



IMPROVING METHODS FOR DETECTING AND DIAGNOSING RAILWAY BEARING FAULTS USING VIBRATION SENSORS

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ANNOTATION

Railway axlebox bearings operate under variable loads, wheel–rail impacts and changing rotational speeds, which complicate the early detection of local defects. This review evaluates vibration-based approaches to identifying inner-race, outer-race and rolling-element faults and examines how sensor location influences diagnostic reliability. A targeted comparative analysis of published railway studies, foundational bearing-diagnostics research and openly documented benchmark datasets was conducted. Root-mean-square (RMS) amplitude and kurtosis are useful for screening, whereas spectral analysis and envelope demodulation provide stronger links to characteristic defect frequencies when speed and bearing geometry are known. Time–frequency and adaptive-band methods can improve interpretability under non-stationary conditions, but their effectiveness depends on signal quality and validation conditions. The review identifies mounting repeatability, transmission-path attenuation, speed variation and domain shift between laboratory and railway data as major obstacles. A three-stage improvement framework is proposed: standardize measurement conditions; compare candidate sensor positions using signal-quality and fault-separability criteria; and apply speed-aware, multi-domain signal analysis before fault classification. This is a literature-based methodological proposal, not a report of newly measured diagnostic accuracy. The study offers a transparent basis for subsequent experimental development of an adaptive sensor-positioning mechatronic system for railway bearing inspection.

Key words: railway axlebox bearing, vibration sensor, fault diagnosis, envelope analysis, sensor positioning, condition monitoring.

INTRODUCTION

Reliable detection of axlebox bearing deterioration is essential to the safe and economical operation of railway vehicles. Localized spalls and cracks can generate repetitive impacts as rolling elements pass over a damaged surface; however, wheel–rail contact, track irregularities, braking and traction also generate substantial vibrations. Compared with industrial motors operating at relatively stable speed,



railway axlebox signals are therefore more variable and difficult to interpret [1, 2]. A diagnostic approach must distinguish bearing-related impulses from operating-condition changes rather than equating every high-amplitude event with a bearing failure.

Vibration-based monitoring has the advantage of being sensitive to mechanical interaction at a defect before severe thermal changes become apparent. Nevertheless, a transducer measures the response at its mounting location, not the excitation at the defect itself. Housing stiffness, propagation distance, mounting torque, orientation and local resonances affect the information received [1, 3]. Sensor placement is consequently a measurement-design problem as well as a practical installation problem. This paper reviews vibration features and processing methods, compares their use in railway conditions and proposes a testable approach to selecting and adapting sensor positions.

Early identification and correct localization are different diagnostic tasks. A sudden rise in broadband vibration may justify inspection, but it does not reliably identify whether an inner race, outer race, rolling element, wheel tread or unrelated drivetrain component is responsible. In practical railway monitoring, alarms must also be evaluated against the costs of unnecessary train withdrawal and the risks of a missed failure. The resulting engineering objective is not simply to maximize a classifier score: a monitoring arrangement should be repeatable, explainable and suitable for the working environment. This distinction supports a fault-diagnosis strategy that reports both a general health indicator and a bearing-specific spectral interpretation.

LITERATURE REVIEW

Tandon and Choudhury [4] reviewed vibration and acoustic methods for localized and distributed bearing damage, establishing the diagnostic value of measurements in time and frequency domains. Randall and Antoni [3] subsequently explained why impulsive bearing events excite structural resonances and how band-limited envelope analysis can reveal fault-related periodicity even when other components mask the raw signal. Antoni [5] developed a fast kurtogram to identify informative bands for transient detection. These methods remain fundamental, although their application assumes that the relevant impact information reaches the sensor with sufficient strength.

Railway-focused evidence introduces additional constraints. Entezami et al. [1] distinguished on-board and wayside condition monitoring, noting that railway axle-bearing demonstrations have historically been less extensive than general industrial bearing studies. Amini et al. [6] analyzed wayside acoustic-emission signals using time spectral kurtosis and reported discrimination of artificially damaged bearings in the



presence of background interference. Their acoustic-emission setting is informative but is not equivalent to direct-contact accelerometer measurements. Vaičiūnas et al. [7] compared axlebox vibration diagnostics with temperature-change monitoring and documented operational limitations of each approach.

Recent studies address complex railway signatures with more elaborate processing. Bai et al. [8] studied train axlebox signals using MSC–SGMD decomposition. Wang et al. [9] proposed dimensionality-reduction fusion and optimized bandpass demodulation for high-speed-train axlebox measurements. Liu et al. [10] examined axlebox-bearing degradation using denoising and sequence-aware neural features. A 2025 review by Abtane et al. [2] synthesized vibration, acoustic and thermal monitoring together with on-board and wayside sensor choices. These publications motivate a staged evaluation: physical measurement quality should be established before assessing sophisticated classifiers.

A recurring issue across these studies is the distinction between sensing modality and signal-processing algorithm. A trackside microphone, an acoustic-emission probe and a contact accelerometer respond to different physical quantities and frequency ranges. Their outputs cannot be compared as though they were recorded by interchangeable sensors. For the proposed adaptive system, a contact vibration sensor is considered the principal modality because its position can be deliberately varied at a bearing housing. Results from wayside acoustic-emission research are discussed only as supporting evidence for the benefit of selecting informative transient bands and rejecting environmental interference. The system is envisaged first for controlled or maintenance-depot inspection; continuous on-board use would require a separate assessment of durability, connectivity and certification.

METHODOLOGY

This article is a targeted, non-systematic comparative literature review and methodological design study. Sources were chosen for their direct relevance to railway axlebox monitoring, established bearing signal-processing methods or traceable benchmark measurements. The comparison covers physical fault interpretability, sensitivity to operating-speed variation, susceptibility to interference, computational requirements and sensor-position dependence. No new vibration recordings, training runs, field trials or classifier accuracy values are presented here. Accordingly, “improvement” denotes a recommended diagnostic workflow and explicit validation criteria rather than a demonstrated performance gain.

Criteria for the comparative review

Five criteria guide the synthesis. Physical interpretability indicates whether a method



connects measured peaks to bearing geometry and rotational frequency. Noise robustness considers the impact of wheel–rail shocks and adjacent mechanical sources. Non-stationary applicability addresses changing speed and load. Measurement sensitivity considers how the sensor position and coupling alter high-frequency content. Finally, implementation burden includes sampling requirements, processing time and repeatability of sensor mounting. The paper does not assign numerical weights or combine accuracy percentages from unrelated studies because those studies do not share a common test population, sensor configuration or train operating scenario. Accordingly, the comparison is structured as engineering reasoning supported by the cited literature, not a quantitative meta-analysis.

Bearing-fault frequencies and vibration features

For an idealized rolling-element bearing with N rolling elements, rolling-element diameter d , pitch diameter D_p , contact angle θ and shaft rotation frequency f_r , the nominal outer- and inner-race defect-pass frequencies are $BPFO = (N/2)f_r[1 - (d/D_p)\cos\theta]$ and $BPFI = (N/2)f_r[1 + (d/D_p)\cos\theta]$. The cage frequency is $FTF = (f_r/2)[1 - (d/D_p)\cos\theta]$. These relations are approximations that neglect slip; actual peaks can shift under changing load or speed [3]. Fault diagnosis should therefore consider harmonics, sidebands and speed variability rather than relying on a single fixed spectral bin.

Given sampled accelerations $x_1, \dots, x_M$, a basic energy descriptor is $RMS = \sqrt{(1/M)\sum x_i^2}$; impulsiveness may be assessed by kurtosis $\kappa = [(1/M)\sum (x_i - \mu)^4] / [(1/M)\sum (x_i - \mu)^2]^2$. RMS responds to overall excitation and may rise under rough-track loading, whereas kurtosis highlights intermittent transients but is also affected by unrelated shocks. The FFT describes frequency content; for localized defects, bandpass filtering followed by Hilbert-envelope analysis can uncover modulations associated with repeated contact impacts [3–5].

EVALUATION OF VIBRATION-BASED DIAGNOSTIC METHODS

The primary comparison is qualitative because the reviewed investigations used different vehicles, rig conditions, sensor technologies and evaluation designs. Table 1 summarizes diagnostic mechanisms and practical limitations without combining incomparable published accuracy figures.



Table 1. Comparison of vibration-based bearing fault diagnosis techniques

Method	Diagnostic information	Main advantage	Main limitation
RMS / crest factor	Overall level and peakiness	Simple and inexpensive	Poor fault-type specificity under track shocks
Time-domain kurtosis	Impulse prominence	Sensitive to intermittent impacts	Spurious response to non-bearing transients
FFT / order spectrum	Periodic components and harmonics	Interpretable when geometry/speed are known	Spectral smearing from changing rotation speed
Envelope analysis	Repetition in resonant high-frequency bands	Highlights localized bearing impacts	Dependent on band choice and signal transfer path
Wavelet / kurtogram	Localized transient energy over time and band	Suitable for changing signal character	Additional tuning and computing cost
Learned features	Multivariate patterns across conditions	Potentially models complex interactions	Label demand, explainability and domain shift

Frequency-domain analysis should be applied with attention to signal acquisition. For an accelerometer with effective bandwidth B and sampling frequency f_s , the acquisition configuration must prevent aliasing and preserve the resonant region chosen for demodulation. The FFT frequency resolution is approximately f_s/M for an M -sample window; a very short window may be insufficient for separating defect harmonics even if it reacts quickly to shocks. Conversely, excessively long windows may combine several shaft speeds and smear the spectrum. Order tracking or short speed-conditioned windows may therefore be required under acceleration and braking. A method selected under constant-speed rig conditions cannot be assumed to work unchanged on a vehicle traversing uneven track [3, 5].



Sensor positioning and measurement reliability

A fixed housing-mounted accelerometer near the bearing generally offers a short mechanical transmission path, while a remote mount can be easier to access but may attenuate high-frequency impacts [3, 12]. Radial and axial orientations should be compared because the load path and housing modes are direction dependent; an optimal point at one speed is not necessarily optimal at another. A portable or robotically positioned sensor adds a further challenge: preload, contact angle and repeated placement must remain sufficiently consistent that positioning-induced variation is not mistaken for a defect.

Table 2. Sensor-location alternatives and validation needs

Candidate position	Practical rationale	Potential problem	Required comparison
A: axlebox housing, radial	Near the target; direct radial response	Exposure, mounting constraints	SNR, impulse repeatability and speed sensitivity
B: housing, axial	Captures a different structural direction	Mode-dependent attenuation	Fault-band energy and between-position consistency
C: accessible remote bracket	Simpler robotic reach / safer access	Longer transmission path	Transfer-path loss and false-alarm rate

Proposed adaptive diagnostic workflow

A defensible improvement strategy is to separate sensor-position evaluation from algorithm selection. First, establish reference healthy and faulty conditions and record shaft speed, loading, measurement direction and mounting method. Second, acquire paired recordings at candidate positions under matched operating conditions, including repeated mount–unmount cycles. Third, preprocess the waveforms, apply speed normalization where necessary, select an informative demodulation band and compute both interpretable fault indicators and nuisance-sensitive quality measures. Fourth, select a position subject to installation feasibility and diagnostic stability; do not optimize solely for maximum RMS, which may favor exposure to wheel–rail shocks rather than bearing faults.



1	RECORD	2	POSITION	3	PROCESS	4	VALIDATE
Speed mounting	• load •	Radial remote	• axial •	Filter FFT	• envelope •	Repeatability false alarms	•

Figure 1. Proposed four-stage workflow (conceptual; not experimentally validated). One possible position score is $J(p) = w_1Q_{imp}(p) + w_2Q_{sep}(p) - w_3V_{rep}(p) - w_4C_{inst}(p)$, where Q_{imp} measures stable bearing-band impulsiveness, Q_{sep} denotes fault/healthy separability on independent recordings, V_{rep} quantifies repositioning variability and C_{inst} penalizes installation burden. The weights must be specified for the intended inspection system before optimization. The score is a design proposal, not a metric fitted or tested in this review.

Validation plan and decision thresholds

In the proposed robotic workflow, candidate positions are first screened for physical access, mounting clearance and repeatable contact force. A short healthy baseline recording is then collected at each feasible position. Subsequent repeated acquisitions should measure whether the same operating condition produces similar band-limited features after the sensor is removed and replaced. Positions with unstable coupling should be excluded before fault classification. Only the remaining locations would be compared using sensitivity to labeled bearing defects and resilience to nuisance events. This sequence reduces the risk of finding an apparently excellent position that is actually sensitive to mounting artefacts.

The final evaluation should use independent test runs and include both signal-level and decision-level metrics. Signal-level metrics can include the relative energy of identified defect-related modulation bands and stability of the selected demodulation band across repeated acquisitions. Decision-level measures should include sensitivity, specificity, precision, and false-alarm counts per inspection or operating hour. If data are markedly imbalanced, precision–recall curves are more informative than raw accuracy. Comparisons should also record the duration of each acquisition, computational latency and robotic positioning time. A method that improves a laboratory classification metric but doubles inspection time may have limited operational value.

RESULTS AND DISCUSSION

The principal literature-supported finding is that physically interpretable, multi-stage processing is more appropriate than a single vibration threshold for railway bearing diagnostics. In particular, RMS or peak measures are useful for rapid screening but cannot by themselves attribute an impact to an axlebox defect [3, 6]. When a fault excites resonances, filtered envelope spectra offer a path to identification through



characteristic pass frequencies, provided sensor bandwidth, bearing geometry and shaft speed are adequate. Adaptive-band and time–frequency processing become especially relevant when changing load, speed and competing excitations mask fault signatures [5, 8, 9]. These statements synthesize published findings; no common experimental performance ranking can be inferred from the heterogeneous studies.

The sensor-position comparison suggests three practical design priorities. Measurement points should be mechanically stable and reproducible; the sensing direction must be recorded; and features should be checked for robustness across operating conditions rather than optimized for a single stationary example. Railway-specific evidence additionally warns against transferring results from laboratory motors directly to in-service wheelsets [1, 2]. For example, the Case Western Reserve University (CWRU) dataset consists of motor-bearing acceleration records from a controlled electric-motor test rig, with seeded faults and accelerometers at different locations [11]. Paderborn University provides synchronized vibration and current measurements for 26 damaged and six healthy bearing states over four operating conditions [12, 13]. These resources are suitable for algorithm development and controlled comparisons, but neither is a substitute for independent railway axlebox validation.

For a future experimental evaluation, at least three bearing states should be represented (healthy, inner-race defect and outer-race defect), with load and rotation-speed ranges spanning the planned application. Each sensor position should be revisited in independent trials and assessed using fault-specific detection sensitivity, false-alarm rate, time to detection, spectral interpretability and variation across re-mounting. Train-wise or bearing-wise holdout is preferable to random window splitting, because adjacent signal windows from the same run are strongly related. Algorithms should be compared on identical partitions; uncertainty should be reported using confidence intervals rather than only best-case accuracy.

There are three important limitations. First, the proposed workflow has not yet been experimentally validated, so no claim of improved sensitivity, optimal position or field readiness can be made. Second, bearing fault frequencies depend on geometry and operating conditions that cannot be inferred from a generic vibration dataset. Third, installation restrictions and sensor transfer functions must be measured in a realistic axlebox assembly before a robotic positioning mechanism can be specified. The strongest next contribution would be a controlled study that varies sensor location and mount repeatability while holding the bearing state and operating condition fixed.



Implications for future railway mechatronics research

A practical robotic sensor carrier would need to coordinate three interacting subsystems: positioning mechanics, measurement electronics and diagnostic software. The mechanical subsystem should provide repeatable positioning and controlled contact without damaging axlebox housings. The acquisition subsystem should record calibrated acceleration, timestamping, sensor orientation and operating-condition metadata. The software subsystem should reject poor-contact acquisitions, correct for speed variation and extract physically interpretable features before issuing any condition assessment. Incorporating a confidence or data-quality flag is preferable to forcing a fault category for every noisy recording. These are system requirements derived from the measurement challenges identified above, not a completed prototype specification.

Future experiments could test whether adaptive repositioning improves the reliability of a fixed diagnostic method under controlled conditions. The comparison should start with a fixed housing sensor as the baseline, then evaluate a movable sensor over a predefined set of locations with the same instrument and sampling settings. A useful experimental design would include repeated runs and re-mounting at each position, healthy and defective bearing states, several load/speed combinations and independent blinded test sessions. Statistical analysis could quantify the effect of location and orientation while accounting for operating condition. Crucially, claimed improvements should be supported by confidence intervals and independent validation on railway-relevant assemblies rather than by a single visually convincing spectrum.

CONCLUSION

This comparative review examined vibration-based methods for detecting and diagnosing railway bearing faults and highlighted the effect of sensor positioning on signal interpretation. Classical RMS and kurtosis features support rapid screening but are not sufficiently specific under wheel–rail impacts. FFT, envelope demodulation and adaptive time–frequency methods supply complementary information for identifying localized bearing defects when supported by accurate operating-speed and geometric data. The review proposes a practical sequence for improving diagnostic methodology: standardize acquisition, compare repeatable sensor locations, extract physically meaningful vibration indicators and validate across independent railway operating conditions. Because no new measurements were performed, the proposed adaptive positioning framework remains a testable research direction. Future work should construct a railway-relevant experimental rig, assess contact-force and orientation repeatability, and quantify both diagnostic performance and inspection time



before deployment in a robotic mechatronic system.

REFERENCES

- [1] M. Entezami, C. Roberts, P. Weston, E. Stewart, A. Amini, and M. Papaelias, "Perspectives on railway axle bearing condition monitoring," *Proc. IMechE Part F: J. Rail Rapid Transit*, vol. 234, no. 1, pp. 17–31, 2020. doi: 10.1177/0954409719831822.
- [2] M. Abtane, K. Dahi, H. Martinez, M. Sedki, H. El Kimi, C. Dahhassi, C. Hlib, and L. F. Borges, "Axle bearing fault diagnosis for high-speed trains: A comprehensive review of methodologies, technologies, challenges and emerging trends," *Measurement*, vol. 251, art. 117098, 2025. doi: 10.1016/j.measurement.2025.117098.
- [3] R. B. Randall and J. Antoni, "Rolling element bearing diagnostics—A tutorial," *Mech. Syst. Signal Process.*, vol. 25, no. 2, pp. 485–520, 2011. doi: 10.1016/j.ymssp.2010.07.017.
- [4] N. Tandon and A. Choudhury, "A review of vibration and acoustic measurement methods for the detection of defects in rolling element bearings," *Tribol. Int.*, vol. 32, no. 8, pp. 469–480, 1999. doi: 10.1016/S0301-679X(99)00077-8.
- [5] J. Antoni, "Fast computation of the kurtogram for the detection of transient faults," *Mech. Syst. Signal Process.*, vol. 21, no. 1, pp. 108–124, 2007. doi: 10.1016/j.ymssp.2005.12.002.
- [6] A. Amini, M. Entezami, Z. Huang, H. Rowshandel, and M. Papaelias, "Wayside detection of faults in railway axle bearings using time spectral kurtosis analysis on high-frequency acoustic emission signals," *Adv. Mech. Eng.*, vol. 8, no. 11, 2016. doi: 10.1177/1687814016676000.
- [7] G. Vaičiūnas, G. Bureika, and S. Steišūnas, "Rail vehicle axle-box bearing damage detection considering the intensity of heating alteration," *Eksplotacija i Niezawodność – Maintenance and Reliability*, vol. 22, no. 4, pp. 724–729, 2020. doi: 10.17531/ein.2020.4.16.
- [8] Y. Bai, H. Xue, and J. Chen, "Train Axlebox Bearing Fault Diagnosis Based on MSC–SGMD," *Sensors*, vol. 24, no. 1, art. 254, 2024. doi: 10.3390/s24010254.
- [9] Z. Wang, Z. Zheng, D. Song, and X. Xu, "A High-Speed Train Axle Box Bearing Fault Diagnosis Method Based on Dimension Reduction Fusion and the Optimal Bandpass Filtering Demodulation Spectrum of Multi-Dimensional Signals," *Machines*, vol. 12, no. 8, art. 571, 2024. doi: 10.3390/machines12080571.
- [10] Z. Liu, L. Zhang, Q. Xiao, H. Huang, and G. Xiong, "Performance Degradation Assessment of Railway Axle Box Bearing Based on Combination of Denoising Features and Time Series Information," *Sensors*, vol. 23, no. 13, art. 5910, 2023. doi: 10.3390/s23135910.



- [11] Case Western Reserve University, “Bearing Data Center,” Case School of Engineering, online data repository. Available: <https://engineering.case.edu/bearingdatacenter> (accessed Oct. 2026).
- [12] Universität Paderborn, “Bearing DataCenter: Data Sets and Download,” online data repository. Available: <https://mb.uni-paderborn.de/kat/forschung/bearing-datacenter/data-sets-and-download> (accessed Oct. 2026).
- [13] C. Lessmeier, J. K. Kimotho, D. Zimmer, and W. Sextro, “Condition Monitoring of Bearing Damage in Electromechanical Drive Systems by Using Motor Current Signals of Electric Motors: A Benchmark Data Set for Data-Driven Classification,” PHM Society European Conf., vol. 3, no. 1, 2016. doi: 10.36001/phme.2016.v3i1.1577.