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Energy-Aware Virtual Machine Clustering for Consolidation in Multi-tenant IaaS Public Clouds

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ABSTRACT

Cloud computing has gained a lot of interest from both small and big academic and commercial organizations because of its success in delivering service on a pay-as-you-go basis. Moreover, many users (organizations) can share server computing resources, which is made possible by virtualization. However, the amount of energy consumed by cloud data centres is a major concern. One of the major causes of energy wastage is the inefficient utilization of resources. For instance, in IaaS public clouds, users select Virtual Machine (VM) sizes set beforehand by the Cloud Service Providers (CSPs) without the knowledge of the kind of workloads to be executed in the VM. More often, the users overprovision the resources, which go to waste. Additionally, the CSPs do not have control over the types of applications that are executed and thus VM consolidation is performed blindly. There have been efforts to address the problem of energy consumption by efficient resource utilization through VM allocation and migration. However, these techniques lack collection and analysis of active real cloud traces from the IaaS cloud. This paper proposes an architecture for VM consolidation through VM profiling and analysis of VM resource usage and resource usage patterns, and a VM allocation policy. We have implemented our policy on CloudSim Plus cloud simulator and results show that it outperforms Worst Fit, Best Fit and First Fit VM allocation algorithms. Energy consumption is reduced through efficient consolidation that is informed by VM resource consumption.

Keywords : Cloud computing, Virtualization, VM allocation algorithm, Energy efficiency, IaaS cloud.

I. INTRODUCTION

Cloud computing has gained a lot of interest from both small and big academic and commercial organizations because of its success in delivering service on a pay-as-you-go basis. To address this need, CSPs are hosting many servers in public cloud datacenters to provide the levels of computing power that is demanded. Additionally, organizations are putting up private cloud data centres to be able to control their own computing needs [1]. However, the amount of energy consumed by the data centres is a worrying concern. Currently, data centres are responsible for consuming 3% of global electrical energy consumption [2]. Enormous energy consumption has negative effects such as increasing operating costs of CSPs and release of carbon dioxide to the environment [3]. According to a report by [4], power bills dominate the operating costs of a data centre.

The reason for energy wastage in the data centre is inefficient workload consolidation [5] [1]. Moreover, inefficient resource utilization and wastage of idle power cause overall server energy wastage [6] [7]. Inefficient consolidation may be as a result of how VMs are mapped to physical servers. For instance, experiments carried out in [8] have shown that co-scheduling VMs with similar profiles in terms of resource demands is not beneficial from energy consumption and performance point of view. If VMs with similar profiles are co-located, there is increased workload interference. As a result, workload tasks run longer and more energy is consumed.

One of the technologies used in cloud computing is virtualization and is poised to be a solution to the problem of energy consumption [8]. This technology enables efficient utilization of resources because many users can use the same physical server to run their applications with secure isolation. This type of sharing is what is termed as multi-tenancy in the cloud. Load balancing can also be achieved through live VM migration, which guarantees zero downtime during migration.

Cloud services are divided into three models: Infrastructure as a Services (IaaS), Platform as a Service (PaaS) and Software as a Service (SaaS) [9]. SaaS model provides service as a complete functioning software over the internet via the browser. PaaS provides a platform with a set of tools, which businesses can use to develop and deploy applications. IaaS model provides virtual computing resources and the users have to set their environment for them to run any applications they choose. For small organizations, IaaS cloud is the most promising service model and thus it is popular [10], [11]. As such, many international CSPs such as Google, Amazon, HP, IBM, Citrix, Rackspace, Microsoft, DigitalOcean, Linode and Vultr are already providing IaaS service [7]. In the IaaS cloud model, users are allowed to pick VM sizes from CSPs' list of available VM types without the knowledge of the type of applications they will execute in them [8]. Besides, the CSPs do not have control or knowledge of the types of applications users execute in the VMs. From the CSP point of view, applications are a black box host in a VM. Nevertheless, the VMs have to be mapped to physical servers immediately. This is dangerous if VMs meant to have similar profiles are mapped to the same physical server according to the conclusion made in [8]. VMs consolidated this way need to be analyzed via their trace logs after they start operating.

The most common method of gaining knowledge of the application host in a VM is to monitor the VM hosting the application [12]. Gaining this knowledge is important for VM deployment and migration. Deployment needs to consider application resource usage, resource usage patterns and interference with other applications that share tenancy in a server. This is known as VM profiling. Trace logs collected from VMs can be analyzed or characterized using statistical techniques. These techniques include VM clustering using k-means, basic statistics such as mean and correlations [13]. K-means has achieved a lot of success VM clustering for consolidation. For instance, in [14], k-means has been used to group jobs submitted in Google cluster trace for purposes of understanding the relationship between task characteristics and associated resource consumption. Research in the area of VM profiling and trace log analysis is made by use of publicly available workload traces such Google cluster trace (GCT), GWA-T-12 Bitbrain dataset, GWA-T-13 Materna dataset, WorldCup trace 98, Facebook Hadoop workloads, OpenCloud Hadoop, Yahoo cluster traces and Eucalyptus IaaS cluster traces [15] [16] [17]. This because it may be time-consuming to collect such traces from production data centres. The outcome from workload trace analysis and characterization can be used to achieve efficient workload consolidation, which in turn reduce energy consumption while maintaining the required level of performance.

In this paper, we propose an architecture for profiling VMs, which are consolidated without the knowledge of the applications to be hosted from a CSP's perspective. This is common in the IaaS cloud service model. Our architecture collects VM logs and the clusters VMs based on resource usage and resource usage patterns for purposes of re-consolidation. Dissimilar VMs are co-located to reduce interference. By achieving this, tasks run faster and consequently, less energy is consumed, which is the objective of this work.

In order to apply our architecture using real workload traces, we have utilized GWA-T-13 Materna dataset, which contains information about VMs hosted in a data centre that supports business-critical workloads in Germany [16]. This dataset is explained in section III. Further, our approach is evaluated by simulating it using a cloud simulator known as CloudSim Plus [18] , which is a fork of CloudSim [19]. This simulator is written in Java language. CloudSim and CloudSim Plus are almost similar cloud simulator except that CloudSim Plus has been re-engineered to remove code duplication and to ensure code compliance to software engineering standards. Besides, CloudSim Plus has more features than CloudSim and is easier to use. CloudSim Plus components are a *Datacenter*, a *Host*, a *Broker*, a *VM* and a *Cloudlet*. A datacenter represents the core infrastructure, which is hardware and software. It holds hosts, which are computing nodes with a specific set of computing resources (CPU core, memory, hard disk and network bandwidth). With virtualization, a host holds VMs, which are rented by customers to run user applications. A cloudlet in CloudSim Plus is synonymous to user applications, which consume computing resources. A broker is used to submit user applications for processing. CloudSim provides a base or abstract classes, which can be extended and interfaces, which can be implemented to change the way resources are managed in a cloud computing environment. For instance, *VmAllocationPolicy* is an abstract class, one can use to implement own algorithm for deciding on the host that runs a particular VM. In section VI, we have shown the specific items that have been used or modified to implement our algorithm. To this end, the main contributions of this work are:

- We propose an architecture for VM resource usage clustering for the purpose of VM allocation with the aim of reducing energy consumption in a centre.
- We propose an approach of clustering VM trace logs using K-means.
- We provide early insights towards understanding Grid Workload Archive Trace 13 (GWA-T-13) Materna cloud dataset.
- We provide an approach for creating VMs and cloudlets in CloudSim Plus for cloud trace log files.

The rest of the paper is structured as follows. Section II discusses related work. Section III elaborates the workload dataset we have used in this paper. In section IV, we explain the target cloud model for this work as well as our proposed system architecture. In section V, we explain the use of k-means for VM clustering. In section VI and VII, we explain our experimental setup and experiment and evaluation results. Finally, in section VIII, we conclude the paper as our planned future work.

II. RELATED WORK

In recent years, there has been a growth of literature on the techniques used to efficiently manage power usage in data centres [20] [21] [22] [23] [3] [24]. However, most of the approaches do not provide an end-to-end approach VM characterization from gaining access to active VM logs, through analysis to VM consolidation based on this analysis. This is more pronounced in IaaS cloud where applications are run in a black box from a CSP perspective.

In [8], the authors have proposed an architecture for mapping tasks to VMs by classifying tasks based on average CPU, memory and disk usage together with task priority, length and rate of submission. In order to apply the architecture using real workload traces, the authors have used GCT. This approach is used to map tasks to the right sizes of VMs through the analysis of actual resources usage. The authors conclude that by use of their technique achieve 73% improvement in energy consumption compared to when VM sizes are estimated by users. The cloud service model targeted for this work is Container as a Service (CaaS).

An analysis in [25] shows that clustering is a necessary analysis tool used to gain behavioural knowledge of VMs and cloud users for prediction purpose. This is because it is difficult to predict each type of resource separately for two reason - VMs have different resources, which makes it difficult to create a prediction technique and different cloud users may request different amounts of a similar resource. So, it makes sense to cluster VMs and then create prediction models for clusters. Thus, the authors have proposed the use of k-means for this purpose.

In [26], the authors have used k-means to group cloudlets (task to be mapped to a VM) using instruction size, execution deadline and cost paid by the customer as a clustering feature set. The Euclidean distance is computed using the three clustering feature set. As such, the priority of an incoming cloudlet is determined by the three parameters. Authors have reported that when their technique is compared to base techniques (existing work), there is an improvement in power consumption, total turnaround time, wait time, processing time and processing cost. Moreover, the work in [27] has reported an improvement in performance while using a similar approach.

In [20], the authors presents a technique for consolidation where jobs to be processed are classified based on their resource usage. Thus, any incoming job's resource usage can be determined based on the group to which it belongs. Moreover, it is easy to map an incoming job to the right VM size because its resource consumption is already known. In addition, this clustering ensures that VMs running similar jobs are not placed in similar physical servers. The objective of this work is to better utilize the involved physical server resource, which minimizes energy consumption. Although the authors have not disclosed the algorithm used to cluster the jobs, clustering has been done anyway.

In [28], the authors propose an algorithm based on dynamic programming that takes advantage of scheduling dissimilar workloads in the same server. This approach is meant to reduce server energy consumption by consolidating workload in fewer servers. The authors observe that co-locating highly correlated workloads lead to VM migrations, which decreases performance. Lowly correlated workload ensures that severs are well parked and idle power well utilized. The approach used in this work is creating copies of VMs in different physical servers and then distributing the incoming requests to these VMs. This reduces the chance of running a similar workload in the same server. The most applicable cloud service model for this approach is SaaS.

Finally, the work in [1] presents an analytical model for predicting the level of interference and impact on the performance of co-located VMs. With this approach, workloads are mapped to a VM, which will lead to low interference with co-tenant VMs. The authors have used micro benchmark applications to generate workloads – *sysbench* for CPU intensive workloads and *fio* for disk-intensive workloads [29]. Although the author does not mention how energy consumption is reduced, the work in [30] has shown that the increase in interference among co-residence VM decreases energy efficiency.

III. GRID WORKLOAD ARCHIVE TRACE 13 (GWA-T-13) MATERNA

The main goal of the Grid Workload Archive (GWA) is to provide a platform where researchers and practitioners can share grid workloads [16]. Any person wishing to share their grid workload can do so as long as they are in a database format (SQLite) or text format (CSV). GWA has collected around 13 workloads shown on their website, Materna being the latest. Materna consists of three traces from a distributed datacenter, namely Materna-trace-1, Materna-trace-2 and Materna-trace-3 with 520 VMs, 527 VMs and 547 VMs respectively. Materna provides service to different organizations featuring different business lines such as government, digital enterprises, IT factory and SAP business consultancy. Materna trace is obtained from a VMware ESX environment. The data's format is csv with the following information (columns) about a VM.

- *Timestamp* – this is the epoch timestamp in milliseconds.
- *CPU cores* – this is the number of vCPUs provisioned to the VM.
- *CPU capacity* – this is the vCPU capacity in MHZ. It is given as the product of number of cores and the speed per core.
- *CPU usage (MHZ)* – CPU capacity that is actually used by workloads in MHZ.
- *CPU usage (%)* - CPU capacity that is actually used by workloads in percentage (%).
- *Memory provisioned* - this is the memory capacity for the VM in KB.
- *Memory usage* (KB) – this is the actively used memory in KB.
- *Memory usage (%)* – this is the actively used memory in percentage (%).
- *Disk write performance* – this is the disk throughput in KB/s
- *Disk size* – this is the size of the HDD in GB
- *Network throughput (received)* - this is the network performance in terms of KB/s
- *Network throughput (transmitted)* - this is the network performance in terms of KB/s

The VMs running in the 3 traces are mostly the same. The traces were collected for a period of 3 months and each of the 3 traces contains information representing one month. For this reason, we choose to work with the first trace. The trace would have een merged but this will be inaccurate because the different number of VMs in the 3 traces makes it difficult to identify the same VM in the three traces.

IV. CLOUD MODEL AND SYSTEM ARCHITECTURE

In this section, we explain the cloud service model chosen and the system components of our proposed solution.

A. Cloud Model

In this work, the proposed cloud model is large scale public IaaS owned by an organization, that provides services to individuals and small organizations. In this model, users choose VM size then sends a request for their creation as shown in **Fig 1**. The requested VM is then created by the Virtual Machine Monitor

(VMM), and placed in a physical server. User applications run on their specific VM and not any other. The user has control of the VM and can configure and execute any type of application. From the CSP point of view, applications are a black box host in a VM. However, in public clouds, users do not have access to VMM, only the CSPs do [31]. To understand the resource usage of the application running in the cloud, the CSPs has to profile VMs. We assume that the CSP has in place an effective method of monitoring VM resource usage. The dataset we have chosen to use shows the resources actively used by the VM, which makes it sufficient for this work [16].

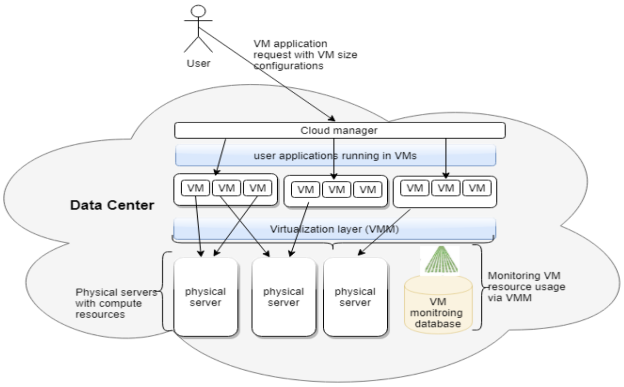

User
VM application request with VM size configurations
Cloud manager
user applications running in VMs
Data Center
VM
VM
VM
VM
VM
VM
VM
VM
VM
Virtualization layer (VMM)
Physical servers with compute resources
physical server
physical server
physical server
VM monitroing database
Monitoring VM resource usage via VMM

Figure 1: *Overview of Cloud Model*

B. *System Architecture*

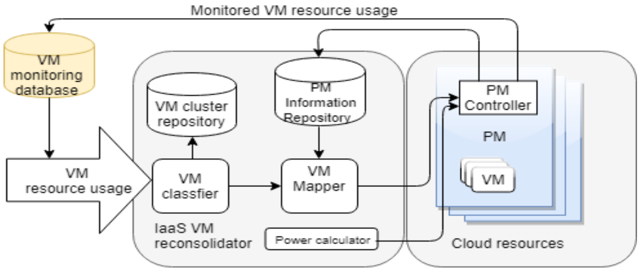


Figure 2: *Proposed Architecture*

Our proposed architecture is shown in **Fig 2** and its components are explained in this section. The first part is called *IaaS VM reconsolidator* because the process of consolidating a VM starts again after A VM has been profiled.

1) *VM Classifier:* this component is used to classify VMs based on their historical resource usage. It is trained using historical data harvested from VMs. It receives VM resource usage from the VM monitoring database and then classifies it based on CPU usage, memory usage and disk usage. The complete process of clustering is discussed in Section V. After a VM has been classified, the classification results are stored in a *VM cluster repository* and forwarded to the VM mapper.

2) *VM Mapper:* this component receives classification results from the VM classifier and determines the new host for the classified VM. This is our modified form of VM allocation policy, which we refer to as *First Fit Increasing Similarity (FFIS).* From the host list, we find all hosts, we call them candidate hosts (*candidateHostList*), which have enough resources to accommodate the classified VM. The candidate hosts are then sorted in order of increasing similarity of VMs in running hosts with classified VM. Similarity Index, *I*, of a host machine with classified VM is computed as shown in Equation 1. The first host in the sorted candidate host becomes the new host. The complete operation of VM mapper is shown in Algorithm 1.

$$I_i = \frac{k_i}{n_i} \ (1)$$

where k is the number of VMs in the i^{th} host machine that shares a group with classified VM and n is the total number of VMs in the i^{th} host machine.

Algorithm 1: VM Mapper Operation

```
Input: hostList, classfiedVm, VmClass, oldHost
Output: newHost, classfiedVm, migrationVerdict
for host in hostList do
    if host has enough resources to accommodate classfiedVm then
        candidateHostList.add(host)
    end if
end for
candidateHostList.sort(VmClass, candidateHostList)
newHost equal to candidateHostList.get(0)
migrationVerdict equals to 'do nothing'
if newHost is not same as oldHost then
    migrationVerdict equals 'migrate'
end if
return newHost, classfiedVm, migrationVerdict
```

3) *PM Controller:* this component runs in the Physical Machine (PM). It periodically checks resource utilization in the PM caused by VM utilization and **sends** it to the PM information repository. Since the IaaS CSP cannot install monitors in the rented VM, the PM controller also monitors resource usage of the VMs via virtualization layer and stores it in the *VM monitoring database*.

4) *PM Information Repository:* this component stores **information** regarding data centre hosts. For instance, it is the source of host list input in **Algorithm 1**.

5) *Power calculator:* this is a simple component that estimates the power consumed by all active hosts at any given time t during the execution of the application. Total power is given by a model shown in **Equation 2**.

$$P_{total} = \sum_{i=1}^{k}((P_i' - P_i) * \left(\frac{n_i}{100}\right) + P_i \quad (2)$$

where k is the number of active hosts at time t, P_{max} is the maximum power consumption of the host, P_{idle} is the power consumed host when completely idle and n is the percentage CPU utilization of the host. We specifically focus on the power consumption by the CPU because of it the only server component that shows the highest variance as regards to its utilization. Energy, E, can be calculated as shown in **Equation 3.**

$$E = PT \quad (3)$$

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

V. VIRTUAL MACHINE CLUSTERING USING K-MEANS

In order to group the pool of VMs (520 in number in Materna-Trace-3) k-means clustering algorithm has been used. The basic k-means algorithm is shown in **Algorithm 2**. Closeness is computed using Euclidian distance as shown in **Equation 4**. As our clustering feature set, we have used the following features for each VM:

1) *VM CPU usage*: the average CPU actually used by the VM for the entire profiling period
2) *VM memory usage*: the average memory actually used by the VM for the entire profiling period

Algorithm 2: **Basic k-means algorithm**

Input: *Historical VM resource usage (CPU and Memory), Number of the cluster, K*

Output: *Centers of cluster*

```
1: Select $K$ points as initial centroids
2: repeat
   3:From $K$ clusters by assigning each to its closest centroid
   4: Recalculate centroids for each cluster
5: until Centroids do not change
```

$$d = \sqrt{(CPU_1 - CPU_2)^2 + (RAM_1 - RAM_2)^2} \quad (4)$$

We have considered VM CPU and memory usage in this case because their shortages during a short period impact QoS negatively.

VI. EXPERIMENT SET UP

In this section, we explain how we have conducted our experiments. We have explained VM clustering and evaluation procedures

A. VM clustering

The dataset used in this paper is Grid Workload Archive Trace 13 (GWA-T-13) Materna as described in (see Section 3 of this paper). There are a total of 520 VMs in trace 1. Each VM has data collected for a period of 1 month at 5 minutes interval. Our choice of clustering of the feature set is explained in Section V and the k-means algorithm has been used to group the VMs. We have used Scikit-learn [32], a python machine learning open source library, which includes k-means clustering. The input to the k-means algorithm, *k*, is determined using the elbow method. We have computed the average CPU and memory usage for all the 520 VM and used it to group the VMs. Each VM has collected over 8300 resource usage pints.

B. Evaluation procedure

We have evaluated our technique on Cloudsim Plus [18] cloud simulator with a datacenter configuration shown in **Table 1**. The datacenter, hosts, VMs and cloudlets configurations are based on workload traces described in section 3.

TABLE 1. CLOUDSIM PLUS DATACENTER CONFIGURATIONS USED FOR EVALUATION

No. of hosts	49
No. of VMs	520
No. of CPUs	69 (454 cores)
Memory size (in GB)	6780
Hypervisor	VMware ESX
No. of cores allocated per VM	Varying (1,2,4,6 and 8)
Memory size allocated per host (in GB)	Varying (2,4,8 and 16)
Host static power	60 % of host peak power

In our evaluation, we have compared our technique (FFIS) with the default VM selection algorithms retained in CloudSim Plus from CloudSim [33]. For instance, we have compared our modified VM placement technique with well-known First Fit (FF), Worst Fit (WF) and Best Fit (BF) VM placement algorithms [24]. FF algorithm searches through the running machines to host a VM in the first host that can provide the resources demanded by a VM.

If no suitable host if found, a new one is activated. BF picks a PM with the least residual resources while WF picks a PM with the most residual resources. Our evaluation follows the IaaS cloud multi-tenant cloud model, which we have explained in section IV. For this reason, each application runs in a specific VM. To ensure correctness, all the algorithms are tested on a similar data centre with similar configurations such as power monitoring intervals, same power model, same VM scheduling intervals. Additionally, all algorithms do not attempt any optimization using VM migration. Our performance metrics are total power consumption and execution time. A summary of our evaluation process is shown in **Fig 3**.

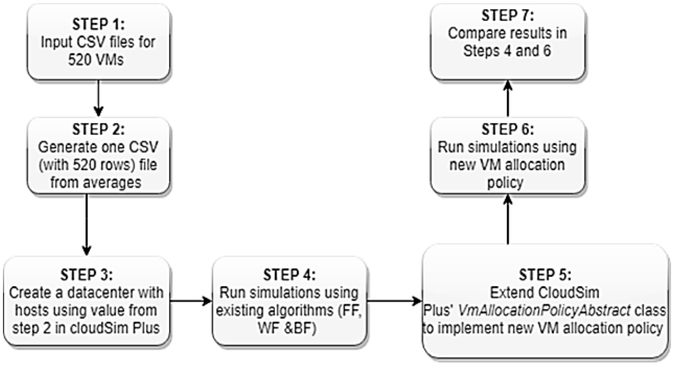

STEP 1:
Input CSV files for 520 VMs
STEP 2:
Generate one CSV (with 520 rows) file from averages
STEP 3:
Create a datacenter with hosts using value from step 2 in cloudSim Plus
STEP 4:
Run simulations using existing algorithms (FF, WF &BF)
STEP 5:
Extend CloudSim Plus' VmAllocationPolicyAbstract class to implement new VM allocation policy
STEP 6:
Run simulations using new VM allocation policy
STEP 7:
Compare results in Steps 4 and 6

Figure 3: Process of evaluation

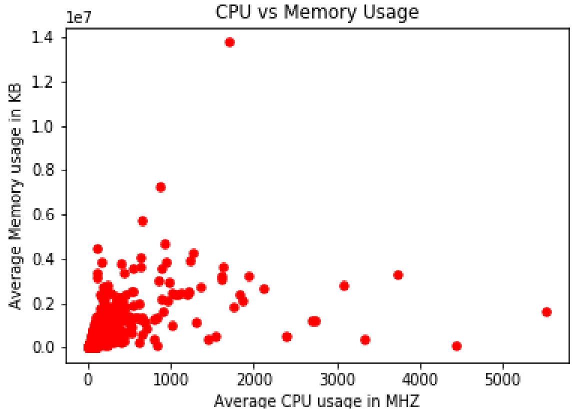
VII. EXPERIMENT RESULTS

A. VM clustering results

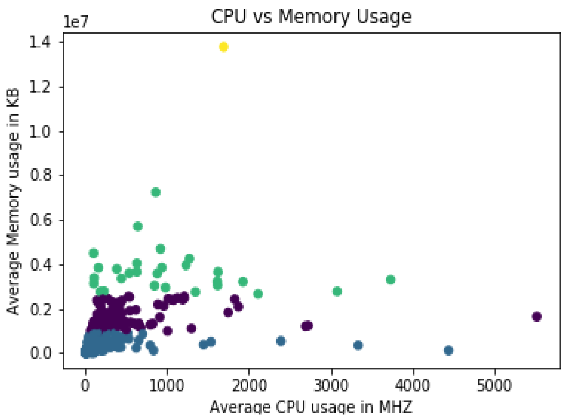
In this section, we go through the results of the k-means clustering of VMs. The elbow method used to determine *k* as an input to k-means has revealed that the optimal value for *k* is 4. The population of VMs in each cluster is summarized in **Table 2**. **Fig 4 (a)** and **(b)** shows scatter plots before and after k-means clustering. From Table 2 or Figure 4 (b), it can be observed that Large VM has only one member and is considered an outliers. Next, we describe the four resultant VM groups.

TABLE 2. POPULATION OF VMS IN EACH RESULTING CLUSTER

Cluster VM type	**Number of VMs**	**% population of each VM type**
Extra small VMs	394	75.77 %
Small VMs	96	18.46 %
Medium VMs	29	5.58 %
Large VM	1	0.19 %
Total	**520**	**100**



a) Scatter plot before clustering



b) Scatter plot after clustering

Figure 4: *Appearance of a scatter plot before and after k-means clustering. Notice the yellow point VM, which we have treated as an outlier.*

1) *Extra small VMs:* this group has a population for 394 VMs out of a total of 520 VMs, which represents 75.77%. Most of the VMs in this group have generally used a very small amount of both memory and CPU except some, around 3, whose CPU demand was high.
2) *Small VMs*: this group has a population of 96 VMs of a total of 520 VMs, which represents 18.46 %. The amount of memory used by these VMs is low but is greater than that of extra small VMs. Generally, the amount of CPU used in this group seems to have not changed significantly when compared with the extra small VMs group.
3) *Medium VMs:* this group has a population for 29 VMs out of a total of 520 VMs, which represents 5.58 %. The amount of memory used by VMs in the group is higher than VMs in extra small and small VMs group. Similarly, the amount of CPU used in this group seems to have not changed significantly.
4) *Large VM:* this group has only 1 VM out of a total of 520 VMs, which represents 0.19 %. We have considered as an outlier because of its position as compared to the other groups. This VM has a high memory consumption with a moderate CPU consumption.

From our observation, we can conclude that memory usage was very important in putting the VMs in their respective groups. Moreover, CPU usage was generally low. Next, we describe the evaluation results.

B. Evaluation results

The results of our evaluation are shown in Figure 5 and 6. The figures show the total amount of energy consumed by all the 46 hosts and the total time of execution respectively when executing dataset workload using different algorithms.

We have compared our new VM allocation algorithm, FFSI with WF, BF and FF. The first noticeable thing is that FFSI consumes the least amount of energy, 18767 joules, compared to the other algorithms. BF consumes the highest among of energy, 22673 joules. FFSI is efficient because it places a VM in a host with least similar VMs in terms of resource demands, which, reduces the interference caused by resource contention, thus making good use of idle power of all the involved computing resources. It is also observed that WF beats FF and BF in terms of energy usage. This is because WF chooses a host with the most residual resources, hence it does not lead to more aggressive utilization and may end using not more than the host's idle power. VMs using WF allocation policy have plenty of resources and it is the reason why it uses the least time for processing as shown in **Fig 6**. Although the total execution time of FFIS is not any better than the other algorithm, the fact that it consumes the least energy shows that its power usage is low over time as compared to the other algorithm. None of these algorithms have attempted to improve performance by use of my migration. Therefore, it is possible that that FFIS' execution time can be reduced by optimizing its execution through VM migration.

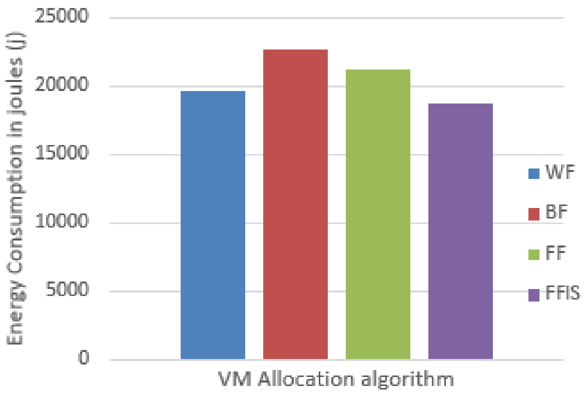


Figure 5: *Total amount of energy consumed by all the 46 hosts for different VM allocation algorithm*

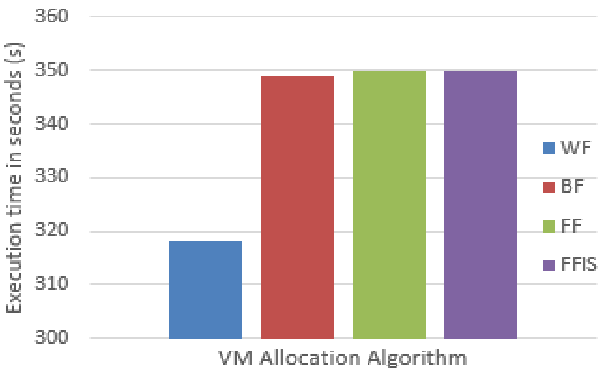


Figure 6: *Total execution time for different VM allocation algorithm*

VIII. CONCLUSION

In this paper we have presented a new VM allocation policy, FFIS that can be used in multi-tenant public cloud. FFIS is motivated by the fact that it is detrimental to schedule VMs running similar workloads in the same server. We have used k-means clustering to identify dissimilar VMs. Our policy has been applied on real cloud workloads and we have implemented and evaluated our policy on CloudSim Plus, which is a highly extensive cloud simulator. We have compared our policy with WF, BF and FF and results show that our policy outperforms them all in energy consumption without a significant increase in execution time. We conclude that there is a big potential for energy savings when scheduling VMs based on their resource consumption. As future work, we plan to apply our VM allocation policy to a wide range of real cloud workloads and to consider other VM resources such as disk usage and network. We also plan to enhance our algorithm through VM migration.

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