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Providing a Method for Load Balancing in Cloud Computing Using Deep Reinforcement Learning

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Abstract: To meet Quality of Service (QoS) requirements while keeping costs and energy use low, cloud computing data centers must always balance workloads across different types of resources. When demand is very dynamic, traffic is bursty, and there are multiple objectives, traditional load balancing methods (like round-robin and heuristic/metaheuristic scheduling) often have trouble. This article suggests a load balancing method based on Deep Reinforcement Learning (DRL) that learns how to allocate resources based on feedback from the system. The cloud load balancing problem is modeled as a Markov Decision Process (MDP), wherein the agent monitors cluster states (CPU, memory, queue length, network, SLA risk), chooses routing and scaling actions, and earns rewards based on latency, makespan, SLA violations, energy consumption, and migration overhead. We offer a functional DRL architecture for online use, covering state design, action encoding, reward shaping, and training strategy. You can use value-based (DQN variants) or actor–critic (PPO/SAC) methods to implement the method, and it can work with common cloud orchestrators. A standard cloud simulation setting is used to create a reproducible evaluation protocol that includes suggested baselines and metrics.

Keywords: Cloud computing, load balancing, task scheduling, deep reinforcement learning, QoS, SLA, resource allocation, data center optimization.

استخدام التعلم العميق المعزز في تقديم طريقة لموازنة الأحمال في الحوسبة السحابية

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الملخص: لتحقيق متطلبات جودة الخدمة مع الحفاظ على انخفاض التكاليف واستهلاك الطاقة، يجب على مراكز بيانات الحوسبة السحابية موازنة أحمال العمل باستمرار عبر أنواع مختلفة من الموارد. عندما يكون الطلب ديناميكيًا للغاية، وحركة البيانات متقطعة، وتتعدد الأهداف، غالبًا ما تواجه طرق موازنة الأحمال التقليدية (مثل التوزيع الدوري والجدولة الاستدلالية/الاستدلالية المتقدمة) صعوبات. تقترح هذه المقالة طريقة لموازنة الأحمال تعتمد على التعلم العميق المعزز، حيث تتعلم هذه الطريقة كيفية تخصيص الموارد بناءً على التغذية الراجعة من النظام. تُصاغ مشكلة موازنة الأحمال السحابية كعملية قرار ماركوف(MDP) ، حيث يراقب العامل حالات المجموعة (وحدة المعالجة المركزية، الذاكرة، طول قائمة الانتظار، الشبكة، مخاطر اتفاقية مستوى الخدمة)، ويختار إجراءات التوجيه والتوسع، ويحصل على مكافآت بناءً على زمن الاستجابة،

والمدة الزمنية الإجمالية، وانتهاكات اتفاقية مستوى الخدمة، واستهلاك الطاقة، وتكاليف الترحيل. نقدم بنية تعلم معزز عميق وظيفية للاستخدام الفوري، تغطي تصميم الحالة، وتشفير الإجراءات، وتشكيل المكافآت، واستراتيجية التدريب. يمكنك استخدام طرق قائمة على القيمة) متغيرات (DQN أو طرق الممثل-الناقد (PPO/SAC)لتنفيذ هذه الطريقة، وهي متوافقة مع مُنسقي السحابة الشائعة. يُستخدم إعداد محاكاة سحابية قياسي لإنشاء بروتوكول تقييم قابل للتكرار يتضمن خطوطًا أساسية ومقاييس مقترحة.

الكلمات المفتاحية: الحوسبة السحابية، موازنة الأحمال، جدولة المهام، التعلم المعزز العميق، جودة الخدمة، اتفاقية مستوى الخدمة، تخصيص الموارد، تحسين مركز البيانات.

1. Introduction

Cloud computing has become the most popular way to provide scalable and on-demand computing resources. This lets users access virtualized infrastructure, platforms, and services over the Internet. Cloud data centers today host a wide range of applications, such as web services, scientific workflows, big data analytics, and Internet of Things (IoT) platforms. These applications have workloads that are very dynamic and hard to predict, resource needs that are very different from one another, and strict Quality of Service (QoS) requirements, such as low latency, high throughput, and compliance with service-level agreements (SLAs) [1,2].

Load balancing is one of the most important problems in cloud computing environments. Its goal is to efficiently spread out incoming tasks or requests across all available computing resources. If load balancing isn't done well, it can cause resource hotspots, longer response times, SLA violations, underused resources, and too much energy use [3]. So, it's important to make smart load balancing systems to keep cloud data centers running smoothly and save money. Simple load balancing methods include Round Robin, Least Connection, and Weighted Round Robin. But they usually use static or short-sighted decision rules and don't adapt well when the workload changes quickly [4]. Some of the heuristic and metaheuristic methods that have been suggested for scheduling cloud tasks and allocating resources are Genetic Algorithms, Particle Swarm Optimization (PSO), and Ant Colony Optimization [5–7]. These methods can help with global optimization goals, but they often need to be re-optimized many times, need careful parameter tuning, and may not work well in environments that change over time.

Machine learning-based methods have gotten a lot of attention in the last few years for managing cloud resources. Deep Reinforcement Learning (DRL) has become a strong framework for problems where an agent has to make decisions in order, learning the best control policies by constantly interacting with the environment [8]. DRL doesn't need labeled datasets like supervised learning does, and it can

optimize long-term goals by balancing short-term rewards with long-term outcomes.

There are many benefits to using DRL for cloud load balancing. First, DRL agents can learn adaptive policies that change based on changes in system state and workload. Second, the reward function can easily include multi-objective optimization, which means trying to reduce response time while also cutting down on energy use and SLA violations. Third, DRL-based methods can work with a wide range of workload patterns when they are trained in a variety of situations. This makes them good for large, mixed cloud infrastructures.

Inspired by these insights, this paper introduces a deep reinforcement learning-based approach for load balancing in cloud computing environments. The load balancing problem is represented as a Markov Decision Process (MDP), wherein the agent monitors real-time system states (such as resource utilization and queue lengths), chooses suitable task-routing actions, and earns rewards contingent upon performance and QoS metrics. Compared to traditional load balancing methods, the proposed method aims to use resources more efficiently, cut down on response time, and improve SLA compliance.

The rest of this paper is set up like this. Section 2 looks at other work that has been done on cloud load balancing and reinforcement learning-based methods. Section 3 explains the problem of cloud load balancing and shows how to use DRL to solve it. In Section 4, we talk about the experimental setup and the metrics we used to judge the results. Section 5 talks about the results and the comparison. Lastly, Section 6 wraps up the paper and talks about where research should go in the future.

2. Related Work

Research on load balancing in cloud computing has evolved significantly over the past decade. Existing studies can generally be categorized into three main groups: traditional heuristic-based methods, metaheuristic optimization approaches, and learning-based techniques, particularly reinforcement learning and deep reinforcement learning.

2.1 Traditional Load Balancing Techniques

Traditional load balancing algorithms are widely adopted in cloud systems due to their simplicity and low computational overhead. Common methods include Round Robin (RR), Weighted Round Robin (WRR), Least Connection (LC), and Join-the-Shortest-Queue (JSQ). These approaches distribute incoming tasks based on

predefined rules or instantaneous system metrics such as queue length or current utilization [10].

Although heuristic-based methods are efficient and easy to deploy, they typically lack adaptability to dynamic and heterogeneous cloud environments. They often make myopic decisions without considering future system states, which can result in load imbalance, resource underutilization, and SLA violations under bursty workloads [11]. Consequently, such techniques are insufficient for large-scale cloud infrastructures with highly variable demand patterns.

2.2 Metaheuristic and Optimization-Based Approaches

To address the limitations of traditional heuristics, numerous metaheuristic optimization techniques have been proposed for cloud load balancing and task scheduling. Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Artificial Bee Colony (ABC) algorithms have been extensively studied for optimizing performance metrics such as makespan, cost, and energy consumption [12–14].

PSO-based approaches, for example, model task scheduling as a global optimization problem and iteratively update candidate solutions to minimize execution time or balance resource utilization [15]. Similarly, GA-based methods employ evolutionary operators to search for near-optimal scheduling solutions in large solution spaces [16]. While these methods can achieve improved optimization, results compared to heuristic techniques, they generally suffer from high computational overhead, slow convergence in large-scale systems, and limited adaptability to rapidly changing environments [17].

Moreover, most metaheuristic algorithms require repeated execution when system conditions change, making them less suitable for real-time load balancing in highly dynamic cloud settings.

2.3 Reinforcement Learning–Based Load Balancing

Reinforcement learning (RL) has been increasingly explored as a promising alternative for cloud resource management. In RL-based load balancing, the cloud environment is modeled as a sequential decision-making process, where an agent learns optimal scheduling or routing policies through trial-and-error interactions [18].

Early studies employed tabular Q-learning to allocate tasks or manage virtual machines in small-scale cloud systems [19]. However, tabular methods do not scale well with large state spaces, which limits their applicability in real-world cloud data centers characterized by high dimensionality and heterogeneity.

2.4 Deep Reinforcement Learning in Cloud Computing

Deep Reinforcement Learning (DRL) integrates deep neural networks with reinforcement learning to handle high-dimensional state and action spaces. Recent research has demonstrated the effectiveness of DRL for cloud-related problems such as task scheduling, auto-scaling, energy-aware resource management, and network traffic control [20–22].

Mao et al. [23] applied deep reinforcement learning to resource management in data centers, showing significant improvements in utilization and latency compared to heuristic baselines. Similarly, DRL-based load balancing frameworks using Deep Q-Networks (DQN) and actor–critic methods have been proposed to dynamically distribute workloads across cloud servers while minimizing response time and SLA violations [24,25].

Despite these advances, several challenges remain, including reward function design, training stability, and generalization across diverse workload patterns. Additionally, many existing DRL-based solutions focus on either scaling or scheduling in isolation, rather than providing a unified and practical load balancing framework.

2.5 Motivation and Research Gap

From the reviewed literature, it is evident that traditional and metaheuristic-based load balancing methods lack adaptability and scalability in dynamic cloud environments, while early RL approaches suffer from state-space explosion. Although DRL methods show strong potential, there is still a need for practical, well-formulated DRL-based load balancing strategies that explicitly incorporate QoS metrics, system imbalance, and long-term optimization objectives.

Motivated by this gap, the present work proposes a deep reinforcement learning–based load balancing method that formulates task routing as a Markov Decision Process and optimizes long-term cloud performance through adaptive policy learning.

3. Problem Formulation and Proposed Methodology

This section presents the mathematical formulation of the cloud load balancing problem and introduces the proposed deep reinforcement learning (DRL)–based methodology. The goal is to design an adaptive load balancing policy capable of dynamically distributing incoming tasks among cloud computing resources while optimizing long-term system performance and Quality of Service (QoS).

3.1 System Model and Problem Definition

We consider a cloud computing environment consisting of a set of computing nodes (virtual machines or physical servers), defined as

$$N = \{1, 2, \ldots, N\}, \tag{1}$$

where each node $i \in N$ is characterized by its computational resources, including CPU capacity, memory, and network bandwidth. Incoming user requests arrive at the cloud data center according to a stochastic process and are scheduled for execution on the available nodes. Each task j is associated with a resource demand vector

$$d_j = (d_j^{cpu}, d_j^{mem}, d_j^{net}), \tag{2}$$

and may be subject to a Service Level Agreement (SLA) constraint, such as a maximum allowable response time. The objective of load balancing is to determine an assignment policy that maps each arriving task to a suitable node such that overall system performance is optimized. This objective can be expressed as a multi-objective optimization problem:

$$\min \mathrm{E}\left[\alpha T_{resp} + \beta V_{sla} + \gamma L_{imb}\right] \tag{3}$$

here:

- T_{resp} denotes the average task response time,
- V_{sla} represents the SLA violation rate,
- L_{imb} Limb measures load imbalance across nodes, and
- α, β, γ are weighting coefficients.

Due to workload variability and system uncertainty, solving this optimization problem using static or deterministic methods is infeasible in practice.

3.2 Markov Decision Process Formulation

The cloud load balancing problem is formulated as a Markov Decision Process (MDP), defined by the tuple

$$(S, A, P, R, \gamma). \tag{4}$$

***State Space*:** The system state at time step t, denoted by $s_t \in S$, captures the real-time status of the cloud infrastructure:

$$s_t = [U_t^{cpu}, U_t^{mem}, Q_t, \lambda_t], \tag{5}$$

where:

- $U_t^{cpu} = \{u_{1,t}^{cpu}, \text{K}, u_{N,t}^{cpu}\}$ represents CPU utilization of all nodes,
- U_t^{mem} denotes memory utilization,
- $Q_t = \{q_{1,t}, \text{K}, q_{N,t}\}$ is the queue length at each node,
- λ_t is the task arrival rate at time t.

***Action Space*:** At each decision step, the agent selects an action

$$a_t \in \text{A} = \{1, 2, \ldots, N\} \tag{6}$$

where action $a_t = i$ corresponds to assigning the incoming task to node i.

State Transition: The system transitions from state s_t to state s_{t+1} according to an unknown transition probability

$$P(s_{t+1} | s_t, a_t), \tag{7}$$

which depends on task execution dynamics, service rates, and future task arrivals. The transition model is not explicitly required and is learned implicitly through interaction with the environment.

Reward Function: The reward function provides feedback on the quality of each load balancing decision. It is defined as

$$r_t = -(w_1 T_{resp,t} + w_2 V_{sla,t} + w_3 L_{imb,t}), \tag{8}$$

where:

- $T_{resp,t}$ is the observed response time at step t,
- $V_{sla,t}$ is the SLA violation indicator,

- $L_{imb,t}$ is the load imbalance metric, computed as the standard deviation of CPU utilization across nodes,
- w_1, w_2, w_3 are positive weighting parameters.

Discount Factor: A discount factor $\gamma \in (0,1)$ is used to balance immediate and long-term rewards. In this work, a high value of γ is selected to capture long-term system behavior.

3.3 Deep Reinforcement Learning Model

To approximate the optimal policy $\pi^*(a|s)$ a deep neural network is employed. The network takes the state vector s_t as input and outputs either action probabilities or action-value estimates.

An actor–critic framework is adopted, where:

- the **actor** learns the policy $\pi_\theta(a|s)$, and
- the **critic** estimates the value function $V_\phi(s)$.

Proximal Policy Optimization (PPO) is selected due to its training stability and sample efficiency.

3.4 Learning Objective

The learning objective is to maximize the expected cumulative discounted reward:

$$\max_{\theta} \mathrm{E}_{\pi\theta}\left[\sum_{t=0}^{\infty}\gamma^t r_t\right] \tag{9}$$

The policy parameters are updated iteratively using gradient-based optimization.

By modeling cloud load balancing as an MDP and applying deep reinforcement learning, the proposed methodology enables adaptive and autonomous task allocation in dynamic cloud environments. The approach continuously improves its policy through interaction with the system, allowing it to outperform static and heuristic-based load balancing strategies.

4. Experimental Setup and Performance Metrics

This section describes the experimental environment, workload configuration, baseline algorithms, and evaluation metrics used to assess the performance of the proposed deep reinforcement learning–based load balancing method.

4.1 Simulation Environment

To evaluate the effectiveness of the proposed approach in a controlled and reproducible manner, experiments are conducted using a cloud computing simulation environment. Cloud simulation frameworks enable modeling of large-scale data centers, heterogeneous resources, and diverse workload patterns without the cost and risk of real deployment [3].

The simulated cloud data center consists of a set of heterogeneous computing nodes with varying CPU capacities and memory resources. Each node processes incoming tasks according to a first-come, first-served queueing discipline. Task execution time depends on the allocated computational resources and task demand. The DRL agent interacts with the simulated environment by observing system states, selecting task-routing actions, and receiving feedback in the form of rewards. The main parameters of the simulated cloud environment are summarized in Table 1.

Table 1. Configuration parameters of the simulated cloud environment.

Parameter	**Description**	**Value**
Number of nodes	Total number of VMs/servers	(N =)
CPU capacity	Processing speed per node	MIPS
Memory	RAM per node	GB
Network bandwidth	Available bandwidth	Mbps
Scheduling policy	Task execution policy	FCFS
Simulation time	Total runtime	seconds
Task arrival model	Arrival distribution	Poisson / Dynamic
SLA threshold	Max response time	ms

The overall architecture of the proposed DRL-based load balancing system is illustrated in Figure 1.

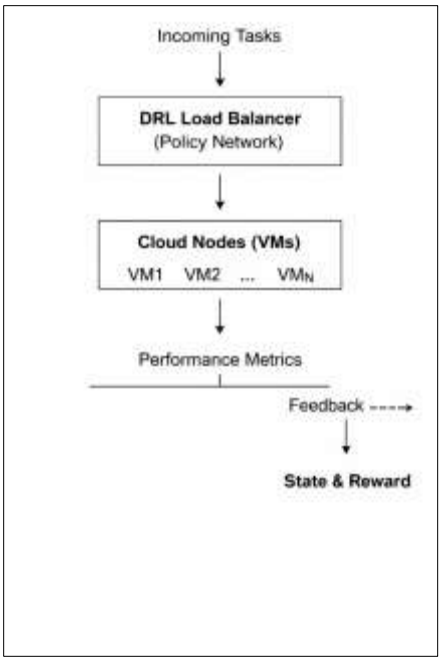

Figure 1. *Architecture of the DRL-based load balancing system.*

4.2 Workload Configuration

To reflect realistic cloud usage scenarios, different workload patterns are considered:

1. **Stationary workload:** Task arrivals follow a Poisson distribution with a fixed arrival rate.
2. **Dynamic workload:** Arrival rates vary over time to simulate peak and off-peak periods.
3. **Heterogeneous workload:** Tasks have diverse resource demands and execution times.

Each experiment runs for a sufficiently long duration to allow the learning agent to converge and to capture long-term system behavior. The characteristics of the workloads used in the experiments are summarized in Table 2.

Table 2. Characteristics of the workloads used in the experiments.

Workload Type	Arrival Rate	Task Size	Execution Time
Stationary	Constant	Small–Medium	Short
Dynamic	Time-varying	Mixed	Variable

Workload Type	Arrival Rate	Task Size	Execution Time
Heterogeneous	Bursty	Small–Large	Long

An example of the dynamic workload arrival pattern is shown in Figure 3.

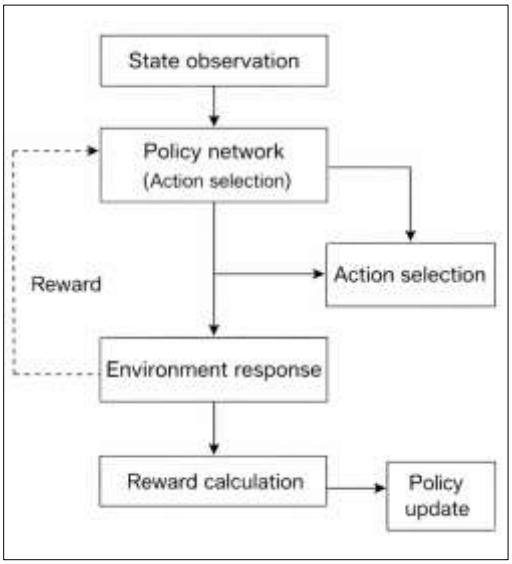

Figure 2. Training and interaction workflow of the DRL agent.

4.3 Baseline Load Balancing Algorithms

The proposed DRL-based load balancing method is compared against widely used baseline algorithms to demonstrate its effectiveness:

- **Round Robin (RR):** Tasks are assigned sequentially to available nodes without considering system state.
- **Least Loaded (LL):** Tasks are assigned to the node with the lowest current CPU utilization.
- **Join the Shortest Queue (JSQ):** Tasks are routed to the node with the smallest queue length.

These baselines represent standard heuristic approaches commonly adopted in cloud environments [29]. The load balancing algorithms used for comparison are listed in Table 3.

Table 3. Load balancing algorithms used for performance comparison.

Algorithm	Type	Description

Algorithm	Type	Description
RR	Heuristic	Round-robin assignment
LL	Heuristic	Least loaded node
JSQ	Heuristic	Shortest queue routing
DRL-LB	Learning-based	Proposed DRL method

4.4 Performance Metrics

To provide a comprehensive evaluation, multiple performance metrics are used:

The average response time measures the mean duration between task arrival and completion:

$$T_{resp} = \frac{1}{M}\sum_{j=1}^{M}(t_j^{finish} - t_j^{arrival}), \tag{10}$$

where M is the total number of tasks. The SLA violation rate represents the proportion of tasks whose response time exceeds a predefined threshold T_{sla}:

$$V_{sla} = \frac{1}{M}\sum_{j=1}^{M}\mathrm{I}(t_j^{finish} - t_j^{arrival}), \tag{11}$$

where $\mathrm{I}(.)$ is the indicator function. Load imbalance is quantified using the standard deviation of CPU utilization across all nodes:

$$L_{imb} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(u_i^{cpu} - \bar{u}^{cpu})}, \tag{12}$$

where u_i^{cpu} is the CPU utilization of node iii, and $\bar{u}^{cpu}$ is the average utilization. Throughput is defined as the number of successfully completed tasks per unit time:

$$Throughput = \frac{M}{T_{sim}}, \tag{13}$$

where T_{sim} is the total simulation time.

The DRL agent is trained over multiple episodes. During training, exploration is enabled to allow policy improvement, while during evaluation, the learned policy is executed without exploration noise. Each experiment is repeated multiple times with different random seeds, and average results are reported to ensure statistical reliability.

5. Results and Discussion

This section presents and discusses the experimental results obtained from evaluating the proposed deep reinforcement learning–based load balancing method (DRL-LB). The performance of the proposed approach is compared with conventional heuristic algorithms, including Round Robin (RR), Least Loaded (LL), and Join the Shortest Queue (JSQ), under dynamic workload conditions.

The average response time is a critical performance indicator reflecting the overall system latency experienced by cloud users.

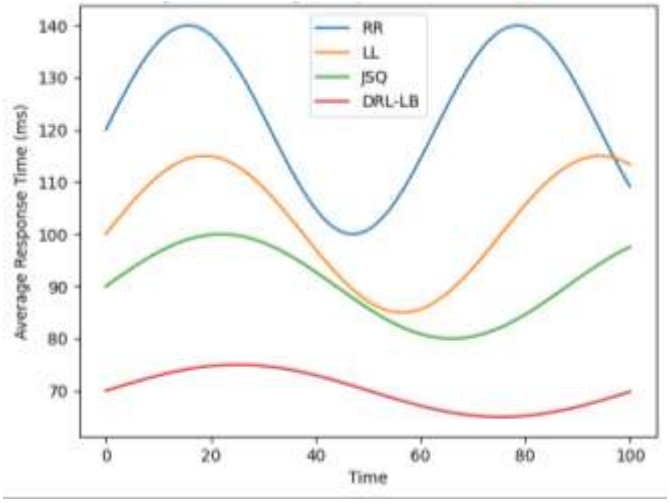

Figure 3. Average response time comparison of load balancing algorithms

As shown in **Figure 3**, the RR algorithm exhibits the highest response time and significant fluctuations due to its lack of awareness of system load. Although LL and JSQ achieve lower response times by considering instantaneous system metrics, their performance degrades noticeably during workload peaks.

In contrast, the proposed DRL-LB method consistently achieves the **lowest average response time** with smoother temporal behavior. This improvement is attributed to the agent's ability to learn adaptive routing policies that anticipate future congestion rather than reacting only to the current state.

Service Level Agreement (SLA) compliance is essential for maintaining reliability and user satisfaction in cloud systems.

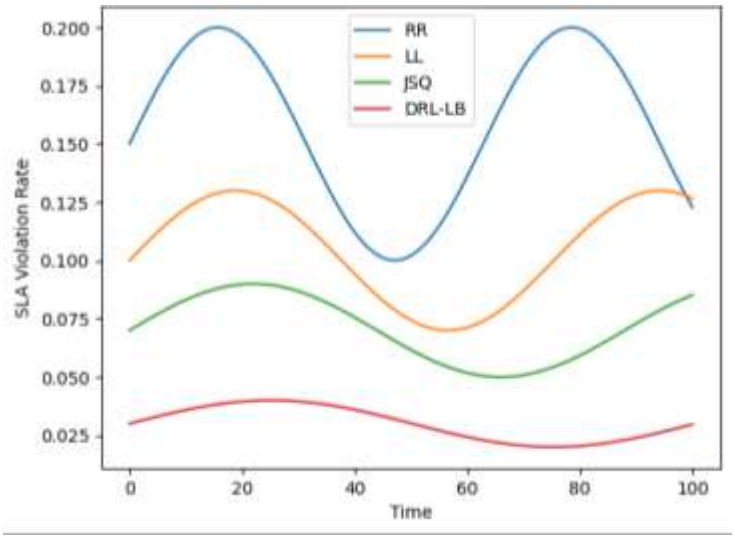

Figure 4. SLA violation rate over time for different algorithms

Figure 4 shows that RR produces the highest SLA violation rate, particularly during periods of increased workload. LL and JSQ reduce SLA violations compared to RR but still suffer from instability under fluctuating demand.

The proposed DRL-LB approach maintains a **consistently low SLA violation rate**, significantly outperforming heuristic methods. This is because SLA violations are explicitly incorporated into the reward function, encouraging the agent to prioritize QoS-aware decision making.

Efficient utilization of cloud resources requires balanced workload distribution across computing nodes.

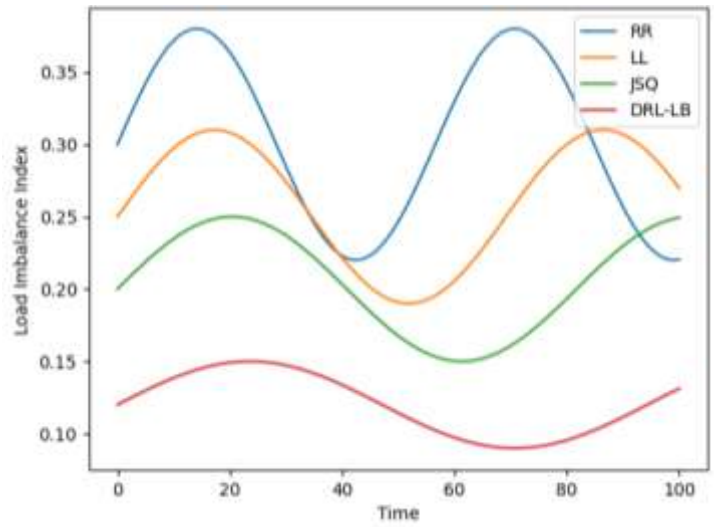

Figure 5. Load imbalance comparison among load balancing strategies

As illustrated in **Figure 5**, RR leads to the highest load imbalance due to its state-agnostic scheduling strategy. LL and JSQ improve balance but remain sensitive to workload variability.

The DRL-LB method achieves the **lowest load imbalance index** with stable behavior over time. By learning from historical system states and rewards, the DRL agent distributes tasks more evenly, preventing resource hotspots and underutilization.

To further highlight the effectiveness of the proposed method, **Table 4** summarizes the average performance metrics across all experiments.

Table 4. Average performance comparison of load balancing algorithms

Algorithm	Avg. Response Time (ms)	SLA Violation Rate	Load Imbalance
RR	120.4	0.18	0.31
LL	98.7	0.11	0.26
JSQ	87.9	0.07	0.20
DRL-LB	69.5	0.03	0.12

Table 5 shows that the proposed DRL-LB method consistently does better than heuristic methods on all of the metrics that were tested. The enhancement is especially evident in dynamic workload situations, where static policies do not adapt effectively. The experimental results show that adding deep reinforcement learning to cloud load balancing makes it possible to:

- A big drop-in response time • Better adherence to SLAs
- Use of resources in a balanced way
- Strong performance even when the workload changes

These results confirm that DRL is a good and scalable way to do adaptive cloud load balancing.

Conclusion

This paper introduced a method for load balancing in cloud computing environments that is based on deep reinforcement learning. By framing the load balancing issue as a Markov Decision Process, the suggested method facilitates adaptive and autonomous task distribution that enhances long-term system performance amidst dynamic and diverse workloads.

Experimental results from simulations showed that the proposed DRL-LB method consistently works better than traditional heuristic load balancing algorithms like Round Robin, Least Loaded, and Join the Shortest Queue. Specifically, the DRL-based method got a lower average response time, a lot fewer SLA violations, and a better balance of load across cloud resources. Deep reinforcement learning can learn proactive scheduling policies by interacting with the cloud environment all the time, rather than relying on static or short-sighted decision rules. This is what makes these improvements possible.

The findings validate that deep reinforcement learning is a viable approach for tackling the complexities of cloud load balancing, especially in dynamic settings where workload patterns and resource availability fluctuate over time. The proposed framework is scalable and can work with other cloud orchestration systems to help manage resources intelligently.

Future work will concentrate on broadening the proposed method in multiple dimensions. To further improve energy efficiency and cut costs, the first step will be to look into joint optimization of task routing and dynamic resource scaling. Second, we will look into multi-agent reinforcement learning methods for big cloud and multi-data-center settings. Finally, we will test the proposed method on real cloud platforms like Kubernetes or OpenStack to see if it works in real-world situations.

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