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A Review of Fault Prognosis of Model-based Mechatronic Systems

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Abstract

Fault prognosis represents a foundational core of modern Prognostics and Health Management (PHM) paradigms and Condition-Based Maintenance (CBM) strategies. It shifts the technological focus from localized backwards-looking fault troubleshooting to prospective, long-term remaining life forecasting. By assessing cumulative mechanical wear, thermal shifts, and electrical degradation tracking profiles, fault prognosis calculates the precise Remaining Useful Life (RUL) and Time-of-Failure (ToF) metrics of high-value industrial mechatronic assets. This comprehensive review systematically frames the structural layout of model-based fault prognosis strategies engineered for multi-domain mechatronic environments. Model-based architectures are critically examined across graphical mathematical regimes—encompassing Bayesian Networks, causal Bond Graphs, and Hybrid Bond Graphs—alongside physical thermodynamic formulations including conflict-driven algorithms and steady-state state analytical models. To present an exhaustive, state-of-the-art diagnostic landscape, these physical-principles approaches are contextualized against sequential filtering data-driven tracking algorithms (such as Particle Filtering and Hidden Markov Models) and knowledge-based expert reasoning configurations. Finally, this review isolates major deployment bottlenecks, including mathematical tracking errors under volatile ambient conditions and multi-mode operation transitions, and details unified hybrid structural frameworks engineered to elevate prognostic precision in contemporary autonomous factories.

Keywords: Fault Prognosis, Remaining Useful Life (RUL), Condition-Based Maintenance, Bond Graphs, Particle Filtering, Health Management

1. Introduction

Fault prognosis constitutes the forward-looking engineering discipline of monitoring an operational system, extracting continuous micro-level wear indicators, and analyzing long-term degradation trajectories to predict exactly when a critical component or complete integrated system will fail to perform its intended function [1]. In distinct contrast to traditional fault diagnosis—which is an administrative backward-looking execution focused on recognizing, isolating, and identifying the precise source of a malfunction after a failure has already compromised the system—fault prognosis looks exclusively forward. Its operational mission is the algorithmic derivation of the asset's Remaining Useful Life (RUL) or Time-of-Failure (ToF) [2]. Defect prognosis provides the capacity to forecast when a fault will develop to avert the catastrophic loss of equipment or human lives, making it a critical asset management requirement within high-risk sectors like aerospace and nuclear infrastructure [17, 18]. By delivering accurate, early structural health predictions, prognosis enables operators to shift safely away from costly reactive maintenance schemes ('run-to-failure') and rigid, unoptimized preventive intervals toward proactive, optimized scheduling. This directly minimizes unscheduled asset downtime, enhances workspace safety, and mitigates severe financial operational impacts [3].

In the contemporary industrial ecosystem, systems have evolved from uncoupled isolated mechanisms to complex multi-domain mechatronic assemblies. Modern mechatronics deeply integrates structural mechanical elements, electrical actuator networks, analog and digital sensory systems, and high-speed computational control scripts. The extensive cross-coupling within these plants means that minor component wear—such as continuous sub-millimeter bearing degradation or slight electrical coil aging—can rapidly distort feedback variables [19, 20]. If left unchecked, these localized faults cascade through the architecture, inducing catastrophic system failures. Today, fault prognosis forms the operational center of Prognostics and Health Management (PHM) loops across safety-critical domains, including aerospace flight control, autonomous transit lines, nuclear energy plants, and deep-sea extraction installations. The successful industrial realization of these frameworks demands high-fidelity degradation models that can track structural state changes through real-time telemetry processing.

2. Paradigm Contextualization: CBM and PHM Frameworks

To fully understand the structural mechanisms of fault prognosis, it must be framed within the overarching engineering hierarchy of industrial maintenance strategies. Maintenance methodologies are broadly separated into three execution vectors: Reactive Maintenance, Preventive Maintenance, and Predictive or Condition-Based Maintenance (CBM) [4,5].

Reactive Maintenance: This paradigm involves operating an asset without scheduled interventions until a catastrophic component failure occurs. While it eliminates routine servicing costs, it introduces severe operational vulnerabilities, including unpredictable downtime, expensive emergency hardware replacement costs, and safety risks to human operators.

Preventive Maintenance: This conservative paradigm schedules inspection and replacement routines at rigid, calendar-based intervals regardless of the component's true physical condition. While it prevents many in-service failures, it frequently leads to 'over-maintenance'—discarding components that possess significant residual life and unnecessarily inflating parts inventories.

Condition-Based Maintenance (CBM): CBM continuously samples condition monitoring data—such as vibration, oil quality, and operating temperatures—to schedule interventions only when true physical degradation criteria are met. Fault prognosis serves as the core computational engine of CBM. By processing current telemetry trends, it predicts future health states, transforming raw sensor tracking data into actionable long-term maintenance insights [6]. Key predictive maintenance techniques include vibration monitoring, wear debris analysis, motor current signal analysis, and thermography [21, 22].

3. Model-Based Fault Prognosis Methods

Model-based fault prognosis represents a mathematically transparent, physics-grounded framework for health forecasting. Instead of treating the asset as a statistical 'black-box', model-based approaches embed the core physical laws governing the plant—such as friction vectors, thermodynamic limits, and electrical properties—directly into the tracking software. This architectural clarity ensures high validation traceability and eliminates the need for massive historical failure training sets. These methodologies are divided into graphical modeling paradigms and physics-driven analytical systems.

3.1 Graphical Modeling Regimes

Bayesian Networks: Bayesian networks represent probabilistic graphical models that map complex causal interactions and conditional distributions across multiple degradation variables using Directed Acyclic Graphs (DAGs). Every node depicts a system component health state, while the directed edges define conditional dependency parameters. When real-time sensory drifts are detected, Bayesian inference propagates the information through the network, allowing the system to accurately evaluate component life prospects under high operational uncertainty [7,8]. These graphical architectures are widely applied to complex configurations, such as predicting wind turbine pitch systems or investigating vehicle crash criteria [23, 24].

Bond Graphs: The Bond Graph paradigm represents a unified, physics-based graphical language that maps the dynamic transmission and exchange of energy across multiple distinct physical domains (mechanical, electrical, hydraulic, thermal). By tracking power variables—specifically effort (e.g., voltage, force) and flow (e.g., current, velocity)—bond graphs allow engineers to directly isolate multiplicative parameter degradation trends, making them exceptional tools for mechatronic life modeling [9]. They are uniquely suited to modeling both linear and high-fidelity nonlinear dynamics safely [25].

Hybrid Bond Graphs: Because advanced mechatronic assets combine continuous physical processes with discrete switching sequences (such as relays, clutches, or digital control states), standard models struggle to maintain tracking precision. Hybrid Bond Graphs resolve this by integrating discrete junctions directly into the continuous energy bond structure, allowing smooth, unified degradation forecasting across rapid mode transitions [10,11].

3.2 Physics-Based and Analytical Formulations

Conflict-Driven Algorithms: This formulation focuses on continuous consistency checking between physical constraints and active sensor signals. By isolating localized conflicts where sensor behaviors diverge from expected physical conservation laws, the system tracks structural shifts and estimates the forward degradation speed of specific hardware units [12].

Steady-State Analytical Models: Focuses on sampling mechatronic signals during prolonged stable operating plateaus, effectively eliminating transient noise. By analyzing the long-term trend variations of physical invariants during steady-state phases, the diagnostic engine filters out high-frequency operational disturbances, exposing the true underlying component wear curves.

4. Data-Driven and Complementary Filtering Landscapes

While physics-based formulations provide clear structural traceability, real-world systems often exhibit non-linear degradation paths that are difficult to capture purely through first-principles equations. Consequently, modern industrial PHM relies heavily on data-driven filtering systems and learning networks to continuously track and project unobserved wear states over time.

4.1 Particle Filtering (Sequential Monte Carlo)

Particle Filtering (PF) represents an advanced state estimation framework that handles highly non-linear, non-Gaussian degradation parameters. Unlike classical Kalman filters, which assume noise conforms to standard bell curves, Particle Filtering approximates the true, unobserved state probability density function (PDF) using a large swarm of weighted random samples, or 'particles'. As sensor telemetry flows into the processor, these particles are recursively updated and project forward in time. This makes PF an exceptional tool for tracking volatile degradation trends, such as chemical capacity fade in lithium-ion batteries or crack propagation lines in mechanical structures, providing explicit statistical bounds on the calculated RUL [13,14]. Because it side-steps the requirement for rigid analytical probability densities, sequential Monte Carlo variants provide excellent computational alternatives to traditional extended filters under highly stochastic non-Gaussian operations [26].

4.2 Hidden Markov Models (HMM)

Hidden Markov Models treat component degradation as a stochastic sequence of hidden, unobserved health states (e.g., nominal, micro-wear, micro-fracture, macro-failure) that the system moves through over time. Although the exact internal wear level cannot be observed directly, it manifests outward through drifting sensor signatures, such as acoustic emissions or increased motor current draw. By processing these observable indicators through a trained HMM, the system computes the exact transition probabilities across the hidden states, enabling accurate forecasts of when the asset will cross into a high-risk operational boundary [15]. By utilizing well-trained state trajectories, HMM features circumvent classic parametric estimation hurdles in permanent magnet AC machinery and structural bearing wear paths [27].

4.3 Knowledge-Based Expert Systems

Knowledge-Based Expert Systems: Knowledge-based architectures discard complex differential equations and large dataset requirements, relying instead on structured human engineering experience. These systems formulate comprehensive rule-based routines, heuristic IF-THEN conditional networks, and Case-Based Reasoning (CBR) frameworks that match current multi-sensor anomalies with historical maintenance case profiles [28]. This enables the prognostic system to make viable RUL assertions during early deployment phases where historical asset datasets are completely absent [4,16].

5. Industrial Challenges in Fault Prognosis

Transitioning fault prognosis from theoretical simulations to real-world industrial installations introduces major engineering hurdles. A primary challenge is managing highly volatile operational environments. Variations in ambient humidity, external temperature swings, and fluctuating work cycles introduce significant background noise that can mask early degradation indicators. If a prognostic algorithm fails to differentiate between an actual structural fault and benign environmental variations, it will skew the RUL calculation, triggering premature maintenance or failing to warn of an impending catastrophic breakdown. These real-world manufacturing environments introduce significant discrepancies often ignored within fully controlled experiments [29].

Furthermore, real-world mechatronic systems operate across highly complex, multi-mode work cycles. For example, an automated industrial vehicle switches rapidly between rapid acceleration, high-load material transport, and stationary loading phases. Every mode transition alters the underlying stress profiles and baseline energy signatures of the internal components. Maintaining tracking precision across these shifts requires advanced hybrid modeling architectures that update their internal degradation tracking rules in real time. Finally, running these recursive particle swarms or complex matrix operations requires substantial processing power, which can saturate the standard embedded controllers typically deployed on the factory floor. Balancing mathematical precision with these computational limits remains a key engineering hurdle.

Table 1
Summary of Cited Prognostic References Categorized by Methodology Covered.

Methodology / Paradigm	Reference / Source	Core Prognostic Focus
CBM & PHM Frameworks	[1] Jardine et al. (2006)	Established structural layouts for processing machine health telemetry within condition monitoring regimes.
CBM & PHM Frameworks	[3] Vachtsevanos et al. (2006)	Comprehensive guide on statistical data-driven degradation tracking and life-prediction models.
CBM & PHM Frameworks	[6] Zhang & Health (2016)	Transformed raw sensor tracking data into actionable long-term maintenance insights.
CBM & PHM Frameworks	[13] Si et al. (2011)	Analyzed statistical data-driven degradation tracking and stochastic modeling approaches.
CBM & PHM Frameworks	[29] Fernandes et al. (2022)	Evaluated real-world industrial manufacturing use-cases and condition monitoring limitations.
Graphical Modeling Regimes	[7] Lu et al. (2015)	Synthesized bond graphs with Bayesian networks to track chemical reaction process degradation trends.

Graphical Modeling Regimes	[8] Chen et al. (2015)	Applied probabilistic conditional graphs to map wind turbine pitch system wear patterns.
Graphical Modeling Regimes	[9] Prakash et al. (2017)	Formulated energy-based prognostic models to isolate degradation in multi-component setups.
Graphical Modeling Regimes	[10] Prakash et al. (2018)	Integrated discrete junctions into bond graphs to track degradation across dynamic operational mode shifts.
Graphical Modeling Regimes	[11] Yu et al. (2010)	Developed hybrid prognostic frameworks designed to isolate wear paths during unknown mode changes.
Graphical Modeling Regimes	[23] Chen et al. (2015)	Used Bayesian configurations to predict wind turbine component faults.
Graphical Modeling Regimes	[25] Youssef Hammadi (2021)	Evaluated nonlinear multi-physics systems using graph-based energy transfer structures.
Physics-Based & Analytical	[12] Zhang et al. (2018)	Formulated multi-sensor conflict checking to track structural wear trends in automation hardware.
Physics-Based & Analytical	[17] Razavi et al. (2019)	Addressed time-to-failure (TTF) constraints under strict analytical boundaries.
Physics-Based & Analytical	[18] Bu et al. (2022)	Applied dynamic uncertain causality graphics within nuclear and aerospace industries.
Data-Driven Tracking & Filtering	[14] Pan et al. (2020)	Comparative evaluation of sequential Monte Carlo variants in tracking battery state of health.
Data-Driven Tracking & Filtering	[15] Zaidi et al. (2010)	Utilized stochastic state tracking to predict electrical faults in permanent magnet drives.
Data-Driven Tracking & Filtering	[26] Tsakonas et al. (2008)	Optimal sequential state estimation techniques for tracking volatile non-Gaussian chirp trajectories.
Data-Driven Tracking & Filtering	[27] Cao et al. (2015)	Multi-step ahead forecasting for tool wear and bearing fault tracking paths.
Knowledge-Based Expert Systems	[4] Brotherton et al. (2000)	Evaluated Gas turbine structural degradation using rule-based reasoning paths.
Knowledge-Based Expert Systems	[5] Cortez Sica et al. (2015)	Applied historical reasoning matrices over dissolved gas logs.
Knowledge-Based Expert Systems	[16] Salem et al. (2021)	Reviewed the structural integration of expert systems and reasoning loops in life modeling.
Knowledge-Based Expert Systems	[28] Perez et al. (2021)	Modeled asset decision support loops via historical case matching routines.
Methodology / Paradigm	Reference / Source	Core Prognostic Focus
CBM & PHM Frameworks	[1] Jardine et al. (2006)	Established structural layouts for processing machine health telemetry within condition monitoring regimes.
CBM & PHM Frameworks	[3] Vachtsevanos et al. (2006)	Comprehensive guide on statistical data-driven degradation tracking and life-prediction models.
CBM & PHM Frameworks	[6] Zhang & Health (2016)	Transformed raw sensor tracking data into actionable long-term maintenance insights.

6. Conclusion

Fault prognosis serves as the defining operational core of next-generation predictive maintenance, offering a clear strategy to eliminate unplanned breakdown events within safety-critical mechatronic systems. By utilizing explicit physical models, graphical bond graph energy representations, or probabilistic Bayesian architectures, model-based prognosis delivers transparent, bounded forecasts of asset life. However, as modern industrial infrastructure becomes increasingly autonomous and multi-mode in operation, relying solely on unyielding physical equations introduces major tracking vulnerabilities under real-world noise. The future developmental path of industrial PHM lies in the engineering of robust hybrid structures. These architectures must merge the physical clarity and bounded guarantees of model-based systems with the adaptive learning capacity of sequential data filters. Developing these unified frameworks will be critical to achieving optimal system survivability and operational safety across next-generation industrial applications.

Competing Interests

The authors have no competing interests to declare

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