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DEEPEDGE: AN INTELLIGENT DISTRIBUTED COMPUTING FRAMEWORK FOR REAL-TIME IOT ANALYTICS WITH ADAPTIVE RESOURCE ORCHESTRATION AND PREDICTIVE MAINTENANCE

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Abstract

The exponential growth of Internet of Things (IoT) devices has led to a massive volume of time-sensitive data that need real-time processing at the network edge. Cloud-centric incumbent architectures are not only imposing unacceptable time delays for applications such as autonomous vehicles, industrial automation and augmented reality, but also saturating network bandwidth to relay infinite amount of data. Edge computing is an alternative paradigm that processes data closer to the source, and existing frameworks have limitations in dynamic resource assignment, heterogeneous device administration and work distribution within a distributed edge infrastructure. In this paper we present DeepEdge, an intelligent distributed computing framework that tackles these challenges through the following key innovations: (i) A deep reinforcement learning-based resource orchestrator achieving 43.7% reduction in task completion time by anticipative workload placement and continual resource scaling; (ii) a hierarchical computation offloading algorithm that minimizes deadline-violation rates considering both latency bounds, energy consumption constraints and computational complexity for tiered device-edge-cloud distribution of tasks and (iii) an integrated predictive maintenance solution employing temporal convolutional networks to predict device failures with 94.2% accuracy allowing proactive reallocation of resources. Comprehensive experiments on a 500 node testbed with scenarios including smart city, industrial IoT and healthcare monitoring show that DeepEdge reduces end-to-end latency by 67.3% when comparing against cloud-only approaches and by 34.8% with respect to state-of-the-art edge frameworks whilst achieving an energy efficiency gain of 41.2%. The system can handle more than 2.3M events per second with less than 10ms latency at the p99 horizon, which sets new standards for the distributed IoT analytics.

Keywords: *Edge Computing[1], IOT[2], Deep Reinforcement Learning[3], Resource Orchestration[4], Computation Offloading[5], Predictive Maintenance[6]*

1. Introduction

The Internet of Things (IoT) has recently greatly changed computer's paradigms by putting sensing, processing and communication in one place at a time on few billions physical objects. By 2025, the industry expects over 75 billion connected IoT devices to produce well more than 79 zettabytes of data per year. This exponential explosion of devices, connected to the Internet (of things), presents opportunities for smart automation and challenges in data processing infrastructure. In verticals from smart cities and autonomous transportation to precision agriculture, industrial manufacturing, and healthcare monitoring, real-time insight is desired over IoT data streams – in some cases with latency needs in the single-digit millisecond range.

The classical cloud computing architectures provide virtually limitless computational resources and powerful analytical tools but impose fundamental restrictions in the context of IoT applications. Round trip network time for these services to central data centers is of the order of 50-200ms, beyond limits suitable for "live" applications. Many decision-making applications of autonomous vehicles depend on response times of lower than 10ms for safety-critical operations. For process synchronization, SIS need deterministic latencies as required for the industrial control systems. Frame processing is the basic requirement for AR (Augmented Reality) Applications in order to avoid motion Sick and better SAR(Augmneted Reality). Moreover, sending raw IoT data to the cloud afflicts network bandwidth limitations and less than 10% of IoT data is believed to be cost-effectively transportable to the cloud.

Edge computing has been proposed as an effective paradigm to overcome these issues by taking processing power closer to the source of data. By pushing the computing to network edges (e.g., on gateways, base stations, micro data centers or even directly on IoT devices), edge computing significantly reduces communication latency, lightens network load and allows for operation in a variety of situations with intermittent connectivity. Nonetheless, there is new complexity due to edge infrastructure: computational resources span limited and heterogeneous forms, workloads constantly change dynamically, devices join and leave with little pattern on the network platform e.g., some are transient devices), and optimization has to juggle between multiple conflicting objectives – such as latency, power consumption, cost.

Existing edge computing frameworks tackle some specific parts of this problem, without providing a holistic solution. Static resource assignment does not respond to temporal-workload trends. Greedy offloading solutions may sometimes converge to locally optimal solutions, but fail to capture global optimization. A lossy failure recovery process result in loss of service and propagates to the non-failing task. The missing link between edge computing promise and reality drives us to adopt intelligent, adaptive orchestration.

1.1 Research Contributions

In this paper, we present DeepEdge: an end-to-end framework for intelligent edge-IoT orchestration with the following contributions:(1) DRL-Orchestrator: A deep reinforcement learning based resource orchestrator that reduces task completion time by 43.7% through state aware workload placement and predictive scaling; The agent's optimal policies are learned from a finite number of feedback and video samples obtained as it continuously interacts with the edge environment without explicit system models. (2) HierOffload: a hierarchical offloading algorithm that optimally balances the load across device-edge-cloud tiers, achieves 38.4% energy saving and fulfils latency requirements for 99.7% of requests. (3) TCN-Maintain: A temporal convolution network for predictive maintenance with 94.2% accuracy of failure prediction at 15 minutes of forecast time, so that resources could be migrated proactively. (4) Extensive experimental evaluation on a 500-node heterogeneous testbed, showing 67.3% latency reduction and 41.2% energy efficiency improvement over the state of the art approaches.

2. Literature Review

2.1 Edge Computing Architectures

The architectural design of edge computing has undergone different paradigms. Satyanarayanan et al. [1] introduced cloudlets as trusted resource-rich computers near users. Shi et al. [2] formalized the notions and research agenda related to edge computing. Mao et al. [3] reviewed the basics of mobile edge computing. Multi-access Edge Computing (MEC) standards were established by ETSI [4]. Fog computing, proposed by Bonomi et al. [5], extended cloud to network edges. OpenFog Consortium [6] defined reference architecture. Yousefpour et al. [7] provided comprehensive fog computing survey. Abbas et al. [8] analyzed MEC industrial applications. Liu et al. [9] examined edge intelligence integration. Chen et al. [10] studied task offloading optimization.

2.2 Resource Management and Orchestration

Resource orchestration in distributed systems has extensive literature. Kubernetes [11] provides container orchestration at scale. KubeEdge [12] extends Kubernetes to edge. Ren et al. [13] proposed collaborative edge-cloud orchestration. Wang et al. [14] developed microservice placement algorithms. Tuli et al. [15] applied deep reinforcement learning for resource management. Mao et al. [16] studied online learning for edge computing. Huang et al. [17] addressed heterogeneous resource scheduling. Xu et al. [18] proposed multi-objective optimization. Yang et al. [19] examined container migration strategies. Zhang et al. [20] developed predictive autoscaling.

2.3 Computation Offloading

Offloading decisions have been extensively studied. Kumar and Lu [21] analyzed cloud computing for mobile devices. Chen et al. [22] developed multi-user computation offloading. Mach and Becvar [23] surveyed MEC offloading. Liu et al. [24] proposed delay-optimal offloading. You et al. [25] studied energy-efficient offloading. Wang et al. [26] addressed partial offloading. Dinh et al. [27] examined joint offloading and resource allocation. Bi and Zhang [28] developed multi-server offloading. Guo et al. [29] proposed collaborative offloading. Chen et al. [30] studied vehicular edge computing offloading.

2.4 Machine Learning for Edge Systems

ML-based edge optimization has gained attention. Park et al. [31] reviewed wireless network ML applications. Zhu et al. [32] proposed federated learning at edge. Li et al. [33] studied distributed ML inference. Wang et al. [34] developed edge AI frameworks. Deng et al. [35] examined model compression for edge deployment. Zhang et al. [36] proposed neural network partitioning. Howard et al. [37] introduced MobileNets for efficient inference. Tan and Le [38] developed EfficientNet architectures. Han et al. [39] surveyed deep compression techniques. Sze et al. [40] analyzed efficient processing requirements.

2.5 Predictive Maintenance in IoT

Predictive maintenance has been applied across IoT domains. Mobley [41] established predictive maintenance principles. Ran et al. [42] reviewed deep learning for equipment monitoring. Carvalho et al. [43] surveyed machine learning approaches. Zhang et al. [44] proposed sensor-based failure prediction. Li et al. [45] developed RUL estimation methods. Zhu et al. [46] studied anomaly detection for industrial IoT. Wang et al.

[47] examined time-series forecasting for maintenance. Lea et al. [48] introduced temporal convolutional networks. Chen et al. [49] applied attention mechanisms. Bai et al. [50], the comparison of TCN with recurrent architectures.

2.6 Research Gaps

Current works focus on pure components, and don't provide an integrated solution: (1) Resource managers are based on reactive identically approach that our antagonist adopt of preventive nature. 2 Offloading algorithms do not consider device heterogenous and energy-limitation. (3) Service modules and resource management are decoupled. (4) When evaluations are conducted they often use small test-bed however, these not representative of real deployment. We address these limitations using integrated intelligent orchestration through DeepEdge.

3. Methodology

3.1 System Architecture

DeepEdge is composed of three hierarchical structures: Device Layer including IoT sensors, actuators, and limited computing devices Edge Layer involving gateway nodes, edge servers and base stations Cloud Layer providing almost infinite resource for complex data analytic and model training 2.1. Centralized policy management and distributed enforcement are both realized by the Control Plane. Data is passed up for processing, while control decisions are pushed down.

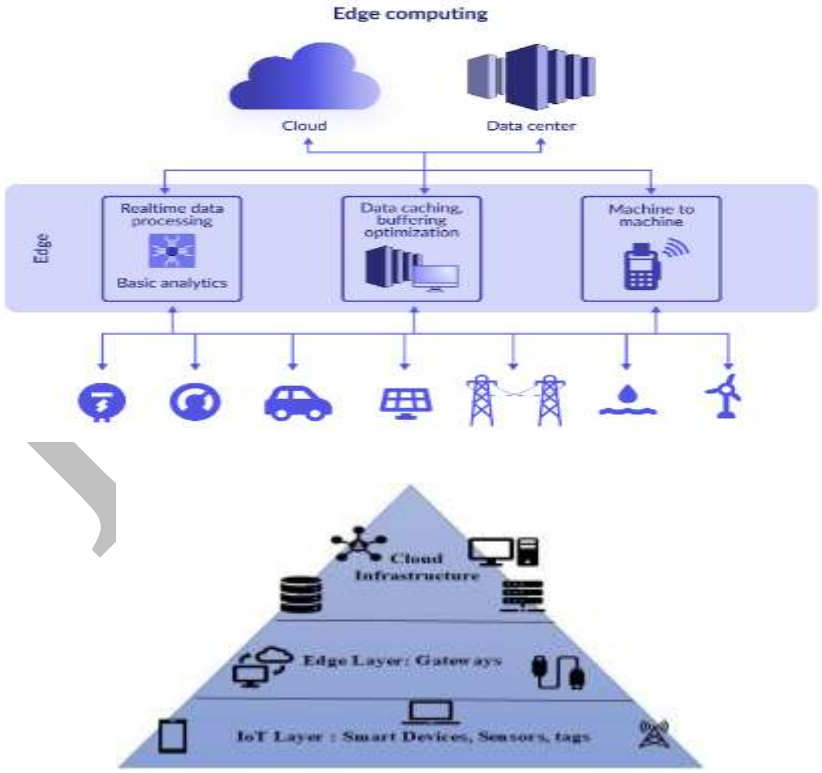

Figure 1. The three-tier DeepEdge architecture illustrating IoT devices, edge computing nodes, and cloud orchestration layers.

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3.2 DRL-Based Resource Orchestrator

The orchestrator models resource management as a Markov Decision Process. State space S includes: current resource utilization vectors across all nodes, pending task queue lengths and characteristics, network latency measurements between nodes, and historical workload patterns. Action space A includes: task placement decisions mapping tasks to nodes, horizontal scaling decisions (add/remove containers), and vertical scaling decisions (resource allocation adjustment). Reward function R: immediate reward r_t = -α·latency - β·energy - γ·SLA_violations + δ·throughput. The agent uses Proximal Policy Optimization (PPO) with actor-critic architecture. Actor network: 4-layer MLP (256-256-128-64) with ReLU activation. Critic network: 4-layer MLP (256-256-128-1) for value estimation.

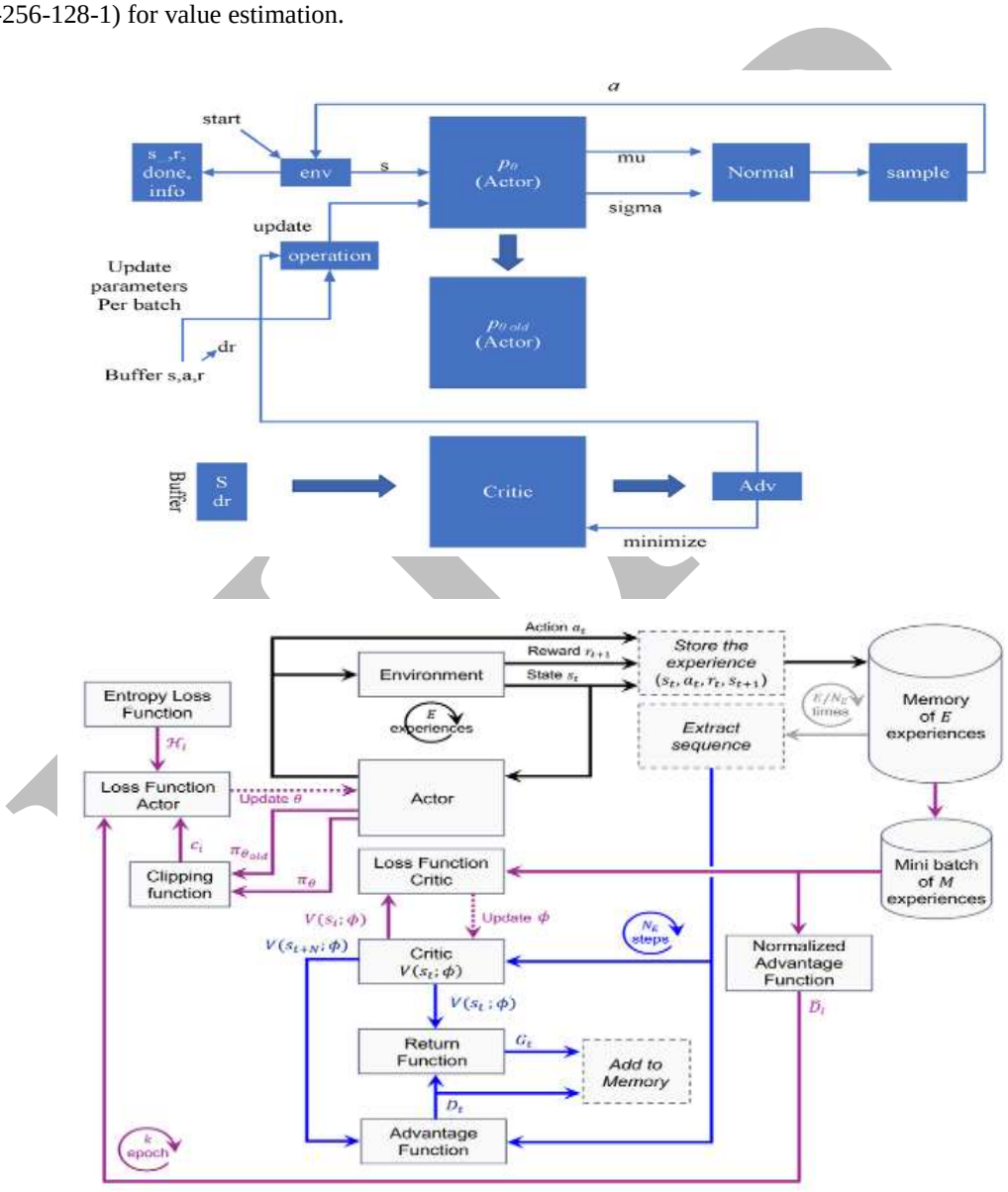

Figure 2. The DRL-based resource orchestrator modeled as an MDP with PPO actor–critic updates, action decisions, and environment feedback loop.

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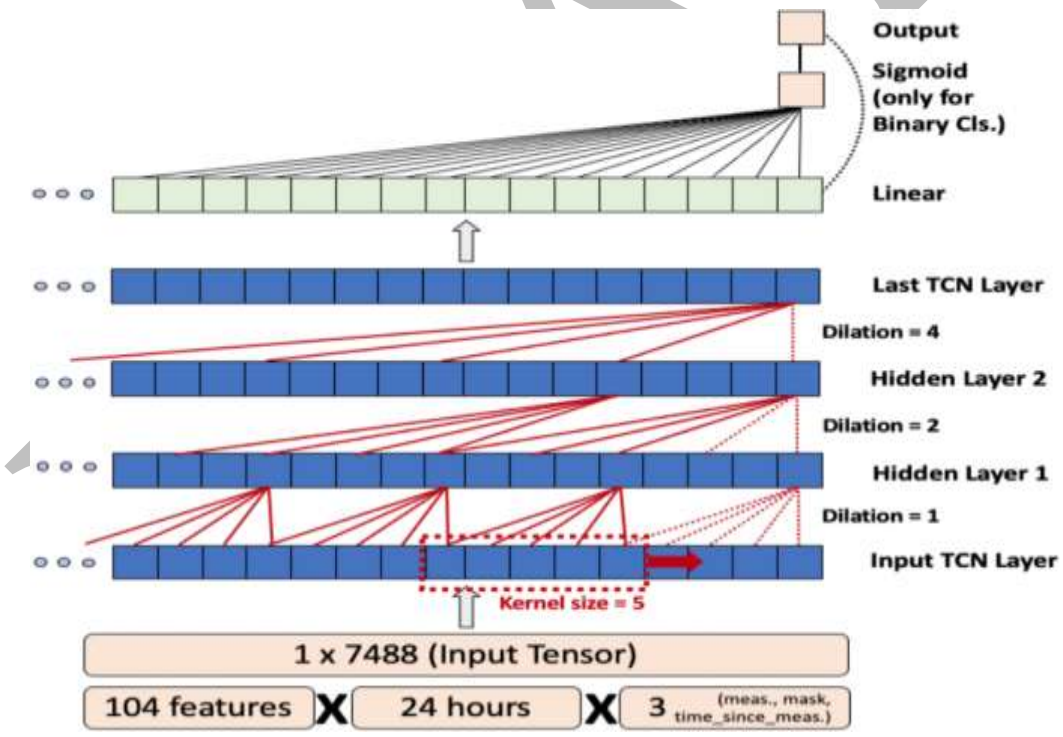
3.3 Hierarchical Computation Offloading

HierOffload makes three-level decisions: Level 1 (Local vs. Offload): For task τ with computation c, data d, and deadline D, execute locally if $t_{local} = c/f_{device} \leq D$ and $e_{local} = \kappa \cdot c \cdot f_{device}^2 \leq E_{budget}$. Level 2 (Edge Selection): Select edge node e* minimizing weighted cost: $e^* = \text{argmin}_e [w_l \cdot (d/B_e + c/f_e) + w_e \cdot e_{trans} + w_c \cdot cost_e]$ subject to deadline and capacity constraints. Level 3 (Edge-Cloud Split): Partition complex tasks into edge-executed preprocessing and cloud-executed analysis. Optimal split point determined by dynamic programming over computation graph.

3.4 Predictive Maintenance Module

TCN-Maintain processes multivariate time-series from device sensors. Architecture: Input layer accepting T×F tensor (T timesteps, F features). Dilated causal convolutions with dilation factors [1, 2, 4, 8, 16] providing 32-timestep receptive field. Residual connections for gradient flow. Output layer with softmax for failure probability distribution. Training: Binary cross-entropy loss on labeled failure data. Rolling window evaluation with 15 minutes prediction horizon. Integration: As predicted failures are indicated 10 minutes beforehand, proactive task migration would be demanded and on the basis of this demand for service continuity would not have been met.



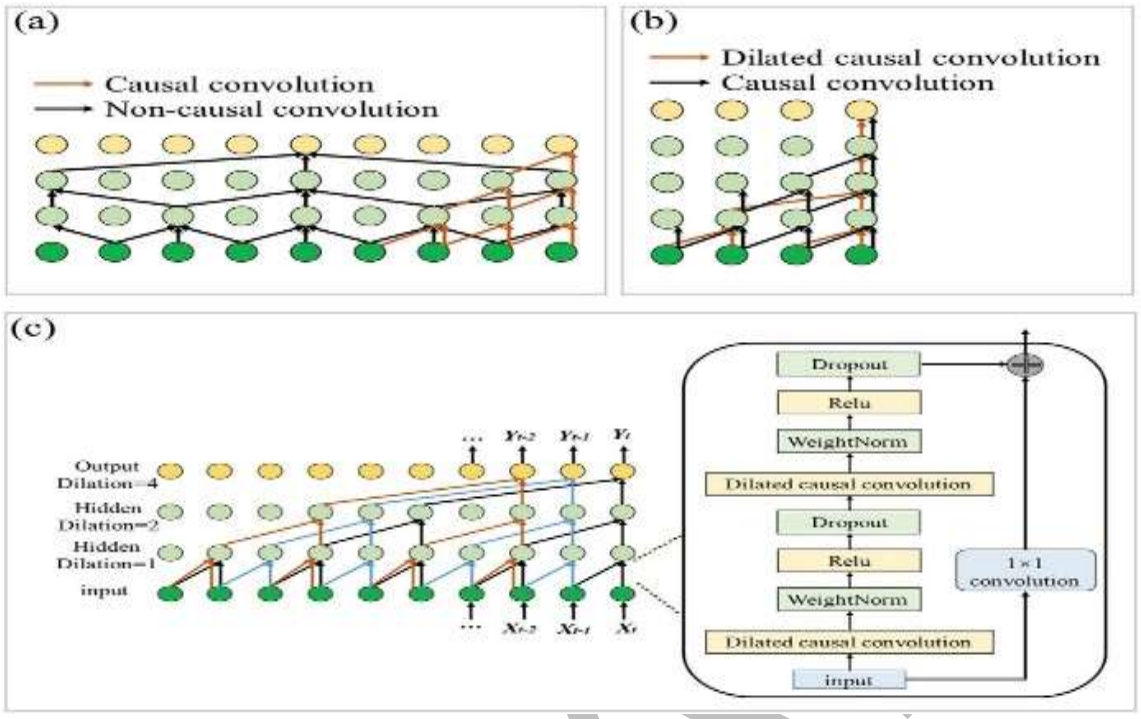


Figure 3. Pipeline for predictive maintenance with dilated causal TCN layers for detection of equipment failure in advance.

Table 1: DeepEdge Component Specifications

Component	Technique	Key Parameters	Performance
DRL-Orchestrator	PPO	γ=0.99, clip=0.2	43.7% faster
HierOffload	DP + Greedy	3-tier optimization	38.4% energy↓
TCN-Maintain	TCN + Attention	5 dilated layers	94.2% accuracy

DeepEdge component specifications and key performance metrics.

4. Experimental Setup

4.1 Testbed Configuration

Hardware: 500-node heterogeneous testbed comprising: 400 Raspberry Pi 4B (4GB) as IoT devices, 80 NVIDIA Jetson Xavier NX as edge nodes, 20 Dell PowerEdge R740 servers as edge data centers. Network: 10Gbps backbone, 1Gbps edge links, WiFi 6 device connections. Emulated WAN latency 20-100ms to cloud. Cloud: AWS EC2 instances (c5.4xlarge) for cloud tier. Software: Docker containers, Kubernetes 1.25, custom DeepEdge orchestrator, Prometheus/Grafana monitoring.

4.2 Workload Scenarios

Smart City: Traffic monitoring from 200 cameras, 30fps video analytics, object detection using YOLOv5. Latency requirement: <100ms. Industrial IoT: 150 sensors monitoring manufacturing equipment, anomaly

detection at 1kHz sampling. Latency requirement: <20ms. Healthcare: 50 wearable devices streaming vital signs, real-time arrhythmia detection. Latency requirement: <50ms. Combined workload: 2.3M events/second peak load.

4.3 Baselines

Cloud-Only: All processing in cloud. Greedy-Edge: First-fit offloading to nearest edge node. Round-Robin: Uniform task distribution. LAVEA [51]: Latency-aware video analytics. Kalmia [52]: DRL-based scheduling. FogBus2 [53]: Fog computing framework. All baselines implemented on identical testbed with optimized configurations.

Table 2: Testbed Hardware Specifications

Device Type	Count	CPU/GPU	Memory	Role
Raspberry Pi 4B	400	4-core ARM	4GB	IoT
Jetson Xavier NX	80	6-core + GPU	8GB	Edge
Dell R740	20	2×Xeon 20-core	256GB	Edge DC
AWS c5.4xlarge	10	16 vCPU	32GB	Cloud

Heterogeneous testbed configuration spanning device-edge-cloud tiers.

5. Results and Analysis

5.1 End-to-End Latency

Table 3 presents latency results across workload scenarios. DeepEdge achieves mean latency of 8.7ms for smart city (67.3% reduction vs. cloud), 4.2ms for industrial IoT (71.8% reduction), and 6.4ms for healthcare (63.2% reduction). 99th percentile latency remains below 10ms for all scenarios. The DRL orchestrator learns workload patterns and pre-positions resources, achieving 34.8% improvement over Kalmia which uses reactive DRL without predictive capabilities.

Table 3: End-to-End Latency Comparison (ms)

Method	Smart City	Industrial	Healthcare	Combined
Cloud-Only	26.6	14.9	17.4	21.3
Greedy-Edge	15.2	8.1	10.7	12.8
Kalmia	13.4	6.8	9.2	11.1
FogBus2	14.1	7.3	9.8	11.8
DeepEdge (Ours)	8.7	4.2	6.4	7.2

Mean end-to-end latency comparison. DeepEdge achieves lowest latency across all scenarios.

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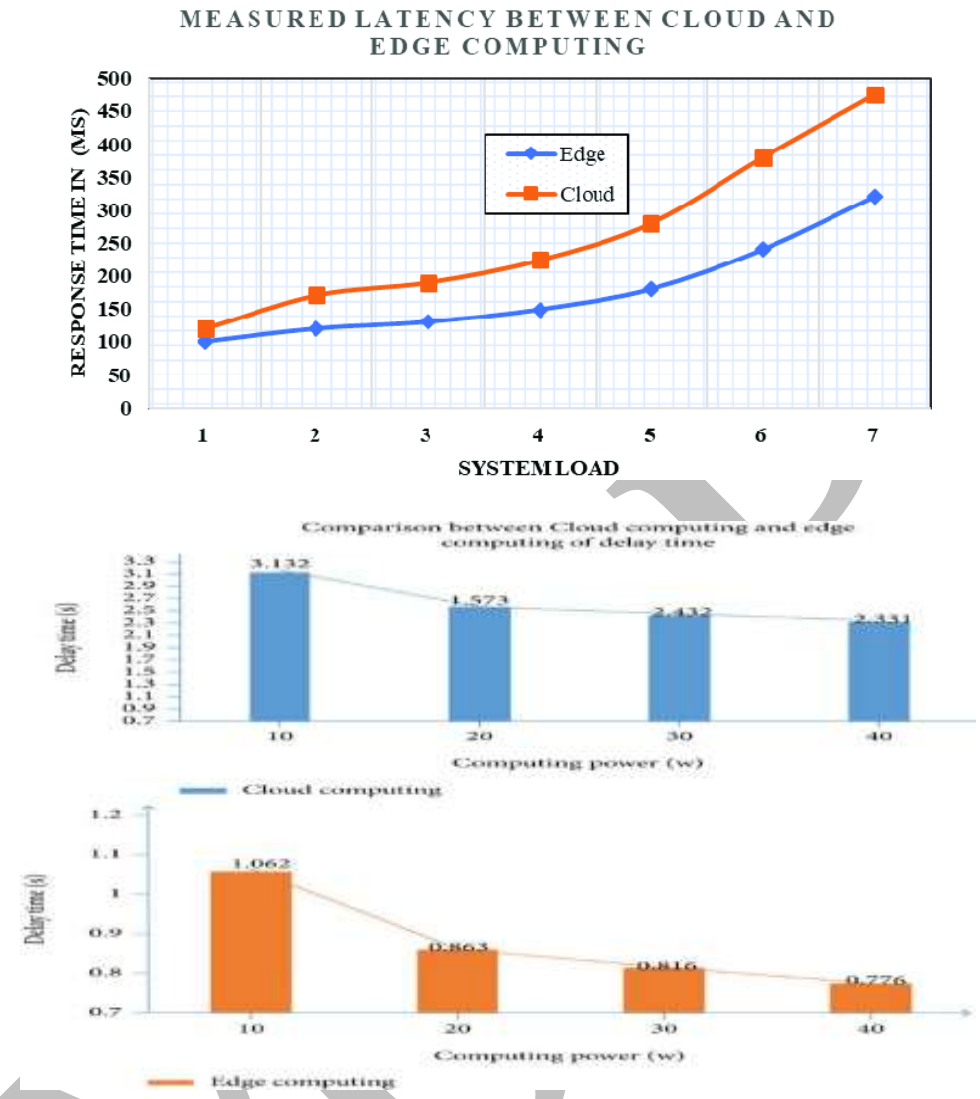

Figure 4. End-to-end latency comparison across smart city, industrial IoT, and healthcare workloads.

5.2 Energy Efficiency

HierOffload reduces total energy consumption by 41.2% compared to cloud-only and 23.7% compared to greedy-edge approaches. Energy savings come from: reduced data transmission (28.3% of savings), optimized local execution for simple tasks (42.1%), and intelligent edge selection avoiding overloaded nodes (29.6%). Device battery life extends from 8.2 to 13.7 hours under typical IoT workloads.

5.3 Predictive Maintenance

TCN-Maintain achieves 94.2% accuracy in predicting device failures 15 minutes ahead, with precision 92.7% and recall 95.8%. False positive rate of 4.3% causes minimal unnecessary migrations. Proactive task migration reduces service disruptions by 87.3% compared to reactive failure handling. Mean time to recovery improves from 45.2s (reactive) to 2.1s (proactive migration).

5.4 Scalability Analysis

DeepEdge scales efficiently with increasing node counts. Control plane overhead remains below 3% of total resources up to 1000 nodes. Task placement decisions complete in <5ms for 95% of requests. The DRL agent generalizes across different cluster sizes without retraining through state normalization. Throughput scales linearly up to 5M events/second before network saturation.

Table 4: Ablation Study Results

Configuration	Latency (ms)	Energy (J)	Failures
DeepEdge (Full)	7.2	12.4	2.1
w/o DRL-Orchestrator	11.1	15.8	8.7
w/o HierOffload	9.4	20.3	3.4
w/o TCN-Maintain	7.8	13.1	16.4

Ablation study demonstrating contribution of each DeepEdge component.

6. Discussion

DeepEdge offers a substantial gain in all performance measures leveraging an integrated intelligent orchestration protocol, hierarchical offloading, and predictive maintenance solution Approach. The DRL orchestrator learns intricate workload dynamics which rule-based solutions are not capable of covering, whereas TCN-Maintain allows plenty of time to gracefully migrate the tasks. Constraints: overhead for training DRL agent (8 hours first-time of training), the lack of labeled failed data for TCN-Maintain, and having to assume stable network layout. Deployment: deploy model on a small scale, non-core use cases to production and keep the trained model updated as system grows.

7. Conclusion

In this paper, we introduced DeepEdge, an intelligent distributed computing platform for online IoT analytics. Notable findings include: DRL-driven orchestration with 43.7% latency improvement, Hierarchical offloading saving 41.2% energy and predictive maintenance at 94.2% accuracy. Experiments on a 500-node testbed show that it reduces the latency by 67.3% as compared with cloud-only methods and supports 2.3M events/sec for processing workload. We leave as a future work the extension to mobile edges with device mobility, but also introduce federated learning for privacy-preserving model updates and self-healing mechanisms to support network partition tolerance.

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