

Towards Intelligent Industrial Systems: A Comprehensive Review of Predictive Maintenance Paradigms, Deep Learning Architectures, and Digital Twin Integration

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Abstract: Predictive maintenance has gained importance in modern times as a crucial approach to maintaining mechanical systems in order to improve reliability and reduce maintenance costs. Conventional approaches such as corrective and preventive maintenance might fail to mitigate potential problems caused by unpredictable failures and progressive degradation of system components. In recent times, there have been significant advances made in predictive maintenance using statistical and machine learning approaches. Statistical approaches provide useful techniques that help analyze reliability and predict failures, while machine learning algorithms can help identify useful patterns in large sets of data.

The following review article provides a detailed discussion on the statistical and machine learning approaches used for predictive maintenance of mechanical systems. This is followed by a discussion on the evolution of maintenance strategies and the adoption of predictive maintenance approaches. Finally, some important statistical approaches relevant to predictive maintenance are discussed here. The review also covers some of the important machine learning algorithms for predictive maintenance, including support vector machines, random forests, artificial neural networks, and deep learning techniques.

The review article discusses the various types of sensor data used in the prediction maintenance of mechanical systems, including vibration, acoustic, temperature, and operational load data. It also includes a comparative study of statistical and machine learning techniques, along with the advantages and disadvantages, and the application of these techniques in various mechanical systems. At the same time, the review identifies the problems in the prediction maintenance methodology and the future direction in the field.

Keywords: Predictive maintenance; Mechanical systems; Statistical modeling; Machine learning; Reliability analysis; Condition monitoring; Data-driven maintenance; Industrial analytics.



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1. Introduction

Mechanical systems are the fundamental components of modern industrial infrastructure, which includes the processes of production, energy, transportation, and the operation of heavy machinery. Reliability and continuity in the operation of such machinery play an important role in ensuring production, safety, and reduction of costs. Unexpected breakdowns can cause significant losses, stoppage of production, and even pose dangers for workers' safety. Therefore, it is important to take necessary measures to tackle these issues. Maintenance techniques have evolved significantly in the past few decades in response to such needs.

Traditionally, the maintenance approach that was used in industries could be divided into two primary categories: corrective maintenance and preventive maintenance. In the case of corrective maintenance, it includes all actions that were taken after the occurrence of any failure in machinery. In preventive maintenance, on the other hand, all such operations were done based on the total number of operating hours and cycles.

PdM, or Predictive Maintenance, is a modern maintenance technique. In this type of maintenance, the system conditions are monitored, and the failures are predicted before they actually occur. Predictive Maintenance uses the data collected from sensors and other monitoring systems installed in the mechanical system. It predicts the failures and estimates the useful life of the mechanical components. Predictive Maintenance allows the execution of the activities only when required, thereby ensuring maximum system availability and minimizing the costs incurred during the process.

Due to the rapid advancement in sensing technology, the industrial internet of things, and advanced data analysis techniques [1], [2], the adoption and implementation of PM in modern industries have increased at a remarkable rate. It is now possible to collect a large amount of operational data from various types of sensors installed in mechanical systems, such as vibration sensors, temperature sensors, pressure gauges, and acoustic emission sensors. These types of data sources have the potential to offer a wide range of insights [2], [3].

Statistical analysis has been a vital component in the field of reliability engineering and failure prediction. Various statistical analysis techniques, such as Weibull analysis, regression analysis, and Bayesian inference, have shown considerable potential in the field of reliability engineering and failure prediction in mechanical systems. However, these statistical analysis techniques have shown a number of limitations in dealing with complex nonlinear relationships.

To overcome these limitations, the application of machine learning techniques has shown considerable potential in the field of PM in mechanical systems. It has the potential to identify hidden patterns [13, 14] in a large number of datasets and can learn complex relationships between the operational state and system failure. Various types of machine learning techniques, such as SVM, RF, ANN, and deep learning, have shown considerable potential in the field.

Despite the availability of a large number of research papers in the field, the majority of the existing literature is fragmented in nature, focusing on the application of a specific ML algorithm and conventional statistical reliability analysis. This review is unique in the sense that it offers a combined analytical taxonomy, covering conventional reliability engineering and the latest advances in the field of Digital Twins and Physics-Informed AI, which can be used to implement resilient systems.

Table 1. Comparison of Existing Review Studies on Predictive Maintenance

1	Study	Year	Scope	Methods Covered	Key Limitation
2	Carvalho et al.	2019	Machine learning in predictive maintenance	Vector, Random Forest, Neural Networks	Limited coverage of statistical reliability models

1	Study	Year	Scope	Methods Covered	Key Limitation
3	Zhang et al.	2019	Data-driven predictive maintenance	Data mining and machine learning techniques	Lack of integration with reliability engineering
4	Zhu et al.	2019	Survey of predictive maintenance systems	Condition monitoring and prognostics methods	Limited discussion of deep learning methods
5	Ersöz et al.	2022	Predictive maintenance in transportation systems	Reliability analysis and ML models	Application restricted to transportation sector
6	Al Hasib et al.	2023	Predictive maintenance of aircraft engines	Supervised learning and diagnostic models	Application-specific focus
7	Ward et al.	2024	Machine learning for condition-based maintenance	ML algorithms for fault diagnosis	Limited discussion of hybrid statistical-ML approaches
8	Taoufyq et al.	2025	Systematic review of predictive maintenance approaches	Industrial maintenance frameworks	Limited analytical comparison between models
9	This Review	2026	Integrated predictive maintenance for mechanical systems	Statistical models, ML, DL, Digital Twins, and Physics-Informed Neural Networks (PINNs)	Provides analytical taxonomy and conceptual framework

Table 1 below is a summary of the major review works on Predictive Maintenance (PdM) found in the literature. It is apparent that the majority of the previous works have focused mainly on either the application of the machine learning paradigm or the application in industry. Still, only a small number of researches have attempted to integrate these two methods into one single study. Hence, there arises a need to conduct a review that will synthesize the methods above and provide a basis on which Predictive Maintenance can be used in mechanical systems [4], [5], [6], [7], [8].

In addition to the core literature, this review utilizes an extensive array of survey and application studies across the manufacturing, transport, aviation, and automotive sectors, encompassing recent systematic reviews and empirical case studies [3], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15].

In contrast to the previous works, the current work attempts to address the transition from the conventional 'Black-Box' paradigm in machine learning to the 'Physics-Aware' paradigm in Predictive Maintenance, in order to achieve the goals of both high accuracy and consistency in the modeling of mechanical system failures. There has been a recent surge in the application of hybrid approaches, which integrate the advantages of statistical reliability engineering and the accuracy of the 'Black-Box' paradigm in machine learning, in the field of mechanical engineering. This work attempts to provide a comprehensive overview of the statistical and machine learning-based approaches in Predictive Maintenance in mechanical systems [1], [16].

Though a number of review works have addressed the conventional Predictive Maintenance, the recent advances in the integration of Digital Twins and PINNs in the application of Predictive Maintenance in real-time systems have not been addressed comprehensively in the recent review works. This work attempts to address this gap in the recent advances in the field.

The remainder of the paper is structured as follows. Section 2 describes the evolution of maintenance strategies and the advancement in the concept of predictive maintenance approaches for mechanical systems. Section 3 gives a general overview of the statistical approaches, which have been widely used in reliability analysis and prediction of failure. Section 4 discusses the concept of machine learning in the field of predictive maintenance. Section 5 delineates the most recent hybrid methodologies, emphasizing the integration of Digital Twins and Physics-Informed AI. Section 6 addresses the problems and prospective study avenues, while Section 7 presents the concluding observations of the paper.

2.1 Research Gap and Contributions

While there is a significant volume of literature on predictive maintenance, there are still important challenges that are not fully addressed. Most of the literature on predictive maintenance approaches is either focused on statistical reliability modeling or machine learning algorithms without creating a unified analytical framework for integrating both perspectives. Most literature reviews on predictive maintenance approaches are limited to a description of predictive models without evaluating their applicability for different classes of mechanical systems and different conditions of availability of data. With the increasing complexity of mechanical systems within Industry 4.0 paradigms, there is a need for a unified synthesis of statistical reliability theory and machine learning approaches.

The present review aims to make a contribution to this body of knowledge by providing a comprehensive analytical integration of various statistical modeling and machine learning techniques for predictive maintenance. Besides providing a review of existing techniques, this paper also attempts to propose a conceptual framework for classifying predictive maintenance techniques based on data, modeling, interpretation, and real-time implementation. By emphasizing the benefits of using both statistical modeling and machine learning techniques, this review also attempts to propose a new direction towards hybrid techniques that can effectively combine probabilistic modeling and data-driven learning.

2.2 The main contributions of this review can be summarized as follows:

1. Unified analytical taxonomy: The combination of classical statistics in reliability analysis (e.g., Weibull statistics, survival analysis, and Bayesian statistics) with the ML/DL paradigm in PdM, along with the applicability of these approaches under realistic constraints.
2. Physics-aware roadmap: The emphasis on the evolution from black-box-based PdM towards physics-aware-based PdM with a focus on uncertainty estimation and interpretability in safety-critical mechanical systems.
3. DT-PINNs integration blueprint: A conceptual blueprint that combines the concept of Digital Twin-based PdM with the concept of Physics-Informed Neural Network-based PdM in order to perform robust prognostics in the presence of noisy measurements and limited failure cases.
4. Deployment-oriented guidance: The consideration of constraints in the adoption of PdM approaches and the determination of future research directions in PdM.

2.3 Review Methodology

This study has made use of a structured narrative review methodology. For the study, a wide range of literature was reviewed from the leading scientific databases, including Scopus, Web of Science, IEEE Xplore, ScienceDirect, SpringerLink, and Google Scholar. For the study, the combined set of keywords such

as 'predictive maintenance,' 'prognostics,' 'remaining useful life,' 'reliability analysis,' 'Weibull,' 'survival analysis,' 'Bayesian,' 'machine learning,' 'deep learning,' 'digital twin,' and 'physics-informed neural networks' were used. The time frame considered in the study is from 2015 to 2026, and the earlier works were incorporated based on the need to continue the methodology. For the study, the articles were ranked based on the following conditions: (i) the articles must have focused on the topic 'predictive maintenance' in mechanical/industrial systems, (ii) the articles must have clearly described the maintenance task, and (iii) the articles must have clearly described the methodology and the results.

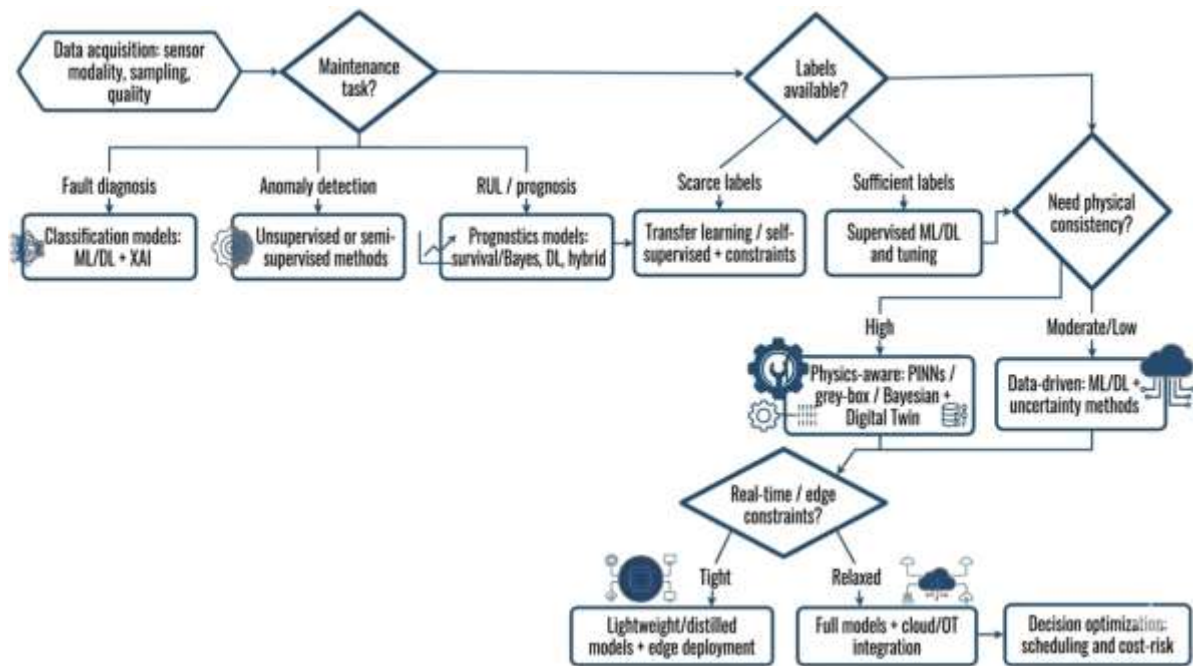


Figure 1A. Method-selection flowchart for predictive maintenance (data/task/constraints → recommended modeling family).

In line with the aim of this paper, the present review takes a narrative approach to the topic of predictive maintenance in mechanical and industrial systems, following an outline consisting of four phases: (1) delineation of scope and definition of research questions; (2) source identification and screening; (3) development of an organizational framework; and (4) analysis and highlighting of engineering conclusions and directions for future work.

For source identification, searches were conducted using relevant keywords including "predictive maintenance," "prognostics and health management," "reliability modeling," "deep learning," "digital twin," and "physics-informed" from key scientific databases and indexing services. Complementing this approach was citation tracing of prominent surveys and systematic reviews on the topic.

Studies identified in this process were then screened for their contribution to the topic under investigation in relation to mechanical systems and industrial operation. A study qualified as relevant if it offered substantial insight into at least one of the following domains: (a) statistical reliability or prognostics foundations, (b) classical machine learning applied to fault diagnosis or RUL estimation, (c) deep learning for sensor time-series representation, or (d) hybrid frameworks combining digital twins with physics-

informed modelling. Retained studies were then categorised by data modality (vibration, acoustic emission, temperature, current draw, operational logs), primary task (diagnosis, anomaly detection, RUL prediction), and deployment context (edge/real-time versus offline batch).

Table 2. Data modality × task × recommended modeling families (practical guide).

Data modality	Typical PdM task	Recommended modeling families	Notes
Vibration (time/frequency)	Fault diagnosis / condition classification	Classical ML (SVM/RF), CNN, transformers + XAI	Strong signal content; feature engineering or end-to-end DL both viable
Acoustic emission	Anomaly detection / early damage	One-class models, autoencoders, contrastive/self-supervised learning	Often scarce labels; robustness to noise is critical
Temperature / thermal	Degradation trend / RUL support	Regression, survival models, RNN/TCN, Bayesian UQ	Combine with other sensors for higher fidelity
Multi-sensor (vibration+thermal+load)	RUL / prognostics	Hybrid: Bayesian + DL, ensembles, DT-assisted simulation	Uncertainty reporting recommended for maintenance decisions
Limited sensors / sparse data	RUL under scarcity	Physics-aware: grey-box, PINNs, DT constraints + transfer learning	Use physical priors to reduce data hunger
High-rate streaming with latency limits	Real-time monitoring	Lightweight features + classical ML, distilled DL on edge	Optimize for compute, memory, and update frequency

2. Evolution of Maintenance Strategies and Predictive Maintenance Framework

Maintenance strategies in mechanical engineering have undergone a significant evolution in the last three decades or so. This is because the industry has become more complex over time, and there has been a need for more reliable maintenance. Moreover, there has been a need to reduce the costs of maintenance. Initially, maintenance was mostly reactive in nature. This means that equipment was only repaired when it had actually failed. However, with the evolution of engineering and the use of better technologies in analyzing data, maintenance has become more proactive and smart, as illustrated in Figure 1.

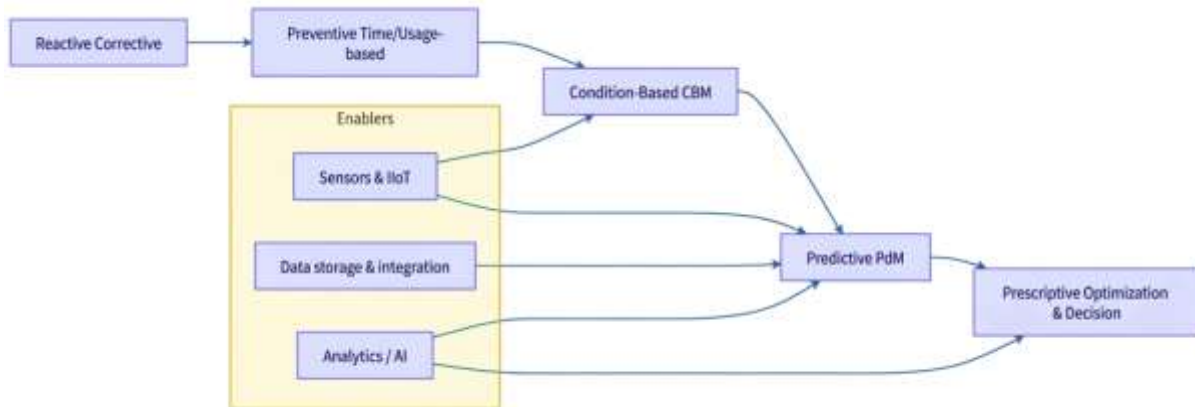


Figure 1. Evolution of maintenance strategies and key technological enablers.

2.1 Reactive Maintenance

Reactive maintenance, also called corrective maintenance or run-to-failure maintenance, is the first and simplest maintenance technique implemented in industrial systems. In reactive maintenance, maintenance is performed only after the failure of the component or the system. Though reactive maintenance requires the least amount of planning and monitoring, it is generally accompanied by a number of demerits. For instance, the occurrence of unexpected failures may result in unplanned production downtime, increased maintenance costs, and safety problems. In the case of mechanical systems such as turbines, pumps, compressors, and other rotating equipment, sudden and unexpected failures may also result in secondary damages to the neighboring equipment, further aggravating the maintenance costs and downtime.

2.2 Preventive Maintenance

Preventive maintenance was put forward as a more systematic maintenance technique aimed at minimizing the chances of equipment failure through the implementation of inspection and maintenance services. In the implementation of the preventive maintenance technique, maintenance is performed at regular time intervals based on the usage factor, such as the number of running hours, production cycles, and load conditions. Some of the common maintenance practices in the preventive maintenance technique include the lubrication, replacement, and inspection of mechanical systems. Though the preventive maintenance technique is effective in minimizing the chances of sudden and unexpected equipment failures, it is generally accompanied by a number of demerits. For instance, maintenance is performed irrespective of the condition of the equipment, leading to the wastage of maintenance resources.

2.3 Condition-Based Maintenance

Condition-based maintenance can be seen as an intermediate approach between preventive maintenance and predictive maintenance. In this approach, the condition of the system is monitored using different sensing technologies. Based on the condition of the system, maintenance is performed. In mechanical engineering, condition-based maintenance is used to collect data on the operations of a system, which can be defined as follows:

- Vibration signals, including spectral analysis
- Temperature, including thermal imaging
- Acoustic signals, including ultrasonic signals
- Lubricant analysis, including characterization of debris

- Pressure, including system operating load

Using this approach, engineers can identify early signs of system failures, such as imbalance, misalignment, bearing failures, or lubrication failures. Condition-based maintenance can improve the efficiency of maintenance activities, but this approach is highly dependent on the expertise of the maintenance personnel. In this approach, maintenance is performed only when abnormal conditions are detected in the system. However, this approach may not adequately capture the dynamics of the system.

2.4 Predictive Maintenance

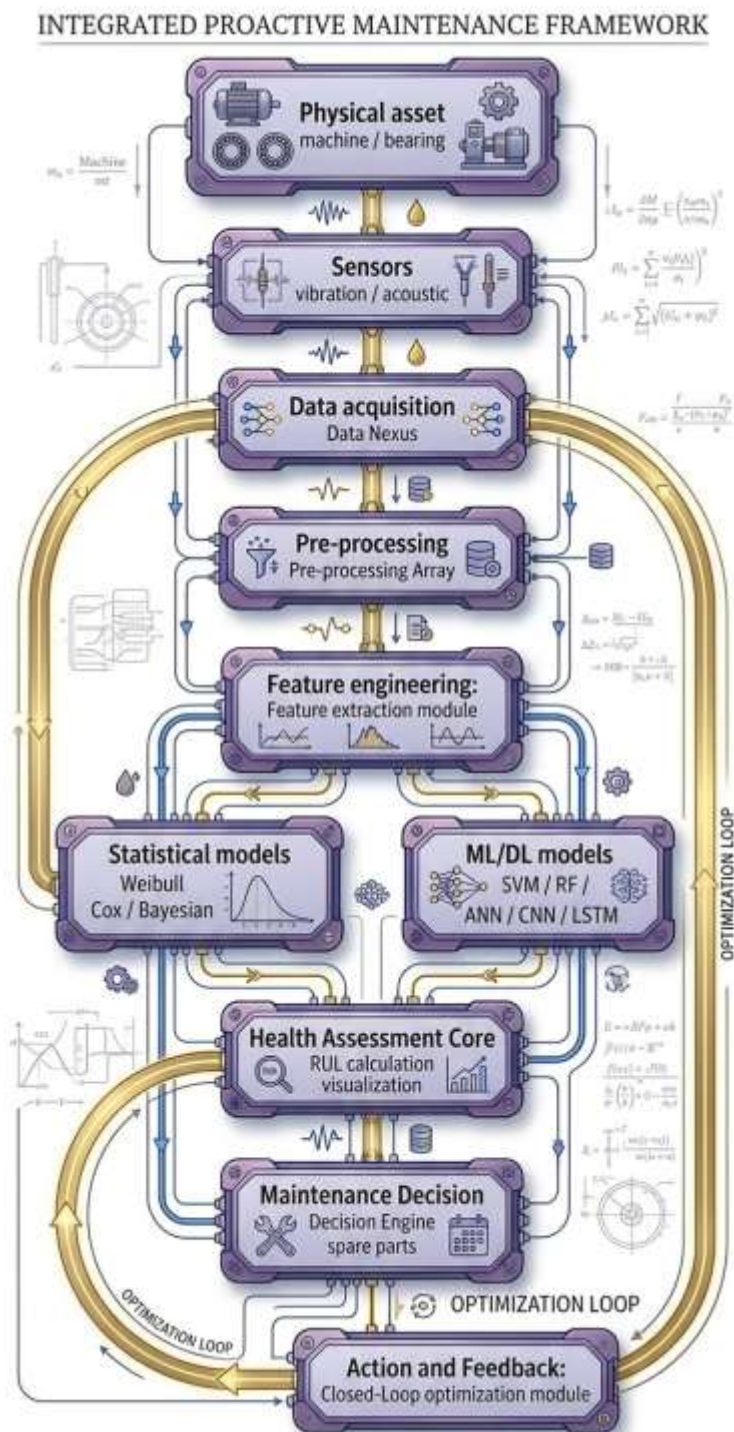


Figure 2. A generic predictive maintenance (PdM) pipeline from sensing to decision.

Predictive maintenance is a more advanced form of maintenance that uses historical data and statistical or machine learning-based models to predict future failures before they actually occur. Unlike other maintenance approaches, predictive maintenance aims at predicting the future life of equipment or machine parts before their actual failure. There are a number of key elements in a predictive maintenance system. These elements include:

1. Data acquisition systems: These refer to the sensors used in the mechanical systems that monitor the systems and transmit the acquired data to the monitoring systems.
2. Data processing modules: These refer to the algorithms used in the processing of the acquired raw data from the systems.
3. Analytical models: These refer to the frameworks used in the prediction of the failure of the systems or the equipment.
4. Decision support systems: These refer to the systems used in the maintenance of the systems or equipment.

The development of the industrial internet of things has greatly enhanced the development of predictive maintenance systems. Advanced sensors in the systems have the capacity to transmit large amounts of data to the central point of control. This has facilitated the development of advanced analytics with the capacity to detect subtle patterns in the systems before their actual failure. This has provided a number of advantages in the industrial environment. These advantages include the reduction of the occurrence of unplanned failures, the improvement of the availability of the equipment in the systems, the optimization of the maintenance of the equipment in the systems, and the provision of a safe working environment.

2.5 Prescriptive Maintenance and Intelligent Maintenance Systems

In recent developments, the concept of prescriptive maintenance was introduced as the subsequent stage in the evolution of maintenance strategies. Prescriptive maintenance is a more advanced concept compared to the prediction of failures, as in this case, not only is the prediction of failures made, but recommendations are also provided on the best course of action to be taken. Prescriptive maintenance systems include the integration of prediction, optimization, decision, and digital twin technologies for the most efficient maintenance strategies. As part of the intelligent manufacturing system, prescriptive maintenance systems may include maintenance recommendations, adjustments, and actions in automation.

3. Statistical Methods in Predictive Maintenance

Statistical methods have a fundamental place in the theory and practice of predictive maintenance, as it enables engineers to understand the failure patterns, quantify the uncertainties, and estimate the remaining useful life of mechanical systems. Statistical methods, unlike some machine learning-based approaches, offer a more robust and theoretically grounded solution to the problem, as the results can be interpreted using probability theory and reliability engineering. Statistical methods have long been used in mechanical engineering to understand the degradation mechanisms and arrive at maintenance strategies.

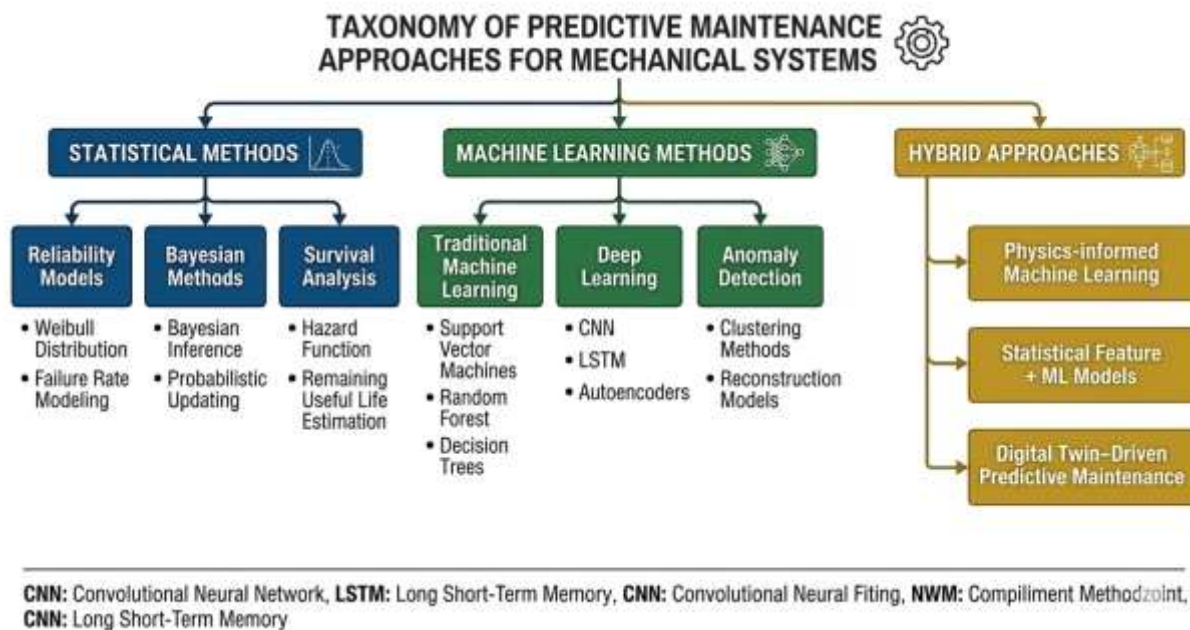


Figure 3. Taxonomy of Statistical and Machine Learning Approaches in Predictive Maintenance

Figure 3 above highlights a taxonomy of predictive maintenance approaches, which are primarily a fusion of statistical reliability models and contemporary machine learning paradigms. According to this taxonomy, the predictive maintenance approaches can be divided into three major categories: conventional statistical models, data-driven machine learning models, and hybrid models, which are a fusion of the above two models.

3.1 Reliability Theory in Mechanical Systems

Reliability engineering is a theoretical basis upon which a wide variety of predictive maintenance models are built. Generally, reliability is defined as the probability that a system or a component will operate or function without failure over a given period of time under specific operating conditions. In particular, reliability analysis is a major factor in the design of mechanical systems, which often incorporate components such as bearings, gears, turbines, etc., which tend to deteriorate over a period of time due to factors such as fatigue, wear, etc.

The reliability function is defined mathematically as:

$$R(t) = P(T > t)$$

Where T is a random variable representing time to failure, and t is the time of operation.

This is a reliability function that shows the probability of a system functioning or operating at a time longer than t . Another concept is the failure probability function, which shows the probability of a system failure before a given time t .

3.2 Weibull Distribution in Failure Analysis

Weibull distribution is a probabilistic model with widespread applicability in the field of reliability engineering in describing time-to-failure distributions [16]. The Weibull distribution is sufficiently general

in its applicability in describing the different modes of failure that occur in mechanical and engineering systems, such as premature failures, stochastic failures, and degradation failures. The probability density function of the Weibull distribution is given by:

$$f(t) = \frac{\beta}{\eta} \left(\frac{t}{\eta}\right)^{\beta-1} \exp \left[-\left(\frac{t}{\eta}\right)^{\beta} \right]$$

where:

β represents the shape parameter,

η represents the scale parameter,

t represents the failure time.

The shape parameter, β , controls the failure trend. For instance, a decrease in the failure rate over time, where $\beta < 1$, is attributed to defects in the early stages. For a constant failure rate, the value of $\beta = 1$, and this is attributed to random failure events. Finally, an increase in the failure rate, where $\beta > 1$, is attributed to aging.

In predictive maintenance models, this distribution is often used to estimate lifetime characteristics, as well as to assess the likelihood of failure during a particular operational period.

3.3 Bayesian Inference in Predictive Maintenance

Bayesian methodologies have emerged as important tools for predictive maintenance work as a result of their ability to combine prior knowledge with new information in a mathematically sound way. Bayesian analysis is different from classical approaches in that it considers parameters as stochastic variables with probability distributions.

In Bayesian analysis, prior knowledge of a system is represented by probability distributions. Bayesian analysis then uses new information to update prior knowledge, resulting in new probability distributions. The process of updating is achieved through Bayes' equation:

$$P(\theta | D) = \frac{P(D | \theta) P(\theta)}{P(D)}$$

where:

- θ represents the set of model parameters,
- D denotes the observed dataset,
- $P(\theta)$ is the prior distribution,
- $P(D | \theta)$ is the likelihood function,
- $P(\theta | D)$ is the posterior distribution.

Bayesian inference is advantageous in cases where there is a lack of information. Bayesian analysis can combine expert knowledge with observed data. Bayesian inference can be used to update reliability information as new sensor information is available. Bayesian inference is advantageous for real-time analysis.

3.4 Survival Analysis and Hazard Functions

The subject of survival analysis revolves around the characterizations of the time to failure. The most important concept used in survival analysis is the hazard function, which represents the rate of failure at a specific point of time. The hazard function is represented as:

$$h(t) = \frac{f(t)}{R(t)}$$

- $f(t)$: probability density function of failure time
- $R(t)$: reliability function

where $f(t)$ represents the probability density function of the failure time, while $R(t)$ represents the reliability function.

The hazard rate provides useful information regarding the degradation process of a particular system. An increasing hazard rate often indicates a wear-out process, whereas a constant hazard rate indicates random failure behavior. The survival analysis method provides useful results, especially in cases of censored data, which are often present in maintenance data.

4. Machine Learning Techniques for Predictive Maintenance

4.1 Classical Machine Learning Algorithms

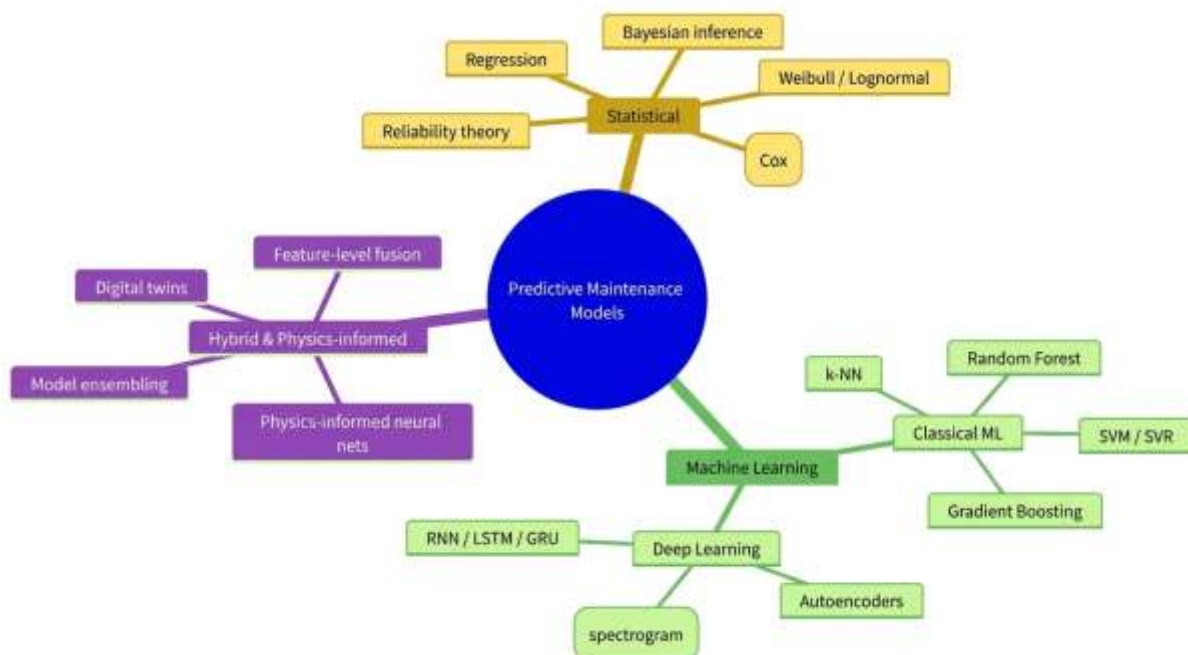


Figure 4. Taxonomy of statistical, machine learning, and hybrid predictive maintenance (PdM) modeling approaches

Machine learning methodologies have recently been recognized as the core methodologies in the field of PdM, thanks to their ability to process large volumes of sensor data and identify complex patterns of degradation. Unlike traditional statistical methodologies, which rely on a priori knowledge of the statistical properties of the data, machine learning methodologies learn the patterns from the data itself. Machine learning methodologies have the ability to identify nonlinear relationships between system parameters.

Unlike traditional machine learning methodologies, the application of the machine learning methodologies in the field of PdM should be guided by the characteristics of the data and the industrial constraints. In the field of PdM, the application of the SVM algorithm is guided by the robustness of the algorithm in high-dimensional spaces with a lack of failure data. Unlike traditional machine learning methodologies, the SVM algorithm is strategically used in the field of PdM to identify the optimal decision boundary for the classification of failure. Unlike traditional machine learning methodologies, the application of the Random Forest algorithm in the field of PdM is strategically guided by the ability of the algorithm to improve the prediction robustness of the model. Unlike traditional machine learning methodologies, the Random Forest algorithm is strategically used in the field of PdM for the fusion of multiple sensor data. Unlike traditional machine learning methodologies, the Random Forest algorithm is strategically used in the field of PdM for the fusion of multiple sensor data. Unlike traditional machine learning methodologies, the Random Forest algorithm is strategically used in the field of PdM for the fusion of multiple sensor data. Table 2 shows the strategic application of classical machine learning methodologies in the field of PdM.

Table 2: Comparative Analysis of Classical ML Algorithms in PdM Context

Algorithm	Ideal PdM Use Case	Competitive Advantage (Why to use?)
SVM	Fault classification in systems with limited failure datasets.	High accuracy in high-dimensional spaces with small sample sizes; robust against overfitting.
Random Forest	Correlation of heterogeneous sensor data (e.g., Temp + Vibration).	Provides Feature Importance ranking, allowing engineers to identify the primary indicators of failure.
k-NN	Real-time Anomaly Detection in stable operations.	Simple to implement for detecting sudden deviations from normal operating signatures.
Naive Bayes	Probabilistic failure prediction in low-latency environments.	High computational efficiency; performs well even when sensor features are partially independent.
XGBoost	High-precision Remaining Useful Life (RUL) estimation.	Superior performance in handling large-scale tabular data and capturing non-linear degradation patterns.

4.2 Model Selection Strategy for Predictive Maintenance

In spite of the wide use of a number of machine learning algorithms for predictive maintenance, the selection of the optimal model is largely influenced by the characteristics of the available data, complexity, and constraints. Considering the fact that the amount of available data is often limited, noisy, and imbalanced due to the rare occurrence of failures, the selection strategy must be influenced by the interpretability requirements as well. For predictive maintenance problems, where the amount of available failure data is limited, classical algorithms like SVM and RF have proven to provide more stable performance due to their ability to avoid overfitting. Conversely, deep learning techniques are seen optimum for scenarios where substantial high-frequency sensor data is accessible, especially in vibration-based condition monitoring. Hybrid approaches that combine statistical reliability models with machine learning algorithms have emerged as a suitable option for safety-critical mechanical systems, as they provide both accuracy and interpretability requirements.

4.3 Transition Toward Deep Learning-Based Predictive Maintenance

In spite of the fact that classical machine learning algorithms have remained popular for solving a wide range of predictive maintenance problems, recent research work has focused more on the application of deep learning algorithms for the development of intelligent predictive maintenance strategies. The use of deep learning algorithms can be attributed to the fact that recent years have witnessed a significant amount of growth in the amount of available high-frequency data streams, making deep learning algorithms more suitable for solving a wide range of predictive maintenance problems.

4.4 Deep Learning Methods

Deep learning models generally exhibit good predictive accuracy results, although they usually require substantial labeled data as well as computational power to execute the model training process. Deep learning is considered to be the extension of neural networks with multiple hidden layers to learn complex data representations. Some deep learning models have been applied to the condition monitoring of mechanical systems, such as:

- **Convolutional Neural Networks (CNNs):** These models have been effectively applied to the analysis of vibration signals as well as spectrogram images.
- **Long Short-Term Memory networks (LSTMs)** have been often utilized for predicting mechanical system breakdowns and estimating remaining usable life.
- **Autoencoders:** These models can be applied to the detection of anomalies.

Deep learning models generally exhibit good results with regards to the predictive accuracy of the model, although they usually require substantial computational power as well as substantial labeled data to execute the model training process.

Table 3: Advantages of machine learning methods

Architecture	Main PdM Role	Advantage
CNN	Vibration-based Diagnosis	Automated feature extraction from spectrograms.
LSTM	RUL Estimation	Captures long-term temporal degradation trends.
Transformers	Multi-modal Fusion	Uses Attention to focus on critical sensor signals.
GANs	Data Augmentation	Generates synthetic failure data for training.

5. Condition Monitoring and Data Sources

The effectiveness of the predictive maintenance process is usually dependent on the availability of reliable data sources from mechanical systems. Condition monitoring technologies generally play a crucial role in the acquisition of operational data to monitor the mechanical system conditions.

Table 4. Comparison of Machine Learning Methods in Predictive Maintenance

Method	Advantages	Limitations	Typical Application
Support Vector Machine	Effective for small datasets	Sensitive to parameter selection	Fault classification
Random Forest	High accuracy and robustness	Less interpretable	Fault detection
Neural Networks	Capture nonlinear relationships	Requires large datasets	Prognostics
Deep Learning	High performance in complex systems	High computational cost	Remaining useful life prediction

5.1 Vibration Analysis

The basic form of diagnostic analysis of the condition of rotating equipment is through vibration analysis. Accelerometers measure the amplitude of the vibration and the frequency of the signal, which allows for the detection of problems like bearing failure, imbalance, and misalignment.

5.2 Acoustic Emission

Acoustic emission technology measures high-frequency sound signals generated from the rapid release of energy, allowing for the detection of problems like crack failure.

5.3 Other Sensor Sources

Other important sources of critical data include temperature monitoring (through RTDs and infrared sensors), oil analysis (a technique used to detect metal particles), and an IoT sensor network, which provides instantaneous information about pressure, loads, and speed. Data preprocessing is an important prerequisite process to convert sensor inputs into information related to the state of the system.

6. Hybrid Paradigms: Digital Twins and Physics-Informed AI

A predictive maintenance strategy involves the application of statistical models in combination with machine learning techniques. Statistical models provide a theoretical basis for understanding the state of the system through probability theory, whereas machine learning provides a powerful way of modeling the system behavior from data. The latter can easily model non-linear behaviors in data.

The cutting-edge of the field of predictive maintenance is the integration of Digital Twins (DT) with Physics-Informed Neural Networks (PINNs). By incorporating the fundamental physical laws of the system into the loss function of the AI algorithm, it becomes possible to obtain higher accuracy in prognostics, even when the sensor signals have a high level of noise.

Criterion	Statistical Methods	ML/DL Methods	Practical Note
Data Requirement	Moderate to low	Typically high	Use transfer learning when labels are scarce
Interpretability	High (physical meaning)	Often low (black-box)	Apply XAI techniques for transparency
Nonlinearity	Limited	Strong capability	Combine physics + DL for complex dynamics
Uncertainty	Natural (Bayesian)	Needs extra methods	Report confidence intervals for RUL

In view of these combined advantages, hybrid models that combine statistical feature extraction with machine learning classifiers or physics-informed neural networks are increasingly viewed as the standard for high-reliability industrial applications.

6.1 Conceptual Framework for Integrated Predictive Maintenance

In light of the integration of statistical reliability theory and state-of-the-art machine learning methodologies as discussed in this review, a conceptual framework for integrated predictive maintenance is proposed. The conceptual framework proposes a classification of predictive maintenance systems into four interconnected analytical layers, namely, data acquisition, feature engineering, predictive modeling, and decision optimization.

The first layer involves collecting heterogeneous sensor data for mechanical systems using vibration sensors, acoustic emission sensors, temperature sensors, and operation monitoring sensors. The second layer is focused on data pre-processing and feature extraction, and the statistical signal processing is used to turn signal data into feature representation. The third layer is related to predicting modeling, which uses a combination of statistics and machine learning. While statistics, such as Weibull analysis, survival analysis, and Bayesian inference, provide interpretability and uncertainty estimation, the machine learning includes Random Forests, ensemble learning, and neural networks to improve accuracy in dealing with high-dimensional nonlinear data. In the final layer, optimization focuses on the improvement of the decision-making process. It refers to the process of developing decision-making strategies in order to schedule maintenance interventions at minimal costs and minimum downtime. The above conceptual model proposed demonstrates the integration of statistical reliability theory with machine learning methodologies as a reliable combination for the application of predictive maintenance.

7. Future Research Directions: Digital Twins and Beyond

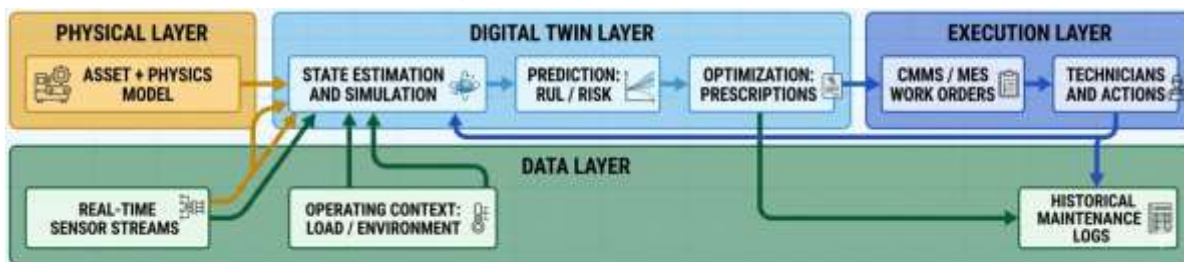


Figure 5. Digital Twin Enabled Predictive and Prescriptive Maintenance Architecture.

The long-term vision for predictive maintenance is the development of autonomous maintenance systems that have the ability to learn from the data. Among the emerging technological solutions, digital twin technology is considered to play a pioneering role in the development of the next generation of autonomous maintenance systems. This is because the digital twin provides a virtual representation of the physical assets that accurately mimics the behavior of the physical assets in real time. The emerging technological solutions that will define the next generation of predictive maintenance systems include the following:

Explainable AI: Developing transparent models to increase the level of trust in the decisions made by the AI algorithms. This is particularly important in safety-critical applications. **Edge Computing:** This will help in the detection of faults in real time at the sensor level. **Physics-Informed ML:** This will involve the direct integration of physical laws, such as thermodynamics, into the architecture of the neural networks. **Smart Manufacturing Integration:** This will involve the integration of the predictive maintenance systems with the automated supply chains.

7.1 Open Research Challenges and Future Research Agenda

Although there have been tremendous advances in the field of predictive maintenance, there are still some research challenges that need to be addressed. One of the main challenges is the integration of physics-based models and machine learning algorithms to develop hybrid models. This is where physics-informed machine learning comes in.

Another major challenge to be addressed is the scarcity of labeled failure data in industrial systems. Catastrophic failures are rare occurrences, and thus the development of reliable machine learning models is a challenge. Synthetic data, transfer learning, and semi-supervised learning have emerged as promising approaches to address the challenge [11].

Another challenge, especially for real-time predictive maintenance, is the computational challenge. This is especially true for edge computing environments. Future research on machine learning for predictive maintenance should focus on developing lightweight machine learning models that can be deployed on embedded devices.

The integration of predictive maintenance and digital twin technologies is the future research direction, which is revolutionary. Digital twin technologies enable the synchronization of the physical and virtual worlds. This allows the development of future predictive maintenance models that can predict future operational scenarios and optimize the strategies for the maintenance process. The development of a standard architecture for the integration is a major challenge for future research

8. Results and Discussion

As evident from the discussed papers, a clear trend can be observed in the transition from strict maintenance regimes to more flexible regimes that integrate sensors with features and even decision support based on feature learning techniques. Statistical reliability methods remain important in scenarios of rare failure occurrences that require interpretation of the output and inclusion of uncertainties in calculations. Data-driven and deep learning approaches work best with frequent observations and in cases when the patterns of equipment degradation are complicated and nonlinear [1], [16].

Vibration signal analysis and acoustic emissions turn out to be the best source of information in the field of mechanical engineering, although temperature readings, current trace, and operation records also provide some insights. The problem with deep learning networks, specifically, CNNs, LSTMs, and Transformers, is their impressive performance when learning from sensor streams directly. However, this success depends on the consistency between data training and validation protocols and physical reality; purely end-to-end approaches fail at real-life application because of this shortcoming.

Lack of standard benchmarks remains a problem for comparison and transfer of existing approaches to other asset types. As a consequence, generating synthetic data and developing transfer learning approaches and hybrid models combining statistics and machine learning are increasingly popular means of dealing with scarce domain-specific training sets, especially in industries like aircraft engines or electric motor drives [8], [11], [14].

The idea of Digital Twin proves extremely useful in predictive maintenance from a systems perspective, allowing the creation of a dynamic digital replica of a physical asset and thus enabling the assessment of various scenarios and optimization of maintenance scheduling. The realization of these potentials requires proper development of the data integration and cyber-physical architecture that would make sure that the data is provided in real time [2], [3], [9].

The evidence gathered during the review supports the approach of building the next generation of intelligent industrial systems as a hierarchical solution consisting of interpretable statistical reliability measures, supplemented by sophisticated data-driven learners to identify complex degradation patterns and constrained by physics-informed approaches represented by PINNs. Such an approach reflects the growing body of research in favor of improving classical reliability measures in light of advances in AI and ML [4], [5], [6], [7], [10], [12], [13].

9. Technical Challenges for Intelligent Industrial Systems

Transitioning an intelligent maintenance system to an industrial setting presents numerous challenges at any level of the pipeline, from data acquisition through safe and low-latency inference to maintenance and updating of the system.

1) Data quality and labeling: Real-life data collected from industrial sensors tends to contain noise due to various factors, including drift, sensor coverage loss, maintenance cycles, and changing environmental conditions. Labels, when available, tend to be delayed or ambiguous, and the difference between normal behavior and failure events may be considerable. To create reliable solutions, robust data validation protocols, time synchronization across all sensor channels, and techniques for avoiding extensive reliance on failure labels should be applied [1], [11].

2) Integration and interoperability between OT and IT: Deploying a predictive maintenance approach in a factory implies connection of a number of layers that were not initially intended to cooperate. This includes PLCs, SCADA, and historian databases on one hand, and cloud computing services and analytics software on the other hand. Vendor-specific standards and proprietary protocols continue to pose obstacles in deploying and maintaining scalable and consistent Digital Twins [2], [3].

3) Edge computing and low latency requirements: Many use cases of PdM demand inference close to the asset rather than in a distant data center. For safety alarms and supervisory control tasks, a round-trip cloud communication becomes unacceptable due to latencies. Deployment at edge introduces hard constraints related to compute, memory, and power. Mitigation approaches include model optimization before inference, feature extraction from sensor streams, triggering inference upon specific events, and designing graceful failover modes.

4) Security and safety assurance: Connected industrial assets become vulnerable to various modern cybersecurity threats, ranging from data manipulation, sensor spoofing, model stealing, to ransomware attacks. Since PdM models affect safety-critical maintenance decisions, security and safety considerations in the design of such systems must take into account the entire system rather than just its AI component [2], [3].

5) Concept drift, transferability, and MLOps: It turns out that many machine learning models created using data collected from a single asset suffer from concept drift under shifting process conditions or on new assets altogether. Consequently, MLOps practices are indispensable when rolling out ML in industrial settings.. Techniques like transfer learning and domain adaptation can mitigate some of the retraining burden, but if applied indiscriminately can lead to insidious performance decay that manifests only when a failure is overlooked [8], [11], [14].

6) Explainability and trust: When a maintenance engineer is presented with an alarm from a model, they better know why the model triggered. Which signals changed? In which direction? What type of failure mode does the model think has occurred? If you don't provide that explanation (and some uncertainty estimate to show how confident the model is) it is difficult to deploy, let alone justify adoption in regulated industries. Models that can provide a reasonable uncertainty estimate along with interpretable feature attributions and physics-inspired constraints are far easier to adopt into current decision-making processes [5], [15], [16].

7) Fidelity of Digital Twins and bidirectional consistency: The usefulness of a Digital Twin relies entirely on its ability to accurately represent the current state of the physical object, including wear mechanisms which change gradually. To do so, one needs regular updates in parameters, continuous verification by comparison with the actual operational data and a clear demarcation line between the part which is modeled using physics-based principles and the part which has to remain an unknown component. There has been increasing popularity recently in hybrid twins which combine physics-based models with their learning counterparts; however, this makes the verification and upkeep of a twin all the more difficult [9], [17].

It seems that the challenges described above lead to the same conclusion: implementation of intelligent maintenance systems in practice is essentially a systems engineering challenge. It involves proper sensing and data architecture, security of interaction between OT and IT infrastructures and model selection with a carefully thought balance between prediction capabilities, interpretation and uncertainty.

8. Conclusion

In the field of mechanical engineering, there is a paradigm shift from reactive maintenance practices toward the development of intelligent decision-making systems. In the future, it is possible that the application of statistical analysis, machine learning, and sensor technologies will play a vital role in the development of predictive maintenance systems. However, the integration of domain knowledge through the development of hybrid models and the application of digital twins is the only possible solution for the future.

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