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VIRTUAL MACHINE PLACEMENT USING OPTIMIZATION TECHNIQUES IN CLOUD COMPUTING MODEL

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ABSTRACT

Nowadays, cloud computing is the dominant technology that propels businesses forward. Several data centres have been built as a direct consequence of the explosion in popularity of cloud computing. As a result of their high energy consumption, data centres are a substantial contribution to global warming and climate change. It was because of this that virtualization was implemented. It's a matter of trial and error to find the optimal location for your virtual machines (VMs). Many algorithms are presented, their performance is evaluated in light of the required metrics, and the best of these are continually improved upon. The primary objective is the location of the virtual machines. The elastic peak workload of cloud transportation planning should not be used to determine how resources should be made accessible. Algorithms that take cues from nature tend to do better in this field because they can sift through a large search space for a promising answer. Floral pollination algorithms, particle swarm optimization algorithms, ant colony algorithms, ant bee colony algorithms, and firefly algorithms are only a few examples of nature-inspired algorithms. The optimization of particle swarms and ant colony techniques stand out among these programmes as the focus of several studies.

Keywords: VM Placement, Reinforcement Learning, Cloud Services and Deadline Awareness.

I. INTRODUCTION

Cloud hosting allows many users to share servers, databases, and networks. Providers of cloud computing services made their offerings accessible to customers, who often accessed them in the form of virtual computers (VMs). As more and more residents come to rely on the city's edge cloud, any disruptions there might drive up costs by boosting CPU use and delaying completion of the project. This is the main technological hurdle that has to be crossed before an edge computing can be built. Virtual machine deployment optimization methods that prioritize efficiency consider both power use and network delay. After a list of virtual machines to migrate has been produced, the GA algorithms are used to rate the vms in accordance with the values supplied to them in the different pairs of rankings (the LRR host device screenings model and the MMT timing model). The simulation findings demonstrate that by using this strategy, it may be possible to decrease latency by 16.11% and CPU use by 20.21% on a cloud system node. When it comes to the theoretical advancement of cloud computing, this optimization model has been crucial. New optimization methods have emerged as a result of the exponential rise in engineering system complexity. Many optimization issues in the real world include many levels and multiple objectives. Today's organizations may benefit greatly from cloud technology. Customers have a wide variety of options to choose from. The ability to set up a virtual machine in the cloud is one of the most fascinating and consequential features of cloud computing (VMP). In order to reduce the stress on the actual computers that make up a network and, by extension, the energy required to run them, Virtual Machine Placement employs evolutionary computing. Using the concept of order transfer, the author analyzes the promising results achieved by the ACS in solving combinatorial problems. To address this challenge, IBM's R&D team developed an original strategy they dubbed OEMACS. The novel approach integrates order exchange and migration local search strategies and is based on ACS (Order exchange and Migration Ant Colony System). The OEMACS method of virtualized assignment has the ability to greatly reduce the number of active servers from the perspective of optimization algorithms. It also helps in reducing the number of unused servers, which is a nice plus. In OEMACS, pheromones are used to move mechanical ants in the appropriate direction. To further reduce unnecessary energy and material use, it also improves the physical placement of virtual devices. This method is used by servers that house virtual machines with varying hardware configurations. The results show that OEMACS works better than regular algorithms like heuristics and other intelligent methods. In computing, "the cloud" refers to a shared pool of resources housed on distant computers. Parallel processing, in which several computers in a network execute the same program simultaneously, is required. Using cloud-based processing power and the idea of virtualization may improve data center efficiency. In order to prevent overloading any one virtual server, internet network protocols divide up the workload equitably across all of them. The virtualization approach enhances server efficiency by creating "instances" of physical state machines. Stochastic modeling is used by providers of cloud services in their dynamic data centers to maximize efficiency. The proliferation of cloud computing as a practice is promising because of the many ways in which it might facilitate improved global trade over the internet. With the help of deployment

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services, you can quickly and easily set up your cloud-based application in a targeted setting. You may use any one of a wide variety of computational ways to communicate with the cloud computing. It is standard practice to migrate virtual machine instances (VMs) in order to move a computational system to a new host without disrupting service to the application or client. By migrating virtual machines, it may be possible to lessen the system's overall energy consumption, workload, and error rate. We separate testing needs from production needs, schedule transfers and shutdowns accordingly. In data centers, the Live Migration procedure may help cut down on power use. The term "cloud computing" refers to the practice of storing data and applications on third-party servers, which is a frequent component of cloud computing. The use of cloud computing and similar techniques has skyrocketed in prominence in the past few years. Because of its massive power needs, the cloud - based data center is a significant contributor to global warming gases. To reduce the number of servers doing work, scheduling virtual machines onto actual servers is the most effective method for saving power in the IaaS cloud. You can lower the data center's total power usage by shutting off servers. The primary goal of this study is to use a variation of the energy-efficient continuous firefly algorithm to schedule as many virtual machines as possible on as few real servers as is physically feasible. It is becoming more common to store and access information through "cloud" servers, which may be accessed from a variety of devices. When "green" is the main design aim, the best way to reduce environmental impact is via smart energy management. Adaptive data transmission may be managed by optimizing the performance of several physical computers located in different data centers. By consolidating resources and then using smart distribution of virtual machines, cloud service providers may be able to raise the bar on service quality. Another well-known technique for maximizing fuel efficiency in virtual worlds is to cluster virtualization technology in close proximity to their real-world counterparts inside a single physical data center. In order to better fulfill the time-sensitive demands of its users, optimization techniques often use cues from model organisms to improve communication, energy usage, management systems, and other areas of effectiveness and efficiency. This research synthesis considers how biological models may be used to categorize techniques for installing virtualized infrastructure. In this article, we explore the essential principles behind VM placement, including their benefits and drawbacks, the accomplishment of tangible and invisible characteristics, the fulfilment of end-user demands and needs, and the difficulties and obstacles in the design and execution of VMs. With the intention of helping readers get a more thorough understanding of the models, we provide a variety of approaches, techniques, and applied mathematics, and evaluate their efficacy on both real and simulated hardware. That's all there is to it when it comes to dependable functioning and power management globally. The essay wraps off by discussing what the future holds for biological systems.

II. LITERATURE REVIEW

This causes delays in responding to user queries and forces the deployment of more resources than are really required. Virtualization's primary goal is to reduce the monetary burden associated with deploying software to various hardware components. Principal Component analysis Analysis (ICA)

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and other stress reduction techniques are used during attribute selection. A revised version of the Cauchy swarm - based approach is utilized to distribute the resources available after an attribute has been selected. Cluster data is used to analyze how many people are able to relocate and how much power is saved by using the technique. The best approach is superior to the status quo and the usual method since it uses less energy and has fewer VM migrations. As a result, the suggested ICA and the very intuitive MCPSO are the optimal choices for dynamically allocating cloud resources. [11]. Optimizing the location of cloud-based virtual computers is the focus of this work, and to that end, researchers provide Fractional Particle Swarm Chicken Swarm Optimisation (Fractional ABCSO) (VMs). A combination of the chicken optimization technique (CSO) as well as the fraction concept (FC), Artificial Bee Colony Optimization (ABCO) aims to maximize bee colonies (ABC). Cloud computing is simulated here by use of a combination of virtual machines (VMs) and actual computers (PM). The selection of a host for a virtual machine (VM) depends on a wide range of system criteria, including central processor unit, number of multiple instruction points, cost of migration, memory, bandwidth, speed, power consumption, and Quality of Service (QoS). Compared to traditional methods, the created Fractional ABCSO methodology only used 0.1614, 0.0535, and 0.0408 times the load, migration cost, and power, respectively. This research suggests an auction-based mechanism that gives weight to energy efficiency when assigning cloud computing resources. The given bidding language in the proposed paradigm enables cloud users to bid on requests for virtual resources, with the disclosure of interconnections and modifiability among some of the resources. The approach employs an optimization model to determine the optimal distribution of virtual servers to end users and the optimal placement of digital resources in relation to physical cloud resources. The model proposes an energy-aware solution to the allocation of resources by factoring in the non-linear energy needs of the material assets in relation to their consumption levels. Integer programming is used to properly describe and explain the related optimization issue. Although the optimization process is notoriously difficult, four heuristic techniques are also presented. A battery of tests is performed on a full-fledged test suite to assess the framework's and the heuristics' usefulness. The outcomes show that the suggested paradigm is helpful and that the proposed methods are effective in generating high-quality outcomes [13]. The goal of this study is to provide a roadmap for addressing the cloud computing industry's bi-level vm placement challenge. This is accomplished by fusing the Stackelberg game theoretic and weighted-sum frameworks with the coupled map lattice (CML) method. Given the complexity and unpredictability of the real world, the VM placement issue was reformulated as a multi-objective (MO) bilevel problem. The effectiveness of particle swarm optimization and the CML method were examined and contrasted. To compare the two sets of data, we create and use a novel bilevel statistic called the cascaded hypervolume indicator. Detailed commentary on the computations is given [14]. This study offers a heuristic approach to reducing energy use and material waste in tandem. Known as MinPR, the suggested strategy prioritizes physical machines with the lowest energy use in order to reduce overall power consumption. Not only does this ensure that machines are using their resources as efficiently as possible, but it also helps to ensure that everyone benefits from the efficiency gains. To this end, we provide a novel paradigm for managing the distribution of available computing resources across several virtual machine instances, including rewards and punishments based on the Resource Usage Factor. Simulations employing cloud consumer virtual machines and Amazon EC2 Instances applications prove the viability of the proposed approach. The suggested strategy may also cut overall energy usage by up to 15% for cloud consumer VMs and so by up to 10% for Amazon EC2 Instances [15]. In this piece, we examine how the virtualization strategy might be used to better optimize cloud data centers. The suggested approach utilizes stochastic modeling to make the most of available cloud data center resources. Data centers in the cloud use load balancing to ensure optimal performance [16]. The Optimal Energy Model has been offered as the system's hourly energy consumption is increasing exponentially, the suggested procedure is in charge of rearranging the nodes and reducing energy consumption thereafter [17], while the VM Method is used to determine the exact number of hosts in the data hub. The primary goal of this study is to use a variation of the energy-efficient continuous algorithms to schedule as many virtual machines as possible on as few real servers as is physically feasible. The suggested technique will thoroughly investigate the available space to locate a configuration that significantly reduces power consumption in data centers. We discover that the proposed method, which includes deploying virtual machines of different configurations to the IaaS cloud, generates better results compared to the Genetic Algorithm and the algorithm for Particle Swarm Optimization [18]. The authors of this work propose a heuristic approach to this issue in an effort to reduce carbon emissions and waste. By selecting the physically most efficient machines and reducing the number of active units, the suggested method, nicknamed MinPR, reduces overall power consumption. Optimal use of machines' resources means less waste, hence this method is preferred. To achieve this, we provide a novel paradigm for regulating the distribution of physical and virtual computing resources using incentives and penalties based on the Resource Usage Factor. The efficacy of the proposed solution is shown via experiments employing cloud user VMs and Amazon EC2 Instances applications. When implemented, the proposed solution may decrease overall energy use by up to 15% for cloud user-customized VMs and up to 10% for Amazon EC2 Instances [19]. In this research, we provide a procedure for creating VMP systems using user-defined PEs. An innovative approach is also offered to solve the VMP issue by making use of RF components in a cloud setting. Discovery, evaluating the surroundings, modeling, extracting variables, limits, adapting the model, issue formulation, and heuristics are all part of the process. Parameter extraction is a vital part of the solution development process. Information is collected, and a PM is chosen to host the appropriate virtual machine. Our suggested VMP approach, when combined with our recommended cloud architectural model, has been shown to be better in simulation results based on artificial workload designs [20].

III. PROPOSED MODEL

Methods for Deciding on a Good Host Machine for a VM. The VM placement is said to be static if the mappings between virtual machines does not vary over time. With a "dynamic VM placement" architecture, the geographical space of virtual servers may alter in accordance to fluctuating resource requirements.

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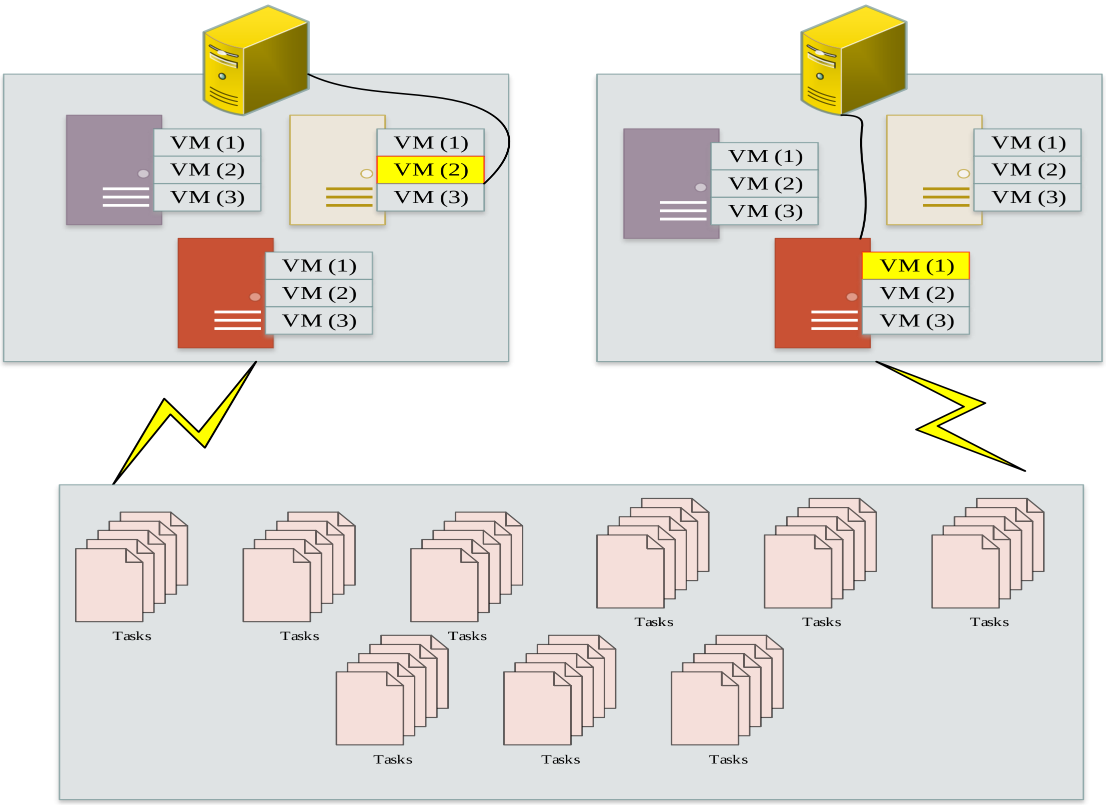

Fig 1: VM Placement Structural Design

The following are some goals that should be met by a good VM placement method:

- Make data centres more scalable.
- Maximize an utilization of resources.
- Increase load balancing.
- Decrease energy wastage.
- Mitigate energy feasting.
- Deliver the Quality of Service (QOS) guaranteed for the consumers.
- Reduce the amount of activity in the data centre.
- Avoid data centre network congestion.
- Superior efficiency.
- Arrange for security
- Upsurge Return on investment (ROI)
- Upsurge security.
- Reduce the number of networking elements that are active.
- Minimize SLA defilements.
- Decrease VM relocations in the future.

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There are two subcategories under dynamic VM placement: reactive and proactive. With reactive VM Placement, adjustments are performed to the setup only after the system has entered an undesirable condition. Alterations to the initial placement of virtual machines (VMs) are permitted in proactively VM Placement as long as they occur before the system achieves a predefined condition. The grey wolf's hierarchical society and strategic hunting style serve as inspiration for GWO. Generally speaking, grey wolves are the apex predators in their ecological niches. The typical pack size for grey wolves is between five and twelve members. There is a clear pecking order in the society of grey wolves. Grey wolf packs are often headed by a female and male who share the alpha role and make important choices for the pack as a whole, including where to sleep, when to hunt, and what time to get up.

In most cases, the members of the pack have little choice but to follow the lead of the alpha. Even yet, certain surprisingly democratic behaviours in the grey wolf social order have been documented (alpha may follow other individuals of the pack). When the alpha makes a choice in a group, everyone else confirms it by holding down their tails. It's also intriguing to learn that the alphas don't need to be the toughest members of the pack. The alpha's primary responsibility is to maintain order throughout the pack. Discipline and order are paramount in a group of grey wolves. The grey wolf pack has a social structure with alpha as the top dog and beta as the next tier down, with beta's primary responsibility being to advise alpha on important matters. When an alpha wolf retires, dies, or is otherwise removed from leadership, the pack looks to its next-in-line successor, known as beta. The beta must submit to the alpha, but has the authority to direct subordinates. Beta is alpha's advisor and is in charge of maintaining order within the pack. Beta supports Alpha's commands and provides feedbacks to Alpha. The grey wolf pack's lowest rank, omega, acts as the scapegoat. Wolves at the omega level are the last to be fed and are required to follow the dictates of those above them. While omega may appear like the least crucial member of the pack, strife and other issues arise when omega is absent. This may be explained by the omega's position as the outlet for the aggression and resentment of other wolves, that serves to both appease the pack as a whole and keep the pecking order of grey wolves in place. In certain packs, the omega is responsible for watching the younger members. Apart than the beta, alpha, and omega wolves, the rest of the pack are referred to as "subordinate" (delta). Delta wolves submit to alpha and beta wolves & exercise dominance over omega wolves. They play several roles within the pack, including scouts, sentries, elders, hunters, and caretakers. Keeping an eye on the region and sounding the alert when danger is present are two of the scouts' primary responsibilities. The establishment of safety is the responsibility of the sentinels. The elders of the pack are the most seasoned candidates for the roles of alpha and beta. Hunters aid the alpha and beta wolves in securing and preparing meals for pack, while carers tend to the needs of the sick, injured, and frail members of the pack.

To begin GWO's optimization process, a completely random community of grey wolves is generated (candidate solutions). As the iterations progressed, $\alpha, \beta,$ and δ During hunting, wolves use probability to determine where their prey is most likely to be (optimum solution). Grey wolves adjust their locations to be closer to the prey. Parameter a should go from 2 to 0 to place more weight on

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exploration and exploitation over other aspects of the search process. If $|\vec{A}| > 1$, the candidate solutions diverge from the prey; and if $|A| < 1$, The potential answers all go towards the bait. If the conditions for halting are met, the procedure proceeds, and the GWO algorithms is finished. Here are some notes that will assist you in comprehending how the Proposed method does its dramatic magic while solving optimization issues:

- The GWO algorithm's use of a social hierarchy idea aids in ranking solutions and keeping the most promising ones in memory for the current iteration.
- In 2D, the encircling mechanism defines a neighbour as a circle, and the answer is also a circle (in higher dimensions, the 2D circle can be extended to a 3D hyper-sphere).
- Grey wolves (potential solutions) may create various hyper-spheres with any radii thanks to the entropy of the parameters (A and C).
- Animals (candidate solutions) may use the GWO algorithm's "hunting technique" to determine where the prey is most likely to be located (optimum solution).
- The GWO algorithm is able to simply switch between both exploring and exploiting because to the parameters' adaptive values, which ensure both exploration and exploitation.
- When A is decreased, exploration receives 50% of the iterations ($|\vec{A}| > 1$) , with the remainder of the iterations devoted to exploitation ($|A| < 1$).

a and C are two main parameters of the GWO algorithm.

Begin
Set the population of grey wolves $X_i (i = 1,2, \dots, n)$
Set a, A, and C
Compute the fitness values of search agents and grade them

($X_\alpha =$ the best solution in the search agent, $X_\beta =$ the second-best solution in the search agent, and $X_\delta =$ the third best solution in the search agent $t = 0$

While ($t <$ Iterations)
For each search agent
Update the position of the current search agent
End for
Update a, A, and C
Compute the fitness values of all search agents and grade them
Update the positions of X_α, X_ρ and X_δ

$t = t + 1$

End while
End

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Pseudocode for Algorithm 1

For all VMs (1…n)
Compute the CPU Usage
Compute the Memory Usage
Compute the Storage Usage
If (all >Threshold)
Then initiate VM Placement procedure
Find PMs which meets the restraints
Contrivance the VM placement
End If
End For

IV. EXPERIMENTAL RESULTS

While doing massive-scale tests in production cloud environments is challenging, the suggested method has been designed and implemented in a cloud simulation environment called cloudsim. Standard algorithms, including ACO, PSO, and GA methods, are used to evaluate the suggested algorithm's efficacy.

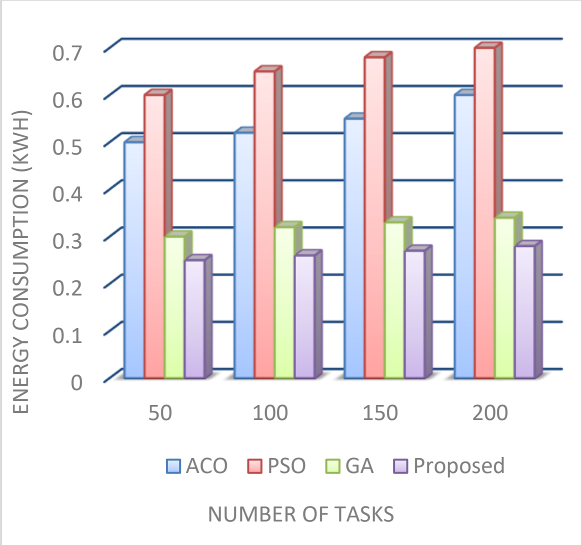
(1) Consumption Of Energy

The datacenter's energy usage will be analysed for this purpose. Processor use has a direct correlation with the power draw. The linkage looks like this:

$$P(\mathrm{u}) = \mathrm{P}_{\mathrm{idle}} + \left(\mathrm{P}_{\mathrm{busy}} - \mathrm{P}_{\mathrm{idle}}\right) * \mathrm{u} \qquad ()$$

Where P(u) what proportion of the CPU's power usage u. P_{idle} how much energy the server uses while it's not doing anything P_{busy} is the amount of electricity used by the server during peak load. While deploying a virtual machine, energy usage should be reduced.

Figure 1 depicts an examination of PSO and the suggested work's performance in terms of energy consumption, where the x-axis shows the number of fog nodes and the y-axis shows the energy used by the system (in Kwh). The graph clearly shows that the suggested method uses far less energy than PSO. Figures shows the results of a performance study for the total number of migrations. In Figures shown that the difference in migration counts between the two techniques is negligible. This is because the suggested technique considers the steadiness factor of the destination physical machine and places the virtual machine on the host with the greatest stability factor, which improves datacenter stability and reduces the need for migrations.

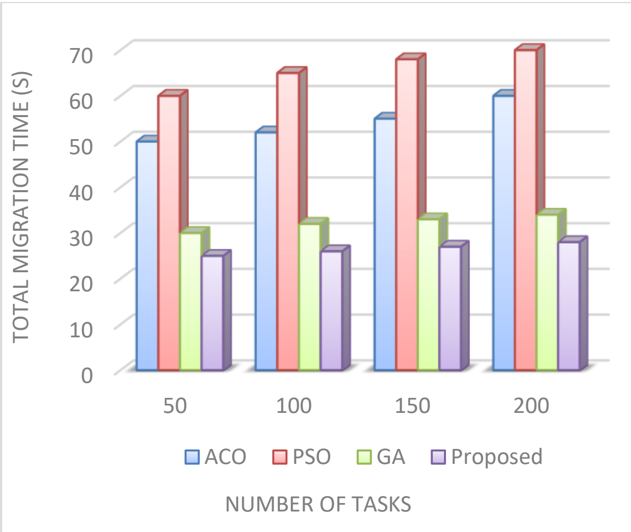


(2) Total Migration Time

Live migration involves a process of memory duplication.

$$T_{\mathrm{mig}} = \mathrm{V}_{\mathrm{mig}} / \mathrm{b}$$

Total migration time (T_{mig}) the amount of memory depends on V_{mig} the amount of data that has to be transmitted from the hosts to the destination and the high bandwidth, b. The entire migration time for a successful VM Placement technique should be less.



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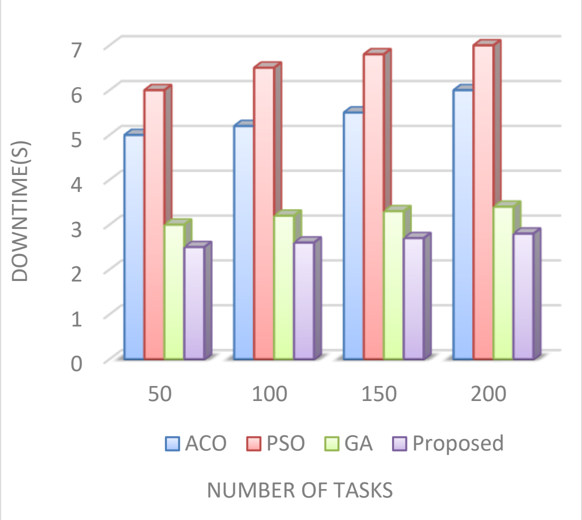
(3) Downtime

With vm migration, there's a brief pause while the host and guest operating system images are matched up before the VM can begin booting on the new host. The following is a definition of the downtime.

$$T_{\text{down}} = (d * L * t_n)/b$$

Where d is the page dirty rate, I is the page size, t_n time taken for the nth pre-copy and connection speed (in bits per second, b). Less downtime is essential for a successful VM placement strategy.



(4) SL. A Violation

The term "service level agreement" (SLA) refers to the agreed upon benchmark for a service provider's performance. In order to provide the promised services, there must be no SLA violations during the VM deployment. A Service Level Agreement Infraction (SLAV) is

$$\text{SLAV} = \text{SLATH} \times \text{PDM}$$

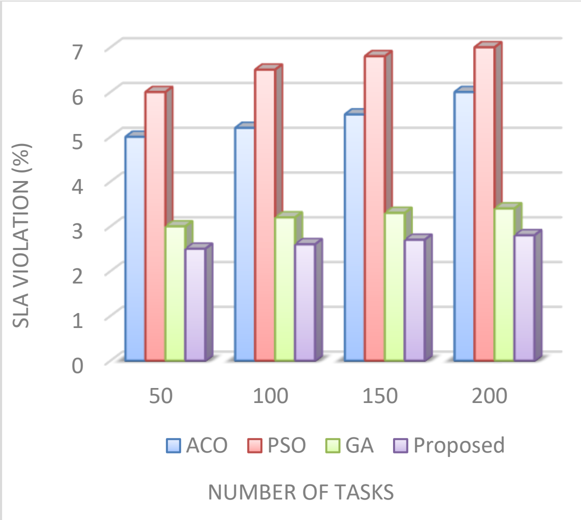
Where SLATH is SLA violation per active host,

$$\text{SLATH} = \frac{1}{\text{N}} \sum T_{\text{sil}} / T_{ai}$$

N is the number of hordes, T_{si} is the cumulative amount of time host i's CPU was at 100%, exceeding the SLA threshold, T_{i} - total time of host i being operational in order to serve virtual machines. PDM stands for "Performance Decline because of Migrations".

$$\text{PDM} = \frac{1}{\text{M}} \sum C_{\text{dil}} / C_{ri}$$

Sum of all VMs, C_{di} - performance degradation of VM j due to migrations, C_{rij} - comprehensive CPU power that was needed to VM j during its lifetime.



V. CONCLUSION

A major difficulty for providers of cloud services is locating a suitable physical server to host each customer's virtual machine. The best PSO method for the VM placement issue is presented in this study. The suggested technique is analysed based on two metrics: overall system energy usage and the number of VM migrations. Computer simulations validated that the suggested method outperforms the gold standard GWO algorithm. Future work may include taking into account network capacity and other resources when deciding where to locate virtual machines (VMs). In addition, the suggested method has been evaluated in a cloud-simulation environment, and its use in a production cloud setting has been shown.

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