An Efficient Hybrid Optimizer for Resource Reuse in a Cloud Environment

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Abstract

In a cloud context, merging complimentary numerous virtual machines (VMs) on an existing physical machine (PM) is the primary method for optimizing physical resources. One well-known area of research concentrates on making better use of VM migration resources when taking into account the dynamically changing resource demands of VMs. Finding the ideal balance between the complexity and performance of the VM migration optimization is the problem here. On the one hand, effective resource reuse is achieved through VM migration planning, and on the other, VM migration frequency is decreased to improve migration efficiency. On the other hand, a cloud data centre's enormous PM and VM population typically makes migration planning more challenging, which impedes the VM migration decision-making process. By reducing the number of VM migration options to make VM migration planning easier and address these issues, this study recommend a hybrid Ant Colony and Genetic Algorithm (AGO) resource pool architecture. Then, establishing this model as a base, we develop the hybrid resource-reuse optimization method, which maximizes resource utilization with a minimal number of VM migrations. Finally, we evaluate hybrid AGO using simulation testing and real-world trials on a working cloud platform. Compared to similar methods, the findings show that hybrid AGO increases average resource utilization by 15%, reduces the use of PMs by 15%, and decreases the average number of migrations by 30%.

Keywords: virtual machine; cloud; physical machine; optimizer; resource pool

1. Introduction

A growing number of businesses and academic organizations are utilizing different applications for scientific computing and large data processing in cloud data centres as a result of the advancement of cloud computing technology [1]. To meet the needs of a wide range of users, in the form of virtual computers (VMs) placed on physical machines (PMs), cloud data centres can elastically offer storage space, computational resources (CPU cores or CPU time), and network bandwidth. For cloud data centers, reusing PM resources more effectively has elevated its crucial challenge management in their efforts to lower energy consumption and operational expenses [2]. It is possible to maximize the use of physical resources by merging several complimentary VMs onto a single PM. Calculating the number of VM resources needed and optimizing VM allocation for better resource utilization are the key areas of focus in some related studies [3]. However, present methods only allow for coarse-grained resource reuse, making them acceptable for one-off VM deployments. Because of their extreme inefficiency, these methods are unable to give the precise resource modification needed to meet the fluctuating resource requirements of running VMs. Many academics have attempted to improve resource reuse's effectiveness through VM migration the time recently when taking into account that resource requirements for VMs are constantly evolving [4]. According to VM dynamic, during the T2 time frame, VM3 can move from PM2 to PM1. As a result, VM1 becomes much more useful, but VM2 is forced out of service. This procedure can be improved (and ought to be) [5].

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The main difficulty here is developing a successful VM migration strategy that adapts VM deployments over time as dynamic changes in resource needs occur. Numerous solutions to this problem have been put out over the years, however, the performance and complexity trade-off offered by current work is insufficient [6]. On the one hand, the majority of solutions don't have good VM migration planning, which leads to inefficient or excessive migrations. In other words, they overlook the dynamically shifting resource needs over various time frames and simply take into account the immediate, current resource demands. On the other hand, numerous effective models that minimize the number of migrations have arisen, but they are challenging to implement in a real data centre for the cloud [7]. This is due to how complicated the solution is and how many PMs and VMs there are in a cloud data centre. Consider, for illustration, a data centre with m PMs and n VMs allotted to each PM. They must take into account n mt potential migrations throughout the following t periods. Rapid decision-making is required for the planning of VM migration, yet a high solution space complexity cannot keep up [8] – [10]. Here, based on our new hybrid resource pool model, we present an effective resource-reuse optimization strategy to resolve this paradox. The concept splits a data centre's PMs into two pools, and it restricts the selection process for moving VMs to only two PMs from each pool. By doing this, it can lower the complexity of the process of deciding whether to consider moving a VM from n to 2 mt. Additionally, using this methodology, the hybrid increases resource reuse effectiveness by increasing physical resource consumption while minimizing VM migrations. Through prudent migration planning, to accommodate the continually shifting resource requirements of various potential periods, the hybrid model can adjust its VM allocation. The following are this paper's main contributions:

1) To make the planning of VM migration for resource reuse in sizable cloud data centers easier, we propose the adoption of a hybrid AGO resource pooling technique.

2) We created the resource-reuse optimization method to boost resource-reuse efficiency by maximizing resource usage with fewer VM migrations.

3) Using simulation testing and testbed studies on a genuine cloud platform, we confirm the models' effectiveness.

The work is structured as: section 2 gives a comprehensive analysis of diverse approaches. The methodology is explained in section 3. The numerical outcomes are provided in section 4 and the conclusion is given in section 5.

2. Related works

Placing (or allocating) VMs and moving VMs have received a lot of attention from researchers who are aiming to maximize the usage of cloud data center resources with resource reuse. According to related research in the area of VM placement [11], VMs can effectively exploit a PM's resource by consolidating complementing VMs on this PM and assigning based on their resource requirements, physical resources to VMs. To maximize resource utilization, some studies [12] have deployed virtual machines (VMs) based on a temporal relations model, co-located VMs with complimentary resource needs, and a single PM properly along a given time interval. Meanwhile, researchers suggested methods for placing virtual machines (VMs) optimally to maximize the use of physical resources in cloud data centres. To model the dynamic change in VM resource requirements, this work applied queuing theory [13], probability statistics [14], and other mathematical techniques.

Recent VM migration research has focused on methods that solely consider moving VMs by the most pressing or recent resource needs. However, since they only take into account resource demands at each time point rather than making a comprehensive plan for the entire VM migration process, in the end, these techniques result in insufficient usage and accessibility of physical resources. They are effective in the short term for addressing specific, limited instances. For instance, Zhang et al. [15] developed a special VM allocation algorithm that enhances the trade-off between host usage and energy consumption in VM migration by using the performance-to-power ratios of different host types. Ding et al. [16] proposed a resource-intensity-aware load-balancing technique in clouds that migrates VMs from severely loaded to lightly loaded PMs to achieve load balance and prevent future load imbalance. Classifying PMs according to their physical resource load [17] provided a heuristic method for resolving fluctuating through actual VM migrations, and VM resource requirements. VMs are allocated resources based on their needs [18].

To increase resource utilization and power consumption, consolidation of work for cloud data centres with assured quality of service via VM migration was explored by Masdar et al. [19]. To combine

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workloads in cloud computing systems, different semi-online job assignment policies were presented by Barroso et al. [20]. To increase the migration's effectiveness, developing VM migration plans have been the focus of several VM migration researchers. The author presented a Markov decision process (MDP)-based migration planning technique. The Markov chain model was utilized by the authors to examine the migration of VMs was planned using the horizon large-scale MDP to address the VM management issue [21].

An effective resource-allocation approach for overcommitted clouds was provided by Yang et al. [22] It reduces PM overloads through resource demand forecasting, the number of active PMs through efficient VM placement, and migration planning, resulting in significant energy savings. Zhou et al. [23] claim that a server consolidation method based on a profiling system maintains the performance of varied workloads while lowering the number of PMs used in data centres. They created two modules: a consolidation planning module that uses an integer programming model to minimize the number of PMs given a set of workloads; and a migration planning module that reduces VM migrations by using a polynomial time to count them technique given two scenarios for the placement of source and target virtual machines. In the upcoming few periods, Yang et al. [24] studied the management of VM migrations with dynamic resource requirements. The authors characterized this topic as an integer programming-based control optimization problem [25]. However, the authors approximated the issue using a Monte Carlo optimization technique due to its complexity.

3. Methodology

Here, we present background information on the architecture and mechanisms for reusing resources in a cloud data centre to help readers better comprehend the challenges at hand. The three tiers of the cloud data centre architecture used in this study are the levels of applications, physical resources, and virtual resources. Physical resources must be made available to tenant VMs for them to function as part of a VM cluster capable of providing adaptable on-demand resources to carry out the various activities required by the application layer cloud providers deploy visualization technologies. This is due to the ease with which virtual machines (VMs) may be quickly installed and configured and the size of the virtual cluster (i.e., the number of VMs) can easily be adjusted to the resource requirements of the application. Virtual machines (VMs) are assigned to different operational applications by an activity scheduler, subject to the typical capacity, queue, and other restrictions. A cloud data centre is now hosting several apps. To fully utilize the platform's resources for distributing VMs to PMs, the cloud provider must select the most effective strategy on such platforms while still upholding resource availability requirements.

Resource over-commitment is currently the fundamental theoretical basis for resource reuse in both industry and academic research. Fig 1 shows the physical capacity of an overcommitted PM of the actual PM is exceeded by the total capacity sought by the provided VMs. This makes it possible to multiplex by sharing physical resources among various VMs; resource reuse implies a large improvement in resource usage. Using a resource-reuse mechanism, for example, VM1 and VM2 can be securely installed on a PM with only three physical CPUs, even if the applications operating in each VM have dynamically changing resource needs during the day. The rationale for this is that the combined utilization of resources for VM1 and VM2 never exceeds the PM's maximum capacity at any given time. The physical resource use of the cloud is maximized in these conditions. Consequently, the over-commitment ratio in this context refers to the level of physical resource reuse.

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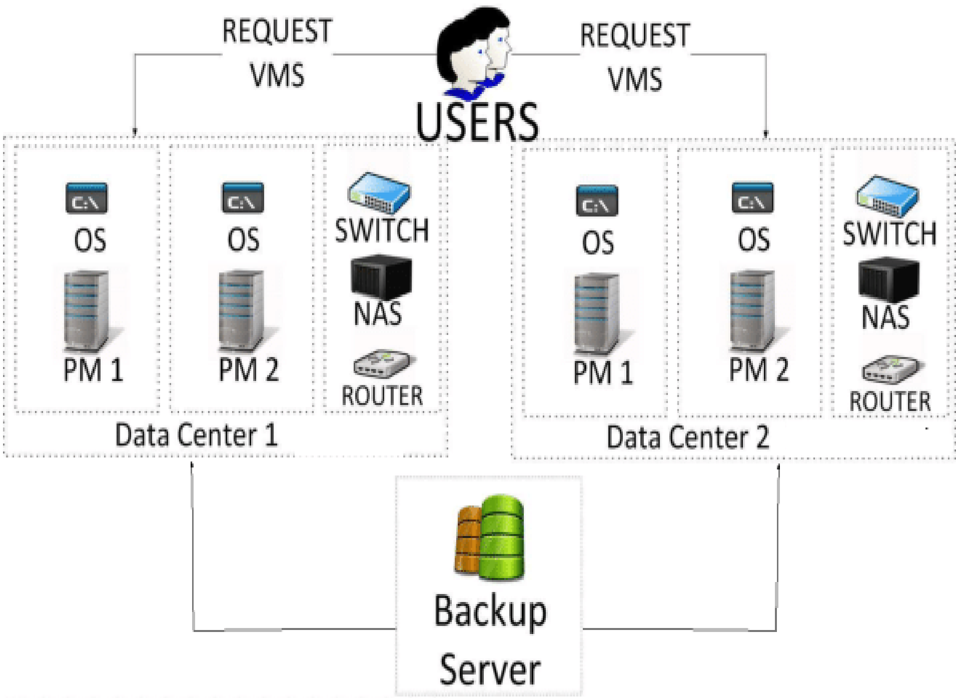

Figure 1: Cloud datacentre architecture

To further optimize physical resource consumption, when a resource can be used more than once, a resource reuse optimization mechanism is employed and there is a risk of resource shortage or underutilization. Specifically, the physical capacity of the shared resources is eventually exceeded by the total resource utilization of the VMs, leading to a considerable decline in VM performance. To make sure that the remaining VMs' resource needs can be met in this instance, we must relocate some VMs outside of the PM. Conversely, during other times, a significant portion of physical resource use is low as a result of virtual machine workloads only sometimes using all of their resources. In this case, to maximize resource usage, other VMs must be moved onto the PM.

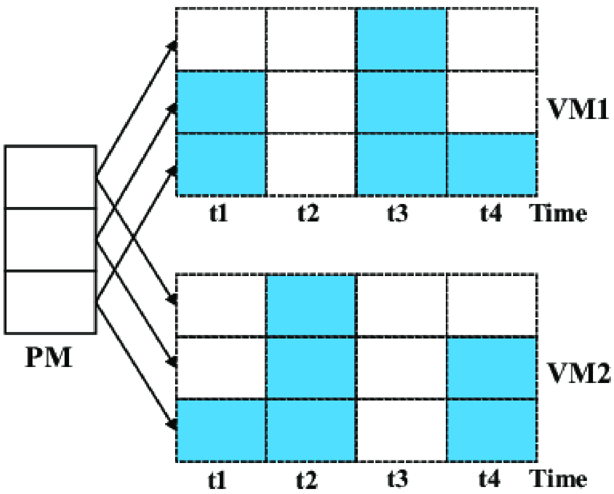

Figure 2: Resource reuse

3.1. Resource utilization

VM migration is incorporated into resource reuse optimization planning to modify VM deployment so that resource use is maximized and the frequency of VM migrations is minimized. For the upcoming periods, choose which VMs should be transferred, where they should go, and when proper migration planning is required. If a PM hosts m virtual machines, additionally, additional PMs may move onto those computers over some time, then n^{m*t} is the potential number of migration strategies, which makes making decisions more difficult and burdensome in terms of dimensionality. We initially

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propose a hybrid resource pool that would limit VM migrations across two PMs to simplify VM migration planning. To maximize the utilization of physical resources, we design an effective resource-reuse optimization approach.

3.2. Hybrid Ant Colony Optimization with Genetic Algorithm (AGO)

Usually, GA creates a randomly chosen starting population. This has a drawback, though, in that it may lengthen the global optimal solution's lengthy convergence process. To obtain a better initial population, GA, therefore, requires ACO. Instead of using a random beginning population, ACO takes into account the offloading factors for cached data: Eq. (1) are the access count (ct), visitation time (tm), and data size (sz).

$$F_{var} = \frac{1}{n}\sum_{i=1}^{n}\frac{x_{var_i} - x_{var_{min}}}{x_{var_{min}} - x_{var_{min}}} \tag{1}$$

As a result, given the goal function, the optimum solution can naturally correlate to this initial population. The beginning population is then used by GA to search for a world-class, convergent solution. Choices made by parents in the crossover mechanism result in offspring in the generation after has a significant impact on GA performance. To avoid a local best-case scenario, every gene on the child's chromosome is changeable. Although GA performs rather quickly, it can potentially become stuck in a stagnant solution. To account for the possibility of the solution stalling in odd-even iterations, the hybrid AGO in this article employs a single-point crossover mechanism. Parent-1 will contribute 70% of the genes in even iterations, and parent-2 will contribute 30%. In contrast, Fig 2 illustrates what happens in the even iteration. The kid chromosomes must be able to get as much stored material (gen=1) because they will only exchange a small portion of it for genes from the more advantageous parent. For this reason, the 70:30's odd-even crossover portion is employed in the GA part. Chromosomes with low fitness won't be chosen as parents. The best chromosome from one of the parents to be crossed can be ensured by the suggested roulette wheel selection (RWS) approach.

$$\tau_i = w_{ct}\,\frac{ct(i)}{total\ (ct)} + w_{tm}\,\frac{tm(i)}{total\ (tm)} + w_{sz}\,\frac{sz(i)}{total\ (sz)} \tag{2}$$

$$\eta_i(t) = \frac{ct(i)fr(i)}{sz(i)} \tag{3}$$

$$P_i(t) = \frac{\tau_i(t)^{\alpha}\eta_i(t)^{\beta}}{\tau_i(t)^{\alpha}\eta_i(t)^{\beta} + \tau_i(t)^{\alpha}\eta_i(t)^{\beta}} \tag{4}$$

Here, w_{ct} specifies weight, F_x represents minimal value, sz specifies data size. The odd-even crossover and RWS techniques that are suggested combine to form a framework that can assist in locating the KP01 combinatorial problem's global optimal solution. By developing an initial answer during the first iteration, ACO aids GA. Based on probability (4) and visibility (η), the ant colony on ACO chooses whether to put object x_j in the bag coming after (3) and pheromone concentration (τ_i) coming after (2). To generate the initial population through ACO, Rank Selection (RS), Tournament Selection (TS), and other selection operators' outcomes and RWS were investigated in this study. The effectiveness of these three selection operators will then be evaluated in comparison to our suggested approach, RWS which is discussed in more detail in the section below.

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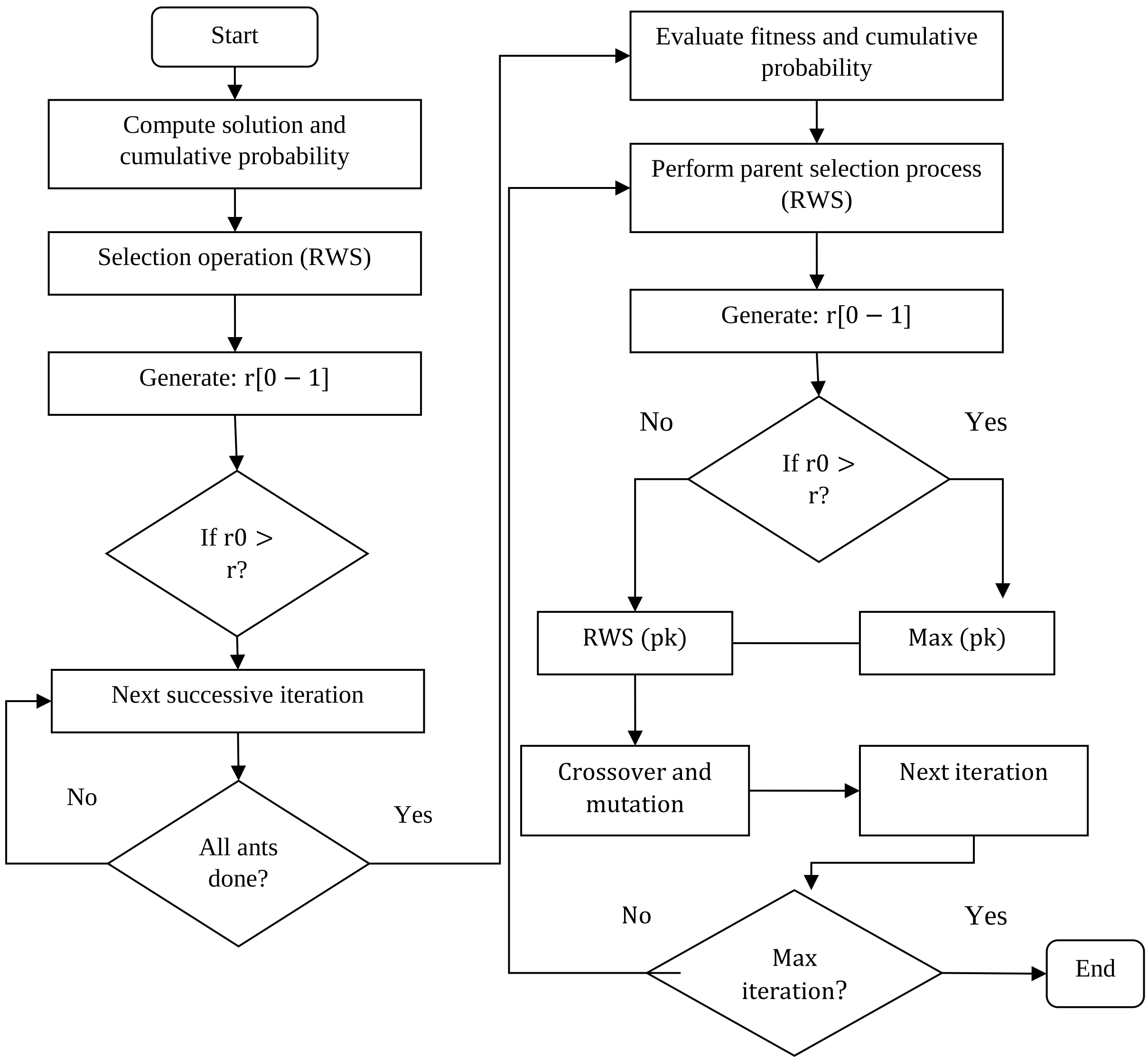

Figure 3: Proposed AGO flowcharts

4. Results and discussion

The suggested technique is run on the MATLAB 2020a environment, which runs on Windows 8 with a Pentium dual-core i7 CPU and 4GB RAM, to validate the performance of the hybrid AGO. The performance of hybrid AGO is tested using experimental instances, and resource bottlenecks in heterogeneous and homogeneous server settings are measured using test cases. Utilizing parameter space, the efficiency is calculated. Since it has been claimed that the performance is superior to that of other methods, the VM's capacity has been measured and examined. The data processing is designed so that the VM will fit the server set flawlessly, demonstrating that server consolidation eliminates resource redundancy. The memory requirements for VM-based computing are in the range [0,100] and the integer requirements are [1,128]. As a result, the ratio between CPU demand and memory is adjusted to 1:1. These problems are quite challenging, and the ideal placements don't use up extra resources on the servers that are at their disposal. The proposed model, it is noticed, achieves superior results and acquires a comparable number of active servers with consistent performance. Even when there are the most servers possible, the current methods perform poorly. The advantages of the suggested paradigm, however, are thought to remain stable as the size of the challenge grows. Another advantage of the suggested hybrid AGO is that, as shown in Fig 4 to Fig 10, it achieves a superior solution than previous techniques with less computational/processing time.

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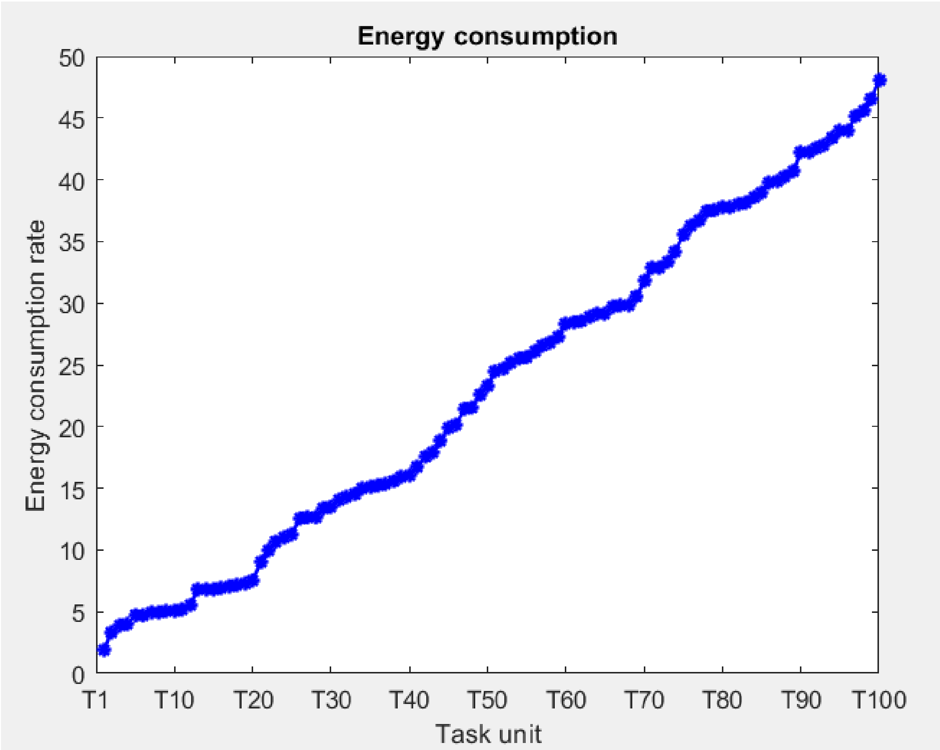

Figure 4: Energy consumption

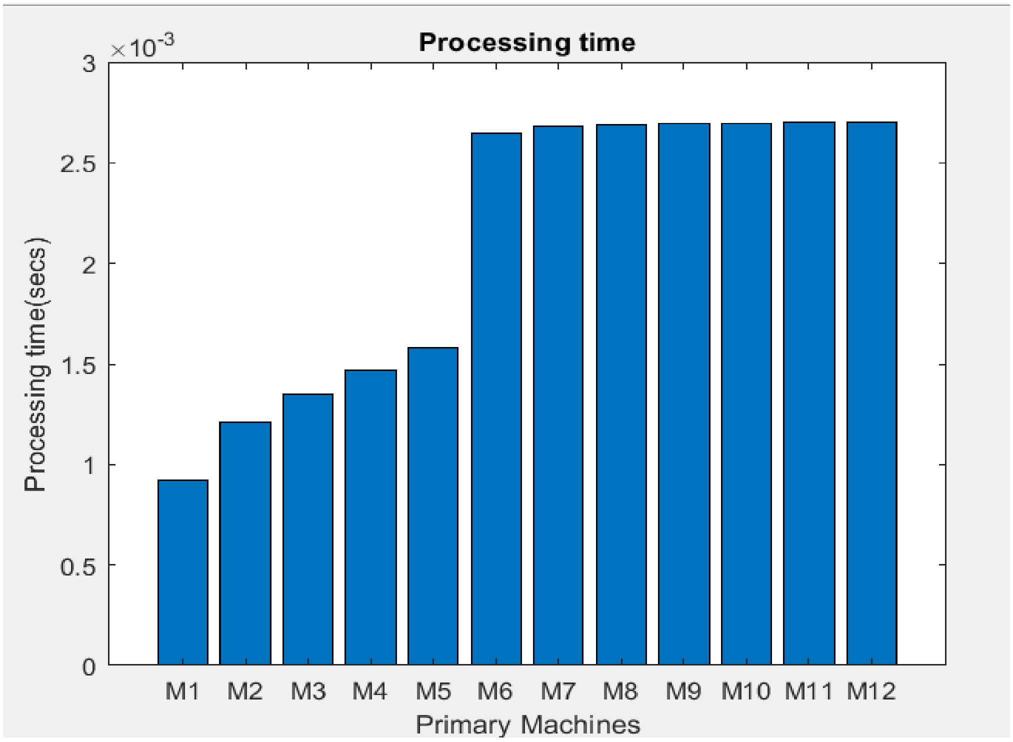

Figure 5: Processing time

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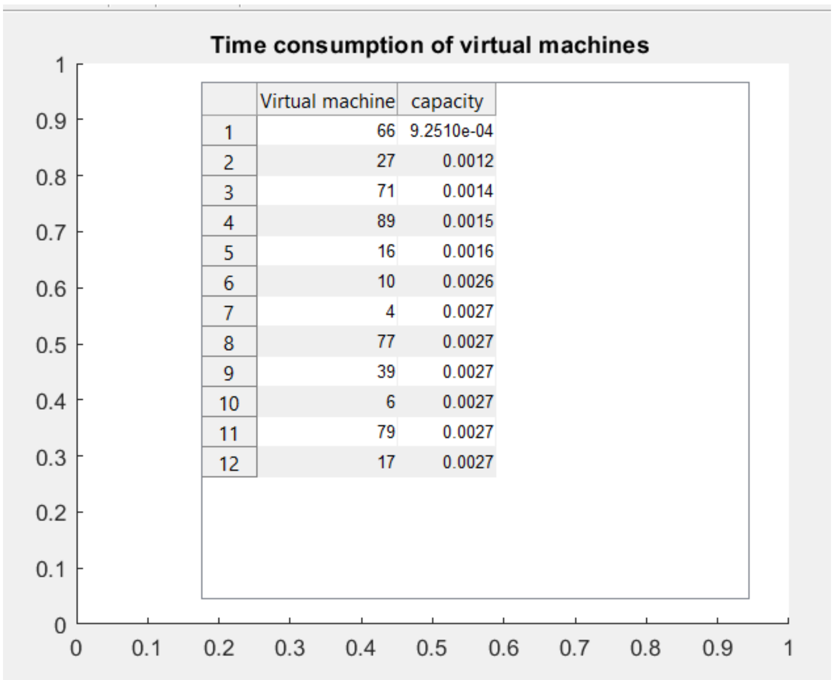

	Virtual machine	capacity
1	66	9.2510e-04
2	27	0.0012
3	71	0.0014
4	89	0.0015
5	16	0.0016
6	10	0.0026
7	4	0.0027
8	77	0.0027
9	39	0.0027
10	6	0.0027
11	79	0.0027
12	17	0.0027

Figure 6: VM time consumption

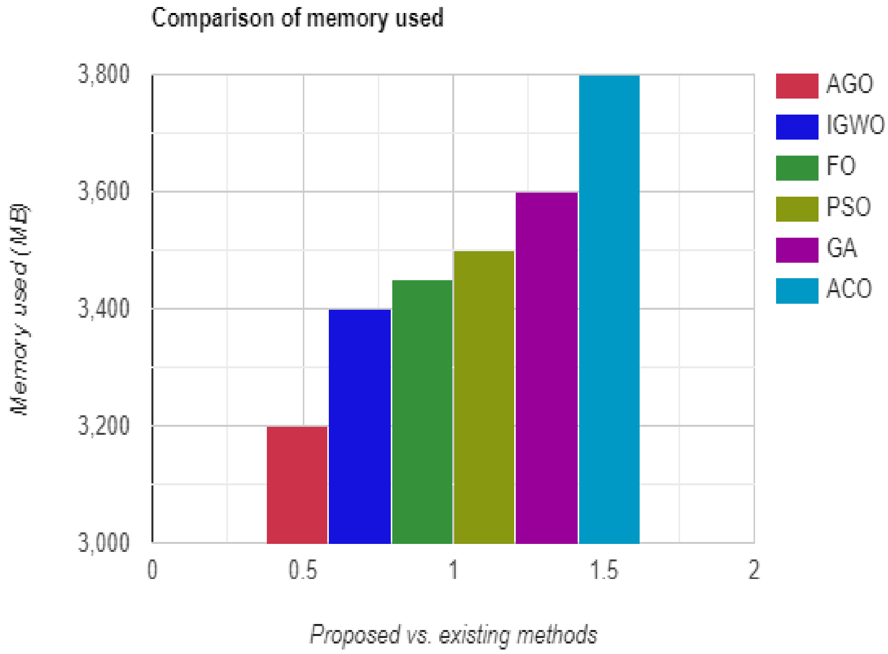

Figure 7: Memory comparison

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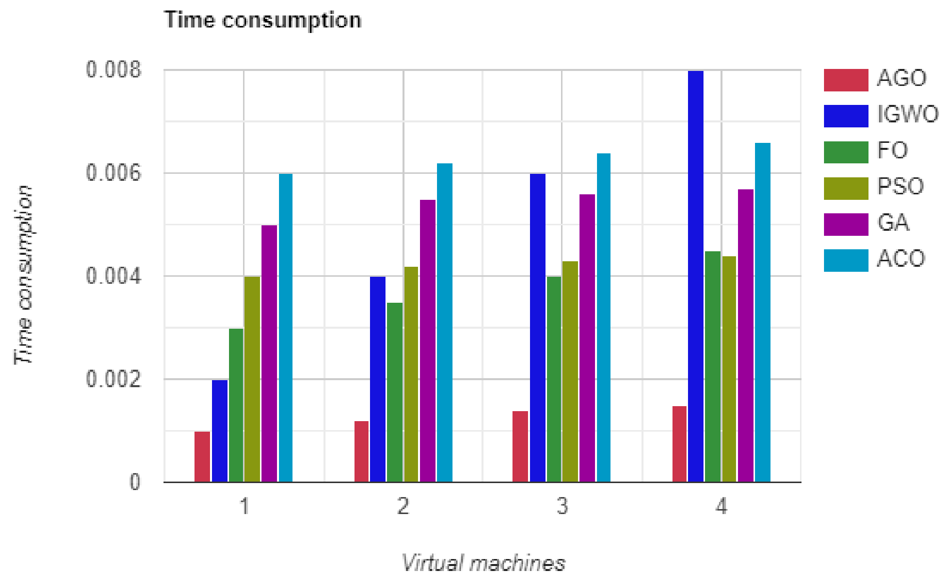

Figure 8: Time comparison

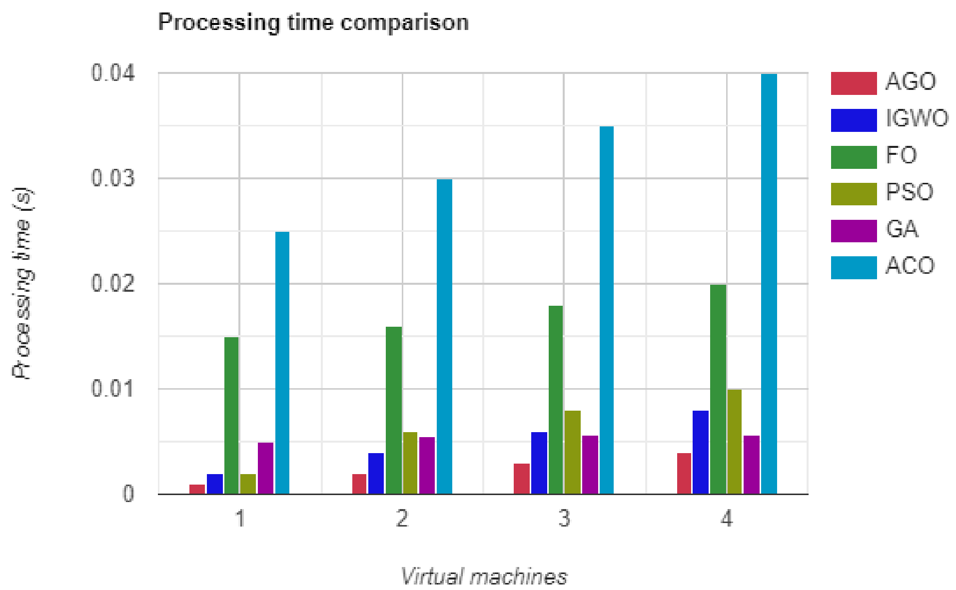

Figure 9: Processing time comparison

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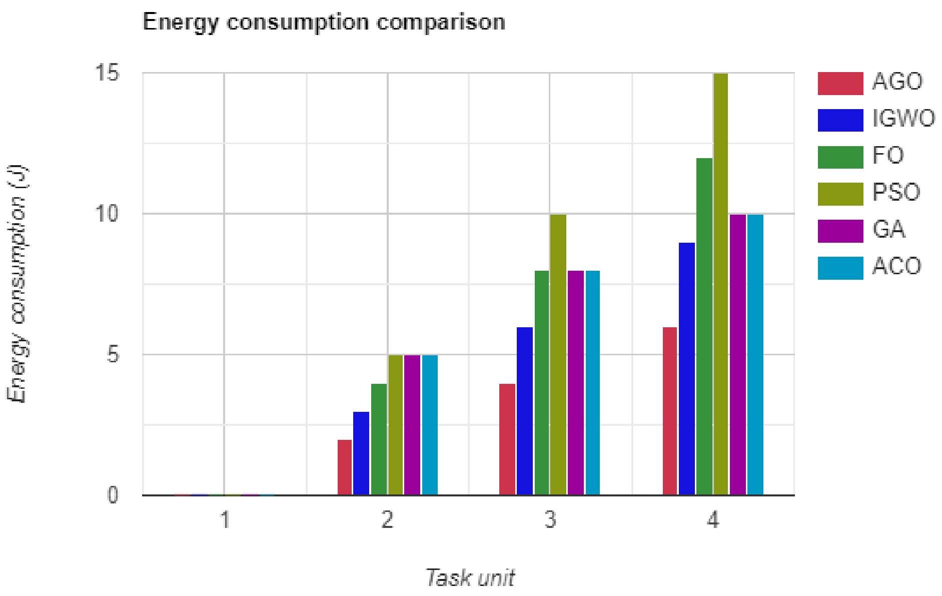

Figure 10: Energy consumption comparison

We created the collection of data using servers and virtual machines in the CC environment along with various bottleneck resources to assess the effectiveness of the predicted approach. The server has 32 GB RAM and a 16-core CPU. Each virtual machine has a CPU with 1 to 8 GB of memory and 1-4 cores chosen at random from the distribution. It is the resource that is at capacity because the likelihood of VM is 0.25. As a result, the overall CPU-to-memory utilization demand ratio is approximately 10:9. Since the instances are generated at random, we cannot find the best answers. Above are graphs showing the total energy usage and processing times. The assignment completed, measured, and the considerable disparity determined based on RAM and CPU usage for all categories show a lack of an efficient balance of various resources. This shows that the memory is considered to be the resource bottleneck and limits the consolidated level and that the model plans to merge VM over high configuration servers superiorly. With greater VM consolidation and better resource efficiency, the average memory utilization is obtained. The comparison of several performance parameters, including memory, time, energy, and processing time is shown in Fig 4 to Fig 10.

5. Conclusion

To take into consideration the continually changing resource requirements of virtual machines in cloud data centres and maximize resource consumption with fewer VM migrations, this paper proposes a practical resource-reuse optimization technique based on a hybrid resource pool model. According to this study, it is possible to reduce the size of some challenging problems because of their enormous magnitude. This research has shown that if we directly analyze the original migration planning problem, the problem is quite large and a challenge to solve. When we limit the VMs' ability to migrate between resource pools, the problem scale will be substantially reduced to 2mt, allowing us to quickly solve it. The proposed hybrid AGO-based virtual resource-reuse optimization mechanism is also simple, useful, and effective. This work will be expanded upon, improved, and further research in three areas will be done. First, we aim to offer a unique algorithm that intelligently finds the suitable over-commitment ratio. Resource reuse and VM migration times would change depending on the resource over-commitment ratio. Second, in this research, we only take into account a one-dimensional CPU demand, but in the future, we expect hybrid AGO can accommodate multidimensional resource requirements. Finally, we just optimize the time it takes to migrate VMs in this study; in later work, we will optimize migration more thoroughly, calculating the cost of communication during migration, energy use, and other considerations.

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