An Effective Virtual Machine Selection Approach for Dynamic Consolidation in Cloud Computing Environment

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Summary
Exponential increasing Cloud Computing services has resulted in setting up large scale virtual Cloud Computing data centres throughout the globe. The increased use in cloud data centres resulted in a tremendous increase in power consumption, and carbon footprint. Therefore, it is an urgent requirement for developing effective methods to reduce their power consumption while meeting service level agreements between cloud service providers and users. Virtual machine consolidation is an effective method for reducing power consumption of data center. Selecting a suitable virtual machine for migrating from over utilized physical machines to others during the virtual machine consolidation process is challenging. This work proposes a power saving virtual machine selection method based upon the current utilization and resource capacity of virtual and physical machines to reduce their power consumption. The proposed approach is validated experimentally in a simulated environment using cloudSim. Its performance is analyzed by measuring power consumption, virtual machine migrations, service level agreement violations, and a combined metric of energy consumption and service level agreement violations. Comparative analysis of the result demonstrates the superiority of the proposed approach. The proposed approach has resulted in significant improvement in the power reduction of cloud data centers.
Keywords:
Cloud computing; VM consolidation; VM selection policy; Energy efficiency

1. Introduction

Recently, Internet of Things (IoT) technology has emerged tremendously in computational sciences [1]. This technology has enabled the computation of tremendous data collected through sensor devices. It involves sensing field data that can be analyzed to make appropriate decisions [2]. Internet of things technology has found many applications in different disciplines such as transportation, smart cities, agriculture, power grid, modern inventory systems, and Healthcare. It has been noted that IoT sensor devices are generating 2.5 Exabyte daily approximately, and millions of the devices are getting connected every day [3]. Therefore, appropriate infrastructure and computing resources are required to store and process the collected data.

Cloud computing technology has enabled the success of processing use amount of data in the cloud having enough computing resources and storage devices to handle IoT collected data. For example, in an agriculture scenario, data collected regarding weather and soil is stored in the cloud for analysis. The computing resources available in the cloud computing environment enabled the timely processing of massive amounts of agriculture data and drawing useful decisions that can help regulate agriculture production and disseminate their analysis reports to end-users. The timely dissemination of analysis reports can help end users or farmers take prepaid actions to prevent their losses [4, 5].

Cloud computing has played a significant role in the development of IoT technology. It quickly adapted IoT-based services to end users based upon pay as you use model [6]. Cloud computing provides unlimited computing and storage resources to the service provider with a minimum human interaction for configuring and installing software and hardware. It provides on-demand access to common computing resources with minimal efforts for their management in allocating or releasing the computing resources [7].

Cloud computing services are offered as services for different resources. These services are provided infrastructure as a service, platform as a service, software as a service, storage as a service and computing as a service [8]. However, cloud users' requirement for cloud services is regularly increasing due to potential benefits of cloud services such as unlimited availability of computing resources storage devices, with the minimum efforts for allocating and provisioning resources. The cloud users pay as you use basis model [9].

With the increase in demand for cloud computing services, there is exponential growth in cloud users and cloud data centres. The growing demand for cloud computing services is fulfilled using the virtualization based concept used in cloud data centres. Therefore, there is increased demand for power for supporting cloud data centres. The power requirements are fulfilled by consuming fossil fuels, leading to an increase in carbon dioxide. The primary factor behind the increase in power consumption includes increased hardware and inefficient resource utilization.

In cloud data centres, virtual machines are created on physical machines to meet the computing needs of cloud user requests [10]. The power requirement of cloud data centres can be optimized by efficient managing of computing resources and virtual machine consolidation [11,

Manuscript received April 5, 2022
Manuscript revised April 20, 2022
https://doi.org/10.22937/IJCSNS.2022.22.4.61

12]. Consolidating virtual machines minimizes active physical machines by accommodating virtual machines on the optimal number of physical machines. It helps to switch off underutilized physical machines by shifting their virtual machines to some other servers, resulting in decreasing their power consumption. The available virtual machine also migrated from over utilized physical machines to free computing resources required for fulfilling cloud user requests. Therefore, virtual machine consolidation is a vital and challenging in the cloud data centre to optimize its power consumption.

Virtual machine selection is an essential and integral task of the virtual machine consolidation process for migrating virtual machines from one over utilized physical machine to another physical machine. An appropriate selection of virtual machines from over utilized physical machines can help in reducing virtual machine migrations while consolidating them. Reducing the number of migrations enables a reduction in power consumption and operational cost while maintaining service level agreement between cloud users and cloud service providers.

The virtual machine migration process comprises four different tasks handling different problems [13]. The first task is to determine over utilized physical machines. The second task identifies underutilized physical machines. The third task handles the problem of selecting appropriate virtual machines from overloaded physical machines to migrate them. The final task is to place the virtual machine to suitable clod server. In case, physical machines are not over utilized or under utilized, then no virtual machine is migrated.

This work focuses on solving the virtual machine selection problem by proposing a energy saving virtual machine selection mechanism. This work primarily focuses on minimizing the power consumption by selecting suitable virtual machines from over utilized machines based upon their CPU and memory utilization and their resource capacity. It also reduces virtual machine migrations while consolidating virtual machines. This work provides an efficient algorithm for the virtual machine selection process and its implementation. It also demonstrates the applicability of the proposed algorithm using real workload traces to reduce virtual machine migrations and power conception by a considerable amount while maintaining service level agreement between cloud users and cloud service provider.

The rest of the article is structured as follows. Section 2 provides recent developments in consolidating virtual machines, specifically for the virtual machine selection task. Section 3 presents the proposed model and the proposed energy saving virtual machine selection mechanism. It describes the virtual machine selection mechanism as an algorithm for better understanding the readers. Section 4 defines the performance metrics most commonly used for measuring the performance of virtual machine selection methods. Section 5 describes the experimental set up and the results for validating the proposed virtual machine selection method. Finally, the paper is concluded in section 6 at the end of the paper.

2. Related work

Many research works have been proposed for achieving the power consumption efficiency of data centres in the cloud computing environment. However, extreme power consumption efficiency can violate service level agreements between cloud service users and providers. Therefore, a trade off should be maintained between service level agreement violations and power consumption [14]. Accordingly, several efforts have been invested in designing green cloud computing architecture [15]. Green cloud computing architecture aims to optimize the power consumption of cloud data centre and minimize carbon dioxide production. These approaches can be broadly divided into two categories, technical solutions and non technical solutions. Non technical solutions focuses on using renewable power sources and other cooling methods to reduce wastage of electricity. In contrast, Technical Solutions focus on virtual machine consolidation, virtualization [16–18], thermal management approaches [19], energy efficient virtual machine scheduling approaches [20] etc.

This paper focuses on virtualization and virtual machine consolidation by proposing a technical solution to select virtual machines from an overloaded physical machine to reduce power consumption and the number of migrations without affecting service level agreement. Virtualization and virtual machine consolidation are considered efficient methods for handling computing resource usage and power consumption problems in the cloud computing environment. Many proposals have been suggested for efficient consolidation of virtual machines, specifically for virtual machine selection.

For example, Jung et al. [21, 22] analyzed the dynamic virtual machine consolidation problem. They used the live migration concept for web applications while maintaining service level agreement based on gradient search and Bin packing methods. Their proposed virtual machine migration method solves the problem of rearranging virtual machines for meeting service level agreements. They proposed using two resource management mechanisms [24], global and local manager. The global managers attempt to gather data from local managers and accordingly take decisions for placing virtual machines. At the same time, the local manager focuses on each physical machine and helps control power consumption cloud data centre.

Cardosa et al. [23] reported an energy efficient virtual machine allocation method by defining three parameters, max, min and shares. The proposed sharing CPUs among different virtual machines based on these three parameters. They demonstrated that their virtual machine consolidation method reduced power usage and improved computing resource utilization in the cloud data centre.

Beloglazov and Buyya [25] introduced a framework for a cloud computing environment for efficient consolidation and migration of the installed virtual machines. The proposed framework has three different phases dedicated to determining physical machines' workload, selecting suitable virtual machines, and placing virtual machines on an appropriate physical machine. During the workload detection phase, the proposed architecture attempts to identify and categorize physical machines into three classes with respect to workload as overloaded physical machines, moderate loaded physical machines, and underutilized physical machines. Virtual machines are selected from over utilized physical machines and migrated to other physical machines based upon the virtual machine placement method. The author proposed four types of virtual machine selection methods: minimum migration time method, minimum utilization method, maximum correlation method, and Random selection method. The authors proposed a dynamic physical machine overutilization detection method and virtual machine selection method considering minimum migration time (MMT) strategy, Random selection (RS) strategy and maximum correlation (MC) strategy for selecting virtual machines in overloaded physical machines. Minimum migration time (MMT) strategy migrates virtual machines having minimum migration time. The migration time is computed as a ratio of virtual machine utilization of memory and network bandwidth. In contrast, the correlation strategy selects the virtual machines having maximum correlation among CPU utilization of virtual machines. Correlation among the virtual machine is calculated using a method proposed by Verma et al. [28].

Some researchers propose to use maximum migration time (MxMT) criteria for selecting virtual machines in a cloud computing environment [44]. Using this approach, they have validated a decrease in power consumption up to 99%. The authors of [43] have suggested using maximum utilization minimum size (MuMs) to select virtual machines with maximum CPU usage and minimum Virtual Machine size. Using this criterion, the authors attempted to minimize over usage risk in the cloud computing environment.

Nadjar et al. [26] suggested energy efficient algorithm for a cloud computing environment. It helps in reducing the number of virtual machine migrations and power consumption. They suggested to select victim virtual machines from over utilized machines with minimum CPU utilization or selecting virtual machines that lead to minimum service level agreement violations for migration. They proposed to estimate under utilized and over utilized physical machines based upon upper and lower threshold values determined using health parameters of physical machines.

Tejha et al. [27] used an evolutionary algorithm, genetic algorithm for virtual machine consolidation process based upon minimum migration time method for selecting virtual machine. They used statistical methods, IQR and LRR, to reduce service level agreement violations and improve service quality in the cloud computing environment.

Fu and Zhou [29] introduced an effective virtual machine selection method in the cloud computing environment. They proposed to select virtual machines from over utilized physical machines that lead to maximum decline due to the difference between overutilized physical machines, CPU utilization, and upper threshold. They provided a comprehensive comparison of their proposed virtual machine selection method with a minimum migration time policy and maximum correlation policy. They used planet data to validate their model based upon the cloudSim simulator in terms of power consumption and service level agreement violations.

Cao and Dong [30] suggested an improved method for selecting virtual machines based upon maximum correlations (MC) strategy [25]. They propose to use the correlation coefficient in place of the squared correlation coefficient. They demonstrated that negatively correlated virtual machines get migrated using scared correlation coefficient. In contrast, they used a correlation coefficient for migrating positively correlated virtual machines. Because positively correlated virtual machine migration can impact workload balancing. They validated their method using planet lab and provided a comparison of minimum migration time policy. The experimental results show a decrease in service level agreement violations.

Zahedi Fard et al. [31] proposed a virtual machine selection method called the maximum fit method. The maximum fit method enables a decrease in the number of migrations in the cloud computing environment. The authors proposed to compute deviation between resource uses of over loaded physical machine and its threshold. They used the binary search method to find suitable virtual machines on physical machines with resource utilization near the deviation. They demonstrated that the hybrid virtual machine selection method performed better than the hybrid method of local aggression and minimum migration time. They used planet lab data to evaluate their proposed approach using a cloudSim simulator. They concluded that minimum migration time based virtual selection methods perform poorly in the cloud computing environment in a highly correlated virtual machine.

Shidik et al. [32] proposed a virtual machine selection method that improves power consumption in cloud data centres. They proposed three virtual machine selection methods using a random selection policy [25] for decreasing virtual machine selection time from overloaded physical machines based upon virtual machine index in the virtual machine list of physical machines.

Wang et al. [33] introduced a method for selecting virtual machines based upon the sorted list of virtual machines in descending order of their CPU utilization. They selected virtual machines with minimum CPU utilization from the top of the list until the physical machine no longer remains overloaded. They validated their approach using cloudsim simulator based upon planet lab data. Comparative results obtained in their experiment demonstrate the superiority of their proposed method over the minimum migration time method for energy consumption of cloud computing data centres.

3. The Proposed System Model

This work applies an extended cloudsim model proposed by Beloglazov et al. [25] for developing energy saving cloud computing environment. The fundamental architecture of Cloudsim possesses different characteristics for implementing energy saving and resource provisioning features of cloud computing proposals. It enables implementing service level agreements and ensures the quality of service to cloud users.

This work assumes that there are fixed number of physical machines equipped with different computing resources such as CPU, memory, and bandwidth. Each physical machine contains the number of virtual machines tagged with different computing resources. The provisioned virtual machines can fulfil the service request of different cloud users as per their requirements.

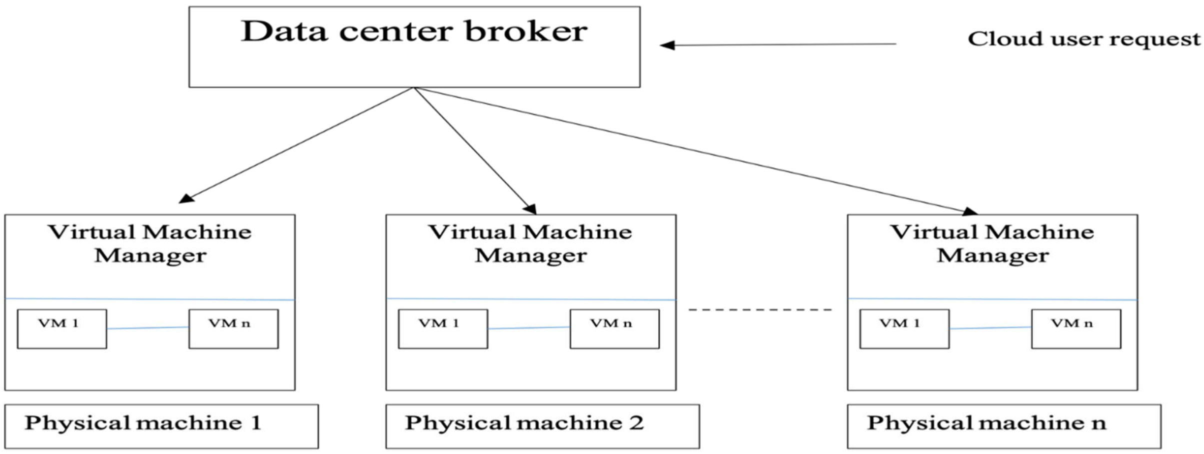

Figure 1: System architecture

The underlying Cloud Computing environment framework in this work is presented in Figure 1.

It contains different components for fulfilling user requests of cloud users by executing them using virtual machines. The vital component includes the data centre broker and virtual machine manager. Data centre broker is responsible for managing user requests of different cloud users and processing and allocating them virtual machines provisioned in physical machines based on their computing resource requirements.

The second component, virtual machine manager, is installed on every physical machine and responsible for monitoring their computing resource utilization and execution status. It determined underutilized and over-utilized physical machines based on their current utilization of computing resources. Upon detecting underutilized and over utilized physical machines, the virtual machine manager triggers a message to the data control broker for any initiating virtual machine migration process to consolidate them.

It also selects virtual machines needing migration from physical machines. The selected virtual machines get migrated from over utilized machines. However, an underutilized physical machine scenario leads to migrating all running virtual machines to other suitable physical machines considering virtual machine requirements for executing respective user tasks.

Therefore, while consolidating virtual machines, selection of virtual machines for migration is an important task in the cloud computing environment. The primary objective of the virtual machine selection process is to minimize the number of migrations and optimize power consumption while fulfilling service level agreements. The selected virtual machines are migrated to other physical Machines by the data centre broker.

3.1 The Proposed power saving virtual machine selection Mechanism

Figure 1 presents an architecture for implementing power saving method for virtual machine selection. The proposed approach selects suitable virtual machines from overloaded physical machines to minimize the number of migration and optimize power consumption while meeting service level agreement. Wrong virtual machine selection can result in virtual machine migrations and can increase power consumption. This work proposes a power saving virtual machine selection mechanism as depicted in the algorithm 1.

CPU utilization of a physical machine is computed using equation 1 at step 1.

$$CPU\_util_j = \frac{w_j + \sum CPU\_util_{vm\_i}}{R\_capacity_j} \quad (1)$$

Where CPU_util is the CPU usage of the jth physical

ALGORITHM 1: THE PROPOSED POWER SAVING VIRTUAL MACHINE SELECTION MECHANISM

```
         Input: PM_list = List of Active physical machine
                VM_list = list of active virtual machine on each physical machine
                Threshold_Up = upper threshold of physical machine utilization
                Threshold_Low = lower threshold of physical machine utilization
         Output: VM_migration_list
Step 1.  Start
Step 2.  Initialize PM_list
Step 3.  Initial VM_list
Step 4.  For p in PM_list do
Step 5.     | CPU-UTILp ← current_utilization of p
Step 6.     | If CPU-UTILp < Threshold_Up
Step 7.     |   | Go to Step 11
Step 8.     | Else
Step 9.     |     Go to Step 29
Step 10.    | End If
Step 11.    | Sorted_VM_list_p ← descending order of utilization of Vm_list on p
Step 12.    | Diff_p ← current_utilization of Sorted_VM_list_p – Threshold_Up
Step 13.    | For vm in Sorted_VM_list_p
Step 14.    |   | RU_vm ← current_utilization of VM - Diff_p
Step 15.    |   | RM_vm ← current_memory_utilization of VM
Step 16.    |   | RU_p + = RU_vm
Step 17.    |   | RM_p + = memory utilization of vm
Step 18.    | End for
Step 19.    | For vm in Sorted_VM_list_p
Step 20.    |     If (RU_vm/RM_vm) > = (RU_p/RM_p)
Step 21.    |   |   X_list.append(vm)
Step 22.    | End for
Step 23.    | If X is empty
Step 24.    |   | VM_migration_list.append(max(RU_vm/RM_vm))
Step 25.    | Else
Step 26.    |   | VM_migration_list.append(max(X_list((RU_vm/RM_vm)))
Step 27.    | End If
Step 28. End for
Step 29.    For vm in VM_list
Step 30.        VM_migration_list.append (vm)
Step 31.    End for
Step 32. End
```

machine. $CPU\_util_{vm\_i}$ is the CPU utilization of all virtual machines on the jth physical machine. $R\_capacity_j$ is the CPU resource capacity of the jth physical machine.

Memory utilization for each physical machine is computed using equation 2 at step 17.

$$Mem\_util_j = \frac{w_j + \sum Mem\_util_{vm\_i}}{R\_capacity_j} \quad (2)$$

Where Mem_util is the memory utilization of the jth physical machine, $Mem\_util_{vm\_i}$ is the memory utilization of all virtual machines on the jth physical machine. $R\_capacity_j$ is the memory resource capacity of the jth physical machine.

4. Metric definitions

Cao and Dong [30] suggested an improved method for selecting virtual machines based upon maximum correlations (MC) strategy [25]. They propose to use the correlation coefficient in place of the squared correlation coefficient. They

demonstrated that negatively correlated virtual machines get migrated using scared correlation coefficient. In contrast, they used a correlation coefficient for migrating positively correlated virtual machines. Because positively correlated virtual machine migration can impact workload balancing. They validated their method using planet lab and provided a comparison of minimum migration time policy. The experimental results show a decrease in service level agreement violations.

4.1 Energy Consumption model

It has been proved that the energy consumption of physical machines in the cloud data centre has a direct Association with CPU utilization [34, 35]. It is found that 70% of the power occurs due to fully utilized physical machines. Therefore, we define power consumption as per equation 3.

$$PC\ (CPU_{util} = PC_{idle} * PC_{max} + (1 - PC_{idle}) * PC_{max} * CPU_{util} \tag{3}$$

Where PC is the power consumption of current CPU utilization CPU_{util} . PC_{idle} is the percentage of power consumption when a physical machine is in an idle state. PC_{max} is the maximum power consumption of a physical machine. For a given physical machine, current CPU utilization CPU_{util} changes with time as per the workload of cloud user requests. Therefore, total energy consumption is computed using equation 4.

$$EU = \int PC\ (CPU_{util}(t)dt \tag{4}$$

4.2 Cost of VM live migration

Live migration of virtual machines in a cloud computing environment enables shifting of virtual machines among physical machines without suspending its execution with short downtime [36]. Live migration of virtual machines negatively affects applications running on virtual machines during the migration process. Many researchers experimentally proved the negative impact during migration of virtual machines and formulated expressions for computing the cost of live migration of virtual machines [37]. Live migration of virtual machines can be a result of service level agreement violation. Therefore, it is necessary to minimize the number of live migrations of virtual machines. Total migration time of the virtual machine is computed using equation 5.

$$MT_i = \frac{Mem_{util_i}}{BW_j} \tag{5}$$

Where, MT_i represents total migration time for ith virtual machine. Mem_{util_i} is total memory utilization, and BW_jj is total bandwidth utilization for ith virtual machine.

The performance degradation due to virtual machine live migration can be computed using equation 6.

$$PD_i = 0.1 * \int CPU_{util}(t)dt$$
(6)

Where PDI represents performance degradation of ith virtual machine over the period of t0 to to+ MT_i.

4.3 Service level agreement violation metric

Multiple cloud users share common computing resources simultaneously by allocating and revoking virtual machines as per their requirements in a cloud computing environment [38]. Their applications are executed simultaneously by sharing a common pool of resources. Service level agreements document the cloud service provider's required quality of service to the cloud users. Quality of service can be computed using throughput or response time [39] as a measurement of service level agreement. Therefore, service level agreement metric is a workload independent metric. It can be determined as a service level agreement violation regarding the percentage of time for the entire CPU utilization over a given period and performance degradation during virtual machine migration. Any service level agreement violation lowers the efficiency of virtual machine migration. Performance degradation due to virtual machine migration can be computed using equation 7.

$$P_{deg} = \left(\frac{1}{VMs}\right) * \sum(\frac{CPU_{mt}}{CPU_{total}}) \tag{7}$$

Where P_{deg} computes the performance degradation while migrating virtual machines. VMs gives total number of virtual machines. CPU_{mt} gives degradation in performance during migration of virtual machines. CPU_{total} is total CPU requirement during lifetime of virtual machine.

Service level agreement violation is computed as percentage of full CPU utilization time as per equation 8.

$$SLA\_PM = \left(\frac{1}{PMs}\right) * \sum(\frac{T_{full}}{T_{active}}) \tag{8}$$

Where PMs denotes physical machine number. T_{full} give cumulative during which physical machine remained 100% utilized. T_{active} give the cumulative time during which the physical machine remained active.

Service level agreement violation can be computed using equation 9.

$$SLAV = SLA_{PM} * P_{deg} \tag{9}$$

4.4 ESLV – A combined metric of service level agreement violations and energy consumption

Power consumption plays a significant role in determining efficiency of virtual machine slection methods. However, it has been observed that power may be reduced considerably by ignoring service level agreement violaions. But, it is not a good option to minimize power consumption. In order to obtain a tradeoff between power consumption and service level agreement violations, a metric has been defined as per equation 10 [25].

$$P_{SLV} = PC * SLAV \tag{10}$$

Where PC represents total power consumption and SLAV shows service level agreement violations.

5. Performance analysis

This section presents setup for validating the proposed approach. It presents the computation of performance metrics for evaluating and comparing the performance of the proposed approach with state of the art in the field. It also highlights experimental reserves and their analysis.

5.1 Experimental setup

The proposed power saving approach for selecting virtual machines in a cloud computing environment is implemented, and many experiments have been conducted. This approach attempts to reduce the power consumption of cloud data centres based upon the current utilization of virtual machines and the computing resource capacity of physical machines. It identifies overloaded physical machines and selects suitable virtual machines to migrate to other machines based on their computing resource utilization.

It is challenging to conduct and repeat experiments in a real-world system to validate virtual machine selection approaches in a cloud computing environment. Therefore, we validated the proposed approach in the cloud Simulation environment, cloudSim. Cloudsim simulator is used for modelling and simulating cloud computing environments [40, 41]. Melbourne University developed it. It can help simulate virtual computing resources and other components of the cloud computing environment such as cloud data centre, physical machines, and virtual machines.

We simulated a cloud data centre consisting of 800 physical machines in this experiment. Out of 800 physical machines, 400 machines are HP ProLiant ML110 G4 servers (Intel Xeon 3040, 2 cores×1 860 MHz, 4 GB) configuration, and the rest are of HP ProLiant ML110 G5 servers (Intel Xeon 3075, 2 cores×2 660 MHz, 4 GB) configuration. There are 500 virtual machines in the simulated cloud data centre of four different categories, Extra Large Instance (2 000 MIPS, 3.75 GB), High-CPU Medium Instance (2 500 MIPS, 0.85 GB), Micro Instance (500 MIPS, 613 MB) and Small Instance (1 000 MIPS, 1.7 GB). Table 1 shows the characteristics of virtual machines created in this set of experiments. Virtual machines are initiated with different computing resources. The allocated resources are changed according to the requirement of workload traces in virtual machines. Dynamic change in computing resources enables dynamic virtual machine consolidation. Experimental results are obtained based upon CPU utilization traces. The CPU utilization traces have been collected through multiple virtual machines working at multiple locations over the globe. We used randomly generated virtual machines and CPU traces over physical machines in the experiments. We fixed a network bandwidth of 1 GBPS.

5.2 Performance metrics

We used four performance metrics, energy consumption, service level agreement violation, number of virtual machine migrations and a combined metric of energy and service level agreement violation in order to measure the performance of the Energy consumption is one significant parameter for measuring the performance of the virtual machine selection method. We computed energy consumption as per Equations 1 and 2. We assumed PCmax maximum power utilization of physical

Table 1. Characteristics of virtual machines

	VM Type			
	Type 1	**Type 2**	**Type 3**	**Type 4**
CPU (MIPS)	500	1000	2000	2500
# Of Cores	1	1	1	1
RAM (MB)	613	1740	1740	870
BW (MB)	100	100	100	100
Storage (MB)	2500	2500	2500	2500

TABLE 2: POWER CONSUMPTION OF HOSTS AT DIFFERENT LOADS

		Host	
		HP ProLiant G5	**HP ProLiant G4**
Power consumption (in Watts) at different load on hosts	0%	93.7	86
	10%	97	89.4
	20%	101	92.6
	30%	105	96
	40%	110	99.5
	50%	116	102
	60%	121	106
	70%	125	108
	80%	129	121
	90%	133	114
	100%	135	117

machine equal to 250 watts under 100% CPU utilization [42] for computing current power utilization of the physical machine. Power utilization of physical machines at different workloads is presented in Table 2.

proposed approach for selecting virtual machines as defined in section 4.

Other performance metrics, such as service level agreement violation, is computed from the service level agreement between cloud user and cloud service provider. The number of virtual machine migrations is computed in real time.

Finally, a energy and service level agreement violation metric is computed using equation 8.

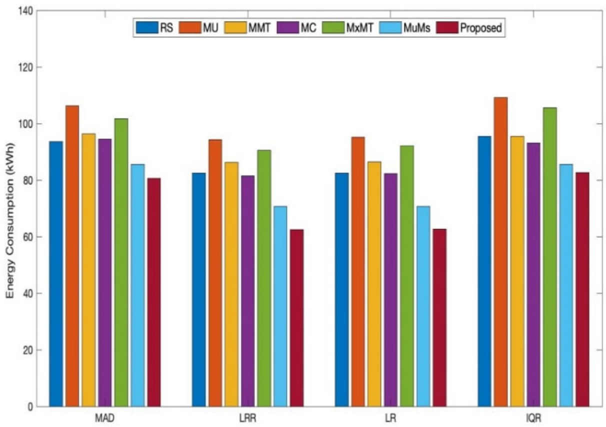

Figure 3. Comparative analysis of power consumption

5.3 Simulation results and analysis

We implemented and executed the proposed approach in the above described experimental setup and state of the art for comprehensive comparative analysis. In this work, we considered random selection (RS) [25], minimum migration time (MMT) [25], maximum correlation (MC) [25], maximum utilization minimum size (MuMs) [43], maximum migration time (MxMT) [44] and minimum utilization (MU) [25]. We computed four metrics for each virtual machine selection method: power consumption, service level agreement violation, number of virtual machine migrations, and a combined metric of power consumption and service level agreement violations. Figure 3 presents the power consumption of the proposed approach in comparison to other methods considered in this work.

It can be observed from Figure 3 that there is not a big change between the power consumption values of random selection (RS) [25], minimum migration time (MMT) [25], and maximum correlation (MC) [25]. The proposed approach demonstrated minimum power consumption, proving its superiority among all other methods. The proposed approach has resulted in a considerable reduction of power by selecting suitable virtual machines from overloaded physical machines. The percentage improvement in power consumption using the proposed approach in different scenarios is provided in Table 3.

It can be noted that our proposed approach resulted in power consumption up to 31% decrease in LRR and LR scenario over random selection method, 52% decrease in LR scenario over minimum utilization method, 37% decrease in LRR and LR scenarios over minimum migration time method, 31% decrease in LR scenario over maximum correlation method, 46% decrease in LR scenario over maximum migration time (MxMT) and 13% decrease in LRR and LR scenarios over maximum utilization minimum size (MuMs) method. It concludes that the proposed approach is suitable for decreasing power consumption by a significant amount over state of the art methods in different scenarios. igure 4 presents the number of

TABKE 3. PERCENTAGE IMPROVEMENT IN POWER CONSUMPTION OF THE PROPOSED APPROACH

Method	*RS*	*MU*	*MMT*	*MC*	*MxMT*	*MuMs*
MAD	*-15.96%*	*-31.71%*	*-19.48%*	*-17.01%*	*-26.08%*	*-6.08%*
LRR	*-31.86%*	*-50.66%*	*-37.89%*	*-30.18%*	*-44.84%*	*-12.95%*
LR	*-31.61%*	*-52%*	*-37.82%*	*-31.31%*	*-46.82%*	*-12.77%*
IQR	*-15.52%*	*-32.04%*	*-15.45%*	*-12.57%*	*-27.69%*	*-3.51%*

virtual machine migrations of F the proposed approach compared to state of the art considered in this work. It can be observed from Figure 4 that there is no considerable difference between the number of virtual machine migrations of random selection (RS) [25], minimum migration time (MMT) [25], and maximum correlation (MC) [25]. The proposed approach demonstrated a minimum number of virtual machine migrations, proving its superiority among all other methods.

This approach resulted in a considerable decrease in the number of virtual machine migrations by selecting suitable virtual machines. The percentage improvement in the number of virtual machine migrations using the proposed approach in different scenarios is provided in Table 4.

It can be observed that the proposed approach resulted in the number of virtual machine migrations up to 500% and 450% decrease in LRR and LR scenarios respectively over random selection method, 700% decrease in LRR and LR scenarios over minimum utilization method, 600% decrease in LRR and LR scenarios over minimum migration time method, 450% decrease in LR scenario over maximum correlation method, 650% decrease in LR scenario over maximum migration time (MxMT) and 150% and 100% decrease in LRR and LR scenarios over maximum utilization minimum size (MuMs) method. It concludes that the proposed approach is suitable for decreasing the number of virtual machine migrations by a significant amount over state of the art methods in different scenarios.

Figure 5 presents the number of service level agreement violations of our proposed approach in comparison to other methods considered in this work.

It can be observed from Figure 5 that there is no considerable difference between service level agreement violations using minimum utilization (MU) [25], maximum correlation (MC) [25], and maximum utilization minimum size (MuMs) [43] methods. Similarly, random selection (RS) [25] and minimum migration time (MMT) [25] demonstrated similar performance in terms of the number of service level agreement violations. The proposed approach has resulted in a considerable decrease in service level agreement violations by selecting suitable virtual machines. The percentage improvement in the number of service level agreement violations using the proposed approach in different scenarios is provided in Table 5.

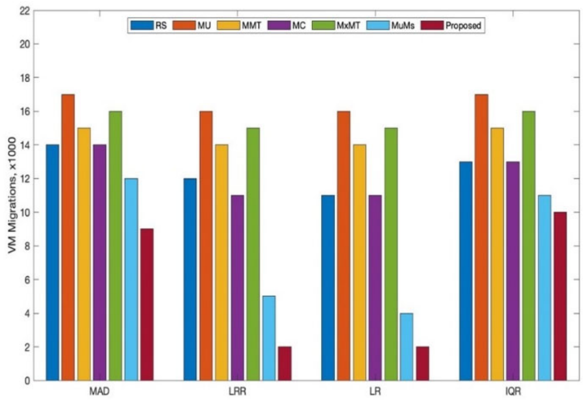

Figure 4. Comparative analysis of the number of virtual machine migrations

TABLE 4. PERCENTAGE IMPROVEMENT IN THE NUMBER OF VIRTUAL MACHINE MIGRATIONS OF THE PROPOSED APPROACH

Method	*RS*	*MU*	*MMT*	*MC*	*MxMT*	*MuMs*
MAD	-55.56%	-88.89%	-66.67%	-55.56%	-77.78%	-33.33%
LRR	-500%	-700%	-600%	-450%	-650%	-150%
LR	-450%	-700%	-600%	-450%	-650%	-100%
IQR	-30%	-70%	-50%	-30%	-60%	-10%

It can be observed that our approach resulted in service level agreement violations up to 75% and 66% decrease in LRR and LR scenarios respectively over random selection method, 93% decrease in LRR and LR scenarios over minimum utilization method, 57% and 78% decrease in LRR and LR scenarios respectively over minimum migration time method, 87% decrease in LRR scenario over maximum correlation method, 54% decrease in LRR scenario over maximum migration time (MxMT) and 21% decrease in LRR and LR scenarios over maximum utilization minimum size (MuMs) method. It concludes that the proposed approach is suitable for decreasing service level agreement violations significantly over state of the art methods in different scenarios.

Figure 6 presents the energy consumption and service level agreement violations metric of the proposed approach compared to state of the art considered in this work.

It can be observed from Figure 6 that there is no considerable difference between combined metric using maximum correlation (MC) [25], minimum migration time (MMT) [25] and maximum migration time (MxMT).

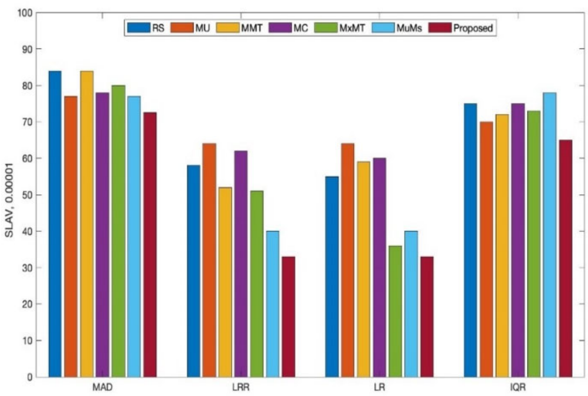

Figure 5. Comparative analysis of the number of service level agreement violations

TABLE 5. PERCENTAGE IMPROVEMENT IN THE NUMBER OF SERVICE LEVEL AGREEMENT VIOLATIONS OF THE PROPOSED APPROACH

Method	RS	MU	MMT	MC	MxMT	MuMs
MAD	-15.86%	18.62%	-15.86%	-7.59%	-10.34%	-6.21%
LRR	-75.76%	-93.94%	-57.58%	-87.88%	-54.55%	-21.21%
LR	-66.67%	-93.94%	-78.79%	-81.82%	-9.09%	-21.21%
IQR	-8.7%	14.49%	-4.35%	-8.7%	-5.8%	-13.04%

The proposed approach has considerably reduced energy consumption and service level agreement violations metric by selecting suitable virtual machines. The percentage improvement in energy consumption and service level agreement violations metric using the proposed approach in different scenarios is provided in Table 6.

It can be observed that the proposed approach has resulted in combined metric up to 65% and 71% decrease in LRR and LR scenarios respectively over random selection method, 111% and 126% decrease in LRR and LR scenarios over minimum utilization method, 47% and 50% decrease in LRR and LR scenarios respectively over minimum migration time method, 52% and 63% decrease in LRR and LR scenarios over maximum correlation method, 75% and 89% decrease in LRR and LR scenarios over maximum migration time (MxMT) and 15% and

19% decrease in LRR and LR scenarios respectively over maximum utilization minimum size (MuMs) method. It concludes that the proposed approach is suitable for decreasing energy consumption and service level agreement violations metric by a significant amount over state of the art methods in different scenarios.

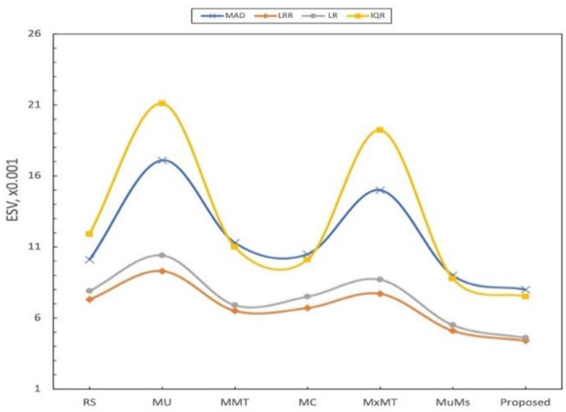

Figure 6. Comparative analysis of energy consumption and service level agreement violations metric

TABLE 6. PERCENTAGE IMPROVEMENT IN ENERGY CONSUMPTION AND SERVICE LEVEL AGREEMENT VIOLATIONS METRIC OF THE PROPOSED APPROACH

Method	RS	MU	MMT	MC	MxMT	MuMs
MAD	-26.38%	-113.75%	-41.25%	-31.25%	-87.5%	-12.5%
LRR	-65.91%	-111.36%	-47.73%	-52.27%	-75%	-15.91%
LR	-71.74%	-126.09%	-50%	-63.04%	-89.13%	-19.57%
IQR	-58.8%	-181.33%	-46.67%	-34.67%	-156.27%	-16.93%

It concludes that our proposed approach is an effective approach to select suitable virtual machines in cloud computing environment that can results in significant improvement over state of art methods regarding power consumption, virtual machine migrations, service level agreement violations and energy consumption and service level agreement violations metric.

6. Conclusion

Significant increase in cloud computing utilization and its number of users has increased the power consumption considerably. An increase in power consumption has increased carbon dioxide. Therefore, there is an urgent need to develop cloud computing methods that can decrease the power consumption of cloud data centres and, hence, carbon footprints.

Virtual machine consolidation in cloud computing effectively reduces power consumption while meeting service level agreements between cloud users and cloud service providers. This work focuses on virtual machine selection, an essential task in virtual machine consolidation that selects appropriate virtual machines from overloaded physical machines and migrates all virtual machines from underutilized machines to reduce power consumption. It proposes a virtual machine selection method based upon the current utilization of virtual machines and the computing resource capacity of physical machines to migrate virtual machines from over utilized machines. The proposed virtual machine selection method is implemented and executed in a simulated environment using cloudsim software. The performance of the proposed approach and state of art is measured in four performance metrics: power consumption, virtual machine migrations, service level agreement violations, and a combined metric of service level agreement violations and energy consumption.

Experimental results show better performance of the proposed approach in terms of the above mentioned performance metrics under different scenarios of the cloud computing environment. The proposed approach has resulted in an overall improvement of 40% in power consumption, 187% in the number of virtual machine migration, 32% in the number of service level agreement violations and 136% in combined metric of energy consumption and service level agreement violations.

The proposed work demonstrated its superiority over state-of-art methods in reducing power consumption to a significant level. This work has been validated in a simulated environment. In the future, we plan to perform more experiments to prove its validity in real world scenarios.

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