Quest Journals
Journal of Software Engineering and Simulation
Volume 12 ~ Issue 10 (October 2026) pp: 01-06
ISSN(Online) :2321-3795 ISSN (Print):2321-3809
www.questjournals.org

Research Paper

Early Detection of Electric Motor Bearing Degradation Using Vibration and Temperature Signatures: Toward Early Fault Warning and Predictive Maintenance

Rahul Nijhavan
Research Scholar, Invictus International.

Jatinder Bhalla
A.P, Department of Mechanical Engineering, Global Group of Institutes, Amritsar.

Abstract— *Rolling-element bearings are among the most failure-prone components of electric motors, and bearing faults account for a large share of motor breakdowns in industry. Because bearing damage progresses from microscopic surface defects to catastrophic seizure, the ability to detect degradation at its earliest stage determines whether maintenance can be planned or whether the plant suffers unplanned downtime. This paper presents a methodology for early bearing-fault warning that combines vibration and temperature signatures. The physical basis of each signature is reviewed, including characteristic defect frequencies, envelope analysis, statistical vibration indicators, and a first-order thermal model of the bearing housing. A staged degradation model links the two signatures to bearing life, and a combined health indicator with adaptive alarm thresholds is proposed for early warning. The integration of the warning logic into condition-based and predictive maintenance workflows, including remaining-useful-life estimation, is described, together with an experimental protocol for validation. The discussion shows that vibration provides the earliest sensitivity, temperature provides slower but robust confirmation and severity assessment, and their combination reduces false alarms while extending the actionable warning period.*

Keywords— *bearing fault detection, vibration analysis, envelope spectrum, thermal monitoring, condition-based maintenance, predictive maintenance, remaining useful life.*

I. Introduction

Electric motors convert the majority of electrical energy used in industry into mechanical work, and their reliable operation is critical to pumps, compressors, fans, conveyors, machine tools, and electric drives. Surveys of motor failures consistently identify bearings as the single most frequent source of faults, followed by stator winding and rotor defects [1], [2]. A bearing failure typically stops the machine, can damage the shaft, housing, or rotor-stator air gap, and in severe cases leads to secondary electrical damage.

Traditional maintenance strategies are either reactive (repair after failure) or preventive (replace at fixed intervals). Reactive maintenance results in unplanned downtime, while time-based preventive maintenance replaces many bearings that still have substantial life remaining and fails to protect against premature failures caused by contamination, misalignment, lubrication problems, or electrical discharge currents. Condition-based and predictive maintenance instead use measured data to infer the health of the machine and schedule intervention when it is needed [1]. The effectiveness of such programs depends on how early a developing fault can be recognized reliably.

Vibration monitoring is the most widely used technique for bearing diagnostics because a defect in a rolling surface produces repetitive impacts that are transmitted to the housing [3], [4]. Temperature monitoring is simpler and cheaper, and reflects the increase in friction and power loss as a bearing deteriorates or loses lubrication. Each measurement alone has limitations: vibration indicators can fluctuate with load, speed, and nearby machinery, while temperature responds slowly and is influenced by ambient conditions and cooling. Using both provides complementary evidence, with vibration giving an early indication and temperature giving a physically independent confirmation of progression.

The objectives of this paper are to (i) describe the staged degradation of motor bearings and how it appears in vibration and temperature; (ii) present signal-processing and modelling tools for extracting early-warning features from both signals; (iii) propose a combined health indicator and an alarm strategy that supports

predictive maintenance decisions; and (iv) specify an evaluation protocol for assessing early-warning performance. The remainder of the paper is organized accordingly, followed by a discussion of limitations and a conclusion.

II. Bearing Degradation Mechanisms

A rolling-element bearing consists of an inner race, an outer race, rolling elements (balls or rollers), and a cage. Under normal operation, subsurface fatigue gradually produces microscopic cracks that eventually reach the surface and release material, a process known as spalling. This is the classical end-of-life mechanism, but many bearings fail earlier because of abnormal conditions: inadequate or contaminated lubricant, excessive radial or axial load caused by misalignment or belt over-tension, ingress of particles or moisture, improper mounting, and electrical damage from shaft currents (fluting and pitting), which is increasingly common in inverter-fed motors [2], [5].

From a monitoring perspective, degradation can be divided into stages, each with a different dominance of vibration and thermal symptoms, as summarised in Table 1. The stage model is a simplification, since transitions depend on load, speed, lubrication, and fault type, but it is useful for defining what 'early' means and for assigning appropriate maintenance actions.

Table 1. Staged bearing degradation and associated signatures

Stage	Physical condition	Vibration signature	Temperature	Typical action
1. Healthy	Normal fatigue accumulation; adequate lubrication	Low broadband level; stable indicators	Stable at load-dependent value	Routine monitoring
2. Incipient	Subsurface cracks, micro-pitting, early lubrication or surface damage	High-frequency resonance bursts; envelope spectrum peaks at defect frequencies; kurtosis rises	No measurable change	Increase monitoring rate; plan inspection
3. Developing	Visible spall, growing defect	Clear defect-frequency harmonics and sidebands; RMS and crest factor increase	Small upward drift	Schedule replacement
4. Advanced	Extensive damage, rough running	Broadband rise; defect harmonics become less distinct; strong low-frequency components	Clear rise above model	Replace at next stop
5. Imminent failure	Severe wear, clearance loss, risk of seizure	Very high RMS; erratic behaviour	Rapid rise	Immediate shutdown

The practical implication is that the largest opportunity for early warning lies in Stages 2 and 3, where vibration changes are detectable but the thermal response is still negligible. Temperature becomes the more informative variable in the later stages, where it helps to confirm that a vibration anomaly represents genuine progressive damage rather than a transient disturbance.

III. Vibration Signatures

3.1 Characteristic Defect Frequencies

When a rolling element passes over a localized defect, or a defect on a rolling element contacts a race, a short impact is generated. Under ideal conditions without slip, the repetition rates are determined by bearing geometry and shaft speed f_r [6]:

$$BPFO = (n/2)\cdot f_r\cdot[1 - (d/D)\cos\varphi] \quad (1)$$

$$BPFI = (n/2)\cdot f_r\cdot[1 + (d/D)\cos\varphi] \quad (2)$$

$$BSF = (D/2d)\cdot f_r\cdot[1 - ((d/D)\cos\varphi)^2] \quad (3)$$

$$FTF = (f_r/2)\cdot[1 - (d/D)\cos\varphi] \quad (4)$$

where n is the number of rolling elements, d the rolling-element diameter, D the pitch diameter, and φ the contact angle. BPFO and BPFI are the ball-pass frequencies of the outer and inner race, BSF the ball-spin frequency, and FTF the cage (fundamental train) frequency. Inner-race defects are additionally modulated at the shaft frequency because the defect rotates through the load zone, producing sidebands spaced at f_r around BPFI. In practice, slip introduces small deviations of a few percent, so spectral peaks should be searched within a narrow tolerance band.

3.2 Envelope Analysis and Band Selection

At the incipient stage, the energy of defect-induced impacts is very small compared with the vibration of shaft rotation, gears, and electromagnetic forces, and the defect-frequency components are usually invisible in the raw spectrum. However, each impact excites structural resonances in a high-frequency band, typically from a few kilohertz to tens of kilohertz. The standard approach is therefore to band-pass filter the signal around a resonance,

extract its amplitude envelope (for example through the Hilbert transform), and compute the spectrum of the envelope, where peaks at BPFO, BPFI, BSF, or their harmonics reveal the fault [3].

The choice of filter band is critical. The spectral kurtosis and the kurtogram identify the frequency band with the most impulsive content and are widely used to select the demodulation band automatically [7]. Pre-whitening or removal of deterministic components, such as shaft harmonics and gear-mesh frequencies, improves the visibility of weak bearing signatures. Benchmark studies show that appropriately configured envelope analysis can detect faults in the public bearing datasets with high reliability but that blind application can fail when interference is strong or the signal-to-noise ratio is low [8].

3.3 Time-Domain and Statistical Indicators

Statistical indicators computed on windows of the raw or band-filtered acceleration provide simple, low-cost trending parameters. Their sensitivity differs by stage, as Table 2 indicates. Kurtosis and crest factor rise first because they respond to isolated impulses, but they can fall again when the damage spreads and the signal becomes more random, so they are poor indicators of late-stage severity. RMS is relatively insensitive early on but tracks severity well and is the basis of standards-based vibration severity assessment of rotating machines [9].

Table 2. Candidate features for early bearing-fault warning

Feature	Domain	Early sensitivity	Comments
Kurtosis / crest factor	Time (raw or filtered)	High at incipient stage	May decrease at advanced stage; load sensitive
RMS of acceleration / velocity	Time	Low early, high late	Standardised; good severity indicator
Envelope-spectrum amplitude at BPFO/BPFI	Frequency	Very high; fault-specific	Requires bearing geometry and speed
Spectral kurtosis (max)	Time–frequency	High	Useful for automatic band selection
Housing temperature rise above model	Thermal	Low early, high late	Robust confirmation of progression
Temperature rate of change	Thermal	Moderate	Sensitive to lubrication loss and overload

IV. Temperature Signatures

The heat generated in a bearing arises from rolling and sliding friction, lubricant churning, and seal drag. As a bearing degrades, surface roughness, lubricant breakdown, and increased clearance or preload raise the friction torque and therefore the power loss, which is transferred to the housing and the shaft. Temperature sensors, such as RTDs or thermocouples placed in or near the bearing housing, or infrared thermography, detect the resulting rise, though only once a substantial increase in losses has occurred [2].

A first-order thermal model of the housing relates measured temperature to the motor operating conditions:

$$T(t) = T_amb + \Delta T_ss \cdot (1 - e^{(-t/\tau)}) \quad (5)$$

where T_amb is the ambient temperature, ΔT_ss the steady-state temperature rise proportional to the power loss in the bearing and the winding heat conducted to the end shield, and τ the thermal time constant, often tens of minutes for medium-size motors. Because motor load and ambient conditions vary, the absolute temperature is a poor degradation indicator. A better approach is to compute the residual between the measured temperature and the value predicted by a model driven by load current, speed, and ambient temperature, which can be fitted on healthy-state data using regression:

$$r_T(k) = T_meas(k) - \hat{T}(k \mid I, \omega, T_amb) \quad (6)$$

A persistently positive residual indicates abnormal heating not explained by operation. Since the housing also receives heat from the stator winding, a second thermal sensor on the non-drive end or the frame improves the discrimination between bearing-originated and winding-originated heating. Temperature rate of change adds timeliness: a rapid rise after relubrication or a load change often indicates lubricant starvation or overgreasing, and can warn of failure before the absolute temperature reaches an alarm limit.

V. Proposed Early-Warning Methodology

5.1 Data Acquisition

A triaxial or radial accelerometer is mounted on each bearing housing, as close as possible to the load zone, with a sampling rate of at least 2.5 times the highest frequency of the demodulation band (commonly 20 kHz or more). Speed is obtained from a tachometer, encoder, or drive. Temperature is recorded at 0.1–1 Hz at the bearing housings together with ambient temperature and motor load current. All channels are time-stamped.

Acquisition occurs periodically (for example every few minutes) or on demand during steady operating windows to reduce the effects of load transients.

5.2 Feature Extraction and Normalization

For each acquisition window the following are computed: kurtosis and crest factor of the band-filtered signal; RMS; envelope-spectrum amplitudes at BPFO, BPFI, BSF, and FTF (with the first harmonics), normalised by the local noise floor; and the temperature residual r_T and its slope. Features are normalised against the baseline of the healthy machine in the same operating regime (load and speed bin). Normalization by regime is critical, because it converts a feature into a deviation from what is expected and reduces false alarms caused by load changes.

5.3 Combined Health Indicator

Let z_v be the vector of standardised vibration features and z_t the standardised thermal features. A health indicator is formed as a weighted combination of the Mahalanobis distances of each group with respect to the healthy baseline:

$$HI(k) = w_v \cdot D_v(k) + w_t \cdot D_t(k), \quad D_g = \sqrt{[(z_g - \mu_g)^T \Sigma_g^{-1} (z_g - \mu_g)]} \qquad (7)$$

The weights reflect the confidence in each source at the current stage. Early on, when thermal changes are negligible, w_v is large; as the indicators indicate progression, w_t is increased so that the thermal evidence contributes to confirmation. Weights can be set from expert knowledge, learned using validation data, or adapted in a Bayesian framework that treats each sensor's evidence as conditionally independent given the bearing state.

5.4 Alarm Logic

To avoid false alarms from isolated disturbances, an exponentially weighted moving average (EWMA) is applied to HI and compared against a control limit derived from the healthy distribution:

$$S(k) = \lambda \cdot HI(k) + (1 - \lambda) \cdot S(k - 1), \quad \text{alarm if } S(k) > \mu_S + L \cdot \sigma_S \qquad (8)$$

where λ (typically 0.1–0.3) sets the smoothing and L (typically 3) the control limit width. A two-tier scheme is proposed. An advisory warning is raised when vibration-based evidence crosses the limit alone on several consecutive windows, prompting more frequent monitoring and inspection planning. A confirmed alarm is raised when the thermal residual also exceeds its limit, or when the fused index continues to increase, indicating progression and requiring maintenance scheduling. This arrangement preserves the early sensitivity of vibration while using temperature to filter nuisance alerts.

VI. Integration with Predictive Maintenance

An early warning is valuable only if it is translated into an action plan. After an advisory, the monitoring interval is shortened, trends are reviewed, and complementary checks (lubrication analysis, ultrasonic measurement, alignment verification, and examination for shaft currents) are carried out. If the trend continues, the replacement is scheduled for the next planned stoppage, spare parts are procured, and technicians are assigned in advance, which converts what would have been an emergency repair into planned work.

Where sufficient run-to-failure data exist, the health indicator trajectory can be extrapolated to estimate the remaining useful life (RUL). Approaches include degradation models such as exponential or Wiener-process models, particle filters that update the model parameters recursively, and data-driven regression with recurrent neural networks [10]. The simplest practical estimator fits a smooth degradation curve to the recent history of S(k) and predicts the time to reach a failure threshold, with a confidence interval that widens when the trend is erratic. Estimates should be treated as decision support rather than a precise forecast, since lubrication events, load changes, and maintenance interventions disrupt the trajectory.

Table 3. Example decision matrix for maintenance actions

Vibration evidence	Temperature evidence	Recommended action
Normal	Normal	Continue routine monitoring
Elevated (defect-frequency or kurtosis)	Normal	Advisory: shorten monitoring interval; inspect lubrication and alignment; plan maintenance window
Elevated and rising	Residual rising	Confirmed alarm: schedule bearing replacement, order spares, assess RUL
Normal	Elevated	Check cooling, load, lubrication level, and winding heat; verify sensor before concluding bearing fault
Very high	Very high / rapid rise	Immediate action: reduce load or stop motor to prevent seizure

6.1 Implementation Considerations

Practical deployment requires attention to several engineering details that strongly influence the quality of early warnings. Sensor mounting should be rigid, preferably by stud, with the sensing axis in the radial direction through the load zone; adhesive or magnetic mounts reduce the usable bandwidth and can mask the high-frequency resonances on which envelope analysis depends. Temperature probes should be in thermal contact with the housing or outer-race seat and shielded from airflow, and their time constants should be known so that fast changes are not misread. Both measurement chains should be checked periodically for drift and loose connections, since a sensor fault can mimic bearing degradation.

Baseline construction is another key step. The healthy-state reference should be collected after commissioning or after a bearing replacement, once the run-in period has finished, and should cover the full range of loads and speeds expected in service. When the machine operates mainly at one point, a narrow baseline is sufficient, but variable-speed drives require speed-dependent reference curves. Baselines should be updated after planned maintenance, such as regreasing, so that the expected transient temperature rise is not interpreted as a fault.

Finally, the computational and data-management burden should be matched to the platform. Envelope spectra and the thermal residual are inexpensive and can be computed on an embedded device at the machine, so that only compact features and alarms are transmitted to the plant historian or cloud platform. Retaining raw waveforms for the most recent alarms is nevertheless advisable, because they permit an analyst to confirm the diagnosis, refine the filter band, and add the event to a library of labelled fault cases that improves later models.

VII. Experimental Validation Protocol

The performance of an early-warning scheme must be shown with run-to-failure or seeded-fault tests, as simulation alone cannot represent the complexity of real bearing deterioration. A recommended protocol is as follows.

- **Test bed:** an induction motor with instrumented drive-end and non-drive-end bearings, a loading device, accelerometers, temperature sensors, and a data acquisition system that records speed, current, and ambient temperature.
- **Fault conditions:** healthy bearings, bearings with seeded outer-race, inner-race, and rolling-element defects of increasing size, lubrication starvation, and, where facilities permit, accelerated life tests, all at several loads and speeds.
- **Public datasets:** established benchmark data may be used for the vibration part, with attention to documented limitations such as the dominance of seeded faults and the absence of temperature channels [8].
- **Metrics:** detection lead time (time between first alarm and defined failure or end of test), detection rate, false-alarm rate per operating hour, fault-type identification accuracy, and RUL prediction error.
- **Baselines:** vibration RMS thresholding according to the standard severity zones [9], vibration-only envelope detector, and temperature-only threshold, so that the benefit of fusion can be quantified.
- **Robustness checks:** performance with added noise, load transients, sensor drift, and loss of a sensor channel, using cross-validation across operating conditions and separate machines to avoid data leakage between training and test sets.

VIII. Discussion

The proposed approach follows from the physical behaviour of bearing damage. Vibration reacts to the mechanical impacts of a microscopic defect, long before the friction losses become significant, and therefore sets the achievable lead time of the warning. Temperature responds to the integrated effect of friction and is therefore delayed, but it is relatively insensitive to the sources of variability that plague vibration indicators, such as structural resonances and sensor mounting. The fusion therefore does not seek to make temperature an earlier detector; rather, it uses temperature as an independent witness that reduces the false-alarm rate and verifies severity.

Several limitations should be recognised. First, envelope analysis requires bearing geometry and reliable speed information, and the defect frequencies may be obscured in low-speed machines, where impacts are weak and widely spaced, or under strong interference from adjacent equipment. Second, thermal models require careful calibration, and thermal behaviour is affected by ambient variations, airflow, nearby heat sources, and winding temperature, so the residual approach needs a sufficiently long healthy-baseline period. Third, inverter-fed motors introduce high-frequency electrical noise and bearing currents that can contaminate sensors and alter degradation mechanisms. Fourth, the quality of RUL estimation is limited by the scarcity of run-to-failure data, and the results from laboratory accelerated tests may not generalise to field conditions.

Future research directions include physics-informed machine learning that embeds bearing kinematics and thermal dynamics in learned models, transfer learning from laboratory to field machines, adaptive thresholds that update with operating context, and the integration of additional modalities such as stator current, acoustic

emission, and lubricant condition sensors. The deployment of lightweight envelope and thermal-residual computation on edge devices embedded in sensors or drives would allow continuous monitoring at low cost and with low communication overheads [10].

IX. Conclusion

This paper has described a methodology for the early detection of bearing degradation in electric motors that uses the complementary nature of vibration and temperature signatures. Envelope analysis and impulsiveness indicators provide the earliest evidence of an incipient defect, while the residual of a load-compensated thermal model provides slower but dependable confirmation of progression. A combined health indicator with EWMA-based alarm logic and a two-tier advisory and confirmation scheme was proposed to extend the actionable warning period while limiting false alarms. When connected to a maintenance decision matrix and remaining-useful-life estimation, the approach supports the transition from reactive and time-based maintenance to predictive maintenance. The experimental protocol outlined provides a basis for quantitative evaluation, which is the main direction for follow-up work.

References

[1]. A. K. S. Jardine, D. Lin, and D. Banjevic, "A review on machinery diagnostics and prognostics implementing condition-based maintenance," Mechanical Systems and Signal Processing, vol. 20, no. 7, pp. 1483–1510, 2006.
[2]. S. Nandi, H. A. Toliyat, and X. Li, "Condition monitoring and fault diagnosis of electrical motors—A review," IEEE Transactions on Energy Conversion, vol. 20, no. 4, pp. 719–729, 2005.
[3]. R. B. Randall and J. Antoni, "Rolling element bearing diagnostics—A tutorial," Mechanical Systems and Signal Processing, vol. 25, no. 2, pp. 485–520, 2011.
[4]. N. Tandon and A. Choudhury, "A review of vibration and acoustic measurement methods for the detection of defects in rolling element bearings," Tribology International, vol. 32, no. 8, pp. 469–480, 1999.
[5]. J. R. Stack, T. G. Habetler, and R. G. Harley, "Fault classification and fault signature production for rolling element bearings in electric machines," IEEE Transactions on Industry Applications, vol. 40, no. 3, pp. 735–739, 2004.
[6]. T. A. Harris and M. N. Kotzalas, Essential Concepts of Bearing Technology, 5th ed. Boca Raton, FL, USA: CRC Press, 2006.
[7]. J. Antoni, "The spectral kurtosis: a useful tool for characterising non-stationary signals," Mechanical Systems and Signal Processing, vol. 20, no. 2, pp. 282–307, 2006.
[8]. W. A. Smith and R. B. Randall, "Rolling element bearing diagnostics using the Case Western Reserve University data: A benchmark study," Mechanical Systems and Signal Processing, vols. 64–65, pp. 100–131, 2015.
[9]. International Organization for Standardization, ISO 20816-1:2016, Mechanical vibration—Measurement and evaluation of machine vibration—Part 1: General guidelines. Geneva, Switzerland: ISO, 2016.
[10]. Y. Lei, N. Li, L. Guo, N. Li, T. Yan, and J. Lin, "Machinery health prognostics: A systematic review from data acquisition to RUL prediction," Mechanical Systems and Signal Processing, vol. 104, pp. 799–834, 2018.