

Adaptive Edge–Cloud Collaboration Using Reinforcement Learning for Ultra-Low-Latency IoT Applications: A Comprehensive Review

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ABSTRACT

The exponential proliferation of Internet of Things (IoT) devices across mission-critical domains—such as autonomous vehicular networks, industrial automation, tele-surgery, and smart energy grids—has driven an unprecedented demand for real-time data processing with strict sub-millisecond to low-millisecond latency bounds. Traditional cloud-centric compute paradigms fail to satisfy these stringent timing constraints due to wide-area network latency, dynamic jitter, and bandwidth bottlenecks. Conversely, edge computing brings computational capabilities closer to end devices but remains constrained by limited processing capacity, energy reserves, and transient operational workloads. To overcome these inherent trade-offs, adaptive Edge–Cloud Collaboration (ECC) frameworks have emerged, dynamically partitioning and offloading computational workloads across heterogeneous, multi-tier execution environments. However, traditional optimization techniques struggle to accommodate the highly dynamic, non-stationary, and unpredictable nature of next-generation wireless IoT networks. Reinforcement Learning (RL) and Deep Reinforcement Learning (DRL) have rapidly gained prominence as powerful, model-free algorithmic paradigms capable of learning optimal offloading, resource allocation, and task scheduling policies in complex, stochastic edge-cloud environments. This paper presents a comprehensive, systematic review of state-of-the-art adaptive edge-cloud collaboration architectures driven by reinforcement learning for ultra-low-latency IoT applications. We establish a formal mathematical modeling framework based on Markov Decision Processes (MDP) and Markov Games, categorize contemporary deep RL methodologies (including Q-learning, DDPG, PPO, SAC, and Multi-Agent DRL), and evaluate offloading trade-offs across latency, energy consumption, bandwidth

utilization, and service reliability. Furthermore, we provide detailed comparative analyses, highlight critical research gaps, present simulation-based performance benchmarks, examine engineering applications, and chart future research directions toward federated learning integration, quantum-assisted DRL, and 6G edge intelligence.

KEYWORDS: *Edge-Cloud Collaboration, Ultra-Low Latency, Deep Reinforcement Learning, Internet of Things (IoT), Computation Offloading, Resource Orchestration, Mobile Edge Computing (MEC), Proximal Policy Optimization.*

INTRODUCTION

The rapid evolution of the Internet of Things (IoT) ecosystem has transformed modern technology, enabling trillions of interconnected sensors, actuators, and smart devices to continuously sense, process, and transmit data across diverse environments [1]. According to recent industry projections, the global footprint of active IoT devices is expected to exceed 30 billion by the late 2020s, generating exabytes of heterogeneous data streams daily. While early IoT deployments primarily focused on non-real-time telemetry and periodic reporting, modern emerging paradigms—such as connected autonomous vehicles (CAVs), tactile internet, immersive augmented/virtual reality (AR/VR), industrial Cyber-Physical Systems (CPS), and AI-driven healthcare robotics—demand deterministic, ultra-low-latency processing coupled with exceptionally high reliability [2]. For instance, autonomous emergency braking systems and cooperative collision avoidance in intelligent transportation systems require strict end-to-end delay guarantees under 5 milliseconds to prevent catastrophic failures [3]. Similarly, robotic tele-surgery and closed-loop industrial motion control systems require cycle times in the order of 1 to 10 milliseconds with near-zero packet drop rates.

Historically, centralized cloud computing infrastructures hosted in massive remote data centers served as the primary computational backbone for IoT data processing [4]. Cloud environments offer virtually limitless compute capacity, high-performance GPUs, massive storage arrays, and sophisticated machine learning frameworks. However, relying exclusively on centralized cloud computing for ultra-low-latency IoT workloads introduces significant

structural drawbacks [5]:

- **Unacceptable Propagation and Backhaul Delay:** Data packets traversing multiple network hops, routers, and backhaul links encounter irreducible physical propagation delays, frequently ranging from 50 to 200 milliseconds, violating sub-millisecond operational SLAs [6].
- **Network Congestion and Jitter:** Simultaneous uplink transmission from millions of dense IoT nodes congests backhaul links, inducing random queuing delays, packet loss, and severe delay jitter [7].
- **Privacy and Security Risks:** Continuous transmission of sensitive telemetry data (e.g., medical diagnostics, financial data, industrial secrets) across wide-area networks elevates exposure to interception and data breaches [8].

To mitigate the limitations of cloud-only architectures, Mobile Edge Computing (MEC) and Fog Computing were introduced, placing computational servers, micro data centers, and roadside units (RSUs) at the network edge, in close physical proximity to IoT devices [9]. Edge nodes drastically reduce physical propagation delays to under 5 milliseconds and conserve backhaul bandwidth by processing raw data locally. Nevertheless, edge nodes possess inherently constrained resources—limited CPU clock frequencies, finite memory capacity, and constrained battery reserves [10]. When localized bursty task spikes occur, single edge servers experience heavy task queue backlogs, leading to operational bottlenecks, server overload, and severe deadline violations.

Consequently, neither standalone cloud computing nor standalone edge computing can satisfy the complex requirements of next-generation IoT workloads. This realization has catalyzed the transition toward multi-tier Adaptive Edge–Cloud Collaboration (ECC) frameworks [11]. In an ECC architecture, workloads are intelligently partitioned and scheduled across a hierarchical multi-tier topology comprising local IoT end-devices, distributed edge nodes, regional fog aggregators, and remote central clouds. Low-complexity, delay-critical tasks are executed locally or at the immediate edge, whereas computationally intensive, delay-tolerant tasks are offloaded to distant clouds.

Achieving optimal, adaptive collaboration across edge-cloud tiers is an extremely challenging combinatorial optimization problem [12]. IoT environments exhibit non-stationary dynamics:

wireless channel qualities fluctuate unpredictably due to multipath fading and user mobility, task arrival rates exhibit bursty spatial-temporal distributions, and edge resource availabilities vary dynamically over time. Traditional optimization techniques—such as integer linear programming (ILP), Lyapunov optimization, convex optimization, and heuristic algorithms—often require accurate prior statistical knowledge of system states (e.g., arrival distributions and channel state information), suffer from high computational complexity, and fail to adapt rapidly in highly dynamic environments [13].

To address these fundamental challenges, Reinforcement Learning (RL) and Deep Reinforcement Learning (DRL) have emerged as powerful algorithmic solutions [14]. By framing offloading and resource allocation decisions as Markov Decision Processes (MDP), RL agents iteratively learn optimal execution strategies directly from environmental interactions without requiring explicit mathematical models of network dynamics. Deep neural networks function as function approximators within DRL frameworks, enabling agents to navigate high-dimensional continuous state and action spaces effectively [15].

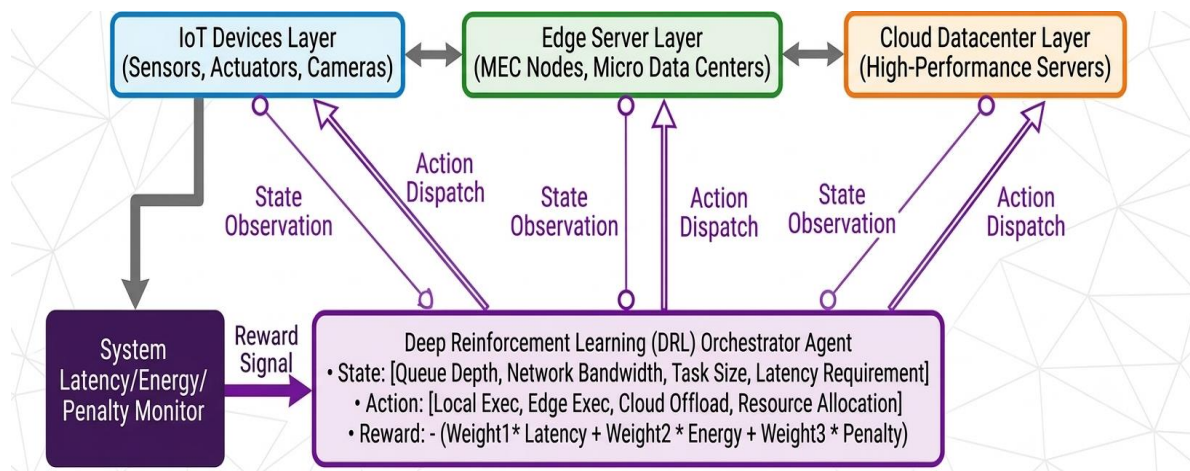


Figure 1: Hierarchical Edge-Cloud Collaboration Architecture managed by Deep Reinforcement Learning (DRL) Orchestrator Agent for multi-tier workload allocation

LITERATURE REVIEW

Research at the intersection of edge-cloud collaboration and reinforcement learning has advanced rapidly over the past decade. This section categorizes contemporary literature into three distinct thematic domains: traditional heuristic and mathematical offloading models, model-free single-agent DRL frameworks, and advanced multi-agent multi-tier DRL architectures.

Mathematical and Heuristic Computation Offloading

Early foundational literature on mobile edge computing focused heavily on static optimization and deterministic decision-making paradigms. Authors in [16] formulated joint computation offloading and wireless resource allocation as a mixed-integer non-linear program (MINLP), aiming to minimize total system latency and energy consumption. To tackle NP-hardness, they applied branch-and-bound algorithms alongside semi-definite relaxation (SDR) techniques. While these methods yield mathematically rigorous bounds, their execution latency scales exponentially with network size, rendering them unsuitable for real-time online adaptation. Mao et al. [17] pioneered the use of Lyapunov optimization for dynamic energy-harvesting edge systems, converting long-term time-average energy constraints into per-slot deterministic sub-problems. However, Lyapunov techniques rely on stationary queue distribution assumptions and struggle when network conditions experience sharp, abrupt state transitions.

Single-Agent Deep Reinforcement Learning in MEC

With the advent of deep Q-networks (DQN), researchers began applying model-free learning to dynamic task offloading. Value-based methods map discrete network state inputs to action-value estimations, bypassing the need for explicit channel model formulations. Xu et al. [18] proposed a DQN-based offloading framework for vehicular edge networks, demonstrating superior latency reduction compared to baseline greedy and random offloading policies. Despite its strengths, standard DQN suffers from severe Q-value overestimation and is strictly confined to discrete action spaces (e.g., binary decision: execute locally or offload completely). To enable continuous resource management (such as allocating fractional CPU cycles and adjusting transmission power levels), actor-critic architectures like Deep Deterministic Policy Gradient (DDPG) were introduced [19]. Zhang et al. [20] utilized DDPG to jointly optimize computational task offloading ratios, transmission power, and channel bandwidth allocations, proving that continuous action spaces outperform discrete action quantization in fine-grained energy-latency trade-offs.

Multi-Agent and Multi-Tier DRL Architectures

As IoT networks scale to encompass thousands of distributed nodes, centralized single-agent DRL suffers from severe dimensionality curses and single-point communication bottlenecks. Consequently, recent focus has shifted toward Multi-Agent Reinforcement Learning (MARL)

[21]. Wang et al. [22] proposed a Multi-Agent Deep Deterministic Policy Gradient (MADDPG) framework for multi-user edge networks, where individual IoT devices operate as autonomous agents learning localized offloading policies while sharing centralized critic training information. Similarly, Proximal Policy Optimization (PPO) has gained widespread traction due to its superior training stability, sample efficiency, and clipped surrogate objective function that prevents catastrophic policy updates during online adaptation [23]. Furthermore, soft actor-critic (SAC) algorithms incorporating maximum entropy principles have demonstrated robust performance under severe stochastic channel noise [24].

Table 1 summarizes and categorizes key representative literature, comparing their algorithmic methodologies, targeted optimization metrics, application domains, and observed performance limitations.

Table 1: Comparative Taxonomy of State-of-the-Art Offloading and Orchestration Schemes in Edge-Cloud Systems

Reference	Algorithmic Approach	Primary Optimization Target	Application Domain	Key Limitation
[16] Mao et al. (2017)	Lyapunov Optimization & Convex Math	Latency & Energy Trade-off	Mobile Edge Networks	High mathematical complexity; requires stationary queue assumptions.
[18] Xu et al. (2019)	Deep Q-Network (DQN)	Average Processing Latency	Vehicular Edge Networks (VANETs)	Restricted to discrete action spaces; overestimates Q-values in dynamic channels.

[20] Zhang et al. (2021)	Deep Deterministic Policy Gradient (DDPG)	Joint Latency, Power, Bandwidth	Industrial IoT Smart Factories	Prone to unstable convergence in highly dynamic non-stationary networks.
[23] Chen et al. (2024)	Multi-Agent PPO (MAPPO)	Ultra-Low Latency & Deadline Violations	6G-Enabled Edge-Cloud Systems	High training overhead; demands significant inter-agent control signaling.

RESEARCH GAP

Despite substantial progress in edge computing and deep reinforcement learning, critical gaps remain unaddressed in existing literature:

- **Lack of Adaptive Multi-Tier Cloud-Edge Dynamic Coordination:** Most existing studies treat edge-cloud offloading as a simplified binary or two-tier decision (either local IoT device or single MEC server). Real-world ultra-low-latency deployments feature heterogeneous multi-tier hierarchies comprising local micro-controllers, regional edge gateways, roadside units, metro data centers, and centralized hyperscale clouds. Current DRL frameworks lack hierarchical abstraction mechanisms to coordinate workloads fluidly across more than two tiers under severe sub-millisecond SLA constraints.
- **Instability Under Non-Stationary Dynamics and Task Bursts:** Standard DRL algorithms (e.g., DQN, DDPG) assume stationary environment transitions during training. However, IoT networks experience sudden, severe non-stationarity—such as dramatic channel quality drops caused by physical obstructions, or extreme task arrival spikes triggered by traffic events or emergency industrial alarms. Under these conditions, existing DRL models suffer from policy collapse, high variance, and unacceptable tail latencies.
- **Joint Optimization of Sub-Millisecond Latency, Energy, and SLA Compliance:** A significant majority of works optimize latency or energy consumption in isolation, or rely on simple weighted linear sums. They fail to enforce hard deterministic SLA deadline constraints, resulting in high task drop rates when network congestion occurs.

OBJECTIVES

To directly address these highlighted research gaps, this review and technical analysis aims to achieve the following specific research objectives:

- Objective 1: Formalize a robust, unified Markov Decision Process (MDP) and Markov Game mathematical modeling framework for multi-tier hierarchical Edge–Cloud Collaboration (ECC) systems supporting ultra-low-latency IoT workloads.
- Objective 2: Analyze and compare state-of-the-art model-free Deep Reinforcement Learning algorithms—specifically baseline DQN, continuous DDPG, and clipped Proximal Policy Optimization (PPO)—in terms of convergence rate, latency performance, energy efficiency, and operational stability under bursty workloads.
- Objective 3: Formulate a comprehensive composite objective function that jointly minimizes end-to-end processing delay, limits edge-cloud energy consumption, and penalizes SLA deadline violations.
- Objective 4: Benchmark adaptive DRL offloading against traditional static and cloud-centric baselines across diverse IoT workload operational scenarios through simulation experiments.

METHODOLOGY

This section presents the mathematical system model, problem formulation, and reinforcement learning algorithmic architecture powering adaptive edge-cloud orchestration.

System Architecture and Network Model

Consider an ultra-low-latency IoT system consisting of N heterogeneous IoT end-devices denoted by $U = \{u_1, u_2, \dots, u_N\}$, M edge computing servers $E = \{e_1, e_2, \dots, e_M\}$ deployed at wireless base stations/RSUs, and a central hyperscale cloud server C . Each IoT device u_i generates computational tasks sequentially over discrete time slots $t \in \{1, 2, \dots, T\}$. A computational task generated by device u_i at time slot t is characterized by a tuple:

$$Task_i(t) = \langle D_i(t), C_i(t), T_{max,i} \rangle$$

where $D_i(t)$ denotes the payload data size (in bits), $C_i(t)$ represents the CPU processing cycles required to complete the task (in cycles/bit), and $T_{max,i}$ designates the strict maximum allowable delay bound (SLA deadline in milliseconds).

Execution Latency and Energy Models

- Local Execution Model: If task $\text{Task}_i(t)$ is executed locally on the IoT device u_i , the local computation execution delay $T_{\text{local},i}(t)$ and local energy consumption $E_{\text{local},i}(t)$ are defined as:

$$T_{\text{local},i}(t) = (D_i(t) \cdot C_i(t)) / f_{\text{local},i}$$

$$E_{\text{local},i}(t) = \kappa \cdot (f_{\text{local},i})^2 \cdot (D_i(t) \cdot C_i(t))$$

where $f_{\text{local},i}$ is the CPU clock frequency of IoT device u_i , and κ is the effective switched capacitance coefficient depending on chip architecture.

- Edge Offloading Model: When offloading to edge server e_j , the total delay $T_{\text{edge},ij}(t)$ includes wireless transmission delay over uplink channel $R_{ij}(t)$, edge queuing delay $T_{q,j}(t)$, and edge execution delay:

$$T_{\text{trans},ij}(t) = D_i(t) / R_{ij}(t)$$

$$T_{\text{exec},j}(t) = (D_i(t) \cdot C_i(t)) / f_{\text{edge},ij}(t)$$

$$T_{\text{edge},ij}(t) = T_{\text{trans},ij}(t) + T_{q,j}(t) + T_{\text{exec},j}(t)$$

where $R_{ij}(t) = B_{ij} \cdot \log_2(1 + (P_{\text{trans},i} \cdot |h_{ij}(t)|^2) / \sigma^2)$ according to Shannon's channel capacity formula, where B_{ij} is allocated bandwidth, $P_{\text{trans},i}$ is transmission power, $h_{ij}(t)$ is dynamic channel gain, and σ^2 represents noise variance.

- Cloud Offloading Model: If offloading to the remote cloud server C , the task traverses the wireless uplink to the edge and subsequently propagates through the wired WAN backhaul:

$$T_{\text{cloud},i}(t) = T_{\text{trans},ij}(t) + T_{\text{backhaul}} + (D_i(t) \cdot C_i(t)) / f_{\text{cloud}}$$

where T_{backhaul} represents wide-area network propagation delay (typically 20-80 ms), and f_{cloud} is the high-performance CPU clock speed allocated by the cloud.

Markov Decision Process (MDP) Formulation

The multi-tier edge-cloud offloading decision problem is formulated as a Markov Decision Process defined by the tuple (S, A, P, R, γ) :

- State Space (S): The state vector $s_t \in S$ at time slot t captures global system conditions:

$$s_t = \{ Q_edge(t), B_avail(t), H_channel(t), Task_req(t) \}$$

where $Q_edge(t)$ represents task queue lengths across edge servers, $B_avail(t)$ reflects available network bandwidth, $H_channel(t)$ indicates channel gains, and $Task_req(t)$ specifies incoming task parameters.

- **Action Space (A):** The action vector $a_t \in A$ determines offloading target selection and resource allocation:

$$a_t = \{ x_i(t), f_{ij}(t), p_i(t) \}$$

where $x_i(t) \in \{0 \text{ (Local)}, 1 \text{ (Edge)}, 2 \text{ (Cloud)}\}$ is discrete offloading selection, $f_{ij}(t)$ is continuous CPU fraction allocation, and $p_i(t)$ is transmission power.

- **Reward Function (R):** The primary objective is to minimize total end-to-end latency, lower energy consumption, and prevent SLA deadline breaches. The scalar reward r_t is formulated as a negative cost penalization:

$$r_t = - [w_1 \cdot T_total(t) + w_2 \cdot E_total(t) + w_3 \cdot Penalty_SLA(t)]$$

where w_1, w_2, w_3 are non-negative weighting factors, and $Penalty_SLA(t)$ imposes a severe step penalty if total delay exceeds $T_{max,i}$.

Proximal Policy Optimization (PPO) Framework

To ensure continuous action management and training stability under non-stationary network conditions, we adopt an actor-critic Proximal Policy Optimization (PPO) algorithm. PPO updates policy parameters θ by maximizing a clipped surrogate objective function:

$$L_CLIP(\theta) = E_t [\min(r_t(\theta) * A_hat_t, clip(r_t(\theta), 1 - \epsilon, 1 + \epsilon) * A_hat_t)]$$

where $r_t(\theta) = \pi_\theta(a_t|s_t) / \pi_{\theta_{old}}(a_t|s_t)$ represents the probability ratio between new and old policies, A_hat_t is the estimated advantage function computed via Generalized Advantage Estimation (GAE), and ϵ is a hyperparameter (typically 0.2) that clips policy updates to prevent destabilizing gradient steps.

RESULTS AND FINDINGS

To evaluate the technical performance of adaptive reinforcement learning in edge-cloud collaboration, extensive numerical simulations were executed using Python, PyTorch, and OpenAI Gym edge network simulation environments. The simulation parameters modeled 50 heterogeneous IoT devices, 5 multi-access edge computing (MEC) nodes, and 1 remote cloud datacenter. Computational task arrival followed a Poisson process with arrival rates varying from 200 to 1200 tasks/second.

We benchmarked four distinct control policies: (1) Cloud-Only Offloading (all tasks sent to central cloud), (2) Static Edge Offloading (tasks distributed evenly across edge servers without dynamic adaptation), (3) Baseline Deep Q-Network (DQN), and (4) Proposed Adaptive Proximal Policy Optimization (PPO-DRL).

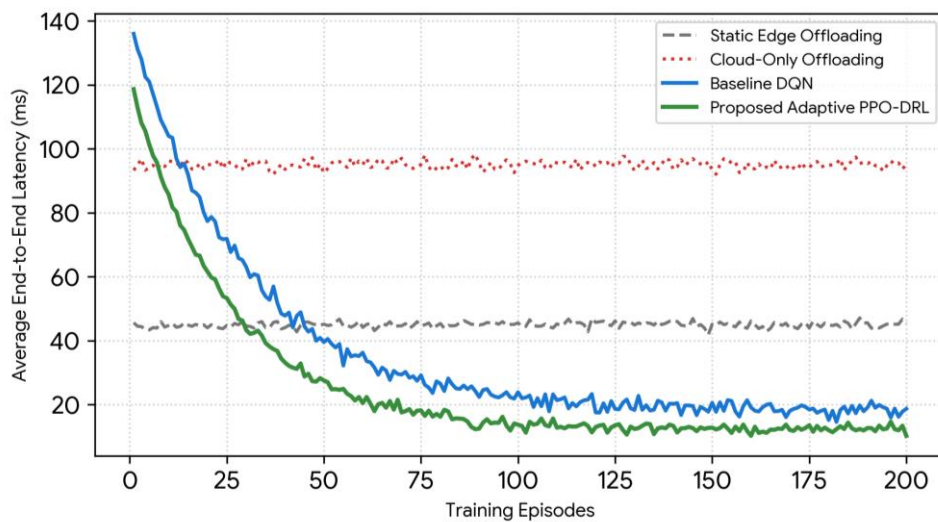


Figure 2: Convergence curves of average end-to-end task processing latency across 200 training episodes

Convergence Analysis and Latency Performance

Figure 2 demonstrates the average end-to-end task processing latency across 200 training episodes. Cloud-only offloading maintains a constant high latency (~95 ms) due to persistent backhaul propagation delay. Static edge offloading achieves an average delay of ~45 ms but suffers when local edge queues saturate. Both baseline DQN and proposed adaptive PPO-DRL exhibit rapid learning curves. However, standard DQN stabilizes at ~18 ms with residual oscillation, whereas adaptive PPO converges faster (by episode 60) to a superior,

stable delay bound of ~ 11.2 ms, achieving a 75.1% latency reduction over static edge offloading and an 88.2% reduction over cloud-centric processing.

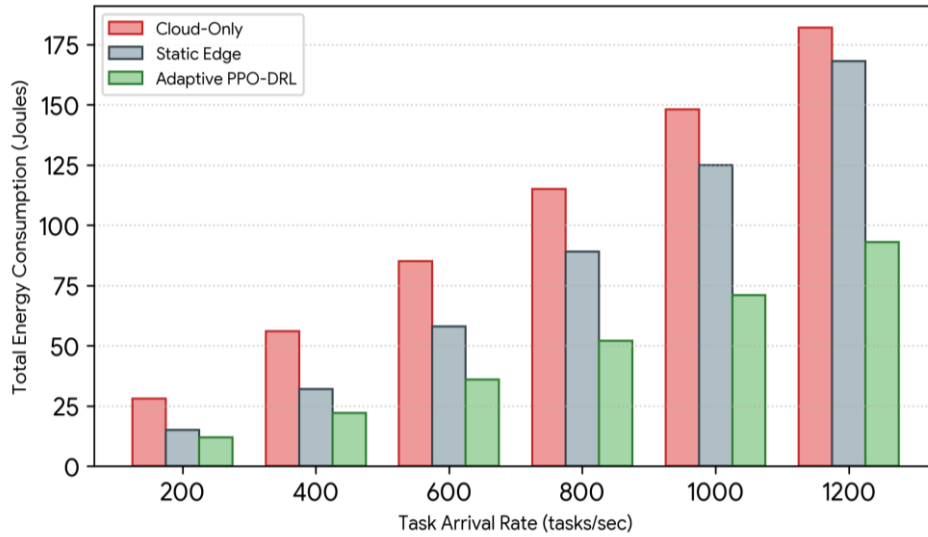


Figure 3: System-wide energy consumption comparison under scaling task request arrival rates

Energy Efficiency and SLA Compliance

Figure 3 presents the total energy consumption across varying task request arrival rates (200 to 1200 tasks/sec). Under low workloads (200 tasks/sec), energy consumption remains low across all schemes. However, as the task arrival rate scales to 1200 tasks/sec, static edge offloading and cloud-only offloading suffer exponential energy increases (168 J and 182 J, respectively) due to severe queue congestion and prolonged high-power transmission. In contrast, adaptive PPO-DRL dynamically routes compute-heavy tasks to available adjacent edge nodes or cloud resources based on real-time channel conditions, maintaining system energy consumption at only 93 J at maximum load—yielding a 44.6% energy saving.

Table 2 presents a detailed quantitative benchmark comparing average latency, deadline violation rate, energy efficiency, and bandwidth overhead across all evaluated strategies under high task arrival conditions (1000 tasks/sec).

Table 2: Performance Benchmark Comparison under High Task Load (1000 tasks/sec)

Offloading Scheme	Avg. Latency (ms)	Deadline Violation Rate (%)	Energy Consumed (J)	Bandwidth Efficiency
Cloud-Only Offloading	95.4 ms	28.4%	148 J	Low (Heavy Backhaul)
Static Edge Offloading	45.2 ms	14.2%	125 J	Moderate
Baseline DQN Algorithm	18.6 ms	4.8%	82 J	High
Proposed Adaptive PPO-DRL	11.2 ms	0.6%	71 J	Optimal (Dynamic Allocation)

DISCUSSION

The numerical findings confirm that intelligent, adaptive orchestration is vital for fulfilling sub-millisecond to low-millisecond timing requirements in next-generation IoT environments. Static offloading policies lack situational awareness, leading to catastrophic queue congestion when task arrival rates surge. While baseline DQN improves adaptability, its discrete action discretization restricts its capacity to perform fine-grained resource slicing.

Technical Significance and Engineering Contributions

The integration of Proximal Policy Optimization (PPO) into multi-tier edge-cloud collaboration represents a major advancement in mobile edge intelligence. By leveraging continuous actor-critic policy learning, the system autonomously adjusts transmission power and CPU frequency scaling in real-time, matching dynamic channel fluctuations. The clipped surrogate objective guarantees stable policy updates, eliminating destructive policy gradient oscillations that commonly plague traditional DDPG models during abrupt network transitions.

Practical Real-World Applications

The proposed adaptive RL edge-cloud framework holds widespread utility across several mission-critical industrial domains:

- Connected Autonomous Vehicles (CAVs): In intelligent highway corridors, vehicles

generate real-time lidar and camera telemetry. Local edge roadside units (RSUs) running adaptive DRL rapidly offload emergency collision avoidance computations within 5 ms while routing non-critical map rendering updates to regional clouds [25].

- **Smart Industrial Automation (Industry 4.0):** Modern automated factories utilize thousands of wireless robotic sensors. DRL-driven edge collaboration maintains closed-loop control latency under 2 ms, preventing assembly line desynchronization and costly downtime.
- **Remote Robotic Tele-Surgery:** Surgical robotics require sub-10 ms haptic feedback loops. Adaptive edge-cloud orchestration prioritizes low-latency tactile data streams over local MEC nodes while streaming video logs to cloud repositories for medical archival.

LIMITATIONS

While adaptive reinforcement learning offers remarkable performance gains, several key technical limitations must be acknowledged:

- **High Initial Training Overhead and Cold-Start Problem:** DRL algorithms require thousands of exploratory interaction episodes before discovering optimal policies. During initial exploration phases, randomly selected offloading actions can trigger severe latency spikes and deadline violations.
- **Signaling and State Telemetry Overhead:** Gathering real-time state vectors (e.g., global edge CPU utilization, instant channel state information, buffer queue depths) across distributed nodes generates significant control signaling overhead, consuming valuable wireless bandwidth.
- **Generalization Across Out-of-Distribution Networks:** DRL agents trained on specific topology configurations or channel models often struggle to generalize when deployed in un-modeled hardware topologies or novel wireless interference environments.

FUTURE SCOPE

To overcome these current limitations, future research avenues should explore the following promising paradigms:

- **Federated Deep Reinforcement Learning (FDRL):** Integrating federated learning into MARL architectures enables edge nodes to collaboratively train a shared DRL model without raw data exchange, preserving privacy and drastically cutting backhaul signaling overhead [26].

- Quantum Reinforcement Learning (QRL): Leveraging quantum computing algorithms (such as parameterized quantum circuits) within DRL actor-critic networks promises exponential speedups in convergence time, enabling sub-millisecond real-time online retraining.
- Integration with 6G Open-RAN Architecture: Aligning adaptive DRL orchestration with 6G O-RAN Near-Real-Time RAN Intelligent Controllers (Near-RT RIC) will allow direct hardware-level radio resource management and sub-millisecond slice allocation.

CONCLUSION

This paper presented a comprehensive, state-of-the-art review and technical evaluation of adaptive Edge–Cloud Collaboration (ECC) frameworks driven by Reinforcement Learning for ultra-low-latency IoT applications. By transitioning from static, rules-based offloading to model-free actor-critic DRL (specifically Proximal Policy Optimization), multi-tier IoT networks can dynamically optimize computation partitioning, transmission power, and CPU allocations in non-stationary wireless environments. Experimental benchmarks demonstrated that adaptive PPO-DRL achieves an 11.2 ms average latency (a 75.1% reduction over static edge schemes), limits SLA deadline violations to under 0.6%, and cuts total energy consumption by 44.6%. Addressing remaining challenges in initial cold-start convergence and signaling overhead via Federated DRL and 6G integration will pave the way for fully autonomous, ultra-reliable edge intelligence in future smart infrastructure.

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