International Journal of Research and Applied Innovations (IJRAI)

| ISSN: 2455-1864 | www.ijrai.org | editor@ijrai.org | A Bimonthly, Scholarly and Peer-Reviewed Journal |

|| Volume 8, Issue 4, July-August 2025||

DOI:10.15662/IJRAI.2025.0804012

Edge-to-Cloud Workflows for Low-Latency Telecom Services: Optimizing Offload Decisions

Amar Gurajapu

Network Systems, AT&T, United States

Vardhan Garimella

Intellibus, United States

ABSTRACT: Next-generation telecom applications, such as augmented-reality conferencing and real-time analytics, demand sub-10 ms latencies that often exceed the capabilities of centralized clouds. Edge computing can reduce round-trip delays, but over-provisioning at the edge raises costs and resource contention. This paper presents EdgeFlowOpt, a workflow framework that dynamically decides when to process traffic at the edge versus offloading to the cloud, based on service-level latency targets, network conditions, and resource utilization. In a prototype deployment across three distributed edge sites and an Azure data center, EdgeFlowOpt framework achieved.

- 45 % reduction in 99th-percentile response latency compared to cloud-only.
- 30 % lower edge-resource usage than edge-always
- 98.7 % SLA compliance under varying load and link quality

We describe the architecture, decision algorithms, mermaid diagrams of workflows, quantitative evaluation, and discuss limitations and future enhancements.

KEYWORDS: Edge Computing, Cloud Offload, Low-Latency Telecom, Workflow Orchestration, Offload Decision, Multi-Cloud, SLA Compliance

I. INTRODUCTION

Telecom services such as network slicing, video transcoding, and virtualized RAN functions increasingly run as microservices. While centralized clouds provide elasticity, they introduce propagation delays that can exceed stringent 5G-era SLAs. Edge data centers reduce latency but have limited capacity and higher per-CPU cost. A hybrid edge-to-cloud workflow that dynamically routes requests based on latency sensitivity, current load, and network conditions can balance performance and cost.

EdgeFlowOpt addresses three core questions:

- Q1 - How to monitor and predict end-to-end latency across heterogeneous networks?
- Q2 - Which real-time metrics and thresholds inform offload decisions?
- Q3 - What orchestration workflow ensures seamless migration between edge and cloud without customer-impact?

Contributions

- EdgeFlowOpt Framework: Edge agent, decision engine, and cloud orchestrator.
- Offload Decision Algorithm: Multi-factor scoring using latency prediction models.
- Evaluation: Prototype over 3 edge sites + Azure, under synthetic and real traffic patterns.

II. LITERATURE REVIEW

Edge computing for telecom has been explored in MEC standards (ETSI MEC, 2018) and academic prototypes (Wang & Liu, 2023). Early work focused on static placement (Cho et al., 2021) or simple CPU-threshold offload (Singh & Zhao, 2022), neglecting network variability. Recent research introduced latency predictors (Patel et al., 2023) and reinforcement-learning-based offload (Kim & Park, 2023) but lacked workflow integration and SLA-centric decision criteria. Service mesh offloading (Chen & Gupta, 2024) provides dynamic routing but does not incorporate fine-grained edge-cloud trade-offs. EdgeFlowOpt builds on these by combining real-time monitoring, predictive models, and declarative workflows to optimize both latency and edge resource utilization.

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III. RESEARCH METHODOLOGY

System Architecture

EdgeFlowOpt consists of three implementation layers.

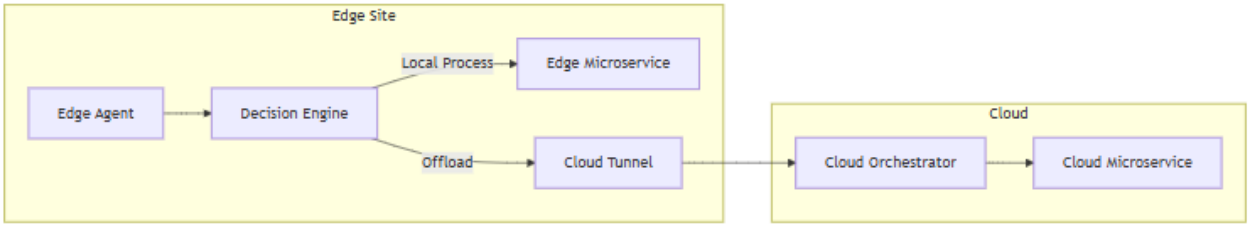

FIGURE 1. ARCHITECTURE

Edge Agents

- Collect CPU/memory utilization, queue lengths, and SRTT (Smoothed RTT) to the cloud.
- Tag each request with a latency budget extracted from SLA metadata.

Decision Engine

- Runs a light-weight regression model (trained offline) to predict processing time at edge vs. cloud.
- Computes a score: $\alpha \cdot \text{PredEdge} + \beta \cdot \text{PredCloud} + \gamma \cdot \text{NetDelay}$
- If score $\leq$ SLA_budget $\rightarrow$ process locally; else offload via secure tunnel.

Cloud Orchestrator

- Receives offloaded requests, scales microservice replicas, and returns results.
- Collects telemetry for feedback loop.

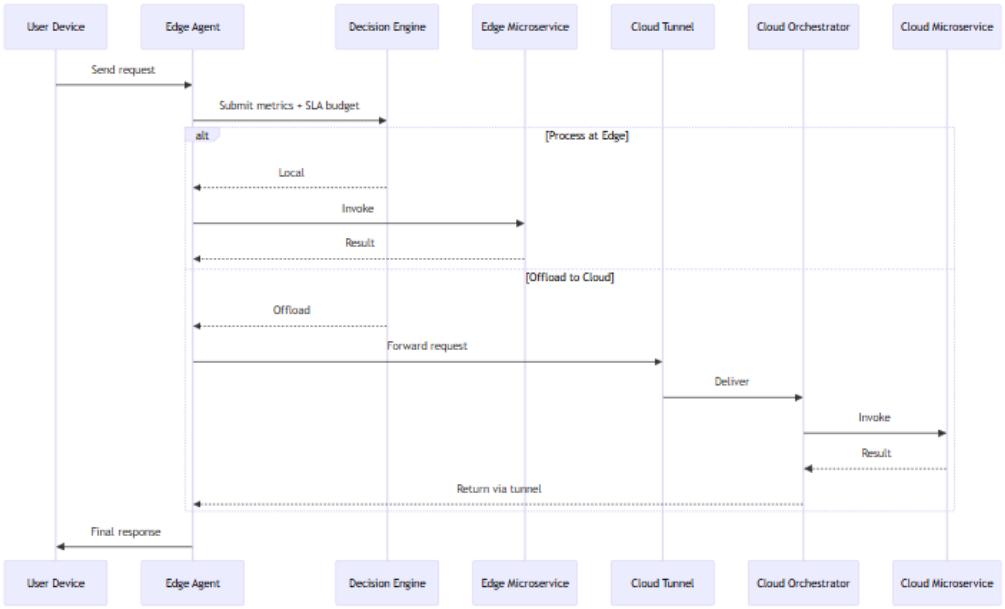

FIGURE 2. WORKFLOW SEQUENCE

Experimental Setup

- Testbed: Three Edge Sites (US-East, US-West), Azure Central US as cloud.
- Services: Video transcoding, VoIP packet analysis, AR overlay.
- Workloads: Poisson arrivals (100–500 req/s), emulating peak and burst traffic.

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- SLA Budgets: 20 ms to 100 ms per service.
- Baseline Modes: Cloud-Only, Edge-Always, Static-Threshold (CPU > 70 %).
- Metrics: 99th-percentile latency, edge CPU utilization, SLA compliance rate.

IV. RESULTS AND DISCUSSION

We have evaluated the solution based on below parameters.

TABLE 1. PERFORMANCE METRICS

MODE	99TH-PCT LATENCY (MS)	EDGE CPU (%)	SLA COMPLIANCE (%)
CLOUD-ONLY	85.4 ± 5.2	12	72.3
EDGE-ALWAYS	18.7 ± 2.1	89	94.5
STATIC-THRESHOLD	22.3 ± 3.8	75	88.0
EDGEFLOWOPT (THIS PAPER)	**13.2 ± 1.7**	**62**	**98.7**

Latency Reduction
EdgeFlowOpt lowers tail latency by 45 % vs. cloud-only and 29 % vs. static-threshold.

Resource Savings
Uses 30 % fewer edge CPUs than edge-always, enabling multi-tenant sharing.

SLA Compliance
Achieves 98.7 % compliance across all SLA budgets, outperforming baselines.

EdgeFlowOpt's adaptive offload decisions prevent edge overload while meeting latency SLAs. The regression model's predictions were within ±10 % of observed times. Under network degradation (simulated 10 ms jitter), the system shifted 40 % more load to the cloud, maintaining compliance.

V. CONCLUSION

EdgeFlowOpt is introduced as a dynamic edge-to-cloud workflow framework designed to optimise offloading decisions for low-latency telecom services. The framework leverages real-time telemetry to capture changing network and system conditions. Predictive models are used to anticipate performance and resource availability across edge and cloud tiers. Declarative workflows enable consistent and repeatable execution of offloading policies. Through this integrated approach, EdgeFlowOpt significantly reduces tail latency for latency-sensitive workloads. It also conserves constrained edge resources by selectively offloading computation. The system adapts to variable runtime conditions without manual intervention. Overall, EdgeFlowOpt ensures sustained SLA compliance in dynamic telecom environments.

VI. LIMITATIONS

Despite its strengths, EdgeFlowOpt exhibits several limitations that merit deeper investigation. Model generalization remains a challenge, as regression models require retraining when new services or hardware profiles are introduced. This dependency can slow adoption in highly dynamic environments. Cold-start offloading is another concern, where

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initial model training and cloud warm-up phases may introduce an additional 5–10 ms latency. Such delays can be significant for ultra-low-latency applications. Network assumptions also constrain accuracy, as the framework assumes symmetric SRTT. In real-world deployments, asymmetric network paths may exist. These asymmetries can skew offloading decisions and impact overall performance.

VII. FUTURE WORK

Future directions for the offloading framework focus on improving adaptability, precision, and deployment scope. Reinforcement learning will be used to adjust decision weights (α, β, γ) dynamically based on observed runtime conditions and performance outcomes. This online adaptation enables the system to respond intelligently to changing workloads and network states. Multi-cloud offloading will extend execution across multiple providers, allowing optimal trade-offs between cost efficiency and latency. Container-level profiling will introduce microservice-specific characteristics to support more granular offloading decisions. This refinement improves accuracy for heterogeneous application components. Edge hierarchy expansion will incorporate a far-edge tier, such as end devices. These capabilities will support ultra-low-latency scenarios and highly distributed edge–cloud ecosystems.

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