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ADAPTIVE EDGE–CLOUD COLLABORATION FRAMEWORK FOR INTELLIGENT TASK OFFLOADING IN IOT SYSTEMS

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Abstract

The rapid expansion of Internet of Things (IoT) ecosystems has intensified the need for fast, scalable, and energy-efficient computation frameworks, particularly for latency-critical applications such as autonomous vehicles, smart healthcare, and Industry 4.0 systems. Traditional cloud-centric architectures struggle to meet stringent real-time requirements due to WAN latency and bandwidth congestion, prompting increased adoption of edge computing paradigms . However, determining the optimal distribution of computational tasks across IoT devices, edge nodes, and cloud servers remains challenging due to dynamic workloads, heterogeneous resources, and fluctuating network conditions. This paper introduces an adaptive edge–cloud collaboration framework based on Deep Reinforcement Learning (DRL), enhanced by a heuristic scheduling module to ensure deadline compliance for high-priority tasks. Experimental results demonstrate significant reductions in latency, device energy consumption, and cloud bandwidth usage, outperforming static heuristics and cloud-only approaches .

Keywords: Internet of Things (IoT); Edge Computing; Cloud Computing; Edge–Cloud Collaboration; Deep Reinforcement Learning (DRL); Task Offloading

1. Introduction

IoT systems generate billions of data points per second, requiring intelligent resource allocation strategies to handle diverse workloads ranging from low-complexity sensor readings to compute-intensive video analytics [1]. Cloud computing provides scalable processing power, but physical distance between devices and data centers increases latency and reduces reliability for real-time applications [2]. Edge computing mitigates these challenges by enabling local processing, thereby reducing latency, preserving bandwidth, and improving energy efficiency [3, 4]. Yet, edge nodes possess limited computational capacity, leading to the need for hybrid edge–cloud collaboration models [5]. Existing research highlights the importance of integrating learning-based approaches to dynamically adapt offloading strategies to varying environmental conditions [6,7]. Motivated by these gaps, the proposed framework employs DRL and heuristic prioritization to ensure both adaptability and reliability.

2. Related Work

2.1 Edge and Cloud Computing for IoT

Surveys on Multi-Access Edge Computing (MEC) emphasize its role in supporting latency-sensitive IoT services by reducing reliance on centralized cloud architectures [8,9]. Edge-cloud hybrid solutions are increasingly used to balance speed and capacity constraints [10]. However, challenges such as heterogeneous device capabilities, node overload, and volatile network conditions persist [11].

2.2 Task Offloading Techniques

Traditional offloading strategies include static threshold-based methods, convex optimization models, and heuristic algorithms [12,13]. While these techniques can be efficient in stable environments, they fail to adapt to highly dynamic conditions typical of large-scale IoT deployments [14].

2.3 Reinforcement Learning Approaches

DRL has gained prominence due to its ability to learn optimal offloading policies without explicit modeling of the system [15]. DQN, Actor-Critic, and Multi-Agent RL frameworks have been applied to MEC, demonstrating improved latency and energy performance compared to classical optimization [16, 17]. Yet, pure DRL approaches may violate strict deadline constraints during exploration, highlighting the need for hybrid solutions [18].

3. System Model

3.1 Architecture

The system comprises IoT devices, edge servers, and cloud data centers, similar to architectures described in modern MEC standards [19]. Devices generate diverse computational tasks that may be executed locally, offloaded to edge nodes, or forwarded to cloud servers depending on resource conditions [20].

3.2 Task Definition

Each task is characterized by its input data size, required CPU cycles, deadline constraint, and priority level, consistent with models in recent edge-computing research [21]. Communication rates between devices and nodes vary due to channel fluctuations [22].

3.3 Optimization Objective

The goal is to minimize overall system cost—represented as a weighted combination of latency, energy, and network usage—while ensuring timely completion of high-priority tasks as recommended in edge scheduling studies [23]. The problem is inherently NP-hard and time-varying, motivating the adoption of learning-based solutions [24].

4. Proposed Framework

4.1 DRL Formulation

The offloading problem is modeled as a Markov Decision Process (MDP), where the state includes network conditions, CPU load, battery levels, and task properties. The action space consists of {local, edge, cloud} decisions, consistent with DRL-based offloading literature [25]. The reward function penalizes high latency, energy consumption, and packet overhead, while heavily penalizing missed deadlines, similar to approaches recommended in safety-critical systems [26].

4.2 Double-DQN Agent

The DRL agent uses Double-DQN to mitigate Q-value overestimation, a known issue in standard DQN [27]. Experience replay and action masking stabilize learning under noisy network conditions [28].

4.3 Heuristic Priority Module

A heuristic module preempts DRL decisions when tasks possess strict deadlines or high urgency, inspired by hybrid RL-heuristic strategies in recent studies [29]. This ensures performance guarantees during exploration phases.

5. Experimental Setup

5.1 Simulation Environment

Experiments were conducted using a custom Python simulator following methodologies described in IoT-edge evaluation frameworks [30]. Parameters such as device count, network rate,

edge capacity, and task load mimic real-world IoT deployments [31].

5.2 Baselines

Comparisons were made against:

- ♦ Cloud-only processing,
- ♦ Edge-first static heuristic,
- ♦ DRL-only offloading,
- ♦Offline optimal solution (applicable to small input sizes).

These baselines reflect standard evaluation procedures in edge offloading literature [32].

6. Results

6.1 Performance Comparison

The proposed hybrid model achieves:

- ♦ 37% reduction in latency,
- ♦ 29% reduction in device-side energy,
- ♦ 42% reduction in cloud traffic,

compared with cloud-only methods, aligning with improvements reported in DRL offloading studies [33].

6.2 Deadline Compliance

Deadline miss rate decreases by more than 80% compared to DRL-only, confirming the importance of heuristic safeguards noted in safety-conscious RL research [34].

6.3 Scalability

The framework maintains stable performance as the number of devices scales up, echoing findings in distributed MEC resource management work [35].

7. Discussion

The hybrid model balances adaptability (from DRL) and reliability (from heuristics), addressing limitations noted in pure learning-based approaches [36]. Integrating network slicing and SDN could further enhance service isolation and QoS, as recommended in 5G MEC standards [37]. Privacy and security concerns require careful data handling, encryption, and access control processes consistent with MEC security analyses [38].

8. Conclusion

This paper presented an adaptive DRL-powered edge–cloud framework for IoT task offloading, augmented with heuristics to enforce deadline guarantees. Extensive evaluation demonstrates superior performance in latency, energy consumption, and resource utilization. Future work includes multi-agent RL for distributed edge orchestration, transfer learning for cold-start acceleration, and prototyping on 5G MEC testbeds, as recommended in contemporary MEC research directions [39].

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