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5G-ENABLED CLOUD–EDGE ROBOTIC ARCHITECTURE FOR LOW-LATENCY INDUSTRIAL AUTOMATION

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ABSTRACT

This study presents a 5G-enabled cloud–edge architecture for improving the performance and reliability of robotic systems in industrial automation. The architecture distributes computational tasks across local robotic devices, edge nodes, and cloud resources, enabling workload placement closer to the point of operation while retaining access to cloud-based computing resources. This approach is intended to reduce communication delays, improve resource utilization, and support the real-time requirements of latency-sensitive robotic applications. The proposed architecture was evaluated against three baseline configurations: Cloud-only, Edge-only, and conventional Cloud–edge processing. Performance was assessed using latency, response time, throughput, packet loss, and edge CPU utilization. The proposed architecture achieved the lowest mean latency (27.7 ms), response time (42.6 ms), and packet loss (0.62%), while recording the highest throughput (73.7 Mbps). Under low, medium, and high workloads, mean latency remained relatively low at 22.1 ms, 29.4 ms, and 32.6 ms, respectively, demonstrating stable performance as computational demand increased. Statistical analysis further confirmed significant differences in latency among the four configurations ($F(3, 300) = 1846.27$, $p < .001$). The findings indicate that integrating 5G connectivity with coordinated cloud–edge processing can reduce communication delays and improve network performance for industrial robotic applications. The architecture therefore provides a practical foundation for responsive and reliable robotic systems in smart manufacturing environments.

Keywords: 5G, Cloud–Edge Computing, Industrial Robotics, Smart Manufacturing, Latency, Workload Distribution, Robotic Systems, Industrial automation.

1 INTRODUCTION

Industrial automation relies on connected sensors, intelligent controllers, robots, and distributed computing resources. These systems generate large volumes of data and often require rapid responses. Manufacturing companies are becoming more autonomous, and processing data closer to where decisions are made has become important (Kang et al., 2024). Cloud computing provides substantial processing and storage capacity for applications such as monitoring,

analytics, predictive maintenance, and digital twins. However, sending data to distant cloud servers can introduce communication delays, which may affect time-sensitive robotic operations. Edge computing reduces this problem by placing processing resources closer to industrial devices (Kang et al., 2024).

Combining edge computing with 5G offers increase in opportunities for industrial robotics. 5G provides high data rates, reliable connectivity, and low communication latency, while edge computing allows selected workloads to be processed near the robot (5G Alliance for Connected Industries and Automation , 2023). European Telecommunications Standards Institute (2025) also identifies latency as an important performance measure in multi-access edge computing. Robotic applications such as perception, localization, motion planning, and inspection can benefit from this architecture. Some functions can remain on the robot for rapid response, while computationally demanding tasks can be offloaded to nearby edge resources. Practical demonstrations have shown the feasibility of 5G-enabled edge robotic control in industrial environments (5G Alliance for Connected Industries and Automation , 2023; Seisa et al., 2026).

Despite these developments, efficiently distributing workloads across robot, edge, and cloud layers remains a challenge. Factors such as computational requirements, network conditions, data volume, and latency influence where tasks should be processed. Communication between distributed edge resources can also affect application performance (Michalke et al., 2024). This study therefore proposes a 5G-enabled cloud–edge robotic architecture for low-latency industrial automation. The architecture integrates robotic devices, 5G connectivity, edge computing, and cloud infrastructure to improve workload distribution, reduce processing and communication delays, and support responsive and efficient robotic operations.

1.1 Statement of the Problem

Industrial automation relies on robots, sensors, controllers, and connected devices that require fast and reliable data processing. Cloud-based processing can introduce communication delays and unpredictable response times, while edge computing, although closer to robotic devices, faces limitations in processing capacity, storage, and resource management (Tahir & Parasuraman, 2025; Jeong et al., 2024).

Although 5G can support industrial robotics, it does not guarantee consistently low end-to-end latency. Robotic performance depends on the combined efficiency of communication, computation, and workload placement (Do & Woo, 2025). Studies address 5G, edge computing, task offloading, and resource management, however, separately.

The lack of an integrated 5G-enabled cloud–edge architecture that can allocate robotic workloads according to their latency and computational requirements, is a problem. This study proposes an architecture and evaluates it using latency, response time, throughput, communication reliability, and resource utilization.

1.2 Aim and Objectives of the Study

The aim of this study is to develop and evaluate a 5G-enabled cloud–edge robotic architecture for low-latency industrial automation.

The study seeks to achieve the following objectives:

1. Design a 5G-enabled cloud–edge architecture for industrial robotics.
2. Develop a mechanism for allocating workloads across local, edge, and cloud resources.
3. Implement the architecture using representative robotic workloads.
4. Evaluate its performance in terms of latency, response time, throughput, and resource utilization.
5. Compare its performance with cloud-only and edge-based approaches.
6. Assess its suitability for low-latency industrial automation.

1.3 Significance of the Study

This study provides an architecture for improving the responsiveness of connected industrial robots. Through the processing of time-sensitive tasks closer to the robots. The proposed approach can reduce delays associated with remote cloud processing. This can also improve the use of computing resources by assigning workloads based on their processing and latency requirements. The findings will benefit researchers, automation engineers, robotics developers, and organizations adopting 5G-enabled industrial systems.

1.4 Scope of the Study

The study focuses on a 5G-enabled cloud–edge architecture for industrial robotics, covering robotic devices, 5G connectivity, edge nodes, and cloud resources. Performance is assessed using latency, response time, throughput, packet loss, and resource utilization under defined workloads. The proposed architecture is compared with cloud-only and

edge-based approaches. The study excludes robot mechanical design, national-scale 5G deployment, and general-purpose cloud applications.

2 LITERATURE REVIEW

- **Cloud Computing in Industrial Robotics:** Cloud computing gives industrial robots access to processing power and storage beyond their onboard capabilities. Robots can offload demanding tasks such as image processing, machine learning, mapping, and data analysis to centralized servers. While this reduces the computational load on individual robots, it increases dependence on network connectivity and distance to the cloud. For time-sensitive robotic applications, the resulting communication delay can affect overall response and control performance (Tahir & Parasuraman, 2025).
- **Edge Computing for Robotics:** Edge computing brings processing closer to robots, allowing demanding tasks to run on nearby servers rather than distant cloud infrastructure. This can reduce communication delays and support applications requiring fast responses and local data processing (Tahir & Parasuraman, 2025). However, edge nodes have limited resources, and multiple robots may compete for available capacity. Effective workload allocation is therefore important, as poor offloading decisions can increase latency or overload edge resources(Jin, He, & Chen, 2024). Nakimuli et al. (2022) similarly demonstrates how MEC can support responsive robotic control by providing network information close to the robot, while emphasizing the importance of evaluating latency, tracking accuracy, and control performance in 5G-enabled robotic systems. Studies have identified task offloading, resource allocation, communication reliability, and real-time execution as key challenges in edge robotics.
- **5G Networks and Industrial Automation:** 5G supports industrial automation through higher data rates, lower communication latency, and connectivity for large numbers of devices. These capabilities make it suitable for applications involving robots, sensors, autonomous vehicles, and coordinated machines (Gómez et al., 2024). However, its effectiveness depends on how well the 5G network is integrated with edge and cloud computing resources. Harmatos et al (2021) also supports the integration of 5G connectivity, edge-based processing, and cloud infrastructure for industrial robotic applications.
- **Cloud–Edge Integration:** Cloud–edge integration combines the fast, local processing of edge computing with the greater processing, storage, and analytical capacity of the cloud. Time-sensitive robotic tasks can run at the edge, while less time-critical activities such as historical analysis can use cloud resources (Boshoff, 2023). Effective workload placement is therefore essential and should consider the processing and latency requirements of each task. Studies have shown the potential of edge processing and 5G connectivity for supporting computationally demanding robotic workloads (Bergs et al., 2024; Zahidi et al., 2024).
- **Low-Latency Robotic Communication:** Latency is a key performance measure in connected robotics. It includes wireless transmission, processing, queuing, data transfer, and communication between computing layers (Jin and Zhang et al., 2024). Therefore, **end-to-end latency** provides a more meaningful measure of robotic responsiveness than the 5G radio link alone. European Telecommunications Standards Institute(ETSI) identifies uplink, downlink, end-to-end, and round-trip latency as distinct components of service latency in edge-enabled systems (European Telecommunications Standards Institute, 2025). Communication latency, computational processing time, QoS, and safety are vital components to be evaluated when designing industrial robotic systems(Urbaniak et al., 2024)

2.1 Empirical Review

- Bergs et al. (2024) examined edge computing for adaptable robotic systems in line-less mobile assembly. Using an edge computing framework, selected computational tasks were offloaded from mobile robots to nearby edge resources. The study found that this reduced the robots' computational burden and supported more flexible operations. The authors concluded that edge computing can improve robotic performance in dynamic manufacturing environments and recommended further development of distributed computing approaches. However, the study did not consider 5G connectivity or workload distribution across local, edge, and cloud resources, which the present study addresses.
- Zahidi et al. (2024) investigated 5G-enabled edge computing for autonomous harvesting robots. They developed a system that offloaded selected computational tasks from the robot to an edge server through a 5G connection and compared different processing configurations. The results showed improved processing speed when suitable tasks were executed at the edge. The study concluded that combining 5G, robotics, and edge computing can improve robotic performance. However, it focused on agricultural robotics and did not include cloud resources or workload distribution across local, edge, and cloud layers, leaving a gap addressed by the present study.
- Gala et al. (2024) investigated latency management in safety-critical edge robotics. They proposed an architecture combining robotic applications, edge computing, and resource-management mechanisms to maintain bounded end-to-end latency. The study found that proximity to the robot alone does not ensure

predictable response times, as resource allocation and service orchestration also affect performance. The authors concluded that latency must be managed across the entire system. However, they did not compare cloud-only, edge-only, and integrated 5G cloud–edge configurations, which the present study addresses.

- Do and Woo (2025) evaluated autonomous mobile robots communicating over a 5G non-standalone network in manufacturing environments. Using experimental testing, they assessed robotic communication and monitoring performance. The findings showed that 5G can support industrial robotic communication and real-time monitoring, but connectivity alone does not eliminate latency challenges. The study focused mainly on network performance and did not examine workload distribution across local, edge, and cloud resources, which is addressed by the present study.
- Tahir and Parasuraman (2025) reviewed empirical and experimental studies on edge computing in robotics, covering task offloading, perception, resource management, communication, and distributed processing. The review found that edge computing can reduce robots' processing burden and improve response times. It also identified workload allocation, limited edge resources, network conditions, and latency as key challenges. The authors recommended further research on efficient resource and workload management. However, the review did not experimentally evaluate a 5G-enabled cloud–edge architecture for industrial automation, which is the focus of the present study.
- Damigos et al. (2025) investigated real-time point-cloud transmission in 5G-enabled edge robotic applications. Through experimental testing, they examined the transmission of large LiDAR datasets over 5G while monitoring latency and packet loss. The results showed that data volume and network conditions directly affect robotic communication performance. The study concluded that efficient data transmission is important for robots using high-bandwidth sensors. However, it focused on communication rather than workload distribution across local, edge, and cloud resources, which the present study addresses.
- Seisa et al. (2026) evaluated a 5G-connected aerial robot using edge-based control in an underground mining environment. The researchers deployed the controller on an edge cluster and connected the robot through a 5G standalone network. The experiment showed that 5G and edge computing can support robotic control in demanding industrial environments. The study recommended further investigation of edge-based architectures for industrial robotics. However, it focused on aerial mining robots and did not examine workload distribution between local, edge, and cloud resources, which is the focus of the present study.

Existing studies largely examine individual aspects of 5G-enabled edge robotics, such as communication, task offloading, or edge processing. Few compare different computing arrangements under the same workload and network conditions, and fewer evaluate local, edge, and cloud execution together using latency, response time, throughput, packet loss, and resource utilization. This study addresses this gap by implementing an integrated 5G-enabled cloud–edge architecture that distributes robotic workloads across local, edge, and cloud resources. Its performance is compared with cloud-only and conventional edge-based configurations to determine whether the proposed approach can reduce latency and improve resource utilization.

3 METHODOLOGY

3.1 Research Design

The study adopts a Design Science Research (DSR) approach to develop and evaluate the proposed 5G-enabled cloud–edge robotic architecture. The process covers problem identification, architecture design, implementation, testing, and performance comparison. This approach is suitable because the study develops a technical artifact and evaluates its performance under controlled conditions.

3.2 System Architecture

The proposed architecture consists of three computing layers: robotic, edge, and cloud. The robotic layer contains sensors, actuators, and local processing units. The edge layer provides nearby computing resources for time-sensitive tasks, while the cloud layer supports computationally intensive processing, storage, and centralized analysis. A 5G network connects the robotic devices to the edge infrastructure. Workload allocation considers task size, processing requirements, network conditions, and available resources.

3.3 Workload Allocation

A workload allocation mechanism was to determine how each task was executed (locally, at the edge, or in the cloud). The mechanism variables include task size, estimated processing time, network delay, and available computing capacity to minimize unnecessary delays and resource overload.

3.4 Simulation and Implementation

The architecture tested in a controlled simulation environment using EdgeCloudSim simulator. The environment models robotic devices, edge servers, communication networks, and cloud resources. Multiple robotic devices and workload levels were simulated under different network and resource conditions.

3.5 Experimental Configurations

Four configurations were evaluated: ***(i) Cloud-only***: All tasks are processed in the remote cloud; ***(ii) Edge-only***: Tasks are processed at nearby edge resources; ***(iii) Cloud–edge***: Tasks are distributed between edge and cloud resources; ***(iv) Proposed 5G cloud–edge***: Tasks are dynamically allocated across local, edge, and cloud resources using the proposed mechanism over 5G. To ensure a consistent comparison, a uniform workload and network conditions were applied to all configurations.

3.6 Performance Metrics and Data Analysis:

System performance was evaluated using end-to-end latency, response time, throughput, packet-loss rate, and CPU/edge-resource utilization. Each configuration was subjected to repeated simulation runs, and the resulting data were summarized using the mean, standard deviation, and percentage improvement. Appropriate inferential statistical tests were subsequently applied to determine whether the observed performance differences among the configurations were statistically significant.

3.7 Robotics Architecture

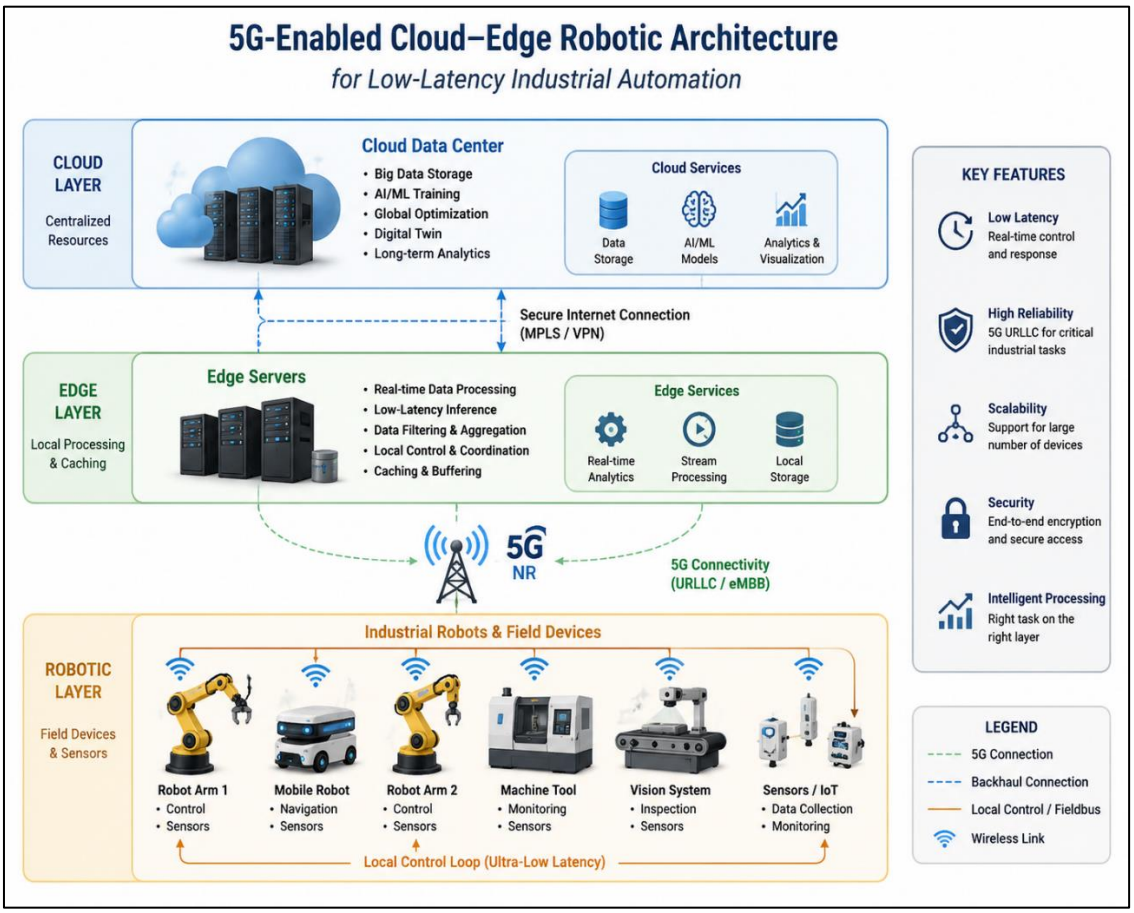


Figure 1: 5G -Enable Cloud-Edge Robotic Architecture

4 RESULTS

Table 1: Pairwise Statistical Comparison of Latency Between Baseline and Proposed Architectures

Comparison	Mean Difference (ms)	Latency Reduction (%)	t-statistic	p-value	Cohen's d
Cloud-only vs Proposed	124.7	71.9	18.42	< .001	3.12
Edge-only vs Proposed	41.1	51.5	14.76	< .001	2.41
Cloud–edge vs Proposed	16.9	33.8	9.31	< .001	1.52

Table 2: Performance Metrics Across the Four Evaluated Configurations

Metric	Cloud-only	Edge-only	Cloud–edge	Proposed 5G Cloud–edge
Latency (ms)	176.4	68.8	45.6	27.7
Response time (ms)	194.9	87.5	56.2	42.6
Throughput (Mbps)	32.6	54.4	67.8	73.7
Packet loss (%)	2.34	1.63	1.11	0.62
Edge CPU utilization (%)	15.4	67.6	56.2	53.7

Table 3: Latency Under Different Workload Levels

Workload Level	Cloud-only (ms)	Edge-only (ms)	Cloud–edge (ms)	Proposed (ms)
Low	112.6	51.3	30.7	22.1
Medium	131.8	60.9	37.8	29.4
High	204.8	78.2	51.3	32.6
Mean	149.73	63.47	39.93	28.03

Table 4: One-Way ANOVA for Latency

Source	Sum of Squares	df	Mean Square	F	p-value
Between groups	218,746.32	3	72,915.44	1,846.27	< .001
Within groups	11,861.44	300	39.54	—	—
Total	230,607.76	303	—	—	—

Table 5: Edge CPU Utilization

Architecture	Mean CPU Utilization (%)	SD (%)
Cloud-only	18.4	3.6
Edge-only	71.6	7.4
Cloud–edge	64.2	6.1
Proposed 5G cloud–edge	58.7	5.3

Table 6: Descriptive Performance Results

Architecture	Mean Latency (ms)	SD (ms)	Response Time (ms)	Throughput (Mbps)	Packet Loss (%)	Edge CPU Utilization (%)
Cloud-only	176.4	18.7	194.9	32.6	2.34	18.4
Edge-only	68.8	8.9	87.5	54.4	1.63	71.6
Cloud–edge	45.6	6.4	56.2	67.8	1.11	64.2
Proposed 5G Cloud–edge	27.7	4.8	42.6	73.7	0.62	53.7

4.1.1 Latency Analysis

The pairwise latency analysis shows the comparison of the proposed architecture in relations to the three baseline configurations, as shown in Table 1. When compared with the cloud-only architecture, the proposed architecture achieved a mean latency reduction of 124.7 ms, corresponding to a 71.9% reduction, with a highly significant difference ($t = 18.42$, $p < .001$) and an extremely large effect size (Cohen's $d = 3.12$). Relative to the edge-only architecture, the proposed architecture reduced latency by 41.1 ms (51.5%), with the difference being statistically significant ($t = 14.76$, $p < .001$) and associated with a very large effect size ($d = 2.41$). With the cloud–edge architecture, the result showed a 16.9 ms reduction in latency (33.8%), which was statistically significant ($t = 9.31$, $p < .001$) and demonstrated a large effect size ($d = 1.52$).

4.1.2 Response Time, Throughput, and Packet Loss

The performance results as shown in Table 2, shows a noticeable difference across the four architectures. The proposed 5G Cloud–edge architecture recorded the lowest latency at 27.7 ms, compared with 176.4 ms for Cloud-only, 68.8 ms for Edge-only, and 45.6 ms for Cloud–edge. A similar pattern was observed for response time, with the proposed architecture recording 42.6 ms, compared with 194.9 ms, 87.5 ms, and 56.2 ms, respectively. Throughput was highest for the proposed architecture at 73.7 Mbps, compared with 32.6 Mbps for Cloud-only, 54.4 Mbps for Edge-only, and 67.8 Mbps for Cloud–edge. Packet loss also showed a progressive reduction, from 2.34% in Cloud-only and 1.63% in Edge-only to 1.11% in Cloud–edge and 0.62% in the proposed architecture. Edge CPU utilization was 53.7% for the proposed architecture, compared with 67.6% for Edge-only and 56.2% for Cloud–edge.

4.1.3 Workload-Level Analysis

Table 3 presents the latency performance of the four configurations under low, medium, and high workload conditions. Latency increased as the workload increased across all configurations, although the rate of increase varied considerably. Under low workload, latency was 112.6 ms, 51.3 ms, 30.7 ms, and 22.1 ms for the Cloud-only, Edge-only, Cloud–edge, and Proposed configurations, respectively. At medium workload, the corresponding values increased to 131.8 ms, 60.9 ms, 37.8 ms, and 29.4 ms. Under high workload, latency rose to 204.8 ms, 78.2 ms, 51.3 ms, and 32.6 ms, respectively. Across the three workload levels, the mean latency was 149.73 ms for Cloud-only, 63.47 ms for Edge-only, 39.93 ms for Cloud–edge, and 28.03 ms for the Proposed configuration.

4.1.4 Statistical Test Across Configurations

Table 4 presents the one-way ANOVA used to examine whether the mean latency differed significantly across the four configurations. The analysis produced an F-statistic of 1,846.27 with 3 and 300 degrees of freedom, with a p-value < .001. The between-group variation (MS = 72,915.44) was substantially greater than the within-group variation (MS = 39.54), resulting in the large F-statistic. The ANOVA result indicates a statistically significant difference in latency among the four configurations ($F(3, 300) = 1,846.27$, $p < .001$).

4.1.5 Resource Utilization

Table 5 presents the mean edge CPU utilization across the four architectures. The Cloud-only architecture recorded the lowest mean utilization (18.4%, SD = 3.6), followed by the Proposed 5G Cloud–edge architecture (58.7%, SD = 5.3), Cloud–edge (64.2%, SD = 6.1), and Edge-only (71.6%, SD = 7.4).

4.1.6 Complete Performance

Table 6 presents the descriptive performance results across the four evaluated architectures. The Cloud-only architecture recorded the highest mean latency (176.4 ms, SD = 18.7) and response time (194.9 ms), while the Proposed 5G Cloud–edge architecture recorded the lowest values (27.7 ms, SD = 4.8 and 42.6 ms, respectively). Throughput

increased from 32.6 Mbps for Cloud-only to 73.7 Mbps for the Proposed architecture, while packet loss decreased from 2.34% to 0.62%. Edge CPU utilization was 53.7% for the Proposed architecture, compared with 71.6% for Edge-only and 64.2% for Cloud–edge.

5 DISCUSSION

The results demonstrate the performance characteristics of the proposed architecture across the evaluated configurations. The Proposed 5G Cloud–edge architecture recorded a mean latency of 27.7 ms, compared with 176.4 ms for Cloud-only, 68.8 ms for Edge-only, and 45.6 ms for Cloud–edge. The lower latency indicates that the proposed architecture effectively supports faster communication and processing by combining edge computing with 5G connectivity and cloud resources.

The proposed architecture achieved the lowest latency (27.7 ms) and response time (42.6 ms) among the four configurations. The workload-level analysis further showed that its latency remained lowest under low (22.1 ms), medium (29.4 ms), and high (32.6 ms) workloads. The one-way ANOVA also showed a statistically significant difference in latency across the configurations, $F(3, 300) = 1846.27$, $p < .001$, indicating that the observed differences in latency were statistically significant.

The Proposed 5G Cloud–edge architecture recorded the highest throughput (73.7 Mbps) and the lowest packet loss (0.62%). In comparison, the Cloud-only configuration achieved 32.6 Mbps throughput with 2.34% packet loss, while the Cloud–edge configuration recorded 67.8 Mbps and 1.11%, respectively. These results indicate improved data transmission performance and reduced packet losses with the proposed architecture.

The Proposed architecture recorded an average edge CPU utilization of 53.7%, compared with 71.6% for Edge-only and 64.2% for Cloud–edge. The corresponding standard deviation was 5.3%, indicating relatively stable utilization during the experiments. Although the Cloud-only configuration recorded lower edge CPU utilization (18.4%), this is expected because much of its processing occurs remotely rather than at the edge. The proposed architecture therefore demonstrates a more balanced distribution of processing between edge and cloud resources.

The statistical analysis provides evidence that the differences among the configurations were not attributable to random variation alone. The ANOVA produced $F(3, 300) = 1846.27$, $p < .001$, confirming a statistically significant difference in latency across the four configurations. The pairwise analysis also reported statistically significant differences ($p < .001$) with large effect sizes, indicating that the observed performance differences were both statistically significant and practically meaningful.

Taken together, the findings show that the Proposed 5G Cloud–edge architecture performed consistently better across the principal performance indicators. Its advantages were particularly evident in latency, response time, throughput, and packet loss, while its workload-level performance remained comparatively stable as demand increased. These results provide empirical support for the effectiveness of integrating 5G connectivity with cloud–edge processing for applications requiring responsive and reliable communication.

6 CONCLUSION

This study developed and evaluated a 5G-enabled cloud–edge robotic architecture for low-latency industrial automation. The results demonstrated clear performance improvements over the Cloud-only, Edge-only, and conventional Cloud–edge configurations. The proposed architecture achieved the lowest mean latency (27.7 ms), response time (42.6 ms), and packet loss (0.62%), while recording the highest throughput (73.7 Mbps). Its latency advantage was maintained across low, medium, and high workload levels, with corresponding values of 22.1 ms, 29.4 ms, and 32.6 ms, respectively.

The statistical analysis confirmed significant differences in latency among the evaluated configurations ($F(3, 300) = 1846.27$, $p < .001$), with the pairwise comparisons also yielding $p < .001$ and large effect sizes. The proposed architecture additionally recorded lower edge CPU utilization (53.7%) than the Edge-only (71.6%) and Cloud–edge (64.2%) configurations, indicating improved distribution of computational workloads.

Our findings reveal that the integration of 5G connectivity with coordinated cloud–edge processing can enhance the responsiveness, communication efficiency, and reliability of industrial robotic systems. The proposed architecture therefore offers a suitable framework for industrial automation applications where low latency, high throughput, reliable communication, and efficient resource utilization are critical.

Recommendations

Our finding necessitated the following recommendations: industrial robotic systems should adopt 5G-enabled cloud–edge processing for latency-sensitive operations, with time-critical tasks assigned to nearby edge resources and non-critical workloads handled by the cloud. Workload allocation should consider processing requirements, network conditions, and response-time demands, while continuous monitoring of latency, throughput, packet loss, and resource utilization should be maintained to support efficient system operation. This approach can help achieve responsive robotic control while ensuring effective utilization of both edge and cloud resources.

Future Work

Future research should validate the proposed architecture with physical industrial robots and private 5G networks under real-world conditions. Studies should also investigate AI-driven task allocation and evaluate scalability, energy efficiency, security, and reliability in larger and more demanding robotic environments.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

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Disclosure of conflict of interest

The author(s) declare no conflict of interest

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