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Application of Bicoherence Analysis on Vibration Data for Condition Based Monitoring of Rotating Machinery

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Abstract: Bicoherence or Bispectrum analysis is emerging as a new powerful technique in signal processing, especially in areas where traditional linear spectral analysis provides insufficient information. It is most effective in analyzing systems with non-linear coupling between frequencies. Faults in rotating machineries leave their signature on the vibration signal sensors and generally manifest themselves as a non-linear transformation in the vibration signal. Bicoherence analysis detects and quantifies the presence of non-linearity in the signal and thus indicates the severity of the fault in the machine. This paper demonstrates the use of bicoherence analysis on both simulated and rig-generated vibration data from a rub-effected rotor-stator system, and shows the application of bicoherence analysis on industrial data from final tailing pumps to detect impeller wear in an oil-sands plant.

Keywords: Rotating Machinery, Fault Detection, Vibration, Bispectrum Analysis

1. INTRODUCTION

Analysis of vibration signals is widely used to detect early faults in rotating machineries, such a gearboxes, motors, pumps, compressors etc. The vibration data collected from a faulty rotating machine can exhibit different nonlinear and transient events. The analysis of such events requires specific techniques which go beyond the classical Fourier approach. A number of machine faults can create complicated modulation patterns which are often difficult to detect and understand. Conventional linear spectral analysis is of limited use in instances when frequency components interact together to form new spectral components due to some non-linear process (Howard, 1997).

Failure of a mechanical system is always preceded with changes from linear or weakly non-linear to strong non-linear dynamics. As faults develop in the system the process becomes chaotic and the amount of non-linearity in the system increases. Therefore, a measure of non-linearity in the vibration signal is a good indicator of the deviation of the process from normal operation to the emergence of a fault in the process. Higher Order Statistics (HOS) can be used to detect and quantify the presence of a non-linearity in the vibration signals (Choudhury *et al.*, 2005). Bicoherence, which is the normalized frequency domain representation of the third order cumulants, successfully detects the emergence of new frequencies due to generation of faults in the system.

Fackrell has applied bicoherence analysis on vibration signal from a loosened beam, air compressor mounted on wooden blocks, and also on domestic vacuum cleaner noise (Fackrell *et al.*, 1995). The results indicate that bicoherence is immune to noise, and to an extent independent of the measurement position used. Moreover, bicoherence analysis has been used by the present authors with success into identifying emerging gear faults in gearboxes (See (Halim *et al.*, 2006)). The authors have shown the combined use of cyclo-stationary and bicoherence analysis on real vibration signals to detect both local and distributed faults in a multiple shaft gearbox. Furthermore, bicoherence or bispectrum analysis has been applied on vibration signals to detect aerodynamic excitation faults and oil whirl faults in a rotor system (Wang *et al.*, 2001), and bearing faults and collector faults in a DC motor (Boltezar and Slavic, 2006).

This paper initially demonstrates the use of bicoherence analysis on both simulated and rig-generated vibration data from a rub-effected rotor-stator system. Finally, it shows the application of bicoherence analysis on industrial data from final tailing pumps to detect impeller wear in an oil-sands plant. The results obtained from the industrial application are promising as bicoherence analysis seems to give consistent results even when the characteristics of the pumped slurry mixture are likely to be inconsistent.

The process fluid or the fluid passed through the impellers may have different amounts of fine or coarse sand mixed with water and gypsum. Based on the composition of the fluid the amplitude of the vibration signal can vary dras-

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tically. As the amplitude of the vibration signal changes, time trend analysis and Classical Fourier analysis fail to give the true measure of impeller wear. But bicoherence analysis is still able to indicate the exact measure of impeller wear and thus is invariant to the density of the process fluid.

2. BICOHERENCE ANALYSIS

The first and second order statistics (e.g., mean, variance, autocorrelation, power spectrum) are popular signal processing tools and have been used extensively for the analysis of process data. However second order statistics are only sufficient for describing linear processes. In practice, there are many situations when the process deviates from linearity and exhibits nonlinear behavior. Such type of processes can be conveniently studied using Higher Order Statistics (HOS). There are three main reasons for using Higher Order Statistics (HOS): to extract information due to deviations from Gaussianity, to recover the true phase character of the signals, and to detect and quantify nonlinearities in the time series (Nikias and Petropulu, 1993). Time domain data itself is a good source of information. Many statistical measures, e.g., moments, cumulants, auto-correlation, cross-correlation have been developed to measure the time domain information in such data. Not all the information content of a signal can be necessarily and easily obtained from time domain statistical analysis of the data. Transforming the signal from time to frequency domain can expose the periodicities of the signal, can detect the nonlinearities present in the signal and can also aid in understanding the signal generating process.

2.1 Theory

Just as the power spectrum is the frequency domain counterpart of the second order moment of a signal and represents the decomposition or spread of the signal energy over the frequency channels obtained from the Fast Fourier Transform, the bispectrum is the frequency domain representation of the third order cumulants. It is defined as

$$B\left(f_1, f_2\right) = DDFT[c_3(\tau_1, \tau_2)] \equiv E[X(f_1)X(f_2)X^*(f_1 + f_2)] \qquad (1)$$

where, B(f_1, f_2) is the bispectrum in the bifrequency (f_1, f_2), DDFT stands for Double Discrete Fourier Transformation, $c_3(\tau_1;\ \tau_2)$ is the third order cumulant, τ_1 and τ_2 are the time-lag variables, *X(f)* is the discrete Fourier transform of any time series *x(k)*, and '*' denotes complex conjugate. Equation 1 shows that the bispectrum is a complex quantity having both magnitude and phase. It can be plotted against two independent frequency variables, f_1 and f_2 in a three dimensional (3d) plot.

Just as the discrete power spectrum has a point of symmetry at the folding frequency, the discrete bispectrum also has 12 regions of symmetries in the (f_1,f_2) plane (Nikias and Petropulu, 1993). The bispectrum, in the principal domain, gives sufficient information. The other regions of the (f_1,f_2) plane are redundant. Each point in such a plot represents the bispectral content of the signal at the bifrequency, (f_1, f_2). In fact, the bispectrum at point (B(f_1,f_2), f_1, f_2) measures the interaction between frequencies f_1 and f_2. This interaction between frequencies can be related to the non-linearities present in the signal generating systems (Fackrell, 1996) and therein lies the core of its usefulness in the detection and diagnosis of non-linearities.

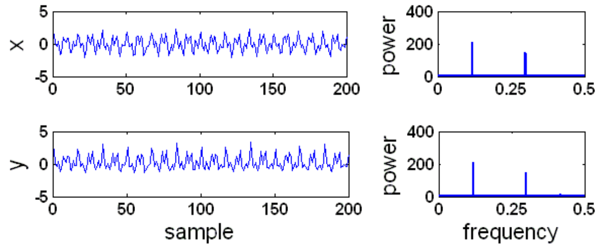
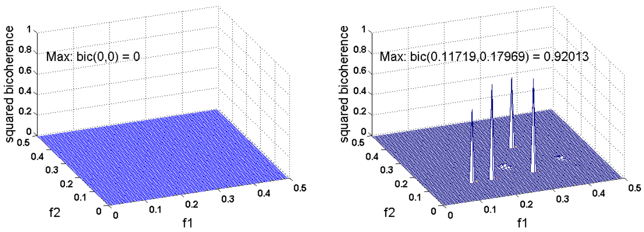


Fig. 1. *Time Trend and Power Spectrum plots of the Linear and Non-Linear Signals.*



(a) *linear signal x* (b) *non-linear signal y*

Fig. 2. *Bicoherence Analysis of Linear and Non-Linear Signals.*

In order to remove the undesired property effect of the variance of the estimated bispectrum (Hinich, 1982), the bispectrum can be normalized in such a way that it gives a new measure called bicoherence whose variance is independent of the signal energy (Fackrell, 1996). Bicoherence is defined as:

$$bic^2(f_1, f_2) \triangleq \frac{|B(f_1, f_2)|^2}{E\left[|X(f_1)X(f_2)|^2\right] E\left[|X(f_1 + f_2)|^2\right]} \qquad (2)$$

where 'bic' is known as the bicoherence function. A useful feature of bicoherence function is that it is bounded between 0 and 1.

For details of estimating the bispectrum/bicoherence, see (Nikias and Petropulu, 1993; Choudhury *et al.*, 2002).

2.2 Bicoherence of a nonlinear sinusoid signal with noise

The objective of this example is to demonstrate the power of the bicoherence in the detection of nonlinearity. An input signal was constructed by adding two sinusoids, each having a different frequency and phase. That is,

$$\begin{aligned} x^{'}(k) &= sin(2\pi f_1 k + \phi_1) + sin(2\pi f_2 k + \phi_2) \\ x(k) &= x^{'}(k) + d(k) \\ y(k) &= x^{'}(k) + 0.1x^{'}(k)^2 + d(k) \end{aligned} \qquad (3)$$

where, $f_1 = 0.12$, $f_2 = 0.30$ on the normalized frequency scale, and $d(k)$ is a white noise sequence with variance 0.04.

The left panel of Figure 1 shows the time series while the right panel shows the power spectrum of the signal x and y, respectively. Neither of these plots help in distinguishing the two signals. However, the use of higher order statistics can successfully detect the nonlinearities present in y. Figure 2 shows the three dimensional squared bicoherence plots of x and y, respectively. For the signal x, the plot shows no peaks and thus clearly indicates that the signal is linear. On the other hand, for the signal y, the plot shows significant peaks indicating the presence of non-linearity in the signal.

The peaks in the bifrequency plane can be explained by rewriting the expression for y as:

$$\begin{aligned} y(k) &= \sin(2\pi f_1 k + \phi_1) + \sin(2\pi f_2 k + \phi_2) \\ &+0.1[1 - \cos(2(2\pi f_1 k + \phi_1)) - \cos(2(2\pi f_2 k + \phi_2)) \\ &+ \cos(2\pi(f_2 - f_1)k + \phi_2 - \phi_1) \\ &- \cos(2\pi(f_1 + f_2)k + \phi_1 + \phi_2)] + d(k) \end{aligned} \tag{4}$$

The nonlinearities are caused by the interactions between any two of the signals with frequencies f_1, f_2, $2f_1$, $2f_2$, f_2-f_1, and $f_1 + f_2$. For the output signal y, the squared bicoherence plot shows peaks at (0.12,0.12), (0.12,0.18), (0.30,0.30), and (0.12,0.30) bifrequencies. These bifrequencies correspond to (f_1, f_1),(f_1, f_2-f_1), (f_2, f_2),and (f_1, f_2), respectively. Therefore, the bicoherence plot correctly identifies the frequency interactions that resulted from the presence of nonlinearity in the signal.

3. SIMULATION CASE STUDY

In this section, rub-impact data of different levels of severity has been simulated and bicoherence analysis has been applied on the data to detect and quantify the fault present in the rotating system. A model of a rotor system based on the Jeffcott rotor model (Chu and Zhang, 1998) has been used to simulate the rub-impact data. The displacements of the disc center in $x-$ and $y-$ direction are denoted as $x(t)$ and $y(t)$. The damping coefficient of the shaft is c with k as its stiffness coefficient. If rubbing occurs, it creates impacts and the interactions of impacts are denoted as forces F_x, F_y. The friction coefficient between the rotor and the stator is f with k_c as the radial stiffness of the stator. The radial displacement of the rotor is given as $e = \sqrt{(x^2 + y^2)}$. The static clearance between the rotor and the stator is δ, and U is the imbalance. The weight of the rotor system acts as a gravitational force of mg with m as the mass and g as the gravitational constant. The differential equations of motion for the rotor system that has rub-impact can be modelled in $x-$ and $y-$ direction as

$$\begin{cases} m\ddot{x}(t) + c\dot{x}(t) + kx(t) = F_x(x,y) + mU\omega^2 cos(\omega t) \\ m\ddot{y}(t) + c\dot{y}(t) + ky(t) = F_y(x,y) + mU\omega^2 sin(\omega t) - mg \end{cases} \tag{5}$$

The forces induced by the rub impacts $F_x(x,y)$ and $F_y(x,y)$ can be further expressed as,

$$\begin{Bmatrix} F_x \\ F_y \end{Bmatrix} = -H(e-\delta)\frac{(e-\delta)k_c}{e}\begin{bmatrix} 1 & -f \\ f & 1 \end{bmatrix}\begin{Bmatrix} x \\ y \end{Bmatrix}. \tag{6}$$

where H is the Heaviside function.

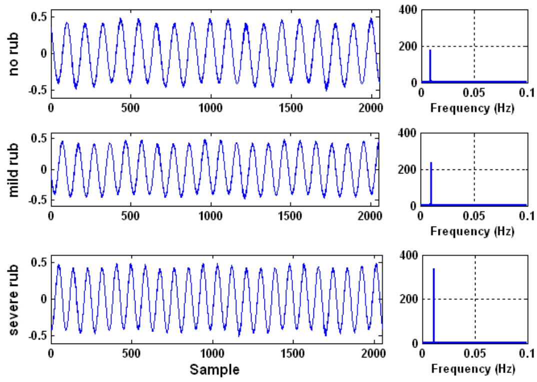
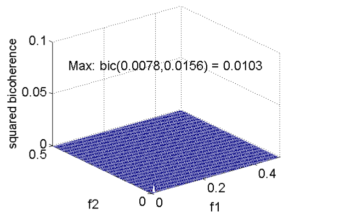
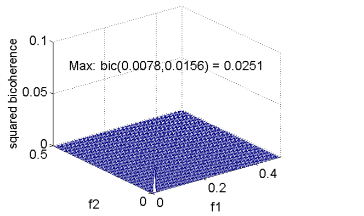


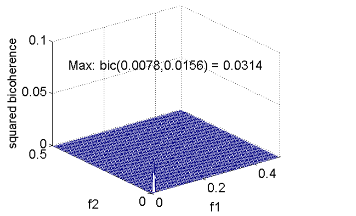
Fig. 3. *Time Trend and Power Spectrum plots of the simulated data sets generated from the Jeffcott rotor model.*



(a) *no rub*



(b) *mild rub*



(c) *severe rub*

Figure	Maximum Bicoherence
(a)	0.010
(b)	0.025
(c)	0.031

Fig. 4. *Bicoherence Analysis of simulated rub signals from Jeffcott rotor model.*

The *SIMULINK* toolbox of *MATLAB*® was used to simulate the rotor model and ode45 (Dormand-Prince) was used to integrate Equation 5 to obtain the simulation data. The parameters used in the computation are, the mass $m = 4$ kg, the damping coefficient $c = 0.12 \times 10^6$ N/m, the stiffness coefficient $k = 0.25 \times 10^6$ Ns/m, the friction coefficient $f = 0.2$, the impact stiffness coefficient $k_c = 0.6 \times 10^8$ Ns/m, and the imbalance $U = 0.1 \times 10^{-4}$ m. Sampling frequency was 5917 Hz.

Based on $\omega_c = \sqrt{(k/m)}$, different levels of rub-impact were simulated in the Jeffcott rotor model by varying the rotational speed. The three levels of rub (none, mild and severe respectively) were produced at three different speeds (500 rpm, 562.5 rpm and 625 rpm respectively). For more details refer to (Chu and Zhang, 1998). Figure 3 shows the time trend and power spectrum plots of the three simulated signals at three levels of rub. Clearly, neither the time trend nor the power spectrum can detect the rub or level of rub.

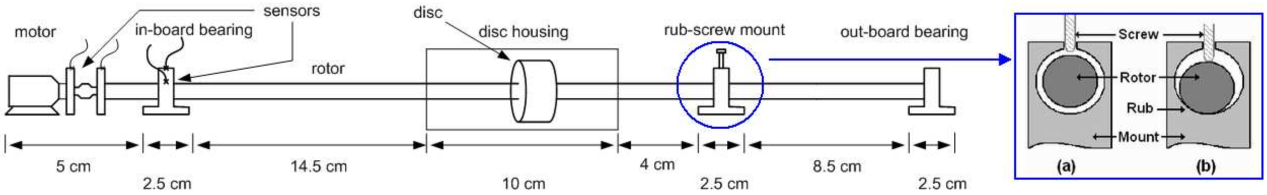


Fig. 5. *Configuration of the test rig used to generate data for the pilot plant case study. (a)normal condition (b) generating rub using screw mount.*

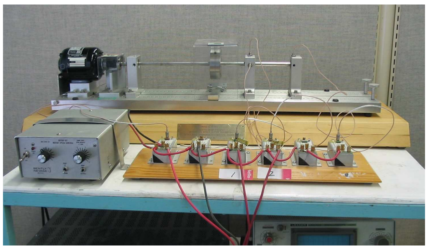


Fig. 6. *Picture of the test rig used to generate data for the pilot plant case study.*

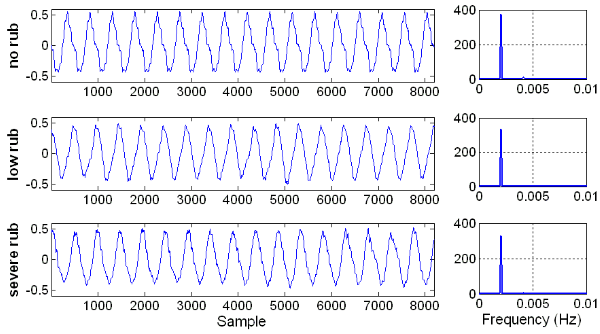
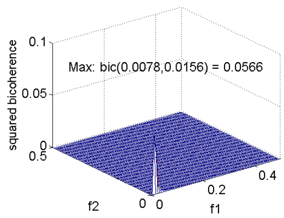
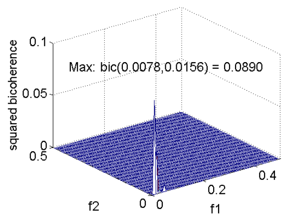


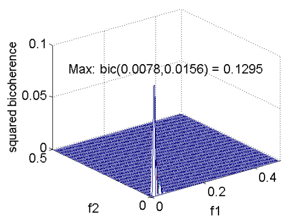
Fig. 7. *Time Trend and Power Spectrum plots of the data sets generated from the test rig for the pilot plant case study.*



(a) *no rub*



(b) *mild rub*



(c) *severe rub*

Figure	Maximum Bicoherence
(a)	0.06
(b)	0.09
(c)	0.13

Fig. 8. *Bicoherence Analysis of real rub signals from the rotor-stator rig.*

Application of bicoherence analysis on the rub-impact data is shown in Figure 4. In case of normal condition there is very little interaction between frequencies and the maximum bicoherence is 0.01. When mild rub is introduced, the interaction between low level frequencies increases and the maximum bicoherence increases to 0.025. As rub is increased to a higher level, the maximum bicoherence increases to a value of 0.03. This clearly indicates that bicoherence can capture the increase of non-linearity in the system due to increased rub between rotor and stator. The maximum bicoherence can be used as an index to indicate the severity of fault in the rotating system.

4. PILOT PLANT CASE STUDY

A pilot plant case study was performed to assess the effectiveness of bicoherence analysis in detection of fault severity in rotating machinery. Data was generated using a test rig that could simulate different levels of rub (Halim *et al.*, 2007). The rig is located in the Reliability Lab in the Mechanical Engineering Building at the University of Alberta, Canada. The configuration of the test rig is shown in Figure 5 and 6. One disc was rotating at the center of the rotor at a rotational frequency of 24 Hz. Four sensors were used to collect the vibration data from the rig. Rub of different levels were introduced to the system using a rub screw mount.

Data from the rig were collected at a sampling frequency of 12,800 Hz. Both vertical and horizontal accelerometer sensors were used to record the vibration produced in the system. For details on the setup and data collection the reader is referred to (Halim *et al.*, 2007). A total of three data sets were selected for analysis, each having 8,192 samples. The data sets were collected under the following conditions:

(1) no rub present
(2) mild rub introduced
(3) severe rub introduced

Figure 7 shows the time trend and power spectrum plots of the data sets. Clearly, it is hard to detect the presence of rub from the time trend and power spectrum plots of the data sets. Figure 8 shows the result of bicoherence analysis on the collected data. Under normal conditions, the maximum bicoherence is as low as 0.056. The value of maximum bicoherence increases to 0.089 with the introduction of mild rub to the system. Under severe rub condition the maximum value of bicoherence increases to 0.129. The result indicates that bicoherence analysis successfully detects and is able to quantify the severity of fault present in the system.

Fig. 9. *A half worn out impeller of a final tailing pump at the Suncor oil sands plant.*

5. INDUSTRIAL CASE STUDY

According to a recent survey, unplanned production shutdowns are the largest cost in the process industries, in some sectors costing \$1 million or more per day (IEE, 2005). Mechanical failure is the largest contributor to such plant shutdowns, causing 43% of the plant incidents. In most cases the failure occurs due to faults in rotating machineries (pumps, turbines, compressors etc.). Almost 60% of the rotating equipments in plants are motor-pump combinations. Therefore, condition monitoring of pumps is crucial for predictive prevention of shutdowns in process industries.

5.1 Process Description

At Suncor Energy's oil-sands plant (located in Fort McMurray, Alberta, Canada), bitumen is extracted from the oil sands, which is in turn upgraded into high-quality refinery-ready crude oil products and diesel fuel. Bitumen is separated from the fine and coarse sand by settling the sand particles in separation cells (also called *Sep-Cells*). The middle and bottom layers of fluid (also known as *Middlings* and *Tailings* respectively) in the Sep-Cells contain mostly fine and coarse sand particles and have to be pumped by *Final Tailing Pumps* (FTP) to settling ponds after a few additional processing steps. There are 4 pump lines, each containing 5 pumps in series. The impeller of the pumps are made of special wear-resistant alloy. However, because of slurry transport of sand plus water the pump impellers have to be replaced every 13 to 18 weeks since they get worn out fast by pumping continuously. Figure 9 shows a worn out impeller. In order to set up a condition based monitoring scheme, a true measure of the wear of the impellers have to be obtained from the vibration data acquired.

5.2 Data Collection

At the Suncor plant, vibration data is collected using a hand-held monitor at a sampling frequency of 1000-1800Hz. Data is collected in horizontal, vertical and axial positions for the motor, gearbox and the casing of each of the 20 pumps. The time of data collection is approximately 3 seconds and data is collected only once every 4 weeks for analysis. Currently the overall RMS value and Classical Fourier Analysis is being used for the analysis of vibration data. But the performance of current monitoring scheme is not satisfactory.

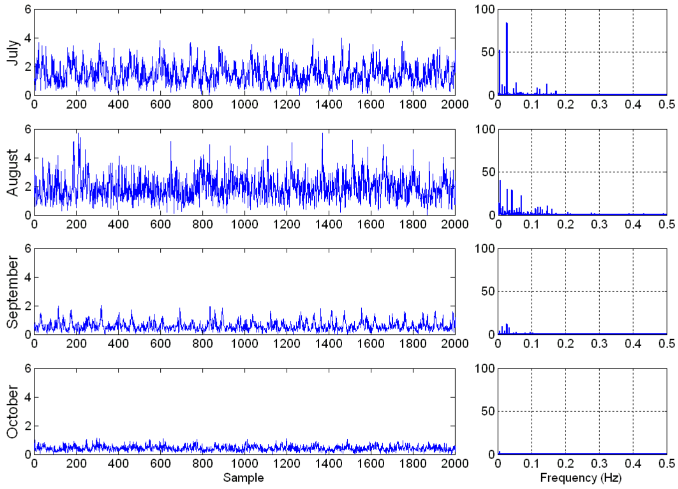


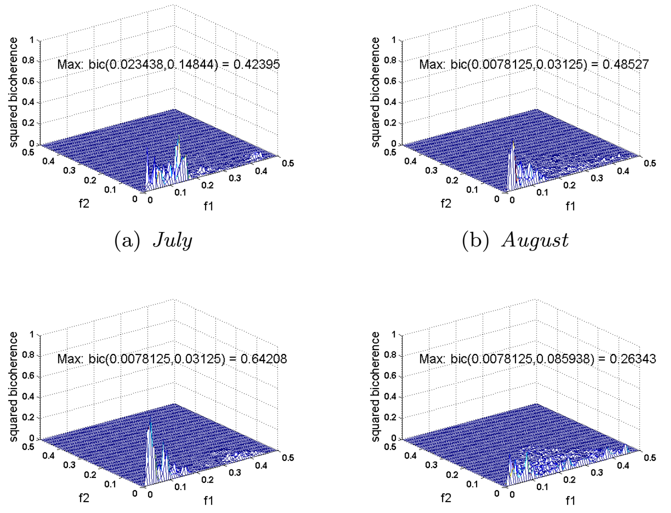
Fig. 10. *Time Trend and Power Spectrum plots (with the same scale) of the vibration data sets collected from the final tailing pumps over the 4 months period at Suncor.*

5.3 Bicoherence Analysis

Initially, 4 data sets were collected over 4 months from July to October of 2006 for a single pump at the pump inboard horizontal position. This pump went through maintenance between September and October of 2006 when the impeller of the pump was changed. Therefore 3 data sets were collected before the maintenance and 1 data set was collected right after maintenance. It is also known that the consistency of the slurry mixture had changed over the period of August and September of 2006. The fluid that passes through the impeller usually carries a specified amount of fine and coarse sand mixed with water and gypsum. Between August and September of 2006 the composition of process fluid had changed and less amount of coarse sand was pumped through the impellers. As a result the amplitude of the vibration signal decreased during the month of September.

Figure 10 shows the time trend and power spectrum plots for the 4 data sets. The scales are kept same for all the cases. Both the amplitudes of the time trend and power spectrum plot increased from the month of July to August, but then decreases in September and decreased further in October. The drop in amplitude from September to October can be related to the replacement of the pump impeller. But the drop in amplitude from August to September can only be related to the process fluid change and not to impeller wear. Therefore, both time trend and power spectrum plots are not enough to capture the condition of the impeller wear from vibration data.

Figure 11 shows the plots of bicoherence analysis on the 4 data sets over the 4 month period. The maximum bicoherence gradually increases from 0.42 in July to 0.49 in August and finally to a maximum of 0.64 in September. The bicoherence peaks indicate that the non-linearity is very high for the month of September signalling that severe wear has occurred to the impeller and replacement is highly required. After maintenance is carried out, the maximum bicoherence of the vibration signal from the pump drops to 0.26 in October. It should be noted that,



(a) *July* (b) *August*

(c) *September* (d) *October*

Fig. 11. *Bicoherence Analysis of vibration signals from the final tailing pumps for the 4 months.*

unlike the time trend or power spectrum plot, the bicoherence plot clearly indicates the severe fault condition of the impeller during the month of September. The impeller had to be changed due to its poor condition and only the bicoherence analysis was able to correctly determine the poor condition of the impeller.

6. CONCLUDING REMARKS

The application of bicoherence analysis to detect the severity of faults present in rotating machineries has been discussed in this paper with three different case studies. The presence of faults in rotating machineries are accompanied by the increased presence of non-linearity in the vibration signal. Bicoherence analysis successfully detects and quantifies the amount of non-linearity present in the signal. The peaks in the plots of bicoherence analysis indicates the presence of non-linear coupling of frequencies in the system which in turn indicates the presence of faults. The number of significant peaks in the plots increases with an increase in the severity of faults present. The application of the technique along with classical Fourier analysis on the industrial data set from the impellers of the tailing pumps indicate that only bicoherence analysis is able to clearly identify the proper amount of impeller wear in the pump even under process fluid changes, whereas other techniques fail. The proper applications of bicoherence analysis on vibration data from simulation, pilot plant and industrial plant demonstrate the strength and efficacy of the technique.

7. FUTURE WORK

Vibration data has been acquired from all the 20 tailing pumps at the Suncor oil sands plant for a period of one year. Currently bicoherence analysis is being carried out on the collected data. Also threshold values of maximum bicoherence is being calculated for the pumps to generate different levels of alarm based on the severity of impeller wear.

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