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Dynamic Optimization of Energy Efficiency and Service Level Agreement violation in Cloud Data Centers via Virtual Machine Consolidation

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Abstract

With the escalating proliferation of cloud computing services, cloud data center providers are actively in pursuit of solutions not only to curtail energy consumption but also to efficiently cater to the unique demands of their users, thereby enhancing user satisfaction. The process of consolidating virtual machines emerges as a viable strategy for striking a balance between energy consumption and Service Level Agreement violation (SLAv), potentially surmounting this predicament faced by cloud service providers. This study aims to minimize energy consumption and SLAv to their utmost feasible extent by utilizing the First Median Threshold (FMT) technique for physical host selection and virtual machine allocation, in conjunction with the Maximum Ratio of CPU utilization to memory Utilization (MRCU) method for virtual machine selection within the framework of virtual machine consolidation. This dual-pronged approach not only translates into cost savings for cloud providers but also ensures the delivery of optimal services to users. Furthermore, a novel method has been introduced for selecting virtual machines for migration and appropriately choosing physical hosts to achieve equilibrium between two critical parameters: energy consumption and SLAv. The proposed methodology is implemented and evaluated using the CloudSim simulator, utilizing real-world PlanetLab data. The comprehensive analysis of the simulation results reveals that the proposed approach can significantly reduce energy consumption while effectively mitigating SLAv for users.

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Keywords: Cloud computing, Energy efficiency, Service Level Agreement violation, virtual machine consolidation, virtual machine selection, virtual machine reallocation.

1. Introduction

The utilization of cloud computing technology is experiencing steady growth, prompting cloud data center providers to actively seek strategies for diminishing energy consumption while upholding an acceptable level of service quality defined by Service Level Agreement (SLA) [1]. Cloud service providers offer a range of services, including Infrastructure as a Service (IaaS), Platform as a Service (PaaS), and Software as a Service (SaaS), enabling users to request specific services tailored to their requirements [1,2]. Nevertheless, the escalating demand for cloud services across diverse networks presents a formidable challenge for cloud providers in the endeavor to deliver services that align with user needs while concurrently minimizing energy consumption, a pivotal cost element in data center operations. Furthermore, the cooling processes essential for data centers not only incur financial expenses but also contribute to environmental pollution. Consequently, cloud providers employ methodologies geared towards optimizing the utilization of their physical host capacities, which entails reducing the number of active physical hosts to curtail energy consumption within these data centers.

However, the reduction in the count of physical hosts may result in an excessive workload on the remaining active hosts, particularly when some hosts are deactivated. This scenario elevates the likelihood of Service Level Agreement (SLA) breaches, which can lead to user discontentment. As a result, cloud providers employ strategies such as virtual machine consolidation, a technique designed to simultaneously uphold an acceptable energy consumption level while mitigating SLAv [1,2,3,4,29].

The virtual machine consolidation process within the cloud typically encompasses several stages: 1) Discerning the workload levels of physical hosts (low, med, high), 2) Selecting virtual machines, 3) Determining the virtual machine migration methodology, and 4) Identifying the target physical host for reallocating virtual machines. Each of these four stages exerts a substantial influence on parameters such as energy consumption, SLAv, migration frequency, and overall system performance [4,5,6].

In this research, a dynamic algorithm is proposed during the initial two stages of the virtual machine consolidation process. Our primary objective is to minimize energy consumption and reduce SLAv for the specific user services requested. an innovative approach is introduced that integrates the First Median Threshold (FMT) method [5] for classifying high, medium, and low-load physical hosts with the Maximum Ratio of CPU Utilization to

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Memory Utilization (MRCU) method [6] for selecting suitable virtual machines to be reallocated to alternative physical hosts. This consolidated approach not only leads to energy consumption reduction but also endeavors to diminish SLAv. While prior studies have attempted to categorize physical hosts as high, medium, or low-load, our consolidation approach offers a more efficient selection and reallocation of virtual machines, aiming to minimize future fluctuations in the distribution of workloads across physical hosts. Processor usage dominates energy consumption, rendering it the most critical parameter in our calculations, despite the significance of other parameters such as memory utilization and network bandwidth, which have relatively negligible energy consumption compared to processor usage. Figure 1 illustrates of total energy consumption within a cloud data center [7].

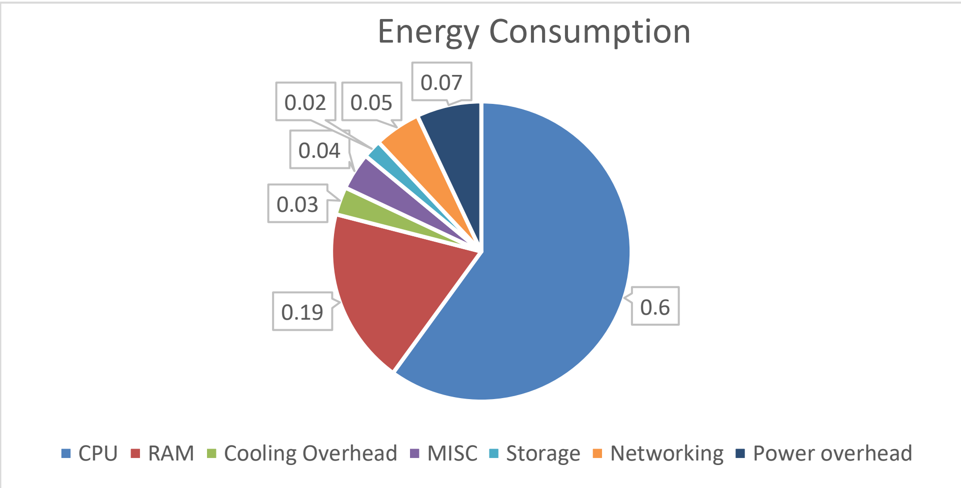

Figure (1): Total Energy Consumption in Cloud Data Centers. [7]

Figure 1 underscores that processors and primary memory account for the highest energy consumption within a cloud data center. Consequently, in this study, processor and primary memory are emphasized as the most pivotal energy consumption factors, serving as the basis for our calculations. Our approach, combining the FMT method [5] for identifying physical hosts and the MRCU method [6] for selecting appropriate virtual machines for migration, is geared towards energy consumption reduction and SLAv mitigation. In following, Section 2 comprises a literature review, comparing and evaluating both classic and contemporary methods and algorithms in terms of their applications and limitations. In Section 3, definitions and outline the proposed parameters and methodology are introduced. Section 4 conducts an examination and evaluation of simulation results, and finally in section5, furnishes insights about conclusion and delineates future research directions.

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2. Background

The allocation of virtual machines to appropriate physical hosts within cloud environments has consistently presented a formidable challenge in the pursuit of reducing energy consumption and mitigating SLAv. As a result, a substantial body of research has been dedicated to the domain of energy-efficient computing, with a particular focus on virtual machine consolidation as one of its central facets. The primary aim of virtual machine consolidation lies in identifying viable strategies for the reallocation of virtual machines to physical hosts, guided by pre-established objectives [8]. In this context, a plethora of algorithms has been introduced for virtual machine consolidation, with an overarching emphasis on curbing energy consumption through the utilization of both heuristic and meta-heuristic methodologies [9,27].

The proposed methodologies aimed at advancing energy consumption reduction and preventing SLAv in cloud environments through virtual machine consolidation typically encompass multiple stages. These stages involve the identification of hosts with high loads and low loads, the selection of appropriate virtual machines for migration from high-load hosts, or the comprehensive migration of all virtual machines from underutilized physical hosts, followed by their redistribution onto other physical hosts [8,9,10]. Even within the domain of heuristic methods, a further classification can be made, distinguishing classic approaches like MMT, MAD, IQR, ST [10], from more recent innovations such as Robust SLR, MAE(10)-SLAV, FMT, and MRCU [4,5,6,7,8,28].

Classic approaches typically tend to focus on a specific phase of the virtual machine consolidation process while sometimes overlooking other critical aspects. Furthermore, these methods predominantly center on a single performance metric, such as energy consumption or SLAv. For instance, the IQR algorithm [11] primarily relies on quartiles to establish threshold levels and identify physical hosts with high and low workloads, paying limited attention to the intricate process of selecting and migrating virtual machines. In contrast, contemporary approaches go beyond host categorization and prioritize the selection of virtual machines based on their energy consumption profiles, along with outlining the methodology for their reallocation to different physical hosts. Multiple performance metrics are rigorously evaluated. For instance, in the Robust SLR study [4], dynamic solutions are proposed for host categorization and the strategic selection of virtual machines for migration, while also considering migration counts.

In the research presented in [5], hosts undergo an initial ranking based on their processor utilization, followed by quartile-based classification. Subsequently, the median of each

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category is computed. This method facilitates a comprehensive evaluation of all categories, enabling the identification of physical hosts with low, medium, and high workloads. However, it exclusively takes into account processor utilization within physical hosts and does not provide a comprehensive strategy for the selection of virtual machines suitable for migration. In contrast, the MRCU method [6] not only identifies physical hosts with high and low workloads but also factors in the processor and primary memory utilization of virtual machines when making selections, potentially augmenting the efficiency of virtual machine selection for migration. Conversely, the FMT method [5], besides identifying hosts with high and low workloads, identifies hosts with medium workloads and, following the selection of a virtual machine for migration, reallocates it to a physical host with a medium workload. This strategic approach facilitates the deactivation of underutilized physical hosts and enables the transformation of heavily loaded physical hosts into a state of moderate workload. Consequently, Table 1 serves as a succinct summary of frequently employed methodologies in recent research pertaining to virtual machine consolidation, delineating the respective approaches, strengths, and weaknesses within each study.

Table (1): Summary of literature review techniques.

Method	Methodology	Strengths	Weaknesses
Interquartile Range (IQR)[11]	Classification Hosts (PMs) by Quartiles	Using upper and lower threshold- minimize energy consumption	Classification only based on CPU utilization as a power consumption – not using VM selection
Minimum Migration Time (MMT) [12]	Migration time consuming	minimize energy consumption	SLA - increasing network traffic
Median Absolute Deviation (MAD)[13]	4 classification and median of each group base on power consumption	Minimum energy consumption - Reduce the amount of VMs migrations	SLA - increasing network traffic - only CPU utilization as a power consumption
Single Threshold (ST)[14]	Only upper threshold	Considering Host Detection and VM selection - minimize energy consumption	Reallocation to just low load Hosts- SLA
Frequency-aware DVFS [15]	Using linear regression and increasing Frequency of Hosts	minimize energy consumption	SLA - Decreasing the CPU frequency will reduce the system performance
Space Aware Best Fit Decreasing [16]	Reallocation VM to best fit Hosts to decreasing energy consumption	minimize energy consumption - VM selection	Reallocate VM to Hosts based on CPU utilization

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Adaptive Energy-Aware Algorithm (MCS) [17]	Classification based on SLA and VM selection for reduce energy consumption and VM migration	minimize SLA - Reduce the amount of VMs migrations	Not considering Energy and resource costs
Optimal Online Deterministic Algorithms [2]	VM selection and migration to classified Hosts	Decrease active Hosts and - minimize energy consumption	Classification only based on CPU utilization as an energy consumption
GradeCent Algorithm [18]	Classification based on the Stochastic Gradient Descent by CPU utilization	Reduce the amount of VMs migrations - minimize energy consumption	Not considering VM reallocation to Hosts
FMT [5]	Classification Hosts based on IQR and Median method to detect mid-load Hosts and reallocation VMs	Reduce SLAv and energy Consumption-Reducing the possibility of hosts being overloaded in the future	Classification only based on CPU utilization as an energy consumption - increasing number of VM migration
Robust SLR Algorithm [4]	Classification based on a linear regression	Proposed a VM migration - VM reallocation	Classification only based on CPU utilization as a power consumption - focused on VM migration
MRCU [6]	VM selection based on CPU and Memory Usage as an energy consumption	minimize energy consumption and SLAv - VM selection	Not considering VM reallocation to Hosts - increasing number of VM migration

In light of the strengths and limitations of the methodologies deliberated upon in the literature review, this research underscores several noteworthy challenges:

1. Conventional approaches for the identification of physical hosts have predominantly neglected the identification of hosts bearing medium workloads within the context of virtual machine consolidation. In this investigation, we leverage the FMT method as one of the relatively scarce techniques available for discerning and reallocating virtual machines to physical hosts characterized by medium workloads.
2. Traditionally, energy consumption metrics have fixated solely on processor usage concerning physical hosts, whereas for virtual machines, due consideration has been accorded to both processor and primary memory usage.
3. The reallocation of resources to mitigate the prospect of overloading physical hosts has not received adequate attention in preceding methodologies. Nonetheless, the proposed

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approach strives to curtail the likelihood of escalated workloads on physical hosts in the future through reallocation to hosts characterized by medium workloads.

In summation, drawing from the findings presented in Table 1, it becomes evident that addressing all facets of the virtual machine consolidation process represents a multifaceted undertaking, with various algorithms endeavoring to surmount these complexities. However, scrutinizing and enhancing all diverse metrics, encompassing energy consumption, SLAv, migration counts, network traffic, service quality, execution time, and more, proves to be an unattainable feat. Consequently, concerted efforts are directed towards proffering an apt resolution for the virtual machine consolidation predicament within the realm of cloud computing by striking an equilibrium amid two or more metrics. Thus, research in this domain persists as a captivating arena for scholars, presenting prospects for the formulation of innovative solutions and algorithms. As delineated in Table 1, the FMT [5] and MRCU [6] methodologies emerge as novel paradigms for identifying hosts characterized by medium workloads and selecting virtual machines for migration. These approaches duly account for both processor and primary memory utilization, with the overarching objective of establishing a judicious equilibrium in curtailing both energy consumption and SLAv [29]. The amalgamation of these two methodologies holds the potential to provide a fitting solution to address the aforementioned requisites.

3. Methodology

In this paper, we endeavor to address the following critical facets by presenting a method that is tailored to the task at hand:

1. The categorization of physical hosts into low-loaded, med-loaded, and low-loaded categories.
2. The identification and selection of appropriate virtual machines for migration from both high-loaded and low-loaded physical hosts.
3. The reallocation of virtual machines to med-loaded physical hosts.

To commence this investigation, it is imperative to classify the physical hosts based on their energy consumption patterns and workload levels. Subsequently, we proceed with the judicious selection of suitable virtual machines for migration. This includes the transfer of virtual machines from high-loaded hosts to those with moderate workloads and the migration of all virtual machines from low-loaded physical hosts to med-loaded ones, with the goal of eventually decommissioning the low-loaded physical hosts. The method of reallocating resources to med-loaded physical hosts may be adapted based on the likelihood of future overloading or under loading of the chosen host. This means that if a med-loaded host, selected

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for resource reallocation, is projected to become high-loaded in the future or if the current reallocation strategy is deemed likely to result in overloading, the reallocation process will be redirected to another med-loaded host. Before delving into the intricacies of the proposed method, the comprehensive definition and elucidate the energy consumption model and SLAv metrics should be provided. In following, Energy consumption model, SLAv, FMT method [5], and MRCU method [6] are explained, respectively.

3.1. Energy Consumption Model:

The energy consumption model relies on an array of parameters, encompassing processor utilization, main memory usage, and network bandwidth consumption. Given that processor utilization stands out as the primary driver of energy consumption [1, 5], one approach to curbing overall system energy consumption is the reduction of active processors (physical hosts). Additionally, an efficient distribution of workloads across various hosts, taking into account processor utilization, is designed to mitigate energy consumption. Recognizing the significant impact of processor and main memory usage, both these parameters are duly incorporated into the energy consumption model [5, 7, 19].

$$P(u) = K_{p(max)} + (1-K)_{P(max)}.U$$

(1)

- $p(max)$: Signifying the peak power consumption when a physical machine is operating at full capacity.
- K_p: Denoting the fraction of power consumed by an idle physical machine.
- U: Reflecting processor utilization, a parameter subject to variation over time due to fluctuations in workload.
- $U(t)$:Depicting processor utilization as a function of time.
- E_i: Representing the energy consumed by physical host i up to time t.
- E: The aggregate energy consumed by the entire cloud system at time T.

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

In our proposed method, the energy consumption for individual physical hosts is meticulously computed employing Equations 1 and 2. Subsequently, the energy consumption values are consolidated to ascertain the overall energy consumption within the cloud at each temporal instance [19, 26]:

$$\mathrm{E} = Tt\sum_{i=0}^{n} E_i \quad (3)$$

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Where:

- n: Denotes the total count of physical hosts.
- E_i: Represents the energy consumed by the i_{th} host.
- E: Signifies the total energy consumed by the cloud system at time T.

It is imperative to note that in Equations 1 to 3, energy consumption is predominantly contingent on processor utilization. Detailed elucidation of memory consumption is expounded upon in the ensuing section.

3.2. Service Level Agreement violation (SLAv):

Since SLA characteristics can diverge significantly across different applications, it is imperative to formulate a metric for the evaluation of SLAs. SLAv (SLA violation) is a composite metric encompassing various factors, with the paramount concern being the allocation of a surplus of virtual machines exceeding the capacity of the physical host. Consequently, this metric is accorded direct scrutiny. In simpler terms, the fulfillment of SLA requirements hinges on a physical host's ability to furnish the requisite resources for a multitude of virtual machines when the need arises. In this article, two distinct metrics have been considered for quantifying SLAv [5, 20].

1- **Percentage of Time:** This metric pertains to the duration during which physical machines are actively engaged and operate at 100% utilization. This duration is referred to as the Service Level Agreement Threshold Approach (SLATHA) violation time.
2- **Diminished Overall Efficiency Due to Excessive Virtual Machine Migrations:** This erosion in efficiency is denoted as the Performance Degradation Metric (PDM). The rationale behind employing SLATHA is rooted in the notion that when a physical host operates at 100% utilization based on the applications it hosts, the effectiveness of those applications is constricted by the physical host's capacity. Consequently, virtual machines, even when meeting the SLA's quality requirements, are unable to operate at full satisfaction. Both SLATHA and PDM metrics autonomously and equitably gauge the degree of SLAv [5, 7, 21]. As such, this article employs a composite metric that takes into account both performance degradation stemming from excessive virtual machine migrations and the load imposed on high-loaded physical hosts. This combined metric is utilized to assess SLAv, as expressed in the Equation 4 and 5:

$$SLATAH = \frac{1}{N}\sum_{i=1}^{n}\frac{T_{si}}{T_{aj}} \tag{4}$$

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$$PDM = \frac{1}{M}\sum_{j=1}^{m}\frac{C_{dj}}{C_{rj}} \tag{5}$$

In this context, N denotes the total count of physical hosts, T_{si} represents the cumulative duration during which the i_{th} physical host operates at full capacity, resulting in a breach of the service level agreement. T_{aj} signifies the overall duration for which the i_{th} physical host remains active. M stands for the number of virtual machines, while C_{dj} provides an estimate of performance degradation experienced by the j_{th} virtual machine due to migration. C_{rj} indicates the total processor capacity requested by vm_i throughout its entire operational duration. Since both the $SLATAH$ and PDM metrics autonomously and equally determine the extent of SLA violation, this article adopts a consolidated metric [5,7,21]. This composite metric takes into consideration both the performance deterioration attributable to excessive virtual machine migrations and the burden imposed on high-loaded physical hosts. This comprehensive metric for SLAv is articulated by the Equation 6:

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

As previously discussed, the process of virtual machine consolidation comprises the following stages:

1. Identification of high-loaded, low-loaded, and med-loaded physical hosts.
2. Selection of virtual machines.
3. Virtual machine migration (migration method).
4. Reallocation of virtual machines to physical hosts.

- **Detection of high-loaded, med-loaded, and low-loaded physical hosts:**

For each segment of the virtual machine consolidation process, various techniques have been developed and investigated by researchers, either in a specific or general context. In this article, we intend to employ the FMT method [5] in the initial stage to identify the workload levels on each physical host. The choice of this method can effectively categorize physical hosts not only as high-loaded and low-loaded but also as med-loaded. This strategic selection, combined with the reallocation of virtual machines to this category of med-loaded physical hosts, significantly reduces the likelihood of their future overloading.

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FMT Method [5]:

The FMT (First Median Threshold) method, presented in this section, employs a threshold value to discern the operational states of physical hosts as high-loaded, low-loaded, or med-loaded. The primary concept underpinning this approach revolves around the identification of med-loaded hosts and the subsequent reallocation of computational resources to these hosts. The objective extends beyond the mere reduction of energy consumption; it also encompasses the mitigation of the likelihood of other hosts transitioning into states of heaviness or lightness. This intricate method leverages the median technique [13] as an integral component within the broader framework of the Interquartile Range (IQR) algorithm [11]. The initial phase of the method entails the computation of the IQR threshold, a critical metric for the identification of host overloads or under-loads.

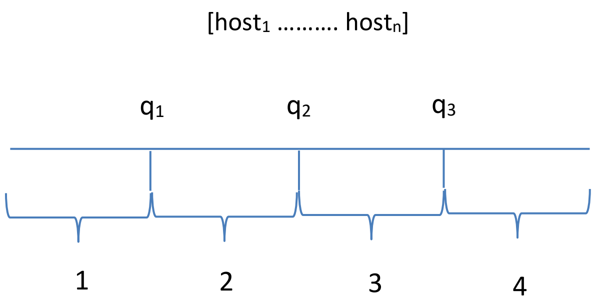

Figure (2): Host Classification Based on Threshold Value

As shown in Figure 2 is the stepwise process employed in categorizing the total population of physical hosts. This categorization categorizes hosts into four distinct groups based on the extent of their computational burdens, a classification that warrants further scrutiny. Subsequently, the median value for each of these predefined categories is computed.

The algorithm for computing the median is executed as follows:

a. Physical hosts are meticulously sorted in an ascending order based on their workload, with the processor usage serving as the yardstick.
b. In the instance where the count of physical hosts is an odd number, the median is determined by selecting the middle host. Conversely, when the count is even, the two middle hosts are chosen, and their arithmetic mean is designated as the median.
c. Through iterative processes, two subsets, denoted as "a" and "c," are systematically generated. The median calculation process for these subsets, "a" and "c," is reiterated until the point of convergence, wherein all physical hosts are collectively enveloped by one singular set.

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Every constituent of the ensemble of physical hosts is accorded due consideration. The central ambition of this article resides in the identification of the optimal locus for the reallocation of resources, an endeavor facilitated by the calculation of the median as stipulated within the IQR threshold methodology, that are shown by Equation 7 and 8.

$$if\ \frac{A_i}{2} = 2x\ (x\ \in 1,2,3,4,5,\dots,\infty) \begin{cases} T_i = median(x_i) \\ T_u = median(x_j) \end{cases} \quad (7)$$

$$if\ \frac{A_i}{2} = 2x + 1\ (x\ \in 1,2,3,4,5,\dots,\infty) \begin{cases} T_i = median(y_i) \\ T_u = median(y_j) \end{cases} \quad (8)$$

Finally, the classification of host states, characterized by overloads and under-loads, is established through the imposition of the ensuing conditions, which are shown by Equation 9 and 10

$$If\ CA_i > T_u\ (A_i = O_h) \quad (9)$$

$$If\ CA_i > T_i\ (A_i = U_h) \quad (10)$$

The methodology introduced in reference [3], operating autonomously, exhibits proficiency in the detection of host overloads and under-loads. Its operational paradigm revolves around the judicious redistribution of resources to hosts carrying lighter computational workloads, a strategy aimed at equitable workload distribution and, consequently, the reduction of SLAv. Nonetheless, it is crucial to underscore that such reallocation can potentially engender a surge in migration instances and energy consumption in specific scenarios, thereby amplifying the prospects of impending overloads or under-loads. Consequently, this article endeavors to embrace a more holistic approach by implementing the IQR algorithm. This algorithm, supplemented by the median technique, furnishes a framework that not only discerns high-loaded and low-loaded hosts but also identifies hosts characterized by a moderate computational burden.

As delineated in Figure 3, the energy consumption dataset, portraying the energy consumption figures corresponding to each physical host, is methodically ordered in ascending sequence. The subsequent application of the IQR threshold algorithm engenders the systematic partitioning of the entire ordered dataset into four distinct categories.

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[List of hosts sorted in ascending order]

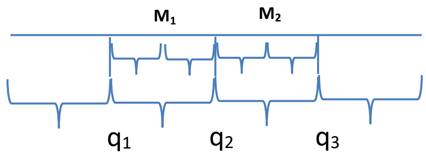

Figure (3): Categorization using the Quartile Method with Calculation

Of the Median of Two Middle Categories

As elucidated in Table 2, hosts with energy consumption values falling below the threshold q_1 are assigned the status of low-loaded, while hosts with values exceeding q_1 but below q_3 are designated as med-loaded. On the other hand, hosts with energy consumption figures surpassing the threshold q_3 are categorized as high-loaded. Furthermore, leveraging the median methodology, median values q_1 and q_2, as well as q_2 and q_3, are meticulously calculated and denoted as M_1 and M_2, respectively which are presented by Equation 11. This alphanumeric arrangement culminates in the establishment of the median M, which inherently encapsulates the midpoint between two distinct intervals. Additionally, the variable C_i is employed to designate the class of med-loaded physical hosts.

$$M_1 = q_1 \,\mathrm{M}\, q_2 \quad , \quad M_2 = q_2 \,\mathrm{M}\, q_3 \qquad (11)$$

The execution of the proposed methodology, entailing the calculation of medians M_1 and M_2, culminates in the systematic categorization of hosts into high-loaded, low-loaded, and med-loaded classes. This classification proceeds as follows Table 2:

Table (2): Host Med-Load between the first quartile and q_2

$< q_1 c_i$	Low-load
$< c_i < q_2 M_1$	med-load
$< c_i q_3$	High-load

The FMT methodology, beyond its role in classifying and identifying high-loaded and low-loaded physical hosts, orchestrates the strategic migration of virtual machines onto high-loaded physical hosts, thereby preempting SLAv. Simultaneously, it oversees the migration of virtual

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machines onto low-loaded hosts with the express intention of their shutdown, an initiative that contributes significantly to the reduction of overall energy consumption. Consequently, the overarching implication underscores that all migrated virtual machines, whether originating from high-loaded or low-loaded physical hosts, find their allocation within the confines of med-loaded physical hosts, a realm characterized by the condition $M_1 < C_i < q_2$.

- **Virtual machine selection:**

MRCU Method [6]:

In the second phase of the virtual machine consolidation process, known as the "Selection of Virtual Machines," we employ the MRCU (Maximum Ratio of CPU utilization to memory Utilization) methodology. Despite the fact that this approach encompasses the classification and identification of high-loaded and low-loaded host machines, in addition to the selection of virtual machines, we opt to focus solely on its utilization for the selection of virtual machines. This decision is rooted in our primary objectives, which are to reduce energy consumption and mitigate SLAv. In this particular methodology, in contrast to the FMT approach, where host machines are categorized and sorted based solely on CPU utilization, the utilization of main memory is taken into account when choosing virtual machines. This consideration is motivated by the observation that Central Processing Units (CPUs) frequently allocate a substantial portion of their processing time to reading from and writing to the main memory. Consequently, we calculate the energy consumption of each virtual machine by considering both the cumulative CPU and main memory usage. Under this methodology, the selection of a virtual machine for migration is determined from the pool of high-loaded physical host machines, with preference given to those that exhibit the maximum ratio of CPU usage to main memory usage. The selection process commences with the calculation of energy consumption for each virtual machine based on their CPU and main memory usage on each physical host machine. Subsequently, the ratio of energy consumption, as calculated based on CPU usage, to that calculated based on main memory usage, is computed for each virtual machine on each physical host machine. The resulting list is then sorted in ascending order, and ultimately, those virtual machines whose energy consumption (as indicated by the Maximum CPU-to-main-memory ratio) surpasses the threshold set for the physical host machine are chosen for migration, which is shown by Equation 12.

$$\frac{C_{VM}^{v}}{M_{VM}^{v}} > \frac{C_{VM}^{e}}{M_{VM}^{e}} \qquad (12)$$

In accordance with Equation 12, the virtual machine denoted as VM v is selected for migration when it exhibits the highest value of (C_{VM}^{v}) / (M_{VM}^{v}). This implies that the virtual machine characterized by the highest CPU consumption (C_{VM}^{v}) and the lowest main memory

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consumption (M_{VM}^{v}) relative to the total resources is the preferred candidate for migration. Furthermore, the ratio (C_{VM}^{e}) / (M_{VM}^{e}) represents the total energy consumption for a physical host machine.

Figure 4 provides a visual representation of the algorithm proposed for the virtual machine consolidation process. This algorithm is founded on the FMT method for the identification of host machines with average loads, their reallocation, and the application of the MRCU method for the selection of virtual machines to be migrated.

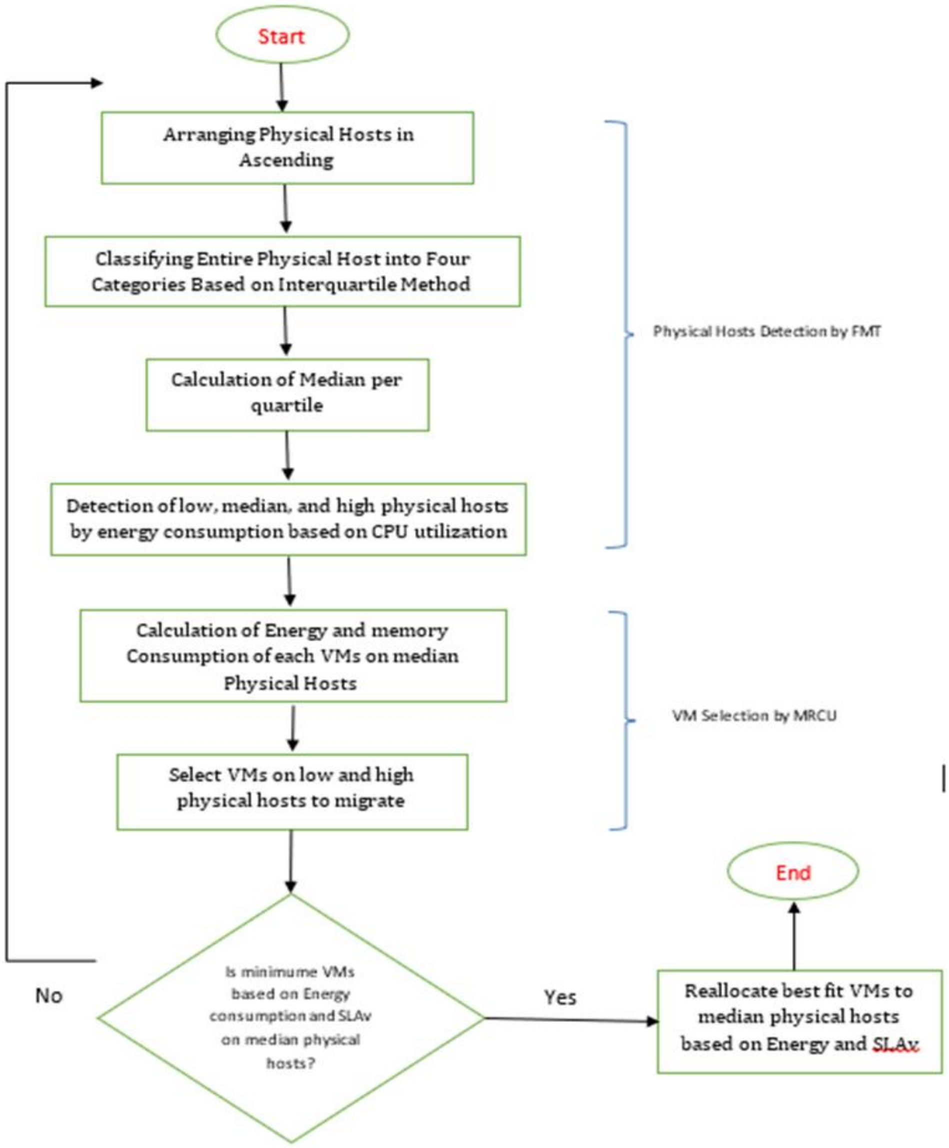

Figure (4): Proposed method flowchart

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4. The simulation and evaluation of results

In order to simulate and evaluate the proposed method in this research, the implementation of the FMT and MRCU methods in the virtual machine consolidation process has been carried out using the CloudSim 4 simulator. Measurable parameters include the total system energy consumption, SLAv, the number of shut-down virtual machines, and the number of migrations, each of which is assessed separately [7, 20, 21]. These parameters are determined based on the model for identifying high-loaded, low-loaded, and med-loaded hosts in physical hosts, as well as the mechanism for selecting virtual machines.

The energy consumption, which was discussed in section 1-3, serves as a measurement metric in the implementation of the proposed method. The objective in this phase is to reduce the overall system energy consumption. The SLAv, as explained in section 2-3, consists of two components: SLATAH and PDM. Since contract violation is directly related to customer satisfaction rates [5, 7, 24], cloud providers strive to meet higher levels of customer demand, making every effort to reduce SLAv. The experimental datasets, evaluation metrics and evaluation of experimental results are presented in following.

4.1. Experimental Dataset

To implement the proposed method on a tested dataset, real-world data has been utilized. These datasets contain actual information, and the results obtained from them are simulated based on real data. These datasets are categorized based on the number of virtual machines derived from precise experimental results and are related to the collection of data on over several thousand virtual machines and physical hosts on different dates. This data is provided in the form of the "Planet Lab" dataset in the CoMon project, which collected information from thousands of physical hosts in 500 different regions every five minutes [22, 23]. The dataset features for each day are presented in Table 3, where the dataset name, the number of virtual machines, the number of physical hosts, and the average workload are specified.

Table (3): Experimental Datasets

Dataset	# VMs	# PHs	Average Workload
2011/03/03	1052	800	12.31%
2011/03/09	1061	800	10.70%
2011/03/22	1516	800	9.26%
2011/04/03	1463	800	12.39%
2011/04/09	1358	800	12.39%
2011/04/20	1033	800	10.43%

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4.2. Evaluation Metrics

To compare the proposed method with previous approaches under identical conditions and scenarios, the datasets in Table 3 are employed. The following evaluation metrics are considered for comparison:

- **Energy consumption:** based on Equation 2 and Equation 12.
- **Service Level Agreement violation (SLAv)**: SLAv, which is calculated according to Equation (13).

Where n represents the number of virtual machines.

$$Overal\ SLAv = \frac{\sum_{k=1}^{n}(requsted\ MIPS) - \sum_{k=1}^{n}(allocated\ MIPS)}{\sum_{k=1}^{n}(requsted\ MIPS)} \quad (13)$$

- **Number of migrations**: Virtual machine migration is a time-consuming process, adding to system overhead, and increasing both energy consumption and network traffic. Therefore, an essential metric in determining the efficiency of the proposed method is the calculation of the number of migrations [24].

- **Efficiency:** Shutting down physical machines and placing them in a low-power state can increase their susceptibility to failures compared to machines that are always on [24, 25]. Therefore, the efficiency of cloud computing systems decreases as the consolidation rate increases. The consolidation rate is the percentage of physical machines that are shut down during the consolidation process. Thus, the consolidation rate is defined according to Equation 14:

$$CR = \frac{\sum_{i=1}^{nc} NTO}{NC \times S} \quad (14)$$

Where NTO represents the number of physical machines that are shut down during each time interval. Additionally, N and NC are the total number of physical hosts and the total number of consolidation processes, respectively. As previously mentioned, in this paper, data from the CoMon project, which monitors the CPU usage of PlanetLab physical hosts every five minutes over a 24-hour period, is utilized. Therefore, the value of NC is equal to 288.

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$SLAv$ and CR are both parameters crucial to the performance of cloud computing systems. These metrics have an inverse relationship, meaning that reducing energy consumption leads to increased $SLAv$ and CR. Therefore, a combined metric, taking all these parameters into account, is defined [25, 28]. This metric, known as ESC, is defined according to Equation 15:

$$ESC = E \times SLAv \times CR \quad (15)$$

In Equation 15, E represents energy consumption, SLAv represents the contract violation rate, CR represents the consolidation rate, and ESC represents the overall system efficiency metric considering all three parameters in the virtual machine consolidation process.

4.3. Evaluation of Experimental Results

In this section, the results obtained from the simulation of the proposed method are evaluated. The tested methods in this section for the six datasets (Table 3) include FMT, MRCU, IQR, MAD, Robust SLR, and MEDTH.

As illustrated in Figure 5, the proposed method, which combines the FMT and MRCU methods, outperforms the other methods in terms of energy consumption in most cases. However, for the dataset with the highest number of virtual machines (1516) on the date

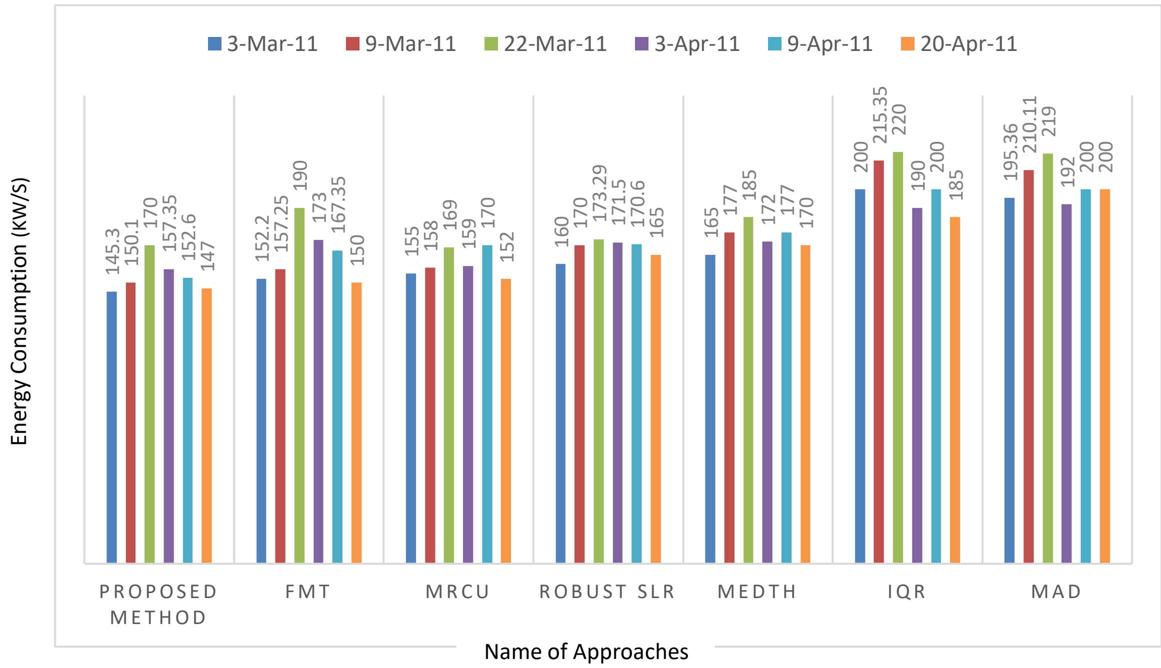

Figure (5): Energy Consumption Comparison in different approaches

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2011/03/22, the proposed method performs similarly to the MRCU method. This trend is also observed for the dataset on 2011/04/03. Additionally, for the dataset with the fewest virtual machines (1033) on 2011/04/20, the proposed method outperforms all the compared algorithms.

This implies that under conditions with a lower count of virtual machines, the proposed method exhibits superior energy consumption performance. To summarize, the performance of all seven algorithms concerning energy consumption can be summarized as follows:

Proposed Method < MRCU < FMT < Robust SLR < MEDTH < IQR < MAD

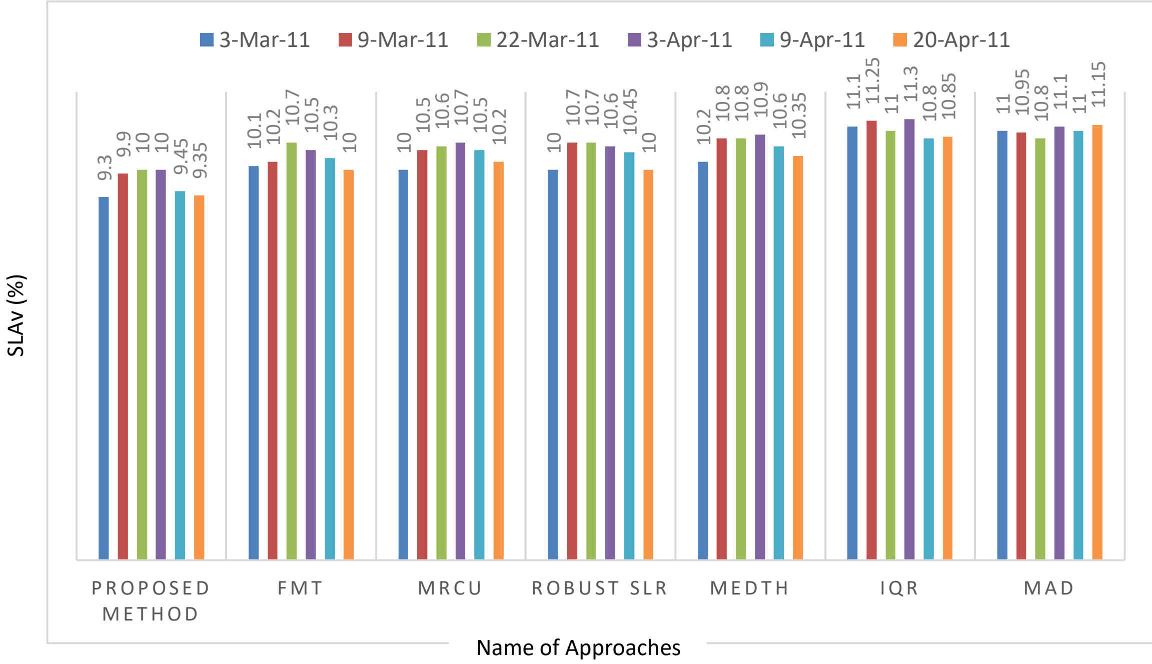

Figure (6): SLA violation Comparison in different approaches

Following energy consumption, the most critical criterion in virtual machine consolidation is the extent of contract violation, as illustrated in Figure 6.

Based on the findings depicted in Figure 6, it becomes evident that the extent of contract violation among the various algorithms under scrutiny closely approximates one another. Notably, the proposed method exhibited its optimal performance concerning SLAv in the dataset corresponding to 2011/03/03, encompassing 1052 virtual machines, registering a contract violation rate of 9.30%. This commendable performance was likewise replicated in the dataset dated 2011/03/22, which featured 1516 virtual machines, resulting in an analogous contract violation rate of 10%. Hence, it is deducible that the proposed method excels in

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mitigating SLAv, particularly in datasets characterized by a higher virtual machine count. Subsequently, following the proposed algorithm, the MRCU and Robust SLR algorithms showcased superior outcomes, followed by the FMT method. In sum, considering the outcomes of our simulations, the performance of the seven algorithms with respect to contract violation rates can be summarized as follows:

Proposed Method < FMT < Robust SLR < MRCU < MEDTH < MAD < IQR

One of the pivotal virtual machine consolidation strategies entails the selection of virtual machines from high-loaded physical hosts, primarily aimed at curtailing energy consumption and SLAv. Additionally, virtual machines are chosen from low-loaded physical hosts for the purpose of powering them down, ultimately leading to an overarching reduction in energy consumption. The number of deactivated physical hosts exhibits a direct correlation with energy consumption reduction. However, the process of powering down a physical host necessitates the migration of all virtual machines hosted on it, thereby potentially increasing the frequency of migrations and subsequently giving rise to network traffic. Figure 7 provides a visual comparison of the number of virtual machine migrations associated with each algorithm.

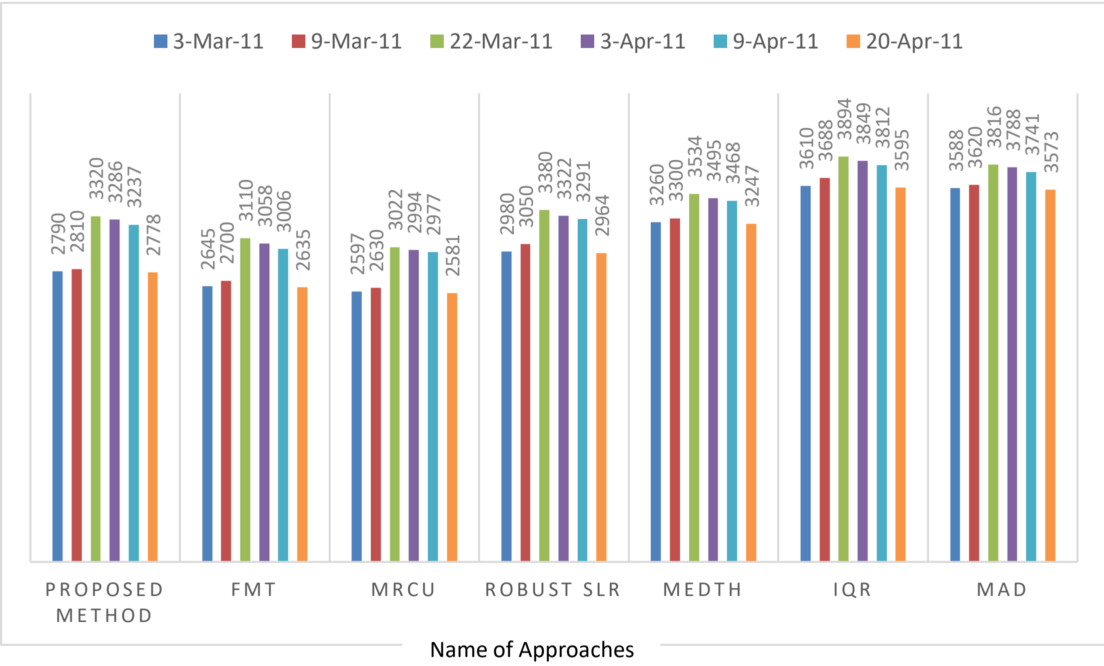

Figure (7): The number of VM Migrations Comparison in different approaches

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Drawing upon the findings presented in Figure 7, it is evident that the proposed algorithm experienced a marginal uptick in the number of migrations when juxtaposed with the FMT and MRCU methods, albeit surpassing the performance of other algorithms. As an illustrative example, within the dataset dated 2011/04/20, characterized by the lowest virtual machine count (1033), the proposed algorithm recorded 2778 migrations, while the FMT method registered 2635 migrations, and the MRCU method tallied 2581 migrations. Table 4 further encapsulates the mean number of migrations across six datasets and the assorted algorithms as delineated in Figure 7.

Table (4): Average number of migrations of VMs

Approaches	**Average number of migrations of VMs**
Proposed Method	3036.83
FMT	2859
MRCU	**2800.16**
Robust SLR	3165.5
MEDTH	3384
IQR	3741.33
MAD	3687.66

Table 4 provides a basis for evaluating the performance of each algorithm, with the number of virtual machine migrations serving as the key criterion for assessment.

MRCU < FMT < Proposed Method < Robust SLR < MEDTH < MAD < IQR

The overall performance of the proposed algorithm in comparison to the MRCU and FMT algorithms can be attributed to its success in reducing both energy consumption and SLAv. As previously elucidated, the principal aim of the proposed algorithm is to achieve equilibrium among various metrics, including energy consumption, contract violation rates, and the count of virtual machine migrations, throughout the virtual machine consolidation process. Consequently, the commendable performance of the proposed approach in curbing energy consumption and SLAv may result in a relatively inferior performance in terms of migration count when juxtaposed with alternative methodologies. Tables 5 and 6 provide an overview of

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the mean energy consumption and contract violation rates across the six datasets subjected to experimentation.

As Table 5 illustrates, the proposed methodology demonstrates the lowest energy consumption at 153.72 KW/h, while the MAD approach registers the highest energy consumption at 202.74 KW/h among the assessed techniques. Conversely, as Table 6 reveals, the proposed method boasts the lowest SLAv rate, standing at 9.66%, whereas the IQR method presents the highest rate at 11.05% among the methods subjected to testing.

Table (5): Average of energy consumption (kw/h)

Approaches	Energy consumption
Proposed Method	**153.72**
FMT	164.9
MRCU	160.5
Robust SLR	168.39
MEDTH	174.33
IQR	201.72
MAD	202.74

Table (6): Average of SLAv (%)

Approaches	SLAv
Proposed Method	**9.66**
FMT	10.30
MRCU	10.41
Robust SLR	10.40
MEDTH	10.60
IQR	11.05
MAD	11

In a broader context, the proposed methodology has consistently exhibited superior performance when compared to each of the assessed algorithms. This superiority is particularly notable in terms of energy consumption reduction and SLAv minimization during the processes of virtual machine selection, identification of hosts with mod-load, and resource reallocation. Comprehensive system performance, as detailed in Table 7 and calculated using Equation 14 alongside other evaluation metrics, provides further insight.

Table (7): Overall performance

Dataset	Approaches	Energy (kw/h)	SLAv (%)	Migration	ESC * 10^{-5}
2011/03/03	Proposed Method	**145.3**	**9.3**	2790	**0.110**
	FMT	152.2	10.1	2645	0.113
	MRCU	155	10	**2597**	0.117
	Robust SLR	160	10	2980	0.121

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	MEDTH	165	10.2	3260	0.124
	MAD	195.36	11	3588	0.145
	IQR	200	11.1	3610	0.150
2011/03/09	Proposed Method	**150.1**	**9.9**	2810	**0.113**
	FMT	157.25	10.2	2700	0.119
	MRCU	158	10.5	**2630**	0.120
	Robust SLR	170	10.7	3050	0.127
	MEDTH	177	10.8	3300	0.132
	MAD	210.11	10.95	3620	0.159
	IQR	215.35	11.25	3688	0.162
2011/03/22	Proposed Method	170	**10**	3320	**0.128**
	FMT	190	10.7	3110	0.142
	MRCU	**169**	10.6	**3022**	**0.128**
	Robust SLR	173.29	10.7	3380	0.131
	MEDTH	185	10.8	3534	0.140
	MAD	219	10.8	3816	0.165
	IQR	220	11	3894	0.166
2011/04/03	Proposed Method	**157.35**	**10**	3286	**0.119**
	FMT	173	10.5	3058	0.130
	MRCU	159	10.7	**2994**	0.120
	Robust SLR	171.5	10.6	3322	0.129
	MEDTH	172	10.99	3495	0.130
	MAD	192	11.1	3788	0.145
	IQR	190	11.3	3849	0.143
2011/04/09	Proposed Method	**152.6**	**9.45**	3237	**0.115**
	FMT	167.35	10.3	3006	0.126
	MRCU	170	10.5	**2977**	0.128
	Robust SLR	170.6	10.45	3291	0.128
	MEDTH	177	10.6	3468	0.132
	MAD	200	11	3741	0.151
	IQR	200	10.8	3812	0.151
	Proposed Method	**147**	**9.35**	2778	**0.111**

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2011/04/20	FMT	150	10	2635	0.113
	MRCU	152	10.2	**2581**	0.114
	Robust SLR	165	10	2964	0.124
	MEDTH	170	10.35	3247	0.128
	MAD	200	11.15	3573	0.151
	IQR	185	10.85	3595	0.140

Table 7 clearly demonstrates that the proposed algorithm surpasses its counterparts in the dataset corresponding to March 3, 2011. Here, it achieves an energy consumption of 145.3, a SLAv rate of 9.3%, and a performance score of 0.110, all of which are highlighted in bold. In contrast, the MRCU method excels in the migration count criterion in this dataset, boasting a count of 2597. In the dataset for March 22, 2011, the MRCU method exhibits more efficient energy consumption with 169 units, in contrast to the proposed method's energy consumption of 170. However, in the SLAv rate metric, the proposed method records a rate of 10%, while MRCU registers 10.6%. Moreover, in terms of the migration count metric, MRCU records 3022 migrations, outperforming the proposed method with its 3320 migrations. Nevertheless, both methods achieve an identical ESC metric score of 0.128. Across the remaining datasets, the proposed method consistently outperforms the other evaluated techniques across all metrics. Consequently, the performance summary for each method, concerning these metrics, can be presented as follows:

Proposed Method < MRCU < FMT < Robust SLR < MEDTH < MAD < IQR

5. Conclusion and Future works

In this research, we have undertaken the utilization of two methods, FMT and MRCU, for the consolidation of virtual machines. Our primary objective extends beyond the mere reduction of energy consumption; we also aim to maintain user SLAv at their lowest possible level. The FMT method operates by reallocating virtual machines to hosts characterized by med, high, and low-loads. This strategic allocation minimizes the risk of overloading physical hosts and further optimizes energy usage through the shutdown of lightly loaded physical hosts. Nonetheless, selecting the most suitable virtual machines from high-loaded physical hosts is pivotal for the process of migrating virtual machines and reallocating them to med-loaded physical hosts. To facilitate this selection, the MRCU method assesses the processor and main memory utilization of virtual machines responsible for overloading physical hosts, subsequently earmarking them for migration.

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Throughout this study, we have diligently aimed to strike a balance while upholding four critical metrics in the virtual machine consolidation process: energy consumption, SLA(v) rates, migration counts, and overall system performance. To validate the efficacy of our proposed method, we conducted simulations employing six datasets sourced from the CoMon project. The simulation outcomes affirm the commendable performance of our proposed approach, not only in terms of reducing energy consumption and mitigating SLAv but also in comparison to several other benchmarked algorithms. However, it is imperative to acknowledge the inverse relationship between energy consumption and the number of migrations; a decrease in energy consumption typically correlates with a relative increase in migration count.

As part of our future research agenda, we plan to extend our considerations beyond energy consumption and main memory utilization, delving into storage memory and network bandwidth. Furthermore, we intend to explore a range of virtual machine migration techniques within the framework of our proposed virtual machine consolidation process. Additionally, we aim to conduct comprehensive assessments, encompassing network bandwidth utilization, the count of powered-off hosts, and the total execution time for physical machines, all within the scope of our proposed algorithm. These endeavors promise to yield valuable insights into the broader landscape of virtual machine consolidation.

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