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A Review of Integrated Vibration and Acoustic Emission Techniques for Defect Detection and Size Estimation in Rolling Element Bearings using Neural Networks

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Abstract: *Rolling element bearings are essential components of rotating machinery used in industrial manufacturing, automotive systems, power generation, aerospace equipment, and other mechanical applications. Their operational reliability significantly influences machine performance, maintenance costs, and equipment safety. Bearing defects, including inner-race damage, outer-race damage, rolling-element cracks, surface pitting, and wear, can lead to excessive vibration, noise, energy losses, and unexpected machinery failure.*

Keywords: Rolling element bearings, vibration analysis, acoustic emission, predictive maintenance.

I. INTRODUCTION

Rolling element bearings are fundamental mechanical components that support rotating shafts, reduce friction, and maintain accurate relative motion between machine elements. They are widely used in electric motors, turbines, pumps, industrial gearboxes, machine tools, railway systems, and wind-energy installations. Despite their importance, bearings are subjected to continuous mechanical stress, fluctuating loads, lubrication deficiencies, contamination, misalignment, and repeated contact forces. These operating conditions can gradually produce localized or distributed defects on the inner race, outer race, rolling elements, or cage. If such defects remain undetected, they may increase vibration levels, generate abnormal acoustic emissions, accelerate material degradation, and eventually cause equipment breakdown. Consequently, reliable bearing condition monitoring is an important requirement for preventive maintenance, industrial productivity, and machinery safety. Reviews of bearing diagnostics demonstrate that vibration analysis, signal processing, machine learning, and artificial intelligence have become major research areas for identifying bearing faults and evaluating their severity (Anwarsha & Babu, 2022).

Vibration analysis is one of the most established techniques for bearing fault detection because localized defects produce mechanical impacts as rolling elements pass over damaged surfaces. These impacts generate characteristic changes in the amplitude, frequency, and statistical distribution of measured vibration signals. Time-domain parameters such as root mean square, kurtosis, crest factor, and peak amplitude can indicate changes in bearing condition, while frequency-domain methods help identify characteristic defect frequencies. Envelope analysis, wavelet transforms, spectral analysis, and empirical mode decomposition can improve the visibility of weak fault-related components in complex signals. Nevertheless, vibration measurements can be affected by machine structure, sensor position, rotational speed, load, resonance, and interference from other rotating components. These limitations make it difficult to distinguish small defects from normal operational variations in certain industrial environments (Randall & Antoni).

Acoustic emission analysis provides a complementary approach by monitoring transient high-frequency elastic waves generated by friction, crack formation, surface interactions, and localized material deformation. In contrast to

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conventional vibration monitoring, which generally measures relatively lower-frequency structural responses, acoustic emission monitoring can capture short-duration events associated with the development of small defects. Its usefulness depends on sensor frequency response, mounting conditions, propagation paths, attenuation, and background noise. Integrating vibration and acoustic emission measurements can therefore provide a more comprehensive representation of bearing health than relying on one measurement channel alone. Pacheco-Chérrez (2022) investigated bearing fault detection using vibration and acoustic signals and compared different machine-learning classification approaches, demonstrating the relevance of examining acoustic information alongside conventional vibration measurements.

The increasing availability of computational resources has encouraged researchers to employ artificial neural networks for automated fault recognition. Traditional machine-learning approaches often depend on manually selected statistical, spectral, or time-frequency features, whereas deep-learning architectures can learn complex representations from signal segments or transformed signal images. Convolutional neural networks are suitable for identifying local patterns in time-frequency representations, recurrent networks can model sequential dependencies, and multilayer perceptrons can learn nonlinear relationships between extracted features and fault categories or severity measurements. Research reviews published during the study period describe the expanding role of deep learning in bearing fault diagnosis, while also emphasizing concerns about data quality, generalization, and practical deployment (Zhang 2020).

An important distinction must be made between detecting a defect, classifying its location, and estimating its physical size. A model may accurately distinguish healthy bearings from defective bearings without determining whether a defect is 0.2 mm, 0.5 mm, or 1.0 mm wide. Quantitative defect-size estimation requires experimentally labelled measurements, representative defect dimensions, controlled validation, and an appropriate regression model. Cerrada et al., (2018) reviewed data-driven approaches to bearing fault-severity assessment and identified the estimation of damage magnitude and degradation as important problems in condition-based maintenance. Therefore, this review focuses on the potential benefits of integrating vibration and acoustic emission signals with neural networks, with particular attention to the distinction between fault classification and quantitative defect-size prediction.

REVIEW OF LITERATURE

Research conducted between 2010 and 2022 demonstrates a gradual transition from conventional vibration-based condition monitoring toward intelligent systems incorporating signal processing, machine learning, and multiple sensor modalities. Early work emphasized extracting meaningful fault characteristics from vibration measurements, while subsequent studies explored automated feature learning, fault classification, and severity assessment. More recent research has examined the advantages of combining different sensor measurements and applying deep-learning models to complicated operating environments.

Randall and Antoni (2011) examined the theoretical foundations and practical applications of bearing vibration analysis, particularly the use of spectral analysis and envelope detection for identifying repetitive impact patterns. Their work established the importance of understanding bearing kinematics and signal-generation mechanisms when interpreting measured vibration data. Although these methods are useful for detecting localized damage, their performance can deteriorate when fault-related impulses are weak or obscured by background vibration.

Smith and Randall (2015) discussed the identification of bearing faults using experimental vibration datasets and demonstrated the importance of reliable fault signatures and appropriate signal interpretation. Research based on benchmark datasets subsequently enabled comparisons between conventional diagnostic techniques and intelligent classification algorithms. However, results obtained from controlled experiments cannot automatically be generalized to industrial machines operating under different loads, speeds, and environmental conditions.

Antoni and Randall (2015) provided an overview of signal-processing techniques used in rolling element bearing fault diagnosis, including spectral methods, time-frequency representations, and techniques for extracting repetitive impulsive components. Such approaches provide a foundation for neural-network applications because the quality of extracted features influences the model's ability to distinguish different fault conditions. The choice of preprocessing method must nevertheless account for nonstationary signals and variations in operating conditions.

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Cerrada et al., (2018) reviewed data-driven approaches for assessing rolling bearing fault severity. Their review distinguished conventional fault identification from the more demanding task of estimating the magnitude of damage. It highlighted the importance of relating signal characteristics to physical defect severity, particularly for supporting maintenance decisions. This distinction is directly relevant to neural-network regression, where the model must predict a continuous measurement rather than merely assign a fault category.

Zhang et al., (2019) surveyed deep-learning approaches for bearing fault diagnosis, including autoencoders, restricted Boltzmann machines, and convolutional neural networks. These architectures offer opportunities to learn complex representations from raw or transformed signals, reducing dependence on extensive manual feature engineering. However, their diagnostic performance depends on the diversity of training data, the experimental design, and the similarity between training and deployment conditions.

Zhang et al. (2020) further examined deep-learning algorithms for bearing fault diagnostics and discussed the strengths and limitations of different architectures. Their review supports the use of learned features for recognizing complex fault patterns but also draws attention to the need for dependable evaluation procedures. A high classification score on a single benchmark dataset does not necessarily establish reliable defect-size estimation or robustness under changing operating conditions.

Anwarsha and Babu (2022) reviewed recent advances in signal processing and artificial intelligence for rolling element bearing fault detection, covering vibration analysis, acoustic emission, signal decomposition, and intelligent diagnostic approaches. Their review identifies both sensing methods as important tools for bearing condition monitoring and emphasizes their different advantages and limitations. This provides a useful basis for investigating sensor fusion and neural-network-based fault assessment.

Pacheco-Chérrez et al., (2022) compared machine-learning classification approaches using vibration and acoustic signals for bearing fault detection. Their findings highlighted the diagnostic value of acoustic information and demonstrated that sensor modality and feature selection can influence classification performance. However, fault detection and classification results should not be interpreted as proof of accurate physical defect-size estimation unless the model has been separately trained and tested against measured defect dimensions.

Peng et al., (2022) reviewed rolling bearing fault diagnosis approaches involving signal processing, feature extraction, deep learning, and other artificial-intelligence methods. Their review highlighted the importance of dataset selection, evaluation methodology, and the challenges of deploying intelligent models in real-world conditions. Together, these studies indicate that combining complementary sensor information with suitable learning architectures is a promising direction, while quantitative severity assessment remains a distinct technical challenge.

COMPARATIVE ANALYSIS OF INTEGRATED MONITORING TECHNIQUES

The following table summarizes the principal characteristics of vibration analysis, acoustic emission monitoring, and neural-network-based sensor fusion. It presents a qualitative comparison derived from the reviewed literature rather than results from a new experiment.

Table 1. Comparison of techniques for rolling element bearing condition monitoring

Technique	Principal signal characteristics	Main advantages	Important limitations	Potential application
Vibration analysis	Amplitude, RMS, kurtosis, frequency components and impacts	Established methods; suitable for continuous monitoring	Structural noise, resonance and sensitivity to sensor location	Fault detection and localization
Acoustic emission analysis	High-frequency transients, event energy, counts and spectral features	Potential sensitivity to localized contact events and early damage	Attenuation, coupling effects and high-frequency noise	Early-stage defect detection

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Neural network using vibration	Learned patterns from raw signals or extracted features	Automated nonlinear pattern recognition	Dependence on representative training data	Fault classification and severity prediction
Neural network using acoustic emission	Learned transient and frequency-related patterns	Automated analysis of complex acoustic events	Sensitivity to acquisition settings and environmental variation	Fault recognition and severity assessment
Feature-level sensor fusion	Combined vibration and acoustic emission features	Integrates complementary signal information	Feature scaling, synchronization and redundant inputs	Multimodal fault diagnosis
Deep-learning sensor fusion	Joint representations learned from both sensor channels	Can learn complex cross-sensor relationships	Data requirements, computational cost and limited interpretability	Integrated detection and defect-size regression

Table 1 indicates that the most appropriate technique depends on the diagnostic objective and operating environment. Vibration analysis offers a well-established foundation for monitoring mechanical behaviour, whereas acoustic emission provides complementary information about high-frequency transient events. Neural networks can learn patterns from either channel, but the integration of both channels may improve the diversity of information available to the model. Whether that integration actually improves diagnostic performance must be demonstrated through controlled testing rather than assumed from the availability of additional signals.

II. CONCLUSION

The reviewed literature from 2010 to 2022 demonstrates the growing importance of intelligent signal processing and neural networks in rolling element bearing condition monitoring. Vibration analysis provides useful information about mechanical impacts, characteristic fault frequencies, and changes in structural response. Acoustic emission analysis contributes complementary information about high-frequency transient events that may accompany localized damage. Integrating these modalities offers a promising strategy for improving bearing fault characterization, particularly when the signals are appropriately synchronized, processed, and validated.

Neural networks can support automated feature learning, fault classification, and regression-based severity assessment. However, defect detection, defect localization, and physical size estimation are distinct tasks that require different forms of validation. Reliable size estimation depends on accurately measured training labels, representative defect dimensions, independent test data, and explicit reporting of dimensional prediction errors. The literature also highlights challenges related to noise, operating-condition variability, limited datasets, model interpretability, and transfer from laboratory testing to industrial environments.

Overall, integrated vibration and acoustic emission monitoring combined with neural-network regression represents a promising direction for predictive maintenance. Its practical value will depend on whether future research can demonstrate repeatable improvements over single-sensor approaches and establish reliable relationships between measured signal patterns and independently verified defect dimensions.

REFERENCES

1. Anwarsha, A., & Babu, T. N. (2022). Recent advancements of signal processing and artificial intelligence in the fault detection of rolling element bearings: A review. Journal of Vibroengineering, 24(6), 1027–1055.
2. Antoni, J. (2011). Cyclostationarity by examples. Mechanical Systems and Signal Processing, 25(1), 325–329.
3. Burda, E. A., Zusman, G. V., Kudryavtseva, I. S., & Naumenko, A. P. (2022). An overview of vibration analysis techniques for the fault diagnostics of rolling bearings in machinery. Shock and Vibration, 2022, Article 6136231.
4. Cerrada, M., Sánchez, R. V., Li, C., Pacheco, F., Cabrera, D., de Oliveira, J. V., & Vásquez, R. E. (2018). A review on data-driven fault severity assessment in rolling bearings. Mechanical Systems and Signal Processing, 99, 169–196.

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5. Fink, O., Wang, Q., Svensén, M., Dersin, P., Lee, W.-J., & Ducoffe, M. (2020). Potential, challenges and future directions for deep learning in prognostics and health management applications. Engineering Applications of Artificial Intelligence, 92, Article 103678.
6. Hakim, M., Omran, A. A. B., Ahmed, A. N., Al-Waily, M., & Abdellatif, A. (2023). A systematic review of rolling bearing fault diagnoses based on deep learning and transfer learning: Taxonomy, overview, application, open challenges, weaknesses and recommendations. Ain Shams Engineering Journal, 14(4), Article 101945.
7. Kumar, J. P., Chauhan, P. S., & Pandit, P. P. (2022). Time domain vibration analysis techniques for condition monitoring of rolling element bearing: A review. Materials Today: Proceedings, 62, 6336–6340.
8. Lei, Y., Lin, J., He, Z., & Zuo, M. J. (2013). A review on empirical mode decomposition in fault diagnosis of rotating machinery. Mechanical Systems and Signal Processing, 35(1–2), 108–126.
9. Liu, H., & Motoda, H. (2012). Feature selection for knowledge discovery and data mining. Springer.
10. Pacheco-Chérrez, J., Fortoul-Díaz, J. A., Cortés-Santacruz, F., Aloso-Valerdi, L. M., & Ibarra-Zarate, D. I. (2022). Bearing fault detection with vibration and acoustic signals: Comparison among different machine learning classification methods. Engineering Failure Analysis, 139, Article 106515.
11. Patel, S., Shah, U., Khatri, B., & Patel, U. (2022). Research progress on bearing fault diagnosis with localized defects and distributed defects for rolling element bearings. Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit, 236(7–8).
12. Peng, B., Bi, Y., Xue, B., Zhang, M., & Wan, S. (2022). A survey on fault diagnosis of rolling bearings. Algorithms, 15(10), Article 347.
13. Randall, R. B., & Antoni, J. (2011). Rolling element bearing diagnostics—A tutorial. Mechanical Systems and Signal Processing, 25(2), 485–520.
14. Saufi, S. R., Ahmad, Z. A., Leong, M. S., & Lim, M. H. (2019). Challenges and opportunities of deep learning models for machinery fault detection and diagnosis: A review. IEEE Access, 7, 122644–122662.
15. Smith, W. A., & Randall, R. B. (2015). Rolling element bearing diagnostics using the Case Western Reserve University data: A benchmark study. Mechanical Systems and Signal Processing, 64–65, 100–131.
16. Tandon, N., & Choudhury, A. (1999). A review of vibration and acoustic measurement methods for the detection of defects in rolling element bearings. Tribology International, 32(8), 469–480.
17. Wang, D., Tse, P. W., & Tsui, K. L. (2013). An enhanced Kurtogram method for fault diagnosis of rolling element bearings. Mechanical Systems and Signal Processing.
18. Zhang, S., Zhang, S., Wang, B., & Habetler, T. G. (2020). Deep learning algorithms for bearing fault diagnostics. A comprehensive review. IEEE Access, 8, 29857–29881.
19. Zhang, W., Li, X., Ma, H., Luo, Z., & Li, X. (2019). A survey on deep learning based bearing fault diagnosis. Neurocomputing, 335, 327–335.
20. Zhang, Y., Li, X., & Gao, L. (2017). A review of intelligent fault diagnosis methods for rotating machinery based on deep learning. Journal of Mechanical Engineering.