Journal of Computer Science
https://dergipark.org.tr/en/pub/bbd
https://doi.org/10.53070/bbd.990814

Journal of Computer Science
ISSN: 2548-1304
Volume: IDAP-2021, Issue: Special, pp: 141-146
@Anatolian Science

Cloud based bearing fault diagnosis of induction motors

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Received: Sep.2,2021 Accepted: Sep.26,2021 Published: Oct.20, 2021

Abstract -- In general, induction motors predictive maintenance is well suited for small to large-scale industries to minimize failure, maximize performance, and improve reliability. The vibration of an induction motor was investigated in this paper in order to gather precise details that can be used to forecast motor bearing failure. With this in view, an induction motor carrying fault detection scheme has been attempted. machine learning algorithms in addition to wavelet transform (WT) and fast fourier transform (FFT), an advanced signal processing technique, are used in this study to analyze frame vibrations during initialization. the Internet of Things (IoT) is at the core of today's accelerated technological growth. A large number of items are interconnected efficiently, particularly in industrial-automation, resulting in condition and monitoring to boost efficiency to capture and process the parameters of induction motor, the proposed approach uses an IoT-based platform. The details gathered can be saved in the cloud platform and viewed via a web page.

***Index Terms*--** Induction motor, fault diagnosis, bearing faults, wavelet transform, Fast fourier transform**.**

I. INTRODUCTION

THE induction motors are workhorses of manufacturing industry, are subjected to a variety of inappropriate stresses during their working lives, leading to faults and setbacks [1]. Since these devices are used in such delicate applications, disastrous motor faults are very expensive. Seeking an effective and accurate fault debugging procedure is becoming increasingly problematic due to the wide prevalent Automation and, as a result, a decrease in computer-interface direct are being used to oversee device performance. It's particularly critical for induction motors. Neural Networks, for example, are a form of data-based model., have strongly developed themselves in the condition management of electrical machinery over the last decade. For decades, vibration tracking has been proposed to track revolving unit faults[2], [3]. Vibration testing is considered to be the most accurate means of determining the total fitness of a rotor system. In order to detect and diagnose defects, each fault in a rotating system induces vibration with different features that can be calculated to reference ones. For studying signals with a transitory characteristic, Standard vibration signal analyses methods, such as the Fast Fourier Transform, are ineffectual for analyzing signals with a transitory characteristic. Furthermore, the analyses are strongly reliant on system load, and identifying Very attached failing frequency Constituents requires greatly high-resolution information [4]. Wavelet, a scalable signal-processing tool, can be used to test transient signals without relying on load. The variable window size allows for retrieval of both low and high frequency information as required [5], [6].

In a modern extraction of the signal function and the method of fault detection for the low-speed machinery fault diagnosis, a statistical filter and wavelet package transform (WPT) are mixed with the hold of moving peak technique has been proposed to extract features of the fault signal, and specific symptom parameters for bearing diagnostic in frequency-domain are described that are sensitive to bearing fault diagnosis [7]. The use of the Discrete Wavelet Transform and Fast Fourier Transform theories to calculate the simple bearing defect frequencies' amplitude in the vibration signal of a rotating system has been proposed [8]. These parameters were used by Neural Fuzzy Inference System the Adaptive ANFIS to facilitate the fault catching and diagnostic method. For the diagnosis of the bearing-fault, a hybrid data-driven motor-current approach has been proposed[8], which uses statistical features, genetic algorithms, and machine learning models. The mathematical properties of the motor current signals are first determined. Second, the Genetic algorithm is used to reduce the number of features in the function database and pick the most appropriate ones. Finally, these features are used to train and test three separate classification algorithms, namely random forest, KNN and decision tree, in order to determine bearing faults [9].

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In this article we cover the system requirement analysis, system composition and functions. This paper begins by providing a brief overview of the vibration signal fault diagnostic mechanism by the using of Discrete Wavelet Transform and Support Victor Machine analysis, followed by an introduction to the modern standard architecture bearing fault. After that, it suggests a vibration signal computing-based system accurate fault diagnostic method. With the aid of the cloud, the device can satisfy real-time fault detection criteria based on vibration, lower network bandwidth utilization and data-loss, and upgrade the end cloud applications.

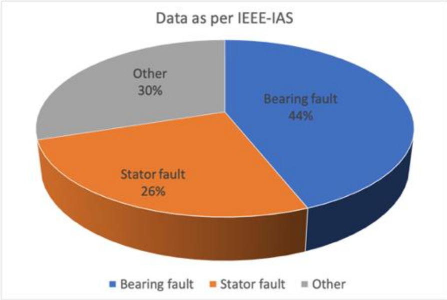


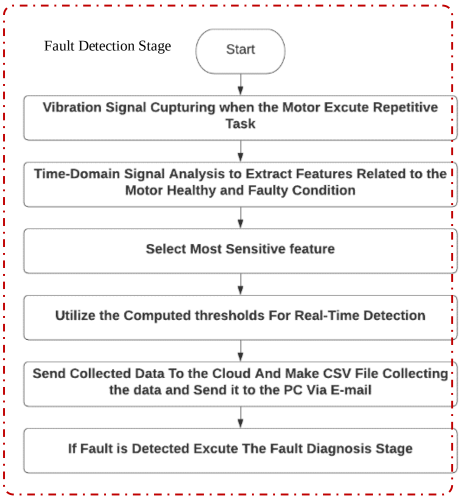
Fig. 1. Percentage occurrence of induction motor-faults [10]

The proposed-inquiry has been limited to bearing faults only between different motor faults because motor reliability-studies indicate that bearing faults account for 44% of induction motor defect, that shown in Fig. 1

Support Vector Machines (SVMs) have recently been discovered to be surprisingly efficient in a variety of real-world systems. SVM's have-been effectively used in a number of ranking and pattern detection activities, but they have gained little consideration in the field of fault diagnosis [11]. SVM's depend on mathematical theory of learning and are built to accommodate smaller sample sizes [12]. SVMs have been used to diagnose equipment faults because it is difficult to collect enough fault samples in operation. These methods, in combination with sophisticated signal-processing technologies such as immediate power FFT, Park's trans-formation, bi-spectrum, and wavelets, the existing research has yielded promising results are expected to play a key role in electric drive device diagnosis. Through using (SVM) as a classifier of fault to classify device defects [13].

II. THE PROPOSED FAULT DIAGNISIS METHOD OF BEARING FAULTS

The proposed system uses the API software architectura1-style to reach the cloud, on which a Matlab client can retrieve the most recent data released by the IoT system. Particle Cloud is used as a connection between the IoT framework and a Matlab client shown in Fig. 2, as an overview of the protocol used to reach IoT-data.



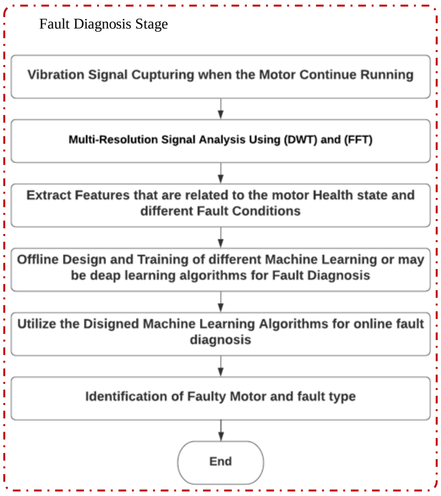


Fig. 2. The proposed fault diagnosis method for bearing faults

Even if the Particle-Proton computer has an embedded Bluetooth device which can be used to share data locally, using the cloud-system can improve the overall system's availability and allow it a lot more versatility. Furthermore, via the built-in presented IOT cloud, any repair operator can access the IoT system remotely.

A. Bearing fault detection using DWT

The following are the basic wavelet-operations:

- Use the wavelet-transform to input to create wavelet-coefficients that allow us to discern the differences correctly.
- To better minimize noise, choose the acceptable specified threshold for each system.
- Signal analysis is used to describe physical processes and diagnose electrical-machines.
- The inverse WT for the coefficients of the wavelet is used to get back to the main signal.

The estimation specifications are minimal as compared to other business instruments. Furthermore, the DWT is included in most packages of the commercial software, so no sophisticated calculations are needed. When a signal is stationary, the Fourier-transform is applied, but vibration signal is not necessarily stationary.
by using time window function, a Fast Fourier Transform approach is used to depict the signal in the frequency and time domains shown in Fig. 3.

The discrete-wavelet-transform is defined as a result of these changes. Mother wavelets come in a variety of shapes and sizes. We'll talk about the best option for producing the best outcomes. For both low pass and high pass band-widths, the signal is separated into two equivalent bandwidths. The high-pass band can be thought of as providing the signal's minor details of concern, while the low pass bandwidth contains the relevant data. In-order to obtain estimations and information, a discrete-wavelet-transform (DWT) of a signal is decomposed using low pass filter and high pass filter in a sequential process [14]. The low pass filter is denoted by LP, and the high pass filter is denoted by HP. The coefficients a1 (estimated form the main signal) and d1 are obtained from the first-decomposition the comprehensive shape form of the main signal. Furthermore, decomposing a1 gives two coefficients, a2 and d2. As seen in Fig. 4, a2 can also result in other decomposition locations.

Fault-detection is a vital move because stopping a device without a failure will lead to a loss of sales for the company, and fail to stop a defective device can result in more damage. Any tool created for this reason needs to be extremely precise. Two methods are looked at in this segment. The first sees the fractures as intermittent, high-frequency events. As a result, irregular behavior can be observed by looking at the energy content of high-frequencies. The next one is built on resonance, which is a mechanical-phenomenon. The mechanical system is designed to resist resonance in order to maintain normal behavior Fig. 3A. If a bearing fails though the resonant-frequencies are more likely to occur as high-frequency peaks in the spectrum Fig. 3B, and Fig.3C the orientation of the frequency peaks aids in the differentiation of normal and irregular behavior.

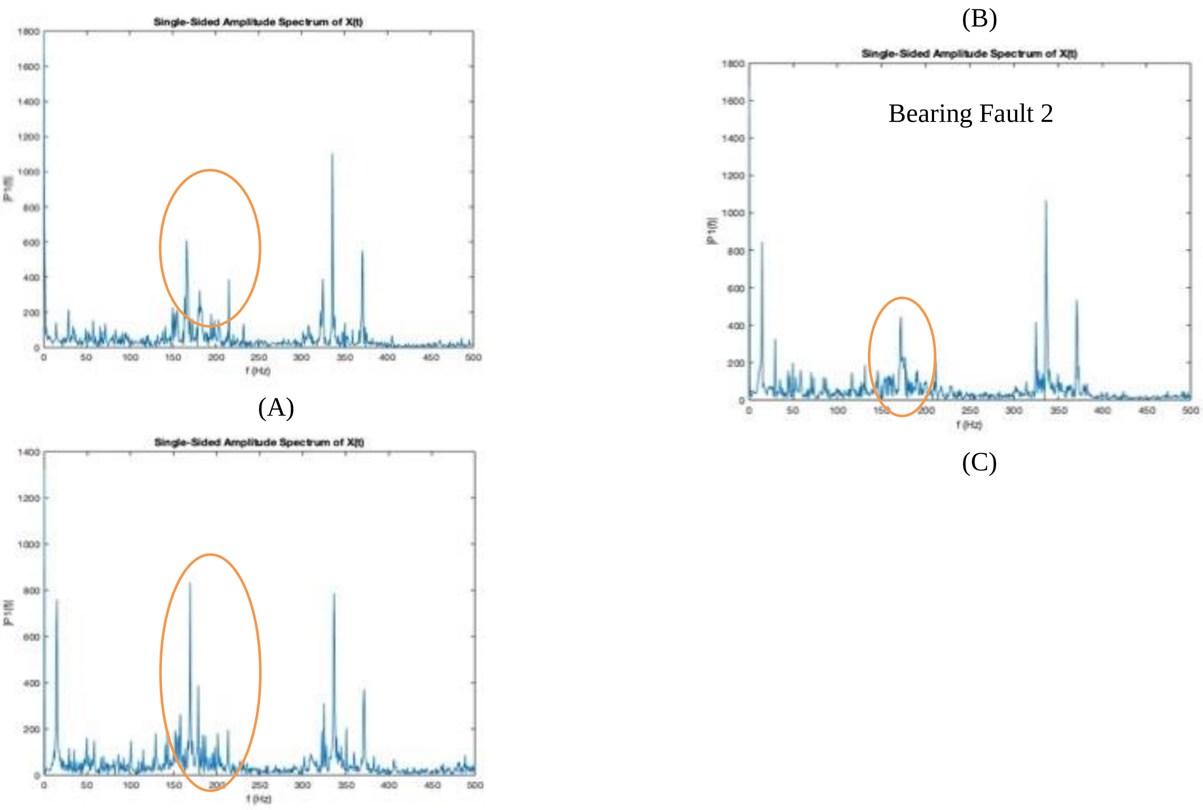


Fig. 3. Bearing signal spectrum for (healthy), (bearing 1), (bearing 2) faults, and the detected faults points

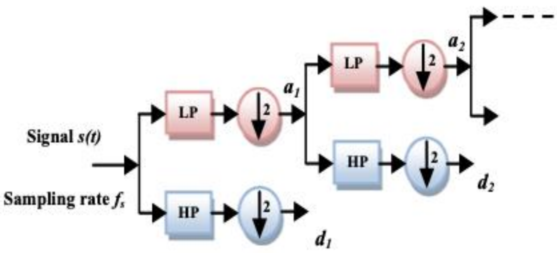
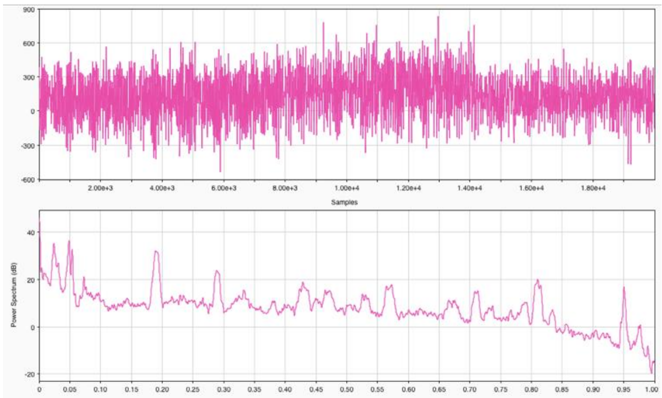
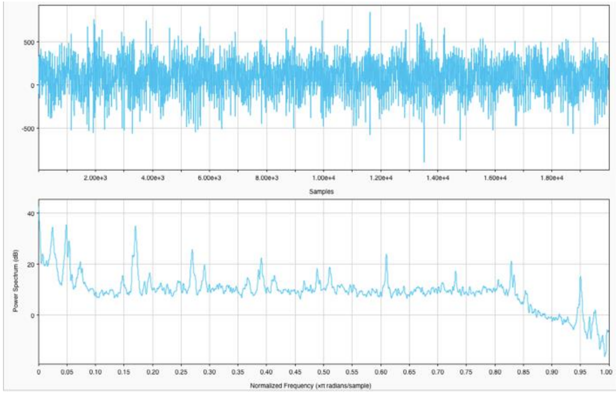


Fig. 4. Discrete wavelet process

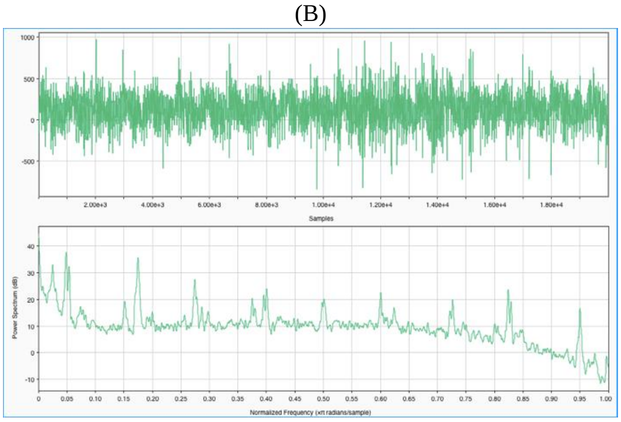
Fig. 5 (A, B, C) shows the frequency domain spectrum of the vibration signal that token from the induction motor in each state (healthy, bearing1 and bearing 2) after Apply (mean) feature, and we can notice that the signal spectrum going smother when the bearing fault increase during every measurement.



(A)



(B)



(C)

Fig. 5. Typical spectrum of vibration data after applying (mean) feature for: (A)Healthy motor, (B) Bearing1 fault (C) Bearing2 fault

When the-first method is used to analyze vibration data, the percentage of energy found that the freq-uencies is high when a failure happens and low when the machine is operating normally. We performed experiments that demonstrate that a wavelet-transform (Daubechies db4) thresholds on the standardised energy found in the frequency sub-band between 0 and 1000 Hz can effectively discern between faulty and normal behavior in a ball bearing . The position of the first three frequency peaks provides good results for the second method as well [15].

III. RESULTS

Data from an actual experimental-setup was used to validate the proposed methods performance. an asynchronous-motor with 0.37 kW provided vibration signals at various operating-frequencies for this purpose, shown in Fig. 6.

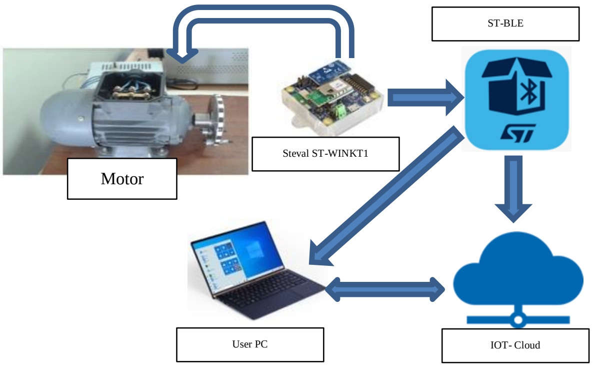


Fig. 6. Experimental Setup

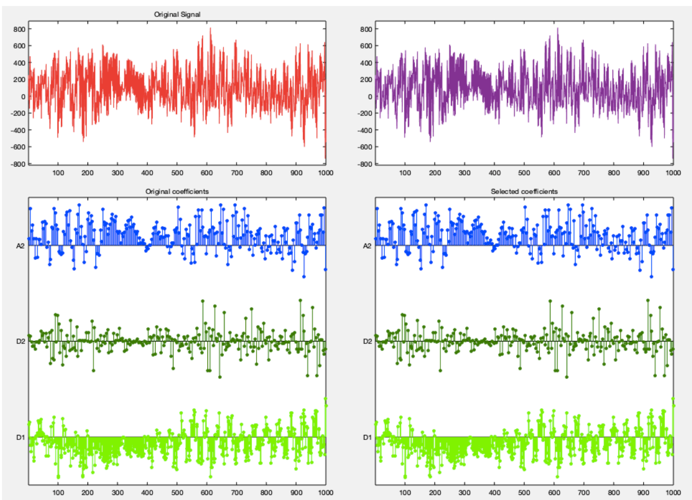
The eccentricity flaw is caused by a disk fixed on the motor-shaft. A discrepancy was created by first adding a screw to the first hole and then to the next hole in the same disc. The vibration signals were obtained using an NI 6211 model data processing card. The sampling-rate of 10 kHz has been chosen. The parameters are given in the Table 1.

Table 1. Motor parameters used in experiments

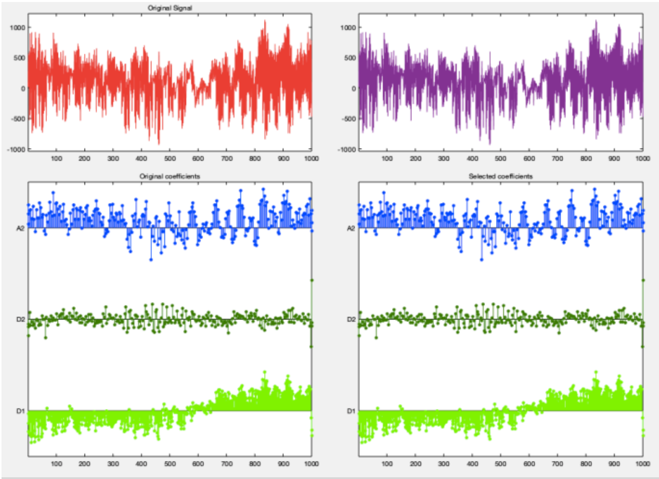
Parameter	**Value**
Power	0.37 kW
Full load Current	1.2 A
Supply frequency	50 Hz
Number of poles	4
Full load speed	1390 rpm
Supply voltage	380 V

For certain applications, simply detecting the fault isn't enough, it's also necessary to pinpoint its location. A flaw in a bearing can be found in one of three places, the ball, the outer race or the inner race. As a result, the fault locating can be viewed as a challenge of classification, with each class representing one fault spot. Appropriate and accurate functionality should be derived from the data to achieve high-classification accuracy. Wavelets-based techniques are discussed and adapted to vibration-data in this article. The signals are decayed using DWT decay, and a Bayesian classifier is used to classify them into different-classes, each describing a fault site various type.

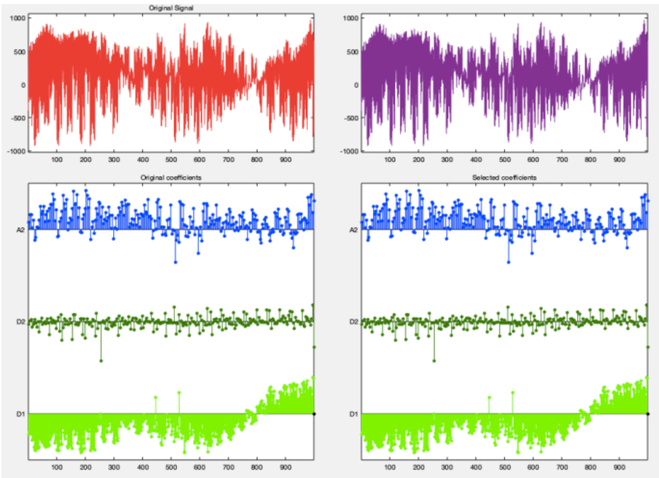
The next move is to choose the right mother wavelet for DWT-based features Fig. 4. shows the classification results for different mother-wavelets extracted using the obtained features from the Discrete Wavelet Transform of the data, the best features derived from the DWT are considered to be the root-mean-square (RMS) and the norm. Sym6, Sym5, Sym4, Db6, Db5 and Db4 are all feasible alternatives for the mother wavelet. in this article Db4 was applied to the database, a perfect-classification was accomplished.



(a)



(b)



(c)

Fig. 7. Discrete Wavelet Transform Features (Db4) for (healthy), (bearing1 fault), (Bearing2 fault) motor respectively.

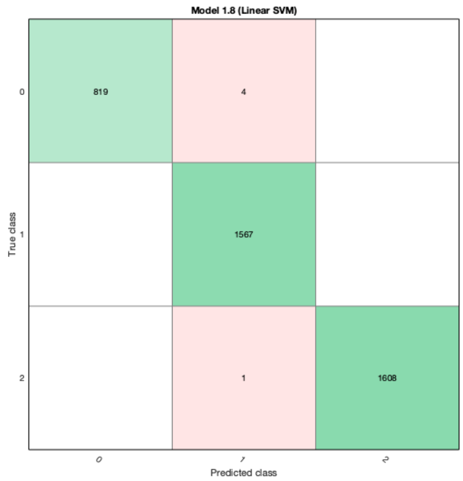


Fig. 8. Confusion matrix (SVM classifier)

as shown in Fig. 8. Just five samples are misclassified. The accuracy rating was found to be 99.9%. The classifier's efficiency was used to other machine learning systems. For this, the Matlab Classification-Learner tool was used. Fig. 9. displays the comparison effects.

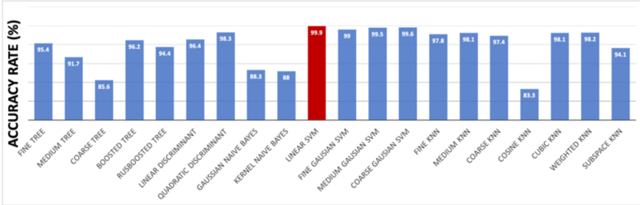


Fig. 9. Different machine learning classification method

Bayes-optimized SVM provided the best results. Another benefit of the suggested approach is that, since the frequency is calculated from the existing signals, the frequencies linked to the defect are automatically received.

IV. CONCLUSION

When defected bearings emit vibration-signals, the Discrete Wavelet Transform (DWT) has been used to detect fault features. The Fast-Fourier-Transform (FFT) is crucial in evaluating results obtained with MATLAB-Toolbox's The use of DWT as a method for detecting fault features in bearings is also sufficient on low-speed systems, however, it is recommended for the DWT performance. Many of these can be monitored remotely without the need to shut-down the system for repairs. As a result, this approach is recommended as an alternative technique for bearing defect detection in real-time monitoring, especially for high-speed systems.

V. REFERENCES

[1] Z. Peroutka, T. Glasberger, and M. Janda, “Main problems and proposed solutions to induction machine drive control of multisystem locomotive,” in *2009 IEEE Energy Conversion Congress and Exposition*, 2009, pp. 430–437. doi: 10.1109/ECCE.2009.5316403.

[2] C. Chen and C. Mo, “A method for intelligent fault diagnosis of rotating machinery,” *Digital Signal Processing*, vol. 14, no. 3, pp. 203–217, 2004.

[3] S. Poyhonen, P. Jover, and H. Hyotyniemi, “Signal processing of vibrations for condition monitoring of an induction motor,” in *First International Symposium on Control, Communications and Signal Processing, 2004.*, 2004, pp. 499–502.

[4] W. R. Finley, M. M. Hodowanec, and W. G. Holter, “An analytical approach to solving motor vibration problems,” in *Industry Applications Society 46th Annual Petroleum and Chemical Technical Conference (Cat. No. 99CH37000)*, 1999, pp. 217–232.

[5] S. Abbasion, A. Rafsanjani, A. Farshidianfar, and N. Irani, “Rolling element bearings multi-fault classification based on the wavelet denoising and support vector machine,” *Mechanical systems and signal processing*, vol. 21, no. 7, pp. 2933–2945, 2007.

[6] K. K. Shukla and A. K. Tiwari, *Efficient algorithms for discrete wavelet transform: with applications to denoising and fuzzy inference systems*. Springer Science & Business Media, 2013.

[7] L. Song, H. Wang, and P. Chen, “Vibration-based intelligent fault diagnosis for roller bearings in low-speed rotating machinery,” *IEEE Transactions on Instrumentation and Measurement*, vol. 67, no. 8, pp. 1887–1899, 2018.

[8] I. Attoui, N. Boutasseta, N. Fergani, B. Oudjani, and A. Deliou, “Vibration-based bearing fault diagnosis by an integrated DWT-FFT approach and an adaptive neuro-fuzzy inference system,” in *2015 3rd International Conference on Control, Engineering & Information Technology (CEIT)*, 2015, pp. 1–6.

[9] C.-Y. Lee and T.-A. Le, “Optimised approach of feature selection based on genetic and binary state transition algorithm in the classification of bearing fault in BLDC motor,” *IET Electric Power Applications*, vol. 14, no. 13, pp. 2598–2608, 2020.

[10] A. K. Verma, S. Radhika, and S. v Padmanabhan, “Wavelet based fault detection and diagnosis using online MCSA of stator winding faults due to insulation failure in industrial induction machine,” in *2018 IEEE Recent Advances in Intelligent Computational Systems (RAICS)*, 2018, pp. 204–208.

[11] Z. Wang, L. Yao, and Y. Cai, “Rolling bearing fault diagnosis using generalized refined composite multiscale sample entropy and optimized support vector machine,” *Measurement*, vol. 156, p. 107574, 2020.

[12] J. Shawe-Taylor and N. Cristianini, *Support vector machines*, vol. 2. Cambridge university press Cambridge, 2000.

[13] J. S. L. Senanayaka, S. T. Kandukuri, H. van Khang, and K. G. Robbersmyr, “Early detection and classification of bearing faults using support vector machine algorithm,” in *2017 IEEE Workshop on Electrical Machines Design, Control and Diagnosis (WEMDCD)*, 2017, pp. 250–255.

[14] F. Li, G. Meng, L. Ye, and P. Chen, “Wavelet transform-based higher-order statistics for fault diagnosis in rolling element bearings,” *Journal of Vibration and Control*, vol. 14, no. 11, pp. 1691–1709, 2008.

[15] G. Niu, *Data-driven technology for engineering systems health management*. Springer, 2017.

VI. BIOGRAPHIES

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