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PREDICTIVE MAINTENANCE IN SOCIETY 5.0: FROM REACTIVE REPAIRS TO AI-DRIVEN SYSTEM RELIABILITY

DOI: 10.5937/PIM26101R

Abstract:
The transition toward Society 5.0 introduces a human-centered paradigm in which advanced technologies such as artificial intelligence (AI), the Internet of Things (IoT), and big data analytics are integrated into industrial systems to enhance efficiency, sustainability, and reliability. This paper analyzes predictive maintenance as a key approach that replaces traditional reactive and preventive maintenance methods with intelligent, data-driven systems based on real-time monitoring and machine learning algorithms. Particular emphasis is placed on the application of IoT and AI technologies in industry, their impact on reducing downtime and operational costs, as well as the challenges of implementation, including data quality and cybersecurity. The results indicate that predictive maintenance represents a significant step toward the development of smart, sustainable, and human-centered industrial systems within the Society 5.0 framework.

Keywords: *Predictive maintenance, Artificial Intelligence, Digital Twin, Society 5.0*

Introduction

Modern industrial systems are undergoing a deep transformation due to the development of digital technologies, artificial intelligence (AI), Internet of Things (IoT) and cyber-physical systems (CPS). This transformation is most often seen through the concept of Industry 4.0, however, in the newer socio-technological framework of Japan, a broader concept known as Society 5.0 has been developed, which goes beyond industrial optimization and focuses on the integration of technology in the service of man and society as a whole [2].

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This paper aims to bridge the gap between theoretical frameworks and industrial application by analyzing the core architectures and AI-driven processes that make such a transformation possible.

Predictive maintenance emerges as a critical enabler of this transformation by improving system reliability and reducing operational risks [5].

Traditional maintenance strategies are no longer sufficient in complex cyber-physical environments, where real-time data streams and interconnected systems require intelligent decision-making.

Society 5.0 integrates physical and digital systems to create human-centered technological environments.

Within this environment, predictive maintenance (Predictive Maintenance - PdM) is becoming a key component of next-generation industrial systems.

Traditional maintenance models, such as reactive and preventive maintenance, show significant limitations in the context of complex and highly interconnected systems. Reactive maintenance leads to costly downtime and unplanned breakdowns, while preventive maintenance often results in unnecessary interventions and suboptimal use of resources.

In contrast, predictive maintenance uses real-time data, sensor networks, and machine learning algorithms to identify patterns that precede system failures. In this way, it is possible to move from a "reactive" and "preventive" approach to a proactive and intelligent system management.

According to research, the implementation of a PdM system can significantly reduce downtime, optimize maintenance costs and extend the life of industrial equipment. The key advantage of this approach is the ability to process large volumes of heterogeneous data (vibration, temperature, pressure, sound, electrical signals) in real time using advanced AI models such as neural networks, random forest algorithms and deep learning architectures. In the context of Society 5.0, PdM is not only a technical solution, but also a strategic element of sustainable industrial transformation. By integrating IoT sensors, cloud computing infrastructure and AI analytics, a smart maintenance ecosystem is

created, in which systems are not only automated, but also adaptive and self-learning.

Additionally, the Digital Twin concept plays a key role in modern PdM architectures. A digital twin enables a virtual replica of a physical system, which enables simulation, analysis and prediction of equipment behavior in real time. This approach significantly improves the accuracy of predictive models and enables advanced optimization scenarios.

All of the above indicates that predictive maintenance represents one of the key pillars of the transition to Society 5.0, where industrial systems are transformed from static and reactive to intelligent, connected and autonomous systems.

This paper reviews predictive maintenance within Society 5.0, focusing on the integration of IoT, AI, and digital twin technologies.

1. IoT Architecture in Predictive Maintenance

Society 5.0 integrates cyber-physical systems, big data analytics, and intelligent automation to solve societal and industrial problems [2].

Its goal is to balance economic advancement with social well-being through technological convergence.

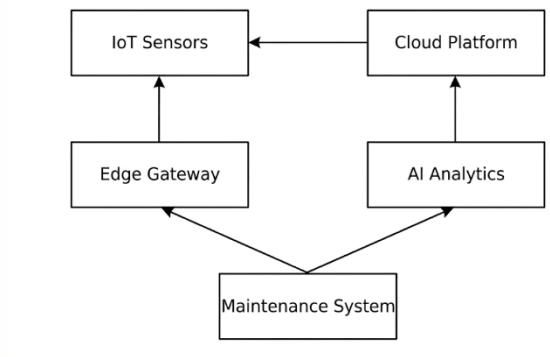
Reactive maintenance addresses failures after they occur, leading to high downtime costs. Preventive maintenance schedules servicing at fixed intervals, often resulting in inefficiency. Predictive maintenance leverages real-time data to anticipate failures before they occur, optimizing resource usage [8].

Picture 1. illustrates a typical IoT-based predictive maintenance architecture.

This diagram represents an IoT-driven Smart Maintenance Ecosystem, illustrating the interconnected flow between hardware, cloud infrastructure, and intelligent analysis:

- IoT Sensors & Edge Gateway: Real-time data is captured by sensors and processed locally at the edge to ensure rapid response times and efficient data handling.

- AI Analytics & Cloud Platform: Data is transmitted to the cloud, where advanced AI algorithms perform deep analysis to identify patterns and predict equipment needs.
- Maintenance System: The final insights are integrated into the core maintenance system, triggering automated alerts or service requests to ensure continuous operational reliability.



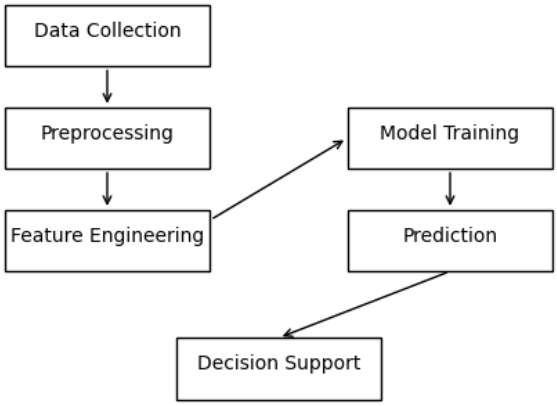
Picture 1. *Architecture of the IoT predictive maintenance system*

IoT sensors continuously collect operational data such as vibration, temperature, and pressure, transmitting it through edge gateways to cloud systems. The interoperability of IoT-based condition monitoring systems is supported by standardized communication architectures defined in International Organization for Standardization 13374-3 [4].

2. AI Pipeline for Predictive Maintenance

This diagram on Picture 2. illustrates a standard AI processing pipeline for predictive maintenance, designed to transform raw industrial data into actionable insights [6]:

The AI pipeline processes sensor data through preprocessing, feature extraction, and machine learning models to detect anomalies and predict equipment failures [3].



Picture 2. *Machine Learning Architecture for Smart Maintenance*

Machine learning models analyze historical and real-time data to detect anomalies and predict equipment failures [3].

Predictive models aim to approximate system behavior using input features:

$$\hat{y} = f(x1, x2, ..., xn) \text{ [1]}$$

Key benefits include reduced downtime, optimized maintenance scheduling, cost reduction, and improved safety [7].

Challenges include data quality issues, cybersecurity risks, high deployment costs, and lack of skilled personnel [3].

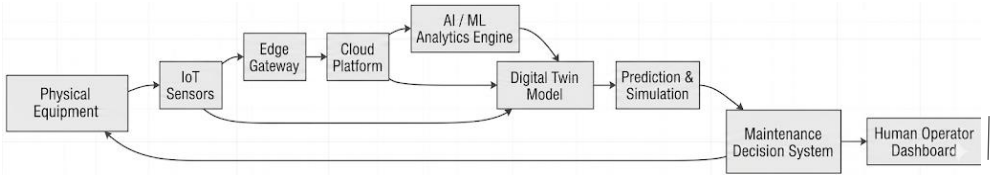
PdM is widely used in manufacturing, aerospace, energy systems, and smart factories, enabling predictive insights and operational efficiency.

Within Society 5.0, predictive maintenance plays a central role in achieving sustainable and resilient industrial ecosystems.

It contributes to balancing automation with human oversight and decision-making.

3. The Role of Digital Twins in the Society 5.0 Vision

The digital twin architecture enables integrated monitoring and decision-making in predictive maintenance systems (Picture 3.).



Picture 3. *Digital twin system architecture for predictive maintenance of physical assets*

The system integrates IoT data acquisition, AI-based analytics, digital twin modeling, and predictive simulation to support maintenance decision-making. It enables continuous monitoring and operational control of physical equipment through a connected digital environment.

The feedback loop enables continuous interaction between physical systems and their digital representation, allowing real-time updates and adaptive maintenance decisions. This improves system reliability by enabling both human-in-the-loop and automated corrective responses.

Digital twins thus support predictive maintenance by enhancing monitoring accuracy, reducing operational risks, and optimizing system performance [9].

3.1 Conceptual Predictive Maintenance Model for Society 5.0

This paper proposes a conceptual predictive maintenance model for Society 5.0. The model consists of four layers:

- Data Acquisition Layer – IoT sensors collect real-time data.
- Data Processing and AI Layer – AI models process data for prediction and anomaly detection.
- Digital Twin Layer – A digital twin simulates system behavior using real-time data.
- Decision and Action Layer – Decisions are made automatically or with human supervision.

The layers form a closed-loop system for continuous optimization.

The interaction between layers forms a closed feedback loop, enabling continuous system learning and optimization.

4. Conclusion

Predictive maintenance is a key component of Society 5.0 industrial systems. It enables the transition from traditional to data-driven maintenance systems. This transition improves system reliability and reduces maintenance costs.

In Society 5.0, PdM integrates humans, machines, and data into a unified system. The integration of AI algorithms with IoT sensors and cloud platforms allows for the creation of intelligent systems that can learn, adapt, and self-optimize. Digital twins improve monitoring accuracy and enable virtual simulation of system behavior.

Challenges include data quality, cybersecurity, and implementation costs. Future developments will likely focus on hybrid models and edge computing to enhance scalability. Predictive maintenance is a key technology for smart industrial systems.

Acknowledgement

This work was supported by the project 2025-1-RO01-KA220-HED-000364478 “HEIstorical – Strengthening green and digital capacities in higher education through collaboration in integrating historical buildings into a sustainable and digital future”, co-funded by the European Union under the Erasmus+ KA220-HED programme. Although the project is primarily focused on digital transformation and sustainability in higher education, the concepts of artificial intelligence, Internet of Things, and data-driven systems presented in this paper within the context of predictive maintenance can contribute to the development of smart, energy-efficient, and sustainable infrastructures, including smart buildings and digital environments.

REFERENCES

[1] Bishop, C. M. (2006). Pattern Recognition and Machine Learning. New York, NY: Springer-Verlag, from Microsoft web site: https://www.microsoft.com/en-us/research/wp-content/uploads/2006/01/Bishop-Pattern-Recognition-and-Machine-Learning-2006.pdf

[2] Cabinet Office Japan. (2016). Report on the 5th Science and Technology Basic Plan Council for Science, Technology and

Innovation Cabinet Office, Government of Japan, from 8. Cao web site: https://www8.cao.go.jp/cstp/kihonkeikaku/5basicplan_en.pdf

[3] IBM. (2024). *AI at Scale*. IBM, from IBM web site: https://www.ibm.com/think/insights/ai-at-scale

[4] International Organization for Standardization. (2012). ISO 13374-3:2012 Condition monitoring and diagnostics of machines — Data processing, communication and presentation — Part 3: Communication. International Organization for Standardization, from CDN web site: https://cdn.standards.iteh.ai/samples/37611/662d186f7ffc4543a752dd75375a0ee1/ISO-13374-3-2012.pdf

[5] Kagermann, H., Wahlster, W., & Helbig, J. (2013). Recommendations for implementing the strategic initiative INDUSTRIE 4.0: Securing the future of German manufacturing industry. acatech – National Academy of Science and Engineering, from Din web site: https://www.din.de/resource/blob/76902/e8cac883f42bf28536e7e8165993f1fd/recommendations-for-implementing-industry-4-0-data.pdf

[6] Lee, J., Bagheri, B., & Kao, H. A. (2014). A cyber-physical systems architecture for Industry 4.0-based manufacturing systems. *Manufacturing Letters, 3,* 18–23, https://doi.org/10.1016/j.mfglet.2014.12.001

[7] McKinsey & Company. (2020). *Capturing the true value of Industry 4.0*, from McKinsey web site: https://www.mckinsey.com/capabilities/operations/our-insights/capturing-the-true-value-of-industry-four-point-zero

[8] Siemens. (2022). Industrial Edge: Make the most of your shopfloor data for predictive maintenance and industrial optimization. Siemens AG, from Siemens web site: https://www.siemens.com/global/en/products/automation/industrial-edge.html

[9] Fu, X., Song, H., Li, S., & Lu, Y. (2025). Digital twin technology in modern machining: A comprehensive review of research on machining errors. *Journal of Manufacturing Systems, 79,* 134–161. https://doi.org/10.1016/j.jmsy.2025.01.005