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PREDICTIVE MAINTENANCE AS A TOOL FOR INTELLIGENT MANAGEMENT OF INDUSTRIAL ENTERPRISES

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Abstract

Predictive maintenance plays a significant role in intelligent industrial management, allowing enterprises to anticipate equipment failures and optimize maintenance planning through the assessment of actual asset conditions and the prediction of their future operational states. The integration of sensors, Industrial Internet of Things technologies, data analytics and machine learning provides new opportunities to move from reactive and time-based maintenance toward proactive and condition-informed decision-making. This paper examines predictive maintenance as a management tool for improving the operational performance of industrial enterprises. The methodology is based on a structured analysis and synthesis of recent scientific literature addressing predictive maintenance, condition monitoring, machine learning, Industry 4.0 and smart manufacturing. Based on the identified technological and managerial functions, a conceptual framework is proposed that links condition monitoring and data acquisition with condition assessment, failure prediction, maintenance decision-making, maintenance execution and performance feedback. The results indicate that the managerial value of predictive maintenance depends on the integration of technical prediction capabilities with maintenance planning, resource allocation, production coordination and performance evaluation. The proposed framework provides a concise basis for understanding predictive maintenance as an integrated management instrument rather than solely as a technical maintenance solution.

Keywords: predictive maintenance, intelligent management, condition monitoring, industrial enterprises, machine learning.

INTRODUCTION

The ongoing digital transformation of industrial enterprises is reshaping conventional approaches to equipment maintenance. Manufacturing systems increasingly incorporate sensors, connected devices, data platforms and analytical technologies that enable continuous observation of equipment condition and production processes. Within this environment, predictive maintenance (PdM) has emerged as an important approach for anticipating equipment failures and supporting maintenance activities before significant operational disruption occurs. Recent research confirms the growing importance of data-driven PdM across manufacturing sectors and its potential to reduce downtime, improve productivity and support more informed operational decisions [1, 2].

Traditional maintenance strategies generally include corrective maintenance, preventive maintenance and condition-based maintenance. Corrective approaches respond to failures after they occur, while preventive approaches schedule interventions according to predefined time or usage intervals. Predictive maintenance introduces an additional forecasting capability by using repeated measurements and analytical models to estimate degradation and anticipate future maintenance requirements. Recent research distinguishes predictive maintenance from condition monitoring by emphasizing that PdM uses information about current equipment condition to forecast future failures and

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determine an appropriate maintenance intervention [3 – 5].

The development of Industry 4.0 has significantly expanded the technological foundations of PdM. Sensors and connected industrial systems generate continuous streams of operational data, while machine learning and other analytical techniques can be applied to detect anomalies, diagnose faults and estimate remaining useful life. A recent review of machine-learning-based condition monitoring emphasizes that the effectiveness of such systems depends not only on the selected algorithm but also on appropriate data processing and the characteristics of the monitoring task [6, 7].

However, the implementation of PdM cannot be considered solely a technical problem. The predictions generated by analytical systems must be translated into maintenance schedules, resource allocation decisions, spare-parts planning, production coordination and risk management. Recent research also identifies data gaps, limited organizational adoption, cybersecurity and difficulties in demonstrating return on investment as important barriers to wider implementation [8].

Therefore, the objective of this paper is to examine predictive maintenance as a tool for intelligent management of industrial enterprises and to develop a conceptual framework linking technical condition monitoring with managerial decision-making. The focus is placed on the transition from equipment data to maintenance decisions and their subsequent integration with industrial operations.

EXPOSITION

1. Methodology

The methodology applied in this study is based on a structured conceptual analysis and synthesis of recent scientific literature on predictive maintenance and intelligent industrial management.

The analysis focused on five thematic dimensions: (1) condition monitoring and data acquisition, (2) data processing and condition assessment, (3) failure prediction and prognosis, (4) maintenance decision-making and (5) maintenance execution and performance feedback. Recent systematic reviews were used to identify technological developments, common applications and implementation challenges in PdM, while selected applied research was considered to illustrate the connection between sensor data, analytical models and maintenance decisions.

The identified elements were synthesized into a conceptual management framework consisting of six interconnected stages:

1. **Condition Monitoring and Data Acquisition** – continuous or periodic collection of equipment and process data;
2. **Data Processing and Condition Assessment** – validation, filtering, aggregation and evaluation of current asset condition;
3. **Failure Prediction and Prognosis** – detection of degradation patterns, prediction of failures and estimation of remaining useful life;
4. **Maintenance Decision-Making** – evaluation of predicted risks and determination of maintenance priorities and interventions;
5. **Maintenance Execution and Coordination** – scheduling and implementation of maintenance activities in coordination with production operations;
6. **Failure Prediction and Prognosis** – detection of degradation patterns, prediction of failures and estimation of remaining useful life;
7. **Maintenance Decision-Making** – evaluation of predicted risks and determination of maintenance priorities and interventions;
8. **Maintenance Execution and Coordination** – scheduling and implementation of maintenance activities in coordination with production operations;
9. **Performance Feedback** – evaluation of maintenance results and use of new operational data to improve subsequent predictions and decisions.

The framework is conceptual and is intended to explain the managerial logic of

PdM rather than prescribe a specific technological architecture or machine-learning algorithm.

2. Predictive Maintenance in Intelligent Industrial Management

Predictive maintenance can be understood as a maintenance approach in which information about the condition and degradation of an asset is continuously or periodically analyzed to forecast future failures and determine an appropriate maintenance intervention. In this respect, PdM extends condition-based maintenance by introducing a predictive component. Its purpose is not simply to identify whether equipment is currently operating normally, but to provide information about what is likely to happen and when maintenance should be performed.

The technological development of PdM is closely connected with the availability of industrial data. Sensors can capture variables such as vibration, temperature, pressure, acoustic signals, current, flow and other parameters associated with equipment condition. These data can subsequently be transmitted through industrial communication networks to edge or cloud platforms where they are stored, processed and analyzed. A sensor-data-based PdM study demonstrates how such information can be integrated with artificial neural networks to support failure prediction and maintenance decision-making [9].

Machine learning represents one of the major analytical approaches used in PdM. Depending on the maintenance objective and available data, classification methods can be used for fault detection, regression methods can estimate degradation or remaining useful life, while anomaly-detection methods can identify deviations from normal operating behavior. A systematic review of industrial failure prediction found broad adoption of machine learning but also considerable heterogeneity in datasets, preprocessing methods, evaluation procedures and reported results [10].

Recent research further demonstrates the increasing integration of PdM with Digital Twins, IoT, Big Data and machine learning. These technologies can provide a more comprehensive representation of equipment condition and facilitate continuous monitoring and prediction. Their integration is also associated with emerging Industry 5.0 perspectives emphasizing human involvement, resilience and sustainability [11].

From a management perspective, the significance of PdM is determined by what happens after a prediction is generated. A technically accurate prediction has limited value if the enterprise cannot convert it into an appropriate maintenance action. Maintenance decisions must consider equipment criticality, production schedules, available personnel, spare parts, maintenance costs, safety requirements and the consequences of potential failure. Consequently, PdM should be integrated with broader maintenance and operational management rather than implemented as an isolated analytical application.

The transition can therefore be described as:

equipment condition → data → condition assessment → prediction → maintenance decision → maintenance action → performance feedback.

This sequence provides the conceptual foundation for the framework proposed in this paper.

The transformation from equipment condition data to a maintenance decision can be represented as an integrated data-to-decision flow. This perspective highlights the intermediate analytical stages through which operational measurements are converted into information supporting maintenance management.

The flow emphasizes that predictive maintenance creates managerial value by connecting equipment data and analytical results with risk assessment, maintenance prioritization and managerial decision-making.

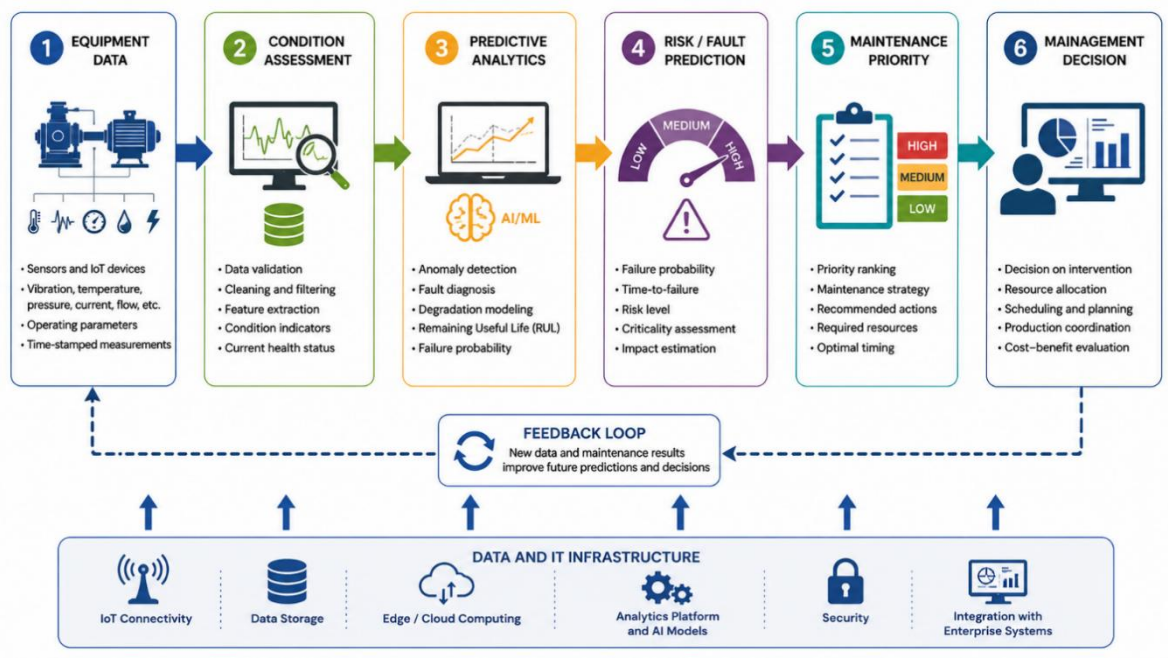


Fig. 1. *Predictive Maintenance Data-to-Decision Flow*

3. Results and Discussion

The main result of the study is the proposed conceptual framework linking predictive maintenance capabilities with intelligent management activities in industrial enterprises.

The proposed framework integrates the technological and managerial dimensions of predictive maintenance by connecting equipment condition monitoring with analytical prediction, maintenance decision-making and operational execution. Its cyclical structure emphasizes the continuous interaction between asset condition, maintenance activities and management processes.

The framework illustrates that PdM should be considered as a continuous management cycle rather than a standalone prediction system. The first stage establishes the data foundation through monitoring of equipment and production processes. The second stage transforms raw measurements into reliable information concerning asset condition. This stage is particularly important because the quality and contextualization of industrial data directly influence the effectiveness of subsequent analytical models.

The third stage introduces predictive capabilities. Analytical models can identify degradation patterns, detect anomalies, diagnose potential faults and estimate the probability or timing of future failures. The literature demonstrates a wide range of machine learning approaches for these tasks, although model selection should reflect the specific maintenance objective, data characteristics and operational constraints.

The fourth stage represents the transition from technical prediction to managerial decision-making. Predicted failures must be assessed according to equipment criticality, production requirements, risk, cost, available resources and the consequences of alternative maintenance strategies. Thus, the decision is not necessarily to perform maintenance immediately. Instead, the enterprise must determine the most appropriate intervention and its timing.

The fifth stage concerns maintenance execution and coordination. Maintenance activities should be integrated with production planning in order to minimize disruption and use personnel, spare parts, tools and other resources effectively.

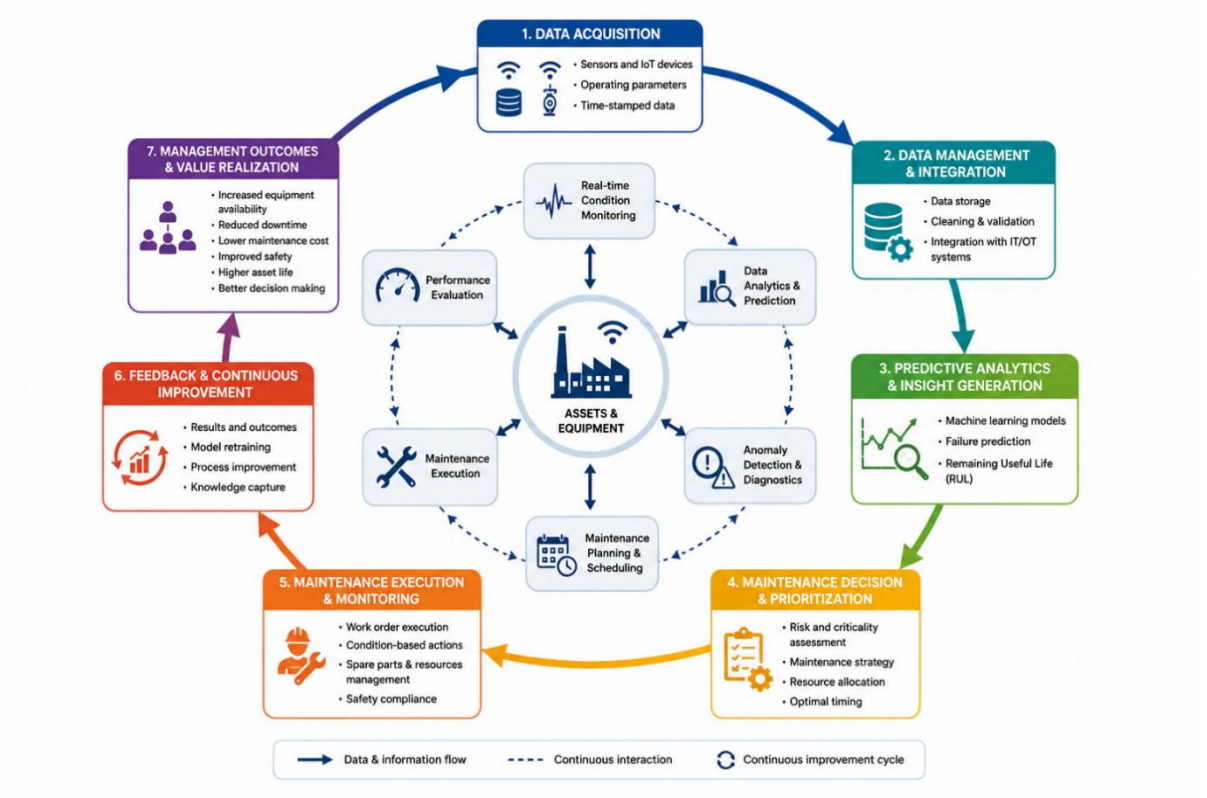


Fig 2. *Conceptual Framework for Predictive Maintenance-Enabled Intelligent Management*

Research on PdM platforms emphasizes the importance of connecting maintenance management with manufacturing operations management because operational information can improve predictive capabilities, while maintenance information can support decisions across production activities.

The final stage provides performance feedback. Information concerning completed maintenance actions, equipment behavior, failures and operational performance can be incorporated into subsequent monitoring and analytical processes. This creates a closed-loop system in which maintenance decisions generate new information that can improve future predictions.

The managerial applications associated with the proposed framework are summarized in Table 1.

Table 1. Predictive Maintenance Functions and Management Applications

PdM function	Main output	Management application
Condition monitoring	Equipment condition data	Asset visibility and monitoring
Data processing	Reliable condition indicators	Performance assessment
Anomaly detection	Early warning signals	Risk identification
Failure prediction	Failure probability or forecast	Maintenance prioritization
RUL estimation	Expected remaining operating time	Maintenance scheduling
Decision support	Recommended intervention	Resource allocation
Maintenance execution	Completed intervention	Production coordination
Performance feedback	Maintenance and operational results	Continuous improvement

The analysis indicates that the managerial value of PdM can be considered at three interconnected levels. The **operational level** concerns equipment availability, downtime, maintenance timing and production continuity. The **resource level** concerns

personnel, spare parts, tools, energy and maintenance costs. The **management level** concerns prioritization, risk management, production coordination and long-term asset decisions.

The main management applications of predictive maintenance can therefore be viewed across several complementary areas of industrial enterprise management. Figure 3 summarizes these applications and their relationship with the information generated by PdM systems.



Fig. 3. *Management Applications of Predictive Maintenance*

Figure 3 demonstrates that predictive maintenance can support not only maintenance-related decisions but also broader management activities, including production planning, resource allocation, cost management, risk management and performance improvement.

This perspective is important because the benefits of PdM cannot be evaluated exclusively through prediction accuracy. A highly accurate prediction model does not necessarily produce economic or operational benefits if the predicted information is not incorporated into maintenance planning and execution. Recent literature on condition-monitoring evaluation similarly points to the need for stronger integration of technical performance measures with economic and operational evaluation.

Several challenges can nevertheless limit the practical effectiveness of the proposed approach. These include insufficient or poor-quality historical data, heterogeneous equipment, integration difficulties, cybersecurity risks, limited analytical expertise and uncertainty concerning the economic return of implementation. The literature also indicates that many studies rely on standardized datasets rather than real industrial environments, which limits the direct transferability of reported results to industrial enterprises.

Consequently, successful implementation of predictive maintenance requires a gradual transition from isolated technical applications toward integrated maintenance-management systems. For industrial enterprises, the most

important objective is not simply to predict failures, but to use predictions as a basis for timely, coordinated and economically justified managerial action.

CONCLUSION

Predictive maintenance represents an important instrument for the intelligent management of industrial enterprises because it connects continuous equipment monitoring and advanced analytics with maintenance and operational decision-making. The analysis presented in this paper demonstrates that the managerial value of PdM emerges from the integration of technological prediction capabilities with organizational processes and resource management.

The proposed conceptual framework consists of six interconnected stages: condition monitoring and data acquisition, data processing and condition assessment, failure prediction and prognosis, maintenance decision-making, maintenance execution and coordination and performance feedback. This structure emphasizes the transition from raw equipment data to actionable managerial information and the importance of maintaining a continuous feedback loop.

The study also indicates that PdM should not be evaluated exclusively according to the technical accuracy of predictive models. Its practical effectiveness depends on whether predictions can support appropriate maintenance priorities, resource allocation, production coordination and performance improvement. Therefore, intelligent predictive maintenance requires the integration of technological, organizational and managerial capabilities.

The proposed framework is conceptual and has not been empirically validated. Future research can extend it through industrial case studies and quantitative evaluation using indicators such as unplanned downtime, equipment availability, maintenance costs, mean time between failures, maintenance response time and return on investment.

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