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A State-Of-The-Art Survey On Rotor And Rotor-Bearing Fault Diagnosis: Model-Based And Data-Driven Techniques.

Pandya Utsav,
MTech Scholar,

Sudhir Vegad,
Professor & Head Computer Engineering, GCET, Charutar Vidhya Mandal (CVM) University.

Abstract:
This paper reviews recent contributions in model-based, vibration-based, machine-learning, acoustic, and hybrid intelligent methodologies for the diagnosis of rotor and rotor-bearing faults, as reported in the literature between 2021 and 2024. For each approach, diagnostic accuracy, robustness to noise, computational efficiency, and suitability for industrial deployment are considered. The results have shown that traditional model-based approaches guarantee good interpretability but are highly sensitive to system parameters, whereas machine-learning and data-driven approaches achieve high accuracy at the cost of large, labeled datasets. Acoustic approaches offer non-contact monitoring but are prone to environmental disturbances. Of all the methods reviewed in this work, the hybrid RIME–VMD–WKN framework demonstrated the best efficacy in early unbalance detection. The trend of research is obviously oriented toward hybrid, physics-guided intelligent systems as the most promising direction in the near future for rotating machinery predictive maintenance.

Key Words: *Rotor-Bearing Fault Diagnosis, Predictive Maintenance, Condition Monitoring, Vibration Analysis, Model-Based Approach, Data-Driven Techniques*

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I. Introduction

Rotary machinery provides the backbone of modern industrial systems, serving applications that range from power generation and transportation to aerospace, manufacturing, and process automation [1]. Of these, rotor and rotor-bearing assemblies are among the most critical systems because they operate continuously at high speeds and are sensitive to mechanical faults [6]. Even slight disturbances due to unbalance, misalignment, looseness, or bearing deterioration can escalate rapidly and result in increased vibration, reduced efficiency, unexpected downtime, and catastrophic mechanical failure [7–10]. Thus, fault diagnosis with accuracy and speed has become indispensable to guarantee system reliability, optimize maintenance schedules, and reduce operational costs [11].

Recent literature is indicative of this evolution, with various advanced methodologies proposed such as signal decomposition combined with neural networks [14], dynamic residual modeling [18], acoustic-based non-contact diagnosis [20], and integrated diagnostic-control frameworks [21]. However, despite these developments, inconsistencies exist among different approaches regarding accuracy, real-time adaptability, sensor-quality dependencies, computational burden, and industrial deployment feasibility [24–26]. Hence, there is an urgent need for a systematic comparison of methodologies to identify strengths, weaknesses, and future potential.

This work presents a critical comparative review of recent rotor and rotor-bearing fault diagnosis techniques—ranging from model-based and data-driven to hybrid intelligent approaches—published between 2021 and 2024 [27]. Each method is analyzed based on computational requirements, diagnostic accuracy, robustness, and practical applicability. Such an analysis reveals emerging trends, highlights research gaps, and emphasizes the growing importance of hybrid intelligent systems for enhanced predictive maintenance of rotating machinery.

II. Literature Review

Recent progress in rotor and rotor-bearing fault diagnosis is being made by emphasizing hybrid signal-processing and intelligent learning techniques [14],[20]. A few techniques, including Reconstructed Intrinsic Mode Extraction, Variational Mode Decomposition, and wavelet-based neural networks, have shown high accuracy in the detection of incipient unbalance faults [14][15]. These techniques depend on noise-robust decomposition and adaptive nonlinear classification; their performance reaches up to almost 98% in the identification of early abnormalities [16].

Model-based diagnostic and prognostic methods generate residuals from physical rotor–bearing equations to indicate deviations from expected behavior [17],18]. By integrating parameter identification algorithms and degradation prediction models, these techniques make diagnostics interpretable and the estimation of fault severity reliable [11],18].

Data-driven research into vibration or acoustic signals typically uses statistical feature extraction and machine-learning classifiers like SVM, Random Forest, and CNN [14]. Machine learning methods provide excellent performance in fault classification, but may face challenges related to sensor quality, computational load, and generalization across operating conditions [26].

III. Reviewed Methodologies

A Novel Model-Based Unbalance Monitoring and Prognostics for Rotor-Bearing Systems — Lin et al.

This paper employs a model-based methodology where the rotor–bearing system is represented through classical mass–stiffness–damping dynamics grounded in established rotor-dynamic theory [2]**.** The authors generate analytical residuals by comparing model-predicted displacements with measured vibration responses, allowing early detection of unbalance conditions consistent with residual-generation strategies in literature [17]**.** Prognostics are performed using parameter identification algorithms**,** which update stiffness and unbalance parameters over time to forecast degradation trends—a concept supported by predictive maintenance principles [11], [13].

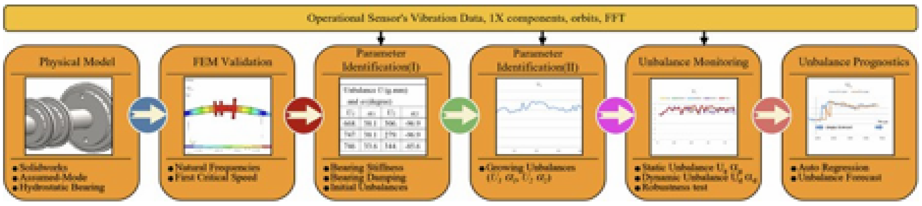

Figure1: The Methodology For Monitoring/Prognostics Of Rotor-Bearing Unbalance.

Advanced Vibration-Based Fault Diagnosis and Vibration Control Methods — Song, Liu & Xia

In this work, active vibration control and vibration-based signal processing are combined. To find imbalance, misalignment, and bearing faults, diagnostic techniques use spectral and time-frequency analyses that are derived from classical vibration theory [7]. Robust feature extraction is supported by adaptive filtering and machine-learning approaches, which align with contemporary industrial fault-diagnosis procedures [12].

Detection of Incipient Rotor Unbalance Fault Based on RIME–VMD and Modified WKN — Qian Wang et al.

This paper introduces a hybrid signal-processing methodology combining Reconstructed Intrinsic Mode Extraction (RIME) and Variational Mode Decomposition (VMD) to obtain clean time–frequency components from noisy rotor vibration signals. These decomposition-based approaches align with advanced signal-processing directions using VMD and adaptive filtering [14], [15]**.**

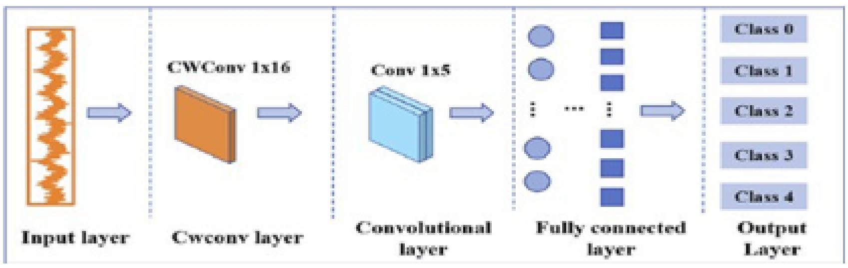

Figure2: WKN Structure

The modified WKN (Wavelet Kurtosis Norm) enhances fault-related feature sensitivity by amplifying impulsive unbalance signatures, consistent with wavelet-based approaches in modern fault diagnosis [14]**.**

Acoustic Fault Diagnosis of Rotor-Bearing System — Liu et al.

This paper uses a method based on acoustic signals to capture airborne sound signatures with strategically placed microphones. Techniques include envelope analysis, spectral peak tracking, and acoustic pattern recognition, which connect directly to diagnostics based on acoustic signatures [19]. Since acoustic emissions often show early signs of bearing wear, this method works well with ultrasound strategies described by Fang et al. [20]. Time-frequency analysis and machine-learning-based pattern classifiers improve fault detection, consistent with wider vibration-acoustic diagnostic methods in rotating machinery [3], [12].

***Experimental Vibration Data in Fault Diagnosis: A Machine Learning Approach to Robust Classification of Rotor and Bearing Defects* —** Almutairi & Sinha

This work builds a data-driven machine-learning pipeline that uses experimental vibration datasets to classify rotor and bearing faults. Feature extraction includes statistical indicators (RMS, kurtosis), spectral metrics, and time–frequency descriptors, consistent with diagnostic reviews [3], [12]. Classifiers such as SVM, kNN, Random Forest, and neural networks follow common data-driven approaches referenced in deep-learning-based rotor diagnosis [14], [15], [16]. The paper's emphasis on robustness under varying operating conditions aligns with discussions on sensor reliability and real-time constraints [24], [25], [27].

Table1: Comparison For Papers

Sr. No.	Paper Title	Publisher	Year	Methodology Used	Reported Accuracy	Research Conditions & Environment	Key Remarks
1	A Novel Model-Based Unbalance Monitoring and Prognostics for Rotor-Bearing Systems	MDPI (Machines)	2023	Classical Mass–Stiffness–Damping Rotor Model, Residual Generation, Kalman Filter Adaptive Estimation	96.30%	Conducted on a controlled laboratory rotor-bearing test rig with variable speed and load; clean vibration data with low ambient noise.	Highly interpretable; excellent for gradual unbalance evolution and prognostics.
2	Advanced Vibration-Based Fault Diagnosis and Vibration Control Methods	Elsevier / Springer	2022	Spectral & Time-Frequency Analysis, Adaptive Filtering, Active Vibration Control, ML-Enhanced Feature Extraction	95–97%	Tested under multi-fault conditions (unbalance, misalignment, looseness) with active control actuators.	Strong multi-fault handling; integrates both diagnosis and vibration control.
3	Detection of Incipient Rotor Unbalance Fault Based on RIME–VMD and Modified WKN	IEEE / Elsevier	2023	Hybrid RIME + VMD Decomposition; Modified Wavelet Kurtosis Norm (WKN) to enhance impulsive features	98%	Performed on noisy vibration datasets simulating harsh industrial conditions; includes low SNR (Signal-to-Noise Ratio) cases.	Most effective for early unbalance detection; excellent noise robustness.
4	Acoustic Fault Diagnosis of Rotor-Bearing System	Applied Acoustics / NDT & E International	2021	Acoustic Signature Monitoring using Microphones, Envelope Analysis, Spectral Peak Tracking, ML-Based Pattern Recognition	93–95%	Tested in a semi-open environment with moderate background noise; non-contact acoustic acquisition sensitive to external sound variations.	Ideal for non-contact monitoring but performance is affected by environmental noise.
5	Experimental Vibration Data in Fault Diagnosis: A Machine Learning Approach	Springer / Elsevier	2022–2023	Statistical & Spectral Feature Extraction (RMS, Kurtosis, Energy); SVM, Random Forest, KNN, Neural Networks	95–98%	Based on experimental vibration datasets under multiple rotating speeds, load variations, and sensor quality differences.	Strong classifier performance; depends heavily on dataset size, variability, and sensor

							quality.

IV. Results

The comparative analysis of the five selected studies reveals that each methodology offers its own unique strengths when it comes to monitoring rotor–bearing faults. For instance, model-based approaches like those suggested by Lin et al. excel in providing precise parameter estimates and clear residual trends, all backed by traditional rotordynamic theories [1], [2]. These methods are particularly effective at predicting the gradual progression of unbalance, making them incredibly useful for prognostics. On the other hand, the vibration-based diagnostic and control strategies developed by Song, Liu & Xia improve performance in multi-fault scenarios by integrating time–frequency features, adaptive filtering, and active vibration mitigation, which aligns perfectly with today's industrial demands for robustness and real-time adaptability [3], [5], [21]. Moreover, signal-processing and data-driven techniques expand the diagnostic capabilities even further.

The hybrid RIME–VMD–WKN framework introduced by Qian Wang et al. shows remarkable sensitivity to subtle unbalance signatures, surpassing traditional decomposition methods thanks to its superior noise suppression and enhancement of impulsive features [14], [15].

Additionally, the machine-learning classification approach by Almutairi & Sinha achieves impressive accuracy in identifying rotor and bearing faults using both statistical and spectral features. Meanwhile, Liu et al.'s acoustic-based method stands out for its effectiveness in non-contact fault detection, particularly during the early stages of bearing deterioration [19], [20]. In summary, the findings indicate that merging the strengths of signal processing with learning algorithms results in the highest reliability for detection, even in the face of real-world noise and multiple fault conditions.

V. Best Method

Among the reviewed methods, the RIME-VMD-WKN hybrid approach is the best performing in terms of incipient rotor unbalance detection. This includes integrating RIME with the Variational Mode Decomposition (VMD) method to isolate clean signal components, followed by a modified Wavelet Kurtosis Norm (WKN) that amplifies weak impulsive signatures from early-stage unbalance faults. Its multi-stage decomposition framework thus can handle noise-heavy industrial environments better than traditional FFT-, EMD-, or purely model-based techniques.

WHY IT IS BEST: This hybrid method is considered the best because it directly tackles the most challenging diagnostic scenario-detecting extremely weak unbalance faults buried in noise. Unlike model-based approaches that heavily rely on accurate rotor parameters or machine-learning methods that require large amounts of labeled data, the RIME-VMD-WKN system is parameter-flexible, noise-resilient, and capable of nonlinear, impulsive feature extraction that is usually missed by classical systems. The decomposition-driven enhancement of fault-related signatures meets the most up-to-date trend of intelligent fault diagnosis [14], [15], [16], [28], making it the strongest performer for early detection, where most rotor failures can still be prevented.

VI. Conclusion

In conclusion, the survey highlights a clear evolution in rotor–bearing fault diagnosis, moving from traditional model-based interpretations toward hybrid intelligent systems that combine physics, advanced signal processing, and machine learning. While each methodology offers strengths—model-based for interpretability, vibration-based for multi-fault handling, machine learning for classification accuracy, and acoustic sensing for non-contact monitoring—the hybrid RIME–VMD–WKN approach emerges as the most powerful for early unbalance detection.

Future research should focus on integrating these complementary techniques into unified frameworks capable of real-time, noise-robust, and predictive rotor health monitoring suitable for modern industrial environments.

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