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A Review of Fault Diagnosis of Model-based Mechatronic Systems

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Abstract

Fault diagnosis is a critical discipline within modern engineering that ensures the operational reliability, structural safety, and maximum availability of complex mechatronic systems. As contemporary automated processes become deeply integrated with mechanical, electrical, and computational sub-units, tracking internal health status transitions from an operational preference to a fundamental necessity. This paper provides an exhaustive, large-scale review of fault diagnosis methodologies, focusing explicitly on the architecture of model-based systems. Model-based fault diagnosis leverages high-fidelity mathematical and topological representations of physical processes to detect, isolate, and identify faults by evaluating analytical discrepancies, or residuals, between actual system responses and anticipated model states. This comprehensive review systematically categorizes these methodologies into qualitative approaches—including abstraction hierarchies, fault tree models, signed directed graphs, and fuzzy logic formulations—and quantitative mathematical techniques, encompassing analytical redundancy, parity spaces, Kalman filtering frameworks, parametric estimation algorithms, and diagnostic observer topologies. Furthermore, complementary architectural considerations, such as hardware redundancy and history-based data analytics, are investigated to build an integrated view of modern industrial developments. A detailed taxonomic synthesis highlights current system implementation hurdles, trade-offs between mathematical precision and computational complexity, and future diagnostic research paradigms for safety-critical systems.

Keywords: Fault Diagnosis, Mechatronic Systems, Model-based Systems, Analytical Redundancy, State Estimation, Residual Generation

1. Introduction

Fault diagnosis represents the systematic engineering process of monitoring system behaviors, recognizing implicit malfunctions or explicit catastrophic structural failures, investigating observable symptoms, and executing mathematical or algorithmic routines to safely isolate the root cause [1, 2]. Historically, the evolutionary lineage of fault diagnosis is traced directly back to the early epochs of heavy industrialization. During the initial transition where factories and industrial infrastructure began relying on sophisticated mechanical configurations to handle production logistics, machinery was prone to highly unpredictable and recurrent component failures. These failures induced prolonged operational delays, compromised industrial safety, and incurred extreme financial losses. Consequently, technicians and engineers began formulating structured procedures to isolate failure modes, establish baseline operational bounds, and implement localized repairs to restore standard production quickly.

In the modern engineering ecosystem, systems have transitioned from isolated mechanical frameworks to integrated mechatronic configurations. Mechatronic systems synthesize complex structural mechanical assemblies, electrical power networks, electronic sensory systems, and high-speed embedded computational units. The multi-domain nature of these assets makes their internal states and cross-coupling dynamics highly complex. Consequently, small localized anomalies—such as a single drifting sensor or minor actuator friction—can rapidly propagate through the feedback control loops, distorting overall output variables and potentially provoking broad system failures. Today, fault diagnosis serves as an irreplaceable operational core across diverse sectors, including high-availability manufacturing lines, automotive systems, commercial aviation, deep-space exploration craft, and nuclear energy generation facilities [3]. Effective diagnosis relies heavily on a distributed fabric of physical sensors, real-time computational processors, and customized diagnostic algorithms that cross-examine expected behavior maps against live telemetry data streams.

The present review offers a model-based fault diagnosis specifically for *mechatronic* systems — i.e., the multi-domain, hybrid-mode assets whose mixed mechanical, electrical, and computational dynamics challenge the assumptions of sector-specific surveys. First, it systematically unifies both qualitative model-based families (abstraction hierarchies, fault trees, signed directed graphs, fuzzy logic) and quantitative techniques (parity space, Kalman/particle filtering, parameter estimation, diagnostic observers) within a single framework, while also positioning hardware- and history-based paradigms as contextual alternatives. Second, it provides a method-level comparative analysis of advantages, limitations, computational demands, and suitable applications that existing reviews do not consolidate. Third, it situates these classical methods inside modern Condition-Based Maintenance and Prognostics and Health Management loops [23,24]. Finally, it examines the emerging convergence of model-based diagnosis with Digital Twins, hybrid physics-informed/data-driven architectures, and Explainable AI [28], thereby updating the model-based narrative to reflect developments of the last five years.

2. General Taxonomy of System Troubleshooting

To structure a unified perspective on system maintenance, diagnostic engineering splits health monitoring into three core processing operational domains: Model-Based paradigms, Hardware-Based redundant frameworks, and History-Based data regimes. This comprehensive classification ensures that engineers can match specific structural knowledge with relevant computational processing limitations. While hardware configurations rely heavily on expensive physical duplicates, model-based and history-based methods focus on algorithmic extraction of discrepancies.

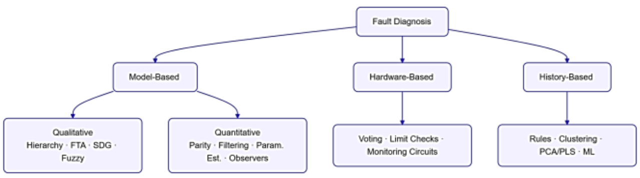

Fig. 1. Taxonomy of fault diagnosis paradigms for mechatronic systems.

2.1 Hardware-Based and Redundant Methods

This methodology involves placing multiple physical duplicates of critical elements (such as sensors, actuators, or processing microcontrollers) within the hardware architecture. If a primary component encounters an structural failure or electrical burnout, backup components instantly accept the operational load, ensuring zero operational downtime. While highly reliable, it significantly inflates spatial demands, system weight, and initial capital expenditures [4].

Frequently coupled with hardware redundancy, voting procedures compile real-time telemetry from three or more identical sensors tracking the same parameter. By executing a real-time voting algorithm—such as simple majority rules, weighted average distributions, or pairwise cross-comparisons—the system isolates any single sensor output that drifts away from the group consensus, effectively isolating localized hardware faults.

Special hardware solutions employ bespoke monitoring circuits, like thermal fuses or dedicated vibration sensors, designed exclusively for structural validation. In parallel, limit-checking techniques continuously monitor whether critical measurements exceed predefined conservative operating boundaries. If a value breaks these guardrails, an automated alarm state is immediately triggered. This limit checking framework matches active system parameters against defined operational bounds to surface potential failures before they manifest as severe breakdowns [20].

This paradigm focuses on converting time-domain signals (such as structural acoustic or vibration signatures) into the frequency domain via Fast Fourier Transforms (FFT). Because specific structural faults like bearing fatigue, cracked gear teeth, or unbalanced shafts generate unique harmonic spectral patterns, frequency analysis enables fast fault identification [5, 6]. Such spectral metrics are fundamental across vibration analytics, structural health monitoring, and wide electrical engineering use cases [21].

2.2 History-Based and Data-Driven Paradigms

History-based methods discard the requirement for physical models or duplicated hardware, relying entirely on large historical operational datasets. By mining long-term telemetry trends, these approaches learn to differentiate standard operating states from anomalous wear trends. They are especially beneficial for complex systems where accurate first-principles physical equations are mathematically impossible to derive.

Fuzzy Logic Systems: Utilizes historical log files to derive linguistic rule bases and membership profiles, avoiding rigid mathematical thresholds. This enables reasoning loops that elegantly handle uncertain, noisy operational histories [7].

Unsupervised Clustering: Unsupervised learning frameworks that organize multi-dimensional data into low-dimensional visual representations. Unsupervised clustering groups similar historical operational states together, making deviations or anomalous behavior points instantly identifiable [8].

Statistical Component Analysis: Leverages advanced statistical tools like Principal Component Analysis (PCA) and Partial Least Squares (PLS) to compress thousands of highly correlated sensor streams into a few independent main directions, highlighting multi-channel sensor drifts.

Expert Systems and Pattern Recognition: Expert systems convert human engineering logic into programmatic IF-THEN statements, allowing automated scripts to emulate an experienced technician's troubleshooting steps. Pattern recognition frameworks use classification algorithms to match real-time signal anomalies with known historical failure profiles [9]. Under small-sample regimes, classifiers like Support Vector Machines (SVM) exhibit enhanced generalizability in condition recognition paths [22].

3. Model-Based Fault Diagnosis Foundations

Model-based fault diagnosis represents the core focus of this review, offering a deterministic approach to troubleshooting. Instead of guessing health states via statistical correlations, model-based frameworks embed deep physical insight directly into the diagnostic software via mathematical equations. The core operational loop relies on residual generation: a mathematical twin of the mechatronic system runs in parallel with the physical asset, processing the exact same control inputs. By subtracting the model's expected outputs from the actual sensor values, a residual vector (r) is produced. Under standard nominal operations, the residual vector remains near zero. When a structural fault or physical change develops, the residual vector shifts away from zero, generating a distinctive signature that diagnostic logic can isolate to locate the exact failing component. Furthermore, model-based paradigms must be contextualized inside modern Condition-Based Maintenance (CBM) and Prognostics and Health Management (PHM) loops, transforming raw telemetry into proactive operational lifecycle insights [23, 24].

4. Qualitative Model-Based Methods

4.1 Abstraction Hierarchy

An abstraction hierarchy structures system knowledge across multiple functional levels. The highest layer defines the overall structural purpose and mass/energy conservation bounds of the plant, while the lowest layer maps the physical components and spatial layouts. When an unexpected signal propagates, the diagnostic engine traces the anomaly vertically through the hierarchy. This isolates how a low-level physical component failure damages high-level operational goals, ensuring engineers understand both the cause and the system-wide effect.

4.2 Fault Tree Analysis (FTA)

Fault Tree Analysis is a top-down, deductive diagnostic architecture that investigates a single critical system failure state by mapping the logical pathways that could cause it. Utilizing Boolean logic gates (AND / OR gates), the tree traces the failure backward to fundamental component anomalies or operator errors. By evaluating these graphical paths, engineers can identify single points of failure and compute the exact probability of complete operational breakdown [10, 11].

4.3 Signed Directed Graphs (Digraphs)

Signed Directed Graphs translate structural process interactions into graphical nodes and directed arcs. Every node embodies a specific physical parameter (e.g., fluid pressure, rotor speed), while the directed arcs reveal the causal dependencies between them, stamped with a positive (+) or negative (-) sign to indicate direction of change. When an asset experiences a fault, the diagnostic script matches the real-time sensor variations with paths on the digraph, tracking the root anomaly even through complex feedback networks [12].

4.4 Fuzzy Logic Diagnosis

Fuzzy logic maps exact numbers into qualitative membership functions (e.g., 'Normal', 'Slightly Warm', 'Critical'). By running these fuzzy states through conditional rules, the system mimics human engineering reasoning. This allows the framework to make highly accurate diagnostic calls even when sensor feeds are corrupted by environmental noise or missing data blocks [13, 14].

5. Quantitative Model-Based Methods

5.1 Analytical Redundancy and Parity Space

Analytical redundancy updates hardware duplicates by using mathematical cross-checks between distinct variables. For example, in an electric motor drive, rotor speed can be checked by checking physical tachometer sensors, but it can also be mathematically derived by processing stator voltage and current equations. Parity space architectures gather these redundant equations, projecting the input/output data onto a specific mathematical subspace designed to remain decoupled from standard system dynamics. This ensures that the resulting residuals react exclusively to structural faults, completely eliminating false alarms caused by standard operational adjustments [15]. Beyond pure algebraic checks, complex multi-domain assets can leverage energy-based graphical languages like Bond Graphs and Hybrid Bond Graphs to model power transmission across mechanical and electrical junctions, capturing discrete mode transitions smoothly [25, 26].

5.2 Kalman Filtering and State Estimation

When mechatronic systems operate in highly volatile environments, sensor observations are inevitably degraded by stochastic noise. The Kalman Filter (KF) resolves this by dynamically fusing the system's mathematical model with live sensor data to compute an optimal, noise-filtered estimate of internal states. For non-linear mechatronic dynamics, the Extended Kalman Filter (EKF) linearizes system states in real time. Diagnostic architectures monitor the internal innovation sequence of the filter—the continuous delta between actual sensor values and the filter's predictions. Any statistically significant variance change in this sequence indicates a structural asset fault [16, 17]. Where degradation features exhibit highly non-linear, non-Gaussian parameters, sequential Monte Carlo approaches like Particle Filtering (PF) offer robust alternatives by projecting sample-driven probability density swarms over long operational horizons [27].

5.3 Parameter Estimation Techniques

Certain physical faults do not directly alter system states, but instead manifest as slow changes in internal parameters, such as a drop in magnetic flux or an increase in mechanical friction coefficients. Parameter estimation techniques continuously calculate these physical parameters by checking input/output data tracks against the system model. These techniques are split into two operational branches:

Recursive Estimation: Algorithms such as Recursive Least Squares (RLS) update parameter models with every new data sample. This makes them ideal for tracking time-varying systems where operational wear develops continuously [18].

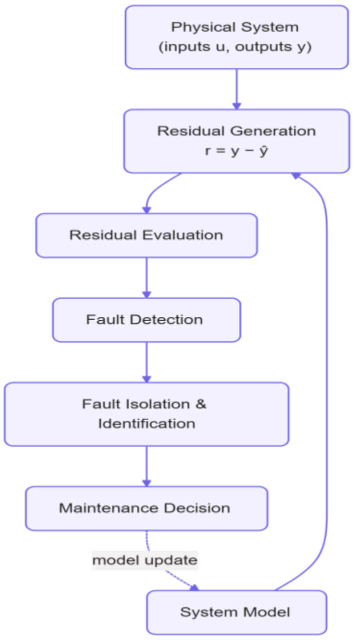

Fig. 2. Generic workflow of model-based fault diagnosis: residual generation, evaluation, detection, isolation, and identification feed a condition-based maintenance loop.

Batch Estimation: Processes large blocks of historical data simultaneously, optimized for static systems or steady-state operations where parameters remain fixed over long intervals [19].

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

Methodology / Paradigm	**Reference / Source**	**Key Contribution to Fault Diagnosis**
General Fault Diagnosis	Isermann (2006) [1]	Established foundational concepts for generating residuals and isolating faults via model-based systems.
Process Fault Diagnosis	Venkatasubramanian et al. (2003) [2]	Produced a detailed review classifying analytical, knowledge-based, and data-driven methods.
Fault-Tolerant Control	Blanke et al. (2006) [3]	Connected real-time diagnostic indicators directly with structural reconfigurable control loops.
CBM Infrastructure	Jardine et al. (2006) [23]	Established structural layouts for processing machine health telemetry logs.
Intelligent PHM	Vachtsevanos et al. (2006) [24]	Comprehensive guide on statistical data-driven degradation and lifetime prediction.
Hardware Redundancy & Limit Checking	Zhang et al. (2018) [20]	Formulated consistency check guardrails to flag operational boundary divergence.
Frequency Analysis	Ciandrini et al. (2010) [5]	Analyzed harmonic frequency spectra to diagnose faults in rotating electrical drives.
Frequency Analysis	Duong et al. (2018) [6]	Formulated robust health indicators by extracting structural frequency features from bearings.
Frequency Analysis	Ullah & Hu (2020) [21]	Identified irreversible demagnetization trajectories using spectral output signs.
History-Based & Machine Learning	Fernandes et al. (2022) [4]	Compared machine learning implementations on mechanical fault datasets in manufacturing lines.
Fuzzy Neural Networks	Jahromi et al. (2016) [7]	Proposed sequential fuzzy clustering structures to process operational histories.
Statistical Clustering	Cortez Sica et al. (2015) [8]	Organized multi-dimensional transformers log files into visual representations.
Expert Systems	Brotherton et al. (2000) [9]	Evaluated human technician logic scripts to isolate gas turbine failure paths.
Classifiers & Support Vector Machines	Wang & Shi (2020) [22]	Demonstrated high generalizability for multi-sensor printing arrays via local classifiers.
Fault Trees / Event Models	Chang et al. (2011) [10]	Applied stochastic event trees to diagnose complex underwater life-support hardware systems.
Petri Nets & Reliability	Zhang (2018) [11]	Modeled system-level verification constraints using graphical pathways and state transitions.
Signed Directed Graphs	Ren & Jiao (2015) [12]	Reviewed graphical signed digraph architectures for tracking fault propagation paths.
Fuzzy Reasoning	Engel et al. (2000) [13]	Manipulated uncertain or incomplete telemetry profiles via conditional rule mappings.

Fuzzy Formalisms	Li et al. (2019) [14]	A systematic review of fuzzy models optimizing bearing health isolation metrics.
Parity Space & Redundancy	Baskaya et al. (2017) [15]	Evaluated fault detection and diagnosis via model-based parity space and machine learning.
Bond Graph Energy Models	Prakash et al. (2017) [25]	Formulated energy-based prognostic models to map multi-domain physical junctions.
Hybrid Dynamic Tracking	Prakash et al. (2018) [26]	Integrated discrete junctions into bond graphs to track paths across active switches.
Kalman Filtering Review	Tran (2009) [16]	Classified dynamic state estimation models across model-based and knowledge-based lines.
Kalman Filtering & Estimation	Djeziri et al. (2013) [17]	Developed structural fault reconstruction models for precise mechatronic state estimation.
Particle Filtering Swarms	Pan et al. (2020) [27]	Comparative evaluation of sample-driven sequential Monte Carlo variants.
Parameter Estimation	Prakash et al. (2017) [18]	Investigated recursive and non-recursive algorithms for physical system parameter tracking.
Batch Parameter Tracking	Prakash et al. (2018) [19]	Processed structural system metrics over fixed intervals for deteriorating setups.

5.4 Diagnostic Observers

Diagnostic observers are software routines designed to estimate unmeasurable internal states by matching measurable outputs with a system model. A corrective gain matrix continuously minimizes the estimation error. In an Eigen-structure Assignment observer, the internal gains are tuned to make the observer sensitive only to specific faults while ignoring external noise. Full-order observers replicate the entire internal state vector, providing full diagnostic clarity at the cost of higher processing demands. Minimum-order observers estimate only the hidden, non-measurable states, offering a streamlined computational footprint ideal for low-cost embedded processors.

6. Recent Developments: Digital Twins, Hybrid Architectures, and AI-Assisted Diagnosis

In the last five years, three complementary trends have begun reshaping the model-based diagnostic landscape. **Digital Twins** extend classical dynamic models into continuously synchronized, data-refreshed virtual replicas of physical assets, enabling condition monitoring, abnormal-pattern identification, and predictive maintenance [29]. Reviews of digital twins for predictive maintenance highlight that the role of machine learning within the digital-twin loop remains incompletely investigated [30], and systematic review of DT-driven prognostics and health management specifically targeting industrial-asset faults — rather than generic health assessment — is only beginning to emerge [31]. Recent work also demonstrates the integration of artificial intelligence with digital twin technology for scalable, context-aware diagnostics in smart grids, manufacturing, and autonomous systems [32], and DT-generated simulated data is increasingly used to augment imbalanced datasets when training diagnostic models [33].

Hybrid model-based/data-driven diagnosis seeks to combine the physical interpretability of first-principles models with the pattern-learning capacity of machine learning [34]. Wilhelm et al. categorize hybrid fault detection, and diagnosis approaches according to the steps of an extended FDD workflow, giving practitioners guidance on which hybrid configuration suits a given application [35]. Because data-driven models excel at capturing patterns from multivariable data but are susceptible to small datasets, while physics-based models embed mechanism or expert knowledge but have limited data-processing flexibility, physics-informed hybrid frameworks are regarded as a promising route to small-data diagnosis [36]. In mechatronic practice, observer-based model detection remains among the most popular and robust techniques, and hybrid architectures have been applied to switched mechatronic systems with multiple operating modes [37]; observed comparisons report that hybrid approaches generally outperform their independent constituents while raising open questions about selecting the appropriate approach, data availability, and fusion strategy [33].

AI-assisted and explainable fault diagnosis. Deep learning has become a leading intelligent paradigm for rotating-machinery diagnosis, enabling automatic feature learning directly from vibration signals without manual engineering [38,39]. Open-source benchmark studies now compare representative deep architectures on public datasets to support reproducible validation [40], and deep transfer learning is actively developed to bridge domain shifts across different machines and operating conditions [41]. Nevertheless, the opaque "black-box" nature of deep models reduces user confidence in diagnostic decisions [42], motivating Explainable AI research: recent surveys distinguish *post-hoc* explanation methods from *ante-hoc* designs that embed physical knowledge directly into the model architecture [43], and systematic reviews of interpretability in intelligent fault diagnosis frame transparency as a core reliability requirement for critical decisions [44]. In Industry 4.0 settings, XAI is regarded as essential for building trust in high-stakes industrial applications [45].

7. Industrial Applications and Challenges

Deploying model-based fault diagnosis within actual industrial mechatronic installations introduces major practical engineering challenges. In controlled laboratory environments, physical parameters are perfectly measured, and mathematical models align flawlessly with actual hardware. However, out in industrial facilities, mechatronic assets encounter severe model mismatch due to manufacturing tolerances, changing thermal conditions, and structural wear. If a model fails to adapt to these shifts, the diagnostic system will mistake normal aging variations for an operational fault, triggering costly false alarms. Furthermore, contemporary mechatronic assemblies operate across multiple distinct modes—such as a robotic manipulator moving between free-space transit and contact force operations. Managing diagnosis across these mode transitions requires advanced hybrid architectures that shift between different mathematical regimes in real time without destabilizing the diagnostic indicators. Finally, embedded microcontrollers on the factory floor have strict computational processing limits. Running high-order differential equations or real-time matrix inversions for Extended Kalman Filters can saturate processor loops, requiring careful optimization to balance diagnostic accuracy with real-time execution limits.

8. Conclusion

Model-based fault diagnosis remains a cornerstone framework for securing operational safety and isolating failures within high-performance mechatronic systems. By embedding physical principles directly into diagnostic algorithms via qualitative causal networks or quantitative state equations, these methods provide deep physical insights that pure data-driven models cannot replicate. However, the rise of highly dynamic, multi-mode automated systems exposes the limitations of relying purely on fixed analytical models. Future research directions must focus on developing hybrid diagnostic architectures that combine the clear physical validation of model-based systems with the adaptive learning capacity of history-based neural networks. Developing these integrated diagnostic tools will be vital to ensuring the safety and operational efficiency of next-generation autonomous infrastructure.

Competing Interests

The authors have no competing interests to declare .

References

[1] Isermann R 2006 Fault-Diagnosis Systems: An Introduction from Fault Detection to Fault Diagnosis (Springer-Verlag)

[2] Venkatasubramanian V, Rengaswamy R, Yin K and Kavuri S N 2003 Computers & Chemical Engineering 27 293

[3] Blanke M, Kinnaert M, Lunze J and Staroswiecki M 2006 Diagnosis and Fault-Tolerant Control (Springer Berlin Heidelberg)

[4] Fernandes M, Corchado J M and Marreiros G 2022 Applied Intelligence 52 14246

[5] Ciandrini C, Guidi M, Giantomassi A, Ippoliti G and Longhi S 2010 Proceedings of IEEE International Symposium on Industrial Electronics p 210

[6] Duong B P, Khan S A, Shon D, Im K, Park J, Lim D S, Jang B and Kim J M 2018 Sensors 18 3740

[7] Jahromi A T, Er M J, Li X and Lim B S 2016 Neurocomputing 196 31

[8] Cortez Sica F, da Silva, G F, Duarte R and Reis A 2015 Electric Power Systems Research 127 109

[9] Brotherton T, Jahns G, Jacobs J and Wroblewski D 2000 Proceedings of IEEE Aerospace Conference p 100

[10] Chang D, Zhang F and West M 2011 Proceedings of IEEE Conference on Prognostics and Health Management p 45

[11] Zhang Y 2018 IEEE Transactions on Reliability 67 540

[12] Ren F and Jiao Y 2015 Proceedings of 12th IEEE International Conference on Electronic Measurement & Instruments p 15

[13] Engel S J, Gilmartin B J, Bongort K and Hess A 2000 Proceedings of IEEE Aerospace Conference p 20

[14] Li C, de Oliveira J V, Cerrada M, Cabrera D, Sánchez R V and Zurita G 2019 IEEE Transactions on Fuzzy Systems 27 1362

[15] Baskaya E, Kemal M and Delahaye D 2017 Proceedings of IEEE/AIAA 36th Digital Avionics Systems Conference p 12

[16] Tran N M 2009 Ph D Thesis (St. Louis: Washington University)

[17] Djeziri M A, Benmoussa S and Ouladsine M 2013 Proceedings of 3rd International Conference on Systems and Control p 80

[18] Prakash O, Verma A K and Bhattacharyya R 2017 Control Engineering Practice 72 1

[19] Prakash O, Verma A K and Bhattacharyya R 2018 Proceedings of European Safety & Reliability Conference p 50

[20] Zhang W, Zhao Q, Zhao H, Zhou G and Feng W 2018 Sensors 18 1016

[21] Ullah Z and Hu J 2020 IEEE ECCE 2020

[22] Wang M and Shi Z 2020 Proceedings of PHM-Besançon

[23] Jardine A K, Lin D and Banjevic D 2006 Mechanical Systems and Signal Processing 20 1483

[24] Vachtsevanos G, Lewis F L, Roemer M, Hess A and Wu B 2006 Intelligent Fault Diagnosis and Prognosis for Engineering Systems (John Wiley & Sons)

[25] Prakash O, Verma A K and Bhattacharyya R 2017 Control Engineering Practice 72 1

[26] Prakash O, Verma A K and Bhattacharyya R 2018 ESREL 2018

[27] Pan D, Ling H and Song Y 2020 IEEE SMDA 2020

[28] Peng Y, Shao H, Xiao Y, Yan S, Wang J and Liu B 2024 Measurement Science and Technology 36 012009

[29] Tao F, Zhang H, Liu A and Nee A Y C 2019 IEEE Transactions on Industrial Informatics 15 2405

[30] Chen C, Fu H, Zheng Y, Tao F and Liu Y 2023 Journal of Manufacturing Systems 71 581

[31] Xiao B, Zhong J, Bao X, Chen L, Bao J and Zheng Y 2024 Scientific Reports 14 13443

[32] Nakti I, Mansouri M, Al-Hmouz R and Khedher A 2025 IEEE Access 13 91860

[33] Gawde S, Patil S, Kumar S, Kamat P, Kotecha K and Abraham A 2023 Engineering Applications of Artificial Intelligence 123 106139

[34] Rai R and Sahu C K 2020 IEEE Access 8 71050

[35] Wilhelm Y, Reimann P, Gauchel W and Mitschang B 2021 Procedia CIRP 99 278

[36] Li C, Li S, Feng Y, Gryllias K, Gu F and Pecht M 2024 Artificial Intelligence Review 57 8

[37] Abboudi A and Belmajdoub F 2021 Journal Européen Des Systèmes Automatisés 54 683

[38] Tama B A, Vania M, Lee S and Lim S 2022 Artificial Intelligence Review 56 4667

[39] Tang S, Yuan S and Zhu Y 2019 IEEE Access 8 9335

[40] Zhao Z, Li T, Wu J, Sun C, Wang S, Yan R and Chen X 2020 ISA Transactions 107 224

[41] Chen X, Yang R, Xue Y, Huang M, Ferrero R and Wang Z 2023 IEEE Transactions on Instrumentation and Measurement 72 1

[42] Saufi S R, Ahmad Z A B, Leong M S and Lim M H 2019 IEEE Access 7 122644

[43] Chen G, Yuan J, Zhang Y, Zhu H, Huang R, Wang F and Li W 2024 IEEE Access 12 103348

[44] Maged A, Haridy S and Shen H 2024 arXiv preprint arXiv:2404.11597

[45] Ahmed I, Jeon G and Piccialli F 2022 IEEE Transactions on Industrial Informatics 18 5031