Original Article
ISSN (Online): 2582-7472

ShodhKosh: Journal of Visual and Performing Arts
July-December 2023 4(2), 4966–4970

A STATE OF THE ART REVIEW ON ADVANCES IN BEARING FAULT DIAGNOSIS USING MACHINE LEARNING APPROACH

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DOI
10.29121/shodhkosh.v4.i2.2023.5976

Funding: This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

ABSTRACT

Diagnosing bearing issues is crucial because bearings are crucial parts of rotating machinery, supporting and guiding shafts, and because faults can result in lost productivity, damaged equipment, and safety hazards. One common technique for identifying bearing problems is vibration analysis. High-frequency resonances are isolated using sophisticated techniques like envelope analysis, fault frequencies are determined using frequency-domain techniques like the Fast Fourier Transform (FFT), and anomalies in signals are identified using time-domain analysis. Machine learning improves fault classification, while time-frequency methods such as wavelet transformations are employed to handle non-stationary signals. Every technique has its limitations: sophisticated techniques offer precision at the expense of complexity; frequency analysis performs well in steady settings but suffers from speed variations; time-domain analysis is straightforward but may reveal early issues. Accuracy, computational demands, and operational requirements must all be balanced when choosing the best strategy for bearing condition monitoring.

Keywords: Bearings, Fault Diagnosis, Vibration Analysis, Condition Monitoring, Machine Learning

1. INTRODUCTION

Petrochemical facilities, airplanes, the chemical industry, and home appliances all require rotating gear, particularly induction motors, which are crucial parts of industrial systems. The essential components of these production lines are the stator, rotor, shaft, and bearings; the bearings are among the most crucial mechanical components since they support and guide the shaft's rotation. Studies have shown that bearing-related problems are one of the main causes of mechanical failures in rotating machinery [1–3]. Industrial reliability relies on condition monitoring and problem diagnosis because of the possibility of large production losses, equipment damage, and safety risks. Vibration signal analysis is one of the greatest diagnostic techniques since it offers a wealth of information for identifying and comprehending bearing defects (BDs).

Condition monitoring improves operational availability and safety by allowing the real-time evaluation of machinery health without compromising output. [4]. A bearing's condition may be evaluated using a variety of methods, including as temperature, noise, current, and vibration monitoring. [5–7]. Vibration monitoring is the most successful of these since it enables the early identification, localization, and categorization of problems (both dispersed and localized) before they deteriorate. [8]. As part of the vibration monitoring process, sensors provide fault signals to a computer-connected data collecting system. [9]. However, the vibrational signal processing technique utilized to extract diagnostic characteristics determines how successful it is. The problem associated with bearings can be identified with help of various techniques such as CA - Cepstrum analysis [13, 14], FFT - Fourier Transform [10–12], WT - wavelet transform [20–22], WVD - Wigner–Ville Distribution [15, 16], STFT - Short Time Fourier Transform [15, 16], and EA - Envelope Analysis [17–19].

Despite being widely used to diagnose periodic faults (like bearing defects), envelope analysis requires prior knowledge of resonance frequencies and filtering bands, which limits its sensitivity to early-stage faults. [17–19]. Short-Time Fourier The transform has a fixed time-frequency resolution due to its static windowing. [14–16], Despite using multi-resolution analysis to address this, the Wavelet Transform has limitations, including border distortion, energy leakage, and selecting the optimal wavelet (e.g., Haar, Daubechies, Morlet). [20–22].

2. EXPERIMENTAL SETUP

The vibration signals used for the study are publicly made available from the Bearing data center of the Case Western Reserve University (CWRU), and the experimental setup is shown in Figure 1 [23]. In this vibration monitoring system, the electric power is coming from the induction motor, which is of 2.3 kW. To record the vibration signal, an Accelerometer is used and it is fixed on the bearing housing. This setup also offers a range of loading from no load condition to 3 horsepower, and the loading is managed by the torque transducer along with the dynamometer. The collected data is available in four different conditions, where there is no fault data and data with a fault either on the inner race, outer race or on the ball. Also the diameters of the fauls are changed as 0.1778, 0.3556 and 0.5334 mm and also the depth of the fault is contact the value of 0.2794 mm. Another variety in the data is offered by the speed of the motor shaft with rpm from 1730-1797. All this data is taken with a 12 kHz sampling rate, and the time interval is of 10s.

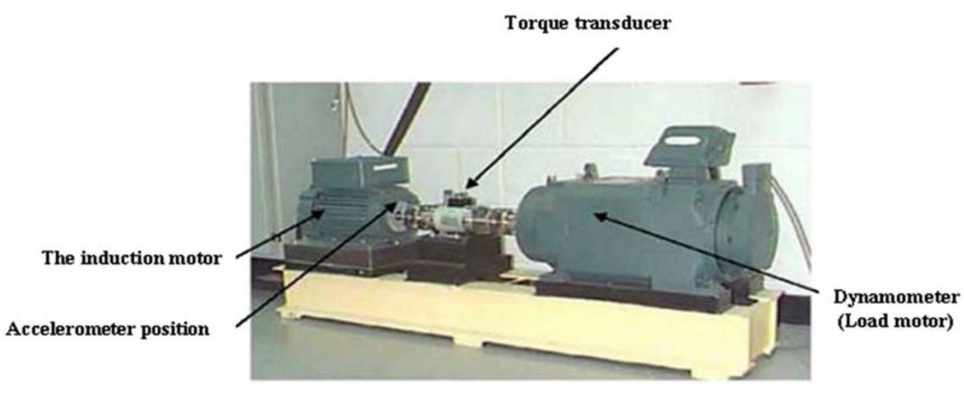

Figure 1 Experimental Setup of CWRU

The study focused on the 6205-2RS JEM SKF deep-groove ball bearing. In a comparative study of fault detection in bearings. The selected condition is one with the highest rpm and no load, and another with the lowest speed and full load. Selected conditions are furthermore checked in three different combinations as faults on the inner race, on the outer race, and in a fault condition. Here, in every sample, a total 4096 data points is taken into consideration. In this type of study, the characteristic frequency of the bearing becomes the key as it changes with dimensions and speed. In bearing fault detection, the BPFI and BPFO, which are inner race and outer race frequency, respectively, are crucial in the identification of the localized faults. Apart from the mentioned two frequencies, also diameters, angle of contact, and frequency of rotation also affect in identification of the location of the fault [24].

3. RECENT ADVANCES

The study by Lee et al. [25] demonstrated the effectiveness of 1D CNNs in fault diagnosis with an accuracy rate of 98.3%. Raw vibration signals were directly processed by the model using three convolutional layers with max pooling and fully connected layers. This approach eliminated the need for manual feature extraction while maintaining superior diagnostic performance. This method has been successful in detecting both local and global patterns connected to different fault types because CNN can automatically extract discriminative features from time-series vibration data. The relatively simple architecture suggests that even shallow CNNs can be highly effective for fault diagnosis when used on properly pre-processed vibration signals.

With an accuracy of 99.4%, the more sophisticated 2D CNN architecture developed by Wen et al. [26] outperformed all the other approaches. Their deeper network consisted of five convolutional layers that included dropout regularization and batch normalization. The ability of this model to learn features hierarchically—with initial layers spotting basic patterns and deeper layers identifying more complex fault characteristics—is what gives it its exceptional performance. The end-to-end learning approach removed the need for manual feature engineering, allowing the network to discover the optimal representations directly from the input data. The incorporation of data augmentation techniques also contributed to the model's strong performance by increasing its ability to generalize under a range of operational conditions.

Lu et al. [27] introduced a creative image-based technique that used STFT to convert vibration signals into 2D time-frequency representations with 98.3% accuracy. Feature extraction using SURF and then reduction of dimensions using t-SNE is a novel approach implemented, and further, PNN is used for classifying bearing faults. In this methodology, the vibration signals are presented visually, which helps in capturing the fault characteristics and also provides the facility to resist the noise. This unique approach of applying the SURF algorithm shows support in increasing the accuracy of the solution. In addition to this, the applied t-SNE technique helps in reducing the complexity of the system.

Ranawat and Kankar [28] explored the conventional techniques of Machine learning, namely SVM and ANN in the field of bearing fault detection particularly for the centrifugal pump. In the comparative study, the conclusion states that the combined methodology of SVM and RBF kernel has achieved 97.7% accuracy, and on the other hand, ANN has achieved the accuracy of 98.3%. Both approaches use the statistical parameters like mean, root mean square, kurtosis and other similar time domain features. The advantages of higher accuracy in ANN are because of its ability it to handle complex data sets and also handle nonlinear relations. In extension to this, deep learning is also checked and compared with the conventional approaches, and the results show that deep learning has some limitations in dealing with manual feature selection. Also, the other limitation of all approaches js surfaced in terms of the bearing fault pattern recognition. Hence, the scope of the work is wide in the field of bearing fault diagnosis.

4. CONCLUSION

This study demonstrates the benefits and drawbacks of deep learning and machine learning techniques for diagnosing bearing problems in rotating machinery. Deep learning models, especially CNNs, achieve higher accuracy by automatically learning patterns from raw or transformed data, whereas traditional ML models, such as SVM and ANN, perform well with manually extracted features. Without requiring a great deal of feature engineering, 2D CNNs and image-based techniques show remarkable fault classification capabilities. However, application requirements, computational resources, and data availability should all be taken into account when choosing a model. In order to improve reliability, reduce downtime, and increase the safety of industrial systems, deep learning presents a promising path for intelligent, real-time condition monitoring.

CONFLICT OF INTERESTS

None.

ACKNOWLEDGMENTS

None.

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