Reallocation of Virtual Machines to Cloud Data Centers to Reduce Service Level Agreement Violation and Energy Consumption Using the FMT Method

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Abstract
Due to the increased use of cloud computing services, cloud data centers are in search of solutions in order to better provide the services demanded by their users. Virtual machine consolidation is an appropriate solution to the trade-off between power consumption and service level agreement violation. The present study aimed to identify low, medium, and high load identification techniques, as well as the energy consumption and SLAv to minimize. In addition to the reduced costs of cloud providers, these techniques enhance the quality of the services demanded by the users. To this end, reallocation of resources to physical hosts was performed at the medium load level using a centralized method to classify the physical hosts. In addition, quartile was applied in each medium to reduce the energy consumption parameters and violation level. The three introduced SMT - NMT and FMT methods for reallocation of resources were tested and the best results were compared with previous methods.The proposed method was evaluated using the Cloudsim software with real Planet Lab data and five times run, the simulation results confirmed the efficiency of the proposed algorithm, which tradeoff between decreased the energy consumption and service level of agreement violation (SLAv) properly.

Keywords: Cloud Computing, Energy Consumption, Service Level Agreement Violation, Virtual Machine Consolidation

1- Introduction

Use of cloud computing is on a rising trend, and cloud providers in cloud data centers constantly attempt to reduce energy consumption, while maintaining an acceptable service level agreement (SLA). Cloud services are offered to users with a wide variety (e.g., Iass-Pass-Sass), and each provided service could offer various services depending on the needs of the cloud providers and users [1, 17]. Due to the growing demand for cloud platforms by numerous users across different networks, the main challenge faced by cloud providers is to provide services that are in proportion to the needs of the users, while also delivering the desired level of services and minimizing the power consumption to save costs through effective measures such as keeping the servers cool and reducing the levels of environmental pollutants [1, 15].
Cloud providers use proper solutions to maximize the capacity of their servers, which in turn reduces the number of the active servers and minimizes the power consumption in these centers. On the other hand, shutting down several servers causes the number of active servers to become overloaded, which increases the probability of a service level agreement violation (SLAV) and ultimately discourages users. For this, cloud providers apply techniques such as virtual machine (VM) consolidation, which simultaneously strives to maintain a proper level of energy consumption and reduce agreement violations. Furthermore, the VM consolidation processes that use both heuristics and meta-heuristic algorithms employ multi-objective functions due to the NP-hard model of cloud computing. Such problems are aimed at finding the optimal solution from among the available solutions, and

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the application of the algorithm may vary depending on the type of the problem [8, 21].
VM consolidation, a balance must trade of between energy consumption and service level agreement by identifying high-load, low-load, and medium-load physical hosts in order to minimize the mentioned parameters.
The present study aimed to minimize the violation of user-demand service contracts by proposing a dynamic algorithm and decrease energy consumption, so that the proper physical host could be determined to reallocate resources based on the usage for minimal changes in the high-load and low-load of the physical host in the future. The consumed power in each cloud data center for each physical host was considered based on the amount of CPU usage in the physical host. Although other parameters are also important in this regard (e.g., main memory usage and network bandwidth), the most consumed power in a physical host is the CPU utilization rate due to the maximum CPU power utilization [8,20,21] , while other parameters (e.g., main memory and network bandwidth) consume small amounts of energy. As a result, high-load and low-load hosts could be distinguished, thereby moving (migration) VMs from the high-load physical host to the appropriate (low-load) host. Due to the migration of these VMs, the intended physical host exits the high-load state, reducing the possibility of agreement violation. However, the energy consumption is likely to increase due to the higher number of the VMs migrating to appropriate physical hosts (low-load).
The proposed method by introducing three policies to resource reallocation for this goal, we used physical hosts and by IQR Method (1) classification. In quartiles then find median of each quartile by median method to find best policies to resource reallocation. It discusses in section 3.
The proposed algorithm attempts to identify the medium-sized hosts that reduce their energy consumption through their reallocation and minimization of the service level agreement violation and to implement and compare the proposed algorithm with other algorithms, we will compare each algorithm during the five stages of program execution, testing, and results, which we will explain in details in Section 4.

2- Literature Review

Allocation of VMs to proper physical hosts in the cloud environment is a substantial challenge to decrease the power consumption and agreement violations (SLAV). Extensive research has been focused on the calculation and reduction of energy consumption, the most important of which is VM consolidation. One of the primary aims of VM consolidation is to find the proper solution for multi-purpose, predefined allocation [1]. In this regard, the algorithms of VM consolidation have been presented based on the approach of reducing energy consumption using heuristic and meta-heuristic methods [2].
The main methods that have been proposed for the further reduction of energy consumption and service level agreement in the cloud based on VM consolidation are implemented in several steps, including the detection of high-load hosts, selection of the proper VM for migration from high-load hosts or migrating all VMs from low-load physical hosts, and reallocation to other physical hosts [1, 3].
In [4], a new VM consolidation algorithm has been proposed based on the VM resource usage history. According to the obtained results, the service quality and energy consumption could be improved through the balancing of the energy consumption and service quality. This method consists of two steps, including the detection algorithm of the low-load physical host, which prioritizes the expansion of the number of the VMs on each host to select the optimal solution and turn off the low-load host to reduce the total system energy consumption, and identification of the high-load hosts to prevent agreement violations. The high-load host is unable to respond to VMs, which necessitates the migration process. For one thing, the energy consumption is kept down in an attempt to decrease the service level agreement [1, 3, 4] as it could increase the number of the migrants, as well as the energy consumption.
In [5], the minimum migration time (MMT) method was employed to migrate VMs from physical hosts and minimize service level agreement by reducing the number of the migrations, and the energy consumption observed a descending trend. In the same study, the number of the migrants had to be minimized in order to establish the efficiency and energy. In the migration process, the migration points are determined, and the hosts with lower efficiency are suspended through the migration of the VM hosts. If a host is over the threshold productivity, it is checked before the migration of its VM [3]. This method has also proposed as a load prediction algorithm to decide whether to induce the migration of a VM and determine which host is to be allocated depending on its workload in the future. According to the findings of the mentioned research, the number of the migrations and amount of consumed energy decreased due to the quality of the service.
The interquartile range (IQR) method [1] is used to identify THE high-load hosts that are above the threshold, assuming a threshold of 25% and minimum of 75% for the CPU utilization. Moreover, the median absolute deviation (MAD) method [1, 12] uses the median absolute deviation. In [7], four classes of VMs were considered based on the amount of the used CPU resources by classifying various physical hosts into different categories, with each category selected to reallocate resources, and only one category was

evaluated. Use of categorical selection and selection of low-load physical hosts for the reallocation of resources [4, 6] often increased the probability of physical hosts to become high-load again.

The single threshold (ST) method uses a single threshold [7], and only the high threshold is used to find the high-load hosts and reallocate the resources to the low-load machines only. On the other hand, multi-threshold methods [3, 8, 9] yield better outcomes in terms of compromising power consumption and agreement violation, while they also increase the rate of high-load physical host in the future. In addition, the middle method uses multiple thresholds to calculate the median of the physical hosts, attempting to determine the proper place for the allocation of the VM [3]. The compromise between two or more parameters (e.g., power consumption, agreement violations, and number of migrations) with direct correlations to service quality could be classified as an NP-hard problem in VM consolidation [1, 11]. Resource allocation is an inherent element in VM consolidation [8, 11].

In [10], GDR and MCP algorithms have been used based on the stable regression model in order to identify high-load hosts, as well as the dynamic BW policy for the selection of the VMs from the productive host to migrate. Although this method could significantly reduce energy consumption, it is still highly likely that the hosts reap the benefits in the future. Due to the use of a linear regression method as a more efficient technique than other methods [1, 10, 13], attempts have been made to predict the amount of the consumed energy by the physical hosts. The mentioned study provided a live migration program by examining the simulation results, while using the MAE algorithm by presenting five methods based on robust SLR [13] high-load and low-load hosts, virtual machine selection for migration, and resource reallocation.

In [13], MAE (10)-SLAV was selected as the optimal outcome based on the simulation results. After the examination and comparison of the introduced algorithms, it was observed that the algorithms that have been introduced so far provide no significant success in the identification of the average hosts that achieve desirable levels of energy consumption by resources reallocation and reduction of agreement violations. Therefore, we attempted to identify the medium-load hosts with the most significant impact on the energy consumption and agreement violation, as well as resource reallocation to the hosts after migration.

3- Methodology

In the present study, the appropriate algorithm was proposed based on the following steps:

1) Identification of the overloaded hosts;
2) Identification of the intermediate (medium) load hosts;
3) Identification of the low-load hosts;
4) Calculation of the probability of high-load/low-load hosts for resource reallocation to the medium-load hosts;
5) Selection of the proper VM from the high-load host to migrate to the medium-load host in accordance with the mentioned parameters (i.e., reduction of power consumption and agreement violation)

After selecting the proper VM to migrate from the high-load host to the medium-load host, the entire VM migrated from the low-load host to the medium-load host in order to turn off the low-load physical host. The manner of resource reallocation to the medium-load physical host with the potential of becoming high-load/low-load hosts may change in the future. In other words, if the medium-load host is reallocated in the future or the probability of being reallocated based on the current reallocation is high, the medium-load host will be reallocated again. In the following section, the proposed algorithm using IQR method (1) to classification physical host into Quartile, as shown in figure 1. Then using the median method (12) to calculating the median of each quartile, as shown in figure 2.

For physical hosts we need processed energy and SLAv that is discussed in section 3.1 and 3.2. In section 3.3 identification (Low-Medium-High) Load physical hosts and present three policies to resource re-allocation. We compare each policy to find the best classification to resource re-allocation.

3-1- Energy Consumption Model

The energy consumption model depends on various parameters, including CPU utilization, main memory utilization, and network bandwidth consumption. Since the maximum power consumption is based on CPU utilization [1, 3, 13], decreasing the number of the active processors (i.e., physical hosts) leads to the reduction of the total energy consumption of the system and proper distribution of the workload to different hosts based on the CPU utilization required to reduce energy consumption. Considering the high CPU utilization rate as energy consumption, the energy consumption model is interpreted based on the CPU utilization rate [1, 13], as follows:

$$P\,(u) = k\,pmax + (1-k)pmax\,.U \qquad (1)$$

In the equation above, p_{max} is the maximum consumed power when the physical machine is fully operational, K represents a fraction of the consumed power by an idle physical machine, and u shows the processor efficiency, which may change over time due to workload variability. As such, CPU efficiency is a function of time expressed as u(t), while the total energy consumption of the physical host is defined as the integral of the energy consumption function over time.

$$E = \int_{t=0}^{t=i} P(u(t))dt \tag{2}$$

Based on the proposed method and Equations 1 and 2, the consumption of the physical hosts and then their energy consumption could be calculated individually and as the sum of cloud energy consumed at a given moment, as follows:

$$\mathrm{E} = Tt\sum_{i=0}^{n} \mathrm{E} \tag{3}$$

In the equation above, n is the total number of the applied physical hosts, Ei represents the energy consumed by the host i to time t, and E shows the sum of the total cloud energy at time t.

3-2- Criteria of the Service Level Agreement Violation

Since service quality characteristics may vary in different applications, a specific criterion has been defined to evaluate SLA. SLAV violation encompasses several factors, most notably the repeated allocation of VMs to the physical host [18, 20]. For this reason, we examined this factor directly.

In other words, service quality is met if the physical host responds to the resources required by the VM for various applications in the required time. In the present study, two main criteria were considered based on [3] in order to measure the SLAV. These criteria are as follows:

1) Percentage of time; when physical machines are active and experience 100% efficiency, it is referred to as the time when each host or SLA threshold approach (SLATHA) violates the service quality.

(2, 19) Reduced overall performance with a large number of VM migrations; the reduction in performance-based migration is referred to as PDM. SLATHA is mainly used because if a physical host experiences 100% efficiency with its programs, the performance of the programs is limited by the capacity of the physical host. Therefore, VMs with the required level of service quality are not satisfied.

$$SLATAH = \frac{1}{N}\sum_{i=1}^{\mathrm{n}} \frac{\mathrm{Tsi}}{\mathrm{Taj}} \tag{4}$$

$$PDM = \frac{1}{M}\sum_{j=1}^{m} \frac{Cdj}{Crj} \tag{5}$$

In the equation above, N is the number of the physical hosts, Tsi shows the total time that incurs while ith (physical host) has 100% efficiency and is subjected to the agreement violation, Tai is the total time of ith active physical host, M estimates the number of the VMs, Cdj shows the violation of the ith VM that has been created by migration, and Crj is the total processor capacity required by the VMj for the entire duration of the same VM.

Since the SLATAH and PDM criteria independently and significantly determine the level of SLAV [1, 10, 13, 19], a composite criterion encompassing the performance violations regarding the high-load physical host was considered for the migration of the VMs. In this paper, a combined criterion for SLAV was used, as follows:

$$SLAV = SLATAH\,.PDM \tag{6}$$

3-3- Identification of the High-load and Low-load Hosts

In the current research, a threshold was used to detect the high-load and low-load hosts and also identify the medium-load hosts. The proposed idea was to find and reallocate the medium-load hosts to reduce the probability of other high-load and load-load hosts, while decreasing the energy consumption. To this end, the IQR algorithm was employed. Initially, the IQR threshold was calculated in order to detect the high-load or low-load physical hosts.

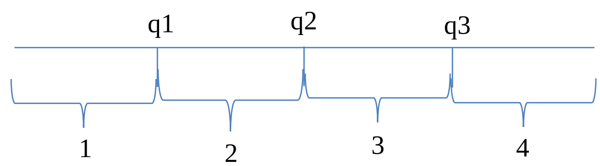

Fig 1. Classification of Hosts Based on Threshold

As is depicted in Figure 1, the IQR threshold was used to divide the total number of the physical hosts into four groups after ascending sorting, while the three considered categories were also investigated.

Table 1. Introduction of Each Category Based on Workload of Each Host

Category	Workload of Each Host
< q1	low-load
q1 <=> q2	medium-load
q2 <=> q3	high-load

In [13], the CPU utilizes the q1-q3 bandwidth set as the low threshold to reallocate resources and use linear regression for its allocation. In this method, four categories are determined using the IQR threshold, and the median method is applied to calculate the median within the range of q1-q2 or the second category (Figure 1) and q2-q3. The following steps are taken for the calculations in the median method:

A. The physical hosts are arranged in an ascending order of workload (CPU usage).
B. If the number of the physical hosts is odd, the middle of the set is selected, and if the number is even, two middle hosts are found, and the average value is considered as the median.
C. In each step, a and c are obtained as the two sets that are repeated for each a and c set until all the physical hosts are in one set.

The name of each member of the physical host sets was determined, and we attempted to find the optimal destination for resource reallocation by calculating the median IQR threshold.

$$\text{If } \frac{Ai}{2} = 2x \ (x \in 1,2,3,4,5,\dots,\infty) \quad \begin{cases} Ti = median(xi) \\ Tu = median(xj) \end{cases} \tag{7}$$

$$\text{If } \frac{Ai}{2} = 2x+1 \ (x \in 1,2,3,4,5,\dots,\infty) \quad \begin{cases} Ti = median(yi) \\ Tu = median(yj) \end{cases} \tag{8}$$

Finally, the high-load and low-load hosts were determined by establishing the following conditions:

$$if \ CAi > Tu \ (Ai = Oh) \tag{9}$$

$$if \ CAi > Ti \ (Ai = Uh) \tag{10}$$

The method applied in [3] could only be effective in the detection of high-load and low-load hosts and resource reallocation to lower-load machines in an attempt to distribute the workload and reduce SLAV. However, this reallocation will increase the number of the migrants and energy consumption, as well as the probability of high-load or low-load hosts in the near future. Therefore, we applied the IQR algorithm to provide four sets using the quartile and median for the detection of high-load and low-load hosts and identify the medium-load hosts.

3-4- Implementation Process of the Proposed Algorithm

As is depicted in Figure 2, the energy consumption list shows the same amount of energy consumption per physical host and is arranged in an ascending order. At the next stage, the IQR threshold algorithm was used to sort the entire list into four main categories.

According to the information in Table 1, the hosts that were smaller than q1 were defined as the low-load hosts, and the hosts that were larger than q1 and smaller than q3, as well as those larger than q3, were defined as the high-load hosts. In addition, the median method was used in this regard to calculate the medians of q1-q2 and q2-q3, which were defined as m1 and m2, respectively, with m considered as the median between the two intervals. Moreover, Ci was considered as the physical host. Table 2 shows the classification scheme of the proposed method.

[Arranged hosts in ascending order]

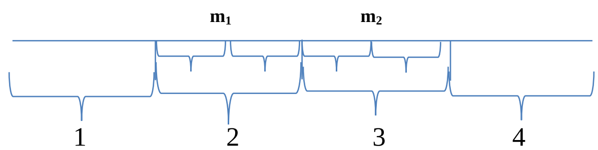

Fig 2. Quartile Sorting by Calculating Median of Two Intermediate

as well as those larger than q3, were defined as the high-load hosts. In addition, the median method was used in this regard to calculate the medians of q1-q2 and q2-q3, which were defined as m1 and m2, respectively, with m considered as the median between the two intervals. Moreover, Ci was considered as the physical host. Table 2 shows the classification scheme of the proposed method.

Table 2. Introduction of Each Category Based on Workload of Each Host in Proposed Method

Category	Workload of Each Host
ci < q1	low-load
q1 < ci < q3	medium-load
q3 < ci	high-load

After using the proposed method to calculate the median of the second and third quartile (m1 and m2), the low- and medium-load hosts were defined, as follows:

- Policy 1: First Median Threshold (FMT)

Table 3. Medium-load Host between First Median and q2

ci < q1	low-load
m1 < ci < q2	medium-load
q3 < ci	high-load

- Policy 2: None-median Threshold (NMT)

Table 4. Medium-load Host between q2 and q3

ci < q1	low-load
q2 < ci < q3	medium-load
q3 < ci	high-load

- Policy 3: Second Median Threshold (SMT) and (median q1)

Table 5. Medium-load Host between Second Median and q1 (SMT)

c_i < q1	low-load
q1 < c_i < m_2	medium-load
q3 < c_i	high-load

In the present study, three policies were considered as the possible solutions for the categorization and selection of the high-load and low-load hosts, while attempting to find the medium-load hosts as well. By reallocating resources, we were able to turn off more low-load hosts or transform the high-load hosts to medium-load hosts. Furthermore, the SLAV could be lowered to achieve better energy consumption and minimize the probability of the future hosts to become high-load and low-load through the accurate identification of the resources. All the proposed policies were used to reallocate resources to the physical hosts. Considering the optimal SLAV level and energy consumption and by reducing the probability of the filling of the physical hosts in the future, we attempted to select the optimal policy for the response to the resource reallocation

Figure 3 shows the sequence and process of implementing the. The first step involved the selection and classification of the FMT, NMT, and SMT policies between the medium-load hosts for resource reallocation.

4- Simulation and Evaluation of the Result

To simulate and evaluate the proposed method, all the introduced policies in the previous section were implemented using a simulator (CloudSim) [7, 16]. The measurable parameters included the total energy consumption of the system, agreement violation, and number of the shutdown machines, which were determined based on the low- and medium-load host identification models. The energy consumption levels have been discussed in Section 3.1 and are the metrics used in the implementation of the proposed method.

At this stage, the main objective of the research was to reduce the total energy consumption of the system.

The agreement violation rates have been described in Section 3.2 in terms of calculation (SLATAH and PDM). Since agreement violation is directly correlated with customer satisfaction rates [6, 10], cloud providers are more likely to attempt the provision of favorable levels of user demand and reduction of the SLAV; even in the cases where the energy consumption increases, customer satisfaction must be prioritized.

We review and compare three proposed host modes (low load - medium load - high load) and using median method to select suitable physical hosts from medium area and reallocate virtual machines to that hosts and the comparison algorithms are presented, considering the use of fixed datasets, each algorithm is run five times for each dataset and finally its average is compared with the other methods.

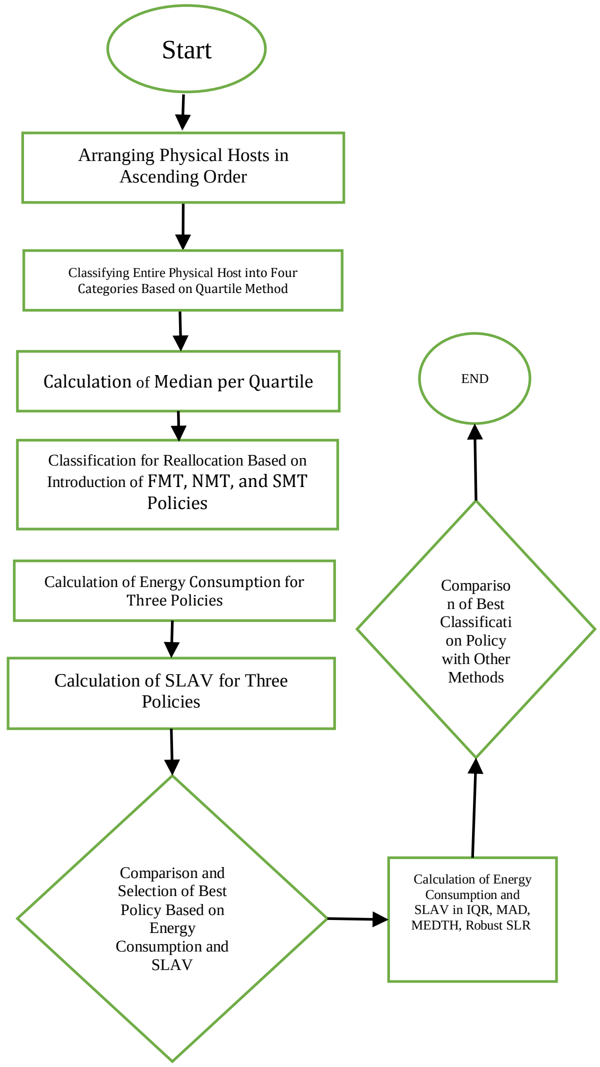

Fig 3. Flowchart of the proposed method.

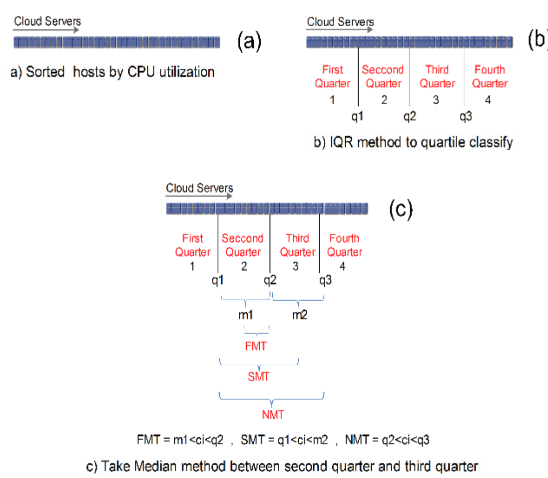

Fig 4. Show implementation of the proposed algorithm

4-1-Tested Dataset

All the introduced policies were used to implement the proposed method on the tested dataset shown in Table 6. The dataset contained actual data, and the results were simulated based on these data. The data were categorized by the number of the VMs, which were derived from the exact results of the experiments. Table 6 shows the data collected in the actual environment based on the number of the physical hosts and virtual hosts tested on specified dates [14].

4-2- Evaluation Criteria

By implementing the proposed method for all the policies and its comparison with the previous methods, as well as the IQR and MAD in similar conditions, the actual data in Table 6 were used. These data were a collection of more than thousands of VMs and physical hosts on various dates in the form of Planet Lab data in the CoMon project [14], which had been obtained on thousands of servers in 500 regions within five minutes. The rates of energy consumption and service level agreement were compared using the proposed method, and the compared criteria were as follows:

1) Calculation of the energy consumption based on the correlations (2, 15);
2) Calculation of the contract breach (6);
3) Calculation of the total agreement violation in the simulation based on the following equation (n=number of VMs) (11, 18, 19);

$$\text{Overal SLAV} = \frac{\sum_{k=1}^{n}(requsted\ MIPS) - \sum_{k=1}^{n}(allocated\ MIPS)}{\sum_{k=1}^{n}(requsted\ MIPS)} \quad (11)$$

4) Number of THE shutdown hosts using the following equation:

$$\text{Host Shutdowns (H)} = \frac{1}{n}\sum_{i=1}^{n} h(i) \quad (12)$$

(h(i): number of the active hosts at the time i, H: number of the shutdown hosts at time 1-n)

Table 6. Test Dataset

Row	Name of data	number of the VMs	number of the physical hosts
1	3 march 2011	1052	800
2	22 march 2011	1516	800
3	20 april 2011	1033	800

Table 7 shows the three proposed policies for the new location of resource reallocation based on the target dataset for the energy consumption and service level agreement in each of the three datasets. By examining the simulation results of the policies, the FMT policy was considered to be the optimal policy for the reallocation the VMs. Considering that this policy accommodates a smaller range of medium-load physical hosts compared to The other proposed policies, the simulation results indicated that the selection of this policy to reallocate resources in terms of energy consumption and service level agreement violation could be further reduced by the other policies.

Table 7. Percentages of Performance Criteria for Policies 1-3

Policy review	Contract breach	Energy consumption(w)	Data	Row
Policy 1 (FMT)	0.1%	155.32	3 march 2011	1
Policy 2 (NMT)	0.106%	169.28	3 march 2011	2
Policy3 (SMT)	0.102%	162.65	3 march 2011	3
Policy 1 (FMT)	0.117%	178.52	22 march 2011	4
Policy 2 (NMT)	0.120%	184.36	22 march 2011	5
Policy 3 (SMT)	0.119%	179.12	22 march 2011	6
Policy 1 (FMT)	0.114%	130.21	20 april 2011	7
Policy 2 (NMT)	0.119%	137.59	20 april 2011	8
Policy 3 (SMT)	0.117%	133.23	20 april 2011	9

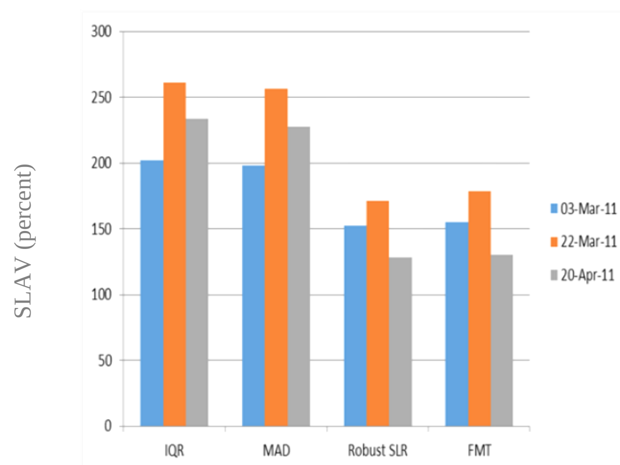

Fig 5. Percent SLA Violation Scenario 1-3

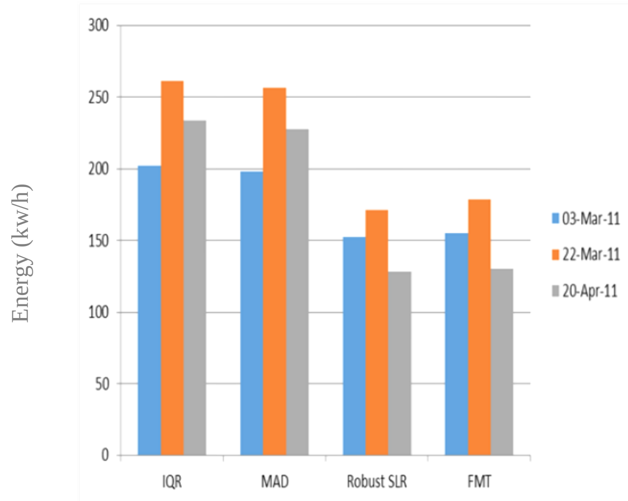

Fig 6. Power Consumption Scenario 1-3

According to the information in Table 7, the number of the VMs per data was compared between the policies in terms of energy consumption and agreement violations, while the response of the previous methods, IQR threshold, MAD threshold [12], median MEDTH method [3], and the robust SLR linear regression method were also compared [13]. Considering the implementation of the introduced policies and proposed method and the measured energy consumption (Figure 6), as well as the rate of agreement violation (Figure 5), Policy 1 (FMT) clearly yielded better results in terms of resource reallocation Furthermore, the increased the number of the shutdown physical hosts reulted in the reduced energy consumption of the entire system. Therefore, policy 1 (FMT) was selected and compared with the other algorithms based on this policy.

After selecting the FMT categorization policy, which enhanced the energy consumption and agreement violation rates, the mentioned policy and previous methods were compared based on the simulation results (Table 9). Accordingly, the proposed FMT classification policy achieved better results using the median method and quartile method in the reduction of both these parameters.

For each algorithms in table 8 and table 9, we used dataset as shown in table 6. However, the results for each algorithm in table 8 and table 9 run for five times and it's average compare together.

Table 8. Comparison of Energy Consumption

Energy Consumption	Dataset	The policy of finding the threshold of low loads
201.92	3 march 2011	IQR [1]
261.37	22 march 2011	IQR
233.64	20 april 2011	IQR
198.16	3 march 2011	MAD [12]
256.18	22 march 2011	MAD
227.67	20 april 2011	MAD
152.66	3 march 2011	Robust SLR [13] MAE (10)-MME 2.5)
171.28	22 march 2011	Robust SLR MAE (10)-MMeE2.5)
128.52	20 april 2011	Robust SLR MAE (10)-MME 2.5)
155.32	3 march 2011	FMT
178.52	22 march 2011	FMT
130.21	20 april 2011	FMT

Table 9. Comparison of Service Level Agreement

contract breach	Dataset	The policy of finding the threshold of low loads	Row
0.350%	3 march 2011	IQR [1]	1
0.295%	22 march 2011	IQR	2
0.329%	20 april 2011	IQR	3
0.366%	3 march 2011	MAD [12]	4
0.318%	22 march 2011	MAD	5
0.351%	20 april 2011	MAD	6
0.123%	3 march 2011	MEDTH [7]	7
0.1195%	22 march 2011	MEDTH	8
0.122%	20 april 2011	MEDTH	9
0.118%	3 march 2011	Robust SLR [13] MAE (10)-MME 2.5-SLAV)	10
0.122%	22 march 2011	Robust SLR MAE (10)-MMeE2.5-SLAV)	11
0.121%	20 april 2011	Robust SLR MAE (10)-MME 2.5-SLAV)	12
0.100%	3 march 2011	FMT	13
0.117%	22 march 2011	FMT	14
0.114%	20 april 2011	FMT	15

As is depicted in Figure 7, the proposed FMT method yielded better results in terms of the reduction of the energy consumption and agreement violations rates compared to other methods based on
The tested datasets; Figure 8 also shows the further variations in this regard. A slight reduction was observed in the FMT with the robust SLR method in terms of energy consumption (same amount of energy consumption), which would significantly reduce the agreement violation rate as well.

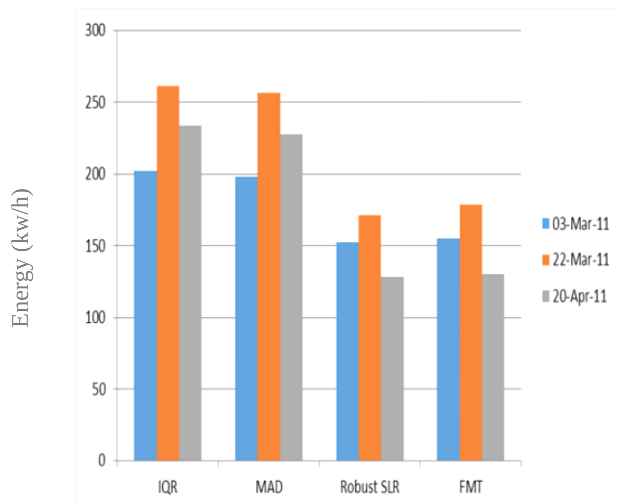

Fig 7. Comparison the energy consumption of the proposed algorithm with other methods

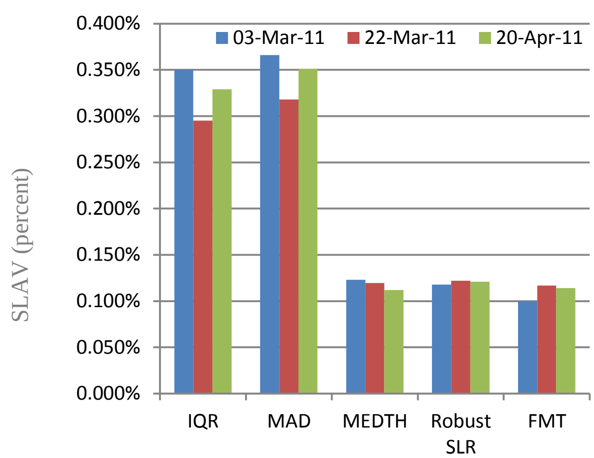

Fig 8. Comparison of contract SLA Violation percentage of proposed algorithm with other methods

5- Conclusions

In the current research, the median and quartile methods were utilized to propose a novel method for the detection of low-, medium-, and high-load hosts and resource reallocation to the medium-load hosts while keeping the energy consumption low and violating the user contract, maintaining it at the lowest level. To this end, three policies were considered based on the detection of the high-load, low-load, and medium-load hosts, and resources were reallocated to the host exhibiting the least consumption over the agreement violation.
According to the findings, the first policy (FMT) was the most viable option for resource reallocation considering the threshold and simulation results in Figures 1 and 4. As is depicted in Figures 6 and 7, the results of the adopted policy yielded better results compared to the other policies although the energy Consumption of the FMT policy was approximately equivalent to the robust SLR policy; with slight variations in the energy consumption, the policy showed a significant reduction in the SLAv. Also, due to the shortage of resource reallocation intervals, this method causes overhead for physical hosts. The proposed algorithm could be used in the future in order to measure the number of migrations, consumed bandwidths, and shutdown hosts, as well as the total execution time and improve them.

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