PAPER REF: 4122

DEVELOPMENT OF INTELLIGENT HEALTH MONITORING SYSTEM FOR ROTATING MACHINERY AND STRUCTURAL COMPONENTS

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ABSTRACT

This paper presents a comprehensive intelligent method for detecting faults in a multi-component complex system (e.g. aircraft engine). This is accomplished in two phases 1) Decompose the signals into components pertaining to system's components 'source separation' and if the components of the system are not well identified, the method used is called 'blind source separation'. The foremost existing mathematical solution to blind source separation is Independent Component Analysis (ICA), 2) in the next step signals from the actual state of the components are compared with the signals in database in order to identify the state of each component. Several artificial intelligent methods such as Neural Networks and Fuzzy Logic are used for the purpose of comparison and decision making.

Keywords: cyclic spectral analysis, cyclostationary, bearing fault detection, complex machinery, condition monitoring

INTRODUCTION

In recent years, the objective of diagnostic of machine by vibration analysis has been considerably changed. The initial objective was the security of machine against the important damages. If the vibration amplitude (displacement, velocity or acceleration) reaches to the limit value, the alarm rings and the machine stop. This type of maintenance is called preventive maintenance. The objective is not only to protect the machine but also to detect and identify defaults in the first step in order to have the necessary time to schedule repairs with minimum disruption to operations and production. This new type of maintenance is called predictive maintenance. The key factor of the predictive maintenance is diagnostic. A diagnosis is not an assumption; it is a conclusion reached after a logical evaluation of the observed symptoms. Then, the diagnostic is based on a systematic inspection in vibration signal to find all susceptible defects, which may affect the machine.

Aerospace industry is leading advanced technology exporter. In order to maintain its competitive edge in Maintenance, Repair and Overhaul (MRO), this sector of industry must employ the latest advanced technologies available. The reliable and secure operation of mechanical systems is critical importance. In the aerospace industry, both structural and non-structural components must be adequately inspected and maintained as long as an aircraft remains in service. The challenge is to develop an intelligent health monitoring system that will adequately address aging aircraft components.

The specific objectives of the present paper fall into the following categories:

A) Develop a Real-Time Health Monitoring System for rotating machinery;

B) Develop of a System for Automatic Detection and Characterization of Hidden Corrosion in Aircraft Components;

C) Develop of a Decision Support Tool capable of automatically detecting different faults, in rotating machinery, at an early stage. The system will take the form of a library for different rotating machinery components.

Bearing failure can lead to major damage to rotating components and its diagnosis and prognosis are therefore of paramount importance. Techniques and approaches for detecting bearing faults abound. However, application of these methods is limited for complex systems such as aircraft engines. This stems from the fact that the complex configuration of the system and inaccessibility make it difficult to place the vibration transducers close to the bearings. In most cases, available instrumentation is limited to a few vibration transducers on the casing of the machine. In such cases, the vibration due to bearing faults are barely detectable using traditional methods, as they normally make only a small contribution to the overall energy and this is to some extent dissipated by the transmission path. For bearing fault detection to be effective in such applications, the methodology must be capable of detecting faint bearing signals and also allow consistent trending and tracking. This study examines these requirements in detail and presents an experimental assessment of newly emerging cyclic spectral analysis in this field for such requirements.

Bearings are one of the key components found in almost any rotating machinery and have notably drawn attention from the health monitoring research community. As bearing failure can lead to catastrophic damage to other rotating components, its diagnosis and prognosis are of paramount importance. Fortunately the mechanics of bearing deterioration are well-known. The development of the very familiar bearing characteristic frequencies (tones) dates back to a few decades ago [Shahan and Kamperman 1976]. These characteristic patterns have enabled monitoring of bearings through vibration data acquired using pertinent transducers. For any fault on the bearing, its corresponding tone is expected to appear on the frequency domain (spectral) representation of vibration signals. Fourier transforms (FT) and their derivatives, namely, Fast Fourier transforms (FFT) and Short Time Fourier Transforms (STFT) are extensively used to obtain such spectral representations. One difficulty with this approach is that the vibration transducers are usually required to be mounted close to the bearings. This is due to the fact that the energy of vibration signals attenuates as one goes farther away from the bearings and the likelihood of detecting bearing tones decreases. Also, in complex systems, interfering noise from other components can further complicate the situation.

In highly sophisticated and complex systems such as gas turbine engines, complexity of the system and inaccessibility make it difficult to place the vibration transducers close to bearings. In most cases, available instrumentation is very limited and only a few accelerometers are available that collect the vibration signal from the casing of the engine. With many components producing vibration, the bearing tones are very hard to distinguish in the spectral representation of the vibration signals. Moreover, they normally generate minimal energy in the early stages of failure and this energy is further dissipated by the complex transmission path.

To tackle the problem of making the faint bearing signal more distinctive among the signals from other components, different signal processing approaches can be adopted. One approach is to regard this case as a blind source separation (cocktail party) problem and turn to developed statistical and mathematical methods for this purpose, mainly Independent

Component Analysis (ICA) [Comon and Jutten 2010], to separate bearing tones from interfering signals. Apart from statistical independence, no other specific assumption is made on the type of signal produced by the bearings. The main focus usually is put on the mixing mechanisms which may be considered either instantaneous (linear) or convolutive. This approach has been experimentally tested by a number of researchers [Comon and Jutten 2010, Capdevielle et al 1996, Gelle et al. 2000 and 2001, Yampa et al. 2002, Servière et al. 2004 and 2005, and Ye et al. 2006] and despite promising preliminary results, it seems to be far from the level of robustness and reliability required for use in common practice. One reason is due to strict ICA requirements such as equality or superiority of the number of sensors to the number of sources. Another reason is the inherent ambiguity in the scale and permutation of the results obtained from ICA. Furthermore, inconsistency between ICA assumptions and the true characteristics of vibration sources can be listed as one of the pitfalls (Antoni 2005).

An alternative approach is to avoid the effort of "separating" the actual bearing signals from the background noise. In this approach, a threshold for the noise level in different regions of the spectral representation of the vibration signal is established and the signal is monitored for any levels which exceed this threshold. Recently, Clifton et al. [Clifton and Tarassenko 2009] introduced a probabilistic method called the probabilistic novel tracked order. In this method, the spectrogram of the vibration signal gathered from an accelerometer on the casing of a jet engine (gas turbine engine) is divided into speed and frequency bins. Then for each bin, by adopting Extreme Value Theory (EVT) concepts, a dynamic threshold is established for the noise floor. It is demonstrated using real engine data that this technique is actually capable of detecting bearing tones as they protrude above the established noise floor. A drawback with this technique, though, is that no distinction between the characteristics of the noise and the actual bearing tone is made. As long as a bearing tone does not exceed the noise threshold, it is considered noise and therefore ignored. Bearing tones must be strong enough to be detected by this technique. Further, should the overall noise level increase for any reason it can mask a bearing tone which could be otherwise detected.

An alternative to above approaches is to use the specifications and characteristics of signals produced due to bearing faults as a basis for distinction. A monitoring scheme can be established that probes the signals acquired to recognize such specifications. Bearing defects are now known to produce vibration with recurring impulsiveness in the energy. Signals with such behaviour are known in technical terms to be cyclostationary. Briefly, this approach consists in detecting any cyclostationary behaviour in the vibration signals and checking for any association with bearing defects. Very recently, Jérôme Antoni published a number of articles ([Antoni et al. 2007 and 2009] and references therein) on this subject. Also, for a more detailed review on bearing fault diagnosis in general, interested readers may consult [Randall and Antoni 2011].

In this study, different aspects of applying cyclostationarity-based methods to the case of bearing fault detection in complex machinery are investigated. For a bearing fault detection technique to be effective in such applications, it must retain two features. One is the ability to detect faint bearing tones as they pass through the transmission path. The other is to allow consistent trending. This paper is structured as follows: first a short description of the mechanics of bearing failures is given. Then, concepts and formulations for cyclostationarity are briefly introduced. Finally, two sets of relevant experiments are provided, followed by a discussion on the results.

BEARING FAULTS AND CYCLOSTATIONARY

Bearing Faults

As mentioned earlier the mechanics of bearing faults are to a great extent known and characteristic frequencies have been formulated. These frequencies for the common case where only the inner race of the bearing is rotating are listed in Table 1.

Table 1: Characteristic frequencies of bearing faults [Darlow et al. 1974]

Rotation frequency of a rolling element assembly	$f_c = \frac{f_s}{2}(1 - \frac{D_B}{D_P} cos\theta)$
Rotational frequency of a rolling element	$f_r = \frac{f_s}{2}\frac{D_P}{D_B}(1 - \frac{D_B^2}{D_P^2} cos^2\theta)$
Over-rolling frequency of one point on the inner ring	$f_{ip} = \frac{f_s}{2} N_B(1 + \frac{D_B}{D_P} cos\theta)$
Over-rolling frequency of one point on the outer ring	$f_{ep} = \frac{f_s}{2} N_B(1 - \frac{D_B}{D_P} cos\theta)$
Over-rolling frequency of one point on a rolling element	$f_r = f_s \frac{D_P}{D_B}(1 - \frac{D_B^2}{D_P^2} cos^2\theta)$
f_s: rotation speed, D_B: roller diameter, D_P: pitch diameter, N_B: the number of balls and θ: the contact angle of the ball	

One misconception regarding the above formulas is that they are often misinterpreted to represent the bearing's natural frequencies. A closer look at the procedure of obtaining these formulas can provide a better understanding of the concept. The procedure for obtaining each one of these formulas is briefly: if any defective point is considered on any of the main bearing components (i.e., rolling element, outer and inner races), then based on the geometry of the bearing components and kinematic concepts the frequency of any possible contact between that point and other components is calculated. For example, if there is a defective point on the inner race of bearing, the rate at which such point comes into contact with the rolling element determines the over-rolling frequency of one point on the inner ring (f_{ir}). Depending on the case, the introduction into and out of the bearing load zone can be of importance, which necessitates calculation of the rolling assembly frequency. Overall, the basis for calculating these formulas is solely kinematics; the bearing's natural frequencies are dependent on the design, geometry and material among many other factors and it is not possible to establish a general formulation for all bearings.

Another misconception related to bearing characteristic frequencies is that bearings are sometimes thought to produce harmonic sinusoidal components at such rates. This may stem from the fact that conventional bearing diagnosis systems are largely based on spectral analysis and consequently Fourier Transforms (FT) which represent signals with harmonic sinusoidal components. It should be clear from the previous paragraph that bearing frequencies are produced by striking of a defective point of a bearing component on other component. Such striking results in excitation (ringing) of the bearing assembly at its natural frequencies. The striking itself occurs at rates equal to the characteristic frequencies (easily computable) and creates impulses in the signal and not harmonic sinusoidal. The ringing effect, on the other hand, occurs at natural frequencies of the bearing components in the shape of a random stationary signal at normally higher frequencies (usually unknown). The combination of these two phenomena creates vibration with repetitive bursts of energy. To be more accurate, vibration signals produced by a bearing defect are modulated signals; vibration energy at natural frequencies of the bearing (carrier frequency) is modulated with characteristic frequencies of the bearing (modulation frequency). Such signals in signal processing terminology are entitled cyclostationary.

According to above discussion, typical spectral (FFT) analysis is not a strong tool for detecting bearing anomalies as it gives the averaged spectral representation (spectrum) based on stationary assumptions. In fact, spectral analysis is only capable of detecting bearing defects when they are greatly developed and in presence of little noise. In such cases the modulation frequency and its harmonics are visible on the spectrum. An alternative for typical spectral analysis is to use spectrogram (STFT) or any other joint time-frequency representation. In this case, the repetitive bursts of energy occurring at higher frequencies (ringing frequencies of the bearing component) are observable throughout the spectrogram. The duration between successive bursts is equal to the inverse of any one of the characteristic frequencies depending on the case. These methods are very representative and appropriate for analysis purposes. On the other hand, they are not suitable for an automated diagnosis system since it is difficult to establish a robust trending and alarming scheme.

Envelope analysis [Darlow et al. 1974] is also one of the methods widely used for bearing fault detection. It consists in spectral analysis of the envelope of the time-domain signal. For envelope analysis to be effective it is usually necessary that sensors be located very close to the bearing so that the repetitive bursts of energy due to bearing faults are discernible in the time-domain signal. This limits its use for applications where the sensors are not mounted as such or where the vibration produced by other components mask the recurring pulses in the signals. One solution to this limitation is to band-pass filter the signal around some appropriate frequency band and then performs envelope analysis on the filtered signal. Again, selecting the appropriate band entails knowing the natural frequency of the bearing assembly a priori.

One might think of performing envelope analysis on the signal narrow-band filtered around all frequencies of interest. This bears a similarity to taking STFT of the signal and then performing envelope analysis on each frequency bin over the range of interest. This concept sets the stage for what is covered in the following section under cyclic spectral analysis.

Cyclic spectral analysis

Given *x(t)* the signal in time, cyclic spectral analysis uses FT to scrutinize the alternation of the spectral contents of the signal at each frequency *f* throughout signal duration T. More accurately, if the narrow-band filtered constituent of the signal *x(t)* around frequency *f* is denoted as $x_f(t)$ then the FT of the square of this signal reads:

$$\lim_{T\to\infty} \frac{1}{T} \int_T \left|x_f(t)\right|^2 e^{-i2\pi\alpha t}\, dt \qquad Eq.\,(1)$$

where α is cyclic frequency (carrier frequency) as opposed to *f* the spectral frequency (modulation frequency). Since the representation obtained using this equation will actually reveal the modulation of the signal in terms of cyclic frequency, it is also called the cyclic modulation spectrum. The above formulation is straightforward and apt for understanding the concept. Nonetheless, deriving the discrete version of this formulation suitable for implementation is not as straightforward. An alternative approach to formulate the same concept is to use correlation approach, which leads to a more straightforward discrete formulation, yet harder to grasp. This approach is described as follows [Gardner 1986]:

According to the definition of cyclostationarity, the mean and the autocorrelation for a cyclostationary signal (or process in general) *x(t)* are periodic and the following equations hold:

$$m_X(t+T) = m_X(t) \qquad Eq.(2)$$

$$R_{XX}(t_1+T, t_2+T) = R_{XX}(t_1, t_2) \qquad Eq.(3)$$

for any possible t, t_1 and t_2 and where T denotes the period. For notational simplicity Eq. 1 can be reformulated as:

$$R_{XX}\left(t+T+\frac{\tau}{2}, t+T-\frac{\tau}{2}\right) = R_{XX}\left(t+\frac{\tau}{2}, t-\frac{\tau}{2}\right) \qquad Eq.(4)$$

Now if the Fourier coefficients of the autocorrelation function for a range of frequencies (α) equal to integer multiples of the fundamental frequency (1/T) are written as:

$$R_{XX}^{\alpha}(\tau) = \frac{1}{T}\int_{-\frac{T}{2}}^{\frac{T}{2}} R_{XX}\left(t+\frac{\tau}{2}, t-\frac{\tau}{2}\right) e^{-i2\pi\alpha t}\, dt \qquad Eq.(5)$$

Then the Fourier expansion of the autocorrelation function reads:

$$R_{XX}\left(t+\frac{\tau}{2}, t-\frac{\tau}{2}\right) = \sum_{\alpha} R_{XX}^{\alpha}(\tau) e^{i2\pi\alpha t} \qquad Eq.(6)$$

To generalize this notation, Eq. 5 must be revised so that it covers the whole range of possible frequencies. By letting T be any possible periodicity in the signal, an extension to Eq. 5 can be expressed as:

$$R_{XX}^{\alpha}(\tau) = \lim_{T\to\infty}\frac{1}{T}\int_{-\frac{T}{2}}^{\frac{T}{2}} R_{XX}\left(t+\frac{\tau}{2}, t-\frac{\tau}{2}\right) e^{-i2\pi\alpha t}\, dt \qquad Eq.(7)$$

According to above notation, the cyclostationarity of a signal *x (t)* will manifest itself as a nonzero Fourier coefficient. Similarly, a non-zero coefficient at any frequency α conveys that the signal exhibits cyclostationarity at that frequency. In its standard terminology frequency α is referred to as cyclic (or cycle) frequency and $R_{xx}^{\alpha}(\tau)$ as a cyclic autocorrelation function. The set of cyclic frequencies for which the cyclic autocorrelation function is non-zero is called the cyclic spectrum. In an analogy to spectral analysis where the spectral density is defined as the Fourier transform of the autocorrelation function, the cyclic spectral density is defined as:

$$S_{XX}^{\alpha} = \int_{-\infty}^{\infty} R_{XX}^{\alpha}(\tau) e^{-i2\pi f\tau}\, d\tau \qquad Eq.(8)$$

Finally, from Eq. (8) the discrete cyclic spectrum for a discrete signal $x(k\Delta t)$ *(for k=0, 1,2,…)* is adapted as:

$$S_{XX}^{\alpha}[f] = \sum_{n=0}^{\infty} R_{XX}^{\alpha}[n\Delta t] e^{-i2\pi n\Delta t f} \qquad Eq.(9)$$

where Δt and K denote the sampling interval and number of samples respectively and the discrete autocorrelation function is obtained as:

$$R_{XX}^{\alpha}[n\Delta t] = \lim_{K\to\infty}\frac{1}{2K+1}\sum_{k=0}^{K} R_{XX}(k\Delta t + n\Delta t, k\Delta t) e^{-i2\pi\alpha\left(k+\frac{n}{2}\right)\Delta t} \qquad Eq.(10)$$

EXPERIMENT

As mentioned earlier, for a bearing detection method to be effective in applications related to complex machinery it must allow consistent trending and be able to detect defects from a weak signal. In this section cyclic spectral analysis is examined for these features using two sets of experiments.

In principle, the transmission path mainly dissipates the energy of the signal but generally should not affect certain characteristics of the signal such as its cyclostationarity. For the transmission path to diminish the signal's cyclostationarity it must operate as a rather complicated filter that evens out the repetitive bursts of energy that occur in a specific frequency range. Therefore, it is reasonable to expect that the cyclostationarity behaviour of the signal is preserved through the transmission path. In our first case study, this premise is tested experimentally by collecting the signals from a faulty bearing using an accelerometer positioned far from the bearing.

In automated health monitoring and fault diagnosis, it is essential for a method to allow robust, attainable and consistent trending. As an example, cyclostationarity due to bearing anomalies can be detected with most time-frequency methods as long as the ringing frequencies or the natural frequencies of the bearing assembly are known to some extent. However, in the majority of cases the natural frequencies of the bearing assembly are not readily available. This limits the application of such methods in automated health monitoring. Another important point is that the feature being tracked must be consistent in the sense that its value bears some correspondence to severity of faults. In our second case study, cyclostationarity is examined for these requirements through a run-to-failure experiment. The description of these two case studies followed by discussion and the results for each case are represented in the following sections.

First Case Study – Experiment Setup and Data Acquisition

In the first case, vibration signals were collected from a test setup at École Polytechnique de Montréal consisting of a 2 HP motor driving a shaft supported by two different bearings. One bearing was an overhauled roller bearing (PWC15) from an aircraft engine provided by Pratt & Whitney Canada. The other bearing was a new SKF ball bearing. Each bearing was contained in housing and bolted to an adjustment base. The adjustment base was also bolted to a main stiff base which was fixed to the concrete floor. An accelerometer was mounted on each bearing housing along with two more on the main base (Figure 1). Signals were gathered at a sampling frequency of 50 kHz during operation of a shaft running at 1200 RPM (20 Hz). One of the accelerometers on the base was positioned about 4ft. away from the shaft assembly. Signals from this accelerometer were used for analyzing the effect of the transmission path on the cyclostationarity of the signals.

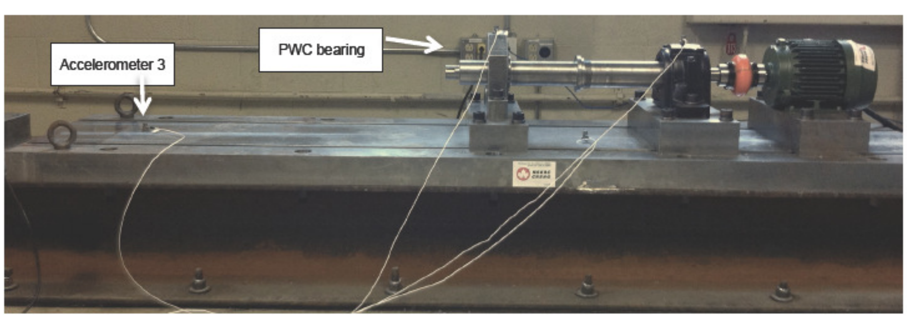

Fig. 1: Test setup at École Polytechnique de Montreal

Results and Discussions for the First Test Case

Visual inspection of PWC15 bearing indicated an outer race fault. The SKF bearing, on the other hand, was a new bearing. Figure 2 shows the cyclic spectrum or cyclic spectral density of the signals gathered by accelerometer no.3. This was obtained from a 1 sec portion of the signal. Two dominant peaks are clearly discernible at cyclic frequencies of 90 Hz and 180 Hz and for a range of spectral frequencies centred around 4 kHz. This indicates that the vibration energy around 4 kHz (the natural frequencies of the bearing assembly) is modulated with a modulation frequency of 90 Hz. This modulation frequency coincides well with the over-rolling frequency of one point of the outer race of the PWC15 bearing given in Table 2.

Table 2: Characteristic frequencies of the bearings used in the experiments

Description		**PWC15**	**Rexnord**
Rotational frequency of rolling element assembly [Hz]	f_c	7.73	14.8
Rotational frequency of a rolling element [Hz]	f_r	41.7	140
Over-rolling frequency of one point on inner ring [Hz]	f_{ip}	147	297
Over-rolling frequency of one point on outer ring [Hz]	f_{ep}	92.7	236
Over-rolling frequency of one point on rolling element [Hz]	f_{rp}	83.5	280

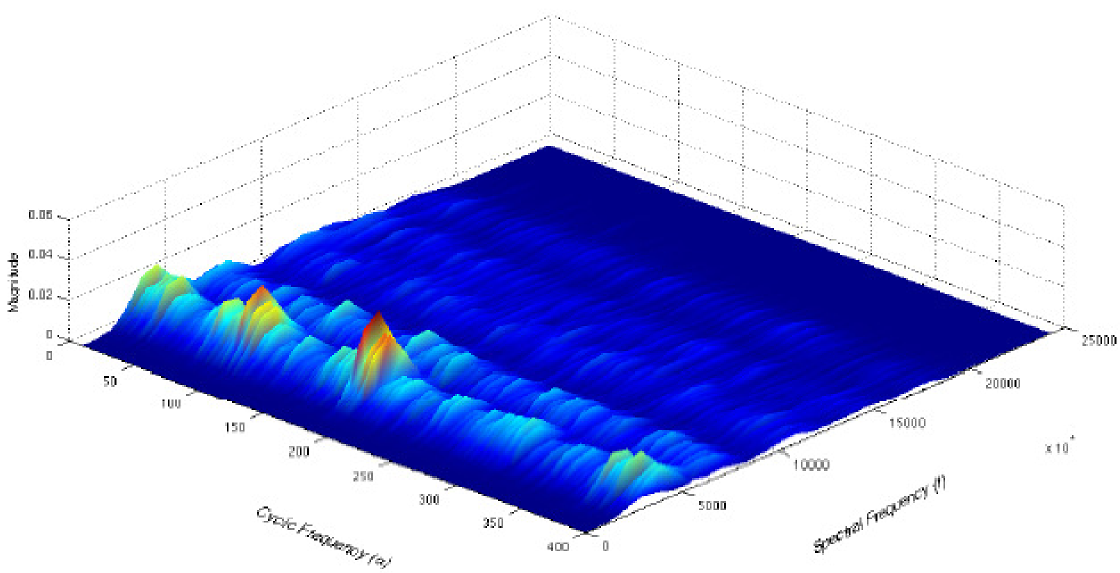

Fig. 2: Cyclic spectral density of the faulty PWC15 bearing

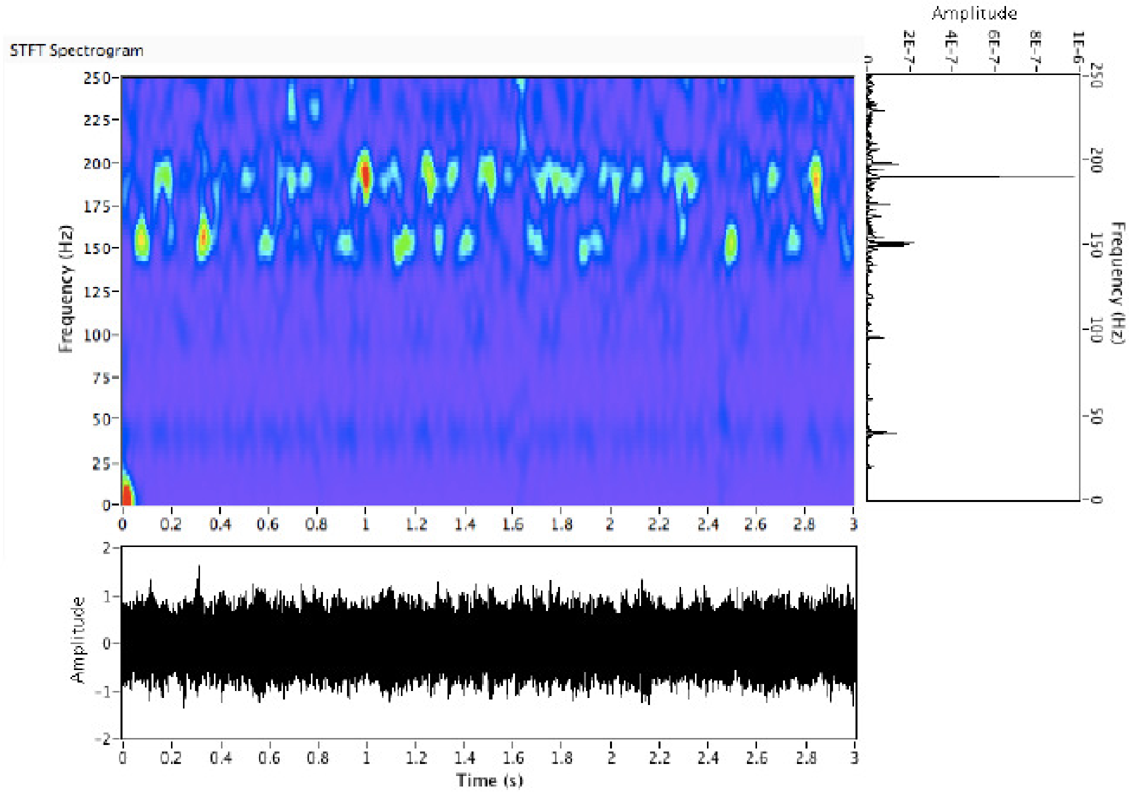

Fig. 3: Low frequency range spectrogram and spectrum of the faulty PWC15 bearing

To compare this method over typical methods, the spectrum and spectrogram of the signals up to 250 Hz are shown in Figure 3 along with the corresponding time-domain signal. As is typical with spectral analysis for the purpose of bearing fault detection, it is expected to have a peak at around 92 Hz on both diagrams. The spectrum in this case shows a minuscule peak around 95Hz. Slightly higher spectral energy can also be observed from the spectrogram around the same frequency. Such low amplitude indications would be completely masked in presence of noise. Moreover, as mentioned earlier the bearing used in this experiment was an overhauled bearing with a predominantly developed outer race fault.

According to the discussion in Section 2, in order for the vibration produced by faulty bearings to be clearly discernible on the spectrogram one needs to look at a broader frequency range. Figure 4 shows the spectrogram and spectrum of signal up to 12.5 kHz. On the spectrogram, the outer race fault manifests itself as a series of bursts taking place at around 3.5 kHz (the natural frequencies of bearing assembly or carrier frequencies) with an interval equal to the inverse of the outer race fault characteristic frequency (modulation frequency). These results suggest that for this approach to be effective in automated monitoring, prior knowledge of the natural frequencies of bearing assembly is required. Moreover, it is necessary that other machine components do not produce vibration within the same frequency band and jumble the signal. This is definitely not the case for complex systems with many components producing vibration.

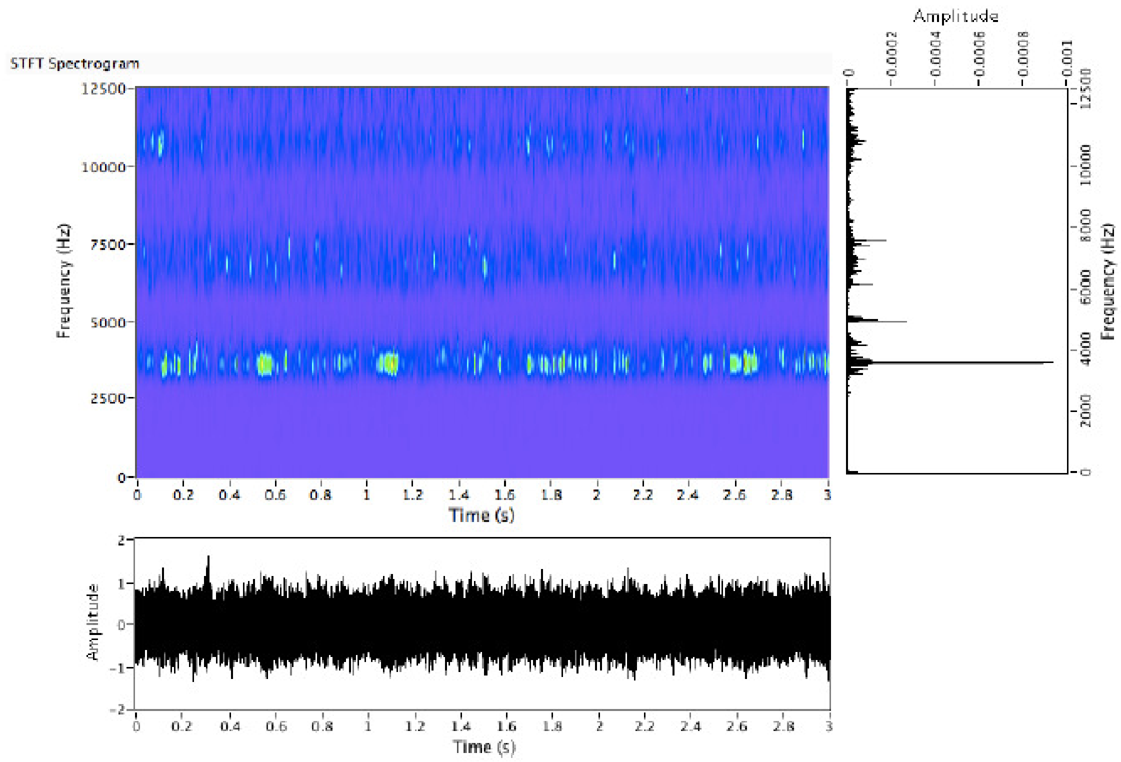

Fig. 4: Wide range frequency spectrogram and spectrum of the faulty PWC15 bearing

Second Case Study – Experiment Setup and Data Acquisition

In order to investigate if the cyclic spectral density enables consistent trending, a bearing data set from a run-to-failure test provided by the Center for Intelligent Maintenance Systems (IMS) of University of Cincinnati through NASA Ames Prognostics Data Repository [Lee et al. 2007] was used.

Results and Discussions for the Second Test Case

In this test four double row Rexnord ZA-2115 bearings were mounted on a shaft driven by an AC motor (Figure 5). Vibration data was gathered using four accelerometers, one on each bearing housing, at a sampling rate of 20 KHz. A spring mechanism exerted a radial load of 6000lbs on the rotating shaft and the bearing. Data snippets of approximately 1 second in duration were gathered at 10-minute intervals throughout a run-to-failure test. In this study, around 50 snippets were selected over a 190 min interval covering the progress of bearing from healthy to faulty. At the end of this test, an outer race fault on the third bearing was observed.

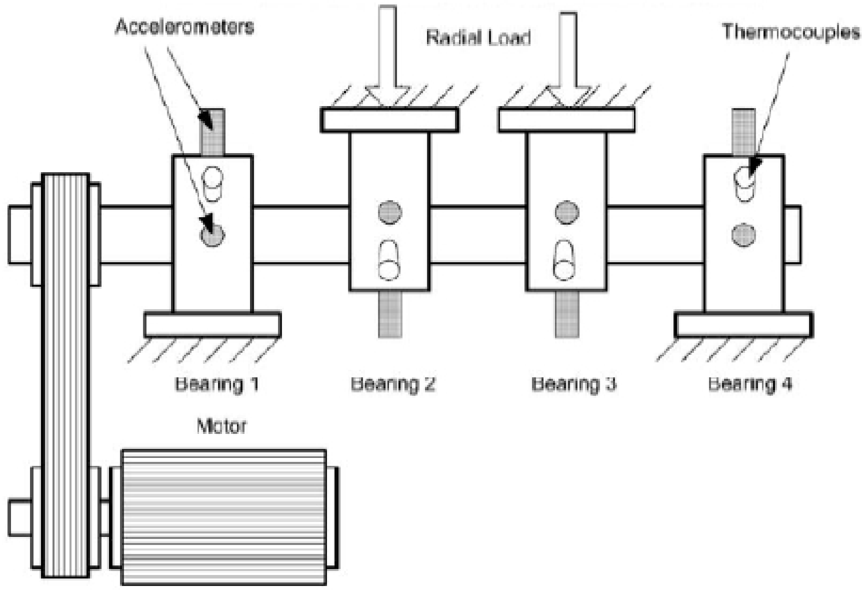

Fig. 5: Schema of the test rig at IMS, of University of Cincinnati (by courtesy of [Lee et al. 2007])

According to Table 1, due to a fault on the outer race of the third bearing, it is expected that the signal exhibit degrees of cyclostationarity at a cyclic frequency of 236 Hz as the fault progresses. Figure 6 shows the cyclic spectrum of the signals gathered by accelerometer 3 on the third bearing when the outer race fault is developed. As shown, the vibration energy distributed around 4.5 kHz is modulated with a frequency of about 230 Hz which slightly deviates from the calculated characteristic frequency for an outer race. This deviation has been reported in [Qiu et al. 2006] as well.

In order to analyse the correspondence between the cyclic spectral energy and the progress of the bearing defect, the overall narrow-band (5 Hz) cyclic spectral energy around the bearing's outer race frequency (231 Hz) is studied. Figure 7 shows the variation of the magnitude of vibration energy values with respect to operation time. According to this graph, first indications of bearing fault appear after 92 hours of operation. Comparing this to the bearing's total service life in number of hours (i.e., 165 hours) this can indeed be considered an early indication. After this early indication, the value of the cyclic energy goes through a number of significant fluctuations, which can be due to healing phenomenon [Williams et al. 2001]. This indicates that strict connections cannot be established between cyclic energy and the severity of fault. Nevertheless, it remains a significant distance from the initial value observed for normal conditions during early hours of operation.

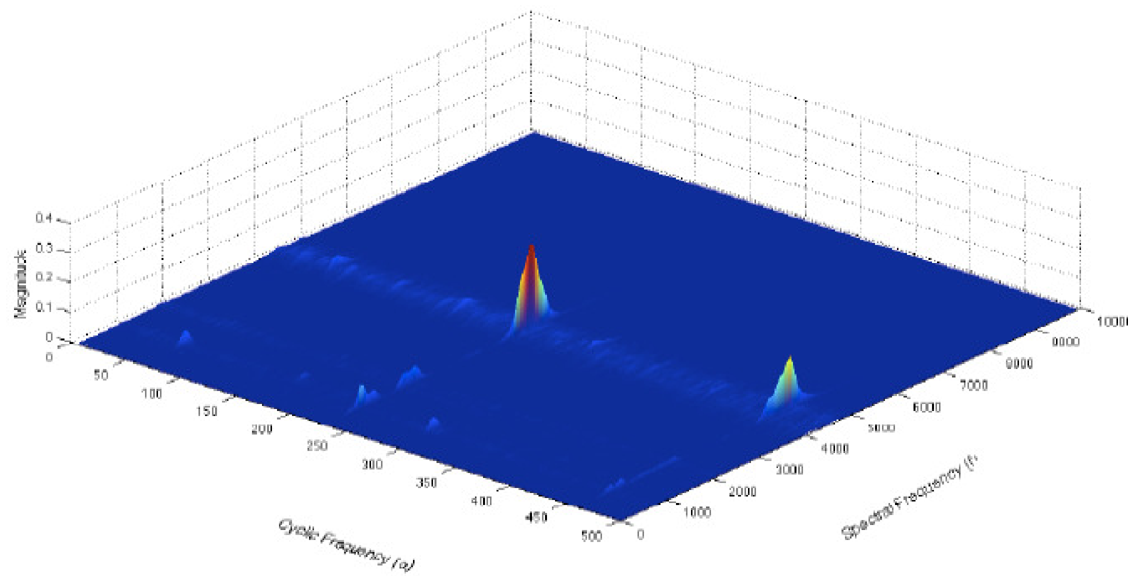

Fig. 6: Cyclic spectral density of faulty Rexnord bearing

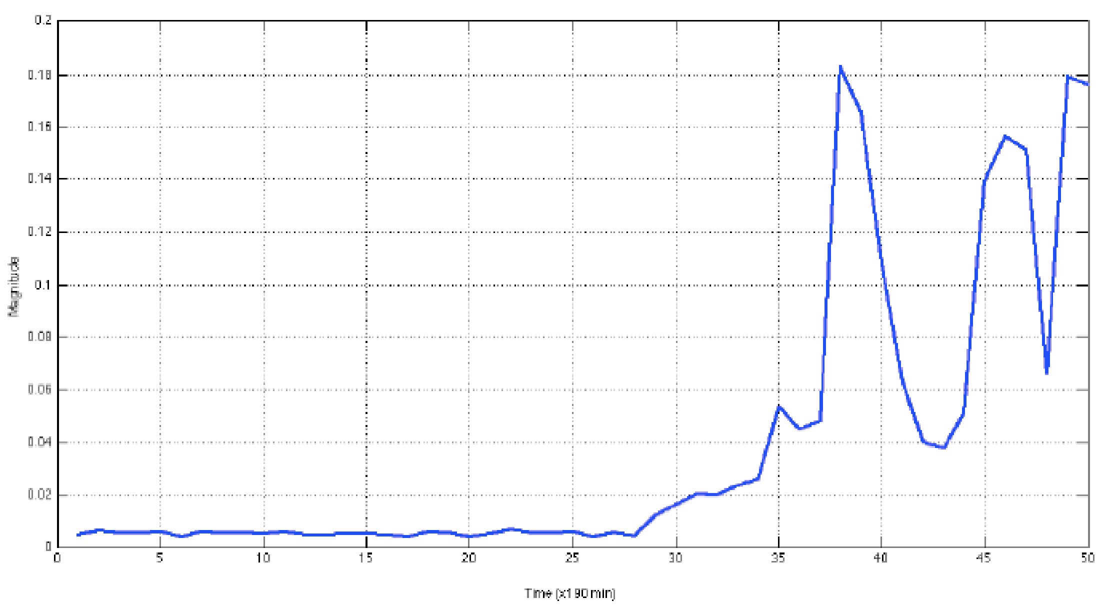

Fig. 7: Progress of banded cyclic spectral density

This experiment demonstrates that cyclic spectral analysis should not be used as a tool to measure the severity of bearing faults. On the other hand, it can be utilized as a reliable monitoring tool because its value always reads higher for a faulty bearing than for a normal one; and also it enables early detection of bearing faults.

CONCLUSIONS

In this study the problem of bearing fault detection in complex machinery was revisited. Two prerequisites for a method to be effective in detecting bearing faults in complex systems were identified to be the capability of detecting bearing faults from a faint signal; and a consistent trending feature. Relevant shortcomings of traditional approaches were discussed. Cyclic spectral density was then argued to be an appropriate candidate that could overcome difficulties with traditional approaches and meet the prerequisites. This was examined through two sets of experiments. In conclusion, the experimental results were satisfactory. As a recommendation for future work, the effectiveness of this method can be further investigated with signals obtained from other test cases as well as a real industrial case.

ACKNOWLEDGMENTS

The authors are greatly in debt to department 9436 of Pratt & Whitney Canada for their generous support and their valuable comments. This project has been made possible by precious support from the collaborative research and development grant (No. CRDPJ-335472-05) of Natural Sciences and Engineering Research Council of Canada (NSERC), Pratt & Whitney Canada, BOMBARDIER Aeronautics and National Research Council of Canada (NRC)

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