International Journal of Creative and Open Research in Engineering and Management
ISSN: **3108-1754 (Online)**
Volume 02 Issue 08 August-2026 | Impact Factor: 3.5

Incipient Fault Diagnosis of Rolling Element Bearings using Vibration, Sound and Tribological Analysis: A Literature Review

Umakant Banswarti, Shashikant Pandey
Department of Mechanical Engineering, Eklavya University, Damoh

How to Cite this Article:

Banswarti, Umakant, and Shashikant Pandey. "Incipient Fault Diagnosis of Rolling Element Bearings using Vibration, Sound and Tribological Analysis: A Literature Review." International Journal of Creative and Open Research in Engineering and Management 02, no. 8 (2026): 1-14. https://doi.org/10.55041/ijcope.v2i8.253.

https://doi.org/10.55041/ijcope.v2i8.253

ABSTRACT

Rolling element bearings are used in rotating machines in aviation, chemical, and nuclear industries. A failure to detect faults in the rolling bearing causes unexpected breakdown of rotating machines. Detecting bearing defects early on is still a challenge since micro-faults have less energy. Early-stage defects from fatigue, misalignment, overload and poor lubrication create low-energy signals that can be masked. This article summarises some key measurement methods, i.e. vibration and acoustic signal measurement, tribological parameter analysis, wear debris analysis, and thermal measurement, in rolling element bearings. All the methods will be evaluated with respect to a sensing mechanism, signal processing algorithm, micro-defect sensitivity, and operational constraints of the anti-friction bearing. To deal with the drawbacks of single sensors, we demonstrate the use of recent advancements in multi-sensor data fusion and machine learning models through examples where kinetic, acoustic and chemical metrics are fused for improved classification outcomes. In summary, multi-sensor data fusion greatly improves the accuracy of early fault detection, and it can greatly enhance predictive maintenance systems.

Keywords: Vibration, Acoustic, Wear Debris, Tribology, Condition Monitoring, Bearing

1. Introduction

Rolling element bearings support shafts and transmit radial and axial loads while reducing friction in machines. The ways they fail include raceway fatigue, spalling, pitting, cracks, abrasive, adhesive corrosion, plastic deformation, and cage damage. Moreover, it includes skidding, electrical erosion, contamination, and distress due to lubricant. Due to the containment of a bearing in a larger rotor, gearbox, motor, turbine, or transmission, local defects can excite structural resonances and propagate along various mechanical and acoustic paths [1]. Thus, damage to a bearing affects more than just the bearing itself. This impact is particularly true for aviation systems running at high speeds, chemical-process machinery, nuclear auxiliaries, wind turbines, rail vehicles, and machine tools. The main task of an incipient diagnosis is not simply classifying a large artificial defect that is large. It aims to identify a weak change in the contact or lubrication state before the defect produces a highly energetic and repeatable signature [2].

A localised fault creates impacts with a certain frequency. The theoretical frequency of these impacts is a function of the number of rolling elements, shaft speed, pitch diameter, rolling-element diameter, and contact angle. The main frequencies are of the order of the ball-pass frequency of the inner race (BPFI), ball-pass frequency of outer race (BPFO), ball-spin frequency (BSF) and fundamental train frequency (FTF) . In practice, speed variation, load-zone variation, slip, structural transfer function, sensor mounting, and modulation, etc, cause the signature to deviate from the idealised frequencies [3]. The literature has advanced in two slightly varied directions. The first signal diagnosis technique features vibration, envelope analysis, cyclostationarity, wavelets, empirical or variational mode decomposition, sparse representation and deep learning. The second is mechanism diagnosis, which applies acoustic emission, friction, lubricant condition, wear debris, temperature, and surface characterisation to assess the underlying degradation process[4].

Recent work is increasingly integrating these pathways. By way of example, oil-debris features can show material removal, whereas vibration shows the periodicity of impacts; acoustic emission can reveal friction and contact events, whereas temperature gives a slower energy-balance indicator; and airborne sound can give auxiliary non-contact spatial information to a structure-mounted accelerometer [5]. This document has five objectives for reviewing these developments. Initially, it elaborates on the physical principles and practical limitations of each sensing type. Secondly, the signal-processing algorithms employed to retrieve weak defect information are compared. Third, it measures the functions of machine learning and multisensor fusion. Next, it highlights chronic flaws in experimental validation. Fifth, it suggests a research framework for the diagnosis of incipient reliability, which is sensitive to mechanical and tribological causes [6], [7].

2. Rolling element bearing degradation

Bearing deterioration occurs as a sequence rather than a single event. When a fatigue case dominates, below a high-stress contact, subsurface microstructural damage develops. Subsequently, this propagates to the surface and eventually gives rise to pitting and spalling. In lubrication-dominated cases, the film thickness diminishes, leads to an increase in asperity interaction, initiates frictional heating and material transfer, and potentially allows debris to invade the contact or be formed there. Contamination can cause dents, three-body wear, indentations, and fatigue[8]. When there is misalignment and overload, it affects the load distribution, which may speed up fatigue and wear. The pathways generate various signals at different lead times. The phrase "incipient fault" is used inconsistently. Other studies define it as the first detectable change in a time series, others as the first stage of an accelerated life test, a small seeded defect, a threshold crossing, or the onset of a degradation indicator[9].

The difference is important because a small artificial notch is not the same as real surface fatigue due to lubricating starvation. For a complete review of rolling-bearing defects, it is necessary that their evaluation includes sensitivity to early-stage faults, timely, robust, interpretable, and economic rather than classification accuracy alone [10], [11]. A helpful operational definition of an incipient fault is a physically meaningful deviation from a healthy operating state which precedes the established defect and can be detected with a certain false-alarm probability under the same operational envelope. A healthy baseline, operating-condition normalisation, a time reference, and uncertainty estimates are required. In the absence of these variables, a high accuracy from the classifier might be due to some change in the speed load test rig or defect-seeding procedure[12].

2.1 Vibration-based incipient fault diagnosis

Physical basis and conventional indicators Vibration remains the most established bearing-monitoring method because localized defects create repeated impacts as rolling elements pass over damaged regions [13], [14]. The impacts excite structural resonances, and the resulting waveform is usually amplitude-modulated by shaft rotation and the load zone. The raw time signal can be summarized with RMS, variance, peak value, crest factor, kurtosis, skewness, impulse factor, and clearance factor. These indicators are computationally inexpensive and useful for trending, but RMS is often insensitive to the earliest defects and kurtosis can be unstable under changing operating conditions (Pandey & Amarnath, 2021; D. Sharma et al., 2026). Frequency analysis using the fast Fourier transform identifies shaft orders, bearing characteristic frequencies, harmonics, sidebands, and structural resonances. The most useful practice is rarely to inspect the raw spectrum alone. Instead, the analyst selects a resonance band, performs amplitude demodulation, and examines the envelope spectrum[16]. The Hilbert transform is commonly used to obtain the analytic signal; peaks near BPFI, BPFO, BSF, or FTF and their harmonics then provide physically interpretable evidence of a component fault. Spectral kurtosis and kurtogram methods automate or guide the selection of a band in which impulsive content is strongest [17].

2.1.1 Weak-signal enhancement

The incipient signal-processing problem is a competition between periodic impacts, deterministic shaft components, broadband noise, and nonstationary operating conditions. Wavelet packet transform, empirical mode decomposition, ensemble empirical mode decomposition, empirical wavelet transforms, variational mode decomposition, local mean decomposition, sparse representation, blind deconvolution, and low-rank methods have all been used to isolate defect-related transients[18], [19]. Zhang et al.'s combines maximal spectral-kurtosis tunable-Q-factor wavelet transform with group-sparsity total-variation denoising; the method selects an oscillatory band and suppresses noise while preserving sharp transient impulses [21]. Xue et al. combine enhanced empirical wavelet transform with correlation kurtosis to select periodic fault components in noisy vibration data [22]. These methods improve sensitivity, but they introduce parameters and failure modes. EMD-family methods may suffer from mode mixing, end effects, and sensitivity to noise. VMD requires the number of modes and penalty factors. Wavelets depend on the basis function, decomposition depth, and boundary handling. Spectral-kurtosis methods may select an interference band when the machine contains strong unrelated impulsive sources. Therefore, algorithmic sophistication should not replace physical validation against calculated defect frequencies, speed, load, and independent evidence such as microscopy or oil debris[11], [23].

2.1.2 Time-frequency analysis and deep learning

Short-time Fourier transform, wavelet scalograms, Wigner–Ville distributions, synchrosqueezing, and time-varying order analysis represent nonstationary signals more effectively than a single stationary spectrum. Recent papers use two-dimensional time-frequency images as inputs to CNNs, ResNets, transformers, and hybrid networks (2023; Fu et al., 2023; B. Zhang & others, 2024). The Sensors study by Zhang et al. converts vibration signals into Gramian angular-field images and uses an attention-enhanced ResNet50 model, illustrating the trend toward automatic representation learning. Other work combines time-frequency images with data augmentation, sparse representations, supervised contrastive learning, or domain adaptation [26]. Deep learning reduces the need for hand-crafted features, but it does not remove the need for experimental discipline. Randomly splitting adjacent windows from the same run into training and test sets can cause leakage and overestimate generalisation. Models trained on seeded defects at one speed may fail on naturally developed damage, another bearing geometry, or another sensor location. Explainable features such as envelope peaks, cyclic frequencies, and tribological indicators should therefore be retained alongside latent embeddings[11], [23].

3. Sound and Acoustic Emission-based condition diagnosis

3.1 Acoustic emission

Acoustic emission (AE) refers to the detection of transient elastic waves that are the result of crack initiation. AE sensors typically function at frequencies that are considerably above those of conventional accelerometers. Cockerill et al. show that AE measurements on a cylindrical roller bearing are speed-dependent. Energy in the 20–60 kHz range is associated with bearing resonances, while higher frequency energy is said to react to contact stress and fatigue-related transients. The authors highlight the importance of a healthy-condition baseline, noting that changes in AE RMS during stepped testing can be linked to a change in operating speed and lubrication regime rather than turn-out damages[27].

The AE technique is promising for early diagnosis because the higher frequency band may have a better signal-to-noise ratio for local contact events than low-frequency vibration. Common features include AE counts, RMS, peak amplitude, energy, duration, rise time, hit rate, frequency-band energy, and spectral descriptors. A recent study shows AE in terms of friction behaviour and machine learning. It shows that shifts in the friction coefficient may take place before significant shifts in the pronounced acceleration as well as the AE amplitude, but only under specific dry or poorly lubricated test conditions [28], [29].

Tandon & Nakra show that AE is quite informative, but also that tribological variables can lead AE depending on the degradation mechanism. The main limitations are attenuation, coupling, position of the sensor, high sampling rates, resonance of the sensor and sensitivity to speed, load, lubricant, geometry of housing, and transfer path. The field system should detail sensor coupling, frequency response, preamplifier and threshold, sampling rate, anti-aliasing, and operating-condition normalisation [30]. Scheeren et al. researched ultrasonic stress-wave transmission in a roller bearing having cylindrical geometry, addressing the importance of contact geometry and transmission paths and how they affect the observability of the acoustic emission [31].

3.2 Airborne sound and ultrasonic monitoring

Airborne sound is non-contact and can be useful in situations where it is difficult to install an accelerometer. For example, on large, hot, rotating, sealed, or otherwise inaccessible machinery. The major disadvantage is that airborne sound is a combination of bearing radiation, motor electromagnetic noise, gears, fans, reflections and room acoustics. The spectrum is strongly dependent on the position and orientation of the microphone. Analysing the co-prime circular microphone array by Chen et al. using spatial processing and direction-of-arrival estimation has been found to facilitate bearing-fault localisation of outer-race, inner-race and rolling-element faults [32]. An individual microphone is low-cost but subject to background noise and measurement geometry. While arrays give spatial information, beamforming and source separation - all of which come at the cost of additional sensors, synchronisation, calibration, and computation. Sound characteristics may consist of narrowband amplitudes, spectral kurtosis, wavelet coefficients, mel-frequency features, cyclic spectra, spectrogram/maps, and spatial beamforming maps. Recent open-access work on acoustic-vibration fusion reports improved robustness under high noise compared with single-modality diagnosis[27], [33].

3.3 Comparative evaluation of noise and vibration.

Generally, vibration is more directly related to the bearing and is well understood in terms of defect frequency. AE is sensitive to small contact events and crack events, but its acquisition and installation are more demanding. Aero-acoustic sound is contactless and scalable in principle, but environmental control or spatial filtering is needed. In practice, the choice should depend on the mechanism rather than a universal ranking. Modality Principal physical sensitivity Incipient strengths Main constraints Accelerometer vibration is studied for structural response to impacts and resonances, with mature hardware; interpretable defect frequencies; low cost, but weak micro-faults can be masked and mounting and transfer path matter. Ultrasonic/AE Detection of crack, friction, asperity, impact, and wear stress waves: high-frequency sensitivity, potentially early detection. High sampling rate – 55M/s – 600kHz – 240Hz – monitor attenuation, coupling, speed/load dependence. Airborne sound is non-contact – radiant acoustic pressure is spatially informative, but background noise, reflections, microphone position, and more mixed and mask the source. An array of microphones is used in synchronisation and calibration, which can also incur cost. In Table 1, a detail comparision between various sound sensors and vibration sensors is presented.

Table-1 Comparison between accelerometer, Acoustic Emission, Airborne Acoustic and Microphone.(“Ban et al., 2007; Delgado-Arredondo et al., 2017; under Speed-Varying Conditions,” 2023; Ban et al., 2007; Delgado-Arredondo et al., 2017; Heng & Nor, 1998; Lu et al., 2016).

Modality	Principal physical sensitivity	Incipient strengths	Main constraints
Accelerometer vibration	Structural response to impacts and resonances	Mature hardware, interpretable defect frequencies, low cost	Weak micro-faults can be masked; mounting and transfer path matter
AE/ultrasound	Crack, friction, asperity, impact, and wear stress waves	High-frequency sensitivity and potentially early detection	High sampling rate, attenuation, coupling, speed/load dependence
Airborne sound	Radiated acoustic pressure	Non-contact and spatially informative	Background noise, reflections, microphone position, source mixing
Microphone array	Sound pressure plus spatial phase	Localization and beamforming	Synchronization, calibration, cost, computation

4. Provision of tribological analyses, lubrication and wear debris. Tribological measurements are important with vibration and sound symptoms are the mechanical responses. The tribological measurements can be closer to the cause of degradation. Lack of lubrication results in thinner film and more contact between asperities. The presence of contamination brings in hard particles and dents. Particles are generated as a result of surface fatigue and abrasive wear. Energy dissipation is characterized by friction and temperature, while material loss involves particle concentration, size, shape, materials and morphology. A vibration signature is a stabilized pattern that defects get once they şpread. The setting up of a web-based on-line system in Lubricants-composite for ‘early-stage damage to re-link AE parameters to friction behaviour and surface morphology’. It explains that the friction coefficient started growing ahead of real increases of the velocity and some AE changes in the tested conditions, while also wear tracks, abrasive debris and scuffing evolved with the AE spectrum [39], [40], [41]. This doesn’t mean that friction is always the first indicator; it means that lead time depends on failure mechanism, speed, load, lubricants and sensor placement. Oil and wear debris monitoring. Methods for analyzing oil debris can be ferrography, spectroscopy, optical particle imaging, inductive or magnetic sensing, capacitive/resistive sensing and online particle counters[42]. Offline ferrography and spectroscopy can be used to characterise the particle morphology, elemental composition, and wear regime; these tests are labour-intensive and are not continuous but intermittent. Optical systems available online provide morphological and statistical information [32]. However, deficiencies may occur due to the presence of bubbles, flow rate, viscosity, sampling geometry and channel size. Inductive sensors are good at detecting ferrous particles; they may miss nonferrous ones. Wang et al. present a higher-flow optical system and implement Otsu-based object extraction and CNN classification to separate bubbles from wear particles at a classification accuracy of 91.8% [40]. A test rig for forced-lubrication rolling bearing measurement is created which combines measurement of vibration, temperature, and online oil-debris analysis was created by Zhao et al. 2023). By utilizing Neighborhood Component Analysis, their feature-selection method helps in identifying features that discriminate abnormal wear states. The study explains what makes fusion important: its early wear and nonferrous contamination, which does not tend to produce a large change in vibration amplitude and temperature can remain a weak or delayed measure[44]. In contrast, oil debris provides a direct record of material removal and contamination. The condition of lubricant refers to the frictional behaviour or lubrication condition. Tribological indicators can be subject to confounding. The viscosity of the lubricant, chemistry of the additives, the filtration, flow rate, reservoir volume, and sampling location influence the generation of particles. The friction will vary depending upon the load, speed, temperature, surface roughness, film thickness, and alignment. A lubricant sensor may detect particle debris from gears, seals or other bearings, but not the bearing of interest. It needs the attribution of the source, knowledge of the flow path, discrimination of particle-material and synchronisation of the mechanical signal[43]. A detailed comparison between tribological parameters and their effect on early fault diagnosis and main interpretation is shown in Table-2.

Table 2- A detailed comparison between tribological parameters and their effect on early fault diagnosis and main interpretation

Tribological variable	Mechanistic interpretation	Early-diagnosis value
Friction coefficient/torque	Asperity interaction and energy dissipation	Potentially very early for lubrication-related wear
Particle count/concentration	Material removal or contamination rate	Useful for wear progression and lead time
Particle size distribution	Severity and wear-regime change	Supports trend and alarm logic
Particle morphology/material	Abrasive, fatigue, adhesive, or contaminant origin	Improves mechanism and root-cause diagnosis
Oil viscosity/chemistry	Lubricant degradation and contamination	Explains changing contact conditions
Ferrographic/spectroscopic composition	Wear material and elemental source	Strong offline confirmation

The friction between bearing rolling elements, especially in the contact area, generates heat. This is also due to lubricant shear, churning, electrical losses, and heat transfer through the bearing and housing. We use thermocouples, resistance sensors, fibre Bragg gratings, and infrared cameras [45]. Infrared thermography has the advantage of being non-contact; in addition, it can generate spatial temperature patterns. Deep-learning classifiers have been applied to thermal images to identify bearing-rotor faults. It is also easy to incorporate temperature into industrial controls. The constraint is both time and space. A small fault that does not alter the total heat balance, particularly when the bearing has high thermal mass, strong cooling, low load, or the fast flow of lubricant [46], [47]. Zhao and others therefore define temperature as useful but secondary in terms of early abnormal wear. The interpretation of thermal data along with speed, loading, lubricant temperature, vibration, and AE data improves its value. A temperature increase that cannot be explained by speed or load is more diagnostic than an absolute limit applied across all operating points of the machinery [48].

5. Machine learning for Multisensor data fusion. Multisensor fusion may occur at the data, feature, decision, or model level. Data-level fusion aligns vibration, sound, acoustic emission, temperature, and oil signals, ensuring compatibility of sampling rates and time bases. Feature-level fusion isolates modality-specific indicators and merges them for further processing into the vector, graph, or any other representation[18], [49]. Merging of posterior probabilities, alarms or health indices. Multimodal neural networks, cross-attention, gating, co-training or shared latent spaces are often utilised for model-level fusion. There are two essential reasons. The dynamic response is observed in vibration; the high-frequency contact and fracture events in AE; the non-contact radiated response in sound; and the accumulation of energy dissipation in temperature and oil/debris monitor material transfer and contamination[50], [51]. This difference should be retained by a fusion model rather than simply concatenating all. Acoustic-vibration fusion is done using adaptive VMD and CNN–BiGRU–attention classifier, which is more robust in noisy conditions than individual techniques [49]. Wang et al. and associates use vibration, temperature and oil debris for abnormal wear. The studies support heterogeneous sensing, but the gains must be weighed against the cost of additional sensors and the risk of channel loss in the field[52]. Families of machine learning. Thresholding, linear discriminant analysis, k-nearest neighbours, decision tree, random forest, support vector machine, fuzzy clustering and shallow neural networks are some of the classical methods. They are frequently easier to understand and need a smaller amount of data[48].

Deep architectures comprise CNNs for spectrograms or images, recurrent networks for time sequence processing, autoencoders for novelty detection, GANs for augmentation, transformers for temporal long-range dependencies, and CNN–RNN or CNN–attention hybrids. Transfer learning and domain adaptation tackle variable speed, load, machine and sensor conditions. Being overly optimistic about datasets is a big risk. Power datasets typically include a large number of windows but only a small number of independent runs. A model can remember a specific amplitude or a laboratory's resonance. Class imbalance is especially worse for early damage, where healthy data dominates and the earliest stage is short [48]. The Lubricants study explicitly discusses the imbalance in normal, early-damage and damage-progression samples. Therefore, a run-wise or machine-wise split, time ordered validation, external datasets, calibration curve, confidence interval, and false alarm for operating hour must be used. Physics-informed and explainable fusion Constraints through physics-informed learning may enforce defect frequency relationships, speed order tracking, load zone modulation, energy monotonicity, or tribological causality.[53], [54] A design that can be put into practice is a dual branch: a signal branch that learns representations with raw data or time-frequency data and a physics branch that receives BPFI/BPFO/BSF/FTF amplitudes, spectral-kurtosis indicators, speed/load variables, temperature residuals and particle features[54]. A gating or attention mechanism then learns when each modality is reliable. Information on how and when the decision is made will be provided. Information on the cause of the alarm will be provided.

6. Comparative evaluation of methods

Table 3 shows the detailed comparison of various bearing condition monitoring methodologies with their sensitivity, interpretability, and online deployment constraints.

Table- 3 detailed comparison of various bearing condition monitoring methodologies

Method	Typical signal processing	Micro-defect sensitivity	Interpretability	Online deployment constraints
Time-domain vibration	RMS, kurtosis, crest factor, statistical trends	Low to moderate	High	Low computational cost; sensitive to speed/load
Envelope vibration	Bandpass, Hilbert transform, envelope spectrum	Moderate to high for localized impacts	High	Requires resonance-band selection and good mounting
Spectral kurtosis/cyclostationarity	Kurtogram, cyclic spectrum, correlation kurtosis	High in noisy impulsive cases	High to moderate	Computational cost and parameter selection
Wavelet/EMD/VMD/sparse methods	Adaptive decomposition and denoising	High when tuned correctly	Moderate	Parameter sensitivity and real-time burden
Deep vibration models	CNN, ResNet, transformer, autoencoder	Potentially high	Low to moderate	Large data, drift, explainability, edge compute
AE/ultrasound	Counts, RMS, energy, burst spectrum	High for contact/friction/crack events	Moderate	Coupling, attenuation, high sampling rate
Airborne sound	FFT, wavelet, spectrogram, beamforming	Moderate, environment-dependent	Moderate	Room noise, source mixing, microphone placement
Oil/debris	Count, size, morphology, material, particle rate	High for wear/contamination	High when particle physics is known	Flow path, bubbles, sampling,

				sensor sensitivity
Thermal	Absolute temperature, residuals, infrared images	Low for earliest isolated defects; higher for severe friction	High	Cooling and ambient conditions; thermal lag
Multisensor fusion	Feature/data/decision/model fusion	Usually highest potential	Variable	Synchronization, missing channels, cost, maintenance

Vibration is the most effective baseline for localised fatigue faults; AE is promising for early contact and crack activity; tribology is key for lubrication and wear; thermal monitoring is a strong complementary channel; multisensor fusion is most useful when each channel observes a different degradation stage[55], [56]. Study deficiencies and suggested structure. Natural injury and real use conditions. Seeded defects are used in many studies due to labelling and reproducibility. Although useful for algorithm development, this may not look like natural crack morphology, progressive spalling and lubricant starvation, contamination, cage damage, or mixed failure[57], [58].

Future tests are advised to incorporate a mixture of accelerated life testing experiments and naturally developed damage, variable speed and load, realistic lubricant conditions, and independent post-test surface characterization[59]. Integrity and Uncertainty of Sensor Various problems such as the detachment of the sensor, saturation of the sensor, damage to the cable, acoustic attenuation, oil bubbles, blocked flow paths, and thermal drift produce false alarms or hide real faults. A diagnostic system should have sensor-health indicators, redundant channels, estimates of confidence and operations with missing modulation. Monitoring signal quality should not be viewed as something separate; it is part of diagnostics[60], [61], [62].

7. Conclusion: A comprehensive analysis shows that early rolling bearing diagnosis is a multi-modal, mechanism-dependent problem. Vibration analysis is still the reference method because its characteristic frequencies are physically interpretable, and its instrumentation is mature. Nevertheless, weak early effects might be concealed by noise, shaft components, structural transmission pathways, and shifting operating circumstances. By using envelope analysis, spectral kurtosis, cyclostationary methods, adaptive decomposition, sparse denoising and time-frequency representations, it is possible to improve sensitivity. However, care must be taken in parameterization and validation of such techniques. Through the use of acoustic emission and ultrasonic sensing, events associated with friction, crack, asperity, and wear events that are too weak for conventional vibration can be observed.

Being airborne allows for contactless measurement and, with microphone arrays, source localization, but is sensitive to the acoustic environment. Tribological analysis provides insight into what is happening. Friction or the state of lubricant or oil chemistry or the nature of the wear debris can indicate failure or contamination. These condition indicators can show material loss before the large vibration or temperature response. Thermal monitoring is useful for confirming trends and the existence of severe frictional states. However, it is often an ancillary indicator of the earliest damage. Recent research shows that by combining vibration, sound, temperature, and oil/debris information, we can make things more robust and classify things better. The most effective system is not simply a larger neural network. These models were tested with natural damage across multiple independent runs. Predictive-maintenance systems of the Future should combine interpretable “characteristic-frequency” features; acoustic and tribological indicators; adaptive machine learning; sensor-health monitoring; standardised lead-time metrics. The combination can change from fault classification in bearing monitoring to a sure early warning and root-cause diagnosis.

References

[1] S. Pandey and M. Amarnath, ‘Applications of vibro-acoustic measurement and analysis in conjunction with tribological parameters to assess surface fatigue wear developed in the roller-bearing system’, *Proceedings of the Institution of Mechanical Engineers, Part J: Journal of Engineering Tribology*, vol. 235, no. 10, pp. 2034–2055, 2021.

[2] V. Kannan, T. Zhang, and H. Li, ‘A Review of the Intelligent Condition Monitoring of Rolling Element Bearings’, *Machines*, vol. 12, no. 7, p. 484, 2024.

[3] D. Sharma, R. S. Rajput, M. K. Pandey, and S. Pandey, ‘Lubrication regime identification in rolling bearings using local mean decomposition and Stribeck-correlated machine learning’, *Proceedings of the Institution of Mechanical Engineers, Part E: Journal of Process Mechanical Engineering*, p. 09544089261472954, 2026.

[4] S. Pandey and M. Amarnath, ‘Experimental investigations to analyze surface contact fatigue wear by using a dynamic response of the roller bearing system’, *International Journal of System Assurance Engineering and Management*, vol. 14, no. 3, pp. 930–949, 2023.

[5] L. Liu, C. Yang, and Y. Sheng, ‘Tribology International Wear model based on real-time surface roughness and its e ff ect on lubrication regimes’, *Tribiology International*, vol. 126, no. February, pp. 16–20, 2018, doi: 10.1016/j.triboint.2018.05.010.

[6] B. Sun *et al.*, ‘State-of-the-Art Detection and Diagnosis Methods for Rolling Bearing Defects: A Comprehensive Review’, *Applied Sciences*, vol. 15, no. 2, p. 1001, 2025.

[7] C. Malla and I. Panigrahi, ‘Review of Condition Monitoring of Rolling Element Bearing Using Vibration Analysis and Other Techniques’, *Journal of Vibration Engineering & Technologies*, vol. 7, no. 4, pp. 407–414, 2019.

[8] J. K. Halme, ‘Condition Monitoring of Oil Lubricated Ball Bearing Using Wear Debris and Vibration Analysis’, *In Proceedings of the International Tribology Conference (AUSTRIB’02)*, no. December, pp. 549–553, 2002.

[9] D. Goyal and B. S. Pabla, ‘The Vibration Monitoring Methods and Signal Processing Techniques for Structural Health Monitoring: A Review’, *Archives of Computational Methods in Engineering*, vol. 23, no. 4, pp. 585–594, 2016.

[10] Y. Ding and N. F. Rieger, ‘Spalling formation mechanism for gears’, *Wear*, vol. 254, no. 12, pp. 1307–1317, 2003, doi: 10.1016/S0043-1648(03)00126-1.

[11] F. Xu, N. Ding, N. Li, and others, ‘A Review of Bearing Failure Modes, Mechanisms and Causes’, *Eng. Fail. Anal.*, vol. 152, p. 107518, 2023.

[12] A. Sharma, M. Amarnath, and P. K. Kankar, 'Feature extraction and fault severity classification in ball bearings', *JVC/Journal of Vibration and Control*, vol. 22, no. 1, pp. 176–192, 2016, doi: 10.1177/1077546314528021.

[13] V. Vakharia, V. K. Gupta, and P. K. Kankar, 'A comparison of feature ranking techniques for fault diagnosis of ball bearing', *Soft comput.*, vol. 20, no. 4, pp. 1601–1619, 2016, doi: 10.1007/s00500-015-1608-6.

[14] P. K. Kankar, S. C. Sharma, and S. P. Harsha, 'Fault Diagnosis of High Speed Rolling Element Bearings Due to Localized Defects Using Response Surface Method', *J. Dyn. Syst. Meas. Control*, vol. 133, no. 3, p. 031007, 2011, doi: 10.1115/1.4003371.

[15] P. K. Kankar, S. P. Harsha, P. Kumar, and S. C. Sharma, 'Fault diagnosis of a rotor bearing system using response surface method', *European Journal of Mechanics, A/Solids*, vol. 28, no. 4, pp. 841–857, 2009, doi: 10.1016/j.euromechsol.2009.03.004.

[16] J. Liu, Z. Xu, L. Zhou, Y. Nian, and Y. Shao, 'A statistical feature investigation of the spalling propagation assessment for a ball bearing', *Mech. Mach. Theory*, vol. 131, pp. 336–350, 2019, doi: 10.1016/j.mechmachtheory.2018.10.007.

[17] Q. Li, 'Bearing Incipient Fault Diagnosis Based upon Maximal Spectral Kurtosis TQWT and Group Sparsity Total Variation Denoising', *Journal of Measurements in Engineering*, vol. 6, no. 4, 2018.

[18] W. Fu, X. Jiang, B. Li, C. Tan, B. Chen, and X. Chen, 'Rolling Bearing Fault Diagnosis Based on 2D Time-Frequency Images and Data Augmentation Technique', *Meas. Sci. Technol.*, vol. 34, no. 4, p. 45005, 2023.

[19] B. Pan *et al.*, 'Feasibility Study on Magnetorheological Finishing of Thin Copper Substrate', *Chinese Journal of Mechanical Engineering*, vol. 37, no. 1, p. 164, Dec. 2024, doi: 10.1186/s10033-024-01154-x.

[20] B. Zhang and others, 'Early-Stage Fault Diagnosis of Motor Bearing Based on Differential Local Mean Decomposition and Current–Vibration Fusion', *Sensors*, vol. 24, 2024.

[21] G. Zhang, X. Liu, and W. Lu, 'A parameter prediction model of running-in based on surface topography', vol. 0, no. 0, pp. 1–9, 2013, doi: 10.1177/1350650113484097.

[22] J. Xue and others, 'Application of Enhanced Empirical Wavelet Transform and Correlation Kurtosis in Bearing Fault Diagnosis', *Meas. Sci. Technol.*, vol. 34, no. 3, p. 35023, 2023.

[23] B. Tao, L. Zhu, H. Ding, and Y. Xiong, 'An alternative time-domain index for condition monitoring of rolling element bearings — A comparison study', vol. 92, pp. 660–670, 2007, doi: 10.1016/j.ress.2006.03.005.

[24] 'Early-Stage Damage Diagnosis of Rolling Bearings Based on Acoustic Emission Signals Interpreted by Friction Behavior and Machine Learning', *Lubricants*, vol. 14, no. 3, p. 95, 2026.

[25] 'Rolling Element Bearing Fault Diagnosis Based on Acoustic-Vibration Data Fusion', *Data Brief*, vol. 49, p. 109398, 2023.

[26] Y. Ding, M. Jia, Q. Miao, and Y. Cao, 'A Novel Time–Frequency Transformer Based on Self-Attention Mechanism and Its Application in Fault Diagnosis of Rolling Bearings', *Mech. Syst. Signal Process.*, vol. 168, p. 108616, 2022.

[27] A. Cockerill, A. Clarke, R. Pullin, and others, ‘Determination of Rolling Element Bearing Condition via Acoustic Emission’, *Proceedings of the Institution of Mechanical Engineers, Part J: Journal of Engineering Tribology*, vol. 230, no. 2, pp. 194–204, 2016.

[28] J. Couturier and D. Mba, ‘Operational Bearing Parameters and Acoustic Emission Generation’, vol. 130, no. April 2008, pp. 1–5, 2017, doi: 10.1115/1.2776339.

[29] S. Pandey, P. Sateesh Kumar, M. Amarnath, T. T. Kumar, and P. Rakesh, ‘Incipient Fault Detection in Roller Bearing Using Ultrasonic Diagnostic Technique’, in *Advances in Metrology and Measurement of Engineering Surfaces: Select Proceedings of ICFMMP 2019*, Springer Singapore Singapore, 2020, pp. 243–251.

[30] N. Tandon and B. C. Nakra, ‘Comparison of vibration and acoustic measurement techniques for the condition monitoring of rolling element bearings’, *Tribol. Int.*, vol. 25, no. 3, pp. 205–212, 1992, doi: 10.1016/0301-679X(92)90050-W.

[31] B. Scheeren, M. L. Kaminski, and L. Pahlavan, ‘Evaluation of Ultrasonic Stress Wave Transmission in Cylindrical Roller Bearings for Acoustic Emission Condition Monitoring’, *Sensors*, vol. 22, no. 4, p. 1500, 2022.

[32] Y. Chen and others, ‘Acoustic-Based Rolling Bearing Fault Diagnosis Using a Co-Prime Circular Microphone Array’, *Sensors*, vol. 23, no. 6, p. 3050, 2023.

[33] N. Tondon and A. Choudhury, ‘A review of vibration and acoustics measurement methods for the detection of defects in rolling element bearing’, *Tribol. Int.*, vol. 32, no. 8, pp. 469–480, 1999, doi: 10.1016/S0301-679X(99)00077-8.

[34] P. A. Delgado-Arredondo, D. Morinigo-Sotelo, R. A. Osornio-Rios, J. G. Avina-Cervantes, H. Rostro-Gonzalez, and R. de J. Romero-Troncoso, ‘Methodology for fault detection in induction motors via sound and vibration signals’, *Mech. Syst. Signal Process.*, vol. 83, pp. 568–589, 2017, doi: 10.1016/j.ymssp.2016.06.032.

[35] J. Ban, B. Rho, and K. Kim, ‘A study on the sound of roller bearings operating under radial load’, vol. 40, pp. 21–28, 2007, doi: 10.1016/j.triboint.2006.01.026.

[36] S. Lu, X. Wang, Q. He, F. Liu, and Y. Liu, ‘Fault diagnosis of motor bearing with speed fluctuation via angular resampling of transient sound signals’, *J. Sound Vib.*, vol. 385, pp. 16–32, 2016, doi: 10.1016/j.jsv.2016.09.012.

[37] R. B. W. Heng and M. J. M. Nor, ‘Statistical analysis of sound and vibration signals for monitoring rolling element bearing condition’, *Applied Acoustics*, vol. 53, no. 1–3, pp. 211–226, 1998, doi: 10.1016/s0003-682x(97)00018-2.

[38] ‘A Sound and Vibration Fusion Method for Fault Diagnosis of Rolling Bearings under Speed-Varying Conditions’, *Sensors*, vol. 23, no. 6, p. 3130, 2023.

[39] A. Aasi, R. Tabatabaei, E. Aasi, and S. M. Jafari, ‘Experimental Investigation on Time-Domain Features in the Diagnosis of Rolling Element Bearings by Acoustic Emission’, *Journal of Vibration and Control*, vol. 28, no. 19–20, pp. 2585–2595, 2022.

[40] P. Wei, Z. Wang, P. Zheng, B. Lv, and J. Qi, 'Online Diagnosis of Small Faults in Rolling Bearings Using FBG Acoustic Emission Sensors inside the Accelerated Life Tester', *IEEE Sens. J.*, vol. 23, no. 3, pp. 2211–2219, 2022.

[41] N. W. Nirwan and H. B. Ramani, 'Condition Monitoring and Fault Detection in Roller Bearing Used in Rolling Mill by Acoustic Emission and Vibration Analysis', *Mater. Today Proc.*, vol. 51, pp. 344–354, 2022.

[42] M. Amarnath and S. K. Lee, 'Assessment of surface contact fatigue failure in a spur geared system based on the tribological and vibration parameter analysis', *Measurement (Lond).*, vol. 76, pp. 32–44, 2015, doi: 10.1016/j.measurement.2015.08.020.

[43] Y. Zhao, X. Wang, S. Han, J. Lin, and Q. Han, 'Fault Diagnosis for Abnormal Wear of Rolling Element Bearing Fusing Oil Debris Monitoring', *Sensors*, vol. 23, no. 7, p. 3402, 2023.

[44] S. Raadnui, 'Wear particle analysis - Utilization of quantitative computer image analysis: A review', *Tribol. Int.*, vol. 38, no. 10, pp. 871–878, 2005, doi: 10.1016/j.triboint.2005.03.013.

[45] T. Mian, A. Choudhary, and S. Fatima, 'Vibration and Infrared Thermography Based Multiple Fault Diagnosis of Bearing Using Deep Learning', *Nondestructive Testing and Evaluation*, vol. 38, no. 2, pp. 275–296, 2023.

[46] C. Oliveira, M. Garcia, A. Gouveia, F. Jr, and A. Jose, 'Thermoanalytical and rheological characterization of automotive mineral lubricants after thermal degradation', vol. 83, pp. 2393–2399, 2004, doi: 10.1016/j.fuel.2004.06.016.

[47] P. Kumar and M. M. Khonsari, 'Effect of starvation on traction and film thickness in thermo-EHL line contacts with shear-thinning lubricants', *Tribol. Lett.*, vol. 32, no. 3, pp. 171–177, 2008, doi: 10.1007/s11249-008-9375-5.

[48] H. Wang *et al.*, 'Online Monitoring of Oil Wear Debris Image Based on CNN', *Mechanics & Industry*, vol. 23, p. 9, 2022.

[49] M. Jiang, M. Luo, C. Zhang, M. Shu, and G. Sun, 'Rolling Bearing Fault Diagnosis Based on Acoustic-Vibration Data Fusion and Mode Decomposition Combined with the Crested Porcupine Optimization Algorithm', *Heliyon*, vol. 10, no. 24, p. e40351, 2024.

[50] H. Tao, J. Qiu, Y. Chen, V. Stojanovic, and L. Cheng, 'Unsupervised Cross-Domain Rolling Bearing Fault Diagnosis Based on Time-Frequency Information Fusion', *J. Franklin Inst.*, vol. 360, no. 2, pp. 1454–1477, 2023.

[51] A. Chennana, A. C. Megherbi, N. Bessous, S. Sbaa, and others, 'Vibration Signal Analysis for Rolling Bearings Faults Diagnosis Based on Deep-Shallow Features Fusion', *Sci. Rep.*, vol. 15, 2025.

[52] Z. Wang *et al.*, 'Rolling Bearing Fault Diagnosis Method Using Time-Frequency Information Integration and Multi-Scale TransFusion Network', *Knowl. Based. Syst.*, vol. 284, p. 111344, 2024.

[53] R. Serrato, M. M. Maru, and L. R. Padovese, 'Effect of lubricant viscosity grade on mechanical vibration of roller bearings', *Tribol. Int.*, vol. 40, no. 8, pp. 1270–1275, 2007, doi: 10.1016/j.triboint.2007.01.025.

[54] P. Taylor *et al.*, 'Elastohydrodynamic Lubrication of Rough Surfaces under Oscillatory Line Contact with Non-Newtonian Lubricant Elastohydrodynamic Lubrication of Rough Surfaces under Oscillatory Line

Contact with Non-Newtonian Lubricant', no. November 2014, pp. 37–41, doi: 10.1080/10402000801888895.

[55] S. Pandey and M. Amarnath, 'Applications of vibro-acoustic measurement and analysis in conjunction with tribological parameters to assess surface fatigue wear developed in the roller-bearing system', *Proceedings of the Institution of Mechanical Engineers, Part J: Journal of Engineering Tribology*, vol. 235, no. 10, pp. 2034–2055, 2021.

[56] M. Amarnath and S. K. Lee, 'Assessment of surface contact fatigue failure in a spur geared system based on the tribological and vibration parameter analysis', *Measurement (Lond).*, vol. 76, pp. 32–44, 2015, doi: 10.1016/j.measurement.2015.08.020.

[57] S. Lee and M. Amarnath, 'Experimental investigations to establish correlation between Stribeck curve , specific film thickness and statistical parameters of vibration and sound signals in a spur gear system', no. December 2013, 2014, doi: 10.1177/1077546314544164.

[58] M. Amarnath and S. Lee, 'Assessment of surface contact fatigue failure in a spur geared system based on the tribological and vibration parameter analysis', *MEASUREMENT*, vol. 76, pp. 32–44, 2015, doi: 10.1016/j.measurement.2015.08.020.

[59] T. Karacay and N. Akturk, 'Experimental diagnostics of ball bearings using statistical and spectral methods', *Tribol. Int.*, vol. 42, no. 6, pp. 836–843, 2009, doi: 10.1016/j.triboint.2008.11.003.

[60] A. M. Al-Ghamd and D. Mba, 'A comparative experimental study on the use of acoustic emission and vibration analysis for bearing defect identification and estimation of defect size', *Mech. Syst. Signal Process.*, vol. 20, no. 7, pp. 1537–1571, 2006, doi: 10.1016/j.ymssp.2004.10.013.

[61] M. Hamel, A. Addali, and D. Mba, 'Investigation of the influence of oil film thickness on helical gear defect detection using Acoustic Emission', *Applied Acoustics*, vol. 79, pp. 42–46, 2014, doi: 10.1016/j.apacoust.2013.12.005.

[62] D. E. P. Gonçalves and A. V Campos, 'An Experimental Study on Starved Grease Lubricated Contacts', pp. 1–18, 2018, doi: 10.3390/lubricants6030082.