

From Corrective and Preventive Maintenance to Prognostics: The Evolution of Machinery Maintenance and Health Management for Enhanced System Reliability and Efficiency

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ABSTRACT

The modern industry faces the challenge of prolonging the lifespan of high-performance systems while maintaining their operational efficiency and cost-effectiveness. Through well-planned maintenance strategies, industries can achieve significant reductions in life cycle costs while minimising operational downtime and improving system reliability and its availability. Prognostics and Health Management (PHM) is an integrative, system-level engineering framework that combines diagnostics, prognostics, and decision-support processes to enable informed asset health management throughout the system lifecycle. While diagnostics and prognostics are core components of condition-based maintenance (CBM) and predictive maintenance (PdM), PHM emphasises their systematic integration within a closed-loop process that links operational activities with organizational and life cycle considerations. Thus, PHM does not replace existing maintenance policies; rather, it provides a unified framework that aligns health information, prognostic outputs, and maintenance decisions with resource constraints, risk, and performance objectives. Despite rapid advances in algorithmic research, a significant gap exists in the foundational conceptual understanding required by practitioners and researchers who are new to the field.

During a literature review of machine and deep learning applications in the field of Predictive Maintenance (PdM) and estimation of the Remaining Useful Life (RUL), the authors observed that while extensive attention is given to algorithmic developments and application-specific studies, a consolidated perspective on PHM's fundamental role, historical evolution, and strategic implementation of PHM

remains notably absent. This perspective article addresses this gap by providing a clear conceptual framework and practical roadmap of maintenance models, ranging from corrective and preventive to condition-based and predictive approaches, rather than introducing new models. This study articulates PHM's core functional elements of PHM and positions it as an integrative, system-level paradigm that contextualises established maintenance strategies, such as CBM and PdM. In addition, it discusses the technological and industrial drivers that led to the emergence of PHM, providing an accessible entry point for researchers and practitioners.

1. INTRODUCTION

Prognostics and Health Management (PHM) serves as a crucial element in the modern industry, supporting the uninterrupted, reliable, and efficient operation of complex systems throughout the industrial and marine sectors, where high availability and safety are essential (Semeraro et al., 2024),(Atamuradov et al., 2020). Historically, PHM has evolved alongside developments in CBM and PdM, leveraging advances in condition monitoring and reliability analysis to better understand the relationship between system degradation and asset longevity (Kalgren et al., 2006),(Enrico Zio, 2022). Given that operational and maintenance costs comprise a large share of the total industrial expenditure, optimising maintenance approaches helps reduce downtime and lifecycle costs (Atamuradov et al., 2020),(Biggio & Kastanis, 2020). Within this context, PHM integrates condition monitoring and prognostic information with maintenance-related decision-making processes in an intelligent and systematic framework (Enrico Zio, 2022),(Huang et al., 2024).

Operation and Maintenance (O&M) decision-making requires identifying which equipment should be immobilised

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for maintenance while maintaining minimal disruption to operational activities (Huang et al., 2024); (Hu et al., 2022). An accurate assessment of asset health, along with RUL estimation, must be paired with analyses of production requirements, logistics, and resource management capabilities (Kim et al., 2017). Moreover, maintenance planning must remain flexible and risk-aware since industrial systems operate under diverse continuously changing operational and environmental conditions (Mishra, 2018),(Jasiulewicz-Kaczmarek et al., 2020)

PHM stands as an advanced engineering approach that enables the continuous evaluation of the health of systems under actual operating conditions while anticipating future states based on the available data (Huang et al., 2024),(Hu et al., 2022). By combining sensing technologies with failure physics, machine learning, modern statistics, and reliability engineering, PHM supports data-informed maintenance planning and operational decision-making. Thus, it reduces reliance on purely corrective maintenance approaches by enabling the earlier detection of degradation and more timely, risk-aware interventions (Huang et al., 2024),(Kim et al., 2017).

At the system level, the implementation of PHM continuously monitors the condition of assets and components, detects incipient failures, and supports optimised maintenance scheduling through timely and informative health assessments (Semeraro et al., 2024),(Biggio & Kastanis, 2020). By enabling earlier and more targeted interventions, PHM can reduce unnecessary preventive actions and the risks associated with reactive maintenance. Real-time data analysis further enhances the quality and timeliness of maintenance-related decisions, ultimately supporting improved asset health and availability (Kim et al., 2017),(Mishra, 2018),(Silvestri et al., 2020).

In addition to supporting maintenance planning, PHM systems contribute to the systematic monitoring and improvement of Key Performance Indicators (KPIs) by linking health-related information with operational performance metrics (Semeraro et al., 2024),(Poór et al., 2019). Rather than focusing solely on fault prevention, PHM enables the continuous assessment of how asset health affects availability, production quality, and operational performance. These dimensions are commonly captured through Overall Equipment Effectiveness (OEE), a comprehensive and widely adopted metric for quantifying manufacturing efficiency (Poór et al., 2019).

It is worth mentioning that PHM is not a maintenance strategy per se, but rather an integrative engineering framework that provides data, analytics, and decision-support mechanisms to enable and enhance advanced maintenance strategies. Whereas maintenance strategies, such as corrective, preventive, condition-based, and predictive maintenance, define specific intervention policies and timing, PHM focuses on the technical and analytical functions that

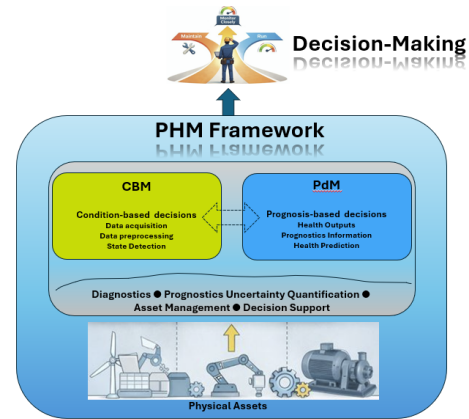


Figure 1- Conceptual relationship between CBM, PdM, and PHM

inform these policies. These functions include health state assessment, diagnosis, prognosis, and uncertainty-aware decision support. In this sense, PHM operates across multiple organizational and lifecycle levels, supporting maintenance decision-making without replacing established maintenance strategies.

To clarify the conceptual relationship between PHM and established maintenance strategies, Figure 1 illustrates the positioning of CBM and PdM as decision-oriented maintenance policies within the broader PHM framework. This representation emphasises that PHM does not replace CBM or PdM but integrates diagnostics, prognostics, uncertainty quantification, and decision support to provide an analytical foundation for maintenance and asset management decisions across the system's lifecycle.

Through an in-depth review of the relevant literature on the application of Deep Learning (DL) techniques for fault detection, classification, and the estimation of the RUL in rotating machinery, the growing presence and significance of PHM in modern industrial manufacturing becomes evident. However, the literature also reveals a lack of clear, consolidated information regarding the fundamental nature of PHM, its purpose, and the methodologies through which it is implemented. This gap is particularly challenging for practitioners (e.g. maintenance engineers and plant managers) and researchers entering the field, who are often confronted with a plethora of technical studies focused on specific models but with limited resources that answer basic questions such as, "What is PHM, fundamentally? How does this relate to the existing maintenance practices? Why should it be adopted? Unlike prior reviews that concentrate mainly on algorithmic techniques or application-specific case studies, this article seeks to synthesize existing knowledge into a coherent conceptual model.

In response to this gap, this study provides the following:

- A clear conceptualisation of PHM as a holistic, closed-loop paradigm positioned in relation to already well-established maintenance strategies such as CBM and PdM.
- A structured roadmap tracing the historical emergence and evolution of maintenance approaches, highlighting the factors that led to increasingly integrated frameworks.
- A synthesis of PHM's core functional elements of PHM within a closed-loop model, illustrating the critical interactions between diagnostics, prognostics, and decision support processes.
- A consolidated conceptual perspective that clarifies the role of PHM in maintenance and asset management practices, addressing a recognised gap in the existing literature.
- An accessible reference framework intended to support both practitioners and researchers in understanding, adopting, and implementing PHM consistently and in an informed manner.

2. MATERIALS AND METHODS

2.1. Searching Strategy

Given that this work is positioned as a perspective rather than a literature review or research article, we adopted a qualitative narrative methodology. The main objective was to explore the historical development of Health Management, synthesise the knowledge across relevant studies, and provide a structured discussion and presentation of the evolution, implementation, and comparative value within maintenance strategies.

To identify pertinent literature, a targeted search was performed across various academic databases, including Google Scholar, IEEE Xplore, Scopus and MDPI. Search terms included variations and combinations of relevant keywords such as "Prognostics and Health Management", "PHM", "predictive maintenance", and "Remaining Useful Life estimation", combined with Boolean operators (e.g., AND, OR). This search strategy ensured broad yet focused coverage of the specific field. While the primary focus was on literature published in the last five years, between 2020 and 2025, earlier seminal works, such as the 2006 foundational introduction of PHM, were also incorporated to provide the essential historical context. In addition to database queries, a snowballing method was applied, where references cited in key articles and piqued our interest were examined to identify relevant studies. The searching queries and corresponding results are briefly presented in **Error! No se encuentra el origen de la referencia.**

Dataset	Searching Area	Type	String	Results
Scopus	Title-Subject	Articles	(Performance and Health Management) OR (PHM)	297
MDPI	Title-Subject	Articles	(Performance and Health Management) OR (PHM)	347
IEEE Xplore	ALL	Conference Papers	(Performance and Health Management) OR (PHM)	247

2.2. Selection Criteria

Given the nature of this paper, the selection of articles finally included as references was guided by qualitative

Table 1 Selection Criteria.

considerations rather than rigid inclusion and exclusion criteria usually used by academics in literature reviews or research articles. Studies were included if they directly addressed the central questions raised in this study, namely:

- the origin and conceptualization of PHM,
- its implementation across different industrial domains,
- the distinctions between PHM and conventional maintenance approaches,
- and their comparative advantages and limitations.

Publications that demonstrated methodological clarity, contributed to the understanding of PHM applications, or highlighted future challenges and opportunities were prioritised in this review. Both experimental studies and conceptual analyses were considered, provided they contributed to advancing the discussion on PHM.

This approach, while not adhering to the formal frameworks used in systematic reviews (for example, PRISMA, PICOT), ensured that the final body of literature reflected both technical robustness and the studies' contextual relevance. The combination of database searching and snowballing offered a comprehensive and reliable basis of 50 academic papers for synthesising knowledge and forming the perspective presented in this study.

3. THE TRANSITION FROM TRADITIONAL MAINTENANCE METHODS TO PHM

3.1. Assets Life Span – Bathtub Trend

The bathtub curve (Figure 2) is not merely a reliability model; it provides a fundamental rationale for a prognostic-centered

approach. It visually argues that a significant portion of an asset's life is affected by unpredictable failures, making time-based maintenance inadequate and creating a strategic imperative for PHM (Biggio & Kastanis, 2020),(Wyatts, 2005). The bathtub-shaped curve comprises three distinct phases. The initial phase, or infant stage, is when a new machine begins its operation (Biggio & Kastanis, 2020). This stage demonstrates high failure rates, given that design and manufacturing defects or early use issues become evident (Ramadhan & Cahit, 2025). These initial machine failures represent false alarms, as they are short-lived, and the machine generally restores its normal operation shortly (Biggio & Kastanis, 2020),(Ramadhan & Cahit, 2025). During the useful life period (Phase 2), the machine functions properly after reaching a stable state (Biggio & Kastanis, 2020). During this stage, the failure rate remains relatively low and stable, assuming proper maintenance and use, until wear and tear start to indicate its decline (Mishra, 2018); (Ramadhan & Cahit, 2025). Finally, during the wear-out phase, the failure curve escalates steeply, indicating that component failures increase because of aging effects and cumulative fatigue damage (Biggio & Kastanis, 2020), (Ramadhan & Cahit, 2025),(Atamuradov et al., 2020).

Considering that most of the time, both infant mortality and wear-out stage failures occur unpredictably, the bathtub curve demonstrates the dangers of neglecting maintenance checks when used with "run to fail" strategies (Biggio & Kastanis, 2020),(Lee et al., 2020). Unexpected failures lead to extensive downtimes and expensive repairs (Ramezani et al., 2019). Maintenance requires careful planning, starting in Phase 2, to ensure continuity and prevent unscheduled shutdowns (Ramadhan & Cahit, 2025),(Afolalu et al., 2024). PdM through advanced PHM methods can help minimise maintenance expenses, reduce human and environmental unpredictability, and extend machine lifespan (Ramadhan & Cahit, 2025),(Afolalu et al., 2024).

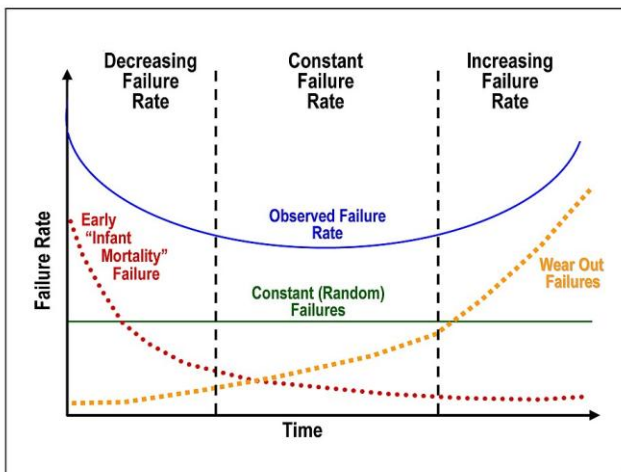


Figure 2. The bathtub curve illustrates the typical failure rates of industrial assets across their lifespan, including the

infant mortality, useful life, and wear-out phases. The model underpins the motivation for predictive and prognostic maintenance. (Biggio & Kastanis, 2020),(Wyatts, 2005)

The complexity growth and maintenance efficiency requirements of modern systems have propelled the transition from conventional maintenance methods to PHM (Jasiulewicz-Kaczmarek et al., 2020),(Silvestri et al., 2020).

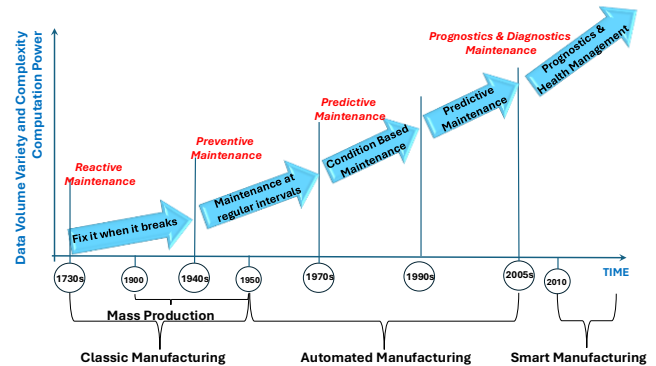


Figure 3. Evolution of maintenance strategies from Industrial Revolution 1.0 to Industry 4.0, showing the transition from corrective and preventive approaches to condition-based, predictive, and PHM frameworks.(Lee et al., 2020),(Flavio Trojan, 2016),(Torre et al., 2023)

The development of maintenance practices throughout the industrial revolutions 1.0 to 4.0 can be categorised into four distinct phases. Figure 3 shows the relevant timelines.

3.2. Corrective Maintenance (Breakdown Maintenance) – Pre-1940s:

During the initial stages of industrialisation, maintenance involved a corrective approach, where machinery was operated until failures occurred, prompting repair or replacement efforts (Poór et al., 2019); (Zadiran & Shcherbakov, 2023). This approach is known as breakdown, reactive, or corrective maintenance (Poór et al., 2019),(Ramadhan & Cahit, 2025). The main rule dictates that the equipment should operate until it is no longer functional. This approach requires minimal planning and initial expenses for spare parts and does not require equipment familiarity (Afolalu et al., 2024),(Zadiran & Shcherbakov, 2023).

However, the unpredictability of corrective maintenance reduces system reliability, leading to longer maintenance periods and increased costs when parts are unavailable during failure (Biggio & Kastanis, 2020),(Lee et al., 2020),(Ramezani et al., 2019).

Breakdown maintenance is beneficial for uncomplicated equipment because it does not require expert knowledge to perform repairs (Ramadhan & Cahit, 2025),(Poór et al., 2019). However, increased machine complexity has revealed significant limitations in this approach, resulting in extended

downtime and expensive repairs (Jasiulewicz-Kaczmarek et al., 2020),(Lee et al., 2020). Breakdown maintenance is widely used in industries where the cost of failure is relatively low and reliability is not critical. Even today, corrective maintenance can account for approximately 40-50% of maintenance activities in many industries (Flavio Trojan, 2016),(Douglas S Thomas & Brian Weiss, 2021).

3.3. Preventive Maintenance (Time-Based Maintenance) – 1940s–1970s

The complexity of industrial machinery has led to faster production growth and increased mechanical breakdown expenses, leading industries to embrace Preventive Maintenance (PM) strategies (Kim et al., 2017),(Poór et al., 2019). Planned Maintenance is another term for PM (Jasiulewicz-Kaczmarek et al., 2020). Henry Ford first recommended preventive maintenance in 1919 through his FORD MANUAL, suggesting regular inspections and immediate repairs (Poór et al., 2019). PM involves scheduled maintenance tasks performed at fixed intervals based on calendar time or operating hours without considering the current equipment state (Ramadhan & Cahit, 2025),(R. Li et al., 2018). Reliability engineering techniques establish maintenance intervals using handbook data and historical records (Kim et al., 2017),(Afolalu et al., 2024). These intervals are set shorter than usual to minimise unplanned failures (Kim et al., 2017),(Lee et al., 2020). The preventive maintenance strategy operates more efficiently than corrective maintenance by reducing equipment downtime and enhancing reliability (Poór et al., 2019),(Afolalu et al., 2024). However, studies have shown that this approach cannot meet the demands of modern technological systems (Kim et al., 2017),(Ramezani et al., 2019),(Afolalu et al., 2024),(Lee et al., 2014). PM often results in excessive maintenance and increased expenses, as components are unnecessarily replaced (Poór et al., 2019),(Afolalu et al., 2024). Currently, 28–39% of industries prioritise preventive maintenance (Douglas S Thomas & Brian Weiss, 2021).

The graph in Figure 4 illustrates the relationship between the costs of different maintenance approaches and the total maintenance cost of the asset. As is evident, the initial preventive cost is high because significant resources are allocated to avoid failures. As time passes, the program matures, and preventive costs decline because of efficiency gains. In contrast, the corrective cost initially remains low and increases as equipment ages and failures become more frequent. The total maintenance cost curve, which is the sum of both, follows a U-shaped trend: it decreases initially, reaches a minimum in the "Optimal Maintenance Zone", and then increases again as corrective costs become more dominant. The optimal zone represents the balance point at which preventive and corrective maintenance are strategically aligned to minimise overall expenses. The "Optimal Maintenance Zone" serves as a conceptual representation of the historical evolution of maintenance

strategies. Its purpose is to illustrate the qualitative trade-off between preventive and corrective maintenance costs, which motivated the emergence of PHM.

3.4. Condition-Based Maintenance (CBM) – 1970s–2000s

The American Defense and Aviation industry first adopted CBM in the 1970s to maximize machinery utilization and

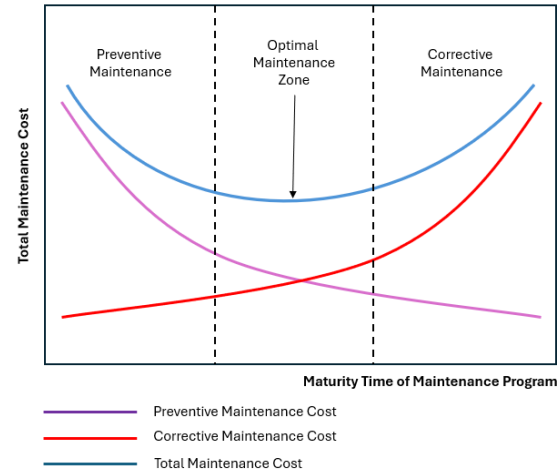


Figure 4. Comparative cost trends for preventive and corrective maintenance approaches over time. The 'Optimal Maintenance Zone' represents the balance point where preventive and corrective efforts minimise the total lifecycle cost. (Mishra, 2018).

It minimises spare part replacement. In the marine sector, DNV introduced "Condition Monitoring" in its "Machinery" class notation in the early 2000s, followed by the Lloyd's Register and the American Bureau of Shipping (Fang et al., 2024).

CBM relies on the assessment of equipment through physical inspections and continuous or periodic monitoring of measurable indicators, such as temperature, vibration, and acoustic emissions, as well as the analysis of lubricants and cooling water properties. Techniques, including ultrasonic, thermographic, and wear particle analyses, provide information on asset degradation and health status. (Kalafatelis et al., 2025),(Chokr et al., 2024).

Within CBM, maintenance actions are explicitly triggered by condition indicators and predefined decision rules, such as alarm thresholds, health indices, or degradation trends, rather than by fixed time-based schedules (Poór et al., 2019),(Ramezani et al., 2019).

With advancements in automation, real-time condition assessment has become feasible, allowing CBM policies to reduce unnecessary maintenance interventions while

mitigating the risk of in-service failure (Rezaeianjouybari & Shang, 2020). However, whereas traditional CBM approaches primarily rely on current or past condition information, ongoing research incorporates prognostic techniques to enable long-term maintenance planning. (Lee et al., 2020),(Li et al., 2018), (Lee et al., 2014).

3.5. Predictive Maintenance (PdM)

PdM extends CBM practices by leveraging predictions of future system behaviour to support maintenance decision-making processes. Rather than relying solely on past or current condition indicators, PdM utilises prognostic information, such as failure probability estimates or RUL predictions, to optimise the timing and type of maintenance interventions, inspection intervals, and resource allocation (Huang et al., 2024),(Ramezani et al., 2019),(Rezaeianjouybari & Shang, 2020),(IEEE Xplore, 2025). In this context, PdM can be considered an inherently decision-oriented maintenance policy in which predictive models inform the trade-offs between operational risk, maintenance cost, and asset availability. Accordingly, many PdM formulations explicitly integrate decision models, optimisation techniques, and control policies to balance inspection intervals, repair and replacement timing, and cost–risk trade-offs under uncertainty (Raouf et al., 2025),(Huang et al., 2024).

Data-driven models, including machine and deep learning models, play a crucial role in PdM by extracting degradation patterns and failure signatures from sensory data. (Rezaeianjouybari & Shang, 2020), (PHM Society, 2025). Architectures such as LSTM networks, CNNs, and Autoencoders are commonly employed to model temporal and multivariate dependencies in condition monitoring data (Huang et al., 2024), (Rezaeianjouybari & Shang, 2020),(Sim et al., 2022). The resulting prognostic outputs enable more informed maintenance planning, supporting optimised maintenance scheduling, reducing unplanned downtime, minimising emergency repairs, and improving spare parts inventory management (Huang et al., 2024),(Ramezani et al., 2019),(Sayyad et al., 2023),(Rezaeianjouybari & Shang, 2020).

3.6. Prognostics and Health Management (PHM) – 2000s–Present

PHM has emerged as an integrated engineering framework driven by advances in machine learning, artificial intelligence, and big data analytics, with the objective of supporting the informed management of asset health across the system’s lifecycle (Enrico Zio, 2022),(Jasiulewicz-Kaczmarek et al., 2020). The concept of PHM was first introduced by Patrick W. Kalgren during the IEEE conference in 2006, under the name “Lexical Evolution Of Maintenance and Logistics”(Kalgren et al., 2006).

PHM advances its capabilities by merging diagnostics, prognostics, and predictive analytics within a unified framework (Guillén et al., 2016),(Li et al., 2018). Through the integration of real-time system monitoring and data-driven models, including physics-based approaches, PHM supports the assessment of the current system health, identification of root causes, and estimation of future degradation behaviour, including RUL (Biggio & Kastanis, 2020), (Lee et al., 2014), (Fang et al., 2024). These capabilities are enabled through the combined use of embedded sensors, machine learning, deep learning techniques, and hybrid modelling approaches, which collectively inform maintenance-related decisions (Shimizu et al., 2023),(Kim et al., 2017).

Predictive abilities enable organisations to implement preventive measures before problems worsen, thereby minimising repair costs and equipment downtime (Huang et al., 2024),(Ramadhan & Cahit, 2025). Advances in connectivity and digitalisation, including the adoption of IoT and Industry 4.0 technologies in conjunction with cloud-based platforms, create a powerful environment for PHM implementation, enabling maintenance strategies to function through automated and interconnected systems while achieving higher efficiency (Huang et al., 2024),(Silvestri et al., 2020),(Jasiulewicz-Kaczmarek et al., 2020),(Torre et al., 2023).

Diagnostics and prognostics represent distinct but complementary functions within the PHM. Diagnostics represent a backward-looking analytical function within maintenance and health management that seeks to recognise and determine the causes of observed faults or abnormal behaviours (Lee et al., 2014). It utilises techniques such as fault detection, classification, and root cause analysis to answer the question, ‘What went wrong?’ (Atamuradov et al., 2020), (Afolalu et al., 2024). While diagnostics provide valuable insights into system behaviour, they primarily focus on current or past states; therefore, when considered in isolation, they offer limited support for longterm maintenance planning (Lee et al., 2020).

In contrast, prognostics is an engineering discipline dedicated to anticipating future system behaviour by estimating when the system or components will cease to perform their designated functions (Mishra, 2018); (Kalafatelis et al., 2025). By analysing current health indicators, historical data, operating conditions, and degradation trends, prognostic models estimate the RUL of assets, addressing the question, “When will it fail” (Atamuradov et al., 2020), (Afolalu et al., 2024). Prognostic information serves as a critical element of Health Management because it enables the creation of risk-aware maintenance planning that enhances equipment reliability and cost efficiency (Huang et al., 2024),(Ramezani et al., 2019). The RUL is defined as the time interval between the current or set observation time (t_{NOW}) and the end-of-life

point (t_{EOL}), as expressed in Equation 1 (Kalafatelis et al., 2025),(Zadiran & Shcherbakov, 2023).

$$RUL = t_{EOL} - t_{NOW} \quad (1)$$

Although RUL prediction has gained significant attention in recent years, it represents only one dimension of PHM (Fang et al., 2024). The different functions of diagnostic and prognostic system architectures require distinct structures (Lee et al., 2014). Diagnostic systems are designed to detect and identify faults using modules that handle data acquisition, signal processing, feature extraction, and fault database maintenance (Enrico Zio, 2022),(Li et al., 2018). To ascertain the causes of failure, experts build diagnostic databases with physical simulations and operational data, which help match known fault patterns to the observed features (Atamuradov et al., 2020), (Huang et al., 2024). Prognostic systems function beyond the basic diagnostic elements. Prognostic systems combine similar data processing and fault identification components with performance evaluation tools, degradation tracking, and predictive analysis capabilities (Atamuradov et al., 2020), (Rezaeianjouybari & Shang, 2020). With these enhancements, prognostic systems can assess the machine status while modelling wear and degradation throughout its lifespan to predict future failures (Jasiulewicz-Kaczmarek et al., 2020). Methods from time-series analysis, statistical inference, or artificial intelligence often drive these predictions to allow the system to determine when the equipment will reach a critical failure point (Shimizu et al., 2023),(Mishra, 2018),(Lee et al., 2014). Effective decision-making requires time-to-failure prediction, which necessitates the inclusion of uncertainties in system behaviour, along with operational conditions and degradation rates, in prognostic models for reliable and actionable insights (Shimizu et al., 2023),(Enrico Zio, 2022).

Figure 5 illustrates the typical progression of machinery degradation from a healthy state to the onset of detectable symptoms and the subsequent estimation of RUL. Based on this estimation, repair or maintenance actions can be effectively scheduled before the system reaches the functional failure point, beyond which the machinery or asset becomes inoperative. The figure also contrasts prognosis and diagnosis; whereas diagnosis focuses on identifying faults after they occur, prognosis begins with the detection of early degradation indicators and extends to the prediction of future failure behaviour. Similar conceptual representations have been widely reported in the PHM literature.

4. TECHNICAL SOCIETIES AND PHM

Technical societies have played a central role in the development, dissemination, and standardisation of concepts

and practices related to Prognostics and Health Management (PHM).

- The IEEE community serves as a fundamental discipline for enhancing the reliability and efficiency of complex engineering systems while contributing substantially to PHM research through its annual International Conference on Health Management since 2008 (IEEE Xplore, 2025).
- The PHM Society has further advanced health management by supporting the development of models, methodologies, and applications, while expanding the global reach and impact of PHM practices. Established in 2009, the society organises an annual conference that brings together researchers and practitioners to exchange knowledge and collaborate to advance their field. Following each conference, the society publishes the International Journal of Prognostics and Health Management, which serves as a dedicated outlet for PHM-related research (PHM Society, 2025).

These conferences have showcased multiple journal publications that support the development and implementation of advanced sensing technologies, machine learning, and model-based approaches to enable real-time fault detection, diagnostics, and RUL prediction (Lee et al., 2020),(Sheppard et al., 2008). These efforts have facilitated the application of PHM frameworks across a wide range of industries, including aerospace, manufacturing, and power systems.

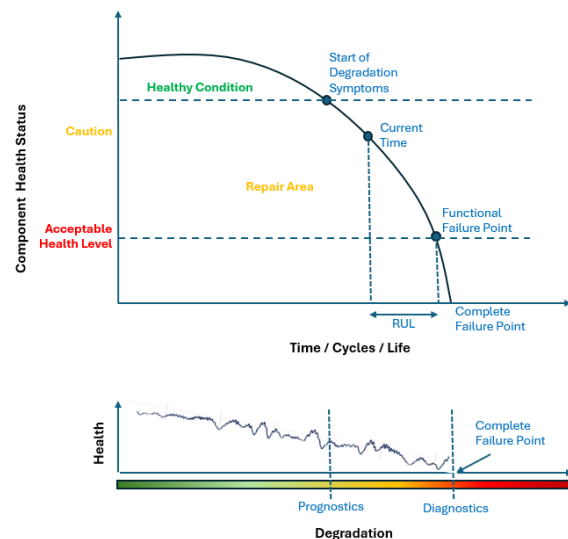


Figure 5. Schematic illustration of the complementary roles of diagnostics and prognostics in PHM. Diagnostics focuses on identifying and isolating the causes of observed faults or abnormal behaviours, whereas prognostics addresses the anticipation of future degradation by estimating the Remaining Useful Life (RUL) once early degradation

indicators become detectable. (Sayyad et al., 2023),(Chokr et al., 2024)

5. DESCRIPTION OF THE MAIN PHM FUNCTIONS

PHM builds upon and integrates concepts commonly employed in CBM and PdM within a unified engineering framework (Ramezani et al., 2019). By combining historical records, real-time operational data, and prognostic information, PHM supports degradation analysis, fault diagnosis, and failure anticipation, while providing an analytical basis for informed maintenance-related decision-making (Lee et al., 2014). As illustrated in Figure 6, PHM is commonly conceptualized as a closed-loop framework in which data acquisition, analysis, prognostics, and decision support are interconnected, allowing the information generated at each stage to inform and refine the others. This section deconstructs this framework by describing the role of each functional component within the overall PHM process (Ramezani et al., 2019);(Kalafatelis et al., 2025).

1. **Observation.** Data acquisition and preprocessing. A variety of data sources provide input for the system, including sensors such as accelerometers and thermocouples, machine controllers, and maintenance records (Lee et al., 2020); (Lee et al., 2014). The raw data undergo preprocessing, including noise reduction and normalisation, along with filtering of outliers and anomalies, to ensure reliability before further analysis and examination (Mishra, 2018),(Kim et al., 2017),(Sim et al., 2022).
 2. **Analysis.** PHM systems analyse operational data to determine whether components operate within acceptable limits or display abnormal behaviours (Lee et al., 2020). The ability to identify severity levels forms an essential part of this process. Successful diagnosis relies on identifying and selecting the most relevant features from the data (Mishra, 2018).
- **Feature extractions.** PHM employs sophisticated signal processing techniques in the time, frequency, and time–frequency domains to obtain significant insights (Hu et al., 2022),(Atamuradov et al., 2020). Stable signals typically employ time-series metrics such as the Root Mean Square (RMS), kurtosis, crest factor, and skewness. Frequency-domain analyses, such as spectral and cepstral analyses, remain essential. The analysis of time-varying signals benefits from the application of techniques such as the Short-Time Fourier Transform (STFT), Wavelet Packet Transform (WPT), empirical mode decomposition (EMD), and Hilbert-Huang transform (HHT) (Lee et al., 2020), (Rezaeianjouybari & Shang, 2020).
 - **Feature selection.** The features extracted from sensor data or signals may contribute unequally to predicting

system health or failure (Enrico Zio, 2022). Certain features may be irrelevant, while others may be duplicative or falsely informative (Enrico Zio, 2022),(Sim et al., 2022). Feature selection is a crucial process for identifying the most informative features that serve as Health Indicators (HIs) to quantitatively describe the current state of a system (Mishra, 2018), (Rezaeianjouybari & Shang, 2020).

- **Health Indicators (HIs).** HIs are particularly important in system health monitoring because they represent quantitative measurements that indicate the current health state or degradation level of systems or components (Huang et al., 2024). Well-designed Health Indicators generate dependable and easily interpreted signals that are useful for both diagnostic assessments and predictive maintenance tasks (Mishra, 2018),(Silvestri et al., 2020). Multiple approaches exist to build Health Indicators, including:
 - Direct feature use, where a single feature value, such as vibration amplitude, can directly indicate bearing wear (Ramezani et al., 2019),(Mishra, 2018),(Huang et al., 2024).
 - Feature Fusion creates a single Health Indicator by integrating multiple features using methods such as Principal Component Analysis (PCA), autoencoders, and linear combinations or weighted sums (Ramezani et al., 2019),(Atamuradov et al., 2020).
 - Statistical or Model-Based Mapping (Xia et al., 2018),(Mishra, 2018),(Huang et al., 2024).

Once the features are extracted, the selection algorithms remove the redundant or irrelevant data. Optimal features are selected using filtering, wrapper, or embedded strategies to create reliable health indicators (Rezaeianjouybari & Shang, 2020),(Atamuradov et al., 2020).

- **Diagnostics.** After the features are selected, the PHM performs diagnostics to determine the system health by evaluating the degradation severity levels (Atamuradov et al., 2020),(Li et al., 2018). Diagnostic methods can vary from basic threshold-based approaches to advanced statistical analyses and machine learning techniques. The aim is to effectively identify and isolate faults or irregularities within the system to enable prompt maintenance and corrective action. Classical supervised machine learning algorithms, such as Support Vector Machines (SVM), random forests, k-nearest neighbours (KNN), artificial neural networks (ANN), and Deep Learning Networks, have been trained on labelled datasets to accurately classify fault types (Enrico Zio, 2022),(Ramezani et al., 2019), (Rezaeianjouybari & Shang, 2020).

- Prognostics determine the early signs of failure while estimating the RUL of a component or system based on its current state and historical data. Various data-driven methods, such as Artificial Neural Networks (ANNs), hidden Markov models (HMMs), Kalman filters, particle filters, and regression-based methods, are utilised by PHM systems for maintenance planning and reliability assessment (Atamuradov et al., 2020),(Mishra, 2018),(Lee et al., 2014),(Li et al., 2018).

The closed-loop model emphasises that these processes are interdependent. Accurate diagnostic identification constrains and improves the predictions of prognostic models. Conversely, observing the degradation path of a system over time (a prognostic function) provides valuable feedback for refining diagnostic algorithms. This synergy enhances the predictive capabilities of the PHM process.

3. Actions and decision support: Closing the loop.

This stage marks the crucial transformation of analytical insights into actionable value —the Health Management phase of PHM. At this point, the system transitions from predictive analysis to supporting maintenance and operational decision-making, effectively completing the PHM loop (Li et al., 2018); (Lee et al., 2020). The system identifies the next necessary actions, answering the question “What should be done next?” and processing the data into actionable steps (Kalgren et al., 2006),(Enrico Zio, 2022). At this stage, determining the best intervention approach requires decision-making by either human operators or automated systems (Atamuradov et al., 2020),(Huang et al., 2024). The following decisions must be made:

- ✓ The optimal intervention method is determined based on the as-set conditions (Ramezani et al., 2019),(Douglas S Thomas & Brian Weiss, 2021).
- ✓ The asset should be immobilised to prevent further degradation or failure and to optimise logistics support (Ramezani et al., 2019),(Li et al., 2018),(Zio, 2022).
- ✓ Resources such as manpower, spare parts, and tools must be allocated (Li et al., 2018),(Ramezani et al., 2019).
- ✓ PHM supports operational decisions beyond repair or maintenance activities by determining whether operational adjustments are required for a specific asset or across the entire plant (Hu et al., 2022),(Huang et al., 2024).

The decisions are prioritised based on their criticality and potential failure impact to effectively mitigate the risks. Additionally, decision support systems can operate at different levels of autonomy (Hu et al., 2022),(Huang et al., 2024):

- ✓ **Manual** – Human operators assess and decide based on the provided information.
- ✓ **Semi-automated:** The PHM system suggests actions, but the operator makes the final decision.

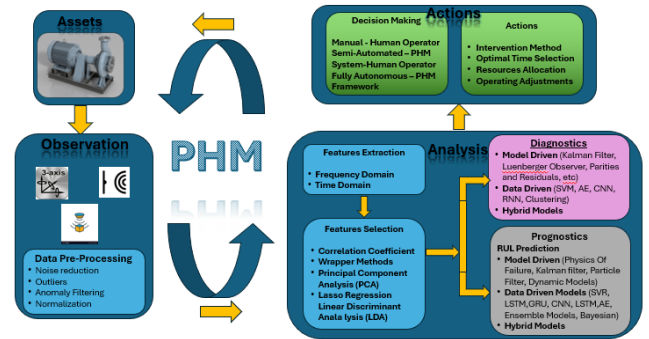


Figure 6. An integrated closed-loop representation of the core functions of Prognostics and Health Management (PHM). This figure synthesises the main PHM functions in a dynamic framework. The process begins with data acquisition and progresses through analysis, diagnostics, and prognostics, followed by decision support and actions. The resulting actions generate new operational data and feedback that continuously inform subsequent analyses and decision-making. This representation emphasises the interdependence of PHM functions within a closed-loop process for asset health management.

- ✓ **Fully Autonomous** - The PHM system independently selects and executes optimal actions.

6. PHM IMPLEMENTATION TECHNIQUES

Currently, there are three primary approaches to PHM: physics-based, data-driven, and hybrid models. Each methodology possesses distinct advantages that match certain application requirements.

Physics-based models, also known as white box models and Physics of Failure (PoF) models, use mathematical representations to illustrate the behaviour of a system (Enrico Zio, 2022),(Mishra, 2018),(Ramezani et al., 2019). These models are based on fundamental physical laws and material properties, as well as geometric features and environmental stresses (Mishra, 2018),(Xia et al., 2018). Unlike statistical methods, which rely solely on data analysis, physics-based models can generate physically consistent predictions based on an explicit representation of the underlying degradation mechanisms (Huang et al., 2024),(Mishra, 2018). They represent the physical behaviour of a system using differential equations and finite element methods, supplemented by other mathematical tools (Kalafatelis et al.,

2025). State estimation methods, such as Kalman and particle filters, operate in conjunction with physical models and structural analysis techniques. These include contact analysis, cumulative damage models, cycle fatigue, crack growth models, and spalling growth estimation models (Atamuradov et al., 2020),(Kim et al., 2017),(Mishra, 2018). The models are simulated and projected in the future to forecast the future state of the system and its potential failures (Kalafatelis et al., 2025).

Advantages (Huang et al., 2024),(Atamuradov et al., 2020),(Kim et al., 2017),(Xia et al., 2018):

- ✓ Provides physically consistent predictions based on the explicit modelling of degradation mechanisms.
- ✓ Suitable for systems with well-defined failure and degradation processes.
- ✓ Enables long-term prediction horizons and exhibits robustness to data sparsity and noise.

Challenges (Huang et al., 2024),(Atamuradov et al., 2020),(Kim et al., 2017),(Xia et al., 2018):

- ✓ Requires detailed knowledge of the system physics, materials, and operating conditions.
- ✓ Model development and parameter identification can be complex and computationally demanding.
- ✓ Performance may degrade when the physical mechanisms are insufficiently understood, or when the system uncertainties are high.

Data-Driven Models simplify predictions by using historical data and machine learning algorithms to forecast the future health of systems. Data-driven modelling techniques study patterns and relationships within datasets, unlike physics-based modelling methods, which rely on physical theories (Mishra, 2018),(Jasiulewicz-Kaczmarek et al., 2020),(Kalafatelis et al., 2025). These systems function as “black boxes” that detect advanced patterns and trends in large datasets. They exhibit powerful adaptability to complex systems, even without a complete understanding of the physical processes (Atamuradov et al., 2020),(Huang et al., 2024),(Ramezani et al., 2019).

Data-based models can be divided into statistical models, including regression models and Bayesian networks, which use statistical techniques for pattern detection and prediction creation, and Machine Learning (ML) and Deep Learning (DL) models, which apply algorithms to find data patterns for prediction outcomes. Commonly used Machine Learning models include Support Vector Machines (SVM), decision trees, and linear regression, whereas deep learning methods encompass Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Autoencoders and Transformers, along with their various combinations and modifications (Biggio & Kastanis, 2020),(Kim et al., 2017),(Mishra, 2018),(Jasiulewicz-Kaczmarek et al., 2020).

Advantages (Atamuradov et al., 2020),(Huang et al., 2024),(Kim et al., 2017),(Mishra, 2018),(Jasiulewicz-Kaczmarek et al., 2020),(Ramadhan & Cahit, 2025),(Xia et al., 2018):

- ✓ It does not require explicit physical modelling or expert-level domain knowledge.
- ✓ It is adaptable to a wide range of applications and system configurations.
- ✓ It is effective in handling large, high-dimensional, and noisy datasets, including nonlinear relationships between the variables.
- ✓ Deep learning techniques can achieve high prediction accuracies.

Challenges (Atamuradov et al., 2020),(Huang et al., 2024),(Kim et al., 2017),(Mishra, 2018),(Jasiulewicz-Kaczmarek et al., 2020),(Ramadhan & Cahit, 2025),(Xia et al., 2018):

- ✓ Depends on the availability of large volumes of high-quality historical data, including run-to-failure records.
- ✓ The model performance is sensitive to data quality, labelling, and representativeness.
- ✓ Limited interpretability and lack of theoretical guidance for model structure and hyperparameter selection remain challenges.

Hybrid Models merge physics-based approaches with data-driven methods to capitalise on their collective advantages, such as integrating the robustness and interpretability of model-based methods with the specificity and accuracy of data-driven methods (Enrico Zio, 2022),(Xia et al., 2018). Hybrid models aim to generate precise predictions, even if data availability is scarce or physical understanding remains partial (Atamuradov et al., 2020),(Enrico Zio, 2022). There are two primary strategies in the literature: serial and parallel hybrid models (Ramezani et al. 2019).

Serial hybrid models operate by applying different techniques in sequential order. The output of one model serves as the input for the next model in this sequence. This approach achieves superior performance by improving the predictions of one model using the other model with combined strategies, including data-driven adjustments to physics-based predictions and vice versa (Biggio & Kastanis, 2020),(Ramezani et al., 2019).

In parallel hybrid models, multiple techniques work together to create a unified decision or prediction based on their combined results. Multiple problem dimensions receive simultaneous attention from parallel models, which leads to potential performance improvements (Atamuradov et al., 2020),(Ramezani et al., 2019),(Xia et al., 2018).

Advantages (Atamuradov et al., 2020),(Enrico Zio, 2022),(Huang et al., 2024),(Mishra, 2018),(Xia et al., 2018)

- ✓ This method combines the high accuracy of physics-based models with the flexibility of data-driven modelling approaches.
- ✓ This can improve the robustness and generalisation of the model.
- ✓ They demonstrate a strong performance when applied to complex systems that integrate physical mechanisms with data-driven insights.
- ✓ They can overcome the limitation of lacking sufficient data

Challenges (Atamuradov et al., 2020),(Kim et al., 2017),(Mishra, 2018),(Xia et al., 2018):

- ✓ The successful deployment of a system requires an exact blend of physical components and data-driven techniques.
- ✓ The development and implementation of these systems can be complex.
- ✓ Domain-specific knowledge may be required to achieve optimal performance in these tasks.
- ✓ In many cases, the computational demand may be excessive and challenging to address.

Figure 7 summarises the different PHM Implementation Methods.

7. PHM IMPLEMENTATION WITH DATA-DRIVEN MODELS

Scientific research and PHM system development prior to the mid-2010s focused primarily on improving sensor performance and developing better analytical and predictive methods (Fang et al., 2024). The rise of big data alongside rapid advancements in computational power has led to the implementation of multiple machine learning techniques, including support vector machines (SVM), random forests,

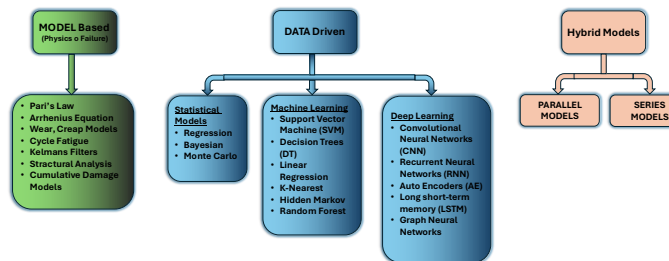


Figure 7. Overview of the implementation methods of PHM: physics-based, data-driven, and hybrid models combining both approaches (created by the authors).

principal component analysis, particle filtering, and hidden Markov models (HMM) (Kalafatelis et al., 2025),(Fang et al., 2024). Expert specialists must possess signal processing knowledge to manually extract vital features for real-world fault diagnosis and prognosis using these methods. Feature extraction relies heavily on domain and diagnostic knowledge, as well as signal processing expertise (Enrico

Zio, 2022),(Biggio & Kastanis, 2020),(Ramadhan & Cahit, 2025).

The implementation of data-driven models in PHM is fundamentally organised around four key analytical tasks: health indicator evaluation, which quantifies the current state of degradation; fault detection, which identifies the presence of an anomaly; diagnostics, which determines the root cause and type of fault; and prognostics, which forecasts the future health state and remaining useful life (RUL). The following deep learning architectures were applied to these tasks, with their typical applications summarised in Table 2.

Deep learning is a major breakthrough in artificial intelligence that has attracted many experts because it produces positive results in the PHM analysis of condition monitoring signals owing to its ability to derive complex data representations from raw inputs (Biggio & Kastanis, 2020). The proficiency of deep learning allows deep neural networks to independently manage complex and nonlinear automated feature extraction from raw data, thereby reducing the reliance on extensive domain knowledge and manual feature engineering (Rezaeianjouybari & Shang, 2020),(Ramadhan & Cahit, 2025). The system autonomously derives hierarchical representations from large datasets, making it an excellent tool for predictive health management applications that handle large industrial data with multiple dimensions (Huang et al., 2024),(Enrico Zio, 2022), (Rezaeianjouybari & Shang, 2020).

The Deep Neural Network (DNN) models can primarily be classified into three categories: generative, discriminative, and hybrid models (Rezaeianjouybari & Shang, 2020). Generative models create combined probability distributions for both input data and target outcomes, allowing the production of new data samples based on the primary data distribution (Rezaeianjouybari & Shang, 2020). This category comprises variational autoencoders (VAE), Deep Boltzmann Machines (DBM), deep belief networks (DBN), and generative adversarial networks (GAN) (Enrico Zio, 2022),(Huang et al., 2024). Discriminative models determine the likelihood of a target variable y , given an observation variable x , by evaluating $P(y|x)$ (Rezaeianjouybari & Shang, 2020). Discriminative models map inputs directly to their desired outcomes without modelling the underlying distribution of the variables (Huang et al., 2024), (Rezaeianjouybari & Shang, 2020). Predictive health monitoring widely uses Convolutional Neural Networks (CNN), recurrent neural networks (RNN), long short-term memory (LSTM), autoencoders (AE), and their different variants as discriminative models (Huang et al., 2024),(Kalafatelis et al., 2025),(Chokr et al., 2024),(Sayyad et al., 2023). The deep learning field is advancing rapidly, with major research focused on developing new architectures that improve performance, such as incremental and adaptive learning methods, to address the dynamic and demanding operating conditions of the assets. Unlike static models, these

systems continuously update themselves with new operational data, enabling them to adjust to specific asset behaviours and operations, as well as new failure patterns without requiring a full retraining process. This approach allows the creation of customised models that enhance the prediction accuracy of critical components while supporting real-time anomaly detection and optimised maintenance planning (X. Li et al., 2025),(J. Zhou & Y. Qin, 2025),(J. Yang et al., 2025).

Simultaneously, digital twins are increasingly influencing PHM research and applications by creating dynamic virtual replicas of physical assets that are continuously updated with real-time sensor data and analysis. The digital twin era has attracted considerable interest from researchers, who have explored sophisticated architectures such as Physical Information Decision (PID) models and Three- and Five-Dimensional Digital Twins (3D and 5D). By integrating sensor data from different assets and installations, digital twins can replicate their operational behaviour and identify anomalies before they lead to a failure. Vibration, temperature, pressure, and fuel consumption time-series data were analysed using deep and machine learning models to identify potential faults, predict component degradation, and optimise maintenance schedules (Q. Lu et al., 2025),(Mao et al., 2025),(Fang et al., 2024).

Hybrid models represent advanced deep learning structures that combine various DNN types, including generative and discriminative models (Rezaeianjouybari & Shang, 2020). The generative part of these models assists the discriminative component by providing better model initialisation, which improves optimisation or reduces model complexity (Biggio & Kastanis, 2020),(Ramadhan & Cahit, 2025),(Rezaeianjouybari & Shang, 2020). These architectures use the inherent strengths of discriminative models in conjunction with those of generative models (Kalafatelis et al., 2025),(Sayyad et al., 2023).

Figure 88 provides an overview of the taxonomy of deep learning architectures used in PHM, and Table 2 summarises the advantages and disadvantages of each model. Owing to the size of the table, it has been added at the end of the paper.

8. SELECTED EXAMPLES FROM RECENT PHM IEEE CONFERENCE LATEST PUBLICATIONS

As mentioned in 4, the IEEE and PHM societies conduct annual conferences, where researchers from all over the world present their work and collaborate to advance the PHM.

The following examples are not intended as an exhaustive analytical review, nor do they propose novel sensing architectures or complex multimodal setups; rather, they serve to contextualise current trends and showcase the breadth of ongoing PHM developments. It is important to

note that these examples are situated within a rich and extensive body of literature in high-impact journals.

(Enshaei et al., 2024) introduced a new vibration signal dataset acquired from a test rig consisting of a driving motor, two-stage planetary gearbox, two-stage parallel gearbox, and magnetic brake. The researchers captured real-time vibration measurements along three directions under 12 operating conditions, focusing on common gear faults in planetary gearboxes.

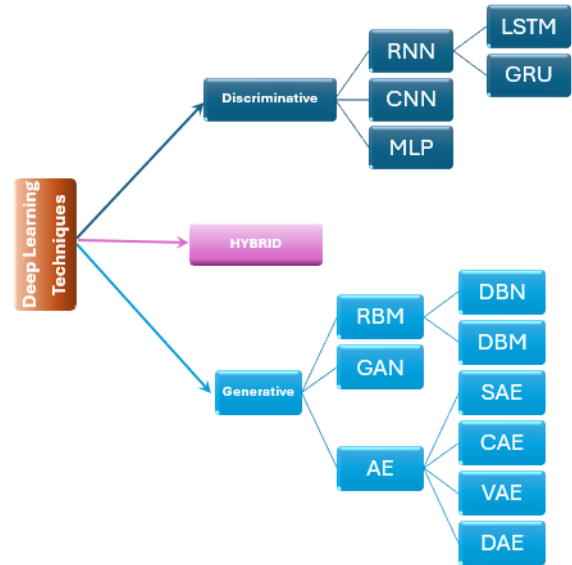


Figure 8. Taxonomy of deep learning techniques applied in PHM, including convolutional neural networks (CNN), recurrent neural networks (RNN), autoencoders (AE), generative adversarial networks (GAN), transformers, and hybrid models. (created by the authors)

Their research complements other publicly available bearing and gear fault datasets, such as XJTU-SY, IEEE PHM 2012, CWRU, Paderborn University, IMS, and Femto (Pronostia).

(Oh et al., 2024) presented a new multivariate attention LSTM multi-scale convolutional network ensemble learning (MALSTM-MCN). The proposed model captures the periodic characteristics of planetary gearbox vibration signals to facilitate fault identification. According to the authors, the experimental results indicated that the proposed method achieved high accuracy and outperformed state-of-the-art methods.

(Kreuzer et al., 2024) presented a novel method for classifying train induction motor rotor imbalances by analysing airborne sound data. The authors developed a residual-based Convolutional Neural Network that utilised a very small number of trainable parameters. The developed model was based on a ResNet architecture. To evaluate their

model, they used real-world data gathered from metro trains during regular operations.

(Chokr et al., 2024) presented a data-driven system for anomaly detection in Renewable Energy Systems based on a bidirectional long short-term memory (LSTM) autoencoder (AE) approach, which was designed to capture temporal features in multivariate time series (MTS) data. The proposed model was trained and evaluated using real raw data from the Supervisory Control and Data Acquisition (SCADA) system of a wind turbine farm.

(Martín Silva & López Droguett, 2024) investigated the application of quantum-based kernel methods for prognostics and health management tasks in rotating machinery. This study evaluated the use of quantum kernel principal component analysis to categorise unlabelled data and reduce data dimensionality. According to the authors, the results showed that the proposed quantum-based approach outperformed conventional methodologies, highlighting the potential of quantum computing techniques and motivating further research in this field.

(Liu et al., 2024) presented a CFF-trans deep learning framework that analysed vibration signals in the frequency domain to extract focused features for accurate fault identification in a high-noise environment. The proposed model uses convolutional layers for initial feature extraction, Fourier transformation for detailed frequency-domain encoding, and transformer encoders for global dependency modelling. This architecture enabled the model to capture complex relationships within the vibration signals and improve the fault recognition performance. The CFF-Trans framework was evaluated using a motor vibration dataset collected under various operating conditions. The dataset included five healthy states and three severity levels for bearing faults, such as imbalance and misalignment.

(Semeraro et al., 2024) discussed in their paper the integration of prognostic and health management (PHM) techniques with Business Intelligence (BI) tools to optimise operational performance. Traditional maintenance practices in manufacturing often rely on corrective approaches, leading to increased downtime and maintenance costs for equipment. The authors presented a methodology for integrating PHM data, including sensor readings and diagnostic information, with BI platforms to enable real-time monitoring, predictive analytics and decision-making. To demonstrate the effectiveness of the proposed method, the authors presented a case study of an energy storage system in which the downtime was reduced while its performance was optimised, significantly improving the production output.

9. INDUSTRY 5.0 AND SUSTAINABILITY

The transition to next-generation Industry 5.0 reshapes the role of PHM by extending its focus not only on the traditional metrics of automation and efficiency but also on the critical

aspects of human-centredness, operational resilience, and sustainability. In this emerging paradigm, PHM can contribute to sustainable manufacturing practices by effectively extending asset lifecycles, reducing material waste, and improving energy efficiency through optimised, condition-informed interventions (Raouf et al., 2025),(Enrico Zio, 2022).

Beyond its fundamental functions, PHM can further support sustainability objectives by integrating lifecycle-oriented environmental performance measures, such as energy efficiency metrics and carbon footprint assessments, into health monitoring systems. In this context, PHM enables maintenance and operational decisions that balance system reliability, environmental impact, and corporate responsibility (Ahmed Murtaza et al., 2024). Simultaneously, Industry 5.0 emphasises the increasing need for fruitful human-artificial intelligence collaboration, where PHM systems are not imagined as standalone, autonomous replacements but as supportive tools that enhance human decision-making through interpretable diagnostics, transparent prognostic insights, and enabling technologies such as augmented reality interfaces (Khanna et al., 2024).

This holistic vision of PHM brings human-machine interaction to the centre of attention as a value that is in sync with Industry 5.0 values, as well as developing resilience and sustainability in industrial practice. This synergy highlights the transformative potential of PHM in creating a more sustainable and human-centred industrial system, ultimately benefiting the greater goals of Industry 5.0.

10. PHM AND UNCERTAINTY

By accurately predicting the health status of assets, PHM systems enable proactive maintenance and failure prevention (Enrico Zio, 2022),(Lee et al., 2014),(Li et al., 2018). However, uncertainty represents a fundamental challenge in PHM, as it directly affects the accuracy of predictive models and the effectiveness of maintenance decisions derived from them (Atamuradov et al., 2020),(Enrico Zio, 2022),(Mishra, 2018). Uncertainty arises from several sources, including sensor noise, variable operation, environmental conditions, model inaccuracies, and limited degradation data (Atamuradov et al., 2020),(Enrico Zio, 2022),(Huang et al., 2024),(Kim et al., 2017).

Experts classify uncertainty into two fundamental groups: aleatory and epistemic (Mishra, 2018),(Ramezani et al., 2019). Aleatory uncertainty originates from the inherent randomness and natural variability of system behaviour and cannot be eliminated, even under identical operating conditions (Atamuradov et al., 2020),(Kim et al., 2017),(Mishra, 2018),(Ramezani et al., 2019).

Epistemic uncertainty occurs when there is incomplete knowledge of the system or the environment in which it operates (Enrico Zio, 2022). Researchers refer to this

uncertainty as subjective or deductible uncertainty, which can be reduced through improved data collection methods and advanced modelling techniques (Atamuradov et al., 2020),(Kim et al., 2017),(Mishra, 2018),(Ramezani et al., 2019).

Uncertainty quantification (UQ) in PHM is the process of identifying, characterising, and managing different sources of uncertainty throughout the lifecycle of an asset to produce probabilistic estimates of its health state and RUL (Ding et al., 2024),(Dewey et al., 2019). UQ serves as a foundational pillar in decision-making by shifting predictions from deterministic to probabilistic and risk-informed guidance. Without UQ, health status estimations can lead to false alarms, such as premature maintenance actions that waste resources or missed detections, where the underlying degradation is not timely determined until a breakdown occurs (Atamuradov et al., 2020). UQ allows operators to balance risk tolerance, schedule maintenance ahead of time, and reduce both unnecessary repairs and unexpected breakdowns by clearly showing confidence bounds around predictions, such as the RUL (J. Yang et al., 2025). In industries where safety is of paramount importance, such as aerospace, nuclear, and oil and gas, UQ allows decisions to be made based on worst-case scenarios within uncertainty bounds (Ding et al., 2024),(Dewey et al., 2019). This mitigates safety risks and ensures compliance with the regulations. Beyond safety, probabilistic health predictions improve fleet-wide maintenance planning, spare-part logistics, and technician scheduling, while increasing operator trust by making model limitations transparent. Uncertainty cannot be eliminated; the ultimate goal is to understand the sources of uncertainty, measure it, and eventually make robust decisions regarding it.

To enhance the reliability and performance of the PHM system, both aleatory and epistemic sources must be effectively addressed (Enrico Zio, 2022). Adaptive models, transfer learning techniques, and ensemble approaches provide PHM systems with the resilience to maintain consistent performance across different operational scenarios (Enrico Zio, 2022),(Hu et al., 2022). Bayesian inference and Monte Carlo simulations, Kalman filtering, and data fusion methods have been employed to remove noise and enhance data integrity for accurate system RUL predictions (Enrico Zio, 2022),(Huang et al., 2024),(Xia et al., 2018),(Fang et al., 2024). Hybrid frameworks that combine physics-based degradation models with data-driven learning techniques enhance further predictive accuracy while providing interpretability, which is essential in high-risk application domains (Enrico Zio, 2022) (Biggio & Kastanis, 2020) (Mishra, 2018)(Ramezani et al., 2019).

A structured performance assessment approach is required to evaluate the PHM prediction accuracy (Guillén et al., 2016),(Enrico Zio, 2022). The lack of standardisation in prognostic evaluation has not prevented several established

metrics from becoming prevalent in the field, such as the Prognostic Horizon (PH), α - λ metric, Relative Accuracy (RA) metric, Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the Concordance Index (CI) (Kim et al., 2017),(Ramadhan & Cahit, 2025),(Xia et al., 2018). The selection of appropriate metrics should be determined based on the specific objectives, failure possibilities, and system criticality of the monitored framework (Guillén et al., 2016),(Enrico Zio, 2022). The combination of hybrid and ensemble modelling approaches requires detailed and sophisticated evaluation methodologies to handle the intricate nature of modern PHM systems (Enrico Zio, 2022),(Huang et al., 2024),(Hu et al., 2022),(Ramezani et al., 2019).

11. ADVANTAGES, LIMITATIONS, OPEN CHALLENGE, AND EMERGING TRENDS IN PHM

PHM represents a shift from traditional maintenance strategies, such as corrective and time-based preventive maintenance, by adopting an integrated, system-level perspective. By integrating diagnostics, prognostics, and decision-support functions within a unified engineering framework, PHM enables a proactive, system-level approach to asset health management.

Figure 9 summarises the main sources of uncertainty in PHM systems.

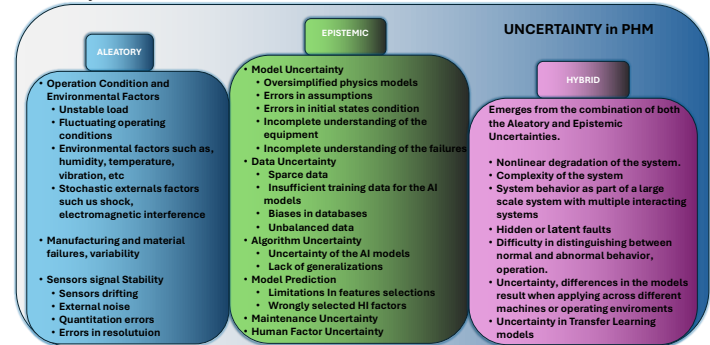


Figure 9. Sources of uncertainty in PHM are categorised as aleatory (intrinsic randomness in system behaviour) and epistemic (knowledge-related uncertainty owing to incomplete models or data).

Unlike conventional approaches based on fixed schedules or reactive interventions, PHM leverages condition monitoring, predictive analytics, and uncertainty-aware reasoning to support informed maintenance planning and operational decision making. (Hu et al., 2022),(Raouf et al., 2025),(Shimizu et al., 2023).

The main advantages of PHM are as follows (Kalafatelis et al., 2025),(Huang et al., 2024),(Sim et al., 2022),(Fang et al., 2024).

- ✓ PHM enables early detection of faults and accurate prediction of RUL, allowing maintenance to be scheduled just-in-time, minimizing unplanned downtime and maximizing asset utilization
- ✓ By reducing unnecessary maintenance and preventing catastrophic failures, PHM can lower maintenance costs, spare part inventories, and production losses.
- ✓ PHM leverages sensor data, AI, and machine learning to provide real-time health assessments and actionable insights, surpassing the limitations of human judgment and scheduled inspections
- ✓ Moreover, by integrating information across components and subsystems, PHM supports root cause analysis and reveals the interdependencies between component degradation and system performance.
- ✓ Continuous monitoring and prognostics improve system reliability and safety, particularly in critical applications such as aerospace, marine, petroleum and gas, and advanced manufacturing.

Despite these advantages, PHM introduces several limitations and challenges (Fang et al., 2024),(Zadiran & Shcherbakov, 2023) ,(Raouf et al., 2025),(Kalafatelis et al., 2025).

- ✓ PHM requires significant investments in sensors, data acquisition systems, and computing infrastructure.
- ✓ The analysis of massive data and maintenance of prognostic models are resource-intensive and require extensive expertise.
- ✓ Data-driven and AI-based models may lack transparency, making it difficult for operators to trust or understand maintenance recommendations.
- ✓ Although deep learning models can excel with abundant labelled data, their performance is critically dependent on the features used to capture the degradation trends. Moreover, prediction models are prone to the phenomenon known as catastrophic forgetting, in which the model's capacity to retain old tasks diminishes while learning new tasks.
- ✓ All PHM predictions involve uncertainty, and insufficiently quantified uncertainty in RUL estimates may lead to premature interventions or missed failure.

Table 3 summarises the main advantages and limitations of PHM compared with conventional maintenance approaches. Owing to the size of the table, it has been added at the end of the paper.

Despite significant progress in recent years, several open challenges and research gaps continue to limit the widespread adoption of PHM systems.

- ✓ A major ongoing issue in this field is the scarcity of standardised high-quality datasets and run-to-failure records. This makes it harder to validate the models across different industrial sectors and operational

conditions.(Fang et al., 2024), (Rezaeianjouybari & Shang, 2020)

- ✓ The diversity of data, sensor noise, and incomplete degradation paths further complicate the problem, often hindering the precision and adaptability of predictive models. (X. Li et al., 2025),(J. Yang et al., 2025)
- ✓ Model interpretability is another major challenge in this field. Although deep learning-based models are highly predictive, they are often considered black-box systems that lack clarity and transparency, making it difficult for operators and decision-makers to fully understand them. (Huang et al., 2024),(Mao et al., 2025),(Semeraro et al., 2024)
- ✓ In addition, the quantification of uncertainty in RUL prediction is still underdeveloped; insufficient representation of epistemic and aleatory uncertainties can result in either premature interventions or overlooked failures, particularly in safety-critical industries.(Ding et al., 2024),(Dewey et al., 2019)
- ✓ In practice, the high costs associated with sensors, data infrastructure, and model implementation and maintenance pose challenges for small- and medium-sized businesses. At the same time, problems related to system integration with existing platforms and cybersecurity risks remain inadequately addressed.(Huang et al., 2024), (Poór et al., 2019),(Kalafatelis et al., 2025),

Concurrently, several emerging trends are influencing the future of PHM. The implementation of digital twins has made it possible to use simulation-based predictive maintenance strategies with high accuracy (Mao et al., 2025). Progress in incremental, online, and transfer learning has enabled PHM systems to dynamically adjust to new operating conditions without the need for complete retraining while addressing the catastrophic forgetting phenomenon (J. Zhou & Y. Qin, 2025),(J. Yang et al., 2025),(X. Li et al., 2025),(Huang et al., 2024). Similarly, hybrid models that integrate physics-based methods with machine and deep learning are gaining traction because they offer both interpretability and predictive accuracy.

On a broader scale, the shift towards Industry 5.0 redefines PHM as a human-centred and sustainability-focused field. Future PHM systems are anticipated to enhance reliability and cost-effectiveness, promote energy efficiency, prolong asset lifecycles, reduce waste, and support environmentally responsible maintenance practices (Khanna et al., 2024),(Ramadhan & Cahit, 2025),(Afolalu et al., 2024),(Ahmed Murtaza et al., 2024).

Taken together, these research directions indicate that while PHM has evolved into a key enabler of reliability and efficiency, its full potential depends on continued progress in data availability, model interpretability, uncertainty

management, and sustainable and cost-effective implementations.

directly contribute to sustainability, resilience, and lifecycle efficiency is required in this regard.

12. CONCLUSIONS

Prognostics and Health Management provide the analytical and decision-support capabilities required to assess asset health, anticipate fault progression, and support maintenance and asset management decisions throughout the system lifecycle. By enabling real-time insights into machine conditions, PHM supports the early detection of incipient failures and the transition from reactive interventions to condition-informed and risk-aware maintenance planning. This reduces unnecessary preventive actions while improving the reliability, safety, and operational efficiency.

PHM is currently at a critical inflection point. Emerging developments, such as digital twins, hybrid modelling, interpretable AI, and the human-centred, sustainability-driven vision of Industry 5.0, offer exciting and promising pathways for future research in this field. However, the next evolutionary step for PHM will be a decisive shift from purely algorithmic performance to the development of trustworthy, explainable, and economically viable systems that can be broadly adopted across industries, including small and medium-sized enterprises (SMEs).

This transition requires a concerted focus on overcoming the fundamental adoption barriers related to cost, system complexity, and model transparency. Three key challenges remain central to achieving this transition: i) improving the interpretability and user trust in advanced PHM models, particularly in safety and risk-critical applications; ii) advancing uncertainty quantification to support probabilistic and risk-informed decision-making; and iii) enabling cost-effective deployment through scalable architectures and reduced infrastructure requirements.

Addressing these challenges will require coordinated efforts from academia, industry, and professional organisations such as the IEEE and PHM Society.

Looking ahead, a long-term roadmap could systematically address these challenges and foster the industrial adoption of PHM technology.

Key directions for such a roadmap may include the following:

- ✓ Improving data quality for marking practices and developing interpretable and hybrid AI models while prioritising cost-effective solutions suitable for small- and medium-sized enterprises (SMEs).
- ✓ Strengthening the integration of PHM with digital twins, hybrid modelling approaches, and Industry 5.0 principles, with an emphasis on sustainability and human–AI collaboration.
- ✓ Progressing towards enterprise-wide predictive ecosystems and PHM decision-support frameworks that

Ultimately, the success of PHM will be measured not only by its predictive accuracy but also by its tangible contributions to industrial sustainability, operational resilience, and lifecycle cost reductions. In this sense, PHM represents an evolving engineering paradigm with the potential to transform maintenance and asset-management practices across industries.

Model	Typical PHM application	Advantages	Disadvantages
CNN	Fault detection, feature extraction from vibration/spectrograms, sensor fusion	<ul style="list-style-type: none"> - Learns discriminative features from raw data - Strong with multidimensional sensor inputs - Well-suited for classification 	<ul style="list-style-type: none"> - Weak at long-term sequence modelling - Needs large labelled datasets - Sensitive to domain shift
RNN / LSTM / GRU	RUL prediction, degradation modelling, time-series forecasting	<ul style="list-style-type: none"> - Captures sequential dependencies - LSTM/GRU mitigate vanishing gradients - Widely validated in NASA C-MAPSS & PHM challenges 	<ul style="list-style-type: none"> - Training instability - Struggles with very long dependencies - Needs temporally rich datasets
Autoencoders (AE / VAE)	Anomaly detection, health indicator extraction, unsupervised feature learning	<ul style="list-style-type: none"> - Learns compact latent health indicators - Useful in unlabelled settings - VAE offers probabilistic interpretation 	<ul style="list-style-type: none"> - Can reconstruct noise - Sensitive to hyperparameters - Limited interpretability for degradation trends
GANs	Data augmentation, domain adaptation, synthetic fault data generation	<ul style="list-style-type: none"> - Generates synthetic data when faults are rare - Supports unsupervised learning - Improves domain adaptation- 	<ul style="list-style-type: none"> - Training instability (mode collapse) - Quality of generated data varies - Hard to tune generator/discriminator
Transformers	Long-sequence modelling, multivariate sensor data, RUL prediction	<ul style="list-style-type: none"> - Captures long-term dependencies better than LSTM - Handles heterogeneous sensors - Scales with big data 	<ul style="list-style-type: none"> - Computationally expensive (quadratic complexity) - Requires large datasets - Less explored in PHM than CNN/LSTM
Hybrid Models (CNN-LSTM, CNN-Transformer, etc.)	Joint feature + temporal learning, RUL prediction, system monitoring	<ul style="list-style-type: none"> - Combines strengths of CNN and sequence models - Strong performance on PHM benchmarks - More generalizable 	<ul style="list-style-type: none"> - Higher complexity - Risk of overfitting - Harder to optimize
Incremental / Online Learning	Update models with new data streams; adapt to non-stationary degradation	<ul style="list-style-type: none"> - Avoids full retraining - Adapts to changing system conditions - Useful for long-term deployment 	<ul style="list-style-type: none"> - Risk of catastrophic forgetting - Needs memory/replay mechanisms - Still underdeveloped in PHM
Domain Adaptation Transfer Learning	Adapt models trained in one domain (machine, environment) to another	<ul style="list-style-type: none"> - Reduces labelling effort - Handles dataset/domain mismatch - Supports real-world generalization 	<ul style="list-style-type: none"> - Domain shift still degrades performance - Adversarial DA may be unstable - Careful sensor/feature alignment needed

Table 2. Comparative overview of deep learning models applied in PHM, with typical applications, key advantages, and main limitations.

Aspect	PHM	Time-based / reactive maintenance
Information	What will happen, and when will it happen? What should the operators do? How does this affect the other equipment?	What happened? Why it happened?
Failure Prevention	Proactively detects and predicts failures before they occur and prolongs asset lifespan	Failures often occur unexpectedly (corrective), or maintenance may be unnecessary (preventive)
	Provides a window of opportunities for implementing measures to avert catastrophic failures	
Cost Effectiveness	It reduces the total lifetime operation and maintenance (O&M) costs by avoiding unnecessary repairs and downtimes.	Higher costs due to unscheduled emergency repairs.
	According to Kalafatis et al, 2025, it can minimize the OPEX by 45%	Higher costs due to scheduled downtimes, even if the condition of the asset is acceptable.
	Results in lower maintenance cost compared to CBM by predicting useful lifetime and allowing components to be fully exploited	
Spare Parts	Inventory optimized based on predictions	Spares must be always available in case an unexpected failure occurs
Resource Use	Optimized scheduling and resource allocation	Unplanned downtime and urgent resource demand
Downtime	Reduces the scheduled and unscheduled inspection time and downtime	Conventional maintenance strategies often compromise time effectiveness and efficiency because of fixed maintenance frequencies.
	Improves the maintenance efficiency	
Planning	Optimized maintenance scheduling, with minimized or even eliminated RUL	Spare parts may be replaced too early (preventive), or too late (corrective)
	Extends useful life by avoiding premature replacement	Poor planning; often needs rapid response or relies on conservative schedules
Safety and Risk Management	It acts as a lever to reduce the risk of catastrophic accidents during the operation of the system.	Unexpected misoperations or asset failures can jeopardise safe operations and even lead to fatal accidents.
	Mitigates the operators', service engineers' work load	Unexpected failures can increase the workload of service engineers beyond normal working hours.
Adaptability	PHM keeps stable maintaining performance in evolving working environments and conditions	Inflexible; fixed schedules don't reflect actual wear or usage
Initial Investment	This requires increased investment in health monitoring platforms and maintenance training.	The initial investment is either nil or minor in these cases.
	Due to the increased initial investment cost, it is deemed unsuitable for small- and medium-scale plants.	
Implementation Complexity	Requires new skills and specialized knowledge	Simple to implement and understand
	However, the implementation of this approach is highly complex. Requires massive, most of the time, run to failure data	

Table 3. A comparison of Prognostics and Health Management (PHM) with conventional maintenance strategies across key dimensions, including information scope, failure prevention, cost effectiveness, time effectiveness, safety, adaptability, and implementation complexity.

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