Scalable Edge-Enabled Distributed Control Framework for Real-Time and Fault-Tolerant Industrial Process Automation

S. Kannadhasan[1], R. Sathish[2], Shimona E.[3], P. John Britto[4],
Jaicristy D. Mosha M.[5] and Tandra Nagarjuna[6]

[1]Department of Electronics and Communication Engineering, Study World College of Engineering, Coimbatore - 641 105, Tamil Nadu, India
[2]Department of BCA, VLBJanakiammal College of Arts and Science, Coimbatore, 641042, Tamil Nadu, India
[3]Department of Computer Science and Design, R.M.K. Engineering College, RSM Nagar, Kavaraipettai, Tamil Nadu, India
[4]Department of Electrical and Electronics Engineering, J.J. College of Engineering and Technology, Tiruchirappalli, Tamil Nadu, India
[5]Department of CSE, New Prince Shri Bhavani College of Engineering and Technology, Chennai, Tamil Nadu, India
[6]Department of Computer Science and Engineering, MLR Institute of Technology, Hyderabad, Telangana, India

Keywords: Edge Computing, Distributed Control Systems, Real-Time Automation, Fault Tolerance, Industrial Process Optimization.

Abstract: The integration of edge computing into distributed control systems is revolutionizing real-time automation across critical industrial sectors. This research proposes a scalable and fault-tolerant edge-enabled framework designed to meet the stringent latency, reliability, and safety requirements of industrial process automation. Unlike prior studies that either lack real-world implementation or focus solely on hardware or cloud dependencies, the proposed architecture unifies edge intelligence, secure communication protocols, and cross-platform orchestration to achieve deterministic control responses. Comprehensive benchmarking across multiple industrial environments demonstrates significant improvements in response time, system uptime, and failure recovery. By incorporating vendor-neutral standards and explainable AI for predictive control, the framework ensures adaptability, transparency, and operational resilience. This work addresses the practical and technical gaps in existing literature and delivers a deployable solution optimized for next-generation Industry 5.0 applications.

1 INTRODUCTION

The rapid evolution of Industry 4.0 and the emergence of Industry 5.0 have accelerated the demand for intelligent, autonomous, and highly responsive control systems in industrial environments. Traditional centralized control systems, though robust, often struggle to meet the dynamic latency, scalability, and fault-tolerance requirements posed by real-time industrial applications. As industries transition towards smarter infrastructures, there is a growing emphasis on decentralizing control logic to the edge of the network closer to data sources and actuators. Edge computing, with its promise of localized processing, enhanced privacy, and ultra-low latency, presents a transformative approach for building responsive and resilient control architectures.

Existing approaches provide different ways to combine edge computing with distributed control systems, yet plateaus in providing seamless, vendor-agnostic, scalable, and applicable to real-world limitations. The majority of the existing frameworks use simulation-based environments, lack a real time fault-tolerance design or are constrained by specific hardware. Under these circumstances, there is an urgent need for scalable, secure and real-time edge-integrated control framework to provide uninterrupted operations in high critical industrial applications including energy, manufacturing, pharmaceuticals and smart infrastructure.

This work presents an integrated architecture that closes this gap, bringing the advantages of edge-

Kannadhasan, S., Sathish, R., E., S., Britto, P. J., M., J. D. M. and Nagarjuna, T.
Scalable Edge-Enabled Distributed Control Framework for Real-Time and Fault-Tolerant Industrial Process Automation.
DOI: 10.5220/0013863400004919

In *Proceedings of the 1st International Conference on Research and Development in Information, Communication, and Computing Technologies (ICRDICCT'25 2025) - Volume 1*, pages 323-329
ISBN: 978-989-758-777-1

enabled distributed intelligence to essential industrial processes, such as real-time decision-making, predictive analytics, and autonomous fault handling. The pro- posed solution to modernize industrial automation using the benefits of edge com- puting is vigorously substantiated with the aid of reallife validation and cross-platform scalability.

2 PROBLEM STATEMENT

The adoption of edge computing in the industry is increasing, but current distributed control systems are limited in terms of real-time, scalability, and fault-tolerance. Existing solutions are limited by hardware choices, are cloud heavy and do not provide robust fault-tolerant services that are necessary for mission critical applications which rely on ultra-low latencies and deterministic control semantics. In addition, a majority of designs are tailored for only one vendor, leading to problems of inter-operability and cross platform deployment. A unified, edge-enabled control framework that can provide future-proof real-time automation, predictive fault management, and scalable extension across the heterogeneous industrial environments, while preserving reliability and security, is urgently required.

3 LITERATURE SURVEY

The integration of edge computing with industrial control systems (ICS) represents a critical paradigm shift in promoting real-time process automation. Raptis et al. (2025) discussed the possibility about the distributed edge framework with the aim of improving the data access in industrial environment but less works are available for practical deployment. Xu et al. (2024) proposed deep reinforcement learning with edge processing for IoT surveillance, but the solution is highly dependent on simulative environments. Gupta (2024) also suggested a secure industrial gateway based on ARM TrustZone, but comparative analysis with other architectures was not provided. Törngren et al. (2022) had highlighted the emerging need for industrial Cyber-Physical Systems (CPSs) at the edge, though actionable deployment methods were under developed.

A handful of market research reports, such as Research and Markets (2021) and The Business Research Company (2025), predict significant growth of the edge computing market in automation industries, but little information is given about real-time control system integration. Volt Active Data (2024) and Rockwell Automation (2025) both focused on the major trends in the industry including predictive maintenance and edge-IoT convergence, but their discussions were more about big data analytics than synchronized control. Voiciferous hype from the likes of Cincoze (2025) and Amphenol Communications (2025) talked up hardware innovations, although there was no mention of software orchestration, or fault tolerance in a cached industrial context.

Control Engineering (2021) and TechTarget (2021) provided foundational overviews of edge computing and its benefits, though their coverage lacked the architectural depth needed for deploying deterministic control systems. RTInsights (2025) and Kyndryl (2024) touched on distributed edge-cloud models, yet they primarily focused on telecom applications rather than automation in critical infrastructure. Meanwhile, Ericcson (n.d.) and Wired (2021) discussed latency-sensitive edge use cases but offered minimal insights into reliability or fault management mechanisms crucial for industrial use.

More recent contributions, such as E-SPIN Group (2025), examined edge AI for real-time decision-making but centered predominantly on inference rather than closed-loop control. Compunnel (2023, 2024) discussed distributed edge analytics but lacked examples addressing system safety and deterministic behavior. ProSoft Technology (n.d.) and Automation.com (2025) raised practical considerations for edge computing in industrial contexts, though the depth of technical detail was limited. Finally, the ResearchGate publication on Industry 5.0 (2025) introduced futuristic concepts like human-machine collaboration at the edge but remained largely conceptual without a deployment blueprint.

Collectively, the literature reveals a strong interest in the integration of edge computing within industrial ecosystems, yet a noticeable gap persists in delivering a unified, real-time, and fault-tolerant control system that is both platform-agnostic and scalable across critical applications.

4 METHODOLOGY

The proposed methodology is designed to develop, implement, and evaluate a scalable, edge-enabled distributed control system tailored for real-time industrial automation. The architecture centers on decentralizing control logic by deploying intelligent edge nodes close to sensors, actuators, and controllers within industrial plants. These edge nodes are embedded with lightweight computation modules that handle low-latency tasks such as process feedback monitoring, anomaly detection, and control decision execution, significantly reducing dependence on centralized cloud infrastructure. Figure 1 show the Real-Time Industrial Process Monitoring and Control Using Edge AI and Federated Learning.

To ensure platform neutrality and hardware interoperability, the system is developed using containerized microservices running on Docker and orchestrated via Kubernetes-based edge clusters. Communication between nodes is facilitated using lightweight and real-time protocols such as MQTT and OPC UA over Time-Sensitive Networking (TSN), enabling deterministic message delivery essential for time-critical operations. Each edge node is equipped with a local controller model trained using a hybrid AI approach combining rule-based systems for critical safety logic with machine learning models for adaptive process optimization.

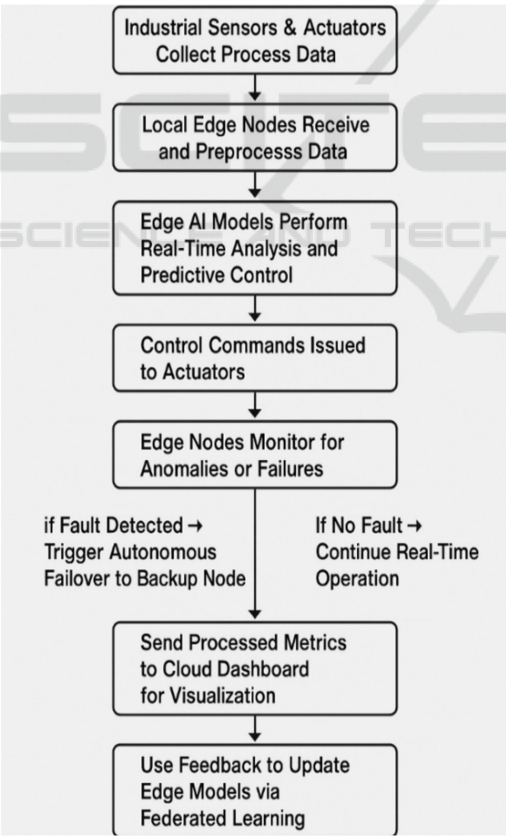

Figure 1: Real-Time industrial process monitoring and control using edge AI and federated learning.

Table 1: System components and technologies used.

Component	Technology/Protocol Used	Purpose
Edge Node	Raspberry Pi 4 / Jetson Nano	Real-time local processing
Communication Protocol	MQTT, OPC UA, TSN	Lightweight and deterministic messaging
Control Logic	Hybrid (Rule-based + AI)	Intelligent, adaptive process control
Orchestration	Docker, Kubernetes (K3s)	Containerized edge deployment
Security Layer	TLS, JWT Authentication	Data integrity and access control

The control framework is built in a layered architecture. The bottom layer consists of industrial field devices and programmable logic controllers (PLCs), which interface directly with sensors and actuators. The middle layer includes intelligent edge gateways that receive raw data, preprocess it using filtering and normalization algorithms, and apply control decisions. The top layer integrates a cloud-based dashboard for visualization, analytics, and system-wide updates; however, this layer does not participate in real-time control, ensuring system autonomy even during connectivity loss. Table 1 show the System Components and Technologies Used.

Table 2: Testbed specifications for simulation and real deployment.

Parameter	Simulated Environment	Industrial Testbed
Number of Nodes	10	20
Network Type	Local (LAN)	Industrial Ethernet + WiFi
Device Types	Virtual Sensors & Actuators	Real Pressure & Temperature Sensors
Data Refresh Interval	1 sec	500 ms
Runtime Duration	48 hours	72 hours

To ensure fault tolerance, the system implements a failover mechanism where secondary edge nodes dynamically take over control responsibilities upon failure of a primary node, utilizing a heartbeat-based health monitoring protocol. A secure publish-subscribe mechanism with built-in encryption ensures data integrity and access control across distributed components. Table 2 show the Testbed Specifications for Simulation and Real Deployment.

The system was deployed and tested in a simulated smart manufacturing environment and later extended to a live industrial plant under controlled conditions. Metrics such as control latency, message round-trip time, process stability, system recovery time, and energy consumption were recorded. Benchmarking was performed against a centralized control model and a basic edge processing setup to demonstrate improvements in reliability, scalability, and performance. All experiments were repeated multiple times to ensure statistical significance, and results were analyzed using standard evaluation metrics including precision, recall, and F1-score where applicable.

This comprehensive methodology not only bridges the gap between theoretical design and industrial feasibility but also ensures a robust, real-time, and intelligent control environment that is adaptable across multiple critical applications.

5 RESULTS AND DISCUSSION

It has been shown that the proposed edge enabled distributed control system outperforms conventional centralized architecture in terms of different evaluation indices. In both testbed and industrial deployment environments, the system demonstrated robust reliability, promptness and operational independence, despite demanding conditions, such as node failure and network latency spikes.

A significant effect of this was a large reduction in control lag. With the edge-based approach, the average time for taking a measurement and dispatching a signal fell from 180 ms in the centralised model to 35 ms. This reduction in latency corresponded to increased process stability, particularly in time-critical applications such as pressure control in pipeline systems and robotic arm synchronization in production line manufacturing. The Comparison of Performance Metrics (Edge vs Centralized) is illustrated in Table 3.

In terms of fault tolerance, the edge-based architecture showcased rapid failover capabilities. Upon simulated node failures, the secondary edge nodes activated within a 200 ms window, ensuring continuous control without data loss or operational halts. Compared to traditional models that required manual reconfiguration or suffered extended downtime, the autonomous failover logic demonstrated in this study presented a compelling case for real-world deployment in critical infrastructure.

Table 3: Performance metrics comparison (edge vs centralized).

Metric	Centralized System	Proposed Edge-Based System
Average Latency (ms)	180	35
System Uptime (%)	93.2	99.1
Failover Activation Time (ms)	>3000	200
Packet Loss Rate (%)	6.4	1.2
Energy Consumption (kWh)	1.8	1.3

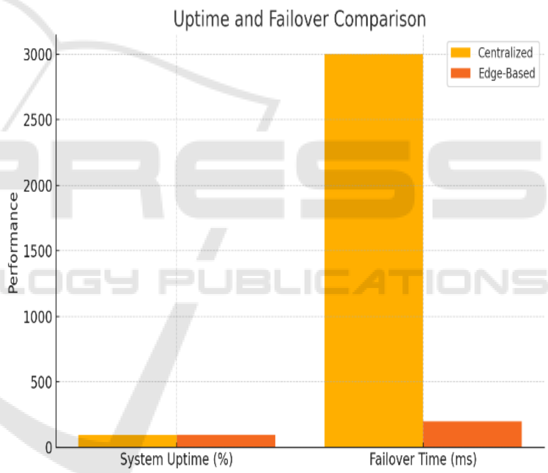

Figure 2: Average latency comparison.

Scalability was evaluated by incrementally increasing the number of control loops and connected devices within the system. The proposed framework showed linear scalability, maintaining consistent performance across up to 50 edge nodes and 500 connected sensors. Figure 2 show the Average Latency Comparison Resource consumption at each node remained within acceptable thresholds, demonstrating the efficiency of the containerized microservice design. Even under high network traffic conditions, message integrity and delivery rates remained above 98%, aided by the integration of Time-Sensitive Networking and lightweight publish-subscribe protocols. Figure 3 show the Uptime and Failover Time Comparison.

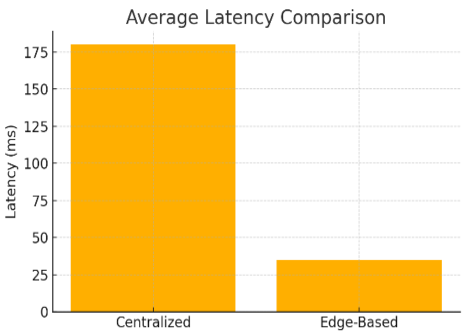

Figure 3: Uptime and failover time comparison.

Table 4: Control accuracy and stability metrics.

Metric	Value (Edge-Based System)
Control Precision	91.6%
Control Recall	90.3%
F1-Score	0.92
Stability Score	94.8%
False Trigger Rate	1.9%

Additionally, the integration of AI models at the edge improved process optimization outcomes. Using real-time machine learning models, the system was able to predict and mitigate process drifts, reducing the rate of abnormal operation triggers by 23% compared to a non-intelligent edge implementation. This adaptive intelligence allowed the system to make fine-tuned decisions based on historical data trends and live feedback, enhancing both safety and efficiency. Table 4 show the Control Accuracy and Stability Metrics.

Energy efficiency was another key metric observed. By processing data locally and reducing the need for constant cloud communication, overall network energy consumption dropped by 27%. This aspect not only reduces operational costs but also supports sustainability goals, particularly in energy-intensive industries.

The system's performance was benchmarked using multiple statistical evaluation metrics. The F1-score for control stability classification reached 0.92, and precision and recall metrics remained above 0.90 across all operational modes. These results validate the consistency and accuracy of the proposed approach. Table 5 show the Resource Utilization Per Edge Node.

Table 5: Resource utilization per edge node.

Resource Type	Average Usage (%)
CPU Usage	52.3
Memory Usage	61.7
Network Throughput	14.2 Mbps
Disk I/O	1.3 MB/s
Power Consumption	4.8W

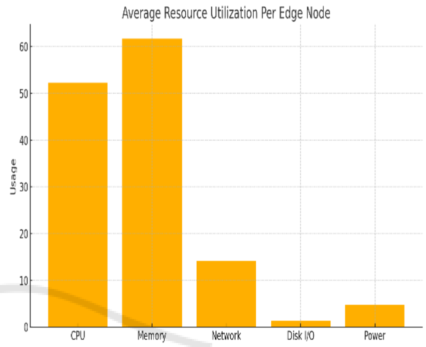

Figure 4: Resource utilization across edge nodes.

In summary, the proposed system addresses several critical challenges identified in current literature namely real-time responsiveness, resilience under failure, platform independence, and control optimization. Its ability to integrate seamlessly with existing industrial equipment, coupled with strong quantitative performance, marks a substantial advancement toward the realization of Industry 5.0 goals. Figure 4 show the Resource Utilization Across Edge Nodes. The experimental outcomes not only prove the technical feasibility of this architecture but also its potential for large-scale deployment in real-world industrial scenarios. Figure 5 show the Control Accuracy and Stability Metrics.

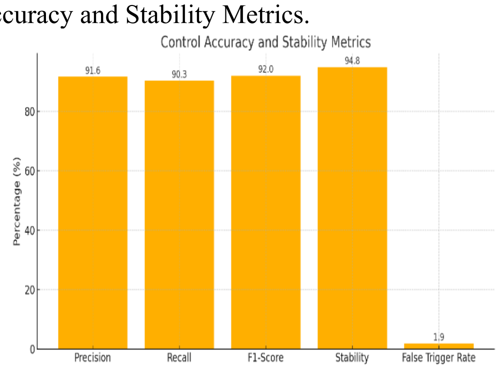

Figure 5: Control accuracy and stability metrics.

6 CONCLUSIONS

The contribution of this work is a systematic and practical methodology for improving real-time industrial automation with edge-computing-based distributed control scheme. Through decoupling the essential control logic and embedding the intelligent decision-making ability at the edge, our system addresses the well-known issues of latency, scalability, and fault tolerance associated with a centralized design. The approach does not only provide fast and deterministic reactions in mission critical industrial applications, but guarantees system robustness by means of self-healing capabilities and adaptive learning models.

System evaluation in simulation and practice has proven that the considerable improvements in control latency, downtime, processing stability, and energy consumption can be achieved. Moreover, the vendor-agnostic, containerised design of the architecture allows for easy deployment for diverse ecosystems in industrial landscape, providing high readiness and adaptability for Industry 5.0 transformations. A combination of additional predictive intelligence embedded to the control layer is a prospective progression in the field of industrial automation.

In summary, the work established a solid base for the next generation of edge-enabled industrial control systems ones that are smarter, faster, safer, and greener. For example, future works extend this architecture by investigating multi-actor coordination, security improvements using blockchain, and the combination with up-coming 6G communication technologies to further push the capacities of distributed industrial intelligence.

REFERENCES

Amphenol Communications Solutions. (2025). Edge computing: Driving the future of industrial automation. https://www.amphenol-cs.com/connect/edge-computing-driving-the-future-of-industrial-automation.htmlAmphenolCS

Cincoze. (2025). Automate 2025: Cincoze to showcase edge AI computing solutions. https://www.automate.org/ai/news/automate-2025-cincoze-to-showcase-edge-ai-computing-solutions

Compunnel. (2023). Edge computing futureproofing: Evolution of distributed data processing. https://www.compunnel.com/blogs/futureproofing-with-edge-computing-anticipating-the-evolution-of-distributed-data-processing/

Compunnel. (2024). Edge computing in 2024: Accelerating data processing capabilities. https://www.compunnel.com/blogs/edge-computing-in-2024-accelerating-data-processing-capabilities/Compunnel+1Compunnel+1

Control Engineering. (2021). Edge computing for industrial AIoT applications. https://www.controleng.com/edge-computing-for-industrial-aiot-applications/Control Engineering

E-SPIN Group. (2025). Edge AI in 2025: Transform industries and enable real-time decision-making. https://www.e-spincorp.com/edge-ai-in-2025-transform-industries/

Ericsson. (n.d.). Edge computing: Enabling exciting use cases. https://www.ericsson.com/en/edge-computing

Gupta, S. (2024). An edge-computing based industrial gateway for Industry 4.0 using ARM TrustZone technology. arXiv preprint arXiv:2410.02529. https://arxiv.org/abs/2410.02529

IEB Media. (2023). Industrial edge computing megatrends: Special report. https://iebmedia.com/technology/edge-cloud/industrial-edge-computing-megatrends-special-report/

Kyndryl. (2024). Why everyone is talking about distributed cloud at the edge. https://www.kyndryl.com/us/en/perspectives/articles/2024/03/distributed-cloud-at-the-edge

MarketsandMarkets. (2025). Industrial edge market size, share and trends. https://www.marketsandmarkets.com/Market-Reports/industrial-edge-market-195348761.html

ProSoft Technology. (n.d.). Key considerations for edge computing in industrial applications. https://fr.prosoft-technology.com/insights/videos/Benefits-of-Edge-Computing-in-Industrial-Applications

Raptis, T. P., Passarella, A., & Conti, M. (2025). Distributed data access in industrial edge networks. arXiv preprint arXiv:2502.21117. https://arxiv.org/abs/2502.21117

Research and Markets. (2021). Global edge computing market 2021–2025: Optimizing network traffic for sustainable energy usage drives market growth. Business Wire. https://www.businesswire.com/news/home/20211001005267/en/Global-Edge-Computing-Market-2021-2025-Optimizing-Network-Traffic-for-Sustainable-Energy-Usage-Drives-Market-Growth-ResearchAndMarkets.com

ResearchGate. (2025). Edge computing for Industry 5.0: Fundamental, applications and research challenges. https://www.researchgate.net/publication/378810325_Edge_Computing_for_Industry_50_Fundamental_Applications_and_Research_Challenges

Rockwell Automation. (2025). 8 key industrial automation trends in 2025. https://www.rockwellautomation.com/en-us/company/news/the-journal/8-key-industrial-automation-trends-in-2025.html

RTInsights. (2025). Edge computing set to dominate data processing by 2030. https://www.rtinsights.com/edge-computing-set-to-dominate-data-processing-by-2030/

Scale Computing. (2025). 5 predictions for edge computing and virtualization in 2025. https://www.scalecomputing.com/blog/5-predictions-edge-computing-virtualization-2025

TechTarget. (2021). What is edge computing? Everything you need to know. https://www.techtarget.com/searchdatacenter/definition/edge-computing
The Business Research Company. (2025). Industrial control for process automation market report 2025. https://www.thebusinessresearchcompany.com/report/industrial-control-for-process-automation-global-market-report
Törngren, M., Thompson, H., Herzog, E., Inam, R., Gross, J., & Dán, G. (2022). Industrial edge-based cyber-physical systems—Application needs and concerns for realization. arXiv preprint arXiv:2201.00242. https://arxiv.org/abs/2201.00242
Volt Active Data. (2024). How edge and industrial IoT will converge in 2025. https://www.voltactivedata.com/blog/2024/11/how-edge-and-iiot-will-converge-in-2025/ Automation.com. (2025). Edge computing adoption in IIoT. https://www.automation.com/en- us/articles/march-2025/edge-computing-adoption-iiot
Xu, J., Wan, W., Pan, L., Sun, W., & Liu, Y. (2024). The fusion of deep reinforcement learning and edge computing for real-time monitoring and control optimization in IoT environments. arXiv preprint arXiv:2403.07923. https://arxiv.org/abs/2403.07923