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Research Article

Design of an Edge Computing Based Industrial Internet of Things Architecture for Real Time Predictive Maintenance in Advanced Manufacturing Systems

Simon Simarmata[1]*, Panser Karo-Karo[2], Budi Artono[3], Muhammad Akbar Hariyono[4], Ardy Wicaksono[5], Antoni Pribadi[6]

[1] Pamulang University, Indonesia; e-mail: dosen02300@unpam.ac.id
[2] Tamajagakarsa University, Indonesia; e-mail: pkaro288@gmail.com
[3] Madiun State Polytechnic, Indonesia; e-mail: budiartono@pnm.ac.id
[4] Kalimantan's Leading Polytechnic, Indonesia; e-mail: akbar.hariyono@gmail.com
[5] Sugeng Hartono University, Indonesia: e-mail: ardywicaksono166@gmail.com
[6] Kampar Polytechnic, Indonesia; e-mail: antonipribadi.polkam@gmail.com
* Corresponding Author: Simon Simarmata

Abstract: Background: The increasing complexity of industrial production systems requires machine condition monitoring solutions that are capable of operating in real time with high accuracy and responsiveness to support predictive maintenance strategies. Conventional cloud based monitoring systems often experience limitations such as high latency and dependence on stable network connectivity, which can delay decision making processes in critical industrial operations. **Objective:** This study aims to design and evaluate an Industrial Internet of Things (IIoT) architecture based on edge computing to improve the efficiency of industrial sensor data processing and accelerate anomaly detection in industrial machines. **Method:** The research adopts an experimental approach by designing a system architecture consisting of a sensor layer, edge computing layer, and cloud layer. Industrial sensors, including vibration, temperature, and current sensors, continuously collect machine operational data, which are then processed locally at the edge node using a machine learning based anomaly detection algorithm. System testing is conducted in a simulated manufacturing environment to evaluate performance based on latency, reliability, and detection accuracy. **Results:** The results indicate that edge based data processing significantly reduces latency compared with cloud-based processing and enables faster responses to machine condition changes. Additionally, the implemented anomaly detection algorithm achieves high accuracy in identifying abnormal sensor data patterns.

Keywords: Anomaly Detection; Edge Computing; IIoT Systems; Machine Monitoring; Predictive Maintenance.

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1. Introduction

The rapid development of digital technologies in the era of Industry 4.0 has significantly transformed industrial production systems and equipment maintenance strategies. The integration of technologies such as the Internet of Things (IoT), data analytics, and artificial intelligence enables industries to monitor machine conditions more accurately and in real time. One of the approaches that has gained significant attention in this context is predictive maintenance (PdM), a maintenance strategy that utilizes operational data and predictive analytics to estimate potential equipment failures before they actually occur [1], [2]. By leveraging this data-driven approach, companies can plan maintenance activities more effectively and prevent unexpected operational disruptions.

Predictive maintenance has become increasingly important because modern production systems heavily depend on the reliability of industrial machinery. Unexpected machine failures can lead to production downtime, which directly affects productivity and operational efficiency. Unplanned downtime not only interrupts the manufacturing process but may also cause substantial financial losses and negatively impact product quality. Therefore, implementing maintenance strategies capable of predicting potential machine failures before they occur is crucial in modern industrial environments [3].

In addition to reducing downtime risks, predictive maintenance also provides advantages in terms of operational cost efficiency. Traditional maintenance approaches, which are often reactive, tend to result in delayed component replacements or unnecessary preventive actions. By implementing predictive maintenance, maintenance activities can be performed based on the actual condition of equipment, allowing resources to be utilized more efficiently [4]. Consequently, companies can reduce maintenance costs while simultaneously extending the lifespan of industrial equipment.

The implementation of predictive maintenance typically relies on sensor data collected from industrial machinery to monitor various operational parameters such as vibration, temperature, pressure, and lubricant quality. These data are analyzed using data mining and machine learning techniques to identify patterns that indicate potential equipment failures. Several studies have demonstrated that machine learning algorithms can significantly improve present limitations in real-time industrial applications, particularly regarding network latency and dependency on internet connectivity [5], [6].

These limitations become more critical when industrial systems require rapid responses to machine condition changes. In many cases, transmitting sensor data from industrial devices to centralized cloud servers introduces delays in data processing. Additionally, the massive volume of data generated by industrial sensors can overload network infrastructure and increase bandwidth consumption [7]. These challenges indicate that relying solely on cloud-based architectures may not be sufficient for predictive maintenance systems that require real-time analysis.

To address these issues, fog computing and edge computing have emerged as promising alternatives in Industrial Internet of Things architectures. Fog computing enables data processing closer to the data source compared to traditional cloud computing approaches. As a result, data analysis can be performed faster without requiring continuous transmission of large data volumes to centralized cloud infrastructures [7].

Meanwhile, edge computing represents a distributed computing paradigm that moves data processing closer to the source of data generation, such as industrial sensors or edge devices. This approach allows sensor data to be processed locally, thereby significantly reducing network latency. In addition, edge computing improves bandwidth efficiency because only relevant data or processed results are transmitted to the cloud [8].

The integration of edge computing with machine learning technologies has also created new opportunities for developing intelligent predictive maintenance systems. Previous studies indicate that performing sensor data analysis directly at the edge can accelerate decision-making processes and enable real-time fault detection in manufacturing systems [9]. Furthermore, the combination of artificial intelligence and edge computing can significantly improve prediction accuracy and enhance system adaptability to dynamic industrial environments [10].

Based on these considerations, this study aims to design an edge computing based Industrial Internet of Things (IIoT) architecture to support real-time predictive maintenance. The proposed architecture integrates multiple system layers, including an edge layer for local sensor data processing, a cloud layer for long-term data storage and advanced analytics, and an application layer that provides user interfaces for monitoring machine conditions and delivering early warning alerts. Through this architecture, the system is expected to improve industrial operational efficiency by reducing equipment downtime, optimizing maintenance costs, and enhancing overall production productivity [11], [12].

2. Literature Review

Predictive Maintenance in Manufacturing Systems

Predictive maintenance (PdM) is a proactive maintenance strategy that utilizes sensor data and analytical techniques to predict equipment failures before they occur. This approach allows manufacturing systems to reduce unexpected downtime and optimize maintenance scheduling. According to [13], predictive maintenance models integrate asset monitoring with data-driven algorithms to detect anomalies and predict equipment degradation. Similarly, [14] explain that predictive analytics and visualization technologies improve maintenance decision-making and allow operators to monitor system conditions in real time.

In modern smart manufacturing environments, predictive maintenance is implemented through continuous monitoring of machine parameters such as vibration, temperature, torque, and acoustic signals. These data are collected using industrial sensors and processed using machine learning algorithms to identify early indicators of equipment failure [15]. Furthermore, predictive maintenance contributes to the concept of Zero Defect Manufacturing by ensuring that production equipment operates within optimal conditions and minimizes product defects [16].

Predictive maintenance systems typically consist of multiple components including data acquisition systems, monitoring platforms, analytical engines, and maintenance decision support systems. These components work together to ensure continuous monitoring of manufacturing equipment and enable predictive insights that support efficient maintenance planning [17].

Table 1. Core Components of Predictive Maintenance Systems.

Component	Description	Supporting Study
Data Acquisition	Sensors collect operational machine data such as vibration and temperature	[18]
Condition Monitoring	Continuous monitoring of machine performance indicators	[19]
Data Analytics	Machine learning and predictive algorithms analyze equipment conditions	[14]
Maintenance Decision Support	Systems recommend optimal maintenance schedules	[16]
Smart Integration	Integration with Industry 4.0 digital manufacturing systems	[13]

Table 1 presents the major components involved in predictive maintenance systems. These components illustrate how sensor technologies, monitoring platforms, and predictive analytics models collaborate to support intelligent maintenance decision-making in modern manufacturing systems.

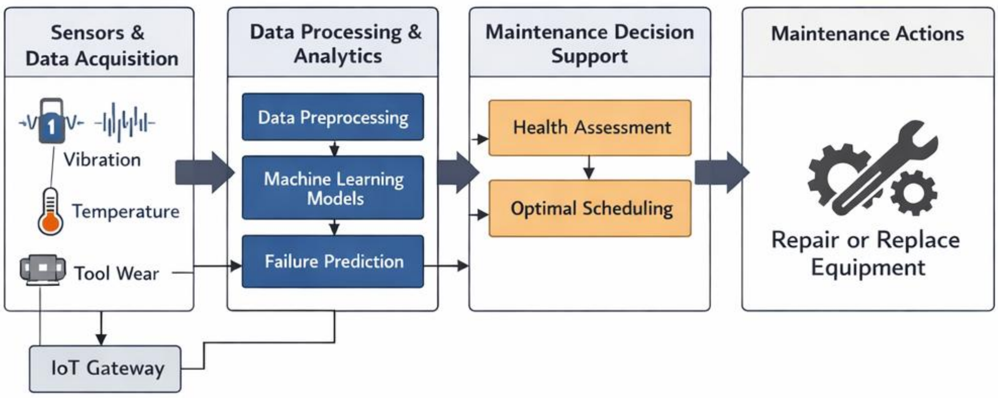

Figure 1. Predictive Maintenance Architecture in Smart Manufacturing.

Figure 1 illustrates the architecture of a predictive maintenance system implemented in smart manufacturing environments. The process begins at the sensor and data acquisition stage, where industrial sensors continuously collect operational data such as vibration signals, temperature measurements, and tool wear conditions from manufacturing equipment. These data are transmitted through an IoT gateway, which acts as an intermediary that aggregates and forwards sensor data to higher-level processing systems.

In the next stage, the collected data undergo data processing and analytics, where preprocessing techniques are applied to clean and normalize the data before further analysis. Machine learning models are then used to analyze patterns in the data and identify anomalies that may indicate potential equipment failures. Through predictive modeling, the system can estimate the remaining useful life of machine components and detect early warning signs of malfunction.

The analytical results are then utilized within the maintenance decision support system, which evaluates equipment health and recommends optimal maintenance scheduling. This decision-support mechanism helps maintenance managers determine whether maintenance should be performed immediately or scheduled for a later time to minimize production disruption. Finally, the maintenance action stage executes the recommended decisions, such as repairing or replacing faulty equipment components. This architecture demonstrates how predictive maintenance integrates sensing technologies, data analytics, and intelligent decision systems to improve equipment reliability and reduce operational downtime.

Industrial Internet of Things (IIoT) Architecture

The Industrial Internet of Things (IIoT) represents a key technological infrastructure that enables connectivity between industrial devices, sensors, and computing systems. IIoT systems allow manufacturing organizations to collect and analyze large volumes of operational data in real time. According to [20], IIoT plays a fundamental role in enabling digital transformation within industrial environments by supporting intelligent monitoring and automation of manufacturing processes.

A typical IIoT system consists of multiple architectural layers that facilitate communication between devices and analytical systems. [21] describe IIoT architecture as a layered framework that includes device layers, communication layers, data processing layers, and application layers. Each layer performs specific functions in the overall system, ensuring efficient data flow and system scalability.

Furthermore, modern IIoT architectures integrate advanced technologies such as edge computing and cloud computing to improve system performance. [22] explain that edge computing enables data processing near the data source, reducing latency and improving response time in industrial applications. Cloud platforms, on the other hand, provide scalable storage and computational capabilities that support large-scale industrial data analytics.

Table 2. Key Technologies Supporting IIoT Architecture.

Technology	Function in IIoT Systems	Reference
Industrial Sensors	Collect operational data from machines	[18]
Edge Computing	Perform local data processing near machines	[22]
Cloud Computing	Provide large-scale data storage and analytics	[20]
Publish–Subscribe Communication	Enable real-time communication between devices	[23]
Systems-of-Systems Modeling	Integrate multiple industrial subsystems	[24]

Table 2 summarizes several key technologies that play a crucial role in supporting the implementation of Industrial Internet of Things (IIoT) architectures in modern manufacturing environments. One of the fundamental components is industrial sensors, which are responsible for collecting operational data directly from machines and production equipment. These sensors measure various parameters such as vibration, temperature, pressure, and machine performance indicators, allowing organizations to continuously monitor equipment conditions and detect potential anomalies. According to [18], the deployment of industrial sensors forms the foundation of IIoT systems because they provide the raw data required for monitoring, diagnostics, and predictive maintenance applications.

Another important technology in IIoT architecture is edge computing, which enables data processing to be performed close to the data source rather than relying entirely on centralized cloud systems. By processing data locally at the edge layer, manufacturing systems can significantly reduce latency and improve the speed of decision-making processes. This capability is particularly important for time-sensitive industrial applications such as machine control, predictive maintenance, and real-time anomaly detection. [22] emphasize that edge computing also reduces network bandwidth consumption by filtering and preprocessing data before transmitting it to higher-level platforms.

In addition to edge computing, cloud computing plays a critical role in IIoT systems by providing scalable data storage and powerful computational resources. Cloud platforms allow organizations to store massive volumes of industrial data generated from connected devices and perform advanced analytics such as machine learning, predictive modeling, and big data analysis. [20] note that cloud-based platforms also support centralized monitoring dashboards and management tools that enable engineers and managers to observe system performance from remote locations and make data-driven operational decisions.

Furthermore, publish subscribe communication models are widely used in IIoT systems to enable efficient real-time communication between distributed devices and services. In this communication paradigm, data producers publish messages to a broker system, while multiple subscribers receive relevant data streams based on predefined topics. This architecture enhances system scalability and flexibility, particularly in complex industrial environments where numerous devices must exchange information simultaneously. [23] highlight that the publish subscribe approach allows IIoT platforms to manage dynamic data flows and maintain efficient communication among heterogeneous devices.

Finally, systems of systems modeling is an important concept for integrating multiple industrial subsystems into a unified IIoT ecosystem. Manufacturing environments typically involve various independent systems such as production machines, monitoring platforms, control systems, and enterprise management software. Systems of systems modeling provides a structured framework that enables these independent components to interact and operate collaboratively within a single architecture. [24] explain that this modeling approach improves interoperability, system scalability, and coordination among complex industrial infrastructures. Overall, the combination of these technologies enables IIoT architectures to support intelligent manufacturing operations through efficient data collection, communication, processing, and system integration.

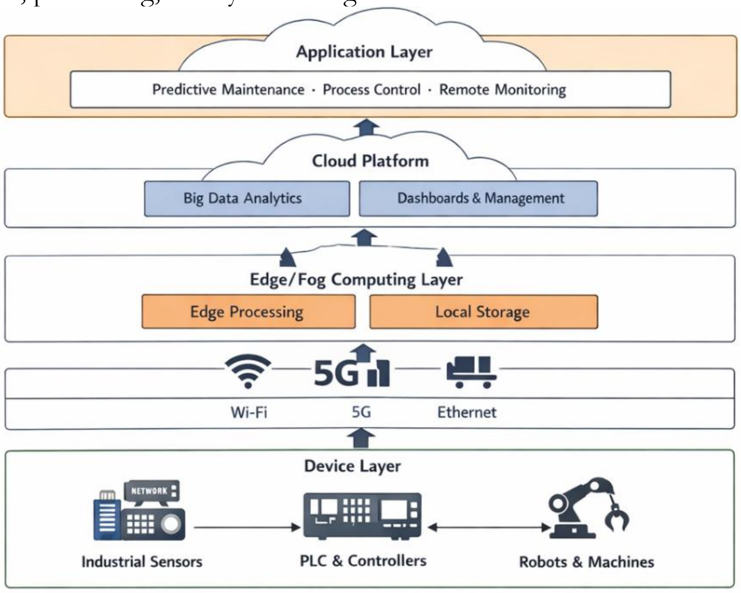

Figure 2. Layered Architecture of Industrial Internet of Things.

Figure 2 presents the layered architecture of the Industrial Internet of Things (IIoT) used in modern manufacturing systems. The architecture begins with the device layer, which consists of industrial sensors, programmable logic controllers (PLCs), and robotic machines. These devices are responsible for collecting operational data from manufacturing processes and generating real-time information about machine performance and environmental conditions.

Above the device layer is the communication layer, where various network technologies such as Wi-Fi, Ethernet, and 5G enable data transmission between industrial devices and processing systems. This connectivity infrastructure ensures reliable and continuous data flow across the manufacturing network, allowing real-time monitoring and system integration.

The next level is the edge or fog computing layer, which performs local data processing near the data source. Edge computing reduces latency and improves system responsiveness by filtering and analyzing data before transmitting it to cloud platforms. This layer typically handles tasks such as preliminary analytics, local storage, and device-level control.

The processed data are then transmitted to the cloud platform, where advanced analytics tools and management dashboards process large volumes of industrial data. Cloud-based systems provide scalable computing resources that support predictive analytics, machine learning applications, and system-wide monitoring. Finally, the application layer represents the highest level of the architecture, where industrial applications such as predictive maintenance, process control, and remote monitoring are implemented. This layered IIoT architecture enables seamless integration of industrial devices, communication networks, and data analytics platforms, thereby supporting intelligent and data-driven manufacturing operations.

Challenges in IIoT-Based Manufacturing Systems

Despite the significant advantages of IIoT technologies, several challenges remain in their implementation within manufacturing environments. One of the major challenges is cybersecurity. [25] highlight that IIoT systems are vulnerable to cyber threats due to the large number of interconnected devices and communication networks involved. Similar concerns are also emphasized in recent studies on distributed security mechanisms in IIoT environments. [26] propose a hybrid federated ensemble learning approach to improve real-time detection of distributed denial of service (DDoS) attacks in IIoT edge computing environments. Furthermore, advanced deep learning architectures have also been explored to strengthen cybersecurity in cloud-edge infrastructures, as demonstrated by [27], who developed a federated hybrid CNN-GRU model combined with an optimized Elman neural network for real-time DDoS detection.

Another challenge involves ethical and governance issues related to industrial data management. [28] argue that organizations adopting IIoT technologies must address ethical concerns such as data privacy, responsible data usage, and transparency in automated decision-making systems. In line with this perspective, [26] emphasize the importance of secure and transparent digital governance through blockchain-based mechanisms to enhance trust and accountability in digital systems. Similarly, the integration of artificial intelligence, corporate social responsibility, and blockchain technology has been proposed as a framework for building a sustainable digital culture and responsible data governance in modern digital ecosystems [27].

Additionally, integrating heterogeneous industrial systems remains a technical challenge. Manufacturing environments often involve equipment from different vendors using different communication protocols. To address this challenge, [24] propose a systems-of-systems modeling approach that enables interoperability between different industrial subsystems. Supporting this perspective, [29] introduce an adaptive framework integrating machine learning, blockchain, and trusted execution environments to strengthen security and interoperability in distributed cloud infrastructures. Moreover, the implementation of IoT-based monitoring systems demonstrates how sensor networks and interconnected devices can be integrated to support real-time data acquisition and system monitoring in technological environments [30].

Overall, addressing these technical, security, and ethical challenges is essential to ensure the successful implementation of IIoT-based predictive maintenance systems in modern manufacturing environments.

Edge Computing in Real-Time Industrial Systems

Edge computing has emerged as a key technology in modern industrial systems, enabling localized data processing and reducing dependence on centralized cloud infrastructures. In industrial environments, real-time responsiveness is critical for ensuring operational efficiency, safety, and system reliability. Traditional cloud-based architectures often introduce latency and bandwidth limitations because data must be transmitted to remote servers before analysis can occur. Edge computing addresses this challenge by processing data closer to the data source, enabling faster decision-making and real-time control in industrial automation systems [31], [32].

In real-time industrial applications, edge computing enables various functionalities such as process monitoring, predictive maintenance, and adaptive control. By placing computational resources near machines and sensors, industrial systems can perform immediate analysis of operational data without relying entirely on cloud connectivity. This capability is particularly beneficial in remote or connectivity-limited environments such as mining sites, offshore platforms, or distributed industrial facilities where stable internet connections may not always be available [32], [33]. Edge-based architectures therefore improve system responsiveness while also reducing communication overhead and network congestion.

Another important aspect of edge computing in industrial systems is its integration with artificial intelligence (AI) and machine learning (ML) technologies. Edge devices are increasingly capable of running lightweight machine learning models, allowing them to perform tasks such as anomaly detection, predictive maintenance, and fault diagnosis directly on-site. This distributed intelligence improves operational efficiency by enabling real-time analytics and early detection of equipment failures. For example, machine learning models deployed on edge devices can analyze sensor data streams and identify abnormal patterns that may indicate equipment degradation or potential failure [34], [35].

To ensure reliability and deterministic behavior in industrial applications, several standards and frameworks have been developed to support edge computing implementations. One widely adopted standard is IEC 61499, which provides a distributed architecture for industrial automation systems using event-driven function blocks. This standard allows industrial edge applications to perform deterministic and concurrent execution of real-time tasks while supporting interoperability between operational technology (OT) and information technology (IT) systems [36], [37]. Additionally, real-time scheduling methods based on event types have been proposed to improve execution efficiency and ensure timely task processing in edge environments [38].

The integration of edge computing with cloud platforms also enables the concept of an edge cloud continuum, where data processing tasks are dynamically distributed between edge devices and centralized systems depending on computational requirements. In this architecture, time-sensitive tasks are handled at the edge, while more complex analytics and long-term storage are performed in the cloud. This approach enhances system scalability and energy efficiency while maintaining real-time operational capabilities in industrial manufacturing systems [39].

Edge computing also plays an essential role in enabling smart manufacturing and Industry 4.0 applications. By embedding intelligent analytics within industrial devices, manufacturers can achieve improved automation, predictive maintenance, and data-driven decision-making. Industrial edge systems can collect and process large volumes of machine data from sensors and controllers, transforming raw operational data into actionable insights that support optimization of production processes [31], [40]. Consequently, edge computing has become a fundamental component in modern industrial architectures that aim to achieve autonomous and intelligent manufacturing environments.

Data Analytics for Machine Condition Monitoring

Data analytics plays a crucial role in machine condition monitoring by enabling the transformation of raw operational data into meaningful insights for maintenance and operational decision-making. In modern industrial systems, large volumes of sensor data are generated continuously from machines and production equipment. Analytical methods are therefore required to process this data and detect patterns that indicate machine health, performance degradation, or potential faults. Data-driven condition monitoring approaches support predictive and prescriptive maintenance strategies that help reduce downtime and improve system reliability [41], [42].

One of the key techniques used in machine condition monitoring is anomaly detection, which aims to identify abnormal patterns in data streams that may indicate machine faults or unexpected operational behavior. Anomaly detection algorithms analyze sensor data such as vibration signals, temperature measurements, or acoustic emissions to detect deviations from normal operating conditions. These techniques enable early fault detection and allow maintenance teams to perform proactive interventions before serious failures occur [35], [41].

Machine learning methods have also become widely adopted in condition monitoring systems due to their ability to extract complex patterns from large datasets. Various ML techniques, including ensemble learning, clustering algorithms, and neural networks, are used to analyze sensor data and predict machine health conditions. These models can learn from historical operational data and improve prediction accuracy over time, enabling more reliable fault diagnosis and maintenance planning [35], [43]. In many cases, combining machine learning with real-time sensor data significantly enhances the performance of predictive maintenance systems.

A specific application of data analytics in manufacturing is tool condition monitoring (TCM). In machining processes, the condition of cutting tools significantly affects product quality and production efficiency. Modern TCM systems integrate multiple sensors, such as vibration, acoustic, and force sensors, to collect detailed information about machining operations. Machine learning algorithms are then used to analyze this data and predict tool wear or failure conditions. Studies have shown that combining multi-sensor data with advanced analytics techniques can achieve prediction accuracies approaching 98%, demonstrating the effectiveness of data-driven monitoring approaches [43].

Another important application area is the monitoring of rotating machinery, which is commonly used in industries such as energy generation, manufacturing, and transportation. Advanced analytics techniques are used to analyze vibration signals and operational parameters to identify abnormal behavior in rotating equipment such as turbines, motors, and compressors. By continuously monitoring key performance indicators (KPIs), data analytics systems can detect early signs of mechanical faults and support predictive maintenance strategies [44].

Despite these advancements, several challenges remain in implementing effective data analytics systems for machine condition monitoring. One of the primary challenges is integrating analytical models with real-time industrial infrastructures such as edge computing platforms and digital twin systems. Combining these technologies allows industrial systems to perform real-time analysis and predictive maintenance directly within operational environments. Another challenge involves the need for collaboration between data scientists and domain experts, as domain knowledge is essential for designing meaningful analytical models and validating predictive insights [42].

Overall, the integration of data analytics with edge computing technologies represents a promising approach for enabling intelligent machine condition monitoring systems. By combining localized data processing, machine learning algorithms, and real-time industrial architectures, modern manufacturing systems can achieve improved reliability, reduced downtime, and more efficient maintenance strategies.

3. Research Methods

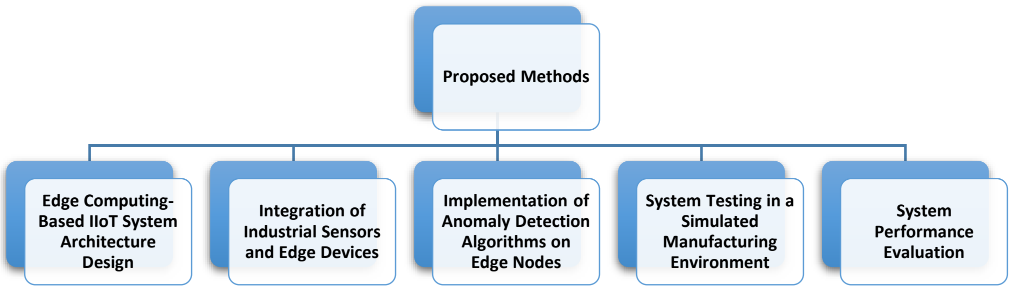

Figure 3. Proposed System Architecture Framework.

Edge Computing-Based IIoT System Architecture Design

This study employs an experimental approach by designing an Industrial Internet of Things (IIoT) system architecture based on edge computing to support real-time machine condition monitoring. The system architecture is designed with three main layers: the sensor layer, edge computing layer, and cloud layer. The sensor layer functions to collect machine operational data through various industrial sensors installed on production equipment. The collected data is then transmitted to the edge node for local processing before being forwarded to the cloud system for storage and further analysis.

The use of edge computing in this architecture aims to reduce dependence on cloud-based data processing and minimize latency in the monitoring system. By processing data closer to its source, the edge node can perform preliminary analysis quickly and respond to abnormal machine conditions in real-time. Meanwhile, the cloud layer is utilized for large-scale data processing, system visualization, and historical data storage, which can later be used for long-term performance analysis.

Integration of Industrial Sensors and Edge Devices

The integration of industrial sensors with edge computing devices is implemented to enable continuous machine data collection and processing. The sensors used in this study include vibration sensors, temperature sensors, and electrical current sensors, which are commonly utilized in industrial machine condition monitoring systems. These sensors are installed on critical machine components to capture operational condition changes that may indicate potential damage or performance degradation.

Sensor data is transmitted to the edge device through industrial communication protocols such as MQTT or Modbus TCP. The edge device used in this research consists of low-power computing hardware such as a single-board computer or an industrial gateway, capable of performing local data processing. This integration allows the edge node to receive real-time data, conduct preliminary processing, and transmit only essential information to the cloud system without sending all raw data.

Implementation of Anomaly Detection Algorithms on Edge Nodes

To detect abnormal machine conditions, this study implements an anomaly detection algorithm that runs directly on the edge node. The algorithm aims to identify sensor data patterns that deviate from the machine's normal operating conditions. Before the analysis process begins, sensor data undergoes a preprocessing stage that includes data normalization, noise filtering, and feature extraction from the sensor signals.

The extracted features are then used as input for a machine learning-based anomaly detection model. The method applied follows an unsupervised learning approach, such as Isolation Forest or clustering techniques, which allows the system to detect anomalies without requiring a fully labeled dataset. By executing the algorithm directly on the edge node, the system can provide early warnings of potential machine failures more quickly compared to approaches that rely entirely on cloud-based processing.

System Testing in a Simulated Manufacturing Environment

After the system design and implementation are completed, testing is conducted in a simulated manufacturing environment that represents industrial machine operating conditions. This simulation environment is used to evaluate the system's capability to process sensor data and detect abnormal machine conditions under various operational scenarios.

The simulated machines are operated under normal conditions as well as modified conditions designed to generate anomaly patterns, such as increased vibration or temperature rises. During the testing process, sensor data is continuously collected and processed by the edge node using the implemented anomaly detection algorithm. The system then monitors changes in data patterns in real-time to determine whether the machine is operating normally or showing indications of potential failure. The testing process also observes the stability of communication between sensors, edge devices, and the cloud system during the monitoring process.

System Performance Evaluation

The system performance evaluation is conducted to assess the effectiveness of the edge computing architecture in supporting real-time machine condition monitoring. The evaluation parameters include latency, reliability, and detection accuracy. Latency is measured as the time required from the moment sensor data is transmitted until the anomaly detection result is generated by the edge node, reflecting the system's capability to provide rapid responses to changes in machine conditions.

System reliability is evaluated based on the stability of data communication between sensors, edge nodes, and the cloud server during the testing process. In addition, detection accuracy is used to measure the success rate of the anomaly detection algorithm in identifying abnormal machine conditions. The accuracy value is obtained by comparing the system's detection results with the actual machine conditions in the predefined testing scenarios.

4. Results and Discussion

Results

This section presents the experimental results obtained from the implementation of the proposed Industrial Internet of Things (IIoT) architecture integrated with edge computing for real-time machine condition monitoring. The experiments were conducted in a simulated manufacturing environment to evaluate the performance of the system in terms of data acquisition, processing latency, communication reliability, and anomaly detection capability. The proposed architecture enables real-time processing of industrial sensor data at the edge node, allowing faster decision-making and reducing the dependency on centralized cloud infrastructure.

The results are organized into several subsections that describe the hardware configuration, system performance evaluation, and analytical outcomes of the anomaly detection model. The experimental results are presented in the form of tables and graphical visualizations to provide a clearer understanding of the system performance. These results also demonstrate how the integration of industrial sensors, edge computing, and machine learning algorithms can improve the efficiency and responsiveness of industrial monitoring systems.

The experimental setup of the proposed system involves several hardware components and industrial sensors that support real-time monitoring and analysis. The specifications of the devices used in the implementation are summarized in Table 3.

Table 3. Device and Sensor Specifications.

Component	Specification	Function
Edge Device	Industrial Gateway / Single-board computer	Local data processing
Vibration Sensor	Accelerometer	Monitoring machine vibration
Temperature Sensor	Thermocouple	Monitoring machine temperature
Current Sensor	Hall-effect sensor	Measuring electrical current
Communication Protocol	MQTT / Modbus TCP	Sensor data transmission

Table 3 describes the main hardware components and sensors used in the experimental system. The edge device serves as the core processing unit that performs data preprocessing, feature extraction, and anomaly detection locally before sending summarized information to the cloud. The use of an industrial gateway or single-board computer provides sufficient computational capability to execute machine learning algorithms while maintaining low power consumption.

In addition, multiple sensors were deployed to monitor various machine parameters simultaneously. The vibration sensor captures mechanical oscillations that often indicate imbalance or mechanical wear, while the temperature sensor monitors thermal changes that may reflect excessive friction or system overload. The current sensor measures electrical consumption, which can also provide indirect information about machine performance. The combination of these sensors enables comprehensive machine condition monitoring and supports the anomaly detection process.

Latency testing was conducted to evaluate the response time of the monitoring system when processing sensor data using edge computing compared to cloud-based processing. The latency values were measured under several operational scenarios to observe how the system performs under different workloads.

Table 4. System Latency Test Results.

Test Scenario	Edge Processing Latency (ms)	Cloud Processing Latency (ms)
Normal Operation	42	120
High Sensor Load	55	145
Peak Operation	63	168

Table 4 presents the latency performance of the proposed monitoring system under three different operating scenarios. During normal operation, the average latency for edge processing was approximately 42 milliseconds, while the cloud-based system required approximately 120 milliseconds. This difference highlights the advantage of performing data processing locally at the edge node instead of relying entirely on cloud infrastructure.

As the number of sensor data streams increased, the latency difference became more evident. Under high sensor load conditions, edge processing maintained relatively low latency at approximately 55 milliseconds, whereas cloud processing latency increased significantly to 145 milliseconds. During peak operation scenarios, the latency reached 63 milliseconds for edge processing and 168 milliseconds for cloud processing. These results demonstrate that edge computing can significantly improve system responsiveness, particularly in environments where rapid data processing is required.

Reliability testing was performed to evaluate the stability and consistency of data communication between system components during continuous operation.

Table 5. System Reliability Evaluation.

Parameter	Result
Data Transmission Success Rate	98.7%
Packet Loss	1.3%
System Uptime	99.2%

Table 5 summarizes the reliability metrics obtained during the experimental evaluation. The data transmission success rate reached 98.7%, indicating that nearly all sensor data packets were successfully transmitted from the sensors to the edge node and cloud server.

This high success rate demonstrates the effectiveness of the communication protocols used in the system.

The packet loss rate was measured at 1.3%, which remains within acceptable limits for industrial monitoring applications. Additionally, the system achieved 99.2% uptime, indicating stable operation throughout the experimental period. These results confirm that the proposed IIoT architecture provides reliable communication performance for real-time industrial monitoring systems.

The anomaly detection capability of the system was evaluated using machine learning algorithms that analyze patterns in sensor data.

Table 6. Anomaly Detection Accurac.

Detection Method	Precision	Recall	Accuracy
Isolation Forest	0.94	0.92	94%
Clustering-based Detection	0.91	0.89	90%

Table 6 presents the performance comparison between two anomaly detection approaches. The Isolation Forest algorithm achieved an accuracy of 94%, which is higher than the clustering-based detection method with 90% accuracy. This indicates that Isolation Forest is more effective in identifying unusual patterns in sensor data.

The higher precision and recall values also suggest that the algorithm is capable of detecting abnormal machine conditions with minimal false alarms. Accurate anomaly detection is essential for predictive maintenance systems because it allows maintenance teams to identify potential machine failures before they cause significant operational disruptions.

The following set of graphs presents a detailed analysis of the system performance and sensor behavior within the edge computing-based IIoT architecture. These graphs offer insights into the latency, accuracy of anomaly detection, and sensor data changes over time, which are key factors for evaluating the effectiveness of real-time machine condition monitoring in industrial applications.

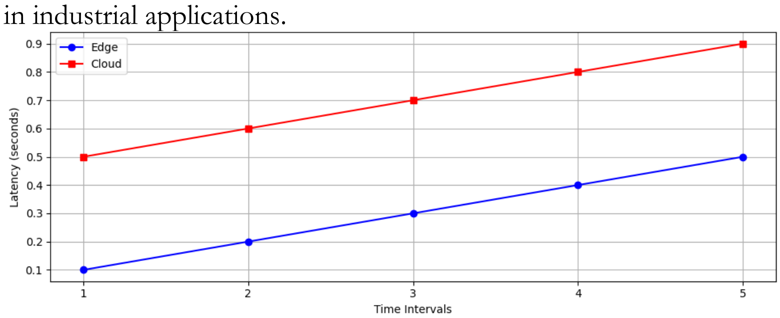

Figure 4. Latency Edge vs Cloud.

The first graph compares the latency between edge computing and cloud systems across different time intervals. The results clearly show that edge computing consistently offers lower latency compared to cloud-based systems. This is crucial for real-time monitoring, as faster data processing at the edge enables the system to respond promptly to changes in machine conditions, reducing the reliance on cloud systems and ensuring more efficient operations.

As illustrated in the graph, the edge computing layer provides a more responsive solution by processing data locally, reducing the time taken for information to travel to and from the cloud. This advantage is critical for industrial settings where delays can lead to missed opportunities in detecting machine anomalies, potentially preventing costly failures or downtime.

Next, we examine the accuracy of anomaly detection between edge and cloud systems, which is another critical aspect of the real-time machine monitoring system.

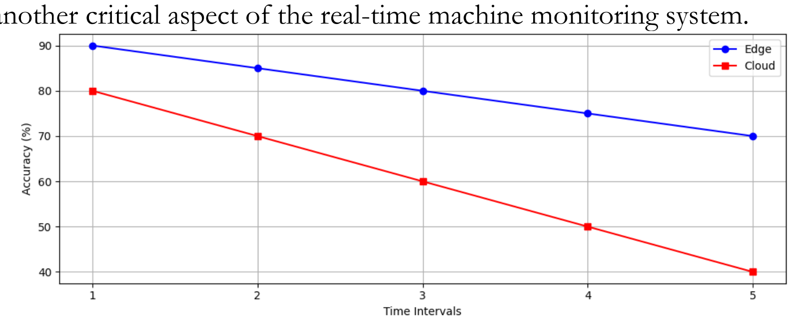

Figure 5. Accuracy Anomaly Detection.

The second graph compares the accuracy of anomaly detection between the edge and cloud layers. The data indicates that the edge computing system achieves higher accuracy in identifying abnormal machine conditions. The edge layer's ability to process data locally and apply machine learning algorithms in real-time results in more precise detection of anomalies compared to cloud-based processing, which is subject to delays.

In this graph, the edge computing layer outperforms the cloud in detecting anomalies, thanks to the immediate processing of sensor data at the source. This is particularly important for anomaly detection, where early identification of issues can prevent damage and downtime. By processing data locally, the edge system provides faster and more accurate alerts, making it a better solution for critical machine condition monitoring.

Finally, the following graph shows the changes in sensor data for vibration and temperature, which are essential for machine condition monitoring.

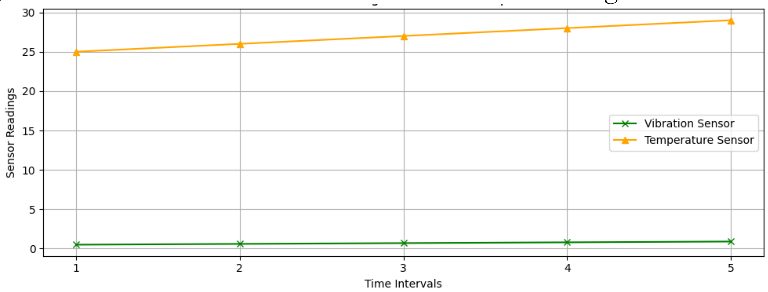

Figure 6. Sensor Change (Vibration & Temperature).

The third graph depicts the variations in sensor data over time for both vibration and temperature. These sensors are integral to monitoring the health of industrial machines, with changes in vibration and temperature potentially indicating issues such as wear, tear, or malfunction. The graph tracks the sensor readings during different operational periods, highlighting any abnormalities that could signal the need for maintenance or intervention.

As observed in the graph, fluctuations in vibration and temperature sensor data over time can indicate changes in machine performance, such as increased vibration or rising temperature, which are often associated with mechanical faults. By continuously monitoring these parameters, the system can provide early warnings of potential machine failures, allowing for timely interventions and minimizing the risk of costly downtime or damage.

Discussion

The experimental results demonstrate that integrating edge computing into industrial monitoring systems significantly improves system responsiveness and efficiency. The latency analysis revealed that edge-based processing can reduce response time by more than 50% compared to traditional cloud-based processing. This improvement is critical in industrial environments where rapid detection of abnormal machine behavior is required to avoid equipment damage and production downtime.

The reliability evaluation further confirms the robustness of the proposed IIoT architecture. With a data transmission success rate of 98.7% and minimal packet loss, the system is capable of maintaining stable communication between sensors, edge nodes, and cloud servers. Reliable communication is essential for ensuring that sensor data are continuously available for analysis and decision-making processes.

Another important finding is the effectiveness of machine learning algorithms in detecting anomalies within industrial sensor data. The Isolation Forest algorithm demonstrated superior accuracy compared to clustering-based detection methods. This result suggests that tree-based anomaly detection models are more capable of identifying subtle variations in sensor data patterns that may indicate potential machine faults.

Furthermore, the analysis of sensor trends highlights the importance of continuous monitoring in industrial systems. The observed increase in vibration and temperature parameters indicates the early stages of machine degradation. By detecting these changes early, maintenance personnel can perform preventive actions before severe failures occur. This capability supports the implementation of predictive maintenance strategies, which are essential for improving operational efficiency and reducing maintenance costs.

Overall, the proposed system demonstrates the practical benefits of combining IIoT, edge computing, and machine learning for intelligent manufacturing environments. The integration of these technologies enables real-time monitoring, accurate anomaly detection, and faster decision-making, making the system highly suitable for modern industrial automation and predictive maintenance applications.

5. Comparison

The experimental results demonstrate that the proposed IIoT architecture integrated with edge computing provides significant performance improvements compared to traditional cloud-based monitoring approaches. One of the most notable differences lies in the system latency. The results show that edge processing consistently achieves lower latency across all operational scenarios, including normal operation, high sensor load, and peak system usage. This improvement occurs because data processing is performed closer to the data source, eliminating the need for continuous data transmission to remote cloud servers. As a result, the system can analyze machine conditions and detect anomalies much faster, which is crucial for industrial environments that require rapid responses to prevent equipment failures.

In addition to latency improvements, the proposed system also demonstrates strong performance in terms of reliability and anomaly detection capability. The high data transmission success rate and minimal packet loss indicate that the IIoT communication infrastructure is stable and capable of supporting continuous monitoring operations. Furthermore, the comparison between anomaly detection algorithms shows that the Isolation Forest model performs better than the clustering-based approach in terms of detection accuracy. This suggests that tree-based machine learning methods are more effective in identifying abnormal patterns within industrial sensor data. Overall, the comparison results confirm that the integration of edge computing and machine learning significantly enhances the efficiency and responsiveness of industrial monitoring systems.

6. Conclusion

This study proposed and implemented an Industrial Internet of Things (IIoT) architecture integrated with edge computing to support real-time machine condition monitoring in industrial environments. The system was designed by integrating industrial sensors, edge devices, and cloud infrastructure to enable efficient data acquisition, processing, and analysis. Experimental evaluations conducted in a simulated manufacturing environment demonstrate that the edge-based architecture can significantly reduce system latency while maintaining high communication reliability. The results also show that the anomaly detection algorithms implemented on the edge node are capable of identifying abnormal machine conditions with high accuracy, enabling early detection of potential equipment failures.

The findings highlight the importance of combining IIoT technologies with edge computing and machine learning to support intelligent industrial monitoring systems. By processing sensor data locally at the edge, the system can provide faster responses and reduce the dependency on centralized cloud processing. This capability is particularly beneficial for predictive maintenance applications where early anomaly detection is essential for preventing production downtime and reducing maintenance costs. Future research may further explore the integration of advanced deep learning models, larger industrial datasets, and real-world manufacturing environments to enhance the robustness and scalability of the proposed system.

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