Experimental Investigation of Failure Thresholds of Rolling Element Bearings

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***Abstract*— The rolling element bearing (REB) is the most common mechanical element used in industrial machinery. Usually, in data-driven prognostic models for predicting the remaining useful life (RUL) of REBs, the failure threshold (FT) is assumed as a constant value of a statistical feature, such as root mean square (RMS), peak or kurtosis, extracted from vibration signals collected by sensors. The procedure to define the FT value is conservative and expert-based. In addition, FT is typically defined only with respect to one of the features. In this paper, to analyze the effect of the definition of FT by only one feature, the correlation of statistical features is studied on accelerated-life datasets of REBs. First, by reviewing the literature in the field of PHM and FT, features including peak, kurtosis, RMS, and level crossing rate are selected to be analyzed. Then, the correlation of these features is investigated on the PRONOSTIA and the Sharif University of Technology accelerated-life datasets. The results show that the correlation of features varies in the different tests of these datasets. As a result, in this paper, it is proposed that the FT is to be defined as a multi-feature fusion, which arises from the relationship between features. This proposed method helps resolve the ambiguity in defining the FT as a single fixed value.**

Keywords—failure threshold (FT), remaining useful life (RUL), multi-feature fusion, signal processing, PRONOSTIA dataset.

I. Introduction

Predictive maintenance of rotating machinery plays an important role for the reliability and safety of industrial systems [1]. Rolling element bearings (REBs) are one of the most common mechanical components of rotating machines, and their failure is the main cause of 45% to 55% of machine failures [2]. Therefore, in the last two decades, methods for the prediction of the remaining useful life (RUL) of REBs have become of interest. The RUL of a REB is defined as the amount of remaining life of the equipment until a feature of the vibration signal reaches a predetermined FT value [3]. Generally, this threshold value is determined experimentally and conservatively. As a result, determining the appropriate FT plays a key role in industrial applications.

In the literature, there are several approaches to determining the FT. Usually, in most RUL prediction works, the FT is defined as a constant value of a statistical feature of the vibration signals (such as the peak amplitude or RMS of the time signal) [4]. By so doing, the process of predicting the RUL becomes straightforward. However, some researchers have taken different approaches to predict the RUL. Peng et al. [5] categorized the FT into soft and hard FTs and assigned a constant value to each. Soft failure occurs due to gradual degradation over time, and hard failure arises because of the effects of sudden impacts. In most life prediction problems of REB, failure is regarded as a soft failure. Wang and Kuwait [6] investigated the effect of the statistical distribution of FT on the reliability of the equipment. In this method, instead of assuming a constant value, the FT is described as a probability distribution because of the variability in the desired reliability values that operators consider for stopping the machines. Hua et al. [7] proposed a method for adaptively determining the FT. Nystad et al. [8] used the gamma probability distribution, in which the mean and standard deviation were determined by experts, to describe the FT in the life prediction process. Liao and Tian [9] also studied the effect of load on determining the FT and explained the dependence of FT on the radial force. Behzad et al. [10] proposed the FT of the REBs as the probability distribution of a vibration feature by using principal component analysis (PCA) and copula models. Finally, they discussed the effect of the proposed FT on the RUL prediction. Works on the RUL prediction of REBs use as case study the data set acquired by the center of Intelligent Maintenance Systems (IMS) at the University of Cincinnati [11] as well as

the PRONOSTIA data set published at the PHM 2012 conference [12]. The FT or stopping criterion is defined as the specific level of accumulated debris in the lubrication system in the IMS dataset. However, in the PRONOSTIA dataset, the peak amplitude of 20g in the acceleration signal is considered as the stopping criterion.

The definition of the FT as a constant value of a signal feature is commonly used in data-driven methods of RUL prediction. These methods describe the REB degradation process by constructing health indicators (statistical features) in the time and frequency domains, through signal processing [13]. Among the most widely used statistical features in the time domain are RMS [14], kurtosis [15], peak [16] and PSW [17]. In the frequency domain, Ball Pass Frequency Inner race (BPFI), Ball Pass Frequency Outer race (BPFO), Ball Spin Frequency (BSF), and Fundamental Train Frequency (FTF) are used [18].

To determine the best features to use as equipment health indicators, Liu et al. [19] studied the correlation between statistical features of vibration signals and the defect size in REBs, using the Case Western Reserve University dataset. They calculated the Pearson correlation coefficient for 25 different statistical features in the time and frequency domains with defect size levels. Features with high and constant correlation coefficients to change operating conditions (speed) were introduced as the best features to describe defect growth. These features include peak, RMS, and skewness for the inner race fault and kurtosis, peak, and skewness for the outer race. Behzad et al. [20] also introduced the level crossing (LC) rate as a feature with a high correlation with defect growth in the inner and outer race of REBs.

In the following sections, first the FT concept in REBs is discussed and explained. Then, the Sharif University of Technology (SUT) and PRONOSTIA accelerated-life data sets are introduced. Finally, the relationship between statistical features of vibration signals in the tests of these data sets is investigated. The purpose of examining this relationship is to challenge the problem of defining a FT by only a single feature value. Eventually, due to the correlation between the features in different failure modes, it is proposed to define the FT as a multi-feature fusion.

II. Failure Threshold

Different failure modes and degradation processes can lead to the failure of REBs in rotating machines [21]. If the REB is designed correctly, properly manufactured and installed and is always adequately lubricated, installed, and aligned during operation, (away from moisture, corrosion, and excessive loading), then the mechanism that could lead to failure is the rolling contact fatigue (RCF) [22]. This is why, in most research studies related to the prediction of the RUL, the mechanism of RCF is considered. In this paper, the determination of the FT is addressed with respect to the physics of failure by spalling. When a defective component comes in contact with another component (defective or healthy), it causes sudden impacts. These impacts stimulate the REB structure and the structure of the components associated with it and cause vibrations. The results of experimental tests show that despite the correlation between the size of the defects and the vibration amplitude, their relationship cannot be described deterministically and, to some extent, random behavior is observed. For instance, in the experiments conducted by the IMS center, the FT is defined based on the physical defect (oil contaminant level). But, the vibration amplitudes at the end of the tests are different.

In ISO 10816-3 [23], the marginal limit of vibration into zone D, which means immediate stop of the machine, can be considered as the FT. This standard defines the entry threshold in zone D in terms of machine power (Table I).

TABLE I. Vibration severity zone limits ISO 10816-3 [23]

<table>
<tr><th>Vibration severity</th><th colspan="4">Power of Machine</th></tr>
<tr><th>Value of Velocity (boundary mm/s)</th><th colspan="2">15 kW ~ 300 kW</th><th colspan="2">300 kW ~ 50 MW</th></tr>
<tr><td>0.71</td><td rowspan="2">A</td><td rowspan="3">A</td><td rowspan="3">A</td><td rowspan="6">A</td></tr>
<tr><td>1.4</td></tr>
<tr><td>2.3</td><td rowspan="2">B</td></tr>
<tr><td>2.8</td><td rowspan="3">B</td><td rowspan="3">B</td></tr>
<tr><td>3.5</td><td rowspan="2">C</td></tr>
<tr><td>4.5</td><td rowspan="2">B</td></tr>
<tr><td>7.1</td><td rowspan="3">D</td><td>C</td><td>C</td></tr>
<tr><td>11.0</td><td rowspan="2">D</td><td rowspan="2">D</td><td>C</td></tr>
<tr><td></td><td>D</td></tr>
<tr><td>Foundation</td><td>Rigid</td><td>Flexible</td><td>Rigid</td><td>Flexible</td></tr>
<tr><td colspan="5">A: Good, B: Satisfactory, C: Unsatisfactory, D: Unacceptable</td></tr>
</table>

In REBs, it is not possible to observe and track the size of the defect in operating conditions, and because there is no deterministic relationship between the defect size and the feature value, the defect size can be described by a distribution of the vibration feature. This distribution is usually assumed to be a Gaussian distribution. The advantage of defining a threshold as a fixed defect size is that it allows an easy reliability computation. However, the difficulty to establish the connection between the physics of defect and statistical features leads to ambiguity in the definition of the FT. Regarding the relationship between defect and vibration features, Liu et al. [19] proposed that the features of kurtosis and peak for the outer race, and RMS and peak for the inner race have an almost linear relationship with the growth of the defect. As a result, these features should also have a linear relationship to each other. In the following sections, the relationships between these features as well as the LC rate feature are analyzed on the accelerated life dataset of SUT and PRONOSTIA. The purpose of this analysis is to show the necessity of defining the FT as a combination of several vibration features. This definition also helps to clarify the relationship between different definitions of FTs as a fixed value of a feature in the literature.

III. Introducing Two REB Data Sets

In this section, two experimental run-to-failure data sets are introduced to study the effectiveness of the proposed method. Dataset-1 corresponds to a set of accelerated life tests of an REB in the laboratory of SUT. Dataset-2 corresponds to a set of accelerated life tests of an REB in the FEMTO Laboratory. The details of these two datasets are introduced in the next subsections.

A. Accelerated Life Test Data Set of SUT

A group of accelerated life tests on REBs was conducted in the condition monitoring (CM) lab of SUT. The test rig is shown in Fig. 1, in which, a test REB is mounted on one end of the shaft. Also, two other REBs have been used to support the weight of the shaft. As a drive system, the shaft is coupled to an electromotor through the pulley and belt. The test REB is a 6907 deep groove single-row bearing. The dimensions and bearing fault frequencies of the test REB are listed in Table II. The loading mechanism forces the housing of the test REB downward. Therefore, the loading zone is located at the top of the test REB. Experiments were conducted in unchanging operational conditions, 2000 rpm rotational speed and 9000 N radial load. In this setup, an accelerometer is installed vertically on the housing of the test REB. The sampling rate frequency for the accelerometer is 25.6 kHz. The stopping criterion or FT was defined on the peak of the acceleration signal. Therefore, reaching the peak of 20g was the final failure criterion, and accelerated life tests were stopped at this moment.

Fig. 1. Test rig of accelerated life tests on REBs.

TABLE II. Characteristics of Test REB

Dimensions	OD	Outer Diameter (mm)	55
	ID	Inner Diameter (mm)	35
	W	Width (mm)	10
	N	Ball numbers	11
BCFs	BPFO	Ball Pass frequency outer race	204.5
	BPFI	Ball Pass frequency inner race	262.1
	BSF	Ball spin frequency	132.9
	FTF	Fundamental cage frequency	14.6
Dynamic Characteristics	C_0	Static load rating (N)	6850
	C	Dynamic load rating (N)	9550

Six run-to-failure tests were performed in the mentioned test rig, and corresponding vibration data were acquired. At the end of each test, the test REB was dismantled, and final failure modes were investigated through visual inspection (Fig. 2). Table III reports the RUL of each test REB and the corresponding verified failure mode at the end of the tests [24].

TABLE III. Summary of Accelerated Life Tests

Test No.	Failure Mode	Useful life (sec)
1	Inner race	10961
2	Inner race	4181
3	Rolling element	81535
4	Inner race	26448
5	Rolling element	6498
6	Rolling element	5546

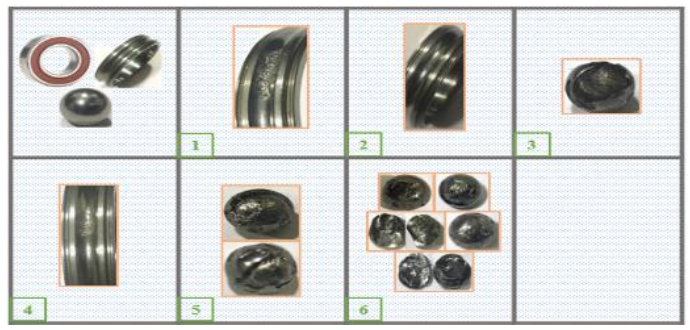

Fig. 2. Visual inspection results of failures in the elements of accelerated life test REBs.

B. Accelerated Life Test Data Set of PRONOSTIA

The FEMTO Laboratory developed an experimental platform to do accelerated life tests on REBs, seventeen accelerated life tests were performed on REB. The test data included vibration measurements in the horizontal and vertical directions throughout the REB life period, and the dataset was named PRONOSTIA. In this test, an electric motor with a power of 250 W and a speed of 2830 rpm was used as a drive system. The engine speed was reduced by a gearbox to less than 2000 rpm. In these tests, reaching the vibration amplitude to 20g is considered the stopping criterion or FT of the REB. Characteristics of the operating conditions and the number of tests performed are given in Table IV. Fig. 3 shows the test rig and its different parts.

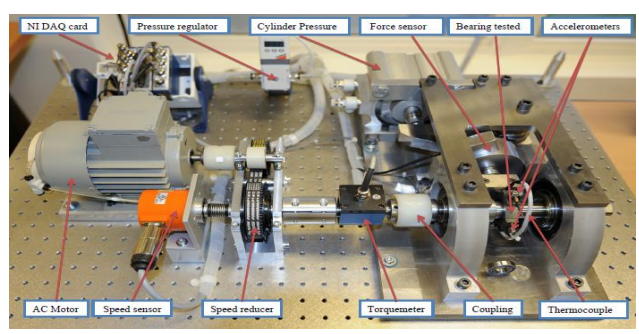

Fig. 3. Overview of PRONOSTIA tests platform [12].

TABLE IV. CHARACTERISTICS OF PRONOSTIA TEST [12]

No. of tests	Load (N)	Speed (rpm)	Operating condition number
7	4000	1800	1
7	4200	1650	2
3	5000	1500	3

IV. RESULTS

Different types of defects can occur in the REBs. The correlation of statistical features is studied on the SUT dataset and seven PRONOSTIA tests in the first operating condition to investigate the importance of considering several features for defining FT. The FT for both datasets is defined to be the 20g acceleration signal peak; measurement points with values higher than that are also observed. Also, both datasets have series of signals in their faulty stages, so comparing features in these datasets make sense.

Graphs of the peak relative to the RMS and kurtosis for the acceleration signal are plotted for both datasets (Fig. 4). These features were also investigated in [19]. According to the results of this work, the linear relationship between the peak and RMS features indicates inner race defect, and a linear relationship between the peak and the kurtosis demonstrates outer race defect. But Fig. 4 shows a linear relationship between two features of the peak and the RMS in all experiments, with different types of defects in the two datasets. As a result, the linearity of the relationship between these features cannot be the only reason for the defect in the inner race. In the relationship between peak and kurtosis, there is no linear relationship between these features in the SUT data set due to the lack of outer race defect on REBs. On the other hand, in the PRONOSTIA data set, tests 2 and 6 show a linear relationship between these features, which may be due to a defect in the outer race of the REB.

Graphs of the LC rate relative to the RMS and the peak for the acceleration signal are plotted in Fig. 5 for the SUT data set and seven tests in the first operating conditions of PRONOSTIA. The graph of the LC rate relative to the peak in the first operating conditions of PRONOSTIA, for tests 1, 3, and 4 to the peak value of 25g, behaves as a parabola and, then, decreases by increasing the peak. This behavior can be due to the combination of failure modes occurring in the REB. This point seems to be 5g in the graph LC rate relative to the RMS. Also, the LC rate graph has almost the same slope compared to the RMS for the three tests 3, 5, and 6 with the ball failure mode in the SUT data set, whereas for the three tests with the inner race failure mode, the slope of these graphs is higher than other failure modes. A similar approach is considered for PRONOSTIA tests. The graphs that have a lower slope than the dashed line shown for PRONOSTIA data are expected to relate to a ball or outer race failure, and those with a higher slope to an inner race failure.

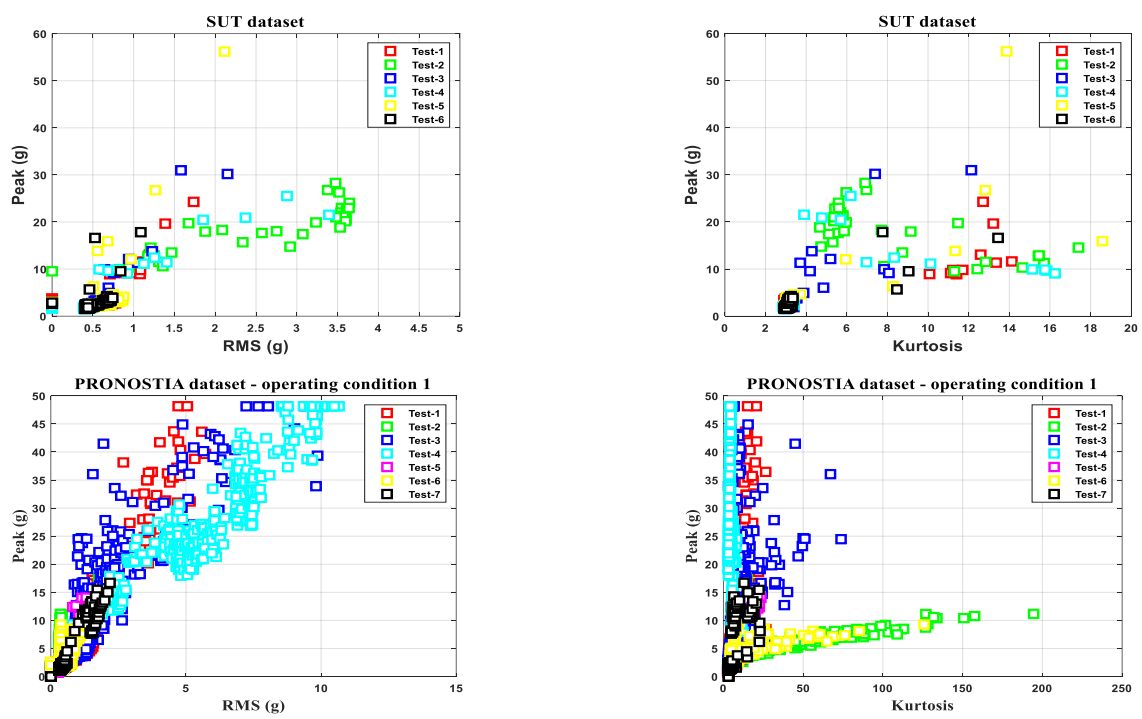

Fig. 4. Peak-RMS and Peak-Kurtosis graphs in the data sets of SUT and PRONOSTIA

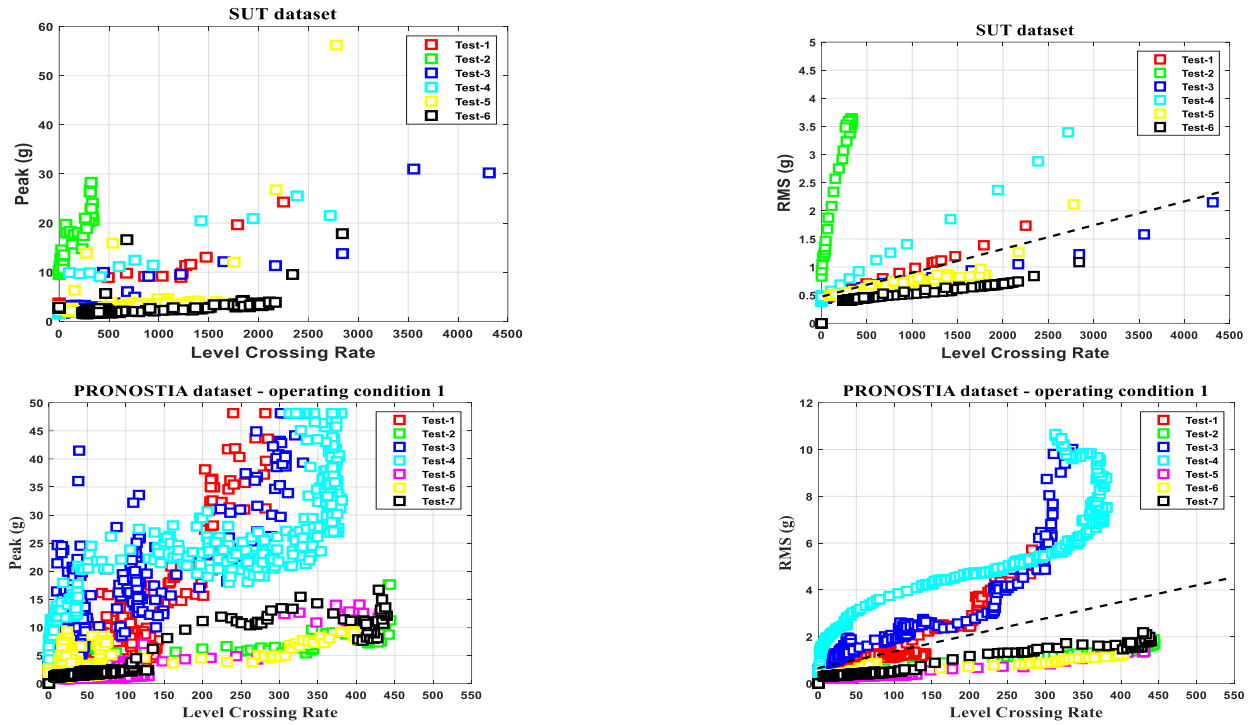

Fig. 5. Peak-Level crossing rate and RMS-Level crossing rate graphs in the data sets of SUT and PRONOSTIA

V. Conclusions

In this paper, we have investigated vibration features in the SUT and PRONOSTIA data sets with the aim of defining the FT. In view of the different possible definitions of FT based on features, the behavior of vibration features such as peak, kurtosis, RMS, and LC rate on two run-to-failure data sets was studied. It is found that the feature of kurtosis is a suitable feature for the growth of outer race defects. Also, the difference between the slope of the RMS relative to the level LC rate graph can be a good health indicator for separating inner race defects from ball and outer race defects. Therefore, to observe the growth of defects in REB components, we need to simultaneously examine various statistical features such as kurtosis, RMS, and LC rate. Consequently, it is necessary to define the FT based on several vibration features that result from the different failure modes of the REB elements.

References

[1] E. Zio, "Prognostics and health management of industrial equipment." Diagnostics and prognostics of engineering systems: methods and techniques. pp. 333-356, 2013.

[2] A. K. Mahamad, S. Saon, and T. Hiyama, "Predicting remaining useful life of rotating machinery based artificial neural network." Computers & Mathematics with Applications, vol. 60, no. 4, pp. 1078-1087, 2010.

[3] International Standards Organization (ISO). Condition Monitoring and Diagnostics of Machines - Prognostics part 1: General Guidelines. In ISO, ISO13381-1. Genève, Switzerland: International Standards Organization, 2015.

[4] D. Wang, and K. L. Tsui, "Two novel mixed effects models for prognostics of rolling element bearings," Mechanical Systems and Signal Processing, vol. 99, pp. 1-13, 2018.

[5] H. Peng, Q. Feng, and D. W. Coit, "Reliability and maintenance modeling for systems subject to multiple dependent competing failure processes." IIE transactions, vol. 43, no. 1, pp. 12-22, 2010.

[6] P. Wang, and D. W. Coit, "Reliability and degradation modeling with random or uncertain failure threshold," in 2007 Annual Reliability and Maintainability Symposium, pp. 392-397, 2007.

[7] C. Hua, Q. Zhang, G. Xu, Y. Zhang, and T. Xu, "Performance reliability estimation method based on adaptive failure threshold." Mechanical Systems and Signal Processing, vol. 36, no. 2, pp. 505-519, 2013.

[8] B. H. Nystad, G. Gola, and J. E. Hulsund, "Lifetime models for remaining useful life estimation with randomly distributed failure thresholds," in First european conference of the prognostics and health management society, vol. 3, 2012.

[9] H. Liao, and Z. Tian, "A framework for predicting the remaining useful life of a single unit under time-varying operating conditions." IIE transactions, vol. 45, no. 9, pp. 964-980, 2013.

[10] M. Behzad, S. Feizhoseini, H. A. Arghand, A. Davoodabadi, and D. Mba, "Failure Threshold Determination of Rolling Element Bearings Using Vibration Fluctuation and Failure Modes." Applied Sciences, vol. 11, no. 1, pp. 160, 2020.

[11] H. Qiu, J. Lee, J. Lin, and G. Yu, "Wavelet filter-based weak signature detection method and its application on rolling element bearing prognostics." Journal of sound and vibration, vol. 289, no. 4-5, pp. 1066-1090, 2006.

[12] P. Nectoux, R. Gouriveau, K. Medjaher, E. Ramasso, B. Chebel-Morello, N. Zerhouni, and C. Varnier, "PRONOSTIA: An experimental platform for bearings accelerated degradation tests." In IEEE International Conference on Prognostics and Health Management, PHM'12. pp. 1-8, June 2012.

[13] Y. Lei, N. Li, L. Guo, N. Li, T. Yan, and J. Lin, "Machinery health prognostics: A systematic review from data acquisition to RUL prediction. Mechanical systems and signal processing," vol. 104, pp. 799-834, 2018.

[14] X. Jin, Y. Sun, Z. Que, Y. Wang, and T. W. Chow, "Anomaly detection and fault prognosis for bearings. IEEE Transactions on Instrumentation and Measurement," vol. 65, no. 9, pp. 2046-2054, 2016.

[15] Z. X. Zhang, X. S. Si, and C. H. Hu, “An age-and state-dependent nonlinear prognostic model for degrading systems.” IEEE Transactions on Reliability, vol. 64, no. 4, pp. 1214-1228, 2015.

[16] A. Malhi, R. Yan, R. X. Gao, “Prognosis of defect propagation based on recurrent neural networks.” IEEE Transactions on Instrumentation and Measurement, vol. 60, no. 3, pp. 703-711, 2011.

[17] Z. Li, D. Wu, C. Hu, and J. Terpenny, “An ensemble learning-based prognostic approach with degradation-dependent weights for remaining useful life prediction.” Reliability Engineering & System Safety, vol. 184, pp. 110-122, 2019.

[18] J. Hu, and P. W. Tse, “A relevance vector machine-based approach with application to oil sand pump prognostics.” Sensors, vol. 13, no. 9, pp. 12663-12686, 2013.

[19] J. Liu, Z. Xu, L. Zhou, W. Yu, and Y. Shao, “A statistical feature investigation of the spalling propagation assessment for a ball bearing.” Mechanism and Machine Theory, vol. 131, pp. 336-350, 2019.

[20] M. Behzad, A. R. Bastami, and D. Mba, “A new model for estimating vibrations generated in the defective rolling element bearings.” Journal of Vibration and Acoustics, vol. 133, no. 4, 2011.

[21] International Standards Organization (ISO). Rolling Bearings-Damage and Failures-Terms, Characteristic and Causes. In ISO, ISO15243. Genève, Switzerland: International Standards Organization, 2017.

[22] T. A. Harris, and M. N. Kotzalas, “Advanced concepts of bearing technology: rolling bearing analysis.” CRC press, 2006.

[23] International Standards Organization (ISO). Mechanical Vibration—Evaluation of Machine Vibration by Measurements on Non-Rotating Parts—Part 3: Industrial Machines with Normal Power above 15 kW and Nominal Speeds between 120 r/min and 15000 r/min. In ISO, ISO10816-3. Genève, Switzerland: International Standards Organization, 2009.

[24] M. Behzad, A. Davoodabadi, H. A. Arghand, and A. Kiakojouri. “Comparison between Shock Pulse Method and Vibration Analysis Methods on Early Fault Detection of Rolling Element Bearing.” Journal of Theoretical and Applied Vibration and Acoustics, 2022.