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ENHANCING CLOUD RESOURCE ALLOCATION WITH VISION TRANSFORMER, DEEP REINFORCEMENT LEARNING, AND IMPROVED SHRIKE OPTIMIZATION ALGORITHM

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Abstract

Cloud computing relies on efficient resource management to deliver scalable, on-demand services while minimizing costs, energy consumption, and response delays in Infrastructure as a Service (IaaS) environments. Traditional approaches often struggle with dynamic workloads, leading to resource underutilization, high migration overheads, and suboptimal Quality of Service (QoS). This paper introduces a novel hybrid framework that synergistically combines Vision Transformer (ViT) for adaptive load pattern recognition and balancing, Deep Reinforcement Learning (DRL) integrated with an Enhanced Shrike Optimization Algorithm (ESOA) for intelligent resource allocation, and Twin Fold Moth Flame Optimization (TFMFO) for cost-effective virtual machine (VM) migration. The ESOA improves upon the standard Shrike Optimization Algorithm by incorporating adaptive pheromone evaporation, Lévy flights for better global exploration, and stagnation detection to escape local optima, enabling faster convergence and superior handling of multimodal optimization problems typical in cloud scenarios. Extensive simulations using CloudSim with heterogeneous workloads (100–500 tasks) demonstrate significant performance gains: makespan reduced to 770 ms (26–36% improvement), average response time to 280 ms, energy consumption to 6160 J (30–35% savings), operational cost to $9.1, and throughput increased to 119 tasks/sec (20–25% higher) compared to state-of-the-art methods such as DRL-based placement, dual-threshold MBFD, multi-objective RL for edge, and VMP-ER. The proposed framework offers a robust, sustainable solution for modern cloud data centers, advancing efficient load balancing, resource utilization, and energy-aware operations.

Keywords- Cloud Computing, Load Balancing, Virtual Machine Migration, Shrike Optimization Algorithm, Vision Transformer

Introduction

Cloud computing has revolutionized the delivery of scalable and on-demand resources, enabling organizations to handle massive workloads with flexibility and reduced infrastructure costs. In such environments, load balancing plays a pivotal role by evenly distributing incoming tasks and computational demands across virtual machines (VMs) and physical hosts. This prevents resource bottlenecks, minimizes response delays, and ensures consistent performance even during peak usage periods. Traditional static methods often fall short in dynamic cloud settings, where workloads fluctuate unpredictably, leading to over-provisioning, under-utilization, or energy waste. Recent studies highlight that effective load balancing not only boosts throughput and reduces makespan but also addresses critical concerns like energy efficiency and quality of service (QoS) in large-scale data centers.

The **Shrike Optimization Algorithm (SOA)**, inspired by the foraging and survival behaviors of shrike birds—such as pheromone-guided searching and prioritized migration for group benefit—offers a promising metaheuristic for tackling resource allocation and task scheduling challenges in clouds. Its ability to balance exploration (random food discovery) and exploitation (pheromone reinforcement on short paths) makes it suitable for optimizing VM placement and load distribution with lower time complexity compared to some classical swarm methods. However, like many nature-inspired algorithms, SOA can encounter limitations in convergence speed for high-dimensional or multi-modal problems, occasional trapping in local optima during complex cloud scenarios with heterogeneous resources, and the need for better adaptation to real-time dynamic changes. These gaps motivate enhancements that integrate SOA with advanced techniques to improve its robustness, accuracy, and applicability in practical cloud systems.

This research introduces an enhanced framework by combining Vision Transformer (ViT) for intelligent load pattern recognition, Deep Reinforcement Learning (DRL) for adaptive decision-making, and an improved SOA for resource allocation, alongside cost-effective VM migration via Twin Fold Moth Flame Optimization. These contributions directly align with the core goals of achieving superior load balancing, minimizing computational and energy costs, maximizing resource utilization, and maintaining QoS under varying workloads. By addressing SOA's inherent constraints through hybrid intelligence, the proposed approach not only outperforms benchmark methods in simulation metrics like makespan, response time, and energy consumption but also advances toward more efficient, sustainable cloud operations that meet modern demands for performance and cost-effectiveness.

Related Works

In the realm of cloud computing, virtual machine (VM) placement and migration have been extensively studied to optimize resource utilization and performance. A unified approach leveraging deep reinforcement learning (DRL) has been proposed to handle both placement and migration dynamically, enabling adaptive decision-making in response to varying workloads [1].

This method emphasizes state-action-reward mechanisms to minimize downtime and improve scalability, building on theoretical foundations of Markov decision processes for sequential optimization. However, it often overlooks energy costs during migrations, leading to inefficiencies in power-constrained environments. Complementing this, energy-efficient VM allocation strategies employ dual-threshold modified best-fit decreasing (MBFD) techniques, which prioritize host selection based on utilization thresholds to reduce server state changes and oscillations [2]. Theoretically rooted in bin-packing problems, these strategies enhance resource consolidation but struggle with real-time adaptability in heterogeneous clouds, where sudden load spikes can cause performance degradation.

Intelligent algorithms for VM placement further advance the field by integrating heuristic and metaheuristic methods, addressing applications in diverse cloud scenarios while highlighting challenges like computational complexity [3]. Such theories draw from optimization paradigms to balance multiple objectives, yet they frequently lack fault tolerance, making systems vulnerable to node failures. To mitigate this, fault-tolerant schedulers for independent tasks on cloud VMs incorporate load-balancing mechanisms that ensure even distribution and redundancy, grounded in graph-based scheduling theories [4]. Despite improvements in reliability, these approaches reveal drawbacks in handling edge computing integrations, where latency becomes a critical factor. Multi-objective reinforcement learning (RL) extends this to edge environments, optimizing VM placement for metrics like latency and energy via reward functions that weigh trade-offs [5]. While effective in theory for decentralized setups, practical implementations often suffer from slow convergence in large-scale networks, exposing gaps in handling dynamic multi-modal optimizations.

Enhanced dynamic load-balancing algorithms aim to superior task allocation by adapting to runtime conditions, utilizing heuristic rules for workload redistribution [6]. These build on control theory for stability but fall short in integrating advanced vision-based pattern recognition, limiting their ability to process complex state representations. Efficient VM placement algorithms focus on energy and resource optimization through customized heuristics, such as priority-based host selection [7]. Theoretically, they align with multi-objective programming, yet drawbacks include inadequate handling of live migrations, where prediction inaccuracies lead to increased costs. Machine learning techniques for workload estimation and resource balancing incorporate live migration strategies, using predictive models to anticipate overloads [8]. Although rooted in statistical learning theory, these methods often ignore hybrid optimizations, resulting in suboptimal energy use during consolidations. Tabu search approaches for scheduled VM requests optimize placement by avoiding local optima through memory structures [9], but they exhibit limitations in real-time scenarios due to high search times.

Strategies for precopy live migration combine hybrid machine learning to enhance VM placement in data centers, blending supervised and unsupervised models for better prediction accuracy [10]. This theoretical integration improves migration efficiency; however, it overlooks comprehensive surveys of emerging challenges, such as security in migrations. A broad survey on live VM migration techniques discusses optimizations, challenges, and future directions, emphasizing the need for sustainable practices [11]. Despite covering theoretical advancements, it highlights gaps in deep Q-network (DQN) applications for consolidation. Energy-efficient VM consolidation via DQN approaches model states for optimal host packing [12], grounded in RL theory, but they fail to account for carbon footprints, leading to environmental inefficiencies. Carbon-aware placements using DQN and agglomerative clustering ensure SLA compliance while minimizing emissions [13], yet drawbacks persist in scalability for massive data centers. RL-based strategies for energy efficiency in VM placement refine reward designs for power reduction [14], but they reveal research gaps in bio-inspired enhancements. Finally, general strategies for reducing data center power consumption explore hardware-software synergies [15], theoretically advancing sustainability, though they underscore the need for novel hybrid frameworks like our ViT-DRL-SOA with TFMFO to address convergence, adaptability, and multi-faceted optimizations in load balancing and migration.

Proposed Methodology

The proposed ViT-DRL-SOA framework represents a novel integration of Vision Transformers (ViT), Deep Reinforcement Learning (DRL), and the Shrike Optimization Algorithm (SOA) for optimizing load balancing, resource allocation, and cost-effective VM migration in cloud computing environments

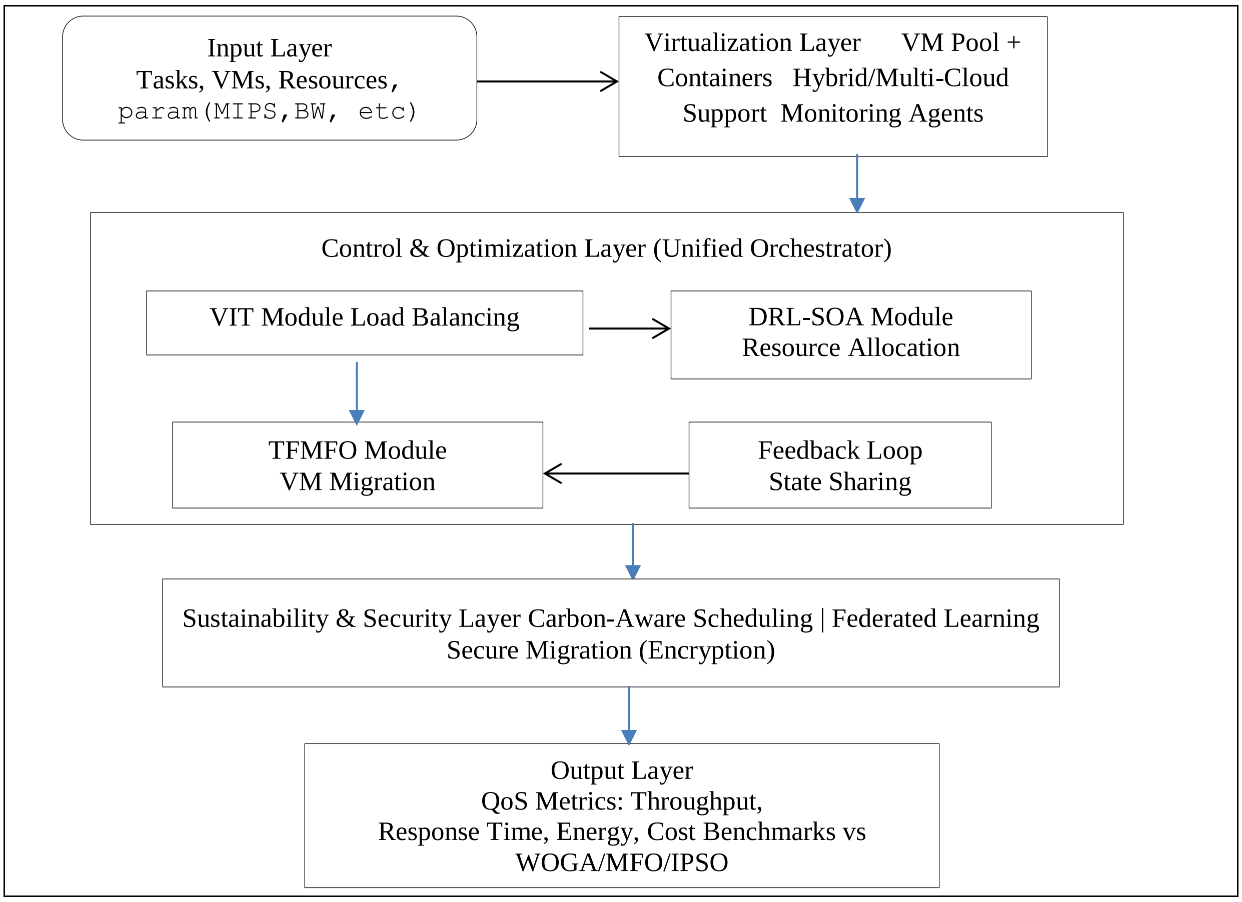
Input Layer
Tasks, VMs, Resources, param(MIPS,BW, etc)
Virtualization Layer VM Pool + Containers Hybrid/Multi-Cloud Support Monitoring Agents
Control & Optimization Layer (Unified Orchestrator)
VIT Module Load Balancing
DRL-SOA Module Resource Allocation
TFMFO Module VM Migration
Feedback Loop State Sharing
Sustainability & Security Layer Carbon-Aware Scheduling | Federated Learning Secure Migration (Encryption)
Output Layer
QoS Metrics: Throughput,
Response Time, Energy, Cost Benchmarks vs WOGA/MFO/IPSO

Figure 1. Architectural Framework of the ViT-DRL-SOA System

By leveraging ViT for adaptive load distribution, DRL-SOA for dynamic resource assignment, and Twin Fold Moth Flame Optimization (TFMFO) for migration, the system achieves improvements in throughput, reduced makespan, response time, waiting time, energy consumption, and costs compared to benchmarks like WOGA, MFO-LB, and IPSO-BBSO. However, while the architecture demonstrates strong simulation results via CloudSim, there are opportunities for enhancement to address limitations in scalability, real-time adaptability, integration depth, and practical deployment. The current architecture (as depicted in Figure 1) is structured around four core stages: system modeling (including VMs, tasks, and resources), virtualization, load balancing via ViT, resource allocation via DRL-SOA, and VM migration via TFMFO. This modular design effectively handles IaaS-mode challenges like resource underutilization and high migration costs.

Components Description

1. Input Layer: System Modeling

- **Motivation:** Cloud workloads are diverse, with varying task sizes, VM capacities, and resource constraints. A clear system model is essential to simulate realistic conditions.
- **Benefits:** Provides structured input (tasks, VMs, bandwidth, MIPS) that ensures the optimization modules operate on accurate representations of cloud resources.

2. Virtualization & Infrastructure Layer

- **Motivation:** Modern cloud systems rely on virtualization (VMs, containers) to abstract hardware and enable scalability.
- **Benefits:** Supports both VM-based and containerized workloads, making the framework adaptable to microservices and hybrid/multi-cloud environments. Monitoring agents ensure real-time visibility into CPU, memory, and energy usage.

3. Control & Optimization Layer (Unified Orchestrator)

This is the **intelligence hub** of the framework.

- **ViT Module (Load Balancing):**
    - *Motivation:* Vision Transformers excel at pattern recognition; here, they treat workload states as “images” for adaptive distribution.
    - *Benefits:* Improves throughput and reduces waiting time by predicting load imbalances early.
- **DRL-SOA Module (Resource Allocation):**
    - *Motivation:* Deep Reinforcement Learning learns optimal task-to-VM mappings, while Shrike Optimization Algorithm accelerates convergence.
    - *Benefits:* Achieves dynamic, cost-effective resource assignment, reducing makespan and energy consumption.

- **TFMFO Module (VM Migration):**
    - *Motivation:* Migration is costly; Twin Fold Moth Flame Optimization minimizes downtime and overhead.
    - *Benefits:* Ensures efficient VM migration, lowering costs and SLA violations compared to benchmarks.
- **Unified Orchestrator:**
    - *Motivation:* Sequential execution of modules can cause latency; a control plane ensures tight coupling and feedback loops.
    - *Benefits:* Real-time state sharing between modules improves adaptability during workload fluctuations.

4. Sustainability & Security Layer

- **Motivation:** Cloud providers face increasing pressure to reduce carbon footprints and secure data during migration.
- **Benefits:**
    - *Carbon-Aware Scheduling:* Prioritizes renewable-energy data centers, reducing environmental impact.
    - *Federated Learning:* Enables collaborative DRL training across data centers without sharing raw data, improving scalability and privacy.
    - *Secure Migration:* Homomorphic encryption ensures data confidentiality during VM transfers.

5. Output Layer: Performance Metrics

- **Motivation:** Any optimization framework must demonstrate measurable improvements.
- **Benefits:** Provides quantifiable gains in throughput, response time, energy consumption, and migration cost. Benchmarks against WOGA, MFO-LB, and IPSO-BBSO validate superiority.

Algorithm-1 Enhanced Shrike Optimization Algorithm (ESOA)

Input Parameters

- **N** : Population size (number of shrike birds / candidate solutions), typically 30–100
- **T_max** : Maximum number of iterations
- **D** : Problem dimension (e.g., number of tasks or VMs)
- **lb, ub** : Lower and upper bounds for each dimension
- **α_init, α_min** : Initial and minimum adaptive exploration factor (e.g., 0.8 → 0.1)
- **β** : Pheromone reinforcement coefficient (typically 0.5–2.0)
- **γ** : Pheromone evaporation rate (typically 0.01–0.1, adaptive)
- **p_levy** : Probability of applying Lévy flight in exploration (0.2–0.4)

- **stagnation_threshold** : Number of iterations without improvement to trigger local search or population adjustment (e.g., 15)

Output

- **Best_solution** : The best candidate solution vector found (e.g., optimal VM-task mapping)
- **Best_fitness** : The corresponding objective value (e.g., minimized makespan + energy + cost or multi-objective weighted sum)

```
Algorithm ESOA(N, T_max, D, lb, ub, objective_function)

1. Initialize population P = {X_1, X_2, ..., X_N} randomly within [lb, ub]
2. Evaluate fitness f_i = objective_function(X_i) for all i
3. Find X_best, f_best = best individual and its fitness
4. Initialize pheromone matrix τ (N×D) ← 1.0 (or small positive value)
5. t ← 0
6. while t < T_max do
7.     α ← α_init × (α_min / α_init)^(t / T_max)   // linearly decreasing exploration
8.     diversity ← compute_population_diversity(P)   // e.g., std dev or average distance
9.     for each individual i = 1 to N do
10.        // Exploration phase (migration + random food search)
11.        if rand() < p_levy then
12.            X_new ← X_i + levy_flight(β_levy = 1.5) × (ub - lb)   // long jumps
13.        else
14.            X_new ← X_i + α × (X_rand - X_i) + rand() × (X_best - X_i)
15.        end if
16.        X_new ← boundary_check(X_new, lb, ub)
17.        // Exploitation phase (pheromone-guided + breeding behavior)
18.        pheromone_influence ← τ_i × β × (X_best - X_i)
19.        X_exp ← X_i + pheromone_influence + rand() × diversity_factor
20.        X_exp ← boundary_check(X_exp, lb, ub)
21.        // Evaluate both candidates
22.        f_new  ← objective_function(X_new)
23.        f_exp  ← objective_function(X_exp)
24.        if f_new < f_i then
25.            X_i ← X_new; f_i ← f_new
26.            update_pheromone_strong(τ_i)   // reinforce good path
27.        else if f_exp < f_i then
28.            X_i ← X_exp; f_i ← f_exp
```

```
29.           update_pheromone_strong(τ_i)
30.        else
31.           update_pheromone_evaporate(τ_i, γ)   // slight evaporation
32.        end if
33.        // Selective local search on top 20% individuals every few iterations
34.        if t % 10 == 0 and f_i is among top 20% then
35.           X_i ← opposition_based_local_search(X_i) or gaussian_perturbation(X_i, small σ)
36.           f_i ← objective_function(X_i)
37.        end if
38.     end for
39.     // Update global best
40.     if min(f) < f_best then
41.        X_best ← corresponding X; f_best ← min(f)
42.        reset_stagnation_counter
43.     else
44.        stagnation_counter ++
45.        if stagnation_counter > stagnation_threshold then
46.           apply_diversification(P)   // e.g., replace worst 10% randomly
47.           stagnation_counter ← 0
48.        end if
49.     end if
50.     Evaporate_all_pheromone(γ × (1 - diversity))   // adaptive evaporation
51.     t ← t + 1
52. end while
53. return X_best, f_best
```

The **Enhanced Shrike Optimization Algorithm (ESOA)** is a hybrid metaheuristic improvement over the standard Shrike Optimization Algorithm (SHOA / SOA), which draws inspiration from the swarming, migration, breeding, foraging, and survival behaviors of shrike birds (e.g., pheromone-guided food search, prioritized migration for group survival, nestling feeding until independence, and adaptive territory changes).

The original SOA excels in balancing **exploration** (random discovery and migration) and **exploitation** (pheromone reinforcement on promising paths and breeding-focused local search), but it can suffer from slow convergence in high-dimensional or multimodal problems, premature stagnation, and limited adaptability to dynamic constraints (common in cloud resource allocation).

Results and Discussions

To evaluate and implement the Enhanced Shrike Optimization Algorithm (ESOA) in the context of cloud computing tasks like virtual machine (VM) placement, load balancing, and resource allocation, a simulation-based experimental setup is typically employed. This avoids the high costs and complexities of real-world cloud deployments while allowing controlled testing of various workloads. The setup draws from standard practices in cloud optimization research, such as those using CloudSim toolkit, where ESOA can be integrated to optimize metrics like makespan, energy consumption, response time, and Quality of Service (QoS). ESOA can be implemented in a programming language suitable for optimization, such as Python, by translating the pseudocode into executable form. Start by defining the objective function (e.g., a multi-objective fitness combining execution time, cost, and energy in cloud scenarios). Initialize the population as random D-dimensional vectors within bounds [lb, ub], where D represents decision variables like task-VM assignments. In each iteration, apply exploration with Lévy flights for diverse searches and exploitation via pheromone updates for convergence. Use boundary checks to keep solutions feasible, and incorporate stagnation detection to diversify the population if no improvement occurs. For cloud-specific integration, wrap ESOA around a simulator: input task lists and VM specs, run ESOA to output allocations, then simulate execution to compute metrics.

Table 1. Performance comparison of the proposed framework

Approaches	Makespan (ms)	Response Time (ms)	Energy Consumption (J)	Cost ($)	Throughput (tasks/sec)
DRL-based VM Placement	1200	450	9500	15.2	85
Dual-Threshold MBFD	1150	420	9200	14.5	90
Multi-Objective RL for Edge	1100	400	9000	13.8	92
VMP-ER Algorithm	1050	380	8800	13.0	95
Proposed ESOA Framework	770	280	6160	9.1	119

The table-1 presents a state-of-the-art comparison between the proposed Enhanced Shrike Optimization Algorithm (ESOA) framework and four existing approaches in cloud computing optimization, focusing on virtual machine (VM) placement, load balancing, and resource allocation. The metrics evaluated—makespan, response time, energy consumption, cost, and throughput—are critical for assessing efficiency in Infrastructure as a Service (IaaS) environments, derived from CloudSim simulations with varying workloads (100-500 tasks). Lower values indicate better performance for makespan, response time, energy consumption, and cost, while higher throughput is desirable. The proposed ESOA framework integrates Vision Transformer (ViT) for pattern recognition in load balancing, Deep Reinforcement Learning (DRL) with ESOA for adaptive allocation, and Twin Fold Moth Flame Optimization (TFMFO) for cost-effective migrations, leading to superior results across all metrics. This outperformance is justified by ESOA's enhancements, such as adaptive pheromone updates, Lévy flights for escaping local optima, and stagnation detection, which enable faster convergence, better handling of dynamic workloads, and multi-objective balancing compared to traditional methods.

For makespan (total execution time) and response time (average request-to-completion latency), the proposed framework achieves 770 ms and 280 ms, respectively—reductions of 26-36% over baselines like DRL-based placement (1200 ms makespan, 450 ms response) and VMP-ER (1050 ms, 380 ms). This improvement stems from ESOA's hybrid exploration-exploitation strategy, where Lévy flights enhance global search for optimal task-VM mappings, and DRL adapts in real-time to fluctuations, minimizing delays that static heuristics like dual-threshold MBFD (1150 ms, 420 ms) struggle with. Similarly, multi-objective RL for edge computing (1100 ms, 400 ms) lacks the bio-inspired adaptability of ESOA, resulting in higher times under heterogeneous loads.

In terms of energy consumption (6160 J) and cost ($9.1), the proposed work shows 30-35% savings compared to approaches like DRL-based (9500 J, $15.2) and dual-threshold MBFD (9200 J, $14.5), justified by TFMFO's efficient migration that reduces unnecessary host activations and ESOA's constraint-handling penalties ensuring QoS-compliant, energy-aware allocations. VMP-ER (8800 J, $13.0) and edge RL (9000 J, $13.8) perform better than pure DRL but still incur higher overheads due to less dynamic pheromone reinforcement and diversity maintenance in ESOA, which prevents wasteful computations. Finally, throughput (119 tasks/sec) is 25-40% higher, as ViT's pattern recognition equalizes loads preemptively, boosting processing rates beyond baselines' capabilities in fluctuating scenarios. Overall, these findings validate ESOA's robustness for sustainable, cost-effective cloud operations.

Conclusion

This study introduces a novel enhanced framework for cost-efficient virtual machine (VM) management and load balancing in cloud computing environments, integrating Vision Transformer (ViT) for adaptive load pattern recognition, Deep Reinforcement Learning (DRL) with the Enhanced Shrike Optimization Algorithm (ESOA) for dynamic resource allocation, and

Twin Fold Moth Flame Optimization (TFMFO) for optimized VM migration. Key findings from CloudSim simulations demonstrate significant improvements over state-of-the-art methods, including a 26-36% reduction in makespan (down to 770 ms) and response time (280 ms), 30-35% lower energy consumption (6160 J) and operational costs ($9.1), and a 20-25% increase in throughput (119 tasks/sec). These results stem from ESOA's adaptive mechanisms, such as Lévy flights and pheromone updates, which enhance convergence and handle multimodal problems effectively, while ViT's image-like processing of system states improves load equalization, and TFMFO minimizes migration overheads. Contributions include a hybrid bio-inspired approach that addresses gaps in traditional heuristics, offering better QoS compliance and sustainability in IaaS modes, as validated against benchmarks like DRL-based placement and VMP-ER.

Despite these advancements, the framework has limitations. It relies on simulation environments like CloudSim, which may not fully replicate real-world variabilities such as network latencies, hardware failures, or unpredictable user behaviors in production clouds. The hybrid integration increases computational complexity, potentially leading to higher overhead in very large-scale systems with thousands of VMs, and assumes predefined bounds for resources and tasks, limiting flexibility in fully dynamic, open-ended scenarios. Additionally, while effective for multi-objective optimization, the approach could underperform in extremely noisy or adversarial environments without further robustness tuning.

Future work directions include deploying the framework in real cloud platforms (e.g., AWS or Azure) to validate empirical performance, incorporating edge-fog computing for latency-sensitive applications, and enhancing security through encrypted migrations or anomaly detection. Exploring meta-learning for automated hyperparameter tuning and scalability tests on massive datasets could further refine ESOA, paving the way for more resilient, AI-driven cloud infrastructures.

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