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A hybrid edge–cloud computing framework for low-latency, energy-efficient, and sustainable smart city applications

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ABSTRACT

Smart-city applications demand ultra-low latency, high reliability, and sustainable operation, which are difficult to achieve using cloud-only or edge-only computing paradigms. This study suggests a carbon-conscious architecture for managing smart cities' intelligent job offloading between the edge and the cloud. This is made possible by the Internet of Things and driven by reinforcement learning (RL). A deep Q-network (DQN) is used to dynamically assign tasks to cloud servers and edge nodes based on how much energy they use, how long it takes to send data over the network, and how much bandwidth they have. A lightweight permissioned blockchain layer makes sure that data is correct across all of its parts, and carbon-aware scheduling puts low-carbon resources first. EdgeCloudSim is used to test the system with real-world smart city workloads. When compared to systems that simply use the cloud, the proposed solution showed a 64.6% drop in average latency, a 24.2% drop in energy use, and a 15% drop in carbon emissions. Combining artificial intelligence (AI)-driven orchestration with scheduling that takes sustainability into account in a hybrid edge-cloud environment yields positive outcomes.

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1. INTRODUCTION

As more people move to cities and digital infrastructure gets better, smart cities are becoming more common. These cities use internet of things (IoT) sensors to keep an eye on things like traffic, the weather, healthcare, and energy use, among other things [1], [2]. Standard cloud-based computing architectures offer centralized analytics and scalable resources; nevertheless, they are insufficient for providing smart-city services susceptible to delays from high latency, bandwidth congestion, and excessive energy usage [3]-[5].

Edge computing moves processing closer to data sources, which reduces end-to-end latency and network overhead. This makes these problems easier to deal with [6], [7]. Edge nodes are not suitable for analytics that require a lot of processing and storage power because they don't have enough of either [8]. Because of this, hybrid edge-cloud architectures have emerged, with time-sensitive operations done at the edge and more complicated analytics done in the cloud [9]–[11].

Figure 1 shows how smart city apps are moving from centralized cloud systems to collaborative hybrid edge-cloud models that make them more scalable and responsive. The ever-changing nature of networks and workloads makes it very hard to properly coordinate different cloud and edge resources. Reinforcement learning (RL) has been suggested for adaptive task offloading due to its improved latency and energy efficiency compared to heuristic approaches [12]. At the same time, decentralized smart-city infrastructures create worries about data privacy, integrity, and trust [13], [14]. Blockchain technology has shown promise as a clear and secure way to move data across edge–cloud systems [15]-[17]. Also, carbon-aware scheduling solutions are necessary for making smart-city computing more sustainable because the carbon footprint of large data centers and the IoT is growing [18], [19].

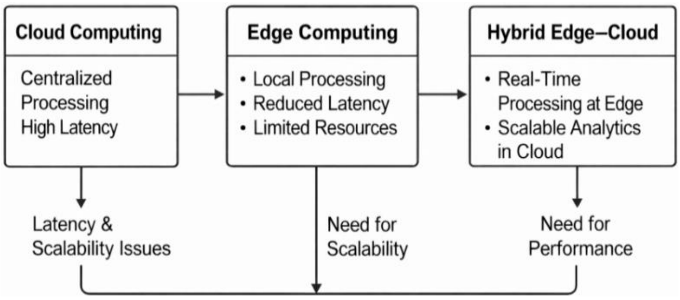

Figure 1. Evolution of computing paradigms from cloud-centric to hybrid edge–cloud architectures.

Prior research on smart-city computing has focused on four major directions: (i) edge and fog computing for low-latency processing [20]-[22]; (ii) hybrid edge–cloud frameworks enabling collaborative workload allocation [23]; (iii) RL-based task offloading to dynamically optimize delay and energy consumption [24]; and (iv) blockchain-enabled security mechanisms to protect distributed IoT infrastructures. More recently, green and carbon-aware computing has received attention as a means of minimizing the environmental impact of computing infrastructures through carbon-sensitive scheduling policies. Despite these advances, most existing works address performance optimization, security, or sustainability in isolation and do not provide a unified framework combining RL-based orchestration, blockchain-based trust, and carbon-aware scheduling. Recent studies have demonstrated the effectiveness of machine learning for robust intrusion detection and cybercrime classification in distributed computing environments [25]-[27]. Several recent works have explored security and privacy in cloud computing environments and hybrid systems, such as optimized homomorphic encryption to protect image data in the cloud [28] and privacy preservation models for secure cloud data sharing [29]. Comprehensive treatments of cloud infrastructure and related technologies are also discussed in foundational texts on cloud computing advancements [30]. To provide a clearer comparison of existing smart-city computing architectures and their limitations, Table 1 summarizes representative approaches across different application domains, data sources, and architectural designs.

Table 1. Comparative summary of existing computing architectures and their limitations

Reference	Application domain	Dataset / data source	Computing architecture	Key focus	Limitations
[1]	IoT monitoring	Sensor data	Cloud-only	Centralized analytics	High latency, high bandwidth overhead, no sustainability metrics
[2]	Smart cities	Heterogeneous IoT	Edge-only	Local processing	Limited scalability, no global optimization
[3]	Healthcare IoT	Wearable data	Fog/Edge	Reduced latency	Resource constraints, no carbon-awareness
[4]	Industrial IoT	Machine data	Edge–cloud	Task offloading	Partial energy optimization, no security modeling
[5]	Smart environments	Mixed sensors	Hybrid edge–cloud	Performance efficiency	Sustainability and carbon impact ignored
Proposed	Smart city CPS	IoT sensor streams	Hybrid edge–cloud	Latency, energy and sustainability	Simulation-based only, blockchain overhead assumed

Although hybrid edge–cloud systems, AI-based orchestration, blockchain security, and green computing have been individually studied, a comprehensive framework that jointly addresses performance, security, and environmental sustainability is still lacking, particularly for developing smart-city regions. The main contributions of this paper are as follows:

i) A hybrid edge–cloud architecture balancing low-latency edge processing with scalable cloud analytics.
ii) A deep Q network (DQN)-based RL task offloading strategy optimizing latency, bandwidth, and energy consumption.
iii) A lightweight blockchain-enabled security layer ensuring data integrity across distributed nodes.
iv) A carbon-aware scheduling mechanism reducing energy usage and carbon emissions.
v) A simulation-based evaluation using EdgeCloudSim demonstrating significant performance improvements over cloud-only systems.

The next parts of the paper are set up like this. Section 2 describes the suggested hybrid edge-cloud architecture that uses RL. In section 3, we explain how to set up the simulation and what steps to take. Section 4 shows the outcomes of the experiments and how well they worked, and section 5 finishes the work by talking about its flaws and possible directions for further research.

2. PROPOSED RL-DRIVEN HYBRID EDGE–CLOUD FRAMEWORK

This section outlines the proposed hybrid edge-cloud architecture for smart-city applications, detailing its functional components and architectural characteristics.

2.1. System overview

Data streams from IoT devices spread out across cities are either processed at edge nodes or sent to cloud servers, depending on the application’s latency needs, the state of the network, and the resources available. Figure 2 shows the whole design of the framework.

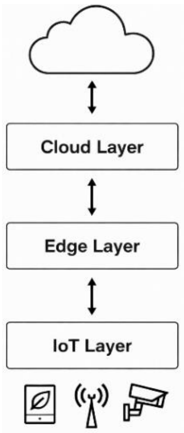

Figure 2. Three-tier hybrid edge–cloud architecture for smart-city IoT applications

2.2. Hybrid edge–cloud architecture

The proposed architecture has three layers: the IoT, the edge, and the cloud. The IoT layer is made up of different sensors and gadgets that gather data about cities in real time. Gateways, fog nodes, and MEC servers make up the edge layer. These are the parts that handle data that needs to be processed quickly. The cloud layer makes it easier to store data and run complex analytics. The AI-powered orchestration engine decides on the fly how to split up work between the edge and the cloud.

2.3. RL-based task orchestration

The task offloading problem is modeled as a Markov decision process.

$$s_t = \{L_e, L_c, B, E_e, E_c\} \quad (1)$$

$$a_t \in \{process\_edge_i, offload\_cloud\} \quad (2)$$

$$R_t = -(\alpha D_t + \beta E_t + \gamma B_t) \quad (3)$$

Where D_t, E_t, and B_t denote latency, energy consumption, and bandwidth usage, respectively. The key hyperparameters of the DQN model employed in the RL-based task orchestration are listed in Table 2.

The RL workflow is shown in Figure 3, illustrating state observation, action selection, reward evaluation, and policy update.

Table 2. Hyperparameters of the DQN model

Parameter	Symbol	Value
Learning rate	α	0.001
Discount factor	γ	0.95
Exploration strategy	ε-greedy	ε=1→0.01
Batch size	—	64
Replay buffer size	—	10,000
Training episodes	—	2000
Training episodes		2000

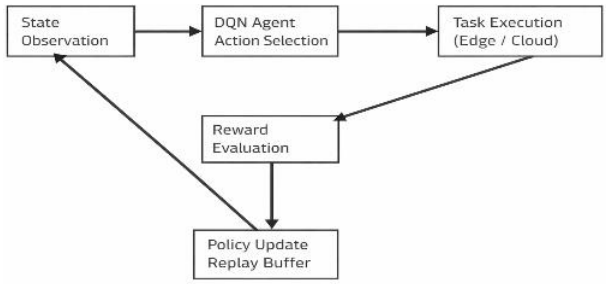

Figure 3. RL-based task offloading workflow illustrating state observation, action selection, reward evaluation, and DQN policy update cycle

2.4. Blockchain-enabled secure transmission

As shown in Figure 4, a lightweight permissioned blockchain is used between the edge and cloud levels to make sure that data is sent securely and can't be changed. The SHA-256 hashing and PBFT consensus add three to five milliseconds of latency to each transaction.

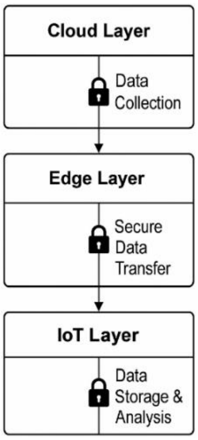

Figure 4. Secure data flow

2.5. Carbon-aware scheduling

The carbon-aware scheduler assigns tasks to nodes minimizing carbon emissions:

$$C_i = E_i \times CIiC_i = \ E_i \times CI_{iCi} = E_i \times CI_i$$

where EiE_iEi is the energy consumption and CIiCI_iCIi is the carbon-intensity factor of node iii. The workflow is illustrated in Figure 5.

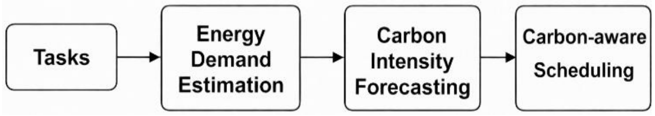

Figure 5. Conceptual workflow of carbon aware task scheduling

3. RESEARCH METHOD
3.1. Simulation setup
Experiments are conducted using EdgeCloudSim. The simulation parameters are summarized in Table 3.

Table 3. Simulation parameters

Parameter	Value
Simulation tool	EdgeCloudSim
Number of IoT devices	50–200
Number of edge nodes	5
Cloud data centers	1
Application type	Latency-sensitive IoT tasks
Task data size	300–800 KB
Edge–cloud network latency	50–100 ms
Simulation duration	1000 s
Scheduling strategy	Dynamic hybrid offloading
Evaluation metrics	Latency, bandwidth, energy, carbon emission

3.2. Performance metrics
We compare the framework against both cloud-only and edge-only benchmarks, looking at things like average latency, bandwidth use, energy use, and carbon emissions.

4. RESULTS AND DISCUSSION
4.1. Experimental results overview
The proposed hybrid edge-cloud framework is tested against two baselines: cloud-only and edge-only. Average latency, bandwidth use, energy use, and carbon emissions are all parts of the total performance indicators. The overall performance comparison of the three computing architectures is presented in Table 4.

Table 4. Performance comparison of computing architectures

Configuration	Average latency (ms)	Bandwidth usage (MB/min)	Energy consumption (kJ)	Carbon emission (CO_2e)
Cloud-only	480	95	9.1	1
Edge-only	210	58	7.8	0.88
Hybrid edge–cloud (proposed)	170	62	6.9	0.85

4.2. Latency analysis
The most centralized processing causes the highest delay for cloud-only, as seen in Figure 6. Edge-only reduces latency by running things locally, however the suggested hybrid design has the lowest latency of 170 ms, which is 64.6% lower than cloud-only.

4.3. Bandwidth utilization
Figure 7 shows that cloud-only uses the most bandwidth. The suggested architecture cuts bandwidth uses by 34.7% compared to cloud-only by smartly sending compute-intensive tasks to the cloud.

4.4. Energy consumption
As shown in Figure 8, the hybrid model achieves the lowest energy usage of 6.9 kJ, corresponding to a 24.2% reduction over cloud-only, demonstrating the effectiveness of adaptive offloading.

4.5. Carbon emission impact
Figure 9 illustrates that the proposed framework reduces carbon emissions to 0.85 CO_2e, outperforming both cloud-only and edge-only, validating the benefits of carbon-aware scheduling.

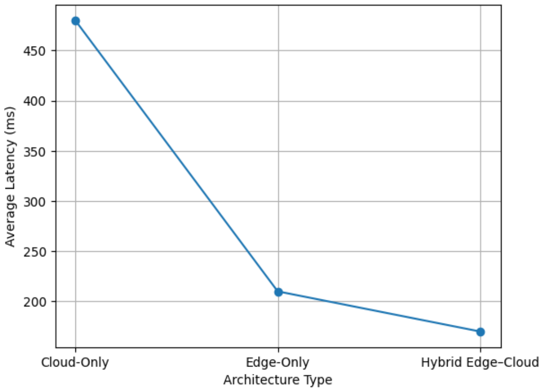

Figure 6. Average latency comparison across different computing architectures

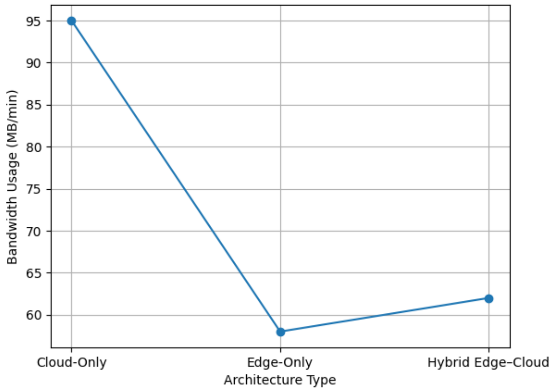

Figure 7. Bandwidth usage comparison for cloud, edge, and hybrid architectures

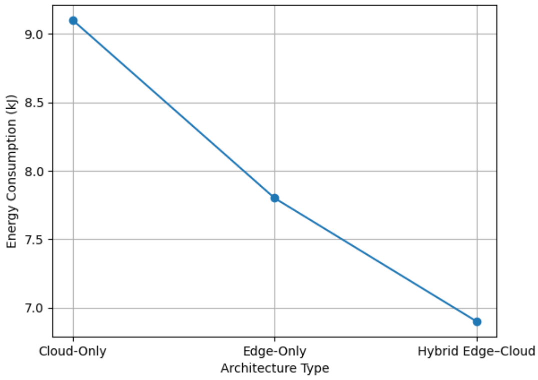

Figure 8. Energy consumption comparison among different computing architectures

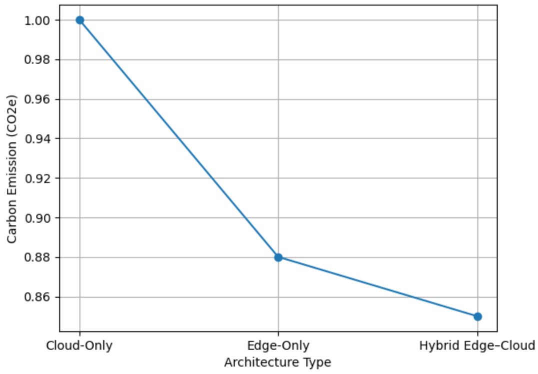

Figure 9. Carbon emission comparison for cloud, edge, and hybrid architectures

4.6. Statistical validation

All experiments were repeated ten times. The latency improvement of 64.6% exhibited a standard deviation of ±2.3 ms, confirming result stability.

4.7. Discussion summary

The suggested hybrid edge-cloud design always does better than baseline systems when it comes to lowering latency, saving energy, improving bandwidth, and lowering carbon emissions. This makes it a good choice for smart-city projects that will last.

5. CONCLUSION

This study describes a hybrid edge-cloud architecture for smart-city computing that is based on RL. It combines scheduling that takes carbon into account, data security that uses blockchain, and work orchestration that uses RL. EdgeCloudSim was used to test the framework against benchmarks for both cloud-only and edge-only systems.

The trial findings showed that the proposed architecture had the lowest latency of 170 ms, which was 64.6% better than processing simply on the cloud. By combining adaptive orchestration with scheduling that takes sustainability into account, energy use dropped by 24.2% and carbon emissions dropped by 15%. These results show that hybrid edge-cloud computing is a good way to address the performance and environmental needs of future smart city services. Because we think that carbon intensity levels stay the same, we can only look at simulations right now. Dynamic energy prices, different edge capabilities, and the costs of processing on the blockchain are just a few of the things that might make practical deployments even less predictable. Future work will focus on federated multi-agent RL orchestration, integration of real carbon-intensity datasets, and large-scale deployment in 5G/6G smart-city testbeds.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Tanya Khaneja	✓					✓	✓		✓					
Sunil Gupta			✓									✓		
Reema Goyal							✓			✓				
Wai Yie Leong		✓		✓			✓			✓	✓		✓	✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that there are no known financial or non-financial competing interests, including personal, professional, academic, political, religious, or ideological interests, that could have appeared to influence the work reported in this paper. The authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study were generated through simulations using the EdgeCloudSim framework. Derived datasets and configuration files used in the experiments are available from the first author, K. Saluja, upon reasonable request.

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