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# EDGE–CLOUD INTEGRATION FOR LOGISTICS QUALITY ASSURANCE

GÁBOR NAGY[1] – SZABOLCS SZENTESI[2]

***Abstract:*** *In today's fast-paced and highly interconnected logistics networks, quality assurance (QA) requires real-time responsiveness, data accuracy, and scalable technological infrastructure. This study investigates the integration of edge computing and cloud platforms to enable real-time quality data analytics across distributed logistics systems. By deploying sensor-based edge devices for immediate data processing and anomaly detection and synchronizing with cloud environments for centralized analytics and decision support, the proposed architecture significantly enhances the responsiveness and transparency of QA operations. The paper presents a modular system design suitable for warehouse quality control and transport condition monitoring, emphasizing low-latency performance, data security, and system scalability. Through application scenarios and performance evaluation, the study demonstrates how digital QA systems can support proactive interventions, reduce product damage, and optimize quality compliance in logistics. Future directions include AI-based predictive analytics and the integration of digital twins to further improve QA intelligence and automation*

***Keywords:*** *real-time analytics, logistics quality assurance, edge computing, cloud integration, Quality 4.0*

## 1. INTRODUCTION

In today's digitalized and fast-moving logistics networks, maintaining high quality standards is increasingly challenging. Traditional quality assurance (QA) methods – such as manual inspections, scheduled audits, and batched data analysis – lack the responsiveness and real-time integration needed in dynamic supply chains. This limitation hinders early detection of deviations and delays corrective actions that are crucial for protecting product integrity and customer satisfaction. Modern logistics systems generate enormous volumes of real-time data from sensors, devices, vehicles, and facilities across global supply chains. Ensuring the quality of goods and services in transit requires continuous monitoring and immediate responsiveness. However, traditional cloud-centric architectures – relying on centralized data centres – often struggle to meet the latency, bandwidth, and reliability requirements of time-sensitive logistics operations. This has spurred growing interest in edge computing, which processes data locally at or near the source to reduce communication delay and improve system resilience. At the same time, cloud computing provides scalable storage and powerful analytics capabilities that enable centralized orchestration and data-driven strategic decision-making [1]. The advent of Industry 4.0 technologies – particularly the Internet of Things (IoT), edge computing, and cloud integration – has enabled decentralized, intelligent quality monitoring across logistics operations. IoT sensors capture granular environmental and operational data in real time yet relying solely on cloud-based processing can cause delays and strain network resources [1]. To overcome these limitations, hybrid edge–cloud architectures are increasingly adopted, harnessing the best of both worlds: low-latency, on-

[1] senior lecturer, University of Miskolc, Institute of Logistics, Hungary
gabor.nagy4@uni-miskolc.hu
[2] senior lecturer, University of Miskolc, Institute of Logistics, Hungary
szabolcs.szentesi@uni-miskolc.hu

site responsiveness at the edge, and high-level coordination and analytics in the cloud. A comprehensive MDPI review affirms that such hybrid systems optimize bandwidth usage and ensure low-latency processing for IoT applications [1]. Furthermore, research demonstrates that edge computing enhances critical quality attributes – such as latency reduction, energy efficiency, and data privacy – required for reliable, real-time logistics operations [2]. In practical applications, these technologies are already proving their value. For example, a real-time IoT-based anomaly detection system applied in cold chain transport used edge-enabled devices to provide immediate alerts upon detecting temperature deviations, significantly reducing product waste [3]. Another study introduced an edge–cloud streaming analytics framework tailored for Logistics 4.0, improving processing efficiency across the logistics lifecycle [4]. In the context of Quality 4.0, the integration of edge and cloud technologies enables intelligent and automated quality control throughout the logistics infrastructure. Edge computing supports immediate data processing at the point of action, while cloud systems aggregate data from multiple sources to support advanced analytics, digital twin modelling, and long-term improvement initiatives. This paper presents a comprehensive overview of Real-Time Quality Data Analytics in Logistics, focusing on how edge computing and cloud integration jointly address the challenges of modern quality control. We explore the types and sources of quality-related data in logistics and discuss how edge computing enables immediate data collection and processing on-site. We then examine the advantages of cloud integration, especially for large-scale analytics, system-wide visibility, and strategic coordination. The synergy of edge and cloud is analysed, highlighting key benefits such as latency reduction, predictive maintenance, and real-time shipment condition monitoring. Practical application scenarios – including warehouse environmental monitoring and cold chain transport tracking – are presented alongside industry case studies (e.g., Amazon, DHL, Maersk, FedEx). Finally, we identify critical implementation challenges – such as data security, device interoperability, and system integration – and outline future research directions aligned with the ongoing digital transformation of logistics systems.

## 2. Literature review

Real-time data analytics for quality management in logistics is an emerging field that intersects with Industry 4.0, Internet of Things (IoT), and intelligent distributed computing paradigms. The digital transformation of quality management – also known as Quality 4.0 – has introduced connected sensors, smart analytics, and integrated platforms to enhance visibility and responsiveness across supply chains.

### 2.1. The evolution of real-time quality analytics in logistics

Traditionally, logistics quality has been measured by on-time delivery, shipment integrity, and compliance with handling or storage requirements. With the proliferation of IoT sensors, companies now monitor detailed environmental and operational data – such as temperature, humidity, vibration, and shock – in real time, significantly increasing the granularity and volume of quality-related data. This shift necessitates rapid and decentralized data processing to ensure proactive quality assurance. Early implementations of real-time monitoring relied on centralized cloud systems, which offered virtually unlimited computing capacity and on-demand storage. Cloud-based platforms have enabled scalable data management, holistic supply chain visibility, and advanced analytics for demand forecasting and risk mitigation. Studies [5, 6, 7] have consistently reported that cloud adoption improves agility, resilience, and forecast accuracy in logistics operations. However, growing IoT deployment has revealed inherent limitations of cloud-only architectures – especially in latency, bandwidth consumption, and network reliability. To address these constraints, researchers and practitioners have turned to edge computing, which processes data locally on distributed nodes, sensors, or gateways, reducing communication delays and offloading central systems. This decentralization aligns with the fog computing model, a layered continuum between cloud and device-level intelligence and reflects a broader shift towards distributed architectures in smart logistics. For example, DHL has implemented on-site machine vision systems to detect damaged packages directly at sorting facilities using edge-based analytics, thus avoiding the latency and data overload associated with cloud processing.

### 2.2. Hybrid edge–cloud architectures for IoT in logistics

Hybrid edge–cloud architectures are increasingly recognized as optimal for real-time IoT applications in logistics. These models combine low-latency edge processing with centralized cloud analytics and orchestration capabilities, balancing responsiveness with scalability. According to Bao et al. (2022), a deep learning framework that integrates reinforcement learning and graph neural networks can efficiently distribute workloads across edge–cloud systems, leading to notable improvements in latency and resource optimization [8]. A comprehensive review by Kompally (2025) supports this view, highlighting that hybrid architectures also enhance bandwidth efficiency, data privacy, and system reliability for real-time data environments [9]. Industry surveys show that over 83% of logistics executives now consider edge computing essential for competitiveness in a highly automated and data-driven logistics sector. A 2024 trend analysis found that while the field is still emerging – citing only ~100 relevant scientific publications – momentum is growing rapidly. Leading organizations such as Amazon, Maersk, and FedEx have begun deploying hybrid models, combining edge-based responsiveness with cloud-level strategic intelligence, thereby improving visibility, speed, and operational resilience.

### 2.3. Edge-based anomaly detection in cold chain logistics

One of the most compelling use cases of edge computing in logistics is cold chain quality monitoring. In temperature-sensitive supply chains – such as those involving pharmaceuticals or perishable foods – edge analytics enables real-time anomaly detection and intervention. Xie et al. (2025) present a practical IoT-based system where edge-deployed sensors monitor cold chain conditions and trigger alerts when thresholds are exceeded, significantly reducing product spoilage [10]. Similarly, Navak et al. (2025) introduce a multi-dimensional Isolation Forest algorithm that efficiently detects anomalies in streaming sensor data and is proven effective for deployment on resource-constrained edge devices [11].

### 2.4. Edge analytics and logistics 4.0 integration

The concept of Logistics 4.0 embraces end-to-end digital integration, real-time decision-making, and smart automation across supply chains. Edge analytics plays a pivotal role in realizing these goals by reducing latency, preserving network bandwidth, and enabling localized control loops. Wen et al. (2018) propose a full-stack software framework for edge–cloud streaming analytics tailored to the logistics lifecycle, enabling intelligent, context-aware responses throughout warehousing, transportation, and delivery [12]. Moreover, Amiri et al. (2024) emphasize the general applicability of edge analytics in time-critical domains, noting its capacity to support autonomous operations and improve resilience in complex environments [13].

## 3. TECHNOLOGICAL FRAMEWORK AND SYSTEM ARCHITECTURE

### 3.1. Key components of real-time quality data systems

In contemporary logistics operations, maintaining rigorous real-time product quality control necessitates a sophisticated, multi-tiered system architecture designed to capture, transmit, process, and analyse diverse data streams continuously. Such real-time quality data systems integrate a hierarchy of advanced technological components to ensure seamless monitoring and proactive management of product integrity throughout the supply chain. The core elements of these systems can be categorized as follows:

- **IoT sensors and data acquisition layer:** This foundational layer consists of an array of highly sensitive, calibrated sensors deployed across critical logistics nodes including warehouses, refrigerated trucks, cargo containers, and sorting facilities [1, 2]. These sensors capture a broad spectrum of environmental and operational variables essential to quality assurance. Measurement parameters include:
  - *Temperature sensors* with precision ±0.1°C using platinum resistance thermometers (PRTs) or thermistors, crucial for perishable goods and pharmaceuticals [3].
  - *Relative humidity sensors* employing capacitive or resistive sensing elements, calibrated to ±1.5% RH accuracy to monitor moisture-sensitive products.
  - *Vibration sensors* such as MEMS accelerometers, reporting root mean square (RMS) and peak acceleration values, enabling detection of mechanical stress and shocks [7].
  - *Geolocation via GPS modules* with positioning accuracy within 5–10 meters, integrated with inertial navigation systems for redundancy during signal loss.
  - *Shock and impact sensors* measuring transient G-forces to identify drops or collisions that could compromise cargo integrity.
  - *Physical state detectors* like magnetic reed switches or proximity sensors for real-time door status monitoring to prevent unauthorized access or exposure.

These sensor nodes employ ultra-low-power communication protocols such as LoRaWAN or NB-IoT, which support long-range wireless transmission while optimizing battery longevity, enabling months to years of maintenance-free operation in remote or mobile environments [8].

- **Edge computing devices and gateways:** Positioned at the network edge, these computational units provide localized, real-time data processing to reduce latency and bandwidth requirements [1, 5]. Powered by embedded microprocessors (e.g., ARM Cortex-A53, Intel Atom x5) with onboard GPUs or AI accelerators, edge devices execute preprocessing tasks such as:
  - *Data cleansing and normalization* to standardize sensor outputs.

- *Compression algorithms* (LZW, Huffman coding) to optimize data payloads.
- *Time-series signal processing* techniques like Fast Fourier Transform (FFT) or wavelet transforms for noise filtering and feature extraction.
- *Implementation of lightweight machine learning models* (e.g., k-means clustering for pattern recognition, Isolation Forest for anomaly detection, or shallow neural networks) enabling immediate identification of deviations indicative of quality breaches [10].

This edge intelligence ensures end-to-end latency below 50 milliseconds, critical for scenarios demanding instant response — such as monitoring vaccine cold chains where temperature excursions must trigger rapid corrective action [9]. Edge gateways also manage secure data transmission to cloud platforms through encrypted MQTT or HTTPS protocols, maintaining data integrity and confidentiality [12].

- **Cloud computing infrastructure:** The cloud layer serves as the centralized orchestration and analytics platform, ingesting vast volumes of processed data from distributed edge nodes [6, 8]. Utilizing scalable cloud-native services (e.g., AWS Lambda, Azure Functions), the system supports:
  - *Batch and real-time stream analytics* to generate actionable insights and KPI reports.
  - *Periodic retraining and refinement of AI/ML* models with historical and contextual data to improve predictive accuracy and anomaly detection robustness [5].
  - *Integration* with advanced visualization frameworks (Grafana, Power BI) providing customizable dashboards for operational oversight, trend analysis, and alert management.

Moreover, cloud-hosted digital twin models replicate the physical logistics environment, enabling simulation-based scenario testing, what-if analyses, and optimization via AI-driven decision support [4, 11]. Communication between cloud and edge is maintained through robust synchronization protocols such as MQTT publish-subscribe mechanisms and RESTful APIs, facilitating seamless bidirectional data exchange, configuration updates, and remote diagnostics.

### 3.2. Data flow and processing models

Logistics quality assurance systems using edge and cloud integration typically adopt one of the following processing paradigms:

- *Stream processing*: Real-time data streams from sensors are ingested via message brokers such as Apache Kafka, RabbitMQ, or Azure Event Hubs and processed using dataflow engines like Apache Flink or Azure Stream Analytics [4, 11]. This model is ideal for low-latency use cases such as perishable goods transport, where each sensor reading may be time-stamped with millisecond precision and processed through real-time windows (e.g., sliding or tumbling windows) for continuous evaluation.
- *Event-driven processing*: Logic is triggered upon threshold violation (e.g., temperature > 8°C for over 3 minutes) or pattern detection. Rules may be defined using complex event processing (CEP) engines (e.g., Esper, Drools) that interpret

sequences of sensor events in real time. The edge node may initiate local interventions — such as activating a refrigeration unit or sending an SMS/email alert — thereby minimizing latency compared to cloud-based interventions [3, 10].

- *Batch processing*: Used for long-term data archival and macro-level analytics, batch processing involves periodic upload of historical data to the cloud for off-line machine learning (e.g., random forest training), compliance reporting, and trend analysis. Hadoop-based data lakes and cloud-native services such as AWS S3 with Athena or Azure Data Lake are typical infrastructures employed in this model [6].

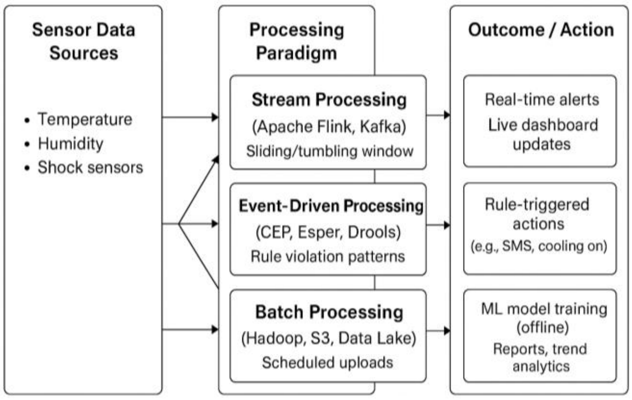


*Figure 1. Processing architectures for sensor data in logistics (own editing)*

Overview of data processing paradigms (*Fig. 1*) in logistics quality assurance systems integrating edge and cloud computing. Fig. 1 illustrates how real-time sensor data are handled via stream, event-driven, or batch processing models, each supporting different types of analytics and operational responses.

### 3.3. Edge–cloud integration patterns

The following architectural patterns are typically implemented in logistics systems:

- **Local-first architecture.** In this pattern, the edge device functions autonomously unless escalation conditions are met. For example, in vibration-sensitive cargo transport, edge nodes perform condition-based monitoring and only communicate anomalies to the cloud. This approach reduces cellular data costs and ensures continuity during network outages [5].
- **Cloud-assisted edge computing.** In this hybrid model, primary analytics occur at the edge (e.g., defect detection using convolutional neural networks on camera feeds), while the cloud periodically validates results, updates inference models, and correlates data across multiple sites. It supports federated learning techniques where model updates are shared, not raw data, preserving bandwidth and privacy [14, 15].
- **Hierarchical edge–cloud models.** Here, fog nodes (e.g., industrial PCs, micro data centres) serve as intermediaries that perform data aggregation, workload balancing, and regional decision support. Latency is further reduced, and fault isolation becomes more manageable. These models are prominent in tiered warehouse networks or large-scale distribution chains [4, 11].

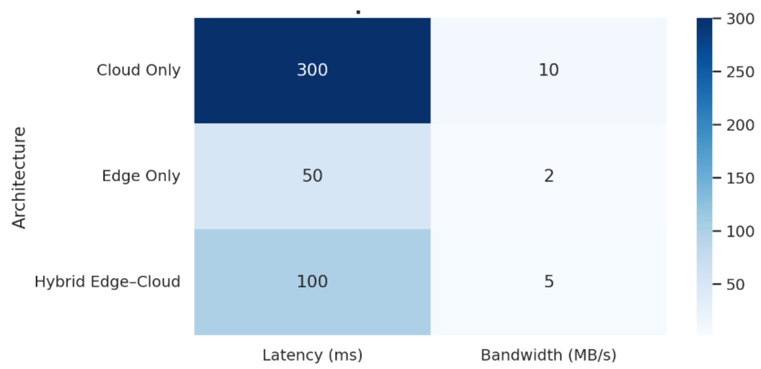


*Figure 2. Performance comparison of architectural models (own editing)*

This heatmap (*Fig. 2)* visualizes the trade-offs between three architectural approaches — Cloud Only, Edge Only, and Hybrid Edge–Cloud — in terms of average latency and bandwidth consumption. Cloud-only systems exhibit high latency and bandwidth usage due to the need to transmit all data to centralized servers. Edge-only systems significantly reduce both but may lack scalability and centralized coordination. Hybrid architectures provide a balanced solution with moderate latency, optimized bandwidth use, and improved resilience, making them ideal for real-time logistics quality monitoring [1, 8, 12].

### 3.4. Enabling technologies

Several technological enablers make edge–cloud logistics systems viable (Fig. 3):

- Edge AI hardware: High-performance edge devices (e.g., NVIDIA Jetson Nano, Google Coral TPU, Intel Movidius Myriad) allow deployment of real-time AI inference directly on-site. These devices support TensorFlow Lite, ONNX Runtime, or PyTorch Mobile for embedded machine learning [7].
- Cloud platforms: AWS IoT Greengrass, Microsoft Azure IoT Hub, and Google Cloud IoT Core offer device provisioning, telemetry processing, and bi-directional messaging. Their ecosystem includes advanced analytics (e.g., AWS SageMaker, Azure Synapse) and storage layers for scalable QA data processing [6, 11].
- Communication protocols: Lightweight M2M protocols such as MQTT, CoAP, and AMQP enable efficient data exchange with low overhead. RESTful APIs facilitate structured access to cloud resources, while OPC UA ensures interoperability with industrial automation systems [2, 12].
- Security technologies: Secure Boot, TPM (Trusted Platform Module), end-to-end encryption (TLS 1.3), and mutual authentication protect data integrity and confidentiality. Zero Trust architectures and secure device onboarding (e.g., X.509 certificates) are recommended for large-scale deployments [1, 5, 16].

In summary, real-time quality assurance in logistics relies on tightly coupled edge–cloud systems, underpinned by efficient data pipelines, robust hardware, lightweight communication, and secure operation. The next section presents practical scenarios where these technologies are applied to improve product quality, operational efficiency, and customer satisfaction in logistics chains.

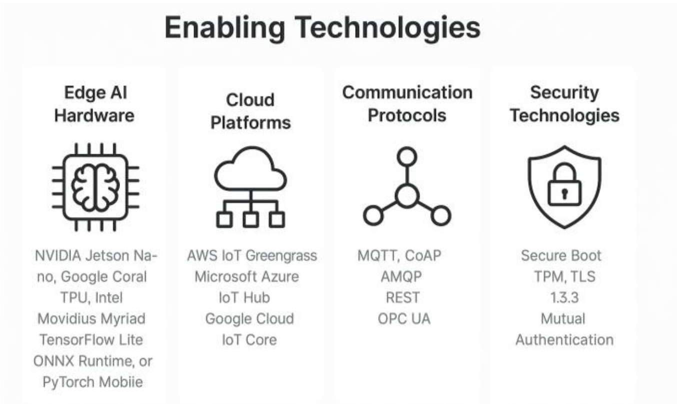


*Figure 3. Key enabling technologies for edge AI and IoT integration (own editing)*

## 4. CONSIDERATIONS TECHNOLOGICAL CONSTRAINTS AND ADAPTATION TO LOGISTICS ENVIRONMENTS

This section explores the deeper engineering principles and logistics-specific constraints underpinning the implementation of real-time quality data analytics using edge and cloud technologies. It addresses the challenges of latency, data volume, energy efficiency, system reliability, and synchronization within distributed environments, which are critical in high-performance logistics applications [1, 2].

### 4.1. Latency, bandwidth, and resource allocation trade-offs

In logistics systems, latency directly affects the timeliness of quality interventions. The total latency $T_{total}$ in a hybrid edge–cloud architecture can be modelled as (1) [3]:

$$T_{\text{total}} = T_{\text{edge}} + T_{\text{network}} + T_{\text{cloud}} \tag{1}$$

where:

- $T_{\text{edge}}$ represents the time required for local data acquisition, filtering, preprocessing, and anomaly detection on edge devices, typically ranging from a few milliseconds to hundreds depending on computational load and hardware efficiency [4],
- $T_{\text{network}}$ denotes the communication latency involved in transmitting data from edge devices to the cloud, including propagation, queuing, and potential retransmission delays due to unreliable or constrained networks (e.g., cellular, LPWAN) [5],
- $T_{\text{cloud}}$ refers to the time consumed by the cloud system to receive, process, analyse, and respond to incoming data, including triggering alerts, updating dashboards, or initiating control signals [6].

Minimizing the overall $T_{\text{total}}$ is essential for real-time logistics quality assurance, especially in latency-sensitive applications such as perishable goods monitoring, just-in-time delivery, or safety-critical shipments [7]. Hybrid edge–cloud architectures are designed to strategically distribute these components to optimize performance [4].

*Table I.*
*Edge–Cloud role division in granularity management (own editing)*

| Parameter | High Precision Monitoring | Low-Cost Monitoring |
|---|---|---|
| **Sampling Rate** | 50–100 Hz | 1–5 Hz |
| **Bandwidth Usage** | High (video, vibration) | Low (temp, humidity) |
| **Edge Processing Complexity** | Medium–High (ML inference) | Low (threshold-based) |
| **Cloud Dependency** | Medium (model retraining) | High (batch analytics) |
| **Total Latency** | ~200–500 ms | ~1–3 sec |

These components must be optimized in tandem to maintain end-to-end latency below application-specific thresholds – e.g., less than 300 ms in cold chain deviations or sub-1s for vibration/shock responses in fragile goods transport [8].

### 4.2. Data volume, sampling frequency, and granularity

In distributed logistics networks, real-time quality assurance systems must handle substantial data volumes due to continuous, multi-parameter monitoring across diverse environments [9]. Sensor networks deployed in warehouses, cargo containers, transport vehicles, and last-mile delivery systems generate high-frequency data streams, encompassing environmental (e.g., temperature, humidity, vibration) and operational (e.g., door status, location, shock) variables. Sensor networks deployed in warehouses and transport systems generate massive data volumes. For example, monitoring 100 parameters at 10-second intervals across 1,000 trucks results in over 864 million data points per day [10].

Granularity impacts detection sensitivity, particularly in dynamic environments. According to the Nyquist criterion (2):

$$f_s > 2f_{\max} \tag{2}$$

where $f_s$ is the sampling frequency and is the highest frequency component of the quality-related signal [11].

Failure to meet this condition can result in aliasing, leading to undetected quality violations [12, 13, 14]. Higher sampling frequencies improve anomaly detection capabilities, allowing real-time quality control systems to capture short-lived or transient deviations. However, they also lead to significant trade-offs in terms of:

- Data volume growth, which burdens storage and transmission infrastructure [13],
- Increased power consumption, especially in battery-operated edge devices [14],
- Elevated processing demands, requiring more capable (and costly) hardware at both edge and cloud layers [15].

The choice of data granularity must therefore be optimized based on:

- The nature of the monitored parameter (e.g., temperature changes vs. vibration spikes),
- The criticality of the logistics scenario (e.g., high-value goods vs. bulk shipments),
- The available computational and communication resources [16].

*Table II.*

*Granularity–resource trade-off matrix (own editing)*

| Metric | High Granularity | Low Granularity |
|---|---|---|
| **Detection sensitivity** | High (better for anomaly capture) | Low (risk of missed deviations) |
| **Bandwidth usage** | High | Low |
| **Edge computation requirements** | Medium–High | Low |
| **Storage demand (edge/cloud)** | High | Low |
| **Energy consumption** | Higher per sample | Lower per sample |

To balance accuracy and efficiency, various optimization technical strategies are applied [15]:

- Adaptive sampling based on operational context (e.g., dynamic adjustment when route or handling conditions change),
- On-device summarization, including statistical aggregation (min, max, mean, standard deviation) over time windows,
- Compression techniques to reduce transmission payload (e.g., delta encoding, Huffman coding),
- Event-triggered logging, where only anomalous or threshold-exceeding data points are transmitted in full detail.

Edge–cloud architectures are particularly well-suited for handling this trade-off: edge nodes can process and filter raw sensor data locally, sending only relevant summaries or alerts to the cloud for central aggregation and longer-term analytics [10].

### 4.3. Synchronization and temporal consistency

In real-time quality monitoring systems for logistics, temporal consistency across data sources is a critical requirement. Edge devices, sensors, and cloud-based analytics often operate on independent clock sources, leading to potential misalignments in timestamps [16]. Such discrepancies can hinder accurate event sequencing, disrupt correlation across heterogeneous data streams, and impair latency-sensitive decision-making processes. The primary sources of temporal inconsistency include clock drift in unsynchronized edge devices, variable network transmission delays, and differences in the sampling resolution of sensors [8, 13]. While cloud environments generally offer high-precision time references, edge nodes often lack synchronized clocks and may rely on low-cost hardware that accumulates drift over time. This results in inconsistencies between the actual time of an event and the timestamp recorded at the point of data capture or ingestion. Temporal misalignment negatively impacts the integrity of time-series data, especially in systems relying on real-time anomaly detection, predictive maintenance, or event-driven control mechanisms [3, 10]. Algorithms that assume strictly ordered inputs can produce inaccurate outputs if the time context is distorted. To mitigate these issues, time synchronization mechanisms are commonly employed.

Basic implementations often utilize the Network Time Protocol (NTP), which synchronizes device clocks with internet-based time servers. While NTP provides sufficient accuracy for many general-purpose applications, its precision – typically within tens of milliseconds – may not meet the stringent requirements of industrial real-time systems. Higher-precision synchronization is achievable through the Precision Time Protocol (PTP, IEEE 1588), which supports sub-microsecond accuracy within local area networks, provided that both hardware and network infrastructure are PTP-aware [12]. In constrained or mobile environments, GPS-based time synchronization can offer reliable absolute time, albeit at the cost of additional hardware and potential signal loss in indoor or shielded areas. As an alternative or supplement, some systems implement post hoc timestamp correction, wherein data received at the cloud level is time-aligned by estimating propagation delays and compensating for known device-specific offsets. This allows for temporal normalization across sources but introduces complexity in modelling and validation. The integration of temporally inconsistent data streams further necessitates techniques such as temporal interpolation, resampling, and buffering. These methods aim to reconstruct a coherent temporal sequence from partially misaligned inputs, enabling effective data fusion and real-time analytics. When packet arrival order is non-deterministic, out-of-order event handling and re-sequencing buffers are required to ensure correct processing. In summary, synchronization and temporal alignment are not ancillary features but foundational to the reliability and responsiveness of real-time logistics systems [16]. Even sub-second deviations can lead to incorrect event attribution, delayed alerts, or missed intervention windows. Therefore, robust time management strategies must be embedded at both the edge and cloud levels of the architecture [8, 15].

### 4.4. Energy and computational constraints at the edge

Edge nodes often operate in constrained environments with limited CPU, memory, and energy availability. This restricts the complexity of onboard analytics and necessitates lightweight models such as:

- Decision Trees or Isolation Forests for anomaly detection,
- Quantized neural networks for real-time inference (e.g. TinyML) [14].

Power consumption must be optimized to enable multi-day or battery-operated deployments, especially in remote logistics environments [2].

The energy required per inference must be kept within the available energy budget. The following constraint must be satisfied (3):

$$E_{\mathrm{inf}} \leq \frac{E_{\mathrm{total}}}{N_{\mathrm{op}}} \tag{3}$$

where:

- $E_{inf}$ : maximum energy available per inference (Joules),
- $E_{total}$: total available energy (e.g., battery capacity),
- $N_{op}$: number of expected operations per charge cycle.

This inequality ensures that edge devices can sustain operation for the desired time interval without recharging or external power input. It is especially critical in logistics scenarios such as in-transit cold chain monitoring, where uninterrupted function is essential [1, 10].

To plan runtime performance, we also consider the average power usage over the total runtime period (4):

$$P_{\mathrm{avg}} = \frac{E_{\mathrm{total}}}{T_{\mathrm{runtime}}} \tag{4}$$

where:
- $P_{avg}$: average power consumption in Watts,
- $T_{runtime}$: required operational duration (e.g., 72 hours).

Lower $P_{avg}$ values correspond to more energy-efficient devices or longer operating times under fixed energy budgets. This relation helps in hardware selection and duty cycle planning for edge deployments [13].
In parallel, edge–cloud systems must include fail-safe mechanisms such as:
- Local buffering in case of network loss,
- Redundant sensors and nodes for critical quality control points,
- Health monitoring of edge devices [6].

Reliability engineering also encompasses software-level protection techniques, including watchdog timers and error recovery protocols. These mechanisms are particularly vital in cold chain applications, where data loss or delays can lead to irreversible quality degradation [3, 8].

### 4.5. Limitations and implementation risks

Despite their advantages, edge–cloud QA systems face the following limitations:
- Interoperability: Incompatibility between heterogeneous device protocols, data formats, and platforms [9].
- Scalability Challenges: Increased node count leads to exponential growth in data integration complexity [5].
- Cybersecurity: Edge devices are exposed to physical and network attacks, requiring robust encryption, authentication, and endpoint protection [7].
- Model Drift: ML models at the edge must be updated periodically; failure to do so can lead to false negatives or over-alerting [4].
- Cost Constraints: High initial investment in sensors, gateways, and integration may delay ROI realization [15].

In conclusion, the effective implementation of real-time QA systems in logistics requires the careful balancing of engineering trade-offs, infrastructure limitations, and operational constraints [2, 12].

## 5. Summary

This paper explores the integration of edge computing and cloud platforms to enhance real-time quality assurance (QA) in modern logistics. Traditional QA methods are inadequate for dynamic, sensor-rich environments due to their latency and lack of scalability. The study introduces a hybrid edge–cloud architecture that combines low-latency, localized processing with cloud-based orchestration and analytics. The system supports anomaly detection, predictive maintenance, and digital twin-based simulations, facilitating proactive quality control in supply chains. Key components include IoT sensors, edge gateways with embedded AI models, and cloud infrastructure for centralized decision-making. The authors analyse data processing paradigms (stream, event-driven, batch), integration patterns, and latency-bandwidth trade-offs, emphasizing real-time responsiveness, energy efficiency, and system reliability. Implementation challenges such as temporal synchronization, edge resource constraints, and cybersecurity are also discussed. Practical use cases, including cold chain monitoring and warehouse quality tracking, demonstrate the framework's applicability. The paper concludes with future directions in AI-driven analytics and smart logistics automation.

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