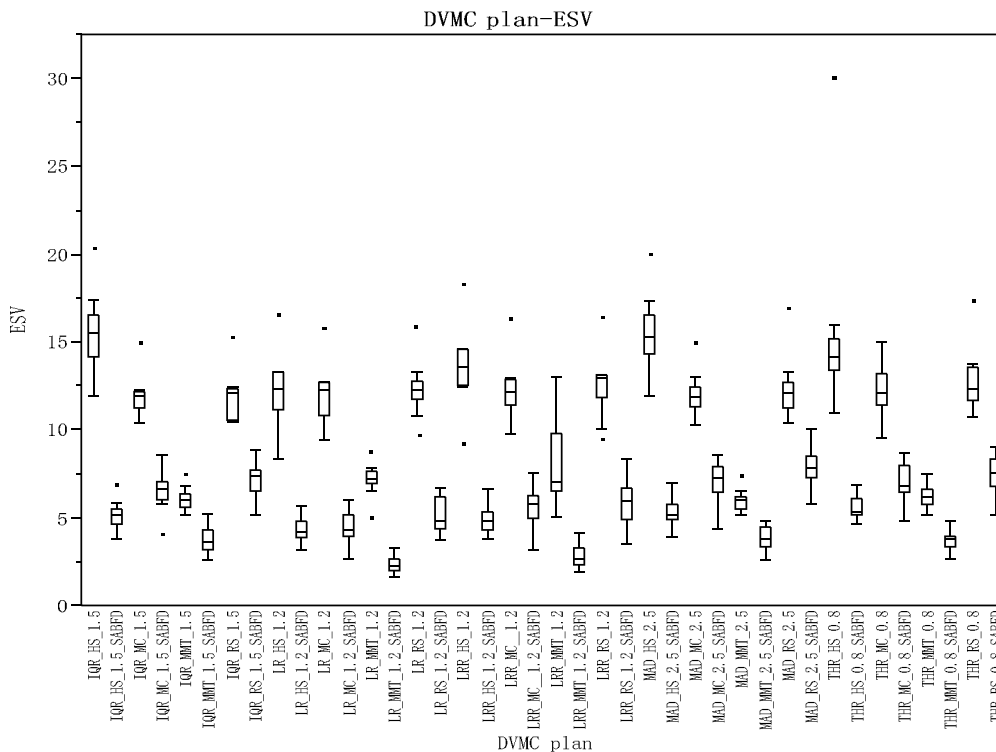


FIGURE 6. ESV vs. DVMC plan.

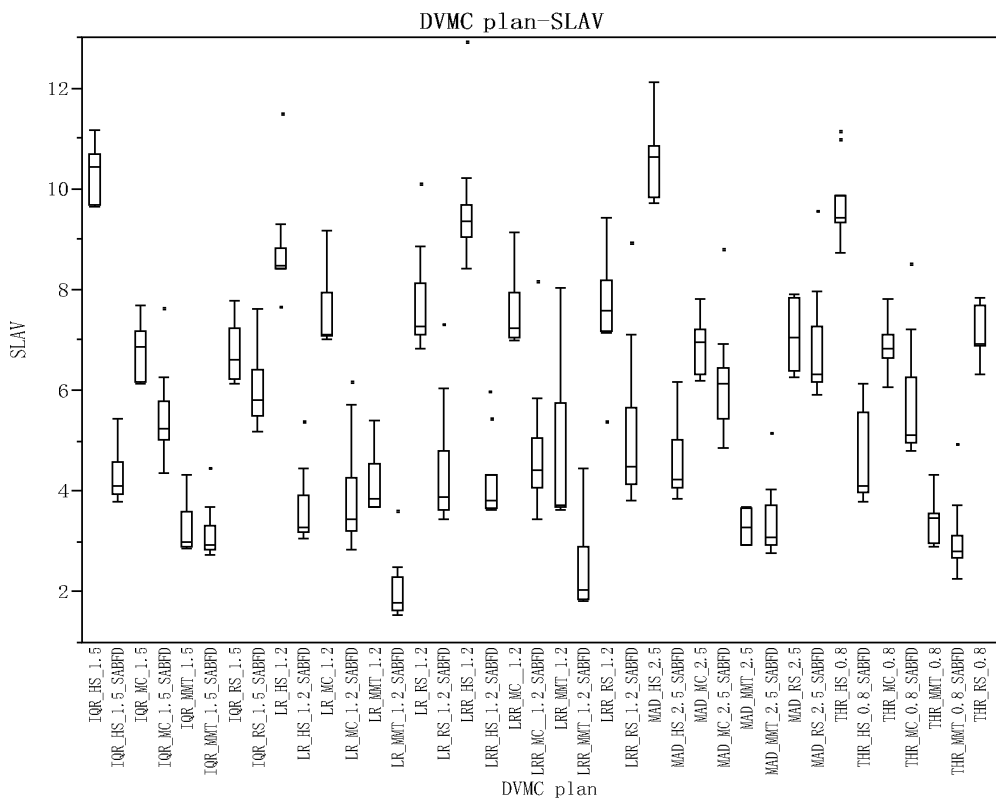


FIGURE 7. SLAV vs. DVMC plan.

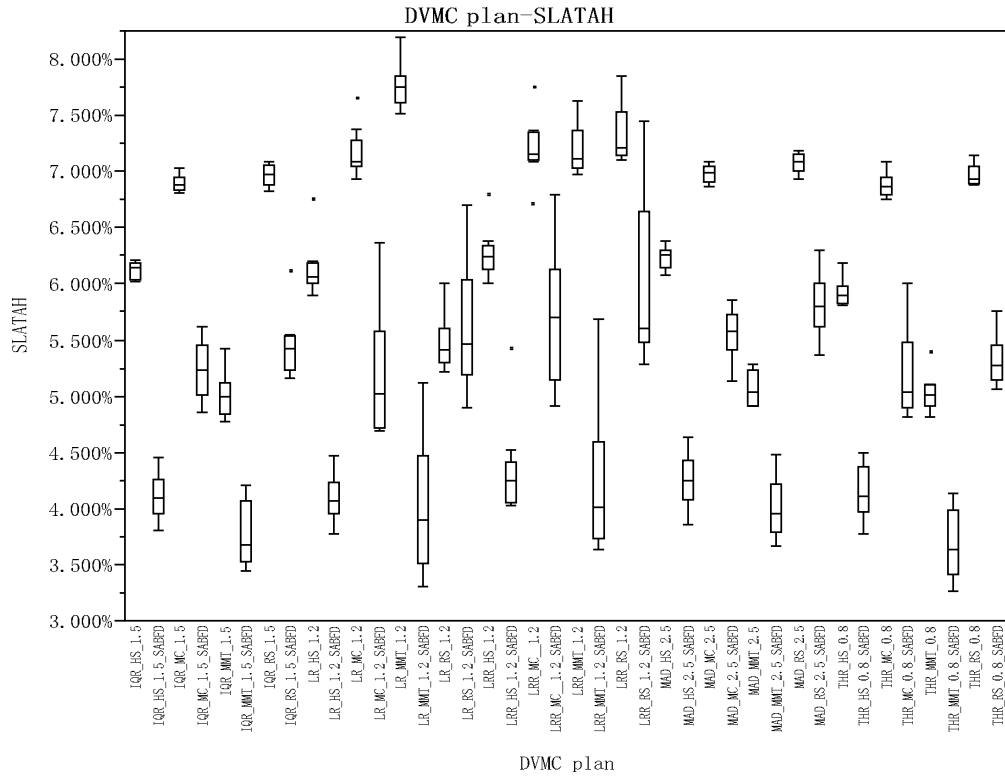


FIGURE 8. SLATAH vs. DVMC plan.

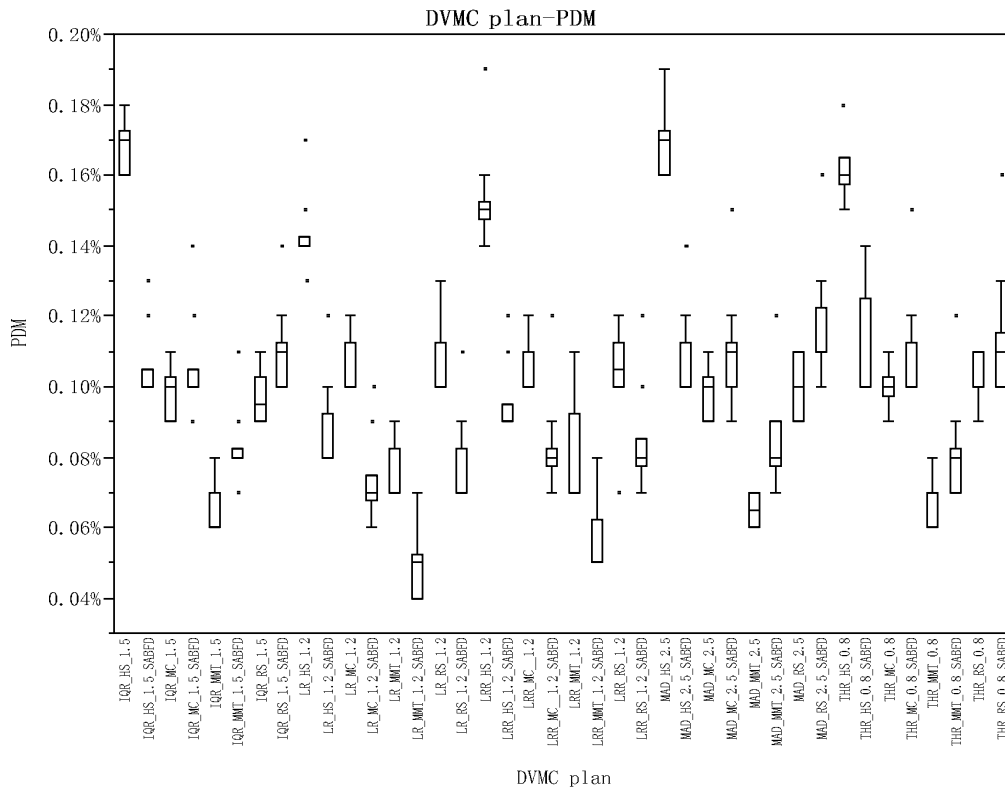


FIGURE 9. PDM vs. DVMC plan.

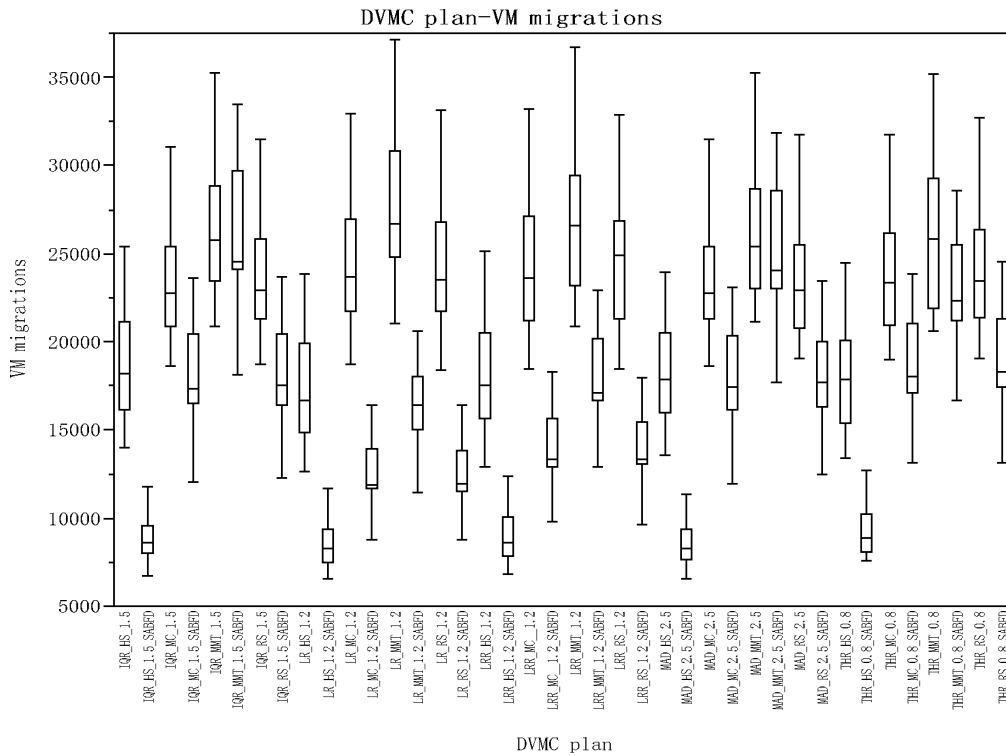


FIGURE 10. VM migrations vs. DVMC plan.

VM selection policies, respectively, the third string denotes safety parameter or threshold, e.g.,

IQR_MC_1.5, IQR_MMT_1.5, IQR_RS_1.5	The safety parameter of IQR policy is set to 1.5
LR_MC_1.2, LR_MMT_1.2, LR_RS_1.2	The safety parameter of LR policy is set to 1.2
LRR_MC_1.2, LRR_MMT_1.2, LRR_RS_1.2	The safety parameter of LRR policy is set to 1.2
MAD_MC_2.5, MAD_MMT_2.5, MAD_RS_2.5	The safety parameter of MAD policy is set to 2.5
THR_MC_0.8, THR_MMT_0.8, THR_RS_0.8	The fixed threshold is set to 80%

and the fourth string denotes VM placement policy, which refers to PABFD in case of blank.

HS and SABFD are our proposed new policies for migration VM selection and VM placement, respectively. All the other policies, for host overloaded detection, migration VM selection, and VM placement, respectively, are taken from [14] and [15].

The simulation results are shown in Table 2 and Table 3. The comparisons of metrics between different DVMC plans are plotted in Fig. 5 to Fig. 11.

From Table 2 and Table 3, it can be seen that energy-aware DVMC plan uses less energy than the NPA policy. All the physical hosts in the cloud datacenter consume the maximum power all the time with the NPA policy. DVMC plans are superior to static allocation policies such as NPA and DVFS. The DVMC plans with SABFD are the best in saving energy and suppressing SLA violation to a low level.

The performance of DVMC plans are analyzed as follows.

Power Savings. The average energy consumption of DVMC plans with SABFD policy is 71.84% that with PABFD policy. MAD_MMT with SABFD VM placement policy consumes minimum energy among all the DVMC plans. IQR_MMT_1.5_SABFD, MAD_MC_2.5_SABFD and MAD_MMT_SABFD consume no more than 120kWh while the average energy consumption is less than 65% that of IQR_MMT_1.5, MAD_MC_2.5 and MAD_MMT with PABFD policy.

SLATAH metric. The average SLATAH metric of DVMC plans with SABFD policy is 74.66% that with SABFD policy. Therefore, DVMC plans with SABFD policy reduce SLATAH metric more effectively than with PABFD policy. This means that the percentage of time that the active hosts experience 100% utilization of CPU with SABFD policy is less than with PABFD policy.

SLAV metric. The average SLAV metric of DVMC plans with SABFD policy is 68.88% that with SABFD policy. The minimum average SLAV metric is achieved by LR_MMT_1.2_SABFD. This means that the SABFD policy is more effective to reduce the performance degradation due to host overloading and VM migration than the

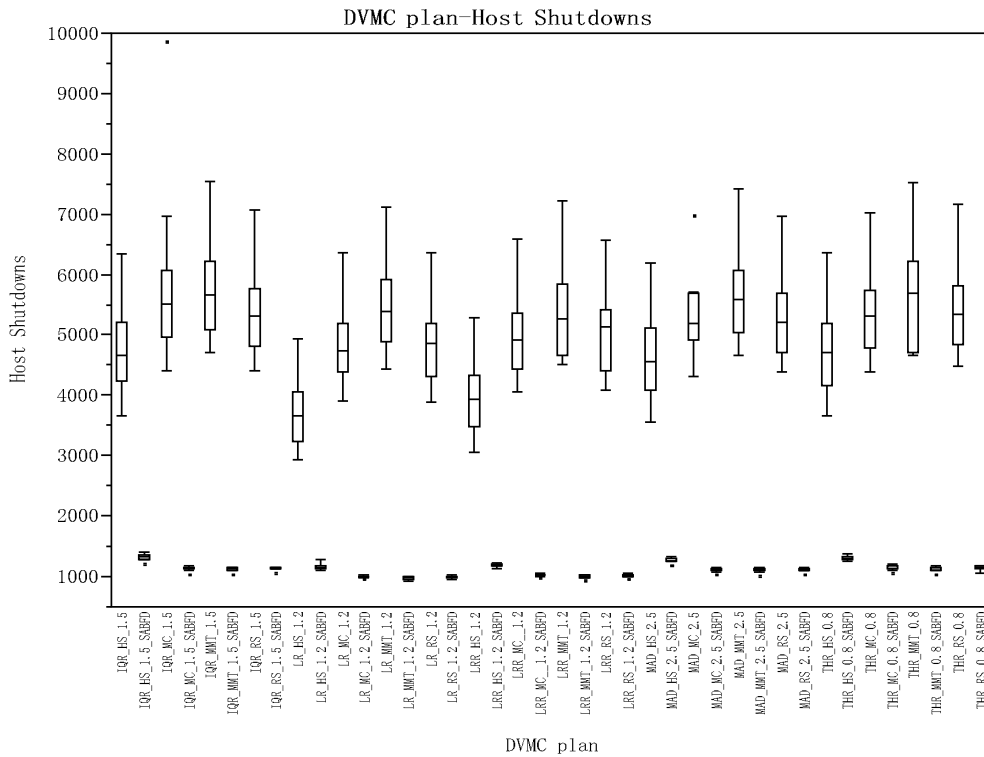


FIGURE 11. Host shutdowns vs. DVMC plan.

PABFD policy. SABFD is helpful for assuring SLA of cloud datacenter to a high level.

ESV metric. This composite metric considers both energy consumption and SLA violation. The smaller the ESV value, the better. The simulation results show that ESV metrics of DVMC plans with SABFD policy are better than with PABFD policy. The average ESV metric with SABFD is 47.46% that with PABFD. The DVMC plans with SABFD policy can reduce both energy consumption and SLAV more effectively. LR_MMT_1.2_SABFD attains the best ESV metric compared to others. For example, by LR_MMT_1.2, the average ESV metric with SABFD policy is 32.14% that with PABFD policy.

Other metrics. The mean time before a host shutdown for DVMC plans with SABFD and PABFD policies is 2712.27 and 1014.70 seconds, respectively. This means that a host is switched to sleep mode after average 2712.27 seconds of active mode with SABFD policy and after average 1014.70 seconds with PABFD policy, respectively. The mean time before a VM is migrated from a host with SABFD policy is 17.74 seconds and 18.25 with PABFD policy, respectively. The simulations show that the number of host shutdown with SABFD policy is significantly less than with PABFD policy. The average host shutdown with SABFD is only 22.26% that with PABFD. Meanwhile, the average number of VM Migrations with SABFD policy is 66.68% that with PABFD policy.

From the simulation results, it can be seen that DVMC plans with SABFD policy can reduce energy consumption and assure higher SLA than with PABFD policy.

The HS policy for migration VM selection can help reduce energy consumption when used in conjunction with VM placement policies PABFD and SABFD, especially with the latter. SLAV is reduced significantly using SABFD policy.

V. CONCLUSIONS

In this paper, we have put forward a new framework of dynamic Virtual Machine (VM) consolidation (DVMC) for green cloud computing. In particular, we have proposed a new VM placement policy, namely Space Aware Best Fit Decreasing (SABFD) and a new migration VM selection policy, namely High CUP utilization based migration VM Selection (HS).

SABFD policy places migration VMs to the candidate host that has minimum available MIPS after VMs being allocated. The simulation results have shown that DVMC plans with SABFD policy outperform those with PABFD policy both on saving energy and assuring SLA. The SABFD policy reduces the migrations of VMs and host shutdowns, which contributes towards saving energy and suppressing SLA violation to a low level. The HS policy for migration VM selection selects VM with the highest CPU utilization to be migrated. The simulation results have shown that HS policy is competitive for migration VM selection that can help save energy and assure SLA as well.

Undoubtedly, the established framework of energy-aware dynamic VM consolidation will take a profound role in tackling real-world critical challenges of green cloud computing by reducing power consumption and suppressing

SLAV of cloud datacenters. The proposed SABFD policy for VM placement and HS policy for migration VM selection will make energy-aware dynamic VM consolidation even more promising for green cloud computing.

REFERENCES

- [1] C.-C. Lin, P. Liu, and J.-J. Wu, "Energy-efficient virtual machine provision algorithms for cloud systems," in *Proc. 4th IEEE Int. Conf. Utility Cloud Comput. (UCC)*, Dec. 2011, pp. 81–88.
- [2] M. Sharifi, H. Salimi, and M. Najafzadeh, "Power-efficient distributed scheduling of virtual machines using workload-aware consolidation techniques," *J. Supercomput.*, vol. 61, no. 1, pp. 46–66, 2012.
- [3] A. Murtazaev and S. Oh, "Sercon: Server consolidation algorithm using live migration of virtual machines for green computing," *IETE Tech. Rev.*, vol. 28, no. 3, pp. 212–231, 2011.
- [4] R. Nathuji and K. Schwan, "VirtualPower: Coordinated power management in virtualized enterprise systems," *ACM SIGOPS Oper. Syst. Rev.*, vol. 41, no. 6, pp. 265–278, 2007.
- [5] A. Beloglazov and R. Buyya, "Adaptive threshold-based approach for energy-efficient consolidation of virtual machines in cloud data centers," in *Proc. 8th Int. Workshop Middleware Grids, Clouds e-Sci.*, 2010, Art. no. 4.
- [6] A. Esnault, "Energy-aware distributed ant colony based virtual machine consolidation in IaaS clouds," Dept. Distrib., Parallel, Cluster Comput., INRIA-IRISA Rennes Bretagne Atlantique, Rennes, France, Tech. Rep., 2012.
- [7] N. Quang-Hung, P. D. Nien, N. H. Nam, N. H. Tuong, and N. Thoai, "A genetic algorithm for power-aware virtual machine allocation in private cloud," in *Information and Communication Technology*. Berlin, Germany: Springer, 2013, pp. 183–191.
- [8] E. Feller, L. Rilling, and C. Morin, "Energy-aware ant colony based workload placement in clouds," in *Proc. 12th IEEE/ACM Int. Conf. Grid Comput. (GRID)*, Lyon, France, Sep. 2011, pp. 26–33.
- [9] X.-D. Zuo and H.-M. Jia, "An energy saving heuristic algorithm based on consolidation of virtual machines," in *Proc. Int. Conf. Mach. Learn. Cybern.*, 2013, pp. 1578–1583.
- [10] D. A. Alboaneen, H. Tianfield, and Y. Zhang, "Glowworm swarm optimisation algorithm for virtual machine placement in cloud computing," in *Proc. Int. IEEE Conf. Ubiquitous Intell. Comput., Adv. Trusted Comput., Scalable Comput. Commun., Cloud Big Data Comput., Internet People, Smart World Congr. (UIC/ATC/ScalCom/CBDCCom/IoP/SmartWorld)*, 2016, pp. 808–814.
- [11] L. Liu *et al.*, "GreenCloud: A new architecture for green data center," in *Proc. 6th Int. Conf. Ind. Session Auto. Comput. Commun. Ind. Session (ICAC-INDST)*. New York, NY, USA, 2009, pp. 29–38.
- [12] H. Jing, K. Wu, and M. Moh, "Dynamic virtual machine migration algorithms using enhanced energy consumption model for green cloud data centers," in *Proc. Int. Conf. High Perform. Comput. Simulation (HPCS)*, 2014, pp. 902–910.
- [13] M. Shaden and A. Heba, "Review of energy reduction techniques for green cloud computing," in *Proc. Int. J. Adv. Comput. Sci. Appl.*, 2016, pp. 184–195.
- [14] A. Beloglazov and R. Buyya, "Optimal online deterministic algorithms and adaptive heuristics for energy and performance efficient dynamic consolidation of virtual machines in Cloud data centers," *Concurrency Comput., Pract. Exper.*, vol. 24, no. 13, pp. 1397–1420, 2012.
- [15] A. Beloglazov, "Energy-efficient management of virtual machines in data centers for cloud computing," Ph.D. dissertation, Univ. Melbourne, Parkville VIC, Australia, 2013.
- [16] R. Calheiros, R. Ranjan, C. A. F. De Rose, and R. Buyya, *CloudSim: A Novel Framework for Modeling and Simulation of Cloud Computing Infrastructures and Services*. Accessed: Oct. 26, 2016. [Online]. Available: <http://www.cloudbus.org/reports/CloudSim-ICPP2009.pdf>
- [17] K. Park and V. S. Pai, "CoMon: A mostly-scalable monitoring system for PlanetLab," *ACM SIGOPS Oper. Syst. Rev.*, vol. 40, no. 1, pp. 65–74, 2006.
- [18] D. C. Snowdon, S. Ruocco, and G. Heiser, "Power management and dynamic voltage scaling: Myths and facts," in *Proc. Workshop Power Aware Real-Time Comput.*, 2005, pp. 1–7.
- [19] A. Beloglazov, J. Abawajy, and R. Buyya, "Energy-aware resource allocation heuristics for efficient management of data centers for cloud computing," *Future Generat. Comput. Syst.*, vol. 28, no. 5, pp. 755–768, 2012.



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