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CASE HISTORY—PEER-REVIEWED

Bearing Failure Analysis Using Vibration Analysis and Natural Frequency Excitation

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Abstract Ball bearings are the most critical components of rotating machinery in oil and gas companies. Typical research has focused on bearing failure detection based on bearing failure frequencies derived from the velocity spectrum. However, most bearing failures are caused by improper or insufficient lubrication. The current research utilizes a case study demonstrating when ball bearings must be replaced or relubricated due to poor lubrication conditions. Poor lubrication is the cause of natural frequency excitation in bearings, where rapid bearing damage is typically induced by poor lubrication film. According to experimental data in this study, the bearing failed due to natural frequency excitation. In addition, when analyzing a signal with the velocity spectrum, high frequencies are displayed. Bearing failure is detected without bearing failure frequencies using the natural frequencies of the bearing in the velocity spectrum signal. Moreover, an experimental investigation of the bearing failure of a liquid ring compressor was conducted utilizing a VIBXPERT II vibration analyzer and the Omni trend software. The velocity spectrum is derived based on a fast Fourier transform from a time signal. After lubricating natural frequencies must be disappeared from the velocity spectrum otherwise, the bearing is failed and must be changed.

Keywords Ball bearings · Natural frequency · The velocity spectrum · Lubrication · Rotating machinery

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Introduction

Ball bearings are continuous systems with an infinite frequency spectrum. The excitation of natural frequencies depends on exciting forces, where size, clearance, and bearing revolutions per minute are crucial for the amplitude of natural frequencies. This study is a case study that was gained at Lorestan petrochemical company. A liquid ring compressor is analyzed using a vibration analyzer based on signal processing. Signals shows when we must change bearings without bearing failure frequencies symptoms. Bearing failure analysis in engines is essential for prediction; thus, identification and classification of antifriction bearing failure in eddy current dynamometers have been investigated [1]. The inner and outer rings of bearings in variable frequency drive (VFD) motors are damaged by stray currents and fluting. Furthermore, fluting is caused by stray electrical motor currents that lack an adequate earthing system. Vibration analysis and signal processing methods were used to determine the bearing failure frequency using envelope and spectrum signals. Early bearing failure due to current damage has been studied, specifically bearing failure at the first time of running [2]. Induction motors are conventional, widely used industrial components. Unpredictable shutdowns due to failure raise maintenance costs. Bearings for induction motors have a substantial effect on production; therefore, early detection of bearing failure reduces costs and permits immediate shutdown. Predictions are made using machine learning as a reliable method to detect and predict bearing failure. This prediction is possible at varying speeds. To this end, the effectiveness of machine learning-based diagnostic methods has been evidenced using experimental data [3]. Bearing failure leads to machine failure, where early detection prevents failure and breakdown of bearings. Vibration analysis and signal processing are generally used to predict bearing failure. However, one study predicted bearing failure using acoustic emission [4]. Bearings are extensively utilized in mechanical and electrical machines. Fractures in mechanical components have detrimental effects on production and increase costs. Another study utilized a simulated annealing algorithm to optimize neural network convolution-based fault diagnosis [5]. The primary cause of bearing failure is wear. Wear occurs gradually and over time. Due to the time-consuming nature of wear, it is typically neglected. The deterioration of a worn bearing surface will increase noise and vibration. The causes and progression of surface wear on motor bearings have been analyzed. The findings indicate that the inner races of motor bearings experience uniform wear [6]. Periodic dynamic loads on ball bearings cause bearing fatigue and failure; thus, uncertainty and experimental analysis for the failure of rolling elements bearing has been performed and studied for silicon nitride bearings [7]. Wind energy is the most effective form of energy generation in the world. The components of a wind turbine are susceptible to complicated failure. The maintenance and dependability of wind turbines are of paramount importance to industry. The bearing is the main component of wind turbine transmission that must be analyzed online or periodically. Wind energy is both recyclable and renewable. Bearings are a delicate component of wind turbines, where numerous bearing failures are attributable to inadequate lubrication. The efficiency and stability of wind turbines are dependent on bearing behavior. With proper maintenance, the dependability and durability of these components have increased. Various bearings and structures of wind turbines have been compared to demonstrate bearing life under variable lubrication conditions [8]. The failure diagnosis of antifriction bearings has been performed using proximity sensors placed at the bearing location for signal analysis. Bearings monitoring and vibrations signal measurement serves primarily to provide a maintenance strategy to prevent catastrophic machine failure. An experimental data-based model (EDBM) has been highlighted in this respect. The authors of [9] developed an experimental model for diagnosing and predicting the failure signal of bearing parts. Different bearing parameters, such as dimensions, loads, and clearances, are effective for estimating bearing life [10]. The use of rotary machines has increased in oil and gas companies, where Bearings are a fundamental component of rotary machines. Bearing failure is crucial for reducing maintenance costs and production in the industry. To this end, vibration spectrum analysis and different fault detection have been conducted. For example, fast Fourier transform (FFT) is one of the standard methods for detecting bearing failure. In addition, vibration has been analyzed using Inverse fast Fourier transformation (IFFT) as a failure detection technique under various failure detection methods [11]. The dynamic behavior of rolling bearings is contingent upon the rolling elements and contact surfaces. Contact effects are essential for model-based fault diagnosis, lifetime estimation, and noise reduction in the machine applications of several companies. A five-degree-of-freedom angular contact ball bearing is formulated and modeled to demonstrate the effect of elastohydrodynamic (EHD) lubrication on bearing contact parts [12]. Ball bearings are essential machinery components for oil and gas companies. These components are widely employed and conventional. Early prediction and detection are two techniques that aid in reducing and minimizing maintenance costs. Fast Fourier transform (FFT) and Inverse fast Fourier transformation (IFFT) have been utilized to demonstrate clear bearing failure frequencies [11]. Over 40% of induction motor failures are caused by bearing failures. Bearing failure has been monitored for decades. Measurements of vibrations and electromagnetic signals are used for early failure detection. In one study, algorithms for evaluating deep learning were designed for automatic fault diagnosis, where induction motor current and external stray flux was detected through a novel method [13]. Intelligent fault diagnosis aids in the early detection of machinery failure and is an effective method for diagnosing bearing and machinery failure. Intelligent methods and extensive vibration signal experiments have been compared to demonstrate the effectiveness of intelligent bearing failure prediction [14]. A hybrid method employing both machine learning and adaptive cascade observer has been developed where the normal signal approximation is obtained for failure detection. Vibration and acoustic emission (AE) datasets were utilized to validate the efficacy of the adaptive cascade observer with the support vector machine (SVM) fault identifier. According to the results, the average vibration and AE fault diagnosis using the adaptive cascade observer with the SVM fault identifier is 97.8 and 97.65%, respectively [15]. In addition, vibration current fusion bearing failure was detected rapidly using statistical features and neural networks (NNs) [16]. A skf6322 code was analyzed for a rotational blower bearing. Furthermore, power spectral density (PSD) generated for failure analysis has been investigated. PSD was used to present excited frequencies such as the shaft rotation speed, blade frequencies, and bearing cage and ball frequencies. For the comparison, the blower vibration trend was analyzed per ISO 10816, which can aid in predictive maintenance and prevent catastrophic failure [17]. Wind turbines are essential for converting wind energy into electricity. In this machine (Table 1), bearings and gearboxes are utilized extensively. Tribology issues in bearings significantly

Table 1 Bearing failure frequencies in a liquid ring compressor at 996 rpm

Input		Output	
Bearing type	7232 BCBM	Shaft speed frequency	16.600 Hz
Pitch diameter	225 mm	Inner race defect frequency (BPFI)	150.744 Hz
Rolling element diameter	39.688 mm	Outer race defect frequency (BPFO)	114.856 Hz
Number of rolling elements (per row)	16	Cage defect frequency (FTF)	7.178 Hz
Contact angle	40 (degrees)	Ball spin frequency (BSF)	46.195 Hz
Rotational speed	996 rpm	Rolling element defect frequency	92.391 Hz
Rotating ring	Inner race		

impact the presentation of tribology-based failure modes. To this end, condition monitoring, fault diagnosis, and failure mode analysis utilizing an experimental scale and signal processing have been investigated. The procedure concludes with a review of the bearing condition monitoring and fault diagnosis method [18]. Since rotary machines comprise most of the industry, fault detection is crucial in these machines. Bearings, gearboxes, and rotors are among the most fundamental components of these rotary machines. Bearing failure are detected using an online monitoring vibrations sensor and portable vibration analyzer. Consequently, different types of machine learning algorithms have been presented to detect bearing parts failure analysis: (a) bearing health conditions (HC), (b) inner race fault (IF), and (d) ball bearing fault (BF). SVM is demonstrated by many comparison methods to be the algorithm with the highest accuracy [19]. In the present study, failure of an angular contact ball bearing is detected without any fundamental train frequency (FTF), ball pass frequency inner race (BPFI), ball pass frequency outer race (BPFO), or 2ball Spain frequency (2BSF) symptoms in the velocity spectrum. The bearing failure is detected by collecting vibration data with VIBEXPERTII and analyzing vibration signals with OMNITREND. The ball bearing failure was detected without any previously calculated bearing failure frequencies. Research has been conducted on the liquid ring compressor for bearing and root cause failure analysis. According to the technical report, Nippon Seikō Kabushiki-gaisha-Japanese Company (NSK) developed, the natural frequency formula depends on bearing dimensions. This study verifies the correlation between experimental bearing natural frequencies and the NSK report frequency.

Ball Bearing Failure Frequencies Calculation

Each bearing's dimensions determine its failure frequency, and mathematical formulas are used to calculate the failure frequencies of the revolution. Equation 1 shows the ball pass frequency inner race (BPFI) identified in the spectrum when the bearing inner race fails. Equation 2 identifies the ball pass frequency outer race (BPFO) in the spectrum. Equation 3 displays the fundamental train frequency (FTF) identified in the spectrum when the bearing cage fails. Equation 4 identifies the ball Spain frequency (BSF) in the spectrum when the bearing balls fail. shows the bearing failure frequencies. All data and bearing failure frequencies are computed for a compressor speed of 996 rpm.

$$\mathrm{BPFI} = \frac{N}{2} \times F\left(1 + \frac{B}{P} \times \cos\theta\right) \quad \text{(Eq 1)}$$

$$\mathrm{BPFO} = \frac{N}{2} \times F\left(1 - \frac{B}{P} \times \cos\theta\right) \quad \text{(Eq 2)}$$

$$\mathrm{FTF} = \frac{F}{2} \times \left(1 - \frac{B}{P} \times \cos\theta\right) \quad \text{(Eq 3)}$$

$$\mathrm{BSF} = \frac{P}{2B} \times F\left(1 - \left(\frac{B}{P} \times \cos\theta\right)^2\right) \quad \text{(Eq 4)}$$

where B is the ball diameter, P is the pitch diameter, Theta is the contact angle, N is the number of balls, and F is rotating unit frequency (speed). In this case the outer ring is stationary and inner ring is rotary.

Nippon Seikō Kabushiki-Gaisha-Japanese Company (NSK) Bearings Technical Report

Bearing failure can occur for numerous reasons. The leading cause of natural frequency excitation and bearing failure is poor lubrication. Per Eq 5 (NSK report), the first mode of natural frequency for 7232 BCBM must be excited at 868 Hz. Researchers from NSK determined the predominant natural frequencies of roller bearings to demonstrate the phenomenon of beating in bearings. This study shows experimental research and NSK bearing failure data regarding which frequencies excite and fail bearings. Inner and outer ring diameters play a crucial role in the excitation of natural frequencies. Eq 5 shows natural frequencies per the NSK technical report [20].

$$F(nf) = 9.41 \times 10^5 \times \frac{k(D-d)}{(D-k(D-d)^2)} \times \frac{n \times (n^2-1)}{\sqrt{n^2-1}} \quad \text{(Eq 5)}$$

D Bearing outer ring diameter (mm), d Bearing bore (mm), K Constant (0.15 for bearing with seal groove, 0.12 for bearing open type), n Bearing mode shape + 1

$$F(nf) = 9.41 \times 10^5 \times \frac{0.15(290-160)}{(290-0.15(290-160))^2} \times \frac{2 \times (2^2-1)}{\sqrt{2^2-1}} = 868 \text{ Hz}$$

Data Analysis Results

Omni trend software is used for data analysis. In this research data analysis and signal processing are based on filtering of the velocity spectrum. As you know, the velocity spectrum is gained from a fast Fourier transform based on a time signal. The velocity spectrum is processed using filtering, so the frequency range is 1600 Hz, the number of lines is 102400, the high pass filter is 0.5 Hz, the average is 3 (Linear), the window is hanning, and the overlap is 50%. As a result of data collection and analysis, the velocity spectrum does not exhibit bearing failure frequencies. Excitation with a high frequency and amplitude indicates that bearings operate under inadequate lubrication conditions. When bearings operate under poor lubrication conditions, they must be relubricated to produce lubrication films. After relubrication, high frequencies with high amplitude must be transformed into high frequencies with extremely low amplitude (Table 2). If high frequencies with high amplitude are again excited, the bearing must be replaced due to inner or outer race failure. Figure 1 depicts the compressor drive end (DE) spectrum waterfall. In Fig. 1, the first five signals with high amplitude represent failed bearings, while the second five signals with low amplitude represent normal bearings.

Figure 2 depicts the velocity spectrum of a failed bearing with high excitation frequencies and high amplitude, respectively. Figure 3 shows the velocity spectrum of a bearing following a change induced by a low-frequency excitation with a small amplitude in both normal and zoom sizes.

Figure 4 depicts a 7232 BCBM bearing examined for this study. displays bearing frequency excitation under poor and normal conditions before and following bearing removal. No bearing failure frequencies were present in the velocity spectrum. Conversely, natural frequencies with high frequencies and high amplitude only were observed for the failed bearing.

Table 2 Bearing failure natural frequencies for a liquid ring compressor at 996 rpm

Natural frequency excitation in failed bearing				Low-frequency excitation in normal bearing			
#	f (Hz)	Value		#	f (Hz)	Value	
1	845.75	0.68	High frequencies and high amplitude	1	16.63	0.25	Rotational speed frequency
2	845.56	0.62		2	43.38	0.21	Low frequencies with low amplitude
3	120.81	0.54		3	36.25	0.15	
4	846.13	0.36		4	37.13	0.15	
5	16.63	0.26	Rotational speed frequency	5	38.75	0.15	
6	178.06	0.22	High frequencies and high amplitude	6	36.50	0.15	
7	852.69	0.19		7	37.63	0.14	
8	849.06	0.18		8	38.94	0.14	
9	838.63	0.18		9	35.69	0.14	
10	852.81	0.18		10	35.94	0.14	

This study's experimental findings indicate that bearing natural frequency is exciting. The natural frequencies of 7232 BCBM bearings range between 845 and 852 Hz. Figures 5 and 6 depict, respectively, a liquid ring compressor and a failed bearing. If the bearing velocity spectrum contains numerous high-amplitude frequencies at high frequencies, the lubrication conditions for ball bearings will be inadequate. Poor lubrication can quickly damage the inner race. When high frequencies are detected, it is necessary to relubricate the bearing. After the bearing has been relubricated, high frequencies must disappear. If high frequencies persist, the course must be altered. High frequencies appeared after data collection between 800 and 1200 Hz. High frequencies remained even after relubricating the ball bearing. Consequently, the bearing was replaced due to a permanent symptom of natural frequencies. As depicted in Fig. 6, inner race failure was evident after the bearing was replaced.

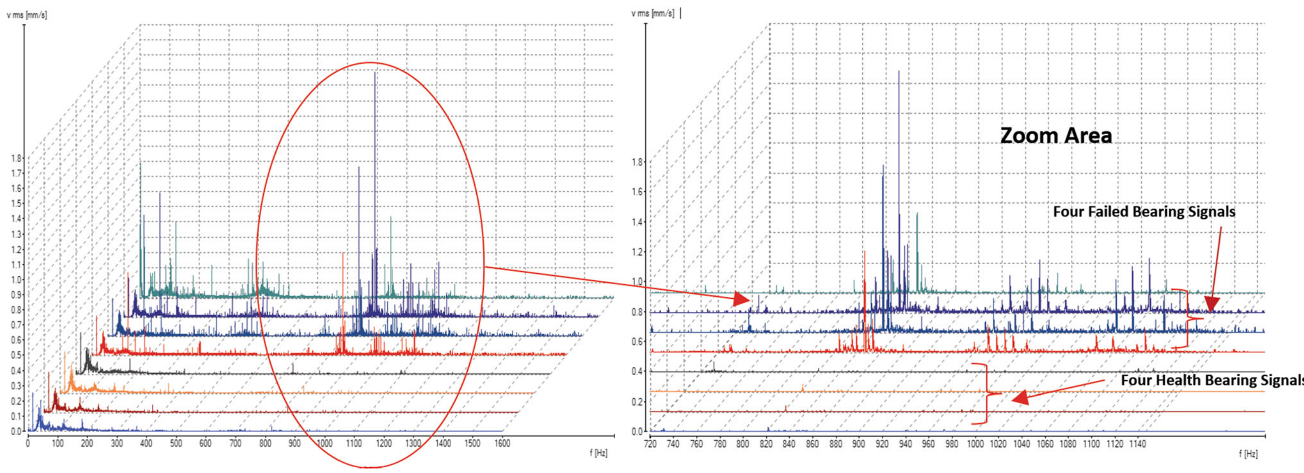

Fig. 1 Waterfall spectrum NDE

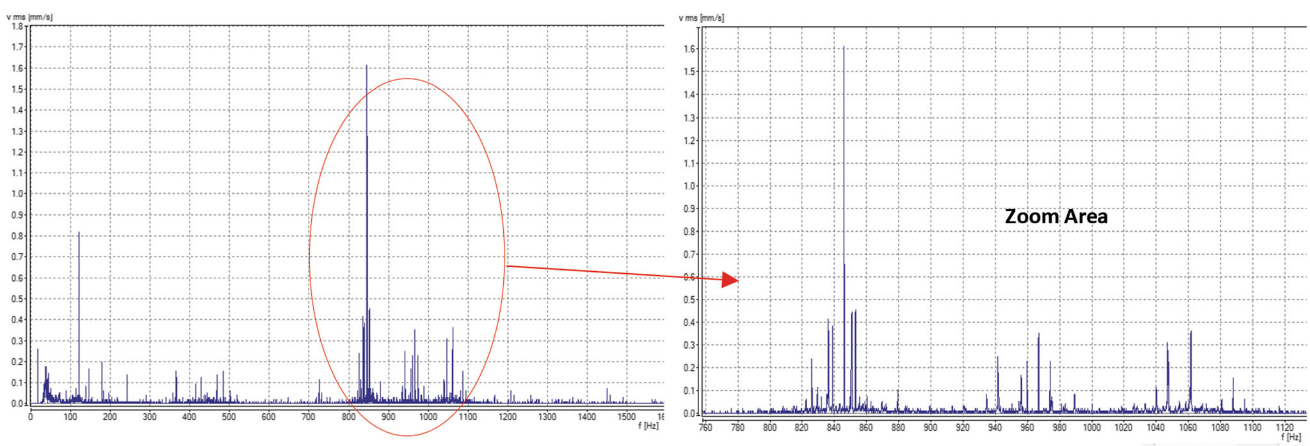

Fig. 2 NDE bearing velocity spectrum before a change in amplitude at high frequencies

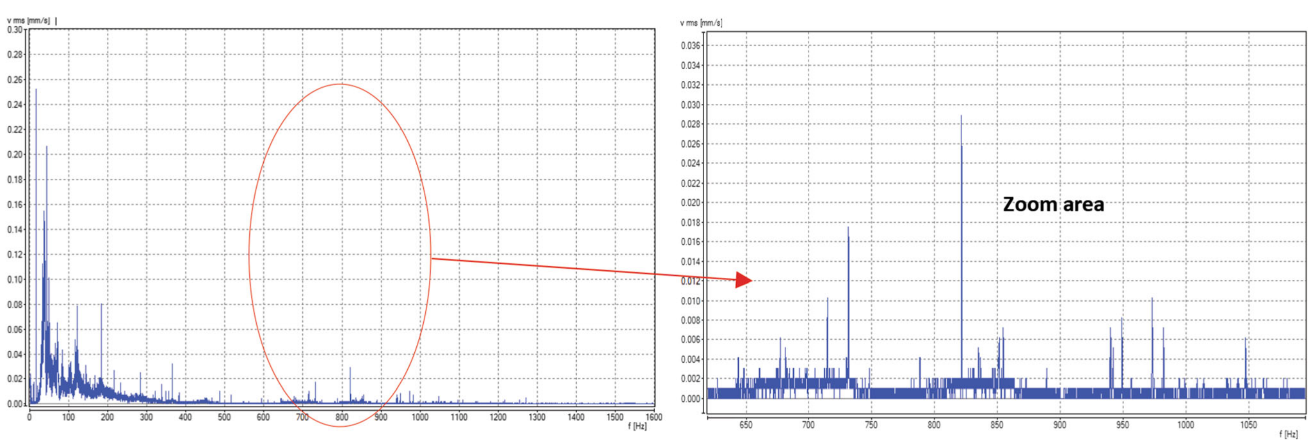

Fig. 3 NDE bearing velocity spectrum after a change with extremely low amplitude at high frequencies

Fig. 4 7232 BCBM analyzed bearing

Fig. 5 Liquid ring compressor data collection location

Fig. 6 Failed antifriction ball bearing

Conclusion

The results of this study confirm the NSK reports' findings. This study indicates that the bearing's natural frequency signal in the velocity spectrum may indicate bearing failure. Using the NSK calculation formulas and results presented in this report, the bearing natural frequencies were calculated to be 868 Hz and 845.72 Hz, respectively. The optimal velocity spectrum response is a signal at 1 rpm with no high-frequency excitation. Natural frequencies with amplitudes greater than the speed frequency of the machine are harmful to bearing health. The results indicate a failed bearing without any calculated bearing failure frequency in the velocity spectrum. The bearing was lubricated by identifying the bearing's natural frequencies at high frequencies. High frequencies did not disappear after lubrication; consequently, the bearing was removed. The primary objective of this study was to validate the NSK report and experimental vibration results to demonstrate how natural frequency excitation causes bearing failure.

References

1. R. Rohani, S.M. Jafari, M. Roozban, Study of ball bearings failure modes in an eddy current dynamometer. J. Eng. Res. **41**, 03–11 (2016)
2. A. Hemati, A case study: fluting failure analysis by using vibrations analysis. J. Fail. Anal. Prev. **19**, 917–921 (2019)
3. P. Zhou, M. Lin, F. Zhou, L. Gong, W. Ao, Bearing characteristics and failure mechanism of a novel plate-short anchor structure for tunnel crack reinforcement. Eng. Fail. Anal. **135**, 106–160 (2022)
4. N.W. Nirwan, H.B. Ramani, Condition monitoring and fault detection in roller bearing used in rolling mill by acoustic emission and vibration analysis. Mater. Today Proc. **51**, 344–354 (2022)
5. H. Nakamura, Y. Mizuno, Diagnosis for slight bearing fault in induction motor based on combination of selective features and machine learning. Energies. **15**, 453 (2022)
6. Y. Liu, Z. Chen, K. Wang et al. Surface wear evolution of traction motor bearings in vibration environment of a locomotive during operation. Sci. China Technol. Sci. **65**, 920–931 (2022)
7. S. Pattabhiraman, G. Levesque, N.H. Kim, N.K. Arakere, Uncertainty analysis for rolling contact fatigue failure probability of silicon nitride ball bearings. Int. J. Solids Struct. **47**, 2543–2553 (2010)
8. A. Dhanola, H.C. Garg, Tribological challenges and advancements in wind turbine bearings: a review. Eng. Fail. Anal. **118**, 104885 (2020)

9. R.G. Desavale, R. Venkatachalam, S.P. Chavan, Antifriction bearings damage analysis using experimental data based models. J. Tribol. **135**(4), 041105 (2013)
10. I.M. Jamadar, D.P. Vakharia, An in-situ synthesized model for detection of defective roller in rolling bearings. Eng. Sci. Technol. Int. J. **19**(3), 1488–1496 (2016)
11. A. Khadersab, S. Shivakumar, Vibration analysis techniques for rotating machinery and its effect on bearing faults. Proc. Manuf. **20**, 247–252 (2018)
12. L. Bizarre, F. Nonato, K.L. Cavalca, Formulation of five degrees of freedom ball bearing model accounting for the nonlinear stiffness and damping of elastohydrodynamic point contacts. Mech. Mach. Theory. **124**, 179–196 (2018)
13. M. Minervini, M.E. Mognaschi, P. Di Barba, L. Frosini, Convolutional neural networks for automated rolling bearing diagnostics in induction motors based on electromagnetic signals. Appl. Sci. **11**(17), 7878 (2021)
14. Lu. Jiantao, W. Qian, S. Li, R. Cui, Enhanced K-nearest neighbor for intelligent fault diagnosis of rotating machinery. Appl. Sci. **11**, 919 (2021)
15. F. Piltan, J.-M. Kim, B.F.I.U.M. Learning, A.C.F. Observer, Appl. Sci. **10**, 5827 (2020)
16. J.J. Saucedo-Dorantes, I. Zamudio-Ramirez, J. Cureno-Osornio, R.A. Osornio-Rios, J.A. Antonino-Daviu, Condition monitoring method for the detection of fault graduality in outer race bearing based on vibration-current fusion, statistical features and neural network. Appl. Sci. **11**, 8033 (2021)
17. J. Castilla-Gutiérrez, J.C. Fortes, J.M. Davila, Control and prediction protocol for bearing failure through spectral power density. Eksploatacja i Niezawodnosc—Maintenance Reliab. **4**, 651–657 (2020)
18. Z. Liu, L. Zhang, A review of failure modes, condition monitoring and fault diagnosis methods for large-scale wind turbine bearings. Measurement. **149**, 107002 (2020)
19. Y.N. Aldeoes, P. Ghockle, S.Y. Sondkar, Comparison of Machine Learning Algorithms for Bearing Failures Classification and Prediction. Advances in Electrical and Computer Technologies. ICAECT 2021, vol. 881, pp. 269–282 (2022)
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