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Machine Learning-Driven Condition Monitoring and Performance Optimization of Thrust Bearings: State-Of-The-Art Review, Challenges, And Future Perspectives

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Abstract

Thrust bearings are critical components in high-capacity rotating machinery such as hydroelectric generators, turbines, compressors, marine propulsion systems, and vertical pumps, where they support axial loads and ensure operational stability. Their performance is governed by complex thermo-hydrodynamic interactions involving lubrication behavior, temperature distribution, structural deformation, and rotor dynamics. Degradation mechanisms including lubrication starvation, thermal instability, wear, fatigue, cavitation, and misalignment can significantly impair efficiency and reliability, making advanced condition monitoring essential for safe and economical operation. Recent advances in Machine Learning (ML) and Deep Learning (DL) have transformed machinery health monitoring by enabling automated fault diagnosis, anomaly detection, health assessment, and Remaining Useful Life (RUL) prediction from multi-sensor data. However, the unique fluid-film lubrication characteristics and coupled thermo-hydrodynamic behavior of thrust bearings present challenges that are not adequately addressed by conventional approaches developed primarily for rolling-element bearings. This review critically examines recent developments in ML-driven condition monitoring and performance optimization of thrust bearings. The analysis encompasses sensing technologies, signal-processing techniques, supervised and unsupervised learning methods, deep learning architectures, transfer learning, prognostic frameworks, and uncertainty-aware RUL prediction. Particular emphasis is placed on Physics-Informed Machine Learning (PIML), which integrates physical laws with data-driven models to improve robustness, interpretability, and predictive accuracy. Emerging technologies including Digital Twins, Explainable Artificial Intelligence, Federated Learning, and Edge Intelligence are also discussed. By identifying key challenges related to data scarcity, model generalization, uncertainty quantification, and industrial deployment, this review provides a structured research roadmap and highlights future directions toward autonomous, reliable, and self-optimizing thrust-bearing management systems.

Keywords: *Condition monitoring; Deep learning; Digital twin; Fault diagnosis; Machine learning; Physics-informed learning; Predictive maintenance; Remaining useful life; Thrust bearing.*

1. Introduction

The adoption of Industry 4.0 technologies and data-driven maintenance strategies has transformed reliability engineering into a critical component of modern industrial systems [1–3]. Rotating machinery forms the backbone of power generation, manufacturing, aerospace, marine transportation, and process industries, where operational reliability directly affects productivity, safety, and maintenance costs [4,5]. Bearings are among the most important machine elements in these systems, providing shaft support, load transmission, and dynamic stability while minimizing friction and wear [6–8]. Among bearing configurations, thrust bearings are specifically designed to support axial loads and are widely employed in hydroelectric generators, steam turbines, compressors, vertical pumps, and marine propulsion systems [9–11]. Unlike radial bearings, thrust bearings operate under complex thermo-hydrodynamic conditions in which lubrication behavior, temperature distribution, load transfer, and rotor dynamics interact simultaneously. These coupled effects significantly influence performance, degradation, and service life. Bearing failures remain a major source of machinery downtime and reliability degradation. Common failure mechanisms in thrust bearings include lubrication starvation, thermal instability, wear, fatigue, misalignment, cavitation, and pad deformation [12–13]. Traditional maintenance strategies based on periodic inspections or fixed replacement schedules often fail to detect early-stage faults and may either increase maintenance costs or lead to unexpected failures [14]. Consequently, condition-based maintenance (CBM) and predictive maintenance (PdM) approaches utilizing vibration analysis, acoustic emission, temperature monitoring, lubricant analysis, and process measurements have become increasingly important [15]. Although conventional monitoring techniques have demonstrated practical value, their effectiveness often depends on handcrafted features, empirical thresholds, and expert interpretation [16–19]. Performance may deteriorate under varying operating conditions, noisy environments, and complex fault scenarios commonly encountered in industrial applications [20–21]. Recent advances in machine learning (ML) and deep learning (DL) have created new opportunities for automated fault diagnosis, anomaly detection, health assessment, and remaining useful life (RUL) prediction through the direct extraction of patterns from sensor data [22]. While extensive research has been conducted on ML-based monitoring of rolling-element bearings, comparatively fewer studies have focused specifically on thrust bearings. Existing reviews frequently address bearing systems in general and do not adequately consider challenges associated with axial loading, thermo-hydrodynamic lubrication, tilting-pad behavior, and fluid–structure interactions [23-27]. Furthermore, emerging technologies such as Physics-Informed Machine Learning (PIML), Digital Twins, Explainable Artificial Intelligence (XAI), and edge intelligence are rapidly influencing intelligent maintenance systems but remain insufficiently reviewed from a thrust-bearing perspective [28–31]. Therefore, this review presents a comprehensive assessment of machine learning-driven condition monitoring and performance optimization of thrust bearings. The paper examines sensing technologies, signal-processing methods, fault diagnosis techniques, prognostic frameworks, Physics-Informed Machine Learning, Digital Twin architectures, and intelligent control strategies. Current challenges, research gaps, and future directions are also discussed to support the development of reliable and autonomous thrust-bearing management systems.

2. Research Methodology

This review was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework to ensure a systematic and transparent literature selection process. The methodology focused on identifying, evaluating, and synthesizing studies related to machine learning-based condition monitoring, fault diagnosis, prognostics, and performance optimization of thrust bearings.

2.1. Literature Search Strategy

A comprehensive literature search was performed using four major scientific databases: Scopus, Web of Science, ScienceDirect, and IEEE Xplore. Publications from January 2010 to May 2025 were considered to capture both foundational

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developments and recent advances in intelligent bearing monitoring. Search queries combined keywords such as thrust bearing, condition monitoring, fault diagnosis, machine learning, deep learning, predictive maintenance, remaining useful life, digital twin, and physics-informed learning. Additional relevant studies were identified through citation tracking of highly cited publications.

2.2.Inclusion and Exclusion Criteria

Only peer-reviewed journal articles and high-quality conference papers addressing AI, machine learning, or deep learning applications in bearing health monitoring were considered. Studies were required to include experimental validation, simulation-based verification, or industrial case studies. Publications lacking sufficient methodological detail, focusing solely on theoretical modeling without data-driven analysis, or unrelated to thrust-bearing operating conditions were excluded.

2.3.Study Selection and Data Synthesis

The initial search yielded 1,487 records. After removing duplicates, 1,175 publications were screened based on titles and abstracts. Subsequently, 286 articles underwent full-text assessment, resulting in the exclusion of 124 studies due to limited relevance or insufficient technical rigor. A total of 80 studies were included in the final review. The selected literature was categorized into six major themes: sensing technologies, signal-processing methods, machine learning-based diagnosis, prognostic approaches, Physics-Informed Machine Learning and Digital Twins, and intelligent performance optimization. This thematic classification enabled a structured assessment of current research trends, industrial challenges, and future directions in intelligent thrust-bearing systems.

3. Theoretical Framework and Degradation Mechanisms

3.1.Structural Typologies of Thrust Bearings

Thrust bearings are tribological components designed to support axial loads while maintaining rotor stability and minimizing friction. Based on load-support mechanisms, they are generally classified as rolling-element, hydrodynamic, and magnetic thrust bearings [32]. Rolling-element thrust bearings utilize balls or rollers operating under elastohydrodynamic lubrication (EHL) conditions. They provide low friction and high rotational accuracy but are susceptible to contact fatigue, wear, and shaft misalignment [33]. Hydrodynamic thrust bearings generate a load-carrying lubricant film between rotating and stationary surfaces, making them suitable for turbines, compressors, and hydroelectric generators operating under high loads [34–36]. Their performance is strongly influenced by lubricant properties, operating speed, and thermal effects, rendering them vulnerable to lubricant starvation and thermal deformation [37,38]. Magnetic thrust bearings employ electromagnetic forces to suspend the rotor without physical contact, eliminating conventional wear mechanisms but requiring sophisticated control systems and continuous power supply [39–41]. Despite these differences, all thrust-bearing systems rely on effective load transfer and adequate surface separation. In fluid-film bearings, this separation is achieved through a converging lubricant wedge that generates hydrodynamic pressure capable of supporting substantial axial loads.

3.2.Thermo-Hydrodynamic Formulation

The performance of fluid-film thrust bearings is governed by hydrodynamic pressure generation within the lubricant film. Under thin-film lubrication assumptions, pressure distribution is commonly described by the Reynolds equation derived from the Navier–Stokes equations [42,43]:

$$\frac{\partial}{\partial x}\left(\frac{\rho h^3}{12\mu}\frac{\partial p}{\partial x}\right)+\frac{\partial}{\partial y}\left(\frac{\rho h^3}{12\mu}\frac{\partial p}{\partial y}\right)=\frac{U}{2}\frac{\partial(\rho h)}{\partial x}+\frac{\partial(\rho h)}{\partial t}$$

where p is hydrodynamic pressure, h is film thickness, μ is lubricant viscosity, ρ is the lubricant density and U is the relative sliding velocity. Hydrodynamic behavior is strongly coupled with thermal effects because viscous shearing generates

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heat within the lubricant film. The resulting temperature rise reduces lubricant viscosity and alters load-carrying capacity. This relationship is commonly approximated by:

$$\mu(T) = \mu_0 e^{-\beta(T-T_0)}$$

where μ_0 denotes the reference viscosity at temperature T_0, and β is the temperature–viscosity coefficient [44-46]. The interaction among pressure generation, heat transfer, lubricant flow, and structural deformation forms the thermo-hydrodynamic lubrication regime. Under severe operating conditions, excessive temperature rise may reduce film thickness, promote lubrication starvation, and accelerate wear, ultimately leading to mixed or boundary lubrication conditions associated with increased friction and vibration [47].

3.3.Failure Mechanisms

Thrust-bearing degradation results from interactions among mechanical loading, lubrication conditions, thermal effects, and material properties. **Fatigue damage** is a common failure mechanism in heavily loaded bearings. Repeated cyclic stresses initiate subsurface microcracks that propagate toward the surface, producing pitting and spalling defects. These defects increase vibration levels and accelerate further deterioration.

Lubrication starvation occurs when lubricant supply, viscosity, or film thickness falls below critical levels. The resulting transition toward mixed lubrication increases asperity contact, friction, and wear.

Thermal crowning and wiping are associated with excessive heat generation. Non-uniform thermal expansion distorts bearing-pad geometry, altering load distribution and potentially causing localized melting or wiping of bearing materials. **Cavitation** arises when localized lubricant pressure falls below vapor pressure, generating vapor bubbles that subsequently collapse and erode bearing surfaces [48]. In practice, these mechanisms rarely occur independently. Lubrication degradation can intensify thermal effects, while cavitation and surface damage may accelerate fatigue progression. Understanding these coupled failure modes is essential for developing reliable machine-learning-based diagnostic and prognostic systems because they directly influence vibration, temperature, acoustic emission, and lubricant-condition signatures used for health assessment.

4. Comprehensive Sensing Infrastructure and Signal Processing

4.1.Multi-Modal Sensing Architectures

Reliable monitoring of thrust-bearing health requires observation of multiple degradation-related phenomena, including vibration, thermal behavior, lubrication conditions, and rotor dynamics. Consequently, modern monitoring systems increasingly employ multi-modal sensing architectures that integrate complementary information sources [49,50]. Vibration accelerometers remain the most widely used sensors because they effectively capture responses associated with imbalance, misalignment, wear, and structural defects. Acoustic emission (AE) sensors provide enhanced sensitivity to early-stage degradation by detecting high-frequency stress waves generated by microcracks, asperity interactions, and lubricant-film disturbances. Thermal monitoring using resistance temperature detectors (RTDs) and thermocouples provides direct information regarding heat generation, lubrication effectiveness, and thermal stability. In hydrodynamic thrust bearings, eddy-current displacement probes are commonly used to measure shaft position and estimate lubricant-film thickness, offering valuable insight into rotor stability and lubrication performance. The integration of vibration, acoustic, thermal, displacement, and process measurements through sensor-fusion frameworks has significantly improved monitoring robustness under varying industrial operating conditions.

4.2.Advanced Signal Processing Techniques

Raw signals acquired from industrial environments are often contaminated by noise, structural

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resonances, and operating variability. Therefore, signal processing plays a critical role in extracting diagnostic information prior to machine-learning analysis.

Time-domain methods utilize statistical features such as RMS, kurtosis, skewness, and crest factor to characterize signal energy and impulsiveness. These techniques are computationally efficient but may exhibit limited sensitivity under complex operating conditions.

Frequency-domain analysis employs spectral techniques, particularly Fast Fourier Transform (FFT), to identify characteristic defect frequencies and resonance behavior associated with bearing faults [51–53]. Because thrust bearings frequently operate under non-stationary conditions, time–frequency methods have become increasingly important. Short-Time Fourier Transform (STFT) generates spectrograms that reveal temporal frequency evolution, while Continuous Wavelet Transform (CWT) provides multi-resolution analysis of transient events. Variational Mode Decomposition (VMD) further enhances signal interpretation by separating complex signals into intrinsic modes with reduced mode-mixing effects. These advanced representations are widely used as inputs for deep learning models, enabling improved extraction of fault-related features from complex industrial datasets.

5. Machine Learning for Fault Diagnosis

Machine learning (ML) has become a key technology for automated thrust-bearing fault diagnosis by enabling data-driven identification of degradation patterns from multi-sensor measurements. A typical workflow involves sensor data acquisition, signal preprocessing, feature extraction, model training, and fault classification (Figure 1). As shown in Figure 1 AI-based framework for thrust-bearing condition monitoring and fault diagnosis. Figure 2. Machine learning-based degradation trajectory and remaining useful life prediction with confidence bounds.

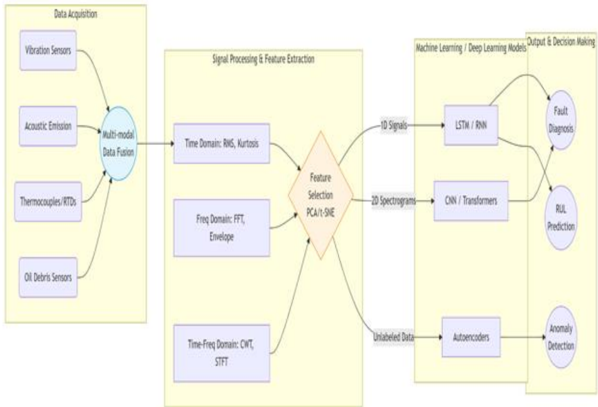

Figure 1 AI-based framework for thrust-bearing condition monitoring and fault diagnosis

5.1. Supervised Learning Methods

Early diagnostic systems relied on handcrafted features combined with supervised learning algorithms. Support Vector Machines (SVMs) are widely used due to their effectiveness with limited datasets and high-dimensional features. Random Forests (RFs) and Decision Trees provide robust classification performance while offering feature-importance information useful for industrial interpretation [54]. Other approaches such as k-Nearest Neighbors (k-NN) and Artificial Neural Networks (ANNs) have also been applied to bearing fault classification and performance prediction.

5.2. Deep Learning Architectures

Deep learning reduces dependence on manual feature engineering by automatically learning hierarchical representations from sensor data [55,56]. Convolutional Neural Networks (CNNs) effectively process vibration signals and time–frequency images, achieving high diagnostic accuracy for bearing faults [57,58]. Long Short-Term Memory (LSTM) networks capture temporal degradation trends and are particularly suitable for sequential monitoring applications [59,60]. Autoencoders support unsupervised anomaly detection through reconstruction-error analysis, addressing the scarcity of labeled fault data [61]. More recently, Transformer architectures have

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demonstrated strong capability for multi-sensor fusion and long-range dependency modeling through self-attention mechanisms.

5.3.Transfer Learning and Domain Adaptation

Industrial deployment often suffers from domain shifts caused by variations in speed, load, lubrication condition, and operating environment. Transfer Learning (TL) adapts knowledge from data-rich source domains to target systems with limited labeled data. Domain Adaptation (DA) techniques such as Maximum Mean Discrepancy (MMD) and adversarial learning reduce feature-distribution differences between operating conditions, improving diagnostic robustness and generalization [62–66].

6. Prognostics And Remaining Useful Life Prediction

6.1.Prognostic Frameworks

Remaining Useful Life (RUL) prediction extends condition monitoring by estimating the time remaining before functional failure. Rolling-element thrust bearings generally exhibit progressive fatigue degradation that can be modeled using statistical or data-driven approaches [67].

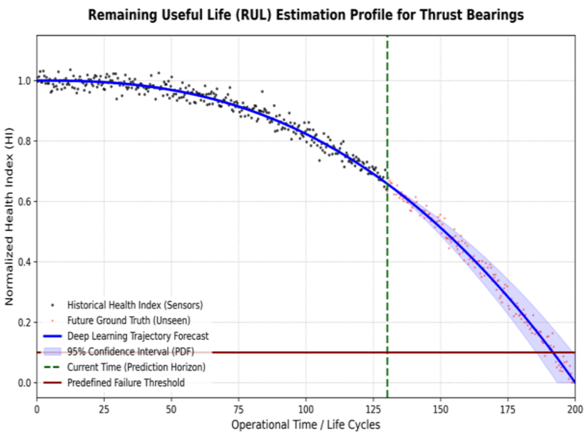

Figure 2 Machine learning-based degradation trajectory and remaining useful life prediction with confidence bounds

In contrast, hydrodynamic thrust bearings experience complex degradation involving wear, thermal distortion, lubricant deterioration, and fluid-film instability. Consequently, modern prognostic systems increasingly rely on multivariate machine-learning models capable of learning nonlinear degradation trajectories from operational data. Figure 2 illustrates a representative machine-learning-based RUL prediction framework. As shown in Figure 2 Machine learning-based degradation trajectory and remaining useful life prediction with confidence bounds

6.2.Health Index Construction

Reliable RUL estimation requires a Health Index (HI) that maps multidimensional sensor measurements into a degradation-sensitive representation. Conventional indicators such as RMS and kurtosis often exhibit poor monotonicity under varying operating conditions [68]. Deep Autoencoders (AEs) and Variational Autoencoders (VAEs) provide effective alternatives by learning healthy-system behavior and generating degradation-sensitive reconstruction errors that serve as robust health indicators [69,70].

6.3.Deep Learning-Based Forecasting

Once an HI is established, sequential learning models are used to forecast future degradation. LSTM and GRU networks remain widely used because of their ability to model long-term temporal dependencies. Transformer-based architectures have recently achieved improved performance by capturing long-range interactions through self-attention mechanisms and parallel sequence processing.

6.4.Uncertainty Quantification

Industrial maintenance decisions require not only RUL estimates but also confidence information. Particle Filtering (PF) provides recursive probabilistic state estimation under nonlinear and non-Gaussian conditions [71,72]. Gaussian Process Regression (GPR) offers probabilistic predictions with explicit confidence intervals [73]. Recent studies additionally incorporate Bayesian deep learning and probabilistic Transformers to quantify prediction uncertainty and support risk-aware

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maintenance planning. As shown in Figure 2 Machine learning-based degradation trajectory and remaining useful life prediction with confidence bounds

7. Physics-Informed Machine Learning

7.1.Motivation

Although deep learning achieves high predictive accuracy, purely data-driven models often suffer from limited interpretability, poor extrapolation capability, and dependence on large labeled datasets [74-76]. These limitations are particularly significant in thrust-bearing applications where failure data are scarce and system behavior is governed by well-established physical laws.

7.2.Physics-Informed Neural Networks (PINNs)

Physics-Informed Neural Networks (PINNs) integrate governing equations directly into the training process by combining data-fitting objectives with physics-based residual constraints [77]. The overall training objective is commonly expressed as a weighted combination of data fidelity and physics-based residual losses

$$L_{total} = L_{data} + \lambda_1 L_{Reynolds} + \lambda_2 L_{Energy}$$

$$\mathcal{L}_{Data} = \frac{1}{N}\sum_{i=1}^{N}\left|p_{pred}(x_i, y_i) - p_{meas}(x_i, y_i)\right|^2$$

$$L_{Reynolds} = \frac{1}{M}\sum_{j=1}^{M}\left|\frac{\partial}{\partial x}\left(\frac{\rho h^3}{12\mu}\frac{\partial p_{pred}}{\partial x}\right) + \frac{\partial}{\partial y}\left(\frac{\rho h^3}{12\mu}\frac{\partial p_{pred}}{\partial y}\right) - \frac{U}{2}\frac{\partial(\rho h)}{\partial x}\right|^2$$

Compared with conventional deep learning models, PINNs improve data efficiency, robustness, and interpretability while reducing the risk of physically unrealistic predictions [78]. These advantages make PINNs particularly attractive for industrial prognostics and health monitoring.

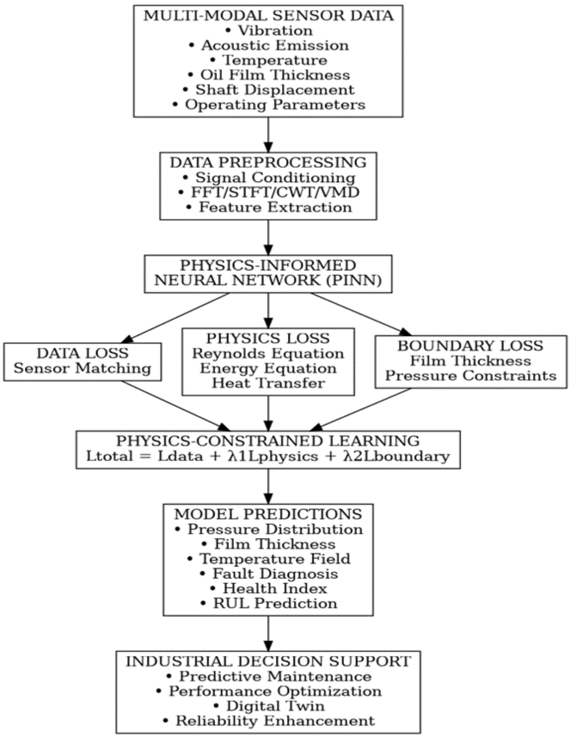

Figure 3 Physics-Informed Neural Network (PINN) framework for intelligent thrust-bearing monitoring and prognostics

7.3.Hybrid Physics–Data Models

Hybrid frameworks combine numerical simulations with machine-learning algorithms to exploit the strengths of both approaches [79]. High-fidelity FEM, CFD, and thermo-hydrodynamic models provide physical insight, while machine learning captures residual phenomena such as localized wear, lubricant degradation, and transient disturbances. Such architectures improve predictive accuracy and robustness under variable operating conditions while maintaining physical consistency.

8. Performance Optimization and Active Control

The role of machine learning is expanding beyond condition monitoring toward real-time performance optimization and autonomous control.

8.1.Intelligent Lubrication Management

Lubrication strongly influences friction, wear, temperature, and bearing reliability. Conventional

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lubrication systems operate using conservative settings that may increase energy consumption. Reinforcement Learning (RL) and Deep Reinforcement Learning (DRL) algorithms can dynamically optimize lubricant flow, pressure, and cooling conditions using real-time sensor feedback [80]. Such adaptive strategies improve efficiency while maintaining adequate lubricant-film thickness and operational safety.

8.2.Active Thermal Management

Thermal gradients within hydrodynamic thrust bearings can induce thermal crowning, reduce load-carrying capacity and accelerate degradation. Machine-learning models trained on operational and simulation data can predict thermal behavior and enable proactive control actions, including adaptive cooling and lubricant redistribution. These approaches support improved reliability and extended service life.

9. Digital Twins, Industrial Challenges, And Future Roadmap

9.1.Digital Twin Architecture

Digital Twins (DTs) provide virtual representations of physical thrust-bearing systems that continuously update using real-time sensor data.

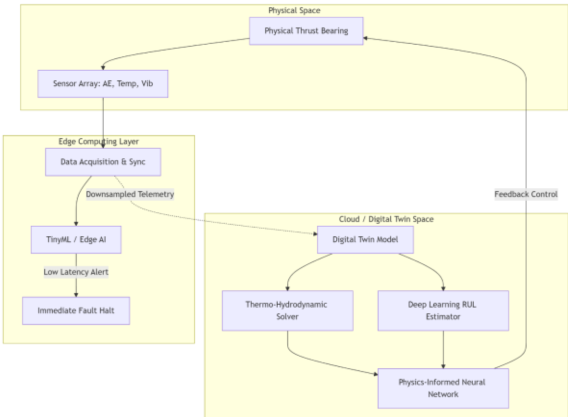

Figure 4 Digital Twin architecture integrating sensing, Edge AI, cloud analytics, and maintenance decision support

Modern DT frameworks typically employ edge–cloud architectures in which local edge devices perform anomaly detection while cloud platforms execute high-fidelity simulations and prognostic analyses. By integrating sensor measurements, physics-based models, and machine-learning algorithms, DTs support continuous health assessment, RUL prediction, maintenance optimization, and operational decision-making. This capability positions DTs as a key enabling technology for Industry 4.0 maintenance systems. As shown in Figure 4 Digital Twin architecture integrating sensing, Edge AI, cloud analytics, and maintenance decision support

9.2.Industrial Implementation Challenges

Despite substantial progress, several challenges continue to limit industrial adoption. Data scarcity and class imbalance: Industrial datasets contain abundant healthy-condition data but relatively few fault examples, complicating supervised learning. Domain variability: Models trained under laboratory conditions often perform poorly when exposed to different industrial operating environments. Interpretability and trust: Industrial users require transparent decision-making processes. Explainable AI techniques such as SHAP, LIME, and Layer-Wise Relevance Propagation (LRP) are increasingly used to improve model transparency and user confidence.

9.3.Future Technological Roadmap

Several emerging technologies are expected to shape future thrust-bearing monitoring systems. Federated Learning enables collaborative model training without sharing sensitive industrial data. TinyML and Edge Intelligence support real-time diagnostics on resource-constrained embedded devices. Self-Supervised Learning (SSL) reduces dependence on labeled datasets by learning representations from large volumes of unlabeled operational data. The convergence of Digital Twins, Physics-Informed Machine Learning, Explainable AI, Federated Learning, and edge computing is expected to accelerate the transition toward autonomous, self-optimizing maintenance ecosystems.

Conclusion

This review examined recent advances in machine learning-based condition monitoring, fault diagnosis, prognostics, and performance optimization of thrust bearings. The integration of multi-modal sensing, advanced signal processing, and data-driven algorithms has significantly improved the capability to detect and predict degradation under complex operating conditions. Deep learning architectures such as CNNs, LSTMs, Autoencoders, and Transformers have demonstrated strong diagnostic and prognostic performance. However, industrial deployment remains constrained by data scarcity, operating-condition variability, and limited interpretability. Physics-Informed Machine Learning and hybrid physics–data models provide promising solutions by combining engineering knowledge with data-driven learning, thereby improving robustness, generalization, and physical consistency. The emergence of Digital Twins, Explainable AI, Federated Learning, Self-Supervised Learning, and Edge Intelligence is expected to further advance intelligent maintenance systems. Future research should focus on uncertainty-aware prognostics, standardized benchmark datasets, cross-domain adaptation, and large-scale industrial validation. Ultimately, the integration of physics-based modeling, machine learning, and cyber–physical systems will play a central role in achieving reliable, autonomous, and self-optimizing thrust-bearing management within Industry 4.0 environments.

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