DIAGNOSIS OF ROLLING ELEMENT BEARING FAULT IN BEARING-GEARBOX UNION SYSTEM USING WAVELET PACKET CORRELATION ANALYSIS

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Abstract: The failure of rotating machinery sometimes involves several faulty components. Existence of both bearing fault and gearbox fault is widely observed and in this situation the vibration feature of the bearing fault can be masked by the faulty gearbox vibration signals. In this research, a method is proposed based on wavelet packet transform and envelope analysis to extract fault features of the rolling element bearing from the masking faulty gearbox signals. Wavelet packet of the test signal containing bearing fault information is selected by correlation analysis and the fault feature is extracted by envelope analysis. Case study shows that the proposed method can detect the outer race fault in a rolling element bearing from the masking signals of a gearbox with worn teeth. Compared with exist methods, the proposed method does not require gearbox fault information, and it reduces the amount of sensors.

Key words: Bearing; correlation coefficient; diagnosis; gearbox; vibration; wavelet packet transform

Introduction: Bearing failure is a main contributor to rotating machinery failures [1]. Vibration analysis is widely used in the condition monitoring of the rolling element bearing. Vibration analysis methods such as Fast Fourier Transform (FFT), Short-Time Fourier Transform (STFT), Envelope Analysis and Wavelet Transform (WT) have been proved useful in bearing diagnosis. However, using any of these methods alone is not effective to diagnose the fault of a rolling element bearing when the bearing signal is masked by the gearbox signals, which is a phenomenon observed in complex systems like wind turbines and helicopters.

Several approaches have been proposed. One approach assumes that the signal of the gearbox is deterministic and the signal of the bearing is non-stationary, which can be used to extract bearing signals from the background containing interfering gearbox signals [2]. This is further generalized as discrete frequency noise. Linear prediction, adaptive noise cancellation, time synchronous averaging (TSA), Self-adaptive noise cancellation (SANC), and discrete/random separation (DRS) have been used in this non-stationary approach [3]. To assume that the gearbox signal is deterministic, it should be kept in mind that this approach is limited by the type and severity of the fault. Another approach assumes that signals from independent sources can be separated using blind source separation methods (BSS), but certain amount of sensors should be used [4]. Independent component analysis (ICA) was used in this approach for bearing diagnosis. In [5] Miao et al. presented a method based on independent component analysis (ICA) to extract bearing fault features.

In this paper, a bearing signal extraction method adopting the idea of BSS is presented. It combines wavelet packet transform (WPT), Pearson correlation coefficient, and envelope analysis to extract the bearing signals from the masking background. The proposed method permits the analysis without considering the type and severity of the gear fault, expanding the range of applications, and it also reduces the number of required sensors.

Wavelet Packet Transform: Wavelet packet transform (WPT) is a time-frequency analysis method which decomposes a signal into a full binary tree of frequency bands. Each decomposition unit contains unique frequency band and time series information. It is capable of processing both stationary and non-stationary vibration signals. Compared with other time-frequency analysis methods, WPT has several advantages over conventional methods, which are useful for bearing signal analysis: short-time Fourier transform (STFT) suffers from fixed frequency resolution across the different frequency bands while WPT has multiple resolutions in different frequency band; wavelet transform (WT) cannot decompose the signal into a full binary tree in the frequency domain, while WPT can; Hilbert-Huang Transform (HHT)'s decomposition results are not orthogonal while WPT is an orthogonal decomposition method. Therefore WPT has been widely used to perform condition monitoring for rolling element bearings. In [6], WPT was combined with energy demodulation operator to diagnose bearing fault. In [7] an improved WPT algorithm is used to assess the performance of the bearing.
Wavelet packet can be decomposed by the following recursive equations:

$$w_{2n}(t) = \sqrt{2}\sum_k h_{0k} W_n(2t-k) \tag{1}$$

$$w_{2n+1} = \sqrt{2}\sum_k h_{1k} W_n(2t-k) \tag{2}$$

where $w_0(t)$ is the scaling function, $w_1(t)$ is the basic wavelet function, h_{0k} is the low pass-filter, h_{1k} is the high-pass filter. Then the wavelet packet functions are formed as

$$W_{jk}^{n}(t) = 2^{\frac{j}{2}} w^{n}(2^{j}t - k) \tag{3}$$

Correlation Coefficient: Pearson Correlation Coefficient (PCC) is a measure of linear dependence of two variables. In this work it is used to measure the linear dependence between the decompositions of the testing signal and the reference signal (bearing signal with known fault).

The Pearson Correlation Coefficient used in this research is defined as follows:

$$corr_b(i) = \frac{cov(s_b(t), c_i(t))}{\sigma_{s_b(t)}\sigma_{c_i(t)}} \tag{4}$$

where $corr_b(i)$ is the correlation coefficient between the *i*th decomposition unit of the test signal and the reference signal; $s_b(t)$ is the bearing fault signal used as reference; $c_i(t)$ is the *i*th decomposition unit of the test signal.

In the estimation of the Pearson Correlation Coefficient, the following equation is used:

$$corr_b(i) = \frac{\sum_t \left(s_b(t) - \overline{s_b(t)}\right)\left(c_i(t) - \overline{c_\iota(t)}\right)}{\sqrt{\sum_t \left(s_b(t) - \overline{s_b(t)}\right)^2} \sqrt{\sum_t \left(c_i(t) - \overline{c_\iota(t)}\right)^2}} \tag{5}$$

where $\overline{s_b(t)}$ and $\overline{c_\iota(t)}$ are the means of signals $s_b(t)$ and $c_i(t)$, respectively.

The Pearson Correlation Coefficient has a value range of [-1, 1]. A higher absolute value represents higher linear dependence between the decomposition of the testing signal and the reference signal.

Envelope Analysis: Vibration signal of the rolling element bearing is a modulated signal [8], and vibration signal model for the rolling element bearing was proposed. In [9] the modulation causes and mechanisms were further investigated. In recent years, the bearing signal was modeled as non-stationary [3], and the modulation of the bearing signal was not changed.

Envelope analysis is a tool that has been widely used to demodulate the bearing signal. For a single degree freedom vibration model, the system's response of the periodic impulses is:

$$x(t) = u(t)v(t) \tag{6}$$

$$v(t) = \sin(2\pi f_0 t) \tag{7}$$

where $u(t)$is the periodic impulses, which contains the fault information. It works as the modulating frequency. $v(t)$ is the system's resonance signal, which works as the carrier frequency. f_0 is the system's resonance frequency.

Envelope analysis is to obtain the original impulse signal, which contains the fault information from the system's response $x(t)$. It can be achieved by using Hilbert transform.

First, the system's resonance signal $v(t)$ is shift $\frac{\pi}{2}$ in phase. The system's new response signal $y(t)$ is

$$y(t) = u(t)\sin\left(2\pi f_0 t + \frac{\pi}{2}\right) = u(t)\cos\,(2\pi f_0 t) \quad (8)$$

Then, the square root of $x(t)$ and $y(t)$ is calculated, and the modulating frequency $u(t)$ containing the fault information is obtained

$$\sqrt{x^2(t) + y^2(t)} = \sqrt{u^2 sin^2(2\pi f_0 t) + u^2 cos^2(2\pi f_0 t)} = u(t) \quad (9)$$

An issue of applying envelope analysis is the selection of the frequency band. In rotating machinery diagnosis, the frequency band of interest is the one containing the primary resonance mode. Spectral kurtosis analysis [10] and genetic algorithm [11] have been used to determine the primary resonance mode, but they cannot tell the primary resonance mode is a result of the gearbox fault or the bearing fault.

The Proposed Method for Rolling Element Bearing Fault Feature Extraction: In a bearing-gearbox union system, both the rolling element bearing and the gearbox's vibration signals are modulated. It is assumed that the impulses generated by the faulty bearing and the faulty gearbox are not the same, and there is a difference between the resonances excited by them. Because of this difference there are frequency bands which are dominated by modulated bearing signals. One of this frequency bands has the highest correlation coefficient value with the reference bearing signal, which is the signal of the faulty bearing obtained without contamination of faulty gearbox's signal.

Accordingly, the proposed method uses WPT to decompose the test signal, which is a mixture of bearing and gearbox signals, to a set of decomposition units that each has unique frequency band, and then selects the decomposition unit which has the highest correlation coefficient value with the reference bearing signal. The selected decomposition unit contains more information of the faulty bearing and less information of the gearbox. After envelope analysis and Fourier transform the fault features of the bearing can be observed from the spectrum.

Flow chart of the proposed method is illustrated in Fig. 1.

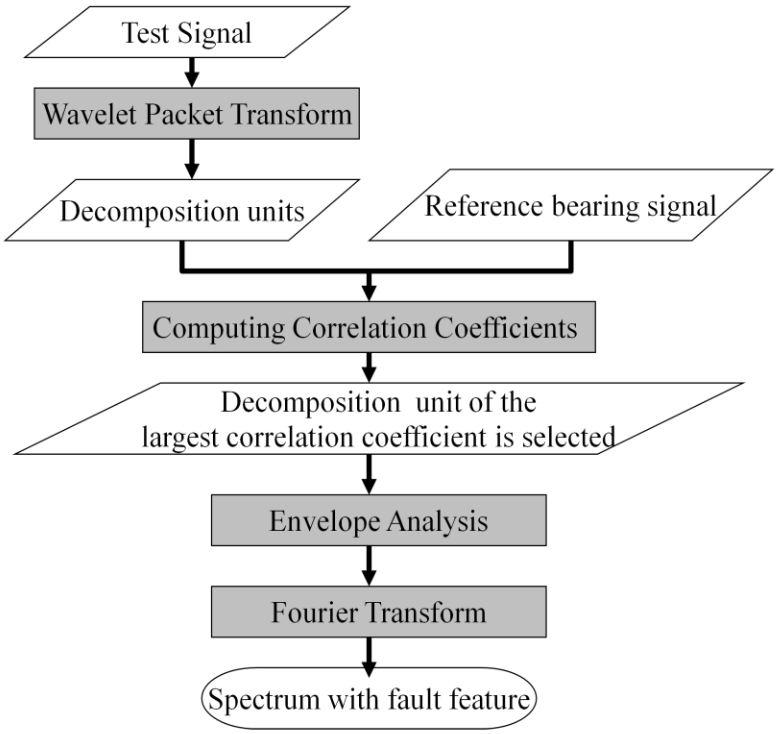

Fig.1: Flow chart of the proposed method

Experimental Study: The experiment is carried out on a Machinery Fault Simulator of SpectraQuest, Inc. Fig. 2 shows the illustration of the simulator.

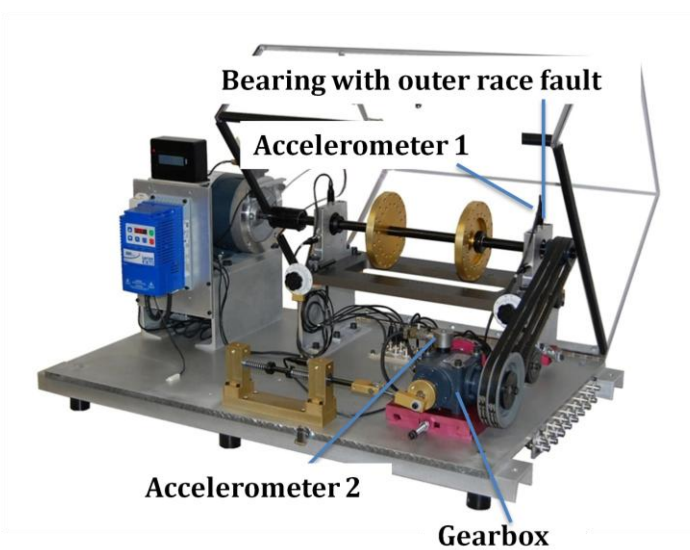

Fig. 2: Experiment setup

In order to generate the signals under study, the simulator was installed with a normal gearbox and a bearing with outer race fault. Accelerometer 1 recorded the faulty bearing signal which has not been interfered by the faulty gearbox signal. Then the gearbox was replaced by a faulty one with uniformly worn pinion teeth. Accelerometer 2 collected the test signal which contained strong masking signal from the faulty gearbox.

The bearing was running at the 600RPM (10Hz) and after the belt transmission the input speed applied on the pinion of the gearbox was 234RPM (3.9Hz). The pinion had 18 teeth and the gear had 27 teeth. The fault feature of the gearbox is the meshing frequency, which is calculated as 70.2Hz.

Model of the bearing is MB ER-12K. Characteristic frequencies of the bearing were calculated at the bearing's rotation speed of 600RPM. They are listed in Table 1. In this research, the fault features to be extracted is the outer race fault feature of BPFO at 30.48Hz.

Table 1: Characteristic Frequencies of the Bearing MB ER-12K

FTF (Fundamental train frequency)	3.78 Hz
BPFO (Ball pass frequency: outer race)	30.48 Hz
BPFI (Ball pass frequency: inner race)	49.5 Hz
BSF (Ball spin frequency)	19.92 Hz

The accelerometer recorded 24 seconds data at a sampling frequency of 5120 Hz when the system was running steadily.

Envelope analysis of the reference signal, which was collected by accelerometer 1, is illustrated in Fig. 3. The fault feature of the outer race fault (f_{BPFO}) is the dominant frequency component of the spectrum.

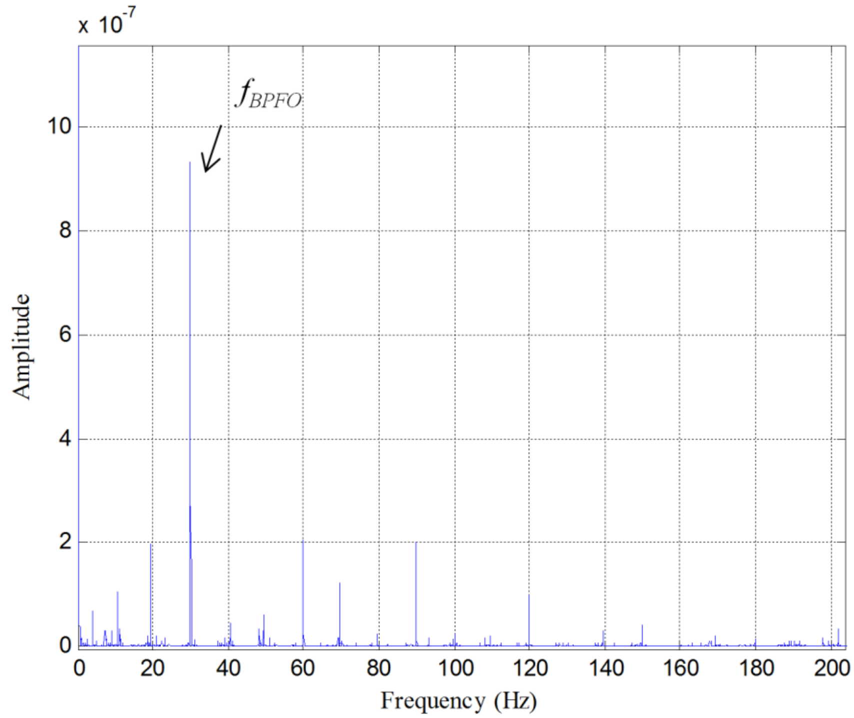

Fig.3 Envelope spectrum of the reference signal from accelerometer 1

Test signal from accelerometer 2 was analyzed after the interfering signal of the faulty gearbox was introduced. Result of the envelope analysis is shown in Fig 4. Fault feature of the bearing was masked by the signal of the faulty gearbox. The dominant frequency component is the meshing frequency of the gearbox (f_{mesh}).

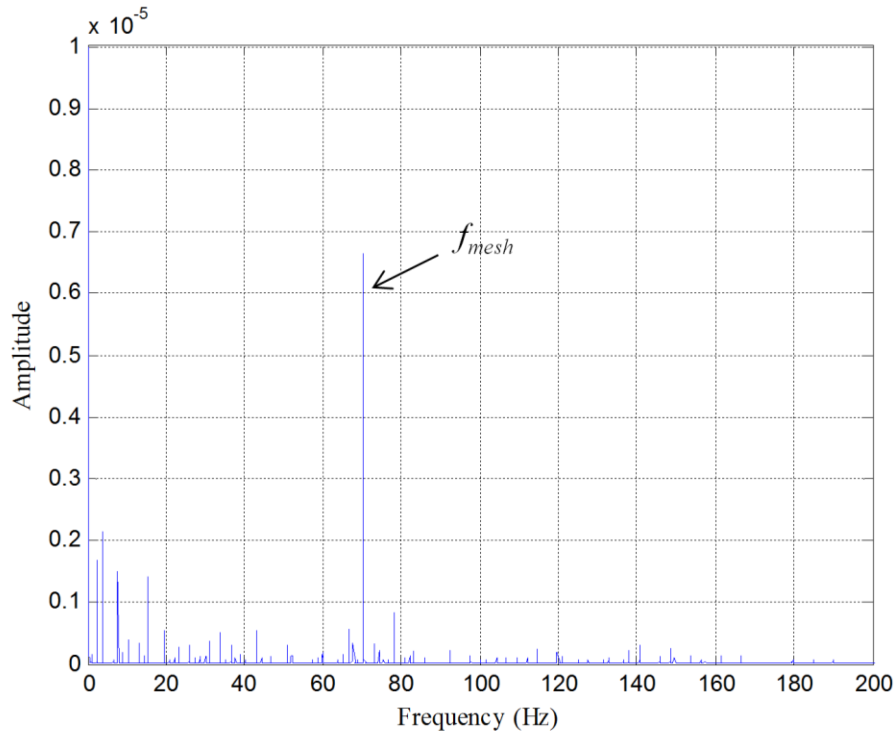

Fig.4 Envelope spectrum of the test signal from accelerometer 2

Then the test signal was analyzed by the proposed method. The test signal was decomposed into 9 levels. Correlation coefficient of each decomposition unit and the reference signal was calculated and normalized. The largest absolute correlation coefficient was found between the reference signal and the 18th decomposition unit at level 8 and this decomposition unit is used to do envelope analysis. The distribution of the normalized absolute correlation coefficient at level 8 is shown in Fig. 5.

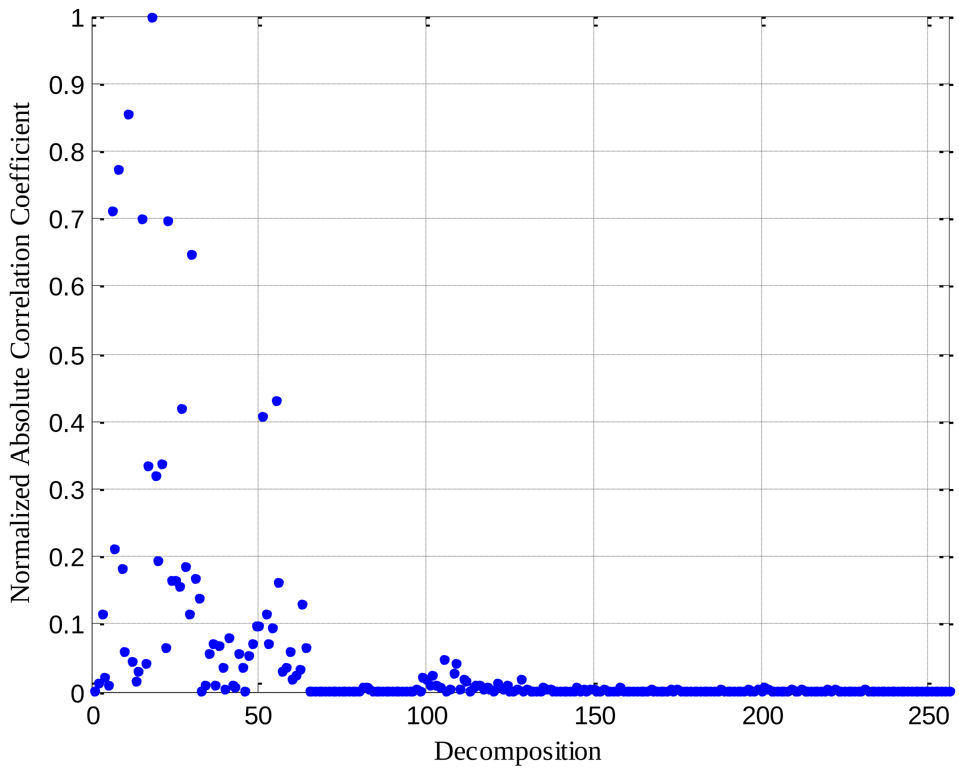

Fig.5 Normalized absolute correlation coefficient between the reference signal and the decomposition units at the 8th decomposition level of the test signal

After envelope analysis, outer race fault feature of the bearing (f_{BPFO}) can be observed in the spectrum, and the interfering gearbox signal was removed. The result is shown in Fig. 6.

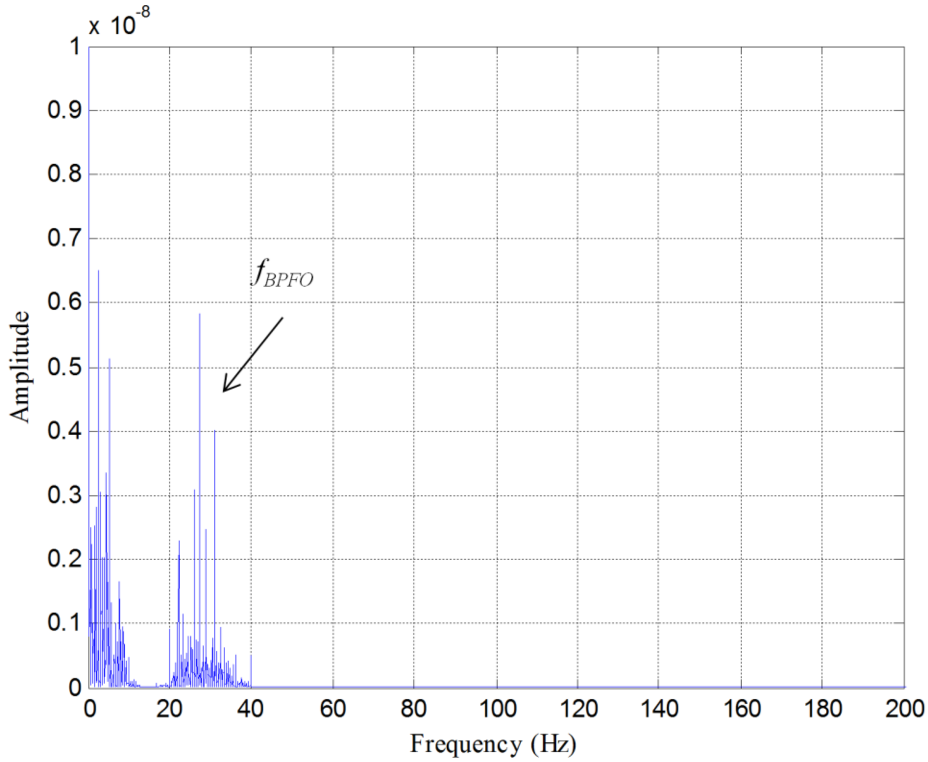

Fig.6 Spectrum of the extracted outer race fault feature using the proposed method

In the experiment, the fault feature of the bearing with outer race fault was successfully extracted from the signal masked by the gearbox with worn teeth. The proposed method did not use any information about the faulty gearbox. Moreover, to separate the faulty bearing signals from the faulty gearbox signals, only one sensor is used to monitor the mix signal.

Conclusions: This paper proposed a method to extract vibration features of the rolling element bearing from the masking background. Wavelet packet which was dominated by bearing fault signal was selected by the correlation analysis, and the fault feature of the bearing was extracted from the selected wavelet packet by the envelop analysis. The case study showed that the proposed method extracted fault features of the bearing with outer race fault from a signal mixed with the signal of a faulty gearbox. The proposed method does not need fault information of the gearbox. Moreover, it does not require the same amount of sensors of source signals. As in the case study, only one sensor (sensor 2) is used to monitor the test signal. However, the proposed method requires a database of bearing faults to provide reference signals. In this research the reference signal was provided by experiment. In the future research simulated bearing signals will be used as references.

References

[1] C. Chen and G. Vachtsevanos, Bearing condition prediction considering uncertainty: an interval type-2 fuzzy neural network approach, Robotics and Computer Integrated Manufacturing, accepted for publication, 2012.
[2] J. Antoni and R.B. Randall, Differential diagnosis of gear and bearing faults, ASME Journal of Vibration and Acoustics, **124** (2) (2002), Pages 165–171
[3] R. B. Randall and J. Antoni, Rolling element bearing diagnostics—A tutorial, Mechanical Systems and Signal Processing, **25** (2) (2011), Pages 485-520
[4] G. Gelle, M. Colas and C. Serviere, Blind source separation: A tool for rotating machine monitoring by vibrations analysis, Journal of Sound and Vibration, **248** (5) (2001), Pages 865-885
[5] Q. Miao, D. Wang, and M. Pecht, Rolling Element Bearing Fault Feature Extraction Using EMD-Based Independent Component Analysis, 2011 IEEE Conference on Prognostics and Health Management (PHM) (2011), Pages 1-6
[6] C. Tang, Q. Miao and M. Pecht, Rolling element bearing fault detection: Combining energy operator demodulation and wavelet packet transform, Prognostics and System Health Management Conference (PHM-Shenzhen) (2011), Pages1-6
[7] Y. Pan, J. Chen and L. Guo, Robust bearing performance degradation assessment method based on improved wavelet packet-support vector data description, Mechanical Systems and Signal Processing, **23** (3) (2009), Pages 669–681
[8] P. D. McFadden and J. D. Smith, Model for the Vibration Produced by a Single Point Defect in a Rolling Element Bearing, Journal of Vibration and Acoustics, **96** (1) (1984) Pages 69–82.
[9] Y. Wang and P. J Kootsookos, Modeling of Low Shaft Speed Bearing Faults for Condition Monitoring, Mechanical Systems and Signal Processing, **12** (3) (1998) Pages 415-426
[10] N. Sawalhi, R.B. Randall and H. Endo, The enhancement of fault detection and diagnosis in rolling element bearings using minimum entropy deconvolution combined with spectral kurtosis, Mechanical Systems and Signal Processing, **21** (6) (2007), Pages 2616-2633
[11] A. Docekal, R. Smid, M. Kreidl, and P. Krpata, Detecting dominant resonant modes of rolling bearing faults using the niching genetic algorithm, Mechanical Systems and Signal Processing, **25** (7) (2011), Pages 2559-2572