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Two Stage Helical Gearbox Fault Detection and Diagnosis based on Continuous Wavelet Transformation of Time Synchronous Averaged Vibration Signals

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Abstract. Vibration signals from a gearbox are usually very noisy which makes it difficult to find reliable symptoms of a fault in a multistage gearbox. This paper explores the use of time synchronous average (TSA) to suppress the noise and Continue Wavelet Transformation (CWT) to enhance the non-stationary nature of fault signal for more accurate fault diagnosis. The results obtained in diagnosis an incipient gear breakage show that fault diagnosis results can be improved by using an appropriate wavelet. Moreover, a new scheme based on the level of wavelet coefficient amplitudes of baseline data alone, without faulty data samples, is suggested to select an optimal wavelet.

Keywords: Condition monitoring, Helical gearbox, Wavelet Transformation, Time synchronous average

1. Introduction

Gearboxes are very important for many industrial applications such as wind turbine, power generators and helicopter aircrafts [1]. Failures of the gearbox may cause personal injury and significant economic loss. Therefore, many techniques have been developed in condition monitoring community to diagnose gearboxes faults as early as possible so as to avoid the consequence of any catastrophic accidents [2]. The faults of gearboxes including manufacturing defects (material, tooth profile, etc), mounting defects (clearance adjustment, misalignment, imbalance etc) and defects appearing during transmission (tooth breakage, wear, crack, eccentricity, etc) [4] generate different types of signals, such as sound, temperature, motor current and vibration which can be used for condition monitoring and fault diagnosis of gearboxes [1, 3]. The vibration signal is mostly used for gearbox condition monitoring since it is easy to gather and reflect the basic excitation motion of gearbox. In the mean time, airborne acoustics or noise, being correlated closely to vibration but measured with more comprehensive information in a remote way, has also been investigated actively for condition monitoring and fault diagnosis of gearbox in last two decades. Nevertheless, both vibration and acoustic signals can be contaminated by different noises and careful analysis with more advanced tools should be carried out to obtain reliable features for fault diagnosis.

Earlier feature generation methods proposed for gearbox faults detection and diagnosis have focused on the time-domain and frequency-domain analysis, such as the spectrum, cepstrum, amplitude and phase demodulation techniques. Most of these conventional techniques are able to detect and indicate faults but could not provide detailed information about location and severity of the fault because they were not suitable for non-stationary signal [5-10]. Vibration signals from a gearbox are usually noisy and with the properties of non-stationary. As a result, it is difficult to find early symptoms of a potential failure without appropriate analysis tools. Therefore, the time-frequency analysis is developed as a more reliable and effective method for machinery condition monitoring. Wavelet transform is a typical and powerful time-frequency tool which is widely applied in machinery fault diagnosis and condition monitoring. It is capable of revealing the time-frequency characteristics of a signal. Especially it is more efficient to disclose small transients and enhance the spikes in signals [11].

As the tooth breakage is one of the common failures in a gearbox, this paper explores the performance of using wavelet analysis based on a two stage helical gearbox with faulty conditions of 20% and 100% tooth breakage. Vibration signals for these different conditions including baseline case are processed by TSA and CWT for feature extraction and fault separation respectively. The paper is organized as follow. Following this introduction section, in section 2, basic theory of CWT and TSA technique is reviewed. In section 3, test facilities and gear faults are presented. In section 4, the results of using wavelet analysis are discussed. Finally, the conclusion is given.

2. Theoretical Background

2.1. Continuous Wavelet Transform

In the field of machinery condition monitoring, the CWT is recognized as a powerful and effective tool for feature extraction from a non-stationary signal. The wavelet algorithm used in this study can be found in reference [12] in details.

If $\psi(t) \in L^2(R)$ and its Fourier transform $\psi(f)$ satisfy the admissibility condition

$$C_\psi = \int_{-\infty}^{\infty} \frac{|\hat{\psi}(\omega)|^2}{|\omega|} d\omega < \infty \quad (1)$$

$\psi(t)$ is a mother wavelet function and $L^2(R)$ is the space of square integral complex functions. The corresponding family of a wavelet consists of daughter wavelets shown as Equation (2).

$$\psi_{a,b}(t) = |a|^{-1/2} \psi\left(\frac{t-b}{a}\right) \quad (2)$$

where a is scale (dilation) factor and b is time location (translation) factor, $|a|^{-1/2}$ is used to ensure energy preservation. The daughter wavelets are the translated and scaled versions of the mother wavelet with the scale factor a and time location b vary continuously.

The CWT of a signal $x(t)$ is defined as the inner products between signal $x(t)$ and the wavelet family, which are derived from the wavelet function by dilation and translation.

$$WT_x(a,b) = \langle \psi_{a,b}(t), x(t) \rangle = |a|^{-1/2} \int x(t) \psi_{a,b}^*(t) dt \quad (3)$$

where $WT_x(a,b)$ denotes the wavelet transforming coefficient, $\psi_{a,b}^*(t)$ represents the complex conjugate of the wavelet function. a is known as a dilation parameter and b gives the location of the wavelet which is known as translation parameter.

For a discrete sequence x_m , let $a = m\delta t$ and $b = n\delta t$, where $m, n = 0, 1, 2, \dots, N-1$, N is the sampling point number and δt is the sampling interval. The CWT of x_m can be defined as:

$$WT_n(a_j) = \sum_{m=0}^{N-1} x_m \psi^* \left[\frac{(m-n)\delta t}{a_j} \right] \quad (4)$$

The amplitude of the feature corresponding to the scale and how this amplitude varies with time can be presented through varying the index j and n corresponding to the scale factor a and time location b , respectively.

Orthogonal and non-orthogonal are two types of wavelet functions commonly used in signal processing. The orthogonal wavelet is a wavelet whose associated wavelet transform is orthogonal, such as Haar, Daubechies, Coiflets, Symlets and Meyer, while the non-orthogonal wavelet functions include Morlet, Mexican hat and DOG [12]. The properties of the wavelet functions are different and can be selected for different applications.

Wavelet coefficients obtained from wavelet transform measure the similarity between the signal of interesting and daughter wavelets which are diluted and translated from a particular wavelet. The more the daughter wavelet is similar to the feature component of the signal, the larger is the corresponding wavelet coefficient [15]. Moreover, wavelet has the oscillating wave-like characteristics and has the ability to allow simultaneous time and frequency analysis with the flexible wavelet functions. To compare with wave having infinite energy, wavelet has its finite energy concentrated around a limited time interval [18]. In addition, it can also represent sharp corner in signal and original signal can be completely reconstructed or recomposed [19, 20]. This allows the transient like signals such as gearbox vibrations to be represented accurately and efficiently.

However, there are high numbers of wavelets, and each has its own particular characteristics. In addition, the understanding of gearbox vibration is also not perfect. It is necessary to choose a proper wavelet function for processing gearbox vibration signal to gain accurate fault diagnosis.

2.2. Time Synchronous Averaging

TSA is an effective technique in the time domain to remove the noise in a repetitive signal and widely used in vibration monitoring and fault diagnosis [9, 13]. The signal-to-noise ratio (SNR) of vibration signal can be improved significantly by suppressing the components which are asynchronous with that of interesting. TSA is applied based on the condition of the knowledge of the revolution of the rotating part. Traditionally, this requirement is met by using an external trigger signal provided by an shaft encoder, and the revolution period of rotating machinery can be obtained. Then, the vibration signal is divided into small segments according to the revolution period of the rotating part, and all the segments are summed up together so that no coherent components and asynchronous components are canceled out. Normally, vibration signals from rotating machinery are a combination of periodic signals with random noise. Assuming a signal $x(t)$ consists of a periodic signal $x_T(t)$ and a noisy component $n(t)$, the period of $x_T(t)$ is T_0 whose corresponding frequency is f_0 , thus the signal can be expressed [17].

$$x(t) = x_T(t) + n(t) \quad (5)$$

The synchronous average of the signal $x(t)$ by using TSA can be expressed as

$$y(t) = \frac{1}{M} \sum_{i=0}^{M-1} x(t + iT_0) \quad (6)$$

where M is the number of the average segments, $y(t)$ is the averaged signal.

3. Test facilities and gear faults

3.1. Test facilities

The gearbox test rig used in this study is shown in Figure 1. It consists of a two stage helical gearbox manufactured by David Brown Radian Limited, a three phase induction motor (11kW, 1465rpm and four poles) produced by the Electro-drive Company, and a load system consisting of two flexible coupling, DC generator and resister bank. The induction motor is flanged in a cantilever type arrangement to the gearbox. The gearbox with 1.45 contact ratio is used in the test with driving gear has 58 teeth and the driven gear has 47 teeth. The input shaft is driven by an AC motor. The motor speed and load is controlled by a variable speed drive for studying condition monitoring performance

under different operating conditions. Vibration of the test gearbox is measured by an accelerometer (Type PCB 338C04) with a sensitivity of 100 mv/g, and frequency response range is from 1Hz to 20 kHz. It is mounted on gearbox housing casing, as indicated in Figure 2. An incremental optical encoder is equipped to measure instantaneous angular speed (IAS) from its 100 pulse train signal and to identify initial phase of the input gear by its once per revolution signal. It is installed to the end of the induction motor shaft. A schematic diagram of the test rig is shown in Figure 2.

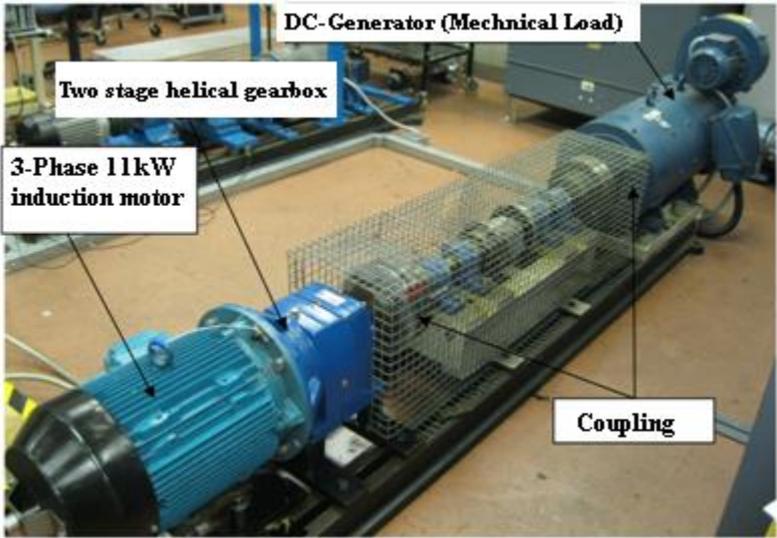


Figure 1. Experimental test rig of gearbox.

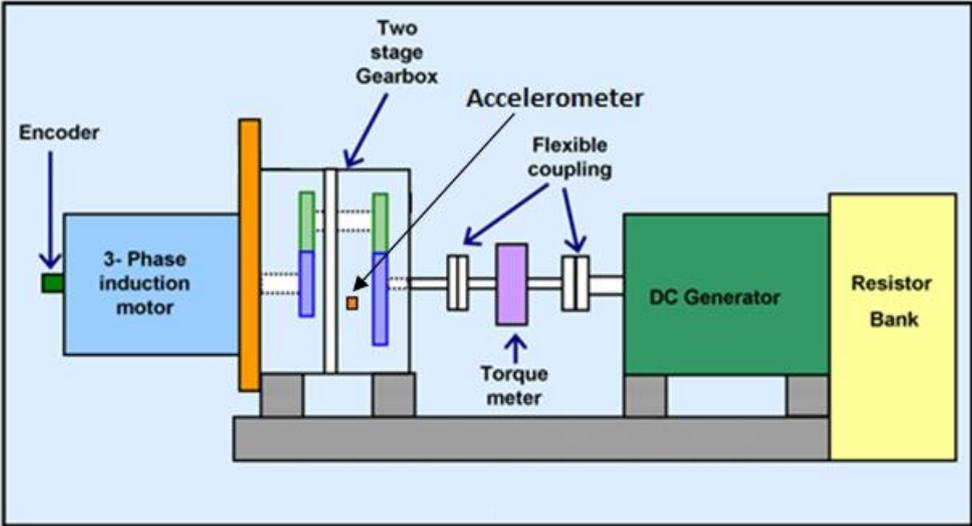


Figure 2. Schematic diagram of test rig.

3.2. Data acquisition system

As shown in Figure 2, an accelerometer and optical encoder are fitted directly on the test rig. Each transducer produces a voltage output which is proportional to the amplitude of the measured parameters and then connected to the data acquisition system (DAS) by coaxial BNC cables. The placement of transducers is presented in Figure 2.

The data acquisition instrument used in the test is the model PD2-MF-16-500/16L PCI board which has 16 analogy input channels. The sampling rate is 500 kHz for each channel with 16 bit data

resolution and the input voltage range is $\pm 10V$. The task of the DAS is to convert the analog signals acquired from the transducers to the digital signals transferred to the computer for the future analysis.

3.3. Gear faults

In this study, two degrees of the tooth breakage: 20% and 100% tooth damage as shown in Figure 3, are simulated to examine the sensitivity of wavelet analysis. They were produced by removing the percentage of the tooth face on the pinion gear in the width direction. Vibration signals collected from a same gearbox in which the two broken gears were tested once a time. The larger fault of 100% tooth breakage is for understanding the potential characteristics of wavelet transform and the 20% tooth breakage is interested in this study to evaluate the performance wavelets in fault detection.

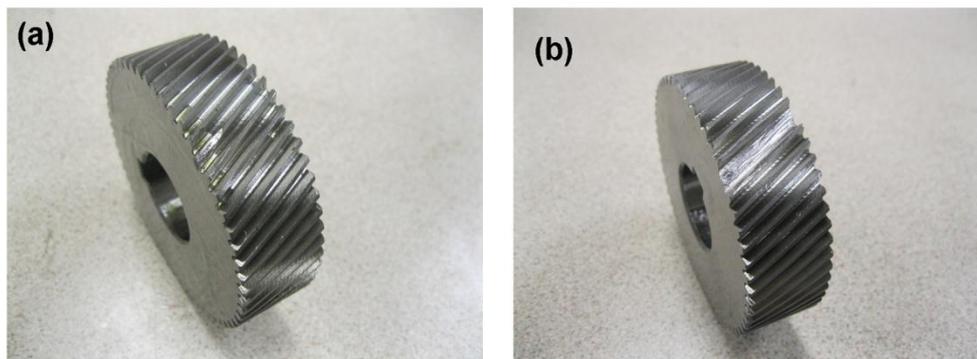


Figure 3. Gear faults: (a) 20% tooth damage (b) 100% tooth damage .

4. Results and discussion

4.1. TSA pre-processing

During the tests, both the vibration and the encoder signals are collected simultaneously by the DAS at a sampling rate of 100 kHz. For each fault case the data is collected under 5 different loads: 12.4%, 21.2%, 30.8%, 39.3% and 42.9% of the full load, respectively. Each collection has 1,600,000 points which is 16 seconds in duration, and around 400 rotating revolutions according to the full speed (1465rpm). This data length is sufficient for random noise suppression in TSA process. The encoder signal includes the shaft revolution events that is used to measure the shaft speed and is the reference for synchronous average of the vibration signal. However, the time interval of the pulses in the encoder signal is not constant due to the oscillation of the shaft speed. Assuming the shaft speed is undergoing constant angular acceleration. The angular acceleration is calculated based on arrival times of the adjacent three pulses known from the sampling of the encoder signal. Then, the correct placement of the resample on the time axis is carried out based on the constant angular acceleration. In this study, the time axis resampling is processed in sections with per section length is 1000 points and 5 sections are selected. Once the resample times are calculated, the vibration signal is resampled according to the resampled time axis for synchronous average.

Figure 4 shows the averaged vibration signal using TSA for three revolutions of the input shaft when the gearbox operates under different loads and faulty cases, where the baseline is the healthy case. It can be seen that the amplitude of the vibration signals increases with the increasing of the loads for all the faulty cases, and the impulse components of the vibration signals are highlighted for all the test conditions, especially for the faulty case of 100% tooth damage. Moreover, TSA signals show much clearer indication of the 100% tooth damage compared with the baseline. However the signals between the baseline and 20% tooth damage cannot be observed with noticeable differences.

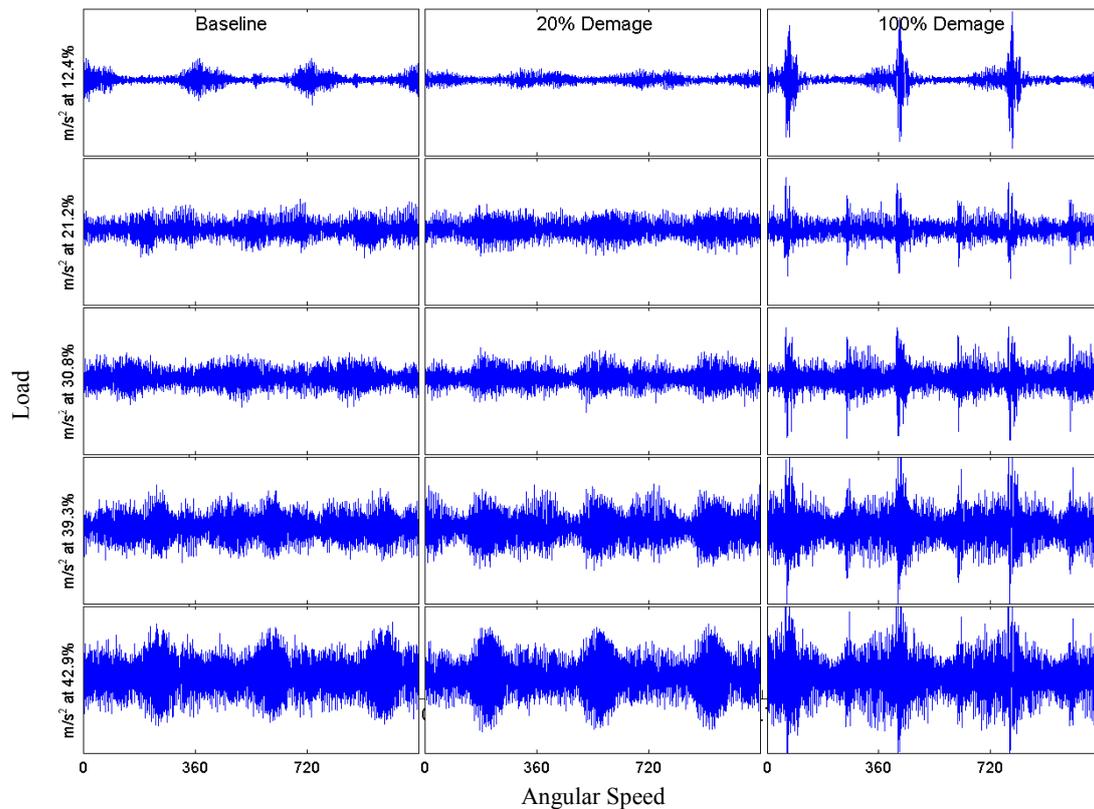


Figure 4. TSA vibration signals under different operating conditions and gear cases.

For a detailed comparison, common feature parameters such as root mean square (RMS) and kurtosis are calculated from the TSA vibration signals. As shown in Figure 5, RMS and kurtosis values have similar performance in separating the three cases over different loads. Comparing with the baseline, the RMS value of 100% tooth damage is clearly separated from the other two cases under all loads and so do kurtosis values. However, the difference between the baseline and 20% tooth damage is not very obvious for fault separation.

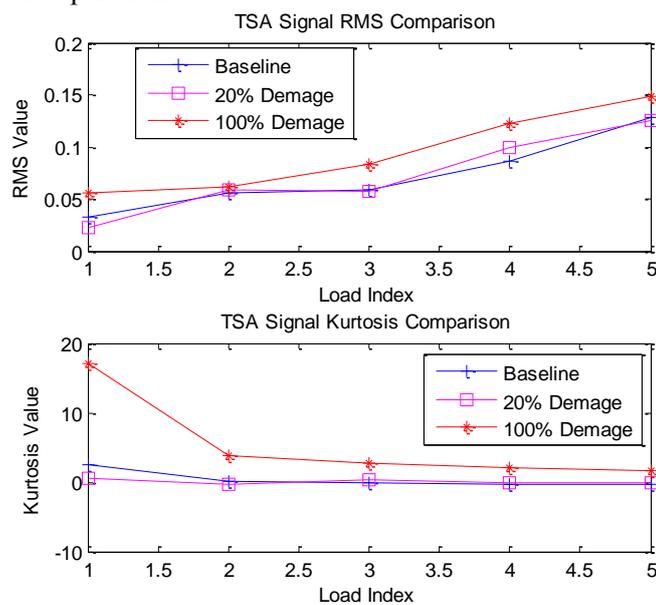


Figure 5. RMS and kurtosis values of TSA vibration signals under different gear cases.

4.2. Feature extraction based on CWT analysis

In the present study, the wavelets of Daubiechies order 1 (db1), Symlets order 2 (sym2) and Coiflets order 3 (coif3) are selected to analyse the TSA vibration signals obtained under different faulty cases of baseline, 20% and 100% tooth damage. These wavelets are all the orthogonal wavelet with the faster, perfect reconstruction and non-redundant decomposition[14-16] and used in many applications.

The scales ranges from 0.5 to 20 are selected for all the wavelets application in this study to investigate the time-frequency properties of the vibration signal. The TSA vibration signal of 5,000 data points are selected to perform CWT analysis for all the test conditions. To show the joint time and scale characteristics, wavelet coefficients are present with contour plots for different wavelets and loads, as shown in Figure 6, 7 and 8. It can be seen that there are clear difference between the baseline and 20% tooth damage for all the wavelets and load conditions. In particular, the wavelet coefficients of db1 were much higher with larger visible areas.

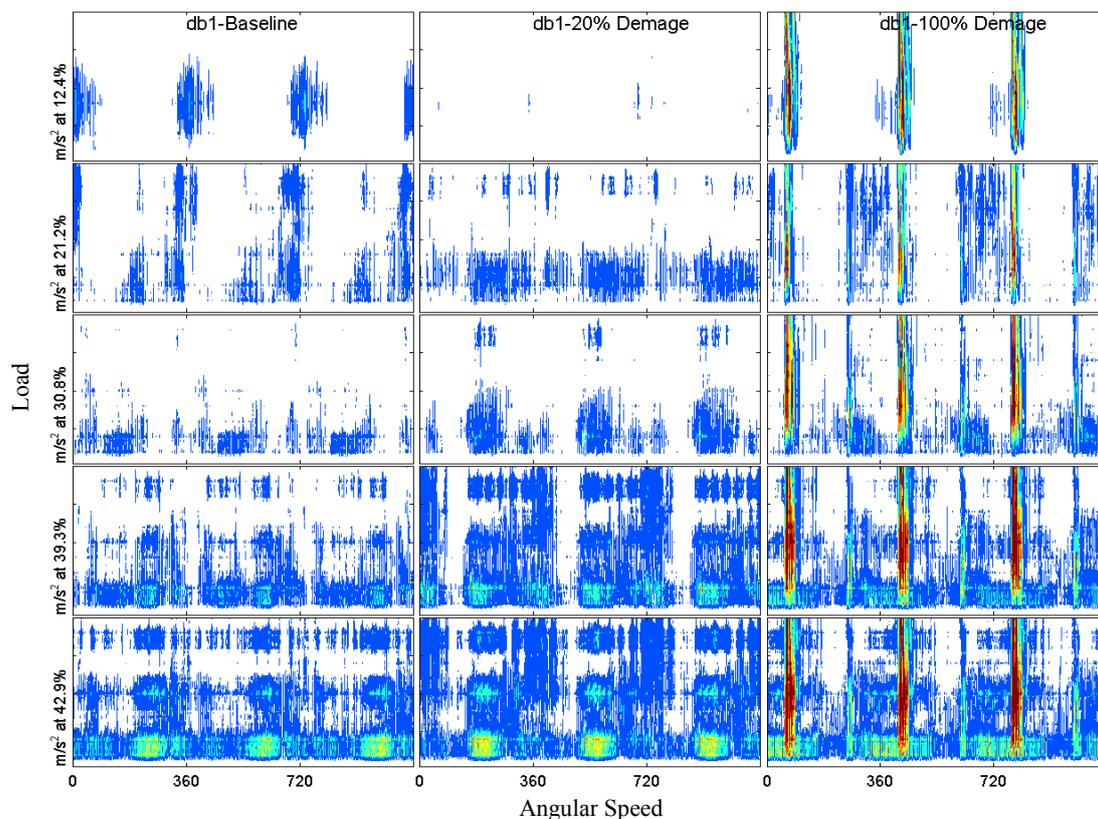


Figure 6. Contour plots of db1 wavelet coefficients for different gear cases.

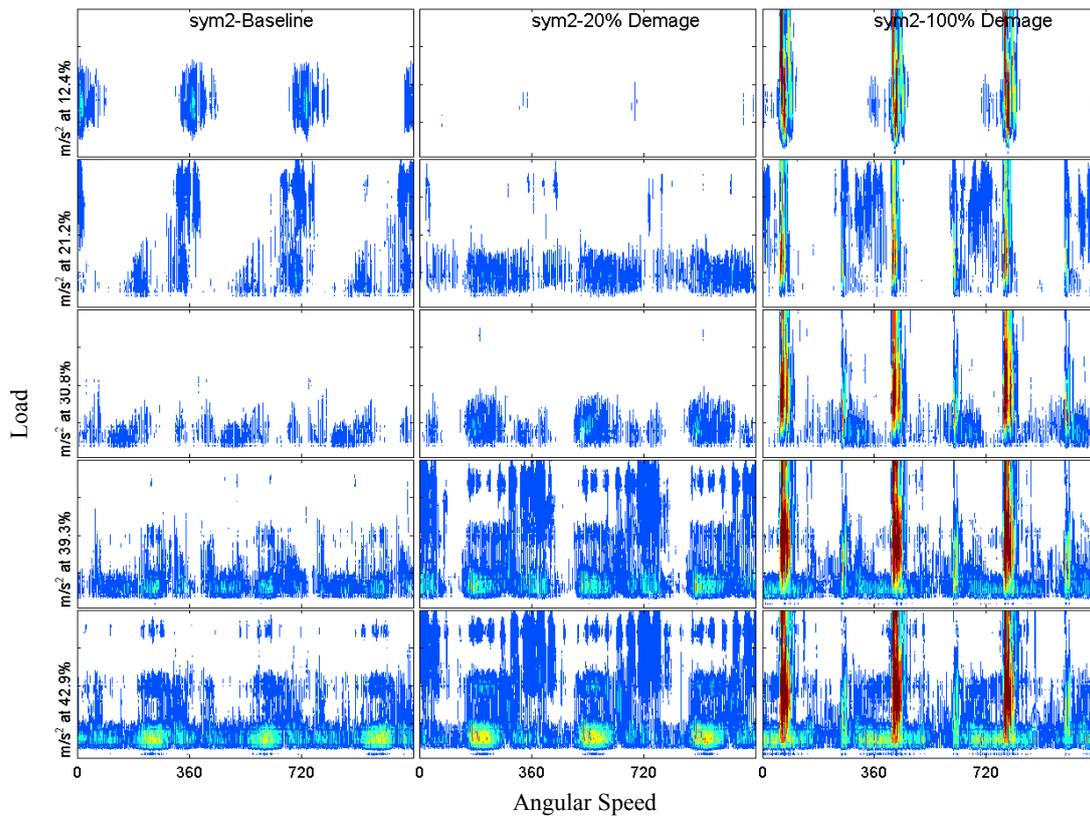


Figure 7. Contour plots of sym2 wavelet coefficients for different gear cases.

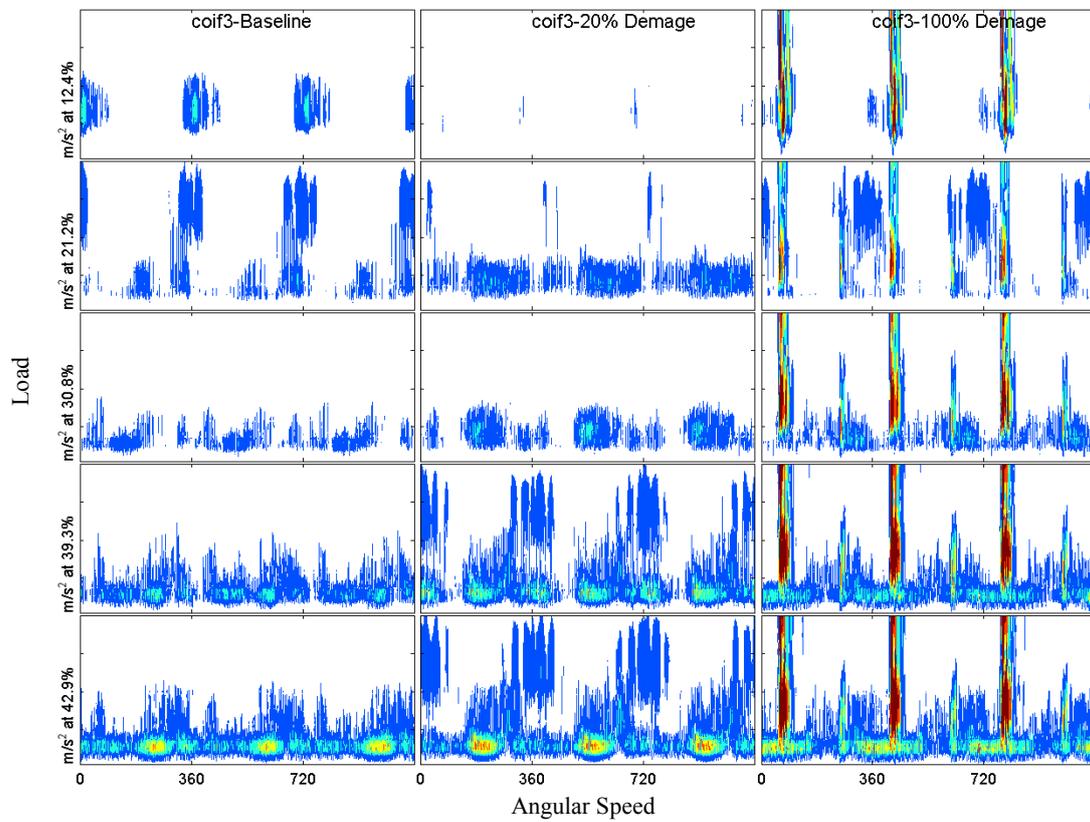


Figure 8. Contour plots of coif3 wavelet coefficients for different gear cases.

From the comparison of Figure 6, 7 and 8, it has found that the three wavelets can give similar behaviors. However, the difference enhancements of three faulty cases are in different degrees. Two common feature parameters, RMS and kurtosis, are extracted from the wavelet results in terms of baseline for comparing the performance of the used wavelets. As shown in Figure 9, it can be seen that RMS values can reveal difference under high loads for the small damage. However, the commonly used kurtosis only showed little difference.

Comparing the analysis results of the TSA and CWT shown in Figure 5 and 9, it can be concluded that CWT can give clearer fault separation results for all the presented faulty cases, while the difference between the small faulty cases, baseline and 20% tooth damage, cannot be observed clearly by TSA.

Although all the three types of the wavelets selected in our study given acceptable performance for faulty cases separation, they enhanced the difference in different degree. In order to analyse which wavelet is more effective and suitable for gearbox condition monitoring and fault diagnosis, RMS values between the three wavelets were compared under baseline case. Figure 10 showed the details of the comparison. As the wavelet of db1 has higher RMS values from baseline data, it thus produced the largest difference (at load 2) for separating the baseline and 20% tooth damage. On the other hand, coif3 could not do separation clearly because of its low RMS values from baseline data. The evaluation analysis from Figure 10 indicated the wavelet of db1 is the best one to classify the different faulty cases among the three wavelets.

Moreover, it has observed that a higher RMS values in the case of baseline will produce a higher difference for the smaller damage. Based on this, an optimal wavelet can be determined without the using of the data sets from damage measurements which are normally not available in condition monitoring practices.

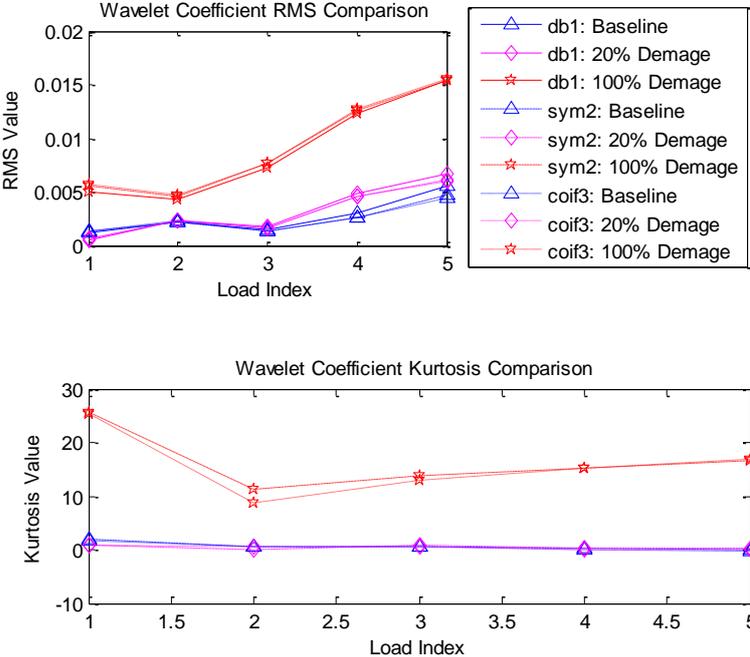


Figure 9. Wavelet coefficients map RMS & kurtosis comparison.

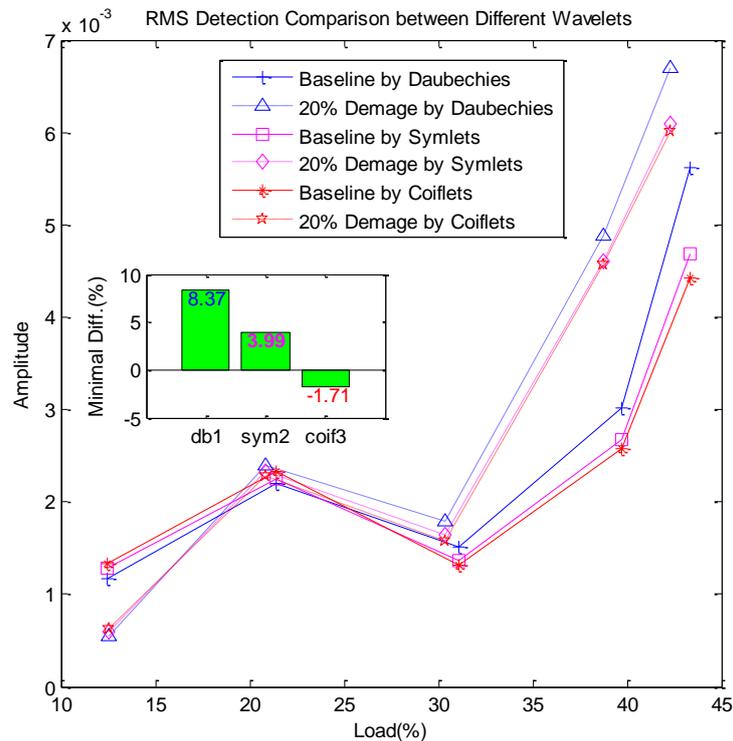


Figure 10. Comparison of RMS between different wavelets.

5. Conclusion

CWT has been shown to be an effective tool for rotating machinery fault detection and diagnosis. In this study, the fault diagnosis of a two stage helical gearbox is carried out based on the CWT analysis and TSA techniques. TSA allows the noisy components to be removed significantly and hence highlights the fault related impulse components which paves the basis for accurate feature extraction. Moreover, three types of wavelets: db1, sym2 and coif3 were explored to find the optimal wavelet for separating the small fault.

The results have shown that wavelet db1 produces the best fault separation whereas the coif3 wavelet fails to do the separation. It means that different wavelets produce different separation results. To obtain the best fault separation, a careful selection of wavelets needs to be carried out. Based on this study, it is suggested that selecting the wavelet that produces a higher RMS value of wavelet coefficients when it is applied to baseline data. This selection scheme does not need any faulty data sets, which is more realistic for condition monitoring practices.

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