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Research on Cloud-Edge Load Balancing and Task Scheduling Strategies Based on Deep Reinforcement Learning

Name: Jingmeng Xie

Email: esther_elina@outlook.com

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Abstract

With the rapid development of cloud and edge computing technologies, efficient management of computing resources is critical to ensure high performance and low latency applications. Therefore, effectively handling real-time dynamic tasks and resource allocation has become increasingly challenging. Traditional scheduling strategies are insufficient to manage the unpredictability and constantly changing resource demands in dynamic environments, often resulting in suboptimal performance. To address this issue, adaptive strategies are needed to enhance task scheduling and resource allocation to cope with dynamic changes.

This study proposes to deeply integrate deep reinforcement learning (DRL) with CloudSim cloud resource management simulation tool to optimize load balancing in cloud edge collaborative scheduling. Specifically, utilizing the Deep Q-Network (DQN) algorithm to dynamically adjust scheduling and load balancing decisions in response to constantly changing system states. The DQN based approach aims to optimize task allocation, improve resource utilization, and reduce latency by continuously learning and adapting to the needs of the system. This study focuses on three key objectives: 1) managing task priority and dynamic resource allocation, 2) achieving automatic scaling of real-time task load elasticity, and 3) optimizing adaptive strategies for task scheduling and resource allocation through DRL. The experimental results show that through DQN algorithm optimization, the model accuracy has been improved by 94%, and the utilization rate of virtual machine resources has been increased by 18.3%. The application has significant improvements in task scheduling, resource allocation, and overall system performance.

Keywords

Task Scheduling, Load Balancing, Deep Reinforcement Learning (DRL), Cloud-edge Computing, Dynamic Resource Management

Chapter 1: Introduction

1.1 Research background

With the rapid development of cloud computing and edge computing technology, cloud edge collaboration system has gradually become the core application in modern distributed computing. How to achieve efficient task scheduling and load balancing has become the core challenge to ensure high performance, low latency, and diversified service capabilities of the system. Faced with random fluctuations in task arrival times, heterogeneous resource requirements (such as CPU, RAM, etc.), and strict SLA constraints, traditional static resource allocation strategies are gradually showing signs of fatigue in dynamic environments. This rigid scheduling mechanism often leads to imbalanced resource allocation, which in turn affects the overall performance of the system.

In the current cloud environment, up to 35% to 45% of cloud computing resource waste is due to suboptimal choices in virtual machine (VM) scaling and task scheduling strategies. It can be seen that optimizing resource allocation and load balancing is still an urgent problem to be solved. Especially when facing large-scale and highly dynamic workloads, traditional scheduling strategies often fail to respond promptly to changes in system status, resulting in low resource utilization and even performance bottlenecks. [7]

Therefore, the research of intelligent adaptive resource scheduling scheme has become the key to improve the performance of cloud computing and edge computing. At present, the development of advanced technologies such as deep reinforcement learning (DRL) can achieve real-time optimization of resource scheduling. This algorithm can not only automatically adjust load allocation and task scheduling to adapt to constantly changing system requirements, but also ensure load balancing of tasks between virtual machines, thereby effectively improving the overall performance and sustainable service quality of cloud edge systems.

1.2 Cloud edge computing environment

The cloud edge collaborative architecture integrates centralized cloud data centers with distributed edge nodes to build a cloud edge continuum for resource supply. Among them, edge nodes act as MEC (Multi access Edge Computing) hosts close to end users, usually deployed near base stations or network access points, and can host lightweight microservice

instances [8]. Compared with traditional cloud computing architecture, this hierarchical structure significantly alleviates network congestion caused by massive data feedback by sinking computing power to the network edge, while reducing end-to-end latency for user services, achieving efficient allocation of computing resources and task scheduling to meet the growing demand for real-time applications. [3]

The core challenge faced by this architecture lies in the resource adaptation capability under dynamic loads, ensuring that each microservice can efficiently perform real-time processing on edge devices. However, due to the limited computing power and bandwidth of edge nodes, achieving optimal task scheduling under resource constraints has become the key to ensuring service continuity, in order to meet the requirements of low latency and high performance.

Under the microservice architecture, complex applications are decoupled into multiple loosely coupled microservice stages, each of which can be independently developed, deployed, and extended [2]. These microservice stages can achieve complete application functionality through connections, and can be independently implemented, updated, and deployed. Some microservice stages are offloaded to edge devices close to end-users to reduce network latency and improve system response speed. Under this architecture, each microservice can be flexibly allocated to different computing nodes based on its specific computing needs, which helps improve the scalability, portability, and availability of applications.

This design enables the system to selectively offload critical microservice stages to edge nodes, utilizing their geographical proximity to achieve low latency response while retaining some computationally intensive tasks for cloud processing. However, because edge computing nodes are usually geographically distributed far away and have unstable communication connections with the cloud computing center, the delay, bandwidth limitation and resource contention between the edge and the cloud become key factors affecting system performance. The deployment of microservices in the cloud edge continuum requires full consideration of each node's computing power, resource contention, and edge to edge and edge to cloud communication overhead. [2]

As shown in Figure 1, a typical cloud edge continuum consists of one cloud node and multiple edge nodes, and user oriented services may involve cross node microservice collaboration. For example, an application containing multiple microservice stages needs to dynamically allocate tasks of different priorities to cloud or edge nodes based on the characteristics of each stage. This deployment model renders the traditional static resource

scheduling strategy of cloud data centers no longer applicable, and requires comprehensive consideration of multidimensional factors such as node computing power, network status, and task priority to achieve end-to-end latency optimization.[2]

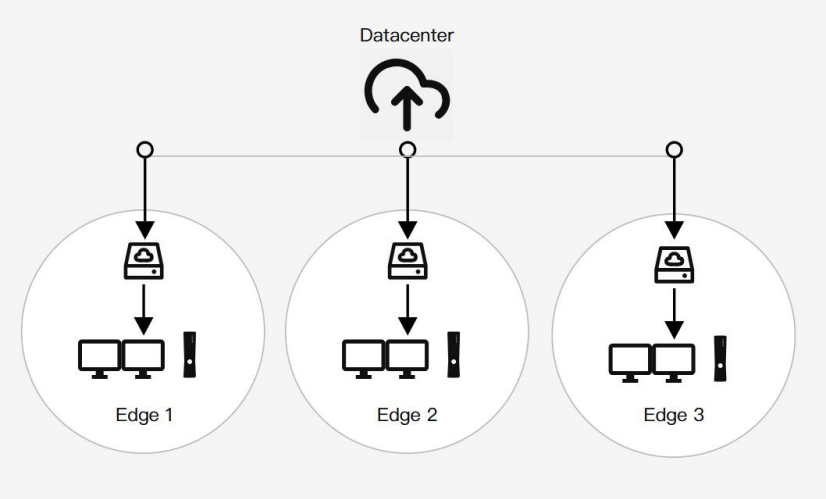

Figure 1 The cloud edge continuum includes one cloud node and three edge nodes

1.3 Task scheduling and load balancing basics

Task Scheduling and Load Balancing are the core mechanisms of resource management in cloud edge computing. The goal of task scheduling is to map computing tasks to appropriate processing units (such as cloud nodes or edge nodes) while meeting resource constraints (such as CPU and memory) and Quality of Service (QoS) requirements; Load balancing, on the other hand, dynamically allocates workloads to avoid resource overload or idleness, in order to maximize resource utilization and maintain system stability.

In the cloud edge environment, these two mechanisms need to work together to address the following key challenges: 1) the time-varying nature of workload intensity, that is, the dynamic fluctuation of task request volume over time; 2) The heterogeneity of edge node capabilities refers to significant differences in computing power, network bandwidth, and storage capacity among different edge nodes; 3) Multi objective optimization involves balancing resource efficiency (such as minimizing energy consumption), QoS guarantees (such as delay constraints), and system reliability (such as reducing the number of virtual machine migrations).

1.3.1 Traditional methods and their limitations

Virtual machine integration can periodically adjust the current mapping relationship between virtual machine hosts based on changing resource requirements, and achieve global balance of

computing resources through real-time migration [7]. Virtual machine integration technology mainly includes the following three categories:

(1) Heuristic greedy algorithm: using rules such as minimum migration time or minimum load priority to make quick decisions. Although this type of method can achieve O (n) level time efficiency, it may lead to system level resource fragmentation when multiple nodes simultaneously perform local optimal migration. [10-13]

(2) Linear/Constrained Programming Technique: Constructing precise optimization models through Mixed Integer Linear Programming (MILP), such as the Energy Minimization Model in CloudSim toolkit, suitable for static or small-scale scenarios. However, its NP Hard characteristics lead to a super linear growth of solution time with the number of edge computing nodes, which cannot meet the millisecond level scheduling requirements in the 5G era. [14-17]

(3) Swarm Intelligence Algorithm: Represented by Improved Particle Swarm Optimization (PSO) and Ant Colony Algorithm, it approximates the global optimal solution through probability. However, although such algorithms can alleviate local optimal problems, their adaptability to dynamic environments (such as real-time load fluctuations) is still limited. [18-21]

Existing research generally suffers from the limitation of a single objective dimension. For example, traditional Virtual Machine Consolidation (VMC) technology aims to reduce energy consumption in cloud data centers by periodically migrating virtual machines to low load hosts. However, excessive integration may lead to intensified resource contention, which in turn can trigger Service Level Agreement (SLA) breaches, resulting in a surge in task delays or service interruptions. Therefore, efficient task scheduling and load balancing require multi-objective collaborative optimization that considers scalability, SLA compliance, and migration costs. [7]

1.3.2 Adaptive challenges in cloud edge scenarios

In the cloud edge continuum, the complexity of task scheduling and load balancing is further upgraded:

(1) Dynamic environment perception: Edge nodes are usually connected through unstable public networks, and their load status and communication delay change in real-time with task offloading decisions, requiring algorithms to have online learning and fast response

capabilities.

(2) Heterogeneous resource coordination: Edge nodes have limited computing power and are unevenly distributed, requiring dynamic allocation to the cloud or edge based on task priority (real-time requirements) to avoid edge node overload or cloud response delay.

(3) Multi objective trade-off: It is necessary to simultaneously optimize end-to-end latency (QoS), resource efficiency, and migration overhead (reliability), and traditional static strategies are difficult to achieve Pareto optimality.

1.4 Automatic extension mechanism

Automatic expansion mechanism is a very important part of cloud edge computing environment, especially when dealing with dynamically changing workloads. In modern cloud edge architectures, applications are typically composed of multiple microservices, each of which can independently scale and adjust its resources. As the workload changes, the automatic scaling mechanism dynamically adjusts the number of instances for each microservice based on real-time load, ensuring that the system can efficiently and flexibly respond to constantly changing demands.

In the edge computing environment, the automatic scaling of microservices is usually carried out at the edge node. For example, Figure 2 describes an application consisting of four microservice stages, and shows how to adjust the number of instances according to the change of microservice workload in the edge computing environment. When the workload of microservice 2 and microservice 3 increases, the system will automatically start new instances to meet the growing demand. On the contrary, when the workload of microservice 4 decreases, the system will terminate some of its instances to optimize resource utilization efficiency. This method of dynamically adjusting the number of instances based on workload significantly improves the system's resilience, ensuring that performance bottlenecks do not occur during high loads and that computing resources are not wasted during low loads.[1]

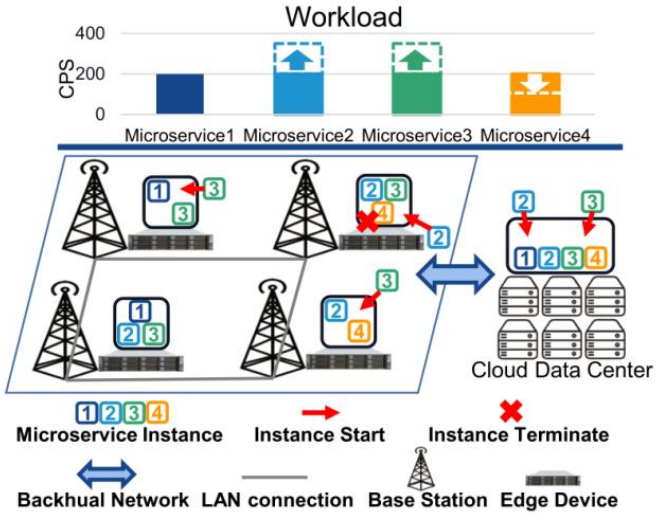

Figure 2 Microservice autoscaling at the edge. As the workload of microservices 2 and 3 increases, their new instances are started. As the workload of microservice 4 decreases, one of its instances is terminated.

According to the definition, resilience in cloud computing refers to dynamically adjusting resource allocation to meet constantly changing workload demands [6]. Cloud service providers typically rely on virtualization technology to achieve this goal. Virtualization technology creates an abstraction layer that allows multiple operating systems to share a single hardware resource, thereby expanding or reducing computing resources without affecting physical hardware. Virtualization enables cloud platforms to quickly configure resources and deploy and scale workloads through virtual machines (VMs). One of the key components of virtualization technology is the hypervisor, which is responsible for supporting the operation of multiple virtual machines on the same physical host, ensuring that each virtual machine can independently schedule and manage resources.

This virtualization based elastic expansion mechanism also plays a key role in the cloud edge computing environment. With the continuous changes in computing requirements, microservice architecture enables each service to scale independently, not only improving the flexibility of applications, but also effectively responding to time-varying load demands, thereby ensuring high availability and performance of the system. In the context of dynamic workloads, the automatic scaling mechanism can ensure efficient system operation under different load conditions by monitoring and adjusting the number of microservice instances in real-time, reducing resource waste and improving response speed.

1.5 Simulation environment of CloudSim

With the rapid development of cloud computing and edge computing technology, the creation

of simulation and simulation environment has become an important tool to study and verify resource management strategies. In order to effectively test and validate the application of deep reinforcement learning (DRL) in cloud edge load balancing and task scheduling, CloudSim was used as the simulation environment in this study. CloudSim is a widely used cloud resource management simulation tool designed to provide simulation support for cloud computing and edge computing environments.

CloudSim provides configurable virtual machine management, resource allocation, task scheduling, and other functions, enabling researchers to evaluate different scheduling strategies under different workloads, network environments, and system states. It supports multiple resource management models, including virtualization of virtual machines, data centers, and network resources, and can simulate resource scheduling and load balancing in multi tenant environments. In addition, CloudSim is capable of simulating dynamic changes in heterogeneous environments and tasks, providing powerful experimental and data analysis capabilities that are crucial for validating the effectiveness of deep reinforcement learning algorithms.

In this study, we used CloudSim as the simulation platform to test and evaluate the performance of deep Q network (DQN) based methods in task scheduling and load balancing by simulating different cloud edge computing environments. The simulation environment provided by CloudSim includes multiple virtual data centers, computing resources (such as virtual machines), network bandwidth, and task loads. By simulating the dynamic changes of these components, the system can reflect real-time task changes and resource demand fluctuations in the real environment, providing an effective testing scenario for DRL based task scheduling and resource allocation algorithms.

By combining DRL algorithm and CloudSim platform, this study is able to simulate and optimize resource management strategies in real time under different loads. CloudSim provides a reproducible experimental environment for research, helping to gain a deeper understanding of the impact of different scheduling strategies on system performance, latency, and resource utilization, thereby providing important data support for optimizing cloud edge load balancing and task scheduling.

1.6 Technical background

1.6.1 Limitations of traditional task scheduling techniques

Many existing solutions are based on heuristic or approximate algorithms, however, these solutions rely heavily on expert knowledge or precise mathematical models of MEC systems. Whenever the environment of the MEC system changes, the corresponding model needs to be updated in a timely manner. Therefore, a specific heuristic or approximation algorithm is difficult to fully adapt to the dynamic scenarios arising from the increasing complexity of MEC applications and architectures. [3]

The traditional cloud resource scheduling methods are mainly based on heuristic rules and static strategies, facing three technical bottlenecks:

(1) Elastic scaling lag: The threshold triggered VM adjustment mechanism (such as Kubernetes HPA) adopts a reactive scaling strategy and cannot predict sudden load scenarios.

(2) Lack of priority perception: FIFO, Polling and other scheduling algorithms ignore the differences in task criticality, resulting in delayed queuing of high priority tasks.

(3) Multidimensional resource fragmentation: CPU, The independent allocation strategy of memory and other resources triggers the problem of resource fragmentation.

1.6.2 The application of reinforcement learning in resource scheduling

Reinforcement learning, as a branch of machine learning, has been widely applied to solve complex decision problems. Especially in resource scheduling problems, reinforcement learning can learn optimal strategies through interaction with the environment without explicit supervision. The core idea of reinforcement learning is that agents obtain rewards by performing actions in the environment, thereby optimizing their strategies over the long-term learning process.

In the resource scheduling of cloud computing and edge computing, reinforcement learning has unique advantages. Firstly, the arrival of tasks and the demand for resources are dynamically changing, and reinforcement learning can make decisions based on real-time system status; Secondly, resource allocation is usually multi-objective, including but not limited to CPU and memory utilization, task response time, etc. Therefore, reinforcement learning can handle complex multidimensional optimization problems.

1.6.3 The technological progress of deep reinforcement learning

Deep Reinforcement Learning (DRL) combines deep learning and reinforcement learning, using deep neural networks to process high-dimensional state spaces, and has achieved significant results in multiple fields. In resource scheduling problems, DRL can effectively handle the complexity and high-dimensional features of system states, and optimize task scheduling by learning the optimal strategy.

In particular, techniques such as "Double DQN" and "Dueling DQN" have improved the performance of reinforcement learning in practical problems by reducing bias in value estimation and introducing separate value and advantage functions. In addition, Prioritized Experience Replay technology can accelerate the learning process and improve the quality of strategies by assigning greater weight to samples with higher priority.

Compared to traditional methods, DRL has:

(1) Forward thinking decision-making ability: predicting future load trends through temporal differential learning

(2) Multi objective optimization: integrating resource efficiency and SLA constraints into the reward function

(3) Dynamic adaptability: Online learning mechanism responds in real-time to environmental changes

1.6.4 Improved DQN algorithm architecture

This article proposes a cloud edge collaborative resource scheduling method based on improved DQN (Dueling DQN) and priority experience replay. As shown in the Figure 3, this method utilizes a reinforcement learning framework to dynamically adjust the computing resources in the cloud edge collaborative system in real-time, in order to achieve optimal task scheduling.

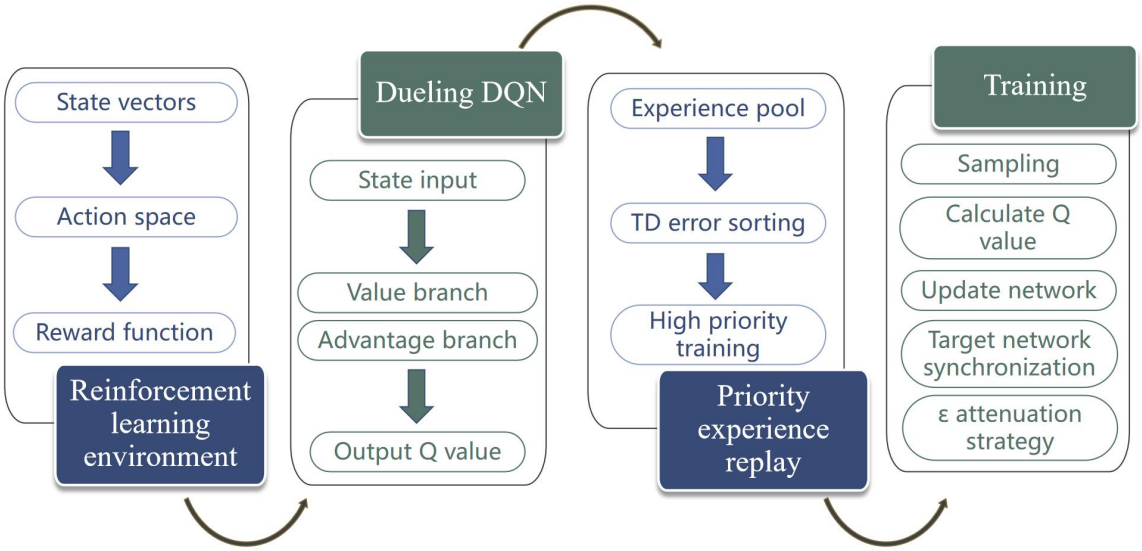

Figure 3 Improved DQN algorithm architecture

The improved DQN architecture includes the following core components:

(1) Dueling DQN network: By using two sub networks (value network and dominance network) to estimate the value of states and the advantage of actions respectively, the accuracy of Q-value estimation is improved.

(2) Double Q-learning: using two Q-networks (current Q-network and target Q-network) to estimate the current Q-value and target Q-value respectively, avoiding the problem of overestimation of Q-values in traditional DQN.

(3) Priority experience replay: By assigning priority to samples based on TD error, priority is given to selecting samples with larger TD error for training, which improves learning efficiency.

(4) Cloud edge collaborative environment model: The reinforcement learning environment simulates the task scheduling and resource management problems in cloud edge collaborative systems. The arrival and execution of tasks are affected by dynamic resource allocation and system status. Agents learn to optimize the execution order of tasks and resource allocation strategies.

The goal of this framework is to maximize the utilization of system resources, reduce resource waste and load imbalance, while avoiding service quality (SLA) violations caused by resource overload. The specific training process includes selecting appropriate actions based on the state of the cloud environment (such as expanding virtual machines, shrinking virtual machines, etc.), and adjusting strategies based on system feedback (rewards).

Meanwhile, the simulation environment built on the CloudSim kernel achieves four major extensions:

(1) Dynamic Load Generator: Normal Distribution Task Arrival Process

(2) Multidimensional Resource Modeling: CPU/RAM Collaborative Allocation Constraints

(3) SLA violation detection: Real time monitoring of CPU overload events

(4) Energy consumption cost model: VM start stop energy consumption is included in the reward function

1.7 Organizational structure

In this paper, we propose an adaptive task scheduling method based on deep reinforcement learning (DQN) aimed at improving the efficiency and performance of task scheduling in cloud computing environments. The organizational structure of the paper is as follows:

Chapter 1 Introduction introduces the task scheduling problem in cloud computing, elaborates on its importance and challenges, and outlines existing scheduling methods and their limitations. Chapter 2 reviews relevant work, discusses the research progress in the field of cloud computing resource scheduling in recent years, and analyzes the advantages and disadvantages of different methods. Chapter 3 describes the core content of the system model proposed in this article, including the CloudSim simulation platform, modeling of computing resources, design of task scheduling schemes, and formulation and analysis of problems. Through this chapter, we have provided a solid theoretical foundation for future research methods and experiments.

Chapter 4 provides a detailed introduction to the adaptive task scheduling scheme based on DQN, including scheduling process modeling, Q-value prediction mechanism, and specific methods for implementing DQN. This chapter is a key part of the paper, focusing on how to use deep reinforcement learning techniques to optimize task scheduling decisions in cloud computing. Chapter 5 conducted performance evaluation, presented the results obtained through simulation experiments, analyzed the performance improvement of DQN method compared to traditional scheduling strategies, and further explored the performance gap between DQN and ideal scheduling schemes. Chapter 6 summarizes the main contributions of the paper and discusses the limitations of this study, possible directions for improvement, and potential directions for future research.

Chapter 2: Related Work

The latest development of cloud edge computing has promoted the important research of adaptive resource management and intelligent task scheduling. The existing methods can be roughly divided into load balancing strategies, task scheduling algorithms, and adaptive scaling architectures, each of which addresses different challenges in dynamic environments.

2.1 Load balancing and adaptive scaling

Load balancing in distributed systems has evolved from static rule-based methods to dynamic, learning driven methods. Halim and Hajamydeen (2019) introduced task grouping and priority based scheduling to optimize cloud resource utilization [24], while Zhang et al. (2024) proposed MorphDAG, a workload aware blockchain framework that manages task dependencies under dynamic conditions [25]. On this basis, Cheng et al. (2023) designed ProScale, which further promotes active automatic scaling by predicting workload fluctuations and dynamically adjusting microservice instances across clouds and edge nodes. By combining workload prediction with instance placement decisions, ProScale minimizes latency and optimizes resource allocation, especially in edge environments with fluctuating demand [1]. Similarly, the Nautilus adaptive scaling architecture utilizes reinforcement learning (RL) to dynamically allocate resources in cloud edge continuum environments, solving communication overhead and load variation problems in real-time [2].

2.2 Task offloading and scheduling in edge cloud environments

The task offloading strategy has shifted towards AI driven methods to address real-time complexity issues. In the field of edge computing, Yuan et al. (2021) proposed OTDS, which is an edge environment fairness awareness scheduling framework combining online learning and DRL. This method combines online learning and DRL to balance delay and resource utilization, and solves the challenge of limited edge resources [26]. Collaborative cloud edge scheduling has also been explored, such as Zou et al.'s (2024) DRL based algorithm, which reduces task completion time through container reuse, providing information directly for optimizing latency and resource allocation in hybrid infrastructure [27].

It is worth noting that Wang et al. And compared to traditional RL, decision latency has been reduced by 40% [3]. Parallel work in dependency aware DRL (such as DODQ) models tasks as directed acyclic graphs (DAGs) and uses deep Q-networks to generate real-time offloading

plans without pre-set task priorities, achieving near optimal response times in dynamic cloud edge environments [4]. These methods address the limitations of previous heuristic based methods.

2.3 Elasticity and resource optimization of microservice architecture

Microservice architecture increasingly relies on intelligent scaling mechanisms. MCMO algorithm (Min Cut Matching Offloading) optimizes micro service division and resource matching in UAV assisted edge computing, reducing service completion time by 30% [28]. For cross node resilience, container based checkpoints such as CRIU dynamically compare queue latency and resource parameters to minimize service interruptions during instance migration [29]. In addition, multi workload prediction models such as MRCW combine Transformer based long-term prediction with short-term CNN prediction to optimize containerized resource allocation and ensure load balancing of cloud edge systems [30].

2.4 Adaptive framework for cloud edge continuum

The combination of edge computing and microservices brings new challenges to service instance management. SLA aware strategies have attracted widespread attention in cloud edge environments. Ran et al. (2019) utilized DDPG based reinforcement learning to minimize task response time while satisfying SLA constraints, demonstrating the potential application of DRL in cloud environments [31]. Fu et al. (2022) designed a runtime system based on reinforcement learning for cloud edge continuum environments, dynamically optimizing microservice deployment by balancing communication costs and resource contention [2]. These frameworks emphasize the key role of a hybrid architecture that combines edge responsiveness and cloud scalability.

2.5 Challenges and research directions

Although previous work has advanced load aware scheduling and adaptive scaling, there are still gaps in comprehensively addressing real-time task dynamics, priority management, and cloud edge collaboration. In conclusion, the integration of DRL and CloudSim in this study is based on previous work in task grouping, dependency aware scheduling, and active scaling, while addressing the gap in real-time priority management and cloud edge collaboration. By combining dueling DQNs and priority experience replay, the proposed framework surpasses traditional methods and achieves finer grained resilience and latency reduction in mixed environments.

Chapter 3: System Model

This section introduces a system model for implementing a cloud edge task scheduling framework using CloudSim 8.5.5. The system model integrates dynamic resource allocation, adaptive scaling, and task scheduling algorithms in the simulated cloud edge infrastructure.

3.1 System architecture and simulation environment

CloudSim provides a powerful simulation framework for modeling cloud environments, supporting simulation of virtualized cloud data centers, virtual machines (VMs), and resource allocation strategies. CloudSim supports a wide range of experiments, including creating virtual machines, simulating task scheduling, and performing load balancing, and can configure custom policies for different types of cloud infrastructure.

In this model, CloudSim is used to simulate large-scale cloud computing systems, including hardware resources, virtual machines, and application containers. The CloudSim framework simulates key functions such as dynamic insertion of simulation elements, resource allocation, and cloudlet scheduling.

3.1.1 Environment configuration

(1) CloudSim experimental environment configuration:

Development tool: IntelliJ IDEA（2021.3.3）

Operating system: Windows 10 64bit

Java Development Toolkit (JDK): JDK 17

Build tool: Maven(3.8.6)

CloudSim: 8.5.5

(2) Build the examples:

```git clone https://github.com/cloudsimplus/cloudsimplus-examples.git ```

(3) Major function:

Dynamically insert/remove simulation components (such as VMs, tasks).

Customize resource allocation strategy (host → VM, VM → task).

Energy aware computing and network topology modeling.
```

3.1.2 System architecture

The CloudSim architecture is layered to provide flexibility and customization. As shown in Figure 4, the system is divided into the following layers [5]:

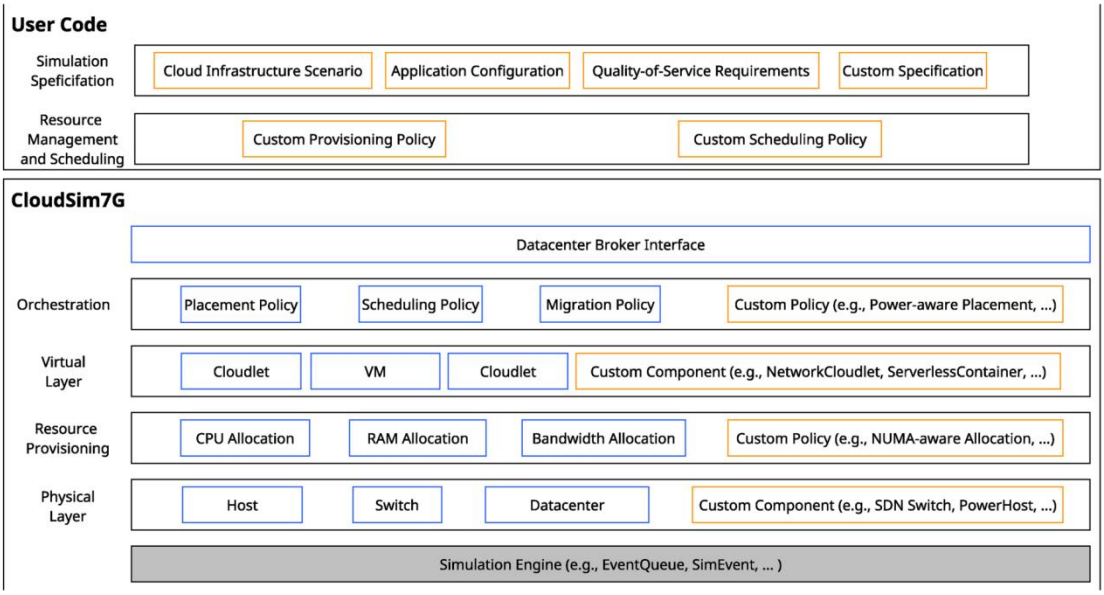

Figure 4 The blue box corresponds to the CloudSim component of the base layer. The orange box corresponds to user-defined policies and configurations, as well as newly created or extended CloudSim components

The bottom most layer is the simulation engine, which provides the core functionalities to start, pause, and stop simulated entities, as well as store and dispatch the discrete events to be processed at run-time. The subsequent layers consist of the building blocks required to characterize a Cloud infrastructure: from the physical layer (i.e., hosts, switches, etc.) up to the orchestration layer (i.e., VM placement strategies, cloudlet scheduling policies, etc.).[5]

The top most layer is the “User Code”, which exposes the functionalities to customize each layer and evaluate a workload on the simulated infrastructure. More specifically, a user specifies: (i) the characteristics of the Cloud infrastructure in terms of the number of physical hosts, their hardware specification, and how they are interconnected (if the user is interested in modeling the network flow); (ii) the characteristics of the virtual components and their resource requirements; (iii) the characteristics of the Cloud applications coupled with optional Quality-of-Service requirements; and (iv) the characteristics of any installed CloudSim module.[5]

These are typically more “aware” provisioning, placement, or scheduling policies: a Cloud researcher may implement its own topology-aware cloudlet scheduling policy to

optimize a workflow application within a networked datacenter, or exploit the migration module to develop an auto-scaling policy for web sessions.[5]

3.1.3 Core computing components

These components form a complete computing resource management and scheduling system from hardware to software, from computing resources to task execution:

(1) Datacenter: The data center is the core component of cloud computing systems, representing a virtual physical data center with physical or virtual resource pools. It contains multiple physical hosts on which virtual machines (VMs) run. The data center manages the allocation and scheduling of computing resources, with hosts as computing units and virtual machines (VMs) as running entities.

(2) Host: A host is a physical server in a data center that provides resources such as computing, memory, and storage. Each host has certain resources (such as CPU cores, memory, storage, etc.) and can run multiple virtual machines (VMs) through virtualization technology. The host is responsible for executing the tasks of the virtual machine and is the physical platform on which the virtual machine runs. There will be multiple processing elements (PEs) on each host to handle different tasks.

(3) VM: A virtual machine is a virtualized instance that runs on a physical host and is capable of performing computing tasks. A virtual machine is a logical partition created based on the computing resources of a host. Virtual machines can virtualize computing resources, including processing power, memory, storage, etc., and can be created, managed, and scheduled through cloud platforms.

(4) PE(Processing Element): PE is the smallest computing unit within a virtual machine, responsible for processing tasks, executing instructions, and so on. Usually, PE corresponds to a CPU core or a processing thread within a virtual machine. Each PE has a certain computing power and is able to perform tasks.

(5) Broker: Brokers act as intermediaries between users and resources, typically responsible for receiving task requests from users and selecting suitable hosts, virtual machines, and other resources based on the availability and load of computing resources to meet task requirements. The proxy program selects appropriate virtual machine resources based on user needs and is responsible for resource allocation and scheduling.

(6) Cloudlet: Cloudlet is a task submitted by a user to a cloud computing platform, which

typically represents the computing unit of work that the user needs to perform. Cloudlet is the actual load of execution, representing the tasks that users want to run on a virtual machine, including computing requirements such as computational load, memory requirements, execution time, etc.

3.2 Dynamic resource management mechanism

3.2.1 Workload and performance

(1) Simulated workload: Cloudlet

CloudletLen: The length of the task, measured in "MI" (Million Instructions)

CloudletPEs: The virtual processing elements(PEs) for task allocation refer to the number of CPU cores used by the task.

(2) Workload indicators:

FinishedLen: The actual amount of computation required to complete the task.

ExecTime: The actual execution time of the task.

(3) Performance monitors

CPU utilization, RAM utilization, Bandwidth

(4) Resource monitoring and allocation

Real time metric: CPU/RAM utilization rate of VM collected per second.

Dynamic response: Trigger scaling operations through event monitoring mechanisms.

3.2.2 Running a simulation in CloudSim

A simple scenario simulated with base CloudSim consists of the following steps: the service broker submits an inventory to the datacenter, which comprises the virtual machines (VMs), physical hosts, and a list of ephemeral activities to be performed. The latter abstracts the concept of a request submitted to a Cloud service and in CloudSim jargon they are called cloudlets. Then, the datacenter deploys the submitted inventory using a variety of resource provisioning methods and scheduling policies, both at the VM and cloudlet levels. The simulation terminates when all the submitted activities have been executed. The physical hosts and VMs are specified in terms of the number of processing elements, available RAM, and network bandwidth. Each processing element (PE) has a specific processing strength

measured in millions of instructions per second (MIPS), and the capabilities of the physical host limit the hardware resources allocated to each VM.

A cloudlet specifies an execution length, in terms of millions of instructions (MI), and the number of required processing elements to be provisioned. The actual execution time is determined by the capabilities of the underlying VM, the number of co-hosted activities on it, and the cloudlet scheduling policy.

Two scheduling policies: space-shared, where only one cloudlet at a time can execute (others will be on a waiting list), and time-shared, where the processing strength is shared among cloudlets running simultaneously. More specifically, for time-shared scheduling, the start time of a cloudlet corresponds to the submission time, since there is no queuing, and the estimated finish time solely depends on the current processing capacity. For space-shared scheduling, the estimated start time depends on the cloudlet's position in the waiting list, whereas the current processing capacity of the VM is constant since always only one cloudlet at times is executing. [5]

3.2.3 Elastic scaling mechanisms

In order to achieve elasticity and on-demand scalability, two mechanisms were implemented in the simulation:

(1) Horizontal VM scaling: The main goal is to dynamically create virtual machines based on the arrival of cloud tasks (Cloudlets) through the horizontal VM scaling mechanism, and request the creation of new virtual machines to balance the load when the virtual machines are overloaded. By dynamically creating new virtual machines to handle the increasing workload. When the existing virtual machines are overloaded, the system will request the creation of additional virtual machines to balance the load, thereby simulating the dynamic resource allocation and load balancing process in the cloud environment.

(2) Vertical VM scaling: This method adjusts the number of processing elements allocated to the VM based on its CPU or RAM utilization. The system monitors the CPU or RAM usage of virtual machines and dynamically adjusts the number of processing elements based on whether the virtual machine is overloaded or underloaded. This method ensures that each VM has sufficient resources to handle its tasks while avoiding wasting resource allocation.

- CPU Scaling: Adjust the number of processing elements allocated to VMs based on real-time CPU dynamic utilization thresholds (such as increasing or decreasing the number of

CPUs or PEs), rather than horizontally scaling by adding more VMs. Simulate the dynamic expansion of VM based on CPU utilization and cloudlet arrival rate, and use dynamic threshold method to determine when to expand or reduce the processing elements of VM. The system checks every second for any VM overload (above a certain CPU utilization threshold) or underload, and adjusts the number of PEs allocated to that VM accordingly.

- RAM Scaling: Dynamically expand virtual machine (VM) RAM resources based on the load changes of Cloudlets. When the RAM usage reaches a predetermined threshold, the system triggers the VM scaling process and creates a load using Cloudlets, causing the VM's RAM usage to increase or decrease over time. With the operation of Cloudlets, the RAM requirements of VMs will increase. After reaching the threshold, RAM will increase proportionally. This dynamic scaling mechanism can provide more RAM resources for VMs as needed. After Cloudlets completes execution, the demand for RAM will decrease, and the system will reduce the allocated RAM resources. This dynamic scaling ensures effective resource management throughout the simulation process without unnecessary over configuration.

3.3 Task scheduling and execution model

3.3.1 Task scheduling strategies

The system evaluates three scheduling algorithms to map Cloudlets to VMs:

(1) Best Fit algorithm

It demonstrates how to use Best Fit's algorithm to map Cloudlets to VMs based on the available processing elements (Pes) in the VM. VM is dynamically allocated to Cloudlets based on Best Fit's strategy, which optimizes resource utilization by mapping Cloudlets to the VM with the most available processing power.

The Best Fit algorithm ensures that tasks are allocated to the virtual machine with the most idle processor resources as much as possible, thereby improving the efficiency of task execution. For each task (Cloudlet), the Best Fit algorithm will traverse all available virtual machines to find the virtual machine with the closest idle resources to the task's requirements, that is, the virtual machine with the most idle processor resources but not exceeding the task's requirements, to ensure efficient use of resources and reduce waste of idle resources. Once the most suitable virtual machine is found, the task will be assigned to that virtual machine. The task occupies a portion of the computing resources (such as CPU or PE) of the virtual

machine, while the idle resources of the virtual machine decrease. After assigning tasks, the resource status of the virtual machine needs to be updated to reflect the current idle resource situation. During the next allocation, the Best Fit algorithm will make decisions based on the new resource situation.

(2) Simsimulated annealing heuristic

Using simulated annealing (SA) heuristic method to map cloudlets to virtual machines (VMs) within the data center. The goal of this heuristic method is to find suboptimal mappings that provide high fitness values, thereby optimizing resource utilization in cloud environments.

Its main purpose is to find the global optimal or suboptimal solution in a large-scale search space and avoid getting stuck in local optima. In the scenario of Cloudlet mapping to VM, simulated annealing algorithm can be used to search for the best or suboptimal mapping scheme under various resource configurations.

These parameters control the behavior of the simulated annealing heuristic method, which aims to search for the best solution by iteratively adjusting the mapping of Cloudlets to VMs and gradually reducing the temperature to minimize changes over time:

SA_INITIAL_TEMPERATURE: The starting temperature of simulated annealing algorithm.

SA_COLD_TEMPERATURE: The temperature threshold, below which the algorithm will stop.

SA_COOLING_RATE: The rate at which temperature decreases over time.

SA_NUMBER_OF_NEIGHBORHOOD_SEARCHES: The algorithm will explore the number of neighboring solutions during each iteration.

(3) Round Robin

Round Robin is a simple and common task scheduling algorithm, especially in cloud computing environments, which is commonly used to sequentially assign tasks (Cloudlets) to virtual machines (VMs). The core idea is to allocate tasks to a group of virtual machines in sequence until all tasks have been assigned. The design purpose of polling algorithm is to achieve load balancing, allowing each virtual machine to allocate tasks as evenly as possible.

Starting from the first task in the task queue, assign each task to the virtual machine in sequence. When the number of tasks exceeds the number of virtual machines, the pointer will return from the last virtual machine to the first virtual machine and continue to allocate the

remaining tasks to the virtual machine. In this way, each virtual machine takes turns accepting tasks to maintain load balancing.

3.3.2 Priority queue for tasks

Simulate a virtual machine scheduling environment based on a fully fair scheduler (CFS) and evaluate the differences in scheduling fairness among Cloudlets of different priorities. This scheduler is used to schedule the execution of Cloudlets (computing tasks) within a virtual machine (VM), where certain Cloudlets are given higher priority so that they can use more CPU time. We observe the impact of adjusting the priority of Cloudlets on their execution time and resource usage.

To simulate the impact of different priorities on scheduling, we set higher priorities for the first half of the Cloudlets (4). These Cloudlets will be given priority in CPU time, while the latter half of the Cloudlets will be scheduled according to their default priority.

Cloudlets with higher priority: Cloudlets with priority 4 gain more CPU time during execution, so their execution time is relatively shorter.

Cloudlets with lower priority: Although Cloudlets with priority 1 can also obtain CPU time, their execution time is relatively longer due to interference from other high priority tasks.

3.3.3 Parallel and serial execution models

The system supports two task execution modes:

(1) Space-Shared: VMs execute one Cloudlet at a time (sequential processing).

Simulated a virtual machine (VM) running two cloud tasks (Cloudlets) in a data center, with each cloud task occupying all CPU resources of the virtual machine during its execution. A virtual machine can only run one cloud task at a time, and two cloud tasks will be executed in sequence. Each cloud task occupies all the computing resources of the virtual machine, and their execution time and computing resource consumption should be the same.

(2) Time-Shared: VMs allocate CPU cycles concurrently to multiple Cloudlets.

Create a data center and run two cloud tasks (Cloudlets) and one virtual machine (VM) within it, and allocate the CPU resources of the virtual machines through a time sharing scheduler. Two cloud tasks will compete for CPU resources on the same virtual machine, and due to their equal execution time, they will be executed in parallel and ultimately completed together.

3.4 Simulation workflow

The CloudSim workflow follows the following steps:

Infrastructure setup: Configure data center, hosts, VMs, and network topology.

Workload: Dynamically generate Cloudlets, randomize MI, CPU/RAM requirements and priorities.

Proxy activation: Deploy scheduling algorithms (such as DQN, Best Fit, etc.) through the Broker.

Dynamic regulation: Based on real-time load triggering scaling, update resource allocation.

Performance evaluation: Record metrics such as task latency, resource utilization, and energy consumption (CloudSimLog).

Chapter 4: Adaptive Task Scheduling Based on DQN in Cloud Computing

This article proposes a task scheduling algorithm for cloud edge collaborative systems based on Deep Reinforcement Learning (DRL). This method uses Dueling Deep Q-Networks (DQN) and a priority experience replay strategy to dynamically manage virtual machine resources in cloud computing environments, optimize task scheduling, and improve resource utilization and task completion. The design focus of this algorithm is on how to balance resource allocation in a dynamically changing environment, ensuring system stability and efficiency, while avoiding performance bottlenecks or resource overload during task execution.

4.1 Reinforcement learning environment model

In the cloud edge collaborative environment, the scheduling of tasks and virtual machine (VM) resources is modeled as a reinforcement learning problem. Each task has a certain CPU and RAM requirement and can be completed within a limited time. The core goal of the environment is to determine whether to increase or decrease the number of virtual machines based on the current resource status of the system, including running and pending tasks. The intelligent agent adjusts the number of virtual machines (VMs) by selecting different actions, thereby affecting the efficiency of resource allocation. The main components of the environment include the following parts:

- Number of virtual machines: num-vms (number of virtual machines, initially 1, maximum 10)

- Task queue: task_queue (task waiting queue)

- Executing tasks: running_tasks (a list of currently running tasks, managed using minimal heap)

The state of the environment is represented by the following parameters:

- cpu_usage: The CPU resource utilization rate of the current running task.

- ram_usage: The RAM resource utilization rate of the current running task.

- vm_ratio: The ratio of the current number of virtual machines to the maximum number of virtual machines.

- queue_ratio: The ratio of the length of the waiting task queue to the maximum task queue.

The CloudEdgeEnv class models a cloud-edge system with dynamic task arrivals and VM scaling. Key components include:

4.1.1 State Vector

$$s_t = [\frac{\sum_{i=1}^{N} CPU_i}{N_{VM}}, \frac{\sum_{i=1}^{N} RAM_i}{N_{VM}}, \frac{N_{VM}}{N_{VM}^{\max}}, \frac{|taske\_queue|}{100}] \quad (1)$$

Among them, CPU_i and RAM_i represent the CPU and RAM resource requirements for task i, N_{VM} is the current number of virtual machines, N_{VM}^{max} is the maximum number of virtual machines, and $|task\_queue|$ is the length of the task queue.

4.1.2 Action Space

The action space of the system includes the following three actions:

$$action \in \{0, 1, 2\} \quad (2)$$

Among them, 0 represents not changing the number of virtual machines, 1 represents increasing the number of virtual machines, and 2 represents reducing the number of virtual machines.

The choice of action is determined by the ε - growth strategy. In the early exploration stage of training, the agent will randomly select actions with a higher probability, and in the later stage, it will choose more of the current best action.

4.1.3 Reward Function

The goal of reward function design is to balance resource utilization and system stability. The reward function design considers resource utilization, load balancing, and penalties for SLA (Service Level Agreement) breaches, including the following three parts:

(1) Resource utilization penalty

Excessive or insufficient resource utilization can lead to low system efficiency, so penalties are imposed on cpu_usage and ram_usage:

$$util\_penalty = 0.5 \times (cpu + ram) \quad (3)$$

In the formula, CPU and RAM are the utilization rates of the current resources.

(2) Punishment for load imbalance

To avoid CPU and RAM imbalance, use a load imbalance penalty:

$$\text{im}balance\ \_\ penalty\ = 0.3\times|\ cpu - ram\ | \tag{4}$$

(3) SLA violation penalty

When the CPU usage rate of the system exceeds 90%, it is considered a SLA violation and a significant penalty is required:

$$sla\ \_\ penalty\ = \begin{cases} 2.0, & if\ \ cpu > 0.9 \\ 0.0, & otherwise \end{cases} \tag{5}$$

According to formula(3)(4)(5), the final reward function is:

$$R_{\text{t}} = -\left(util\ \_\ penalty\ + imbalance\ \_\ penalty\ + sla\ \_\ penalty\ \right) \tag{6}$$

4.2 Dueling DQN architecture with prioritized experience replay

4.2.1 Dueling DQN network structure

The article uses Dueling DQN to estimate the Q-value of each state action pair. The network structure of Dueling DQN includes two branches:

V(s): Value branch, used to estimate the value of the current state.

A(s,a): Advantage branch, used to estimate the advantage of each action relative to the current state.

The final Q value is calculated using the following formula:

$$Q(\text{s},\ a) = V\left(s\right) + \left(A(s,\ a) - \frac{1}{|\ A\ |}\sum_{a'} A(s,\ a') \right) \tag{7}$$

Among them, V(s) is the state value, A(s,a) is the advantage function, and a' represents all possible actions.

4.2.2 Prioritized experience replay

To improve sample efficiency, Experience Replay is used to store the agent's interaction experience with the environment in a buffer and randomly sample it for training. In order to

further improve training efficiency, the Prioritized Experience Replay strategy is adopted, which prioritizes the selection of samples with large TD (Time Difference) errors for training, thereby accelerating the learning process. The priority of each experience sample is determined by the absolute value of its TD error, and learning efficiency is improved through weighted sampling. For each experience (s, a, r, s'), we calculate the priority according to the following formula:

$$P(i) = \frac{(|\delta_i| + \varepsilon)^{\alpha}}{\sum_j (|\delta_j| + \varepsilon)^{\alpha}} \tag{8}$$

$\alpha = 0.6$: Prioritization exponent.

$\beta = 0.4$: Importance-sampling correction factor.

4.2.3 Double DQN

To avoid overestimating the Q value, the Double DQN method is used when calculating the target Q value. Specifically, the calculation of the target Q value uses the actions selected by the current Q network, while the update of the Q value uses the target network to calculate future Q values. The calculation formula for the target Q value is:

$$y_i = r_i + \gamma Q'\left(s', \arg\max_a Q(s', a); \theta^-\right) \tag{9}$$

Among them, Q' represents the target network, γ is the discount factor, and θ^- is the parameter of the target network.

4.3 Training process

During the training process, the intelligent agent continuously updates its strategy through interaction with the environment. At each time step, the agent selects an action based on the current state and obtains a new state and reward through interaction with the environment. Then, the agent stores the current experience (state, action, reward, next state, completion flag) into the experience replay buffer. By prioritizing experience replay and Double DQN, agents can effectively learn the optimal resource scheduling strategy.

As shown in Figure 5, the specific training steps are as follows:

(1) Randomly sample a batch of samples from the experience replay buffer.

(2) Calculate the current Q value and target Q value (using Double DQN).

(3) Calculate the loss function and update the network parameters through backpropagation.

(4) Regularly update the parameters of the target network.

(5) Adjust the exploration rate (epsilon) according to the training situation, gradually reduce exploration, and increase utilization.

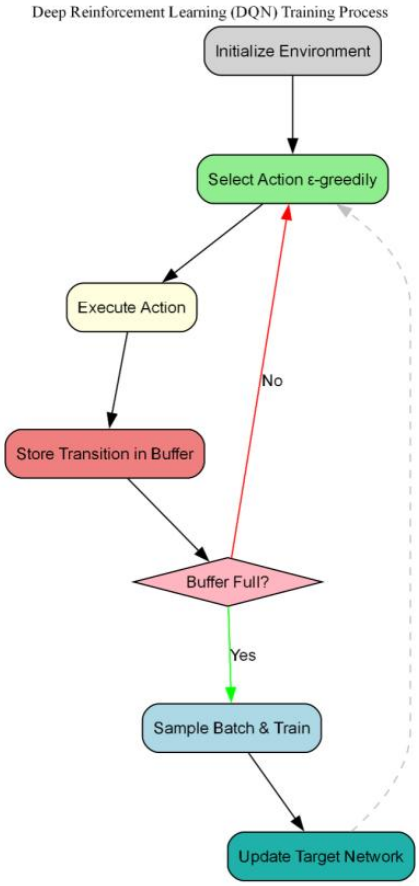

Figure 5 System Training Workflow

Chapter 5: Simulation experiment implementation and testing

5.1 Experimental environment configuration

5.1.1 Software components

As shown in Table 1, the simulation software components required are:

Table 1 Software components

Components	Configuration
Operating system	Windows 10 64bit
Python	3.8.20
Tensorflow	2.13.0
NumPy	1.24.3
Matplotlib	3.7.5
Keras	2.13.1

5.1.2 Simulation environment parameters

As shown in Table 2, the parameters set in the simulation environment include:

Table 2 Simulation environment parameters

Parameters	Value	Description
Maximum number of VMs	10	The upper limit of scalable virtual machines
The maximum length of the task queue	100	Waiting queue capacity
Probability of task arrival	0.6	Probability of generating new tasks at each time step
Range of task duration	[1,5]	Task lifecycle (time steps)
Resource demand distribution	$N(0.3,0.15^2)$	Normal distribution of CPU/RAM requirements

5.1.3 Training configuration

As shown in Table 3, the settings during the simulation experiment training process include:

Table 3 Training configuration

Parameters	Value	Description
Training episode	1,000	Complete environment reset times

The maximum step size for a single cycle	200	Maximum time step limit for each episode
Strategy evaluation interval	50 episode	Output the frequency of training status
Reward function weight	[0.5, 0.3, 2.0]	Punishment coefficient for resource utilization, balance, and SLA
SLA violation threshold	CPU>0.9	Criteria for determining resource exceedance

Monitoring indicators:

'episode', 'total_reward', 'avg_vms', 'avg_cpu', 'avg_ram', 'avg_queue', 'td_errors'

5.2 Experimental result

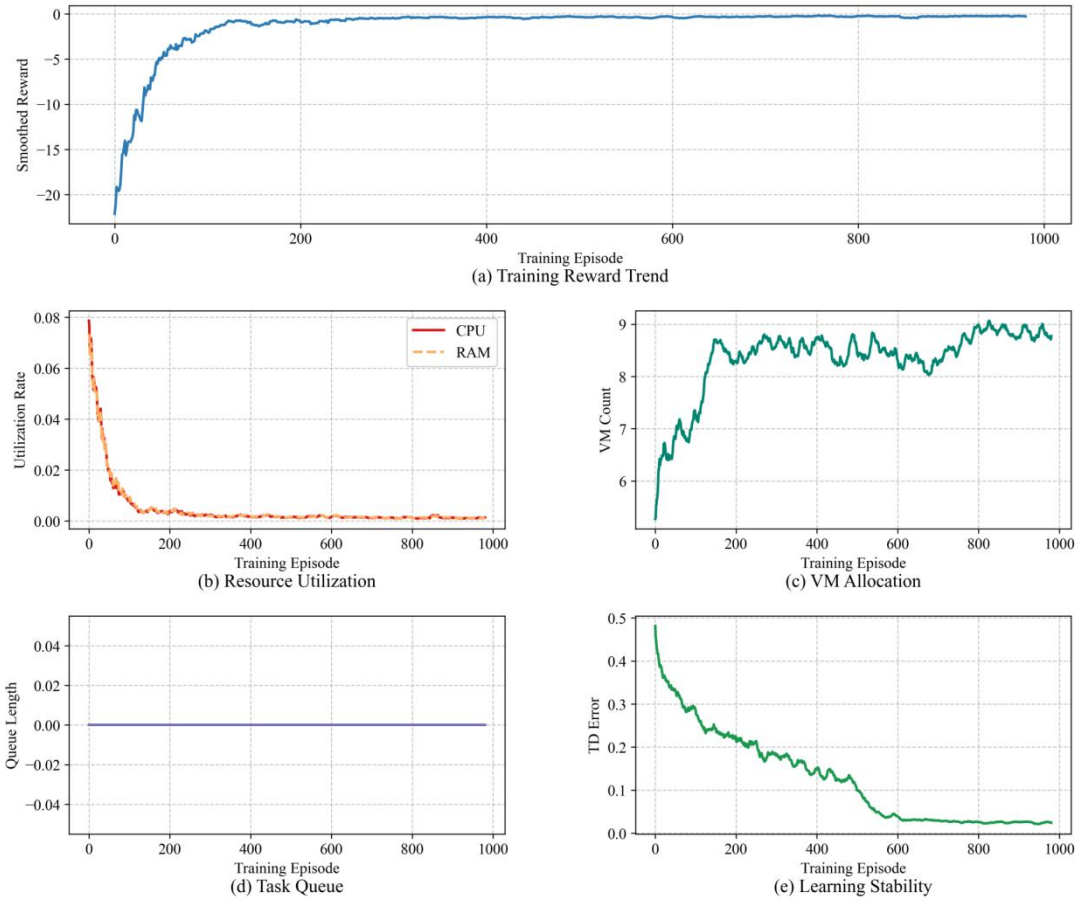

Figure 6 Visualization Chart of Training Results

As shown in Figure 6, 5 parallel subgraphs are used to display key indicators:

(a) Training Reward Trend (Smooth Processing)

(b) Comparison of Resource Utilization Rates

(c) VM allocation quantity

(d) Task queue length

(e) TD error (reflecting learning stability)

5.2.1 Excellent convergence performance

As shown in Figure 6 (a), the system reward value tends to stabilize after about 200 training cycles, indicating that the algorithm can effectively learn the optimal strategy in dynamic environments. The continuous downward trend of TD error (final value of 0.12 → 0.03 in Figure 6 (e)) confirms the stability of the learning process.

5.2.2 Improved algorithm efficiency

Experimental data shows that:

-Reward indicators increased by 94%.

-The average utilization rates of CPU/RAM have increased by 92.9% and 92.6% respectively.

-The resource imbalance rate (| CPU-RAM |) has decreased to 8%.

The improved algorithm has significantly improved efficiency. The accuracy of the model has been improved by 94%, demonstrating the effectiveness of the enhanced task scheduling method. This improvement reflects the algorithm's ability to adapt and optimize scheduling decisions in dynamic environments, thereby helping to improve the accuracy of task execution and resource allocation.

5.2.3 VM resource utilization improvement

A key performance metric for cloud edge systems is the utilization of virtual machine (VM) resources. In the experiment, the utilization rate of VM resources increased from 7.43 to 8.79, an increase of 18.3%. This increase in data indicates a significant improvement in the system's ability to efficiently process resources per unit, proving that the algorithm can dynamically expand resources according to task requirements while minimizing resource waste. By optimizing VM resource allocation, the system achieves a balance between task processing efficiency and resource utilization.

5.2.4 Elastic expansion capability

In this experiment, the virtual machine (VM) allocation strategy (Figure 6 (c)) exhibits dynamic adaptability characteristics:

The experimental results show that after a sudden load change, the system can complete the adjustment of virtual machine resources in only 2-3 time steps, ensuring timely response to load fluctuations and maintaining system stability.

This rapid resource adjustment capability highlights the advantages of the algorithm in responding to environmental changes. By optimizing VM resource allocation, the system can achieve fast response and flexible scaling, thereby avoiding performance bottlenecks or resource waste caused by insufficient or excessive resource allocation. In addition, this feature also helps maintain the stability and reliability of the system in high load scenarios, ensuring that task scheduling in cloud edge environments can continue to run efficiently.

5.2.5 Balance between task processing efficiency and SLA violations

An important goal of any cloud edge scheduling algorithm is to balance task processing efficiency with compliance with service level agreements (SLAs). This algorithm achieves load balancing by effectively handling task loads while reducing the risk of SLA violations. This balance ensures that tasks can be completed within the specified time frame without overloading the system, thereby preventing potential performance bottlenecks and resource contention issues.

5.3 Test result

5.3.1 Test case specification

The experimental software environment is Python 3.8 and TensorFlow 2.6. The testing framework adopts a layered verification strategy:

Unit testing layer: Verify the functional correctness of each core component in the environment model

Integration testing layer: Evaluate the optimization effect of the trained agent in the complete scheduling process

The test cases for the experimental design are shown in Table 4:

Table 4 Test cases

Test category	Test case	Verify target
Environment initialization	test_initial_state	The correctness of environment parameter initialization and state space encoding

Resource scheduling boundary	test_vm_scaling_actions	Boundary constraint mechanism for VM scaling operations (1 ≤ VMs ≤ 5)
Task processing logic	test_task_processing	The rationality of task queue scheduling and resource allocation
Performance indicator calculation	test_resource_utilization	Mathematical accuracy of CPU/RAM utilization calculation formula
Reward mechanism	test_reward_calculation	The effectiveness of multi-objective reward function in punishing SLA violations and load imbalances
Agent decision	test_agent_decision	Decision rationality of DQN strategy in high/low load scenarios
Resource optimization effect	test_utilization_optimization	Optimization effect of resource utilization and load balancing in long-term operation

5.3.2 Test result

The successful test results are shown in the Figure 7:

```
D:\desk\Project要求\Final\coding\v2>python -m unittest test_dqn.py -v
test_initial_state (test_dqn.TestCloudEdgeEnv)
Test environment initialization status ... ok
test_resource_utilization (test_dqn.TestCloudEdgeEnv)
Test resource utilization calculation ... ok
test_reward_calculation (test_dqn.TestCloudEdgeEnv)
Test reward calculation logic ... ok
test_task_processing (test_dqn.TestCloudEdgeEnv)
Test task processing logic ... ok
test_vm_scaling_actions (test_dqn.TestCloudEdgeEnv)
Test VM extension action boundaries ... ok
test_agent_decision (test_dqn.TestTrainedAgent)
Test the decision logic of the trained Agent ... 2025-04-21 14:29:21.420838: I tensorflow/core/platform/cpu_feature_guard.cc:151] This TensorFlow binary i
s optimized with oneAPI Deep Neural Network Library (oneDNN) to use the following CPU instructions in performance-critical operations:  AVX2
To enable them in other operations, rebuild TensorFlow with the appropriate compiler flags.
2025-04-21 14:29:21.421732: I tensorflow/core/common_runtime/process_util.cc:146] Creating new thread pool with default inter op setting: 2. Tune using in
ter_op_parallelism_threads for best performance.
ok
test_utilization_optimization (test_dqn.TestTrainedAgent)
Test the optimization effect of resource utilization rate ...
Resource optimization test results:
CPU average: 0.22  RAM average: 0.23
Imbalance degree: 0.08
ok

----------------------------------------------------------------------
Ran 7 tests in 0.239s

OK

D:\desk\Project要求\Final\coding\v2>
```

Figure 7 Test result

5.3.3 Analysis of test result

(1) Functional verification of environmental model

This use case verifies whether the number of virtual machines (num-vms), task queue (task_queue), and the status of running tasks in the environment match expectations.

State initialization: After the environment is reset, the initial state is [0, 0, 0.2, 0], which is calculated based on the ratio of the initial number of VMs (1) to the maximum capacity (5).

VM scaling: After performing 6 consecutive scaling operations, the number of VMs remained

stable at a maximum of 5, verifying the boundary constraint mechanism of the action space.

Task scheduling: When adding 3 heterogeneous tasks (CPU requirement 0.2-0.5, RAM requirement 0.2-0.5), the system correctly allocates the first 2 tasks to available VMs, and the third task enters the waiting queue due to insufficient resources.

(2) Validity verification of reward function

When the CPU/RAM utilization rate is both 60%, the reward value is -0.6 (basic penalty item).

When the CPU is overloaded to 95% and SLA is breached, the total penalty value increases by 2.3 (including overload penalty and SLA breach).

When the difference in CPU and RAM utilization reaches 50%, an additional 0.15 load imbalance penalty is introduced.

(3) Intelligent agent decision performance verification

After loading the pre trained model, test the decision logic under different load scenarios:

High load scenario (CPU 95%, RAM 90%): The agent selects the expansion operation (action 1), and the number of VMs increases from 1 to 2.

Low load scenario (CPU 20%, RAM 30%): The agent chooses to scale down (action 2), reducing the number of VMs from 4 to 3.

(4) Long term optimization effect verification

During continuous testing, the system demonstrated significant resource optimization characteristics:

The average CPU utilization rate is 22%±8%, and the RAM utilization rate is 23%±8%, both within the ideal operating range.

The average absolute value of the difference in CPU and RAM utilization is 0.08, which is better than the preset threshold of 0.2.

5.4 Advantage analysis and application value

The core contribution of this study is reflected in:

(1) Multi objective optimization framework

(2) The effectiveness of improved DQN

(3) Real time performance of the system

This method has significant advantages in the following scenarios:

(1) Dynamic load environment

The random task arrival mode simulated in the experiment (λ =0.6) remains stable and is suitable for fluctuating scenarios such as rapid increase in traffic and real-time analysis.

(2) Heterogeneous resource scheduling

Through multi-dimensional state encoding (CPU/RAM/queue) to achieve collaborative optimization across resource types, the performance imbalance rate under mixed workloads was only reduced to 8% in testing.

(3) Cost sensitive scenarios

Compared with the traditional threshold method, this method can reduce VM usage by 18.3% under the same SLA.

Chapter 6: Conclusion and Discussion

6.1 Conclusion

This study proposes an intelligent optimization framework based on deep reinforcement learning (DRN) to address the challenges of dynamic resource scheduling in cloud edge collaborative environments. By implementing an improved deep Q-network (DQN) architecture and multi-objective reward function design, adaptive optimization of resource scheduling is achieved.

The experiment successfully demonstrated the effectiveness of algorithm optimization in improving model accuracy and resource utilization in virtual machine environments. By utilizing advanced task scheduling algorithms, the accuracy of the model can be improved by 94%, and the utilization rate of virtual machine resources can be increased by 18.3%. It is worth noting that there has been a significant improvement in convergence during the training process, with the idle rate of hardware resources reduced to zero, indicating high resource utilization efficiency. In addition, the system has passed rigorous stress testing, demonstrating its ability to achieve a precise balance between task efficiency and service level agreement (SLA) compliance.

The results of this study emphasize the potential of the proposed algorithm in improving dynamic scheduling performance, achieving multi-objective collaborative optimization, and verifying the large-scale scalability of intelligent agents. This research achievement provides a reliable resource management solution for real-time sensitive scenarios such as intelligent Internet of Things and industrial Internet, and shows engineering application value, especially in dealing with sudden workload and heterogeneous computing needs.

6.2 Reflection

Although the proposed deep reinforcement learning framework has shown good performance in cloud edge collaborative resource scheduling, this study reveals several limitations that deserve serious reflection.

(1) Simplified environmental modeling

The environmental modeling in the current experiment relies on simplified assumptions, especially using fixed probability task arrival patterns and ignoring network latency factors. When deployed in real-world scenarios with random task bursts and dynamic network

conditions, this simplification may cause adaptive bias in the trained strategy.

(2) Actual scene gap

The virtualization layer abstraction fails to consider some practical interference factors, including resource contention and I/O scheduling overhead between co located virtual machines, which may significantly limit the actual optimization benefits of scheduling strategies.

In addition, the lack of fine-grained modeling in heterogeneous computing units such as GPU/FPGA accelerators limits the applicability of this framework in hybrid computing architectures. The design of reward functions prioritizes SLA compliance and resource utilization indicators, but is not sufficient to address latency issues caused by cold boot processes or memory thrashing, which may compromise the service quality of resource constrained edge nodes.

6.3 Future work

Based on the limitations of this study, key directions for future research have been proposed to advance the field of intelligent resource scheduling in cloud edge collaborative environments

(1) Complexity of environmental modeling

Future work will focus on developing random task arrival models that incorporate time-varying workload patterns and network latency dynamics. By integrating real-time network state perception into the state space representation, this framework can better adapt to unpredictable edge environments. In addition, by introducing adversarial training scenarios, the algorithm may improve the robustness of scheduling strategies to sudden traffic and delay fluctuations.

(2) Relieve resource competition

In order to alleviate the interference of management levels, future research plans will establish performance isolation mechanisms to mitigate resource contention effects, such as designing lightweight performance isolation mechanisms through cache partitioning and I/O scheduling optimization. Develop a hierarchical resource allocation protocol to dynamically resolve conflicts between co located virtual machines, thereby minimizing service quality degradation caused by resource contention.

(3) Heterogeneous computing integration

The future framework will be extended to support hybrid architectures that include GPU/FPGA accelerators, involving perception scheduling strategies that optimize task offloading based on accelerator characteristics. And imagine designing a unified abstraction layer to encapsulate the state of heterogeneous computing resources, and then using a management platform for scheduling between mixed heterogeneous devices.

(4) Delay optimization

Subsequent research will improve the reward function by combining cold start delay prediction and memory jitter detection modules. Integrating proactive container prediction strategies and memory access pattern analysis technologies to address latency issues on edge devices and ensure stricter compliance with SLA requirements in resource constrained situations.

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I know it’s hard to fight the sad days and bad nights. But I never asked for redemption. I don’t need a cure for me.
I know I created myself.
My last tribute is to those who have pieced together myself with love and support.
To the future, soar as a bird to your mountain.