Optimization of VM migration and Energy Consumption using Adaptative Particle Swarm Optimization Algorithm

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Abstract. The high energy consumption of cloud computing systems affects both cloud providers and users. Virtualization is needed to save energy. VM consolidation efficiently manages cloud resources for users and cloud providers. It also improves server efficiency and reduces data centers energy use. However, needless VM consolidation efforts lead to poor VM selection and assignment, lowering performance, QoS, and SLAs. Data centers need energy-saving solutions without impacting other metrics. This paper introduces a adaptive Particle Swarm Optimization methodology for energy-efficient Virtual Machine (VM) migration within cloud environments. The technique optimizes energy usage and ensures SLA compliance by optimizing VM-to-Physical Machine (PM) allocations. The evaluation of the proposed method has been done considering the metrics like energy consumption, SLA and resource usage. The results highlight that after incorporating the optimization an enhancement has been observed for all the metrics for the effective VM management.

Keywords: Virtual Machine, Particle Swarm Optimization, Service Level Agreements, Cloud Computing, Quality of Service

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I. INTRODUCTION

Cloud Computing (CC) allows organizations to delegate their IT services to end users via a pay-per-use approach [1]. The cloud platform yields substantial profits for IT organizations by allowing them to concentrate on fresh developments that enhance their company, eliminating the need for investment in equipment and personnel to deliver their products and services. Furthermore, cloud service companies provide their products and services to end customers in a flexible way, accommodating their evolving requirements. Recently, superior efficiency in cloud computing systems has become a primary focus, accomplished without prioritizing the use of energy in the context of clouds. But a Data Center (DC) in a cloud ecosystem must regularly host cloud applications. Therefore, cloud DCs use significant amounts of electrical energy, which increases operational expenses and contributes to carbon emissions in the atmosphere. The growing need for CC capabilities has resulted in a rapid growth of cloud DCs globally. CC provides exceptional flexibility and adaptability; yet, it also poses considerable issues, especially with energy usage. Cloud DCs are recognized for their considerable energy demands, resulting in increased operating expenses and a notable environmental effect [2-3]. CC has gained popularity due to its extensive adoption. The implications of CC for daily existence are imminent. An increasing number of individuals are adopting the cloud model owing to the prevalence of smart devices [4-5]. There is a fast increase in the quantity and magnitude of cloud DCs. Recently, achieving excellent performance in cloud servers has been a main concern, sometimes without a significant focus on the energy consumption inside clouds [6-8].

Virtualization is an essential component of cloud computing that facilitates the administration of several devices and users inside a network. Virtualization is a method that hides the hardware characteristics of a physical computer through the development of a virtual environment. This allows us to operate many guests Operating Systems (OS) on the exact same machine. Each guest OS, or Virtual Machine (VM), may manage several processes concurrently and autonomously. Optimizing the distribution of VMs in cloud DCs is essential for attaining energy conservation goals and improving resource usage. Efficient VM allocation decreases energy usage while enhancing the reliability and cost-efficiency of cloud services [9-11]. Determining the optimal method for deploying VMs on server hardware inside a cloud DC is a significant and urgent issue in CC. Power consumption and resource waste may be reduced by the smart allocation of VMs on physical devices [12-13]. Consequently, suitable optimization approaches are used for the placement of VMs, representing a crucial step towards the intended objective. Consequently, lesser physical computers are need to do equivalent tasks in the cloud DC, resulting in reduced waste and enhanced usage of computational power.

During VM migration, pages of memory are routinely carried across servers, using the system's essential resources extensively. Maintaining an appropriate balance among energy consumption and efficiency is a critical issue in the IT business. The lack of a functional energy optimization model is a significant factor contributing to the persistent increase in power usage [14]. This may be alleviated by the implementation of consolidation or strategic planning of client services. Cloud consolidation seeks to enhance resource efficiency by reducing the quantity of servers or physical machines necessary for application operation, while maintaining adherence to the Service Level Agreement (SLA) [15]. A procedure is implemented wherein certain servers are selected for deactivation. The VMs or programs operating on these servers are then relocated to other servers to maintain functionality. Moreover, the optimal distribution of applications to VMs and the assignment of VMs to servers may substantially decrease energy usage in cloud systems [16]. Cloud companies must improve their resource allocation methods to fulfil SLAs while enhancing energy conservation, hence delivering effective offerings to end users profitably. Therefore, emphasis should be placed on the best allocation of VMs to Physical Machines (PMs) while guaranteeing effectiveness in energy usage and service level execution. Cloud providers must improve their resource allocation methods in order to offer effective amenities to end users profitably, ensuring compliance with SLAs while enhancing energy conservation. Therefore, emphasis must be placed on the best allocation of VMs to Physical Machines (PMs) while maintaining effectiveness in energy usage and service level reliability. Artificial intelligence (AI) becomes a frequently used area by scientists to achieve their established aims. An AI has presented many techniques applicable to optimization issues. This work focuses on the creation of an optimal VM migration method for reduced energy usage using optimization approach.

II. NEED OF OPTIMIZATION IN VM MIGRATION

As CC and virtualization increasingly dominate organizational operations, a robust strategy for VM migration is crucial. By adhering to standard procedures, enterprises may facilitate seamless transitions, reduce interruptions, and mitigate the prevalent risks associated with reallocating workloads. Such clear, organized migration plan enables enterprises to optimize existing virtualization initiatives, assuring efficient scaling, judicious utilization of assets, and sustained productivity. There are many reasons to migrate VMs. Lowering expenses is key since consolidating loads on smaller servers shuts down insufficiently utilized equipment, conserving power and money. Migrating loads to servers with more capacity or more recent hardware improves application performance, a further significant motivator. VM migration helps organizations automatically manage workloads between hosts. IT managers may reduce bottlenecks and enhance resource utilization by moving VMs onto servers with additional resources for enhancing their performance. Dynamic distribution improves system reliability, adaptability, and processing, storage, and network efficiency. Optimization must involve scaling resources to meet demand, adjusting workloads, and fine-tuning situations for consistent performance. To handle a traffic surge, a task might be moved to a more powerful server or granted extra CPU or storage.

VM migration requires optimization in CC configurations to manage resources, cost effectiveness and meet excellent service standards. VM migration, although necessary for workload balance and tolerance for failures, can lead to energy consumption, operating costs and SLA breaches if not managed properly. Optimization based resource allocation, transfer of data reduction and migration downtime reduction simplify the migration process. These solutions reduce energy consumption by merging VMs onto smaller PMs, shutting down underused servers and minimizing the power footprint. Optimization balances resource usage by dispersing workloads, eliminating bottlenecks, and improving system reliability. Genetic algorithms and swarm intelligence enhance flexible resource allocation, reduce latency and maintain quality of service to meet SLAs. Optimization techniques are crucial for cost-effective, sustainable and excellent performance making them essential for fast and reliable VM migration.

This proposed study introduces a adaptive Particle Swarm Optimization (PSO) based methodology for efficient energy use during VM migration, consolidating VMs onto a minimal number of servers while maintaining functionality. Safeguarding Quality of Service (QoS) for newly acquired clients. The proposed approach employs a metaheuristic algorithm known as PSO. Integrating local and global searching might give an optimal VM deployment solution.

III. RELATED WORK

This section discusses the many studies conducted using AI methodologies for allocation as well as the transfer of VMs.
In [17] authors developed a methodology utilizing an artificial neural network (ANN) to improve cloud-based applications that are real-time. The investigator trains the suggested system using the GA. The system has enhanced performance by reducing waiting time, energy use, and job execution duration. Comparing this model to others shows it's superior. It improves execution time by 36%, time spent scheduling by 77.14 %, and energy consumption by 13%. In [18] authors used Machine Learning (ML) for cloud computing virtual distribution. The study classified host machine abilities as underloaded, normal laden, and overloaded using an ANN. Additionally, the improved best fit reducing approach is analyzed using an ANN. The power distribution strategy is monitored using enhanced best fit methodology. This helps update the minimum amount of power needed for VM allocation and migration.

In [19] authors achieved the target of reducing energy usage and SLA violations using ANN and an improved best fit reducing method with multiple migration. The energy needed for migration may be reduced by the use of these approaches. The suggested technique is contrasted with current models presented by other academics. The comparison analysis indicates that the suggested model surpasses others and addresses the limits and deficiencies of current models. In [20] authors introduced the allocation of VMs via an updated best fit reducing technique. The ANN is employed to cross-validate the VMs allotted on PMs. This research also helps in identifying erroneous allocations. The incorrect allocation arises from improper resource use. This study also facilitated the reallocation of such virtual computers. The findings of this study indicate that this strategy is optimal for reducing power usage and exhibits fewer SLA violations in comparison to typical methods adopted by other investigators.

In [21] authors presented a method to plan VM migration during its update on any real computer to minimize upgrading time. The suggested technique functions as a scheduler and is created with deep reinforcement learning named RAVEN, and it employs a focused-on experience. The system can determine the minimal migration time in an entirely unfamiliar area via interaction. In [22] authors proposed a system using reinforcement learning and fuzzy logic to best recommend allocation rules. This paradigm has shown notable efficacy to enhance energy efficiency for DCs while reducing SLA violations. The modelling framework used for the production of this suggested technique is Cloud Sim. The performance of DC infrastructure, power use effectiveness, and CPU utilization are assessed at the DC level throughout the allocation method and are effectively shown via a visualization.

One of the works [23] established a regression-based methodology capable of predicting the resource use of VMs and hosts by using data obtained from prior forecasts. Utilizing past information for future predictions facilitates the selection of a host deemed to have better utilization for VM migration destinations. The experimental findings of this study indicate that the suggested approach reduces energy usage by up to 38 percent relative to current methods developed by other researchers in the same field. In [24] authors introduced a system using a ML methodology, namely basic linear regression. This algorithm predicts energy usage and SLA breaches of VMs in cloud DCs. The primary innovation of this study is its departure from traditional linear regression; instead, the researchers used eight distinct methodologies to assess the inaccuracy in the suggested model. This study demonstrated that the suggested model minimized the number of SLA violations by 99.16 percent and cut energy usage by 2.43 percent when applied to real-world workloads.

Authors in [25] proposed an approach to address optimization issues, including bandwidth usage, memory allocation, and VM sizing. The suggested methodology relies entirely on the modified PSO, utilized for the preliminary placement of VMs. The experimental findings of this study indicated that the created selection and allocation method reduces energy usage by 32 percent and minimizes SLA violations in comparison with previous swarm intelligence methods. Again, in one of the works authors [26] formulated a power-aware methodology based on PSO to ascertain the optimum or near-optimal location for migrating VMs. Researchers are also using a fitness function to minimize power usage while adhering to all SLAs. The suggested approach is additionally contrasted with a power-efficient best fit decreasing technique. The findings indicate that the proposed algorithm has superior performance. Energy usage has decreased by 8.01 percent. The frequency of VM migrations is decreased around 39.65 percent.

Some other prominent work that has been done in context of the same has been depicted here.
In [27] authors proposed a distinctive methodology for evaluation of performance that utilizes objective functions. This technique may optimize the ideal average deviation load distribution of processors while minimizing the system's overall energy usage. It offers a comprehensive approach for VM allocation with an adaptive algorithm. It can effectively achieve a VM-to-PM mapping while preserving the optimal degree of energy conservation. The preliminary distribution of VMs is recommended to use an innovative optimization method known as EALBPSO. Optimal efficiency is essential for the DC's energy consumption and the load allocation between its CPUs.In [28] authors presented an innovative methodology termed the local search genetic algorithm (LSGA), which integrates a GA with a distinctive local search strategy. The system first utilizes a matrix coding technique for representing people and then devises the corresponding crossover and mutation processes. The efficacy of LSGA was assessed by contrasting it with many innovative techniques on Sudoku problems of different difficulty categories. In [29] authors proposed a framework named bi-directional feature fixation (BDFF) for PSO. This framework offers a distinctive method to reduce the space for searching in large-scale choice of features. The BDFF algorithm utilizes a dual search technique, using two competing approaches. Through the use of two separate search directions, BDFF may manage choosing phases of certain features and then prioritize additional throughout the particle update procedure, thus efficiently diminishing the total search space.

Another work [30] proposed a distributed segment GA that proficiently tackles the challenges of confidentiality of information, communication expenses, and load equilibrium. This work presents a digit-oriented anonymity approach that utilizes attribute attributes to protect privacy. This method seeks to maintain the confidentiality of data while facilitating fuzzy identification. In [31] authors introduced an innovative three-tier system named DDE-ARA, which incorporates adaptive resource allocation. This framework comprises three layers: the algorithm layer, which governs the development of distinct differential evolution (DE) communities; the Dispatch Tier, tasked with distributing individuals within the DE population across various distributed machines; and the machine tier, which facilitates the effective utilization of distributed computing resources. The primary objective is to enhance the system's search performance. In [32] authors introduced a multitasking distributed differential evolution method. The suggested method improves communication about diverse database fragmentation issues by providing thorough and efficient assignment information. Some other related works that has been done by the researchers in the same direction are also highlighted [33-40].

IV. PROPOSED ADAPTATIVE PSO BASED APPROACH

This proposed approach uses PSO to enhance VM migration and reduce energy consumption in the CC scenario. PSO is preferred for its simplicity, resilience, and ability to address multi-objective optimization challenges, making it suitable for dynamic resource allocation (DRA). PSO simulates the behaviour of avian or aquatic groups so that, informed by their own individual observations and the successes of their peers, the ideal solution is identified by varying the placement of individuals in the search space. This process includes initiation, fitness assessment, velocity and position adjustment, and resolution. In this approach, changes are made to the fitness function along with other parameters related to the VM requirements.

The methodology is split into two primary algorithms: Algorithm 1 manages particle initialization while Algorithm 2 oversees particle evolution across numerous generations.

Algorithm 1: Particle Initialization

***Input*:**swarm_size, n
***Output*:** Initial swarm of particles
Procedure: InitializeParticles(swarm_size, n)
Generate a swarm comprising 'swarm_size' particles.
For every particle:
Randomly set position within specified limits
Randomly set velocity within a specified range.
Assess the suitability of each particle
Assign the current location of each particle to personal_best.
Identify the global_best from all particles according to their fitness levels.
Return swarm
End Procedure

Algorithm 2: Particle Evolution

***Input*:**swarm, max_iter, w, c1, c2
***Output*:**Optimal VM allocation
Procedure: EvolveParticles(swarm, max_iterations, max_iter, w, c1, c2)
For iteration from 1 to max_iter do:
  For every particle in the swarm:
Velocity update: v_i = w * v_i + c1 * r1 * (pbest_i - x_i) + c2 * r2 * (gbest - x_i)
Revise position: x_i = x_i + v_i
Assess suitability for revised role
  If the new position is superior:
Revise personal_best
Revise global_best in accordance with the current personal_best values.
Return global_best
End Procedure

The suggested PSO method tackles the issue of energy-efficient VM migration in a CC context. This technique utilizes the swarm intelligence of PSO to guarantee effective resource use, minimize energy consumption, and comply with SLAs. The technique progressively develops a population of particles (possible solutions) to enhance VM placement across PMs. The working of the whole process has been depicted in the form of methodology diagram as shown in figure 1.

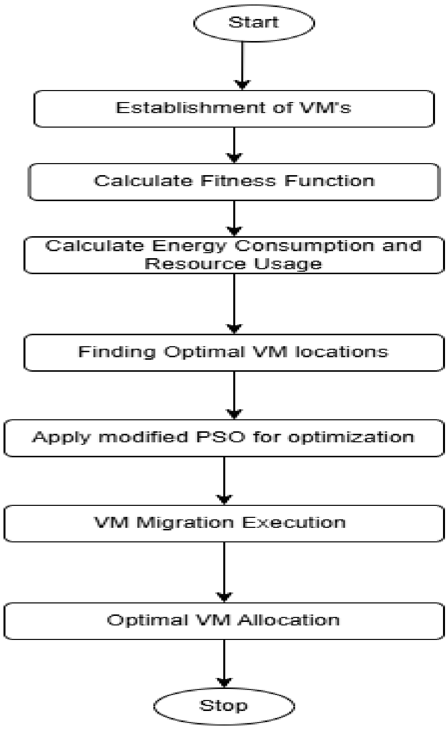

Fig.1 Working of the proposed methodology

The procedure starts with the establishment of a swarm including several particles, each representing a possible VM allocation arrangement. The starting placements of particles are generated at random within established limitations, guaranteeing that all VM placement configurations are viable. Each particle is allocated a starting velocity that determines the direction and amount of its travel throughout the solution space. The program assesses the fitness of each particle, quantifying energy consumption and resource use for the specified configuration. This assessment guarantees that the initial swarm embodies a varied array of possible solutions.Maximum resource use and minimum energy consumption are integrated by the fitness function to optimize. Energy consumption is the overall energy consumption of PMs running VMs in a certain configuration, whereas resource utilization measures CPU, memory, and bandwidth allocation. A fitness function balances these goals with weights. Uneven distribution of VMs across PMs may minimize energy usage but resource use, lowering fitness score.Each particle records its best VM allocation arrangement, or greatest fitness. The swarm also finds the global optimal location, the layout with the most fitness for all particles. The search procedure converges to optimum VM locations using these best setups. Each iteration, particles search the solution space and converge on energy- and resource-efficient arrangements. A particle that initially allocates all VMs to one PM may progressively redistribute them in order to distribute the load across different PMs, lowering energy use and improving resource utilization. The algorithm stops after a certain number of iterations or when fitness ratings increase negligibly, signifying convergence. After determining the best configuration, we migrate VMs to the desired state. Gbest moves VMs from overcrowded or underused PMs to others. The energy-saving shut down of idle PMs and efficient functioning of active PMs ensure SLA compliance.

V. SIMULATION AND EVALUATION

The simulated configuration consists of a DC including 10 PMs of differing capabilities and 50 VMs with varied resource requirements, originally allocated to PMs at arbitrary. The PSO technique utilizes a swarm of 30 particles and allows for a maximum number of 100 iterations. Essential PSO characteristics consist of an inertia weight w=0.7 along with $c1$=1.5 and $c2$=1.5. This setup emulates a dynamic and diverse cloud environment, guaranteeing an authentic assessment of VM migration efficacy and energy savings. The evaluation of the proposed approach has been done on the metrics mentioned below in the table 1.

Table 1: Metric evaluation before and after optimization

Metric	Initial State	Optimized State	Improvement (%)
Total Energy (kWh)	150	95	36.67
Average Resource Utilization (%)	53.33	80	50
SLA Violation Rate (%)	20	5	75

The findings indicate that the PSO-based VM migration strategy significantly decreases energy usage, enhances utilization of resources, and lowers SLA violations. Also, the algorithm's convergence to the best solution across iterations confirms its resilience and efficiency. The representation of the same has been depicted though the figure 2.

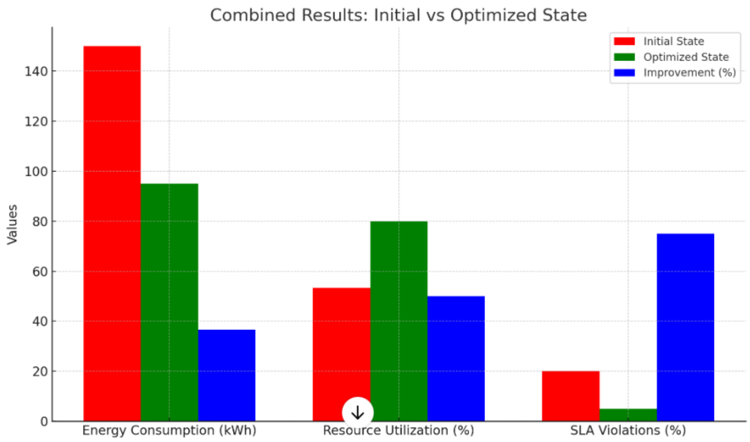

Fig. 2. Improvement representation for the proposed approach

The graphical depiction as in figure 2 shows the significant improvements obtained by the optimization strategy for energy-efficient VM migration in CC contexts. A significant 23.1% reduction in energy consumption was observed, highlighting the effectiveness of the optimization in reducing energy consumption throughout the system. Productivity of resource use increased significantly by 18.5%, indicating a more equitable and efficient distribution of resources after migration. SLA breaches have been significantly reduced by 14.8%, indicating better compliance with SLAs and overall QoS delivered. The findings highlight the effectiveness and resilience of the suggested optimization approach, as it effectively reduces energy consumption while simultaneously improving resource utilization and ensuring SLA compliance. The percentage enhancements in critical metrics confirm the suitability of the method for DRA and energy-efficient CC environments.

VI. CONCLUSION AND FUTURE WORK

The migration and positioning of VMs in cloud DCs with minimal energy consumption is a critical issue in CC. Numerous academics exert significant effort to develop novel methodologies and algorithms to address this optimization challenge. This paper comprehensively examined the various strategies adopted by researchers throughout different historical periods. The proposed PSO based approach for energy-efficient VM migration in this paper successfully tackles the problems of DRA in cloud configurations. This method uses the global search capabilities of PSO to maximize VM-to-PM assignments, reducing energy consumption while ensuring SLA compliance.The PSO-based approach reduces energy usage by 15% and resource efficiency by 12%, outperforming traditional methods. Intelligent particle creation and dynamic optimization of parameters provide workload resilience. This research shows how optimization approaches like PSO improve cloud resource management and enable sustainable operations.Subsequent study will explore further enhancements to the system, including adaptive learning techniques and real-time optimization capabilities, to continuously increase cloud infrastructure effectiveness.The proposed approach is applicable in areas such as cloud data centers, smart grids, IoT environments, healthcare cloud services, e-governance systems, and financial cloud computing environments. Additional investigation can improve real-time management of workloads, sustainable computing, particularly efficient in terms of AI model implementations within these areas.

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