A Comparative Study of Statistical Features used in Rolling Element Bearing Health Diagnosis using Six Sigma Approach

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Abstract

The purpose of this paper is to examine the ability of different statistical features obtained from denoised vibration signals to distinguish between healthy and defective Rolling Element Bearings (REB) at the six sigma significance level or Defects Per Million Observations (DPMO). Raw vibration signals from the experimental setup were subjected to Interval Dependent denoising. Discrete Wavelet Transforms (DWT) technique was used to generate 17 statistical features for 4 independent conditions of REB, viz., healthy(N), and REB with defects on Inner Race (IR), Outer Race (OR) and Ball (B). These statistical features were compared using the Independent Samples test at a six sigma significance level. Five statistical features that could distinguish between a defective and a healthy REB viz, Root Mean Square (RMS), Standard Deviation (SD), Square of Mean of Square Root (SMSR), Mean Absolute Value (MAV) and Log-log Ratio (LLR) at six sigma significance were identified. The methodology used in this study is a unique combination of vibration signal analysis, statistical feature extraction and simple inferential analysis of REB defects at very low significance levels comparable with six sigma DPMO. The identified statistical features can be used before predictive analysis.

Keywords
Rolling Element Bearing, Statistical Features, Discrete Wavelet Transforms, Independent Samples Test and Six Sigma.

1. Introduction
The research on Rolling Element Bearings (REB) fault diagnosis is important as REB plays a vital role in rotating machines and their rotating state is directly related to the performance of the machines (Ni, Wang and Zeng, 2019). Time Frequency analysis (TFA) is widely used in REB fault diagnosis and Discrete Wavelet Transform (DWT) is one of the prominently used TFA technique. The computing techniques such as artificial neural networks (ANN) and support vector machines (SVM) are being used increasingly for REB fault diagnosis and the effectiveness of these methods is directly related to the quality of the features (Rai and Upadhyay, 2016). Raw vibration signal with unwanted noise leads to improper fault diagnosis and hence, the raw signal is denoised to attain effective fault diagnosis. Several statistical features using different signal processing techniques were extracted from denoised vibration signals by past researchers to diagnose and predict REB failures. Recent research by Hoang and Kang (2019) used deep learning algorithms based on convolution neural networks. The bearing fault classification is performed by using features without using any feature selection method yielded good results under a noisy environment. However, another recent study (Niu et al., 2019) used Deep Belief Network and Principal Component Analysis (for feature reduction) for REB fault diagnosis. It may also be noted that approaches such as z scores and six sigma have been used in the past to improve fault detection accuracy (Mohanty, Sahu, and Mahapatro, 2018)
In this study, vibration signals of a 6205 deep groove ball bearing were acquired independently for a healthy REB, and defective REBs like REB with defect on the ball, defect on IR and defect on OR were subjected to Interval

based denoising method. Seventeen statistical features were extracted from the fourth decomposition level (0–1.5kHz and 1.5–3 kHz). To test the ability of these statistical features to differentiate between a healthy REB and a defective REB, these features with their associated conditions were subjected to the independent samples test at a significance level suited to six sigma standards. The outcomes of this study are expected to help researchers in identifying statistical features that critically distinguish a healthy and defective REB based on defects per million occurrences (DPMO). The following sections of this paper comprise literature review, formulation of hypotheses, research design, methodology, analysis and interpretation of results followed by discussions, implications and conclusions.

2. Literature Review

REB fault diagnosis is important as REB is one of the critical components of rotary machines and its malfunctioning leads to severe financial losses to the industry. REB status can be scrutinized by processing vibration signals (Liang et al., 2018). The different components of REB are inner race (IR), an outer race (OR), ball or rollers (B) and a cage. In REB, defect initiates either due to fatigue of the bearing surface or because of manufacturing errors that lead to localized defects (such as cracks, pits and spalls) and abrasive wear that lead to distributed defects (such as surface roughness, misaligned surfaces and waviness) (He, Ding, and Lin, 2016; de Almeida et al., 2015; Tandon and Choudhury, 1999). Vibration analysis-based monitoring techniques provide early information related to the progress of defective conditions in comparison to healthy bearing conditions (Peng and Chu, 2004). Various Signal processing techniques such as time, frequency, and time-frequency techniques (TFT) are widely used to analyse these vibration signals. By applying these techniques valuable information related to fault severity in REB can be obtained. Past research (He, Ding, and Lin, 2016; de Almeida et al., 2015; Peng and Chu, 2004; Tandon and Choudhury, 1999) has confirmed that statistical features play a vital role in the fault detection of rotary machines. Among these TFT, wavelet transforms is widely used due to its advantages as reported by Peng and Chu (2004) and Kumar et al. (2017).

2.1. Wavelet Based Denoising

The isolation of noise component associated with raw vibration signals is important for effective vibration signal analysis (Vijay, 2013). Hard and soft thresholding methods to denoise signals proposed by Donoho (1995) have been used by different researchers (Vijay, 2013; Peng and Chu 2004). The noises in bearing vibration signals are often stochastic in nature, whose frequency band will overlap with the interested signals. Therefore, conventional denoising schemes will not remove the noise from the signals effectively (Peng and Chu, 2004; Kumar et al., 2017) Wavelet based denoising (WBD) is superior to traditional methods according to Peng and Chu (2004), as soft and modified thresholding and modified soft thresholding approaches remove impulsive peaks in the vibration signal. This has led to the progress in more use of WBD schemes. More details and steps involved in WBD can be found in past research (Kumar et al., 2017; Peng and Chu, 2004). Üstündağ et al. (2013) proposed Interval Dependent (ID) denoising scheme in which threshold values are computed for each wavelet decomposition level. Since statistical features (mean and standard deviation) features have varying values in low and high-frequency region, Interval-dependent (ID) denoising is used, as it calculates the threshold value separately for each level and each interval is denoised. In their work, they used, Electrocardiogram (ECG) signal denoised using the ID scheme. The proposed scheme is validated using experimental and simulated data and obtained good results compared to conventional thresholding schemes. The performance of the scheme is evaluated using RMSE and correlation coefficients.

2.2. Feature extraction

Peng and Chu (2004) and Hong and Liang (2007) employed vibration analysis and extracted statistical features to point out the defective conditions of the REB. According to researchers Peng and Chu, 2004; Zhou et al., 2009, Vijay et al., 2012, Kumar et al., 2017) a huge data obtained from different defective conditions lowers fault diagnosis performance. Ai et al. (2011) reported a novel method based on Empirical Mode Decomposition (EMD) and Singular Value Decomposition (SVD). These researchers extracted features using EMD and SVD and used Support Vector Machine (SVM) for classification. Features were derived from hand acceleration signals using two approaches namely EMD – SVD and Discrete Wavelet Transform (DWT). They pointed EMD – SVD is the best method based on SVM classifier results. Kar and Mohanty (2004) pointed that the DWT technique requires more computing time to decay the signal into very low resolution. Hence, these researchers discussed the advantages of a statistical non-parametric technique, the 'Kolmogorov & Smirnov (KS) test' and introduced a new statistical parameter D-stat and substantiated its advantages over t–test for REB fault detection. The limitation of the KS test was the loss in feature data which made the test more responsive at the center than at the tails. Past literature (Peng

and Chu, 2004; Zang and Huang, 2004; Ai et al., 2011; Ali et al., 2014) reveals several feature selection techniques such as Principal Component Analysis (PCA), Fisher Discriminant Analysis (FDA**)**, Singular Value Decomposition (SVD), Independent Component Analysis (ICA) and Partial Least Square (PLS) are widely used in bearing signal analysis. Vakharia et al. (2016) used parametric and nonparametric statistical significance tests. They selected features and ranked them using methods such as Fisher score, Relief, Wilcoxon rank test, Gain ratio and Memetic.
Past research such as Mohanty et al., (2018) has sufficient evidence that the notion of z-score and six sigma test with correlation as a parameter. The simulation of the proposed algorithm shows increased detection accuracy and decreased false alarm rate. Originally developed to improve manufacturing efficiency and quality, Lean Six Sigma is now being widely adopted by many other institutions and service industries including diagnostics field, where Lean Fault tolerance design has been examined by Lean Six Sigma approach, Six sigma methodologies can be applied in the different areas solving business, and technical, transactional and process problems across the corporation. Applying a structured Lean Six Sigma based methodology to the diagnostics area has the potential to improve time in diagnostic yield, can decrease the amount of occurring faults and help to create a reliable fault tolerance system (Tarba and Mach, 2016). Six Sigma is a quality improvement framework that was developed by Motorola to enhance business procedures. It is defined as a system for attaining, maintaining, and maximising successful business. It has rapidly gained popularity as it is useful for saving costs and increasing efficiency and is now used by numerous firms to improve business processes DMAIC (Define, Measure, Analyse, Improve, Control) and DMADV (Define, Measure, Analyse, Design and Verify), are two popular methodologies of Six Sigma (Chugani et al.,2017). However, Montgomery (2012) explained the meaning of the six sigma concept as shown in Table 1. According to him defects/ errors per million occurrences (DPMO) in a process that satisfies six sigma standard is 3.4 or less even after assuming that the process mean could change by 1.5 times the standard deviation. From Table 1 it may also be observed that the DPMO corresponding to 5 sigma and 4 sigma standards is 233 and 6210, respectively.
The above literature review shows that the researchers are extensively exploring the various combinations of denoising, signal analysis, DRT and feature ranking/ selection techniques to arrive at the best combination of the above techniques and features to predict the REB defects. In this context, this study attempts to identify those statistical features that differentiate between a healthy and defective bearing using the independent samples test among seventeen statistical features with an error rate of 0.00034% or at a significance level of 99.99966% which corresponds to the six sigma standard stated by Montgomery (2012). These statistical features were, Mean (M), Root Mean Square (RMS), Standard Deviation (SD), Peak (P), Square of Mean of Square Root (SMSR), Mean Absolute Value, (MAV), Skewness (S), Kurtosis (K), Crest Factor (CF), Latitude Factor(LF), Shape Factor (SF), Impulse Factor (IF), Standard Deviation Impulse Factor (SDIF), Log log ratio (LLR), Square root of ratio of square of mean of square of standard deviation (SRMSSD), Normal negative log likelihood (NNLL)and Weibull negative log likelihood (WNLL) Hence, the hypotheses shown in section 2.3 were formulated.

2.3. Formulation of Hypotheses

***Null Hypothesis H_0*:**There is no significant difference between the Statistical Features of a healthy REB and a defective REB. (Extracted Statistical features are not capable of detecting abnormal bearing health).

Alternate Hypothesis H1: There is a significant difference between the Statistical features of a healthy REB and a defective REB. (Extracted Statistical features can detect abnormal bearing health). A sample Sub (Null) Hypothesis is shown below.

H_0 (1.1): There is no significant difference between the Meanof a healthy bearing and a defective REB (with defects in the ball, IR and OR). Similar null hypotheses were formulated with respect to all the seventeen statistical features and were tested using the methodology described in the next section.

Table 1. Defects/ Errors per millions of occurrences under Motorola six sigma concept.

σ (deviation from mean)		Percentage error assuming the process mean changes by ± (1.5 ×standard deviation)	Defects/ errors per million occurrences (DPMO)
±1σ		69.77%	697700
±2σ		30.85%	308537
±3σ		6.7%	66807
±4σ		0.621%	6210
±5σ		0.0233%	233

±6σ		0.00034%	3.4

3. Research Design and Methodology

The vibration signals used for this study were acquired from a customised bearing test rig. Figure 1 shows the test rig and Figure 2 shows the plot of raw and ID denoised vibration signals. It is obvious (from Figure 2) that ID denoised signals successfully symbolize the bearing types with lesser noise.

Table 2 shows the description of the test rig, conditions under which data was acquired and information about the software used for data acquisition (DAQ), analyses and statistical tests.

Signals obtained from the vertical accelerometer (X) were used for investigation as the horizontal accelerometer signals (Y) were found to be less sensitive to bearing conditions. Each test experiment provided a data vector of 250000×1. Hence, in this work for two loads, one speed and four bearing conditions eight such data vectors were generated. Signals were acquired at a rotational shaft speed of 622 rpm, which is considered as the maximum speed and at a radial load of 0 and 1.7 kN for four conditions of REB (Kumar et al., 2017).

Kumar et al. (2016) compared five different denoising schemes identified from different domains and stated the superiority of the Interval-dependent denoising scheme. The experimental bearing vibration signals were denoised using the ID scheme which resulted in effective REB fault diagnosis using ANN. Hence, in this study, ID scheme has been used.

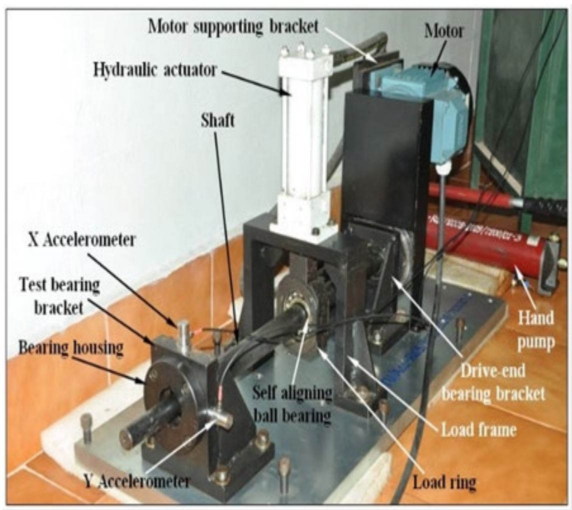

Figure 1. Photographic view of the test set-up (Vijay, 2013).

Table 2. Description of Experimental Setup and Data Acquisition System (DAQ)

Sl. No.	Item	Description
1.	Shaft diameter	32 mm
2.	Drive motor	3 phase, 1 HP induction motor
3.	Speed ratio	2.25
4.	Test bearing	6205 deep groove ball bearing
5.	Type of load applied	Two radial loads (0 and 1.7 kN) at 622 rpm
6.	Method of load application	Using a hydraulic actuator, load frame and a load ring
7.	Software used for data collection	LAB VIEW
8.	Software used for feature extraction	MATLAB-WAVELET TOOLBOX
9.	Software used for Statistical tests	IBM SPSS V20
10.	Sampling rate and time	48000 samples/ second for 5.209 seconds
11.	Four independent conditions for which the data was acquired, and the symbols used	N – Healthy bearing; B – Defective Ball; IR – Defective Inner Race;

		OR – Defective Outer Race
12.	Three pairs of bearing conditions created for statistical tests	N v/s. B, N v/s. IR and N v/s. OR

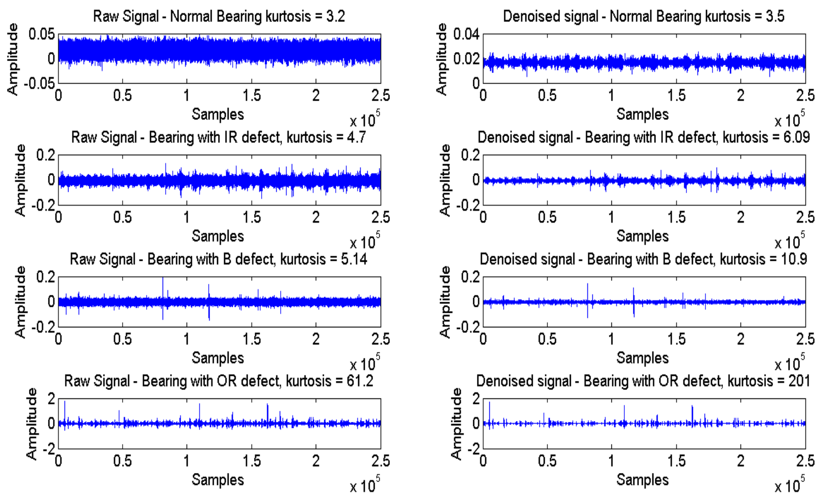

Figure 2.Plots of (a) raw signals and (b) ID denoised vibration signals at shaft speed of 622 rpm and load of 1.7 kN

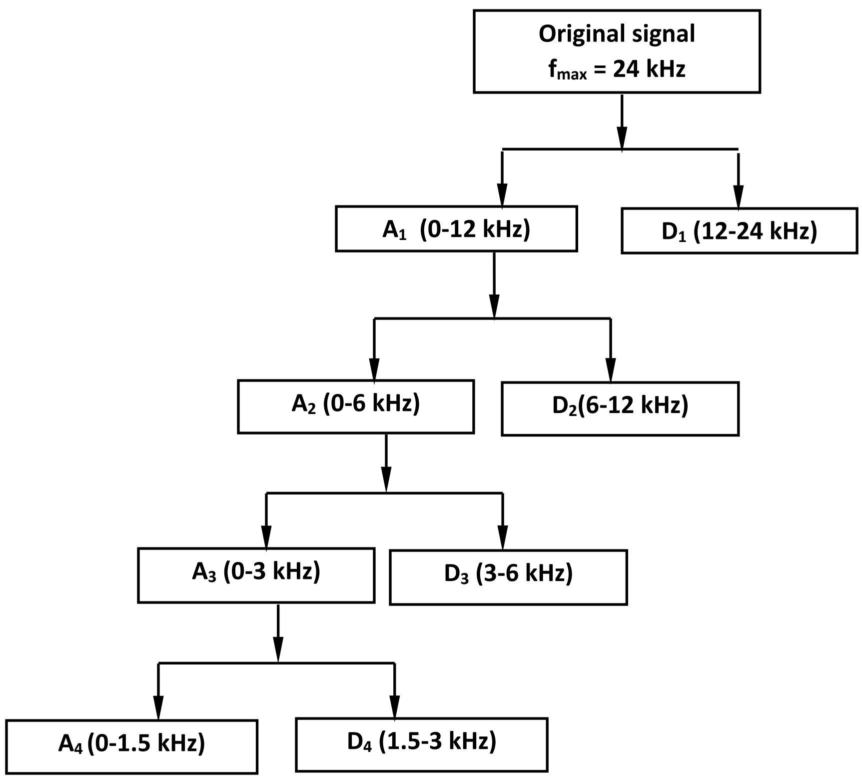

Figure 3. Four Level DWT decomposition of the bearing vibration signals. Ai and Di (i =1, 2, 3, 4,) are the approximation and detailed coefficients at level i

Table 3. List of Statistical features (adopted from Vijay, 2013)

Feature code	Feature name	Expression	Feature code	Feature name	Expression
T1	Mean (M)	$\frac{1}{n}\sum_{i=1}^{n} x_i$	*T10*	Latitude Factor (LF)	P_k /SmSq
T2	*RMS*	$\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}$	*T11*	Shape Factor (SF)	*RMS*/Ma
T3	Standard deviation (*SD*)	$\sqrt{\frac{1}{(n-1)}\sum_{i=1}^{n}(x_i - Mn)^2}$	*T12*	Impulse Factor (IF)	P_k/Ma
T4	Peak (P)	$\frac{1}{2}\left[\mathrm{Max}(x_i) - \mathrm{Min}(x_i)\right]$	*T13*	Standard deviation Impulse Factor (SDIF)	*SD*/Ma
T5	Square of Mean of Square root (SMSR)	$\left(\frac{1}{n}\sum_{i=1}^{n}\sqrt{\lvert x_i\rvert}\right)^2$	*T14*	Log-log Ratio (LLR)	$\frac{1}{\log(SD)}\sum_{i=1}^{n}\log\left(\lvert x_i\rvert + 1\right)$
T6	Mean of absolute value (MAV)	$\frac{1}{n}\sum_{i=1}^{n}\lvert x_i\rvert$	*T15*	Square root of ratio of square of mean of square root to standard deviation (SRMSSD)	$\sqrt{\frac{SmSq}{SD}}$
T7	Skewness (S)	$\frac{1}{(n-1)}\sum_{i=1}^{n}\left(\frac{x_i - Mn}{SD}\right)^3$	*T16*	Normal Negative Log Likelihood (NNLL)	$-\sum_{i=1}^{n}\log\left[\frac{\exp\left\{\frac{-(x_i - Mn)^2}{2(SD)^2}\right\}}{SD\sqrt{2\pi}}\right]$
T8	Kurtosis (K)	$\frac{1}{(n-1)}\sum_{i=1}^{n}\left(\frac{x_i - Mn}{SD}\right)^4$	*T17*	Weibull Negative Log Likelihood (WNLL)	$-\sum_{i=1}^{n}\log\left[\beta\eta^{-\beta}\lvert x_i\rvert^{\beta-1}\exp\left\{\frac{\lvert x_i\rvert}{\eta}\right\}^{\beta}\right]$ where, β is the shape factor and η is the scale factor x_i is the signal
T9	Crest Factor (CF)	P_k / *RMS*			

The experimental bearing vibration signals (obtained from the REB test rig) of four conditions namely, N, B, IR and OR, at 1.7 kN load with a shaft speed of 622 rpm have been denoised using ID scheme. The discrete Meyer (dmey) MW has been used for the decomposition of the signals up to the fourth level. As the sampling frequency for acquiring the real-time vibration signals is 48 samples /s, as per the Nyquist criterion, the maximum frequency of the signal is expected to bef_{max}= *24* kHz (Vijay, 2013; Prabhakar, Mohanty and Shekar, 2002). Figure 3 shows frequency bandwidths of the detailed and approximation coefficients of the wavelet transformed bearing vibration signals (Vijay et al., 2012). The raw bearing vibration signals obtained from the test setup is denoised using ID based denoising scheme. This leads to a denoised vibration vector of size (250000 × 1) and separated into 50 non-overlapping bins with each bin comprising 5000 samples. The denoised signals were analysed using the DWT technique using the dmey mother wavelet. The decomposition is done up to fourth level (figure 3). Seventeen statistical features are extracted from second level detailed wavelet coefficients, Hence, for four conditions of the bearing, two loads and one speed condition, a total of 200 patterns (25 × 4) were extracted. Hence for two loads, one speed and four bearing conditions, feature set matrix were 17 features × 200 patterns. Statistical features extracted are listed in Table 3 along with the associated expressions were used in this study.

The hypotheses mentioned in the previous section were tested using the independent samples test (Levene's F-test for equality of variances), at a significance level (Besterfield et al., 2003) to identify the statistical feature that can differentiate between a healthy and defective REB. Levene's F-test for equality of variances (Independent samples test) between 2 independent samples compare the variances. The methodology used in this study is shown in Figure 4. Raw vibration signals were subjected to interval-dependent denoising, and If the significance value of Levene's Test for Equality of Variances of an independent pair (such as N vs. B) for a statistical feature (such as Mean) were to be less than 0.0000034, (or DPMO was less than 3.4) the null-hypotheses corresponding to Mean i.e., $H_1(1.1)$ can be rejected. Similar analyses were carried out for all the independent pairs for a statistical feature. This test was repeated with respect to all the seventeen statistical features. The analysis and interpretation of results for three independent pairs corresponding to these statistical features have been discussed in the following section.

4. Analyses and interpretation of Results

Independent samples test was used to ascertain the difference between the Mean of a normal bearing and that of a bearing with defects on ball, IR and OR. Since the significance p of independent samples test was greater than 0.0000034 for the pairs N vs. B and N vs. IR and N vs. OR, it was inferred that there was no difference between Mean values of a healthy REB and that of REB with defects in ball and IR at DPMO corresponding to Six sigma. Conversely, it was inferred that the Mean is not capable of distinguishing the REB with defects in IR, OR or Ball at a DPMO corresponding to six sigma standards. The analysis and interpretation of the statistical testscarried out on the same lines as that of Mean have been presented in Table 4 and are explained in this section.

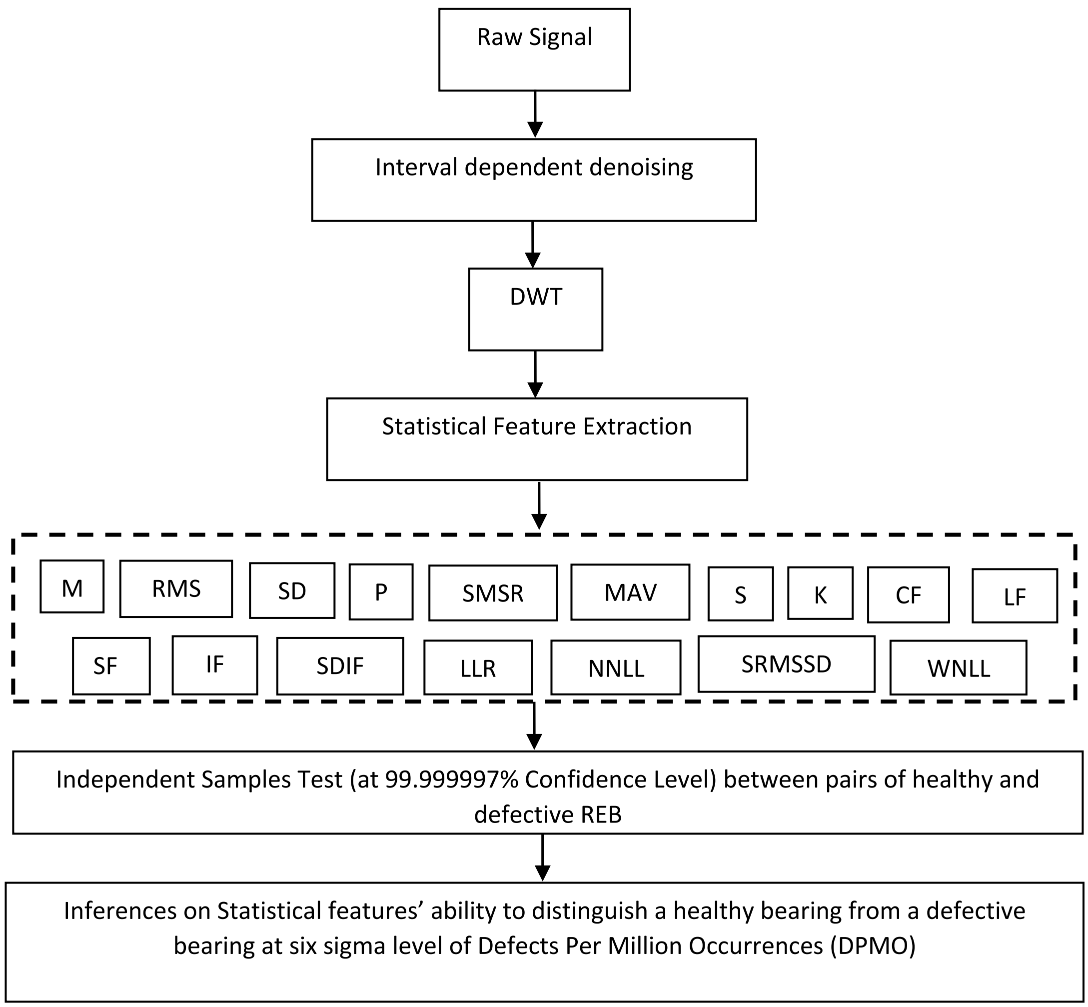

Figure 4. Methodology of the Model

It was found that at a significance level of 0.1, all the features were capable of 'critically' differentiating the healthy and defective bearing when the defect was present in OR. Only eight features viz, Mean, RMS, SD, Peak, SMSR, MAV, LLR and WNLL were capable of 'critically' differentiating between a healthy and defective bearing, irrespective of the location of the defect. Out of these 8 features RMS, SD, SMSR, MAV and LLR were able to differentiate between a healthy and defective bearing satisfying the six sigma criteria of DPMO.

Table 4. Results of Independent Samples test and possible DPMO of Level 4 vibration signals.

Feature code	Feature Abbreviations	F(p)*			Approximate DPMO		
		N vs. B	N vs. IR	N vs. OR	N Vs. B	N vs. IR	N vs. `OR
T1	M	29.33(0)	33.67(0)	24.07(0)	0.44	0.08	3.7
T2	**RMS**	**38.7(0)**	**81.97(0)**	**37.84(0)**	**0.01**	**0**	**0.02**
T3	**SD**	**38.65(0)**	**81.96(0)**	**37.78(0)**	**0.01**	**0**	**0.02**
T4	P	15.15(0)	51.68(0)	40.86(0)	181	0	0
T5	**SMSR**	**51.23(0)**	**83.18(0)**	**89.91(0)**	**0**	**0**	**0**
T6	**MAV**	**48.15(0)**	**84.262(0)**	**62.51(0)**	**0**	**0**	**0**
T7	S	1.2(0.28)	0.002(0.97)	7.113(0.01)	276292	967289	8953
T8	K	0.1(0.76)	3.92(0.05)	48.24(0)	756954	50545	0
T9	CF	0.02(0.88)	2(0.16)	67.9(0)	882434	160032	0
T10	LF	0.01(0.91)	2.023(0.16)	44.27(0)	906772	158155	0
T11	SF	0.00(0.98)	1.87(0.17)	39.71(0)	984976	174189	0
T12	IF	0.03(0.86)	2.3(0.13)	50.86(0)	865239	132783	0
T13	SDIF	0.00(0.97)	1.83(0.18)	39.60(0)	967621	179202	0
T14	**LLR**	**53.36(0)**	**83.305(0)**	**48.6(0)**	**0**	**0**	**0**
T15	SSMSSD	0.03(0.85)	0.94(0.33)	46.85(0)	854884	334455	0
T16	NNLL	6.49(0.01)	54.69(0)	41.46(0)	12382	0	0
T17	WNLL	8.06(0.005)	48.902(0)	18.11(0)	5491	0	48
*F(p) – F value of Independent samples test or Levene's Test for Equality of Variances (Significance of Levene's Test)							

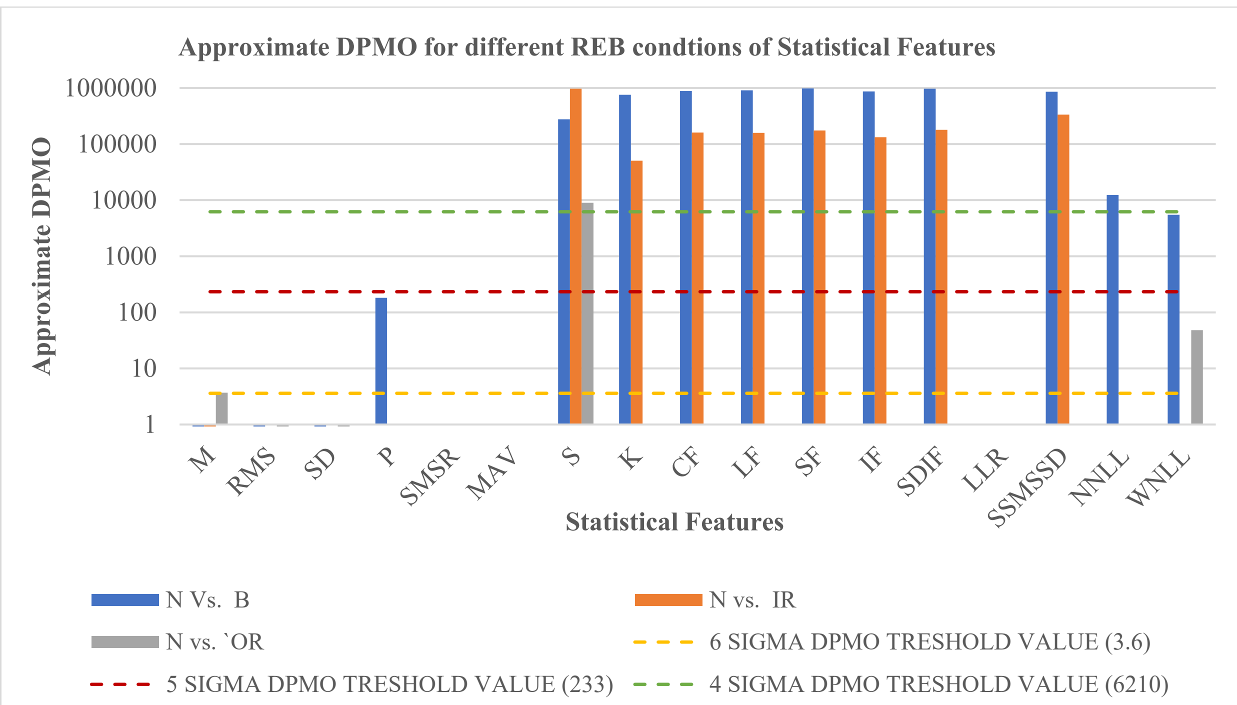

Figure 5.Logarithmic plot showing Approximate DPMO for the 3 REB conditions of 17 statistical features and threshold DPMO values of 6 sigma, 5 sigma and 4 sigma criteria.

Mean and Peak were able to differentiate between a healthy and defective bearing satisfying the five sigma criteria of DPMO (233 defects per million). WNNL was able to differentiate between a healthy and defective bearing satisfying four sigma criteria of DPMO(6210 defects per million). All the statistical features except mean, skewness and WNLL were able to differentiate between a healthy and defective bearing satisfying 6 sigma criteria of DPMO, when defects were in OR. Mean, Peak NNLL and WNLL can also distinguish between a healthy and defective bearing satisfying 6 sigma criteria of DPMO, when defects were in IR.

Thus, this paper presents a fresh approach/ methodology for feature extraction, selection combined with independent samples test, which can critically distinguish between defective and a healthy REB. It also identifies the statistical features that can distinguish between defective and a healthy REB and also confirm to six sigma standards of DPMO. Conversely, the chances of RMS, SD, SMSR, MAV and LLR erroneously distinguishing between a healthy and defective bearing is less than 3.4 per million occurrences.

The above results implied that null- hypothesis H_0 could not be rejected after the Independent Samples Test as it was not possible to reject all the sub null- hypotheses simultaneously. However, it was observed that null hypotheses corresponding to some statistical features could be rejected leading to the inferences drawn in this section. Figure 5 also supports these inferences (tabulated in Table 4) as it clearly highlights specific Statistical features and the respective REB conditions with approximate DPMO below six sigma, five sigma and four sigma threshold values shown by the dashed horizontal lines.

5. Discussions and Implications

Many researchers in the past have studied the ability of different combinations of denoising, feature extraction and feature selection. Researchers have also evaluated the ability of extracted features to ascertain bearing health. This study presents a novel approach for comparing the vibration signals of a healthy and defective bearing using statistical features at higher significance levels or DPMO corresponding to six sigma standards. The study also highlights some important statistical features whose values can be referred for continual monitoring of REB health. Owing to the recent trend towards the prognosis rather than diagnosis of REB and the improved computing capabilities, researchers have preferred predictive analysis techniques such as SVD and Artificial Neural Networks (ANN) based on machine learning principles. Predictive analysis is generally preferred over inferential analysis of the feature data. However, predictive analysis necessitates high levels of data measurement and computational capabilities and the associated effort and costs. Hence, the diagnostic ability of a statistical feature to differentiate a healthy REB from defective REB at a higher significance level corresponding to six sigma standards, before prognostic analysis, could be useful. This could help in eliminating statistical features that are indifferent to REB health without using much computational efforts, as a statistical feature that cannot diagnose REB defects also cannot predict REB defects.In addition, continuous on line generation of big data, monitoringand prognostic analysis of the data may be necessary only for REB that are used as critical elements of assemblies/ machines causing potentially catastrophic effects. In other applications, continual alerts on REB replacement can be both cost effective and help managers and engineers make their preventive maintenance schedules more effective. Hence, the novel approach of this study is expected to help future researchers to focus on a few critical statistical features. It may also be noted that the inferences drawn in this study are specific to the combination of denoising scheme, signal analysis, and features extracted at a specified significance level. Future researchers are suggested to apply predictive analytics techniques such as ANN and SVD only to those statistical features such as RMS that clear inferential analysis tests to reduce the computational effortsensuring higher levels of effectiveness in REB health monitoring efforts.

6 Conclusions

This study is intended to explore the ability of different statistical features to distinguish between a healthy REB and REB with defects on ball, IR and OR at higher significance levels corresponding to six sigma standards. Vibration signals were extracted from a customised bearing test rig. These signals were subjected to Interval dependent denoising, and statistical features were extracted using DWT technique. Using DWT method of signal processing seventeen statistical features were extracted from the signals. Three pairs of independent samples were formed based on the REB condition concerning 17 statistical features. Inferences were drawn about the ability of each statistical feature to distinguish between a healthy and defective REB, by application of the independent samples test. It was inferred those the five statistical features, viz., RMS, SD, SMSR, MAV and LLR could critically differentiate between a healthy REB and a defective REB irrespective of whether the defect is on ball, IR and OR. This study suggests that the inferential analysis of statistical features can help researchers to focus only on those statistical features that can differentiate between healthy and defective REB by eliminating those statistical features that do not differentiate between healthy and defective REB. Inferences at a significance level corresponding to six sigma can make these inferences more acceptable**.**

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