Using power spectral density and vibration analysis for fault diagnosis of kind of low speed electromotor (case study: a starter motor used in vehicles)

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Abstract: Different researches have been shown that vibration technique in a machine condition monitoring program provides useful reliable information. The aim of this paper is to study the relation between vibration analysis and starter motor fault diagnosis. This was achieved by vibration analysis of a starter motor. Vibration data produced by vibration analysis was compared with previous data. The results of this paper have given more understanding on the dependent roles of vibration analysis in detection of starter motor faults. For these types of vibration, it would be more accurate, or more interest to analyze and test them using random vibration. In this research we have calculated RMS and PSD (Power Spectral Density) of starter motor in different faults conditions. G(rms) and PSD have calculated for different faults. The results indicated that different faults have different PSD. The results showed that by calculating PSD we could detect the faults of starter motor before serious damage occurs.
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Key words: Condition monitoring ; Vibration analysis; Power Spectral Density; Starter Motor

1.Introduction

Many vibration environments are not related to a specific driving frequency and may have input from multiple sources which may not be harmonically related.

Because of increasing demand for higher performance as well as for increased safety and reliability of dynamic systems, fault diagnosis has been becoming more important for machine monitoring. Early diagnosis of machine faults while the machine is still operating in a controllable region can help avoid abnormal event progression, which in turn can help avoid major system breakdowns and catastrophes. Hence, fault diagnosis is a major research topic attracting considerable interest from industrial practitioners as well as academic researchers [6,7,14,15,16].

One of the most applications of condition monitoring is fault diagnosis of electrical machines [5,9,10]. Even though motor current analysis has been widely utilized for electric machines, vibration monitoring is also accepted for diagnosis of faults for these machines [3,5]. Vibration monitoring of electrical machines has become an attractive region for many researchers, and also has gained industrial acceptance since it is related to almost all of the machinery failures and it does not require modification of the machine or access to the supply lines [4,5,11,12,13]. There are several fault types, mechanical and electrical, which can induce undesired vibration levels in electrical motors such as misalignment, broken rotor bar, short circuits, imbalance, stator winding faults, and bearing failures [3,5].

2. Power Spectral Density (PSD)

Vibration analysis in particular has for some time been used as a predictive maintenance procedure and as a support for machinery maintenance decisions. Condition monitoring is a valuable preventative maintenance tool to extend the operating life of an starter motor. Among the available techniques, vibration monitoring is the most widely used technique in industry today[10,11,17]. Many vibration environments are not related to a specific frequency and may have different inputs from multiple sources which may not be harmoniously related. Examples may be excite from turbulent flow as in air flow over a wing or past a car body, or acoustic input from jet engine exhaust, wheels running over a road, etc. For these types of vibration, it would be more accurate, or of more interest to analyze and test them using random vibration. Unlike sinusoidal vibration, acceleration, velocity and displacement are not directly related by any specific frequency. Of primary concern in random testing, the complete spectral content of the vibration being measured or generated. Most random vibration testing is conducted using Gaussian random suppositions for both measurement and specification purposes. With Gaussian assumptions, there is no definable maximum amplitude, and the amplitude levels are measured in RMS (root-mean-squared) values. Random vibration can be thought of as containing excitation at all frequencies within the specified frequency band but no excitation at any specific single frequency. An acceleration spectrum is normally specified in terms of its acceleration density using the units of g^2 per Hz. Acceleration density is defined as [1,2]:

$$g_d = \lim \frac{a^2}{\Delta f} \quad , \Delta f > 0 \qquad (1)$$

Where: gd=acceleration density, a = rms acceleration, Δf =band width

A plot of the acceleration density for each component frequency verses frequency gives a curve of g^2/Hz over the frequency spectrum of interest. This curve is known as the PSD or Power Spectral Density curve. The PSD curve is the normal method used to describe random vibration specifications. Since the PSD curve is a plot of acceleration density, the overall rms acceleration can be found by summation of the density over frequency [1,2].

$$g_{rms}{}^2 = \sum_{f_1}^{f_2} g_d \cdot \Delta f \quad \text{so} \quad g_{rms} = \sqrt{\left[\int_{f_1}^{f_2} g(f) \cdot df\right]}$$

(2)

Where: grms=overall acceleration, f1 and f2=band frequencies If a random specification calls for a flat PSD curve, the overall acceleration level is easily calculated from the following equation [1,2].

$$g_{rms} = \sqrt{(f_2 - f_1) \cdot g_d} \qquad (3)$$

Bands of spectra with non-flat, but straight line (log-log), acceleration density characteristics can substitute the following equation for overall acceleration [1,2].

$$g_{rms} = \sqrt{\left[\left(\frac{g_1}{f_1^s}\right)\left(\frac{f_2^{s+1} - f_1^{s+1}}{s+1}\right)\right]} \qquad (4)$$

(Where g1 and g2 are band limit levels)

$$s = \frac{\log\frac{g_2}{g_1}}{\log\frac{f_2}{f_1}} \qquad (5)$$

Bands of different acceleration density can be added as the areas under the PSD curve as follows [1,2]:

$$g_{rms} = \sqrt{[(f_{21} - f_{11}) \cdot g_{d1} + (f_{22} - f_{12}) \cdot g_{d2} + \cdots]}$$

(6)

3. Experimental and testing

The experiment setup is shown in Figure 1. A piezoelectric accelerometer of model VMI 102 (VMI Ltd, Sweden) was mounted on the starter motor body in horizontal direction. Through the signal conditioners, the vibration data was acquired by APC 40 Spectrum Analyzer (A/D converter, APC Ltd, Korea) and Dell Vostro 1320 laptop (data acquisition unit). Rotational speed of central shaft of motor was inspected using a contact tachometer (DT-2235B model, Lotron Ltd, Taiwan). Vibration data was acquired when motor reaches to its maximum speed (between 2000-2800 rpm).

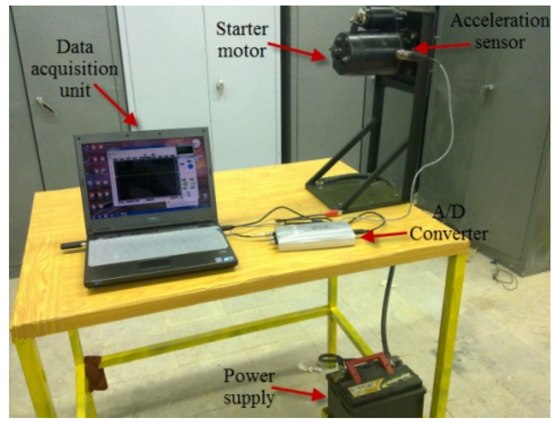

Figure 1. The experimental setup

Vibration data of motor in good condition (Healthy) was used for comparison with faulty condition of motor. Considered faults were motor, with crack in rotor body (CRB), unbalancing in driven shaft (UDS), and wear in bearing (WB), as shown in Figure 3. Unbalancing was created by gluing three nuts on the outer body of driven shaft ring. Table 1 shows the description of fault conditions.

Table 1. The description of faulty starter motor

Fault condition	Fault description
Crack in rotor body (CRB)	Number of broken bars: 27
Unbalancing in driven shaft (UDS)	Unbalancing mass: 3nuts×2.6gr
Wear in bearing (WB)	Increase of internal diameter: 1.6%

4. Result and discussion

The signal of frequency domain result starter motor in healthy, Crack in rotor body (CRB), Unbalancing in driven shaft (UDS) and Wear in bearing (WB), have shown in figures 2. The results showed that different faults showed different FFT .

The results showed that with calculating power spectral density, we could diagnose starter motor faults very fast. It was shown that power spectral density provides a good and easy method to show faults of starter motor. The results of this work have given more understanding on the dependent roles of vibration analysis and power spectral density curves in predicting and diagnosing of an starter motor faults. These are shown in the figure 3. The difference between healthy conditions from fault conditions is really visible in this figure.

The frequency spectrum of each fault was different and overall vibration values also were different at the same frequency. The results showed that the area under Power Spectral Density curves indicated a problem. More area below Power Spectral Density curve showed that the faults were deeper. Figure 4 showed the power spectral density of CRB of starter motor in different conditions. There was a big different among PSD of CRB fault and other faults. The results showed that with calculating PSD we could find some fault and the starter motor diagnosis as soon as possible. Results showed that when we had deeper faults such as CRB the area under PSD curves was grown.

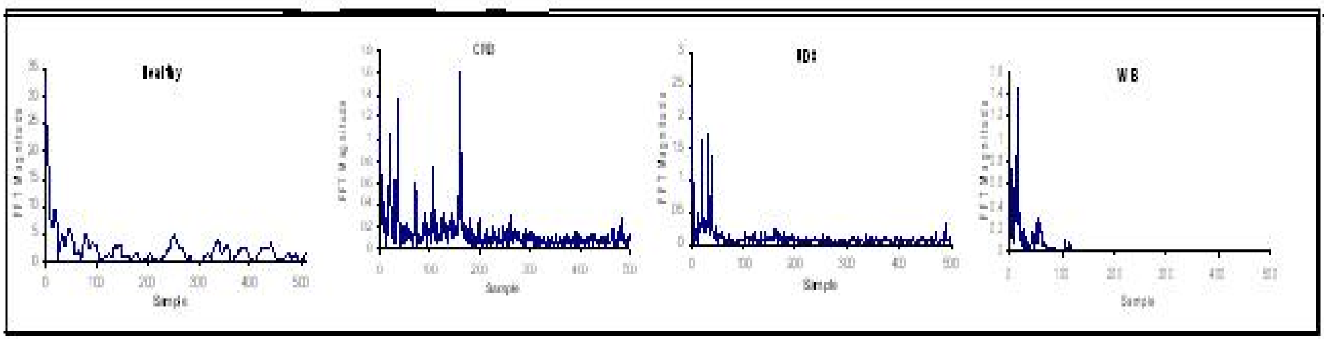

Figure 2. Typical vibration spectra of starter motor faults(FFT diagram)

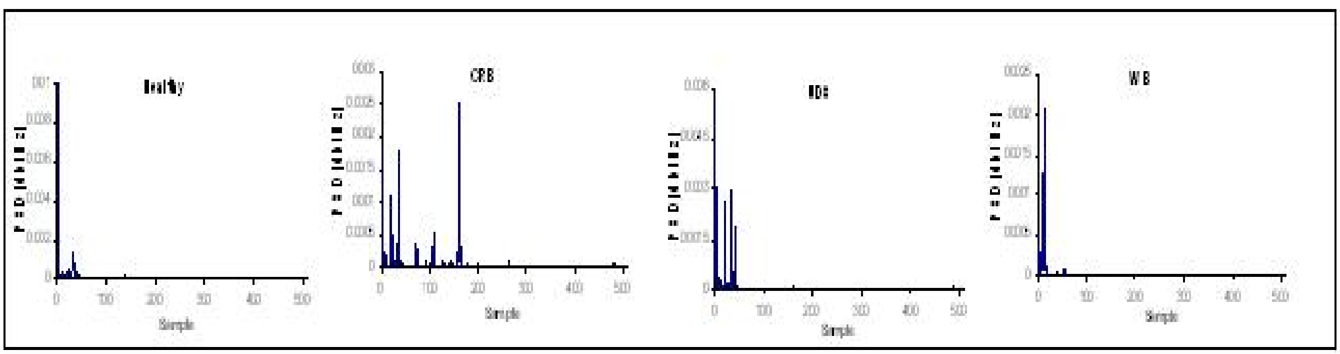

Figure 3. Typical vibration spectra of starter motor faults(PSD diagram)

5. Conclusions

The results show the applicability and effectiveness of this method to detect the fault in the starter motors. Vibration analysis (FFT diagrams) and Power Spectral Density technique could find faults of the starter motor. Vibration analysis and Power Spectral Density could provide fast and accurate information on the condition of the starter motor on different faults. By combination of vibration analysis and Power Spectral Density analysis could indicate more understanding about diagnosis of the starter motor and other rotating machinery.

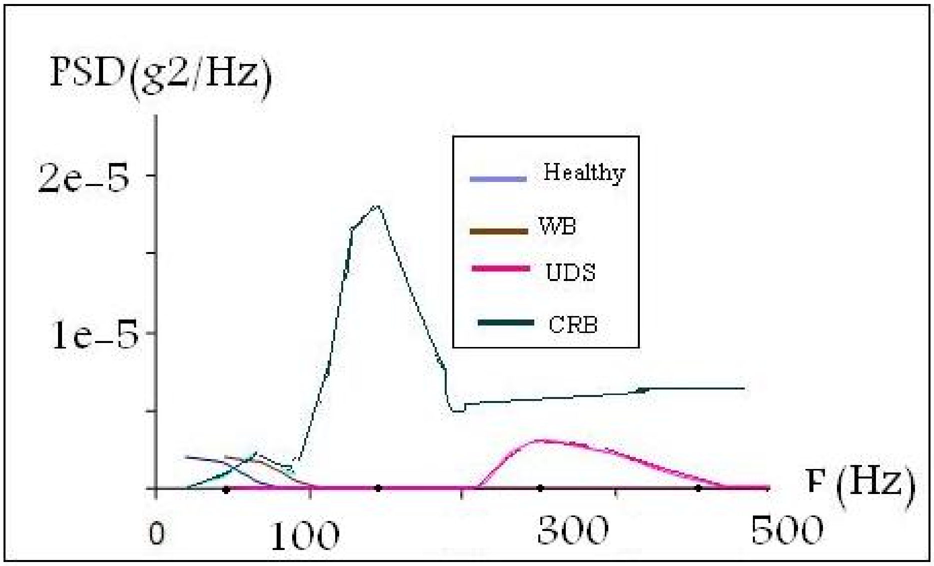

Figure 4. Power Spectral Density results of starter motor on healthy and fault conditions

Acknowledgments

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