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# Performance Comparison of Virtual Machine Selection Policies in Cloud Environment

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## ABSTRACT

Many solutions have been proposed in the past to protect data center from inefficient resource usage. However, better utilization of the resources while providing desired Quality of Services (QoS) is still an open research challenge. Researchers continuously working on novel resource management strategies focuses on Virtual Machine (VM) Placement, Load Balancing, Task Scheduling and Virtual Machine Selection for designing an optimal solution. Among these, Virtual Machine Selection has emerged as a more consistent solution to combat against such resource wastage that in turn contributes to high energy consumption. In this strategy, a careful decision of choosing a virtual machine for migration is taken since, the selection decision directly influences migration time and CPU resource utilization. A wrong selection can increase energy consumption and Service Level Agreement (SLA) violations in a data center. Literature evidences number of virtual machine selection solutions implementing Heuristic, Metaheuristic or Machine Learning techniques. This paper systematically reviews and compares commonly used Heuristic approach based Virtual Machine Selection policies. Such an exhaustive comparison will surely help the research community to provide more robust and reliable Virtual Machine Selection policy.

**Key words:** Virtual Machine Selection, Energy Consumption, Workload Traces, Live Migration, Resource Management.

## 1. INTRODUCTION

Reduction of energy consumption in a data center has always remain a concern of every Cloud Service Provider (CSP). In a data center, high energy consumption is not due to high resource usage but, inefficient usage of these resources. A recent study presented by Reiss et al. [1] shows that a 12,000-nodes Google cluster achieves aggregate CPU utilization only of 25%-35% and memory utilization of 40% and rest of their resources are wasted. Moreover, each idle server consumes power equal to 70% of its peak power usage. So, efficient handling of these resources is need of an hour.
Virtualization is a technique pervasively applied in a data center to enhance resource utilization [2]. Virtualization leverages VM live migration strategy with the goal of better physical server utilization and reduction in energy consumption within the data center. VM live migration involves transfer of running VMs between servers without execution suspension [3]. However, excessive migrations are not preferred due to performance disruption involved in migration that further exacerbates the problem of non-compliance to SLA violations. VM Selection plays an important role in optimization of VM live migration technique. It ensures selection of optimal VM(s) from an overloaded server for migration aiming better migration time or resource utilization. Many VM Selection policies have been suggested by the researchers that implements heuristic, meta-heuristic or machine learning techniques. This paper investigates performance of some commonly used VM Selection policies implementing heuristic approaches. A comparative analysis among these policies are also done on CloudSim toolkit. The performance of these policies is tested on different workload traces. Moreover, to cover every aspect that could affect performance of an algorithm, the polices are tested on different adaptive threshold policies as well.

Rest of the paper is organized in the following manner. The next section details existing VM Selection policies suggested by researchers, contributing to dynamic resource management in cloud data center. Section 3 details performance parameters considered in this study to evaluate the policies. The experimental setup and obtained results are presented in further section. The last section discusses conclusion obtained from the analysis.The authors of the accepted manuscripts will be given a copyright form and the form should accompany your final submission.

## 2. LITERATURE REVIEW

Numerous resource management techniques have been adopted by the researchers to attain the objective of high return on investments satisfying SLA constraints. The domain of static resource management is well known in cloud computing area. However, for dynamic workload environment, adaptive resource management policies are required. Nathuji and Schwan initiated power management concept on virtualized data centers [4]. They proposed an idea of resource profiling at local as well as global level and resource reallocation decision is taken based upon the collected information. However, no specific policy is suggested for automatic resource reallocations. To reallocate virtual resources, live migration technique is implemented in a data center that allows migration of VMs between hosts without execution suspension [5]. However, live migration has negative impact on application performance due to execution downtime during VM migration. Voorsluys et al. investigates the effect of migration and concludes that downtime depends upon number of pages needs to be updated during migration and it is approximately 10% of the CPU-MIPS utilization [6]. Therefore, selection of an optimal VM for migration is a crucial decision. To ensure low performance degradation, a careful VM selection policy is needed. Because a wrong selection sometime increases reallocations and SLA violations. This work analyses performance of some commonly used VM Selection algorithms as described further.

**Anton et al. [7]** The Minimum Migration Time (MMT) VM Selection policy is suggested that aims to reduce migration time of a VM. The VM is selected that satisfies the following criteria:

$$\frac{RAM_u(v)}{NET_j} \leq \frac{RAM_u(a)}{NET_j}, \qquad v \in V_j \; and \; \forall a \in V_j$$

In this equation, $RAM_u(v)$ is the current RAM utilization by VM *v* and $NET_j$ is the spare network bandwidth for the host *j*. Another VM Selection policy- Maximum Correlation (MC) is suggested that selects a VM for migration having highest CPU correlation with other VMs. The belief behind the idea is, higher correlation in CPU usage among VMs eventually increases probability of server overloading.

Minimization of Migrations (MM) [8] policy ensures selection of minimum number of VMs for migration. The working principle of the policy is defined as:

$$(U_j - \sum_{v \in S} U_a(v)) < T_u, S \in P(v_j) \; and \; |S| \rightarrow minimum$$

Here, $U_j$ is CPU utilization of the server *j*, $U_a(v)$ represents CPU utilization allocated to VM *v* and $T_u$ is upper threshold value of the server. S is a subset of VMs which is kept as small as possible.

**Zhou et al. [9]**A policy- Maximum Ratio of CPU Utilization to Memory Utilization (MRCU) is proposed that takes into account both CPU and RAM utilization of a server in VM Selection decision when the server is over-loaded by CPU-intensive tasks. The task is designated CPU-intensive when its completion time is determined y speed of processor. The policy selects the VM that meets the following criteria:

$$\frac{C_{v_i}}{M_{v_i}} > \frac{C_{v_j}}{M_{v_j}}, v_i \in V, \forall v_j \in V \; and \; i \neq j$$

Here, $C_{v_i}$ and $M_{v_i}$ represents respective utilization of CPU and memory in VM *i*. The VM with highest ratio is selected for migration.

**Fu et al. [10]** A Meet Performance (MP) VM Selection policy is proposed aiming reduction in power consumption and SLA violation rate. The policy attempts to ensure minimum free MIPS on the server after VM migration. Moreover, an aspect of SLA resource satisfaction is considered in selection decision calculated as:

$$Sla = \frac{U_{reqd} - U_{alloc}}{U_{reqd}}$$

Where, $U_{reqd}$ and $U_{alloc}$ are respective requested and allocated MIPS of VM. The VM with lowest resource satisfaction is selected for migration.

## 3. PERFORMANCE PARAMETERS

Providing QoS to customers is responsibility of every CSP. QoS are defined in terms of SLA between CSP and the client. It specifies minimum quality levels to be provided to the client and the penalty if the performance is not achieved. In this study, performance is measured in terms of Energy Consumption (EC), Energy Performance Metric (EPM), SLA Violations per Active Host (SLATAH), Performance Degradation Due to Migration (PDM) and Service Level Agreement Violations (SLAV). The next sub-section briefly describes these parameters.

*Energy Consumption (EC):* This metric computes EC by all hosts involved in simulation. In this work, EC is computed considering CPU utilization level in a host and then mapping is done using SpecPower [11] analytical model. This model shows EC by hosts at varying CPU utilization levels. Energy Consumption can be defined as:

$$EC = \sum_{i=1}^{h} E(u_i)$$

Here, $u_i$ represents CPU utilization of a host in percentage and $E(u_i)$ is the EC for the utilization level according to SpecPower analysis.

*SLA Violation (SLAV):* It measures the time for which desired QoS are not provided to the user. The violations occur when a VM could not get its requested resources. In a host, SLAV can be defined as product of Service Level Violations per Active Host *(SLATAH)* which measures the ratio of time for which an active host experienced 100% utilization and Performance Degradation due to Migrations *(PDM)* which measures the performance disruptions caused due to involvement of extra resources in migration of a VM. It is assumed that a penalty is paid by CSP to the user in case of violations in SLA.

*Energy Performance Metric (EPM):* EPM is the combination of EC and SLAV defined as: SLAV * EC. There is trade-off between the two. The attempt for energy reduction results in increased SLA violations and vice-versa. The algorithm is considered efficient if it ensures lower EC keeping SLA intact.

## 4. EXPERIMENTAL SETUP AND RESULT EVALUATION

This study reviews and compares performance of VM Selection policies. The policies are implemented on CloudSim simulation toolkit [12]. To carry out simulation, a data center with 800 hosts has been created with two different configurations: HP Proliant G4 (Xeon 3040 processor, dual core, 1860 MHz CPU frequency, 4GB RAM) and HP Proliant G5 (Xeon 3075 processor, dual core, 2660 MHz CPU frequency, 4GB RAM). Power utilization in a host at varying utilization levels is defined as per SpecPower dataset as described in Table 1.

4.1 **Workload Traces:** A rapid variation in workload patterns is observed in data centers. To ensure continued adoption of Cloud Computing services, analysis of these variation and modification in adopted resources management strategies is need of an hour. To test robustness and consistency of algorithms, it is a key concept to run these algorithms on different workload traces. In this paper, the algorithms are executed on fastStorage, Rnd, PlanetLab and Random workloads. Next subsection details these workload traces.

*Bitbrains:* [13] Bitbrains is a CSP dedicated to provide business computing services. Two workload traces FastStorage and Rnd have been collected from the data center of Bitbrains by observing utilization of its servers. The dataset consists of 7 performance metrics (the number of cores provisioned, the provisioned CPU capacity, the CPU usage, the provisioned memory capacity, the actual memory usage, the disk I/O throughput, and the network I/O throughput.) per VM, sampled every 5 minutes. Table 2. details feature of these datasets.

*PlanetLab:* [14] The workload traces from the infrastructure of PlanetLab were observed for 10 days by CoMon project. The traces are collected from thousands of running VMs by observing their CPU Utilization every 5 minute. The features of these workload traces are described in Table 3.

To test performance of algorithms these policies are also implemented on random workload generated using stochastic function. The graphical representation of the obtained results is shown by Figure 1. Table 4 to Table 7 shows quantitative experimental results of parameters -Energy Consumption, Migration Count, SLA Violation and Energy Performance Metric on these datasets.

**Table 1:** Power Consumption by Servers on varying Utilization Levels

| Host | 0% | 10% | 20% | 30% | 40% | 50% | 60% | 70% | 80% | 90% | 100% |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Proliant G4** | 86 | 89.4 | 92.6 | 96 | 99.5 | 102 | 106 | 108 | 112 | 114 | 117 |
| **Proliant G5** | 93.7 | 97 | 101 | 105 | 110 | 116 | 121 | 125 | 129 | 133 | 135 |

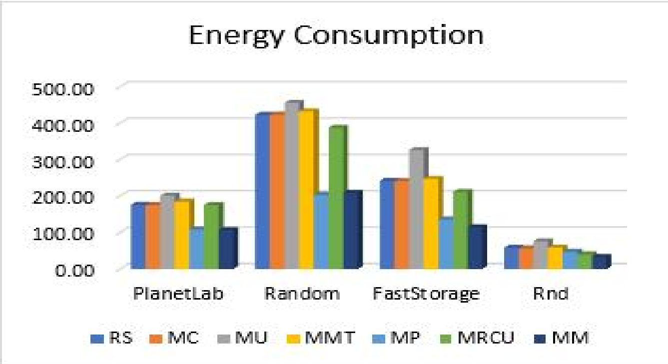
| Trace Name | # VM | Data collected for | Storage Tech. | Total Memory | # Cores |
|---|---|---|---|---|---|
| fastStorage | 1250 | 1 month | SAN | 17729 GB | 4057 |
| Rnd | 500 | 3 months | NAS, SAN | 5485 GB | 1444 |

**Table 2:** Characteristics of Bitbrains Datasets

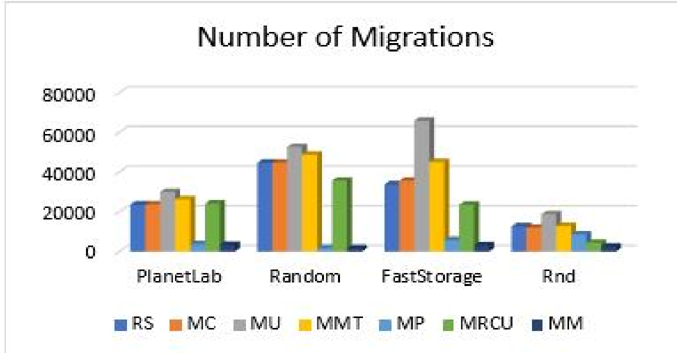
**Table 3:** Characteristics of PlanetLab Dataset

| Date | # VM | Mean | Quartile 1 | Quartile 3 |
|---|---|---|---|---|
| 03-03-2011 | 1052 | 12.31% | 2% | 15% |
| 06-03-2011 | 898 | 11.44% | 2% | 13% |
| 09-03-2011 | 1061 | 10.70% | 2% | 13% |
| 22-03-2011 | 1516 | 9.26% | 2% | 12% |
| 25-03-2011 | 1078 | 10.56% | 2% | 14% |
| 03-04-2011 | 1463 | 12.39% | 2% | 17% |
| 09-04-2011 | 1358 | 11.12% | 2% | 15% |
| 11-04-2011 | 1233 | 11.56% | 2% | 16% |

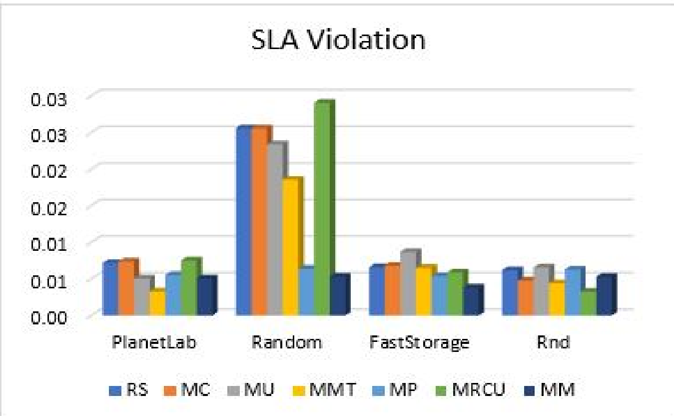
| | | | | |
|---|---|---|---|---|
| 12-04-2011 | 1054 | 11.54% | 2% | 16% |
| 20-04-2011 | 1033 | 10.43% | 2% | 12% |



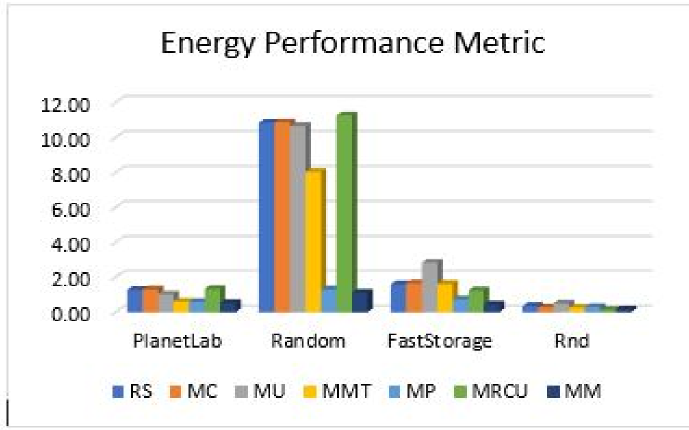

(a) Energy Consumption




(b) Number of Migrations




(c) Service Level Agreement Violations




(d) Energy Performance Metric

Figure 1 (a-d): Performance Comparison among Policies with different Workload Traces

From the experimental results, a performance consistency has been observed in MM policy with all workload traces. The policy performs well in terms of energy consumption and migration count since, it attempts to utilize server to the maximum. However, a significant reduction in SLAV and EPM is also observed in MMT policy because, the policy attempts to reduce total time of VM migration that reduces VM downtime thus positively impacts SLAV and EPM. The policy performs better with PlanetLab workload traces whereas, MRCU works well with traces of Rnd. A high variation has been observed in EPM parameter of all policies. The performance of MP policy is also optimal in terms of energy consumption and migration count with all workload traces except Rnd as it shows increase in migration count as compared to other workloads.

**Table 4:** Energy Comparison among VM Selection policies on different Workload Traces

| | RS | MC | MU | MMT | MP | MRCU | MM |
|---|---|---|---|---|---|---|---|
| PlanetLab | 176.58 | 176.13 | 200.40 | 184.88 | 107.72 | 176.13 | 105.86 |
| Random | 423.80 | 424.30 | 455.40 | 433.02 | 202.98 | 387.26 | 208.66 |
| fastStorage | 241.96 | 241.40 | 326.57 | 247.82 | 135.88 | 211.28 | 113.94 |
| Rnd | 58.12 | 56.43 | 76.11 | 58.66 | 47.16 | 39.63 | 32.44 |

**Table 5:** Migration Count Comparison among VM Selection policies on different Workload Traces

| | RS | MC | MU | MMT | MP | MRCU | MM |
|---|---|---|---|---|---|---|---|
| PlanetLab | 23653 | 23691 | 30051 | 26292 | 3693 | 24186 | 3354 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Random | 44777 | 44797 | 52615 | 48810 | 1831 | 35733 | 1742 |
| fastStorage | 33812 | 35671 | 65906 | 45125 | 5841 | 23583 | 3143 |
| Rnd | 12727 | 12050 | 18861 | 12876 | 8711 | 4428 | 2457 |

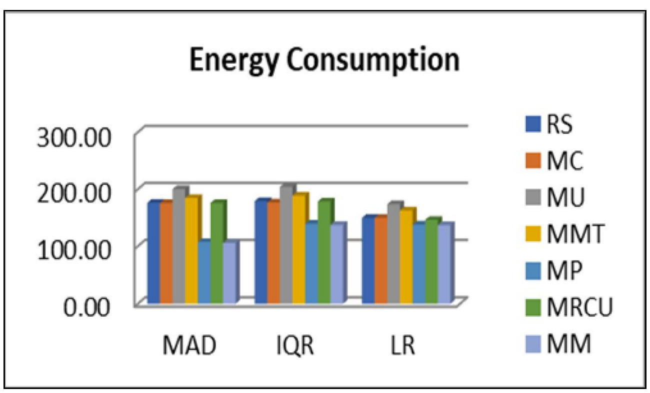
**Table 6:** SLAV Comparison among VM Selection policies on different Workload Traces

| | RS | MC | MU | MMT | MP | MRCU | MM |
|---|---|---|---|---|---|---|---|
| PlanetLab | 0.0072 | 0.0074 | 0.0051 | 0.0033 | 0.0056 | 0.0075 | 0.0051 |
| Random | 0.0256 | 0.0256 | 0.0234 | 0.0186 | 0.0064 | 0.0291 | 0.0053 |
| fastStorage | 0.0066 | 0.0068 | 0.0087 | 0.0065 | 0.0054 | 0.0059 | 0.0038 |
| Rnd | 0.0062 | 0.0048 | 0.0066 | 0.0044 | 0.0063 | 0.0033 | 0.0053 |

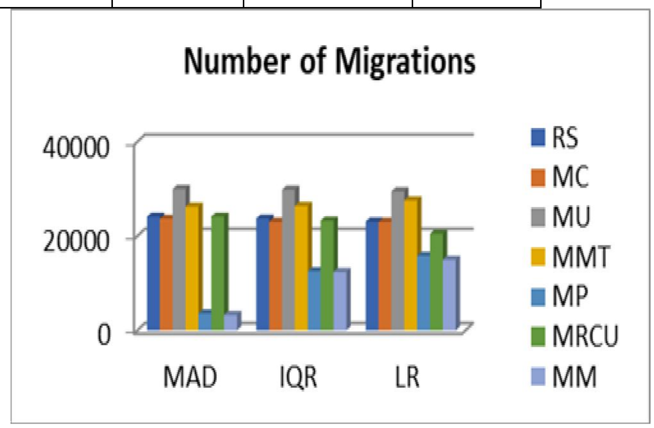
**Table 7:** EPM Comparison among VM Selection policies on different Workload Traces

| | RS | MC | MU | MMT | MP | MRCU | MM |
|---|---|---|---|---|---|---|---|
| PlanetLab | 1.27 | 1.30 | 1.02 | 0.61 | 0.60 | 1.33 | 0.54 |
| Random | 10.86 | 10.87 | 10.66 | 8.04 | 1.30 | 11.27 | 1.11 |
| fastStorage | 1.60 | 1.65 | 2.84 | 1.62 | 0.73 | 1.25 | 0.44 |
| Rnd | 0.36 | 0.27 | 0.50 | 0.26 | 0.30 | 0.13 | 0.17 |

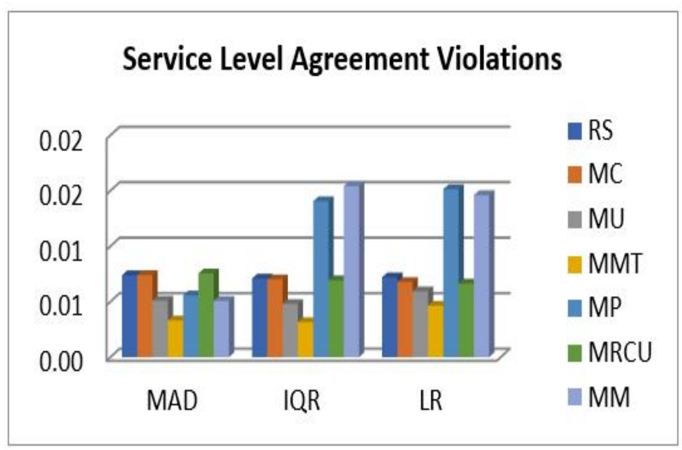
**4.2 Adaptive Threshold Policies:** To study effect of different threshold policies on the performance of VM Selection algorithms, the algorithms are tested on three different threshold policies – Median Absolute Deviation (MAD), Inter-quartile Range (IQR), and LR (Local Regression). MAD and IQR policies implement statistical techniques on historical data to calculate the threshold limit whereas LR is based on regression analysis. The graphical representation of the obtained results is shown by Figure 2 and the exact quantitative analysis can be made from Table 8 to Table 11.



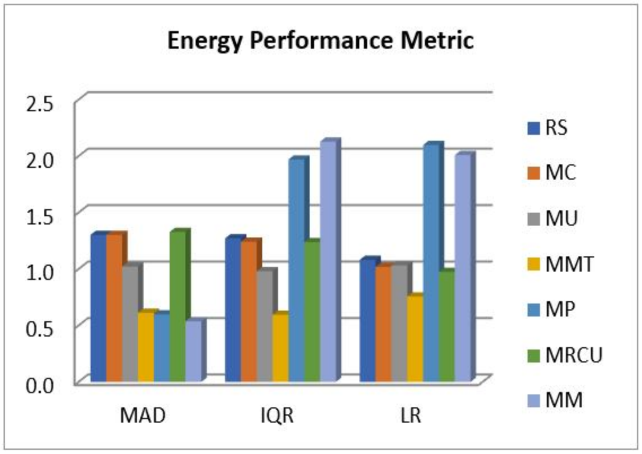

(a) Energy Consumption




(b) Number of Migrations




(c) Service Level Agreement Violations




(d) Energy Performance Metric

**Figure 2 (a-d):** Performance Comparison among Policies with different Threshold policies

**Table 8:** Energy Comparison among VM Selection policies with different Threshold Algorithms

| | RS | MC | MU | MMT | MP | MRCU | MM |
|---|---|---|---|---|---|---|---|
| MAD | 176.57 | 176.13 | 200.40 | 184.88 | 107.72 | 176.13 | 105.86 |
| IQR | 179.49 | 177.10 | 204.22 | 188.86 | 140.19 | 178.90 | 138.06 |
| LR | 150.36 | 150.33 | 174.24 | 163.15 | 138.62 | 146.80 | 137.62 |

**Table 9:** Migration Count Comparison among VM Selection policies with different Threshold Algorithms

| | RS | MC | MU | MMT | MP | MRCU | MM |
|---|---|---|---|---|---|---|---|
| MAD | 24169 | 23691 | 30051 | 26292 | 3693 | 24186 | 3354 |
| IQR | 23765 | 23035 | 29901 | 26476 | 12600 | 23284 | 12417 |
| LR | 23064 | 23004 | 29555 | 27632 | 15846 | 20503 | 14986 |

**Table 10:** SLAV Comparison among VM Selection policies with different Threshold Algorithms

| | RS | MC | MU | MMT | MP | MRCU | MM |
|---|---|---|---|---|---|---|---|
| MAD | 0.0074 | 0.0074 | 0.0051 | 0.0033 | 0.0056 | 0.0075 | 0.0051 |
| IQR | 0.0071 | 0.0070 | 0.0048 | 0.0031 | 0.0140 | 0.0069 | 0.0154 |
| LR | 0.0072 | 0.0068 | 0.0059 | 0.0046 | 0.0151 | 0.0066 | 0.0146 |

**Table 11:** EPM Comparison among VM Selection policies with different Threshold Algorithms

| | RS | MC | MU | MMT | MP | MRCU | MM |
|---|---|---|---|---|---|---|---|
| MAD | 1.3022 | 1.3021 | 1.0211 | 0.6121 | 0.5987 | 1.3276 | 0.5370 |
| IQR | 1.2717 | 1.2412 | 0.9802 | 0.5943 | 1.9695 | 1.2381 | 2.1279 |
| LR | 1.0816 | 1.0184 | 1.0320 | 0.7561 | 2.0982 | 0.9740 | 2.0094 |

From the analysis, a significant impact of threshold policies has been observed on performance of VM Selection policies. The following observations have been made:

- Performance of MP and MM policies is highly optimal with MAD threshold policy as compared to IQR and LR policies.
- As compared to IQR and LR threshold policies, a respective reduction of 23.16% and 22.29% in energy consumption and 70.69% and 76.69% in migration count is observed in MP VM Selection policy taking MAD as a threshold policy.
- A respective reduction of 23.32% and 23.07% in energy consumption and 72.99% and 80.29% in migration count is also observed in MM policy with MAD threshold policy as compared to IQR and LR policies. This reduction further declines SLA violations and EPM value.
- There is no significant variation in the outcomes of other policies. However, performance of some VM Selection policies such as RS, MC and MRCU is slightly better with LR threshold policy.

## 5. CONCLUSION

The rapid growth of cloud-based services and applications lead to increase in energy consumption and deterioration of QoS. This high energy consumption is not due to high resource usage but inefficient usage of these resources. In virtual cloud environment, many solutions have been devised in the past to ensure better resource utilization. Virtual Machine Selection is one of the most reliable and robust solutions, leveraging the VM Live Migration strategy to combat world-wide issues of high energy consumption and inefficient resource management.

This paper investigates performance of some benchmark as well as state-of-the-art VM Selection algorithms. To ensure much reliable and consistent evaluation, the algorithms are executed on different workload traces and adaptive threshold policies. From the comprehensive analysis, a performance consistency has been observed in the outcomes of MM and MP VM Selection policies with all workload traces. A significant impact of threshold policies is also concluded from the experiment. Some policies like MM and MP performs better with MAD threshold policy whereas performance of other policies like MRCU and MMT is slightly better with LR policy.

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