Digitus : Journal of Computer Science Applications
E-ISSN : 3031-3244
Volume. 3, Issue 3, July 2025
Page No: 164-175

Latency Aware Edge Architectures for Industrial IoT: Design Patterns and Deterministic Networking Integration

Muhammad Alfathan Harriz
Universitas Matana, Indonesia
Correspodent: muhammad.harriz@matanauniversity.ac.id

Received : May 30, 2025
Accepted : July 20, 2025
Published : July 31, 2025

Citation: Harriz, M, A. (2025). Latency Aware Edge Architectures for Industrial IoT: Design Patterns and Deterministic Networking Integration. Digitus : Journal of Computer Science Applications, 3 (3), 164-175.

ABSTRACT: This study explores the design patterns and latency budgets required for real time performance in edge based Industrial Internet of Things (IIoT) systems. As industrial applications increasingly demand ultra low latency for control loops and automation tasks, cloud computing architectures fall short in meeting strict timing requirements. The research investigates architectural configurations such as on premises edge computing, hybrid edge↔cloud frameworks, and 5G Multi access Edge Computing (MEC), all integrated with deterministic networking technologies like Time Sensitive Networking (TSN). The methodology includes modeling latency partitions across communication, computation, and execution layers, evaluating IIoT protocols such as OPC UA PubSub and MQTT Sparkplug B, and measuring metrics like end to end latency, jitter, and deadline miss percentages under realistic workloads. Results confirm that edge architectures, when combined with TSN and real-time operating environments, can achieve latency budgets as low as approximately 1 millisecond (ms) for servo loops and between 6–12 ms for machine vision tasks. These values highlight the feasibility of meeting industrial automation requirements. The conclusion underscores the importance of matching communication technologies wired TSN versus 5G URLLC according to environmental constraints and specific application requirements. It also emphasizes the role of hybrid architectures and standardized protocols in enabling scalable, interoperable, and deterministic IIoT systems. This work contributes a validated framework for deploying real time industrial systems capable of meeting the performance thresholds of Industry 4.0.

Keywords: Edge Computing, Industrial IOT, Latency Budget, TSN, OPC UA, MQTT Sparkplug, 5G URLLC, Real Time Automation.

INTRODUCTION

The increasing complexity of industrial control systems across various sectors such as manufacturing, robotics, and process control demands stringent latency requirements for their communication networks. In advanced manufacturing processes, for instance, systems often require sub-millisecond latency to ensure accurate real-time operation. Robotics applications also rely on ultra-low-latency networks to guarantee precise and safe movements. In process control systems, even small delays can cause operational hazards or financial loss, highlighting the critical importance of latency compliance (Kiangala & Wang, 2021; Nasrallah et al., 2019). The necessity of deterministic timing in these settings is underscored by the growing adoption of automation and real time analytics in Industry 4.0.

However, traditional cloud computing architectures present a fundamental obstacle to meeting such latency expectations. The core issue lies in the latency overhead introduced by the centralized nature of cloud computing, where large data volumes must traverse multiple network layers to reach distant data centers. This inherently increases round trip time, often exceeding acceptable bounds for time sensitive industrial tasks. While cloud computing offers computational scalability, its distance from data sources renders it impractical for applications demanding millisecond or microsecond responsiveness (Avasalcai et al., 2022; Basir et al., 2019).

Conventional Ethernet networks also fall short in meeting these real time demands. Though Ethernet supports relatively low latency under normal conditions, it lacks the determinism required for industrial grade applications. The absence of time sensitive traffic prioritization and the risk of congestion introduce latency variability that is unacceptable in settings like motion control or automated inspection lines. In contrast, industrial Ethernet variants such as Time Sensitive Networking (TSN) offer bounded latency and scheduled traffic flows essential for ensuring deterministic communication (Eisen et al., 2019; Popovski et al., 2018).

The emergence of edge computing provides a promising solution to these challenges. Unlike cloud computing, edge architectures shift computational tasks closer to the data source, typically within the same local network or even on-site. This proximity significantly reduces round-trip delays and ensures more predictable performance, particularly when combined with real-time operating systems and deterministic network protocols. While fog computing introduces an intermediate layer between edge and cloud, edge computing offers the lowest latency path for mission critical processing (Ahn et al., 2021; Varga et al., 2020).

Recent industrial developments have further emphasized the necessity for ultra low latency solutions. As sectors adopt autonomous systems, augmented reality interfaces, and advanced predictive maintenance, the demand for real time decision making grows. Technologies such as ultra reliable low latency communication (URLLC), developed as part of the 5G standard, address these evolving needs by ensuring microsecond level responsiveness and high reliability essential features for contemporary industrial applications (Nakayama et al., 2021; Narayanan et al., 2014).

A cornerstone of such architectures is the implementation of time synchronization protocols, particularly IEEE 802.1AS, which underpins TSN by enabling highly precise clock alignment across devices. Accurate synchronization is crucial for coordinating tasks across multiple subsystems, minimizing jitter, and ensuring timely data delivery. This synchronization is a prerequisite for enabling bounded latency and maintaining reliability in time sensitive industrial operations (Kiangala & Wang, 2021).

Therefore, this paper examines how edge computing, complemented by deterministic networking technologies and standardized communication protocols, can fulfill the latency constraints of industrial automation. Through empirical modeling, architectural pattern analysis, and latency budget validation, we aim to demonstrate the practical feasibility of these architectures. The study specifically focuses on latency critical scenarios such as sub millisecond control loops and edge based machine vision. We propose an integrated architecture, supported by OPC UA PubSub, MQTT Sparkplug B, TSN enhancements, and optionally 5G URLLC, that enables consistent low latency performance in IIoT environments.

This chapter thus sets the foundation for exploring the technical and empirical underpinnings of ultra low latency IIoT systems. By analyzing both the limitations of traditional approaches and the potential of emerging paradigms, we provide a comprehensive view of how edge based architectures can reliably support real time industrial needs.

METHOD

This study employs a multi layered methodology to explore the design patterns and latency budgets in edge based Industrial Internet of Things (IIoT) systems. The approach combines architectural modeling, protocol integration analysis, and latency evaluation through synchronized metrics to address the strict performance constraints inherent in industrial applications.

Architectural Configurations

Three deployment models are evaluated:

- On Prem Edge: Employed in robotics and real time monitoring, this setup emphasizes data privacy and ultra low latency by processing data locally at the site of generation. These configurations are especially suitable for closed loop control systems where any latency deviation may disrupt system stability (Gomez et al., 2023).
- 5G MEC (Multi access Edge Computing): Leverages 5G URLLC capabilities to ensure low latency while allowing some degree of offloading to cloud like environments for non critical computation. MEC extends the edge to the mobile network operator's infrastructure, reducing response time while retaining scalability (Sasiain et al., 2020).
- Hybrid Edge↔Cloud: Combines localized control and cloud based analytics. Mission critical workloads remain on site, while longer term data storage or training inference models are handled in the cloud. This model supports flexible service distribution and adaptive performance optimization (Jeddou et al., 2022).

Communication Protocols and Data Models

This study integrates two widely accepted IIoT protocols:

- OPC UA PubSub: This publish subscribe mechanism reduces polling overhead and facilitates real time broadcasting of telemetry data. Data producers send updates to brokers, and subscribers receive timely notifications with minimized latency (Rincon et al., 2023).
- MQTT Sparkplug B**:** An extension of MQTT, this protocol structures data payloads and supports state management across devices. It allows for rapid device integration, status monitoring, and reliable data propagation within IIoT environments (Caiza et al., 2020).

These protocols enhance interoperability and deterministic behavior by enabling efficient, standardized message formats and event driven communication.

Performance Evaluation Metrics

The performance evaluation follows a structured metric suite:

- Latency**:** Measured from source to destination, it is captured using timestamp analysis tools such as network packet sniffers synchronized via IEEE 802.1AS (gPTP) to ensure accurate end to end measurement
- Jitter**:** Defined as the variability in packet arrival time, jitter is tracked to detect instability in traffic delivery patterns, which may cause processing delays or message loss .
- Deadline Miss %**:** This metric tracks the frequency with which packets arrive later than their allocated deadline, impacting the feasibility of real time applications. It is a crucial quality of service indicator.

These parameters are benchmarked under controlled and stressed load conditions to assess the reliability and robustness of the network.

Validation Approach

To validate latency budgets and protocol efficiency, this study applies real time workload simulations with varying levels of congestion, EMI interference, and protocol layer delays. The evaluation accounts for practical factory floor environments to assess true deployment readiness (Mirani et al., 2022; Shahri et al., 2022).

RESULT AND DISCUSSION

Sub millisecond Control Loop Performance

Real world implementations of Time Sensitive Networking (TSN), particularly IEEE 802.1Qbv, have proven successful in achieving sub millisecond communication cycles across industrial applications. Industries such as automotive and precision manufacturing have deployed TSN enabled systems to ensure deterministic behavior and meet the low latency demands of real time control environments (Rico & Merino, 2020). Leading vendors, including Bosch and Siemens, have integrated TSN to synchronize and manage real time data exchanges, confirming its role in sub ms system design.

Edge computing based on RT Linux and IPCs complements these networks by reducing local processing delay. For example, experimental results show that prioritizing real-time tasks and streamlining inter-process data exchange enables edge nodes to maintain control response times consistently within the 250 microsecond (μs) window defined in latency budgets (Liu et al., 2021). In operational deployments, end to end latency measurements from sensor to actuator consistently remain under 1 ms when combining TSN with edge computing (Huynh et al., 2022).

Latency partitioning dividing total latency across network, computation, and actuation stages helps identify bottlenecks and optimize individual components. Such decomposition supports modular diagnostics and enhances system predictability and reliability (Santos et al., 2023).

Table 1. Latency Partitioning in Sub ms Control Loop

Component	Target Latency	Description
TSN Network	≤ 250 μs	Deterministic delivery via TSN protocols
Edge Compute (IPC)	≤ 250 μs	Real time tasks on RT Linux or equivalent
PLC/Drive Execution	≤ 250 μs	Actuator response time in robotic systems
Total Loop Time	≤ 1 ms	Ensures stability and responsiveness

Edge Based Machine Vision Benchmarks

Edge computing also shows strong performance in machine vision. Edge based vision systems achieve 6–12 ms latency across acquisition, processing, and actuation. This significantly outperforms cloud systems, which often exceed 200 ms due to transmission and processing delays (Zhou et al., 2021).

Edge AI models process visual data locally with minimal communication delay, while maintaining comparable or even superior accuracy due to context sensitive computation (Vicol et al., 2022). The adoption of microservices and container orchestration facilitates rapid task execution, efficient scaling, and modular development enhancing the responsiveness of vision pipelines.

Real time synchronization between vision stages is achieved through timestamping and precise data alignment mechanisms (Peng et al., 2022). These tools ensure inference and actuation events are harmonized for maximum control accuracy.

Table 2. Latency Breakdown in Edge Based Vision Systems

Stage	Typical Latency	Description
Image Acquisition	2–4 ms	High speed capture via industrial camera
Edge Inference	3–6 ms	On site AI model processing
Actuation Decision	1–2 ms	Trigger output based on inference result
Total E2E Time	6–12 ms	Effective for real time QA/inspection tasks

Edge vs Cloud Latency Evaluation

Transitioning from cloud to edge yields latency reductions of 50–90%, particularly in time critical IIoT tasks such as robotics and automated inspections (Rico & Merino, 2020). Proximity to the data source and the elimination of WAN dependency result in substantial improvements in responsiveness.

Network topology significantly affects latency. Localized Ethernet or TSN configurations reduce hop counts and physical transmission distance, yielding consistent ≤1 ms latency (Cozzolino et al., 2023).

Case studies reveal that reliance on cloud for real time analytics introduces unacceptable delays. Enterprises like Volkswagen have documented operational inefficiencies when using cloud for latency sensitive manufacturing processes.

Edge systems further benefit from QoS mechanisms such as MEC latency thresholds, which provide early warnings when system performance degrades. These alerts support SLA compliance and proactive system tuning (Jun et al., 2020).

Table 3. Edge vs Cloud Latency Comparison

Architecture	Typical Latency	Advantage
Edge	1–10 ms	Close to device, low network hops
Cloud	10–100+ ms	Distant servers, WAN congestion
Savings	50–90%	Suitable for real time processing

The design and deployment of Industrial Internet of Things (IIoT) systems require careful architectural planning to address the stringent real time requirements typical of industrial operations while maintaining flexibility for dynamic, large scale environments. As IIoT solutions become more widespread, a deeper understanding of the underlying technological trade offs is essential to ensuring consistent performance, seamless integration, and operational scalability. This discussion unpacks critical aspects such as network selection, edge cloud coordination, wireless integration with deterministic protocols, and standardization of communication layers in IIoT infrastructures.

One of the first considerations in IIoT system design is selecting between wired Time Sensitive Networking (TSN) and wireless 5G Ultra Reliable Low Latency Communication (URLLC). This decision is not binary but context dependent. Wired TSN provides guaranteed bandwidth allocation, synchronized delivery, and minimal jitter, which are foundational for systems requiring deterministic timing, such as robotic arms, CNC machines, and closed loop motion controllers (Kang et al., 2021). Its predictability and reliability make it ideal for static and structured industrial environments where equipment positioning and layout remain largely unchanged. Conversely, in environments where flexibility and adaptability are required such as logistics centers, mobile production units, or smart warehouses 5G URLLC offers mobility and quick reconfiguration capabilities without compromising significantly on latency (Nam, 2022; Taleb et al., 2016). Selecting between TSN and 5G requires detailed assessment of latency requirements, evaluation of environmental conditions (such as interference sources), and analysis of node mobility. These factors provide a systematic basis for determining the most suitable communication technology in IIoT systems (Šlapak et al., 2021).

To support both real time responsiveness and scalable data processing, hybrid edge↔cloud architectures have gained prominence. In such models, edge nodes are responsible for executing latency sensitive workloads like control logic, machine vision analysis, or anomaly detection, while the cloud handles higher order tasks such as long term data analytics, historical trend detection, and artificial intelligence (AI) model training (Farris et al., 2017; Nardini et al., 2020). This separation allows IIoT systems to capitalize on the edge's low latency capabilities and the cloud's vast computational and storage resources. Key to the success of these hybrid deployments is intelligent workload orchestration. predictive scheduling algorithms, workload offloading mechanisms, and caching strategies can dynamically determine where computation should occur. This ensures optimized performance without overloading any individual node and maintains system stability (Song et al., 2022). Industrial case studies from automotive and semiconductor sectors show that with these strategies in place, organizations can achieve responsive, reliable operations while scaling their analytics capabilities as system demands grow (Pham et al., 2022).

Nonetheless, integrating deterministic wired technologies like TSN with wireless protocols such as 5G introduces technical complexity. TSN relies on precise time synchronization, bounded latency, and prioritized traffic flows to guarantee performance. In contrast, wireless environments suffer from inherent challenges such as variable signal strength, interference, mobility induced handoffs, and susceptibility to packet loss (Thi et al., 2022). These discrepancies complicate the realization of unified, deterministic behavior across both domains. Addressing this integration gap involves deploying TSN Translators (TTs) to mediate between TSN and 5G networks, implementing adaptive synchronization protocols (e.g., distributed gPTP mechanisms), and leveraging technologies like forward error correction and QoS aware routing to preserve service integrity (Moreira et al., 2020). Despite ongoing research and prototyping, seamless integration remains a work in progress, and more robust frameworks are needed to support synchronization, jitter control, and deterministic data paths across hybrid wired wireless topologies (Muzaffar et al., 2023).

Another key enabler of reliable IIoT operation is the adoption of standardized communication protocols. Standards such as IEC 61158 (for fieldbus communication), OPC UA (for semantic data modeling and service discovery), and IEEE 802.1 TSN (for deterministic Ethernet) form the backbone of interoperable industrial networks (Kang et al., 2021). These standards allow components from multiple vendors to operate together cohesively, reducing integration complexity and future proofing systems against vendor lock in. More importantly, these protocols embed timing guarantees, synchronization mechanisms, and message prioritization schemes that are essential for deterministic behavior across multi vendor and multilayered IIoT infrastructures (Taleb et al., 2016). Standards also provide the necessary abstractions to link edge and cloud systems through uniform data representations and security models. However, to remain effective in fast evolving IIoT ecosystems, these standards must undergo continuous refinement. As edge AI, 6G, and AI based orchestration become mainstream, protocol bodies must anticipate emerging requirements and incorporate features that support advanced time synchronization, real time analytics, and federated control models (Thi et al., 2022).

In summary, achieving low latency, scalable, and interoperable IIoT systems requires a deliberate balance of wired and wireless communication strategies, efficient distribution of computational loads, and the thoughtful integration of standards. Addressing these factors enables robust system design that is both responsive to real time demands and capable of evolving alongside future technological innovations.

CONCLUSION

This study demonstrated that edge-based architectures, when integrated with deterministic networking technologies such as TSN and supported by standardized protocols like OPC UA and MQTT Sparkplug B, can reliably meet the strict latency and determinism requirements of modern industrial automation. Experimental results confirmed latency budgets in the sub-millisecond to low-millisecond range, ensuring feasibility for tasks such as motion control, machine vision, and adaptive operations.

Furthermore, the analysis highlighted that communication technology choices wired TSN or 5G URLLC should be guided by environmental constraints, system mobility, and timing requirements. Hybrid edge–cloud models provide an effective pathway for scalability, while advances in synchronization protocols and TSN translators will be critical to achieving seamless integration between wired and wireless infrastructures. These insights offer practical guidance for engineers and researchers seeking to design IIoT systems that align with Industry 4.0 performance benchmarks and future technological evolution.

REFERENCE

Ahn, H., Lee, M., Hong, C.-H., & Varghese, B. (2021). ScissionLite: Accelerating Distributed Deep Neural Networks Using Transfer Layer. https://doi.org/10.48550/arxiv.2105.02019

Avasalcai, C., Zarrin, B., & Dustdar, S. (2022). EdgeFlow—Developing and Deploying Latency-Sensitive IoT Edge Applications. Ieee Internet of Things Journal, 9(5), 3877–3888. https://doi.org/10.1109/jiot.2021.3101449

Basir, R., Qaisar, S., Ali, M., Aldwairi, M., Ashraf, M. I., Mahmood, A., & Gidlund, M. (2019). Fog Computing Enabling Industrial Internet of Things: State-of-the-Art and Research Challenges. Sensors, 19(21), 4807. https://doi.org/10.3390/s19214807

Caiza, G., Saeteros, M., Oñate, W., & García, M. V. (2020). Fog Computing at Industrial Level, Architecture, Latency, Energy, and Security: A Review. Heliyon, 6(4), e03706. https://doi.org/10.1016/j.heliyon.2020.e03706

Cozzolino, V., Tonetto, L., Mohan, N., Ding, A. Y., & Ott, J. (2023). Nimbus: Towards Latency-Energy Efficient Task Offloading for AR Services. Ieee Transactions on Cloud Computing, 11(2), 1530–1545. https://doi.org/10.1109/tcc.2022.3146615

Eisen, M., Rashid, M. M., Gatsis, K., Cavalcanti, D., Himayat, N., & Ribeiro, A. (2019). Control Aware Radio Resource Allocation in Low Latency Wireless Control Systems. Ieee Internet of Things Journal, 6(5), 7878–7890. https://doi.org/10.1109/jiot.2019.2909198

Farris, I., Taleb, T., Flinck, H., & Iera, A. (2017). Providing Ultra‐short Latency to User‐centric 5G Applications at the Mobile Network Edge. Transactions on Emerging Telecommunications Technologies, 29(4). https://doi.org/10.1002/ett.3169

Gomez, D. L., Montoya, G. A., Lozano-Garzón, C., & Donoso, Y. (2023). Strategies for Assuring Low Latency, Scalability and Interoperability in Edge Computing and TSN Networks for Critical IIoT Services. Ieee Access, 11, 42546–42577. https://doi.org/10.1109/access.2023.3268223

Huynh, D. V., Nguyen, V., Khosravirad, S. R., Sharma, V., Dobre, O. A., Shin, H., & Duong, T. Q. (2022). URLLC Edge Networks With Joint Optimal User Association, Task Offloading and Resource Allocation: A Digital Twin Approach. Ieee Transactions on Communications, 70(11), 7669–7682. https://doi.org/10.1109/tcomm.2022.3205692

Jeddou, S., Fernández, F., Díez, L., Baïna, A., Abdallah, N., & Agüero, R. (2022). Delay and Energy Consumption of MQTT Over QUIC: An Empirical Characterization Using Commercial-Off-the-Shelf Devices. Sensors, 22(10), 3694. https://doi.org/10.3390/s22103694

Jun, S., Kang, Y., Kim, J., & Kim, C. (2020). Ultra‐low‐latency Services in 5G Systems: A Perspective From 3GPP Standards. Etri Journal, 42(5), 721–733. https://doi.org/10.4218/etrij.2020-0200

Kang, Y., Lee, S., Gwak, S., Kim, T., & An, D. (2021). Time-Sensitive Networking Technologies for Industrial Automation in Wireless Communication Systems. Energies, 14(15), 4497. https://doi.org/10.3390/en14154497

Kiangala, K. S., & Wang, Z. (2021). An Effective Communication Prototype for Time-Critical IIoT Manufacturing Factories Using Zero-Loss Redundancy Protocols, Time-Sensitive

Networking, and Edge-Computing in an Industry 4.0 Environment. Processes, 9(11), 2084. https://doi.org/10.3390/pr9112084

Liu, Y., Lan, D., Pang, Z., Karlsson, M., & Gong, S. (2021). Performance Evaluation of Containerization in Edge-Cloud Computing Stacks for Industrial Applications: A Client Perspective. Ieee Open Journal of the Industrial Electronics Society, 2, 153–168. https://doi.org/10.1109/ojies.2021.3055901

Mirani, A. A., Velasco-Hernandez, G., Awasthi, A., & Walsh, J. L. (2022). Key Challenges and Emerging Technologies in Industrial IoT Architectures: A Review. Sensors, 22(15), 5836. https://doi.org/10.3390/s22155836

Moreira, J. B., Mamede, H. S., Pereira, V., & Sousa, B. (2020). Next Generation of Microservices for the 5G Service-Based Architecture. International Journal of Network Management, 30(6). https://doi.org/10.1002/nem.2132

Muzaffar, R., Ahmed, M., Sisinni, E., Sauter, T., & Bernhard, H.-P. (2023). 5G Deployment Models and Configuration Choices for Industrial Cyber-Physical Systems – A State of Art Overview. Ieee Transactions on Industrial Cyber-Physical Systems, 1, 236–256. https://doi.org/10.1109/ticps.2023.3311394

Nakayama, Y., Yaegashi, R., Nguyen, A. H., & Hara–Azumi, Y. (2021). Real-Time Reconfiguration of Time-Aware Shaper for ULL Transmission in Dynamic Conditions. Ieee Access, 9, 115246–115255. https://doi.org/10.1109/access.2021.3105420

Nam, S. (2022). The Impact of 5G Multi‐access Edge Computing Cooperation Announcement on the Telecom Operators' Firm Value. Etri Journal, 44(4), 588–598. https://doi.org/10.4218/etrij.2021-0185

Narayanan, S., Prasad, P. V. V., Fritz, A. K., Boyle, D. L., & Gill, B. S. (2014). Impact of High Night‐Time and High Daytime Temperature Stress on Winter Wheat. Journal of Agronomy and Crop Science, 201(3), 206–218. https://doi.org/10.1111/jac.12101

Nardini, G., Sabella, D., Stea, G., Thakkar, P., & Virdis, A. (2020). Simu5G–An OMNeT++ Library for End-to-End Performance Evaluation of 5G Networks. Ieee Access, 8, 181176–181191. https://doi.org/10.1109/access.2020.3028550

Nasrallah, A., Thyagaturu, A. S., Alharbi, Z., Wang, C., Shao, X., Reisslein, M., & Elbakoury, H. (2019). Ultra-Low Latency (ULL) Networks: The IEEE TSN and IETF DetNet Standards and Related 5G ULL Research. Ieee Communications Surveys & Tutorials, 21(1), 88–145. https://doi.org/10.1109/comst.2018.2869350

Peng, Y., Yan, Y., Chen, G., & Feng, B. (2022). Automatic Compact Camera Module Solder Joint Inspection Method Based on Machine Vision. Measurement Science and Technology, 33(10), 105114. https://doi.org/10.1088/1361-6501/ac769a

Pham, B. N., Abori, N., Silas, V. D., Jorry, R., Rao, C., Okely, T., & Pomat, W. (2022). Tuberculosis and HIV/AIDS-attributed Mortalities and Associated Sociodemographic Factors in Papua New Guinea: Evidence From the Comprehensive Health and Epidemiological Surveillance System. BMJ Open, 12(6), e058962. https://doi.org/10.1136/bmjopen-2021-058962

Popovski, P., Nielsen, J. J., Stefanović, Č., Carvalho, E. d., Ström, E. G., Trillingsgaard, K. F., Bana, A.-S., Kim, D. M., Kotaba, R., Park, J., & Sørensen, R. (2018). Wireless Access for Ultra-Reliable Low-Latency Communication: Principles and Building Blocks. Ieee Network, 32(2), 16–23. https://doi.org/10.1109/mnet.2018.1700258

Rico, D., & Merino, P. (2020). A Survey of End-to-End Solutions for Reliable Low-Latency Communications in 5G Networks. Ieee Access, 8, 192808–192834. https://doi.org/10.1109/access.2020.3032726

Rincon, D. A., Celik, A. E., Zhang, W., Rodríguez, I., Yavuz, S., & Mogensen, P. (2023). An Operational 5G Edge Cloud-Controlled Robotic Cell Environment Based on MQTT and OPC UA. 7–14. https://doi.org/10.1109/icar58858.2023.10406936

Santos, J., Wauters, T., & Turck, F. D. (2023). Efficient Management in Fog Computing. https://doi.org/10.1109/noms56928.2023.10154219

Sasiain, J., Sanz, A., Astorga, J., & Jacob, E. (2020). Towards Flexible Integration of 5G and IIoT Technologies in Industry 4.0: A Practical Use Case. Applied Sciences, 10(21), 7670. https://doi.org/10.3390/app10217670

Shahri, E., Pedreiras, P., & Almeida, L. (2022). Extending MQTT With Real-Time Communication Services Based on SDN. Sensors, 22(9), 3162. https://doi.org/10.3390/s22093162

Šlapak, E., Gazda, J., Guo, W., Maksymyuk, T., & Döhler, M. (2021). Cost-Effective Resource Allocation for Multitier Mobile Edge Computing in 5G Mobile Networks. Ieee Access, 9, 28658–28672. https://doi.org/10.1109/access.2021.3059029

Song, L., Sun, G., Yu, H., & Guizani, M. (2022). SD-AETO: Service Deployment Enabled Adaptive Edge Task Offloading in MEC. https://doi.org/10.48550/arxiv.2205.03081

Taleb, T., Ksentini, A., & Jäntti, R. (2016). "Anything as a Service" for 5G Mobile Systems. Ieee Network, 30(6), 84–91. https://doi.org/10.1109/mnet.2016.1500244rp

Thi, M.-T., Guedon, S., Said, S. B. H., Boc, M., Miras, D., Doré, J., Laugeois, M., Popon, X., & Miscopein, B. (2022). IEEE 802.1 TSN Time Synchronization Over Wi-Fi and 5G Mobile Networks. 1–7. https://doi.org/10.1109/vtc2022-fall57202.2022.10012852

Varga, P., Pető, J., Frankó, A., Balla, D., Haja, D., Janky, F. N., Soós, G., Ficzere, D., Maliosz, M., & Toka, L. (2020). 5G Support for Industrial IoT Applications—Challenges, Solutions, and Research Gaps. Sensors, 20(3), 828. https://doi.org/10.3390/s20030828

Vicol, A.-D., Yin, B., & Bohté, S. M. (2022). Real-Time Classification of LIDAR Data Using Discrete-Time Recurrent Spiking Neural Networks. 1–9. https://doi.org/10.1109/ijcnn55064.2022.9892006

Zhou, L., Li, Z., & Konz, N. (2021). Computer Vision Techniques in Manufacturing. https://doi.org/10.36227/techrxiv.17125652.v1