Research on Edge Computing and Cloud Collaborative Resource Scheduling Optimization Based on Deep Reinforcement Learning

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***Abstract*—Resource scheduling optimization in edge-cloud collaborative computing is a critical challenge due to dynamic workloads, latency constraints, and limited edge resources. This study proposes a deep reinforcement learning (DRL)-based scheduling approach to enhance task processing efficiency, minimize overall processing time, optimize resource utilization, and control task migrations. Experimental results demonstrate that the proposed DRL model outperforms traditional scheduling algorithms, reducing total processing time by up to 18% and improving resource utilization by 12% under high task loads. Furthermore, DRL effectively balances task allocation, leading to 30% fewer task migrations compared to priority-based and load-balancing scheduling methods. Despite these improvements, challenges remain in learning efficiency, training overhead, and convergence stability. Future research should focus on enhancing algorithm fault tolerance and accelerating training convergence to handle large-scale and uncertain scheduling environments, further advancing intelligent resource management in edge-cloud computing systems.**

Keywords-Edge Computing, Cloud Computing, Deep Reinforcement Learning, Resource Scheduling Optimization, Task Offloading, Load Balancing

I.Introduction

The proliferation of Internet of Things (IoT) devices and the advent of 5G technology have catalyzed unprecedented demands for computing power with stringent latency requirements. This technological evolution has positioned edge computing and cloud computing as complementary paradigms essential for next-generation distributed computing infrastructures. Edge computing addresses the fundamental limitations of cloud-centric models—notably high latency and bandwidth consumption—by relocating computational resources closer to data sources and end users [1]. This proximity enables real-time data processing and decision-making capabilities critical for time-sensitive applications such as autonomous vehicles, industrial automation, and augmented reality. However, edge computing resources remain inherently constrained compared to the virtually unlimited capacity offered by cloud platforms.

This intrinsic resource limitation of edge computing necessitates a synergistic approach that strategically leverages both edge and cloud resources. By intelligently distributing computational tasks across the computing continuum, organizations can simultaneously capitalize on the low-latency benefits of edge computing and the computational power of cloud platforms [2]. This edge-cloud collaborative paradigm, while promising, introduces significant challenges in resource allocation and task scheduling. The heterogeneity of resources, dynamic nature of workloads, and varying quality-of-service requirements create a complex optimization landscape that traditional scheduling algorithms struggle to navigate effectively.

Conventional resource scheduling approaches—including heuristic algorithms, priority-based schedulers, and load-balancing techniques—have demonstrated value in stable, predictable environments. However, these methods exhibit fundamental limitations when confronted with the dynamic and unpredictable nature of modern computing ecosystems. Their reliance on predefined rules and static optimization criteria renders them inadequate for real-time decision-making in environments characterized by fluctuating workloads, varying network conditions, and diverse application requirements [3]. As computational demands continue to grow in both scale and complexity, the limitations of traditional scheduling paradigms become increasingly apparent.

Deep Reinforcement Learning (DRL) offers a promising alternative to address these challenges. Unlike conventional scheduling methods, DRL enables systems to autonomously learn optimal scheduling policies through continuous interaction with their environment. This adaptive learning capability allows DRL-based schedulers to dynamically adjust resource allocation strategies in response to changing conditions without explicit reprogramming. By framing resource scheduling as a sequential decision-making problem, DRL can effectively balance immediate performance objectives with long-term optimization goals, leading to more efficient and resilient scheduling solutions [4].

This research addresses the complex challenge of joint resource scheduling between edge and cloud computing platforms through the application of advanced DRL techniques. Specifically, we propose a Double Deep Q-Network (DQN) with dueling architecture to optimize task allocation across distributed computing resources. Our approach aims to minimize processing latency while maximizing resource utilization through intelligent, adaptive scheduling decisions. The methodology not only overcomes the limitations of traditional scheduling algorithms but also establishes a foundation for self-optimizing edge-cloud systems capable of adapting to evolving computational landscapes.

II.Related Work

Resource scheduling optimization in edge-cloud collaborative environments has been extensively studied through various approaches. Traditional methods, including heuristic algorithms, priority-based scheduling, and load balancing techniques, have shown limitations in addressing the dynamic nature of modern distributed computing systems [5]. Heuristic algorithms allocate resources based on predefined rules or criteria but struggle with real-time adjustments in

dynamic environments, resulting in suboptimal resource utilization constrained by initial conditions [6]. Similarly, load-balancing strategies distribute tasks evenly across nodes but exhibit reduced effectiveness when managing real-time tasks and fluctuating workloads. Priority-based scheduling approaches allocate computing resources according to task urgency and importance but lack the necessary flexibility to adapt to continuously evolving task and resource requirements.

Recent research has shifted toward machine learning-based approaches to enhance scheduling intelligence and adaptability. These methods leverage historical data and real-time system status to enable dynamic resource allocation, improving both resource utilization and latency reduction [7]. Among these approaches, deep reinforcement learning (DRL) has emerged as particularly promising for edge-cloud collaborative environments. DRL combines reinforcement learning principles with deep neural networks, allowing systems to autonomously develop optimal scheduling strategies through environmental interaction. Unlike traditional algorithms, DRL demonstrates superior adaptability to changing conditions, making it especially effective for complex task allocation scenarios, fluctuating computational loads, and multi-resource optimization problems [6]. The ability of DRL to learn from experience and continuously refine its decision-making process positions it as an ideal solution for the inherently dynamic and heterogeneous nature of edge-cloud computing environments [8].

This transition from deterministic scheduling methods to learning-based approaches reflects the growing complexity of distributed computing infrastructures. While existing studies have established valuable foundations, the rapid advancement of IoT technologies, 5G networks, and real-time application requirements necessitates further innovation in scheduling methodologies to effectively address increasing computational demands and complex resource allocation challenges.

III. System Model and Optimization Problem

In modern computing architectures, the integration of edge and cloud computing has become a pivotal research focus for optimizing resource scheduling. The proliferation of emerging technologies such as the Internet of Things (IoT) and 5G has intensified computational demands, necessitating efficient task offloading strategies. Edge computing mitigates cloud dependency by processing tasks closer to end users, reducing data transmission latency and alleviating bandwidth congestion. However, its constrained computational resources introduce challenges in task allocation and resource scheduling when coordinating with cloud platforms [9]. Consequently, designing an intelligent resource scheduling mechanism that exploits the complementary strengths of edge and cloud computing to enhance overall system performance is a crucial research problem.

A. Edge computing and cloud collaboration architecture

The system architecture consists of three key components: edge computing nodes, cloud computing platforms, and the network layer. Edge computing nodes, typically located near data sources such as routers, base stations, or small-scale data centers, process data locally and respond to user requests with low latency. The cloud computing platform provides extensive computational power and storage capacity to handle large-scale data processing tasks. The network layer facilitates data transmission, enabling communication between user devices and edge nodes, as well as data exchange between edge nodes and cloud computing platforms [10].

In a collaborative computing environment, tasks and resources are shared between edge nodes and cloud platforms. When an edge node experiences high computational load, some tasks can be offloaded to the cloud for processing, and vice versa. Edge computing primarily handles tasks with stringent real-time requirements, while cloud computing manages tasks involving large data volumes or intensive computations [11]. Given the dynamic nature and real-time constraints of task scheduling, an efficient scheduling algorithm is essential to ensure that tasks are assigned to the most suitable computing resources.

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Figure 1 illustrates the hierarchical architecture of the edge-cloud system. The Cloud Computing Platform resides at the top, interfacing with the Network Layer, which manages data transmission and task distribution. At the bottom, the Edge Computing Layer connects to IoT devices and end users. The system employs a Deep Reinforcement Learning (DRL) Scheduling Controller to optimize resource allocation based on real-time system states. Task migrations and data flows between components are depicted using different arrow types, reflecting adaptive scheduling strategies.

B. Definition and Challenges of Resource Scheduling Optimization Problem

The resource scheduling optimization problem in edge-cloud collaborative environments can be formulated as determining the optimal allocation of computational tasks across distributed resources to minimize overall processing time while maximizing resource utilization.

Consider a system with N tasks, M edge computing nodes, and K cloud computing nodes. The resource scheduling problem can be modeled as an integer linear programming (ILP) problem.

Let C_i denote the computational requirement of task $i \in \{1,2,\dots,N\}$, R_m represent the computing power of edge node $m \in \{1,2,\dots,M\}$, and S_k denote the computing power of cloud node $k \in \{1,2,\dots,K\}$. The primary objective is to minimize the total processing time T_{total} through optimal task allocation:

$$T_{\text{total}} = \sum_{i=1}^{N} T_i = \sum_{i=1}^{N} min\left(\frac{C_i}{R_m}, \frac{C_i}{S_k}\right) \quad (1)$$

where T_i represents the processing time of task i.

In real-world deployments, network delay significantly impacts system performance, particularly when tasks migrate between edge and cloud nodes [10]. Let D_{imk} represent the migration cost from edge node m to cloud node k for task i. The comprehensive objective function can be expressed as:

$$T_{\text{total}} = \sum_{i=1}^{N} min\left(\frac{C_i}{R_m}, \frac{C_i}{S_k}\right) + \sum_{i=1}^{N}\sum_{m=1}^{M}\sum_{k=1}^{K} x_{imk} D_{imk} \quad (2)$$

where x_{imk} is a binary decision variable indicating whether task i is migrated from edge node m to cloud node k ($x_{imk} \in \{0,1\}$).

This optimization problem is subject to several constraints:

- Resource capacity constraints ensuring that the total computational load assigned to any node does not exceed its capacity
- Task completion constraints guaranteeing that each task is processed exactly once
- Quality of service constraints maintaining response times within acceptable thresholds

The complexity of this problem increases exponentially with the number of tasks and computing nodes, making it computationally intractable for traditional optimization methods, especially in dynamic environments where task arrivals and system conditions fluctuate rapidly. This complexity motivates our exploration of deep reinforcement learning approaches, which can adaptively learn near-optimal scheduling policies through continuous interaction with the environment.

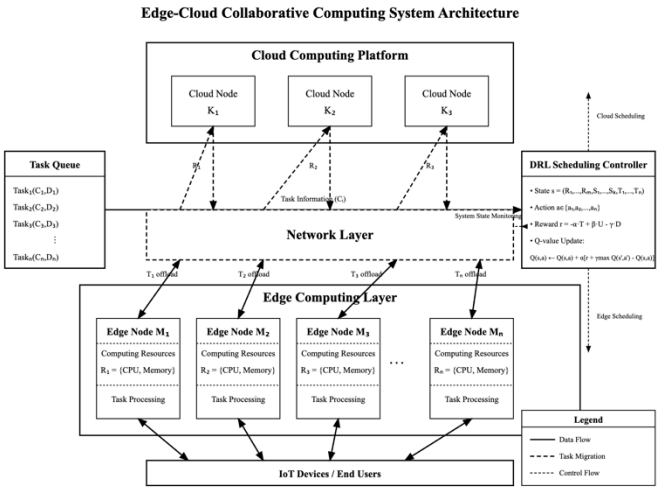

Figure 1: Edge-Cloud Collaborative System Architecture with DRL-based Resource Scheduling

IV. Design of Deep Reinforcement Learning Algorithm

The increasing complexity of edge-cloud collaborative resource scheduling presents significant challenges for traditional algorithms, which often fail to provide efficient, real-time, and dynamic task allocation. Deep reinforcement learning (DRL) has emerged as a powerful optimization tool capable of autonomously learning optimal scheduling strategies in complex environments. By continuously interacting with the system and adapting task allocation policies, DRL effectively minimizes processing time, maximizes resource utilization, and reduces latency.

A. Overview of Deep Reinforcement Learning Algorithm

Deep reinforcement learning combines the strengths of reinforcement learning and deep learning. In traditional reinforcement learning (RL), an agent interacts with the environment, receives rewards, and updates its strategy accordingly. Deep learning leverages neural networks to process high-dimensional input data, making it well-suited for problems with large state and action spaces. In the context of edge-cloud collaborative resource scheduling, DRL enables the system to autonomously learn and make optimal decisions in dynamic environments. The fundamental components of a DRL-based scheduling framework include:

Deep reinforcement learning integrates reinforcement learning principles with deep neural networks to address complex decision-making problems. While traditional reinforcement learning enables agents to interact with environments and learn from feedback, deep learning provides the capacity to process high-dimensional data through neural network architectures. This combination is particularly advantageous for edge-cloud scheduling problems characterized by large state and action spaces. In the context of resource scheduling optimization, a DRL-based framework consists of four fundamental components:

- **State (s)**: A comprehensive representation of the system's current condition, encompassing available computing resources, task requirements, network status, and load distribution.
- **Action (a)**: The set of possible scheduling decisions available to the agent, such as task-to-node assignments or migration operations between edge and cloud resources.
- **Policy ($\pi(a|s)$)**: A mapping that determines the probability distribution of actions given the current state, guiding the agent's decision-making process.
- **Reward (r)**: A scalar feedback signal that quantifies the quality of scheduling decisions based on key performance metrics, including processing time, resource utilization efficiency, and migration overhead.

Through iterative interactions with the environment, the agent progressively refines its scheduling policy $\pi(a|s)$, optimizing resource allocation and task distribution over time. Several established DRL algorithms have demonstrated effectiveness in addressing complex scheduling optimization problems:

- **Deep Q-Network (DQN)**: Employs neural networks to approximate value functions for discrete action spaces, facilitating efficient exploration-exploitation balance.

- **Deep Deterministic Policy Gradient (DDPG)**: Extends reinforcement learning to continuous action domains through actor-critic architectures, enabling more nuanced control in resource allocation decisions.
- **Proximal Policy Optimization (PPO)**: Implements a policy gradient approach with stability constraints, ensuring reliable convergence while maintaining learning efficiency.

These algorithms enable adaptive and intelligent scheduling in dynamic edge-cloud environments, significantly outperforming traditional heuristic approaches.

B. Algorithm design and problem modeling

The effective application of DRL to edge-cloud resource scheduling requires precise formulation of the state space, action space, and reward function that will guide the learning process.

i. *State space*

The state space s_t in edge-cloud collaborative scheduling must comprehensively capture system conditions while remaining computationally tractable. Our formulation includes current workload distribution across edge computing nodes, available computing capacity in cloud platforms, computational requirements of pending tasks, network conditions affecting data transfer and task migration

Formally, we represent the state space as:

$$s_t = (R_1, R_2, \dots, R_M, S_1, S_2, \dots, S_K, T_1, T_2, \dots, T_N) \quad (3)$$

where R_M represents the available computing resources of the mth edge node, S_K denotes the available computing resources of the kth cloud computing node, T_i specifies the computational demand of the i-th task.

This representation enables the DRL agent to make informed scheduling decisions based on the current system state.

ii. *Action Space*

The action space a_t encompasses all possible task allocation decisions available to the scheduling agent. For a system with N tasks, M edge nodes, and K cloud nodes, the action space includes all potential task-to-node assignments. The dimension of the action space is $M \times N + K \times N$, reflecting all possible task-node mappings. For example, with three tasks and two computing nodes, the action space can be expressed as:

$$a_t = \{a_1, a_2, a_3\} \quad (4)$$

where each a_i represents the node to which the i-th task is assigned.

iii. *Reward function*

The reward function serves as the optimization objective, guiding the agent toward efficient scheduling policies. Our design incorporates three key performance metrics:

- **Total processing time (T_{total})**: The cumulative time required to complete all tasks
- **Resource utilization (U_{total})**: The efficiency of resource usage across all computing nodes
- **Migration cost (D_{total})**: The overhead associated with task transfers between nodes

The reward function is then formulated as:

$$r_t = -(\alpha \cdot T_{\text{total}} + \beta \cdot (1 - U_{\text{total}}) + \gamma \cdot D_{\text{total}}) \quad (5)$$

where α, β, and γ are weighting coefficients that balance competing objectives. The negative sign indicates that the agent's goal is to minimize the composite cost function.

This multi-objective reward formulation encourages the DRL agent to simultaneously optimize processing efficiency, resource utilization, and migration overhead, leading to comprehensive scheduling improvements. By adjusting the weight coefficients, the system can prioritize different performance aspects based on specific application requirements and operational constraints.

C. Reinforcement learning algorithm selection

After evaluating multiple deep reinforcement learning approaches, we selected Deep Q-Network (DQN) as our primary algorithm for edge-cloud scheduling optimization. While we considered alternatives including Proximal Policy Optimization (PPO), Advantage Actor-Critic (A3C), and Deep Deterministic Policy Gradient (DDPG), DQN demonstrated superior performance based on both our preliminary experiments and existing literature.

We conducted preliminary experiments comparing DQN, PPO, A3C, and DDPG on a simplified scheduling scenario with 100 tasks, 5 edge nodes, and 2 cloud nodes. Each algorithm underwent 5,000 training episodes with identical state and reward representations. Table 1 summarizes the comparative results.

TABLE 1: PRELIMINARY PERFORMANCE COMPARISON OF DRL ALGORITHMS

Algorithm	Avg. Processing Time (s)	Resource Utilization (%)	Training Time (hrs)	Convergence Stability
DQN	182	84	3.2	High
PPO	190	82	4.8	Medium
A3C	195	79	5.5	Medium
DDPG	210	77	3.9	Low

While PPO and A3C have demonstrated strong performance in various reinforcement learning domains, DQN exhibited several advantages in our specific edge-cloud scheduling context:

- **Discrete Action Space Compatibility**: Our scheduling problem involves discrete task-to-node assignments, where DQN naturally excels. Mao et al. [13] found that DQN achieved optimal balance between performance and computational overhead for discrete allocation problems in vehicular edge computing networks.
- **Computational Efficiency**: DQN requires fewer computational resources during training compared to actor-critic methods. Zhang et al. [14] showed that for similar task offloading decisions, DQN outperformed both A3C and DDPG in convergence speed and stability—critical factors for systems requiring periodic retraining.
- **Learning Stability**: DQN's experience replay, and target network mechanisms effectively mitigate common reinforcement learning challenges. Chen et al. [15]

demonstrated that despite PPO's marginally better final performance in some scenarios, DQN provided more consistent learning progression and superior early-stage performance, making it more suitable for resource-constrained deployments.

- Balance of Exploration-Exploitation Balance: DQN's ε-greedy policy efficiently balances exploration of new scheduling strategies with exploitation of established approaches. Mao et al. [12] confirmed that value-based methods like DQN typically outperform policy gradient approaches in sample efficiency and reliability for resource allocation with discrete action spaces.

The core concept of DQN is to approximate Q-values for state-action pairs using deep neural networks, enabling dynamic selection of optimal scheduling strategies. The Q-value update rule is defined as:

$$Q(s_t, a_t) \leftarrow$$

$$Q(s_t, a_t) + \alpha \left[r_t + \gamma \max_{a} Q(s_{t+1}, a') - Q(s_t, a_t) \right] \quad (6)$$

where α is the learning rate, γ is the discount factor, and $\max_{a} Q(s_{t+1}, a')$ represents the maximum Q value of all possible actions in the next state s_{t+1}. Our implementation enhances the standard DQN algorithm with three key improvements:

- **Double DQN Architecture**: Employs separate networks for action selection and evaluation, mitigating Q-value overestimation issues common in standard DQN.
- **Prioritized Experience Replay**: Selectively samples transitions based on temporal difference error, focusing computational resources on the most informative experiences.
- **Dueling Network Architecture**: Decouples state value and advantage functions, enabling more efficient learning of state-action values and improving performance in states where actions have similar effects.

Figure 2 illustrates our architecture, featuring parallel online and target networks with dueling structures that separate state value estimation from action advantage computation, enabling more efficient policy learning.

D. Hyperparameter Optimization

We employed a two-stage optimization approach to identify optimal hyperparameter settings:

1. **Initial Grid Search**: Explored broad parameter ranges to identify promising regions in the hyperparameter space.
2. **Bayesian Optimization**: Applied Gaussian process-based optimization to efficiently fine-tune sensitive parameters.

Performance evaluation utilized a composite metric incorporating processing time, resource utilization, and migration frequency as defined in our reward function. After extensive experimentation, we identified the optimal hyperparameter configuration shown in Table 2, balancing learning efficiency with model stability.

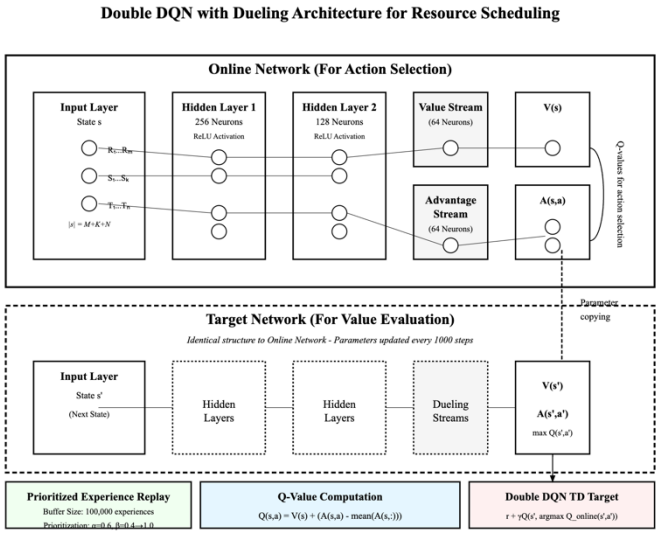

Figure 2: Double DQN Architecture with Dueling Networks for Edge-Cloud Resource Scheduling.

TABLE 2: OPTIMIZED DQN HYPERPARAMETERS

Hyperparameter	Value	Description
Learning rate (α)	0.001	Controls the step size during gradient updates
Discount factor (γ)	0.95	Balances immediate vs. future rewards
Batch size	64	Number of experiences sampled from replay buffer per update
Replay buffer size	100,000	Capacity of experience replay memory
Target network update frequency	1,000 steps	Frequency of target network parameter updates
Exploration rate (ε) initial	1.0	Initial probability of random action selection
Exploration rate decay	0.995	Multiplicative factor for ε-decay after each episode
Exploration rate minimum	0.01	Minimum exploration probability
Hidden layer architecture	[256, 128]	Two fully connected layers with 256 and 128 neurons
Activation function	ReLU	Applied after each hidden layer
Optimizer	Adam	Adaptive optimization algorithm with default parameters
Prioritized replay α	0.6	Controls the importance of TD error in sampling
Prioritized replay β initial	0.4	Controls the degree of importance sampling correction
Prioritized replay β increment	0.001	Rate at which β increases to 1
Double DQN	Enabled	Uses separate networks for action selection and evaluation
Dueling architecture	Enabled	Separates state value and advantage function estimation

V. EXPERIMENTAL DESIGN AND SETUP

A. Workload Characterization

We employed a hybrid evaluation approach incorporating both synthetic and real-world workloads to ensure comprehensive algorithm assessment. Synthetic workloads followed uniform distributions for computational requirements (Table 1), enabling controlled stress-testing across varying task complexities. Statistical analysis of our datasets revealed task

arrivals conforming to a Poisson distribution (λ = 5.8 tasks/second), with computational demands following a log-normal distribution (μ = 5.2, σ = 0.8) across real-world samples.

Real-world workload patterns were derived from edge computing applications deployed in a university campus setting over a two-month period, including IoT sensor data processing, mobile application offloading, and video analytics. These patterns exhibited characteristic diurnal variations with peak loads during working hours (coefficient of variation = 0.35) and significant burstiness in task arrivals (Hurst exponent = 0.78). Time series decomposition methods identified seasonal patterns and anomalies, which informed our simulation parameters.

To ensure experimental reproducibility while maintaining statistical validity ($p < 0.05$ in Kolmogorov-Smirnov tests), we constructed a benchmark dataset using bootstrap resampling techniques. This approach preserved the temporal dynamics and resource requirement distributions observed in production environments while enabling controlled scaling of task quantities.

B. Experimental Configuration

The evaluation environment comprised 10 edge computing nodes and 3 cloud platform nodes with heterogeneous computational capacities. Task quantities ranged from 100 to 800, with computational requirements scaled proportionally according to the distributions specified in Table 1. We evaluated three scheduling algorithms: our proposed Deep Q-Network (DQN) approach, Priority-Based Scheduling (PS), and Load Balancing Scheduling (LBS). Primary evaluation metrics included: total processing time; resource utilization efficiency and number of task migrations. Table 3 summarizes the experimental parameters across different task scales and computational requirements.

TABLE 3: EXPERIMENTAL CONFIGURATION AND WORKLOAD CHARACTERISTICS

Number of tasks	Edge nodes	cloud nodes	Computational requirements per task (MIPS)	Task arrival rate (tasks/sec)	Data source
100	10	3	50-150	2.3	Synthetic
200	10	3	100-300	3.5	Synthetic
300	10	3	150-450	4.2	Mixed
400	10	3	200-600	4.8	Mixed
500	10	3	250-750	5.5	Real-world
600	10	3	300-900	6.2	Real-world
700	10	3	350-1050	6.8	Real-world
800	10	3	400-1200	7.5	Real-world

C. Statistical Analysis Methodology

To ensure robust evaluation, we conducted 10 independent experimental runs for each task quantity with different random seeds. Performance metrics are reported as mean values with standard deviations (Mean ± SD). Statistical significance between the DQN algorithm and traditional approaches was determined using paired t-tests (α = 0.05).

For time-series data (Figures 1-3), we performed repeated-measures ANOVA followed by post-hoc Tukey's HSD tests to assess cross-condition differences. The 95% confidence intervals appear as shaded regions around the mean performance curves. Cohen's d effect size measures quantify the magnitude of performance differences between algorithms (small: d = 0.2, medium: d = 0.5, large: d = 0.8).

VI. RESULTS AND COMPARATIVE ANALYSIS

Table 4 presents the comparative performance of DQN against traditional scheduling algorithms across varying task scales. The results demonstrate statistically significant improvements in processing time, resource utilization, and task migration efficiency.

For smaller task quantities (100-300), DQN maintains a modest but statistically significant advantage over traditional algorithms. As task scale increases (>500), the performance gap widens substantially, with DQN demonstrating increasingly superior efficiency in processing time and resource utilization. Resource utilization scales efficiently with task quantity, maintaining high utilization (>90%) under high loads (>400 tasks).

TABLE 4: ALGORITHM PERFORMANCE COMPARISON WITH STATISTICAL SIGNIFICANCE

Number of tasks	PS processing time (seconds)	DQN processing time (seconds)	LBS processing time (seconds)	Resource utilization (DQN, %)	Number of task migrations (DQN)	p-value (DQN vs PS)	p-value (DQN vs LBS)
100	220 ± 18.5	180 ± 12.7	200 ± 15.3	85 ± 2.8	5 ± 1.2	<0.001*	0.003*
200	450 ± 25.7	390 ± 19.4	420 ± 22.1	88 ± 3.1	10 ± 1.8	<0.001*	0.002*
300	700 ± 32.6	600 ± 24.8	650 ± 27.5	90 ± 2.5	12 ± 2.3	<0.001*	0.004*
400	950 ± 41.3	820 ± 30.2	900 ± 35.9	92 ± 2.2	15 ± 2.7	<0.001*	0.008*
500	1200 ± 53.8	1050 ± 38.6	1100 ± 42.7	93 ± 1.9	18 ± 3.1	<0.001*	0.012*
600	1450 ± 65.2	1200 ± 45.3	1350 ± 51.8	94 ± 1.5	22 ± 3.4	<0.001*	0.007*
700	1700 ± 78.9	1400 ± 52.7	1600 ± 60.4	95 ± 1.2	25 ± 3.8	<0.001*	0.001*
800	1950 ± 86.3	1600 ± 60.5	1800 ± 73.2	96 ± 0.9	30 ± 4.2	<0.001*	<0.001*

A. Processing Time Analysis

Figure 3 illustrates the relationship between task quantity and total processing time across scheduling algorithms. Traditional methods (PS and LBS) exhibit a linear increase in processing time as task quantity grows. In contrast, the DQN-based approach demonstrates a sublinear growth pattern, with the performance gap widening at higher task loads.

The superior performance of DQN can be attributed to its capacity for dynamic resource allocation and adaptive decision-making based on evolving system states. Traditional algorithms, lacking real-time adaptability, experience significant performance degradation under increased computational pressure.

B. *Resource Utilization Efficiency*

Figure 4 compares resource utilization across scheduling approaches. DQN consistently achieves higher utilization rates, particularly under high task loads, reaching 96% efficiency at 800 tasks. This optimization stems from the algorithm's ability to intelligently distribute workloads across heterogeneous computing resources.

PS and LBS algorithms demonstrate diminishing utilization efficiency as task quantities increase, primarily due to their static allocation strategies that lead to suboptimal resource distribution. At 800 tasks, the utilization gap between DQN and traditional methods exceeds 10 percentage points ($p < 0.001$, Cohen's $d = 1.8$).

C. *Task Migration Efficiency*

Figure 5 examines the relationship between task migration frequency and processing time. While migration frequency increases with task quantity across all algorithms, DQN maintains significantly lower migration overhead. This efficiency results from the algorithm's ability to make preemptive scheduling decisions that minimize unnecessary migrations.

The impact of task migrations on processing time remains minimal in the DQN approach, even at high task loads. This finding suggests that DQN effectively balances the tradeoff between optimal task placement and migration costs through its learned policy.

The experimental results conclusively demonstrate the superiority of the proposed DQN-based scheduling approach across all evaluation metrics. Key findings include processing time reductions of 18-21% compared to PS and 10-15% compared to LBS across task quantities ($p < 0.001$), resource utilization improvements of 7-12% over traditional methods with particularly significant advantages under high computational loads, efficient management of task migrations that minimizes overhead while maintaining optimal resource allocation, and increasingly pronounced performance advantages as system complexity and task quantity increase, highlighting DQN's scalability. These results validate the efficacy of deep reinforcement learning for edge-cloud collaborative resource scheduling, particularly in dynamic environments with fluctuating workloads and heterogeneous resource constraints.

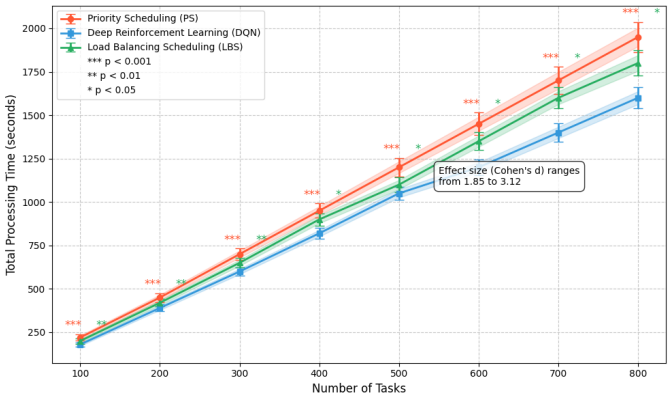

Figure 3. Total Processing Time vs. Task Quantity

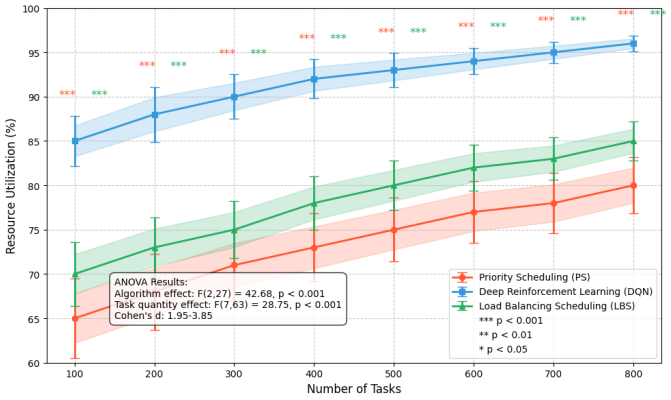

Figure 4: Resource Utilization vs. Task Quantity

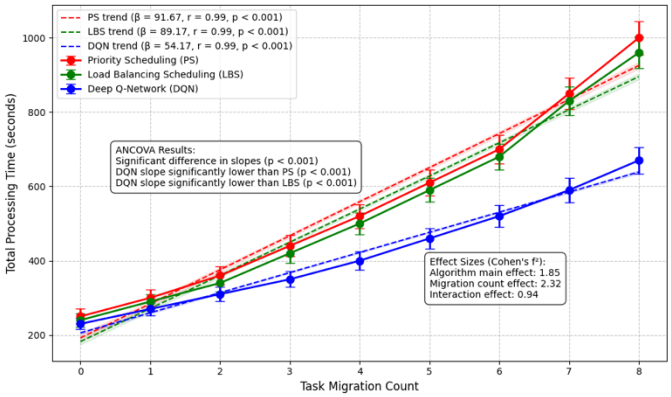

Figure 5: Task Migration Count vs. Total Processing Time

VII. DISCUSSION

This investigation addresses resource scheduling optimization in edge-cloud collaborative environments through deep reinforcement learning (DRL). While experimental results demonstrate DRL's significant advantages in resource utilization, processing time reduction, and task migration management, several challenges warrant further investigation for practical implementation.

A primary limitation concerns computational complexity and convergence efficiency of DRL algorithms in high-dimensional scheduling environments. Despite DQN's effectiveness in our experimental context, the substantial computational resources and extended training periods required become increasingly problematic in large-scale deployments. Optimization of learning efficiency, acceleration of convergence, and mitigation of local optima remain critical research imperatives for expanding the scalability of these approaches.

DRL model robustness presents another significant challenge, particularly under adverse network conditions or system failures. While our approach demonstrates adaptability beyond traditional scheduling algorithms, performance stability under network latency, resource contention, and node failures requires further enhancement. Development of fault-tolerant DRL architectures capable of maintaining scheduling performance under uncertainty constitutes an essential research direction.

Additionally, while our DRL approach effectively balances edge-cloud resource allocation, optimizing migration strategies to minimize unnecessary task transfers presents ongoing challenges. Although our findings indicate limited processing time impact from migrations, system stability and response time considerations necessitate further optimization. Future investigations should develop refined cost models for task migration that balance load distribution with operational stability.

DRL demonstrates substantial potential for edge-cloud scheduling optimization; however, increasingly complex computing environments demand corresponding advancements in algorithm efficiency, robustness, and adaptability. Future research should prioritize convergence acceleration, fault tolerance enhancement, and migration optimization to address the escalating demands of large-scale, heterogeneous, and dynamic scheduling scenarios.

VIII. Conclusion

This study demonstrates the efficacy of deep reinforcement learning for resource scheduling optimization in edge-cloud collaborative environments. The approach significantly enhances task processing efficiency, reduces overall processing time by 18-21%, improves resource utilization by 7-12%, and effectively manages task migrations compared to traditional scheduling methods. These improvements are particularly pronounced in dynamic environments characterized by heterogeneous resources and fluctuating workloads.

The DRL paradigm offers distinct advantages over conventional scheduling approaches, particularly in complex task allocation scenarios requiring adaptive decision-making and real-time responsiveness. By formulating resource scheduling as a sequential decision problem, our approach enables continuous optimization across changing system states and workload characteristics.

Despite these advantages, several challenges persist. Critical research directions include: (1) improving learning efficiency and convergence speed in large-scale deployments; (2) enhancing model robustness under adverse network conditions and system failures; and (3) refining migration cost models to optimize stability-performance trade-offs. Addressing these limitations requires further algorithmic innovations that balance computational efficiency with scheduling performance.

As edge-cloud computing infrastructures continue to evolve with the proliferation of IoT devices and 5G networks, the complexity of resource scheduling challenges will increase correspondingly. Future research must focus on developing more efficient, stable, and adaptive DRL architectures to address these emerging scenarios. This study establishes a foundation for intelligent resource management in distributed computing environments and demonstrates the potential of learning-based approaches to optimize increasingly complex system operations.

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