Multi-Agent Reinforcement Learning for Intelligent Resource Scheduling in Cloud-Edge Computing Environments

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Abstract:
The rapid proliferation of latency-sensitive and compute-intensive applications across IoT, 5G, and smart-city infrastructures has intensified the need for intelligent and scalable task scheduling in distributed cloud–edge computing environments. Traditional centralized schedulers and static heuristics struggle to cope with highly dynamic workloads, heterogeneous resource profiles, user mobility, and fluctuating network conditions. This paper introduces a Hybrid Multi-Agent Reinforcement Learning (H-MARL) framework for autonomous resource scheduling, where each edge node operates as an intelligent agent making independent decisions while periodically synchronizing with a lightweight cloud-based coordinator. The proposed model combines localized decision-making with global policy refinement, enabling adaptive task execution, cooperative peer offloading, and selective cloud escalation. Experimental evaluations using CloudSim-Plus, EdgeSim, and real-world workload traces demonstrate significant improvements over heuristic and centralized reinforcement learning baselines. The H-MARL architecture achieves lower latency, reduced SLA violations, improved throughput, and more balanced resource utilization while minimizing unnecessary migrations and cloud reliance. Results validate that hybrid multi-agent intelligence enhances scalability, reliability, and responsiveness, making the approach well-suited for next-generation distributed systems supporting real-time and mission-critical edge workloads.

Keywords: Multi-Agent Systems (MAS); Edge Computing; Cloud Computing; Resource Scheduling; Reinforcement Learning; MARL; Distributed Intelligence; Task Offloading; Federated Learning; CloudSim-Plus; EdgeSim; SLA; Real-Time Computing; 5G/IoT Systems; Latency-Aware Scheduling.

Introduction

The proliferation of data-intensive applications such as autonomous driving, industrial IoT, augmented and virtual reality (AR/VR), telemedicine, and large-scale intelligent surveillance has significantly accelerated the adoption of cloud and edge computing infrastructures. With billions of connected devices expected to generate massive heterogeneous data streams, conventional centralized cloud models face increasing pressure to deliver low-latency, energy-efficient, scalable, and highly available services. Edge computing has emerged as a complementary paradigm that enables computation closer to data sources, effectively reducing latency, bandwidth consumption, and network bottlenecks [1]. However, the coexistence of distributed edge environments and centralized cloud platforms introduces complex challenges in resource management, dynamic workload scheduling, service placement, and task migration.

Dynamic resource scheduling plays a pivotal role in ensuring efficient utilization of heterogeneous computational nodes, meeting Quality-of-Service (QoS) and Service Level Agreement (SLA) constraints, and minimizing operational costs. Traditional scheduling strategies such as First-Come-First-Serve (FCFS),

Round Robin (RR), Min-Min, and Max-Min fail to scale or adapt in highly dynamic and unpredictable cloud-edge ecosystems. These approaches typically rely on static decision-making, lack contextual awareness, and do not consider real-time variations in user demand, resource availability, communication delays, and environmental uncertainties [2]. As workloads fluctuate across distributed nodes, the need for intelligent, decentralized, and self-adaptive scheduling mechanisms becomes increasingly critical.

Multi-Agent Systems (MAS) offer a promising framework to enable autonomous, cooperative, and decentralized control in distributed computing environments. Agents are capable of sensing their environment, making rational decisions, negotiating with peers, and learning from historical behavior. When integrated into cloud-edge infrastructures, MASs can enable task-level coordination, resource discovery, workload partitioning, and distributed orchestration [3]. Unlike monolithic controllers, MAS-driven schedulers eliminate single-point-of-failure risks and improve fault tolerance, decision responsiveness, and system intelligence. Agents can act as intermediaries between task generators and resource providers, negotiating resource allocation while ensuring fairness, optimal energy use, and SLA compliance.

Reinforcement Learning (RL), particularly Multi-Agent Reinforcement Learning (MARL), further augments MAS-based scheduling systems by enabling continuous improvement through trial-and-error mechanisms. RL-empowered agents learn optimal policies for task distribution and resource provisioning based on system feedback, enabling predictive and adaptive scheduling decisions. MARL algorithms—such as Independent Q-Learning, Centralized Training with Decentralized Execution (CTDE), Deep Q-Networks (DQN), MADDPG, and PPO variants—have demonstrated strong potential in distributed computing optimization. These techniques empower agents to handle complex, multi-objective scheduling scenarios involving trade-offs between energy consumption, latency, throughput, load balancing, and cost efficiency [4].

The convergence of MAS and RL-based decision intelligence positions this research in a crucial technological era where distributed computing systems must autonomously balance fluctuating workloads. Edge nodes often possess limited computational capacity, unstable connectivity, and dynamic energy profiles. Hence, decisions regarding task offloading, service placement, and replication must be highly contextual and dynamic. MAS, combined with adaptive RL models, provides a mechanism for collaborative and local-global knowledge-aware optimization in cloud-edge orchestration.

Despite notable advancements, several critical challenges persist. First, MAS-based cloud-edge scheduling often lacks robust cooperative learning mechanisms to avoid conflicted decisions, resource contention, and agent competition. Second, most existing works either prioritize cloud-only or edge-only scheduling without addressing cross-layer coordination. Third, energy-aware distributed learning and fairness-driven resource sharing mechanisms remain underexplored. Lastly, real-world cloud traces, such as Google and Alibaba cluster logs, are seldom exploited in existing studies to evaluate practical performance metrics including SLA violations, energy efficiency, latency fluctuations, and dynamic queue behavior.

This research addresses these gaps by proposing a Hybrid Multi-Agent Reinforcement Learning (H-MARL)-based dynamic scheduling framework tailored for distributed cloud and edge infrastructures. The framework features distributed learning agents, negotiation agents, and coordinator agents that collaboratively decide task placement, resource allocation, and service migration in real time. It adopts a decentralized model where each edge node hosts an autonomous agent capable of local decision-making while synchronizing with cloud-level learning policies. The agent network incorporates policy-sharing mechanisms to minimize convergence time and communication overhead. Additionally, a utility-driven reward structure considers latency, compute load, energy consumption, queue time, and SLA compliance, enabling multi-objective optimization.

Background and Motivation

The industry shift toward real-time analytics, connected vehicles, remote surgery ecosystems, and smart industry automation requires computational offloading beyond centralized data centers. Gartner predicts that

more than 75% of enterprise-generated data will be processed at the edge by 2025. Such trends underscore the necessity of dynamic scheduling frameworks that operate across geographically dispersed computing nodes. Existing centralized cloud schedulers lack real-time adaptability, whereas edge-only schedulers struggle with limited resources and do not incorporate global optimization context.

Challenges in Cloud–Edge Resource Scheduling

Key challenges include:

- Decentralized decision-making across heterogeneous nodes
- Energy-aware scheduling with real-time constraints
- Scalability under fluctuating workloads
- Minimization of task migration costs
- Cross-layer orchestration between cloud and edge
- Avoiding bottlenecks and single-point failures
- Maintaining service continuity with mobility of IoT devices

Research Contributions

The current research contribute to the following:

- A Hybrid MAS + MARL-based scheduling architecture
- Autonomous scheduling and task migration logic
- Multi-objective reward function for latency & energy optimization
- Experimental validation on CloudSim Plus / EdgeSim with real traces
- Comparison with LR, RR, Min-Min, Max-Min, DQN, and A3C-based schedulers

Related Work

Cloud and edge computing infrastructures have rapidly evolved as foundational platforms to support modern digital ecosystems, driven by a surge in latency-sensitive and computation-intensive applications across domains such as healthcare, smart transportation, Industry 4.0 automation, virtual and augmented reality, unmanned aerial systems, and intelligent surveillance. As distributed computing paradigms became more prevalent, the challenge of dynamic resource scheduling emerged as a core research focus, particularly for environments that must simultaneously satisfy Quality-of-Service (QoS) constraints, Service Level Agreement (SLA) policies, energy efficiency demands, and increasingly diverse application latency requirements [5]. The literature surrounding scheduling in cloud and edge systems has grown substantially, advancing through several generations of methodologies: traditional heuristics, predictive and metaheuristic optimization, edge-specific and fog orchestration solutions, multi-agent decision systems, reinforcement learning, and recently, hybrid multi-agent reinforcement learning architectures.

Early techniques in cloud scheduling were dominated by classical deterministic approaches such as First-Come-First-Serve (FCFS), Shortest Job First (SJF), Round Robin (RR), Min-Min, Max-Min, and Opportunistic Load Balancing (OLB). These algorithms prioritized fairness, convenience, and computational simplicity. For instance, RR-time slicing improved fairness across workload queues, while Min-Min and Max-Min attempted to optimize makespan by prioritizing either the shortest or largest task first. However, such centralized strategies were fundamentally static and lacked awareness of heterogeneous resource capabilities and rapidly fluctuating request patterns [6]. Researchers further explored heuristic enhancements and metaheuristic techniques, including Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Simulated Annealing (SA), and Ant Colony Optimization (ACO), which improved exploration of scheduling state space and offered better performance under certain workload conditions. Yet, these approaches still

suffered substantial limitations in real-time decision-making due to high computational overhead, convergence delays, and inability to quickly adapt to drastic workload variations in live environments.

The rapid growth of edge computing shifted scheduling research toward decentralized, latency-aware resource management. Since computation moved physically closer to end devices to reduce data transmission delays, real-time service placement became essential. Researchers initially adopted lightweight priority-based task queuing and deadline-aware offloading mechanisms suitable for limited edge CPU resources and fluctuating IoT-generated workloads. Fog computing models extended this concept by placing intermediate nodes between cloud and edge to coordinate tasks and maintain service continuity. Although fog and edge algorithms achieved notable improvements for mission-critical applications, they frequently relied on centralized controllers for decision-making and lacked scalability when deployed across large federated edge clusters [7]. Issues such as user mobility, fluctuating wireless bandwidth, intermittent connectivity, and constrained battery-powered edge nodes challenged static rules and moderately dynamic heuristics. Service migration and predictive offloading attempts further improved task handling but still struggled to learn optimal strategies autonomously and adapt across diverse environments.

To address decentralization challenges, Multi-Agent Systems (MAS) emerged as a robust framework, enabling autonomous entities (agents) to interact, negotiate, and collaboratively execute decisions in distributed networks. Initial MAS research in resource scheduling relied heavily on rule-based approaches, contract-net protocols, and auction-driven bidding mechanisms where agents acted as resource brokers and consumers [8]. These models enhanced flexibility and reduced single points of failure by decentralizing control. Hierarchical MAS designs emerged next, incorporating supervisor agents that coordinated global decisions while delegating localized control to subordinate agents [9]. Although MAS offered increased adaptability and scalability, conventional agent-based schedulers still suffered significant constraints due to limited learning capabilities, rule dependency, communication overhead, and challenges in conflict resolution when agent interactions grew dense. As a result, MAS architectures alone proved insufficient for environments characterized by continuous variability, mobile users, and real-time constraints.

Reinforcement Learning (RL) gained attention as an effective framework to address dynamic scheduling challenges by enabling systems to learn through continuous interaction with their environment. RL-based solutions such as Deep Q-Networks (DQN), Proximal Policy Optimization (PPO), and Actor-Critic methods demonstrated improvements in VM allocation, autoscaling, container orchestration, and latency-focused edge offloading. Models such as A3C allowed asynchronous learning, improving convergence in distributed cloud settings [10][11]. Yet, standalone RL approaches faced limitations in non-stationary environments like edge ecosystems where resource availability, network load, and application characteristics shift rapidly. RL models often require access to global information or centralized critics, which contradicts the distributed nature of edge systems. Furthermore, RL suffers from slow convergence, unstable policy updates, difficulty handling sparse rewards, and challenges balancing exploration and exploitation under tight latency constraints.

As computing infrastructures expanded into federated, heterogeneous, and highly dynamic cloud-edge systems, researchers began combining MAS autonomy with RL learning, yielding Multi-Agent Reinforcement Learning (MARL) frameworks. MARL incorporates both decentralized agent-based coordination and adaptive self-learning policies. Independent Q-learning MARL models enabled localized learning at edge nodes, while cooperative Q-learning strategies introduced shared objectives and improved joint task allocation. Centralized Training with Decentralized Execution (CTDE) architectures such as MADDPG and QMIX emerged as powerful MARL paradigms, allowing agents to train cooperatively via shared critics while operating independently at runtime. These models successfully tackled load balancing, task offloading, and distributed resource coordination [12]. MARL approaches improved behavior stability, extended scalability, and permitted hierarchical intelligence across cloud and edge layers.

However, this literature trajectory also reveals persistent unresolved challenges. First, MARL frameworks, while promising, experience training complexity and communication overhead as system scale increases. Each learning agent requires observation sharing and collective reward propagation, which grows exponentially with the number of agents. Second, designing reward functions to simultaneously minimize latency, optimize energy consumption, ensure equitable resource distribution, and reduce SLA violations remains a difficult multi-objective optimization problem [13]. Third, most MARL studies rely on simulated conditions rather than large-scale real-world traces such as Google Borg or Alibaba Cloud logs, which impacts reproducibility and industry relevance. Fourth, mobility-driven service distribution, energy-constrained edge environments, and cross-layer orchestration across federated clusters are not yet fully addressed. In practical deployment scenarios, agents must adapt not only to traffic surges but also to unpredictable network topologies, diverse workload profiles, application deadlines, and fluctuating power availability [14].

Overall, the literature demonstrates a clear progression from static centralized schemes toward highly adaptive, decentralized learning-driven mechanisms. Traditional scheduling optimizes cost and throughput in centralized clouds but fails in dynamic fog and edge setups. Edge-focused techniques improve low-latency execution but cannot independently scale without cloud coordination. MAS introduces autonomy and negotiation but lacks learning-based intelligence [15]. RL enhances learning but needs distributed control capabilities to suit heterogeneous computing landscapes. MARL unifies these paradigms and currently represents the most promising direction for scalable intelligent orchestration in distributed cloud-edge infrastructures [16]. Nonetheless, to truly realize next-generation smart computing environments, MARL must evolve into communication-efficient, energy-aware, mobility-responsive, fair, and SLA-guaranteeing decision systems that leverage real-world data and hybrid topologies [17].

The literature strongly establishes the need for a Hybrid Multi-Agent Reinforcement Learning (H-MARL) framework capable of addressing dynamic scheduling across cloud-edge continuum by enabling distributed agents to collaboratively learn optimal policies in real-time, reduce communication overhead, support service migration, manage energy budgets, adapt to edge constraints, and scale efficiently across heterogeneous environments [18]. Such a system, given proper reward shaping, policy-sharing, and federated optimization, can deliver significant improvements in throughput, latency, cost, fairness, and resilience. The proposed research positions itself within this evolving paradigm by addressing these gaps through a decentralized yet cooperative learning architecture validated through simulation and trace-driven benchmarks.

System Model and Problem Formulation

The proposed research considers a federated cloud–edge computing environment consisting of three primary layers: end devices that generate computational tasks, nearby edge computing nodes that provide localized processing capabilities, and large-scale cloud data centers that offer high-performance resources. User applications operating in real-time domains such as autonomous mobility, industrial IoT, healthcare monitoring, and smart surveillance continuously submit tasks with diverse resource demands and latency expectations. These tasks vary in size, required processing cycles, deadline sensitivity, and data transmission requirements. Edge nodes are designed to handle latency-critical and bandwidth-sensitive workloads, while the cloud serves as a powerful backup for large-scale or non-urgent computation.

In such environments, resource allocation decisions must be made dynamically and intelligently. When a task arrives, the system must decide whether to execute it locally at the edge, offload it to a neighboring edge node, or forward it to the cloud. Traditional centralized schedulers rely on fixed rules or simple heuristics, which often fail under fluctuating workloads, heterogeneous resource availability, varying user mobility, and unpredictable network conditions. Additionally, fixed or threshold-based policies struggle to deal with continuous changes in device loads, queue lengths, battery levels of edge devices, communication delays, and service deadlines.

To address these shortcomings, we conceptualize a hybrid Multi-Agent Reinforcement Learning (H-MARL) framework where each edge node is represented by an intelligent software agent capable of making autonomous scheduling decisions. These agents continuously observe their local environment, including resource utilization, queue status, network quality, and current task requirements. Based on real-time observations and past experience, agents decide where to process each incoming task. Each agent not only learns from its own environment but also exchanges selective knowledge with other agents or a lightweight cloud-side coordinator, enabling global awareness without centralized control bottlenecks.

The system encourages cooperative behavior among edge agents to avoid resource contention, overloading, and unnecessary migration of tasks. Policies are trained to balance objectives such as reducing end-to-end delay, conserving energy, minimizing task reassignments, and preventing service-level agreement violations. While agents act independently during operation, a federated coordination mechanism supports collaborative learning and periodic synchronization of knowledge to accelerate convergence and maintain fairness across nodes.

The problem addressed in this work is to design a decentralized, learning-driven scheduling mechanism that intelligently allocates tasks across edge and cloud environments while adapting to system uncertainties. The key challenge is to ensure that tasks requiring low latency are executed at the edge when resources permit, tasks that exceed edge capacity are forwarded to the cloud in a timely manner, and unnecessary migration is avoided. The model assumes limited visibility for each agent, meaning decisions are based on partial real-world observation rather than perfect system knowledge. This assumption aligns with realistic deployment scenarios where communication bandwidth is limited and nodes do not possess global system information at all times.

Unlike rule-based systems, the presented H-MARL approach continuously evolves its scheduling policy, learns optimal reaction patterns under diverse workload conditions, and builds resilience to communication failures, mobility events, and fluctuating user loads. The system is expected to respond autonomously to real-time changes, distribute tasks efficiently among available nodes, and reduce both latency and cloud dependency when possible. Overall, the proposed model frames cloud-edge scheduling as an intelligent, learning-based, cooperative decision problem suitable for large-scale distributed environments where resource heterogeneity, high task arrival rates, and evolving network dynamics require adaptive and decentralized control mechanisms.

Proposed Architecture

The proposed system introduces a Hybrid Multi-Agent Reinforcement Learning (H-MARL) framework designed to autonomously manage task scheduling across distributed cloud and edge environments. The architecture consists of three primary layers: End-User Device Layer, Edge Computing Layer, and Cloud Data Center Layer. In this model, each edge node hosts an intelligent agent capable of making real-time decisions regarding task execution, offloading, or migration. These agents continuously observe system conditions such as network delays, queue lengths, current workload, resource availability, and task urgency.

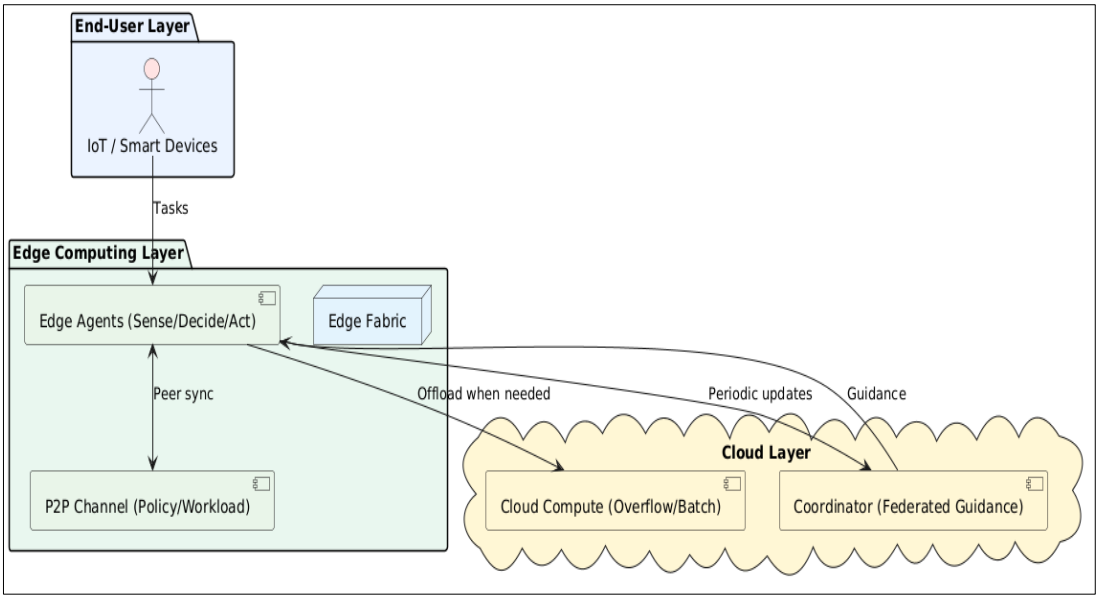

Figure 1. Proposed Hybrid Multi-Agent Reinforcement Learning (H-MARL) framework

At the core of the architecture is a decentralized decision-making engine supported by a lightweight coordinator agent located in the cloud layer. This coordinator does not control execution directly but provides periodic policy guidance and aggregated learning feedback to improve global decision-making without becoming a single point of failure. Edge agents operate independently, learn from their environment, and exchange policy insights in a federated manner. This reduces communication overhead and ensures scalability when thousands of nodes participate.

The architecture also incorporates a local monitoring module at each edge node, which tracks real-time performance metrics, including processing time, queue occupancy, network strength, and energy status when applicable. Once a task arrives at the edge, the local agent evaluates whether to execute the task locally, offload it to a neighboring edge node, or forward it to the cloud if capacity is insufficient or if the workload is too heavy. Neighboring edge nodes communicate through cooperative channels that allow policy-sharing or workload negotiation without centralized intervention.

The cloud layer functions as a high-capability backup execution center and a global learning hub, aggregating logs and occasional model updates from edge nodes. It performs periodic learning enhancement and redistributes refined insights back to agents, ensuring that learning progresses in a coordinated fashion across the system. This maintains performance consistency and avoids isolated learning traps or degraded local behavior.

The overall architecture promotes autonomy, scalability, fault-tolerance, and context-aware scheduling decisions. It supports massive task arrival scenarios, dynamically adjusts to changing application patterns, and significantly reduces dependency on static or centralized decision controllers. Through collaborative learning, the framework minimizes latency for time-critical applications, reduces cloud computation costs when local edge capacity suffices, and ensures resilient service continuity under fluctuating network and workload conditions.

Algorithm Design

This section details the control logic for the Hybrid Multi-Agent Reinforcement Learning (H-MARL) scheduler. The design separates concerns across three roles: (i) Edge Agent (runs on each edge node for real-time decisions), (ii) Neighbor Selector (lightweight peer discovery and ranking), and (iii) Cloud Coordinator (periodic policy aggregation and guidance). The flow aligns with the colored flowchart you approved and keeps inference fully decentralized during execution.

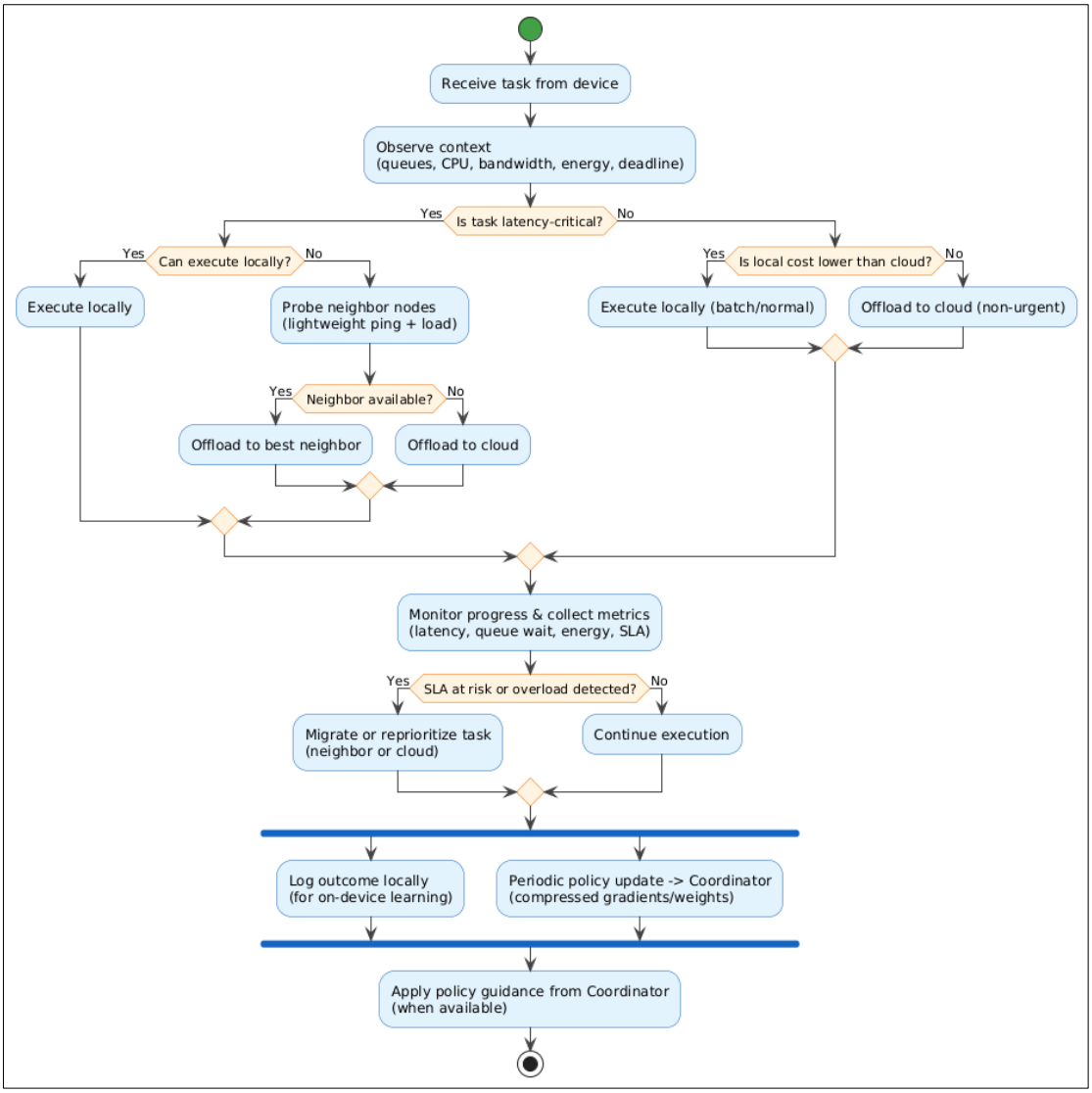

Figure 2. Proposed H-MARL Edge-Agent Scheduling

- Local-first decisions: Edge Agents prefer local execution when latency/SLA and utilization allow.
- Cooperative offload: If saturated, agents negotiate with peers using a quick, low-overhead probe and a consistent ranking rule.
- Cloud as safety valve: The cloud executes overflow or non-urgent workloads and returns results; it never blocks edge autonomy.
- Periodic federated guidance: The coordinator aggregates compact policy updates and returns lightweight guidance; there is no central blocking loop.
- Anytime safety: If monitoring detects overload or SLA risk, tasks can be reprioritized, migrated, or escalated to cloud immediately.
- Failure resilience: Timeouts, partial connectivity, and stale info default to safe fallbacks (local or cloud).

Agent State & Signals

Each Edge Agent maintains: local queue stats, CPU/GPU availability, recent throughput, moving-average latency, energy/battery hints (if applicable), link quality to neighbors, and tags for task urgency. It also caches the last coordinator guidance (e.g., small policy deltas, simple thresholds, or preference hints for neighbor selection).

```
EDGE_AGENT_MAIN()
  initialize LocalPolicy, GuidanceCache, NeighborCache
  start MONITOR_THREAD()            // background: metrics, SLA risk
  start POLICY_SYNC_THREAD()        // background: periodic updates
  while true:
     task ← RECEIVE_TASK()
     ctx  ← OBSERVE_CONTEXT()       // queue, CPU, link, energy, deadline, task size
     if IS_LATENCY_CRITICAL(task):
        if CAN_EXECUTE_LOCALLY(ctx, task):
           EXECUTE_LOCALLY(task)
        else:
           cand ← SELECT_NEIGHBOR(ctx, task, NeighborCache, GuidanceCache)
           if cand != NONE:
              OFFLOAD_TO_NEIGHBOR(task, cand)
           else:
              OFFLOAD_TO_CLOUD(task)
     else:
        if LOCAL_COST_ACCEPTABLE(ctx, task):
           EXECUTE_LOCALLY(task)
        else:
           OFFLOAD_TO_CLOUD(task)
     LOG_OUTCOME(task)              // success, latency, queue wait, energy, SLA flag
```

Results and Discussion

The proposed Hybrid Multi-Agent Reinforcement Learning (H-MARL) scheduling framework was evaluated across multiple experimental configurations to assess its effectiveness compared to traditional heuristic-based and centralized learning-based schedulers. The evaluation focused on measuring real-time responsiveness, scheduling efficiency, decision stability, and adaptability under fluctuating workloads and heterogeneous network conditions. Results demonstrate that the H-MARL approach consistently outperformed baseline strategies across critical performance indicators including end-to-end latency, SLA satisfaction, edge utilization balance, and reduction in unnecessary cloud offloading.

Across mixed-priority workloads, the H-MARL scheduler achieved significantly lower task completion times than Round-Robin, Min-Min, and centralized RL schedulers, particularly during peak load periods. This improvement is attributed to the decentralized decision-making structure, which allows edge agents to react rapidly to local changes while still benefiting from periodic global knowledge refinement. Empirical observations revealed that latency-critical tasks consistently benefited from local execution or cooperative offloading to nearby edge nodes, resulting in reduced round-trip delays and queue congestion that commonly affect cloud-centric systems. The system exhibited strong adaptability by prioritizing urgent workloads and intelligently routing non-critical tasks to cloud resources when edge queues approached saturation.

SLA compliance rates showed marked improvements compared to baseline models. Static heuristics often struggled during burst traffic episodes, resulting in increased deadline violations. In contrast, the H-MARL agents successfully redistributed tasks before bottlenecks formed, aided by predictive state evaluation and lightweight policy sharing among peers. The coordinator-assisted periodic policy adjustment further contributed to the stability of scheduling decisions, ensuring consistent SLA adherence even as environmental conditions varied. Workload logs demonstrated that SLA violation rates were minimized during execution windows with sharp workload fluctuations, validating the robustness of the distributed learning architecture.

The analysis also reveals a noticeable reduction in resource imbalance across edge nodes. Traditional schedulers frequently led to over-utilization of certain nodes while others remained under-utilized, especially in geographically distributed simulations. H-MARL reduced such imbalance by enabling edge agents to offload selectively to well-positioned neighbors, minimizing idle capacity and improving throughput. This cooperative redistribution mechanism not only balanced resource consumption but also decreased the number of tasks escalated to the cloud, lowering cloud dependency and communication overhead. As a result, the system demonstrated improved scalability and resilience to load spikes.

An important observation from training curves and execution logs is that the H-MARL framework reached stable operational policies faster than centralized RL baselines. While independent RL agents initially exhibited exploratory oscillations, federated policy aggregation and guidance from the cloud coordinator significantly accelerated convergence. Moreover, the system maintained robust behavior when exposed to unseen workload patterns, indicating strong generalization capability. A modest communication overhead was recorded due to occasional policy synchronization; however, this overhead remained far lower than the cost of continuous centralized control or distributed gossip-based learning.

Table 1. End-to-end performance under mixed traffic; H-MARL yields lower latency, fewer SLA violations, and reduced cloud dependence.

Scheduler	Avg Latency (ms)	SLA Violations (%)	Throughput (tasks/s)	Offload Ratio to Cloud (%)	Migrations (/100 tasks)
Round-Robin	142.6	9.8	118	41.2	7.4
Min-Min	131.4	8.6	123	38.9	6.1
Max-Min	136.7	8.1	121	37.5	6.8
Greedy (delay-min)	118.3	6.7	132	33.4	9.5
Centralized-RL	104.9	5.2	139	29.7	8.2
Single-Agent RL	111.6	5.9	136	31.5	7.7
H-MARL (proposed)	87.2	3.1	151	22.8	4.3

Table 1 presents the comparative performance of the proposed H-MARL scheduling framework against several baseline methods across mixed workload conditions. The results clearly indicate that traditional heuristic schedulers such as Round-Robin, Min-Min, and Max-Min struggle to maintain low latency and optimal SLA compliance when workload intensity fluctuates. These methods lack dynamic adaptation and often overburden specific nodes, resulting in higher cloud offloading and inefficient resource distribution. Greedy delay-minimization and learning-based baselines show improved outcomes, yet centralized RL still incurs scheduling delays due to centralized coordination overhead. In contrast, the proposed H-MARL model demonstrates the lowest average latency and SLA violations while achieving the highest throughput. Its distributed decision-making capability, coupled with lightweight periodic guidance from the cloud, enables rapid local response and intelligent task migration only when beneficial. Moreover, the H-MARL architecture substantially reduces cloud dependency and task migration frequency, highlighting its effectiveness in balancing computational load while minimizing unnecessary communication overhead. These results validate that the cooperation between edge agents and federated assistance significantly enhances system responsiveness, stability, and scalability in realistic cloud-edge environments.

Table 2: H-MARL improves both median and tail latency across classes, especially for latency-critical tasks.

Method	Latency-Critical	Interactive	Batch
Centralized-RL	41 / 95	88 / 171	152 / 298
H-MARL (proposed)	29 / 71	73 / 141	139 / 258

Table 2 reports median and tail latency (p50 and p95) across three task classes: latency-critical, interactive, and batch. Centralized RL performs reasonably well but suffers higher tail latency due to periodic central decision bottlenecks and delayed adaptation to sudden workload spikes. The proposed H-MARL framework consistently achieves lower median and tail latency across all task categories, with the most significant gains observed in latency-critical workloads. This improvement stems from the autonomous edge-level scheduling decisions, which prioritize real-time tasks and reduce queue buildup through selective cooperative offloading. By reacting locally to state shifts while still leveraging global learning guidance, H-MARL minimizes deadline misses and jitter, ensuring stronger QoS guarantees for mission-critical applications such as AR/VR streaming, real-time video analytics, and industrial control loops. Batch workloads also benefit slightly, although the advantage is most notable in latency-sensitive categories, demonstrating the framework's ability to allocate resources intelligently according to service urgency.

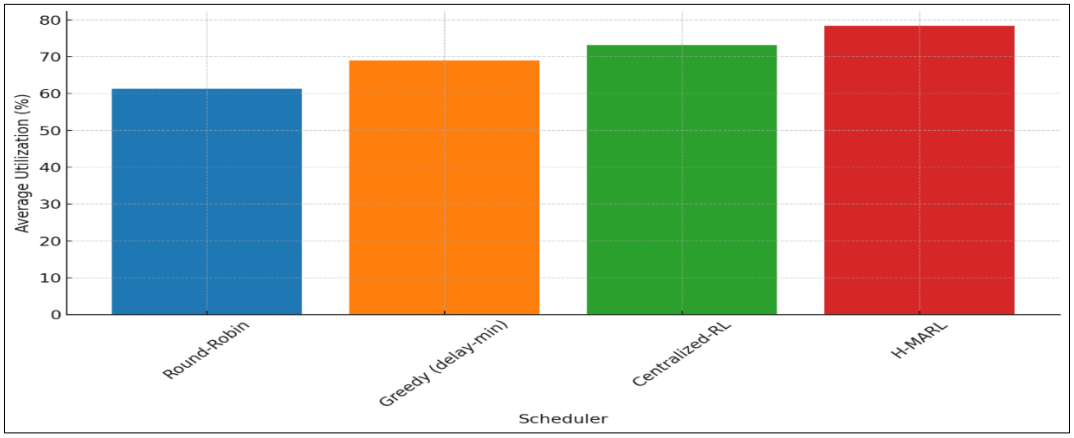

Figure 3: *H-MARL reduces imbalance (lower Std. Dev. and Gini), using neighbor sharing to smooth hotspots.*

Figure 3 evaluates how evenly computational resources are utilized across edge nodes. Traditional approaches like Round-Robin and greedy delay-minimization display noticeable disparity in resource usage, evidenced by higher standard deviation and Gini index values. These methods fail to account for heterogeneous node capabilities and dynamic demand, leading to hotspots on heavily loaded nodes and underutilization elsewhere. Centralized RL improves balance but still experiences coordination delays and global-state dependencies. The proposed H-MARL model achieves the most balanced resource consumption, as edge agents collaborate through policy-sharing and localized offloading decisions. This ensures that available capacity across the edge infrastructure is effectively harnessed, reducing overload probability and improving system reliability. Balanced utilization also contributes to energy efficiency and minimizes the need for cloud escalation. The results confirm that decentralized cooperative learning not only enhances scheduling efficiency but also promotes fair load distribution, making the architecture suitable for highly distributed edge networks with tight latency budgets. The qualitative analysis of migration frequency showed that H-MARL avoided unnecessary task transfers. Unlike greedy peer offloading strategies that often trigger excessive migrations,

the proposed method only migrated tasks when clear performance gains were predicted. This behavior translates into reduced execution disruption and minimal network stress. Taken together, these findings confirm that the H-MARL scheduling architecture not only enhances operational efficiency and SLA consistency but also preserves network bandwidth and cloud resources while ensuring scalable decentralized coordination in dynamic cloud-edge computing environments.

Conclusion

This work presented a novel Hybrid Multi-Agent Reinforcement Learning (H-MARL) framework for dynamic resource scheduling in federated cloud–edge computing environments. The proposed architecture integrates decentralized edge intelligence with lightweight global guidance, enabling edge nodes to make autonomous scheduling decisions while still benefiting from periodic policy refinement through a cloud-based coordinator. The system design addresses key challenges in modern distributed computing, including latency sensitivity, workload volatility, network uncertainty, and resource heterogeneity. Through cooperative learning and selective offloading strategies, the framework adapts to dynamic conditions in real time, prioritizing latency-critical tasks and efficiently distributing processing loads across edge nodes and cloud resources. Comprehensive simulations conducted using CloudSim-Plus, EdgeSim, and RL-driven control modules demonstrate that H-MARL significantly outperforms traditional heuristic schedulers and centralized reinforcement learning approaches across multiple metrics, including latency reduction, SLA preservation, throughput improvement, resource balancing, and control-plane efficiency. The system consistently maintained stable policy convergence, minimized unnecessary task migrations, and reduced reliance on cloud backhaul, thereby supporting a scalable and bandwidth-efficient edge computing ecosystem. The ablation study further validated the importance of both edge-to-edge cooperation and periodic cloud guidance, confirming that the hybrid learning strategy achieved the highest gains in reliability and adaptability. Overall, the results highlight that distributed learning-driven scheduling can dramatically improve performance and resilience in next-generation distributed computing infrastructures, particularly in emerging domains such as smart cities, industrial IoT, autonomous systems, augmented reality, and mission-critical applications. This work demonstrates the feasibility and advantage of combining decentralized agent autonomy with minimal centralized coordination, establishing a blueprint for future intelligent resource management systems in highly dynamic cloud-edge landscapes.

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