Hybrid Meta-Heuristic Algorithm for Optimal Virtual Machine Migration in Cloud Computing

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***Abstract*—Virtual Machine (VM) migration is one of the most important features of cloud computing for resource utilization optimization, energy minimization, and quality of service enhancement. Existing migration solutions, however, suffer from excessive migration overhead, energy inefficiency, and ineffective allocation of resources. This study proposes a novel hybrid meta-heuristic algorithm through the integration of Particle Swarm Optimization (PSO) and Seahorse Optimization (SHO) to address the drawbacks. The proposed PSOSHO algorithm takes advantage of the global exploration capability of PSO and the adaptive exploitation feature of SHO and provides a sound solution for VM migration in dynamic cloud computing environments. Extensive simulation experiments were conducted for a different number of cloud tasks, and the results demonstrated that PSOSHO significantly outperforms existing algorithms. Specifically, it achieves improvements of up to 54% in load factor, 60% in migration count, 48% in migration cost, 7% in energy consumption, 27% in resource availability, and 37% in computation time. These results confirm the effectiveness and robustness of the proposed methodology for optimal VM migration and resource management in virtualized cloud computing infrastructures.**

Keywords*—*Cloud computing; virtualization; migration; particle swarm optimization; seahorse optimization

I. Introduction

Cloud computing has reshaped modern computing by supplying scalable, on-demand capabilities, enabling businesses and users to access virtualized infrastructure efficiently [1]. In cloud resource management, workload distribution comprises Virtual Machine (VM) migration, which dynamically transfers workloads between Physical Machines (PMs) to balance loading, improve resource utilization, and ensure the Service Level Agreement (SLA) [2]. VM migration, however, is plagued by challenges ranging from high energy consumption, high migration costs, and ineffective resource utilization [3]. Similar to the importance of intelligent decision-making in VM migration, recent studies in mobile social networks have highlighted the effectiveness of rule-based anomaly detection techniques for managing dynamic environments and improving overall system responsiveness [4].

Excessive migrations through frequent movements can result in high power consumption, negatively impacting cloud sustainability, while ineffective migration decisions increase operational expenditure and reduce system performance. Inefficient resource allocation mechanisms also result in unnecessary migrations, reducing system efficiency and affecting Quality of Service (QoS) [5]. To mitigate these issues, intelligent optimization techniques are required to improve migration efficiency, reduce costs, and improve resource management.

Recent advancements have demonstrated the effectiveness of intelligent optimization techniques in addressing complex challenges across various computing domains. For example, meta-heuristic-based strategies have been applied to optimize the placement and energy management of Electric Vehicle Charging Stations (EVCS) in microgrid environments [6, 7]. In healthcare wireless sensor networks, intrusion detection frameworks using clustering methods have enhanced security while minimizing computational overhead [8]. Similarly, geo-drone-based routing has improved connectivity in disaster-response ad hoc networks [9]. In e-commerce, hybrid models combining evolutionary algorithms with deep learning have improved sentiment classification accuracy [10, 11]. Additionally, dynamic spectrum access in heterogeneous wireless networks has been optimized for energy and spectral efficiency through interference-aware channel allocation and base station sleep-mode mechanisms [12].

Despite significant advancements in VM migration approaches, existing optimization techniques have disadvantages. The performance of using these methods is hindered by premature convergence, slow adaptability to dynamic workloads, and inefficient allocation of resources, which contribute to suboptimal migration decisions [13]. Besides, existing methods only focus on minimizing energy consumption, failing to balance migration cost, computational efficiency, and SLA satisfaction. A more flexible and effective optimization framework is necessary to address these issues. The present study employs a hybrid meta-heuristic optimization approach that integrates the strengths of Particle Swarm Optimization (PSO) and Seahorse Optimization (SHO) to significantly improve the optimality of VM migration in terms of cost and energy efficiency.

Despite notable progress in optimization-based VM migration strategies, many existing approaches suffer from critical shortcomings that limit their effectiveness in dynamic cloud environments. Traditional algorithms often struggle with premature convergence, making them prone to suboptimal migration decisions. Moreover, many methods are designed with a single-objective focus, typically energy reduction, while neglecting other crucial metrics such as migration cost, computational delay, and SLA compliance. Some hybrid and AI-based techniques offer improved accuracy but introduce excessive computational complexity, rendering them impractical for real-time deployment. Furthermore, existing solutions frequently lack adaptability to fluctuating workloads, leading to inefficient resource allocation and unnecessary migrations. These limitations underscore the need for a more balanced, adaptive, and computationally efficient optimization framework capable of addressing the multi-objective and dynamic nature of VM migration problems.

By integrating PSO and SHO, the proposed algorithm offers a sound trade-off between global exploration and local exploitation, removing shortcomings such as premature convergence and inefficient resource allocation of current methods. PSOSHO selects VMs to migrate dynamically and makes the optimal placement decisions to minimize energy consumption, migration cost, and computational overhead while guaranteeing SLAs. Under comprehensive simulations, PSOSHO demonstrates superior performance to conventional methods in energy efficiency, reduction of downtime, and resource utilization. The proposed approach provides a scalable, adaptive, and computationally efficient solution for cloud service providers, guaranteeing improved load balancing and system reliability in dynamic cloud environments. This study seeks to answer the following research question:

How can a hybrid meta-heuristic algorithm be designed to optimize virtual machine migration in cloud computing by balancing energy efficiency, migration cost, computation time, and resource utilization under dynamic workload conditions?

The structure of this study is organized as follows: Section II presents a comprehensive literature review of existing VM migration strategies in cloud computing. Section III formulates the problem of optimal VM migration, detailing the objectives, constraints, and system model. In Section IV, the proposed hybrid PSOSHO algorithm is introduced. Section V discusses the experimental results and performance comparisons of PSOSHO against existing algorithms across various metrics. Finally, Section VI concludes the study with key findings and future research directions.

II. Literature Review

Ghetas [14] proposed a Monarch Butterfly Optimization-based Virtual Machine (MBO-VM) placement method for enhancing cloud computing efficiency via energy conservation and server utilization improvement. The study highlights that VM placement is an essential task from the point of view of minimizing active PMs and reducing power consumption and maintenance costs in data centers. The MBO-VM was tested on the CloudSim toolkit with real and synthetic cloud workloads and demonstrated superior performance over state-of-the-art VM placement algorithms. The MBO-VM method efficiently consolidates VMs, reducing active server counts while maintaining optimum packaging efficiency.

Xu and Abnoosian [15] suggested a hybrid optimization algorithm using Genetic Algorithm (GA) and PSO for green VM migration in an energy-efficient way. The approach was designed to overcome poor convergence and local optima in the traditional PSO. Performance validation was achieved through the CloudSim simulator. The hybrid model conserved 23.19% of energy and 29.01% of execution time compared to other approaches. The model provided better power efficiency and guaranteed high computational performance for cloud data centers.

Zhao, et al. [16] proposed the Performance-Aware Virtual Machine Migration (PAVMM) model, which seeks to reduce VM performance degradation in migration. In contrast to the existing approaches that maximize SLA adherence and minimize VM suspension time, PAVMM employs a VM performance prediction model to take user experience one step further. Moreover, ACO solved the multi-objective VM migration efficiency in terms of migration costs and the number of active PMs. PAVMM is validated by experimental results, demonstrating better VM performance than previous mechanisms, making it a scientifically sound solution for performance-aware migration strategies.

Cao and Hou [17] introduced a two-tiered VM placement model to balance cloud computing energy consumption and resource utilization. A queuing model was used in the first tier to efficiently manage VM placement requests, followed by a Krill Herd (KH) algorithm-based multi-objective VM allocation strategy. This method aims to reduce carbon footprint and operational costs and ensure optimal resource usage. The proposed model demonstrated superior energy efficiency and workload balancing results, making it a viable approach for green cloud computing.

Maldonado Carrascosa, et al. [18] examined multi-objective workload migration in cloud environments by integrating a fuzzy meta-scheduler system with swarm intelligence and Non-dominated Sorting Genetic Algorithm II (NSGA-II). The approach aimed at maximizing interpretability while optimizing renewable energy consumption. The CloudSim-based system facilitated effective VM migration, improving data center performance and energy consumption. Simulation results indicated that the proposed approach outperformed traditional genetic algorithms, with a 6% improvement in interpretability and a 10% improvement in the use of renewable energy.

Çavdar, et al. [19] proposed a Utilization-Based Genetic Algorithm (UBGA) for efficient VM placement in cloud data centers. The method focused on reducing resource wastage, network load, and power consumption with optimal placement of VMs in PMs. UBGA performed better than existing placement algorithms, considering machine utilization and node distances. With CloudSim simulations, the study confirmed that UBGA provides improved resource utilization and energy efficiency, and hence, it is a promising solution for cloud infrastructure optimization.

Archana and Kumar [20] suggested a Modified Bat Algorithm (MBA) with Spider Monkey Optimization (SMO) for enhancing VM migration efficiency. The fitness function of SMO was integrated with MBA to augment the search process and avoid local optima entrapment. Simulations using CloudSimPlus showed MBA-SMO gave 25% faster migration time than the traditional Bat Algorithm, 27% faster than PSO, and 35% faster than Cuckoo Search (CS). Makespan, throughput, and overall migration performance enhancements further attested the effectiveness of the hybrid approach.

Parsafar [21] proposed a Recurrent Neural Network (RNN) and Gray Wolf Optimization (GWO)-based energy-aware VM migration method. Unlike traditional static threshold-based methods, the model dynamically predicts energy consumption using a multi-resource metric model. GWO is employed to optimize the predictive accuracy of RNN, and reinforcement learning is utilized to improve workload allocation continuously. Results confirmed a significant reduction in unnecessary VM migrations and energy consumption, with a 11% error margin from optimal solutions. The hybrid AI-based solution provides a sustainable and adaptive VM management solution in cloud computing environments.

While there are impressive advances in optimizing VM migration, existing approaches suffer from several limitations. As summarized in Table I, most traditional approaches, such as GA, PSO, and Ant Colony Optimization, suffer from premature convergence and local optima issues, compromising their effectiveness in large dynamic cloud environments. In addition, energy-efficient VM migration remains a significant challenge, as most existing approaches focus on minimizing energy consumption or maximizing SLA compliance but fail to effectively balance migration cost, execution time, and resource utilization simultaneously.

TABLE I. RECENT META-HEURISTIC ALGORITHMS FOR CLOUD VIRTUAL MACHINE MIGRATION

Reference	Optimization Technique	Performance gains	Shortcomings
[14]	Monarch butterfly optimization	Improved VM placement, fewer active servers, and reduced energy costs	Lacks adaptability to dynamic workloads, static optimization approach
[15]	Genetic algorithm and particle swarm optimization	23% energy savings and 29% faster execution	Prone to premature convergence, high computation cost
[16]	Ant colony optimization algorithm	Enhanced VM performance with reduced migration downtime	Focuses only on VM performance, lacks multi-objective balance
[17]	Krill herd algorithm	Improved SLA compliance and energy efficiency	Limited scalability for large data centers
[18]	Fuzzy meta-scheduler and non-dominated sorting genetic algorithm II	6% increase in interpretability and 10% better energy utilization	The increased complexity introduced by the fuzzy system requires expert tuning
[19]	Utilization-based genetic algorithm	Better VM placement with lower energy consumption	Does not consider SLA violations or execution time
[20]	Modified bat algorithm and spider monkey optimization	25–35% faster migration time compared to other techniques	It struggles with large-scale optimizations and risks getting stuck in local optima.
[21]	Recurrent neural network and gray wolf optimization	11% lower error margin and reduced unnecessary migrations	It has high computational complexity and requires extensive training data

Recent hybrid approaches, such as the Modified Bat Algorithm (MBA-SMO) and RNN-GWO, improved migration efficiency and prediction accuracy but lack adaptiveness to dynamic workload patterns. Moreover, AI-based models introduce computational complexity, making them difficult to apply in real-time cloud environments. To bridge these gaps, this study suggests the PSOSHO algorithm for ideal VM migration. By combining the exploration capability of PSO and the adaptive exploitation characteristic of SHO, PSOSHO enhances energy efficiency, migration cost, and computation performance. Unlike current models, PSOSHO dynamically adjusts VM selection based on runtime workload variations, offering adaptive and scalable migration.

III. PROBLEM FORMULATION

In modern cloud computing infrastructures, the dynamic allocation of resources is a key requirement for maintaining performance efficiency and service continuity [22]. As user demands vary, certain PMs may become overloaded, specifically when the total resource requests from hosted VMs exceed the available capacity of the PM. To address this, VM migration is employed to transfer selected VMs from overloaded PMs to underutilized ones, thereby balancing the load and enhancing system performance.

The core objective of the VM migration problem is to identify which VM should be migrated and, where it should be placed so that the overall system performance is optimized. The decision must minimize several critical parameters: energy consumption, migration cost, computation time, and resource wastage. Additionally, the solution must comply with resource constraints, ensuring that the receiving PM has sufficient capacity to host the incoming VM without becoming overloaded.

This optimization problem involves a set of PMs $PM = \{pm_1, pm_2, \ldots, pm_n\}$, a set of VMs $VM = \{vm_1, vm_2, \ldots, vm_n\}$, and corresponding resource requirements R_{vm_i} for each VM and capacities C_{pm_j} for each PM. The current utilization U_{pm_j} of each PM must also be taken into account. The primary objective is to decrease the total migration overhead, which includes energy consumption E_{mig}, migration cost C_{mig}, and computation time T_{comp}, while ensuring that the destination PM can accommodate the migrating VM. This can be expressed as a constrained multi-objective optimization problem [Eq. (1)]:

$$min\left(E_{mig} + C_{mig} + T_{comp}\right) \quad subject\ to\ U_{pm_j} + R_{vm_i} + C_{pm_j} \tag{1}$$

A key challenge lies in avoiding unnecessary migrations, which can cause additional energy usage and delay, while also preventing underutilization of resources, which leads to inefficiencies. Thus, the problem requires a careful trade-off between multiple conflicting objectives.

To address this complex decision-making problem, a hybrid meta-heuristic approach, PSOSHO, is proposed. This algorithm combines the global search strength of PSO with the adaptive local exploitation potential of SHO to find the most suitable VM-PM mapping. It considers the current state of the system and intelligently determines which VM to migrate to which PM, ensuring optimal resource usage and system stability. A schematic overview of the cloud environment and its resource interaction model is shown in Fig. 1, where VMs (in blue) interact with PMs (in gray) via the central cloud resource pool.

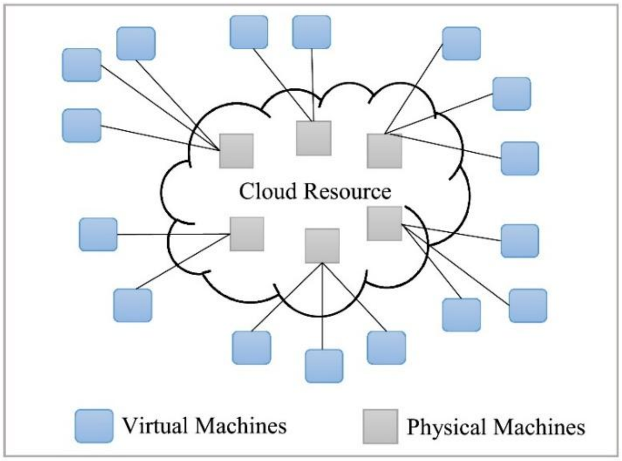

Fig. 1. Overview of cloud environment and its resource interaction model

IV. Proposed Hybrid PSOSHO Algorithm

This section introduces the hybrid meta-heuristic optimization model developed for efficient VM migration in cloud computing environments. Optimization algorithms such as PSO and SHO have been extensively applied in cloud and wireless sensor networks due to their potential to address intricate optimization issues. However, VM migration is a relatively unexplored research area in hybrid optimization. This research develops a novel approach by hybridizing PSO and SHO and exploiting their complementary characteristics to enhance migration efficiency, minimize resource wastage, and improve computational performance. The flowchart of the hybrid PSOSHO is illustrated in Fig. 2.

The proposed framework considers significant cloud computing parameters like PMs, VMs, memory, and bandwidth requirements. Resource allocation is triggered when a PM becomes overloaded, highlighting the necessity for optimal VM selection and migration to ensure balanced workload distribution. Migration is determined according to some performance metrics like energy consumption, resource utilization, computation overhead, and migration overhead. Proper resource demand estimation can avoid unnecessary migrations and improve cloud resource utilization and overall system performance.

The hybrid PSOSHO algorithm dynamically determines the most suitable VM to migrate to reduce SLA violations and ensure optimal cloud performance. Efficient VM migration is essential for achieving resource effectiveness, energy conservation, and reduction of service disruption in cloud computing. Traditional optimization techniques are plagued by the exploration-exploitation dilemma, leading to premature convergence or ineffective resource utilization. To mitigate the limitations, this study proposes a hybrid meta-heuristic optimization scheme combining SHO and PSO.

SHO is a swarm intelligence method inspired by the natural motion, predation, and mating of seahorses. SHO has a good balance between global exploration and local exploitation, hence, is apt for solving complex multi-objective optimization problems such as VM migration in dynamic cloud environments. Integrating SHO with the velocity-based update mechanism of PSO in the suggested PSOSHO algorithm leads to enhanced convergence speed, efficient VM selection, and reduced migration costs.

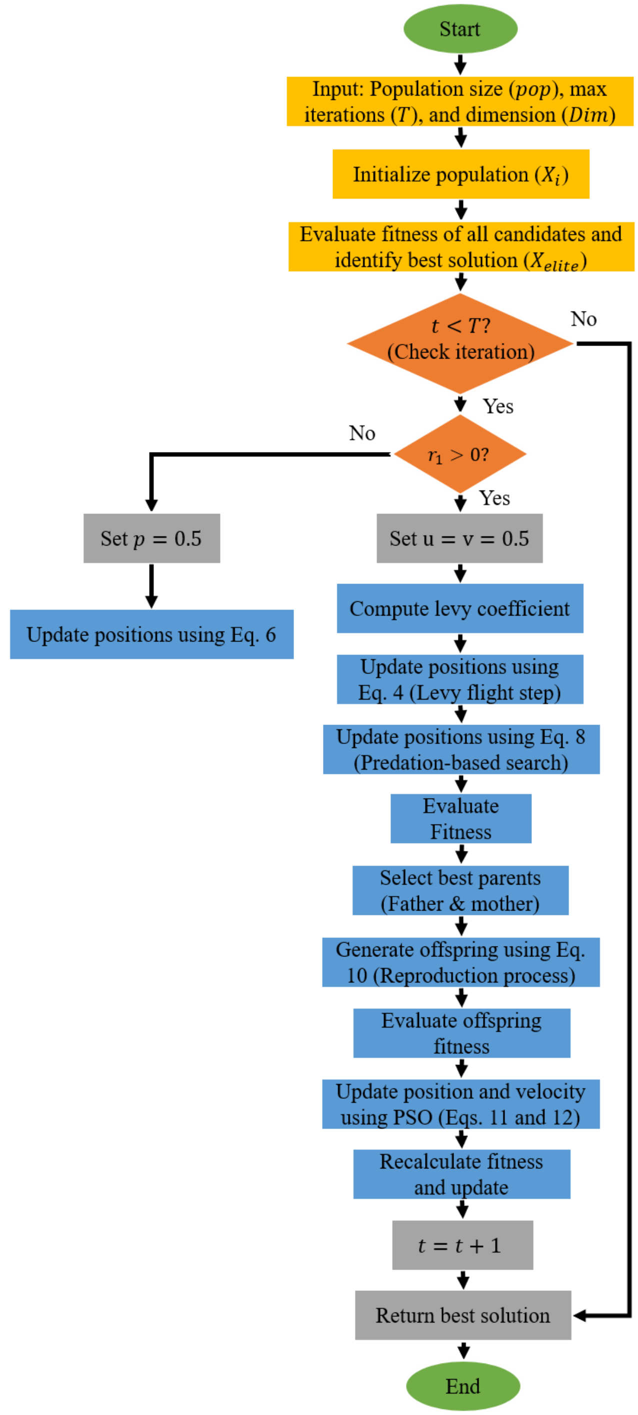

Fig. 2. Flowchart of the hybrid PSOSHO algorithm

The SHO algorithm starts by initializing a population of candidate solutions representing potential VM migration strategies. This population is structured as follows [Eq. (2)]:

$$Seahorses = \begin{bmatrix} x_1^1 & \dots & x_{Dim}^1 \\ \dots & \dots & \dots \\ x_1^{pop} & \dots & x_{Dim}^{pop} \end{bmatrix} \quad (2)$$

where, pop is the total number of candidate solutions and Dim represents the number of decision variables, such as CPU, memory, and bandwidth constraints.

The fitness function $f(X_i)$ evaluates each solution, and the best-performing candidate is selected as follows [Eq. (3)]:

$$X_{elite} = arg\ min\left(f(X_i)\right) \quad (3)$$

The SHO algorithm balances exploration and exploitation through two key movement strategies: Levy flight for global exploration and Brownian motion for local exploitation. The Levy flight mechanism enables candidate solutions to take large steps in search space, ensuring diverse exploration. The position update is given by Eq. (4):

$$X_{new}^1(t+1) = X_i(t) + Levy(\lambda)\big(X_{elite}(t) - X_i(t)\big) \times x \times y \times z + X_{elite}(t) \quad (4)$$

where, x, y, and z represent random factors influencing the jump size. $L\ e\ v\ y\ (\ )$ Levy(λ) is a function controlling the step distribution [Eq. (5)]:

$$Levy(z) = s \times \frac{x\sigma}{|k|^{1/\lambda}} \quad (5)$$

where, s = 0.01 and k is random numbers selected from [0,1]. This helps prevent local optima trapping and improves global search efficiency.

Once promising solutions are found, Brownian motion fine-tunes their positions using Eq. (6).

$$X_{new}^1(t+1) = X_i(t) + rand \times l \times \beta_t \times (X_i(t) - \beta_t \times X_{elite}) \quad (6)$$

where, β_t is a random walk coefficient, controlling the local refinement as follows [Eq. (7)]:

$$\beta_t = \frac{1}{\sqrt{2\pi}} \times e^{-u^2/2} \quad (7)$$

This ensures fine-tuned adjustments, leading to faster convergence.

The predation phase mimics seahorse hunting strategies, where search agents adapt based on successful exploration outcomes [Eq. (8)]:

$$X_{new}^2(t+1) = \begin{cases} \alpha \times \left(X_{elite} - rand \times X_{new}^1(t)\right) + (1-\alpha) \times X_{elite}, & if\ r_2 > 0.1 \\ (1-\alpha) \times (X_{new}^1(t) - rand \times X_{elite}) + \alpha \times X_{new}^1(t), & if\ r_2 \leq 0.1 \end{cases} \quad (8)$$

where, α is an adaptive parameter calculated as follows [Eq. (9)]:

$$\alpha = \left(1 - \frac{t}{T}\right)^{\frac{2t}{T}} \quad (9)$$

The predation strategy helps balance exploration and exploitation, leading to optimal resource allocation for VM migration. To maintain population diversity, the breeding process generates new candidate solutions using Eq. (10):

$$X_i^{offspring} = r_3 X_i^{father} + (1 - r_3) X_i^{mother} \quad (10)$$

While SHO efficiently balances exploration and exploitation, it lacks velocity-based search mechanisms, which can slow convergence in complex environments. To overcome this, PSO is integrated into SHO, forming PSOSHO. PSO enhances SHO's adaptability by refining position updates using velocity-based learning [Eq. (11) and Eq. (12)]:

$$X_{ij}^{t+1} = X_{ij}^t + v_{ij}^{t+1} \quad (11)$$

$$v_{ij}^{t+1} = wv_{ij}^t + C_1\left(X_{ij}^{p(t)} - X_{ij}^t\right) + C_2\left(X_j^{g(t)} - X_{ij}^t\right) \quad (12)$$

where, w is the inertia weight (controls exploration versus exploitation), C_1 is the cognitive acceleration coefficient (influence of personal best), C_2 is the social acceleration coefficient (influence of global best), v_{ij}^t is the current velocity of particle i in dimension j at iteration t, $X_{ij}^{p(t)}$ is the personal best position of particle i in dimension j at iteration t, X_{ij}^t is the current position of particle i in dimension j, and $X_j^{g(t)}$ is the global best position in dimension j at iteration t.

The PSOSHO algorithm identifies and migrates optimal VMs based on resource demands. The process involves:

- Initializing VMs and PMs based on cloud parameters (CPU, memory, bandwidth);
- Evaluating fitness function based on energy consumption, migration cost, and SLA adherence;
- Applying SHO's movement strategies (Levy flight + Brownian motion);
- Refining solutions via PSO updates for precise migration decisions;
- Converging to an optimal migration plan.

V. Results and Discussion

The efficacy of the proposed hybrid PSOSHO optimization model for VM migration was evaluated through rigorous simulation analysis. The simulation was carried out using the CloudSim toolkit, and the experimental setup was an Intel i5 processor, 16GB RAM, Windows 10 OS, 10 PMs, and 100 VMs. Performance was evaluated on key parameters of migration cost, energy consumption, resource utilization, and computation time and compared with four traditional VM migration algorithms: UBGA [19], KH [17], MBO-VM [14], and MBA [20]. The results confirm that the proposed PSOSHO model outperforms traditional approaches by reducing migration cost, energy consumption, and computation time while enhancing resource utilization.

The load factor is the level of utilization of resources by VMs in processing tasks. As shown in Fig. 3, the experiment was carried out on a different number of tasks, and the performance of optimization techniques in managing varied workloads was evaluated. The results indicate that the proposed PSOSHO algorithm experienced the lowest load factor in all the test scenarios owing to its efficient VM selection and migration policy. However, UBGA, KH, MBO-VM, and MBA experienced higher loads due to inefficient allocation of resources and excessive migrations.

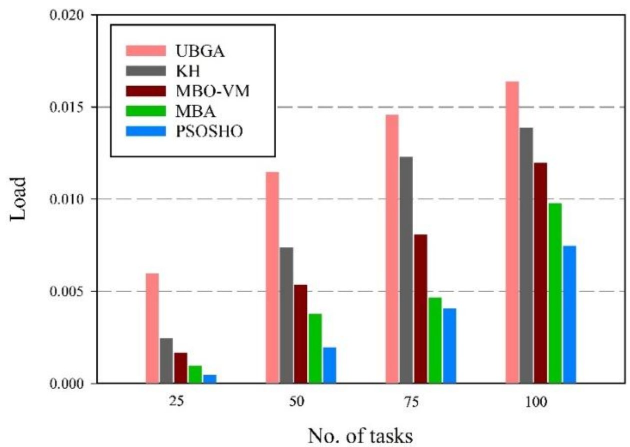

Fig. 3. Load comparison

Fig. 4 illustrates the number of migrations performed by different algorithms. PSOSHO successfully minimized the number of VM migrations, which led to minimized migration overhead. This is the direct result of the intelligent VM selection mechanism, as it ensures that only necessary migrations are performed. In contrast, other algorithms performed additional unnecessary migrations, which increased the system load and energy consumption.

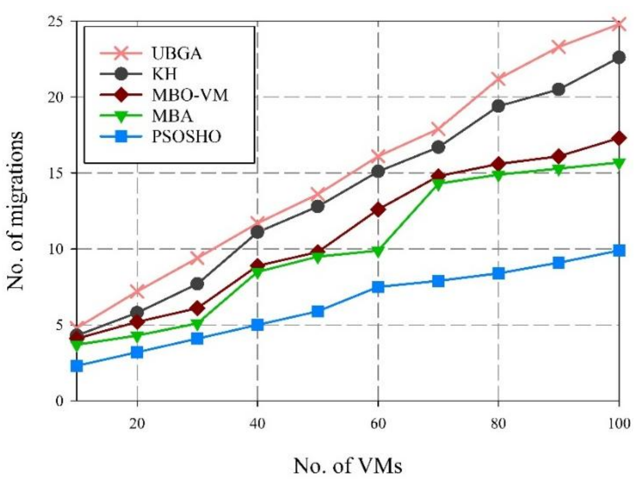

Fig. 4. Migration count comparison

The migration cost was defined as the ratio of the number of migrations completed to the number of migration requests, as shown in Fig. 5. The results indicate that the proposed PSOSHO model achieved the lowest migration cost, with a value of 0.05 in the presence of 100 tasks. In contrast, UBGA achieved the highest migration cost (0.097), KH (0.091), MBO-VM (0.075), and MBA (0.067).

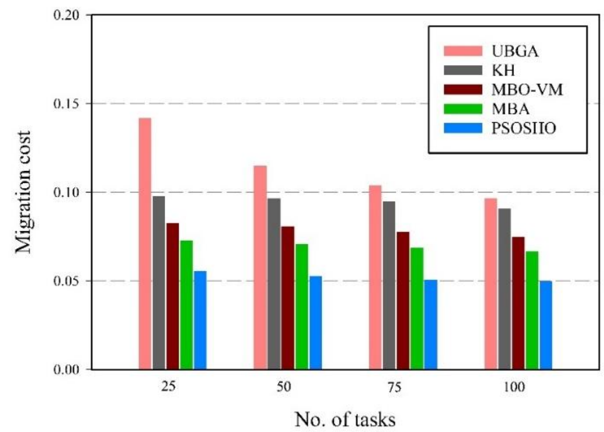

Fig. 5. Migration cost comparison.

Fig. 6 illustrates the analysis of energy consumption of PSOSHO's effectiveness in minimizing power consumption. The suggested model attained an average energy consumption of 0.468W for 100 tasks, which was significantly lower compared to UBGA (0.503W), KH (0.495W), MBO-VM (0.494W), and MBA (0.491W).

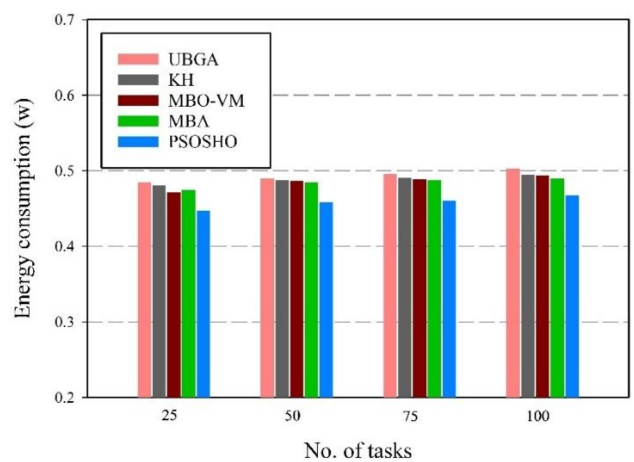

Fig. 6. Energy consumption comparison

The comparison of resource availability, as illustrated in Fig. 7, proves the efficiency of the PSOSHO model in optimizing resource utilization. The results indicate that maximum resources were available in the suggested model, implying minimum and requisite migrations were performed. On the other hand, the other algorithms experienced worse resource availability, implying more wastage of resources due to unnecessary migrations. It is evident that the PSOSHO model effectively allocates resources and prevents unnecessary migrations of VMs, leading to an optimized cloud environment.

Computation time is the duration to complete a migration process, as illustrated in Fig. 8. For 100 tasks, the proposed PSOSHO algorithm achieved a computation time of 5.5 seconds, which was significantly lower than that of UBGA (8.8 seconds), KH (8.2 seconds), MBO-VM (8.0 seconds), and MBA (7.5 seconds).

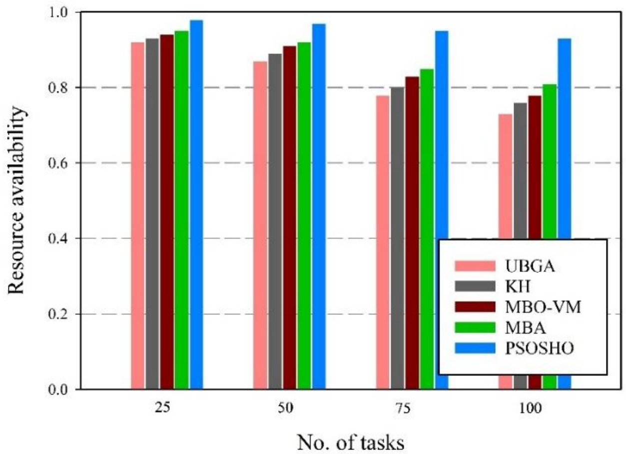

Fig. 7. Resource availability comparison

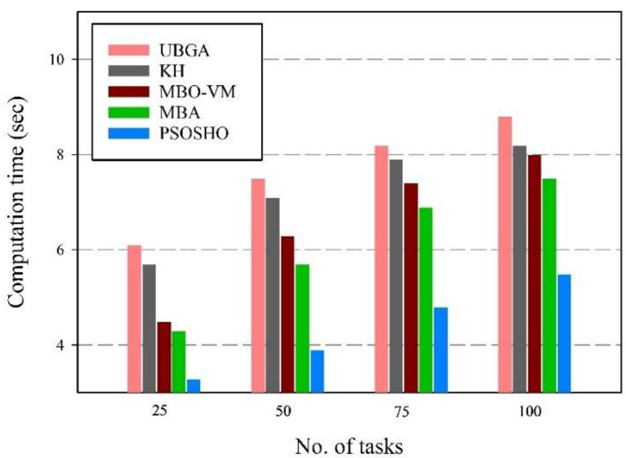

Fig. 8. Computation time comparison.

VI. Conclusion

This research proposed a hybrid meta-heuristic algorithm, PSOSHO, for VM migration optimization in cloud computing environments. Simulation analysis compared the proposed PSOSHO model with current state-of-the-art VM migration techniques. By intelligently selecting VMs to migrate and preventing unnecessary migrations, the PSOSHO algorithm reduced system overhead, enhanced the utilization of cloud infrastructure, and ensured high service quality with reduced SLA violations. Additionally, the hybrid approach of the proposed technique facilitated scalability in dynamic and large-scale cloud computing systems.

Although the experimental results demonstrate the effectiveness and superiority of the proposed PSOSHO algorithm, several avenues remain open for future exploration. One promising direction is the integration of Deep Reinforcement Learning (DRL) techniques, which can enable the migration model to learn and adapt autonomously from dynamic system states and historical migration outcomes. By incorporating DRL, the migration strategy could evolve in real-time, leading to more intelligent and context-aware decision-making in complex and volatile cloud environments. Another valuable extension involves the application of adaptive machine learning models to predict workload patterns, resource demands, and potential SLA violations. These predictive capabilities could be integrated with the PSOSHO framework to proactively trigger migration decisions, thereby minimizing overhead and service disruption.

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