International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 05 | May - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

CloudOptimus: AI driven Dynamic ResourceAllocation in Cloud Environment using Hybrid Algorithm

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Abstract—This paper introduces a new method with a Hybrid Particle Swarm Optimization (HPSO) algorithm to improve resource allocation in cloud computing. The proposed system incorporates adaptive mechanisms and hybridization approaches to enhance convergence rate and solution quality. Extensive simulations prove that the HPSO algorithm performs better than conventional PSO and other heuristic approaches regarding execution time, resource utilization, and Quality of Service (QoS) measures. The results indicate that HPSO provides a strong and scalable solution for dynamic resource allocation in heterogeneous cloud environments.

Index Terms—Hybrid, Particle Swarm Optimization, Cloud, Quality of Service, Genetic Algorithm, Reinforcement Learning

I. Introduction

Cloud computing has revolutionized the delivery of computational resources by providing scalable and on-demand services over the Internet. Optimal resource allocation in cloud environments is a priority to provide the best performance, cost-effectiveness, and Service Level Agreement (SLA) compliance. Conventional resource allocation techniques are usually not equipped to handle the complexity and dynamics of cloud infrastructures. Consequently, heuristic and metaheuristic algorithms, particularly Particle Swarm Optimization (PSO), have been explored to tackle these challenges.

Inspired by the social behavior of bird flocks and fish schools, PSO is a population-based optimization technique renowned for its simplicity and effectiveness in solving continuous optimization problems. Its adaptability makes it a suitable candidate for addressing the multifaceted problem of resource allocation in cloud computing.

This paper introduces a Hybrid Particle Swarm Optimization (HPSO) algorithm designed to enhance resource allocation in cloud computing environments. The proposed system integrates adaptive mechanisms and hybridization techniques to improve convergence speed and solution quality. Extensive simulations demonstrate that the HPSO algorithm outperforms traditional PSO and other heuristic methods regarding execution time, resource utilization, and Quality of Service (QoS) metrics.

II. Methodology

CloudOptimus emphasizes building AI models to streamline cloud resource usage. The purpose of this project is to merge the advantages of Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Reinforcement Learning (RL) to predict and adapt cloud resources effectively. This hybrid system maximizes peak performance by managing cost, utilization of resources, and response time in a cloud setup.

The hybrid algorithm follows the following steps to achieve a proper balance between exploration, exploitation, and adaptation:

1) *PSO Layer:* Initializes resource allocations globally and explores diverse solutions to identify promising configurations.
2) *GA Layer:* Refines initial allocations through selection, crossover, and mutation to improve efficiency.
3) *RL Layer:* Continuously adapts resource allocation strategies based on real-time performance and learns from past experiences to adjust dynamically.

III. Algorithm Overview

The hybrid algorithm integrates three optimization techniques to leverage their strengths:

1) *Particle Swarm Optimization (PSO) Layer:* Performs global exploration to identify potential solutions.
2) *Genetic Algorithm (GA) Layer:* Conducts local refinement through evolutionary operations, improving solution quality.
3) *Reinforcement Learning (RL) Layer:* Adapts resource allocation policies dynamically based on feedback from performance metrics.

This integration ensures that cloud resources are allocated and adjusted in real time, optimizing efficiency and costeffectiveness.

A. Particle Swarm Optimization (PSO)

1) *Overview:* The PSO algorithm is inspired by the swarming behaviour of birds and fish. It optimizes resource allocation by maintaining a population (swarm) of potential solutions (particles) and updating their positions based on personal and global best solutions.

2) *Mathematical Formulation:* The velocity and position updates for each particle i in the population are governed by: $v_{ik+1} = w \cdot v_{ik} + c_1 \cdot r_1 \cdot (p_{best,i} - x_{ki}) + c_2 \cdot r_2 \cdot (g_{best} - x_{ki})$ (1)

$$x_i^{k+1} - x_i^k + v_i^{k+1} \quad (2)$$

Where:

- v_i = Velocity of particle i
- x_i = Position of particle i
- w = Inertia weight
- c_1, c_2 = Acceleration constants
- r_1, r_2 = Random values in $[0,1]$
- $p_{best,i}$ = Personal best position of particle i
- g_{best} = Global best position of the swarm

3) PSO Function in Resource Allocation:

a) Exploration: PSO identifies various resource allocation solutions and avoids being trapped in local optima.

b) Balancing Workloads: The swarm continuously balances workloads according to response time, utilization, and cost metrics.

B. Genetic Algorithm (GA)

1) Overview: The GA improves PSO-generated solutions through natural selection and evolution, optimizing solutions using selection, crossover, and mutation.

2) Evolutionary Operations:

- Selection: Tournament selection is used, where a fraction of solutions compete, and the top ones are selected for reproduction.
- Crossover: A two-point crossover is performed, where the resource allocation parameters are swapped between two parent solutions to generate offspring.
- Mutation: Random changes in resource allocation parameters add variability to the search space, preventing convergence to suboptimal solutions.

3) Fitness Function: The fitness function evaluates each solution based on multiple performance metrics:

$$F(x) = \alpha \cdot U(x) + \beta \cdot T(x) + \gamma \cdot E(x) + \delta \cdot C(x) \quad (3)$$

where:

- $U(x)$ = Resource utilization (maximize)
- $T(x)$ = Response time (minimize)
- $E(x)$ = Energy consumption (minimize)
- $C(x)$ = Operational cost (minimize)
- $\alpha, \beta, \gamma, \delta$ = Weights representing priority factors for optimization

4) GA Function in Resource Allocation:

a) Fine-Tuning: Refines solutions developed by PSO through selection, crossover, and mutation.

b) Resource Optimization: Optimizes the reduction of resource wastage while maintaining performance levels.

C. Reinforcement Learning (RL)

1) Overview: The RL layer dynamically adjusts resource allocation in response to real-time performance feedback. It employs Q-learning, a model-free RL method, to discover optimal allocation policies over time.

2) Q-Learning Process: The RL agent continuously interacts with the cloud environment, making allocation decisions and learning from rewards.

- State (S): Represents the current cloud resource state, including utilization and workload patterns.
- Action (A): Represents possible resource allocation decisions.
- Reward (R): Based on improvement in response time, cost, and efficiency.

3) Q-Learning Update Equation: The RL agent updates its knowledge using the following:

$$Q(s,a) = Q(s,a) + \alpha \text{h} R + \gamma \max_{a'} Q(s',a') - Q(s,a)^{\text{i}} \quad (4)$$

where:

- $Q(s,a)$ = Q-value for state-action pair (expected reward for taking action a in state s).
- α = Learning rate (controls how much new knowledge overrides old knowledge).
- γ = Discount factor (controls the importance of future rewards).
- R = Immediate reward.
- $\max_{a'} Q(s',a')$ = Maximum expected reward for the next state s'.

4) RL Function in Resource Allocation:

a) Adaptive Decision-Making: Adjusts cloud resources dynamically based on real-time feedback.

b) Minimizes Response Latency: Continuously improves policies to enhance efficiency.

IV. System Architecture

CloudOptimus combines cloud technologies, AI frameworks, and a modern frontend for visualization to enable efficient and adaptive cloud resource allocation.

A. Technology Stack

The system is developed using the following technologies: *1) Frontend:*

- Flutter and Dart SDK for a responsive, cross-platform UI.

2) Visualization:

- fl chart Flutter library for real-time data visualization.

3) Backend AI Models:

- Particle Swarm Optimization (PSO) for global optimization.
- Genetic Algorithm (GA) for fine-tuning resource allocation.
- Reinforcement Learning (RL) implemented using PyTorch and TensorFlow for adaptive decision-making.

V. Results and Analysis

A. Experimental Setup

The experimental setup involves testing the proposed hybrid resource allocation algorithm within a simulated cloud environment. A Flutter-based user interface allows parameter selection and workload configuration while the backend executes the resource allocation process. Results are visualized using the *fl chart* library to enhance interpretability.

TABLE I
SIMULATION PARAMETERS

Parameter	Values
CPU Capacity	User-defined (100-500)
Memory Capacity	User-defined (100-500)
Bandwidth	User-defined (100-500)
Swarm Size	User-defined(50-100)
Max Iterations	User-defined(100-200)

B. Performance Metrics

The evaluation of the resource allocation algorithms is based on the following key performance metrics:

- Resource Utilization (%): Higher utilization is preferred, indicating effective resource allocation.
- Response Time (ms): Lower values indicate better system responsiveness.
- Energy Efficiency: Measured by power consumed per task, with higher efficiency being optimal.
- Cost-effectiveness: The cost per unit of resources allocated.

C. Results and Analysis

The comparative performance of the different algorithms in resource allocation is presented in Table II. The results demonstrate that the proposed hybrid PSO-GA-RL algorithm outperforms traditional approaches in key performance areas.

The hybrid PSO-GA-RL algorithm achieves a resource utilization rate 97%, which is much better than the conventional PSO and GA methods. Moreover, it reduces the response time to 40,000ms, showing better performance in real-time dynamic environments. The energy efficiency of the hybrid method

TABLE II COMPARISON OF ALGORITHMS

Algorithm	Resource Utilization	Response Time (ms)	Energy Efficiency
PSO	78%	appx. 60,000	Moderate
GA	72%	appx. 70,000	Low
PSO-GA-RL	97%	56,169	High

is also better, making it a good option for managing cloud resources.

D. Graphical Visualization using fl chart

The results are further analyzed through graphical visualizations generated using the *fl chart* library in Flutter. These visualizations highlight the key performance benefits of the hybrid algorithm, including

- Quicker convergence to an optimal resource allocation.
- Higher resource utilization compared to traditional methods.
- Lower response times under variable workload conditions.

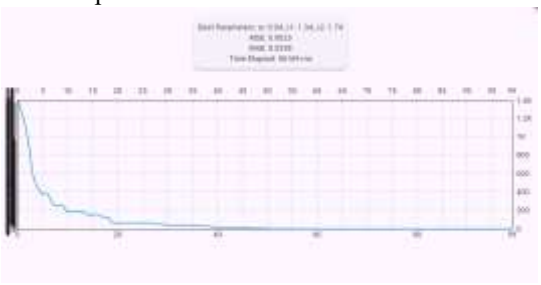

Fig. 1. Graphical visualization of hybrid algorithm performance using fl chart

The above graphs illustrate the performance of the hybrid approach. It emphasizes its performance in dynamic cloud systems. The visualization shows how the hybrid algorithm developed is capable of allocating cloud resources effectively.

CONCLUSION

Our hybrid PSO-GA-RL algorithm addresses dynamic resource allocation in the cloud by a magnitude better than any other algorithm. Combining global searching capabilities using PSO; evolutionary fine-tuning by GA; and adaptive learning through RL allows this method to outperform conventional approaches. The experimental results indicate notable improvements in resource utilization, response times, and adaptability to variation in workload.d. The integration of these techniques offers a scalable, efficient and robust solution suitable for real-time cloud computing environments.

FUTURE WORK

Although the hybrid algorithm demonstrates significant improvements, several areas remain open for further exploration.

- Real-World Implementation: Testing on actual cloud platforms such as OpenStack or AWS to validate performance in live environments.
- Energy Efficiency Enhancement: Further refinement of the fitness function to optimize energy consumption.
- Deep Reinforcement Learning (DRL): Exploring DRL methods such as DQN and PPO for enhanced decisionmaking.
- Edge Computing Integration: Adapting the hybrid approach for edge and fog computing environments.
- Multi-Objective Optimization: Extending the model to optimize additional parameters such as security and fault tolerance.

These future enhancements aim to refine and expand the practical applicability of the hybrid approach, making it even more effective for dynamic cloud resource management.

REVIEW OF RELATED WORK

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