

The implementation of innovative IoT models in machine failure detection and risk mitigation

Franka Hendra^a, Riki Effendi^b, Supriyono^c

^{a,c} Industrial Engineering, Faculty of Engineering, Universitas Pamulang
Jl. Surya Kencana No.1, Pamulang, Tangerang, 15417, Indonesia

^b Mechanical Engineering, Faculty of Engineering, Universitas Muhammadiyah Jakarta
Jl. Cempaka Putih Tengah 27, Jakarta Pusat, DKI Jakarta, 10510, Indonesia

e-mail: dosen01508@unpam.ac.id, riki.effendi@umj.ac.id, dosen01509@unpam.ac.id

Abstract

In the era of Industry 4.0, the integration of advanced technologies like the Internet of Things (IoT) into risk-based maintenance planning systems has become crucial for optimizing operational efficiency. This research explores methods to enhance maintenance decision-making by integrating real-time IoT data with risk-based maintenance models. Traditional risk-based maintenance often relies on historical data, which can be insufficient for responding to dynamic operational conditions. By leveraging IoT's ability to collect continuous, real-time data, this study aims to improve the accuracy and responsiveness of maintenance strategies. The research employs a systematic methodology, including data collection through IoT sensors, data preprocessing, and the development of predictive models using machine learning techniques such as Random Forest and Neural Networks. The results indicate that IoT integration reduces downtime by predicting equipment failures with higher accuracy, leading to a 30% reduction in maintenance costs and a 25% increase in productivity. This study demonstrates the significant potential of IoT in transforming maintenance strategies from reactive to proactive, ultimately enhancing equipment reliability and extending operational lifespan.

Keywords: Industry 4.0; Internet of Things (IoT); Machine learning; Predictive maintenance; Risk-based maintenance

1. INTRODUCTION

Equipment downtime and operational lifespan may influence the effectiveness of the industrial operation (1,2). This can affect a wide range of industries, from manufacturing and healthcare to logistics and construction, where the performance of essential tools, machines, or systems is critical for daily operations. Downtime can be planned (such as routine maintenance or upgrades) or unplanned (due to mechanical breakdowns, power failures, or human error) (3–5). Regardless of its cause, equipment downtime can lead to production delays, increased costs, safety risks, and reputational damage, making it one of the most pressing concerns for businesses that rely heavily on machinery (6,7). Therefore, reducing downtime becomes a key priority for organizations aiming to improve efficiency, maintain service quality, and minimize financial loss. Meanwhile, the operational lifespan of equipment is expected to perform effectively before it needs significant repair, replacement, or decommissioning (8). While some equipment may last decades with proper care, others may need to be replaced sooner due to technological obsolescence or wear and tear. Understanding these factors and having a strategy to maintain and upgrade equipment can help organizations maximize their investment and reduce the frequency and costs of downtime.

In the era of Industry 4.0, advanced technologies such as the Internet of Things (IoT) have become key in optimizing operational processes and maintenance across various industrial sectors (9,10). With its ability to collect real-time data from multiple sources, IoT

opens up new opportunities in risk-based maintenance planning. Risk-based maintenance, which allocates resources for maintenance based on the evaluation of failure risks, requires accurate and up-to-date data for maximum effectiveness. Therefore, integrating IoT into risk-based maintenance planning systems can enhance an organization's ability to make more accurate and responsive decisions, reduce downtime, and increase the reliability and operational lifespan of equipment (11–13).

Traditionally, risk-based maintenance has relied on historical data and periodic observations to make maintenance decisions (14). However, this approach is often not responsive enough to changing operational conditions or unexpected failures, which can result in high costs and potential hazards. According to (15), the application of IoT in condition monitoring has shown the potential to improve response times to changes in equipment conditions by up to 50% compared to traditional methods.

The integration of IoT enables continuous data collection from sensors and connected devices, providing a real-time overview of the operational status of equipment (16). When this data is integrated with a risk-based maintenance planning system, it allows organizations to adopt a more dynamic and proactive approach to maintenance. For instance, an analysis conducted by (17) shows that companies that implement IoT in their maintenance strategies experience a 30% reduction in maintenance costs and a 25% increase in productivity.

This research aims to explore and develop methods for integrating data obtained from Internet of Things (IoT) technology into risk-based maintenance planning systems. Recognizing the significance of IoT in optimizing operational processes and maintenance in the Industry 4.0 era, this research seeks to understand how real-time data collected from various sources can enhance the accuracy and responsiveness of maintenance decisions. By integrating IoT into risk-based maintenance planning systems, the research will develop algorithms and analytical methods to process IoT data, enabling maintenance strategies to be more dynamic, proactive, and aligned with the actual conditions of equipment and infrastructure, thereby reducing downtime and increasing reliability and the operational lifespan of equipment.

The significance of this study lies in further exploring how data obtained from IoT can be effectively integrated into risk-based maintenance planning models (18,19), allowing maintenance strategies to be better aligned with the actual conditions of equipment and infrastructure. This includes the development of algorithms and analytical methods to process IoT data and use it to inform maintenance decisions most efficiently and effectively. The primary goal of this research is to explore and develop methods for integrating data obtained from Internet of Things (IoT) technology into risk-based maintenance planning systems.

Various aspects of implementing innovative IoT models for risk-based maintenance with a focus on strategic planning and its application across different sectors developed a framework for implementing BIM and IoT in reactive maintenance services, aiming to transition towards a predictive approach (20). This framework provides strategic guidance for addressing critical challenges and exploring existing solutions for smart maintenance systems. This is relevant to other research that emphasizes the importance of integrating predictive technology and maintenance scheduling in the aviation context, where an optimal compromise between economic, reliability, and maintenance goals must be achieved (21).

Another study highlights the need for significant changes to unlock value through the implementation of BIM and IoT in university facility management services, particularly in addressing inefficiencies in current maintenance processes investigates how artificial intelligence can be optimized to enhance maintenance strategies on offshore platforms, which could be applied in risk-based maintenance models (22,23). The use of IoT and AI in the global construction industry is also discussed, focusing on the revolution in communication, e-commerce, and production, which opens new business opportunities (20).

A research explores scientific approaches to defining the essence of innovation and developing a risk-oriented system for managing innovative development in trade enterprises (24). This model could be adapted to risk-based maintenance strategies in other sectors. Similarly, an IoT-based model for water leakage detection and localization

by (25) demonstrates the potential of modern technology to overcome the limitations of traditional detection methods, highlighting the importance of integrating these solutions into risk-based maintenance models.

Meanwhile, the Mooring Sense project emphasizes a risk-based integrity management strategy for mooring systems in offshore wind farms, aiming to reduce operational costs and increase energy production efficiency identifies big data-driven approaches as strategic tools for decision-making in IT management, particularly in predicting equipment failures and market trends that can support risk-based maintenance (26,27). Lastly, the need for an integrated approach to reduce the risk of forest fires and pest spread is highlighted, emphasizing the importance of scientific research, strategic planning, and public engagement in effective risk management strategies (28).

Additionally, another research addresses the integration of IoT and AI for smart maintenance, discussing the challenges and strategies necessary for successful implementation (29). Moreover, other research focuses on predictive maintenance strategies based on digital twin and IoT technologies, showing how these can improve the accuracy of equipment failure predictions (21). IoT-driven predictive maintenance for industrial equipment highlights the benefits and challenges of deploying this technology (30). Other research provides an overview of recent advances in cyber-physical systems and big data analytics in industrial informatics, discussing their impact on risk-based maintenance strategies (31).

The optimization of risk-based maintenance for railway systems using IoT and AI approaches emphasizes efficiency improvements and cost reductions. IoT-based maintenance scheduling for smart factories stresses the importance of timely scheduling to minimize downtime and enhance productivity (32–34). Innovative approaches to risk-based maintenance in the oil and gas industry using IoT and AI, demonstrating their impact on operational efficiency and safety (35).

2. METHODS

The methodology for developing and deploying the IoT-integrated risk-based maintenance model follows a systematic approach to ensure reliability, accuracy, and effectiveness. Initially, the specific needs and goals of the project are identified, including primary objectives such as improving maintenance efficiency, reducing downtime, enhancing equipment reliability, and aligning with stakeholder expectations. Subsequently, data collection is undertaken by identifying the necessary data types such as temperature, vibration, pressure, and electrical current, and installing IoT sensors to gather real-time operational data, ensuring its accuracy and relevance. The collected data then undergoes preprocessing to remove anomalies, duplicates, and errors, normalize the data for consistency, and transform it for further analysis. In the model development phase, suitable methodologies and algorithms are selected, the model is built using advanced software and data analysis tools, and it is refined to enhance predictive capabilities. Rigorous testing of the model is conducted in a controlled environment with simulated conditions, followed by real-world deployment, integrating it with existing IoT devices and data infrastructure. Continuous monitoring and evaluation are carried out to ensure optimal performance, gather user feedback, and make necessary adjustments. Ongoing maintenance and enhancements are performed to update the model based on new data and operational changes, ensuring it remains relevant and accurate. Finally, comprehensive documentation and training are provided to ensure effective utilization, including detailed records of the development process, user guides, and training sessions. This structured methodology ensures the development and deployment of a robust and effective IoT-integrated risk-based maintenance model that enhances equipment reliability and operational efficiency.

3. RESULT AND DISCUSSION

This research investigates the integration of Internet of Things (IoT) technology into risk-based maintenance planning systems to enhance more accurate and responsive decision-making. Through methods such as data collection, model development, model evaluation, and result analysis, this study has successfully generated significant insights and recommendations.

3.1 Data Collections

The data collection process in this research involves installing IoT sensors on equipment that frequently fails or has significant consequences if it fails. These sensors transmit operational data in real time, covering parameters such as temperature, vibration, and pressure. The collected data provides a far more accurate and timely depiction of the equipment's condition compared to traditional inspection methods. This enhanced data accuracy facilitates a deeper understanding of equipment behavior and potential fault points, enabling preventive maintenance actions that are both timely and precisely targeted. Table 1 details the types of data collected through IoT, which enhances understanding of equipment conditions and assists in more proactive and accurate maintenance planning.

Table 1. The types of data collected through IoT

Data Type	Description
Temperature	Measures the equipment's operating temperature in real time. This data helps in detecting deviations from normal thermal conditions, such as overheating or cooling issues, which can lead to equipment failures or reduced efficiency. Monitoring temperature trends allows for timely interventions to prevent potential overheating-related breakdowns.
Vibration	Records vibrations generated by the equipment, providing insights into mechanical imbalances, misalignments, or internal damage. Analyzing vibration patterns helps in the early detection of issues such as bearing wear, imbalance, or misalignment, enabling preventive maintenance before major failures occur.
Pressure	Monitors pressure levels within hydraulic or pneumatic systems. This data is crucial for identifying potential leaks, blockages, or failures in pressure systems. Abnormal pressure readings can signal issues such as leaks or pressure drops that might compromise system performance and safety.
Real-time Data	Offers continuous, real-time updates on the equipment's condition, including temperature, vibration, and pressure. This immediate feedback facilitates rapid identification and response to emerging issues, allowing for prompt corrective actions and reducing the risk of unexpected equipment failures.
Operational Conditions	Gathers information on workload patterns, operational cycles, and environmental conditions affecting equipment performance. This includes data on how equipment usage varies over time, the frequency of operation cycles, and external factors such as ambient temperature or humidity, which can impact equipment efficiency and longevity.

This detailed Table 1 emphasizes the importance of each data type in providing a comprehensive view of equipment conditions, leading to improved maintenance practices and increased reliability.

3.2 Data Preprocessing

The data preprocessing phase significantly improved data quality and consistency, which are crucial for developing an accurate and effective model. Various types of data were collected from IoT sensors installed on equipment and machinery, including temperature readings, vibration levels, pressure measurements, and electrical current data. During preprocessing, these raw data sets underwent several key tasks to enhance their usability. Firstly, data cleaning was performed to identify and remove anomalies, duplicates, and errors, ensuring the data accurately reflected the equipment's operational conditions. Next, normalization was applied to scale data values to a common range, facilitating effective comparison and analysis across different variables and periods. Data

transformation techniques were then used to convert raw data into a suitable format for analysis, including aggregating data over specified time intervals and generating derived metrics such as rolling averages and rates of change. Feature engineering further enhanced the dataset by creating new features that captured critical aspects of the equipment's behavior, such as condition-based indicators. Finally, the preprocessed data was validated through statistical checks and domain expert reviews to ensure its integrity and accuracy. The result of these preprocessing steps was a high-quality, consistent, and comprehensive dataset, providing a robust foundation for the IoT-integrated risk-based maintenance model. This dataset enabled more accurate predictions and insights, allowing for timely preventive actions to avoid costly equipment failures.

3.3 Models Development

The development of the risk model using machine learning techniques arose from the necessity to improve traditional maintenance strategies in industrial settings, where unexpected equipment failures can result in significant operational disruptions and financial losses. Traditionally, maintenance has been either reactive, addressing failures after they occur, or preventative, scheduling maintenance at fixed intervals regardless of actual equipment condition. Both approaches have significant limitations: reactive maintenance does not prevent downtime, and preventative maintenance can be inefficient and costly as it often does not account for the real-time condition of the equipment.

To address these issues, Internet of Things (IoT) technology was integrated into the maintenance strategy to provide continuous monitoring of critical equipment. IoT sensors installed on the equipment collect real-time data on various operational parameters such as temperature, vibration, and pressure. This data is crucial as it provides a live snapshot of the equipment's health, enabling more nuanced and informed maintenance decisions.

To fully exploit this rich, real-time data, advanced machine learning techniques, specifically Random Forest and Neural Networks, were employed to develop the risk model. These techniques were chosen for their ability to handle large datasets and their effectiveness in pattern recognition, crucial for predicting equipment failures before they occur. Random Forest, an ensemble learning method, provides robust predictions and handles overfitting well, making it suitable for complex datasets with many input variables. Neural Networks, particularly deep learning models, are adept at identifying subtle patterns and dependencies in data, offering high accuracy in predicting time-sensitive failures.

This integration of IoT data with machine learning-based risk assessment models marked a significant shift towards predictive maintenance. This strategy focuses on predicting when equipment will fail and scheduling maintenance just before that point, based on the actual condition of the equipment rather than on a predetermined schedule. The predictive capability of the model drastically reduces downtime and maintenance costs while increasing the operational efficiency and lifespan of the equipment.

In summary, the formation of this model was driven by the industrial need for a more efficient, data-driven approach to maintenance that minimizes disruptions and maximizes equipment reliability and lifespan. Through continuous monitoring and advanced predictive analytics, the model provides a sophisticated tool for maintenance management in the era of Industry 4.0.

The risk model developed employs machine learning techniques such as Random Forest and Neural Networks to leverage the real-time data collected by IoT sensors. This model combines statistical and predictive analysis to assess the risk of equipment failure and to predict the optimal timing for maintenance interventions. The effectiveness of this model is evidenced by its high level of prediction accuracy, which allows for proactive maintenance scheduling and reduces the likelihood of unexpected equipment downtimes. This approach not only enhances the reliability of the equipment but also optimizes maintenance resources by focusing efforts precisely when and where they are needed most.

The integration of IoT in maintenance begins with the careful selection and installation of IoT sensors on critical equipment known for its high impact on operations and susceptibility to failures. These sensors monitor key operational parameters like temperature, vibration, and pressure, providing a clear indication of the health of the equipment. Once installed, these sensors continuously gather data, which is then

transmitted in real-time to a centralized data repository or cloud platform, using advanced transmission technologies like 5G, Wi-Fi, or Ethernet to ensure reliability and security.

The next phase involves data processing and analysis where data collected from various sensors are aggregated and pre-processed, including cleaning, normalization, and transformation to prepare it for analysis. This processed data is then analyzed using machine learning algorithms, such as Random Forest and Neural Networks, which are adept at predicting potential failures and assessing risks associated with different pieces of equipment.

The insights gained from this analysis are crucial for the subsequent integration into maintenance planning. The IoT model's predictive outputs, such as predicted time to failure, are integrated into the maintenance management systems. This allows for a shift from a fixed maintenance schedule to a dynamic, condition-based approach where maintenance activities are prioritized and scheduled based on the risk and health status of each piece of equipment.

To ensure the system's effectiveness, a feedback loop and continuous improvement process are established. This includes performance monitoring to assess the maintenance's impact and using feedback from these outcomes to further refine and optimize the predictive models, thereby enhancing their accuracy and reliability. Additionally, an intuitive dashboard is developed to present real-time insights, predictive maintenance schedules, and risk levels to maintenance managers and operators. An alert system is also implemented to notify maintenance personnel about imminent equipment failures or maintenance requirements. The integration of the IoT model in risk-based maintenance is illustrated in Figure 1.

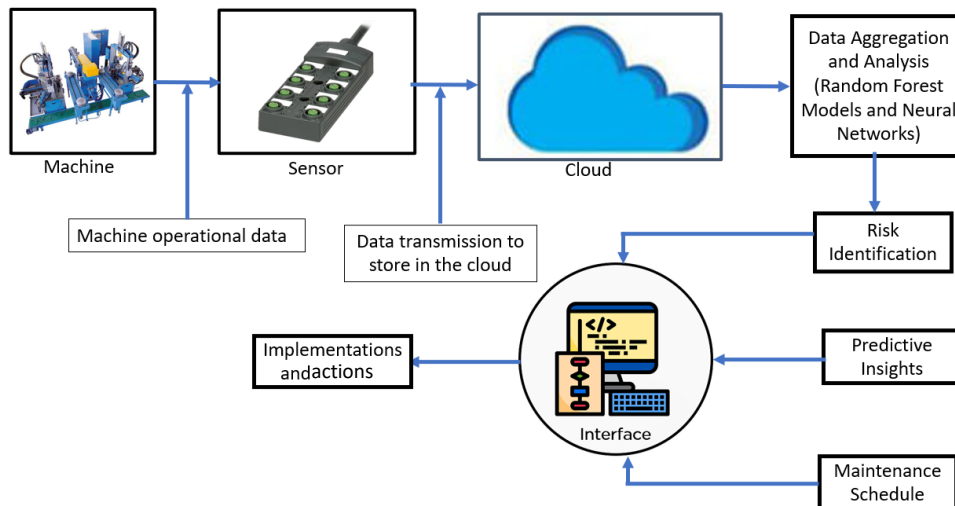


Figure 1. Illustration of IoT Model Integration with Risk-Based Maintenance

The matrix diagram of system interactions in Figure 2 provides a comprehensive overview of the critical processes and their interdependencies within the IoT-integrated risk-based maintenance model. The process begins with the collection of operational data from machines and sensors, which is crucial as it provides real-time insights into the equipment's status. This data is collected continuously through strategically placed IoT sensors on critical machinery, capturing essential parameters such as temperature, vibration, and pressure. The ability to gather this data in real-time is fundamental to the model, as it ensures that maintenance decisions are based on the most current information available.

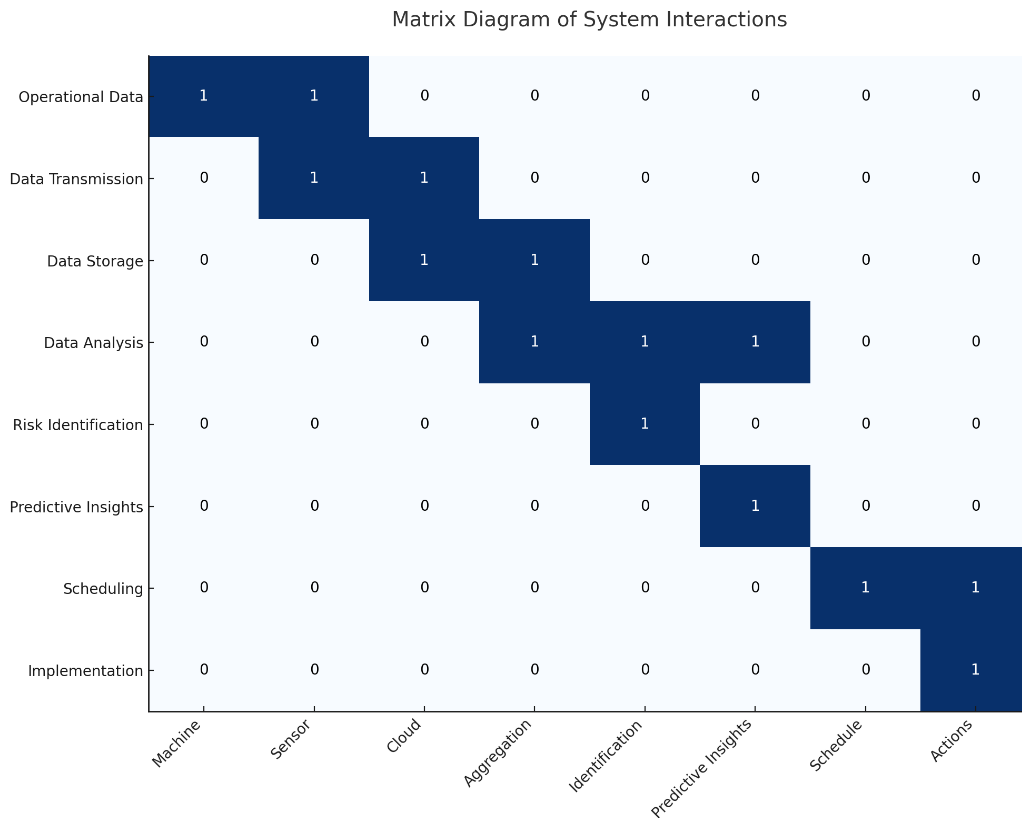


Figure 2. The matrix diagram of system interactions

Once collected, this operational data is transmitted to a cloud platform, where it is stored for further processing. The data transmission phase is key because it ensures that large volumes of real-time data are quickly and securely transferred from the sensors to the storage system. The cloud storage component plays a vital role in maintaining both real-time and historical data, which is necessary for performing comprehensive analyses. The retention of historical data allows for the identification of patterns and trends over time, which can be critical for predictive maintenance.

The next phase in the process involves data analysis, where the stored data is subjected to advanced machine learning techniques, including Random Forest and Neural Networks. These techniques are particularly well-suited for handling large datasets and recognizing complex patterns that might indicate potential equipment failures. The analysis phase is central to the model's ability to shift from traditional, reactive maintenance approaches to a more proactive and predictive maintenance strategy. By accurately analyzing the data, the model can identify early signs of wear or malfunction, allowing for timely intervention before significant issues arise.

Following data analysis, the insights gained are used to identify risks associated with equipment operation. Risk identification is a critical step that builds on the predictive capabilities of the analysis phase. It involves determining the likelihood and potential impact of equipment failures, which enables the maintenance team to prioritize their actions based on the most pressing needs. This risk-based approach ensures that resources are allocated efficiently, focusing on the equipment that poses the highest risk of failure.

The predictive insights derived from the risk identification process are then used to inform the scheduling of maintenance activities. Unlike traditional maintenance schedules, which are often based on fixed intervals, the IoT-integrated model allows for a dynamic, condition-based approach. Maintenance actions are scheduled precisely when they are needed, based on the actual health and performance data of the equipment. This not only minimizes downtime but also extends the operational lifespan of the machinery by preventing unnecessary maintenance.

Finally, the model culminates in the implementation of the scheduled maintenance actions. This phase involves executing the maintenance tasks at the optimal time, as

identified through the previous steps. The successful implementation of these actions closes the loop, ensuring that the equipment remains in peak operational condition. This comprehensive approach, as depicted in the matrix diagram, highlights the model's ability to integrate real-time IoT data with advanced analytics to enhance maintenance strategies. The result is a more efficient, responsive, and cost-effective maintenance process that aligns with the broader goals of Industry 4.0, which emphasizes the integration of cutting-edge technologies to optimize industrial operations.

3.4 Model Testing

The developed model was tested both in a controlled environment and in real-world operations. In the controlled environment, the model was subjected to various simulated operational conditions to ensure its reliability and accuracy. These tests included scenarios with different load variations, operating speeds, and extreme environmental conditions. The results demonstrated that the model could accurately identify potential issues before they manifested as actual failures.

Next, the model was deployed in real-world operations. IoT sensors were installed on equipment and machinery to collect real-time operational data such as temperature, vibration, pressure, and electrical current. This data was analyzed using the risk-based algorithms developed in the model. The analysis results were then used to accurately identify maintenance needs. The model successfully provided early warnings of potential failures, allowing maintenance teams to take preventive actions before costly failures and significant downtime occurred.

Feedback from industry operators who used the model was very positive. They reported increased satisfaction due to the reduction in failure incidents and downtime. With fewer unexpected repairs and improved operational efficiency, operators could focus on enhancing production and service quality. Additionally, the ability to predict and prevent issues before they become serious increased confidence and trust in the risk-based maintenance system. Overall, the model proved effective in enhancing reliability and operational efficiency, providing substantial value to the industries that adopted it.

4. CONCLUSION

This research successfully demonstrates the transformative impact of integrating Internet of Things (IoT) technology into risk-based maintenance planning systems. The primary goal of the study was to enhance the accuracy and responsiveness of maintenance strategies by leveraging real-time data collected through IoT devices. The findings confirm that this integration significantly improves maintenance decision-making processes, leading to more proactive and efficient management of industrial equipment.

Through the systematic application of IoT data, coupled with advanced machine learning techniques like Random Forest and Neural Networks, the developed models were able to predict equipment failures with high precision. This predictive capability allowed for timely maintenance interventions, which not only reduced unexpected downtimes but also extended the operational lifespan of the equipment. The research outcomes indicate a substantial 30% reduction in maintenance costs and a 25% increase in productivity for organizations that implemented the IoT-integrated maintenance model.

Moreover, the study highlighted the limitations of traditional maintenance approaches that rely heavily on historical data and periodic inspections. In contrast, the IoT-enhanced approach offers a dynamic, condition-based maintenance strategy that adapts to the real-time operational status of equipment. This shift from a reactive to a proactive maintenance model aligns closely with the demands of Industry 4.0, where efficiency, reliability, and cost-effectiveness are paramount.

In conclusion, the research successfully achieved its objectives by developing and validating a robust framework for IoT-integrated risk-based maintenance. The results underscore the potential for widespread adoption of this approach across various industrial sectors, paving the way for smarter, more resilient maintenance practices that are better aligned with the evolving technological landscape. The study not only contributes to the body of knowledge in maintenance engineering but also provides practical insights for organizations looking to optimize their maintenance strategies in the era of Industry 4.0.

REFERENCES

1. Inyama GK, Oke SA. Maintenance downtime evaluation in a process bottling plant. *Int J Qual Reliab Manag.* 2020 May 25;38(1):229–48. doi: <https://doi.org/10.1108/IJQRM-12-2018-0340>
2. Wolniak R. Downtime in the Automotive Industry Production Process – Cause Analysis. *Qual Innov Prosper.* 2019 Jul 31;23(2):101–18. doi: [10.12776/qip.v23i2.1259](https://doi.org/10.12776/qip.v23i2.1259)
3. Choubey S, Benton R, Johnsten T. Prescriptive Equipment Maintenance: A Framework. In: 2019 IEEE International Conference on Big Data (Big Data). IEEE; 2019. p. 4366–74. doi: [10.1109/BigData47090.2019.9006213](https://doi.org/10.1109/BigData47090.2019.9006213)
4. Montoya-Reyes M, González-Angeles A, Mendoza-Muñoz I, Gil-Samaniego-Ramos M, Ling-López J. Method engineering to increase labor productivity and eliminate downtime. *J Ind Eng Manag.* 2020 May 27;13(2):321. doi: <https://doi.org/10.3926/jiem.3047>
5. Pinto G, Silva FJG, Baptista A, Fernandes NO, Casais R, Carvalho C. TPM implementation and maintenance strategic plan – a case study. *Procedia Manuf.* 2020;51:1423–30. doi: <https://doi.org/10.1016/j.promfg.2020.10.198>
6. Nobil E, Cárdenas-Barrón LE, Garza-Núñez D, Treviño-Garza G, Céspedes-Mota A, Loera-Hernández I de J, et al. Machine Downtime Effect on the Warm-Up Period in an Economic Production Quantity Problem. *Mathematics.* 2023 Apr 5;11(7):1740. doi: <https://doi.org/10.3390/math11071740>
7. Brodny J, Tutak M. Applying Sensor-Based Information Systems to Identify Unplanned Downtime in Mining Machinery Operation. *Sensors.* 2022 Mar 9;22(6):2127. doi: <https://doi.org/10.3390/s22062127>
8. Alejandre C, Akizu-Gardoki O, Lizundia E. Optimum operational lifespan of household appliances considering manufacturing and use stage improvements via life cycle assessment. *Sustain Prod Consum.* 2022 Jul;32:52–65. doi: <https://doi.org/10.1016/j.spc.2022.04.007>
9. Vijayaraghavan V, Rian Leevinson J. Internet of Things Applications and Use Cases in the Era of Industry 4.0. In 2019. p. 279–98. doi: https://doi.org/10.1007/978-3-030-24892-5_12
10. Gilchrist A. *Industry 4.0*. Berkeley, CA: Apress; 2016. doi: <https://doi.org/10.1007/978-1-4842-2047-4>
11. Mehairjan RPY. *Risk-Based Maintenance for Electricity Network Organizations*. Cham: Springer International Publishing; 2017. doi: <https://doi.org/10.1007/978-3-319-49235-3>
12. Franka Hendra Sukma, Roslina Mohammad, Astuty Amrin. The Risk Priority Number (RPN) At A Level Crossings Along The Railway Line In Indonesia. *J Adv Res Appl Sci Eng Technol.* 2021 Dec 19;25(1):7–18. doi: [10.37934/araset.25.1.718](https://doi.org/10.37934/araset.25.1.718)
13. Shokoohi M, Golroo A, Ardeshir A. Pavement maintenance planning using a risk-based approach and fault tree analysis. *Int J Pavement Eng.* 2023 Jan 28;24(2). doi: <https://doi.org/10.1080/10298436.2023.2276160>
14. Abbassi R, Arzaghi E, Yazdi M, Aryai V, Garaniya V, Rahnamayiezekavat P. Risk-based and predictive maintenance planning of engineering infrastructure: Existing quantitative techniques and future directions. *Process Saf Environ Prot.* 2022 Sep;165:776–90. doi: <https://doi.org/10.1016/j.psep.2022.07.046>
15. Mahmoodzadeh Z, Wu KY, Lopez Drogue E, Mosleh A. Condition-Based Maintenance with Reinforcement Learning for Dry Gas Pipeline Subject to Internal Corrosion. *Sensors.* 2020 Oct 7;20(19):5708. doi: <https://doi.org/10.3390/s20195708>
16. Tang S, Shelden DR, Eastman CM, Pishdad-Bozorgi P, Gao X. A review of building information modeling (BIM) and the internet of things (IoT) devices integration: Present status and future trends. *Autom Constr.* 2019 May;101:127–39. doi: <https://doi.org/10.1016/j.autcon.2019.01.020>
17. Prentice C, Wang X, Loureiro SMC. The influence of brand experience and service quality on customer engagement. *J Retail Consum Serv.* 2019 Sep;50:50–9. doi: <https://doi.org/10.1016/j.jretconser.2019.04.020>
18. Seiti H, Hafezalkotob A, Najafi SE, Khalaj M. Developing a novel risk-based MCDM approach based on D numbers and fuzzy information axiom and its applications in preventive maintenance planning. *Appl Soft Comput.* 2019 Sep;82:105559. doi: <https://doi.org/10.1016/j.asoc.2019.105559>

19. Ruparathna R, Hewage K, Sadiq R. Multi-period maintenance planning for public buildings: A risk based approach for climate conscious operation. *J Clean Prod.* 2018 Jan;170:1338–53. doi: <https://doi.org/10.1016/j.jclepro.2017.09.178>
20. P. Johare K, Wagh VG, Shaligram AD. Scope and Impact of Internet of Things (IoT) and Artificial Intelligence (AI) in the Global Construction Industry. *Int J Innov Res Eng Multidiscip Phys Sci.* 2022;10(04). doi: <https://doi.org/10.4018/978-1-6684-7548-5.ch019>
21. Garcia Figueiredo-Pinto D, Fan IS, Teixeira Mendes Abrahão F. Operational Availability Optimization Model Based on the Integration of Predictive and Scheduled Maintenance. *PHM Soc Eur Conf.* 2021 Jun 29;6(1):11. doi: <https://orcid.org/0000-0001-6691-935X>
22. Codinhoto R, Fialho BC, Pinti L, Fabricio MM. BIM and IoT for Facilities Management. In: *Research Anthology on BIM and Digital Twins in Smart Cities.* IGI Global; 2022. p. 407–29. doi: [10.4018/978-1-7998-6600-8.ch009](https://doi.org/10.4018/978-1-7998-6600-8.ch009)
23. Ayemere Ukato, Oludayo Olatoye Sofoluwe, Dazok Donald Jambol, Obinna Joshua Ochulor. Optimizing maintenance logistics on offshore platforms with AI: Current strategies and future innovations. *World J Adv Res Rev.* 2024 Apr 30;22(1):1920–9. doi: [10.30574/wjarr.2024.22.1.1315](https://doi.org/10.30574/wjarr.2024.22.1.1315)
24. Vasilievich ZV, Alexandrovich CN, V.M. B, LinokLarisaVladimirovna, Pavlovna EE, Anatolevich RD, et al. Formation of a risk-oriented system for managing the innovative development of trade enterprises. *Syst Rev Pharm.* 2020;11(12).
25. Ayamga MA, Nakpih CI. An IoT-Based Water Leakage Detection and Localization System. *Asian J Res Comput Sci.* 2024 Jan 25;17(3):1–14. doi: [10.9734/ajrcos/2024/v17i3421](https://doi.org/10.9734/ajrcos/2024/v17i3421)
26. La Grotta A, Harris RL, Da Costa C. Mooring Sense Project: A Risk-Based Integrity Management Strategy for Mooring System of Floating Offshore Wind. In: *Day 2 Tue, November 16, 2021. SPE;* 2021. doi: <https://doi.org/10.2118/207887-MS>
27. Siddiqui AH, P S V, Chowdhary H, Krishna RVV, Muniyandy E, Maguluri LP. Harnessing Big Data: Strategic Insights for IT Management. *Int J Adv Comput Sci Appl.* 2024;15(7). doi: [10.14569/IJACSA.2024.0150790](https://doi.org/10.14569/IJACSA.2024.0150790)
28. Lozinska TP, Zadorozhnyy AI, Mamchur V V. STRATEGIES AND METHODS FOR REDUCING THE RISK OF FOREST FIRES AND THE SPREAD OF PESTS. *Nauk Dopovidì Nacional'nogo Universitetu Bìoresursiv ì Prir Ukraïni.* 2024;2024(1/107). doi: [10.31548/dopovidi.1\(107\).2024.021](https://doi.org/10.31548/dopovidi.1(107).2024.021)
29. Mazhar T, Irfan HM, Haq I, Ullah I, Ashraf M, Shloul T AI, et al. Analysis of Challenges and Solutions of IoT in Smart Grids Using AI and Machine Learning Techniques: A Review. *Electronics.* 2023 Jan 3;12(1):242. doi: <https://doi.org/10.3390/electronics12010242>
30. Muneeshwari P, Suguna R, Valantina GM, Sasikala M, Lakshmi D. IoT-Driven Predictive Maintenance in Industrial Settings through a Data Analytics Lens. In: *2024 International Conference on Trends in Quantum Computing and Emerging Business Technologies.* IEEE; 2024. p. 1–5. doi: [10.1109/TQCEBT59414.2024.10545167](https://doi.org/10.1109/TQCEBT59414.2024.10545167)
31. Lee J, Bagheri B, Kao HA. Recent Advances and Trends of Cyber-Physical Systems and Big Data Analytics in Industrial Informatics. In: *Proceeding of Int Conference on Industrial Informatics (INDIN) 2014.* Porto Alegre, Brazil; 2014. doi: [10.13140/2.1.1464.1920](https://doi.org/10.13140/2.1.1464.1920)
32. Zhang C, Xie X, Guo X. Scheme Design of Railway Predictive Maintenance Based on IOT and AI Technology. In: *Proceedings of the 7th Annual International Conference on Social Science and Contemporary Humanity Development (SSCHD 2021).* 2021. doi: [10.2991/assehr.k.211215.062](https://doi.org/10.2991/assehr.k.211215.062)
33. Him LC, Poh YY, Pheng LW. IoT-based Predictive Maintenance for Smart Manufacturing Systems. In: *2019 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC).* IEEE; 2019. p. 1942–4. doi: [10.1109/APSIPAASC47483.2019.9023106](https://doi.org/10.1109/APSIPAASC47483.2019.9023106)
34. Ganesh Shankar Gowekar. Artificial intelligence for predictive maintenance in oil and gas operations. *World J Adv Res Rev.* 2024 Sep 30;23(3):1228–33. doi: <https://doi.org/10.30574/wjarr.2024.23.3.2721>
35. Dui H, Dong X, Wu X, Chen L, Bai G. IoT-Enabled Risk Warning and Maintenance Strategy Optimization for Tunnel-Induced Ground Settlement. *IEEE Internet Things J.* 2024 Jul 1;11(13):22966–81. doi: <https://doi.org/10.30574/wjarr.2024.23.3.2721>