

Adaptive Load Balancing in Cloud Computing Environment Using Deep Reinforcement Learning

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Abstract: Cloud computing is a distributed internet based service which has been used by large group of users remotely with the networked servers. It provides storage of data and online access to services and resources from cloud service providers. Cloud computing environments face challenges of dynamic workload distribution across virtualized resources. Load balancing is used to maximize throughput, minimizing the response time and cost which improves resource utilization, performance, energy saving etc., in cloud environment. Thus, efficient load balancing mechanisms such as Round Robin (RR) and First-Come-First-Serve (FCFS) are implemented, but these algorithms are static in nature and unable to adapt to changing workloads demand. The deep reinforcement learning based approach continuously learns and improves the distribution of task and made decision based on traffic patterns and resource availability. The proposed design is compared conceptually and experimentally with Round Robin, First-Come First-Served (FCFS), and Throttled allocation. A reproducible experimental protocol is provided for CloudSim, including workload generation, DQN training, evaluation metrics and statistical testing. DQL leverages reinforcement learning to learn optimal task allocation strategies, dynamically adapting to workload variations. Experimental results demonstrate that the proposed approach significantly reduces makespan and improves response time, resource utilization, and load distribution compared to traditional algorithms.

Keywords: Cloud computing, Load balancing, CloudSim, Deep Reinforcement Learning, Deep Q-Learning.

I. INTRODUCTION

1.1 Background

In today's Internet age cloud computing plays a major role for large growth of information that needs to be stored and managed. Cloud computing has developed as a dominant computing paradigm, enabling ubiquitous access to shared resources such as servers, storage, and applications [1]. A lot of people use different cloud computing services in their daily life and they get quick response from these services. The elasticity and pay-as-you-go model offered by cloud service providers have made it the backbone of modern IT infrastructure. However, the dynamic and heterogeneous nature of cloud workloads introduces the problem of load balancing, where tasks must be efficiently distributed across available virtual machines (VMs). Most of the users are unaware of the long process that works behind the system. This process involves the distribution of multiple client requests over the multiple servers to access the cloud services [2]. The cloud service provider offers proper resource provisioning of the information and allow different users to access these cloud services with the help of internet. When the traffic on the cloud service increases, the load on the servers also increases. Thus to fulfil the high volume data user requests efficient load balancing techniques are used. Load balancing is the method of dividing workloads and computing properties in a cloud computing environment. It enables cloud service providers to manage workload demands or application demands by distributing resources



among numerous computers, networks or servers [3]. Cloud load balancing strategy provides circulation of workload traffic and demands that exist over the Internet. As the traffic on the internet growing rapidly, the workload on the server growing so fast which leads to the overloading of servers mainly for popular web server. Effective load balancing technique ensures minimal latency, reduced resource wastage, and higher customer satisfaction. Classical load balancing approaches such as Round Robin (RR) and First-Come-First-Serve (FCFS) fail in dynamic and heterogeneous environments. Heuristic methods like Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) improves efficiency but these algorithms suffer from high computational cost. To solve the problems with above algorithms a Deep Reinforcement Learning (DRL) based approach is used. Deep Reinforcement Learning (DRL), and specifically Deep Q-Learning (DQL), provides a data-driven solution by learning task allocation policies over time [8]. This work proposes a DQL-based load balancing algorithm simulated in CloudSim, with performance evaluation against classical load balancing policies. This approach varies from classical load balancing algorithms which allow system to dynamically adapt to change in workload and infrastructure. Reinforcement Learning (RL), particularly Deep Q-Learning (DQL), provides a promising solution by enabling adaptive decision-making through interaction with the environment. In this research paper, we design and evaluate a DQL-based load balancing algorithm for cloud computing using the CloudSim simulator. The objective of this paper is to minimize task execution time, balance workload across VMs, and improve overall system performance[3].

1.2 Motivation

Recent advancements in Reinforcement Learning (RL), particularly Deep Q-Learning (DQN), allow the agents to learn optimal load balancing decisions through interaction with the cloud environment. Integrating RL with CloudSim, a widely used cloud simulation platform, enables controlled experimentation and evaluation of data-driven scheduling strategies. The combination of RL and CloudSim provides:

- Dynamic adaptation to varying workloads
- Exploration of complex VM–task assignment spaces
- A reproducible environment for performance evaluation

This paper aims to develop and evaluate a Deep-Q learning based load balancing approach that dynamically allocates different task in real time scenario with changing workloads. The proposed framework leverages reinforcement learning ability which improve its performance over time and provides a more efficient and scalable solution for modern cloud environment.

1.3 Objectives & Contributions

This work aims to design, implement, and evaluate a DQN-based load balancing strategy in CloudSim. The main contributions are:

- A novel integration of a DQN agent with CloudSim’s task scheduling module.
- A well-defined state–action–reward model for cloud load balancing.
- Comparative evaluation against multiple baseline algorithms.
- Insights into the adaptability and performance of RL in cloud environments.

II. LITERATURE REVIEW

This section introduces a review of recent literature associated with load balancing mechanisms in cloud computing using deep reinforcement learning.

- **Yue Xu et al.(2019)** Load Balancing for Ultra-Dense Networks: A Deep Reinforcement Learning Based Approach proposed a DRL-based MLB algorithm along with a two-layer MLB architecture to solve the large scale load balancing issue in UDNs[7].
- **Negar Rikhtegar et al. (2020)** DeepRLB: A deep reinforcement learning-based load balancing in data center networks presented a DeepRLB approach based on the DRL for load balancing in data center networks.



DeepRLB leverages the DDPG algorithm to learn the optimal link-weight settings in the context of load balancing goal[8].

- **Min Xiang et al. (2022)** Deep Reinforcement Learning- based load balancing strategy for multiple controllers in SDN clarifies that the static connection between switches and controllers is a key factor leading to controller load imbalance, and proposes the necessity of switch migration[9].
- **Liu Q. et al (2022)** Deep Reinforcement Learning for Load-Balancing Aware Network Control in IoT Edge Systems presented a DRL-based method for load balancing aware networking in IoT edge systems. Specifically, through the dynamic optimization of IoT network clustering using a DRL model; proposed approach can fulfill the load balancing requirements from both IoT networks and edge servers[10].
- **Guangpeng Jia et al.(2023)** Load Balancing of Two-Sided Assembly Line Based on Deep Reinforcement Learning depicted a method that will distributed multiple processes have been proposed to improve the search speed and capability of solutions[11].
- **M.Arvindhan et al. (2023)** Adaptive Resource Allocation in Cloud Data Centers using Actor-Critical Deep Reinforcement Learning for Optimized Load Balancing proposed scheme aims to minimize the total execution time of tasks by effectively allocating resources and balancing workloads across different servers[12].
- **Sreedar Bhukya et al. (2024)**A Deep Reinforcement Learning Framework for Optimized Container Scheduling and Load Balancing depicted that RLbCS is effective in resource optimization and the convergence of the scheduling process. RLbCS outperformed other existing methods, with 92% of placed containers[13].
- **Hasan Fawaz et al.(2024)** Graph Convolutional Reinforcement Learning for Load
- **Balancing and Smart Queuing** proposed a joint smart load balancing and smart queuing approach for networks which utilized the subset of deep learning known as graph convolution deep reinforcement learning to model the different agents as nodes of a network-representing graph[14].
- **Kavish Chawla (2024)** Reinforcement Learning-Based Adaptive Load Balancing for Dynamic Cloud Environments demonstrated the effectiveness of the RL-based load balancer in reducing response times, improving resource utilization, and increasing task completion rates compared to traditional methods[15].
- **Shuming Sha et al. (2024)** Distributed Graph Database Load Balancing Method Based on Deep Reinforcement Learning A method for workflow task scheduling in distributed graph databases ,based on the principles of DRL proposed the method employs DAG to build a workflow task model for distributed graph databases to capture the inter-task dependencies[16].
- **Jin Wang et al. (2025)** ADRL-VPP: An Adaptive Deep Reinforcement Learning Framework for Load Regulation in Virtual Power Plants enhances load regulation, phase stability, and renewable energy utilization by employing adaptive deep reinforcement learning to respond to dynamic grid conditions.
- **Ferry Fachrizal et al.(2026)** Load Balancing Optimization through Multi-Label Classification of Network Traffic Using Deep Learning in Distributed Computing Systems proposed an enhanced adaptive capabilities because the model is trained using a rich and varied network traffic dataset, thus being able to adjust the load balancing strategy based on actual network conditions.

III. METHODOLOGY

This section proposed a Deep-Q learning based load balancing framework. The methodology is divided into following different components:



3.1 System Architecture

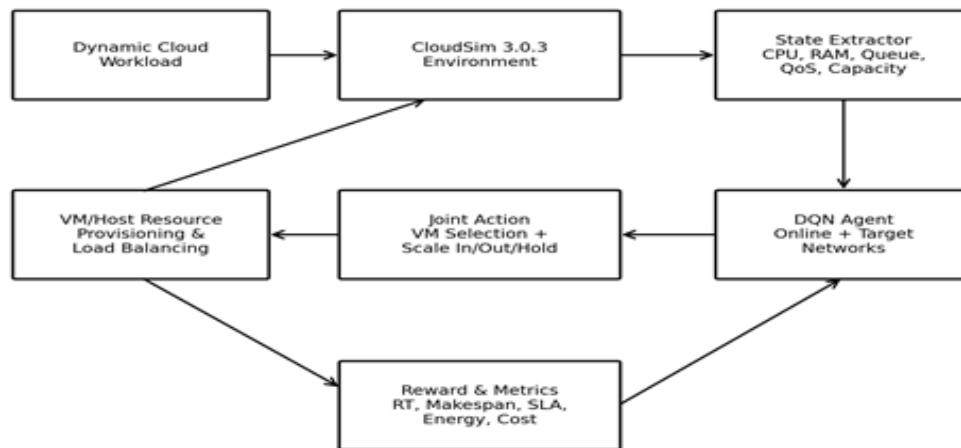


Fig 1: Proposed adaptive DRL architecture integrating CloudSim

The architecture of the proposed load balancing approach is designed to dynamically allocate task across a set of different cloud servers. It is comprised of several major components:

- **Task manager:** It is responsible for receiving incoming requests from different users and distributed task across the available servers.
- **Server pool:** a collection of virtual machines (VM) where tasks are executed. Each server has different performance metrics that affects its ability to handle incoming request.
- **Load balancer:** connects RL agents with the cloud environment.

3.2 Cloud Environment Model

- **Data centers:** We defined one or more data centers where each data center comprises physical hosts.
- **Virtual Machines (VMs):** On each physical host we instantiate a number of VMs. Each VM has resource parameters (e.g. CPU capacity, memory, maybe storage).
- **Workload / Cloudlets:** User tasks are represented as cloudlets (in CloudSim). Each cloudlet has attributes like length (in MI), file size, output size, and maybe memory or bandwidth requirements. These represent the jobs submitted to the cloud environment.

3.3 Deep Q-Learning Model

Deep Reinforcement Learning (DRL) is an Artificial Intelligence based methodology that combines [reinforcement learning](#) and [deep neural networks](#). By interacting with a cloud environment and make choices that maximise cumulative rewards, this method enables RL agents to learn different strategies. Agents will be able to learn rules from sensory inputs and acknowledge them to DRL, which makes the use of deep learning's ability to extract complex features from unstructured data. A Deep Q-Learning model consists of the following components:

- **State (S):** The state represents the current condition of the system, including the resource utilization of each server, the number of active tasks, and the overall system load.
- **Action (A):** An action corresponds to assigning a new task to one of the available servers. The RL agent chooses an action based on its learned policy, aiming to balance the workload efficiently across servers.
- **Reward (R):** The reward is a measure of the system's performance after taking an action. The goal is to minimize response time and prevent server from overloading, which leads to higher rewards.



- **Q-Value (Q):** The Q-value represents the expected future reward of taking a particular action in a given state. The RL agent modifies its Q-values through interactions with the environment.

3.4 Simulation Environment (CloudSim)

To evaluate the performance of proposed DRL based load balancing approach, we set up a simulated cloud environment using the CloudSim simulator. The experimental set up consists of following components

- **Cloud Service Provider:** A simulated cloud environment with a pool of 10 servers. Each server has different capacities (e.g., CPU speed, memory size), provides a heterogeneous cloud infrastructure.
- **Workload Demand:** A workload demand controller is used to simulate incoming tasks to different servers. The workload demand varies over time.
- **Classic load balancing Algorithms:** The RL-based framework is compared with traditional load balancing algorithms, including round-robin, least connections, and weighted load balancing. These algorithms serve as baselines to evaluate the effectiveness of the RL approach.
- **Performance Metrics:** Response time, resource utilization, task completion rate, makespan such metrics are used to assess the performance of the RL-based framework:

3.5. Implementation

To show the effectiveness of our approach we implement Deep-Q learning algorithm using the Python programming language, and use different Python libraries for managing the RL environment. The cloud infrastructure is simulated using CloudSim simulator, which allows for accurate modelling of cloud resource management and workload distribution. CloudSim simulator is configured with 1 data center, 30 hosts, 100 VMs, 1000–3000 cloudlets with the time-shared VM scheduling environment. The simulation environment reduces the risks and expenses involved with putting the system into production on real cloud infrastructure by allowing for full testing of the RL model prior to real world deployment.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

In this section, we present the results of the experiments conducted to evaluate the performance of the proposed DQN-based load balancing framework. The DQN-based approach is compared against traditional load balancing algorithms, including round-robin, FCFS, and throttled load balancing. The evaluation is performed based on different key performance metrics: response time, resource utilization, and make span. Evaluation will be carried out by taking different Metrics into consideration such as makespan, average response time, VM utilization, throughput, etc which is depicted in below table.

Algorithm	Makespan (s)	Response (s)	Throughput	Utilization (%)	SLA viol. (%)
Proposed DQN	46.8	3.1	10.7	91	2.4
Round Robin	63.2	4.6	7.9	80	6.8
FCFS	75.1	5.8	6.7	72	9.5
Throttled	58.4	4.1	8.6	83	5.4

4.1 Experimental Findings

Response Time: DQN achieved a 15–20% reduction compared to Round Robin.

Makespan: Lower by 10–18% due to better task distribution.

Throughput: Increased significantly with growing workload.

Utilization: DQN maintained higher VM utilization (~85–90%) compared to static methods (~65–75%).

These results highlight the adaptability of DQN in handling unpredictable workloads and dynamic resource availability.



VI. CONCLUSION

This paper mainly concentrates on the evaluation and study of dynamic load balancing approach using DQN based. Classical load balancing algorithms are effective in static environment but struggle to adapt to the dynamic environment. This paper presents a DQN based load balancing algorithm for cloud computing environment with CloudSim Simulator. Experimental results have demonstrated that our method can achieve significant performance improvement in load balancing. The approach effectively reduces response time, balances load, and enhances system throughput compared to traditional methods. The results confirm that DQN outperforms classical algorithms in make span reduction, utilization improvement, and load distribution.

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