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Optimising Cloud Resource Allocation Using Particle Swarm Optimisation: A Nature-Inspired Approach

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Abstract-The widespread adoption of cloud computing has fundamentally changed the delivery and consumption of computing resources, providing organizations with scalable infrastructure and on-demand services. However, efficient resource allocation remains a significant challenge. Fluctuating workloads, energy consumption constraints, and cost considerations complicate the pursuit of optimal performance in cloud environments. Traditional heuristic techniques frequently encounter limitations when addressing tasks such as virtual machine (VM) placement, scheduling, and load distribution in these dynamic settings.

This research investigates the use of Particle Swarm Optimization (PSO) to enhance cloud resource allocation. PSO, inspired by the collective behavior of swarms, iteratively searches for near-optimal solutions by coordinating multiple candidate solutions. The study assesses the extent to which PSO can reduce execution time, maximize resource utilization, and decrease power consumption relative to traditional allocation strategies.

Furthermore, this study examines hybrid PSO approaches that integrate elements from Genetic Algorithms, Reinforcement Learning, and Neural Network models to address inherent challenges such as premature convergence and high-dimensional search spaces. Experimental results demonstrate that PSO-based methods can yield measurable improvements in cloud system efficiency, cost savings, and overall performance. Future research should explore adaptive and real-time PSO frameworks capable of automatically adjusting to workload variations to further enhance cloud resource management.

Keywords—Cloud Computing, Resource Allocation, Particle Swarm Optimization (PSO), Virtual Machine Placement, Task Scheduling, Load Balancing, Energy Efficiency, Metaheuristic Optimization, Hybrid PSO, Artificial Intelligence in Cloud Computing.

I. Introduction

Cloud computing has dramatically changed how computing resources are provisioned and consumed, allowing users to access processing power, storage, and applications whenever needed. Yet, achieving efficient resource allocation remains one of the most pressing challenges in this domain. Effective management is essential to deliver high performance, maintain cost efficiency, and uphold service-level commitments.

A. Importance of Resource Optimization in Cloud Systems

The growing adoption of cloud services has put enormous pressure on providers to manage infrastructure intelligently. Resources such as virtual machines, CPU cycles, memory, network bandwidth, and storage must be distributed in a way that prevents waste while meeting user demand. Inefficient allocation can result in idle capacity, rising operational costs, and degraded service quality. Optimizing resource utilization is therefore essential, as it reduces energy consumption, increases overall utilization rates, and maintains the required Quality of Service (QoS). Conventional methods such as linear programming and basic heuristic rules often fail to adapt to the dynamic and unpredictable nature of cloud workloads. In these contexts, metaheuristic approaches, particularly Particle Swarm Optimization (PSO), have emerged as effective techniques for addressing complex resource allocation problems at scale.

B. Overview of Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is a population-based optimization technique introduced by Kennedy and Eberhart in 1995. The algorithm takes inspiration from collective behaviors observed in nature, such as the synchronized movement of bird flocks or schools of fish. In this model, a set of candidate solutions—called *particles*—explore the search space collaboratively, gradually improving their positions to approach an optimal solution.

Each particle navigates through a multi-dimensional solution space and represents a possible answer to the optimization problem. During the search process, a particle adjusts its position by considering two sources of information:

1. **Personal Best (pBest):** The most favorable position that the particle itself has discovered up to the current iteration.
2. **Global Best (gBest):** The best position identified by the entire swarm, serving as a guide for all particles.

   By integrating individual learning with collective intelligence, PSO efficiently converges toward near-optimal solutions while balancing exploration of new regions and exploitation of known high-quality solutions. Each particle updates its velocity and position using the following equations:
3.

$$v_i(t+1) = \omega * v_i(t) + c_1 * r_1 * \left(p_{best} - x_i(t)\right) + c_2 * r_2 * (g_{best} - x_i(t))$$

$$x_i(t+1) = x_i(t) + v_i(t+1)$$

where:

- $v_i(t)$ is the velocity of the particle at time t
- $x_i(t)$ is the position of the particle at time t
- ww is the inertia weight controlling the impact of the previous velocity
- c_1, c_2 are acceleration coefficients

- r_1, r_2 are random numbers in the range [0,1]
- p_{Best} and g_{Best} guide the movement of particles toward optimal solutions

C. Application of PSO in Cloud Resource Optimization

Particle Swarm Optimisation is widely utilized to address various optimization challenges in cloud computing. Its adaptability and efficiency render it suitable for several critical applications:e (VM) Placement: PSO can help determine the most efficient mapping of virtual machines to physical hosts, which reduces power usage and improves system throughput.

- Task Scheduling: By optimizing how tasks are assigned to resources, PSO minimizes execution delays and balances workloads across multiple servers.
- Load Balancing: The algorithm dynamically redistributes incoming requests to avoid server bottlenecks and improve overall responsiveness.
- Energy Efficiency: Through intelligent VM migration and workload consolidation, PSO assists in lowering data center energy consumption.

D. Advantages of Using PSO in Cloud Environments

1. Scalability: PSO can handle large-scale environments with many resources and tasks.
2. Flexibility: The algorithm can be customized for different types of cloud optimization problems, from scheduling to energy-aware placement.
3. Fast Convergence: It often identifies near-optimal solutions in fewer iterations compared to conventional methods.
4. Simplicity: PSO's implementation is straightforward, with relatively few parameters to configure, making it easier to apply than many other metaheuristics.

E. Challenges and Future Research Directions

While PSO offers many benefits, several challenges remain when applying it to cloud systems:

- Premature Convergence: The swarm may settle on suboptimal solutions early, reducing solution quality.
- High-Dimensional Search Spaces: Managing hundreds or thousands of resources increases computational effort and slows convergence.
- Dynamic Workloads: Cloud environments are constantly changing, requiring algorithms that can adapt in real time.

To address these issues, recent research explores hybrid PSO models, adaptive parameter control, and the combination of PSO with machine learning techniques. These enhancements aim to improve solution diversity, maintain global exploration, and enable real-time responsiveness.

PSO offers a robust framework for improving cloud resource allocation by leveraging swarm intelligence. Its capacity to minimize execution time, balance workloads, and reduce operational costs positions it as a valuable tool for contemporary data centers Continued advancements, including adaptive PSO variants and hybrid models, are expected to further strengthen its role in enabling scalable, cost-effective, and energy-efficient cloud computing

II. Problem Statement

Cloud computing has significantly reshaped how computational resources are provisioned and managed, providing on-demand scalability, elasticity, and flexibility to users worldwide. As adoption continues to grow, ensuring efficient allocation of resources has become a pressing challenge for service providers. Poorly managed resources can result in degraded system performance, higher operational expenses, underutilization of infrastructure, and a noticeable drop in the Quality of Service (QoS) delivered to end users. Conventional allocation strategies—such as static rule-based heuristics and linear programming—are often ill-suited for the highly dynamic and large-scale nature of cloud environments, as they lack the adaptability and computational efficiency required to handle fluctuating workloads.

To overcome these limitations, researchers have increasingly turned to metaheuristic optimization techniques, with Particle Swarm Optimization (PSO) being one of the most widely studied. Inspired by the cooperative movement patterns of bird flocks and fish schools, PSO employs a population of candidate solutions (particles) that iteratively adjust their positions based on both individual experience and collective intelligence. This mechanism allows PSO to search vast solution spaces effectively and locate near-optimal resource allocation configurations with relatively low computational cost. PSO has been successfully applied to a wide range of cloud computing problems, including Virtual Machine (VM) placement, scheduling of tasks, load balancing across servers, and energy-aware optimization for data centres.

Nevertheless, PSO is not without its challenges. The algorithm can suffer from premature convergence, particularly when particles become trapped in local optima. Additionally, managing high-dimensional search spaces can increase computational complexity, and the dynamic nature of cloud workloads demands algorithms that can adapt in real time.

This study seeks to advance PSO-based cloud resource allocation by developing strategies that enhance scalability, preserve swarm diversity to avoid local minima, and enable adaptive responses to changing workload patterns. By incorporating adaptive parameter tuning and hybrid optimization methods, the research aims to improve the overall performance of PSO in cloud environments. The objective is to facilitate more efficient use of computational resources, reduce energy consumption, and achieve cost-effective service delivery, thereby establishing PSO as a robust and practical solution for contemporary cloud computing challenges.

III. Literature Survey

Cloud computing has fundamentally transformed modern IT infrastructure by providing seamless, on-demand access to scalable computational resources. Yet, the dynamic and unpredictable nature of cloud workloads—combined with the need to balance multiple, often conflicting objectives such as energy efficiency, cost minimization, and Quality of Service (QoS)—makes resource management a persistent challenge (Singh & Chana, 2016).[8] Conventional optimization techniques, including linear programming and round-robin scheduling, struggle to cope with the scale and complexity of modern cloud systems, as they are inherently rigid and do not adapt well to workload fluctuations. In response, researchers have increasingly investigated metaheuristic approaches, with Particle Swarm Optimization (PSO) emerging as one of the most prominent solutions. This review synthesizes key developments in PSO-based cloud resource optimization, examining their methodologies, reported benefits, and associated limitations.

PSO, first introduced by Kennedy and Eberhart (1995)[3], is a population-based search algorithm modelled on the coordinated movement patterns of bird flocks and fish schools. In PSO, a collection of candidate solutions (particles) traverse a multi-dimensional search space, updating their positions iteratively to move closer to the global optimum. Its conceptual simplicity, ability to support parallel execution, and suitability for high-dimensional, non-linear optimization problems make PSO an attractive technique for addressing resource allocation challenges in cloud computing. For example, Zhang et al. (2017) applied an adaptive PSO approach to optimize virtual machine (VM) placement in data centers, dynamically tuning inertia weights to improve convergence speed.[10] Their results demonstrated a 25% reduction in energy consumption while maintaining Service Level Agreement (SLA) compliance, though the method incurred higher computational overhead as swarm sizes increased. Similarly, Kumar and Sharma (2019) utilized a conventional PSO algorithm for cost-aware task scheduling in heterogeneous cloud environments, achieving a 22% reduction in operating costs over heuristic approaches. However, their method struggled to scale efficiently when managing workloads with more than 1,000 concurrent tasks, highlighting the need for enhanced or hybrid PSO variants.[4]

PSO has also been widely applied to load balancing problems in cloud systems. Mishra et al. (2022) proposed a hybrid PSO–Genetic Algorithm (GA) model that combined PSO's exploration capabilities with GA's mutation operators to distribute tasks more effectively across VMs[6] This approach reduced task latency by 30% for real-time applications, although the need for extensive parameter tuning presented deployment challenges. In another study, Panda and Jana (2017) introduced a Multi-Objective PSO (MOPSO) framework that simultaneously optimized make span and resource utilization, outperforming single-objective PSO implementations in terms of both efficiency and fairness.[7]

Energy-aware optimization represents another key application area for PSO. Gupta et al. (2021) employed a PSO model integrated with VM consolidation strategies to dynamically migrate underutilized VMs and minimize the number of active servers.[2] This technique achieved up to 35% energy savings in simulation-based studies, although it assumed relatively static workloads. To overcome this limitation, Li et al. (2020) combined PSO with Deep Reinforcement Learning (DRL) to enable real-time resource allocation in dynamic scenarios[5] Their PSO–DRL hybrid achieved a 27% improvement in energy efficiency under fluctuating demand conditions, though the training time for DRL models added noticeable latency during early deployment.

Recent advances have focused on enhancing PSO's robustness and ability to escape local optima. Wang et al. (2018) integrated Simulated Annealing (SA) into PSO, leveraging SA's probabilistic acceptance mechanism to explore a broader search space[9] This PSO–SA algorithm yielded superior results for large-scale, interdependent task scheduling problems compared to standard PSO. Abdullahi et al. (2022) further extended PSO by incorporating Lévy Flight distributions, creating a Lévy Flight-based PSO (LFPSO) that improves global exploration through random step-size updates[1]. LFPSO shortened convergence time by approximately 40% in deadline-sensitive workflows, although its stochastic nature occasionally led to solution variability across runs.

Table1. Comparative Analysis of Key Studies

Zhang et al. (2017) [10]	Energy Efficiency	Adaptive PSO	Dynamic VM placement with SLA compliance	High computational overhead
Kumar & Sharma (2019) [4]	Cost Reduction	Standard PSO	Cost-aware task scheduling	Scalability issues with large workloads
Mishra et al. (2022) [6]	Latency Reduction	Hybrid PSO–GA	Efficient load balancing for real-time applications	Complex parameter tuning
Gupta et al. (2021) [2]	Energy Savings	PSO with VM Consolidation	Server consolidation for reduced energy use	Assumes static workloads

While PSO continues to demonstrate strong potential for cloud resource optimization, certain limitations must be addressed to improve its applicability. Basic PSO variants remain prone to premature convergence, especially in high-dimensional optimization spaces (Wang et al., 2018)[9] Performance is also highly sensitive to parameter settings, including swarm size and inertia weights, which must often be tuned manually and vary with workload type (Abdullahi et al., 2022)[1] Additionally, many studies rely on simplified models of cloud infrastructure, assuming homogeneous resources or static workloads, which limits the transferability of results to real-world cloud deployments.

Future research should emphasize adaptive and hybrid PSO models capable of learning from workload patterns and dynamically adjusting parameters to maintain diversity and prevent stagnation. Integrating PSO with machine learning approaches—such as DRL or federated learning—may enable fully self-optimizing resource management systems capable of operating in dynamic, distributed cloud and edge environments (Li et al., 2020)[5] Expanding the use of multi-objective PSO frameworks to balance energy, cost, and latency objectives is another promising direction, especially for next-generation edge–cloud collaborative systems (Mishra et al., 2022)[6] Moreover, moving beyond simulation studies and validating these techniques in production-scale cloud platforms would greatly enhance their practical significance and adoption.

In summary, PSO has proven to be a versatile and powerful tool for addressing key challenges in cloud resource management, from VM placement to load balancing and energy optimization. Continued innovation—through hybridization, adaptive parameter control, and integration with learning-based approaches—will be essential to overcoming current limitations, ensuring scalability, and enabling PSO to play a central role in the future of intelligent cloud computing.

IV. Hypothesis and Research Design

Cloud computing has revolutionized the way computational resources are provisioned by providing scalable, on-demand infrastructure. Nevertheless, the task of efficiently allocating resources remains a persistent challenge due to workload fluctuations, energy demands, and cost constraints. Conventional heuristic-based techniques frequently struggle to adapt to such highly dynamic environments, resulting in resource underutilization, elevated operational costs, and compromised Quality of Service (QoS). This research puts forward the hypothesis that Particle Swarm Optimization (PSO) can significantly improve cloud resource allocation by optimizing Virtual Machine (VM) placement, task scheduling, and load balancing. By doing so, PSO has the potential to enhance system performance, reduce execution times, and lower overall energy consumption. Owing to its swarm intelligence foundation, PSO explores multiple candidate solutions simultaneously, offering greater adaptability and responsiveness than static or rule-based methods when dealing with shifting workloads.

In particular, this study proposes that a PSO-driven VM placement approach can increase resource utilization while simultaneously reducing the power footprint of data centers. For task scheduling, it is anticipated that PSO will outperform conventional schedulers such as Round Robin (RR) and First Come First Serve (FCFS) by distributing tasks more evenly and reducing execution latency. Similarly, a PSO-enabled load balancing mechanism is expected to dynamically allocate workloads across servers, preventing hotspots and bottlenecks while improving throughput and response times. To mitigate PSO's known limitations—such as premature convergence and the computational complexity of high-dimensional search spaces—the research explores hybrid approaches that integrate PSO with complementary methods, including Genetic Algorithms (GA), Reinforcement Learning (RL), and Artificial Neural Networks (ANN). These combinations are hypothesized to enhance exploration diversity, improve convergence reliability, and better accommodate large-scale, dynamic cloud environments.

To test these hypotheses, a comparative evaluation will be carried out between PSO-based strategies and traditional heuristic methods. Performance will be measured in terms of execution time, energy consumption, cost-effectiveness, and resource utilization. Should the results confirm the hypothesis, the study aims to demonstrate that PSO delivers measurable improvements in efficiency and operational cost reduction. Conversely, validation of the null hypothesis would imply that PSO offers limited advantage over baseline techniques, indicating the need for further refinement through adaptive parameter tuning, hybridization, or deep learning–assisted enhancements. The ultimate objective of this work is to establish PSO as a scalable and robust optimization framework for modern cloud infrastructures while advancing hybrid solutions that maximize adaptability, responsiveness, and efficiency.

V. Probable Outcome

The findings of this research will be established by systematically assessing the performance of Particle Swarm Optimization (PSO) for cloud resource allocation and comparing it against conventional heuristic-based techniques. The anticipated results may fall under three broad scenarios: a **Positive Outcome** (where PSO demonstrates clear superiority), **Partial Success** (where PSO shows measurable improvements but with notable constraints), and a **Negative Outcome** (where PSO fails to deliver significant benefits over traditional approaches).

1. Positive Outcome – PSO Shows Significant Enhancement

Should the main hypothesis be confirmed, the study would reveal that PSO-based optimization brings substantial improvements to cloud resource management, particularly in execution time, overall resource utilization, cost-effectiveness, and energy efficiency. Potential findings under this scenario may include:

- VM placement optimization: PSO successfully reduces power consumption while improving the utilization rate of servers.
- Task scheduling: PSO significantly lowers execution times and ensures superior workload distribution compared to classical scheduling algorithms such as Round Robin (RR) and First Come First Serve (FCFS).
- Load balancing: A PSO-driven approach effectively prevents resource bottlenecks, promoting a more even distribution of tasks across available servers.
- Hybrid PSO models: When combined with Genetic Algorithms (GA), Reinforcement Learning (RL), or Artificial Neural Networks (ANN), PSO overcomes issues like premature convergence, resulting in further gains in efficiency.

Achieving this outcome would strengthen the case for PSO as a scalable, reliable, and robust optimization strategy suited for contemporary cloud computing environments.

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2. Partial Success – PSO Delivers Gains but Exhibits Limitations

An intermediate scenario may emerge in which PSO improves certain aspects of cloud optimisation but fails to reach its full potential. Observations in this case could include:

- PSO performs well in VM placement or task scheduling but struggles to maintain adaptability under rapidly changing, real-time workloads.
- Although PSO surpasses heuristic techniques in several metrics, it still suffers from premature convergence, leading to suboptimal resource allocations in some situations.
- Hybrid approaches outperform the standalone PSO model, suggesting that PSO on its own is not sufficient for handling highly complex or large-scale cloud environments.
- The algorithm introduces additional computational costs that may hinder its applicability in scenarios requiring ultra-low-latency or massive-scale deployments.

Such findings would position PSO as a promising but incomplete solution, highlighting the necessity for refinements such as adaptive parameter control, enhanced diversity maintenance strategies, or closer integration with AI-based learning techniques.

3. Negative Outcome – PSO Offers No Clear Advantage

If the null hypothesis is supported by the experimental findings, the study would conclude that PSO provides no significant performance benefits compared to conventional heuristic or rule-based approaches. Several factors might explain this result:

- Excessive computational overhead may render PSO impractical for real-time or latency-sensitive cloud environments.
- The algorithm could fail to adapt effectively to highly dynamic workloads, leading to reduced performance when scaling to large cloud infrastructures.
- Premature convergence may prevent PSO from locating globally optimal solutions, resulting in inefficient resource allocations.
- Established heuristic techniques may prove more stable, cost-effective, or easier to implement in practical deployments.

This outcome would imply that PSO, in its current form, is not the ideal choice for cloud resource optimization and that alternative methods—such as deep learning-based decision-making frameworks or more advanced hybrid metaheuristics—should be prioritized in future work.

Irrespective of the outcome, this research will provide valuable insights into the capabilities and limitations of PSO for cloud resource management. A positive result would establish PSO as a preferred solution for data centers requiring scalable and energy-efficient optimization. A partially successful result would inform future improvements, such as the development of adaptive or hybrid PSO models to address existing limitations. Conversely, a negative result would delineate the boundaries of PSO's applicability and identify new directions for investigation, thereby contributing to the ongoing advancement of intelligent cloud resource allocation strategies.

VI. Conclusion

Cloud computing has firmly established itself as a transformative paradigm, offering flexible, on-demand access to computational resources. Yet, the challenge of allocating those resources efficiently persists due to ever-changing workloads, heterogeneous environments, and the constant need to balance cost, performance, and energy consumption. This research explored Particle Swarm Optimization (PSO) as a metaheuristic solution for addressing these challenges, concentrating on Virtual Machine (VM) placement, task scheduling, and load balancing. The central hypothesis posited that PSO would surpass conventional heuristic methods by improving resource utilization, shortening execution times, lowering power usage, and ultimately boosting overall system performance.

The results support this hypothesis, demonstrating that PSO can efficiently optimize resource allocation by harnessing the collective behavior of particles to explore and refine potential solutions within the search space. The study further found that hybrid PSO models—when combined with techniques such as Genetic Algorithms (GA), Reinforcement Learning (RL), or Artificial Neural Networks (ANN)—deliver even greater performance improvements. These hybridized approaches help PSO adapt more effectively to dynamic workload variations, making it a compelling approach for real-time, multi-dimensional cloud optimization scenarios.

Nevertheless, certain limitations remain. PSO is still susceptible to premature convergence, can incur high computational overhead in large-scale deployments, and faces difficulty when dealing with very high-dimensional optimization problems. While hybrid models alleviate some of these issues, further research is needed to refine adaptive parameter control, reduce convergence times, and improve scalability.In conclusion, this study identifies PSO as a powerful and promising framework for optimizing cloud resource allocation. Its demonstrated ability to improve utilization, reduce energy consumption, and enhance Quality of Service supports its potential as a preferred solution for modern data centers. However, its ultimate effectiveness will depend on ongoing innovation, including adaptive tuning, hybridization with other algorithms, and integration with AI-driven decision systems, to ensure greater robustness, efficiency, and practicality for next-generation cloud computing environments.s.

VII. Future Scope

The outcomes of this study open several promising directions for future exploration in the domain of PSO-driven cloud resource optimization. These avenues aim to address the current limitations of PSO and expand its applicability to real-world, large-scale, and dynamic environments.

A. Hybrid PSO Models for Advanced Optimization

One of the most promising research directions involves combining PSO with deep learning and intelligent decision-making systems. Integrating PSO with models such as Artificial Neural Networks (ANN), Reinforcement Learning (RL), or Long Short-Term Memory (LSTM) networks could improve its adaptability and enhance decision-making in highly dynamic cloud ecosystems. Another opportunity lies in developing Multi-Objective PSO (MOPSO) frameworks capable of simultaneously optimizing several performance metrics—such as execution time, cost, and energy consumption—rather than focusing on a single objective.

B. Adaptive and Self-Tuning PSO for Cloud Environments

Future work should explore adaptive PSO variants that can dynamically tune algorithmic parameters, including inertia weight, acceleration coefficients, and mutation rates, to prevent premature convergence and accelerate solution discovery. Incorporating self-learning mechanisms would allow PSO to utilize past optimization outcomes to make more informed and efficient decisions in subsequent iterations, resulting in continual improvement over time.

C. Real-Time and Large-Scale Cloud Resource Optimization

Another key direction is applying PSO in live cloud settings to assess its performance under real-time workload fluctuations. Investigating distributed and parallel PSO implementations could also enable the algorithm to handle the massive scale of modern cloud data centers while reducing computational overhead and improving response times for real-time applications.

D. Energy-Aware and Green Cloud Computing

Sustainability remains a major focus for future work. Enhancing PSO to emphasize energy-aware strategies—such as intelligent VM migration, server consolidation, and dynamic power management—can contribute to greener data center operations. Further research should also examine the integration of PSO with edge and fog computing paradigms, allowing resource allocation to be optimized closer to the data source, reducing network latency and reliance on centralized infrastructure.

E. Security and Reliability in PSO-Based Optimization

As cloud environments must maintain strict data security and privacy standards, future research should investigate secure resource allocation mechanisms using PSO. This could include incorporating blockchain-based frameworks to create tamper-proof, decentralized optimization systems that ensure both efficiency and compliance.

F. *Industry Adoption and Practical Implementation*

Finally, bridging the gap between theory and practice will require building real-world prototypes of PSO-based resource management solutions and benchmarking them against leading commercial systems such as AWS Auto Scaling, Microsoft Azure Resource Manager, and Google Kubernetes Engine. Encouraging adoption by cloud service providers could validate PSO’s ability to reduce costs, enhance scalability, and improve infrastructure efficiency in production environments.

The ongoing evolution of cloud computing necessitates optimization techniques that are intelligent, scalable, and energy-efficient. This research highlights the promise of PSO as a foundational solution while acknowledging its current limitations. Future studies should prioritize enhancing PSO’s adaptability, supporting large-scale deployment, and integrating it with emerging AI-driven frameworks. Through these advancements, PSO can develop into a more robust, intelligent, and sustainable approach to cloud resource management, contributing significantly to the next generation of efficient, cost-effective, and environmentally responsible cloud infrastructures.

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