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Topical Review

Intelligent reliability assurance methodologies for engineering systems: advances and challenges

Zhiliang Liu[1], Qin Zhang[1], Yu Liu[1], Yaguo Lei[2] and Mingjian Zuo[3,4,5,*]

[1] School of Mechanical and Electrical Engineering, University of Electronic Science and Technology of China, Chengdu, Sichuan 611731, People's Republic of China
[2] Key Laboratory of Education Ministry for Modern Design and Rotor-Bearing System, Xi'an Jiaotong University, Xi'an, Shaanxi 710049, People's Republic of China
[3] School of Qilu Transportation, Shandong University, Jinan 250061, People's Republic of China
[4] Qingdao Mingserve Technology Ltd, 171 Jinshui Road, Qingdao, Shandong 266000, People's Republic of China
[5] Department of Mechanical Engineering, University of Alberta, Edmonton, Alberta T6G 1H9, Canada

E-mail: zuo.mingjian@mingserve.com

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Abstract

Effective reliability assurance is essential for ensuring the safe, dependable, and cost-efficient operation of modern engineering systems. Over the decades, researchers and practitioners have developed a wide range of methodologies, evolving from preventive maintenance to predictive maintenance (PdM) paradigms. This paper presents a comprehensive review of reliability assurance strategies, with a particular emphasis on the recent advancements in intelligent PdM. At the core of this new paradigm is the concept of an intelligent agent capable of monitoring system operations, detecting fault initiation and progression, assessing health conditions, estimating the remaining useful life of critical components and systems, and autonomously making maintenance decisions regarding spare parts provisioning and scheduling. The reviewed approaches are categorized into three major types: statistics-based methods, physics-based methods, and intelligent methods. Special focus is given to intelligent methods, including aspects of data sources (e.g. vibration, image and video, acoustic emission, ultrasonic, and current signals), analysis approaches (rule-based, statistical, physics-based, shallow and deep learning approaches), and target equipment (batteries, bearings, gas turbines, wind turbines, chips, and mechatronic systems). Real-world applications in sectors such as high-speed rail, aerospace, and nuclear energy are also discussed. The paper concludes by highlighting key

* Author to whom any correspondence should be addressed.

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research challenges and prospects, including data standardization, security and sharing, edge computing, data fusion algorithms, reasoning under uncertainty, quantifiable decision-making, large-scale foundation models, and digital twins for further development of intelligent reliability assurance solutions.

Keywords: intelligent reliability assurance, predictive maintenance, prognostics and health management, engineering system

Abbreviations

AI	Artificial intelligence
CBM	Condition-based maintenance
CM	Condition monitoring
CNN	Convolutional neural network
DL	Deep learning
DT	Digital twin
IoTs	Internet of Things
ISO	International Organization for Standardization
ML	Machine learning
FMEA	Failure mode and effect analysis
NN	Neural network
PHM	Prognostics and health management
PM	Preventive maintenance
PdM	Predictive maintenance
RCM	Reliability-centered maintenance
R&D	Research and development
RM	Reactive maintenance
RUL	Remaining useful life
SCADA	Supervisory control and data acquisition
SVMs	Support vector machines

1. Introduction

Today's society relies on the safe, reliable, and cost-effective operation of a diverse array of engineering systems, including transportation [1], energy infrastructure [2], manufacturing [3], and medical systems [4]. These engineering systems serve as the backbone of economic growth and societal development. Over the years, significant advancements have been made to enhance the reliability and safety of engineering systems, including reliability-based design, improved manufacturing technology [5], advanced monitoring techniques [6], and systematic reliability practices [7]. However, system failures and operational disruptions still occur due to unforeseen environmental conditions, human errors, aging infrastructure, and inadequate maintenance strategies, leading to significant safety risks, financial losses, and environmental damage [8].

To ensure the reliability of engineering systems, researchers, engineers, and practitioners have developed and implemented various maintenance strategies over the centuries. The earliest naïve approach is the so-called RM, wherein a failure event triggers equipment repair and maintenance while no preventive measures are taken at all. Later, as lifetime data are obtained from field and laboratory testing, lifetime distributions and reliability theory have been developed to determine PM intervals. With further development in measurement and sensing technology, reliability theory, and computing technology, approaches such as CBM, RCM, and PdM have appeared. PHM serves as a key enabling technology for CBM, RCM, and PdM. PHM provides a sensor data-driven analytical framework that encompasses tasks such as CM, fault diagnosis, RUL prediction, and maintenance decision optimization. Figure 1 illustrates the development progress of maintenance practices relying on the rising data volume, variety, and complexity [9]. In the following, we provide additional descriptions of the strategies shown in this figure.

Traditional maintenance approaches are based on statistical distributions that describe the lifetime behavior of a population of similar objects (referring to a component or a system) under specified loading conditions as a function of usage measured in clock time, loading cycles, kilometers, or other measures as appropriate. The risk of failures and the cost of carrying out preventive actions are balanced to come up with appropriate maintenance strategies, including RM, usage-based PM, usage-based preventive replacement, and periodic inspections [10–12]. These approaches are designed predominately based on the lifetime distribution of a population of similar objects with a limited understanding of failure mechanisms and inadequate inspection and diagnostic tools, and applied to all individual units of the population. Thus, oftentimes redundant inspections and/or over-maintenance are performed, causing high maintenance costs and service interruptions, which result in negative economic and societal impact [12, 13]. However, many of these traditional approaches have been codified into standards of many industries, and these maintenance practices are often costly. For example, the maintenance costs in wind farms [14], the mining industry [15], and nuclear power plants [16] were over 20%, 30%, and 60% of the total lifecycle costs of the assets.

The concept of CBM refers to 'a preventive action carried out before failure, but initiated as a result of the knowledge of the real conditions of the components, obtained through regular or continuous monitoring'. Modern terms following this line of thinking are called PHM and PdM. PHM is the approach of ensuring the reliable operation of an engineering system that (1) uses the knowledge of the operation physics of the system including its failure modes and vital signs, (2) acquires relevant data during its operation including loading and usage profile, past maintenance actions, and responsive data such vibration, temperature, and acoustics as appropriate, (3) analyzes such data to assess its dynamic health condition by detecting fault initiation, diagnosing fault location and fault type, and quantifying the degree of its health deterioration, (4) predicts the future degradation trends and estimates the RUL of the running equipment, and (5) provides optimal

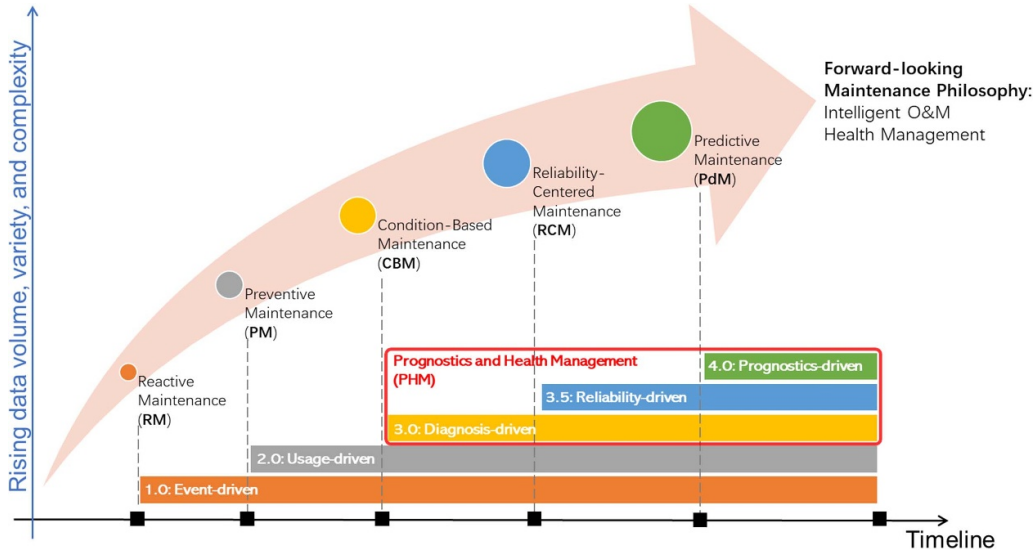


Figure 1. The development progress of maintenance strategies.

preventive decisions including when and what maintenance actions are to be performed. A successful PHM program relies on advanced algorithms that can process diverging types of big data in real-time and generate accurate assessment results and optimal decisions. The R&D under the paradigm of PHM has been going on for decades with significant achievements in all of its five aspects including failure modes and reliability behavior of new engineering materials and systems, advanced sensors capable of capturing accurate high-frequency data of various signals, signal processing algorithms for fault severity assessment and fault diagnosis, cyber-physics models for RUL prediction, and maintenance strategy optimization.

Recent advancements in AI have propelled the development of intelligent PHM by providing effective and timely PdM suggestions and decisions, particularly for large-scale and complex systems [17–19]. AI dynamically learns from complex and evolving datasets, enabling it to identify subtle patterns, adapt to changing conditions, and optimize decision-making in real-time [20, 21]. AI also excels at solving large-scale problems by approximating global solutions through deep reinforcement learning and leveraging simulation environments for risk-free optimization [22–24]. It is capable of adapting solutions across diverse scenarios and domains using transfer learning, enabling efficient decision-making in complex systems [25, 26]. For example, Ong *et al* [25] utilized deep reinforcement learning to solve PdM problems in the industrial IoT, achieving a 58% reduction in the training time of the deep reinforcement learning network through the integration of transfer learning and expert demonstrations.

The performance of engineering systems is inherently multifaceted, encompassing functionality, safety, reliability, and sustainability [27–29]. These aspects are interdependent and collectively determine the overall effectiveness of a system. Functionality ensures that the system fulfills its intended purpose. Safety safeguards against hazards to humans and the environment. Reliability minimizes downtime and disruptions. Sustainability emphasizes resource efficiency and environmental stewardship. AI-driven methodologies are uniquely positioned to address these dimensions holistically. By integrating real-time data, predictive analytics, and optimization algorithms, AI can enhance system performance across all these metrics.

The paradigm of RCM provides a logical framework for selecting maintenance strategies based on failure modes, operating conditions, and asset criticality to achieve the desired reliability levels. ISO denotes asset management as 'coordinated activity of an organization to realize value from assets' and realization of value normally involves a balancing of costs, risks, opportunities, and performance benefits [30]. These organization-level guidelines are the umbrella under which we develop and adopt maintenance strategies to ensure the safe, reliable, and cost-effective realization of functions and services of engineering systems.

This survey focuses on AI-powered intelligent reliability assurance methodologies. By establishing an industrial closed-loop framework for 'diagnosis—assessment—decision-making', it analyzes their reliability assurance mechanisms in complex engineering systems, while uncovering technological evolution paths and bottlenecks spanning data standardization, edge computing, to DTs. To streamline subsequent discussions of the ever-evolving reliability assurance strategies, we categorize them into three groups, namely, statistics-based methods, physics-based methods, and intelligent methods, based on their main underlying principles. Statistics-based methods are characterized by their reliance on historical failure data and probabilistic modeling techniques, such as lifetime distributions and regression analysis, without explicitly utilizing degradation and failure physics. Physics-based methods are grounded in deterministic models derived from material science and failure mechanics, including stress–fatigue equations and crack propagation laws, which directly capture the physical mechanisms of failure. Both statistics-based methods and physics-based methods are later referred to as traditional methods. Intelligent methods are the

future of reliability assurance as they utilize real-time, data-driven algorithms—such as ML and deep learning—to perform dynamic health assessment, integrate multi-source data, and support autonomous decision-making. Intelligent methods are also referred to as hybrid approaches as they are capable of incorporating knowledge in lifetime distributions and failure physics.

The remainder of this paper is rolled out as follows. Section 2 reviews the traditional reliability assurance approaches, which are generally statistics-based and physics-based. Section 3 reviews intelligent PHM methods encompassing data acquisition, fault detection and fault diagnosis, health assessment and RUL prediction, and maintenance decision-making. Section 4 covers a few applications of the PHM approach in real-world scenarios. Finally, section 5 provides a summary and points out future R&D directions.

2. Traditional reliability assurance approaches

2.1. Statistics-based methods

(1) PM

Traditionally, reliability researchers and practitioners adopt the belief that objects of the same design, manufactured the same way, and used under the same environment have similar lifetimes. Their lifetimes are not the same because there are variations in material properties, manufacturing processes, operating conditions, and operating environment. This uncertainty in the lifetime of a population of identical objects has predominantly been described by a random variable. Reliability has commonly been defined as the probability of an object performing its intended functions satisfactorily under specified operating conditions for a specified period of time [31].

Mathematically, the lifetime of a component is denoted by a random variable T, whose definition domain is non-negative real numbers. This random variable T is characterized by its probability density function $f_T(t)$, cumulative distribution function $F_T(t)$, and reliability function $R(t)$. The reliability of such an object is defined as the probability that its lifetime T is not shorter than a specified time duration of length t, and mathematically expressed as:

$$R(t) = \Pr\{T \geqslant t\} = 1 - F_T(t) = 1 - \int_0^t f_T(u)\,\mathrm{d}u. \quad (1)$$

Based on this definition, several reliability measures have been derived from the statistical point of view, such as the mean time to failure which is the mathematical expectation of random variable T, and the failure/hazard rate function $\lambda(t)$ which is the probability of an object failing in the next instant of time given that it has been functioning satisfactorily up to time length t.

Under this paradigm, the uncertainty in the lifetimes of identical objects in the same population is quantified only by the statistical nature of T. This means that different types of objects may follow different types of lifetime distributions. Typical statistical distributions that have been used to represent lifetime distributions include the normal distribution, lognormal distribution, exponential distribution, uniform distribution, Weibull distribution, and Gamma distribution. Among these types of distributions, the Weibull distribution, capable of modeling increasing failure rate, decreasing failure rate, and constant failure rate patterns of objects, is the most extensively used one in reliability applications [32].

To characterize the randomness in the lifetime of a population of identical objects, one needs to have available an adequate number of observed lifetimes or failure times of such objects. Regression analysis can be performed on these data to find the distribution type with the best goodness-of-fit and obtain its corresponding parameter estimates. Data from both laboratory testing and field cases may be used for fitting lifetime distributions; however, the data must be for the same type of objects working under the same operating conditions. When failure data under real operating conditions are inadequate, researchers have also reported approaches for using censored data and accelerated life testing data to obtain the appropriate lifetime distributions [33].

In addition to measuring lifetime with clock time, such as hours and years, other measures have also been used, for example, kilometers traveled have been used to measure the life longevity of tires, loading cycles have been used to measure that of structural materials, and volume of liquid pumped to measure that of pumps. When such measures are used in place of time measures, we can still use the statistical approach summarized above. We still refer to the distributions as lifetime distributions.

Based on statistical lifetime distributions, maintenance strategies such as PM, preventive replacement [34], opportunistic maintenance [35], and group maintenance [36] have been developed. Optimal time intervals have been determined and used to carry out such preventive measures to ensure the reliability of the target components and systems, considering the costs of failure and costs of maintenance actions. PM aims to restore deterioration within a system before the system fails or loses functionality. Whenever maintenance actions are being performed, opportunistic maintenance takes advantage of the system downtime to inspect other relevant components of the system and perform additional maintenance actions as needed with the aim of improving the overall health of the system, preventing possible future failures, and reducing overall maintenance costs. Group maintenance schedules maintenance actions on a group of objects together so that maintenance resources are efficiently utilized, covering multiple assets within a short concentrated downtime of these components and systems.

The approaches outlined above are often referred to generally as PM. This approach has been utilized in various industry standards and is the most widely used maintenance strategy in practice. The main reasons for its widespread adoption include rigorous statistical theory, ease of scheduling maintenance resources, and lack of accurate and economical methods to assess the health condition of engineering systems in use. This approach is very effective when adequate failure data are

available and the fitted lifetime distribution has a small standard deviation. When either of the two conditions is not met, researchers have made various efforts to utilize CM data and expert knowledge.

When failures are not self-revealing, for example, for emergency devices that are usually not needed, the periodic inspection approach has been developed to discover hidden failures. Periodic or sporadic inspection intervals may be followed based on knowledge of the lifetime distributions of such devices. There are reported optimal periodic inspection interval determination methods. The optimization of periodic inspection intervals plays a pivotal role in minimizing maintenance costs and enhancing the efficiency of such a system [37]. For various system structures and failure mechanism models, the optimal periodic inspection interval may be determined based on heuristic algorithms, genetic algorithms, and other intelligent algorithms [38, 39].

The periodic inspection approach helps reveal hidden failures. They are also useful in helping assess the health status of the inspected devices. In this case, the approach also matches the philosophy of PHM and PdM.

(2) Degradation analysis

Once a system is put into operation, if its health degradation can be observed in some way during the operational stage and there exists a degradation threshold exceeding which means the system's functional failure, the reliability of the system can be defined in terms of this degradation measure. With $D(t)$ denoting the measured degradation magnitude at time instant t and ω denoting the maximum allowed degradation threshold, the reliability function of this system at time t can be expressed as:

$$R(t) = \Pr\{\inf\{t_1 | D(t_1) \geqslant \omega, t_1 > 0\} > t\}, \tag{2}$$

where $\inf\{t_1 | D(t_1) \geqslant w, t_1 > 0\}$ is called the first hitting time. Regression models have been used to fit degradation curves when a degradation observation series is available [40]. Tire tread wear and cutting tool tip wear are good indicators of the degradation of such components. For many engineering systems, such degradation is difficult to quantify and/or difficult to measure without interrupting the use of the systems. However, assuming that degradation measurements are available, many theoretical advancements have been made.

A key challenge of the shift from lifetime-based reliability assessment to degradation analysis is the accurate determination of the threshold of the observed degradation parameter. One approach is through the integration of degradation thresholds with survival analysis models, which estimate failure probability given a degradation trajectory. Another strategy is to establish empirical correlations between degradation indicators and functional failure time using historical data and ML techniques. Additionally, hybrid models combining statistical lifetime distributions and degradation-based reliability assessments have been reported to enhance predictive accuracy. These efforts aim to refine the mapping between degradation progression and the actual onset of system failure.

Stochastic process models with the s-independent increment property, such as the Wiener process, Gamma process, and inverse Gaussian process, have been employed to model the degradation behavior, i.e. $D(t)$, of engineering systems [41]. Various stochastic process models addressing issues such as unit-to-unit heterogeneity, bi-variant and multi-variant observations, and multiple phases of degradation have been reported [42–44]. The pre-specified degradation threshold ω which correlates degradation to functional failure is difficult to determine. In addition, it could be a random variable or a stochastic process by itself [45].

The aforementioned models treat the degradation behavior as a continuous-state stochastic process. In some engineering scenarios, a system may exhibit multiple discrete health states distinguished by either performance capacity or damage severity, and these are the so-called multi-state systems. The degradation behaviors of multi-state systems and their constituent components have been modeled by discrete-state stochastic models, such as the Markov model, semi-Markov model, and hidden Markov model [46]. Compared to traditional binary-state systems, which have only two possible states, either perfectly functioning or completely failed, reliability assessment for systems with a multi-state nature is more challenging. Graph-based methods and analytical tools, such as universal generating function, Bayesian network, and decision diagram, have been developed to assess system reliability by mapping components' state combinations to system states [46].

(3) Approaches when failure data are limited

Directly confronting the issue of a lack of failure data or a lack of lifetime data, researchers have utilized alternative lines of thinking [47]. Bayes's theory has been employed to integrate the prior knowledge from experts' experience or similar engineering systems with limited field failure data of the target device to obtain the posterior reliability distributions [48]. Several non-probabilistic approaches, such as fuzzy set theory [49], interval analysis [50], Dempster–Shafer evidence theory [51], and probability boxes [52], have been used to quantify the so-called epistemic uncertainty due to lack of knowledge/data in reliability assessment. Experts' knowledge and reliability data collected across multiple hierarchical levels of engineering systems have been merged to achieve system-level reliability assessment [53, 54]. Challenges faced in this scenario, including data overlapping, data dependency, and conflict of imprecise knowledge from multiple sources, have to be addressed [55, 56].

Summarizing the materials presented earlier in this section, we can see that lifetime data have been utilized to fit lifetime distributions, capturing the uncertainty in the lifetime of identical objects. Such distributions have been used to optimize PM (e.g. inspection intervals) in engineering system reliability assurance. When failure data are insufficient, expert knowledge, information fusion, and Bayesian theory have been used to generate knowledge and models to enable the development of appropriate maintenance decisions for reliability assurance. The theoretical development in degradation

Table 1. The physics-based models for different types of components.

Products type	Failure mechanism	Physics-based models	Mathematical expression
Electronic products	Thermal failure	Arrhenius model [64]	$L = A \times e^{\frac{E_a}{kT}}$
		Eyring model [65]	$r = \frac{kT}{h} \times e^{\frac{\Delta S}{R}} \times e^{-\frac{\Delta H}{RT}}$
		Power law model [66]	$L = B \times S^{-n}$
	Electrical failure	Electro-migration model [67]	$\mathrm{MTTF} = A \cdot j^{-n} \cdot \exp\left(\frac{E_a}{kT}\right)$
Mechanical products	Fatigue failure	Basquin model [68]	$\sigma_a = CN_f^{-b}$
		Coffin–Manson model [69]	$N_f = C \times (\Delta\varepsilon_p)^{-m}$
		Halford model [70]	$\frac{\Delta\varepsilon}{2} = \frac{\sigma_f'}{E}(2N_f)^b + \varepsilon_f'(2N_f)^c$
		Marco–Starkey model [71]	$\frac{\Delta\gamma}{2} = \frac{\tau_f'}{G}(2N_f)^b + \gamma_f'(2N_f)^c$
	Wear failure	Archard model [72]	$Z = k\frac{Fv}{A_s H}$
		Crack growth model [73]	$\frac{da}{dN} = C(\Delta K)^m$
	Creep failure	Power law creep model [74]	$\dot{\varepsilon} = A\sigma^n$
		Sinusoidal creep model [75]	$\dot{\varepsilon} = A\sinh\left(\frac{\sigma}{\sigma_0}\right)$
	Corrosion failure	Uniform corrosion model [76]	$m = \frac{MIt}{nF}$
		Paris model [77]	$\frac{da}{dN} = C(\Delta K)^m$
	Fracture failure	Stress–strength model [78]	$F = P\{C < S\} = \int_{-\infty}^{\infty} f_C(c)\left[\int_C^{\infty} f_S(s)\mathrm{d}s\right]\mathrm{d}c$
		Norton model [79]	$\dot{\varepsilon} = B\sigma^n$

analysis is very much in line with the philosophy of PHM and PdM for data-driven approaches for reliability assurance.

Fuzzy set theory, interval analysis, Bayes theorem, and Dempster–Shafer evidence theory all provide innovative ideas for data and information fusion. With the advancement of sensing technology, communication technology, computing technology, and AI in today's society, we are in the era of being able to fully utilize various types of knowledge and data, including abstract, descriptive, photos, videos, high-frequency measurements, and failure data. PdM for operating engineering systems has the largest opportunity to realize its fullest potential in cost-effective assurance of the functionality, safety, and reliability of engineering systems.

The philosophy of RCM is now as useful as before. We can choose and deploy the right maintenance strategy to the right application scenario, be it RM, preventive replacement, PM, periodic inspection, online continuous CM, or redesign. The upcoming intelligent PHM agent is capable of safeguarding the reliability of each heterogeneous individual engineering system [57].

2.2. *Physics-based methods*

The statistics-based methods reviewed in the earlier section rely on the premise that the operating condition or the loading condition is relatively stable or within a narrow-specified range. The loading conditions of an object may be thermal stress, mechanical stress, electromagnetic stress, fluid stress, or chemical stress. When an engineering system is in field operation, its stress is rarely constant and often has a wide fluctuation range. Such stress variations cause the lifetime distributions, which statistics-based methods depend on, to be inaccurate enough in practical applications. To address these challenges, researchers have studied stress physics, failure modes, and their lifetime implications on certain materials. Physics-based methods aim to capture the relationship between the lifetime of a type of object and its stress levels.

For electronic products, their failure modes may include corrosion, fatigue, and electromigration [58]. For mechanical components, their failure modes may include material yield, stress fracture, corrosion, wear, creep, shock, and fatigue [59]. Many studies have been conducted to model degradation phenomena by physics-of-failure methodologies under different stress conditions [60, 61]. Physics-based models have also been utilized to model the degradation processes/failures of mechanical components, such as bearings, rotors, and gears [62, 63]. For different types of products, their common failure physics models are shown in table 1.

The equations in table 1 provide empirical relationships between the corresponding average life and a constant stress level. In field applications, a component or material may experience different stress levels throughout its lifetime. If one can record and divide the experienced stress of a material into n levels, that is, s_1, s_2, …, and s_n, and the corresponding average lifetimes under these stresses are μ_1, μ_2, …, μ_n, respectively, then the so-called damage accumulation model may be used to estimate the average RUL (expressed as a percentage) of mechanical materials using its discrete stress histories, which can be expressed as [80]:

$$\mathrm{RUL}_{\%} = 1 - \sum_{i=1}^{n} \frac{t_i}{\mu_i}, \tag{3}$$

where t_i is the time span during which the applied stress level is s_i and μ_i is the mean life or characteristic life of the material if the applied stress is maintained at the constant level s_i, for $i = 1, 2, \ldots, n$.

The models reviewed above in this section have linked the average life of the target component or material with the stress level based on the failure modes and the failure physics. These models provide the central tendency of a population of components under the same level of stress. If the load histories are measured, recorded, and grouped into discrete narrow intervals, the damage accumulation model can indicate roughly how much percentage of the average life is left for this component. The uncertainty in this RUL percentage depends largely on the standard deviation of the lifetime distribution of the material under various constant stress levels. Thus, the physics of failure models provide useful knowledge on general life consumption due to load, but are incapable of providing accurate RUL estimation for individual components. There are reported efforts to expand the physics-based models into probabilistic physics-of-failure models that provide rigorous frameworks accounting for such uncertainties and model inaccuracies [81, 82].

Generally speaking, the philosophy of physics-based models reviewed in this section is in line with the philosophy of PHM and PdM, as the loading histories experienced by the target components are used in maintenance decision-making for the objective of reliability assurance [83].

As mentioned earlier in section 1, PHM aims to utilize historical data, current health assessment, and predictive information through the process of monitoring the operation of engineering systems, evaluating their dynamic health status, detecting early faults, diagnosing fault types and locations, tracking the degradation process, predicting future degradation trends, estimating the RUL, and providing effective timely failure prevention maintenance actions [84]. In other words, it aims to utilize knowledge and data in all relevant areas, including lifetime distributions, physics-based models, and data-driven models [85].

Traditional reliability assurance methods, while foundational, are increasingly challenged by the complexities of modern engineering systems. The dependence of these methods on stable operating conditions and homogeneous populations restricts their applicability to systems exposed to variable loads and heterogeneous environments. Furthermore, these traditional approaches do not utilize real-time, multi-modal sensor data, leading to generalized, population-level assessments and decisions that are usually not optimal for individual components or systems. However, the emergence of intelligent reliability assurance represents a paradigm shift. By integrating real-time data acquisition, adaptive algorithms, and autonomous decision-making, intelligent PHM enables PdM tailored to individual system conditions. This transition addresses the limitations of traditional frameworks and paves the way for intelligent reliability assurance methodologies, which are to be elaborated in detail in the following section.

3. Intelligent reliability assurance approaches

Some of the methods reviewed above have shown intentions of coming up with maintenance decisions based on the health conditions of the target system. To be able to assess the health status of a running device, we must rely on timely quality data. Recent advances in sensor technology and communication technology have enabled the collection of huge volumes of various types of data. Yet, the abundance of data brings with it new demands in terms of storage, transmission, and processing. Therefore, an intelligent data acquisition process—capable of capturing quality data for health assessment and fault diagnosis while minimizing redundancy—is critical.

The data acquisition process is governed by three critical parameters: sampling frequency, sample length, and segment interval (figure 2). The sampling frequency (Hz) dictates temporal resolution, wherein a higher frequency enhances fault detection sensitivity at the expense of increased computational and storage requirements. Sample length, defined as the number of data points per segment, influences analytical precision, with larger sample lengths improving signal fidelity but demanding greater processing resources. The segment interval determines sampling continuity, wherein shorter intervals are closer to continuous monitoring while proportionally increasing data volume. Collectively, these parameters must be selected properly to optimize the trade-off between detection accuracy, computational efficiency, and storage costs.

The combinations of these three sampling parameters form the foundation of two primary data acquisition strategies: fixed and dynamic (see table 2). Fixed data acquisition uses fixed values of these three parameters. Dynamic data acquisition, often enabled by smart sensors, allows real-time adjustments in these sampling parameters based on observed anomalies or system operating conditions. Under normal conditions, low-frequency sampling and long segment intervals reduce data load. When anomalies are detected, sensors switch to higher-resolution modes to capture fault-relevant data for in-depth analysis. Such adaptive strategies maximize data utility while minimizing consumption of storage and computational resources.

With appropriate acquisition strategies in place, quality data becomes available. The approaches like PHM and PdM can utilize these data to drive improvements in fault detection, health assessment, RUL prediction, and maintenance decision-making, which are to be reviewed in later sections. Figure 3 provides the taxonomy of subsequent sections, which are components of the intelligent reliability assurance approaches.

3.1. Fault detection and fault diagnosis

Fault detection refers to the detection of the initiation or early progression of a certain or a combination of failure modes. Such faults are in their early stages of development, and they have not negatively affected the satisfactory performance of

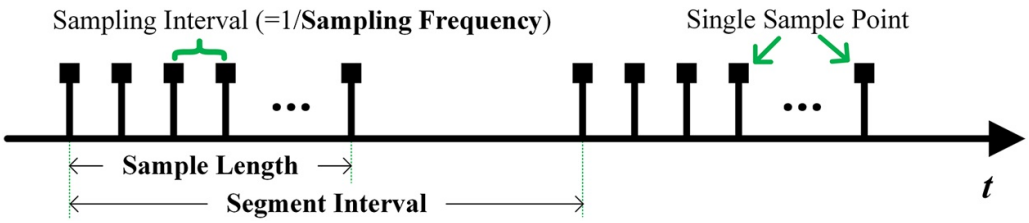


Figure 2. Data acquisition parameters in a sampling process [86].

Table 2. Comparison of fixed vs dynamic data acquisition strategies.

Strategy	Parameter values	Advantages	Limitations	Application
Fixed acquisition	Predefined	Simple implementation; consistency	Data redundancy	Stable systems
Dynamic acquisition	Real-time adaptive adjustment	High efficiency; transient response	Needs edge intelligence	Dynamic systems

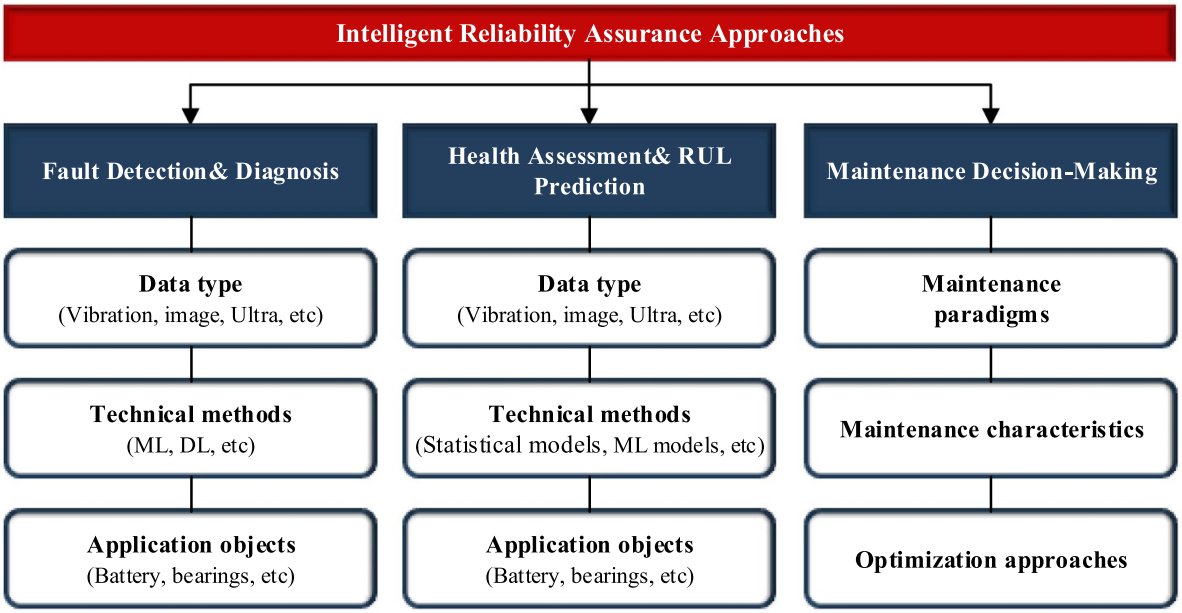


Figure 3. Taxonomy of intelligent reliability assurance approaches.

the system yet. Fault diagnosis refers to the identification of the dominant failure mode that has caused the health deterioration. The key point here is early fault detection and early fault diagnosis. Though faults have occurred, failure has not occurred yet. Such early fault detection and fault diagnosis are supposed to provide us with adequate lead time to take appropriate prevention measures at the right time so that system failures are prevented, asset value is fully utilized, and overall maintenance cost is minimized. In the following, we refer to fault detection and fault diagnosis methods as diagnostic methods.

Reported diagnostic methods rely on advanced data analytics and algorithmic models to capture subtle variations in system health conditions and rapidly identify the dominant fault types or fault locations. These methods possess diverse characteristics depending on the available data types, the adopted algorithmic techniques, and optimization strategies targeting specific application systems. Hybrid approaches that integrate data-driven methods, physics-based models, and multi-source data fusion offer enhanced adaptability and robustness while achieving notable progress in uncertainty quantification.

We next examine reported methods for fault detection and fault diagnosis from three dimensions, namely, the used data type, the adopted technical approach for data analysis, and the monitored equipment object, as illustrated in figure 4. First, these methods are categorized based on the used data types such as vibration, image and video, acoustic emission, and current signals, as well as the fusion of multi-modal signals. Next, we examine the adopted technical approaches, including traditional ML approaches and DL approaches. Finally, we classify these methods according to the application objects such as batteries, bearings, gas turbines, and wind turbines.

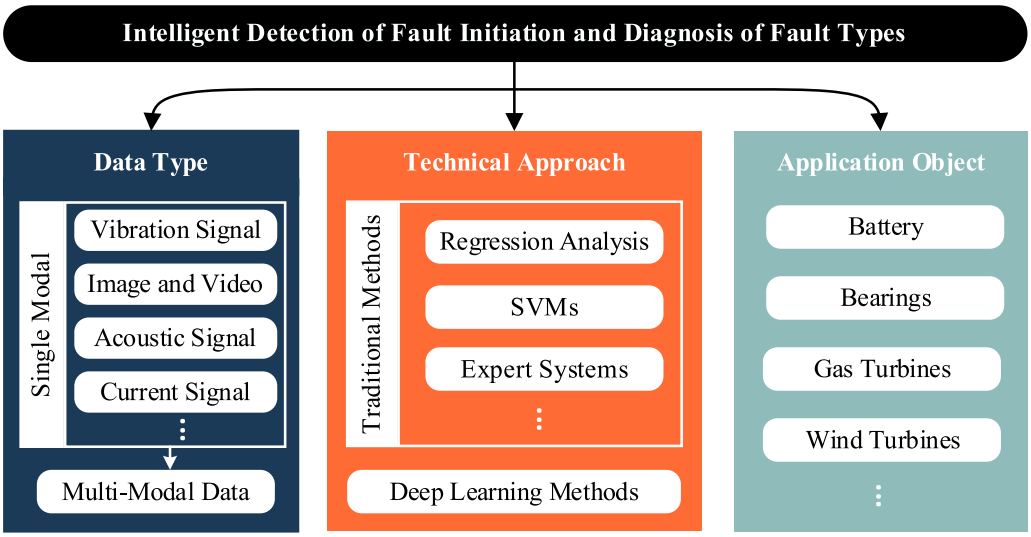


Figure 4. Multi-dimensional taxonomy of fault detection and fault diagnosis methods.

3.1.1. Categorization in terms of types of data used. The type of data used in diagnostic methods directly determines the input features of the input data. Different data types have different characteristics and carry different information codes about the system's health and operation conditions. Different data types may require different data acquisition methods. Different data types may be suitable for different application objects and application scenarios. This section examines reported applications of vibration signals, images and videos, acoustic emission signals, current signals, and multi-modal data fusion in reported diagnostic methods.

(1) Vibration signal

Vibration signals directly reflect the energy fluctuations during the operation of machinery, making them particularly suitable for rotating and reciprocating machinery. Fault modes such as wear, impacts, and imbalance often induce changes in acquired vibration signals, typically manifested in amplitude, frequency, and phase characteristics of such signals.

The analysis approaches for vibration signals include time-domain, frequency-domain, and time–frequency domain techniques. Time-domain methods utilize statistical features (e.g. mean, variance, kurtosis) to assess the overall signal characteristics [87–92]. These statistical features are called time-domain features. Frequency-domain methods employ Fourier transforms to reveal the periodic components and harmonic features in the frequency domain, useful for the identification of typical fault frequencies [93–96]. Such features obtained in the frequency domain are called frequency features. Time–frequency domain methods, such as short-time Fourier transform and wavelet transform, capture the transient characteristics and multi-scale features of signals [97–101], resulting in time–frequency features. Intelligent methods for vibration signal analysis have used raw vibration signals, time-domain features, frequency-domain features, and/or time–frequency features as inputs. For example, CNN can directly extract deep features from time-series signals or spectrograms [88], while SVM classifies faults using extracted time–frequency features [102]. Furthermore, temporal models such as recurrent NNs excel at processing dynamic information in long sequences [88], enabling the capture of the temporal evolution of fault characteristics. In complex working environments with multiple faults or overlapping fault frequencies, integrating multi-channel vibration signals [103] enhances the robustness and generalization capability of diagnostic methods.

(2) Image and video data

Image and video data provide visual images of surfaces and structures, making them suitable for detecting surface defects (e.g. cracks, corrosion, wear) and tracking their visual changes [104–107]. Their high resolution, intuitiveness, and dynamism are their unique advantages for visual inspection and dynamic visual monitoring. Thermal images, for instance, can reveal potential faults induced by friction or overheating, supplementing the detection of internal abnormalities [108].

Image-based diagnostic methods utilize image preprocessing to enhance data quality [109] and rely on feature extraction to obtain key fault characteristics [110]. Image data are often first transformed into feature-space representations for fault classification and localization. For example, Yang *et al* [104] first preprocessed images to extract crack features under varying lighting conditions and then employed fully convolutional NNs for image classification or segmentation to simultaneously identify and measure various cracks. For thermographic data, extracting thermal distribution features can reveal potential issues caused by internal friction or thermal runaway [110]. When video data is available, diagnostic methods can track the dynamic behavioral changes over time. Temporal models or 3D convolutional NNs [111, 112] extract spatiotemporal features from video data, supporting the accurate detection of fault initiation points. Additionally,

integrating information from multiple video frames improves the analysis of complex motion behaviors [113].

(3) Acoustic emission signal

Acoustic emission signals, characterized by high-frequency properties and strong penetration, are widely applied in detecting material internal defects and early faults. Their effectiveness lies in their high sensitivity to minute defects (e.g. cracks, voids) and accurate reflection of internal structural states in metals and composites.

Time-domain methods have been developed for acoustic emission signal analysis to rapidly locate defect positions and assess the fault severity by analyzing echo delays, amplitudes, and shapes [114, 115]. Frequency-domain methods have been used to extract spectral features for quantitative defect description [116], while time–frequency analysis methods enhance resolution in complex environments [117]. Ultrasonic data and the corresponding analysis techniques are particularly suitable for scenarios requiring high precision in detecting internal defects, such as welds and corrosion [118, 119]. However, their application is costly and susceptible to energy attenuation and background noise interference [120], often necessitating integration with other data types for comprehensive diagnostics.

(4) Current signal

Current signals have been used for fault detection in motors. They are easily accessible, cost-effective, and applicable for real-time monitoring of operating states and fault characteristics. Faults like rotor imbalance or winding short circuits cause variations in the amplitude, frequency, or phase of the current signals, providing crucial clues for fault diagnostics, particularly for early fault detection.

Current signal-based diagnostic methods exploit the interaction between electrical and mechanical components in motor-driven systems. Stator turn faults disrupt the uniformity of the electromagnetic field, leading to identifiable second harmonic distortions in the current spectrum [121]. In contrast, power connector faults manifest as transient signal spikes caused by intermittent contact resistance, which can be detected using prognosis models [122]. Inverter-interfaced microgrids experience dynamic instabilities reflected in current fluctuations, making transient analysis an effective tool for fault detection [123]. Moreover, rotor imbalance and bearing faults introduce characteristic modulations in current signals due to their influence on the motor's electromagnetic torque, enabling advanced classification techniques such as linear discriminant analysis to enhance diagnostic precision [124]. By leveraging the frequency-domain characteristics of current signals in conjunction with motor slip estimation, these approaches improve fault identification and isolation in complex operating conditions.

(5) Multi-modal data fusion

Sometimes, single data types have inherent limitations in diagnostic accuracy and applicability. Multi-modal data fusion overcomes these constraints by integrating information from multiple types of data, such as vibration, image, ultrasound, and others as applicable, thereby providing a more comprehensive understanding of system health status.

Reported multi-modal data fusion approaches can be categorized into data-level fusion, feature-level fusion, and decision-level fusion. Data-level fusion combines raw data from different modalities to form a unified dataset, preserving the completeness and richness of each modality. Representative methods such as signal synchronization and data alignment have been applied in variable-speed machinery diagnosis [125] and validated under deep multimodal learning frameworks [126]. Feature-level fusion integrates extracted feature vectors across modalities to capture cross-domain correlations. For example, Xiao *et al* proposed a hierarchical fusion framework that unifies multisensor features for rotating machinery diagnosis [127], offering a structured approach to feature integration. Decision-level fusion integrates diagnostic results from each modality through weighted voting, logistic regression, or random forest methods. These methods have been successfully implemented in multimodal attention-based fault diagnosis [128] and systematically reviewed in intelligent multi-sensor fusion contexts [129], offering greater flexibility and computing efficiency.

Building on the discussed data types, vibration signals effectively detect mechanical faults but are noise-sensitive. Image and video data enable visual defect tracking, yet environmental factors limit reliability. Acoustic emission signals excel in internal defect detection but face cost and noise challenges. Current signals offer cost-effective motor diagnostics, though system-specific. Multi-modal fusion enhances accuracy but requires complex integration.

3.1.2. Categorization in terms of techniques used. The development of diagnostic methods relies on continually evolving technical approaches and computing algorithms. From traditional regression analysis to modern DL techniques, advancements in these technical approaches have significantly improved the accuracy and adaptability of diagnostic methods. This section examines these approaches, ranging from rule-based approaches, statistical modeling approaches, traditional ML approaches, to DL approaches, discussing their application characteristics and advantages in fault detection and fault diagnosis.

(1) Rule-based approaches

Rule-based approaches use expert knowledge and heuristic 'if-then' rules to infer faults based on machine characteristics and fault patterns. While easy to implement and interpret, its applicability is limited by the predefined rule set, making it less effective for complex or unknown faults. It is most suitable for detecting and warning known or simple fault types.

Guo *et al* devised a diagnosis strategy for variable refrigerant flow systems based on expert rules, with the knowledge derived from expert insights and system characteristics and encompassing 10 rules for the outdoor unit and 12 for the indoor unit [130]. This method, which requires no training

process and is computationally simple, enables easy integration into the building's automatic control system for online fault diagnosis, achieving an overall diagnostic accuracy of over 85%. In situations where constructing effective rules is challenging, Chen *et al* developed a case-based reasoning system with a novel similarity measure for fault diagnosis of aero-engines, retrieving 143 accurately diagnosed cases of successfully resolved faults [131]. The system integrates a semantic graph to capture the relationship between fault parts and fault modes within the aero-engine tree structure, demonstrating high retrieval accuracy.

(2) Statistical modeling approaches

Statistical modeling approaches are widely applied in fault diagnosis by establishing mathematical relationships between operational parameters and fault characteristics to detect anomalies and predict fault trends. These methods effectively infer system states under data uncertainties by leveraging probabilistic distribution models. Statistical modeling is particularly useful in scenarios where noise or incomplete data must be handled.

Regression analysis is one of the earliest statistical methods in fault diagnosis, aiming to establish mathematical relationships between operational indicators and fault severity for trend prediction and early detection. Pandya *et al* applied multinomial logistic regression to wavelet packet transform features of vibration signals in mechanical systems [132], identifying microscopic local defects in bearings and classifying normal and faulty states with multiple fault types. Jiang and Yin employed principal component analysis-optimized recursive regression methods to enhance the detection efficiency of vehicular cyber-physical systems [133], enhancing suitability for complex, real-time scenarios. Jufri *et al* applied regression on expected power generation under solar irradiance as input to an SVM model for anomaly detection in photovoltaic systems [134], providing a cost-effective and high-performance fault detection solution. Spataru *et al* employed regression models to predict online parameters of photovoltaic arrays [135], detecting power losses by comparing predicted and measured output power values. Principal component analysis is also a widely used technique in fault diagnosis, focusing on reducing data redundancy through dimensionality reduction by extracting key features. Bencheikh *et al* used reduced kernel principal component analysis to minimize redundancy in temperature, pressure, speed, and current signals [136], significantly enhancing the robustness and sensitivity of fault diagnosis in cement rotary kilns.

(3) Traditional ML

Traditional ML approaches diagnose faults by learning from historical data to extract fault characteristics and classify operational states. These methods identify fault patterns by analyzing data and distinguishing between normal and faulty states based on learned features. Traditional ML approaches do not rely on domain knowledge and can handle complex fault patterns, and they have unique advantages depending on application scenarios and data characteristics.

SVMs are classification methods based on statistical learning theory, separating fault patterns by constructing optimal hyperplanes in high-dimensional space. Their core concept is identifying decision boundaries that maximize the classification margin, ensuring strong generalization. SVM-based models are widely used for fault diagnosis in bearings, gearboxes, motors, and rotor systems [137–140], with improvements focusing on enhancing SVM models and improving optimization algorithms. Model enhancements have led to advanced versions addressing diverse diagnostic needs. Li *et al* improved SVM with least squares to enhance computational efficiency in planetary gearboxes [141, 142], while Qiao *et al* tailored one-class SVM focusing on efficient anomaly detection only instead of fault diagnosis [143]. Heidari and Li *et al* developed Wavelet SVM and multi-kernel SVM to address the non-stationary signals of gearboxes and the operational data deviations, such as temperature and flow, in gas turbines [144, 145]. On the other hand, algorithmic optimizations further increase SVM applicability and efficiency, particularly for high-dimensional data and complex diagnostic scenarios. Cuong-Le *et al* introduced particle swarm optimization to improve the training efficiency [146]. Yin and Li *et al* developed heuristic search algorithms for model parameter selection [147, 148], while Alcaraz *et al* designed a bi-objective evolutionary algorithm to optimize feature selection in SVM models [149].

ML methods have offered valuable alternatives for addressing diverse diagnostic challenges. Gohari and Eydi employed k-nearest neighbor and decision tree algorithms to detect shaft unbalance under conditions of small sample sizes and clear feature distributions [150]. Praveenkumar *et al* utilized decision trees to model normalized time-domain vibration data, achieving efficient gearbox gear fault recognition [151]. Zhang *et al* further combined this approach with weighted minority oversampling to improve diagnostic accuracy under imbalanced data conditions [152]. Tang *et al* applied random forests to model fault characteristic vectors of rolling bearing envelope spectra [153]. Mayadevi *et al* used fuzzy clustering to describe the boundaries of extracted parameters under different fault conditions, enabling the detection and diagnosis of drive faults in an induction motor drive system [154]. Dattachaudhuri *et al* incorporated domain knowledge of different non-healthy states into an NN through the construction of an expert system [155], enhancing the interpretability of the diagnostic results and addressing the 'black-box' issue inherent in the diagnostic process [156].

(4) Deep learning

DL approaches have gained attention for processing large-scale, complex data. It automatically extracts features from raw sensor data and models nonlinear relationships through multi-layer NNs, effectively identifying hidden fault characteristics. Despite high diagnostic accuracy, these methods demand substantial computational resources and large

datasets, making them ideal for large-scale industrial systems and complex fault diagnosis.

Jin *et al* used deep belief networks to learn vibration components (Intrinsic Mode Functions) of train axle box bearings obtained via optimized variational mode decomposition, addressing weak fault diagnosis in train axle bearings [157]. Tian and Xu applied deep belief networks to process multisource signal features from both time and spatial dimensions, achieving fault diagnosis and early warning for reciprocating compressors [158]. Ruan and Choudhary *et al* employed CNNs to extract spatial and temporal features of bearing vibrations and acoustic signals [159, 160]. Wang, Chen, and Yang *et al* employed different variants of autoencoders to learn low-dimensional data representations for energy systems and rotating machinery [161–163], facilitating data compression and feature extraction. Dao and Wang *et al* applied long short-term memory and GRUs to capture long- and short-term dependencies in time-series data [164, 165], improving the accuracy of hydroelectric turbine fault diagnosis and nuclear power plant diagnostics when combined with graph convolutional networks. Fang and Du *et al* utilized generative adversarial networks to generate high-quality synthetic data [166, 167], enhancing diagnostic accuracy for analog circuits and HVAC systems under limited fault data. Imane *et al* further combined dual-threshold attention to diagnose under speed fluctuation conditions [168]. Despite challenges such as training instability, DL's exceptional feature extraction capabilities and flexible architectures offer immense potential for improving diagnostic accuracy and robustness in complex scenarios.

Following the reviewed diagnostic techniques, rule-based approaches offer interpretability but struggle with complex faults due to rigid rule sets. Statistical modeling excels in handling noisy data, yet its reliance on predefined relationships limits its adaptability. Traditional ML provides robust classification but requires manual feature engineering. Deep learning automatically extracts complex features, achieving high accuracy in large-scale systems, but it demands significant computational resources.

3.1.3. Categorization in terms of application objects. By application objects, we refer to the target engineering system whose safe and reliable performance needs to be ensured. To achieve effective fault detection and fault diagnosis on such systems, we must utilize their unique features in structure, working physics, failure modes, and operation environment dynamics. As a result, many diagnostic methods tailored to specific application objects such as batteries, bearings, gas turbines, and wind turbines have been reported. In the following, we review reported diagnostic methods for some of these application objects.

(1) Battery

Battery faults typically fall into three categories: overcharging, over-discharging, and internal or external short circuits. These faults, if not detected and corrected early, cause safety issues and reduce battery lifespan. Reported diagnostic methods for batteries can be divided into threshold-based methods, model-based methods, and data-driven methods.

Threshold-based diagnostic methods monitor key battery parameters (e.g. voltage, current, and temperature) to detect when they exceed predefined thresholds and thus identify faults [169, 170]. This method is simple, highly responsive, and effective in quickly addressing common faults such as overcharging and over-discharging, preventing severe safety incidents. However, its limitations lie in its reliance on latent symptoms and its dependency on pre-defined threshold settings, which may lead to misjudgments or missed detections. Model-based diagnostic methods rely on mathematical models of the battery's physical and chemical behaviors, including electrochemical models, equivalent circuit models, and black-box models. Electrochemical models use a series of highly nonlinear differential equations to describe the internal material transport and exchange processes of the battery [171]. While this approach can offer a deeper analysis of battery dynamics during charging and discharging, it is costly and difficult to implement. Equivalent circuit models use combinations of resistors, capacitors, and inductors to simulate the dynamic characteristics of the battery [172, 173]. These models are simple and computationally efficient, making them the most widely used in practice, though they have weak physical significance and limited capability for diagnosing complex faults. Data-driven models, on the other hand, use large amounts of current and voltage data and DL approaches [174, 175] to characterize the input-output relationship of the battery. This intelligent diagnostic approach can handle complex nonlinear relationships, but its excessive reliance on training data may pose challenges in adapting to new conditions.

(2) Bearing

Bearings are critical components in rotating machinery, directly affecting system performance and lifespan. Common faults such as pitting, cracking, wear, and lubrication failure can lead to increased vibration, noise, and even machine downtime. Many diagnostic methods for bearings have been reported in the literature [176–178]. These methods can be divided into signal processing-based methods and AI-based methods.

Signal processing-based methods tap into the time domain and the frequency domain of CM signals such as vibration, acoustic emission, and temperature to detect and diagnose faults [179–181]. These methods typically use time-domain, frequency-domain, and/or time–frequency domain feature extraction techniques, such as envelope analysis, wavelet transforms, and empirical wavelet decomposition, to extract characteristic frequencies of fault patterns [182–184]. These methods are simple to implement and particularly effective for stationary signals. However, they are sensitive to noise and highly dependent on effective signal preprocessing and feature extraction, making them less adaptable to complex and/or non-stationary operating conditions. AI-based diagnostic methods are data-driven, automatically extracting fault features and classifying them using ML and DL technologies.

Traditional ML methods, such as SVM and random forests [185, 186], rely on manually designed features and classification models, making them suitable for structured data diagnosis. Recently, DL methods have emerged [187], capable of automatically learning complex features from multi-dimensional, unstructured data, enabling end-to-end fault diagnostics. AI-based methods excel at handling complex nonlinear problems and multi-source data, particularly under conditions involving multiple faults and dynamic operating scenarios. However, these methods require high-quality training datasets and computing resources, and there are higher demands for model interpretability and generalization of these models.

(3) Gas turbine

Gas turbines play a critical role in power generation, aircraft propulsion, and transportation. Despite extensive research on gas turbine health management, diagnostic methods specific to these applications often have limitations due to their dynamic operating conditions. This section discusses diagnostic methods for gas turbines used in power generation and aircraft turbofan engines.

Gas turbines are key equipment in power generation systems. Early fault detection is crucial to ensure continuous power generation, reliability, and safety [188]. Combustion systems and hot gas path components are key parts, as high temperatures and fluctuating fuel flow rates can easily lead to faults [189]. Methods such as extreme learning machine and stacked denoising autoencoders have proven effective for early fault detection in gas turbines [190]. Additionally, clustering analysis methods, such as hierarchical clustering and self-organizing map NNs, have demonstrated better performance than traditional principal component analysis [191]. Deep NN models have achieved significant results in predicting RUL for various applications, but they are often limited to single faults [192]. To address this, anomaly detection and RUL estimation methods based on SVM and long short-term memory NN have emerged, capable of integrating the effects of multiple faults [193]. Additionally, due to the lack of labeled data, semi-supervised statistical models based on DL have been proposed to detect anomalies by performance differences [194]. Advanced techniques based on DL and clustering analysis can cope with complex dynamic operating conditions [195].

(4) Wind turbine

Wind turbines are key equipment in renewable energy generation, and their performance directly affects energy production. Common faults include gear wear, lubrication failure, and bearing damage, which can result in increased vibration, noise, or downtime. Wind turbine fault diagnostic methods can be generally categorized into model-based, signal-based, and data-driven approaches.

Model-based methods involve establishing physical or mathematical models to simulate the operational states of wind turbines, thereby identifying potential faults. These methods typically use dynamic models, fault models, or system simulations to detect anomalies by comparing normal and faulty states. In recent years, nonlinear dynamic models have been applied to analyze gearbox faults [196]. However, due to the complexity of wind turbine systems, these models face challenges in terms of modeling accuracy and adaptability. Finite element method simulations have also been used for dynamic simulations [197] to model the dynamic response of gearbox faults, achieving good detection results. Although model-based methods provide in-depth physical explanations, their complexity and accuracy requirements make them difficult to apply in real-world, dynamic operating environments. Signal-based methods analyze signals such as vibration, noise, and temperature generated by wind turbines during operation to identify faults. These methods extract characteristic fault frequencies or patterns using time-domain, frequency-domain, or time–frequency-domain analysis techniques [198, 199]. The advantages of these methods lie in their real-time capabilities and ease of implementation, especially for early fault detection. However, they are highly sensitive to noise and have poor robustness in complex conditions, requiring strong signal preprocessing capabilities. Data-driven methods have emerged with the rapid development of AI technologies. These methods analyze large volumes of operational data to automatically extract potential fault features, classify them, and make predictions. Deep NNs have been widely applied to process SCADA data and vibration signals from wind turbines [200]. These techniques can effectively detect gearbox faults and other fault modes. Data-driven methods using SCADA data and ML techniques to model and extract fault features from massive datasets, identifying abnormal patterns in wind turbine operations. They offer efficient and flexible advantages [201].

Building on the exploration of diagnostic methods, battery diagnostics balance simplicity in threshold-based methods against adaptability in data-driven models, yet struggle with complex fault detection. Bearing diagnostics excel in signal processing for stable conditions but falter under noise, with AI methods offering versatility at the cost of data dependency. Gas turbine diagnostics leverage deep learning for dynamic environments, though often limited to single faults. Wind turbine methods, spanning from model-based to data-driven, provide insights but face complexity and noise challenges.

To summarize, we have reviewed intelligent reliability assurance approaches in the aspect of fault detection and fault diagnosis. Our next section focuses on health assessment and RUL prediction.

3.2. Health assessment and RUL prediction

With the rapid development of Industry 4.0 and smart manufacturing, intelligent health assessment and RUL prediction have become popular research topics in fields such as mechanical engineering, electronics, and energy [202, 203]. By leveraging advanced data analysis and modeling techniques, the efficiency and accuracy of health assessment and RUL prediction can all be improved. This section provides an overview of research on intelligent health assessment and RUL prediction from the three perspectives of data types, technical approaches, application objects, and uncertainty quantification. Figure 5 provides the multi-dimensional taxonomy of this

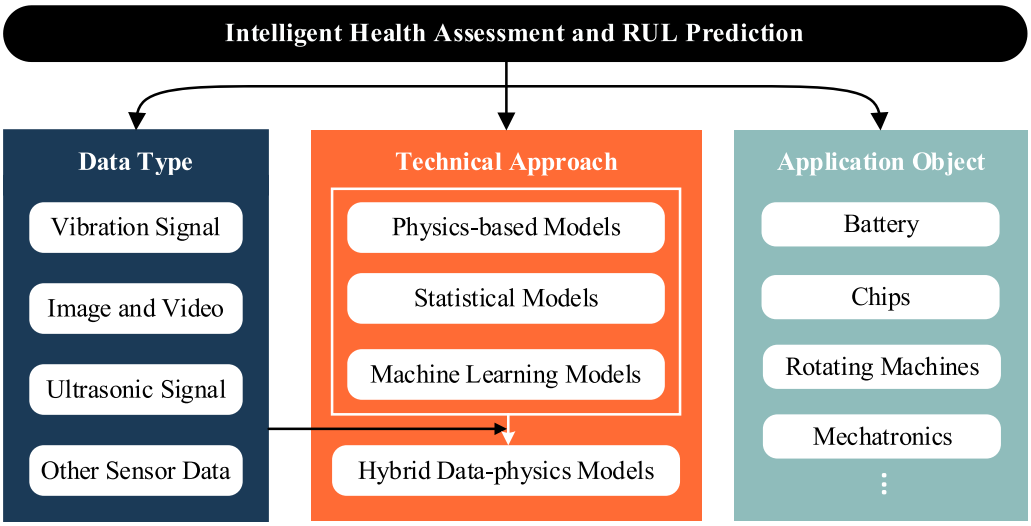


Figure 5. Multi-dimensional taxonomy of health assessment and RUL prediction.

section of the review focusing on health assessment and RUL prediction.

3.2.1. Categorization in terms of types of data used. The type of data plays a crucial role in shaping the analysis approaches and determining the effectiveness of the models employed. Different types of data can provide unique insights into the health condition of engineering systems. The primary categories of data types are as follows.

(1) Vibration data

Vibration data reflects the dynamic behavior of mechanical components, capturing degradation phenomena such as wear and fatigue. By applying time-domain, frequency-domain, and time–frequency analyses, characteristic patterns of faults can be extracted, enabling early detection and risk mitigation. Yin *et al* [147] proposed a health assessment method that utilizes genetic algorithms and support vector data descriptions to predict RUL based on vibration trends. Aivaliotis *et al* [62] integrated physical gear models with vibration-based monitoring to quantify uncertainty in RUL prediction, enhancing estimation accuracy. Aydemir and Acar [192] introduced an anomaly monitoring strategy that identifies critical shifts in vibration signals, marking degradation onset and improving RUL estimation under varying conditions. Ruan *et al* [92] developed a lightweight CNN optimized for vibration-based fault diagnosis and RUL prediction, making real-time monitoring feasible in resource-constrained environments. These advancements reinforce the role of vibration data in PdM, enabling precise fault detection and RUL estimation.

(2) Image and video data

Image and video data play a crucial role in machinery CM and RUL prediction by providing direct visual insights into component degradation. Machine vision techniques enable surface texture analysis for fault detection, as reviewed by Liu *et al* [204]. Acoustic imaging using phased microphone arrays, discussed by Merino-Martínez *et al* [205], captures sound-based fault signatures that complement visual inspections. Optical microscopy offers high-resolution defect identification [206], while thermal imaging detects temperature anomalies indicative of early faults [207]. High-speed video further aids in analyzing dynamic failure mechanisms such as crack propagation and impact damage [208]. Recent advances in DL have enhanced image-based diagnostics using event-based cameras, as demonstrated by Li *et al* [209]. These developments significantly improve automated health assessment and RUL prediction, making image and video data a powerful complement to traditional vibration and acoustic methods.

(3) Ultrasonic data

Ultrasonic testing is a non-destructive technique that uses high-frequency sound waves to detect internal defects and assess material integrity. It is widely applied for identifying cracks, corrosion, and voids in structural components. Laser ultrasonic techniques enhance defect detection in composites by improving signal resolution and sensitivity [210]. Advances in non-destructive testing have improved defect characterization and material assessment [211]. Ultrasonic methods also enable early corrosion detection, reducing failure risks in industrial applications [212]. DL and computational models further refine the analysis of anisotropic acoustic properties, enhancing diagnostic precision [213]. In practice, ultrasonic-guided wave technology enables long-range pipeline corrosion monitoring with high accuracy [214]. In aerospace, laser ultrasonic testing ensures real-time structural integrity assessment for high-performance components [215]. Ultrasonic-based mechanical characterization techniques support damage evaluation in advanced composite materials, allowing precise assessment of internal structural changes [216].

(4) Other sensor data
In addition to the previously mentioned types, sensor data such as temperature, torque, and current are also useful for health monitoring, providing valuable insights into system behavior and operational conditions. In machining, tool CM in milling processes enhances product quality, reduces downtime, and extends tool life. It uses multi-sensors and ML to predict tool wear, breakage, and RUL, addressing challenges in sensor integration and data analysis. This allows for proactive maintenance and improved process efficiency [217]. Similarly, flexible temperature sensors are vital for wearable devices that monitor body temperature, which reflects human health status. These sensors, designed for real-time, sensitive detection, face challenges from environmental influences on body surface temperature. Advancements in sensor materials and fabrication have improved their sensitivity and accuracy, supporting better health assessment [218].

Building on the discussion of data types, vibration data remains fundamental for capturing mechanical degradation, enabling early fault detection and RUL estimation through time-domain, frequency-domain, and time–frequency analyses. Image and video data provide visual insights into component degradation, enhancing fault detection and RUL prediction with machine vision and deep learning techniques. Ultrasonic data enables non-destructive testing, detecting internal defects and assessing material integrity using high-frequency sound waves. Other sensor data, such as temperature, torque, and current, offer valuable insights into system behavior and operational conditions. Recent advancements in ML and data fusion have improved the accuracy and reliability of health monitoring and RUL prediction, though challenges remain in integrating multiple data types and ensuring scalability and robustness.

3.2.2. Categorization in terms of technical approaches.

Various approaches have been developed to achieve the health assessment and RUL prediction in academic literature. These prediction approaches can be categorized into four types: physics-based models, statistical models, ML models, and hybrid data-physics models [219].

(1) Physics-based model
Physics-based models rely on understanding the fundamental degradation mechanisms of materials and components [220]. These models are grounded in physical laws and principles, allowing for precise predictions under well-defined conditions. A common example is the Paris–Erdogan model [166], which describes crack growth in materials based on stress intensity factors. Furthermore, many improved versions of the Paris–Erdogan model have been introduced in the field of RUL prediction by capturing the relationship between crack propagation and stress cycles [221, 222]. Over time, several adaptations have emerged to enhance its applicability, including the Trantina–Johnson method [223, 224], which uses statistical approaches to construct relationships between stress variations and crack propagation; the Walker method [225, 226], which accounts for mean stress effects on crack growth rates; and the Forman method [227], focusing on surface crack growth through empirical relationships. Some physics-based models are grounded in wear mechanisms [228]. Models in this category often incorporate cumulative damage theories, such as Miner's rule [229]. While physics-based models can be highly accurate, their effectiveness is often limited by the complexity of the systems being modeled and the availability of detailed physical data.

(2) Statistical model
Statistical models focus on analyzing historical data to fit degradation trends and predict future performance [230]. These models of RUL prediction utilize data observations to characterize the probabilistic behavior of degradation processes, which fit available observations into random coefficients or stochastic process models using probabilistic methods [231]. Common statistical models include the auto-regressive models, Wiener process, Gamma process, Markov chain, and inverse Gaussian process [219]. Many review works of literature have systematically outlined the progress of statistical models in degradation modeling, emphasizing the challenges associated with incomplete data scenarios [232]. Here, we provide a brief overview of various models.

Auto-regressive models use past observations to predict future values, making them well-suited for time-series data where historical behavior influences future trends [233]. Auto-regressive models are particularly popular due to their simplicity and effectiveness, widely applied in fields such as finance, engineering, and climate research [234]. Wiener processes model continuous-time random motion, effectively capturing the random fluctuations affecting degradation over time [235]. The Gamma process models gradual, non-negative, cumulative degradation effectively and captures the stochastic variability in wear and fatigue, making it suitable for systems with continuous degradation trends [236]. Inverse Gaussian processes provide a flexible framework for modeling time until failure, accommodating varying degradation rates and non-linear trends [86]. This adaptability makes them particularly useful in applications where degradation patterns change over time. Markov chains model systems where future states depend only on current conditions [237]. This memoryless property enables the modeling of discrete degradation processes, making it suitable for decision-making for maintenance interventions.

Statistical models have good performance in scenarios with sufficient historical data. However, they may struggle to account for the physical mechanisms driving degradation, making them less effective in complex systems without well-defined statistical relationships.

(3) ML model
ML models have gained significant attention in health assessment and RUL prediction due to their powerful ability to

handle high-dimensional, nonlinear data [238, 239]. Unlike traditional physics-based or statistical models, ML models focus on learning machinery degradation patterns directly from available observations, making them particularly effective for complex systems. This data-driven nature enables remarkable flexibility in degradation relationship construction, providing good results even when detailed physical knowledge is limited [240].

ML models can be broadly categorized into shallow ML and DL [241]. In shallow learning methods, SVM is effective for classification tasks by finding optimal hyperplanes that separate different classes [242]. In addition, decision trees and random forests offer interpretability, allowing users to understand the decision-making process behind predictions [243, 244]. Expert systems represent another category within shallow learning approaches [245]. These systems use a knowledge base and a set of rules to simulate the decision-making ability of a human expert. In contrast, DL methods leverage NNs to automatically learn features from raw data, making them well-suited for more complex datasets [246, 247]. Techniques like CNNs [248] are good at processing image and video data, while recurrent NN [249], long short-term memory NN [250], transformer [251], and attention mechanism [252] effectively capture intricate temporal dependencies in degradation processes. These DL approaches often outperform shallow ML methods, particularly in scenarios characterized by non-linear relationships and high-dimensional feature spaces [253]. Moreover, the integration of multi-source data for DL frameworks enhances RUL prediction capabilities [254]. By combining data from various sources, such as vibration signals, images and videos, and environmental parameters, ML models can provide a more comprehensive assessment of the degradation process.

(4) Hybrid data-physics model

Hybrid models combine the strengths of the many models mentioned above, offering a robust framework for RUL prediction. These models attempt to incorporate the advantages of physical degradation mechanisms or statistical models while leveraging data to fine-tune predictions. Some studies first utilize ML and other methods to extract features from degradation data and construct health indicators. Subsequently, they apply stochastic degradation process models to analyze the related degradation trends, thereby predicting RUL [255]. Other studies incorporate degradation mechanisms into the construction of DL models, allowing prior knowledge of degradation to assist in evaluating degradation states [256]. This integration enhances the ability of DL methods to account for uncertainty in RUL prediction.

Building on the discussion of technical approaches, physics-based models offer accuracy under known conditions but depend on detailed system knowledge. Statistical models leverage historical data but falter with unclear degradation patterns. ML models handle high-dimensional, nonlinear data well but demand large datasets and high computation. Hybrid models combine these strengths for improved robustness, though their integration remains challenging. Current research trends favor data-driven and hybrid approaches, with key gaps in model adaptability and uncertainty handling.

3.2.3. Categorization in terms of application objects. Intelligent health assessment and RUL prediction are applied across various domains, each with its specific characteristics and challenges. We have listed four main categories of application objects, including batteries, chips, rotating machines, and mechatronics, as follows.

(1) Battery

With the rise of electric vehicles and renewable energy storage systems, precise battery health assessment and accurate RUL prediction have become critical. Battery degradation stems from factors such as charge cycles, temperature fluctuations, and electrochemical reactions, necessitating advanced predictive models for lifespan estimation and performance optimization. Recent studies have introduced innovative approaches to enhance battery health assessment. Li *et al* [257] developed a variant of long short-term memory NN, leveraging temporal dependencies in battery degradation data for improved state-of-health estimation and RUL prediction. Deng *et al* [258] proposed a physics-informed NN to model battery thermal dynamics, integrating electrochemical principles with ML for more accurate spatiotemporal predictions. Ge *et al* [259] conducted a comprehensive review of state-of-health estimation and RUL prognostics, highlighting the evolution from traditional empirical models to hybrid ML-based approaches. Gou *et al* [260] introduced a hybrid data-driven method, fusing statistical and ML techniques to enhance prediction robustness and adaptability across different operational conditions. These advancements significantly improve the reliability and accuracy of battery health assessment and RUL prediction, addressing key challenges in degradation modeling and optimizing battery management strategies.

(2) Chip

Chips serve as the processing core of modern electronic devices, playing a crucial role in applications ranging from smartphones and computers to medical instruments and industrial automation systems. Their reliability is of paramount importance, as failures can lead to severe functional disruptions in critical systems. Gupta *et al* [261] conducted a comprehensive analysis of system-on-chip architectures, highlighting how advancements in heterogeneous integration and power-efficient designs mitigate degradation effects while improving performance scalability. Ghoneim and Hussain [262] reviewed the development of physically flexible nonvolatile memory, showcasing its potential to enhance chip resilience in next-generation electronics, particularly for the Internet of Everything applications. Huang *et al* [263] investigated electromigration-induced degradation in power grid networks, integrating thermal stress modeling to improve chip-level reliability predictions. Their study provided valuable insights into mitigating failure risks in densely packed semiconductor circuits. These advancements not only deepen our understanding

of chip degradation mechanisms but also drive the development of more robust and adaptive semiconductor technologies, ensuring greater reliability and extended service life in modern electronics.

(3) Rotating machine

Rotating machines are widely used in industrial applications but are prone to degradation due to wear, fatigue, and continuous operation. Key failure modes can significantly accelerate deterioration if not identified early. Therefore, advanced health assessment and RUL prediction methods are essential for ensuring reliability and minimizing unexpected failures. Zhou *et al* [264] reviewed the RUL prediction methods with health indicator dependence for rotating machines to outline the current research status and state-of-the-art methods. Hou *et al* [265] used the difference mode decomposition to adaptively extract degradation features from vibration signals, facilitating long-term RUL prediction. Chen *et al* [266] developed an unsupervised health indicator to reduce the noise influence in the frequency domain, which improves feature extraction for degradation trend analysis, leading to more precise RUL estimation. Buzzoni *et al* [267] introduced a cyclostationarity-based blind deconvolution method, which enhances the tracking of progressive degradation in rotating components, enabling more reliable health trajectory modeling. By leveraging advanced signal processing, adaptive feature extraction, and hybrid physics-informed modeling, these methods significantly improve the accuracy of health assessment and RUL prediction for rotating machinery.

(4) Mechatronics

Mechatronic systems, combining mechanical, electronic, and computing elements, are essential in robotics and automation, yet their complex mechanical–electronic interactions create significant challenges for health assessment and RUL prediction. Iqbal *et al* [268] provided a comprehensive review of robotic applications in industrial automation, highlighting the increasing demand for real-time CBM and PdM. Ding and Jia [269] proposed an adaptive performance health assessment framework designed to work with limited and unlabeled data, demonstrating its effectiveness in diagnosing faults under data-scarce conditions. This approach integrates physics-based modeling with data-driven techniques, significantly improving degradation trend prediction and extending system lifespan. By leveraging hybrid modeling techniques and adaptive learning frameworks, modern methods enhance PdM strategies, ensuring higher reliability and efficiency.

Building on the exploration of application objects, optimized system reliability models have been applied in diverse engineering applications. Battery diagnostics leverage hybrid models for accurate degradation prediction but struggle with complex electrochemical dynamics. Chip reliability benefits from advanced thermal and electromigration modeling, yet scalability remains a challenge. Rotating machines excel with adaptive signal processing for degradation tracking, though noise sensitivity persists. Mechatronics integrates hybrid approaches for complex systems, but data scarcity hinders robustness.

3.2.4. Uncertainty quantification in health assessment and RUL prediction. Information on the uncertainty of RUL prediction is a crucial aspect, as it quantifies confidence in the predictive outcomes of models [270]. It is essential for making informed maintenance decisions and managing risks in industrial applications. The sources of uncertainty can be summarized into two aspects, namely, measurement uncertainty and model uncertainty [271]. The measurement uncertainty includes errors in data acquisition from sensors and instruments, which can be influenced by environmental factors, calibration errors, and sensor drift. For model uncertainty, all predictive models rely on assumptions and simplifications that may not fully capture the complexities of real-world systems. This may result in discrepancies between predicted and actual performance.

Approaches to assess uncertainty range from probabilistic methods that assess variability through statistical models [272] to more advanced techniques like variational inference [273] and Monte Carlo simulations [274]. Probabilistic modeling, such as Bayesian methods, allows for the incorporation of prior knowledge and updating beliefs based on new data [275]. This provides a framework for estimating the uncertainty associated with model parameters and predictions. The Monte Carlo technique involves running multiple simulations using random sampling of input variables to estimate the distribution of outcomes [276]. It helps quantify the uncertainty in RUL predictions by providing confidence intervals and probabilistic forecasts.

Recent advancements in health assessment and RUL prediction leverage diverse data types (e.g. vibration, image, ultrasonic) and hybrid methodologies integrating physics-based, statistical, and ML models. These approaches address uncertainty quantification through probabilistic frameworks and adaptive techniques, enhancing predictive accuracy across applications such as batteries, rotating machinery, and mechatronic systems. By combining multi-source data fusion, degradation mechanism insights, and real-time monitoring, modern strategies enable robust, resource-efficient prognostics, supporting informed maintenance decisions in industrial and energy systems.

Building on the analysis of uncertainty quantification, health assessment, and RUL prediction faces challenges from measurement and model uncertainties. Probabilistic methods effectively incorporate prior knowledge to quantify variability, but rely on accurate data inputs. Advanced techniques, such as variational inference and Monte Carlo simulations, provide robust confidence intervals, yet demand high computational resources. Hybrid methodologies integrating physics-based, statistical, and ML models enhance accuracy by leveraging multi-source data, though complexities in real-world systems persist.

3.3. Maintenance decision-making

Maintenance plays a crucial role in the operational lifespan of engineering systems. It aims to prevent failures and restore system performance if failure does occur with minimal costs. The development of advanced PHM and PdM technologies

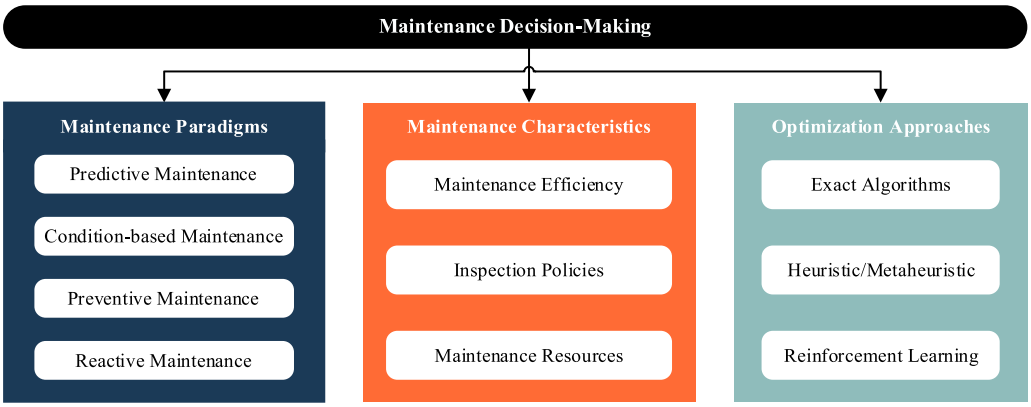


Figure 6. A panoramic view of 3.3 maintenance decision-making.

and computational methodologies has led to the emergence of novel maintenance paradigms and intelligent decision-making techniques. We review maintenance decision-making-related research work from three perspectives, namely, paradigms of maintenance policies, maintenance characteristics, and advanced optimization approaches. Figure 6 provides a panoramic view of this section of the review focusing on maintenance decision-making.

3.3.1. Paradigms of maintenance policies. The paradigms of maintenance policies have evolved from RM to PM, and more recently to CBM and PdM. Corrective maintenance is a reactive approach that addresses system failures after they occur, aiming to restore operational status as quickly as possible. However, RM is unplanned and can lead to high costs due to unexpected repairs and potential production losses. It is useful for non-critical systems and their components.

PM is proactive, with maintenance activities scheduled in advance to prevent failures before they happen. Traditionally, PM has been scheduled at regular intervals based on time or usage, often referred to as time-based maintenance and usage-based PM. This approach is still widely used in industrial practices due to its ease of implementation and its theoretical basis of lifetime distributions. The selected interval in time or usage plays a critical role in this paradigm. If it is too short, over-maintenance occurs, and the maintenance cost is high. If it is too long, unexpected failures cause production interruptions and emergency maintenance with high total costs. This PM practice is useful when the operating conditions are stable and/or well-controlled and the lifetime distribution of the target system has a low standard deviation.

With advancements in sensor technology, real-time monitoring of system conditions has become readily accessible. This has paved the way for CBM, which utilizes CM information to recommend maintenance activities [277]. CBM allows for maintenance to be performed only when needed, that is, when the system or components show signs of deterioration that may lead to potential failure, thus focusing resources on components and systems at risk of failure, rather than following fixed time or usage schedules. PdM takes CBM a step further by integrating advanced prognostic methods to predict the RUL of components and systems. By forecasting the evolution of system health status and estimating the RUL of components, PdM enables maintenance to be conducted only when necessary, reducing unnecessary maintenance activities and enhancing overall system reliability [278].

Building on the discussion of maintenance paradigms, RM addresses failures reactively, offering simplicity but risking high costs from unplanned downtime. PM proactively schedules upkeep to prevent failures, yet its fixed intervals may lead to over-maintenance or unexpected failures if poorly timed. CBM leverages real-time monitoring to target deteriorating components, improving efficiency but requiring robust sensor systems. PdM advances this by forecasting RUL, minimizing unnecessary interventions, though it demands sophisticated prognostics.

3.3.2. Maintenance characteristics. The effectiveness of maintenance decision-making is influenced by several key factors, including maintenance efficiency, inspection policies, and resource consumption.

Maintenance efficiency refers to the quality and effectiveness of a maintenance action in restoring or improving a system's performance. Three primary models of maintenance efficiency are commonly used in maintenance optimization: perfect maintenance, minimal repair, and imperfect maintenance. Perfect maintenance restores the system or component to its as-good-as-new condition, ensuring optimal performance. However, it typically involves high costs and significant time requirements due to the extensive work needed to fully restore a system to a brand-new state. Minimal repair is a type of maintenance where a failed system is restored to the condition it was in just before the failure, essentially an as-bad-as-old condition. The system becomes operational again, but its failure intensity remains the same as it was before the failure. The main goal of minimal repair is to quickly return the system to service, often at a lower cost. Imperfect maintenance occurs when a component or system is restored, but not to its full original perfect condition. It represents a compromise between perfect maintenance and minimal repair.

Imperfect maintenance is often used when perfect restoration is not necessary, but the system must be brought back into a more reliable state than it would be with minimal repair.

Inspection is a critical activity in determining the need for maintenance by providing valuable data on system conditions. From the perspective of inspection accuracy, inspection activities can be categorized into perfect inspection and imperfect inspection. Perfect inspection provides entirely accurate and detailed information about the system's health condition, while imperfect inspection offers only partial or less precise information. In terms of frequency and timing, inspection activities can generally be classified into three categories: continuous inspection, periodic inspection, and non-periodic inspection. Continuous inspection involves constant monitoring of system conditions, providing real-time data that allows for immediate decision-making. This approach is particularly valuable for high-risk or critical systems where failure could have severe consequences. Periodic inspection involves checking the system at fixed and predetermined time intervals. Though this approach is more cost-effective, it may fail to detect signs of deterioration that occur between inspections. Non-periodic inspection involves inspecting the system at time-varying intervals. In some industries, periodic inspections may not be feasible due to high costs, and non-periodic inspections provide a more cost-effective alternative by focusing on irregular inspection schedules based on system conditions or other triggers.

Maintenance decisions are also shaped by the availability and allocation of resources, which can be categorized into renewable and non-renewable resources [279]. Non-renewable resources refer to consumables with finite availability over the planning horizon, including time, cost, and spare parts. Renewable resources, on the other hand, are resources required during the execution of maintenance activities but can be reused after the activity is completed, including repairpersons, repair facilities, and space, and have been recently studied in [279, 280]. Maintenance resources, therefore, serve as a vital constraint in maintenance decision-making. Non-renewable resources impose a limit on the total number of maintenance activities that can be executed over the planning horizon, while renewable resources restrict the number of maintenance activities that can be performed simultaneously. Effective management of both types of resources is crucial to optimizing the scheduling and execution of maintenance activities [279, 280].

Building on the analysis of maintenance paradigms, maintenance characteristics, efficiency, inspection policies, and resource consumption directly impact decision-making. Perfect maintenance offers full system restoration but at a high cost, while minimal and imperfect strategies reduce cost at the risk of incomplete recovery. Similarly, perfect inspections ensure accuracy but are resource-intensive; imperfect or non-periodic inspections trade precision for efficiency. Resource constraints affect scheduling. Key challenges lie in optimizing imperfect maintenance and inspection under constraints, with current trends favoring adaptive, resource-efficient strategies to improve reliability.

3.3.3. Advanced optimization approaches. Maintenance optimization is frequently formulated as an integer programming or mixed-integer programming model. Traditional mathematical programming methods, such as branch-and-bound algorithms [281], linear programming [282], and dynamic programming [283], have been employed for maintenance optimization. While these approaches are effective for maintenance problems involving smaller-scale systems, they often encounter challenges when addressing real-world scenarios where decision variables are numerous. To overcome the limitations of traditional methods, heuristic and metaheuristic algorithms have been increasingly utilized in maintenance decision-making. These methods aim to identify near-optimal solutions for complex optimization problems within a reasonable timeframe. Heuristic algorithms, such as the greedy search algorithm [284] and priority-based heuristic [285], provide solutions based on problem-specific knowledge and are relatively straightforward to implement. It is noteworthy that heuristics can also result in poor performance due to the cognitive biases of decision-makers. Metaheuristic algorithms, including genetic algorithm [286], simulated annealing [287], and particle swarm optimization [288], offer more efficient approaches for exploring large and complex solution spaces.

With the rise of AI, various AI-based methods have been introduced to the maintenance optimization community. Reinforcement learning, as a critical paradigm in the field of ML, has emerged as a powerful and effective tool for solving complex maintenance optimization problems. Reinforcement learning learns the optimal policy by interacting with an environment and receiving feedback in the form of rewards or penalties. In maintenance decision-making, reinforcement learning algorithms can be used to model dynamic environments, where the system's condition evolves over time. The reinforcement learning agent learns optimal maintenance policies through trial and error, maximizing long-term performance. Deep reinforcement learning, such as the deep Q-network algorithm [289], deep value network [290], and proximal policy optimization [291], integrates DL techniques to handle complex maintenance optimization problems with large state and action spaces. Deep reinforcement learning leverages the efficient function approximation and generalization capabilities of deep NNs to handle high-dimensional and continuous state spaces effectively, thereby overcoming the 'curse of dimensionality' faced in engineering applications.

Before moving on to the success stories of intelligent reliability assurance methods, we provide a summary of the methods reviewed above. In the earliest history of using machinery, only the run-to-failure practice was used. Statistics-based methods and physics-based methods were later developed and applied widely in industrial practices. Nowadays, the consensus is that intelligent approaches for reliability assurance encompass the advantages of all earlier adopted approaches in addition to the newly added strength in data processing and AI. The following table 3 provides a comparative summary of these approaches in terms of accuracy, computational cost, data requirements, and typical applications.

Table 3. Comparative analysis of reliability assurance methods.

Method category	Accuracy	Computational Cost	Data requirement	Limitations
Statistics-based methods	Medium	Medium	Medium	Requires adequate lifetime data; assume identical operating conditions.
Physics-based methods	Medium	Low to medium	Small to medium	Requires adequate physics experiments; requires loading measurements
Intelligent methods	High	High	Large	Needs large labeled datasets; risk of overfitting; explainability issues

Intelligent reliability assurance methods have embedded advantages of the traditional statistics-based and physics-based methods, with added new powers in data processing and AI. They offer superior accuracy and are better suited for nonlinear, multi-sensor data, but they come with high computational costs and demand for large-scale labeled datasets. Remaining challenges for further development of intelligent reliability assurance methods will be outlined in section 5.

4. Application stories

Advanced reliability assurance methodologies have already been successfully applied in various sectors, including high-speed trains, aircraft engines, electric vehicle batteries, aerospace vehicles, and nuclear power plants. Figure 7 presents the number of published articles across these fields, illustrating the increasing research interest and advancements in intelligent reliability assurance methodologies for complex engineering systems. This section discusses transformative applications and success stories from these industries.

4.1. High-speed train

High-speed trains are essential to modern transportation, where reliability and safety are critical to ensuring operational efficiency and passenger satisfaction. In recent years, the field of high-speed train PHM has witnessed rapid growth in research interest, as reflected in the steadily increasing number of publications. Cutting-edge approaches such as DL, transfer learning, and hybrid modeling are being widely adopted to improve fault detection, prediction accuracy, and real-time monitoring capabilities, paving the way for safer and more efficient railway systems.

China Academy of Railway Sciences has implemented a bogie CM system on high-speed trains [292]. This system deploys temperature sensors, velocity sensors, pressure sensors, and frequency sensors for real-time CM. The bogie's condition data is transmitted via a communication network to a central data center. Subsequently, the data center performs fault diagnosis for bogie frame faults, bearing faults, wheelset faults, gearbox faults, motor faults, and air spring faults using an adaptive multi-sensor fault diagnosis method based on the residual-squeeze graph attention network model built on a residual-squeeze network framework. This model constructs a directed graph for the bogie system. It captures spatiotemporal features by leveraging sensor data correlations and integrates a graph attention network to replace traditional convolutions with node aggregation operations. This approach significantly reduces data redundancy while enhancing the accuracy of fault feature extraction. The model employs six units to extract features under six distinct operating conditions and utilizes a global average pooling layer for classification. Numerical results indicate that the model achieves an average classification accuracy of 95.31% across six datasets, demonstrating exceptional robustness on small-scale datasets, maintaining an accuracy of 85.65% even when the dataset size is reduced by 50%. Comparative and ablation studies validate the critical role of the residual-squeeze net framework and graph attention network units in fault classification. Compared to traditional methods and other graph NN-based models, the model achieves a balanced trade-off between accuracy and efficiency, enabling the rapid integration of spatial features for bogie systems. This method has been preliminarily deployed in railway management data centers, providing essential technical support for the safety and health management of high-speed trains in operation.

For the Nanning Metro Line 1 [293], key components prone to failure, such as the axle box and gearbox, were studied in depth. By analyzing historical maintenance records, fault characteristics such as screw plug damage, dustproof plug loss, gearbox paint peeling, and oil leakage from injection holes were identified using Pareto chart analysis and FMEA. An improved Beluga whale optimization algorithm was proposed for parameter estimation of a three-parameter Weibull distribution model. By introducing mechanisms for global exploration, local exploitation, and iterative validation, a total cost model was constructed that comprehensively considers fault risks and maintenance costs. The optimization capability of the model was enhanced by integrating the particle swarm optimization algorithm with Lévy flight mechanisms. Experimental results indicate that the axle box and gearbox, identified via Pareto analysis and FMEA, are critical components of the bogie system. The axle box exhibits a higher failure rate than the gearbox. Further analysis demonstrates that the improved Beluga whale optimization algorithm outperforms traditional algorithms by effectively avoiding local optima when fitting actual fault distribution data. Under different risk factor conditions, optimization analysis shows that when the fault risk factor is 2.34, the axle box achieves high reliability and availability while maintaining low maintenance cost rates, reflecting excellent economic and safety performance. This enhances system stability and sustainability,

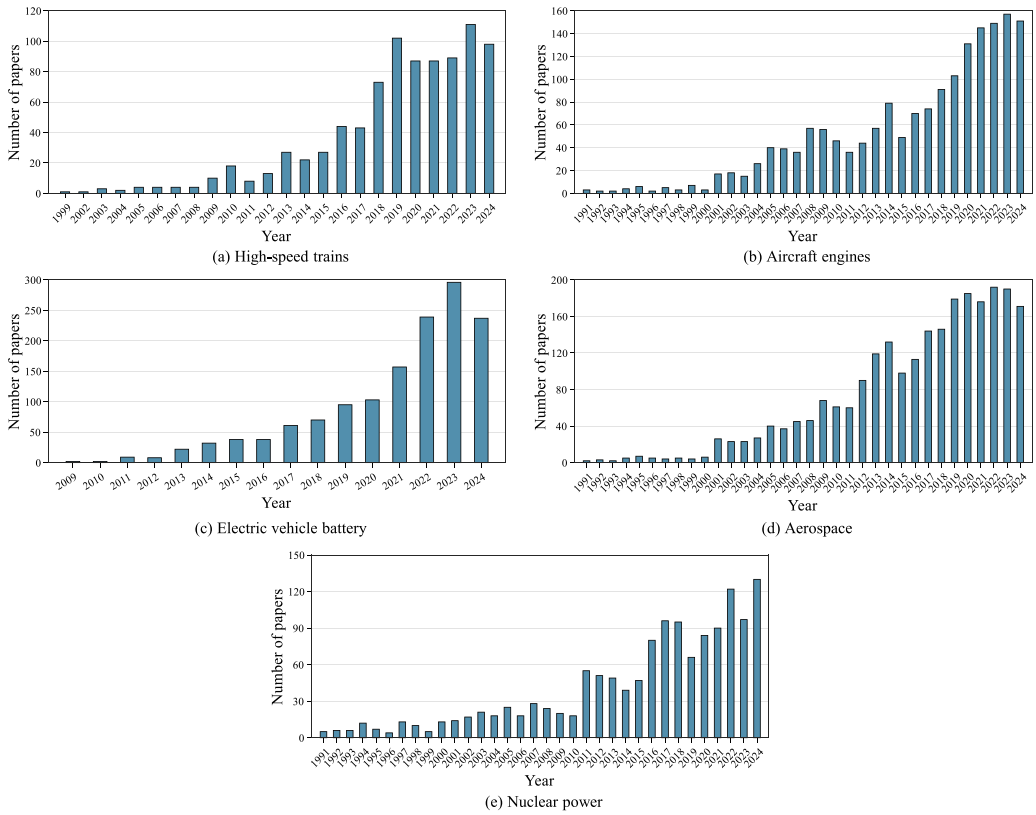


Figure 7. Publications by year retrieved from Web of Science (1990–2024).

providing theoretical support and technical assurance for the cost-effective operation of metro systems.

Changchun Railway Vehicles Co. conducted degradation state evaluations for the bogies of the CRH3-380 high-speed train [294]. Key features such as temperature, vibration, and impact signals were collected using four homogeneous sensors. A three-layer predictive framework for real-time degradation state analysis was proposed based on a Belief Rule Base model with a priority scheduling strategy. The first layer adopts a time-series prediction model that predicts future states using historical data through a multi-module belief rule base. Each module processes a single feature's time series as input and outputs predictions for the next time step. The Akaike information criterion is utilized to select the most suitable time lag, enhancing the model's ability to capture temporal dependencies while preventing overfitting. The second layer introduces grey relational analysis, dynamically adjusting feature priorities based on their correlation with operational health states. High-priority features, such as temperature and vibration, are selected as inputs for the next layer. The third layer establishes a health state assessment model that classifies bogie health into three states: healthy, sub-healthy, and faulty. The healthy state corresponds to low vibration amplitudes and natural temperatures, the sub-healthy state to moderate values, and the faulty state to high amplitudes. Experimental results show that the online-updated belief rule base model accurately fits dynamically changing data, reducing the mean squared error of health state predictions from 0.3740 in the initial model to 0.0633, with the best performance for the healthy and the faulty states. The priority scheduling strategy effectively matches system dynamics, significantly improving the accuracy of real-time health state assessments.

4.2. *Aircraft engine*

Aircraft engines are vital to modern aviation, where performance and reliability are critical to ensuring operational safety and passenger confidence. In recent years, the field of aircraft engine PHM has experienced significant growth, as evidenced by a rising number of research publications. State-of-the-art techniques, including DL, domain adaptation, and DT modeling, are increasingly employed to enhance fault detection, improve predictive accuracy, and enable real-time health assessment, contributing to safer and more efficient aviation operations.

Nanjing University of Aeronautics and Astronautics has developed a fault mode identification method for the gas path of twin-shaft turbofan engines [295]. A simulation study with varying flight altitudes and Mach numbers generated 11 488 data samples, including 4424 normal samples and 1766 samples each for fan faults, high-pressure compressor faults, high-pressure turbine faults, and low-pressure turbine faults. To optimize the identification process, the generalized robust kernel extreme learning machine was introduced. It restructures the dual optimization problem and employs an alternating iterative optimization algorithm to address non-smooth issues. Its objective function incorporates an empirical risk

minimization term and a regularization term, where the regularization enforces a sparse output weight structure using an $\ell 2$, 1-norm. During optimization, the algorithm dynamically adjusts node importance by computing the diagonal elements of a sparse coefficient matrix and minimizes the loss function by updating the weight matrix α. The iterative process typically converges within 20 cycles, with theoretical guarantees of monotonicity and convergence. Experimental results demonstrate that the node selection process effectively reduces redundancy between training samples and hidden nodes, lowering computational costs and significantly improving real-time performance during testing. The method achieves high classification accuracy even with limited training data, providing an innovative solution for aero-engine health assessment and fault prediction.

Beihang University conducted studies on turbofan engine performance degradation under multiple operating conditions to predict RUL [296]. Using data from 14 key sensors, including temperature, pressure, and rotational speed, researchers generated fixed-length time-series segments through normalization and sliding window processing. Window sizes ranged from 15 to 30, depending on dataset characteristics, with each segment labeled by its corresponding RUL. The degradation process was modeled using a piecewise linear approach, and a hybrid framework combining a channel-attention-based CNN and a time-attention-based transformer model was proposed. The CNN extracts degradation features from sensor data, emphasizing critical features via channel weighting mechanisms, while the transformer captures long-term temporal dependencies through multi-head self-attention mechanisms. The final features are dimensionally reduced via a fully connected layer for RUL prediction. Experimental results indicate that this framework significantly reduces mean squared errors in RUL predictions and demonstrates robust performance under complex conditions and multiple fault modes. Moreover, its ability to maintain high performance with small windows and low-dimensional features highlights its advantages in feature redundancy control and model simplification. The study strikes an effective balance between prediction accuracy and model efficiency, providing key technological support for aero-engine health management.

A collaborative team from the University of Glasgow, the University of Cambridge, and Rolls-Royce developed a reliability modeling framework for civil aero-engines using real-world historical maintenance records under varying operational conditions [297]. The study employed two lifecycle metrics: flight hours and flight cycles, and used a Copula-based model to integrate their marginal distributions, accounting for their combined contributions to reliability assessment. To overcome the limitations of traditional parametric methods, a non-parametric approach based on Monte Carlo simulation was proposed, optimizing the dependency parameters to enhance model accuracy. A reliability contour map was constructed through dimensionality reduction, simplifying three-dimensional reliability surfaces into two-dimensional representations for practical application. The framework employs an iterative dynamic grid search to identify optimal maintenance intervals under different flight conditions, maximizing fleet availability. Furthermore, a visualization tool was developed to integrate reliability contour maps with operational trajectories, enabling both individual and fleet-level health assessment and resilience analysis. This tool combines reliability assessment, maintenance interval optimization, and RUL prediction, offering efficient and intuitive decision-making support for aero-engine operations and maintenance.

4.3. Electric vehicle battery

Electric vehicles have rapidly emerged as a cornerstone of sustainable transportation. A key component of electric vehicles is the lithium-ion battery, which serves a critical role in powering the vehicle and significantly impacts its performance, lifespan, and safety. As the adoption of electric vehicles continues to grow, ensuring the reliability of lithium-ion batteries has become a primary focus of R&D. While lithium-ion batteries offer high energy density and long cycle life, they are susceptible to various reliability issues, including degradation from overcharging, overheating, and internal short circuits. Additionally, factors such as charge–discharge cycles, environmental temperature, and loading conditions can accelerate battery aging, compromising the overall performance of the vehicle. Therefore, ensuring the reliability and safety of lithium-ion batteries is essential for the long-term success of electric vehicles.

To address these challenges, several vehicle manufacturers, battery enterprises, and supervisory organizations, such as Huawei, CATL, BYD, and Tesla [298], have developed advanced electric vehicle battery management systems. These systems integrate a variety of advanced models and algorithms and have seen successful practical applications. By leveraging real-time data from sensors embedded within the battery, these systems monitor key parameters such as voltage, temperature, and state of charge. With the help of AI-driven algorithms, they can predict potential failure points and provide insights into battery health, enabling proactive maintenance and optimized energy management.

4.4. Aerospace vehicle

The space industry has witnessed tremendous advancements in recent decades, ranging from satellite communication to deep space exploration. As space missions become increasingly complex, ensuring the reliability of space systems, from satellites to deep space exploration vehicles, has become critical. Space systems face unique challenges, including exposure to extreme radiation, micrometeoroid impacts, thermal cycling, and prolonged operations in vacuum conditions. These harsh conditions contribute to the degradation of materials and components over time, leading to potential failures. Furthermore, the remoteness of space systems makes traditional maintenance techniques infeasible, as manual inspections and repairs are often not viable, especially for deep space missions. For

satellites and space exploration vehicles, ensuring reliability requires not only the design of robust systems but also the ability to monitor and maintain these systems once they are in orbit, often for many years. In response to these challenges, advanced reliability assurance methods are being employed, with an emphasis on in-orbit maintenance, predictive analytics, and autonomous repair technologies. These methods heavily rely on real-time monitoring, ML, and the integration of autonomous systems that can detect issues and perform maintenance activities in space, thereby reducing dependence on Earth-based interventions.

One of the most notable examples of intelligent reliability methods in space systems is the development of robotic servicing technologies that enable in-orbit maintenance of satellites. A prime example is NASA's Restore-L mission, which demonstrates how autonomous robotic systems can be utilized for satellite servicing [299]. This mission involves a robotic spacecraft that performs autonomous rendezvous and servicing tasks, including refueling, repairing, and replacing components of a satellite that would otherwise become nonfunctional due to wear or malfunction. Using AI algorithms and real-time monitoring, the system can detect malfunctions or degradation in satellite systems, such as power loss, communication failures, or sensor damage. Once an issue is identified, the robot can perform repairs or replace damaged components, extending the satellite's operational life and ensuring its continued functionality. This innovation eliminates the need for costly and time-consuming spacewalks or Earth-based interventions, marking a new era in space system maintenance.

4.5. Nuclear power plant

The nuclear power industry is vital to global energy production, supplying a substantial portion of low-carbon electricity. As nuclear power plants extend their operational lifespans, ensuring the reliability and safety of these systems has become increasingly critical. Nuclear systems face unique challenges, such as exposure to extreme radiation, thermal cycling, and degradation of materials due to long-term exposure to high temperatures and radiation. These challenges can lead to potential failures, compromising both plant efficiency and safety. To address these challenges, advanced reliability assurance methods have been developed, with a strong emphasis on PdM, real-time monitoring, and DT technologies. DTs, virtual replicas of physical systems, have become a key component of these methods, enabling plant operators to monitor and predict the behavior of nuclear components under various operating conditions and to proactively address potential issues.

One of the leading examples of DT technology in the nuclear power sector was reported by Electricite De France Group in France, which has successfully implemented DT solutions to monitor and maintain the integrity of critical reactor components [300]. The 'Nuclear Excellence' program developed by Electricite De France integrates sensors with DT models to simulate the real-time condition of reactor pressure vessels and other key components. These virtual models continuously reflect the physical state of the reactor and predict potential failures based on real-time data, historical performance, and operating conditions. For instance, the program can predict the degradation of the reactor vessel and other components, allowing operators to anticipate maintenance needs and reduce unplanned downtime. By simulating various operating scenarios, DTs enable PdM policies that extend the lifespan of nuclear reactors and optimize plant performance. The reliability assurance for the core systems in the nuclear plant has also been recently reported in [301].

5. Remaining challenges and prospects

Intelligent reliability assurance methodologies are essential for the safe and cost-effective operation of engineering systems in today's society. As we have reviewed above, significant advances have been made over the past many years by researchers and practitioners in the R&D of these methodologies. The paradigms of these reported technologies have progressed from RM, PM, CBM, RCM, all the way to PdM. The recent thrust is on the intelligence level of the PHM solutions for large-scale and/or complicated industrial systems. The recent large-scale foundation models, such as those surveyed by Li *et al* [302], also demonstrate promising applications in PHM, particularly in retrieving past case scenarios, conducting logical reasoning and comparisons, and presenting reasoning trails to enhance the interpretability of recommended real-time maintenance decisions. Specifically, we summarize the following areas of challenges that deserve further efforts and investigations.

(1) Data standardization, security, and sharing

Data standardization serves as a fundamental prerequisite for accurate PdM purposes. However, several significant challenges persist. First, the heterogeneity of data sources in industrial environments—characterized by inconsistent formats, sampling rates, and naming conventions—hinders seamless data integration and interoperability. Additionally, the absence of unified semantic models and standardized metadata impairs effective data sharing across systems. Data quality issues such as sensor degradation and faults, missing values, and noise contamination further compromise the reliability of PHM models. Moreover, the current landscape of data standards is fragmented, with limited cross-industry applicability and poor interoperability, while large volumes of historical data remain underutilized due to a lack of standardized structuring. Looking forward, the advancement of data standardization in PdM should focus on several key directions: developing unified industrial ontologies and semantic models to ensure consistent data interpretation; promoting cross-industry standard systems to enable interoperability; building automated toolchains for data labeling, cleaning, and transformation; establishing scalable data middle platforms to support standardized collection, storage, and service layers; and integrating edge computing to enhance data timeliness and reliability. Achieving semantic consistency, automation, platform integration, and open standards will be critical to enabling intelligent and scalable PdM systems across industries. These

hierarchical levels of standardization work need to be accomplished via the cooperation of sensor and data acquisition system manufacturers, data centers, industry consortia, and standardization agencies.

Data security and data sharing represent two critical yet inherently conflicting aspects. On one hand, PdM systems involve large volumes of sensitive data—such as equipment conditions, operational parameters, and fault histories—which remain vulnerable to leakage and cyberattacks due to insufficient protection mechanisms during data transmission, storage, and access. On the other hand, effective data sharing is essential for enabling collaborative diagnostics and intelligent decision-making, yet is often hindered by concerns over intellectual property protection, unclear data ownership, lack of incentive mechanisms, and inconsistencies in data formats. Additionally, increasingly stringent requirements for data compliance and privacy protection pose further challenges to cross-regional data processing. Looking ahead, future efforts should focus on enhancing data security through zero-trust architectures, encryption, and access control; leveraging blockchain technology for trustworthy sharing and traceability; developing auditable and privacy-preserving data platforms; and improving governance frameworks for data classification, graded authorization, and sharing incentives. By achieving a dynamic balance between 'trusted protection' and 'collaborative sharing', PdM systems can evolve toward more intelligent, interoperable, and ecosystem-oriented solutions.

(2) Edge computing

Sensors inevitably degrade over time due to uncontrollable external conditions and inherent material degradation, resulting in possibly poor quality of the sensing data. Thus, sensor reliability assurance approaches also deserve further attention. Furthermore, from the system design perspective, it is also interesting to explore the optimal sensor placement or CM system design schemes that can achieve the trade-off between reliability prediction capability and the additional cost due to mounting sensors.

Through quality sensors and the data acquisition system, data of the appropriate type (for example, vibration, video, and acoustic) with appropriate sampling frequencies or frame rates at the appropriate time intervals are captured. The stored raw data must also be linked to peripheral information such as the type of monitored object, its physical structure parameters, its possible failure modes, its operation and maintenance history, and its operation environment. Only if such quality and complete data are available, can intelligent PHM algorithms mine the best diagnostic and prognostic knowledge from them. From such raw data, features such as mean, standard deviation, and characteristic frequencies may be computed by either edge computing sensors or central servers (local or cloud servers) and stored for possible subsequent uses.

(3) PHM methodologies

With more data of various types becoming available, further development of data processing and information processing algorithms is needed. Edge computing solutions are needed to enable dynamic data acquisition and data transmission. For example, redundant data may be simply dropped instead of being transmitted to central servers, data acquisition may be activated on demand instead of periodic acquisition, and sampling frequency may be adjusted as needed. Edge computing may also provide local alarms in emergencies. Intelligent algorithms on central servers have to possess the following capabilities. Multi-source heterogeneous data fusion technologies are needed to handle the many types of data collected in parallel from the target object. In actual data processing, they are capable of taking care of data imbalance issues. They utilize transfer learning and self-supervised learning to reduce the reliance on large amounts of labeled data. High-performance computing frameworks and distributed training algorithms can be used to improve the efficiency of massive data processing.

Complex fault situations may arise in industrial applications where multiple faults occur alternately or simultaneously. When such scenarios arise, characteristic frequencies of different faults may overlap or interfere with one another. This situation is complex, as laboratories often focus on single fault types. Traditional signal processing methods struggle to effectively separate and identify the characteristic signals of compound faults, while intelligent diagnostic models face high complexity and inadequate generalization capability when dealing with multi-modal, multi-source heterogeneous data. Future research needs to focus on DL methods and foundation models to process, learn, and accumulate knowledge on such complex application scenarios.

Dynamic reliability assessment and prediction of RUL utilizing various data/information crossing multiple physical levels of an individual system are essential to decision-makers. Reported works associated with the RUL can be regarded as a dynamic reliability assessment method with data collected from a single entity (either component or system), because the reliability function in future time can be mathematically derived from the probability distribution of RUL. Uncertainty quantification in dynamically predicted RUL needs further research.

With the growing complexity of engineering missions, the deployment of system fleets to collaboratively execute complicated missions has become increasingly common, rather than relying on a single system. This shift necessitates a transition in maintenance decision-making from a single-system mode to a fleet or system-of-systems paradigm. However, the interdependencies, resource constraints, and heterogeneity among systems within a fleet introduce significant challenges to maintenance modeling and optimization as compared to single-system scenarios. The expanding scale of system fleets exponentially increases the computational complexity of maintenance optimization, referred to as the 'curse of dimensionality'. Addressing these challenges requires the development of novel fleet-wide maintenance optimization models and the adoption of advanced computational techniques, such as deep reinforcement learning, multi-agent deep reinforcement learning, and large-scale foundation models, to derive optimal maintenance decisions in a computationally efficient manner.

(4) Large-scale foundation model and DT

The application of large-scale foundation models introduces significant opportunities for intelligent reliability assurance. However, several critical challenges persist, including a strong dependence on large volumes of high-quality industrial data, limited generalization and interpretability, high computational and deployment costs, and insufficient understanding of industrial semantics and domain-specific knowledge. Future research and development should focus on constructing domain-specific large-scale foundation models tailored to industrial scenarios, enhancing their ability to fuse heterogeneous data sources and incorporate physical and expert knowledge. Additionally, techniques such as few-shot learning and self-supervised training are essential to address data scarcity issues. Improving model interpretability and trustworthiness will be key to fostering user acceptance, while lightweight architectures and edge-cloud collaborative frameworks are needed to enable efficient deployment in real-time industrial environments. Ultimately, the integration of large-scale foundation models into PdM should evolve toward human–AI collaborative systems that combine machine intelligence with expert knowledge. By advancing in areas such as knowledge fusion, data-efficient learning, trustworthy AI, and scalable deployment, large-scale foundation models are poised to play a transformative role in the future of PdM, driving the transition toward more intelligent and ecosystem-oriented asset management.

DT systems create virtual representations of physical assets to enable real-time PHM decisions, demonstrating great potential in intelligent reliability assurance. However, the practical implementation of DTs still faces several critical challenges. These include high modeling complexity, difficulties in integrating multidisciplinary domain knowledge, insufficient coordination between data-driven and physics-based modeling approaches, limited real-time performance due to computational and resource constraints, and a lack of unified standards leading to system fragmentation. Future development should focus on building hybrid modeling frameworks that integrate physical principles with data-driven learning, promoting standardized and modular DT component libraries to support efficient engineering deployment, enhancing edge-cloud collaborative architectures to balance computing demands, and establishing unified data interfaces and modeling languages to ensure interoperability across heterogeneous systems. Furthermore, incorporating AI techniques such as knowledge graphs and causal inference can enhance semantic understanding and intelligent decision-making within DT systems. Through continued advancements in modeling methodologies, system architecture, technical standards, and ecosystem integration, DTs are expected to evolve from static representations to dynamic closed-loop systems and from isolated applications to interconnected multi-layer ecosystems, thereby unlocking their full potential in intelligent reliability assurance.

The prospectus on critical engineering systems our society relies upon is bright as we continue to make progress in developing intelligent PHM methodologies, solutions, and tools.

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ORCID iD

Mingjian Zuo 0000-0002-8607-2923

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Zhiliang Liu received the PhD degree from the School of Automation Engineering, University of Electronic Science and Technology of China, Chengdu, China, in 2013. He is currently a Full Professor with the School of Mechanical and Electrical Engineering, University of Electronic Science and Technology of China. From 2009 to 2011, he studied at the University of Alberta, Edmonton, AB, Canada, as a Visiting Scholar. His primary research focuses on intelligent testing, diagnostics, and maintenance of complex equipment. He is selected as a Fellow of the International Society of Engineering Asset Management (ISEAM), listed among the world's top 2% of scientists, a reserve candidate for Academic and Technical Leaders of Sichuan Province, and a Senior Member of IEEE. He is currently an Associate Editor of *IEEE TIM* and *IEEE Sensors.*



Qin Zhang received a BE degree in Industrial Engineering from the University of Electronic Science and Technology of China, Chengdu, China, in 2020. He is currently working toward a PhD degree in Mechanical Engineering with the School of Mechanical and Electrical Engineering, University of Electronic Science and Technology of China. His research interests include maintenance optimization and reinforcement learning.



Yu Liu received a PhD degree in Mechatronics Engineering from the University of Electronic Science and Technology of China, Chengdu, China, in 2010. He is currently a Full Professor with the School of Mechanical and Electrical Engineering, University of Electronic Science and Technology of China. He was a Visiting Predoctoral Fellow with the Department of Mechanical Engineering, Northwestern University, Evanston, IL, USA, from 2008 to 2010, and a Postdoctoral Research Fellow with the Department of Mechanical Engineering, University of Alberta, Edmonton, AB, Canada, from 2012 to 2013. He has authored/co-authored more than 100 peer-reviewed papers in international journals and conferences. His research interests include system reliability modeling and analysis, maintenance decisions, prognostics and health management, and design under uncertainty. Prof Liu is on the editorial board of *Reliability Engineering & System Safety*, *Quality and Reliability Engineering International*, and *Engineering Optimization*. He is also an Area Editor for the *Journal of Reliability Science and Engineering* and an Associate Editor for *IISE Transactions* and *IEEE Transactions on Reliability*. He is an ISEAM Fellow.



Yaguo Lei received BS and PhD degrees in Mechanical Engineering from Xi'an Jiaotong University, PR China, in 2002 and 2007, respectively. He is currently a Full Professor of Mechanical Engineering at Xi'an Jiaotong University. Prior to joining Xi'an Jiaotong University in 2010, he was a Postdoctoral Research Fellow with the University of Alberta, Canada. He was also an Alexander von Humboldt Fellow with the University of Duisburg-Essen, Germany. His research interests are intelligent fault diagnosis and remaining useful life prediction. Prof Lei is a Fellow of ASME, IET, and ISEAM. He is currently an Associate Editor or Editorial Board member of more than ten journals, including *IEEE Transactions on Industrial Electronics* and *Mechanical Systems and Signal Processing*.



Mingjian Zuo received a Bachelor of Science degree in Agricultural Engineering in 1982 from the Shandong Institute of Technology, China, and a Master of Science degree in 1986 and a PhD degree in 1989, both in Industrial Engineering from Iowa State University, Ames, Iowa, USA. He is a Professor at Shandong University, Principal Scientist at Qingdao Mingserve Technology Ltd, and Professor Emeritus of the University of Alberta. His research interests include system reliability analysis, maintenance modeling and optimization, signal processing, and fault diagnosis. He served as Co-Editor-in-Chief of *Journal of Reliability Science and Engineering*, Department Editor of *IISE Transactions*, Associate Editor of *IEEE Transactions on Reliability*, Associate Editor of *Journal of Risk and Reliability*, Associate Editor of the *International Journal of Quality, Reliability and Safety Engineering*, Regional Editor of the I*nternational Journal of Strategic Engineering Asset Management*, and Editorial Board member of *Reliability Engineering and System Safety, Journal of Traffic and Transportation Engineering*, and *International Journal of Performability Engineering*. He is a Fellow of the Canadian Academy of Engineering, a Fellow of the Institute of Industrial and Systems Engineers (IISE), a Fellow of the Engineering Institute of Canada (EIC), a Founding Fellow of the International Society of Engineering Asset Management (ISEAM), and a Fellow of IEEE.