Webology (ISSN: 1735-188X)
Volume 18, Number 6, 2021

Regression Using Logistic Method For Physical Machine Overload Finding And Host Power Method For Physical Machine Under Load Finding Algorithm In Cloud Datacenter

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Abstract:

Cloud computing is becoming increasingly prevalent in today's generation. In addition, the number of users who use cloud resources is growing by the day. The number of active host machines in a datacenter consumes a lot of energy to execute user requests. As a result, a significant amount of carbon dioxide is emitted into the atmosphere. To reduce carbon emissions, energy-efficient algorithms and approaches are necessary. The logistic regression for Host machine Overload detection and Host Power for Host machine Underload detection are discussed in this paper. The main goal is to increase physical machine utilization while lowering energy consumption by efficiently recognizing overloaded or underloaded host machines to avoid performance degradation and energy waste. Cloud Sim Toolkit is used to test this technique. The efficiency of an algorithm is measured using factors such as EC, SLAV, PDM, ESV, VM migration, and SLATAH.

Keywords: Energy Consumed by physical machine (EC), Service Level Agreement Violation (SLAV), performance deprivation because of migration (PDM), Energy Service Level Agreement Violation (ESV), migration of Virtual Machine and Service Level Agreement Violation Time per active host (SLATAH).

I. INTRODUCTION

Because of the network benefit, cloud users can manage and utilize information without having to establish any physical machine resource infrastructure. Cloud customers can access their data from any geographical place without worrying about maintenance or security issues. The main benefit of cloud computing is that it allows multiple users to share cloud resources via virtualization. Virtualization maximizes the resource utilization of physical machine.

[2] It is necessary to go over all of the areas where the host machine's power consumption and Quality of Service (QoS) are affecting each other, and to restructure everything in order to save energy on the host machine. One such point is Host Machine Overload and Underload Detection. Virtualization is the technology that powers the cloud, so when it comes to running apps or providing services to clients, VMs will start to work, and running VMs on host computers consumes a lot of power. When the VM load on the host system grows to the point that it exceeds the host machine's capacity, the host machine begins to consume a large amount of power.To decrease the load on the host machine, VM is essential to migrate to the other active host machine. Similarly when the number of VM’s and its load is less in host machine below the average capacity. Then the host machine is underloaded and there is wastage of energy to run entire host machine capacity. To avoid the wastage of energy all the VM’s are migrated to another active host machine which has the capacity to run the VM’s. As our aim is to lesser the energy consumed of physical machine and lesser the carbon footprints to the environment, it is require to balance the tasks and predict the upcoming load for the VM placement on a host machine. Best use of processors will leave less carbon footprint and consumes less power and release less heat.Processors that are used to their full potential will have a lower carbon footprint, require less electricity, and emit less heat.

This work proposes logistic regression for detecting Host machine Overload and HostPower for detecting Host machine Underload. The main goal is to increase physical machine utilization while lowering energy consumption by efficiently recognizing overloaded or underloaded host machines in order to avoid performance degradation and power waste.

The remaining paper will be written as follows: The second section discusses the research's related work. The workings of Logistic Regression for the Host Machine Overload detection algorithm are discussed in Section III. The workings of Host Power for the Host Machine underload detection method are discussed in Section IV. The simulation setup, performance measurements, outcomes, and analysis are all explained in Section V. This research comes to a close in Section VI.

II. RELATED WORK

In today's world, datacenters are expanding on a global scale, and resource management issues are becoming more prevalent in order to meet consumer demands. As a result, datacenters require a significant quantity of electricity. One of the primary challenges is reducing energy usage, maximizing resource efficiency, and preserving the quality of service supplied to cloud users.

To boost VM consolidation, the author [1] used hybrid factors. For physical machine overload detection, they developed a multiple regression technique that incorporates physical machine CPU utilization, physical machine memory use, and physical machine bandwidth consumption. The Multiple regression physical machine overload detection algorithm reduces server machine power consumption while maintaining a high level of SLA commitment. Instead of a single component, physical machine CPU utilization, it gives an actual sign of physical machine usage based on three elements (physical machine CPU, physical machine Memory, and physical machine Bandwidth).

The author [2] presented Mode Absolute Deviation for VM consolidation by recognizing Over Utilized hosts machines and reducing the number of migrations by applying pattern matching. It looks at future CPU consumption data to detect the CPU usage pattern and determines the dynamic thresholds for VM migration. The mode absolute deviation technique was able to reduce the number of migrations while saving energy.

The author [3] proposed a new approach called the percentage of overload time fraction threshold (POTFT), which determines whether a Virtual Machine should migrate if the current overload time period fraction result of the host machine exceeds a well-defined percentage of permitted maximum overload time period fraction value, in order to avoid exceeding the permitted maximum resultant overload time period fraction value later in a Virtual Machine migration decision or during Virtual Machine migration. The POTFT technique is used in conjunction with Virtual Machine to increase the time between Virtual Machine migrations and achieve the QoS target.

The author [4] proposed a mark ov prediction model to predict the host machine's future work load condition. It tries to predict the next overloaded / underloaded hosts machine state in order to avoid VM migration on the instant. The suggested VM placement method determines the set of host machines that will receive the migrated VMs in the near future, hence reducing the number of VM migrations.

The author [5] developed a physical machine overloading/underloading detection approach as well as a unique Virtual machine placement algorithm built from a robust simple linear regression prediction model for SLA-aware and power-efficient virtual machine consolidation in cloud data centers. By adding the inaccuracy to the estimation, it amends the estimation and squints toward overestimation. For the actual work task load, the results demonstrate that it reduces Service Level Agreement violation rates by 99.16 percent at most and power consumption by 25.43 percent at most.

The author [6] introduced a better way for scheduling, sharing, and moving Virtual Machines for a basket of cloud jobs that is designed and built to reduce power consumption while maintaining a high throughput of the system. The strategy is based on a better first-fit reducing algorithm combined with a Virtual Machine recycling approach. As a result, there is a higher resource utilization rate and fewer power consumption.

For physical machine overload detection, the author [7] suggested a novel method for generating long-term estimations of VM resource requests. A probability distribution model of the estimate error is created to account for the improbability of long-term estimates. A decision theoretic strategy is proposed to make live migration judgments that take into account overheads based on the probability distribution of the estimate error. By accounting for the ambiguity of long-term estimates as well as the overhead in live migration, the technique achieves increased performance and stability.

The author [8] proposed a logistic regression model and median absolute derivation-based universal server overloading detection algorithm. Cloud service providers are primarily concerned with answering two key concerns that have a significant impact on their infrastructure utilization and usage. If we need to relocate the VMs, we must first pick where to transfer them and then where to place them. Migration of VMs as part of the Virtual Machine Consolidation approach will aid in protecting the host machine from being overwhelmed or reducing the number of active host machines for better resource usage and power savings. Effectively detecting server machine overload will aid in fine-tuning system performance in the cloud and lowering total operational costs, allowing the cloud provider to compete in the market. The technique reduced datacenter power usage as well as Service Level Agreement (SLA) violations.

III. LOGISTIC REGRESSION HOST OVERLOAD DETECTION ALGORITHM

A. Logistic Regression using Sigmoid:

The classification algorithm logistic regression is used to assign statements to a distinct set of classes. Unlike linear regression, which delivers sequential numerical results, logistic regression turns its results to a probability outcome that may then be plotted to two or more separate groups using the logistic sigmoid method.

B. Sigmoid function:

In machine learning, the Sigmoid Function is used as a triggering method. To introduce non-linearity to a machine learning model, the sigmoid approach is utilized. In simple terms, it chooses which numbers to pass as a result and which numbers to reject. The sigmoid method is used to plot predicted numbers to probabilities. The method converts any real number into a number between 0 and 1. It's used in machine learning to plot estimates to probabilities.

Equation (1)

$$S(z)=1/1+e^{-z}$$

s(z) = result among 0 and 1 (probability prediction)
z = input to the method (algorithm’s estimation e.g. mx + b)
e = base of natural log

C. Logistic Regression Host Overload Detection Algorithm:

The Host machine overload detection problem is solved using a Logistic Regression Algorithm in this subsection. The data center is home to a number of physical machines. The number of Virtual Machines running on each real machine contributes to the work load. If the work load exceeds the host machine's capability, the host machine's performance worsens, resulting in a SLA violation. The host machine overload detection technique locates and reports the overloaded physical machine. A few Virtual Machines are selected from the overloaded physical machine and relocated in another active host system with sufficient capacity to run the VM.

The resources(CPU, RAM, and BW) of each VM are taken into account when developing an algorithm. To run a virtual machine, a host machine must provide the resources necessary by the virtual machine, which include the CPU, memory, storage, and network bandwidth of the host machine. There isn't a straightforward formula for calculating physical machine use. In this research, we employ a measure that captures the joint CPU-Memory-Network job load of the VM and host machine to compute physical machine utilization based on several parameters using the formula designed in [18]. As shown in equation(1), the capacity of a host system or virtual machine is well-defined as the result of its CPU, memory, and network task loads.

$$Volnode = W1/\ (1\text{-}CPU) * W2/\ (1 - Memory) * W3/\ (1 - Net) \quad (1)$$

Where
Wi: the weight of (CPU, memory and network load),
Cpu: the server machine utilization of CPU,
Memory: the server machine utilization of memory,
Net: the server machine utilization of network port.

In this research, we offer a Logistic regression host machine overload detection approach that uses many measures to improve Virtual Machine consolidation. Alogrithm1 contains the pseudo code for the Logistic regression host machine overload detection technique.

Algorithm1. Logistic regression host machine overload detection algorithm
Input: CPU utilization of VM’s, Ram utilization of VM’s, BW utilization of VM’s
Output: a decision on whether the host is overloaded so VM is migrated

1- Foreach host in host list do
2- CPU utilization→calculate CPU Utilization(host)
3- Memory utilization→calculate Memory Utilization(host)
4- Network utilization→calculate Network Utilization(host)
5- Y → W1/(1 – CPU) * W2/(1 – Memory) * W3/ (1 – net)
6- X → Multidimensional Matrix {CPU, RAM, BW}
7- Calculate the predicted Utilization using Logistic Regression(Y, X)
8- If predicted Utilization< 1 then
9- Repeat step2 to step8
10- End
11- End
12- Return predicted Utilization>= 1 and host is overloaded

To begin, each host machine's CPU, RAM, and BW utilization are calculated. Two measures are used as input to the Logistic regression algorithm:

• The first input is a two-dimensional array termed X, with rows equal to the amount of the information and columns equal to the number of independent components, which in this approach are three (VM's CPU consumption, VM's RAM consumption, and VM's BW use).

• The second input is a one-dimensional array named Y that comprises a sample of server consumption data computed using equation (1)

The Logistic regression approach is used to compute the predicted utilization. The technique starts with the assumption that if predicted utilization is more than or equal to 1, the server machine is overloaded. The next Virtual Machine to be transferred from the overloaded host will be chosen by VM placement.

IV. HOST POWER FOR HOST MACHINE UNDERLOAD DETECTION ALGORITHM

In this part, a host power is used as a solution to the problem of host machine underload detection. The data center is home to a number of physical machines. The number of virtual machines running on each physical machine contributes to the work load. If the work load is low and the host machine's capacity is not fully utilized, the host machine's energy usage is wasted. The host machine underload detection technique locates and reports the underloaded host machine. All of the VMs on the underloaded host machine are picked and moved to another active host machine that has the ability to host them.

The power consumption of the physical equipment is taken into account when developing an algorithm. We propose Host Power to detect an underloaded host machine in this study. Algorithm2 contains the pseudo code for the Host Power for Host machine underload detection technique.

Algorithm2. Host power for Host underload detection algorithm
Input: host power
Output: a decision on whether the host is underload so VM is migrated.

1- Min power→double. MAX
2- Foreach host in host list do
3- Power→host Power ()
4- If power > 0 && power <Min power
5- Min power = power
6- Host underload = host
7- End
8- End
9- Return host is underloaded.

To begin, each host machine's host power is calculated. The underloaded host computer is then chosen as the one that consumes the least amount of power. All of the VMs on the underloaded host machine are chosen by VM placement and placed on another active host system that has the capacity to host them.

V. TESTING ENVIRONMENT

A. Simulation setup

Using the Cloud Sim 3.0.3 toolkit, the performance of the Logistic Regression Algorithm for Host Overload detection and Host Power of Host machine for Host Underload detection is compared to three different algorithms for the identical problem of Host machine overload and underload detection. The simulation includes 800 heterogeneous real machines, with half of them being HP ProLiant G4 servers and the other half being HP ProLiant G5 servers. Table 2 shows the power consumption of G4 and G5 servers. Table 3 lists the server configurations. Table 4 shows the virtual machine's configuration. For this simulation, we used real-world work load data from the Co Mon Project, a Planet Lab monitoring infrastructure, which is listed in Table 5.

B. Metrics for Assessing Performance

The following metrics are used to evaluate the algorithm's performance.

1. Power consumed - The total amount of physical machine power consumed in a datacenter is referred to as power consumed.
2. Service Level Agreement Violation – If cloud consumers' requests are not met, Service Level Agreement violations are likely to occur.
3. SLATAH - When the allocated MIPS is less than the requested MIPS, SLATAH is used to total up all the physical machine violations.
4. PDM - average performance degradation caused by migrations in each physical machine.
5. Number of Virtual Machines Migrated — Virtual Machines that have been carefully selected for migration from overloaded or underloaded servers.
6. ESV — a combination of energy usage and a breach of the Service Level Agreement.

Table 2 Energy consumption by the selected servers at different load levels in Watts

Machine Type	Power Consumption Based on CPU utilization					
	0%	20%	40%	60%	80%	100%
HP G4 (Watt)	86	92.6	99	106	112	117
HP G5 (Watt)	93.7	101	110	121	129	135

Table 3 Server's Configuration

Machine Type	Description
HP G4	1860MIPS, 1GB/s network bandwidth
HP G5	2660 MIPS, 1GB/s network bandwidth

Table 4 VM's Configuration

Table 5. Selected trace-based workloads.

VM types	Description
High-CPU Medium Instance	2500 MIPS, 0.85 GB
Extra Large Instance	2000 MIPS, 3.75 GB
Small Instance	000 MIPS, 1.7 GB
Micro Instance	500 MIPS, 613 MB

Workload	No. of VMs	Workload	No. of VMs
20110303	1052	20110403	1463
20110306	898	20110409	1358
20110309	1061	20110411	1233
20110322	1516	20110412	1054
20110325	1078	20110420	1033

C. Simulation outcome and Examination

The simulation is run using the Cloud Sim toolbox. The proposed Logistic Regression Algorithm for Host Overload detection and power spent by physical machine for Host Underload detection is compared to the other three techniques presented in Tables 6 and 7 for the identical problem of host machine overload and underload detection. The suggested approach employs VMs Mean Minimum Utilization (MU) as a Virtual Machine Selection policy and VMs Mean FFD as a Virtual Machine placement strategy. Our suggested technique decreases energy usage while maximizing host machine use, according to simulated results.

Discussion on the proposed Logistic Regression Analysis the Host machine Overload detection algorithm is listed here, along with the other three Host machine Overload detection algorithms.

1. Power consumption – when compared to the remaining Host machine Overload detection approach, the suggested algorithm consumes less power. The result of the energy utilized is shown in Figure 1.

2. Service Level Agreement Violation - The Local Regression Algorithm indicates that a lower SLA violation ensures better QoS. The result of the Service Level Agreement violation is shown in Figure 2.

3. SLATAH - The Local regression algorithm has the shortest time to violate a Service Level Agreement per active host. The outcome of SLATAH is shown in Figure 3.

4. PDM – due to migration, the proposed approach shows less performance impairment. The result of PDM is shown in Figure 4.

5. Number of migrated Virtual Machines - the proposed approach has less migrating Virtual Machines. The number of transferred Virtual Machines is shown in Figure 5.

6. ESV – the Local Regression Algorithm has a lower joint power and is less likely to violate the Service Level Agreement. The result is shown in Figure 6.

In the most of the performance measures used to compute the performance, the proposed algorithm outperforms the past three Host machine Overload detection algorithms. It demonstrates that the suggested technique increases physical machine utilization by effectively recognizing and reporting overloaded host machines. The VM placement then considers a few of the VMs from these overloaded host machines and migrates them to a more active physical machine, lowering energy consumption.

Below is a discussion of the suggested Host Power of Host machine for Underload detection, as well as three other Host machine Underload detection algorithms.

1. Power consumption - when compared to the remaining Host machine Underload detection approach, the suggested approach uses less power. The result of the power utilized is shown in Figure 9.

2. Service Level Agreement Violation - The proposed Algorithm shows that a lower SLA violation guarantees better QoS. The effect of the Service Level Agreement violation is depicted in Figure 13.

3. SLATAH - The proposed Algorithm has the shortest time to violate a Service Level Agreement per active host. The outcome of SLATAH is shown in Figure 11.

4. PDM – the proposed algorithm shows that migration causes less performance degradation. The result of PDM is shown in Figure 12.

5. Number of migrating Virtual Machines - the proposed technique has a less number of migrating Virtual Machines. The result of the Virtual Machine migration numeral is shown in Figure 10.

6. ESV – the proposed algorithm has a lower joint power and is less likely to violate the Service Level Agreement. The result is shown in Figure 14.

In the majority of the performance measures used to compute the performance, the proposed approach outperforms the other three Host machine Underload detection algorithms. It demonstrates that the suggested technique increases physical machine utilization by recognizing and reporting underloaded host machines. The Algorithm then moves all of the VMs from the underutilized host system to a more active physical machine, lowering energy consumption.

Table 6. Summary of all the Host machine Overload detection Algorithms

	Local Regression	OLS Multiple Linear Regression	GLS Multiple Linear Regression	Logistic Regression
Energy Consumption (kWh)	110.26	85.85	109.78	81.38
VM Migration	9699	1350	17473	1147
SLATAH	7.18%	76.06%	8.19%	85.18%
PDM	0.01%	0.00%	0.03%	0.00%
SLAV (10^{-2})	0.44%	12.03%	0.47%	15.82%
ESV (10^{-2})	0.11	0.1868	0.2582	0.1869
Average SLA Violation	9.45%	16.27%	10.04%	17.59%
Number of Host Shutdowns	805	783	856	777

Table 7. Summary of all the Host machine Underload detection Algorithms

	Logistic	Loess	WLS	Host Power
Energy Consumption (kWh)	90.72	90.82	83.24	81.38
VM Migration	4152	4390	1595	1147
SLATAH	71.3%	71.65%	80.26%	85.18%
PDM	0.02%	0.02%	0.00%	0.00%
SLAV (10^{-2})	13.24%	13.84%	14.39%	15.82%
ESV (10^{-2})	1.5812	1.6207	0.3262	0.1869
Average SLA Violation	16%	16.42%	17.31%	17.59%
Number of Host Shutdowns	778	778	778	777

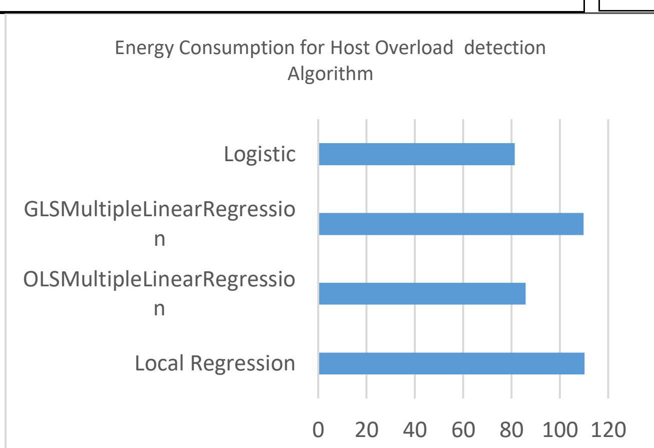

Figure 1 Energy Consumption chart for Host Overload detection Algorithm

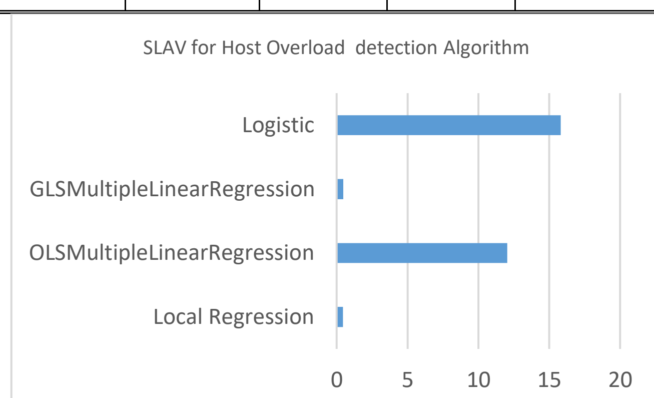

Figure 2 SLA Violation Chart for Host Overload detection Algorithm

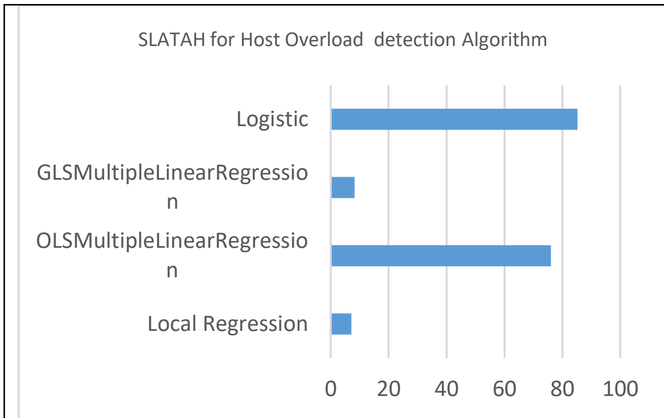

Figure 3 SLATAH Chart for Host Overload detection Algorithm

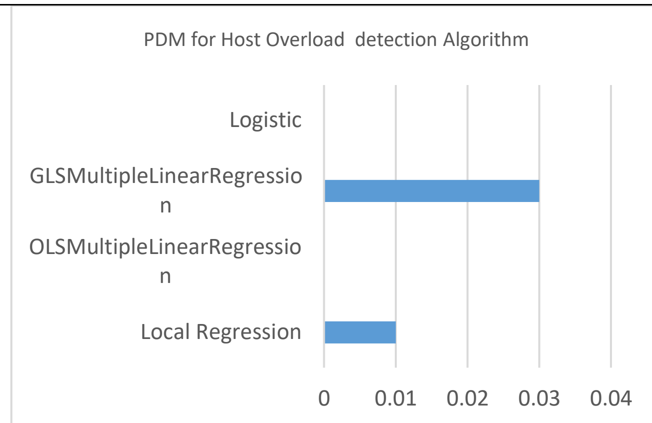

Figure 4 PDM Chart for Host Overload detection Algorithm

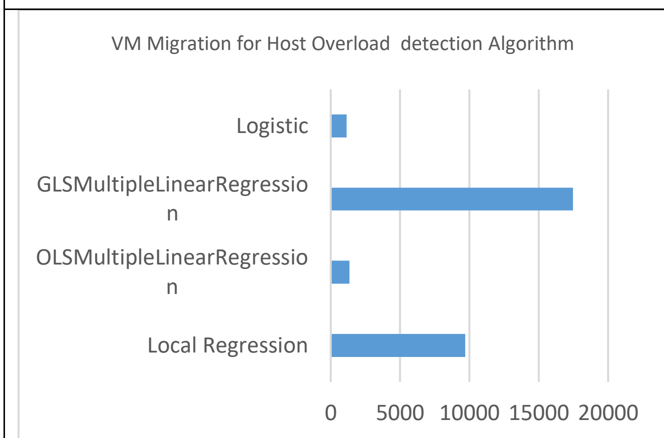

Figure 5 VM Migration Chart for Host Overload detection Algorithm

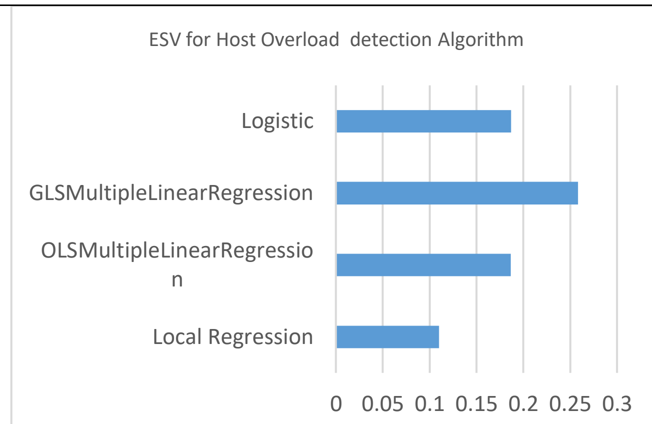

Figure 6 ESV Chart for Host Overload detection Algorithm

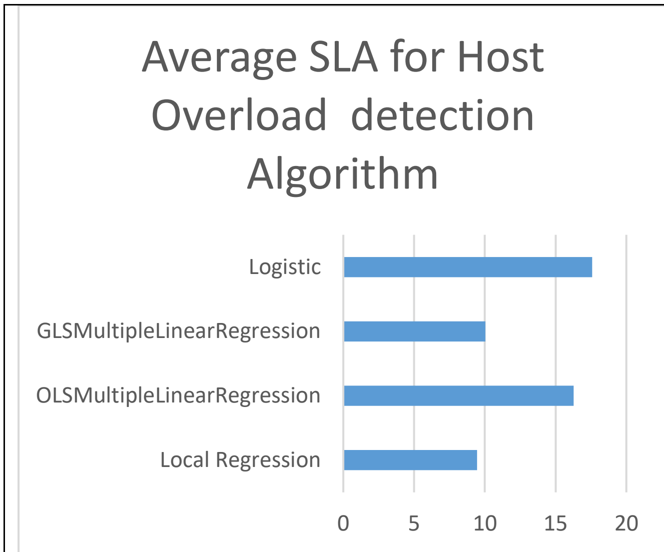

Figure 7 Average SLA Chart for Host Overload detection Algorithm

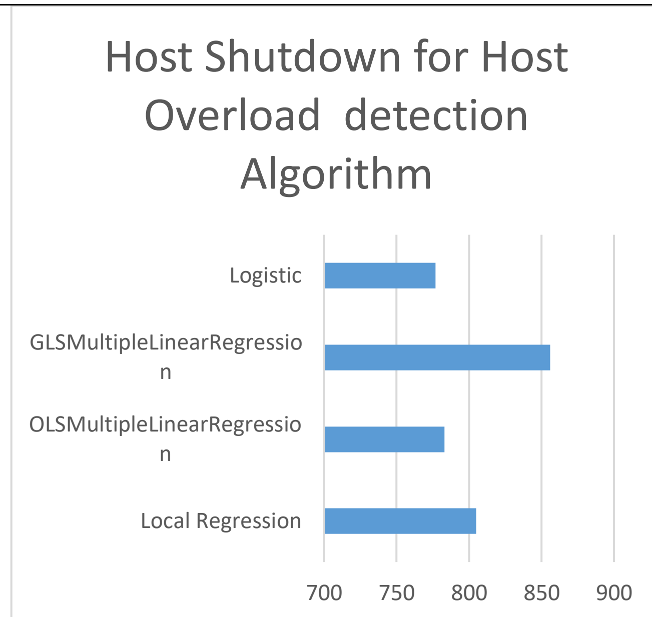

Figure 8 Host Shutdown Chart for Host Overload detection Algorithm

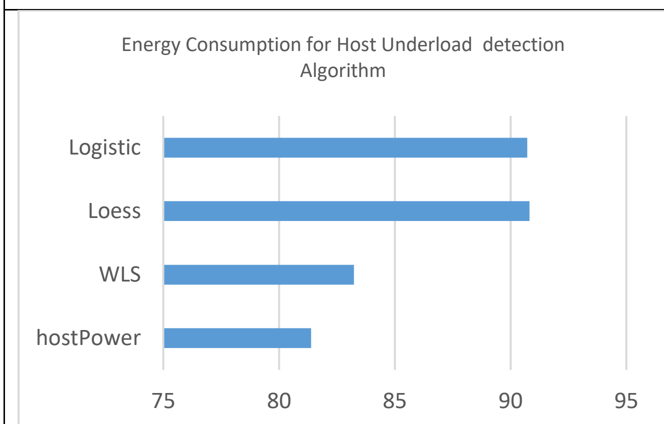

Figure 9 Energy Consumption Chart for Host Underload detection Algorithm

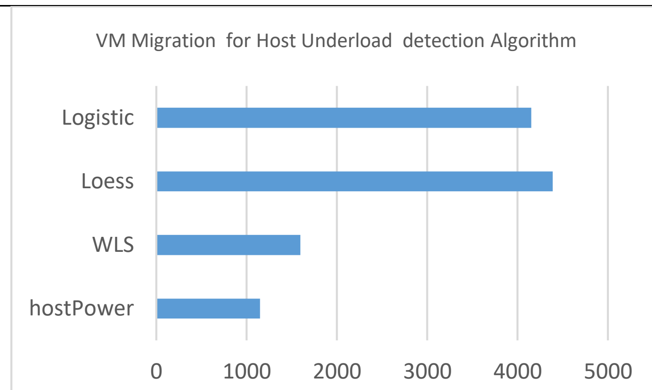

Figure 10 VM Migration Chart for Host Underload detection Algorithm

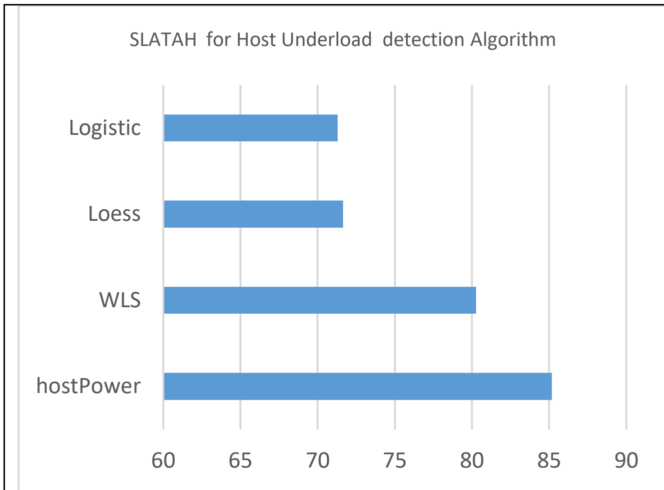

Figure 11 SLATAH Chart for Host Underload detection Algorithm

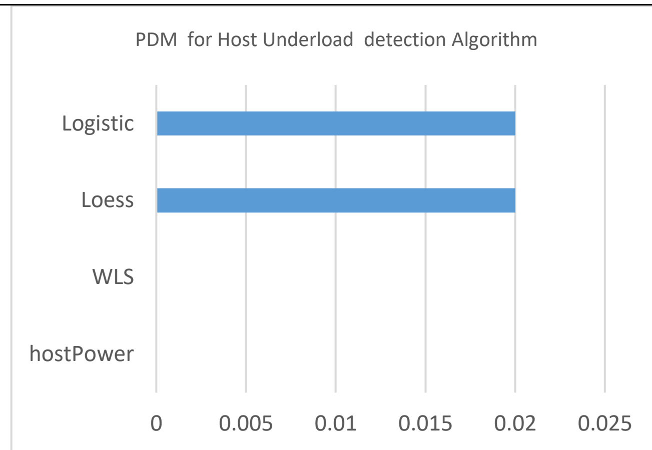

Figure 12 PDM Chart for Host Underload detection Algorithm

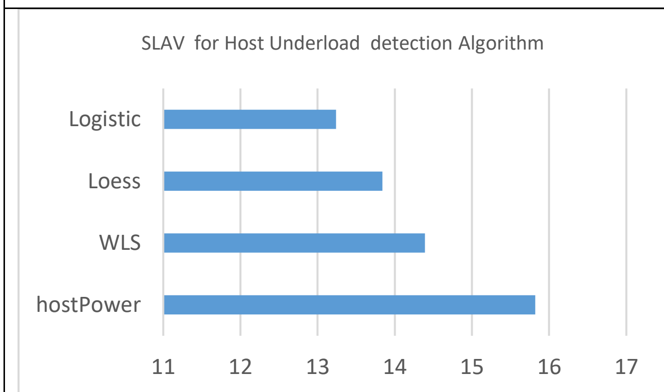

Figure 13 SLAV Chart for Host Underload detection Algorithm

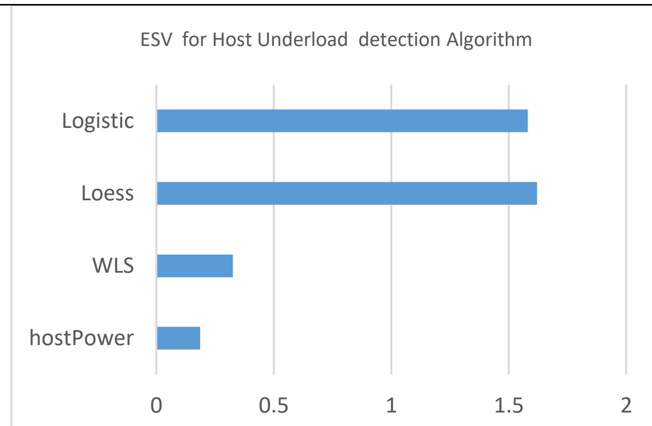

Figure 14 ESV Chart for Host Underload detection Algorithm

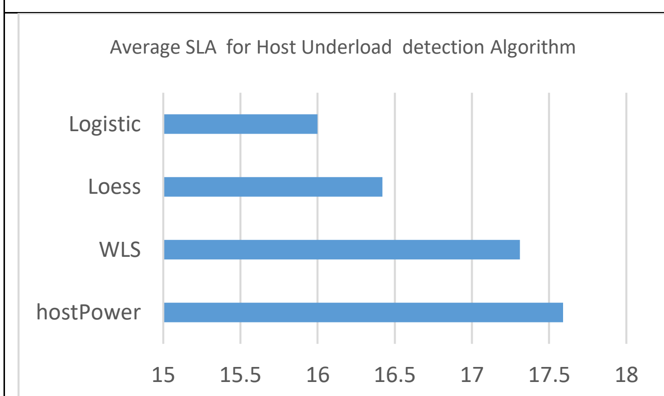

Figure 15 Average SLA Chart for Host Underload detection Algorithm

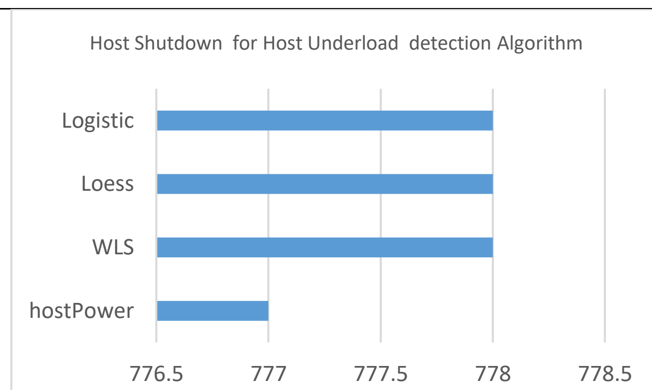

Figure 16 Host Shutdown Chart for Host Underload detection Algorithm

VI. CONCLUSION

The major goal is to increase physical machine utilization while lowering energy consumption by identifying overloaded or underloaded host machines efficiently to avoid performance degradation and energy waste. The suggested logistic regression method for Host machine Overload detection and Host Power algorithm for Host machine Underload detection detects and notifies Host machine Overload or Underload early. Following that, the virtual machines from these host machines are moved to another active host machine. We are able to achieve our main goal of effective resource utilization and reduced power consumption with our proposed technique.

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