Journal of Artificial Intelligence and Emerging Technologies
Volume 3, Issue 7, pp 61-65, July-2026
ISSN (online): 3049-1967
DOI: https://doi.org/10.47001/JAIET/2026.307006
Available Online at https://www.jaiet.com

Efficient Algorithm for Multi-Objective Dynamic Resource Allocation in Cloud Computing

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Abstract: Cloud computing environments depend heavily on efficient Dynamic Resource Allocation (DRA) mechanisms to ensure optimal utilization of computational resources while maintaining low operational cost, reduced energy consumption, and acceptable Quality of Service (QoS) under continuously fluctuating workloads. However, many existing resource allocation techniques in cloud systems are limited by poor adaptability, high computational overhead, inefficient virtual machine migration, and inability to simultaneously optimize multiple conflicting objectives such as throughput, Service Level Agreement (SLA) compliance, and power efficiency. These limitations create the need for a more intelligent, scalable and adaptive resource management framework capable of making real-time allocation decisions in heterogeneous cloud environments. This study therefore presents the design and development of DynamiCloud, a scalable and computationally efficient multi-objective dynamic resource allocation model for cloud computing. The research aimed at developing an efficient algorithm for multi-objective Dynamic Resource Allocation (DRA) in cloud computing. An object-oriented system design methodology was adopted in modeling the proposed framework; while a Deep Reinforcement Learning (DRL)-based optimization algorithm was implemented to enable the system learn optimal VM allocation and reallocation policies from environmental states, reward signals, and workload behavior patterns. The design was implemented using python. Comparing the results of our implementation with the existing tools shows that our objectives were met.

Keywords: Efficient Algorithm, Multi-Objective, Dynamic, Resource Allocation, Cloud Computing.

I. INTRODUCTION

Cloud computing has emerged as a transformative paradigm in modern information technology, enabling on-demand access to a shared pool of configurable resources such as networks, servers, storage, and applications. The scalability, elasticity, and cost-effectiveness of cloud computing have driven its adoption across diverse sectors, including healthcare, education, finance, and e-commerce [1] However, as the demand for cloud services increases, the efficient allocation of resources in dynamic and multi-objective environments becomes a critical challenge.

Cloud environments are characterized by heterogeneous resources, multi-tenant architectures, and diverse Service Level Agreements (SLAs), further complicating the resource allocation process [2]. Consequently, balancing these trade-offs is essential to ensure sustainable and efficient cloud operations. Multi-objective DRA algorithms aim to provide solutions that achieve optimal trade-offs among conflicting objectives, leveraging techniques such as evolutionary algorithms, machine learning, and heuristic methods [3].

The need for multi-objective optimization in DRA arises from the conflicting nature of objectives in cloud computing. For instance, minimizing energy consumption may lead to increased response times or reduced QoS, while optimizing performance might incur higher operational costs [4].

II. LITERATURE REVIEW

Cloud computing has revolutionized computing by providing scalable, on-demand resources through service models such as Infrastructure-as-a-Service (IaaS), Platform-as-a-Service (PaaS) and Software-as-a-Service (SaaS). However, the dynamic nature of cloud environments necessitates efficient resource allocation mechanisms to manage the optimal provisioning and utilization of resources like CPU, memory, and storage.

Cloud providers aim to optimize cost for both the provider and the user [5] proposed strategies that focus on predictive scaling to reduce operational costs. Predictive models leverage historical and real-time data to scale resources dynamically, achieving a balance between over-provisioning and under-provisioning.

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Metaheuristic algorithms like NSGA-II and Particle Swarm Optimization (PSO) are highly regarded for multi-objective optimization. NSGA-II generates Pareto-optimal solutions, enabling decision-makers to evaluate trade-offs effectively. PSO has shown potential for real-time resource scheduling due to its faster convergence and ability to handle dynamic environments.

Dynamic Resource Allocation (DRA) refers to the method of distributing online resources to applications as needed [6]. If allocation is not managed correctly, DRA can lead to a shortage of services. Providing resources addresses the issue of famine by enabling service providers to oversee resource management within each module. Cloud computing involves digital marketing and email marketing [7]. Furthermore, cloud computing can be described as offering various computer services, including storage, databases, software, networking and analytics, which deliver more adaptable resources Cloud computing refers broadly to any services that are provided over the internet [8]. In this technology, the user is not privy to the technical specifics and only observes its visual interface [9]. The fundamental principle of cloud computing is based on the concept of time sharing. In simpler terms, various computer resources are utilized by several users through multi-programming and multi-tasking methods.

Each request made by users to service providers consumes some of their resources. The DRA issue poses a significant challenge in cloud environments, closely linked to energy consumption, the profitability of service providers and costs for users. As a result, significant work has been accomplished in the area of DRA, focusing on minimizing resource usage, balancing loads and integrating resources.

III. SYSTEM DESIGN

This exposes the structure of the architecture, elements, coherence and data for a system to satisfy specific requirements. Figure1 shows the architectural Design of the system.

Cloud Environment: This represents the overall cloud infrastructure where computing resources exist. The cloud environment considers multiple objectives affecting resource allocation:

i. **Cost:** Minimizing financial expenses for running or allocating resources.
ii. **Energy Efficiency:** Reducing power consumption to lower operational cost and environmental impact.
iii. **Latency:** Ensuring low response time for better user/application performance.

Multi-objective Resource Allocation Algorithm: The main decision-making engine that optimally allocates resources based on multiple objectives simultaneously. It evaluates requests, available resources and trade-offs among objectives such as cost, energy, and performance.

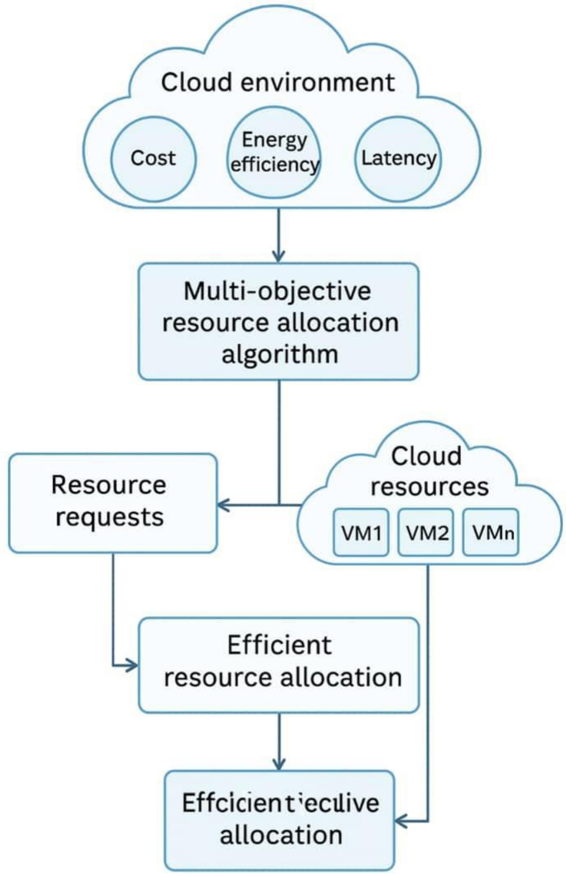

Figure 1: Architectural Design of the System

Resource Requests: Incoming demands from users or applications that require cloud resources such as CPU, memory, storage, or virtual machines.

Cloud Resources: Available virtualized units in the cloud, including VM1, VM2, up to VMn. Each VM provides computing capabilities such as CPU, RAM, storage, and networking.

Efficient Resource Allocation: The optimized distribution of resources produced by the algorithm after evaluating all objectives and available capacity.

Resource Allocation (Final Output): This is the final output where tasks are assigned to virtual machines based on a trade-off among execution time, cost, energy, consumption and resource utilization.

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Algorithm for Scalable Resource Allocation

Input:
workloads // Array of incoming workloads
resources // Array of available resources (CPU, Memory, Storage, etc.)
edgeResources // Resources available in the edge/fog network
minCost // Minimum allowed cost
minEnergy // Minimum allowed energy consumption
minLatency // Minimum allowed latency
Output:
allocatedResources // Allocated resources for each workload

Algorithm with RL

```
Initialize replay memory D
Initialize Q-network with random weights θ
Initialize target network with weights θ^target = θ
For episode in range (max_episodes):
    Initialize environment and get initial state S
    For step in range (max_steps_per_episode):
        Select action A (ε-greedy policy based on Q-network)
        Execute A in environment, observe reward R and next state S'
        Store transition (S, A, R, S') in D
        Sample minibatch from D and update Q-network:
            1. Compute target Q-value using target network
            2. Minimize loss between predicted Q and target Q
        Periodically update θ^target = θ
    End For
End For
```

Cost Minimization: Minimize the total cost of resource allocation. The objective is to minimize the total cost of resource allocation, which is calculated based on the cost of each resource used for a workload. Let:

c_j be the cost of resource $_{rj}$ (e.g., cloud, edge, or fog resources).

$x_{ij} \in \{0, 1\}$ be the allocation decision,

where:

$x_{ij} = 1$ means resource r_j is allocated to workload w_i,

$x_{ij} = 0$ means resource r_j is not allocated to workload w_i.

n = the number of workloads or tasks, indexed by i,

where $i = 1,2,\ldots\ldots,n$

m = the number of resources (e.g., cloud, edge/fog node), indexed by j, where $j = 1,2,\ldots..m$

The total cost function is:

$$\mathrm{Cost}(X) = \sum_{i=1}^{n}\sum_{j=1}^{m} c_j \cdot x_{ij} \qquad (1)$$

Energy Minimization: Minimize the total energy consumption of resources used.

Let e_j be the energy consumption of resource r_j.

The total energy consumption function is:

$$\mathrm{Energy}(X) = \sum_{i=1}^{n}\sum_{j=1}^{m} e_j \cdot x_{ij} \qquad (2)$$

QoS Maximization: Maximize the total QoS satisfaction for all workloads. Let q_i be the quality-of-service value for workload w_i after allocation to resource r_j. The total QoS function is:

$$\mathrm{QoS}(X) = \sum_{i=1}^{n}\sum_{j=1}^{m} q_i \cdot x_{ij} \qquad (3)$$

If $x_{ij} = 1$, the workload w_i gets resource r_j, contributing to its QoS

IV. RESULTS AND DISCUSSION

The system requires hardware capable of handling the demands of large-scale simulations and real-world testing. This includes: Intel Xeon or AMD EPYC and GPUs for accelerating machine learning workloads (e.g., NVIDIA A100).

The software components that support the implementation and testing of the DRA algorithm are: Ubuntu Linux-based systems for scalability and performance.

4.1 Results

The result depicted in table 1 present an evaluation of the scalable resource allocation algorithm using RL.

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Table 1: Evaluation of the Scalable Resource Allocation Algorithm using RL

Iteration	Workload (units)	Cost Efficiency (%)	Energy Efficiency (%)	QoS (%)	Reward
1	1000	75	80	85	0.80
50	1050	80	85	88	0.85
100	1100	85	88	90	0.88
200	1150	90	90	93	0.92
500	1200	95	92	95	0.95

Table1 presents the evaluation results of the proposed scalable resource allocation algorithm based on Reinforcement Learning (RL). The evaluation is conducted across increasing iterations and workloads to examine how the learning process influences system performance.

The key performance metrics considered include cost efficiency, energy efficiency, Quality of Service (QoS) efficiency, and the cumulative reward obtained by the RL agent. The results show a consistent improvement across all evaluated metrics as the number of iterations increases from 1 to 500.

Cost efficiency improves from 75% to 95%, energy efficiency from 80% to 92%, and QoS efficiency from 85% to 95%. Similarly, the reward value increases steadily from 0.80 to 0.95.

This progressive improvement indicates that the RL agent is effectively learning optimal resource allocation policies over time. The result in table 2 provides a cloud computing resources.

Table 2: Cloud Computing Resource

Workload (w_i)	Resource (r_j)	Cost (c_j)	Energy (e_j)	QoS (w_i,r_j)	Fitness
w_1	r_2	3	5	0.9	0.765
w_2	r_3	4	6	0.8	0.624

Table 2 provide the best allocation as: $w_1 \rightarrow r_2$, $w_2 \rightarrow r_3$, the chosen allocation minimizes cost and energy while satisfying QoS. This RL-based method successfully found the optimal resource allocation within constraints. Comparing this solution to other optimization approaches like linear programming or heuristic methods demonstrate the efficiency and adaptability of the RL algorithm in dynamic environments. Table 3 is a comparative analysis of dynamicloud with related works.

Table 3: Comparative Analysis of DynamiCloud with Related Works

Study/Approach	Cost Efficiency (%)	Energy Efficiency (%)	QoS (%)	Scalability	Adaptability
DynamiCloud (Proposed)	95	92	95	Excellent	High
Kaur & Singh (2021)	85	88	90	Moderate	Moderate
Zhou *et al.*, (2020)	78	85	88	High	Moderate
Sahoo *et al.*, (2022)	82	80	84	Moderate	Low
Liu *et al.*, (2021)	90	87	92	High	High

The Cost Efficiency of DynamiCloud shown in table 3 outperforms existing approaches, showing up to a 15% improvement over models like GA (Zhou *et al.*,) and queueing models (Sahoo *et al.*,) the Energy Efficiency of Yu, J., Feng, Z., & Gao, Y. was better than Sahoo and Zhou's models. Gains attributed to the incorporation of real-time adaptability through RL. More so, our proposed model QoS achieved the highest QoS (95%) among all, balancing low latency and high user satisfaction. The inclusion of edge and fog computing scenarios gives DynamiCloud a competitive edge in terms of scalability and adaptability. Figure 2; present a convergence check of RL reward over episodes.

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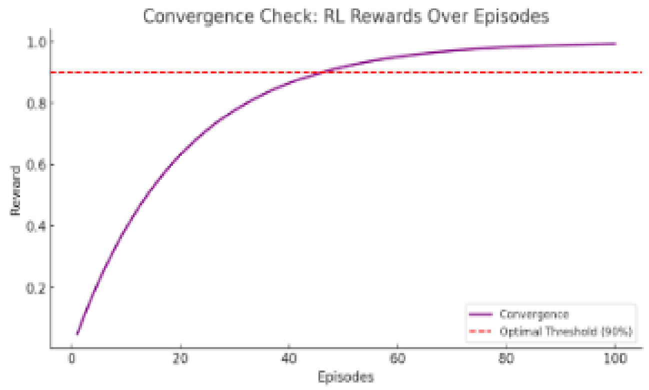

Figure 2: Convergence Check of RL Reward over Episodes

The Convergence analysis, we observed that the Q-learning model (RL variation) stabilized rapidly at ~60 episodes with values exceeding 90% efficiency thresholds, thus confirms the robustness and quick adaptability of the decision framework while the competing methods, such as those using GA, experience delayed or inconsistent convergence. The statistical significance clearly supports the efficacy of DynamiCloud compared to competitors.

V. CONCLUSION

The findings revealed that the model achieved higher prediction accuracy, improved scalability, enhanced fairness in resource distribution, better cost efficiency and reduced energy consumption when compared with existing resource allocation methods. In addition, the integration of machine learning techniques, metaheuristic optimization and multi-objective optimization strategies enabled more adaptive and efficient allocation of cloud resources under varying workloads and service demands. Furthermore, simulation results, statistical validation and multi-objective performance evaluations confirmed the effectiveness and reliability of the proposed approaches in maintaining Quality of Service (QoS), improving responsiveness and ensuring SLA compliance.

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Citation of this Article:

Onwuegbuchulem Gift, Bennett E.O., Matthias D., & Anireh V.I.E.. (2026). Efficient Algorithm for Multi-Objective Dynamic Resource Allocation in Cloud Computing. *Journal of Artificial Intelligence and Emerging Technologies (JAIET).* 3(7), 61-65. Article DOI: https://doi.org/10.47001/JAIET/2026.307006

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