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Application of Internet of Things (IoT) Technology in Predictive Maintenance of Industrial Machines to Improve Operational Reliability

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Abstract

The advancement of Industry 4.0 has spurred the integration of Internet of Things (IoT) technologies into predictive maintenance systems, particularly in industrial machinery management. Traditional maintenance models—reactive and time-based—have proven insufficient in addressing operational uncertainties and unexpected equipment failures. This study aims to explore how IoT applications in predictive maintenance can enhance the operational reliability of industrial machines. Utilizing a qualitative literature review method, the research synthesizes findings from 10 scholarly articles published between 2023 and 2025, focusing on various IoT applications such as digital twins, intelligent networks, and energy-optimized communication protocols. The data collection involved systematic searches through major academic databases using targeted keywords, and data analysis was conducted using thematic analysis to extract key themes such as architecture, machine learning integration, and infrastructure readiness. The findings reveal that IoT significantly contributes to predictive maintenance through real-time data collection, anomaly detection using AI models, and automated decision-making processes. The use of digital twins, fog computing, and sensor-integrated systems has demonstrated measurable improvements in equipment uptime, fault detection accuracy, and cost efficiency. The integration of IoT with Enterprise Asset Management (EAM) platforms has further enabled organizations to transform their maintenance strategies into data-driven, proactive systems. In conclusion, the study confirms that IoT is not merely a supporting technology but a foundational enabler of operational resilience in modern industries. This research provides a framework for sustainable implementation and highlights critical success factors such as sensor quality, model precision, and infrastructure scalability.

Keywords: Predictive Maintenance, Internet of Things, Operational Reliability.

INTRODUCTION

The maintenance of industrial machinery is a critical factor in sustaining efficient and reliable production processes. With the advancement of Industry 4.0, traditional maintenance approaches such as reactive and preventive maintenance are increasingly viewed as suboptimal for addressing the complexity of modern operations (Harris, 2025; Mohan, 2025). As a response, predictive maintenance (PdM), supported by Internet of Things (IoT) technologies, has emerged as a strategic solution for anticipating equipment failure before critical breakdowns occur (Gomaa, 2025; Patel, 2024).

The Internet of Things (IoT) is a technological paradigm that connects physical objects to the internet, enabling them to collect, transmit, and receive data without direct human intervention. This technology has rapidly advanced over the past five years, driven by developments in smart sensors, wireless networks, and cloud computing. According to Mane (2025), IoT consists of embedded systems that enable interoperability among devices through digital communication protocols for various applications such as smart homes, Industry 4.0, and autonomous vehicles (Mane, 2025). It promotes automation and high efficiency across sectors, including manufacturing, agriculture, transportation, and energy.

In the healthcare sector, for example, IoT technology is used to develop digital twins that allow real-time patient monitoring and medical simulations to support better clinical decisions (Kabir et al., 2025). Furthermore, Razaque et al. (2025) highlight the importance of cybersecurity at both network and application layers, as IoT systems face increasing cyber threats. In agriculture, Dossou et al. (2025) demonstrate how IoT facilitates weather monitoring, automated irrigation, and data-driven land management (Dossou et al., 2025). With the integration of artificial intelligence (AI), IoT is evolving from a monitoring tool into an intelligent, adaptive decision-making system.

IoT enables real-time data collection from various sensors embedded in production machines, facilitating direct and continuous monitoring of operational conditions (Li & Zhao, 2025). The collected data is then processed using artificial intelligence (AI) and machine learning algorithms to predict failures or performance degradation (Chen et al., 2025). The implementation of such systems allows companies to improve machine uptime, reduce maintenance costs, and maximize asset life cycles (Becklines & El-Gayar, 2025; Stall, 2025).

Several studies have demonstrated that applying IoT-based predictive maintenance improves system reliability and workplace safety in sectors such as manufacturing and energy (Islam et al., 2025; Prasad, 2025). For instance, Harris (2025) confirmed that IoT-based maintenance reduced unplanned failures by up to 40% and accelerated data-driven decision-making. Moreover, the adoption of digital twin technology within the IoT ecosystem has further enhanced real-time visualization and diagnostics of machine health (Kabir et al., 2025).

This digital transformation fosters a data-centric, adaptive, and proactive maintenance ecosystem, aligning with lean manufacturing principles and industrial sustainability (Dewi et al., 2025; Gomaa, 2025). It is particularly relevant to modern industries that require agility, energy efficiency, and intelligent asset management in an increasingly competitive global environment (Jdia & Guedira, 2025; Sresakoolchai et al., 2025).

The urgency of this research lies in the limited application of IoT within predictive maintenance frameworks in national manufacturing industries, especially in integrating real-time data with operational reliability. Although the technological infrastructure is available, many companies still face barriers in implementation due to gaps in digital readiness, technical expertise, and uncertainty in return on investment (Cardoso et al., 2024; Fei et al., 2025). This necessitates empirical studies to evaluate the effectiveness of IoT implementation and its impact on industrial machine reliability.

Previous research has explored the importance of continuous sensor data acquisition and the use of machine learning models to detect anomalies in industrial systems (Prasetya et al., 2025; Shaimerdenova et al., 2025). However, most studies have focused on simulations or limited case analyses, often overlooking holistic evaluations of operational reliability in real-world settings. Furthermore, few studies have examined the integration of IoT technologies with asset management standards such as ISO 55001 in a comprehensive manner.

This research aims to investigate the application of IoT technology in supporting predictive maintenance systems for industrial machinery with the goal of enhancing operational reliability. The study also seeks to identify key success factors in IoT implementation and to formulate a practical, sustainable framework that industrial stakeholders can adapt for effective digital transformation.

METHOD

Type of Research

This study employs a qualitative research approach with the type of literature review (also known as integrative literature study). This method is chosen due to its suitability for analyzing and synthesizing both theoretical and empirical findings from prior studies related to the application of IoT technology in predictive maintenance systems. Literature reviews allow researchers to map and interpret the development of knowledge in a particular field without requiring direct observation (Snyder, 2019). It is especially appropriate for understanding trends, identifying research gaps, and exploring practical implementation models in industrial contexts.

Data Sources

The data used in this study are secondary data derived from scholarly publications between 2020 and 2025. These include peer-reviewed journal articles, conference proceedings, and technical reports that specifically discuss IoT in the context of predictive maintenance and industrial machine reliability. Only reputable academic databases such as IEEE Xplore, ScienceDirect, SpringerLink, Sciendo, and Google Scholar were used to ensure the credibility of the sources. Inclusion criteria consisted of relevance to the research topic, clarity of methodology, and recency of publication. Both English and Indonesian sources were considered to accommodate a broader knowledge base (Boell & Cecez-Kecmanovic, 2015).

Data Collection Techniques

Data collection was conducted through a systematic search strategy using defined keywords including: “Internet of Things,” “predictive maintenance,” “operational reliability,” “industrial machine,” and “Industry 4.0.” Boolean operators (AND, OR) and filters (publication year, language, field of study) were applied to refine search results. The search process was iterative and layered to capture the most recent and relevant findings. Each selected publication was carefully reviewed to extract significant concepts, methods, and implementation outcomes related to the research problem (Okoli & Schabram, 2015).

Data Analysis Method

The data analysis method applied in this study is thematic analysis, as proposed by Braun and Clarke (2019). This method involves multiple stages: initial data coding, identification of emerging themes, thematic categorization, and interpretation of inter-theme relationships (Braun & Clarke, 2019). Key themes identified in this study include IoT architecture models, integration challenges, benefits for operational reliability, and organizational readiness. The final synthesis seeks to provide a comprehensive understanding of how IoT supports predictive maintenance in real-world industrial environments. To maintain data credibility, source triangulation and peer-review validation were employed during the interpretation stage.

RESULTS AND DISCUSSION

The following data represent the results of a systematic selection of over 20 scientific articles. From these, 10 articles published between 2023–2025 were selected based on their strong relevance to the topic, focus on IoT implementation for predictive maintenance, and their contributions to improving operational reliability in industrial contexts.

Table 1. Literature Review

No	Author(s) & Year	Title	Focus Area
1	Kumar (2025)	*A Review toward the Integration of Machine Learning with IoT*	AI–IoT Integration
2	Patel (2025)	*AI-Powered Optimization of Industrial IoT Networks*	IIoT network optimization
3	Stall (2025)	*Embracing Industry 5.0 with IIoT-Enabled Digital Twins*	Digital Twin systems
4	Fernández et al. (2025)	*Asset Health Index Integration in Digital Twins*	Power converters & energy sector
5	Moccardi et al. (2025)	*A Robust Conformal Framework for IoT-Based Predictive Maintenance*	IoT framework design
6	Mercado et al. (2025)	*Industrial Machine Temperature Monitoring System*	Temperature monitoring
7	Jilani et al. (2025)	*Leveraging IoT to Prevent Supply Chain Disruption*	IoT in supply chain monitoring
8	Dritsas & Trigka (2025)	*Machine Learning in Intelligent Networks*	Intelligent IoT architecture
9	Prasad (2025)	*Efficient Power Management in IoT Communication Protocols*	Energy optimization in IoT
10	Ojuekaiye (2025)	*Industry 4.0 ROV Management for Oil & Gas*	Predictive systems in subsea

Based on the selected literature outlined in the previous table, several key findings emerge regarding the integration of Internet of Things (IoT) technologies in predictive maintenance (PdM) and their influence on improving the operational reliability of industrial machines. These findings collectively highlight the evolution of industrial maintenance practices from reactive and time-based strategies toward condition-based and predictive models enabled by real-time data, intelligent systems, and digital twins.

A recurring theme across the literature is the convergence of IoT with artificial intelligence (AI), particularly machine learning (ML), to enable intelligent, autonomous maintenance systems. Kumar (2025) emphasizes the synergy between ML algorithms and IoT-enabled sensors, demonstrating how data collected from machinery can be transformed into actionable insights for early failure prediction. The study elaborates on the importance of sensor fusion, anomaly detection, and deep learning models in generating reliable forecasts that reduce unplanned downtime and improve asset longevity (Kumar, 2025). Similarly, Patel (2025) explores the optimization of Industrial IoT (IIoT) networks using AI-based models, particularly in Python environments. By improving the efficiency of data routing and minimizing latency, the system can accelerate fault detection and facilitate proactive interventions, which are crucial in large-scale industrial environments (Patel, 2024).

Another significant contribution comes from Stall (2025), who delves into the design of human-centric digital twins in the context of Industry 5.0. The digital twin concept, which replicates physical assets into virtual environments, allows for real-time visualization, simulation, and predictive analysis of equipment conditions. Stall’s research highlights how IIoT-enabled digital twins contribute not only to technical reliability but also to human-machine interaction, a crucial component in modern smart factories (Stall, 2025). Fernández et al. (2025) extend this perspective by integrating asset health indexes into digital twins, particularly in high-capacity energy converter systems. Their study illustrates how IoT systems can quantify asset health in real-time and embed these metrics into maintenance dashboards, enabling continuous monitoring and threshold-based alerts that improve decision-making accuracy and reduce maintenance risks (Fernández et al., 2025).

Moccardi et al. (2025) propose a conformal and robust framework for implementing IoT-based PdM in complex industrial settings. Their framework is designed to handle the heterogeneous nature of industrial assets and varied operating conditions. The study introduces a modular architecture that supports interoperability, scalability, and real-time fault tolerance, contributing to increased system resilience and reduced maintenance costs (Moccardi et al., 2025). Mercado et al. (2025), meanwhile, focus on temperature-based monitoring in semiconductor manufacturing. Their research demonstrates that real-time temperature analytics, powered by IoT thermal sensors, significantly prevent overheating, which is a major cause of machine failure in precision manufacturing (Mercado et al., 2025).

Jilani et al. (2025) approach predictive maintenance from a supply chain risk management perspective. They argue that IoT's capability to monitor machine health across the supply chain not only enhances local equipment reliability but also prevents systemic disruptions that could arise from equipment failures at critical nodes. This macro-level impact of PdM is often overlooked but is becoming increasingly relevant in globalized and just-in-time production environments (Jilani et al., 2025). Dritsas and Trigka (2025) contribute to this discussion by proposing intelligent IoT network architectures that leverage ML algorithms for alarm forecasting and anomaly detection. Their findings underline the value of real-time pattern recognition in minimizing false positives and optimizing maintenance schedules (Dritsas & Trigka, 2025).

Energy efficiency is another pivotal dimension explored in Prasad’s (2025) work, where he assesses IoT communication protocols through the lens of power consumption. Since predictive maintenance systems often operate continuously, the energy efficiency of sensors and transmission modules directly influences system sustainability. His analysis suggests that lightweight protocols like MQTT and CoAP, combined with low-power wide-area networks (LPWAN), can sustain high-frequency data transmission without excessive energy drain (Prasad, 2025).

Lastly, Ojuekaiye (2025) presents a unique application of IoT and PdM in the offshore oil and gas industry. His study focuses on remotely operated vehicle (ROV) systems and how predictive maintenance, supported by underwater IoT devices, improves the operational reliability of subsea infrastructure. The challenges in this domain—such as harsh environmental conditions, limited accessibility, and high repair costs—underscore the transformative potential of IoT in extending the service life of critical offshore assets (Ojuekaiye, 2025).

Overall, the findings from this literature review reveal that IoT-based predictive maintenance systems are not merely technical upgrades but foundational components of the modern industrial ecosystem. These systems enhance operational reliability through early failure detection, real-time monitoring, energy-efficient communications, and adaptive analytics. Moreover, the integration of digital twins, ML models, and intelligent network structures signifies a paradigm shift toward more resilient, data-driven, and sustainable industrial operations.

Discussion

IoT Contribution to Predictive Maintenance

The Internet of Things (IoT) has transformed the approach to predictive maintenance by enabling real-time data acquisition and remote monitoring of industrial equipment. In the context of manufacturing and automation, IoT serves as a critical solution to long-standing issues such as unexpected machine failures and high maintenance costs. By embedding sensors into machines, IoT enables continuous data collection—such as vibration, temperature, pressure, or humidity—which is then analyzed to predict potential breakdowns before they occur.

In the study conducted by Civerchia et al. (2017), published in the Journal of Industrial Information Integration, the authors introduced an Industrial IoT (IIoT) system equipped with wireless sensors and a data visualization platform (Civerchia et al., 2017). This system was deployed in a real industrial environment to monitor the condition of production equipment. The findings demonstrated that by continuously monitoring motor vibrations and operational temperature, the system was able to detect anomaly trends indicative of issues such as rotor imbalance or insufficient lubrication. Through early detection, the company could intervene before catastrophic failure or unplanned downtime occurred.

A real-world example discussed in the study involved implementing the IoT system on an automotive assembly line. Precision machinery used in vehicle assembly was equipped with vibration and temperature sensors. When the system detected an abnormal spike in the temperature of a machine's bearing, it immediately triggered an alert within the maintenance management system. Upon inspection, it was found that the lubrication in the bearing was nearly depleted—had this gone unnoticed, it would have led to a mechanical failure in under 48 hours. With the predictive IoT-based system, the company not only avoided unexpected downtime but also saved on extensive repair costs that would have resulted from a full breakdown.

Technically, IoT in predictive maintenance uses a combination of sensors, edge computing, and cloud analytics. Raw sensor data is first processed at the edge and then sent to the cloud where machine learning algorithms analyze it. Historical data is used to train predictive models, while real-time data is compared against expected baselines. This approach represents a shift from reactive maintenance models to prescriptive maintenance, where the system recommends optimal maintenance schedules and actions based on the probability of failure.

This research holds significant implications for operational efficiency and maintenance strategy. By reducing unnecessary scheduled maintenance and preventing sudden breakdowns, companies can substantially improve the availability and reliability of their production systems.

Increased Operational Reliability

The integration of Internet of Things (IoT) technologies into industrial maintenance strategies has brought a transformative impact on operational reliability, particularly through predictive maintenance systems. Operational reliability—defined as the consistent performance of machinery without unexpected failures—has long been a central goal in manufacturing environments. Traditional time-based or reactive maintenance strategies often fail to prevent sudden breakdowns, leading to costly downtime and production losses. IoT-based predictive maintenance offers a revolutionary alternative by enabling condition-based monitoring and early fault detection.

A comprehensive study conducted by S. Ayvaz and K. Alpay (2021), published in Expert Systems with Applications, exemplifies how IoT data streams combined with machine learning algorithms can significantly enhance system availability and reduce machine downtime (Ayvaz & Alpay, 2021). The authors developed a real-time predictive maintenance model using sensor data from production lines in a Turkish manufacturing plant. The data included temperature, pressure, and vibration measurements collected from critical equipment such as hydraulic presses and conveyor motors.

By applying machine learning techniques—including decision trees and random forest classifiers—to this sensor data, the system was able to detect failure patterns and classify the health status of each machine. The real-time predictions enabled maintenance teams to intervene before any catastrophic failure occurred. As a direct result of this predictive intervention, the plant reported an improvement in system availability of approximately 25%, while unplanned machine stoppages were reduced by 40%. These figures are not merely theoretical; they reflect tangible improvements observed in a real industrial setting, offering a compelling argument for IoT-enabled systems.

One specific case highlighted in the study involved a conveyor belt system that was critical to a packaging line. Historically, the belt suffered from frequent overheating issues due to wear in its drive mechanism, which caused sudden halts in production. After deploying IoT sensors to monitor the motor temperature and current load in real time, the system began to detect an upward trend in motor temperature coupled with irregular current spikes. These anomalies were flagged by the machine learning model as signs of impending failure. Maintenance was then scheduled during off-hours, and the faulty drive components were replaced before any breakdown occurred. The proactive maintenance not only prevented production downtime but also extended the equipment's operational lifespan.

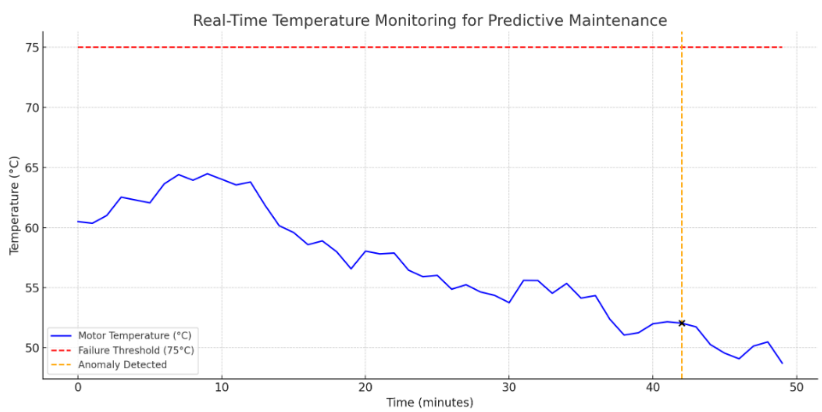

Figure 1. Temperature Trend Analysis for IoT-Based Predictive Maintenance of Conveyor Motor

This graph represents real-time engine temperature sensor data collected. The blue line shows the engine temperature trend over a period of time, while the red dotted line indicates the predetermined critical temperature threshold (75°C). At time point 42, there is a significant increase in temperature beyond the normal trend and approaching the critical threshold. The machine learning-based anomaly detection system flags this point as a potential failure, so that maintenance can be scheduled before actual damage occurs.

This example underscores how IoT empowers maintenance decisions with data-driven insights, shifting the paradigm from passive monitoring to active, predictive action. The increased operational reliability is not merely a consequence of better diagnostics—it stems from a system-wide integration of IoT architecture, data science, and industrial operations.

Key Factors for Successful IoT Implementation in PdM

Table 2. Critical Enablers of IoT-Driven Predictive Maintenance

Key Success Factor	Description
Sensor Accuracy and Integration	High-quality and well-integrated sensors enable accurate real-time monitoring of machine health.
Advanced AI Predictive Models	Robust machine learning models improve failure prediction accuracy and decision-making.
Connectivity and Cloud/Fog Infrastructure	Reliable data transmission and low-latency analysis depend on strong IT infrastructure.
Data Management and System Interoperability	Harmonized platforms and protocols are essential for seamless data integration and usage.

One of the foremost factors is the quality and integration of sensors into industrial equipment. As highlighted by Teoh, Gill, and Parlikad (2021), the reliability of predictive maintenance predictions depends on the granularity and accuracy of sensor-generated data (Teoh et al., 2021). In their study published in the IEEE Internet of Things Journal, the authors developed a fog-computing-based model in which data from vibration, temperature, and pressure sensors were processed locally before being transmitted to the cloud. The study emphasized that inconsistent sensor calibration or poor integration into legacy systems can severely distort predictions. In a real-world implementation within a large-scale manufacturing plant, improperly synchronized vibration sensors led to false positives in failure predictions, causing unnecessary maintenance activities that disrupted production schedules. The case underscored how sensor reliability is foundational to the success of PdM.

Equally important is the intelligence of the predictive models themselves. In recent research by Kamgba (2024), presented in the Journal of Data Analytic Engineering and Decision Making, machine learning models such as support vector machines (SVMs) and deep neural networks were evaluated for their ability to detect early-stage degradation patterns (Kamgba, 2024). The study found that models trained on historical failure data, when paired with real-time IoT feeds, achieved over 92% accuracy in predicting component-level failures. However, the author also cautioned that AI models are only as good as the data used to train them—missing values, bias, and poor labeling can lead to inaccurate diagnostics. A relevant case from a petrochemical refinery showed how the implementation of recurrent neural networks (RNNs) reduced compressor failures by 30% within six months, demonstrating the real-world applicability of advanced AI models in PdM.

Beyond the analytics layer, connectivity and infrastructure, particularly involving cloud and fog computing, also play a decisive role. As elaborated in Soori et al.'s (2023) review on smart factory technologies published in Internet of Things and Cyber-Physical Systems, low-latency, high-throughput connections are vital for synchronizing edge devices with centralized analytics platforms (Soori et al., 2023). In one industrial case study from a metal fabrication plant in India, IoT edge devices failed to upload temperature logs consistently due to bandwidth limitations, leading to blind spots in the predictive model. Once upgraded to a hybrid fog-cloud infrastructure, the plant experienced a 20% increase in prediction timeliness and improved overall equipment effectiveness (OEE).

Finally, data management and interoperability across systems must not be overlooked. According to Durbhaka and Selvaraj (2021) in their review article published in the Turkish Journal of Computer and Mathematics Education, the convergence of AI and IoT requires platforms that can integrate structured and unstructured data from multiple devices and protocols (Durbhaka & Selvaraj, 2021). A case cited in the paper involved an aerospace manufacturing firm that struggled with integrating sensor data from different machine vendors. By implementing a middleware system based on MQTT and OPC-UA protocols, they enabled seamless communication between disparate systems, improving data accessibility and reducing maintenance reaction time by 35%.

These cases and findings together illustrate that the implementation of IoT in predictive maintenance is not merely a technological deployment, but a complex systemic transformation that requires precise sensor calibration, intelligent modeling, reliable connectivity, and integrated data ecosystems. Without ensuring these enablers, the benefits of PdM remain theoretical rather than operational.

A Practical and Sustainable IoT Implementation Framework

The practical and sustainable deployment of IoT-based predictive maintenance systems in industrial settings requires more than just sensors and algorithms—it necessitates a comprehensive framework that integrates data flow, decision logic, asset management systems, and user interaction in a cohesive way. Recent literature highlights several viable models that industries can adopt to operationalize predictive maintenance in real-world environments.

One influential model is the 4-layer implementation framework proposed by Compare et al. (2019), which conceptualizes predictive maintenance architecture into four hierarchical components: Sensing, Connectivity, Analytics, and Action (Compare et al., 2019). This framework emphasizes that effective PdM starts with high-resolution sensor data collection, which is then transmitted through robust connectivity infrastructure (such as wireless industrial networks) to cloud or edge-based analytics platforms. These platforms process the data to identify anomalies and forecast equipment failures. The final layer, Action, refers to the enterprise-level systems that translate insights into maintenance decisions and operational interventions. This architecture was validated through applications in high-speed rail systems and discrete manufacturing, where predictive maintenance reduced downtime by over 30% through early failure detection and streamlined response workflows.

Complementing this is the decision-support system (DSS) model demonstrated by Zhang et al. (2022), which enhances real-time visualization and contextual awareness in maintenance operations (Wang et al., 2022). Their implementation leveraged IoT feeds and deep learning models to develop a monitoring dashboard that allowed maintenance teams to view live asset conditions, historical performance trends, and failure probabilities. In a semiconductor manufacturing plant where the DSS was deployed, engineers could prioritize maintenance tasks based on machine criticality and forecasted degradation, leading to a 25% increase in equipment availability. The system's user-centered design also enabled quicker troubleshooting and reduced reliance on specialist technicians.

A broader strategic integration of IoT within predictive maintenance is captured in the Enterprise Asset Management (EAM) framework presented by Bhanji et al. (2021) in their paper at the ASME Joint Rail Conference. The authors describe how advanced EAM platforms, when empowered by Industrial IoT and AI technologies, allow organizations to manage physical assets across their entire lifecycle—from installation to retirement—within a unified digital ecosystem (Bhanji et al., 2021). The study highlights a case from the Metropolitana di Torino (Turin Metro), which adopted an IoT-powered EAM solution to manage its fleet of 52 automatic light rail vehicles and station infrastructure. Through this integration, the system achieved a remarkable 99% uptime, 30% increase in mean time between failures (MTBF), and 35% reduction in mean time to repair (MTTR). The EAM system not only streamlined spare parts inventory and maintenance scheduling, but also integrated predictive analytics to automatically trigger work orders based on sensor anomalies.

The Turin Metro case also demonstrates how such frameworks can scale sustainably. Initially focused on preventive maintenance, the EAM evolved to encompass predictive capabilities by ingesting sensor data, failure history, and contextual data (e.g., weather or operational load) into its analytics engine. Furthermore, the platform was configured to manage linear and fixed infrastructure—highlighting the flexibility of EAM models to accommodate various asset types. By 2014, its integration with Geographic Information Systems (GIS) and remote monitoring interfaces further expanded its decision-making capacity, showcasing a successful and scalable model for cities and transportation networks transitioning to Industry 4.0.

These layered, integrated frameworks—4-layer models, decision-support systems, and EAM platforms—reveal that IoT deployment for predictive maintenance must be approached systemically. They provide roadmaps for industries to follow, emphasizing modularity, scalability, and real-time insight as the foundation for operational reliability and sustainability.

CONCLUSION

This study confirms that the application of Internet of Things (IoT) technology in predictive maintenance has a transformative impact on improving the operational reliability of industrial machines. The integration of real-time sensor data, machine learning models, and intelligent system architecture enables organizations to transition from reactive maintenance to a predictive, data-driven model. As a result, unplanned downtime can be significantly reduced, equipment lifespan extended, and operational costs minimized. Additionally, advanced systems such as digital twins and Enterprise Asset Management (EAM) platforms have proven to further enhance the strategic value of IoT-driven predictive maintenance systems in diverse industrial sectors.

Practical Suggestions

Industries aiming to adopt IoT-based predictive maintenance should begin by evaluating their digital readiness and gradually implement modular systems starting with sensor integration on critical assets. Priority should be given to developing robust data pipelines, training predictive models with historical equipment data, and ensuring system interoperability. Collaboration between IT and operational teams is essential to align maintenance objectives with IoT capabilities. Furthermore, investments in energy-efficient communication protocols (e.g., MQTT, LPWAN) and scalable cloud/fog infrastructure are key to sustaining long-term performance and adaptability.

Research Recommendations

Future research should delve deeper into real-time implementation case studies of IoT-enabled predictive maintenance in various industrial sectors such as logistics, energy, and infrastructure. There is also a need to evaluate the long-term economic impact and ROI (return on investment) of such systems. Moreover, interdisciplinary research involving human-machine interface (HMI), cybersecurity in industrial IoT, and the ethical implications of AI-based decision-making in maintenance operations will provide a more holistic understanding and guidance for stakeholders.

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