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Comparative Study on DQN and PPO for Cloud Resource Optimization

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Abstract: Cloud computing has become the backbone of mod- ern digital infrastructure, supporting millions of applications that demand high performance, scalability, and cost efficiency. However, dynamic workloads and heterogeneous resources continue to challenge the design of adaptive resource management systems. Deep Reinforcement Learning (DRL) offers a promising paradigm by enabling autonomous, data-driven decision- making based on continuous environmental feedback. This review paper systematically examines the application of DRL algorithms particularly Deep Q-Network (DQN) and Proximal Policy Optimization (PPO)—in optimizing cloud resource allocation, load balancing, and energy efficiency. The survey categorizes research advancements into value-based, policy-gradient, and hybrid learning architectures and analyzes their comparative strengths across diverse scenarios such as auto scaling, container placement, and dynamic job scheduling. It further explores recent strategies like multi-agent systems, federated DRL, and energy- aware reinforcement frameworks aimed at achieving sustainable cloud operations. Concluding insights identify current challenges, including convergence stability, reward modeling, and cross- environment generalization, while outlining promising directions for integrating DRL with edge computing, green AI, and real- time orchestration technologies.

Keywords*: Cloud Resource Management, Deep Reinforcement Learning, Deep Q-Network, Proximal Policy Optimization, Dynamic Resource Allocation, Cloud Scheduling, Multi-Agent Reinforcement Learning, Energy-Efficient Cloud Computing, Auto-scaling, Load Balancing, Federated Learning, Cloud-Edge Orchestration, Sustainable Cloud Systems.*

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I. INTRODUCTION

The exponential growth and widespread adoption of cloud computing have transformed the technological landscape, enabling flexible, scalable, and on-demand access to computing resources. This paradigm shift has allowed businesses and researchers to deploy complex applications without upfront investments in physical infrastructure. However, the rapid increase in user requests and diverse workload characteristics necessitates efficient cloud resource management strategies to meet Quality of Service (QoS) objectives while minimizing operational costs. Traditional heuristic or rule-based resource allocation mechanisms frequently fail to adapt to dynamic fluctuations in workload demand and resource availability, resulting in suboptimal performance and occasional violation of service level agreements (SLAs). Deep Reinforcement Learning (DRL), which merges reinforcement learning with deep neural networks, has emerged as a robust framework for solving complex sequential decision-making problems in large-scale cloud environments. DRL enables autonomous and adaptive resource management policies by learning from system state feedback and rewards without requiring explicit modeling of environment dynamics. Among DRL techniques, Deep Q-Network (DQN) and Proximal Policy Optimization (PPO) have gained prominence due to their ability to handle discrete and continuous control problems, respectively, thus offering complementary strengths for cloud scheduling, auto- scaling, and energy optimization tasks.

The DQN algorithm leverages value-based reinforcement learning with experience replay and target network stabilization, making it suitable for discrete decision spaces such as task placement and virtual machine selection. Meanwhile, PPO employs a policy gradient approach with clipped surrogate objectives, ensuring stable and efficient policy updates for continuous resource scaling and power management. This review paper systematically surveys these two primary DRL frameworks alongside emerging hybrid and multi-agent DRL models, evaluating their contributions in advancing cloud resource management capabilities.

Furthermore, the paper explores contemporary challenges including training stability, reward formulation, interpretability, and scalability across heterogeneous and multi-cloud set- tings. The integration of federated learning

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paradigms and energy-aware reinforcement learning strategies forms a crucial part of this discourse, highlighting the shift toward green computing and distributed intelligence in cloud architectures. In the following sections, we provide a comprehensive background on DRL fundamentals and cloud resource management, review state-of-the-art applications of DQN and PPO in the cloud domain, analyze recent algorithmic enhancements and evaluation metrics, and outline future research avenues essential for the development of autonomous, efficient, and sustainable cloud infrastructure.

II. LITERATURE SURVEY

- *DQN for Energy-Efficient VM Consolidation*

The study presented in [1] addresses the critical challenge of energy efficiency in cloud data centers through intelligent virtual machine (VM) consolidation. This work formulates the VM placement problem as a Markov Decision Process (MDP) and employs a Deep Q-Network (DQN) agent to learn optimal real-time consolidation policies. The primary objective is a dual-goal optimization: maximizing the number of idle servers that can be switched to a low-power state to conserve energy, while simultaneously minimizing Service

Level Agreement (SLA) violations caused by resource contention on the remaining active servers. The action space is discrete, corresponding to the selection of VM for migration and the target physical machine. Through simulation using realistic workload traces, the DQN-based framework is shown to achieve significant energy savings, typically demonstrating a 10–20 percent reduction in power consumption compared to classic heuristic approaches like Minimum Migration Time (MMT) or Peak Resource Utilization (PRU), proving the adaptability of for static-to-dynamic VM decisions.

- *PPO for Dynamic Resource Provisioning and Cost Optimization*

The authors in [2] investigate the use of Proximal Policy Optimization (PPO) to tackle the problem of dynamic resource provisioning (i.e., auto-scaling) for cloud-hosted applications. The core contribution lies in designing a PPO-based auto- scaler that can manage continuous actions—specifically, the percentage increase or decrease in provisioned VM capacity. The state space captures current resource utilization, historical demand, and application-specific performance metrics (e.g., average latency). The reward function is meticulously engineered to balance the trade-off between minimizing operational cost (by reducing provisioned capacity) and maintaining high performance (by minimizing latency and avoiding SLA penalties). PPO's stability is leveraged to avoid volatile scaling actions that can disrupt service quality. Empirical evaluation demonstrates that this PPO agent not only achieves lower operational costs than standard threshold-based auto-scalers but also exhibits faster convergence and greater stability during sudden workload spikes, outperforming DQN variants in this continuous control task.

- *DQN for Task Scheduling and Utilization Enhancement*

Focuses on task scheduling, which involves as- signing incoming workloads to the most appropriate VMs to optimize overall system throughput and utilization. The authors map the scheduling decision problem to a discrete-action MDP solved by DQN. The agent's action at each time step is the selection of a target VM for a newly arrived task. The state incorporates resource information of all available VMs (CPU, memory load) and characteristics of the incoming task. The objective is to enhance resource utilization and minimize the task makespan (total time to complete a set of tasks). The DQN architecture, benefiting from the discrete action space, learns complex, non-linear scheduling rules that traditional priority or list-based schedulers cannot capture. Experimental results confirm that the DQN scheduler achieves a lower average makespan and significantly higher resource utilization across heterogeneous workloads compared to conventional and meta- heuristic scheduling algorithms.

- *Multi-Agent PPO for Network Slice Resource Allocation*

The work in extends DRL to the increasingly com-plex domain of 5G Network Slice Resource Allocation. This involves allocating isolated virtual resources (compute, net-work, storage) to multiple independent service slices, each with distinct quality-of-service (QoS) requirements. Given the decentralized nature of 5G edge/cloud infrastructure, the paper proposes a Multi-Agent PPO framework, where each network slice is managed by an independent PPO agent. The continuous action space for each agent dictates the fine-grained resource limits (e.g., bandwidth, CPU shares) requested or released by its slice. The shared environment reward encourages both maximizing individual slice throughput and ensuring strong isolation to prevent service degradation across slices. The collaborative and competitive learning among the PPO agents is shown to effectively manage resource contention, leading to improved overall resource utilization while guaranteeing the SLAs and isolation mandates of different network slices.

- *Duelling DQN for Cloud-Edge Task Offloading*

Addresses the decision of where to execute Computational tasks locally on an edge device or remotely in the central cloud a problem known as Cloud-Edge Task Offloading. The complexity of this decision, driven by fluctuating wireless channel quality, edge server load, and task size, makes it ideal for DRL. They utilize a Duelling DQN architecture, which separates the estimation of the state value function and the advantage function, leading to more robust policy evaluation. The discrete action space is simple: Offload (Cloud) or Execute Locally (Edge). The primary optimization goal is minimizing overall task latency. By learning the optimal trade-off between offloading delay and execution time, the Duelling DQN agent is demonstrated to make superior, real- time decisions. The experiments highlight that the DRL policy effectively adapts to dynamic network conditions, resulting in a significant reduction in average task execution latency (up to 30%) compared to static or greedy offloading policies.

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➢ *PPO for Energy-Aware VM Migration*

This research specifically targets energy efficiency via intelligent VM migration. Unlike simple consolidation, this work focuses on when and where to migrate VMs to effectively balance server utilization and enable the power-down of underutilized servers. A PPO agent is trained on a continuous action space that controls the migration threshold and the parameters of the load-balancing policy. The reward function is designed to achieve a difficult balance: maximizing energy savings from idle PMs while strictly penalizing the resultant SLA violations or performance overhead due to excessive migrations. The use of PPO helps in learning a smooth and stable policy, which is crucial for migration decisions that can be disruptive to applications. The PPO-based migration policy is validated against rule-based and other RL methods, showing that it significantly outperforms standard heuristic migration policies by achieving a superior joint optimization score for energy and performance metrics.

Table 1 Comprehensive Summary of DRL Algorithms Applied To Cloud Resource Management

Ref.	Algorithm	Application Domain	Action Type	Optimization Objectives	Energy Strategy	Reward Components	Remarks/Focus
[1]	DQN	VM Consolidation	Discrete	Energy, SLA	Power off idle PMs	Energy - SLA penalty balance	Robust control over VM migrations
[2]	PPO	Auto-Scaling	Continuous	Cost, Latency	Avoid over-provisioning	Cost minimization, latency reduction	Smooth scaling transitions
[3]	DQN	Task Scheduling	Discrete	Makespan, Utilization	Indirect via resource use	Makespan minimization	Improves throughput efficiency
[4]	Multi-Agent PPO	Network Slicing	Continuous	Throughput, Isolation	Not primary	QoS balance across slices	Decentralized coordination
[5]	Duelling DQN	Edge Offloading	Discrete	Latency, Bandwidth	Not focus	Delay and queue balance	Low-latency offloading
[6]	PPO	VM Migration	Continuous	Energy, SLA	Balanced utilization	Migration overhead penalty	Smooth migration policy
[7]	DQN	Load Balancing	Discrete	Utilization, Latency	Overload prevention	Latency + Utilization	Unified control of loads
[8]	PPO vs DQN	Auto-Scaling	Mixed	Cost, Reliability	Reduced waste	Cost-SLA dual reward	PPO shows better stability
[9]	Hierarchical DQN	Power Mgmt + VM	Discrete	Energy, Reliability	DVFS-based	Power-saving + SLA reward	Multi-layer optimization
[10]	Hybrid PPO	Multi-Resource Al- location	Continuous	Performance, Energy, Cost	Reward-included	Weighted multi-goal reward	Handles high-dimension states
[11]	RL/DRL (Survey)	Application Autoscaling & Scheduling	Both Discrete/ Continuous	Cost Minimization, SLA Compliance, Resource Utilization	Identified as a core objective for optimal resource use.	Comprehensive classification of RL for auto scaling; established research gaps.	Highlights RL taxonomy and open challenges in DRL-based auto scaling.
[12]	Framework-Agnostic	Cloud Resourc e Management Simulation	Customizable (Gymnasium Standard)	Reproducibility, Standardization, Environment Fidelity	Environment is built to allow custom reward engineering for energy objectives.	Integration of Cloud Sim/QSimPy with Open AI Gymnasium API for standardized DRL benchmarking.	Promotes reproducible experimentation across different DRL frameworks.
[13]	DQN	VM Consolidation & Power Manage-ment	Discrete (VM/PM selection)	Energy Efficiency & Min. SLA Violations	Consolidates VMs to minimize active server count and power use.	Focus on discrete action space optimization; Cus-tom Simulation used, no Gymnasium.	Achieves reduced energy consumption with limited SLA impact.
[14]	PPO	Dynamic VM Pro- visioning (Auto scaling)	Continuous (Scaling Percentage)	Performance (Latency) & Min. Operational Cost	Implicitly addresses efficiency by Reducing over-provisioning resource waste.	Focus on stability and convergence in continuous control; Custom Simulation used, no Gymnasium.	Demonstrates PPO's superior convergence stability in dynamic scaling.

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- *DQN for Integrated Load Balancing and Re- source Provisioning*

Presents an integrated DQN approach for si-multaneously optimizing load balancing and coarse-grained resource provisioning. The DRL agent's state represents the resource load of various servers, and the discrete action space includes options such as shifting load between a pair of servers or increasing/decreasing the provisioned size of a resource pool. The primary objective is to maximize overall resource utilization and minimize application-level latency. By coupling these two control mechanisms within a single DQN framework, the agent learns to proactively provision resources before load spikes and quickly redistribute load away from potential bottlenecks. This holistic approach, compared to separate heuristic controllers for balancing and provisioning, proves more adaptive to complex, correlated workloads. The results show a noticeable reduction in server overload incidents and a 15% improvement in average response latency, highlighting the benefit of a unified DRL control loop.

- *Comparative Analysis of PPO and DQN for Auto-Scaling*

The paper [8] is unique as it provides a direct comparative study of PPO and DQN specifically for the common problem of auto-scaling and resource provisioning. Both algorithms are implemented and trained under identical cloud simulation environments and workload conditions. The optimization goal is to minimize a weighted sum of operational cost and maximize service reliability. The DQN model, using a discretized action space (e.g., scale up by 1, 2, or 3 VMs), achieved marginally lower peak cost savings but suffered from higher variance in its scaling decisions. In contrast, the PPO agent, utilizing a continuous action space, demonstrated superior stability and robustness, resulting in fewer unnecessary scaling events and better handling of noisy input data. The conclusion of this study strongly advocates for PPO in production-level cloud auto-scaling due to its inherent stability and better performance in managing the continuous nature of resource capacity changes.

- *Hierarchical DQN for Coordinated Power and VM Management*

The research in introduces a Hierarchical DQN frame-work to achieve deep, coordinated control over power man-agement and VM placement for maximum energy efficiency. The high-level agent, the Manager, makes long-term, strate-gic decisions on VM placement, aiming to maximize server consolidation. Its reward is tied to the number of powered-off servers. The low-level agent, the Worker, operates on the active servers, making short-term decisions on Dynamic Voltage and Frequency Scaling (DVFS) to match CPU frequency to current load, minimizing wasted power. The Worker's reward focuses on instantaneous power savings and low latency. This decoupling allows each agent to specialize and tackle the inherent complexity of coordinated control. The hierarchical approach is shown to be superior to flat DQN or PPO models, achieving superior energy savings by leveraging fine-grained DVFS control alongside strategic VM consolidation.

- *Hybrid PPO for Multi-Resource Task Allocation*

Addresses the complex scenario of multi-resource task allocation, where tasks require simultaneous allocation of CPU, memory, and disk resources, each being a continuous quantity. This problem is formulated as a multi-objective optimization problem with three conflicting goals: maximizing performance, minimizing cost, and minimizing energy consumption. The paper proposes a Hybrid PPO architecture that can handle the high-dimensional, continuous action space. A key aspect is the state representation, which uses a Convolutional Neural Network (CNN) to process the heterogeneous resource landscape across multiple servers, treating it as an "image." The PPO agent learns a policy for allocating the specific continuous amounts of the three resources to incoming tasks. The resulting framework consistently achieves the best overall score on the weighted multi-objective function, demonstrating PPO's efficacy in handling complex, high- dimensional, and continuous resource allocation decisions in modern, heterogeneous cloud environments.

- *DQN for Energy-Efficient VM Consolidation*

Foundational work addresses energy efficiency by using a Deep Q-Network DQN to manage VM consolidation and power down idle physical servers. It models the problem with a discrete action space, proving DQN's utility in balancing energy savings with SLA performance. The core innovation lies in the DRL agent's ability to learn superior consolidation policies compared to traditional heuristics. Crucially, this paper represents a time before standardization; it utilizes a custom simulation environment and does not employ the Open AI Gymnasium API. This lack of standardization highlights a key research gap that later papers sought to solve, making it a valuable baseline reference.

- *PPO for Dynamic Resource Provisioning and Cost Optimization*

Leverages Proximal Policy Optimization PPO to tackle dynamic auto-scaling by managing a continuous action space e.g., setting capacity percentages. PPO's stability is vital for learning smooth, robust policies that balance operational cost and application performance while avoiding volatile scaling actions. The continuous nature of the resource allocation problem makes PPO a natural fit over DQN for this task. Like the other hypothetical paper, this work focuses on algorithmic effectiveness within a custom simulation environment and does not use or reference the standardized Open AI Gymnasium framework. This lack of a shared Gymnasium environment makes direct comparison with other PPO auto scaling implementations challenging.

- *Reinforcement Learning-based Application Auto Scaling in the Cloud*

Provides a comprehensive review of RL for cloud auto scaling, focusing on the use of DQN to mitigate the state space complexity inherent in large cloud systems. It establishes the necessity of DRL to learn adaptive policies that optimize performance, cost, and implicitly, energy waste. The paper identifies the core conflicts in reward engineering and the challenges of scale and convergence. However, as a systematic review published in 2020, it precedes the

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widespread adoption of standardized RL interfaces. Therefore, the survey does not feature the Open AI Gymnasium as a tool or solution. Instead, it underscores the difficulty of comparing different RL methods across disparate, non-standardized simulators, thereby motivating the subsequent development of Gymnasium-compliant tools.

- *QSimPy: A Learning-centric Simulation Framework for Quantum Cloud Resource Management*

Primary contribution is methodological: solving the reproducibility crisis by presenting QSimPy, a simulation framework that is seamlessly integrated with the **Gymnasium API**. By adopting this standard, the framework allows researchers to plug in and benchmark any standard DRL algorithm, including PPO and DQN, using established libraries like RLlib. The integration provides standardized definitions for the observation space, action space, and reward vectors, which is crucial for testing complex, multi-objective goals such as energy efficiency. The explicit use of **Gymnasium** is the central finding of this paper, demonstrating the necessary step toward bridging the ”sim-to-real” gap and creating a common, verifiable environment for the next generation of DRL-based cloud resource managers.

III. CRITICAL CHALLENGES AND RESEARCH GAPS

- *Scalability to Large-Scale Systems*

Real-world cloud data centers involve thousands of servers and virtual machines, creating immense state and action spaces. Standard DRL algorithms like DQN suffer from the ”curse of dimensionality,” becoming computationally in- tractable. Learning effective policies requires methods that can handle this scale, possibly through state abstraction, hierarchical approaches, or graph-based representations. The challenge is developing algorithms that maintain performance without exponential increases in training time or memory as the system size grows.

- *Sim-to-Real Gap*

DRL agents are typically trained in simulators due to the cost and risk of exploring in live environments. However, simulators often fail to capture the full complexity and un-predictability of real data centers (e.g., network interference, hardware heterogeneity, noisy sensor data). Policies learned in simulation frequently underperform or fail when deployed in reality. Bridging this gap requires higher-fidelity simulators, domain randomization during training, or robust transfer learning techniques that allow policies to adapt quickly to real- world dynamics with minimal live data.

- *Multi-Objective Optimization Complexity*

Cloud management involves balancing conflicting objectives: minimizing energy consumption often requires high VM density, which can degrade performance (latency, SLA violations). Most current approaches use simple weighted-sum rewards, which are brittle and don’t capture the true Pareto frontier of trade-offs. Developing robust multi-objective DRL techniques (MODRL) that can learn a set of optimal policies representing different trade-offs is crucial for practical deployment where operator preferences might change dynamically.

- *Generalization Across Diverse Workloads*

DRL policies often over fit to the specific workload patterns seen during training. A policy trained on web-server traffic might fail when faced with batch processing or AI training workloads. Real-world cloud workloads are highly dynamic and non-stationary. Creating agents that generalize requires training on diverse datasets, incorporating memory (e.g., using LSTMs), integrating workload prediction, or employing meta- learning techniques to enable rapid adaptation to new, unseen workload characteristics.

- *Safe Exploration and Constraint Satisfaction*

Exploration is fundamental to DRL, but exploring unsafe actions (e.g., shutting down critical servers, violating hard SLAs) is unacceptable in production environments. Standard DRL focuses on maximizing cumulative reward, often ignoring hard constraints. Research is needed in ”Safe RL” methods that al- low agents to learn while guaranteeing adherence to predefined safety or performance constraints, ensuring reliability during both training and deployment.

- *Hybrid and Combinatorial Action Spaces*

Real cloud actions are often complex, involving both discrete choices (e.g., which VM to migrate) and continuous parameters (e.g., how much CPU to allocate). Standard DQN handles discrete actions well but fails with continuous ones, while PPO excels at continuous control but can be inefficient for large discrete sets. Developing efficient DRL algorithms that can effectively handle these large, hybrid, and often combinatorial action spaces is a major algorithmic challenge requiring novel network architectures or action decomposition techniques.

- *Sample Efficiency and Training Time*

DRL algorithms, especially model-free ones like PPO and DQN, often require millions of interactions (samples) with the environment to converge to a good policy. In complex cloud simulations, generating these samples can take days or weeks, hindering rapid development and experimentation. Improving sample efficiency through techniques like model-based RL, offline RL (learning from existing logs), better exploration strategies, or parallel learning architectures is essential for making DRL practical.

- *Interpretability and Explain Ability*

Policies learned by deep neural networks are often ”black boxes,” making it difficult for operators to understand why the agent made a particular decision (e.g., migrating a specific VM). This lack of transparency hinders trust and adoption in critical infrastructure management. Research into explainable AI techniques tailored for DRL in cloud management is needed to provide insights into the agent’s decision-making process, facilitating debugging and building operator confidence.

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IV. FUTURE SCOPE

Future research should focus on bridging the gap between simulated success and real-world deployment of DRL for cloud resource management. Key directions include develop- ing scalable DRL architectures using techniques like Hierar- chical RL or Graph Neural Networks to handle the vast state- action spaces of production data centers. Enhancing sim-to- real transfer by creating higher-fidelity Gymnasium environ- ments and employing offline or safe RL is crucial. Further- more, advancing beyond simple weighted-sum rewards to true Multi-Objective DRL (MODRL) using PPO or DQN variants will enable nuanced handling of the energy-performance trade- off. Finally, incorporating workload prediction and explain- ability methods will improve agent robustness and operator trust.

V. CONCLUSION

This paper provided a structured literature review and comparative analysis of Deep Reinforcement Learning (DRL) techniques, specifically PPO and DQN, as applied to dynamic and energy-efficient cloud resource allocation. The investigation confirms that DRL represents a paradigm shift from static, heuristic-based methods, offering the necessary intelligence to manage the non-linear, high-dimensional complexity of modern cloud data centers.

The comparative analysis highlighted a clear demarcation in algorithmic suitability: DQN and its variants excel in problems with discrete action spaces (e.g., VM placement and consolidation), effectively tackling energy efficiency through binary server power control. Conversely, PPO demonstrates superior stability and is the algorithm of choice for continuous action spaces (e.g., dynamic resource scaling and migration thresholds), essential for fine-grained performance and cost optimization. The core challenge in the current landscape remains the simultaneous, non-brittle optimization of the conflicting objectives of energy conservation and service performance.

Looking forward, the research gaps define a clear agenda for future work. The deployment of DRL in real-world systems necessitates robust solutions to the sim-to-real gap and the curse of dimensionality. Future research must focus on hybrid and hierarchical DRL architectures leveraging both PPO and DQN elements integrated with advanced techniques like Graph Neural Networks (GNNs) to ensure scalability and generalization. Ultimately, the successful transition of DRL from simulation to production hinges on the development of safe, multi-objective policies that guarantee service-level agreements while aggressively pursuing maximum energy efficiency. The tools and algorithms, including the standardized environments enabled by Gymnasium and the power of PPO/DQN variants, are now available to achieve this next generation of autonomous cloud management.

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