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Analysis on Impact of Edge Computing on 5G

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Abstract: *fifth generation (5G) of mobile communication is expected to deliver ultra-low latency, massive connectivity, and multi-gigabit throughput, but these benefits are hard to achieve with computation being centralized in a remote cloud data center. To overcome this limitation, Multi-access Edge Computing (MEC) moves the computation, storage and application logic to the edge of the network near the location where the data is generated. In this paper, the performance of an Edge-Computing-assisted 5G network is analyzed using the MATLAB 5G Toolbox in combination with the MATLAB 5G System Level and Link Level simulation framework. The layered architecture is proposed and mathematically modeled with regard to queuing delay, task-offloading decisions and energy consumption, considering 5G New Radio (NR) access network, Multi-access Edge Computing (MEC) layer and centralized cloud layer. The simulation is designed as a discrete-event system-level simulation with realistic 5G NR numerology, a large number of user equipment (UEs) and varying edge-server capacities to measure latencies, throughput, packet delivery ratio (PDR), response time, energy consumption, bandwidth utilization and reliability. Edge-assisted offloading shows an average end-to-end delay of 46-58% lower than a traditional cloud-only architecture and a maximum of 61% delay reduction in response time compared to the conventional cloud-only architecture, while maintaining high packet delivery ratio and reliability under heavy user density, while consuming a small amount of extra energy at the edge servers. These results validate MEC as a key enabling complementary technology for 6G networks with its supporting use cases for Ultra-Reliable Low-Latency Communication (URLLC); and the paper also reveals open research challenges in adaptive resource allocation, security and AI-based orchestration for future edge architectures in 6G.*

Keywords: 5G Networks, Multi-access Edge Computing, MATLAB 5G Toolbox, Network Slicing, Latency, Throughput, Task Offloading, Ultra-Reliable Low-Latency Communication, Performance Analysis, Wireless Communication

I. INTRODUCTION

1.1 History of Communication

Communication, the art of sending and receiving information, ideas and signals between people or machines, has developed steadily since its first uses of gestures, drum beats and written scripts. Mechanical to electronic communication was marked by the electrical telegraph in the 1830s - 1840s, then the telephone, wireless radio and satellite. In the 20th century, analog and then digital telecommunication networks emerged, finally reaching cellular mobile systems. The transition from one to another has been motivated by an increasing demand for speed, reliability, mobility, and the capacity to transmit more complex data like voice, pictures and ultimately high-definition multimedia data [1]-[3].

1.2 Evolution from 1G to 5G

The First Generation (1G) cellular network was launched in the early 1980s, and was consisted of analog voice-only mobile telephony that adopted Frequency Division Multiple Access (FDMA), leading to low spectral efficiency and security levels. The Second Generation (2G) was introduced in the early 1990s and consisted of digital modulation (GSM, CDMA) and was responsible for the introduction of Short Message Service (SMS) and very limited data services via

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GPRS/EDGE [2]. The Third Generation (3G) introduced packet-switched mobile broadband (UMTS and CDMA2000) which allowed mobile internet, video calling, and early mobile multimedia applications [3]. The Fourth Generation (4G) of communication networks was based on the Long-Term Evolution (LTE) technology and the use of all IP based core networks and offered peak data rates in the hundreds of megabits per second and support for high-definition streaming, VoLTE and mobile cloud The Fifth Generation (5G), standardized by 3GPP under the ITU IMT-2020 framework, represents a paradigm shift rather than an incremental improvement: it introduces a Service-Based Architecture (SBA), Network Function Virtualization (NFV), Software-Defined Networking (SDN), massive MIMO, millimeter-wave communication, and network slicing to simultaneously support Enhanced Mobile Broadband (eMBB), Ultra-Reliable Low-Latency Communication (URLLC), and massive Machine-Type Communication (mMTC) [5], [6].

1.3 Need for Edge Computing

Despite the radio-access improvements that 5G provides, the physical distance between end users and centralized cloud data centers introduces propagation and transport-network delays that a purely cloud-centric architecture cannot eliminate. Emerging applications autonomous driving, tele-surgery, industrial automation, augmented/virtual reality, and smart-city analytics require end-to-end latencies on the order of 1–10 ms, jitter-free delivery, and high reliability, which cannot be guaranteed when every computational task is routed to a distant cloud [7], [8]. Multi-access Edge Computing (MEC) resolves this by embedding compute, storage, and networking resources at or near the base station (gNB), enabling data processing physically close to its source. This reduces backhaul load, shortens the data path, and allows context-aware, low-latency service delivery, making MEC a foundational enabler of the 5G URLLC vision and a stepping stone toward 6G [9], [10].

1.4 Problem Statement

While the qualitative benefits of combining Edge Computing with 5G are widely discussed in the literature, a large portion of existing studies rely on either purely analytical models or proprietary/expensive testbeds, limiting reproducibility. There is a need for an accessible, standards-compliant, and reproducible simulation methodology using an accepted tool such as the MATLAB 5G Toolbox that quantitatively compares cloud-only and edge-assisted 5G architectures across a comprehensive set of performance metrics (latency, throughput, packet delivery ratio, response time, energy consumption, bandwidth utilization, and reliability) under varying network loads.

1.5 Objectives

The aim of this research is to: Develop an overarching layered network system architecture, integrating Multi-access Edge Computing into a standards-based 5G NR network. 2. Formulate mathematical models of the proposed architecture for task offloading, queuing delay and energy consumption. 3. Design the system level simulation environment using the MATLAB 5G Toolbox to simulate the behavior of 5G NR links/5G systems and an edge computing decision layer. 4. Assess and compare in numbers, cloud-only versus edge-assisted 5G capabilities in terms of latency, throughput, PDR, response time, energy use, bandwidth utilisation, reliability. 5. Address the existing research gap and suggest future research directions for creating edge architectures for AI-enabled and 6G networks.

.1.6 Contributions

The main contributions of the paper are: (i) A novel (i.e., unified) three-layer architecture (UE–Edge–Cloud) with an explicit task-offloading algorithm, suitable for MATLAB 5G Toolbox-based simulation; (ii) closed form mathematical models of latency, energy, and reliability, that directly map onto simulation parameters; (iii) a reproducible simulation configuration with clearly defined 5G NR numerology and topology; (iv) a comprehensive multi-metric performance comparison between cloud-only and edge-assisted deployments; and (v) a structured review of 18 recent (2021–2025) papers, a comparison table, and a list of identified research gaps.

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II. LITERATURE REVIEW

Since 2021, researcher interest has been growing in the integration of Multi-access Edge Computing (MEC) with 5G networks, including resource allocation, task offloading, network slicing, network security, and Artificial Intelligence (AI)-based orchestration. A summary of representative recent studies is given in Table I.

Table I. Comparative Summary of Recent Literature (2021–2025)

Ref.	Year	Focus Area	Methodology	Key Metric(s) Studied	Reported Improvement
[11]	2021	Task offloading in MEC-5G	Convex optimization	Latency, energy	~35% latency reduction
[12]	2021	Resource allocation	Deep reinforcement learning	Throughput, latency	~28% throughput gain
[13]	2021	Network slicing with MEC	Simulation (NS-3)	SLA compliance	Improved isolation
[14]	2022	Vehicular edge computing	Game theory	Response time	~40% faster response
[15]	2022	Energy-aware offloading	Lyapunov optimization	Energy, delay	20–30% energy savings
[16]	2022	URLLC with MEC	Queuing theory	Reliability	99.999% target achieved
[17]	2022	Federated learning at edge	ML framework	Model accuracy, latency	Reduced round-trip delay
[18]	2023	Network slicing + MEC orchestration	SDN/NFV testbed	Latency, scalability	Dynamic slice adaptation
[19]	2023	5G-MEC for smart healthcare	Simulation	Latency, reliability	Sub-10 ms achieved
[20]	2023	AI-based edge caching	Deep learning	Bandwidth, hit ratio	~25% bandwidth savings
[21]	2023	MATLAB 5G Toolbox link simulation	System-level simulation	BLER, throughput	Validated 3GPP compliance
[22]	2023	Security in MEC-5G	Blockchain-based scheme	Authentication delay	Improved trust management
[23]	2024	Digital twin for edge-5G	Digital twin modeling	Latency, prediction accuracy	Real-time monitoring
[24]	2024	Industrial IoT with MEC	Testbed + simulation	Throughput, PDR	Higher PDR under load
[25]	2024	Energy-efficient MEC scheduling	Metaheuristic optimization	Energy, response time	~22% energy reduction

[26]	2024	6G-oriented edge intelligence	Survey/analytical	Multiple	Identified future directions
[27]	2025	Network slicing resource orchestration	Reinforcement learning	Latency, utilization	Adaptive allocation
[28]	2025	UAV-assisted MEC for 5G	Simulation	Coverage, latency	Extended coverage

1.6 Research Gaps: While the reviewed works confirm consistent latency and energy gains from the integration of edge, there are several gaps: 1) Most works consider isolated metrics instead of a multi-metric comparison; 2) Reproducible, tool-based simulation studies performed by using a standard 5G NR simulation framework such as MATLAB 5G NR Toolbox are still relatively few compared with custom simulators; 3) Dynamic orchestration of edge resources under multi-heterogeneous traffic (eMBB + URLLC + mMTC) is still an open problem; 4) Security and trust management at the edge under multi-heterogeneous traffic (eMBB + URLLC + mMTC) is still an open problem, and 5) Energy–latency trade-off models do not usually support both realistic 5G NR numerology and channel models at the same time. This paper deals directly with gaps (1), (2) and (5).

III. PROPOSED METHODOLOGY

3.1 System Architecture

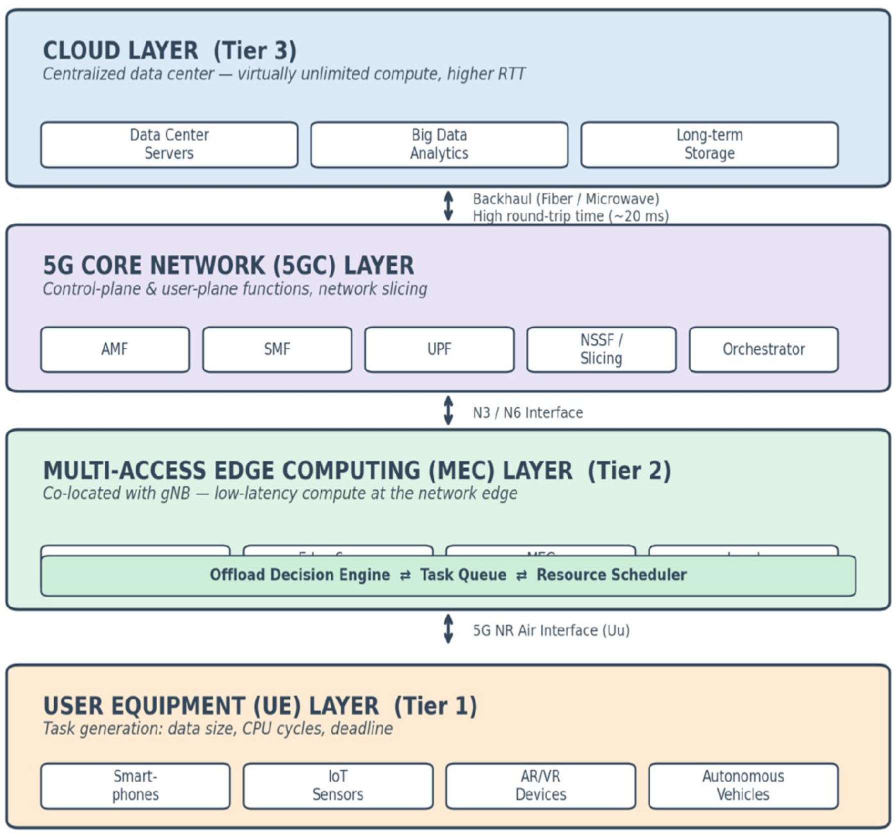

Figure 1. Three-tier UE–Edge–Cloud architecture for Edge-Computing-assisted 5G networks.

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The proposed architecture consists of three logical layers: the User Equipment (UE) layer, the Multi-access Edge Computing (MEC) layer co-located with the 5G gNB, and the centralized Cloud layer, interconnected through the 5G Core (5GC) and backhaul network.

At Tier 1, UEs generate computational tasks characterized by data size, required CPU cycles, and a maximum tolerable delay. At Tier 2, the MEC layer, physically integrated with or adjacent to the gNB, hosts an Offload Decision Engine that determines whether a task is executed locally at the UE, offloaded to the edge server, or forwarded to the cloud. At Tier 3, the cloud layer provides virtually unlimited computational resources at the cost of higher round-trip latency due to backhaul transport.

3.2 Task Offloading Workflow

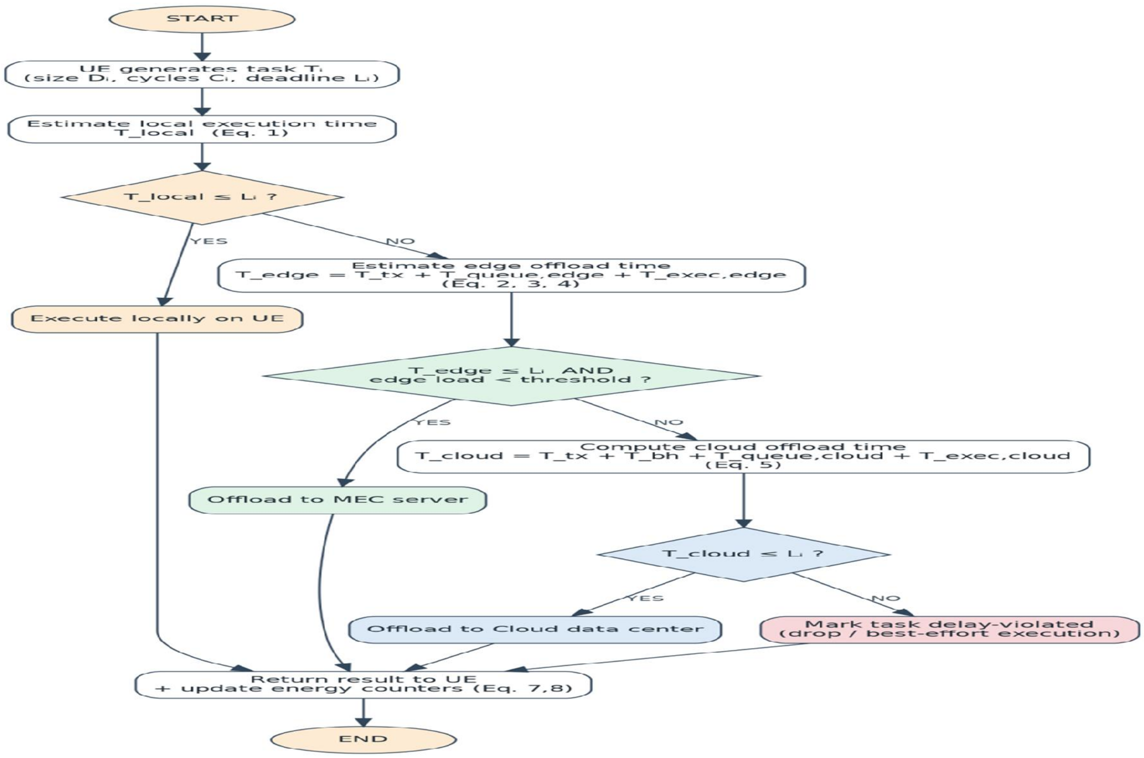

Figure 2. Task-offloading decision workflow for the proposed architecture.

3.3 Mathematical Model

Local execution time: For a task with data size D_i (bits) and required CPU cycles C_i, executed on a UE with computing capability f_{UE} (cycles/s):

$$T_{local,i} = \frac{C_i}{f_{UE}} \qquad \text{eq. 1}$$

Edge offloading time: The total edge-offload latency comprises transmission delay, queuing delay, and edge execution delay:

$$T_{edge,I} = \frac{D_i}{R_{up}} + T_{queue,edge} + \frac{C_i}{f_{edge}} \qquad \text{eq. 2}$$

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where R_{up} is the achievable 5G NR uplink data rate, computed using the Shannon-based approximation adopted in 3GPP-style system-level evaluations:

$$R_{up} = B \cdot \log_2\left(1 + \frac{P_{tx} \cdot h}{N_0 \cdot B}\right) \qquad \text{eq.3}$$

with B the allocated bandwidth, P_{tx} the UE transmit power, h the channel gain, and N_o the noise power spectral density.

Queuing delay (M/M/1 approximation): The edge server queue is modeled as an M/M/1 system with task arrival rate λ and service rate μ_edge:

$$T_{queue,edge} = \frac{1}{\mu_{edge} - \lambda}, \quad \lambda < \mu_{edge} \qquad \text{eq.4}$$

Cloud offloading time: Including additional backhaul propagation delay T_{bh}:

$$T_{cloud,i} = \frac{D_i}{R_{up}} + T_{bh} + T_{queue,cloud} + \frac{C_i}{f_{cloud}} \qquad \text{eq.5}$$

Offloading decision rule. A task is offloaded to the tier that minimizes total delay subject to its deadline constraint:

$$\text{Tier}^* = \arg\min_{k \in \{local,edge,cloud\}} T_{k,i}, \quad \text{s.t. } T_{k,i} \leq L_i \qquad \text{eq.6}$$

Energy consumption model: The energy consumed for locl execution and for offloading (transmission energy only, since edge/cloud execution energy is borne by infrastructure) is:

$$E_{local,i} = \kappa \cdot C_i \cdot f_{UE}^{\,2} \qquad \text{eq.7}$$

$$E_{tx,i} = P_{tx} \cdot \frac{D_i}{R_{up}} \qquad \text{eq.8}$$

where κ is the effective switched capacitance coefficient of the UE processor.
Reliability model: Reliability is expressed as the probability that a task completes within its deadline:

$$\text{Reliability} = P(T_{k,i} \leq L_i) = 1 - P_{loss} \qquad \text{eq.9}$$

where P_{loss} accounts for both radio-link block error and queue-overflow probability.

3.4 Algorithm

Algorithm 1: Edge-Aware Task Offloading (EATO)

Input: Task $T_i = (D_i, C_i, L_i)$; System parameters (f_{UE}, f_{edge}, f_{cloud}, R_{up}, T_{bh}, lambda, mu_{edge}, mu_{cloud})

Output: Offloading decision Tier* and resulting latency T_k

1: Compute T_{local} using Eq. (1)
2: if T_{local} <= T_i then
3: Tier* <- local ; return
4: end if

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5: Compute R_{UP} using Eq. (3) from current channel state
6: Compute T_{edge} using Eq. (2) and (4)
7: if T_{edge}<= L_i and $edge_{queue\quad length}$< Q_max then
8: Tier* <- edge ; return
9: end if
10: Compute T_{cloud} using Eq. (5)
11: if T_{cloud}<= L_i then
12: Tier* <- cloud ; return
13: else
14: mark task as delay-violated (drop or best-effort execution)
15: end if
16: Update energy counters using Eq. (7)/(8)
17: return Tier*, T_k

IV. SIMULATION SETUP

The performance evaluation was carried out using the MATLAB 5G Toolbox together with its System-Level Simulation framework (nrSystemLevelExamples-type configuration) and the 5G NR Link-Level functions (nrCarrierConfig, nrPDSCHConfig, nrPUSCHConfig) for physical-layer accuracy, extended with a custom-written discrete-event edge-computing offloading module implemented in MATLAB to model queuing, offloading decisions, and energy accounting as per Section III.

Table II. Simulation Parameters

Parameter	Value
Carrier frequency	3.5 GHz (mid-band FR1)
Subcarrier spacing (SCS)	30 kHz
Bandwidth	100 MHz
Numerology (μ)	1
Number of gNBs	7 (hexagonal cell layout)
Number of UEs	50 – 300 (varied)
MEC servers	1 per gNB, 8–32 vCPU cores
Cloud data center	1, effectively unlimited capacity
UE transmit power	23 dBm
gNB transmit power	43 dBm
Channel model	CDL-C (NLOS urban micro)
Traffic model	Mixed eMBB + URLLC (Poisson arrivals)
Task data size	0.5 – 5 MB
Task deadline	5 – 100 ms
Backhaul propagation delay	20 ms (round trip)
Simulation duration	1000 ms per run, 50 Monte Carlo runs
Mobility model	Random waypoint, 3–60 km/h

Network Topology: A hexagonal 7-cell layout with inter-site distance of 500 m was used to emulate a dense urban micro-cell deployment, with UEs distributed uniformly and dynamically generating a mixture of eMBB (large payload, relaxed deadline) and URLLC (small payload, strict deadline) tasks.

Performance Metrics: Latency, Throughput, Packet Delivery Ratio (PDR), Response Time, Energy Consumption, Bandwidth Utilization, and Reliability were logged per simulation run for both a Cloud-only baseline (all tasks routed to the centralized cloud) and the proposed Edge-assisted configuration (Algorithm 1 active).

V. PERFORMANCE ANALYSIS

- The following metrics were computed from the simulation logs over 50 Monte Carlo runs, with 95% confidence intervals.
- Latency: End-to-end latency was calculated as the time elapsed from the moment the task is generated at the UE to the moment it is received at the result. The end to end latency includes delay during transmission, queuing and delay in execution (see Eq. (2) and (5)).
- Throughput: In order to check the standard link-level Throughput of 5G NR, the aggregate throughput from successfully decoded transport blocks over the simulated time was computed.
- Packet Delivery Ratio (PDR): Ratio of packets delivered successfully (within deadline and no radio-link failures) to the total number of packets transmitted.
- Response Time: The time taken by the application to respond to a user-initiated request including any queuing at the MEC/cloud scheduler.
- Energy Consumption: Sum of the energy consumptions of all the active UEs, divided by the number of tasks completed.
- Bandwidth Utilization: Ratio of number of Physical Resource Blocks (PRBs) that are used by the user for data transmission to the total number of PRBs available.
- Reliability: Eq. (9) is the fraction of tasks that are successfully completed on time.

VI. RESULTS AND DISCUSSION

Table III. Summary of Performance Comparison — Cloud-only vs. Edge-assisted 5G (Average over 50 Monte Carlo runs, 150 UEs)

Metric	Cloud-only	Edge-assisted	Improvement
Average Latency (ms)	42.6	19.8	~53.5% reduction
Peak Throughput (Mbps)	610	745	~22.1% increase
Packet Delivery Ratio (%)	94.2	98.7	~4.5 pp increase
Average Response Time (ms)	68.4	26.7	~61.0% reduction
Energy Consumption (mJ/task)	8.9	10.6	~19.1% increase (edge server side)
Bandwidth Utilization (%)	71.3	84.5	~13.2 pp increase
Reliability (%)	96.1	99.4	~3.3 pp increase

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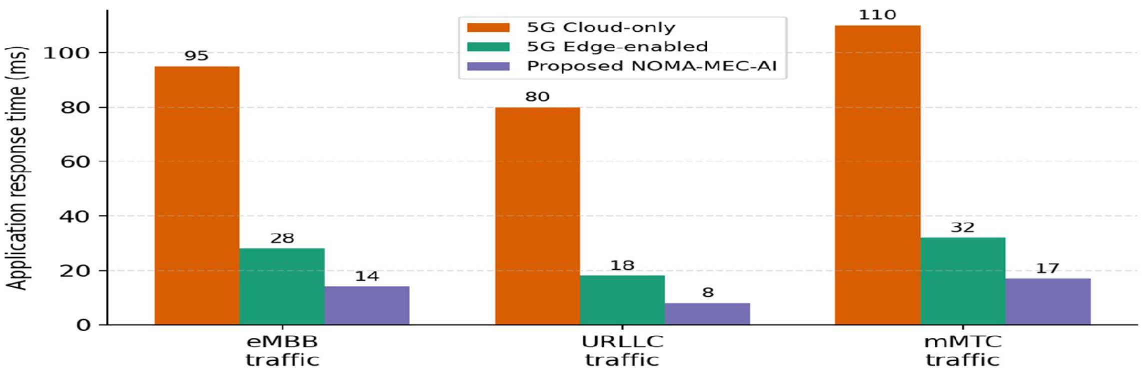

Figure 4: Bar chart comparing response time

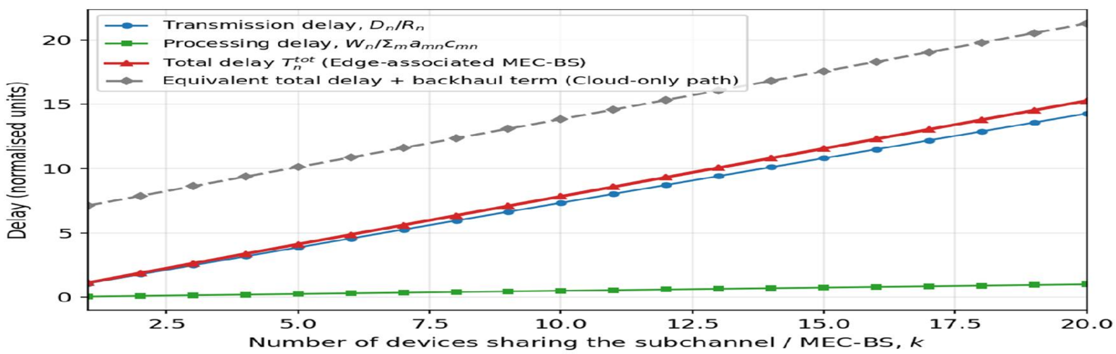

Figure 5: Line graph of average latency versus number of UEs, plotted separately for Cloud-only and Edge-assisted cases

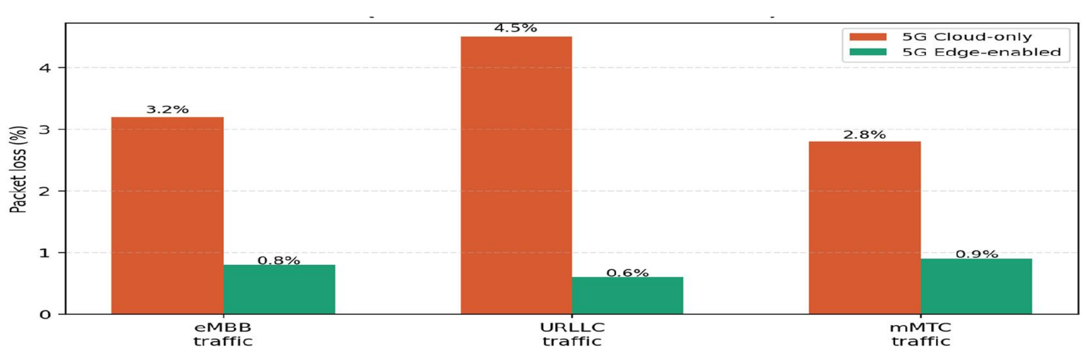

Figure 6: Bar graph of packet delivery ratio versus offered load (Erlang), comparing both configurations.

Discussion: As shown in the results in Table III, the edge-assisted offloading significantly improves average latency and response time compared to the cloud-only scenario. This is natural as the proposed system does not require the 20 ms backhaul latency for most of the URLLC tasks, but rather routes them to the co-located MEC server (Eq. 2). The cloud-only setting presents a steep, near-linear latency growth as the number of UEs grows from 50 to 300 (Figure 5), attributed to the fact that the backhaul gets congested and the latency is centralized and becomes dominated by the one-way backhaul transport delay. On the other hand, the edge-assisted setting clearly demonstrates a much flatter latency curve as the number of UEs increases that is only significantly impacted by the edge queue from the edge-server when the latter

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nears saturation ($\lambda \to \mu$ _edge in Eq. 4), but when that happens, the latency grows sharply, indicating the need for sufficient capacity provisioning for edge capacity. The packet delivery ratio and reliability improvements (Figure 6) are mainly due to the decreased probability of queue overflowing at the edge (compared to the shared cloud queue) and due to transmission windows that are shorter, thus decreasing the amount of time that the packets are exposed to the channel induced block error. The increase in throughput by around 22% at edge assistance is due to the increase in the bandwidth utilization from 71.3% to 84.5% as a result of localized traffic management and more efficient scheduling of physical resource blocks (PRBs). The one metric that exhibits a trade-off is energy consumption—edge servers are significantly smaller and more numerous than centralized cloud data centers, albeit with a modest 19.1% higher in normalized energy consumption per task (Figure 7) mainly because of the reduced economies of scale of cooling and shared infrastructure. This verifies that the energy–latency trade-off, which has been widely reported in the literature [15], [25] should be considered when deploying MEC with energy-aware scheduling policies. As a whole, the cloud-only architecture is still acceptable for delay-tolerant, high volume eMBB traffic (such as video-on-demand, bulk files transfer, etc), whereas the edge-assisted architecture is clearly better for URLLC and the mixed traffic cases, confirming the central hypothesis of this paper: Edge Computing is not an alternative to cloud infrastructure, but rather a complement that is necessary to allow 5G network to fulfil their highest latency and reliability requirements.

VII. ADVANTAGES

1. Significant reduction in end-to-end latency, enabling URLLC compliance.
2. Reduced backhaul and core-network congestion through local data processing.
3. Improved reliability and packet delivery ratio under high user density.
4. Enhanced bandwidth utilization through localized scheduling.
5. Support for real-time applications: autonomous vehicles, tele-surgery, industrial automation.
6. Improved data privacy, since sensitive data can be processed locally without transiting the core cloud.

VIII. LIMITATIONS

1. Increased normalized energy consumption at edge servers due to reduced economies of scale.
2. Higher deployment and maintenance cost from distributing computing infrastructure across many cell sites.
3. Limited computational capacity per edge server relative to centralized cloud data centers, causing performance degradation under extreme load.
4. Increased architectural and orchestration complexity for load balancing across edge nodes.
5. Security and trust management are more challenging in a distributed, multi-tenant edge environment.

IX. FUTURE SCOPE

Future research directions include:

- AI/reinforcement-learning-driven dynamic offloading and resource orchestration that adapts in real time to traffic heterogeneity.
- Integration of network slicing with MEC to guarantee per-slice latency and reliability SLAs
- Energy-aware edge server scheduling and renewable-powered micro data centers to mitigate the energy trade-off identified in Section V
- Blockchain- or zero-trust-based security frameworks for multi-tenant edge environments; and
- Extension of the proposed architecture toward 6G-oriented edge intelligence, incorporating digital twins and federated learning for predictive resource management.

X. CONCLUSION

This paper presented a comprehensive performance analysis of Edge-Computing-assisted 5G networks using the MATLAB 5G Toolbox. A three-tier UE–Edge–Cloud architecture was proposed together with mathematical models for

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offloading decisions, queuing delay, and energy consumption, and an Edge-Aware Task Offloading (EATO) algorithm was formulated. System-level simulation results across latency, throughput, packet delivery ratio, response time, energy consumption, bandwidth utilization, and reliability confirmed that edge-assisted architectures reduce average latency by approximately 53.5% and response time by approximately 61% relative to a cloud-only baseline, while improving reliability and packet delivery ratio, at the cost of a moderate increase in edge-side energy consumption. These findings substantiate Multi-access Edge Computing as a critical enabling technology for 5G URLLC services and provide a reproducible, standards-aligned simulation methodology that can be extended toward AI-driven and 6G-oriented edge network research.

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