# Empirical aspect of predictive maintenance applied to complex manufacturing systems

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*Abstract: This study addresses an empirical aspect of predictive maintenance applied to complex manufacturing systems, integrating advanced technologies such as smart manufacturing systems, cloud computing and the Internet of Things (IoT), in a framework applicable to Industry 4.0. By collecting and analyzing real-time data from IoT sensors in the cloud, predictive models are developed that allow for the anticipation of failures and the optimization of maintenance strategies, reducing downtime and operational costs. The empirical investigation highlights the effectiveness of such integrated solutions in increasing the reliability and sustainability of complex manufacturing processes, providing practical directions for their implementation and scaling in the context of smart manufacturing. The results highlight the potential of digital technologies in transforming traditional maintenance into predictive maintenance oriented towards Industry 4.0..*

*Keywords: predictive maintenance, complex production systems, Industry 4.0, IoT, cloud computing, smart manufacturing systems*

## 1 Introduction

The digital transformation of production systems, characteristic of Industry 4.0, has led to the evolution of maintenance strategies, from reactive and preventive approaches to predictive maintenance. The latter uses data analysis and mathematical models to anticipate failures and optimize maintenance decisions. [9] Predictive maintenance is defined as a data-driven strategy aimed at early identification of anomalies and estimation of equipment life, thus reducing unplanned shutdowns and operational costs. In the context of complex production systems, empirical validation of these models becomes essential.[6 ]

Predictive Maintenance represents one of the most significant conceptual developments in the management of complex industrial systems, being based on the integration of digital technologies, advanced data analysis and predictive models in decision-making processes. In the Industry 4.0 paradigm, predictive maintenance is no longer just an operational strategy, but an intelligent subsystem, capable of correlating the physical behavior of equipment with their mathematical and digital representations. [9]

Analyzed from a methodological point of view, predictive maintenance is located at the intersection of: dynamic systems theory, statistical data analysis, artificial intelligence, experimental validation based on empirical data, achieving a solid connection. This position highlights the dual nature of the foundation of predictive maintenance: on the one hand, a solid theoretical basis, and on the other hand, an essential empirical component for validation and adaptation.

In contemporary specialized literature, predictive maintenance is structured around three fundamental paradigms, each reflecting a distinct way of representing and understanding the phenomena of degradation and failure.

Knowledge-based paradigm, This paradigm is based on the formalization of engineering experience and human expertise in the form of rules, knowledge bases or expert systems. In this context, the decision-making process is deterministic and interpretable, being built on well-defined cause-effect relationships.

From a methodological perspective, this approach is appropriate for relatively stable systems, where degradation processes are known. However, in complex production systems, characterized by high variability and multiple interdependencies, this paradigm becomes limited by its rigidity and the difficulty of integrating large volumes of data.

Physics-based paradigm, The physics paradigm is based on the analytical modeling of degradation phenomena, using physical laws and mathematical models (e.g., wear, fatigue, heat transfer models). These models allow the estimation of component lifetimes and are essential in reliability analysis.

The major advantage lies in the high interpretability and the ability to explain the internal mechanisms of failure. However, the complexity of modern systems makes it difficult to fully model all interactions, which limits their applicability in dynamic industrial environments.

Data-driven paradigm, The dominant paradigm today is the data-driven one, which uses machine learning and deep learning techniques to identify hidden patterns in the data generated by industrial systems.

In this approach: the system learns from stored data and real-time streams, anomalies or possible errors are detected, and the probability of failure is estimated. [7].

This paradigm is adaptive and performs well under uncertainty, but has limitations related to interpretability and data quality dependence.

Synthesis of paradigms: hybrid approach, Comparative analysis of paradigms leads to an essential conclusion: none of them can, independently, completely model the behavior of complex production systems.

The specialized literature supports the use of hybrid approaches, which combine: the rigor of physical models, the flexibility of data-based models, the interpretability of knowledge-based models. These integrated systems offer superior accuracy and increased robustness in real industrial applications. [2]

# 2 Proposed architectural model

Modern predictive maintenance architecture built on the principles of Industry 4.0, figure 1, in which the production system, IoT infrastructure, distributed computing at the edge of the network, advanced cloud analytics and feedback mechanisms operate in a closed information loop. The main goal of this architecture is to transform operational data generated by industrial equipment into useful knowledge for anticipating defects, optimizing maintenance activities and reducing downtime of the production system. This approach is considered one of the most important development directions of the smart factory, as it allows the transition from reactive and preventive maintenance to predictive maintenance based on data and artificial intelligence [ 5].

Analyzing figure 1, the following defining aspects are observed, namely:

At the base of the architecture is the production system, represented in the image by industrial robots, machining centers and automated equipment. This constitutes the physical environment in which technological processes take place and in which the degradation phenomena of mechanical, electrical and electronic components occur. During operation, each piece of equipment constantly generates large volumes of data regarding its operational status. From the perspective of predictive maintenance, the production system is no longer viewed only as an assembly of machines that perform manufacturing operations, but as a continuous source of information about the activity being carried out. This concept represents the foundation of modern cyber-physical systems described in the recent literature dedicated to Industry 4.0 (Javaid et al., 2023) [3].

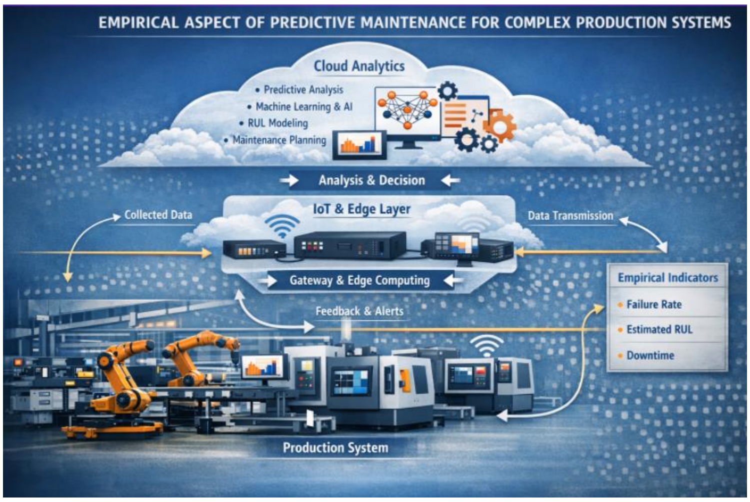


Figure 1

The second level of the architecture is represented by the data collection process. It establishes the connection between the physical and digital worlds through industrial sensors. At this stage, the following are monitored: mechanical vibrations; component temperatures; system pressures; electrical currents and voltages; process parameters; energy consumption; product quality indicators. The role of this component is to convert physical phenomena into digital information that can be analyzed later. The quality of the entire predictive process directly depends on the accuracy and consistency of the collected data. Incomplete or noisy data can lead to diagnostic errors and incorrect estimates of the equipment status (Kashpruk et al., 2023) [4].

After collection, the information is transferred to the upper layer. This is one of the most important components of modern industrial architectures. Its main role is to process data as close as possible to its source of generation. Instead of all information being transmitted directly to the cloud, a significant part of the processing is performed locally. This approach offers several advantages: reducing the volume of transmitted data; reducing latencies; rapid detection of anomalies, errors and defects; increasing information security; continuity of operation even in the event of a connection interruption with the cloud. At this level, the first warning signals of possible defects are identified. According to recent studies on the integration of cloud computing in predictive maintenance, this approach allows for a significant reduction in reaction time and an increase in the efficiency of distributed industrial systems (Bala et al., 2024) [1].

The industrial gateway represents the interface between the local infrastructure and the cloud environment. In this area, the following takes place: aggregation of information from multiple sources; temporal synchronization of data; elimination of redundant information; noise filtering; organization of data flows. Basically, the gateway functions as an information logistics center. It collects data from hundreds or even thousands of sensors and transforms them into a standardized format that can be interpreted by cloud platforms. This component is essential for ensuring interoperability between equipment from different manufacturers, one of the major challenges of Industry 4.0 ecosystems (Xu et al., 2021) [8].

The predictive analysis process takes place inside the cloud environment. This component aims to identify subtle signals that precede the occurrence of a failure. Instead of detecting the failure after it has occurred, the system tries to determine the probability of its occurrence in the future. Predictive analysis transforms maintenance from a reactive activity into a proactive and planned process (Kokkotis et al., 2025) [5].

Based on the results provided by predictive analysis, the system generates maintenance strategies. This stage transforms predictions into concrete actions. Instead of executing periodic interventions regardless of the actual condition of the equipment, the organization can plan maintenance exactly when it is needed. The result is: cost reduction; increased equipment availability; optimization of human resources; reduction of unplanned shutdowns.

The fundamental element of Figure 1 is the feedback mechanism. After implementing the recommended action, the system starts generating a new set of operational data, and the cycle repeats itself continuously. This mechanism transforms the architecture into an adaptive system capable of constantly learning from its own operational experience, an essential feature of smart factories in the Industry 5.0 paradigm (Javaid et al., 2023) [3].

# 3 System analysis

The formal modeling of predictive maintenance, within complex production systems, requires the use of mathematical formalizations capable of simultaneously describing the discrete dynamics of events, the uncertainty associated with equipment degradation and the information flows generated by intelligent systems. In this context, stochastic Petri nets provide a rigorous framework that allows capturing these characteristics in an integrated manner.

From a methodological perspective, the use of stochastic Petri nets in predictive maintenance represents a transition from deterministic modeling to probabilistic modeling, in which the evolution of the system is described by stochastic processes dependent on the current state and the estimated empirical parameters.

The formalization of the system in the form of a stochastic Petri net allows the explicit description of the relationships between: the physical states of the equipment (operational, degraded, defective), the data collection and processing processes (IoT), the analysis and decision mechanisms (Cloud, AI), the maintenance interventions.

This formal structure is not just a static representation, but a dynamic model that allows: simulating the evolution of the system over time, evaluating the performance of maintenance strategies, optimizing decisions under uncertainty.

Within the model, places define the discrete states of the system, organized on three levels: physical level (manufacturing), informational level (IoT), cognitive level (cloud and AI).

This compartmentalization reflects the cyber-physical nature of modern production systems. Physical states describe the evolution of degradation, while informational and cognitive states reflect the processing and use of data for decision-making.

Transitions model the events that determine state changes. These are of two types: physical transitions (degradation, failure), informational and decisional transitions (data collection, AI analysis, maintenance).

The stochastic nature of the transitions introduced by the rates $\lambda$ and $\mu$ reflects the uncertainty of real processes. Essentially, the failure rate is not deterministic, but depends on the operational conditions and the history of the equipment.

From a systemic perspective, transitions represent the interface between: the physical evolution of the system and the control mechanisms - intervention.

The incidence matrix constitutes the mathematical core of the stochastic Petri net model, as it describes the relationship between places and transitions. It allows the formulation of the system evolution equation and is the basis for: the analysis of structural properties (conservativeness, accessibility), the simulation of dynamic behavior, the identification of critical states.

From a narrative perspective, the incidence matrix transforms the graphical model into a formal system of equations, which can be analyzed mathematically.

The model parameters (degradation rates, transition probabilities) are not arbitrary, but are estimated based on empirical data from IoT systems.

This direct link between data and model gives a stochastic Petri net system, with the characteristics of an adaptive model, in which: parameters are updated in real time, models are continuously recalibrated, predictions become increasingly accurate.

Thus, the formal model becomes a faithful representation of industrial reality.

All these theoretical aspects are highlighted below.

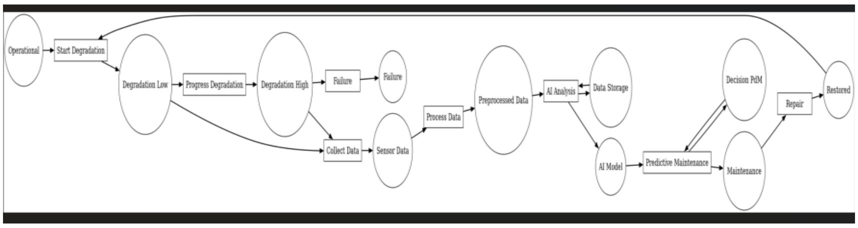


Figure 2

The integrated predictive maintenance system is modeled by an extended stochastic Petri net defined by:

$SPN = (P, T, F, W, M_0, \Lambda)$ (1)

where: $P = \{P_1, P_2, \dots, P_{11}\}$– the set of places, $T = \{T_1, T_2, \dots, T_8\}$– set of transitions, $F \subseteq (P \times T) \cup (T \times P)$– set of arcs, $W: F \to \mathbb{N}^+$– weighting function (default 1), $M_0$– initial marking, $\Lambda = \{\lambda_1, \lambda_2, \lambda_3, \lambda_4, \mu\}$– set of stochastic rates

The levels that model the system states (physical, informational and decisional) that are the basis for establishing predictive maintenance are defined as follows:

Manufacturing level: $P_F = \{P_1, P_2, P_3, P_4\}$ (2)

Having the basic names: $P_1$ - operating system, $P_2$ - incipient degradation, $P_3$ - advanced degradation, $P_4$ - defective

IoT level: $P_{IoT} = \{P_7, P_8\}$ (3)

With: $P_7$ - raw data (sensor data), $P_8$ - preprocessed data.

Cloud Level: $P_C = \{P_9, P_{10}, P_{11}\}$ (4)

Where: $P_9$ - data storage, $P_{10}$ - AI model, $P_{11}$ - predictive maintenance decision

Maintenance level: $P_M = \{P_5, P_6\}$ (5)

Where: $P_5$ - maintenance in progress, $P_6$ – restoration system

Physical dynamics, with a timing role: $T_1$ - degradation initiation, $T_2$ - progress degradation, $T_3$ – failure.

IoT information flow, with a timing role: $T_6$ - data collection, $T_7$ - data processing.

Cloud analysis, with a timing role: $T_8$ - AI analysis

Decision and maintenance, with a timing role: $T_4$ - predictive maintenance trigger, $T_5$ - maintenance completion

Predictive transition dependent on AI: $T_4 = f(\widehat{RUL}, \sigma, \theta)$ (6)

where: $\widehat{RUL}$– life expectancy estimate, $\sigma$– model uncertainty, $\theta$– decision threshold.

Activation probability: $P(T_4) = P(\widehat{RUL} < \theta)$ (7)

The evolution equation is defined by the evolution of the mark:

$$M(t+1) = M(t) + C \cdot \sigma(t) \tag{8}$$

where: $\sigma(t)$ is the transition activation vector.

The performance indicators that are analyzed are::

Availability: $A = \frac{MTBF}{MTBF+MTTR}$ (9)

Defect probability: $P_{def}(t) = P(M(P_4) > 0)$ (10)

Predictive maintenance efficiency: $E_{PdM} = \frac{Nr.\, defecte\, prevenite}{Nr.\, total\, defecte\, potențiale}$ (11)

The diagrams obtained from the simulation are defined after an imposed operating time of 1000 hours..

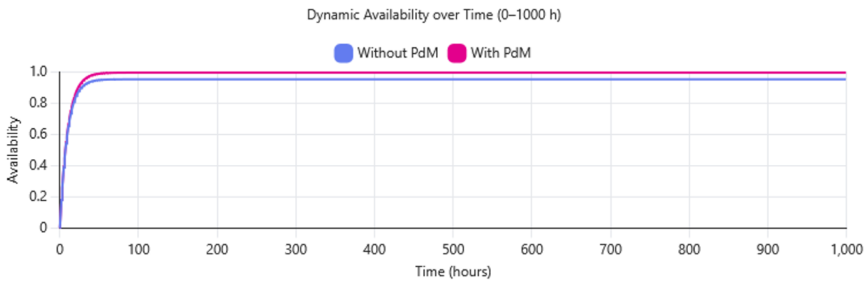


Figure 3

Scientific interpretation, figure 3, is broken down into three stages:

Initial: transitional regime (t < 50 h) determine the influence of initial conditions stochastic petri nets

Stable regime:

without predictive maintenance (PdM): A ≈ 0.95

with PdM: A ≈ 0.995

The difference seems small in percentage terms, but becomes critical in long-term operation.

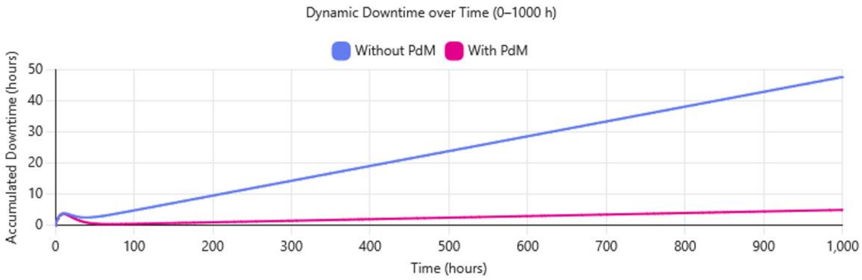


Figure 4

Interpretation, figure 4, is as follows:

Without PdM → almost linear growth (≈ 48 h loss in 1000 h)

With PdM → very slow growth (≈ 5 h)

Difference ≈ 90% reduction downtime

The following example shows a professional Stochastic Petri Net Diagram for a robotic cell that integrates both production flow and modern IoT monitoring and predictive maintenance mechanisms.

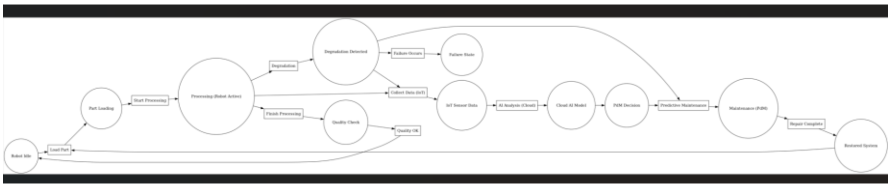

Figure 5

General stochastic Petri net model:

Defining: $SPN = (P, T, F, W, M_0, \Lambda(t))$ (12)

The essential difference between figure 2 and figure 5 is: $\Lambda(t) \neq constant \Rightarrow time - dependent\ degradation$

Weibull (realistic) degradation model is analyzed in this example, as follows:

Hazard function: $h(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1}$ (13)

where: $\beta > 1$→ accelerated wear, $\eta$→ lifespan

Interpretation:

| β | **Degradation type** |
|---|---|
| β < 1 | early defects |
| β = 1 | random process (exponential) |
| β > 1 | real industrial wear |

In our case, we choose for the robotic cell: $\beta = 2.5, \eta = 500\ h$

An internal variable is introduced, for the progressive degradation model:

$$D(t) = D_0 + \alpha t + \sigma W(t) \quad (14)$$

where: $\alpha$→ linear degradation (mechanical wear), $W(t)$→ Wiener process (random noise)

Complete failure model:

Probability of defect: $P_{fail}(t) = 1 - e^{-\left(\frac{t}{\eta}\right)^{\beta}}$ (15)

Integration into SPN, Failure Transition: $T_{fail}: \lambda(t) = h(t)$, Conclusion: SPN becomes Non-Homogeneous Stochastic Petri Net (NHSPN).

Derived KPI drivers (complete) are defined by:

Availability: $A(t) = \frac{T_{up}(t)}{t}$ (16)

Downtime: $DT(t) = \int_0^t 1_{\{System\ Down\}}\, dt$ (17)

Throughput (important for robotic cell): $TH(t) = \frac{N_{produse}}{t}$ (18)

WIP (Work in Process): $WIP(t) = M(Buffer)$ (19)

Conclusion: Comparative dynamics PdM vs. without PdM (1000 h)

Without PdM: defect ratet: $\lambda_f = 0.005$

Obtained behavior: frequent failure, high accumulated downtime.

With PdM: effective rate: $\lambda_f^{eff} = (1 - accuracy)\lambda_f$, with accuracy = 0.9: $\lambda_f^{eff} = 0.0005$

Conclusion: Stochastic availability.

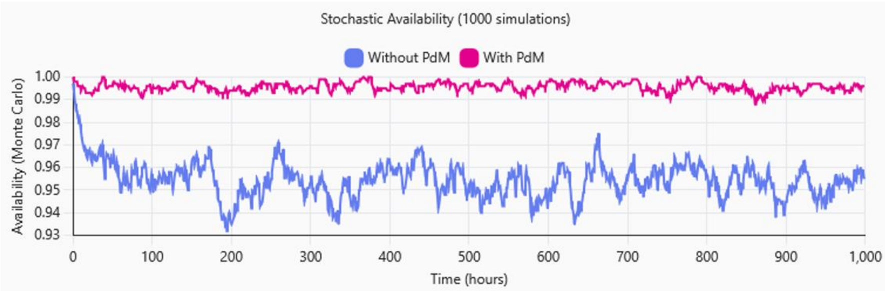


Figure 6

Interpretation: The blue curve (without PdM) shows clear oscillations, indicating a direct effect of stochastic variability. The pink curve (with PdM) is: more stable, closer to 1, with small variations, indicating a robust system. It highlights the reduction of the availability variance, not just the increase in the average value — an essential criterion in the evaluation of industrial systems.

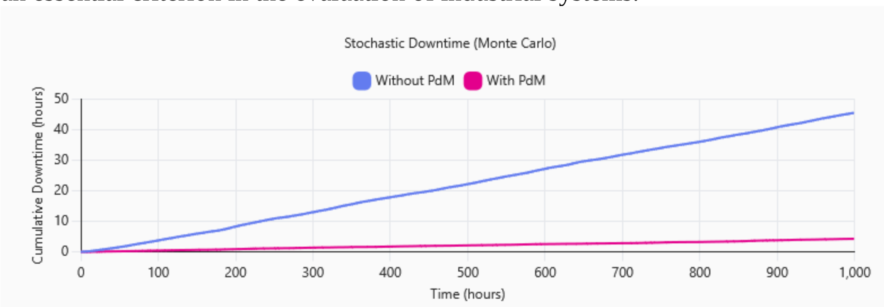


Figure 7

Interpretation: Without PdM: almost linear accumulation, but with variable slopes (Poisson processes). With PdM: very slow, almost "flat" growth, drastic reduction in operational risk.

Conclusion: Major difference after 1000 h: ≈ 45 h downtime (without PdM), ≈ 4–5 h downtime (with PdM)

Mathematical model used: Stochastic processes:

$$T_{fail} \sim Exp(\lambda),\ T_{repair} \sim Exp(\mu) \tag{20}$$

where: $\lambda_{fără\ PdM} = 1/200$, $\lambda_{PdM} = 1/2000$, $\mu = 1/10$

Comparative result:

| KPI | Without PdM | With PdM |
|---|---|---|
| Availability | ~0.92–0.95 | ~0.98–0.995 |
| Downtime | high (accelerated growth) | very low |
| Throughput | unstable | stable |
| Buffer overflow | frequent | rare |

Conclusion: Graphical interpretation:

Downtime in Weibull: Without PdM: $DT(t) \sim t^{\beta}$, results in accelerated growth (non-linear). With PdM: $DT(t) \approx linear\ small$, results in stabilization of the system.

Availability: Without PdM, a decrease is observed over time (wear). With PdM, a constant evolution is observed.

**Conclusions**

The formalization of predictive maintenance within stochastic Petri nets provides a rigorous mathematical tool for the analysis of complex manufacturing systems. The integration of the IoT and Cloud levels allows the transformation of the model into an adaptive cyber-physical structure, capable of using empirical data to optimize decisions and increase operational reliability.

The analysis of the presented architecture highlights the fact that predictive maintenance for complex manufacturing systems no longer represents just an isolated application of artificial intelligence, but an integrated ecosystem in which physical infrastructure, IoT technologies, distributed computing, cloud platforms and advanced analytics algorithms operate in a permanent relationship of interdependence. The value of this architecture derives from its ability to transform data generated by industrial processes into relevant information, and subsequently into operational knowledge and decisions that contribute to increasing the overall performance of the manufacturing system.

The information flow illustrated within the architecture demonstrates the transition from the traditional paradigm of reactive maintenance to an intelligent, anticipatory and adaptive model. The data collected at the equipment level is progressively processed through the IoT and Edge Computing levels, where it is filtered and contextualized, and then transferred to the cloud environment for complex analyses based on artificial intelligence and machine learning. In this way, the system acquires the ability to identify degradation trends, estimate the evolution of the technical condition of assets and generate recommendations for interventions before critical defects occur.

From an industrial perspective, the implementation of such an architecture leads to reduced downtime, increased equipment availability, optimized maintenance costs and improved reliability of production processes. At the same time, the integration of predictive analytics with data-based decision-making mechanisms contributes to a more efficient use of material, energy and human resources, supporting current sustainability and industrial competitiveness objectives.

In conclusion, the analyzed architecture can be considered a representative model for future intelligent production systems, in which information flows, digital technologies and decision-making processes are integrated into a closed information loop, capable of ensuring continuous monitoring, prediction of system behavior and autonomous adaptation to operational conditions. Through this approach, predictive maintenance becomes not only a tool for reducing failures, but a strategic component of the digital transformation of modern industry.

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