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Review

Overview on Predictive Maintenance Techniques for Turbomachinery

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Abstract

Within the Industry 5.0 paradigm, the management of critical assets requires advanced digital architectures capable of ensuring resilience and operational sustainability. The present systematic review analyzes the state of the art in predictive maintenance (PdM) technologies for turbines and turbomachinery, providing a technical examination of anomaly and fault detection frameworks, extended to remaining useful life (RUL) estimation and root cause analysis (RCA). The work addresses inherent sectoral challenges, ranging from the processing of high-dimensional multivariate time series (MTS) from Supervisory Control and Data Acquisition (SCADA) systems to labeled data scarcity and signal non-stationarity in real-world environments. Both purely data-driven frameworks and hybrid physics-informed models, such as Physics-Informed Neural Networks (PINNs), are critically evaluated against performance indicators. A significant contribution of this study lies in the classification of methodologies based on their readiness for real-time inference, emphasizing the role of Explainable AI (XAI) in providing transparent insights to domain experts, who remain central to decision-making processes. The primary objective of this review is to offer an analytical overview of progress to date against current technological gaps, tracing a clear trajectory for future developments. In this regard, the adoption of Generative AI and Large Language Models (LLMs) is identified as a fundamental step toward evolving into interactive, human-centric decision support systems.

Keywords: predictive maintenance; turbomachinery; anomaly detection; deep learning; physics-informed neural networks; remaining useful life; root cause analysis; SCADA data; Industry 5.0

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1. Introduction

1.1. Motivations

In recent years, Predictive Maintenance (PdM) has increasingly taken hold in the manufacturing landscape, particularly within the turbomachinery sector. This field has evolved from manual vibration monitoring toward advanced digital architectures based on artificial intelligence [1,2]. Such technological progression currently aligns with Industry 5.0 principles, which incorporate human-centricity, sustainability, and resilience to foster adaptive production processes and minimize environmental impact [3].

PdM has emerged as a superior solution to address the primary challenges posed by equipment failures, which can lead to significant financial losses, operational disruptions, and damage to a company's reputation [4]. By utilizing real-time data and advanced analytics to monitor equipment conditions continuously, such a predictive approach enables the

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early detection of potential issues, allowing for timely and precise interventions. The proactive nature of PdM minimizes unplanned downtime, extends asset lifespans, and reduces wasteful maintenance spending [5].

The implementation of PdM in modern power generation facilities and industrial plants has demonstrated substantial operational benefits. For instance, the authors in [6] demonstrate the advantages of transitioning from condition-based maintenance (CBM) to a fully predictive maintenance strategy, showing significant reductions in operational downtime (70–75%) and maintenance costs (20–50%) for wind turbines. In other industrial contexts, Romanssini et al. [7] demonstrate that implementing PdM on rotating machinery yields reductions in operational downtime up to 50%, decreased maintenance costs (8–12% compared to conventional preventive maintenance), extended asset lifespan, improved operator safety, and enhanced overall plant reliability.

However, applying these strategies to turbomachinery presents unique challenges. The implementation of a PdM strategy begins with the analysis of the anomalies and failures that characterize the system. In turbomachinery, the main issues include metallurgical degradations such as creep, High Cycle Fatigue (HCF), and Low Cycle Fatigue (LCF), alongside corrosion and erosion [8]. An equally major category consists of rotordynamic anomalies, which primarily manifest as mass unbalance, shaft misalignment, and rubbing phenomena (involuntary rotor–stator interaction) [2,9]. Additionally, mechanical degradation of transmission components and fouling phenomena [10] are frequently observed, potentially accelerating long-term failures. In turbomachinery, the onset of such failures is often tracked by monitoring the condition of bearings, including Rolling (RB), Journal (JB), and Thrust (TB) types, in terms of vibrations and extreme temperatures [11–13]. Being wear components, they are assessed during both scheduled inspections and CBM strategies [14].

The evolution toward decarbonization imposes new operational challenges: gas turbines must adapt to low-carbon fuels (hydrogen) to back up renewables [15,16], while wind turbines face variable environmental conditions [17]. Such a shift to flexible and cyclic operation accelerates degradation mechanisms, reducing overall efficiency [16,18,19]. These evolving operational requirements highlight the need for advanced monitoring and prediction capabilities integrated within a Digital Twin (DT) [1,20,21]. Building on these foundations, the DT integrates AI, Machine Learning, and advanced analytics to enable learning from multi-source data, adaptive behavior under changing operating conditions, and support for predictive decision-making [20].

1.2. Background

The success of PdM stems from its unique ability to balance cost efficiency with operational reliability, enabled by the convergence of fundamental technologies: (1) IoT (Internet of Things): Sensors enable massive equipment data collection; (2) Big Data: Processes raw IoT data into actionable insights; (3) Deep Learning: Powers fault diagnosis and Remaining Useful Life (RUL) prediction; (4) Deep Reinforcement Learning (DRL): Optimizes maintenance decisions in dynamic environments; (5) Hardware: GPUs/TPUs accelerate complex model training [22,23]. Despite persistent implementation challenges for PdM across industries, it remains the most cost-effective approach for minimizing downtime and failure-related expenses compared to reactive maintenance (RM) and preventive maintenance (PM) [24].

From a data analysis perspective, signals collected via SCADA systems constitute complex Multivariate Time Series (MTS) [25]. One of the major challenges in this domain lies in the scarcity of labeled data [26,27]. In fact, many faults are extremely rare by design, especially in high-safety applications [28]. This is compounded by the difficulty of identifying the exact moment of the initial anomaly and by variations in operating conditions (domain shifts), which lead to false alarms if the model is not robust [29]; finally, obtaining reliable ground truth is expensive and often impossible [30].

To overcome these obstacles, the PdM pipeline has shifted toward Deep Learning processes and hybrid approaches, which are necessary to manage long-term temporal dependencies and enable unsupervised learning. In this scenario, Anomaly Detection assumes a priority role over Fault Detection: while Fault Detection aims to isolate a specific fault requiring prior knowledge, Anomaly Detection identifies deviations from nominal behavior without needing labels, ensuring the timeliness essential for preventing catastrophic failures. The study by Sepe et al. [9] exemplifies this hybrid approach, accurately predicting creep damage in Baker Hughes turbomachinery with a 28.5% error margin relative to the failure interval, enabling the estimation of Remaining Useful Life (RUL) specific to each turbine.

Although advanced commercial frameworks for lifecycle monitoring exist (e.g., GE Vernova's SmartSignal [31], Siemens's ATOM [32], and EPRI's Digital Twin [33]), focusing on real-time diagnostics and predictive maintenance, the analysis in this review will cover both purely data-driven techniques (AI/ML) and hybrid approaches like Physics-Informed Neural Networks (PINNs) and Physics-Informed Machine Learning (PIML) [18]. The latter will be examined in the context of accelerating computational simulations (CFD, FEM), estimating parameters using a priori physical knowledge, and integrating mixed models without strict physical constraints [16,34].

1.3. Contributions

Existing surveys either focus purely on data-driven methods for anomaly detection or on prognostics or are limited to specific turbine types. A holistic, comparative review that integrates anomaly detection, RUL, and RCA across turbine types and critically evaluates the role of physics-informed AI is currently missing. Therefore, the objective of this work is not to propose a unique PdM framework but rather to provide a systematic state-of-the-art review of the fundamental methodologies that constitute its backbone: Anomaly Detection, Fault Detection, RUL estimation, and Root Cause Analysis (RCA). The main contribution of this survey is threefold. First, it provides a structured taxonomy and a comparative in-depth analysis of modern architectures for Anomaly and Fault Detection, categorizing them into two main families: purely Deep Learning methods and hybrid-physics (data-driven and physics-informed) approaches. Second, it separately and in-depth analyzes recent advancements in the other two pillars of PdM: RUL estimation and RCA, applying this same cross-cutting dichotomy. Finally, the work discusses open challenges and future perspectives, identifying research gaps and outlining promising directions, such as the synergistic integration of Large Language Models (LLM) and Human-in-the-Loop (HITL) [35] approaches to bridge the semantic gap between AI model outputs and operational decisions, in full adherence to Industry 5.0 paradigms [36].

To provide a clearer overview of the study's structure, a visual organizer of this review is presented in Figure 1.

The remainder of this paper is organized as follows: Section 2 presents the review methodology. Section 3 introduces a taxonomy of Deep Learning architectures for anomaly detection. Section 4 evaluates anomaly and fault detection methods (forecasting, reconstruction, contrastive, and physics-informed). Section 5 covers RUL estimation techniques. Section 6 reviews RCA approaches. Section 7 provides a comparative analysis. Section 8 discusses challenges and concludes.

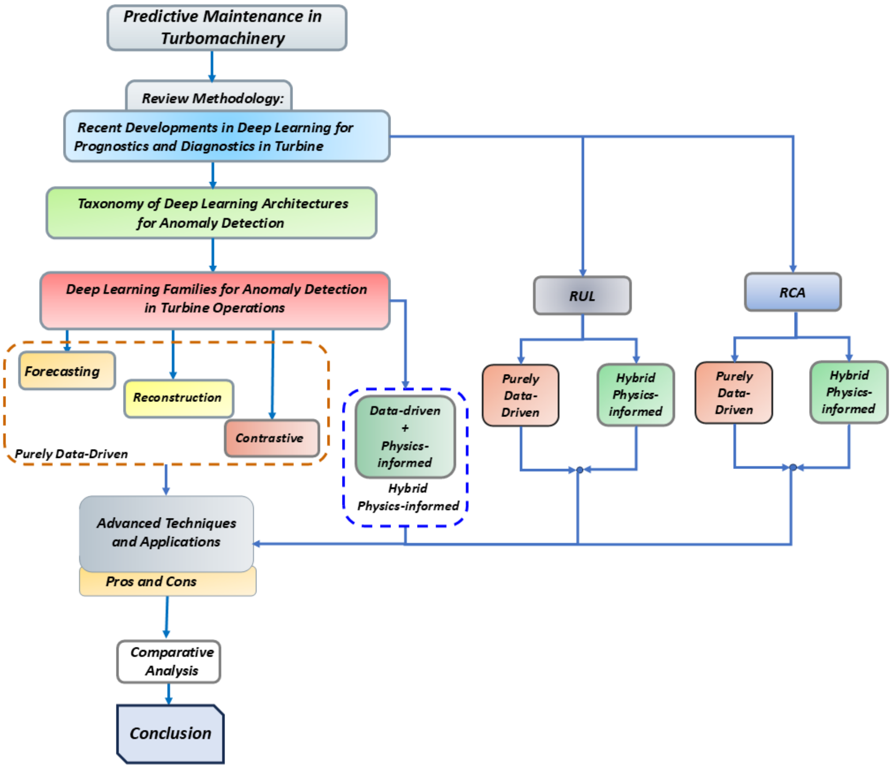
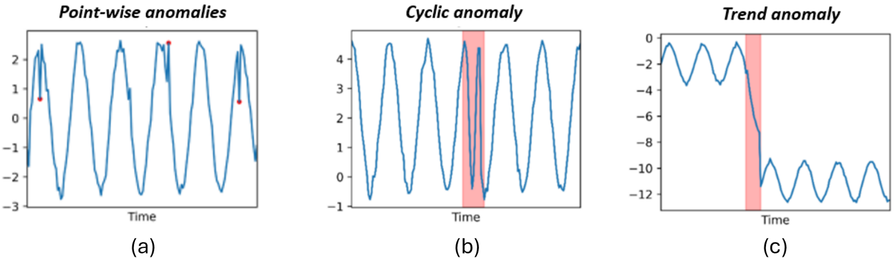


Figure 1. Structural roadmap and organizer of the review paper.

2. Review Methodology

The typical PdM pipeline consists of several layers. One of the core stages, performed immediately after data acquisition and pre-processing, is anomaly detection [1,20]. The evolution of anomaly detection has largely moved beyond traditional machine learning techniques, increasingly shifting toward deep learning processes. The transition is primarily driven by distinct advantages, such as the ability to effectively handle long-term temporal dependencies (e.g., via LSTM, GRU, or Transformer architectures), capture non-linear relationships between variables, enable label-free learning (unsupervised or self-supervised approaches), and ensure robustness against noise and non-stationarity [37]. From a practical perspective, these aspects are vital. Indeed, data collected via acquisition units and sensors distributed across turbomachinery allow for the reception of signals sampled through SCADA systems. Mathematically, these signals constitute evolving time series. Since they often require processing via online inference, it is essential to adopt data-driven models optimized for real-time execution, ensuring that computational requirements are compatible with resource-constrained platforms. The analysis of these signals results in a Multivariate Time Series (MTS), representing heterogeneous physical quantities within turbomachinery monitoring [25]. During MTS analysis, anomalies can manifest in various forms as the data not only evolve temporally but are also interconnected by linear or non-linear relationships between variables. Consequently, a distinction is generally made between two main families of anomalies: intra-metric anomalies, relating to the temporal evolution within a single variable, and inter-metric anomalies, relating to inconsistencies caused by the violation of expected correlations between different metrics [38,39].

In rotating systems characterized by stationary dynamics, anomalies usually do not involve point-wise anomalies (where the anomalous behavior of a single time point may appear as a spike or glitch) [38]. Instead, typical anomalies often involve trend anomalies, where the series suddenly deviates from a long-term trend, or cyclic anomalies, such as the occurrence of a seasonal peak with altered amplitude, frequency, or periodicity, as shown in Figure 2. Furthermore, Figure 3 illustrates the system architecture, which begins with raw data acquisition and subsequent pre-processing for cleaning and meaningful feature extraction. The resulting stage yields fundamental health indicators, such as time series, function transforms, and monitoring parameters, which feed into the diagnostic (Anomaly and Fault Detection) and prognostic modules for RUL estimation. In this context, RCA provides indispensable decision support for the operator, translating identified deviations into diagnostic information regarding the triggering causes, necessary for precisely planning maintenance interventions on the physical system. The following section addresses condition monitoring and fault detection techniques, with a specific focus on Anomaly Detection applied to turbines and turbomachinery in general, providing an analysis and review of Deep Learning methodologies, demonstrating their effectiveness in this field, and introducing a Deep Learning scheme for time series anomaly detection in the turbomachinery sector.



(a) (b) (c)

Figure 2. Visual classification of anomaly families in turbomachinery time series: (**a**) Point-wise anomalies; (**b**) Cyclic anomalies; (**c**) Trend anomalies [38].

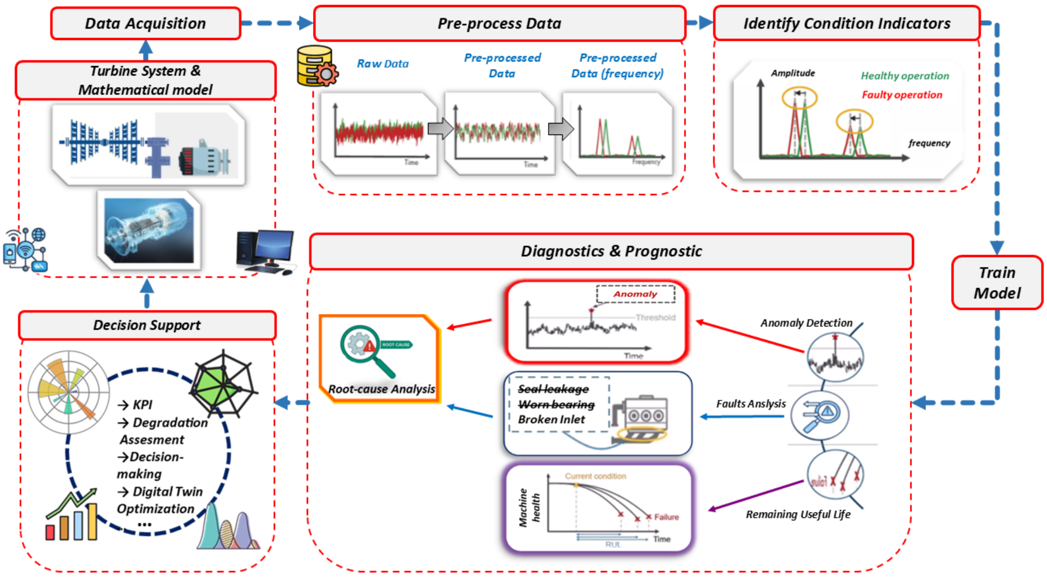


Figure 3. Schematic representation of the PdM paradigm. The process comprises Diagnostics: encompassing Anomaly Detection for deviation identification and Fault Detection for cause isolation and Prognostics: which estimates the Remaining Useful Life (RUL) to anticipate functional failure.

Trends in Deep Learning for Turbomachinery Monitoring

Deep Learning is increasingly gaining ground in modern industrial monitoring applications. In fact, relying solely on physical modeling of the system under analysis is becoming increasingly difficult, particularly for systems that are complex in terms of both mathematics and physics. With the availability of a wide range of signals from various acquisition systems, including SCADA logs and raw sensor data, and enabled by modern architectures such as High-Performance Computing (HPC), enabling real-time processing, the analysis of these data streams becomes the fundamental input for system health monitoring. Consequently, in recent years, Anomaly Detection and Fault Analysis have shifted increasingly from statistical regression techniques (such as AR, ARIMA, ARX, NLARX, or SARIMA) and Machine Learning approaches towards Deep Learning [38,40]. While statistical and regression-based methods prove effective in analyzing single-variable temporal trends or Univariate Time Series (UTS), they struggle to capture the complex correlations among hundreds of distinct sensors simultaneously. Similarly, algorithms such as One-Class Support Vector Machine (OCSVM) and Support Vector Data Description (SVDD) represent valid alternatives; however, traditional Machine Learning methods generally face inherent scalability and performance limitations when handling large, complex multivariate datasets or MTS [37,38,40]. Furthermore, as system complexity increases, these approaches encounter significant challenges driven by the scarcity of labeled anomaly data, as previously discussed [37,38].

In this regard, Zamanzadeh et al. [37] address the issue of data scarcity, noting that generic Machine Learning methods require balanced datasets that rarely exist in the real world. The advantage highlighted here is that Deep Learning enables unsupervised or self-supervised approaches (such as Representation-based methods) that learn the intrinsic characteristics of normal data without the need for fault labels, thereby overcoming the main bottleneck of classical statistical methods, which require a priori definitions. Parallel to this, there is a technical limitation regarding traditional One-class classifiers (such as OCSVM): designed for fixed-dimension data, they struggle to capture temporal dependencies [41–43]. In practice, they treat each data point as an isolated or static event, losing the fundamental information residing in the temporal sequence, which recurrent architectures (e.g., RNNs and LSTMs) or Transformers handle natively [44,45]. Finally, the difficulty in managing unpredictability persists; indeed, statistical regression methods based on anomaly forecasting fail when the system changes rapidly or is intrinsically chaotic. For instance, given a volatile time series, a statistical method will consistently generate a high prediction error, confusing normal behavior with an anomaly. Reconstruction-based Deep Learning methods, conversely, circumvent this issue by analyzing the internal structure of the current data rather than relying solely on its future projection [37,46]. The effectiveness of Deep Learning has been confirmed not only by its high computational performance but also by its increasing prevalence in the scientific literature dedicated to health monitoring, specifically in Anomaly and Fault Detection. In recent years, it has seen pervasive adoption, increasingly replacing classical Machine Learning approaches as well as purely physics-based models or visual inspections, a trend clearly observable within the turbomachinery sector [47]. To support this evidence, a systematic analysis of scientific publications over the last decade (2015–2025) was conducted. The literature acquisition process was executed through an automated pipeline utilizing the public APIs of Semantic Scholar, arXiv, Crossref, Elsevier (Scopus), IEEE Xplore, and OpenAlex. To mitigate potential publication bias and ensure a balanced overview, the search strategy explicitly included pre-print servers (e.g., arXiv) and international conference proceedings. This approach allows for capturing a broader spectrum of results, including early-stage theoretical advancements and industrial case studies that might otherwise be omitted from journal-only syntheses, which are often characterized by a higher frequency of positive outcomes. To ensure a systematic search, 16 targeted queries were used (e.g., "turbomachinery anomaly detection", "instability detection in combustion systems"), strictly excluding overviews, reviews, and surveys to isolate original contributions only. The search queries concerned not only the detection phase but the entire spectrum of health-monitoring, diagnostics, and prognostics.

The identified works were cataloged into three methodological macro-categories:

- Deep Learning (DL): layered neural architectures capable of autonomously extracting feature hierarchies from complex data, including generative models, recurrent architectures, and hybrid solutions that integrate different deep learning paradigms.

- Machine Learning (ML): supervised and unsupervised learning algorithms based on mathematical models that do not exploit deep structures, focusing on data regression and partitioning aimed at identifying logical patterns or optimal decisions.
- Alternative Methods (AM): including physics-based models, deterministic models, autoregressive models, practical-visual analyses, and direct measurements.

The selection and classification were governed by a rigorous multi-stage filtering process:

- Inclusion Criteria: (i) original research implementing DL, ML, or AM architectures; (ii) specific focus on turbomachinery assets (gas, steam, wind, or hydro turbines and compressors); (iii) English-language full-text availability.
- Exclusion Criteria: (i) non-industrial applications (e.g., medical or clinical studies); (ii) conference abstracts lacking detailed mathematical formulations.

After a deduplication stage based on normalized title matching, 411 unique articles were selected. The assignment to the DL or ML categories was determined by a keyword-based scoring system: architectures featuring multi-layered structures (e.g., CNN, LSTM, PINNs) were assigned to DL, while shallow models (e.g., SVM, Random Forest) were categorized as ML. The results obtained from this analysis are illustrated in Figure 4. The analysis shows that 2020 marked a significant surge in the use of Deep Learning techniques compared to classical Machine Learning. It is also evident that, as of 2017, Machine Learning methods in general, including Deep Learning, have surpassed traditional physics-based approaches. The latter are often computationally too slow, as seen with FEM or CFD simulations, or limited in precision for effective real-time monitoring. This trend aligns with the observations of C. Tsallis et al. [48], who provide a systematic literature review confirming the expansion of AI within the broader PdM sector. Similarly, M. de Castro-Cros et al. [47] offer a detailed overview of machine learning applied specifically to gas turbine condition monitoring. While these studies provide valuable qualitative summaries, our review introduces a distinct methodological advancement. Unlike prior works that categorize literature by algorithm family or component type, we propose a dual-axis taxonomy that characterizes methods by both their functional objectives as pure data-driven approaches and their physics-informed integration paradigms. Moreover, we implement a quantitative benchmarking framework utilizing synthetic indices to evaluate industrial trade-offs, providing an analytical depth not explored in previous surveys.

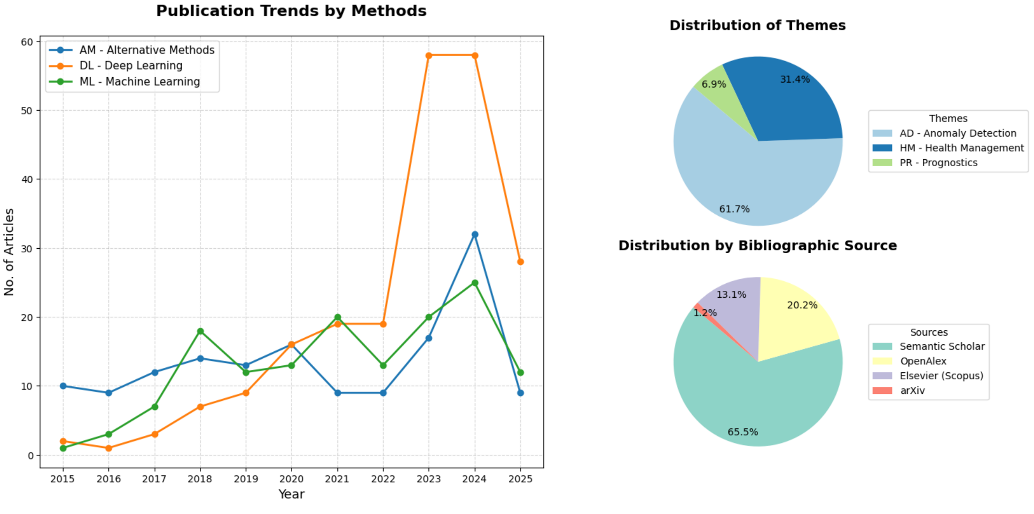


Figure 4. Bibliometric analysis of the reviewed literature. (**Left**) Historical evolution of publication trends, showing a clear shift towards Deep Learning (DL) for Anomaly Detection (AD), Health Monitoring (HM), and Prognostics (PR) tasks, surpassing traditional Machine Learning (ML) and Alternative Methods (AM) in recent years. (**Right**) Distribution of thematic areas within the PHM framework and breakdown of the bibliographic sources.

The analysis results shown in Figure 4 represent the only works exclusively focused on Anomaly Detection while also considering its integration within a broader framework, such as Prognostics and Health Management (PHM), thereby addressing topics like health monitoring and system prognostics. Furthermore, many studies share common methodologies; this not only leads to attribution of multiple techniques to a single work but also demonstrates that certain scientific branches continue to persist and evolve, albeit to a lesser extent than others. Finally, the research procedure and data extraction stages for the literature review are shown in Figure 5.

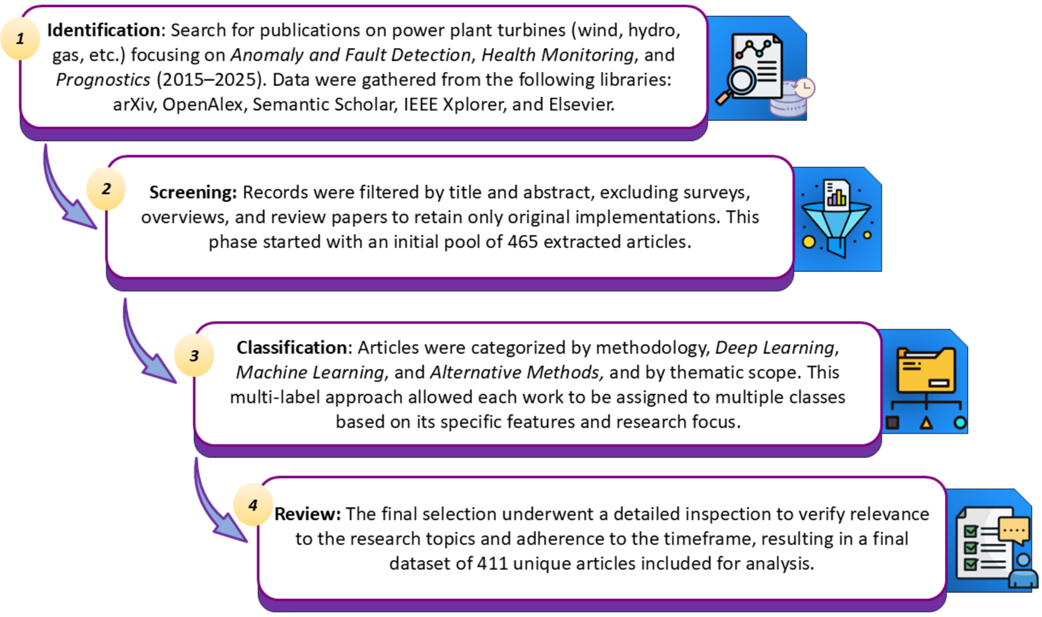


Figure 5. Systematic workflow of the bibliographic search and selection process.

3. Taxonomy of Deep Learning Architectures for Anomaly Detection

The analysis in this section focuses primarily on Deep Learning architectures, their structural frameworks, and their applications. The inputs for these recent models have transitioned from individual time steps to sliding windows. These windows aggregate data over time to capture underlying temporal patterns and inter-variable relationships. In real-world scenarios, data often exhibit complex structures such as noise, seasonality, and trends; furthermore, anomalies typically manifest as persistent patterns over a duration rather than isolated points [38], as illustrated in Figure 2, especially in sophisticated systems such as turbines. Such a transition toward Deep Learning for processing complex datasets reflects a broader trend in safety-critical infrastructures. For instance, similar architectures are systematically employed in rail track monitoring to detect defects and ensure operational reliability [49]. To establish a consistent taxonomy across all PdM tasks, including Anomaly Detection, RUL estimation, and RCA, this review categorizes methodologies into two overarching families: the Purely Data-Driven approach and the Hybrid Physics-Informed paradigm. The former relies exclusively on statistical data patterns. Conversely, the latter acts as a cross-cutting layer where physical domain knowledge is seamlessly integrated into deep learning architectures, such as forecasting or reconstruction models, to constrain predictions within physically plausible bounds. In the context of data streaming, a clear taxonomy can be established based on the temporal execution of training and inference phases. Generally, three primary operational frameworks are identified: Online Training and Online Inference, where the model continuously updates its parameters and detects anomalies as data flows; Offline Training and Online Inference, the most common approach in industrial applications, where a validated model is deployed to monitor live streams; and Offline Training and Offline Inference, typically used for post-process diagnostic analysis [50]. In the turbomachinery sector, the framework based on offline training and online inference is the most suitable for addressing specific operational challenges. The Online inference is essential for the timely analysis of sensor signals such as vibrations, temperatures, and pressures, enabling the detection of incipient faults in real-time. Simultaneously, offline training is preferred over online methods to ensure system stability and prevent continuous learning from erroneously interpreting slow degradation as normal behavior. This approach also overcomes the computational limitations of industrial hardware, allowing for the deployment of strictly validated models and ensuring the reliability required in PdM applications.

Another fundamental aspect concerns the distinction between step-by-step and end-to-end architectures [37]. In step-by-step solutions, the model initially generates an intermediate output, such as a reconstruction error or an anomaly score, which requires a subsequent statistical stage to establish the actual presence of a fault. In this context, adopting techniques such as Nonparametric Dynamic Thresholding (NDT) or Peaks-Over-Threshold (POT) is decisive for defining adaptive thresholds capable of converting raw data into decision labels [37,50]. Given that high safety requirements characterize the turbomachinery sector, the step-by-step structure appears preferable to the end-to-end counterpart, which integrates the entire process into a single neural network. Indeed, the availability of an intermediate score guarantees greater physical interpretability within Anomaly or Faults Detection. Similarly, the use of algorithms like POT or NDT allows for better stochastic management of the nature of industrial signals, offering superior control over system sensitivity compared to the 'black-box' nature of end-to-end models [37,38]. Such an approach can be observed in [51], where the authors implement NDT for turbine monitoring, achieving a drastic reduction in false alarms due to the threshold's ability to autonomously adapt to the machine's operational variations. Similar results are found in the study by [52], where the use of the POT technique allows for the statistical management of extreme events in turbomachinery signals, ensuring timely fault detection without constant supervision. On the other hand, Ref. [53] proposes an end-to-end framework that, while outperforming classical models in accuracy and class-imbalance management, sacrifices granular explainability for direct, integrated classification.

Shifting to the frequency domain offers substantial advantages in turbomachinery diagnostics, enabling the extraction of information latent in the time domain. Spectral analysis facilitates the identification of cyclic patterns (Figure 2). Since rotating systems exhibit periodic behavior, the use of Fast Fourier Transform (FFT) allows for isolating dominant frequencies to detect anomalies or faults related to vibrations and mechanical imbalances that would appear only as noise in the raw signal, using these as inputs for the network [54]. Furthermore, signal transformation achieves a reduction in complexity by filtering random fluctuations and allowing the network to focus on the spectral signature of the machinery. It improves precision and reduces false alarms, particularly in architectures featuring filtering blocks such as Wavelet-based models [55] or FEDformer, which employs a Frequency Enhanced Block to manage global dependencies [56]. The frequency domain also enables a multidimensional representation. Models such as TimesNet [57] exploit dominant periodicities to transform 1D time series into 2D representations, jointly capturing temporal evolution and signal rhythms. Moreover, FFT-based formulations improve computational efficiency. In this context, Autoformer [58] replaces classical self-attention with a period-based auto-correlation mechanism, efficiently identifying long-term dependencies and trends. This facilitates the detection of anomalies and supports real-time monitoring in wind turbine applications. A summary scheme of the discussed topics is shown in Figure 6, where, as opposed to the Temporal module, which captures time-dependent patterns, the

Spatial module learns the normality of the system through inter-variable dependencies, enabling the detection of inter-metric anomalies that are essential for identifying complex fault conditions in multivariate turbine datasets.

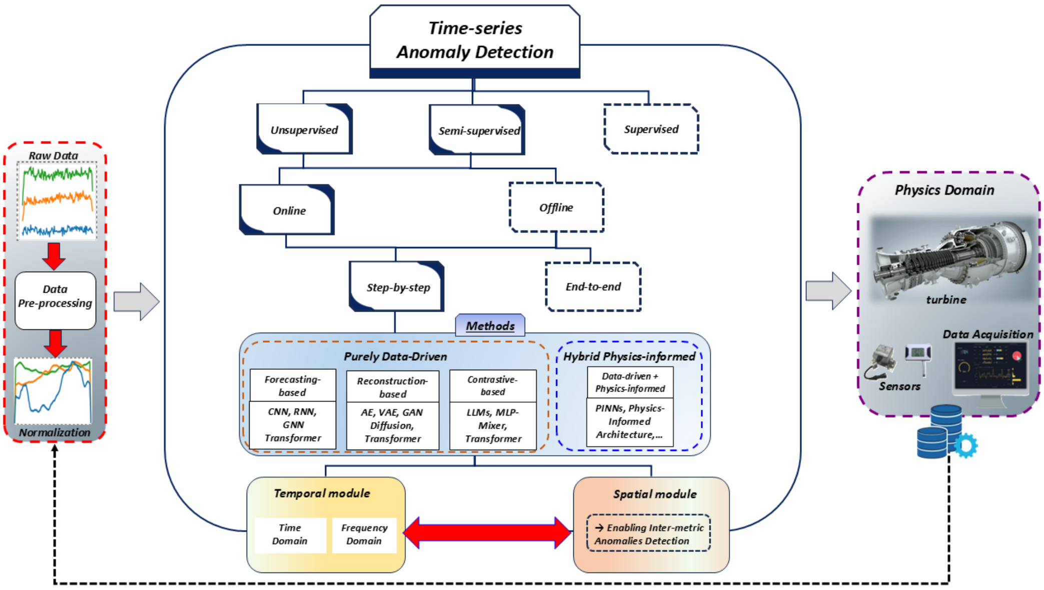


Figure 6. Proposed learning scheme for Time Series Anomaly Detection related to the turbomachinery sector.

4. Deep Learning Families for Anomaly Detection in Turbine Operations

Within the context of turbine monitoring, Deep Learning architectures have evolved to handle the high dimensionality and non-linear nature of sensor data. According to recent literature, anomaly detection approaches can be broadly divided into two overarching families: Purely Data-Driven and Hybrid Physics-Informed paradigms. The first family includes methods that rely exclusively on historical data patterns, primarily categorized into Forecasting, Reconstruction, and Contrastive methods [38]. Conversely, the second family, such as Physics-Informed Neural Networks (PINNs), integrates physical principles into the learning process [16], embedding domain knowledge directly into the model to form hybrid strategies that enhance generalizability and ensure that the detected anomalies remain physically consistent with the turbine's operating logic. Consequently, this section analyzes the specific methodologies reported in the literature for turbomachinery, moving from purely data-driven models to hybrid physics-based solutions. Furthermore, dedicated summary tables are provided to systematize the reviewed contributions. To facilitate a comparative technical evaluation and practical implementation, these tables extend beyond basic categorization (i.e., learning paradigm, turbomachinery system, and year) by introducing three additional classification criteria:

- Input Data Types (Input): detailing the nature of the ingested signals. These are categorized as Multivariate Time Series (MTS) for standard SCADA logs, Spatio-Temporal MTS (ST-MTS) for graph-based topologies, Vibration signals (VIB) for high-frequency monitoring, Images/Spectrograms (IMG/SPEC), or Physics (e.g., thermodynamic residuals, PDE constraints, or calculated physical parameters).
- Validation Metrics (Metrics): specifying the mathematical criteria used to assess model performance, such as RMSE, MAE, MAPE and R^2 for forecasting errors, or F1-Score, Accuracy, and AUC for classification capabilities.
- Computational Complexity (Comp.): providing a qualitative assessment based on the architectural depth and hardware requirements. This metric is classified as Low (L) for shallow neural networks or single-layered architectures (e.g., simple CNNs or single-

layer LSTMs) ensuring immediate inference on standard edge devices; Medium (M) for deep architectures or attention-based mechanisms (e.g., Deep LSTMs, Transformers, or CNN-LSTM hybrids) requiring GPU acceleration for efficient training; and High (H) for computationally intensive frameworks, such as Physics-Informed Neural Networks (PINNs) or Generative Adversarial Networks (GANs), which involve complex iterative mathematical operations or massive parameter spaces.

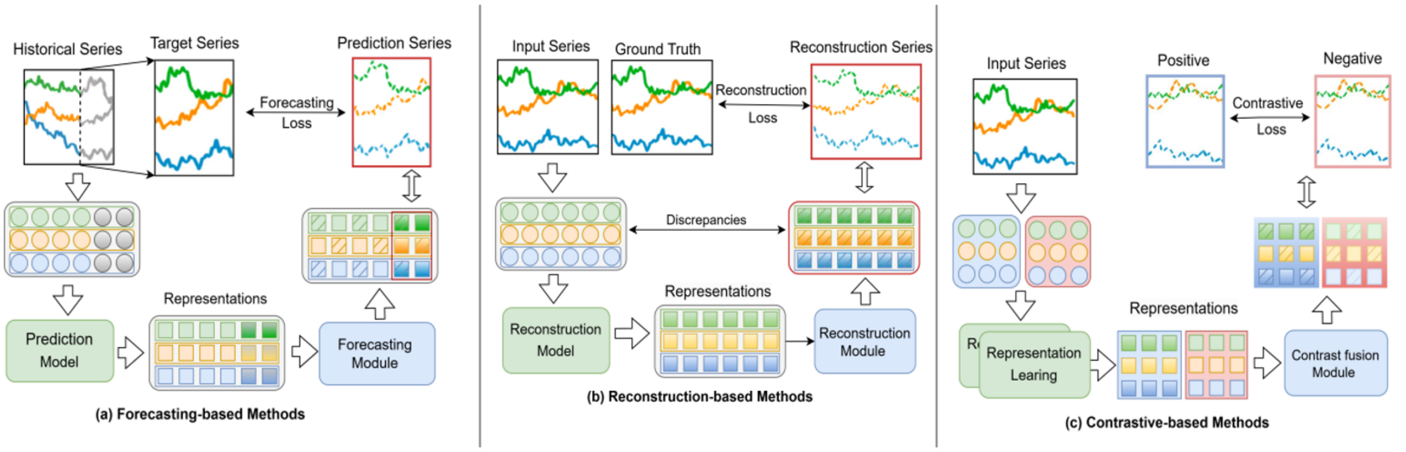
4.1. Purely Data-Driven Family

The Purely Data-Driven family for Anomaly Detection relies exclusively on historical sensor data to model the nominal behavior of turbomachinery without explicit physical rules. This category is structured into three primary methods, each utilizing specific architectures to process complex multivariate time series:

- Forecasting: Forecasting strategies utilize historical sensor streams to model the temporal evolution of turbine parameters, enabling the prediction of future operational states. In this framework, anomalies are identified by quantifying the residual between the model's estimation and the actual physical measurement, where a significant deviation signals a departure from nominal behavior. The reference architectures employed within this predictive paradigm primarily include models such as CNN, RNN, LSTM, GNN, and Transformers [37,59].
- Reconstruction: Reconstruction-based methods focus on modeling the distribution of nominal behavior by mapping input signals into a compressed latent space. Unlike predictive approaches, these models aim to synthesize the original input, using the reconstruction error as a metric for Anomaly Detection. In the context of gas turbines, Ref. [47] highlights that these unsupervised architectures are particularly effective for identifying hidden patterns in multidimensional time series. In fact, by accessing the full temporal context related to the use of sliding windows, these models can effectively reconstruct complex operational scenarios [37]. Within this framework, nominal behavior is captured by encoding training subsequences into low-dimensional latent spaces. Under the assumption that anomalies are rare, such patterns are typically difficult for the model to reconstruct accurately. Therefore, detection is initiated when the reconstruction error, defined as the difference between the actual and synthesized observations, is high or when the reconstruction probability remains below a specific threshold. While this approach may introduce a minor delay, it is often favored in the condition monitoring of turbines and their related plants because it provides the high accuracy needed to reduce maintenance expenses and prevent critical equipment failures [47]. The specific implementations related to this method rely on various frameworks, including AE, VAE, GAN, Transformer, and Diffusion models.
- Contrastive: Contrastive learning paradigms for Anomaly Detection define a self-supervised approach centered on the agreement between different views of the same data [37]. These methodologies typically employ a twin-branch architecture (often referred to as a dual-tower model) where multivariate time series are processed through distinct encoding networks to produce high-dimensional representation vectors [38]. The model identifies consistent features of nominal behavior by analyzing the signal from multiple perspectives, such as diverse temporal scales or data augmentations [59]. To ensure synchronization across complex sequences, a fusion module incorporates alignment techniques like upsampling to map these representations to each timestep [50]. The training objective is governed by a contrastive loss function that quantifies the similarity between branches, marking instances of low correlation as potential anomalies [38]. This framework establishes a robust baseline without requiring manual labels, making it ideal for the unsupervised monitoring of industrial

assets. The techniques included in these works primarily include Transformer-based, MLP-based, and LLM-based models.

The specific applications, architectural nuances, and performance trade-offs of these methodologies will be detailed in the following sub-subsections of this part dedicated to purely data-driven methods. To provide a clearer visual summary of these purely data-driven architectures, a conceptual representation is illustrated in Figure 7.



(a) Forecasting-based Methods

(b) Reconstruction-based Methods

(c) Contrastive-based Methods

Figure 7. Overview of the purely data-driven families for Anomaly Detection: (**a**) forecasting, (**b**) reconstruction, and (**c**) contrastive learning [38].

4.1.1. Forecasting Methods

A relevant trade-off for managing complex time series in turbomachinery involves the integration of advanced statistical models with learning techniques. Along these lines, Goyal [60] proposed a hybrid approach for gas turbines, combining Generalized Additive Models (GAM) with ARFIMA and GARCH processes to account for residual volatility and non-stationary data. This concept extends to sensor virtualization, where predictive models validate physical instruments or replace missing ones. The research projects by Gori et al. [61] and Shetty et al. [62] developed Continual Learning and Granger causality strategies for Anomaly Detection in gas turbines. Using LSTM networks, these models develop virtual sensors to detect sensor drift or failure. In this context, Farahani [63] addresses the challenge of high-dimensional data in gas turbines by coupling an Autoencoder for feature extraction with a deep LSTM for forecasting. This hybrid strategy effectively reduces noise and dimensionality before performing time-series prediction, managing operational shifts from a forecasting perspective.

To improve sensitivity toward critical components such as main bearings, specialized architectures have been recently proposed [64,65]. While B. Wang et al. [64] introduced a Feature Alignment LSTM (FA-LSTM) to account for the component's thermal inertia by synchronizing previous temperature states with current variables, Chen et al. [65] developed the Norm-linear-ConvNeXt-TCN framework to isolate degradation signals with higher computational efficiency. Utilizing Temporal Convolutional Networks (TCN), this latter approach successfully separates thermal degradation patterns from standard operational fluctuations.

Similarly, in the hydropower sector, B. Liu et al. [66] integrated CNNs and LSTMs with Generative Adversarial Networks (GANs) to balance datasets lacking sufficient failure samples, enhancing the identification of anomalies in generation units under variable loads. Purely temporal models, however, often struggle to capture the dependencies between interconnected subsystems. Graph Neural Networks (GNNs) address this by representing the turbine as a network of nodes. Related to this, Pinciroli et al. [67] utilized a GAT-GRU framework to weight sensor correlations, ensuring the system remains sensitive to fault patterns that automatic control systems might otherwise obscure. A significant contribution in this field is the TempGNN model by G. Jiang [68], which focuses on system-level monitoring through a decoupling stage designed to remove the influence of time-varying conditions, identifying overheating in the main bearing, generator components, and converters with high precision. Further extending this spatial analysis, Y. Zhan et al. [69] implemented deep spatio-temporal modeling for anomaly detection in small hydropower stations, successfully capturing the co-evolution of state variables. In the wind sector, Daenens et al. [70] utilized GNNs to model correlations across offshore wind farms, where interactions such as the wake effect significantly influence regional power forecasting.

Finally, the forecasting literature highlights two distinct philosophies in graph construction: Y. Zheng et al. [71] proposed a hierarchical GNN for wind turbine pitch systems, integrating autocorrelation mechanisms to detect blade jamming or encoder errors through a data-driven adjacency matrix. In contrast, X. Jin et al. [72] emphasized the use of prior physical knowledge to define the graph topology. Their GSTN framework maps a fault propagation chain across sensors, enhancing the explainability of the diagnostic results. Addressing regional-scale management across wind turbine clusters, J. Wang et al. [73] implemented an improved DBSCAN anomaly detection as a preprocessing step to clean SCADA data from maintenance or grid curtailment artifacts. This ensures that the subsequent Graph Convolutional Recurrent Network (GCRN) receives reliable inputs for power forecasting, maintaining the integrity of the dispatching process.

Pros and Cons. In summary, forecasting architectures provide a robust framework for real-time monitoring and early degradation detection, particularly when integrated with spatial awareness or physics-informed modules. Their primary advantage lies in the direct explainability of the prediction residual as a physical indicator of system health. Nevertheless, these methods remain sensitive to signal noise and non-stationary operational shifts [60,61], which can induce false alarms if the baseline is not meticulously refined against artifacts such as outliers or concept drift [74]. As evidenced by the latest scientific literature, the frontier of this paradigm lies in the trade-off between the flexibility of deep learning and the structural reliability provided by physical constraints [72] and robust data pre-processing [73]. The works related to forecasting are reported in Table 1.

Table 1. Summary of the illustrated works on forecasting for turbomachinery Anomaly and Fault Detection.

Work	Learning Paradigms	System	Year	Input	Metrics	Comp.
[60]	GAM, ARFIMA, and GARCH	Gas Turbine	2021	MTS	RMSE, MAE	L
[61]	RNN and Continual Learning	Turbomachinery	2022	MTS	MSE, RMSE	M
[62]	RNN-LSTM and Granger Causality	Turbomachinery	2023	MTS	MSE, RMSE	M
[63]	Hybrid Autoencoder and Deep LSTM	Gas Turbine	2021	MTS	MSE, RMSE	M
[64]	FA-LSTM (Feature Alignment)	Wind Turbine	2025	MTS	RMSE, MAE, R^2	M
[65]	Norm-linear, ConvNeXt, and TCN	Wind Turbine	2024	MTS	F1-score	M
[66]	CNN-LSTM-GAN	Hydropower	2025	MTS	Acc, F1-score	H
[67]	GAT and GRU (Graph Attention)	Wind Turbine	2025	ST-MTS	F1-score, AUC	M
[68]	TempGNN (Temperature-based GNN)	Wind Turbine	2022	ST-MTS	RMSE, MAE	M
[69]	Deep Spatio-Temporal Modeling	Hydropower	2025	ST-MTS	F1-score	M
[70]	Spatio-Temporal GNN (STGNN)	Wind Turbine	2025	ST-MTS	RMSE, MAE, MAPE	M
[71]	Hierarchical ST-Autocorrelation GNN	Wind Turbine	2024	ST-MTS	F1-score, RMSE	M
[72]	GSTN (Graph Sensor Transformer)	Wind Turbine	2024	ST-MTS	Acc, F1-score	M
[73]	Improved DBSCAN, GBM, and AGCRNN	Wind Turbine	2025	ST-MTS	RMSE, MAE, R^2	M

Note: PIL: Physics-Informed Loss; PIA: Physics-Informed Architecture; PDDG: Physics-Driven Data Generation; MTS: Multivariate Time Series; ST-MTS: Spatio-Temporal MTS; VIB: Vibration; IMG/SPEC: Image/Spectrogram; RMSE: Root Mean Square Error; MAE: Mean Absolute Error; Acc: Accuracy; F1: F1-score.

4.1.2. Reconstruction Methods

The foundations of this approach lie in deep autoencoders and their robust variants, designed to operate in industrial contexts where data is often unlabeled. W. Xie et al. [75] use a Sparse Autoencoder (SAE), a reconstruction network that introduces a sparsity constraint in the latent space to force the model to learn only the most significant features of vibrations in aeroderivative gas turbines. By integrating Transfer Learning techniques, the authors successfully transfer knowledge between different engines, solving data scarcity and achieving a diagnostic accuracy of 92%.

The vast expansion of wind farms, particularly in China, generates massive amounts of SCADA data often affected by noise and disturbances. C. Zhang [76] attributes these issues to electromagnetic interference and outliers during startup or shutdown phases, while J. Chen [77] highlights the impact of communication failures and packet loss during standstill periods. A widely adopted solution for managing these corrupted signals is based on the Stacked Denoising Autoencoder (SDAE). This architecture forces the network to reconstruct the original input from a version corrupted by artificial noise, pushing the model to ignore random components and learn only the most robust latent features of the signal. C. Zhang [76] integrates a Local Outlier Factor algorithm to clean the dataset before training and fuses the SDAE with LSTM cells and an XGBoost classifier to create a complex diagnostic pipeline. In contrast, J. Chen [77] proposes an approach based on the purity of reconstruction, where temporal dependency is handled through an integrated sliding window within the SDAE. In this architecture, training is performed across multiple noise levels to refine the network's ability to distinguish salient features, making the reconstruction error a highly sensitive anomaly indicator. Within this family of methods, Yan and Yu [78] apply the SDAE to gas turbines to extract hierarchical features from exhaust gas temperature profiles, overcoming the limitations of traditional combustor monitoring. To address the issue of training datasets polluted by unreported faults, consisting of unlabeled data that might contain anomalies mistaken for normality, S. Fu [79] introduces the Re-optimized Deep Auto-encoder (R-DAE) for gas turbines. This architecture solves the inefficiency of classic models, which, if trained on unfiltered data, tend to reconstruct faults well, making their identification difficult. The R-DAE implements a selection mechanism that purifies the training set and combines latent features with reconstruction residuals to feed an Isolation Forest, defining a more accurate decision boundary. Within the same Gas Turbine environment, G. Lee [26] optimizes monitoring efficiency via a Convolutional Auto-encoder (CAE); this specific reconstruction architecture utilizes convolutional filters to capture structural patterns while drastically reducing the number of network parameters compared to dense models, ensuring low computational costs for long-term malfunction detection. Following this technological path, D. Liu et al. [80] proposed the CSiamese framework, which integrates a Convolutional Auto-encoder with a Siamese network to measure reconstruction similarity. This method addresses the critical problem of data imbalance in gas turbines, where the extreme rarity of abnormal samples hinders the training of standard models. By optimizing parameters exclusively on normal samples, CSiamese enhances anomaly detection performance specifically for such imbalanced datasets.

Temporal analysis represents another fundamental challenge that reconstruction methods address. Jalil Pour [81] focuses on sensor modeling for gas turbines using LSTM-Autoencoder networks to identify early signals of internal degradation through the drift of thermodynamic parameters. In this context, Fahmi et al. [82] demonstrate the superiority of Temporal Convolutional Network-Autoencoder (TCN-AE) networks over LSTM in terms of speed and accuracy for gas turbines. A significant contribution to the development of digital twins is offered by Y. Ma and others [83], who developed a Performance Digital Twin based on LSTM-Autoencoder networks for aviation Gas Turbines. This reconstruction architecture does not merely model nominal behavior, but actively quantifies operational uncertainty, making detection reliable even during complex operational transients. To extend the applicability of reconstruction-based models to entire Wind Turbine fleets, Roelofs et al. [84] demonstrate that an Autoencoder pre-trained on a source turbine can be successfully adapted to target units with just a few months of historical data, thanks to Transfer Learning, effectively monitoring new plants where historical data is still insufficient.

Research in recent years has moved towards modeling spatial correlations via graphs and multi-scale analysis, placing itself among the most advanced reconstruction architectures. A critical problem for wind turbines is blade icing, which remains a significant concern for these due to its negative impact on aerodynamics and structural integrity. Wang et al. [85] address this issue via the beta-VGATAE framework, employing Graph Attention Networks (GAT) to extract the spatial structure of sensor interactions. Although ice identification often concerns diagnostics, the authors highlight how this model provides a fundamental anomaly detection tool, identifying the dynamic discrepancy between a nominal and an iced blade. Similarly, Duan et al. [86] introduce the TCAD model, based on Transformer and ResNet, to associate global and local dependencies in multivariate sequences. Following this direction, the work by Y. Zhan [69], previously discussed in the context of forecasting, exploits its hybrid structure to bridge the gap between predictive and reconstruction-based anomaly detection, integrating next-value prediction with spatial reconstruction via Graph Attention Networks. Through this approach, the model identifies anomalies by highlighting the discrepancy between predicted dynamics and global signal coherence. Luo [87] completes this landscape with the METG model, which combines graph networks and memory modules to prevent rare anomalous patterns from being reconstructed too faithfully, thereby increasing the system sensitivity in distinguishing critical deviations from nominal behavior.

The adoption of probabilistic generative models has further refined the detection of incipient faults under heavy noise. Fan et al. [88] propose the TCVAE-GAN model for wind turbine bearings, combining the stability of the VAE with the discriminative strength of GAN. For Steam Turbines, Xu and Zhang [89] present the ELSTMVAE (Enhanced Long Short-Term Memory Variational Autoencoder) architecture. This model integrates an LSTM architecture to handle time series with a Variational Autoencoder (VAE), utilizing a Gaussian Mixture Model (GMM) in the latent space; this integration allows modeling complex distributions and eliminating inherent training anomalies, ensuring precise classification. Alper [90] confirms the effectiveness of these approaches for gearboxes, while Yang et al. [91] fuse VAE and Neural ODE (Ordinary Differential Equation) to predict the dynamic response of Wind Turbine blades. This model identifies progressive degradation, such as erosion or cracks caused by mechanical fatigue and cyclic aerodynamic loads, by analyzing the deviation between reconstructed and measured dynamics. In the maritime sector, Dabaja [92] uses GAN-based architectures identify faults in marine engine air systems weeks in advance.

The evolution of these methodologies leads to the integration of reconstruction with specialized detection paradigms. For instance, Peng [93] introduces the DUA-SVDD (Deep Unsupervised Adaptive Support Vector Data Description) model, which defines a geometric hypersphere to enclose normal operational data. The network simultaneously minimizes the reconstruction error and the hypersphere volume, providing adaptive alarm thresholds for wind turbines. To conclude, Liang et al. [94] introduce ExpertAP, a framework applied to steam turbines that addresses the limitations of single-unit monitoring. By learning from historical patterns across multiple units, similar to human experts, the model mitigates the scarcity of anomaly labels through multi-unit pretraining and knowledge transfer, significantly improving the identification of potential failures.

Pros and Cons. In summary, reconstruction methods for anomaly or fault detection in turbomachinery strike a balance between extraction capability and architectural complexity. While AE architectures, extensively applied to gas turbines and wind farms [76,77], allow for the automatic extraction of salient parameters, they often show limits in the physical interpretation of the reconstruction error. To address this, VAE models provide a solid probabilistic basis for health-monitoring systems [85], although the assumption of Gaussian distributions may limit their precision in capturing highly non-linear operational shifts. Higher fidelity in modeling such complex distributions is ensured by GANs [92], despite their potential for training instability. At the same time, diffusion models [78] prove effective against SCADA signal noise, yet they require specific adjustments to handle the rapid temporal dynamics of turbomachinery. This evolution currently trends toward hybrid and multi-unit frameworks [69,94], which aim to overcome individual constraints by integrating diverse paradigms to achieve more reliable and interpretable diagnostics. The studies focusing on reconstruction-based methods are summarized in Table 2.

Table 2. Summary of recent literature on reconstruction-based methods for turbomachinery Anomaly and Fault Detection.

Work	Learning Paradigms	System	Year	Input	Metrics	Comp.
[75]	Sparse Autoencoder (SAE) with Transfer Learning	Gas Turbine	2022	VIB	F1-score, Acc	M
[76]	LSTM-SDAE and XGBoost	Wind Turbine	2022	MTS	F1-score, AUC	M
[77]	Stacked Denoising Autoencoders (SDAE)	Wind Turbine	2020	MTS	F1-score, RMSE	M
[78]	SDAE for Hierarchical Features	Gas Turbine	2019	MTS	F1-score, Acc	M
[79]	Re-optimized Deep Auto-encoder (R-DAE)	Gas Turbine	2021	MTS	F1-score, AUC	M
[26]	Convolutional Auto-encoder (CAE)	Gas Turbine	2020	MTS	F1-score, MSE	M
[80]	CSiamese (CAE + Siamese Network)	Gas Turbine	2023	MTS	F1-score, Acc	M
[81]	LSTM-Autoencoder (Sensor Modeling)	Gas Turbine	2022	MTS	MSE, MAE	M
[82]	TCN-Autoencoder (TCN-AE)	Gas Turbine	2024	MTS	RMSE, R^2	M
[83]	VAE-based Performance Digital Twin	Gas Turbine	2023	MTS	RMSE, MAE	M
[84]	Transfer Learning with Autoencoders	Wind Turbine	2024	MTS	F1-score, AUC	M
[85]	Beta-VGATAE (Graph Attention Networks)	Wind Turbine	2024	ST-MTS	F1-score, Acc	M
[86]	TCAD (Transformer and ResNet)	Wind Turbine	2022	MTS	F1-score	M
[69]	Deep Spatio-Temporal Modeling	Hydropower	2025	ST-MTS	F1-score	M
[87]	METG (Memory-enhanced Transformer)	Wind Turbine	2024	ST-MTS	F1-score	M
[88]	TCVAE-GAN and Correlation Enhancement	Bearing	2023	VIB	F1-score, Acc	H
[89]	ELSTMVAE-DAF-GMM (Enhanced VAE)	Steam Turbine	2025	MTS	F1-score, AUC	M
[90]	AE, VAE, and Deviation Networks	Gearbox	2023	VIB	F1-score, AUC	M
[91]	VAE and Neural ODE Integration	Wind Turbine	2024	VIB	F1-score, RMSE	H
[92]	GAN-based Unsupervised Detection	Marine Engine	2024	MTS	F1-score	H
[93]	DUA-SVDD (Deep Unsupervised SVDD)	Wind Turbine	2025	MTS	F1-score, AUC	M
[94]	Semi-supervised Sequence Reconstruction	Steam Turbine	2025	MTS	F1-score	M

Note: PIL: Physics-Informed Loss; PIA: Physics-Informed Architecture; PDDG: Physics-Driven Data Generation; MTS: Multivariate Time Series; ST-MTS: Spatio-Temporal MTS; VIB: Vibration; IMG/SPEC: Image/Spectrogram; RMSE: Root Mean Square Error; MAE: Mean Absolute Error; Acc: Accuracy; F1: F1-score.

4.1.3. Contrastive Methods

The evolution from reconstruction-based detection toward learning discriminative latent representations has redefined the monitoring of rotating machinery. As discussed in the previous subsection, D. Liu et al. [80] introduced the CSiamese framework, which integrates a CAE with a Siamese network to measure reconstruction similarity. This method, while sharing roots with previously analyzed reconstruction models, employs a triangle loss to optimize parameters on imbalanced datasets, overcoming the limitations of standard models in gas turbines. A recurring problem in industrial contexts like turbines is the difficulty of obtaining a database covering all possible fault types. In this regard, J. Chen [95] addresses the scarcity of labels: the model does not search for a specific fault but learns to master the machine's normal behavior. He proposes the TCN framework, an unsupervised approach that utilizes neural transformations and temporal contrastive learning to capture complex patterns without requiring negative samples, thereby preventing representation collapse. This network, which the author applies to steam turbines, acts as a sort of short-to-medium-term historical memory. Thanks to dilated convolutions, it can perceive a very wide temporal window. If the signal sequence (e.g., pressure rising while temperature falls anomalously) does not correspond to what was learned during training, the model generates an alert. The peculiarity of Chen's approach is that it does not require fault examples for training; instead, it compares the current signal with a transformed version of itself (a self-supervised approach) to verify the consistency of the latent representation. Managing the intrinsic challenges of SCADA data, such as imbalance and environmental noise, is a central theme of recent research. Sun et al. [96] developed the Matching Contrastive Learning (MCL) method, which introduces fixed reference points (bollards) in the latent space to guide data distribution toward stable centers, ensuring separability even with few fault examples. In another work, the same authors [97] adopt non-parametric regression to purify signals in scenarios of high meteorological variability. Since the relationship between environmental variables and turbine response is non-linear, this method models nominal behavior to calculate the discrepancy between expected and measured values. By isolating this clean signal, contrastive learning defines sharper boundaries between healthy and broken blades, regardless of aerodynamic loads or fluctuations induced by weather conditions, proving effective for the anomaly detection of blades. For managing rare or new faults, X. Liu et al. [98] utilize the Meta-Analogical Momentum Contrast Learning (MACL) method, based on a momentum encoder and one-shot learning logic, allowing for the identification of anomalies with a single example. Similarly, the problem of blade icing is addressed, as ice subtly alters the blade's mass and aerodynamic profile. Researchers like Z. Wang [99] apply the Unsupervised and Imbalanced Semi-Supervised Contrastive Learning (UISSCL) framework, which optimizes recognition in semi-supervised contexts. Using contrastive learning, this model learns to extract fundamental signal features (vibration, power, and wind speed) during training; then, the few available labeled data are introduced. The network uses these anchors to map the rest of the dataset. Finally, the framework optimizes the position of data in the latent space so that rare icing events are not suppressed or ignored by the massive amount of normal data. Changing strategy but remaining within the contrastive learning family, Guo et al. [100] construct a K-Nearest Neighbor Graph (KNNG) to map sensor interconnections and then use Graph Contrastive Learning (GCL) to train the network to recognize faults based on the graph's structure. The fusion of contrastive-based deep learning methods and physical knowledge represents a further methodological support. In this view, Qiao et al. [101] utilize prior knowledge by integrating fault characteristic frequencies into a model termed Prior Knowledge Embedding Contrastive Attention Learning Network (PKECALN). It consists of a backbone based on a 1D Deep Convolutional Neural Network (1D-DCNN) integrated with a custom Sequential Attention Module (SAM) to extract multi-scale time-frequency features from vibration signals and integrate prior knowledge (fault frequencies) to improve diagnosis with small samples. Miyamoto [102] and C. Wang [103] use contrastive learning to resolve visual confusion in anomaly detection. Specifically, Miyamoto proposes the Adaptive Activated Anomaly Detection (AAAD) model, which isolates inspection targets from variable backgrounds to find potential faults with few labeled images. Meanwhile, ref. [103] introduces the Spatial Contrast and Semantic Difference Perception Network (SSPN) for precise damage segmentation on aero-engine blades, achieving extreme accuracy at damage boundaries and preventing the loss of spatial details during image processing. Qin [104] proposes the Time-series and Image Pre-trained Encoder (TIPE) model based on ResNet, which aligns pressure signals and combustion images to detect thermo-acoustic instabilities through a multi-modal contrastive learning framework within gas turbines. Finally, the current research frontier shifts toward the integration of descriptive semantics offered by LLM. For decision support, Y. Li et al. [105] developed LLM-YOLOMS, based on YOLO (You Only Look Once) [106], where visual detection results performed at Multi-Scale (MS) are converted into textual attributes and interpreted by an LLM to provide maintenance recommendations. Tang et al. [107] introduce an LLM-based interpreter capable of translating high-frequency SCADA data into natural language health assessments, overcoming traditional diagnostic rigidity, where it is nearly impossible for a human operator to identify anomalies without intermediate tools and where classical anomaly detection systems often provide only a binary alarm (0 or 1) without further explanation.

Pros and Cons. Contrastive learning offers significant advantages for rotating machinery monitoring, particularly in managing extreme class imbalance through stable latent centers [96] and learning from unlabeled data to capture nominal behavior [95]. Its ability to integrate prior knowledge [101] and align multimodal signals [104] improves diagnostic robustness under low-label conditions. However, these methods often require meticulous design of negative samples to prevent representation collapse, a limitation effectively addressed by hybrid architectures like CSiamese [80], which utilize reconstruction objectives and triangle loss to stabilize training. Furthermore, pure contrastive models can be sensitive to environmental noise without specific pre-processing [97]. Conversely, LLM-based frameworks [105,107] provide superior semantic interpretability for maintenance technicians and few-shot adaptability, transforming structured detection into actionable maintenance advice. Despite these strengths, the direct application of LLMs to time series data remains a challenge, requiring specific prompting strategies to be effective. Moreover, as highlighted in current surveys [38], LLMs risk generating hallucinations when indexing or explaining anomaly points and may struggle with highly complex, context-dependent temporal anomalies. Consequently, adhering to Industry 5.0 paradigms, the integration of a Human-in-the-Loop (HITL) approach remains essential to validate AI inferences against domain expertise, ensuring that deep learning outputs act as decision support rather than autonomous replacements [35]. The works related to contrastive learning are reported in Table 3.

Table 3. Summary of the literature on contrastive learning for turbomachinery Anomaly and Fault Detection.

Work	Learning Paradigms	System	Year	Input	Metrics	Comp.
[80]	CAE and Siamese Network	Gas Turbine	2023	MTS	Acc, F1-score	M
[91]	DCdetector (Dual Attention Contrastive)	Wind Turbine	2023	MTS	F1-score	M
[108]	1D-CNN and Supervised Contrastive	Steam Turbine	2024	VIB	Acc, F1-score	M
[99]	UISSCL (Semi-supervised Contrastive)	Wind Turbine	2023	MTS	F1-score, AUC	M
[101]	PKECALN (Contrastive Attention)	Bearings	2024	VIB	Acc, F1-score	M
[104]	TIPE (Multimodal Contrastive Learning)	Combustors	2023	IMG/SPEC + MTS	F1-score	M
[103]	SSPN (Spatial and Semantic Contrast)	Aeroengine Blade	2025	IMG/SPEC	F1-score	M
[105]	LLM and YOLOMS Semantic Interpretation	Wind Turbine	2025	IMG/SPEC	Acc, F1-score	H
[95]	CNT (Graph-based Contrastive Learning)	Steam Turbines	2025	ST-MTS	F1-score, AUC	M
[96]	Matching Contrastive Learning	Wind Turbine	2023	MTS	F1-score	M
[102]	AAAD (Contrastive and Segmentation)	Wind Turbine	2025	IMG/SPEC	AUC	M
[98]	One-Shot (Meta-Analogical Momentum)	Wind Turbine	2022	MTS	Acc, F1-score	M
[100]	Graph Contrastive Learning (GCL)	Wind Turbine	2025	ST-MTS	Acc, F1-score	M
[97]	Environment-adapted Contrastive	Wind Turbine	2023	MTS	F1-score	M
[107]	LLM-based SCADA Interpreter	Wind Turbine	2025	MTS	Acc, F1-score	H

Note: PIL: Physics-Informed Loss; PIA: Physics-Informed Architecture; PDDG: Physics-Driven Data Generation; MTS: Multivariate Time Series; ST-MTS: Spatio-Temporal MTS; VIB: Vibration; IMG/SPEC: Image/Spectrogram; RMSE: Root Mean Square Error; MAE: Mean Absolute Error; Acc: Accuracy; F1: F1-score.

4.2. Hybrid Physics-Informed Family

Representing the second family for Anomaly and Fault Detection, hybrid methodologies integrate domain knowledge. A primary approach involves sequential coupling, where physics-based models are used to generate reference features that are subsequently analyzed through deep learning architectures [109]. Alternatively, Physics-Informed Neural Networks (PINNs) embed partial differential equations (PDEs) directly into the loss function. These frameworks address forward problems by acting as efficient surrogates for traditional numerical methods (such as FEM or CFD), enabling real-time estimation of unmeasurable critical quantities like equivalent stress, fatigue, or entire velocity and pressure fields [110]. Simultaneously, in inverse problems, PINNs infer unknown parameters or source terms (such as heat fluxes) from observed sensor data [111]. For diagnostics, this enables Anomaly Detection based on physical inconsistencies and direct comparisons between model outputs and sensor readings or nominal references, facilitating direct fault quantification and providing a basis for complex turbine health management [16]. Although various distinct approaches fall under this Hybrid Physics-Informed family, they will be analyzed collectively within this single subsection.

Analysis of Hybrid Physics-Informed Architectures

Methods integrating neural networks with physical laws make it possible to overcome the limitations of each individual approach, creating robust and reliable systems. These approaches help data-driven techniques cope with data scarcity, overfitting, and scenarios in which physical-domain computations are costly, accelerating CFD simulations by up to 70% and enabling online monitoring and real-time optimization [112,113]. In particular, they allow known physical information to be exploited even when operational data are noisy or incomplete, ensuring predictions that remain consistent with domain laws.

The first research line integrates physical equations directly into the optimization process through PINNs. Lai et al. [114] propose a multi-stage framework for nuclear turbines: the model decomposes the problem into sequential phases by solving the Navier–Stokes equations, monitoring flow rate and flow coefficient (C_v), and detecting obstructions, internal leakage, and stiction phenomena with respect to reference benchmarks. In the wind energy sector, Pei et al. [115] develop a hierarchical architecture: a data-cleaning module removes anomalies from SCADA signals, a GRA-LSTM network evaluates the turbine state, and a BiLSTM-PINN predicts power constrained by the fundamental theoretical kinetic energy equation ($P \propto v^3$). While real-world turbines typically operate at a lower exponent (approximately 2–2.5) due to mechanical-electrical losses and the Betz limit, the architecture utilizes such physical grounding to correct inconsistent deviations. Mittal et al. [116] address faulty sensors using clustering-based imputation, enabling the PINN to regularize the power curve while preserving physical coherence even in the presence of uncertain data. Gijon et al. [117] combine PINNs with Evidential Deep Learning on real SCADA data, directly parameterizing probabilistic distributions on the outputs (power, torque, and power coefficient). Physical constraints make it possible to distinguish epistemic and aleatoric uncertainty, respecting fundamental aerodynamic relationships and reducing uncertainty in sparsely sampled operating regions. For mechanical components, Zhang et al. [118] propose CNN-IPINN: the CNN extracts features from gearbox vibration signals, while the PINN solves the gear mesh stiffness equations. This dual approach ensures that fault diagnosis is consistent with mechanical dynamics, going beyond simple statistical pattern recognition.

A second research line concerns embedding physical coherence into generative models and architectures. Zideh and Solanki [119] develop a Physics-Informed Convolutional Autoencoder (PIConvAE) to protect power grids with high penetration of Distributed Energy Resources (DER). Unlike traditional autoencoders, which minimize only the statistical reconstruction error, this model integrates the residuals of nodal power balance equations into the loss. In this way, an anomaly is detected not only when data deviate from learned patterns, but also when physical constraints are violated, enabling the detection of stealth cyber-attacks such as False Data Injection, which are statistically camouflaged but physically inconsistent. In wind turbine monitoring, Wu et al. [120] develop a Physics-Informed Patch Transformer that primarily functions as a forecasting model while integrating physics directly into its architecture. This distinction serves to differentiate between autonomous feature learning and hybrid models where physical consistency is structurally enforced. The model constrains the attention mechanism through physical coherence over temporal segments. The approach stabilizes turbine behavior modeling, anticipates faults up to 5 days before the critical event, reduces post-repair false alarms, and allows maintenance personnel to accurately locate the fault source, optimizing maintenance interventions. In the context of geared transmissions, Yue et al. [121] propose the Physics-Informed Attention-aided Multiple Autoencoder (PI-AMAE) for zero-shot scenarios, where fault histories are unavailable. The framework incorporates a lumped-parameter dynamic model that generates synthetic fault data, referred to as signal twins, allowing the system to recognize anomalies never observed in operation, thanks to a prior physical signature. In parallel, Duan et al. [122] address noisy and stochastic data in wind turbines using a PyGRU (Physics-informed Gated Recurrent Unit), integrating physical constraints to model uncertainty. The PyGRU reduces epistemic uncertainty on normal data and increases sensitivity on anomalous data, improving detection and reducing false alarms caused by fixed thresholds.

Physics also facilitates the generation of synthetic data to train networks under limited data conditions. Alblawi [109] simulates gas turbine degradation to train Multi Feedforward Artificial Neural Networks (MFANNs) and isolate environmental effects, while Schröder et al. [123] address wind load monitoring scarcity through Transfer Learning, using aeroelastic simulations for physical pre-training before refinement with real-world data. Such Virtual Sensing strategies enable accurate real-time fatigue load estimation using only SCADA data. Similarly, Huber et al. [124] demonstrate the effectiveness of physics-informed data augmentation by generating physics-based fault trajectories and mixing them with nominal data to train classifiers capable of recognizing rare faults. In the context of extreme class imbalance in rotating machinery, Li et al. [125] adopt a generative strategy based on physical models to create signal twins and train contrastive networks. In this case, the authors do not use standard PINN architectures: physics does not enter as a constraint in the cost function, but is employed upstream through a lumped-parameter dynamic model, generating synthetic replicas of fault vibrations that serve as training data. Perez-Sanjines et al. [126] and Jamil et al. [127] develop fault detection methodologies for wind turbines, arguing that raw data are often too noisy for direct deep learning. Instead, they use Cyclic Spectral Coherence, a signal processing technique based on rotating component kinematics to extract cyclostationary signatures hidden in noise. These physically meaningful 2D maps are used as inputs to deep classifiers (CNNs) and enable reliable detection of incipient faults in gearboxes across entire fleets. Freeman et al. [128] address rotor imbalance detection in marine turbines, a condition often masked by hydrodynamic instability. The authors integrate turbulence intensity, computed from the flow, into a 1D CNN. The combined use of TI as both an explicit input feature and as a regulator within a physics-informed loss function allows the model to separate environmental fluctuations from real structural anomalies, improving the detection of hidden faults. The integration of physical features with advanced optimization algorithms is investigated by Lee et al. [129,130] and Chen et al. [131]. Lee utilizes Particle Swarm Optimization (PSO) to calibrate CatBoost classifiers on imbalanced wind SCADA data, while Chen maximizes the discrepancy between real data and physically simulated fault states to optimize LSTM sensitivity to damage symptoms. Finally, Khan et al. [132] apply a physics-guided Bayesian neural network to wind turbine sensor networks, exploiting physical correlations among operational variables to detect sensor faults with a probabilistic measure of confidence.

Pros and Cons. As evidenced by the review of the aforementioned works, the integration of physical knowledge into deep learning models can be traced back to three integration paradigms, each with specific advantages and limitations. The first paradigm, Physics-Informed Loss (PIL), typical of PINNs, utilizes physics as an external constraint: the network maintains a standard architecture but is penalized when its predictions violate fundamental domain laws [115–117]. Key advantages include high efficiency with limited data and a mesh-free nature, which simplifies the modeling of complex geometries without requiring discretization grids [114]. Furthermore, the ability to solve both forward and inverse problems within a single framework represents a unique strength for identifying unknown parameters [111]. However, PINNs face significant optimization challenges: stiff and multi-scale loss landscapes make convergence difficult, requiring extremely precise weight tuning. They also exhibit marked sensitivity to noise in inverse problems, where signal degradation can lead to biased parameter estimations. The second paradigm, Physics-Informed Architecture (PIA), ensures greater stability by structurally incorporating physical knowledge directly into the network's building blocks, as implemented in the Patch Transformer [120], the PI-AMAE framework [121], or the PyGRU cell [122]. This method ensures that every intermediate model state adheres to physical constraints, improving structural robustness. Finally, the third paradigm, Physics-Driven Data Generation (PDDG), utilizes physics to create ideal synthetic datasets to train the network [109,123,125]. While this strategy radically solves class imbalance and the scarcity of real-world samples, its effectiveness depends entirely on the fidelity of the original physical model: any upstream modeling error is inevitably inherited by the deep learning system. Table 4 provides an overview of studies on physics-informed methods; in this case, instead of the publication date in the last column, the integration paradigms (PIL, PIA, and PDDG) are reported.

Table 4. Summary of recent literature on hybrid physics-informed methods for turbomachinery Anomaly and Fault Detection.

Work	Learning Paradigms	System	Integration	Year	Input	Metrics	Comp.
[114]	Multistage PINN	Nuclear Valve	PIL	2024	Physics + MTS	F1-score, RMSE	H
[115]	BiLSTM-PINN Architecture	Wind Turbine	PIL	2026	Physics + MTS	RMSE, MAE	H
[116]	Error Detection PINN	Wind Turbine	PIL	2024	Physics + MTS	RMSE, MAE	H
[117]	PINN with Uncertainty Quantification	Wind Turbine	PIL	2026	Physics + MTS	RMSE, MAE	H
[118]	CNN-IPINN (CNN + PINN)	Gearbox	PIL	2025	Physics + VIB	F1-score, Acc	H
[119]	PI-Convolutional Autoencoder	Power Grid	PIL	2025	Physics + MTS	F1-score, RMSE	H
[128]	Turbulence Intensity Infusion PINN	Marine Turbine	PIL	2022	Physics + MTS	F1-score, Acc	H
[129]	Deep CNN and AEPSO-Catboost	Wind Turbine	PIL	2025	Physics + MTS	F1-score, Acc	H
[130]	Deep CNN and AEPSO-XGBoost	Wind Turbine	PIL	2024	Physics + MTS	F1-score, Acc	H
[132]	Physics-Guided Bayesian NN	Wind Turbine	PIL	2025	Physics + MTS	F1-score, RMSE	H
[127]	PI-Multivariate Deep Learning	WT Drivetrain	PIL	2023	Physics + MTS	F1-score, Acc	H
[120]	Physics-informed Patch Transformer	Wind Turbine	PIA	2026	Physics + MTS	F1-score, Acc	H
[121]	Attention-aided Multiple AE (PI-AMAE)	Gearbox	PIA	2025	Physics + VIB	F1-score, Acc	H
[122]	Probabilistic Physics-informed AE	WT Electromech.	PIA	2025	Physics + MTS	F1-score, AUC	H
[126]	PI-Cyclic Spectral Coherence DL	WT Gearbox	PIA	2023	Physics + VIB	F1-score, Acc	H
[109]	Thermodynamic Model and MFANN	Gas Turbine	PDDG	2020	Physics + MTS	RMSE, MSE	M
[123]	PI-ML with Transfer Learning	Wind Turbine	PDDG	2022	Physics + MTS	RMSE, MAE	M
[124]	ML with Physics-informed Augmentation	Gas Turbine	PDDG	2023	Physics + MTS	F1-score, Acc	M
[125]	Physical-Knowledge Contrastive Learning	Rotating Mach.	PDDG	2025	Physics + VIB	F1-score, Acc	M
[131]	Physics-Informed LSTM (Hyperparameters)	Gearbox	PDDG	2022	Physics + VIB	F1-score, RMSE	M

Note: PIL: Physics-Informed Loss; PIA: Physics-Informed Architecture; PDDG: Physics-Driven Data Generation; MTS: Multivariate Time Series; ST-MTS: Spatio-Temporal MTS; VIB: Vibration; IMG/SPEC: Image/Spectrogram; RMSE: Root Mean Square Error; MAE: Mean Absolute Error; Acc: Accuracy; F1: F1-score; AUC: Area Under the Curve; MSE: Mean Square Error.

Synthesizing the Anomaly Detection landscape analyzed throughout this section, while the reviewed architectures have reached a high level of development, their ability to generalize across different turbine fleets and maintain accuracy under severe sensor noise represents a significant frontier, further examined in "Section Research Gaps and Future Perspectives".

5. Prognostics and RUL Estimation in Modern Turbine Systems

In the past decade, predictive maintenance for turbine systems has progressively transitioned from classical machine learning to Deep Learning architectures [133,134]. This transformation is driven by the superior capability of deep models to handle high-dimensional monitoring data and autonomously extract degradation patterns, effectively bypassing manual feature engineering [135,136]. However, RUL estimation remains largely dependent on supervised paradigms requiring extensive datasets with complete run-to-failure histories [134]. To align with the overarching taxonomy established in the previous section for Anomaly Detection, the methodologies for RUL prediction can be strictly classified into two primary families: Pure Deep Learning for RUL and Physics-Guided RUL. To address the scarcity of comprehensive labeled data, recent research indicates that integrating physical principles with neural networks as a cross-cutting layer can overcome the limitations of purely data-driven models [16,137]. Despite the success of standard Deep Learning, the future of prognosis also lies in hybrid methodologies [36]. Reflecting this core methodological split, the following discussion analyzes recent developments by explicitly contrasting these two architectural domains.

5.1. Pure Deep Learning for RUL

Research within the purely data-driven domain focuses extensively on feature extraction from complex data streams and overcoming the dependence on heavily labeled datasets through semi-supervised paradigms or deep architecture optimizations. J. Sun [138] proposes a DT for the performance of aerospace gas turbines using a semi-supervised method. Instead of a complete physical model, they use Deep Learning to build a Performance Digital Twin (PDT) capable of extracting multi-dimensional health indicators. Similarly, Y. Wang et al. [139] introduce the FCDAE-CNN-LSTM model for turbofan engines, a semi-supervised system that employs autoencoders for signal denoising, reducing the error induced by environmental noise and the scarcity of diagnostic labels. Focusing strictly on deep feature extraction, Elsherif et al. [140] apply the supervised CAELSTM network to turbofan engines, monitoring multi-sensor telemetry (temperatures, pressures, and rotational speeds) from the C-MAPSS datasets. Despite the model's complexity, the approach remains strictly data-tied, using a convolutional autoencoder for noise reduction and attention mechanisms to identify the most relevant temporal degradation sequences. In the context of wind turbine gearbox bearings, Ke He et al. [141] focus on high-frequency vibration signal analysis by introducing the Self-Calibration Temporal Convolutional Network (SC-TCN). This supervised model is purely Deep Learning, but introduces a significant mathematical innovation: an architectural self-calibration module designed to preserve local information from vibration sensors, which is typically lost in the dilated convolutions of standard TCNs. This allows for capturing micro-variations in the vibratory signal symptomatic of incipient wear, overcoming the gaps of classical temporal networks. The flexibility of these systems is further explored by Jiaze Li [142], who applies Multimodal Transfer Learning to aircraft turbines to transfer RUL knowledge across different operating regimes.

Finally, the expansion of prognosis to diverse physical signals completes the data-driven landscape. Atsafack et al. [143] use IoT data and supervised CNN-LSTM networks for the RUL of hydraulic turbines, monitoring electrical and hydraulic parameters in real-time. In thermoelectric power plants, Dayang Li et al. [142] forecast the degradation trend of steam turbines by correlating online oil monitoring data (viscosity, humidity, and wear particles) with the output power through LSTM networks. This connects to the work of Lei Sun et al. [144], which confirms the effectiveness of supervised RNNs and CNNs for power prediction in steam turbines. Closing the review, Rengasamy [145] proposes the use of asymmetric loss functions in deep models for aero-engines, optimizing supervised prognosis to avoid RUL underestimations that could compromise operational safety.

5.2. Physics-Guided RUL

To bridge the interpretability and generalization limits of the purely statistical models discussed above, prognostic literature highlights a growing interest in the integration of physical models and deep neural architectures for Remaining Useful Life (RUL) estimation. In this context, Ang Li [146] presents the Phy-DeepLSTM framework applied to marine steam turbines. This represents a supervised, hybrid physics-informed approach to system-wide Digital Twin modeling; the model integrates thermodynamic constraints into the DeepLSTM network to ensure physical consistency during operational transients, thereby improving accuracy over traditional black-box methods. Similarly, Yucesan and Viana [110] introduce a supervised PINN for the RUL estimation of wind turbine main bearings. Their model is fully hybrid, designed to fuse physical layers (modeling fatigue based on torsional and axial loads) with data-driven layers tasked with capturing complex stochastic phenomena, such as the chemical degradation of lubricating grease.

The management of thermomechanical stress characterizes the work of Zhang et al. [147], who develop a PINN to predict the creep-fatigue life of components operating at elevated temperatures (gas and steam turbines). This supervised model integrates physical knowledge through both dedicated feature engineering and a constrained loss function that allows for effective operation even with reduced datasets. Within the wind energy sector, Zheng Wang et al. [148] address the RUL of gearbox bearings using a supervised hybrid PI-LSTM network. The integration of prior knowledge regarding mechanical wear mechanisms guides the network's learning even in the presence of limited samples. Similarly, Huber et al. [124] extend this philosophy to gas turbines, utilizing hybrid models where physics supports data augmentation to generate synthetic failure scenarios, making the supervised prognosis significantly more robust against the scarcity of real data. Expanding on the concept of physics-driven data generation, Lu et al. [137] propose a Digital Twin-driven architecture for gearbox RUL estimation. By employing a high-fidelity virtual model to simulate degradation trajectories, their framework effectively compensates for the lack of real-world run-to-failure data. Additionally, the authors introduce a water-wave information transmission network to process multivariate time series, which captures long-term dependencies more stably than conventional recurrent networks. An overview of both purely data-driven and physics-guided research on RUL prediction methods is presented in Table 5.

Concluding the review of prognostic methodologies, while physics-guided RUL models demonstrate high reliability, managing the inherent uncertainties of aging systems and optimizing these models for constrained edge hardware remain primary challenges, as detailed in "Section Research Gaps and Future Perspectives".

Table 5. Summary of recent literature on RUL prediction and performance prognostics for turbomachinery.

Learning Paradigms	System	Family	Year	Input	Metrics	Comp.
[138] Performance Digital Twin (PDT)	Gas Turbine	Pure DL	2023	MTS + DP	RMSE, MAE	M
[139] FCDAE-CNN-LSTM (Semi-supervised)	Turbofan Engine	Pure DL	2023	MTS	RMSE, MAE	M
[140] CAELSTM with Attention	Turbofan Engine	Pure DL	2025	MTS	RMSE, MAE	M
[141] Self-Calibration TCN (SCTCN)	Wind Turbine	Pure DL	2022	VIB	RMSE, MAE	M
[149] Multimodal Transfer Learning	Turbine Engine	Pure DL	2025	MTS	RMSE, MAE	M
[143] CNN-LSTM and IoT Data	Hydraulic Turbine	Pure DL	2025	MTS	RMSE, MAE, R^2	M
[142] LSTM and Oil Monitoring	Power Plant Turbine	Pure DL	2024	MTS	RMSE, MAE, MAPE	M
[144] RNN and CNN Power Prediction	Steam Turbine	Pure DL	2021	MTS	RMSE, MAE, MAPE	M
[145] DL and Asymmetric Loss Functions	Gas Turbine	Pure DL	2020	MTS	RMSE, MSE	M
[146] Physics-informed DeepLSTM	Steam Turbine	Phys-Guided	2025	Phys + MTS	RMSE, MAE	H
[110] Physics-informed Neural Network	Wind Turbine	Phys-Guided	2021	Phys + MTS	RMSE, MAE	H
[147] PINN (Feature Engineering + Loss)	Steam Turbine	Phys-Guided	2021	Phys + MTS	RMSE, R^2	H
[148] PI-LSTM and Prior Knowledge	Wind Turbine	Phys-Guided	2022	Phys + MTS	RMSE, MAE	H
[124] ML and Physics-informed Augmentation	Gas Turbine	Phys-Guided	2023	Phys + MTS	RMSE, MAE	M
[137] Digital Twin and WITRAN	Gearbox	Phys-Guided	2025	Phys + VIB	Acc, RMSE, MAE	H

Note: PIL: Physics-Informed Loss; PIA: Physics-Informed Architecture; PDDG: Physics-Driven Data Generation; MTS: Multivariate Time Series; ST-MTS: Spatio-Temporal MTS; VIB: Vibration; Phys: Physics-based inputs; DP: Design Parameters; RMSE: Root Mean Square Error; MAE: Mean Absolute Error; MAPE: Mean Absolute Percentage Error; MSE: Mean Square Error; R^2: Coefficient of Determination; Acc: Accuracy.

6. Root Cause Analysis in Modern Turbomachinery Diagnostics

Starting from the classics of Root Cause Analysis (RCA), such as the Ishikawa Diagram and FMEA, in the Industry 5.0 era, the analysis of root causes is evolving towards a modern and highly automated approach [150]. The high operational complexity of modern turbomachinery renders purely manual diagnosis obsolete, necessitating a shift towards Data-Driven methodologies, as widely discussed in the literature [151]. In the current industrial landscape, established frameworks rely on probabilistic and causal reasoning. Bayesian Networks (BN) assume a central role: utilizing joint probability and a priori knowledge, they allow for precise Root-Cause Isolation by tracing fault propagation across subsystems. Alongside these, Fuzzy Cognitive Maps (FCM) are widely employed to model causal relationships under conditions of uncertainty, providing a logical layer that is easily interpretable by operators. To handle the complexity of raw sensor streams, these reasoning tools are increasingly integrated with Deep Learning architectures. In this context, CNNs are adopted to extract specific fault signatures (feature extraction) rather than merely for classification, while LSTM networks and Attention mechanisms have become the de facto standard for capturing long-term temporal dependencies. However, as highlighted by Pietsch et al. [35], the massive adoption of these algorithms encounters the limit of sparse semantics: although Deep Learning is powerful in detecting numerical correlations, it often fails to explain the physical reasons. To bridge this gap, the most advanced research is moving towards GNN to preserve the machine topology and LLM to process unstructured knowledge such as maintenance logs. This shift paves the way for a Hybrid Intelligence, where computational power is validated by the presence of the expert (human-in-the-loop). This synergy perfectly embodies the Industry 5.0 paradigm: a human-centric approach where technology supports the operator, enhancing irreplaceable skills such as complex decision-making and advanced problem-solving. Accordingly, this section analyzes recent works related to turbomachinery RCA, focusing exclusively on purely data-driven models.

Frontiers of Root Cause Analysis in Turbomachinery

As prognostics evolve, research has increasingly targeted the automation of RCA to shift diagnostics from reactive to proactive by integrating probabilistic models, graphs, and artificial intelligence. In this field, Gugaliya [152] proposes an approach based on Multi-PCA for gas turbines. This method enhances traditional PCA capabilities by managing system non-linearities through the clustering of operational data; the added value lies in isolating faults via the identification of statistical deviations in individual sensors, acting as a link between classical statistics and machine learning.

To enhance explainability, C. Zhang et al. [108] introduce an AIOps framework for wind turbines using LSTM-AVAGMM models and the SHAP technique. The application of SHAP addresses the opacity of deep learning by quantifying the contribution of each sensor to the onset of the anomaly, providing a transparent diagnosis to the operator.

The most recent research frontier explores the use of graph-based architectures to respect the physical topology of the machinery. L. Yuan et al. [153] present the GAT-BN model, which combines Graph Attention Networks and Bayesian Networks for aircraft engines. This architecture allows for the autonomous learning of node criticality, modeling fault propagation along the physical structure of the engine. Building on this topological perspective, Mourya and Tyagi [154] propose a system based on GNN and Dynamic Bayesian Networks for offshore turbomachinery, introducing the concept of the Maintenance Causality Loop to bridge the gap between siloed signals and prioritized maintenance action.

Real-time diagnostic capabilities are further expanded by Ofoedu et al. [155], who employ LSTM networks to capture temporal causality in sequential data and Bayesian Networks to model probabilistic dependencies in offshore process failures. Their hybrid framework effectively integrates distributed sensor streams to isolate root causes with high accuracy; specifically, the combined use of deep learning for time series and probabilistic inference allows for managing the intrinsic uncertainty of live data, drastically reducing false alarms compared to threshold-based systems. Finally, generative AI is transforming the management of unstructured knowledge. Vitale [156] explores the use of LLMs and information retrieval for gas turbines and compressors, translating natural language descriptions into structured diagnostic insights. Complementing this approach, R. Shi et al. [157] propose an intelligent RCA method for steam turbines based on Knowledge Graphs and LLMs. Their system constructs a domain-specific graph of turbine components (e.g., blades, bearings) and employs the reasoning capabilities of the language model to identify root causes of quality accidents and operational failures. Studies addressing RCA methods are listed in Table 6.

Table 6. Summary of recent literature on RCA and advanced diagnostics for turbomachinery.

Work	Learning Paradigms	System	Year	Input	Metrics	Comp.
[152]	Multi-PCA and HDBSCAN Clustering	Gas Turbine	2020	MTS	F1-score, Acc	L
[156]	Generative AI and LLMs	Turbomachinery	2024	MTS	F1-score, Acc	H
[157]	Knowledge Graph and LLM	Steam Turbine	2025	Physics + MTS	F1-score, Acc	H
[153]	Improved Bayesian Network and GAT	Aircraft Engine	2026	ST-MTS	F1-score, Acc	M
[154]	AI-Enabled Operational Intelligence	Offshore O&G	2025	MTS + VIB	F1-score, Acc	M
[108]	LSTM-AVAGMM and SHAP-based RCA	Wind Turbine	2024	MTS	F1-score, AUC	M
[155]	LSTM and Bayesian Networks	Offshore Processes	2022	MTS	F1-score, Acc	M

Note: PIL: Physics-Informed Loss; PIA: Physics-Informed Architecture; PDDG: Physics-Driven Data Generation; MTS: Multivariate Time Series; ST-MTS: Spatio-Temporal MTS; VIB: Vibration; IMG/SPEC: Image/Spectrogram; Phys: Physics-based inputs; RMSE: Root Mean Square Error; MAE: Mean Absolute Error; Acc: Accuracy; F1: F1-score; AUC: Area Under the Curve.

Reflecting on the diagnostic strategies for root cause identification, while the emergence of XAI and Large Language Models provides a semantic bridge for human operators, the formal integration of physical consistency and the mitigation of technical hallucinations in critical operations remain the primary challenges, as detailed in “Section Research Gaps and Future Perspectives”.

7. Comparative Analysis

To evaluate architectures objectively, five synthetic indices are introduced to reflect fundamental aspects of industrial monitoring:

- Performance Index (P-Index): Quantifies diagnostic reliability by prioritizing the F1-score or, in its absence, Accuracy, AUC, and prediction error or normalized prediction error.
- Data Efficiency Index (DE-Index): Evaluates the volume of historical data required to make the system operational, rewarding models capable of converging with minimal training sets compared to architectures necessitating extensive data baselines.
- Inference Time Index (IT-Index): Assesses responsiveness and suitability for deployment on limited hardware, distinguishing between fast parallelizable architectures and dynamic models burdened by the recalculation of spatial relationships.
- Interpretability Index (I-Index): Measures the ability to support the identification of fault causes, distinguishing between black-box models and transparent architectures that allow for the explicit visualization of the sensors driving the alarm.
- Generalization Capability Index (GC-Index): Quantifies the readiness of the model to be extended to a fleet without the need for retraining. In turbomachinery, generalization is hindered by sensor tolerances, the environment, and the degradation state of systems.

7.1. Methodology for Synthetic Index Definition

To ensure reproducibility and objectivity, the assigned scores derive from a meta-analytic synthesis algorithm. This approach allows for mapping the technical characteristics and numerical results of the surveyed works onto a common metric.

7.1.1. Methodological Derivation of the P-Index

The performance index is determined according to a rigorous protocol based on the following eight rules:

1. F1-score Priority: This constitutes the primary metric for monitoring. Given the rarity of faults in the sector, the F1-score is the most reliable indicator for evaluating the actual anomaly detection capability on imbalanced classes.
2. Accuracy/AUC Hierarchy: In the absence of the F1-score, Accuracy or AUC is adopted as a proxy indicator. Operating already on a 0–1 scale, these values are integrated directly into the calculation.
3. Inverse Normalization of Errors: Utilized in the presence of reconstruction or prognostic errors when F1-score, Accuracy, or AUC are unavailable. To compare such error metrics with performance indicators, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Squared Error (MSE) values are transformed using inverse linear normalization:

$$P_i = 1 - \frac{M_i - M_{min}}{M_{max} - M_{min}}$$

   where P_i represents the index result for the i-th work and M_i is the reported error metric value. The parameters M_{min} and M_{max} are the minimum and maximum values, respectively, extracted within the same methodological family or related to the same benchmark, especially when such data results are isolated (i.e., present in only 1 or 2 works).
4. MAPE Management: In the absence of RMSE and MAE, the Mean Absolute Percentage Error (MAPE) is treated analogously to other error indicators, being normalized and inverted to preserve statistical information in forecasting works.

5. Heterogeneous Metrics Management: If a sub-family presents mixed metrics, individual normalization is performed for each work reporting prediction errors, making them comparable with native 0–1 scale values (F1-score, Accuracy, AUC).
6. Maximum Value Rule (SOTA): For each study, the result of the best-performing configuration is extracted, thus mapping the maximum potential of the proposed architecture.
7. Single Case Management (External Benchmark): If an error metric appears in a very small number of works (1 or 2) within a sub-family, hindering a meaningful internal normalization, the value is compared against a consolidated external benchmark or the known SOTA for that system.
8. Pooled Average Calculation: The final P-Index of the sub-family is the global arithmetic mean of all individual P_i values, ensuring that each study contributes equally to the final statistical weight.

Certain methodological boundaries apply to the proposed framework. Scoring depends on author-reported metrics of varying rigor, while arithmetic aggregation weights all studies equally regardless of research scale. Additionally, diverse datasets and protocols hinder direct cross-study comparisons. The resulting indices serve as relative benchmarks for identifying architectural trends rather than absolute performance measurements.

7.1.2. Scoring Criteria for Qualitative Indices (DE, IT, I, GC)

The indices related to architectural and operational properties are determined through an ordinal mapping of the declared technical characteristics. The final score of each sub-family is obtained by calculating the average of the values assigned to individual works according to the following scoring structure Table 7:

Table 7. Ordinal scoring rubric for qualitative synthetic indices based on architectural and operational features.

Value	DE-Index	IT-Index	I-Index	GC-Index
1.0	Physics-Informed or Few-Shot paradigms. Requires minimal training sets due to prior physical knowledge.	Low (L) complexity. Shallow models or parallelizable TCNs ready for real-time edge computing.	Physics-explicit architectures or structural transparency models allowing the visualization of sensors driving the alarm.	Fleet-wide or Zero-Shot systems. Validation on machines different from those used in training.
0.7	Semi-supervised or Hybrid paradigms. Utilizes unlabeled data or partial physical regularization.	Medium (M) complexity. Deep LSTM or Transformers. Requires GPU acceleration but is manageable in industrial contexts.	Models with Attention Weights or GNNs. Visualization of critical sensors (structural XAI).	Validation on real-world data, multi-regime, and with sensor noise, limited to a specific variant.
0.3	Pure DL paradigms. Requires massive historical databases and full seasonal cycles for convergence.	High (H) complexity. Iterative PINNs or massive GANs. High computational load or cloud latency.	Black-Box models (Standard LSTM/CNN). They signal anomalies without providing evidence regarding the root causes.	Validation on a single system or exclusively on synthetic data (numerical simulations).

In this framework, the DE-Index assignments primarily reflect a qualitative synthesis of the training requirements inherent to each paradigm. Higher scores (1.0) are typically associated with Physics-Informed or Few-Shot models that utilize prior knowledge to reach convergence with limited samples, whereas lower scores (0.3) generally characterize Purely Data-Driven architectures that often necessitate extensive historical baselines to effectively model system dynamics. We acknowledge that this meta-analytic synthesis, while based on rigorous criteria, is influenced by author-reported data and the specific experimental configurations of the original works. The methodology, however, allows for overcoming purely qualitative assessments, providing a quantitative guide for the adoption of AI solutions in the turbomachinery sector.

Relying on these evaluative metrics, the following subsections systematically assess and benchmark the methodological architectures across the three primary PdM tasks: Anomaly and Fault Detection, RUL estimation, and RCA.

7.1.3. Illustrative Example: GC-Index Calculation for Graph-Based Methods

To address the requirement for methodological transparency, Table 8 illustrates the scoring process for the Generalization Capability Index (GC-Index) within the "Graph-based Reconstruction" sub-family. This example demonstrates how qualitative features extracted from the literature are mapped to ordinal scores (0.3, 0.7, 1.0) to derive the final aggregate value.

As shown, the resulting index of 0.6 is not an arbitrary assignment but the result of a reproducible aggregation of the architectural characteristics and validation setups declared by the authors. Similar procedures were applied to all papers for the calculation of P, DE, IT, and I indices, ensuring a standardized benchmarking across different methodological families.

Table 8. Detailed scoring example for the GC-Index in Graph-based Reconstruction methods.

Work [Ref]	**Validation Framework**	**Score**	**Rationale (from Table 7)**
Wang [85]	Validated on synthetic datasets with limited noise scenarios.	0.3	Synthetic data/Single regime
Zhan [69]	Tested on standard benchmark datasets without cross-domain validation.	0.3	Single system/Lab-scale
Luo [87]	Validated on multi-sensor industrial data with varying operating conditions.	0.7	Real-world data/Multi-regime
Liang [94]	Validated across different turbine fleets with structural prior knowledge.	1.0	Fleet-wide/Zero-Shot
Aggregate	Arithmetic Mean: (0.3 + 0.3 + 0.7 + 1.0)/4	0.575	≈0.6 (Final GC-Index)

7.2. Anomaly and Fault Detection: Methodological Benchmarking

This subsection evaluates Anomaly and Fault Detection methods, explicitly contrasting the Purely Data-Driven family against the Hybrid Physics-Informed one. Subsequently, physics-guided methods are structured and analyzed according to their specific integration paradigm. In conclusion, a Global Comparison aggregates the average results to objectively benchmark the overall operational impact between these two families concerning Anomaly Detection.

7.2.1. Comparative Analysis for the Purely Data-Driven Family

Purely data-driven methods (forecasting, reconstruction, and contrastive) are analyzed here by dividing them into specific sub-families; this approach allows for the grouping of works that employ similar Deep Learning architectures, thereby evaluating their varying performances according to the indices defined previously in this section.

Forecasting-Based Architectures

The examination of the works focused on forecasting allows for a clear mapping of the technological evolution in turbomachinery monitoring, which is shifting from simple temporal analysis toward models capable of mapping the physical layout and relationships between different sensors. Within this landscape, four main architectural sub-families have been identified, as summarized in Table 9.

Table 9. Summary of architectural sub-families for forecasting-based methods.

Sub-Family	Key Features & Applications	References
GNN	Represents the dominant and most innovative trend, capable of mapping spatial and topological relationships between sensors.	[67–73]
RNN/LSTM	The established standard for handling complex sequential and temporal dependencies.	[61–64]
CNN/TCN	Dedicated to computational efficiency and highly suitable for edge monitoring applications.	[65,66]
Statistical Hybrid	Employs classical models (e.g., GAM, ARFIMA) for operational contexts characterized by high stationarity.	[60]

Once the individual indices were calculated for each work in the forecasting group, the values were aggregated by family using the arithmetic mean to generate the Radar Plots presented in Figure 8. This quantitative synthesis not only highlights the strengths of each paradigm but also provides a decision-making guide for selecting the most suitable architecture based on specific industrial constraints. Despite GNNs being the most prominent sub-family in recent literature, the metrics highlight a significant trade-off: while these architectures excel in interpretability and spatial accuracy, they demand considerably higher computational resources and data volumes. In contrast, LSTM and TCN-based models remain highly efficient solutions, offering a superior balance between execution speed and industrial readiness, albeit at the expense of some diagnostic transparency.

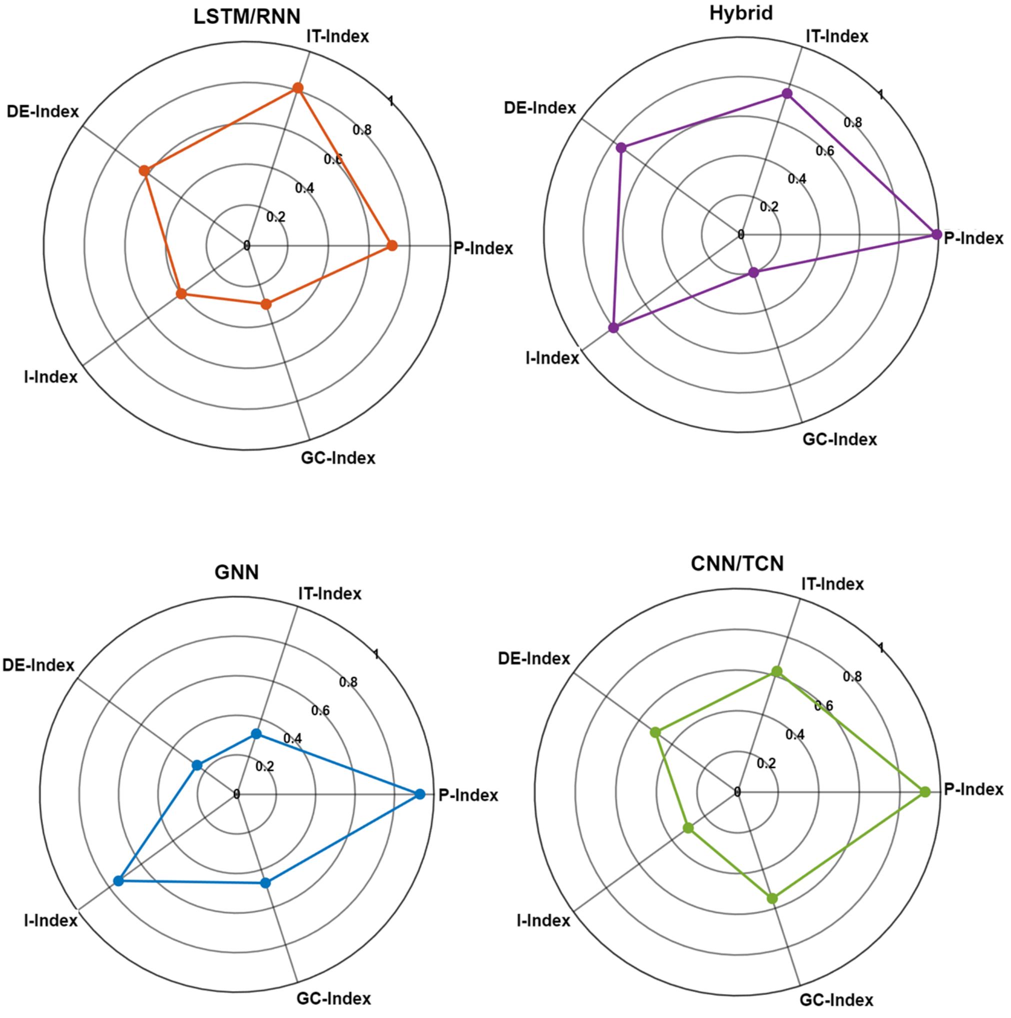


Figure 8. Comparative analysis of forecasting architectural sub-families.

Reconstruction-Based Architectures

Adopting the same evaluation protocol used previously, we examined the 22 contributions belonging to the Reconstruction Methods macro-family. The literature analysis allowed for the identification of four distinct architectural sub-families, as summarized in Table 10.

The average performance of these sub-families, calculated according to the five introduced indices, is visualized in the Radar Plot in Figure 9. The data reveal that the Recurrent AE sub-family emerges as the most balanced solution, guaranteeing maximum diagnostic reliability with moderate computational costs. However, when the primary constraint is execution speed, such as in deployment on edge systems or high-frequency vibration analysis, the Convolutive sub-family clearly dominates in terms of temporal efficiency, with only minimal sacrifice in precision. A notable result concerns the Graph-based sub-family: although computationally more demanding, it excels not only in interpretability but also in generalization capability. This result is driven by recent contributions such as ExpertAP [94], demonstrating how the graph structure facilitates knowledge transfer (Transfer Learning) between different units of a fleet, overcoming the limits of traditional models trained on a single unit.

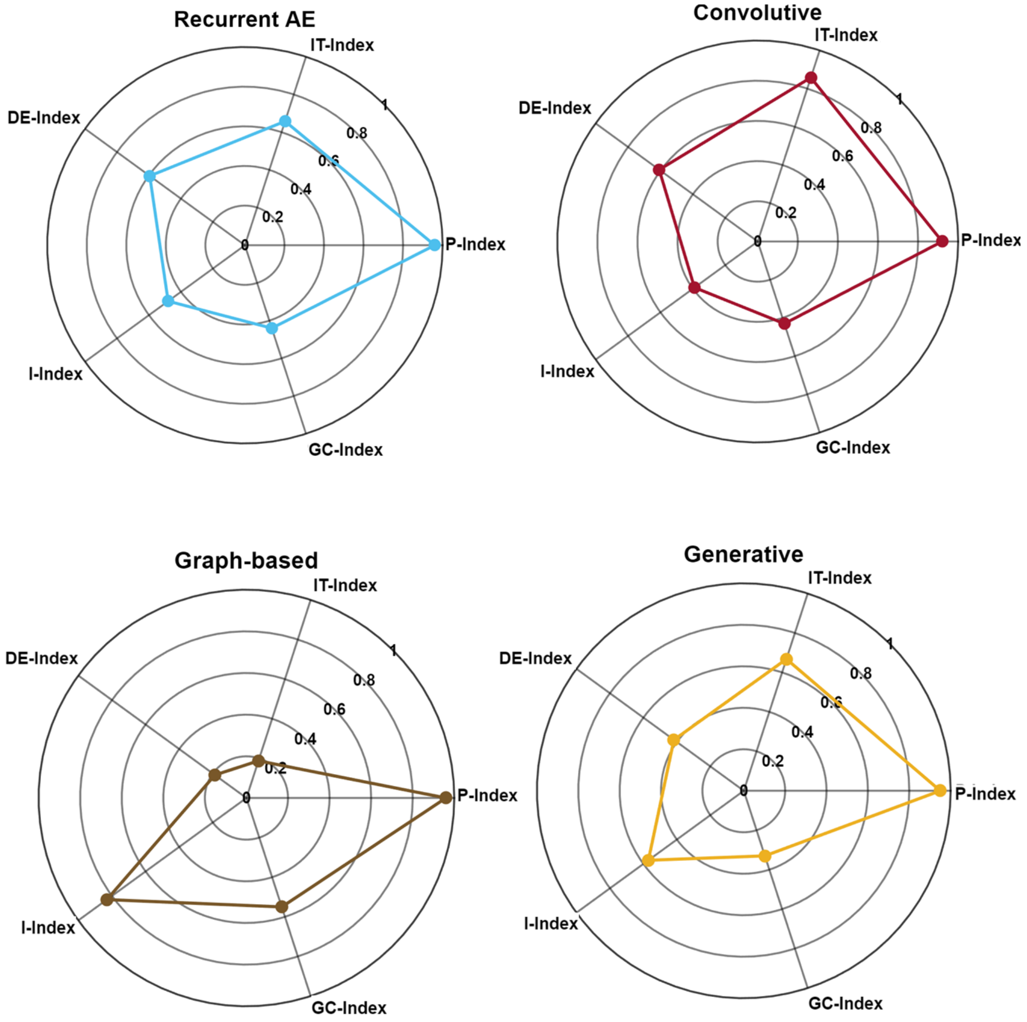


Figure 9. Comparative analysis of reconstruction architectural sub-families.

Table 10. Summary of architectural sub-families for reconstruction-based methods.

Sub-Family	Key Features & Applications	References
RNN-AEs	Represents the most numerous and consolidated group, effectively constituting the industrial standard for the reconstruction of complex time series.	[76,77,81,83,84,89,91,93]
Convolutive (CNN/TCN)	Focused on computational efficiency through the use of spatial or temporal filters for fast feature extraction.	[26,75,78–80,82,86]
Graph-based	The most recent cluster, specifically oriented toward capturing topological dependencies and interactions between sensors.	[69,85,87,94]
Generative (GAN/VAE)	Offers probabilistic approaches to deeply model the statistical distribution of nominal data.	[88,90,92]

Contrastive-Based Architectures

The analysis of contributions related to Contrastive Learning highlights how this paradigm is redefining the limits of generalization in industrial anomaly detection. Unlike reconstructive methods, which focus on point-wise error, these approaches learn a metric space where distinct operating conditions are geometrically separated. Within this landscape, four main architectural sub-families have been identified, as summarized in Table 11.

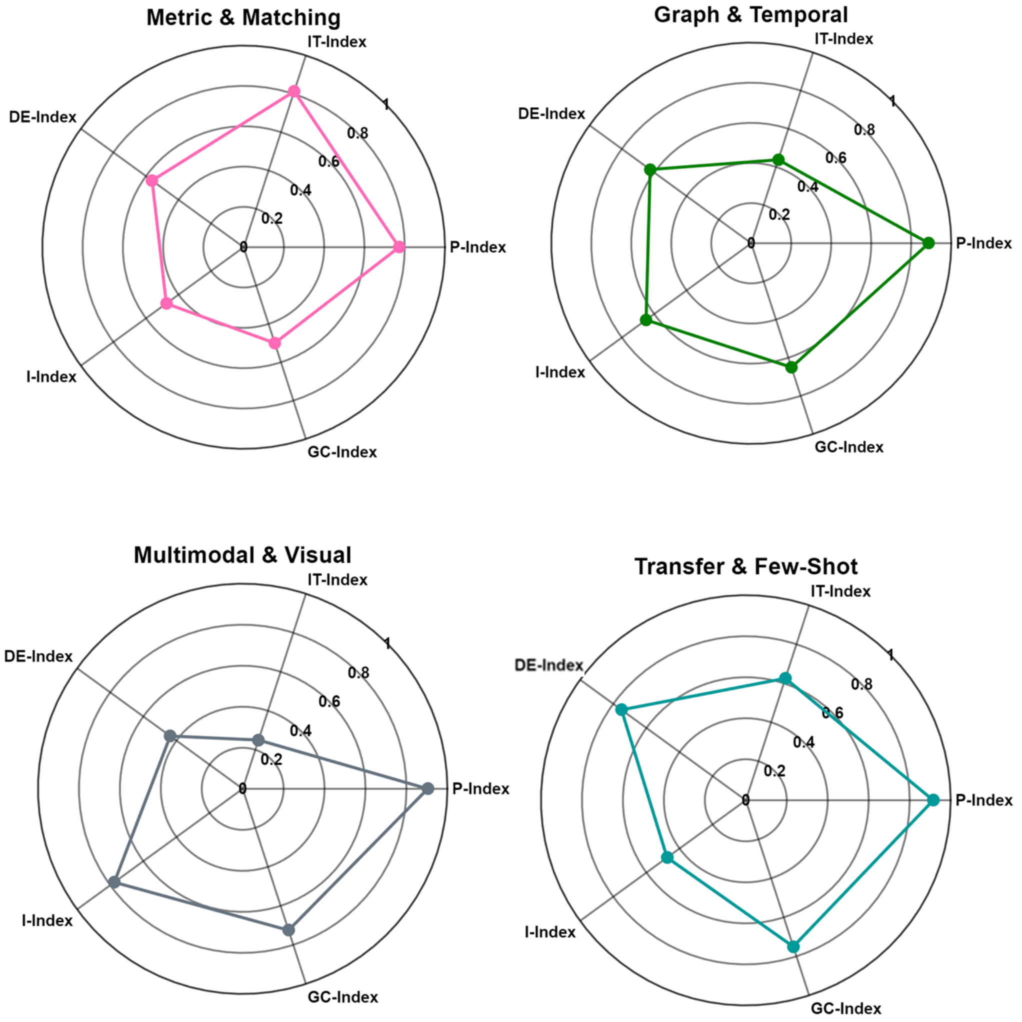
Table 11. Summary of architectural sub-families for contrastive-based methods.

Sub-Family	Key Features & Applications	References
Metric & Matching	Directly optimizes the distance between classes using Siamese architectures or Triplet losses for high-accuracy applications.	[80,96,101,108]
Graph & Temporal	Extends the contrastive metric space to complex data structures, capturing spatio-temporal dependencies.	[91,95,99,100]
Multimodal & Visual	Represents an emerging trend that integrates visual data or semantic descriptions through the use of LLMs.	[102,103,105,107]
Transfer & Few-Shot	Employs pre-training strategies to operate effectively in scenarios characterized by extreme data scarcity (One-shot learning).	[97,98,104]

The performance profiles, illustrated in the Radar Plot in Figure 10, reveal significant operational trade-offs across these groups. The Metric & Matching sub-family proves to be the highest performing in terms of inference speed and pure accuracy, making it ideal for standard applications with stringent latency requirements. However, the innovation lies elsewhere: the Transfer & Few-Shot sub-family dominates in data efficiency, demonstrating superior capabilities in adapting to new machines with very few examples through One-shot learning strategies. In parallel, the integration of LLMs within the Multimodal sub-family has pushed interpretability and generalization to unprecedented levels, providing natural language explanations for detected anomalies, albeit at the cost of high computational demand, which currently limits real-time responsiveness.

7.2.2. Comparative Analysis for the Hybrid Physics-Informed Family

In this subsection, the methodologies belonging to the Hybrid Physics-Informed family are structured and divided into specific sub-families based on their integration paradigms. This approach allows for a targeted analysis of their performance variations and operational trade-offs across different structural approaches. The integration of domain knowledge into deep learning models represents the frontier for reliable prognostics in safety-critical systems. Analyzing the 20 selected works, we identified three distinct integration strategies, as summarized in Table 12.


Metric & Matching

Graph & Temporal

Multimodal & Visual

Transfer & Few-Shot

Figure 10. Comparative analysis of contrastive architectural sub-families.

Table 12. Summary of architectural sub-families for hybrid physics-informed methods.

Sub-Family	**Key Features & Applications**	**References**
PIL	Embeds physical laws (e.g., fluid dynamics or energy conservation) as regularization terms in the loss function.	[114–119,127–130,132]
PIA	Embeds physical constraints directly into the neural network layers, such as using specialized attention mechanisms or signal processing layers.	[120–122,126]
PDDG	Utilizes thermodynamic simulations or physical models to generate synthetic faulty data, addressing the chronic lack of run-to-failure records.	[109,123–125,131]

The quantitative assessment in Figure 11 reveals clear operational distinctions. The PIA sub-family achieves the highest Data Efficiency Index, as the structural constraints significantly reduce the volume of training data required to reach convergence. Conversely, the PDDG approach excels in inference speed, as the physics is offloaded to the training phase, leaving a lightweight standard model for deployment. The PIL methods offer the best balance for diagnostic transparency, as the adherence to physical laws provides an intrinsic validation of the model's predictions, although this often comes at the cost of increased training complexity.

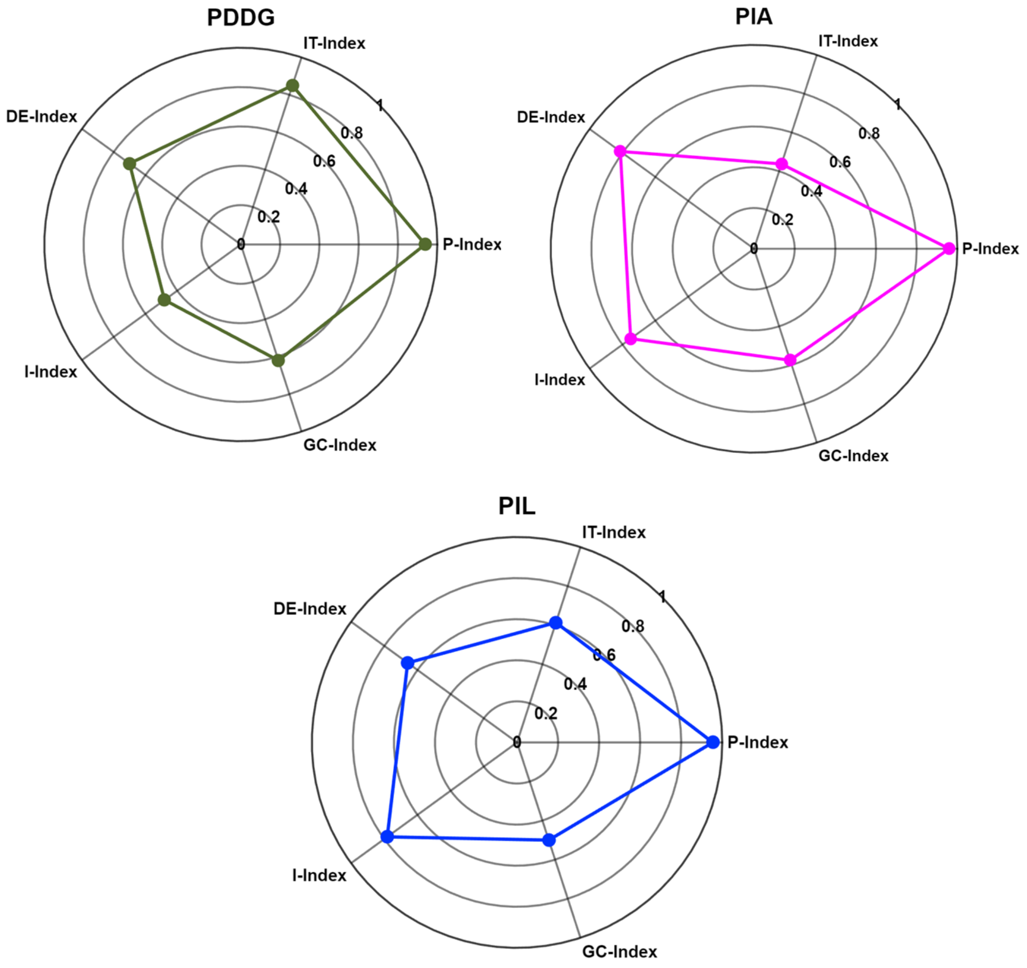


Figure 11. Comparative analysis of physics-informed integration strategies.

7.2.3. Global Comparison: Purely Data-Driven vs. Hybrid Physics-Informed

To characterize the global operational behavior of the reviewed architectures for Anomaly and Fault Detection, performance metrics were aggregated and averaged to directly contrast the Purely Data-Driven family against the Hybrid Physics-Informed family. This overarching analysis highlights the macroscopic trade-offs between empirical learning and domain-knowledge integration, guiding industrial model selection based on the defined performance indices. The quantitative results demonstrate that Hybrid Physics-Informed architectures excel in overall reliability (P-Index) and data efficiency (DE-Index). The mathematical embedding of physical constraints acts as a powerful regularizer, effectively compensating for the scarcity of labeled run-to-failure samples. Furthermore, these models achieve a higher Interpretability Index (I-Index), as the adherence to physical laws inherently provides a validation of the network's internal logic. Conversely, while the Purely Data-Driven family offers a highly versatile baseline, its aggregated scores highlight limitations in Generalization (GC-Index) across varying operating conditions. Notably, the Physics-Informed family also exhibits superior average Inference Time scores (IT-Index). This counterintuitive result is explained by the fact that strategies like PDDG and PIL offload the heavy computational burden of physical simulations entirely to the offline training phase, leaving a lightweight and highly responsive model for real-time deployment, whereas the Data-Driven average is penalized by computationally intensive dynamic graph models. The trends emerging from this methodological dichotomy are summarized graphically in the radar diagram in Figure 12.

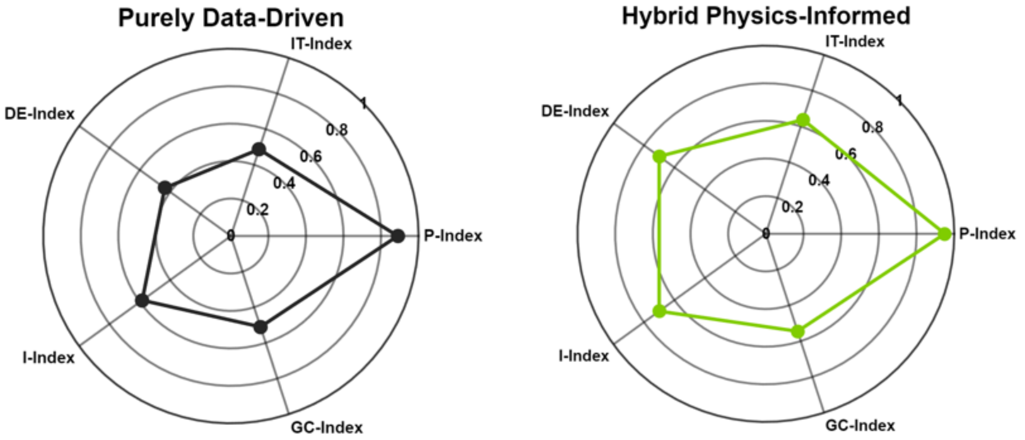


Figure 12. Global comparative analysis of anomaly detection families: Purely Data-Driven vs. Hybrid Physics-Informed. Note: The high Inference Time Index (IT-Index) of the hybrid family stems from offloading physical computations to the training phase, as explained in Section 7.2.3.

7.3. Operational Profiling of RUL Models: Pure Deep Learning vs. Physics-Guided

Following the overarching taxonomic split established in Section 5, the performance evaluation of RUL models is structured by explicitly contrasting the Pure Deep Learning family against the Physics-Guided family. This binary classification distills the evolution of prognostic methodologies, moving from purely statistical algorithms toward hybrid architectures capable of embedding component degradation mechanisms. The main characteristics and references for these two domains are summarized in Table 13.

Table 13. Summary of architectural families for RUL prediction methods.

Family	Key Features	References
Pure Deep Learning	Employs purely statistical and data-driven algorithms to model degradation mechanisms, ensuring fast real-time predictions without heavy thermodynamic constraints.	[138–145,149]
Physics-Guided	Integrates physical domain knowledge (e.g., fatigue laws, digital twins) acting as a robust mathematical regularizer to ensure diagnostic reliability and data efficiency.	[110,124,137,146–148]

The quantitative assessment of these two domains, visualized in the Radar Plot in Figure 13, reveals significant operational trade-offs. The Physics-Guided family overwhelmingly dominates in the DE-Index and the I-Index. The integration of physical domain knowledge, such as fatigue and creep laws or high-fidelity digital twin simulations, acts as a robust mathematical regularizer; this structural constraint allows the network to converge effectively even with extremely limited historical run-to-failure samples, particularly when synthetic degradation trajectories are utilized to augment the dataset, and offers an intrinsically transparent logic that justifies the remaining life estimation.

Conversely, the Pure DL family, while exhibiting lower structural transparency, presents a higher IT-Index. The advantage stems from optimized architectures (CNNs/LSTMs) that bypass physical constraints during inference, while hybrid models offload this complexity to the training phase. However, recent hybrid frameworks, including dedicated acceleration modules, are beginning to close this computational gap. Regarding absolute diagnostic reliability (P-Index), the physics-informed approaches maintain a slight superiority, confirming that constraining a neural network within physically plausible bounds prevents inconsistent extrapolations, especially as the component approaches the end of its life cycle.

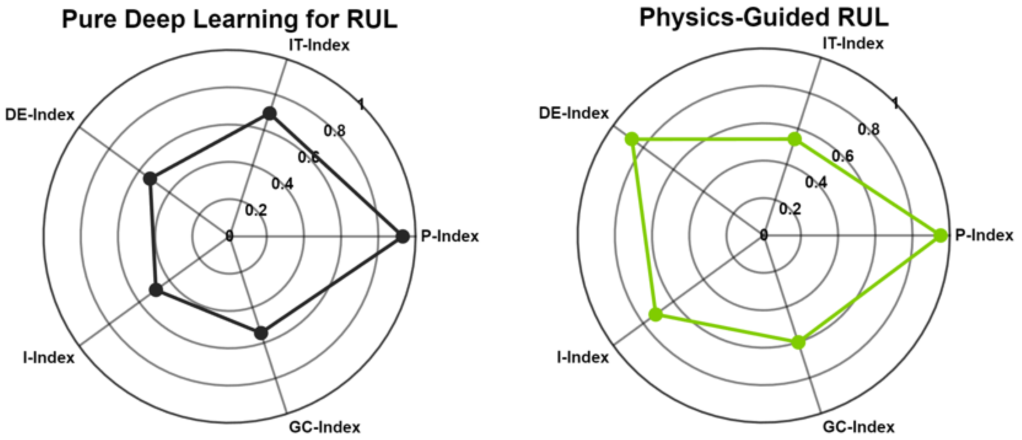


Figure 13. Comparative radar plot illustrating the operational trade-offs between Pure Deep Learning and Physics-Guided models for RUL estimation.

7.4. Root Cause Analysis: Methodological Benchmarking

The automation of fault diagnosis in turbomachinery requires not merely detecting anomalies but precisely isolating their origin. Given the statistical and data-driven nature of the selected RCA methodologies, the evaluation framework defined in the previous section was maintained. Analyzing the selected works, we identified four distinct methodological sub-families, as summarized in Table 14.

Table 14. Summary of methodological sub-families for Root Cause Analysis.

Sub-Family	Key Features	References
Causal & Graph	Utilizes tools like Bayesian Networks not only to localize anomalies but also to reconstruct the directional propagation of faults, mapping causal influences between signals.	[153–155]
Knowledge-Augmented	Employs Generative AI, LLMs, and Knowledge Graphs to reason over unstructured data, delivering high interpretability.	[156,157]
Explainer (XAI)	Focuses on making "black-box" models transparent through feature attribution techniques.	[108]
Statistical/Multivariate	Relies on dimensionality reduction to isolate pure mathematical deviations with low computational cost.	[152]

The quantitative assessment in Figure 14 reveals clear operational trade-offs. It is essential to note that for the calculation of the P-Index, priority was given to Accuracy over F1-score in this context. While the F1-score is the standard for anomaly detection due to class imbalance, RCA studies typically operate on balanced subsets of known fault categories. In such scenarios, Accuracy provides a more direct measure of the model's ability to unequivocally identify the faulty component among competing failure modes, effectively guiding maintenance decisions and preventing erroneous interventions. Under this lens, the Causal & Graph and Explainer methods exhibit the most robust performance. However, the Knowledge-Augmented sub-family sets the benchmark for the I-Index: the use of LLMs allows for delivering diagnoses in natural language, effectively bridging the semantic gap between sensor data and human understanding. Conversely, the Statistical/Multivariate approach excels in inference speed (IT-Index), owing to the lower computational cost of linear algebra compared to deep neural networks.

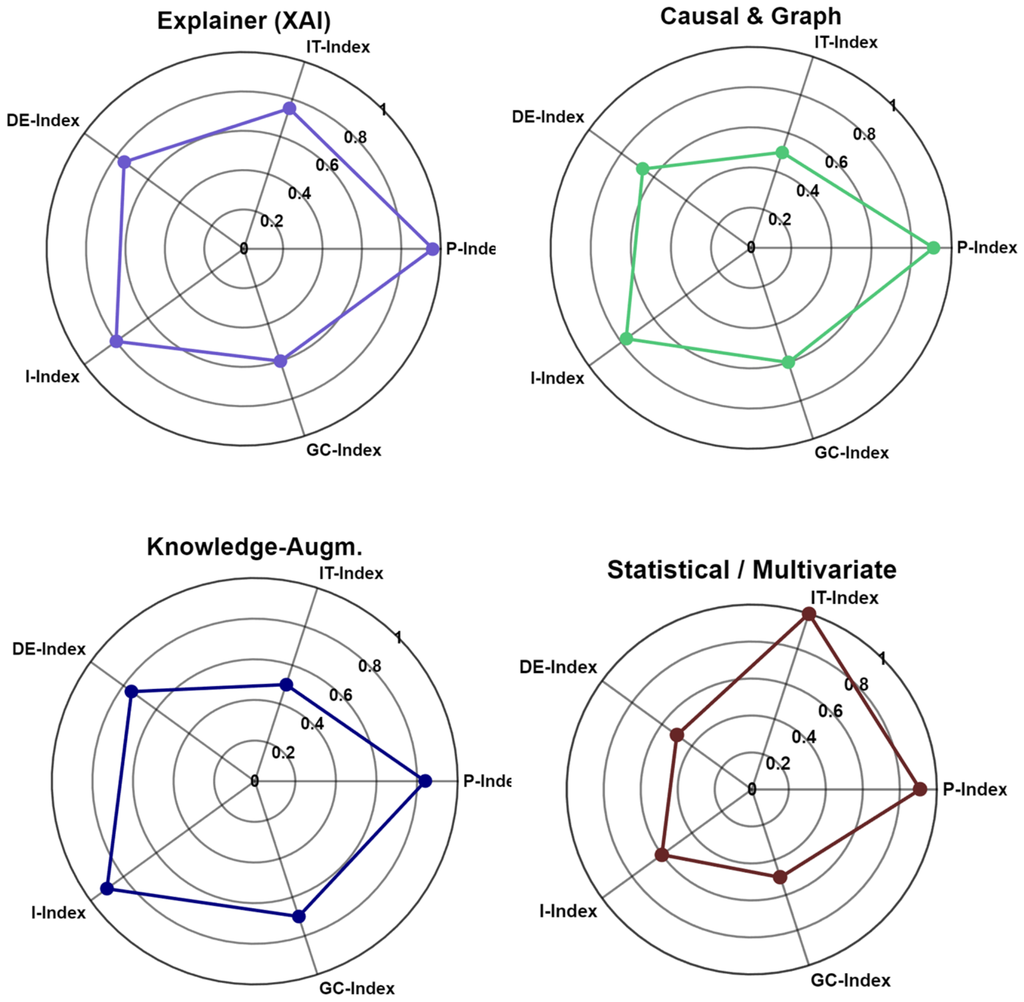


Figure 14. Comparative analysis of root cause analysis strategies.

7.5. Industrial Deployment: Technical Trade-Offs and Decision Guidelines

Building on the previous methodological analysis, this section synthesizes the core technical trade-offs and provides practical guidelines for model selection based on industrial infrastructure. The objective is to facilitate deployment by balancing diagnostic accuracy with real-world operational constraints.

7.5.1. Global Synthesis of Technical Trade-Offs

The aggregated metrics reveal three fundamental tensions that govern architectural selection in turbomachinery monitoring:

- Reliability vs. Training Complexity (P-Index vs. Complexity): Hybrid Physics-Informed models achieve superior reliability and data efficiency by embedding physical laws as mathematical constraints [16]. While their high complexity (Class H) requires significant offline training effort, they provide an important industrial advantage: they maintain a high Inference Time Index (IT-Index) during deployment by offloading physical simulations to the training phase.
- Interpretability vs. Deployment Versatility (I-Index vs. Purely Data-Driven): Graph-based architectures (GNNs) represent the benchmark for interpretability by mapping the physical sensor topology. However, they require a detailed structural map of the asset. Conversely, Purely Data-Driven models (e.g., RNN-AEs) are more versatile and quicker to deploy across different systems, though they operate as “black boxes” with lower diagnostic transparency.

- Data Efficiency vs. Generalization (DE-Index vs. GC-Index): Contrastive Learning frameworks excel in the GC-Index, making them ideal for managing diverse fleets. However, in scenarios with a total absence of historical faulty data, Physics-Informed solutions and performance Digital Twins are unparalleled (High DE-Index), as physical constraints serve as a surrogate for missing empirical information [16,83].

7.5.2. Guidelines for Industrial Implementation

Model selection must align with specific hardware capabilities and operational environments, focusing on the balance between edge and cloud processing:

- Scenario A: Real-time Edge Monitoring: For deployments integrated into local SCADA or edge devices with limited hardware, Convolutive (CNN/TCN) or lightweight RNN architectures are recommended [158]. Their balance between execution speed and resource demand minimizes network latency and optimizes streaming data management in decentralized nodes [159].
- Scenario B: High-Fidelity Diagnostics for Critical Assets: In safety-critical contexts (e.g., steam turbines or nuclear valves), Hybrid Physics-Informed (PINN) models and Digital Twins with uncertainty quantification are the primary choice [16,83]. Their physical consistency meets non-negotiable safety requirements; however, while the offline training and high-fidelity synchronization of such models require scalable cloud infrastructures to handle the underlying mathematical complexity, their real-time inference remains lightweight and suitable for responsive monitoring [158].
- Scenario C: Large-scale Fleet Management: For managing distributed assets, such as offshore wind farms, cloud-based remote monitoring platforms are the most efficient [160]. These architectures facilitate Transfer Learning strategies, reducing the need for unit-specific retraining and minimizing long-term O&M costs [16,160].

The practical adoption of these architectures depends on their alignment with international standards, such as ISO 13374 for data processing and ISO 13379-1 for diagnostic interpretation [161,162]. Specifically, the Interpretability Index (I-Index) serves as a metric for diagnostic traceability, reflecting the transparency requirements mandated by these norms. Architectures with high I-Index scores facilitate the verification of fault root causes, ensuring that AI-driven insights remain auditable and compliant with industrial safety protocols. Mapping the evaluation framework to normative compliance reinforces the transition from experimental black-box models to certified monitoring solutions.

8. Conclusions

This work presents a systematic and thorough review of the state of the art in PdM applied to the critical turbomachinery sector. Through the analysis of recent literature, primarily concentrated over the last five or six years, the core pillars composing the modern PdM pipeline have been examined: from diagnostics, focused on anomaly and fault detection, to prognostics for RUL and the complex discipline of RCA. Various frameworks used in the presented works were observed, providing not only a general overview but also analyzing the positive and negative aspects of using these methods. As a technical and application-oriented review, the analysis focused not only on architectural theory but also on the management of dataframes and real-world data flows [20,35,47]. In the field of diagnostics, the approach chosen to classify scientific contributions follows a clear tripartition of forecasting, reconstruction, and contrastive learning strategies [38]. The quantitative benchmarking through synthetic indices revealed that architectural choice is strictly driven by industrial trade-offs: GNN-based models excel in the Interpretability Index by mapping sensor topologies, while RNN and TCN architectures remain the most viable solutions for real-time edge deployment due to their superior Inference Time Index [67,71].

These methods are increasingly supplemented by the integration of physics-informed components, including specific architectures like PINNs [109,121,126]. This study highlights that Physics Integration, particularly the PIL and PIA approaches, acts as a primary enabler for the Data Efficiency Index, allowing models to converge with significantly reduced historical datasets and overcoming the traditional requirement for full seasonal operational cycles [110,114,127]. Regarding time-series forecasting, advanced frameworks utilized hybrid approaches to capture transient turbine dynamics [67,72], while signal reconstruction-based architectures, such as those employing spatial and temporal autoencoders [85,89], proved essential for identifying subtle anomalies in noisy environments. Regarding RUL estimation, the integration of physics and Deep Learning emerged as a winning strategy. Works based on physics-informed Deep-LSTM architectures [146] and hybrid models for modeling mechanical fatigue in bearings [110] demonstrated how domain knowledge can stabilize predictions over long time horizons. In parallel, RCA has undergone a topological and semantic revolution. The quantitative assessment identifies Causal & Graph approaches, such as improved Bayesian networks [153], as essential for reconstructing the directional propagation of faults. Furthermore, the pioneering use of LLMs [156,157] has set a new benchmark for the Interpretability Index, introducing automated reasoning capabilities that effectively bridge the semantic gap between raw sensor data and human understanding. Overall, this work confirms that PdM for turbomachinery is now a mature digital ecosystem, where the fusion of data and physics guarantees higher levels of reliability, safety, and sustainability in line with Industry 5.0 requirements.

However, to ensure a transparent and objective perspective, it is essential to acknowledge the limitations of this review itself. First, a potential publication bias may exist in the surveyed literature, as studies reporting positive or highly accurate results are inherently more likely to be published. Second, the search scope was restricted to English-language publications, which may exclude relevant theoretical advancements or industrial applications documented in other languages. Lastly, the deliberate focus on post-2015 deep learning and hybrid AI trends means that some long-validated traditional methods, which remain the standard practice in certain industrial sectors, might not be fully represented in this analysis.

Research Gaps and Future Perspectives

Despite the progress described, several technical bottlenecks define future research directions:

- Generalizability and Domain Shift: Purely data-driven models often struggle to adapt across different engine variants or operational sites, requiring costly unit-specific retraining to handle varying sensor noise and operating envelopes [16,38].
- Edge Scalability: Transitioning from single-unit success to fleet-wide monitoring exposes hardware constraints in edge nodes, demanding more robust model compression techniques and secure, low-latency data pipelines [159,160].
- Hybrid Integration Challenges: Balancing physical consistency with empirical data in a joint loss function remains mathematically complex, particularly for aging assets where degradation and fluctuating environmental conditions make nominal physical laws increasingly imprecise [16,83].

The benchmarking analysis conducted in Section 7 provides a direct empirical grounding for these directions. The low GC-Index recorded for purely data-driven architectures quantitatively confirms the severity of the domain shift problem, motivating the development of future models that explicitly incorporate fleet-level transfer mechanisms, such as Few-Shot contrastive pre-training validated across heterogeneous turbine populations. The DE-Index advantage consistently observed for Physics-Informed approaches points toward the development of lightweight PIA variants deployable on constrained edge hardware, directly addressing the scalability bottleneck identified above. Finally, the IT-Index penalty associated with dynamic graph models highlights the need for architectural compression strategies that preserve topological expressiveness without sacrificing real-time responsiveness. This progression is consistent with the hybrid AI maturity roadmap outlined by [16]. It confirms that the directions identified here represent validated next steps rather than speculative research avenues. Addressing these gaps is essential to move beyond isolated numerical RUL estimations toward operationally integrated monitoring systems. To bridge the semantic gap that limits the practical impact of even high-performing models, a promising direction lies in the evolution of LLMs as engines for contrastive learning [95,105], creating a semantic bridge between AI outputs and operational decisions. Integrating LLMs with explainability techniques [107] enables a transition toward prescriptive maintenance through a three-stage architecture: a predictive core identifies anomalies, while a semantic translator based on Retrieval-Augmented Generation (RAG) cross-references findings with technical manuals [156]. The objective is a conversational interface explaining not only when a component will fail but also why, suggesting immediate actions.

However, the deployment of LLMs in safety-critical turbomachinery environments is constrained by the risk of technical hallucinations, where models may generate ungrounded or factually false diagnostic prescriptions [163]. To ensure operational safety, future research must implement proactive mitigation strategies, such as utilizing physics-informed frameworks to evaluate LLM-generated scenarios against established physical constraints [164]. Furthermore, managing the computational trade-offs remains a fundamental challenge; while large-scale models offer superior reasoning, the energy sector and edge environments require efficient architectures to balance inference latency with the high energy demands of these models [165].

Alongside these challenges, a significant gap exists regarding standardization and interoperability. The lack of open standards currently hinders the large-scale adoption of AI models across industrial fleets [16]. Closely tied to this is the alignment between scholarly methodologies and the normative frameworks governing real industrial deployments. Standards such as ISO 13374 [166] and ISO 13379-1 [167] impose strict constraints on model validation and transparency that purely data-driven approaches do not inherently satisfy. Additionally, reconciling academic research with industrial 'gray literature', such as technical white papers and OEM best practices, represents a pivotal direction. Aligning research outputs with normative compliance ensures that data-driven solutions meet the operational requirements of the turbomachinery sector. Ultimately, the role of the human operator (Human-in-the-loop) remains the core element of this evolution. In line with Industry 5.0 paradigms, artificial intelligence is not intended to replace the expert but to enhance their decision-making capabilities. Regarding the implementation of HITL, two main paths emerge: LLM interpreters and XAI-enhanced RCA. While LLMs offer the most immediate solution for improving human–machine interaction through natural language [156], XAI-enhanced methods provide the technical transparency required for industrial safety [108]. We argue that an integrated approach, combining the interpretability of RCA with the accessibility of LLMs, represents the most viable trajectory for Industry 5.0 applications. The challenge for the future will therefore be the creation of digital mentoring systems capable of preserving the knowledge of senior experts and democratizing access to complex diagnoses [35].

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References

1. Zhu, T.; Ran, Y.; Zhou, X.; Wen, Y. A survey of predictive maintenance: Systems, purposes and approaches. *arXiv* **2019**, arXiv:1912.07383.
2. Pusey, H.C. Turbomachinery condition monitoring and failure prognosis. *Sound Vib.* **2007**, *41*, 10–15.
3. Hein-Pensel, F.; Winkler, H.; Brückner, A.; Wölke, M.; Jabs, I.; Mayan, I.J.; Kirschenbaum, A.; Friedrich, J.; Zinke-Wehlmann, C. Maturity assessment for Industry 5.0: A review of existing maturity models. *J. Manuf. Syst.* **2023**, *66*, 200–210. [CrossRef]
4. Jezzini, A.; Ayache, M.; Elkhansa, L.; Makki, B.; Zein, M. Effects of predictive maintenance (PdM), Proactive maintenace (PoM) & Preventive maintenance (PM) on minimizing the faults in medical instruments. In *Proceedings of the 2013 2nd International Conference on Advances in Biomedical Engineering*; IEEE: New York, NY, USA, 2013; pp. 53–56.
5. Achouch, M.; Dimitrova, M.; Ziane, K.; Sattarpanah Karganroudi, S.; Dhouib, R.; Ibrahim, H.; Adda, M. On predictive maintenance in industry 4.0: Overview, models, and challenges. *Appl. Sci.* **2022**, *12*, 8081. [CrossRef]
6. Tazi, N.; Châtelet, E.; Bouzidi, Y. Using a hybrid cost-FMEA analysis for wind turbine reliability analysis. *Energies* **2017**, *10*, 276. [CrossRef]
7. Romanssini, M.; de Aguirre, P.C.C.; Compassi-Severo, L.; Girardi, A.G. A review on vibration monitoring techniques for predictive maintenance of rotating machinery. *Eng* **2023**, *4*, 1797–1817. [CrossRef]
8. Dowson, D. Metallurgical Failure Analysis of Steam Turbine, Compressor, and Hot Gas Expander Components. In Proceedings of the Asia Turbomachinery & Pump Symposium, Singapore, 12–15 March 2018.
9. Sepe, M.; Graziano, A.; Badora, M.; Di Stazio, A.; Bellani, L.; Compare, M.; Zio, E. A physics-informed machine learning framework for predictive maintenance applied to turbomachinery assets. *J. Glob. Power Propuls. Soc.* **2021**, *2021*, 1–15. [CrossRef]
10. Suman, A.; Morini, M.; Aldi, N.; Casari, N.; Pinelli, M.; Spina, P.R. A compressor fouling review based on an historical survey of asme turbo expo papers. *J. Turbomach.* **2017**, *139*, 041005. [CrossRef]
11. Shin, D.; Yang, J.; Tong, X.; Suh, J.; Palazzolo, A. A review of journal bearing thermal effects on rotordynamic response. *J. Tribol.* **2021**, *143*, 031803. [CrossRef]
12. Decker, T.; Jacobs, G.; Raddatz, M.; Röder, J.; Betscher, J.; Arneth, P. Detection of particle contamination and lubrication outage in journal bearings in wind turbine gearboxes using surface acoustic wave measurements and machine learning. *Forsch. Ingenieurwesen* **2025**, *89*, 17. [CrossRef]
13. Malla, C.; Panigrahi, I. Review of condition monitoring of rolling element bearing using vibration analysis and other techniques. *J. Vib. Eng. Technol.* **2019**, *7*, 407–414. [CrossRef]
14. Ding, A.; Ren, X.; Li, X.; Gu, C. Friction power analysis and improvement for a tilting-pad journal bearing considering air entrainment. *Appl. Therm. Eng.* **2018**, *145*, 763–771. [CrossRef]
15. Farhat, H.; Salvini, C. Novel gas turbine challenges to support the clean energy transition. *Energies* **2022**, *15*, 5474. [CrossRef]
16. Farhat, H.; Altarawneh, A. Physics-Informed Machine Learning for Intelligent Gas Turbine Digital Twins: A Review. *Energies* **2025**, *18*, 5523. [CrossRef]
17. Castellani, F.; Eltayesh, A.; Becchetti, M.; Segalini, A. Aerodynamic analysis of a wind-turbine rotor affected by pitch unbalance. *Energies* **2021**, *14*, 745. [CrossRef]
18. Liu, Y.; Jiang, X.; Ge, X.; Wei, M. A physics informed machine learning approach for performance degradation monitoring of gas turbine. In Proceedings of the PHM Society Asia-Pacific Conference, Tokyo, Japan, 11–14 September 2023; Volume 4.
19. Malik, T.H.; Bak, C. Full-scale wind turbine performance assessment using the turbine performance integral (TPI) method: A study of aerodynamic degradation and operational influences. *Wind Energy Sci.* **2024**, *9*, 2017–2037. [CrossRef]
20. Molęda, M.; Małysiak-Mrozek, B.; Ding, W.; Sunderam, V.; Mrozek, D. From corrective to predictive maintenance—A review of maintenance approaches for the power industry. *Sensors* **2023**, *23*, 5970. [CrossRef]
21. Zhang, M.; Sui, F.; Liu, A.; Tao, F.; Nee, A. Digital twin driven smart product design framework. In *Digital Twin Driven Smart Design*; Elsevier: Amsterdam, The Netherlands, 2020; pp. 3–32.

https://doi.org/10.3390/machines14040396

22. Nunes, P.; Santos, J.; Rocha, E. Challenges in predictive maintenance—A review. *CIRP J. Manuf. Sci. Technol.* **2023**, *40*, 53–67. [CrossRef]
23. Zhang, W.; Yang, D.; Wang, H. Data-Driven Methods for Predictive Maintenance of Industrial Equipment: A Survey. *IEEE Syst. J.* **2019**, *13*, 2213–2227. [CrossRef]
24. Sanchez-Londono, D.; Barbieri, G.; Fumagalli, L. Smart retrofitting in maintenance: A systematic literature review. *J. Intell. Manuf.* **2023**, *34*, 1–19. [CrossRef]
25. Miele, E.S.; Bonacina, F.; Corsini, A. Deep anomaly detection in horizontal axis wind turbines using graph convolutional autoencoders for multivariate time series. *Energy AI* **2022**, *8*, 100145. [CrossRef]
26. Lee, G.; Jung, M.; Song, M.; Choo, J. Unsupervised anomaly detection of the gas turbine operation via convolutional auto-encoder. In *Proceedings of the 2020 IEEE International Conference on Prognostics and Health Management (ICPHM)*; IEEE: New York, NY, USA, 2020; pp. 1–6.
27. Zhang, C.; Yang, T. Anomaly detection for wind turbines using long short-term memory-based variational autoencoder wasserstein generation adversarial network under semi-supervised training. *Energies* **2023**, *16*, 7008. [CrossRef]
28. Michau, G.; Fink, O. Unsupervised transfer learning for anomaly detection: Application to complementary operating condition transfer. *Knowl. Based Syst.* **2021**, *216*, 106816. [CrossRef]
29. Rombach, K. Fault Diagnostics Under Label and Data Scarcity. Ph.D. Thesis, ETH Zurich, Zurich, Switzerland, 25 July 2023.
30. Algan, G.; Ulusoy, I. Image classification with deep learning in the presence of noisy labels: A survey. *Knowl. Based Syst.* **2021**, *215*, 106771. [CrossRef]
31. Cook, J. GE Vernova Talks AGP XPAND's Impact, Supply-Chain Resiliency. *Turbomachinery International*, 8 May 2025.
32. Surendra, A. ATOM: Digital Twin of Siemens Gas Turbine Fleet Operations. 2023. Available online: https://www.anylogic.com/resources/case-studies/atom-digital-twin-of-siemens-gas-turbine-fleet-operations/ (accessed on 28 March 2026).
33. Lim, J.; Perullo, C.A.; Milton, J.; Whitacre, R.; Jackson, C.; Griffin, C.; Noble, D.; Boche, L.; Seachman, S.; Angello, L.; et al. The EPRI Gas Turbine Digital Twin—A Platform for Operator Focused Integrated Diagnostics and Performance Forecasting. In *Proceedings of the Turbo Expo: Power for Land, Sea, and Air*; American Society of Mechanical Engineers: New York, NY, USA, 2021; Volume 84966, p. V004T09A009.
34. Abdelillah, F.M.; Nora, H.; Samir, O.; Sidi-Mohammed, B. Hybrid Data-Driven and Knowledge-Based Predictive Maintenance Framework in the Context of Industry 4.0. In *Proceedings of the Model and Data Engineering*; Mosbah, M., Kechadi, T., Bellatreche, L., Gargouri, F., Eds.; Springer: Cham, Switzerland, 2024; pp. 319–337.
35. Pietsch, D.; Matthes, M.; Wieland, U.; Ihlenfeldt, S.; Munkelt, T. Root cause analysis in industrial manufacturing: A scoping review of current research, challenges and the promises of AI-driven approaches. *J. Manuf. Mater. Process.* **2024**, *8*, 277. [CrossRef]
36. Zhang, W.; Vatn, J.; Rasheed, A. A review of failure prognostics for predictive maintenance of offshore wind turbines. In *Proceedings of the Journal of Physics: Conference Series*; IOP Publishing: Bristol, UK, 2022; Volume 2362, p. 012043.
37. Zamanzadeh Darban, Z.; Webb, G.I.; Pan, S.; Aggarwal, C.; Salehi, M. Deep learning for time series anomaly detection: A survey. *ACM Comput. Surv.* **2024**, *57*, 1–42. [CrossRef]
38. Wang, F.; Jiang, Y.; Zhang, R.; Wei, A.; Xie, J.; Pang, X. A survey of deep anomaly detection in multivariate time series: Taxonomy, applications, and directions. *Sensors* **2025**, *25*, 190. [CrossRef] [PubMed]
39. Li, Z.; Zhao, Y.; Han, J.; Su, Y.; Jiao, R.; Wen, X.; Pei, D. Multivariate time series anomaly detection and interpretation using hierarchical inter-metric and temporal embedding. In *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining*; ACM: New York, NY, USA, 2021; pp. 3220–3230.
40. Munir, M.; Chattha, M.A.; Dengel, A.; Ahmed, S. A comparative analysis of traditional and deep learning-based anomaly detection methods for streaming data. In *Proceedings of the 2019 18th IEEE International Conference on Machine Learning and Applications (ICMLA)*; IEEE: New York, NY, USA, 2019; pp. 561–566.
41. Darban, Z.Z.; Webb, G.I.; Pan, S.; Aggarwal, C.C.; Salehi, M. CARLA: Self-supervised contrastive representation learning for time series anomaly detection. *Pattern Recognit.* **2025**, *157*, 110874. [CrossRef]
42. Yue, Z.; Wang, Y.; Duan, J.; Yang, T.; Huang, C.; Tong, Y.; Xu, B. Ts2vec: Towards universal representation of time series. In *Proceedings of the AAAI Conference on Artificial Intelligence*; AAAI: Washington, DC, USA, 2022; Volume 36, pp. 8980–8987.
43. Zhang, X.; Zhao, Z.; Tsiligkaridis, T.; Zitnik, M. Self-supervised contrastive pre-training for time series via time-frequency consistency. *Adv. Neural Inf. Process. Syst.* **2022**, *35*, 3988–4003.
44. Ruff, L.; Vandermeulen, R.; Goernitz, N.; Deecke, L.; Siddiqui, S.A.; Binder, A.; Müller, E.; Kloft, M. Deep one-class classification. In *Proceedings of the International Conference on Machine Learning*; PMLR: Westminster, UK, 2018; pp. 4393–4402.
45. Shen, L.; Li, Z.; Kwok, J. Timeseries anomaly detection using temporal hierarchical one-class network. *Adv. Neural Inf. Process. Syst.* **2020**, *33*, 13016–13026.
46. Golestani, A.; Gras, R. Can we predict the unpredictable? *Sci. Rep.* **2014**, *4*, 6834. [CrossRef]
47. de Castro-Cros, M.; Velasco, M.; Angulo, C. Machine-learning-based condition assessment of gas turbines—A review. *Energies* **2021**, *14*, 8468. [CrossRef]

48. Tsallis, C.; Papageorgas, P.; Piromalis, D.; Munteanu, R.A. Application-wise review of Machine Learning-based predictive maintenance: Trends, challenges, and future directions. *Appl. Sci.* **2025**, *15*, 4898. [CrossRef]
49. Ji, A.; Woo, W.L.; Wong, E.W.L.; Quek, Y.T. Rail track condition monitoring: A review on deep learning approaches. *Intell. Robot.* **2021**, *1*, 151–175. [CrossRef]
50. Correia, L.; Goos, J.C.; Klein, P.; Bäck, T.; Kononova, A.V. Online model-based anomaly detection in multivariate time series: Taxonomy, survey, research challenges and future directions. *Eng. Appl. Artif. Intell.* **2024**, *138*, 109323. [CrossRef]
51. Kini, K.R.; Harrou, F.; Madakyaru, M.; Sun, Y. Enhancing wind turbine performance: Statistical detection of sensor faults based on improved dynamic independent component analysis. *Energies* **2023**, *16*, 5793. [CrossRef]
52. Zou, Z.; Chen, G.; Xie, L.; Wang, J.; Yang, Z. Thermo-Mechanical Fault Diagnosis for Marine Steam Turbines: A Hybrid DLinear–Transformer Anomaly Detection Framework. *J. Mar. Sci. Eng.* **2025**, *13*, 2050. [CrossRef]
53. Cheng, X.; Shi, F.; Liu, X.; Zhao, M.; Chen, S. A novel deep class-imbalanced semisupervised model for wind turbine blade icing detection. *IEEE Trans. Neural Netw. Learn. Syst.* **2021**, *33*, 2558–2570. [CrossRef] [PubMed]
54. Aravanis, T.; Papadopoulos, P.; Georgikos, D. Fourier Feature-Enhanced Neural Networks for Wind Turbine Power Modeling. *Electricity* **2025**, *6*, 70. [CrossRef]
55. Yao, K.; Wang, Y.; Fan, S.; Fu, J.; Wan, J.; Cao, Y. Improved and accurate fault diagnostic model for gas turbine based on 2D-wavelet transform and generative adversarial network. *Meas. Sci. Technol.* **2023**, *34*, 075104. [CrossRef]
56. Gou, P.; Zheng, D.; Tang, L.; Liu, M. A Transformer-Based Time Series Prediction Model with Contrastive Learning for Nuclear Power System State Monitoring. In *Proceedings of the 2024 Global Reliability and Prognostics and Health Management Conference (PHM-Beijing)*; IEEE: New York, NY, USA, 2024; pp. 1–6.
57. Qiao, W.; Liu, X.; Huang, J.; Wu, G. Fault diagnosis method based on the timesnet model under variable speed and strong noise. In *Proceedings of the 10th International Symposium on Test Automation & Instrumentation (ISTAI 2024)*; IET: Stevenage, UK, 2024; Volume 2024, pp. 110–117.
58. Kishore, B.; Kabilan, K.; Rahul, L.; Priyadarshan, G.P.; Vishnutheerth, E.; Satheesh, R.; Kolhe, M.L. Advancing short-term wind power forecasting by AI-driven models for improved accuracy. *Electr. Eng.* **2025**, *107*, 14795–14810. [CrossRef]
59. Schmidl, S.; Wenig, P.; Papenbrock, T. Anomaly Detection in Time Series: A Comprehensive Evaluation. *Proc. VLDB Endow.* **2022**, *15*, 1779–1797. [CrossRef]
60. Goyal, V. Anomaly Detection and Failure Prediction in Gas Turbines. Ph.D. Thesis, University of Central Florida, Orlando, FL, USA, December 2021.
61. Gori, V.; Veneri, G.; Ballarini, V. Continual Learning for anomaly detection on turbomachinery prototypes-A real application. In *Proceedings of the 2022 IEEE Congress on Evolutionary Computation (CEC)*; IEEE: New York, NY, USA, 2022; pp. 1–7.
62. Shetty, S.; Gori, V.; Bagni, G.; Veneri, G. Sensor Virtualization for Anomaly Detection of Turbo-Machinery Sensors—An Industrial Application. *Eng. Proc.* **2023**, *39*, 96.
63. Farahani, M. Anomaly Detection on Gas Turbine Time-Series' Data Using Deep LSTM-Autoencoder. Master's Thesis, Umeå University, Umeå, Sweden, 2021.
64. Wang, B.; Zhou, B.; Zhu, D.; Zou, M.; Rao, Z.; Luo, H. Feature Alignment LSTM for Detecting Anomalies in Wind Turbine Main Bearing Temperature Based on SCADA Data. *J. Eng. Res.* **2025**, *14*, 303–314. [CrossRef]
65. Chen, N.; Shao, C.; Wang, G.; Wang, Q.; Zhao, Z.; Liu, X. Anomaly detection of wind turbine based on norm-linear-ConvNeXt-TCN. *Meas. Sci. Technol.* **2024**, *35*, 076107. [CrossRef]
66. Liu, B.; Wang, X.; Zhang, Z.; Zhao, Z.; Wang, X.; Liu, T. Fault Prediction of Hydropower Station Based on CNN-LSTM-GAN with Biased Data. *Energies* **2025**, *18*, 3772. [CrossRef]
67. Pinciroli, L.; Baraldi, P.; Zio, E. Graph Neural Networks for Anomaly Detection in Wind Turbines. In Proceedings of the 35th European Safety and Reliability & the 33rd Society for Risk Analysis Europe Conference (ESREL-SRA-E2025), Stavanger, Norway, 15–19 June 2025.
68. Jiang, G.; Li, W.; Fan, W.; He, Q.; Xie, P. TempGNN: A temperature-based graph neural network model for system-level monitoring of wind turbines with SCADA data. *IEEE Sens. J.* **2022**, *22*, 22894–22907. [CrossRef]
69. Zhan, Y.; Yang, B.; Ma, Y. Anomaly Detection for Small Hydropower Based on Deep Spatio-Temporal Modeling. In *Proceedings of the 2025 6th International Conference on Mechatronics Technology and Intelligent Manufacturing (ICMTIM)*; IEEE: New York, NY, USA, 2025; pp. 624–630.
70. Daenens, S.; Verstraeten, T.; Daems, P.J.; Nowé, A.; Helsen, J. Spatio-temporal graph neural networks for power prediction in offshore wind farms using SCADA data. *Wind Energy Sci.* **2025**, *10*, 1137–1152. [CrossRef]
71. Zheng, Y.; Wang, C.; Huang, C.; Li, K.; Yang, J.; Xie, N.; Liu, B.; Zhang, Y. Hierarchical spatial–temporal autocorrelation graph neural network for online wind turbine pitch system fault detection. *Neurocomputing* **2024**, *586*, 127574. [CrossRef]
72. Jin, X.; Lv, S.; Kong, Z.; Yang, H.; Zhang, Y.; Guo, Y.; Xu, Z. Graph spatio-temporal networks for condition monitoring of wind turbine. *IEEE Trans. Sustain. Energy* **2024**, *15*, 2276–2286. [CrossRef]

73. Wang, J.; Kou, M.; Li, R.; Qian, Y.; Li, Z. Ultra-short-term wind power forecasting jointly driven by anomaly detection, clustering and graph convolutional recurrent neural networks. *Adv. Eng. Inform.* **2025**, *65*, 103137. [CrossRef]
74. Blázquez-García, A.; Conde, A.; Mori, U.; Lozano, J.A. A review on outlier/anomaly detection in time series data. *ACM Comput. Surv.* **2021**, *54*, 1–33. [CrossRef]
75. Xie, J.; Schmidt, K.; Budeanu, N.; Letendre, V.; Zhao, Y.F. Combining feature learning and transfer learning in balancing anomaly detection for gas turbine engine vibration analysis. In *Proceedings of the International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*; American Society of Mechanical Engineers: New York, NY, USA, 2022; Volume 86212, p. V002T02A082.
76. Zhang, C.; Hu, D.; Yang, T. Anomaly detection and diagnosis for wind turbines using long short-term memory-based stacked denoising autoencoders and XGBoost. *Reliab. Eng. Syst. Saf.* **2022**, *222*, 108445. [CrossRef]
77. Chen, J.; Li, J.; Chen, W.; Wang, Y.; Jiang, T. Anomaly detection for wind turbines based on the reconstruction of condition parameters using stacked denoising autoencoders. *Renew. Energy* **2020**, *147*, 1469–1480. [CrossRef]
78. Yan, W.; Yu, L. On accurate and reliable anomaly detection for gas turbine combustors: A deep learning approach. *arXiv* **2019**, arXiv:1908.09238. [CrossRef]
79. Fu, S.; Zhong, S.; Lin, L.; Zhao, M. A re-optimized deep auto-encoder for gas turbine unsupervised anomaly detection. *Eng. Appl. Artif. Intell.* **2021**, *101*, 104199. [CrossRef]
80. Liu, D.; Zhong, S.; Lin, L.; Zhao, M.; Fu, X.; Liu, X. CSiamese: A novel semi-supervised anomaly detection framework for gas turbines via reconstruction similarity. *Neural Comput. Appl.* **2023**, *35*, 16403–16427. [CrossRef]
81. Jalil Pour, Z. Sensor Modelling for Anomaly Detection in Time Series Data. Master's Thesis, Linköping University, Linköping, Sweden, 1 June 2022.
82. Fahmi, A.T.W.K.; Reza Kashyzadeh, K.; Ghorbani, S. Advancements in Gas Turbine Fault Detection: A Machine Learning Approach Based on the Temporal Convolutional Network–Autoencoder Model. *Appl. Sci.* **2024**, *14*, 4551. [CrossRef]
83. Ma, Y.; Zhu, X.; Lu, J.; Yang, P.; Sun, J. Construction of data-driven performance digital twin for a real-world gas turbine anomaly detection considering uncertainty. *Sensors* **2023**, *23*, 6660. [CrossRef]
84. Roelofs, C.M.; Gück, C.; Faulstich, S. Transfer learning applications for autoencoder-based anomaly detection in wind turbines. *Energy AI* **2024**, *17*, 100373. [CrossRef]
85. Wang, L.; He, Y.; Shao, K.; Xing, Z.; Zhou, Y. An unsupervised approach to wind turbine blade icing detection based on beta variational graph attention autoencoder. *IEEE Trans. Instrum. Meas.* **2023**, *73*, 2500912. [CrossRef]
86. Duan, Y.; Xiang, M.; Zhou, B.; Fu, D.; Liu, H. TCAD: Unsupervised anomaly detection based on global local representation differences. *IEEE Access* **2022**, *10*, 114683–114693. [CrossRef]
87. Luo, Q.; Dong, J. Time Series Anomaly Detection Model Based on Memory-enhanced Transformer and Graph Network Joint Training. In *Proceedings of the 2024 4th International Conference on Computational Modeling, Simulation and Data Analysis*; ACM: New York, NY, USA, 2024; pp. 357–363.
88. Fan, Z.; Wang, Y.; Meng, L.; Zhang, G.; Qin, Y.; Tang, B. Unsupervised anomaly detection method for bearing based on VAE-GAN and time-series data correlation enhancement (June 2023). *IEEE Sens. J.* **2023**, *23*, 29345–29356. [CrossRef]
89. Xu, W.; Zhang, P. Steam turbine anomaly detection: An unsupervised learning approach using enhanced long short-term memory variational autoencoder. *Appl. Therm. Eng.* **2025**, *278*, 127138. [CrossRef]
90. Alper, O.C.; Doğan, H.; Öztürk, H. Gear pitting fault detection: Leveraging anomaly detection methods. In *Proceedings of the 2023 14th International Conference on Electrical and Electronics Engineering (ELECO)*; IEEE: New York, NY, USA, 2023; pp. 1–5.
91. Yang, Z.; Xu, M.; Wang, S.; Li, J.; Peng, Z.; Jin, F.; Yang, Y. Detection of wind turbine blade abnormalities through a deep learning model integrating VAE and neural ODE. *Ocean Eng.* **2024**, *302*, 117689. [CrossRef]
92. Dabaja, H.; Youssef, A.; Noura, H.; Ouladsine, M. Fault Detection in Scavenge Air System of a Marine Dual-Fuel Engine using GAN-based Unsupervised Anomaly Detection. In Proceedings of the 6th International Conference on Control and Fault-Tolerant Systems (SysTol'25), Ayia Napa, Cyprus, 6–8 October 2025.
93. Peng, D.; Desmet, W.; Gryllias, K. Reconstruction-based deep unsupervised adaptive threshold support vector data description for wind turbine anomaly detection. *Reliab. Eng. Syst. Saf.* **2025**, *260*, 110995. [CrossRef]
94. Liang, Y.; Zheng, X.; Pang, D.; Zhu, W.; Liu, M.; Xue, S.; Cao, H. ExpertAP: Leveraging Multi-unit Operational Patterns for Advanced Turbine Anomaly Prediction. In *Proceedings of the International Conference on Intelligent Robotics and Applications*; Springer: Berlin/Heidelberg, Germany, 2024; pp. 344–359.
95. Chen, J. Deep Learning Frameworks for Anomaly Detection in Time Series and Graphs with Limited Labels. Ph.D. Thesis, University of Waterloo, Waterloo, ON, Canada, 29 April 2025.
96. Sun, S.; Hu, W.; Liu, Y.; Wang, T.; Chu, F. Matching contrastive learning: An effective and intelligent method for wind turbine fault diagnosis with imbalanced SCADA data. *Expert Syst. Appl.* **2023**, *223*, 119891. [CrossRef]
97. Sun, S.; Li, Q.; Hu, W.; Liang, Z.; Wang, T.; Chu, F. Wind turbine blade breakage detection based on environment-adapted contrastive learning. *Renew. Energy* **2023**, *219*, 119487. [CrossRef]

98. Liu, X.; Guo, H.; Liu, Y. One-shot fault diagnosis of wind turbines based on meta-analogical momentum contrast learning. *Energies* **2022**, *15*, 3133. [CrossRef]
99. Wang, Z.; Qin, B.; Sun, H.; Zhang, J.; Butala, M.D.; Demartino, C.; Peng, P.; Wang, H. An imbalanced semi-supervised wind turbine blade icing detection method based on contrastive learning. *Renew. Energy* **2023**, *212*, 251–262. [CrossRef]
100. Guo, J.; Liu, C.; Liu, S.; Liu, W. Graph contrastive learning for semi-supervised wind turbine fault diagnosis with few labeled SCADA data. *Measurement* **2025**, *245*, 116531. [CrossRef]
101. Qiao, W.; Liu, X.; Huang, J.; Wu, G. A Prior Knowledge Embedding Contrastive Attention Learning Network for Variable Working Conditions Bearing Fault Diagnosis With Small Samples. *IEEE Sens. J.* **2024**, *24*, 39967–39980. [CrossRef]
102. Miyamoto, K.; Lee, T.Y.; Minezawa, A. AAAD: Adaptive Activated Anomaly Detection on Varied Backgrounds. In *Proceedings of the 2025 IEEE International Conference on Advanced Visual and Signal-Based Systems (AVSS)*; IEEE: New York, NY, USA, 2025; pp. 1–6.
103. Wang, C.; Chen, H.; Wang, Y.; Zhao, S.; Liu, K. Spatial contrast and semantic difference perception network for aeroengine blade damage segmentation. *IEEE Trans. Aerosp. Electron. Syst.* **2024**, *61*, 2040–2056. [CrossRef]
104. Qin, Z.; Wang, X.; Han, X.; Lin, Y.; Zhou, Y. Pre-trained combustion model and transfer learning in thermoacoustic instability. *Phys. Fluids* **2023**, *35*, 037117. [CrossRef]
105. Li, Y.; Wang, Y.; Li, M.; Li, X.; Feng, J. LLM-YOLOMS: Large Language Model-based Semantic Interpretation and Fault Diagnosis for Wind Turbine Components. *arXiv* **2025**, arXiv:2511.10394.
106. Redmon, J.; Divvala, S.; Girshick, R.; Farhadi, A. You only look once: Unified, real-time object detection. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*; IEEE: New York, NY, USA, 2016; pp. 779–788.
107. Tang, Y.; Fu, J.; Cui, Q.; Dai, B.; Xiong, J. Wind Turbine SCADA Data Interpreter Based on Large Language Models. In *Proceedings of the Electrical Artificial Intelligence Conference*; Springer: Berlin/Heidelberg, Germany, 2024; pp. 530–541.
108. Zhang, C.; Hu, D.; Yang, T. Research of artificial intelligence operations for wind turbines considering anomaly detection, root cause analysis, and incremental training. *Reliab. Eng. Syst. Saf.* **2024**, *241*, 109634. [CrossRef]
109. Alblawi, A. Fault diagnosis of an industrial gas turbine based on the thermodynamic model coupled with a multi feedforward artificial neural networks. *Energy Rep.* **2020**, *6*, 1083–1096. [CrossRef]
110. Yucesan, Y.A.; Viana, F.A. A physics-informed neural network for wind turbine main bearing fatigue. *Int. J. Progn. Health Manag.* **2020**, *11*, 003. [CrossRef]
111. Gao, H.; Zahr, M.J.; Wang, J.X. Physics-informed graph neural Galerkin networks: A unified framework for solving PDE-governed forward and inverse problems. *Comput. Methods Appl. Mech. Eng.* **2022**, *390*, 114502. [CrossRef]
112. Zerrougui, I.; Li, Z.; Hissel, D. Physics-Informed Neural Network for modeling and predicting temperature fluctuations in proton exchange membrane electrolysis. *Energy AI* **2025**, *20*, 100474. [CrossRef]
113. Sahibzada, S.; Malik, F.S.; Nasir, S.; Lodhi, S.K. AI-Augmented Turbulence and Aerodynamic Modelling: Accelerating High-Fidelity CFD Simulations with Physics-informed Neural Networks. *Int. J. Innov. Res. Comput. Sci. Technol.* **2025**, *13*, 91–97. [CrossRef]
114. Lai, C.; Ahmed, I.; Zio, E.; Li, W.; Zhang, Y.; Yao, W.; Chen, J. A multistage physics-informed neural network for fault detection in regulating valves of nuclear power plants. *Energies* **2024**, *17*, 2647. [CrossRef]
115. Pei, F.; Zhang, B.; Long, S.; Yuan, M. BiLSTM-PINN-based Wind Turbine Power Prediction Architecture and Anomaly Data Identification. *Renew. Energy* **2026**, *261*, 125182. [CrossRef]
116. Mittal, S.; Narasinh, V.; Kulkarni, N.; Minz, R.L.; Chakravortty, N.; Mital, P. *Robust Power Prediction of Wind Turbine Using Error Detection, Clustering-Based Imputation and Physics-Informed Learning*; IARIA: Wilmington, DE, USA, 2024.
117. Gijón, A.; Pujana-Goitia, A.; Perea, E.; Molina-Solana, M.; Gómez-Romero, J. Prediction of wind turbines power with physics-informed neural networks and evidential uncertainty quantification. *Eng. Appl. Artif. Intell.* **2026**, *164*, 113331. [CrossRef]
118. Zhang, Z.; Wan, C.; Li, L.; Pang, Y.; Xiong, G.; Zhang, C.; Fan, X.; Wang, Y. CNN-IPINN: A method study on applying physics-informed neural networks to gear fault diagnosis. *Meas. Sci. Technol.* **2025**, *36*, 106101. [CrossRef]
119. Zideh, M.J.; Solanki, S.K. Multivariate physics-informed convolutional autoencoder for anomaly detection in power distribution systems with widespread deployment of distributed energy resources. *Sustain. Energy Grids Netw.* **2025**, *44*, 102022. [CrossRef]
120. Wu, R.; Luo, D.; Han, T. A Physics-Informed Patch Transformer with Interpretable Reasoning for Early Anomaly Warning in Wind Turbines. *Meas. Sci. Technol.* **2025**, *37*, 036205. [CrossRef]
121. Yue, K.; Li, Z.; Yao, X.; Du, W.; Yu, W.; Huang, W.; Wang, L. Physics-informed attention-aided multiple autoencoder for gear anomaly detection under zero-shot condition. *Measurement* **2025**, *257*, 118725. [CrossRef]
122. Duan, H.; Zhao, K.; Li, C.; Zhang, W.; Xu, Z. Reliable anomaly intelligent detection for electromechanical system of wind turbines based on probabilistic physics-informed autoencoders. In *Proceedings of the IET Conference Proceedings CP949*; IET: Stevenage, UK, 2025; Volume 35, pp. 1841–1847.
123. Schröder, L.; Dimitrov, N.K.; Verelst, D.R.; Sørensen, J.A. Using transfer learning to build physics-informed machine learning models for improved wind farm monitoring. *Energies* **2022**, *15*, 558. [CrossRef]

124. Huber, L.G.; Palmé, T.; Chao, M.A. Physics-informed machine learning for predictive maintenance: Applied use-cases. In *Proceedings of the 2023 10th IEEE Swiss Conference on Data Science (SDS)*; IEEE: New York, NY, USA, 2023; pp. 66–72.
125. Li, G.; Liu, Q.; Chen, Z.; Cheng, Y.; Wei, M.; Wu, D. Intelligent fault diagnosis of rotating machinery driven by physical information and contrastive learning under extreme sample imbalance conditions. *Meas. Sci. Technol.* **2025**, *36*, 106132. [CrossRef]
126. Perez-Sanjines, F.; Peeters, C.; Verstraeten, T.; Antoni, J.; Nowé, A.; Helsen, J. Fleet-based early fault detection of wind turbine gearboxes using physics-informed deep learning based on cyclic spectral coherence. *Mech. Syst. Signal Process.* **2023**, *185*, 109760. [CrossRef]
127. Jamil, F.; Peeters, C.; Verstraeten, T.; Helsen, J. Wind turbine drivetrain fault detection using physics-informed multivariate deep learning. In Proceedings of the Surveillance, Vibrations, Shock and Noise, Toulouse, France, 10–13 July 2023.
128. Freeman, B.; Tang, Y.; Huang, Y.; VanZwieten, J. Physics-informed turbulence intensity infusion: A new hybrid approach for marine current turbine rotor blade fault detection. *Ocean Eng.* **2022**, *254*, 111299. [CrossRef]
129. Lee, C.Y.; Maceren, E.D.C.; Huang, C.H. An Integrated Physics-Informed Deep CNN and Adaptive Elite-Based PSO-Catboost for Wind Energy Systems Fault Classification. *IET Renew. Power Gener.* **2026**, *20*, e70175. [CrossRef]
130. Lee, C.Y.; Maceren, E.D.C. Physics-informed anomaly and fault detection for wind energy systems using deep CNN and adaptive elite PSO-XGBoost. *IET Gener. Transm. Distrib.* **2025**, *19*, e13289. [CrossRef]
131. Chen, Y.; Rao, M.; Feng, K.; Zuo, M.J. Physics-Informed LSTM hyperparameters selection for gearbox fault detection. *Mech. Syst. Signal Process.* **2022**, *171*, 108907. [CrossRef]
132. Khan, M.A.; Rahman, A.; Mahmud, F.U.; Bishnu, K.K.; Nabil, H.R.; Mridha, M.; Hossen, M.J. A Physics-Guided Bayesian Neural Network for Sensor Fault Detection in Wind Turbines. *IEEE Open J. Comput. Soc.* **2025**, *6*, 931–942. [CrossRef]
133. Badihi, H.; Zhang, Y.; Jiang, B.; Pillay, P.; Rakheja, S. A comprehensive review on signal-based and model-based condition monitoring of wind turbines: Fault diagnosis and lifetime prognosis. *Proc. IEEE* **2022**, *110*, 754–806. [CrossRef]
134. Sun, T.; Yu, G.; Gao, M.; Zhao, L.; Bai, C.; Yang, W. Fault diagnosis methods based on machine learning and its applications for wind turbines: A review. *IEEE Access* **2021**, *9*, 147481–147511. [CrossRef]
135. Shah, S.S.; Daoliang, T.; Kumar, S.C. RUL forecasting for wind turbine predictive maintenance based on deep learning. *Heliyon* **2024**, *10*, e39268. [CrossRef]
136. Pandit, R.K.; Astolfi, D.; Durazo Cardenas, I. A review of predictive techniques used to support decision making for maintenance operations of wind turbines. *Energies* **2023**, *16*, 1654. [CrossRef]
137. Lu, Q.; Huang, X.; Wu, G.; Shen, X.; Zhu, D. Digital twin-driven water-wave information transmission and recurrent acceleration network for remaining useful life prediction of gear box. *Eng. Res. Express* **2025**, *7*, 025202. [CrossRef]
138. Sun, J.; Yan, Z.; Han, Y.; Zhu, X.; Yang, C. Deep learning framework for gas turbine performance digital twin and degradation prognostics from airline operator perspective. *Reliab. Eng. Syst. Saf.* **2023**, *238*, 109404. [CrossRef]
139. Wang, Y.; Wang, Y. A denoising semi-supervised deep learning model for remaining useful life prediction of turbofan engine degradation. *Appl. Intell.* **2023**, *53*, 22682–22699. [CrossRef]
140. Elsherif, S.M.; Hafiz, B.; Makhlouf, M.; Farouk, O. A deep learning-based prognostic approach for predicting turbofan engine degradation and remaining useful life. *Sci. Rep.* **2025**, *15*, 26251. [CrossRef]
141. He, K.; Su, Z.; Tian, X.; Yu, H.; Luo, M. RUL prediction of wind turbine gearbox bearings based on self-calibration temporal convolutional network. *IEEE Trans. Instrum. Meas.* **2022**, *71*, 3501912. [CrossRef]
142. Li, D.; Zhou, F.; Gao, Y.; Yang, K.; Gao, H. Power plant turbine power trend prediction based on continuous prediction and online oil monitoring data of deep learning. *Tribol. Int.* **2024**, *191*, 109083. [CrossRef]
143. Atsafack, B.M.; Kabiri, C.; Rushingabigwi, G. Predictive maintenance for hydraulic turbine unit: A comparative deep learning approach using internet of things data in real-time. *IEEE Access* **2025**, *13*, 158340–158352. [CrossRef]
144. Sun, L.; Liu, T.; Xie, Y.; Zhang, D.; Xia, X. Real-time power prediction approach for turbine using deep learning techniques. *Energy* **2021**, *233*, 121130. [CrossRef]
145. Rengasamy, D.; Rothwell, B.; Figueredo, G.P. Asymmetric loss functions for deep learning early predictions of remaining useful life in aerospace gas turbine engines. In *Proceedings of the 2020 International Joint Conference on Neural Networks (IJCNN)*; IEEE: New York, NY, USA, 2020; pp. 1–7.
146. Li, A.; Guan, F.; Hu, H.; Liu, Z.; Xiao, B.; Huang, W.; Yang, Y. Physics-informed DEEPLSTM for digital twin modeling of steam turbine full-operating condition. *Appl. Therm. Eng.* **2025**, *278*, 127439. [CrossRef]
147. Zhang, X.C.; Gong, J.G.; Xuan, F.Z. A physics-informed neural network for creep-fatigue life prediction of components at elevated temperatures. *Eng. Fract. Mech.* **2021**, *258*, 108130. [CrossRef]
148. Wang, Z.; Gao, P.; Chu, X. Remaining useful life prediction of wind turbine gearbox bearings with limited samples based on prior knowledge and PI-LSTM. *Sustainability* **2022**, *14*, 12094. [CrossRef]
149. Li, J.; Yang, Z. Remaining Useful Life Prediction of Turbine Engines Using Multimodal Transfer Learning. *Machines* **2025**, *13*, 789. [CrossRef]

150. Wolniak, R.; Gajdzik, B.; Grebski, W. The usage of Root Cause Analysis (RCA) in Industry 4.0 conditions. In *Scientific Papers of Silesian University of Technology*; Organization and Management Series; Silesian University of Technology: Gliwice, Poland, 2023; pp. 223–235.
151. Papageorgiou, K.; Theodosiou, T.; Rapti, A.; Papageorgiou, E.I.; Dimitriou, N.; Tzovaras, D.; Margetis, G. A systematic review on machine learning methods for root cause analysis towards zero-defect manufacturing. *Front. Manuf. Technol.* **2022**, *2*, 972712. [CrossRef]
152. Gugaliya, J.K.; Vij, R.K.; Ramaswamy, S.; K, L.S.M. Multi-PCA Driven Approach for Fault Detection and Root Cause Analysis of Process Equipment. In Proceedings of the AAAI Spring Symposium: Combining Machine Learning with Knowledge Engineering, Palo Alto, CA, USA, 23–25 March 2020; Volume 1.
153. Yuan, L.; Han, G.; Dong, P. Improved bayesian network with graph attention and prior algorithm for aircraft engine fault root cause analysis. *Sci. Rep.* **2026**, *16*, 5924. [CrossRef]
154. Mourya, M.; Tyagi, T. Predict, Prevent, Decide: AI-Enabled Root Cause Analysis and Operational Intelligence for Offshore Performance. In *Proceedings of the Abu Dhabi International Petroleum Exhibition and Conference*; SPE: Richardson, TX, USA, 2025; p. 229267.
155. Ofoedu, A.T.; Ozor, J.E.; Sofoluwe, O.; Jambol, D.D. A Root Cause Analytics Model for Diagnosing Offshore Process Failures Using Live Operational Data. *Int. Sci. Ref. Res. J.* **2022**, *5*, 226–244.
156. Vitale, M.; Youssef, A.; Mishra, P.; Shetty, S.; Sharma, M.; Vanzo, G.; Veneri, G.; Vieri, L.; Bettini, A. Harnessing Generative AI for Interactive System Failure Diagnostics: A User-Centric Approach to Streamlined Problem Solving and Maintenance. In *Proceedings of the Abu Dhabi International Petroleum Exhibition and Conference*; SPE: Richardson, TX, USA, 2024; p. 222033.
157. Shi, R.; Liu, W.; Guo, C.; He, Y. Intelligent Root Cause Analysis Approach for Quality Accidents Based on Knowledge Graph and Large Language Model. In *Proceedings of the 2025 16th International Conference on Reliability, Maintainability and Safety (ICRMS)*; IEEE: New York, NY, USA, 2025; pp. 1–6.
158. Ferrari, P.; Rinaldi, S.; Sisinni, E.; Colombo, F.; Ghelfi, F.; Maffei, D.; Malara, M. Performance evaluation of full-cloud and edge-cloud architectures for Industrial IoT anomaly detection based on deep learning. In *Proceedings of the 2019 II Workshop on Metrology for Industry 4.0 and IoT (MetroInd4.0 & IoT)*; IEEE: New York, NY, USA, 2019; pp. 420–425.
159. Yang, Q.; Duan, L.; Song, W.; Zhang, S. A service-based cloud-edge fusion approach for abnormality detection of power generation equipment. *IEEE Access* **2024**, *12*, 51556–51569. [CrossRef]
160. Oliver, S.; Engber, M.; Mich, R.; Bohra, D. Cloud Based Implementation of a Gas Turbine Remote Monitoring System. In Proceedings of the GPPS Forum 18, Montreal, QC, Canada, 7–9 May 2018.
161. Hurtado Carreon, A.; Veldhuis, S.C. Practical Application of Condition-Based Monitoring (CBM) Technologies in the Modern Manufacturing Industry: A Review. *Processes* **2025**, *13*, 4084. [CrossRef]
162. Kurkin, A.; Kabaldin, Y.; Zhelonkin, M.; Mancerov, S.; Anosov, M.; Shatagin, D. Multiparametric Vibration Diagnostics of Machine Tools within a Digital Twin Framework Using Machine Learning. *Appl. Sci.* **2026**, *16*, 982. [CrossRef]
163. Tikka, P.; Karjalainen, J.; Alesani, A.; Goriachev, V. Large Language Model hallucination mitigation in three industrial use cases. *IEEE Access* **2026**, *14*, 25564–25576. [CrossRef]
164. Jia, M.; Cheng, Q.; Tao, C.; Hu, Y.; Hong, Q.; Cheng, W.; Liu, Z. A physics-informed train on synthetic and test on real method for evaluating large language model-generated safety-critical traffic scenarios. *Comput.-Aided Civ. Infrastruct. Eng.* **2025**, *40*, 5153–5169. [CrossRef]
165. Mirshekali, H.; Shadi, M.R.; Ladani, F.G.; Shaker, H.R. A Review of Large Language Models for Energy Systems: Applications, Challenges, and Future Prospects. *IEEE Access* **2025**, *13*, 163162–163188. [CrossRef]
166. *ISO 13374-1*; Condition Monitoring and Diagnostics of Machines—Data Processing, Communication and Presentation—Part 1: General Guidelines. Technical Report; International Organization for Standardization: Geneva, Switzerland, 2003.
167. *ISO 13379-1*; Condition Monitoring and Diagnostics of Machine Systems—Data Interpretation and Diagnostics Techniques—Part 1: General Guidelines. Technical Report; International Organization for Standardization: Geneva, Switzerland, 2025.