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To cite this article: C K E Nizwan *et al* 2013 *IOP Conf. Ser.: Mater. Sci. Eng.* **50** 012026

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# A wavelet decomposition analysis of vibration signal for bearing fault detection

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**Abstract.** This paper presents a study of vibrational signal analysis for bearing fault detection using Discrete Wavelet Transform (DWT). In this study, the vibration data was acquired from three different types of bearing defect i.e. corroded, outer race defect and point defect. The experiments were carried out at three different speeds which are 10%, 50% and 90% of the maximum motor speed. The time domain vibration data measured from accelerometer was then transformed into frequency domain using a frequency analyzer in order to study the frequency characteristics of the signal. The DWT was utilized to decomposed signal at different frequency scale. Then, root mean square (RMS) for every decomposition level was calculated to detect the defect features in vibration signals by referring to the trend of vibrational energy retention at every decomposition. Based on the result, the defective bearings show significant deviation in retaining RMS value after a few levels of decomposition. The findings indicate that Wavelet decomposition analysis can be used to develop an effective bearing condition monitoring tool. This signal processing analysis is recommended in on-line monitoring while the machine is on operation.

## 1. Introduction

Rolling element bearings has vast domestic and industrial applications. Appropriate function of these appliances depends on the smooth operation of the bearings. In industrial applications, bearings are considered as critical mechanical components and a defect in such a bearing causes malfunction and may even lead to catastrophic failure of the machinery.

Presently, vibration monitoring method becomes the most reliable tool as a part of preventive maintenance for rotating machines [1,2]. The vibration data often contain fault signatures where several signal processing techniques; often adapted to a precise defect type, results to online monitoring system.

There are many condition monitoring methods used for detection and diagnosis of rolling element bearing defects such as vibration measurements, temperature measurement, shock pulse method (SPM), and acoustic emission (AE). Various researchers suggested that stator current monitoring can provide the same indications without requiring access to the motor. This technique utilizes results of spectral analysis of the stator current or supply current of any part nearest to the rolling bearing element for diagnosis purpose [3]. Other signal processing technique for condition monitoring method includes averaging technique [4], adaptive noise cancelling [5], and high-frequency resonance technique (HFRT) [6] was developed to improve signal-to-noise ratio for more effective detection of



bearing defect. Among all these monitoring methods, the high-frequency resonance technique is more popular for bearing fault detection. However, most of the method requires additional computations and several runs of impact tests to find the bearing resonance frequency. Therefore, extra instruments such as vibration exciters and their controller are needed for HFRT [7].

Wavelet Transform (WT) on the other hand, were proven to be one of the best condition monitoring method/effective tool for detecting single and multiple faults in the ball bearings [7,8,9]. A clear review on using DWT as condition monitoring method and possible early detection was given by Giaccone et al. [10], Tandon and Choudhury [2], Kim et al. [11], Schmitt et al. [12], and Staszewski [13].

Discrete wavelet transform (DWT) provides a time-scale information of a signal, enabling the extraction of features that vary in time. This property makes wavelets an ideal tool for analyzing signal of a transient or non-stationary nature [7]. The continuous wavelet transform (CWT) of  $f(t)$  is a time-scale method that may be identified as the sum over all time of the signal multiplied by scaled, shifted versions of the wavelet function  $\Psi(t)$ . Mathematically as proposed by McFadden and Smith [14],

$$WT(a, b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} f(t) \Psi^* \left( \frac{t-b}{a} \right) dt \quad (1)$$

Where  $\Psi(t)$  denotes the mother wavelet. The parameter  $a$  represents the scale index which is a reciprocal of frequency. The parameter  $b$  indicates the time shifting (or translation). The DWT is derived from the discretization of CWT ( $a, b$ ) and the most common discretization is dyadic, given also by McFadden and Smith [15] as,

$$DWT(j, k) = \frac{1}{\sqrt{2^j}} \int_{-\infty}^{\infty} f(t) \Psi^* \left( t - \frac{2^j k}{2^j} \right) \quad (2)$$

Where  $a$  and  $b$  are replaced by  $2^j$  and  $2^j k$ . An effective way to apply this method using filters was developed by Mallat in 1989 [16].  $f(t)$  passes through two complementary filters and emerges as low and high frequency signals. The decomposition may be iterated with successive approximations begin decomposed in turn, so that signals may be broken down into lower-resolution components.

This paper focus on the analysis of vibration signals at difference bearing condition using time frequency transform approach. The discrete wavelet transform method was used to transform the time domain vibration signal into time frequency domain in order to detect the abnormal features of the faulty bearing.

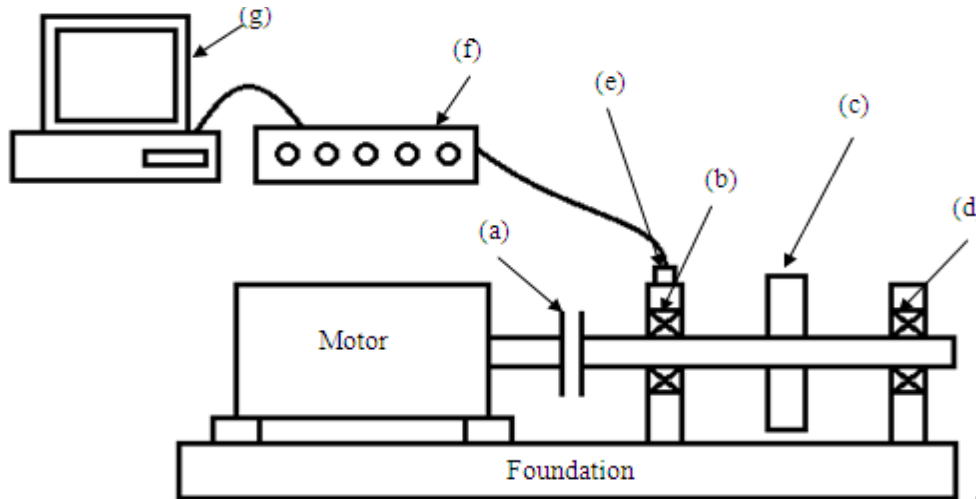
## 2. Experimental Setup

The test rig for this experiment was design to investigate failure and vibration characteristic of ball bearings. It was designed specifically to imitate the applications of ball bearings in the industry. The shaft was driven by a variable-speed 0.37kW, 50Hz electric motor with a frequency converter in order to control the speed of the motor. The motor and shaft were connected by using a spring coupling where it could minimize shaft alignment error. The front side of the shaft is fitted with tested bearing and the other will be fitted with a good bearing acting as a dummy.

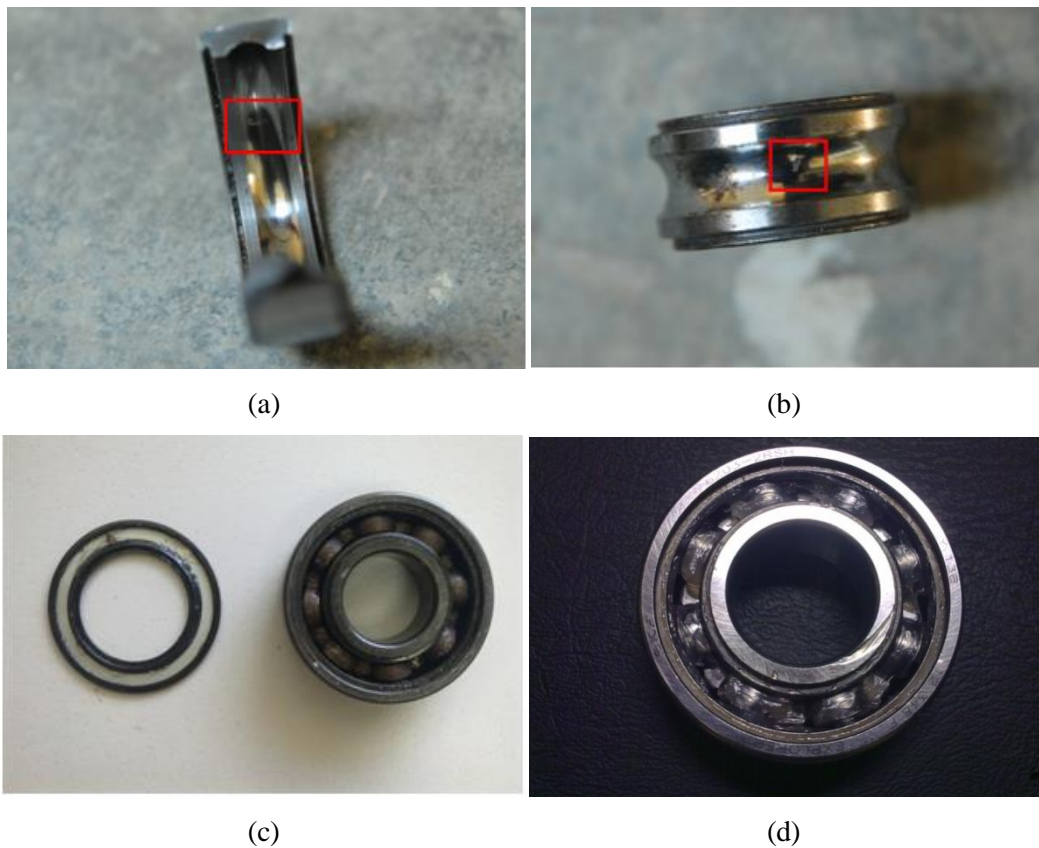
A set of good bearings and another three bearings with different type of defectives were used for testing. A flywheel is installed at the middle of the spindle in order to apply load to the shaft and at the same time minimizing the speed oscillations of the shaft. The angular speed is set to 287 rpm, 1466 rpm, and 2664 rpm (which are 10%, 50% and 90% of the maximum motor speed respectively), and the vibration signals were acquired by using the Bruel&Kjær (B&K) 4506B accelerometer. Sensors were placed on horizontal directions to collect the data because horizontal bearing types were tested. Accelerations signals are acquired by using a personal computer (PC) based data acquisition system

with sampling frequency of 20 kHz ( $\Delta t = 0.039$  ms). The tools arrangement for this experiment are as shown in Figure 1.

There are four bearings that were tested for this experiment and three of them are defected. Figure 2 shows the bearings used in this research i.e. outer race defect point defect corroded and healthy bearing. The types of defect and the location of each defect specifically were summarized in Table 1.



**Figure 1.** Bearing fault detection test rig consist of: coupling (a), tested bearing (b), flywheel (c), healthy bearing (d), accelerometer (e), data acquisition system (f), and a PC (Analyzer) (g).



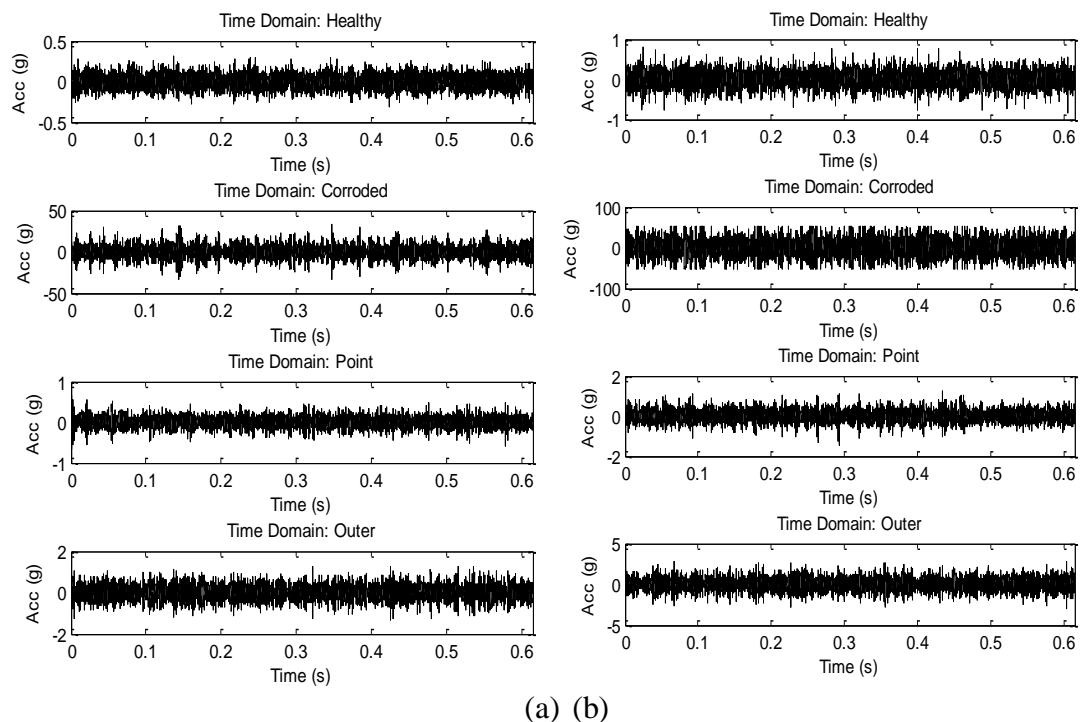
**Figure 2.** (a) Outer race defect (b)Point defect (c) Corroded (d)Healthy bearing

**Table 1.** Types and location of defect

Types of Defect	Location of Defect
Outer race defect	One scratch mark on the outer race
Point defect	Single point mark on the inner race
Corroded defect	Ball bearing were left to open air and water

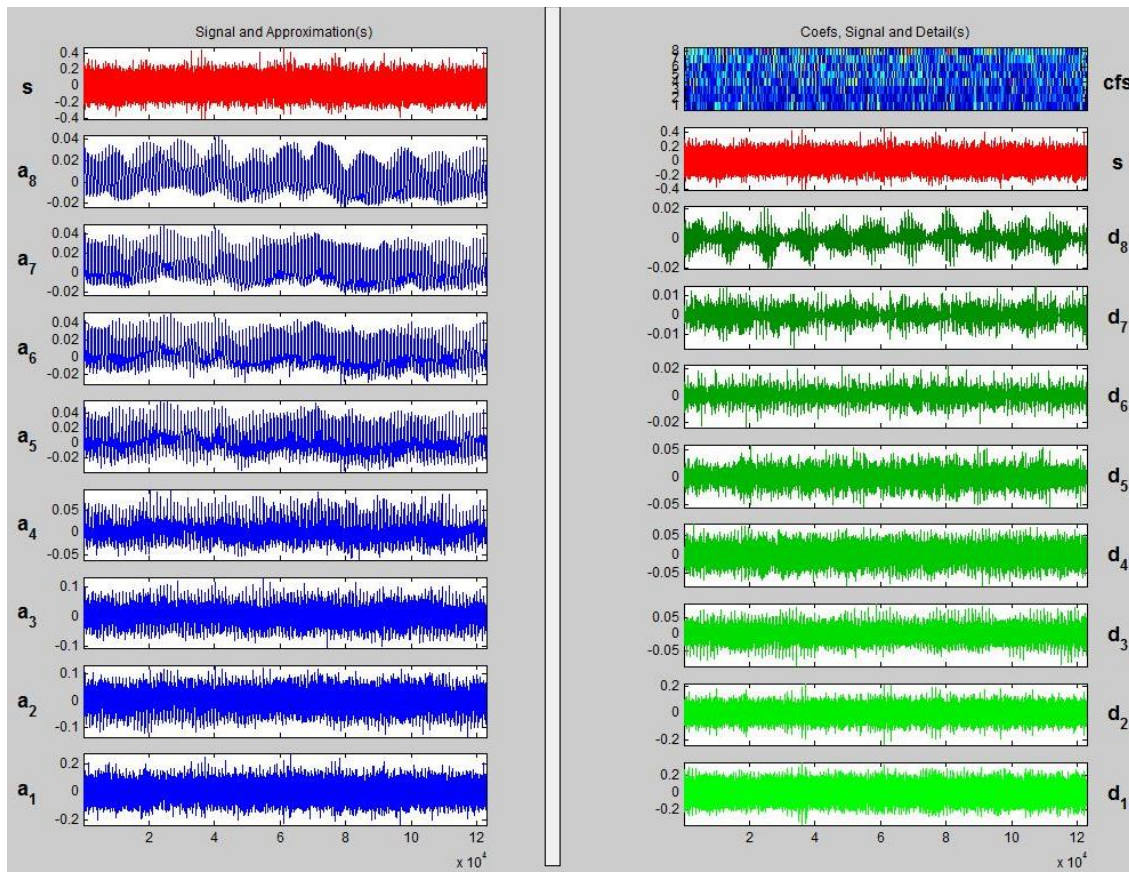
### 3. Results and Discussion

From the experiment, the time series acceleration data at different bearing condition were acquired. Figure 3 shows the time domain acceleration data which recorded at the speed of 1466 rpm, and 2664 rpm. Analysis for this project is done by using MATLAB®'s Discrete Wavelet Transform's Toolbox:Wavelet 1-D. The analysis starts off by reading the desired raw data. Then, the raw data were decomposed into eight level of frequencies scale using 4th order Daubechies wavelet ('db4'). Figure 4 and Figure 5 show the decomposition of vibration signal acquired from healthy and corroded bearing at 1466 rpm. Visually, the defect features can be observed from the decomposition of level 2 and above where the amplitude of decomposed signals shows significant decrement compare to the healthy bearing.

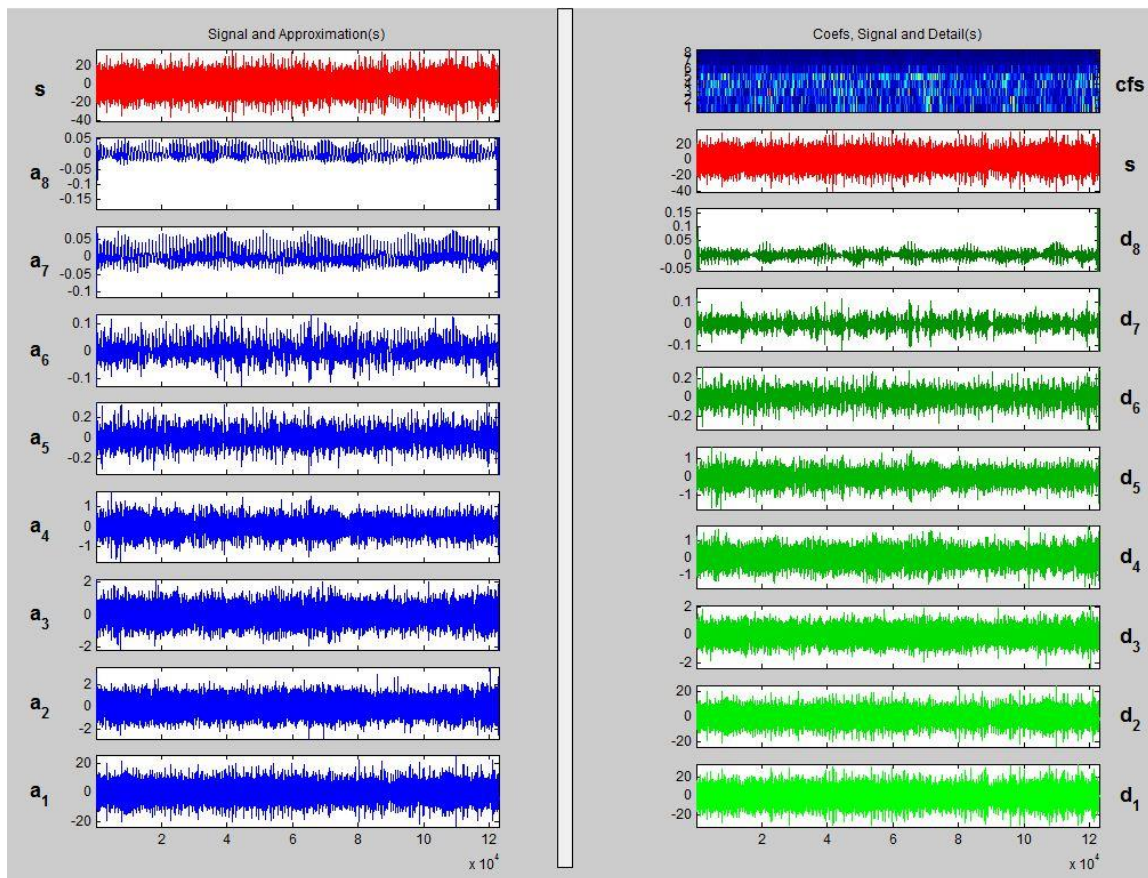


**Figure 3.** (a) Time domain data acquired at 1466 rpm. (b) Time domain data acquired at 2664 rpm.

For data of insufficient frequency excitation, calculating the RMS value for each decomposition level and finding the percentage towards the original input seems to yield understandable trend when a graph is plotted. Cartwright [17] proved in his paper the effectiveness of RMS by simple means without calculus. This method uses the definition of RMS of a waveform which is found simply by squaring that waveform, taking the mean of that squared form, and then computing the square root.



**Figure 4.** Decomposition result for healthy bearing at 1466 rpm



**Figure 5.** Decomposition result for corroded bearing at 1466 rpm

Any percentage value or graph plotted that is below the healthy line may be considered defected. This is because; decomposition process is where the frequency amount of each level gets smaller as the decomposition level increases. Therefore, if the RMS value of the next level declines at an irregular rate or stays flat on its line, the bearing may be considered as defected.

Figure 6 shows the trend generated by the RMS percentage value of each decomposition level. From the plotted graph, it seems that all of the defected bearing's RMS values for each decomposition level are below the healthy line, red region (except for 287rpm) thus proving that RMS is an excellent statistical tool to support DWT decomposition result during speed-up (2800 rpm) was sufficiently useful as also proven by Kim *et al.*, (2007). For the data at 287rpm, it's probably due to low excitation. Research by Tandon&Choudhury [2] yields similar result where it was found out that the direct vibration spectrum from a defective bearing may not indicate the defect at the initial stage.

However, the most defected bearings; corroded, is still below the lines of healthy (red circle) where this is most probably due to giving enough frequency excitation. This is because of how DWT itself decomposes the data. As shown previously in Figure 4, the input was divided into approximate (cA) and detailed (cD) output at each level of decomposition. By referring to raw data transformed into frequency domain, FFT graph of 10,000 Hz in Figure 7; at first level of decomposition, 10,000-length of data were decomposed to 5,000-length data of  $cA_1$  and 5,000-length data of  $cD_1$ . As the DWT proceeds with decomposition process,  $cA_1$  was then divided into two parts again leaving 2,500-length data each for  $cA_2$  and  $cD_2$  at level 2. At level 1's decomposition, the energy was divided with most of it towards  $cD_1$  rather than  $cA_1$ . While at level 2's decomposition, most of the energy were left

at  $cA_2$  and low amount of energy are seen at  $cD_2$ . As the decomposition process continues up to level 8, the energy left at  $cA_8$  would be the lowest thus making it having a low value RMS.

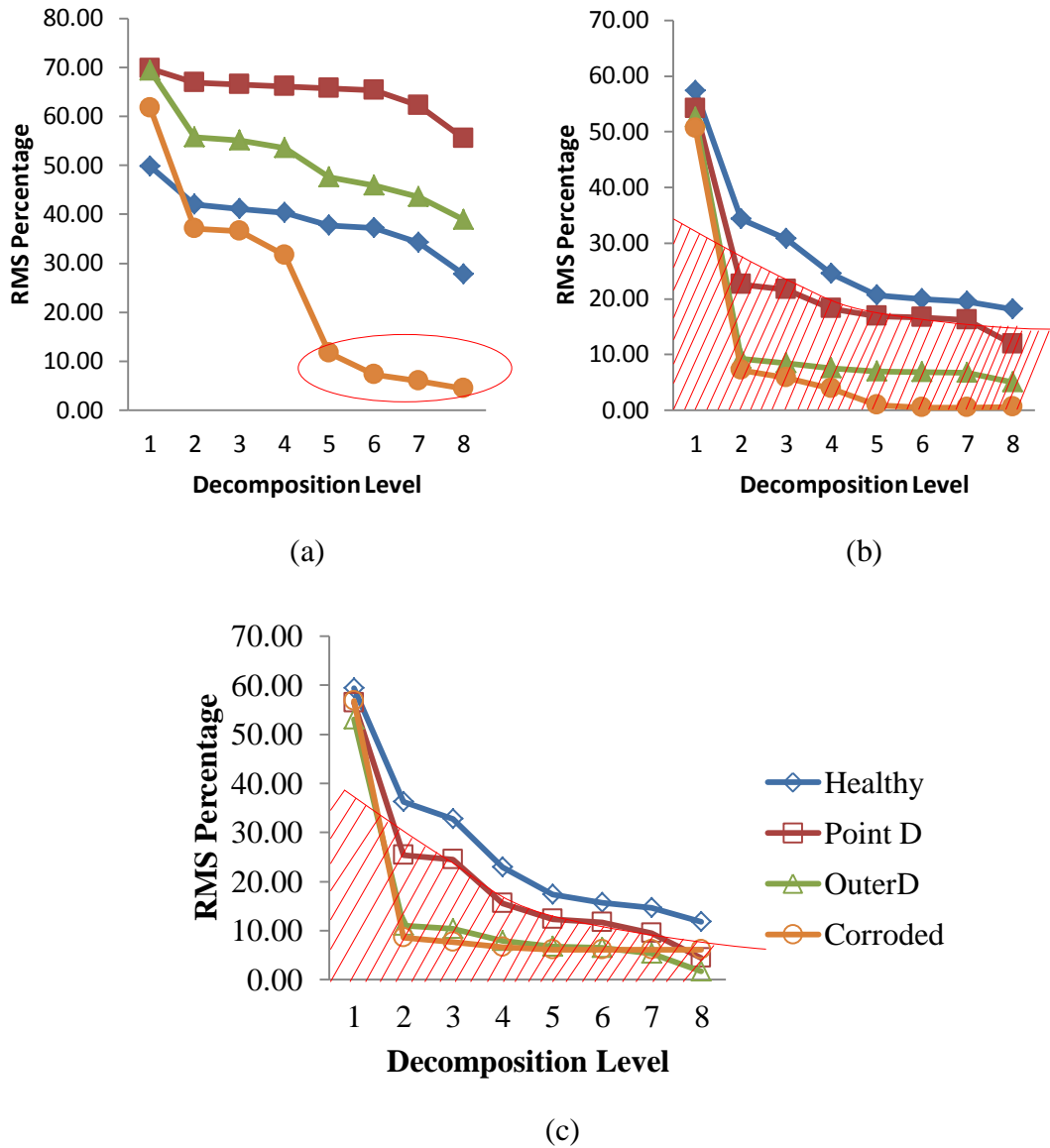
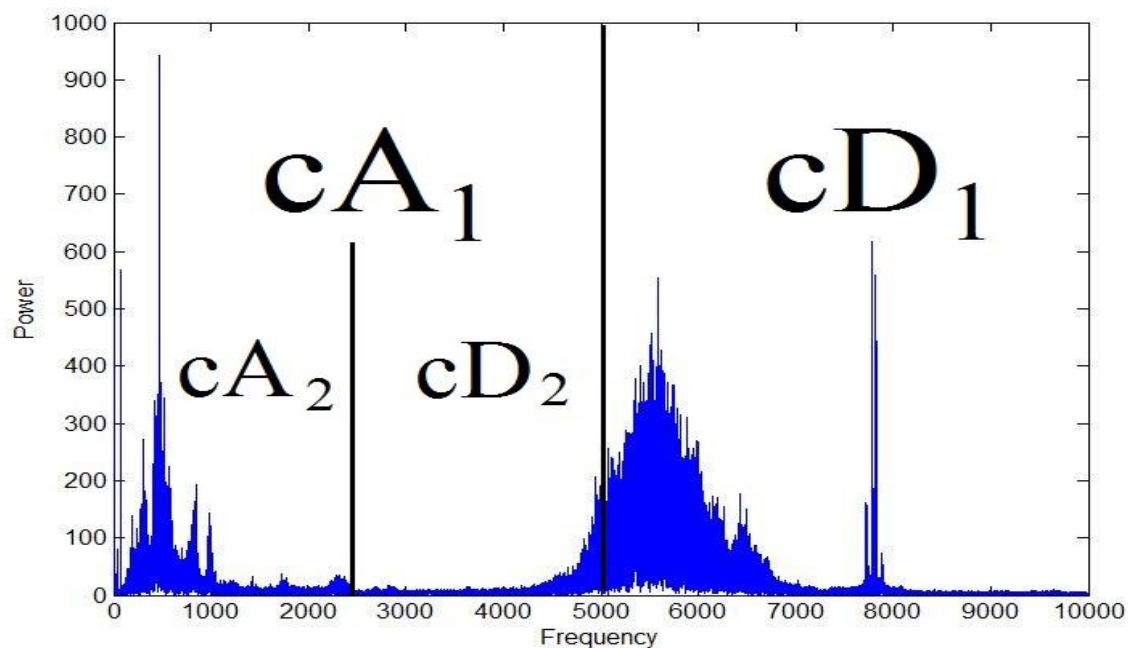


Figure 6. RMS percentage vs. decomposition level for speed of (a) 287 rpm (b) 1666rpm (c) 2664 rpm





**Figure 7.** FFT result for corroded bearing at speed of 287 rpm

#### 4. Conclusion

Discrete Wavelet Transform (DWT) was used to detect defect features from defected bearings as they produce vibration signals. Fast Fourier Transform (FFT) and Root Mean Square (RMS) plays an important role in supporting results analyzed by using DWT from MATLAB®Toolbox. Using DWT is indeed appropriate as an effective tool in detecting defect features in bearings. However, on systems of low speed, it is recommended for the DWT results to be enhanced by using RMS value of each decomposition level. All of these are possible for online monitoring without shutting down the machine for maintenance purpose. Therefore, this method is suggested as an alternative technique in bearing fault detection online monitoring, especially for system running on high speed.

#### 5. Acknowledgements

The authors would like to express their gratitude to Universiti Malaysia Pahang especially Faculty of Mechanical Engineering and Automotive Engineering Center through the fund of RDU120322, for supporting this research activity.

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