ICSV14
Cairns • Australia
9-12 July, 2007

14th International Congress on Sound & Vibration

SYMMETRIC WAVE DECOMPOSITION AS A MEANS OF IDENTIFYING THE NUMBER OF DAMAGED ELEMENTS IN A SLOW SPEED BEARING

Craig Moodie[1], A.K.Tieu[2] and Simon Biddle[3]

[1]School of Mechanical, Materials and Mechatronic Engineering, Faculty of Engineering, University of Wollongong, NSW, Australia
[2]School of Mechanical, Materials and Mechatronic Engineering, Faculty of Engineering, University of Wollongong, NSW, Australia
[3]Senior Condition Monitoring Engineer, Bluescope Steel , Port Kembla, NSW
cam920@uow.edu.au

Abstract

This paper discusses a symmetry transformation (Symmetric Wave Decomposition - SWD) that identifies the ‘source’ forcing functions that are contained in a time-series.

Knowledge of the number of active elements (principal components) in a roller bearing is crucial to identifying how many elements may be defective and or if external forcing functions are dominant.

With an understanding of these ‘active components’ the vibration data is decomposed into each active component wave. From this it can be estimated how many active components are associated with an event or events, if the damage is local or likely to be external and the extent of the damage.

Vibration data from a large industrial machine containing large (4.2m diameter) slow speed (4 rpm) slew bearings has been processed with the SWD transform and the results are presented. The SWD algorithm is being implemented on an experimental test-rig that has been specifically built for the monitoring of slow speed (1rpm) bearings.

1. INTRODUCTION

A primary characteristic of slew bearings is the large number of moving parts; rolling elements and /or independent geometric components (IGC’s) that combine to form the resultant vibration that emanates from the structure at the measurement location.

In this paper we describe a new tool that we add to our existing toolbox of methods for the condition assessment of a bearing. This tool is a decomposition process that transforms the measurement data into a series of sub-vectors. Each sub-vector contains a central element which obtains contributions not only from itself but also its neighbours; at some predefined interval from itself. This process is the same for all data elements. A roller bearing can be considered as a good candidate for this model. Each rolling element has a neighbour at some interval either side of itself that contributes to its own behaviour.

In this paper we describe a novel algorithm; the Symmetric Wave Decomposition (SWD) of data, where a data element is assumed to contribute to itself and its fixed neighbours via a recursive symmetry operator. No data fitting occurs. There is no residual. The result of the symmetric recursion is then decomposed into a known number of vectors (waves). Orthogonality of the waves is checked but not imposed. The algorithm does require a terminating condition which is defined by the number of iterations/repeatable cycles and the number of waves to extract. This last requirement; the number of waves to extract, is in fact something we wish to establish. We do this by pre-testing the data with the upper bound value; the number of IGC's. In the subsequent plotting of the energy of each wave we obtain a cut-off at some number less than the upper bound. This number is then the 'active' number of components or number of waves. The 'active' number of components is nearly always greater than the number of *principal components* obtained from an eigenvalue analysis [1] of the data. By reusing the 'active' number as the number of waves we are able to extract the vector representing each wave.

Typically the process involves three stages. Initially, we establish the number of iterations then the number of waves. Finally we extract each wave.

This is a very different approach to decomposition when compared with two other closely related methods; Empirical Mode Decomposition (EMD)[2,3,4,5,6,7,8,9] and Intrinsic Mode Functions (IMF's). In these methods a mode (vector) is obtained at each step and removed from the original leaving a residual. This process is repeated until a small residual is all that remains. Each vector (mode) extracted represents some fundamental behaviour such that the sum of all the modes and residual returns the original data (vector). The algorithm is quite complex and assumes that each mode is a smooth function that is fitted by a cubic spline. It requires a specification of the residual to accept as a terminal condition. It does not require a known number of modes to extract.

The data we will present comes from a large Coal Reclaimer slew bearing and a small slew bearing undergoing 'run to failure' testing on an experimental test-rig. These slew bearings contain two horizontal and one vertical row of cylindrical roller bearings. The Coal Reclaimer (4.2mØ) has two vertically mounted slew bearings supporting the reclaiming buckets which rotate at approximately 4.3 rpm in one direction in a continuous mode. The slew bearing (0.3mØ) in the test-rig is horizontally mounted and can operate in the speed range 1 to 10 rpm. The test-rig data presented in this paper is at 1 rpm.

Current condition monitoring methods applied to the Coal Reclaimer provide a sample of acceleration data that is short in duration containing a few thousand samples (4096 in g) at 240 samples per second at 8 bit resolution. The test rig provides 125,000 samples per channel (in mV) per time block at 16 bit data resolution over the range of 2K-2M samples per second.

2. SYMMETRIC WAVE DECOMPOSITION

To decompose is to 'separate into elements' [10]. Symmetric wave decomposition is an empirical method for separating an n_{pts} time-series, $\overset{>}{x}$, into $m = nwave$ waveforms. Each waveform $\overset{>}{r_k}, k \in nwave$ represents an excitation function contained in the time-series $\overset{>}{x}$. It is an empirical method because it requires a constant f to enable the 'energy' to disperse within the start and finish of the time-series. We do not want the information to accumulate at the start and/or finish of the dataset.

The method consists of a symmetry breaking [11] operator that utilises the local symmetry contained in a time-series $\overset{>}{x}$. The local symmetry is obtained by considering the domain of sub-vectors $\vec{x}_s \in \vec{x}$ where $\vec{x}_s = \left\langle \vec{x}_{i-m}, \vec{x}_i, \vec{x}_{i+m} \right\rangle$ and $i \in \mathrm{I}$ the set of numbers $i = m, m+1, \ldots, n_{pts} - m - 1$. The symmetric mean value of $\vec{x}_{s_i}$ is $\vec{x}_i = 1/3\left(\vec{x}_{i-m} + \vec{x}_i + \vec{x}_{i+m} \right)$. The domain N is the set of $iterates \le nwave$ that also satisfy the condition that the resulting state-space of $\vec{x}^{\,n+1}$ is bounded by an ellipse. The ellipse represents the state space of a sine wave. To counter the directional dispersion of $\vec{x}^{\,n+1}$ in the domain I we require the domain ϑ which is the reverse of I.

For $\vec{x}_i^{\,0} = \vec{x}_i$ and $i \in \mathrm{I}$ we say

For every $n \in$ N

For every $i \in \mathrm{I}$ and $j \in \vartheta$

$$\vec{x}_i^{\,n+1} = 1/(3f)\left(\vec{x}_{i-m}^{\,n} + \vec{x}_i^{\,n} + \vec{x}_{i+m}^{\,n} \right) \text{ And } \vec{x}_j^{\,n+1} = 1/(3f)\left(\vec{x}_{j-m}^{\,n} + \vec{x}_j^{\,n} + \vec{x}_{j+m}^{\,n} \right)$$

The empirical factor $f <= 1.0$ is required to ensure dispersion is contained in the domain I. The resulting 'energy' of all waveforms is accumulated at the boundaries of I if $f > 1.0$. A satisfactory domain N is achieved if $f = 0.8$. This transformation is a non-linear filter of order 1. With $f = 1.0$ it is also the average of a window of three elements.

After the recursive operation, the data set $\vec{x}^{\,n+1}$ is rescaled to the original $\vec{x}$ to enable comparison with historical datasets .Each wave k is obtained by extracting from the vector, $\vec{x}^{\,n+1}$, a sub-vector, $\vec{r}_k = \left\langle \vec{x}_k^{\,n+1}, \vec{x}_{k+m}^{\,n+1}, \vec{x}_{k+2m}^{\,n+1}, \vec{x}_{k+3m}^{\,n+1}, \cdots \vec{x}_{k+qm}^{\,n+1} \right\rangle$ such that $k + qm \le n_{pts}$.

We can define the instantaneous energy of r_k at $k+m$ as $(\vec{x}_{k+m}^{\,n+1})^2$. From this we can obtain the cumulative energy for individual waves as $e_k = \sum_{p=0}^{p=q} (\vec{x}_{k+pm}^{\,n+1})^2$ and the total energy for all waves $\mathrm{E} = \sum_{k=0}^{k=nwave-1} e_k$. We define the energy probability $p_k = e_k / \mathrm{E}$ and compute the overall entropy [12] $\mathrm{H} = \sum_{k=0}^{k=nwaves-1} p_k \ln(p_k)$. H provides us with an overall measure of disorder which we retain for long term condition monitoring.

In this method we need to identify $m = nwave$. An upper bound is available from an understanding of the number of IGC's. Using this value and plotting the energy content of each resultant wave we can identify the 'active' number of waves. The 'active' number of waves is the last wave number which contains non-zero energy. This then represents the true $nwave$. If we do not know the number of IGC's then we can still guess a number; much greater than the number of principal components, as a starting point. If we do not know the principal components in the data then we just use a large number.

The number of data points in $\vec{x}$ can be a limiting factor. If there is insufficient data then the $nwave$ may turn out to be considerably less than the expected IGC's. This outcome leads to a discussion on the amount of data required. A typical analysis should involve a minimum of 8*10*IGC data points where the number of points defining a cycle = 8 and the number of cycles per wave = 10. For a large slew bearing the number of IGC's can be greater than 350. This then says we should be collecting at least 28,000 data points. In the case of only a small sample; like 4096 data points, we can only expect to see about 50 waves which are typically just enough to cover the number of principal components.

5. SWD OF COAL RECLAIMER DATA

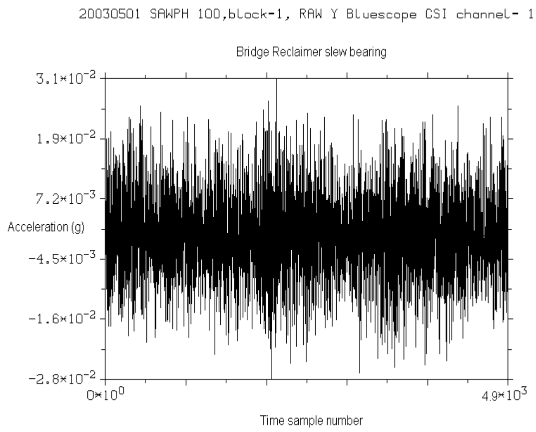


Figure1. $\vec{x}$ Accel'n vs. time at 01/05/2003.

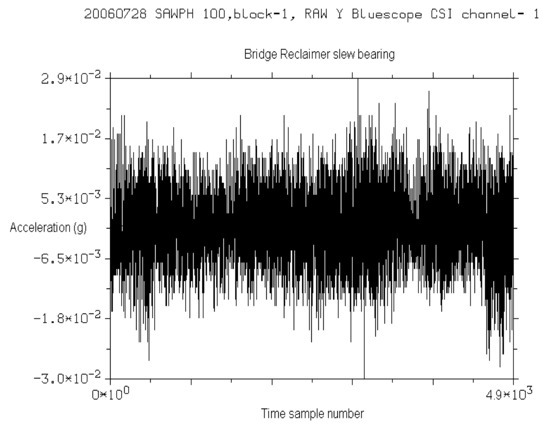


Figure2. $\vec{x}$ Accel'n vs. time at 28/07/2006.

Figures 1 and 2 represent the raw acceleration data for the Coal Reclaimer at 01/05/2003 and 28/07/2006. This data has 4096 data points obtained at 240 samples per second. Notice that it is difficult to see anything particularly different about the two sets of data.

In Figures 3 and 4 we show two dimensional views of all the waves in each dataset. Each colour identifies an individual 'decomposed' wave. There is repetition in the use of colour at distinct intervals of 8 waves. We now start to get a sense that there may be some differences as the wave forms look 'busier' at 28/07/2006. Notice that some of the waves are more 'peaky' due to local impacts which are either caused by some external force or internal defect.

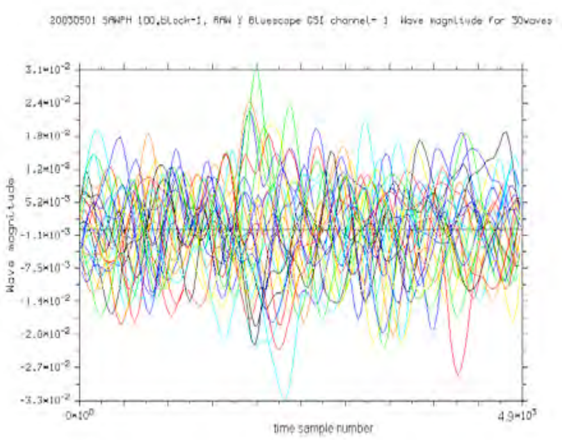


Figure3. SWD Accel'n vs. time at 01/05/2003.

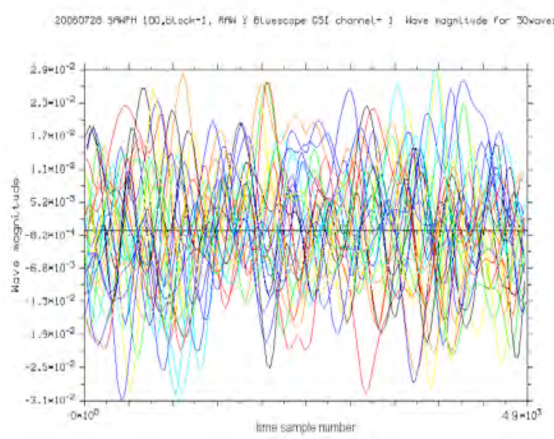
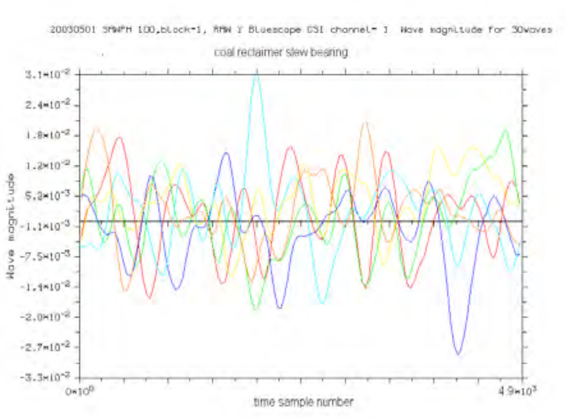


Figure4. SWD Accel'n vs. time at 28/07/2006.



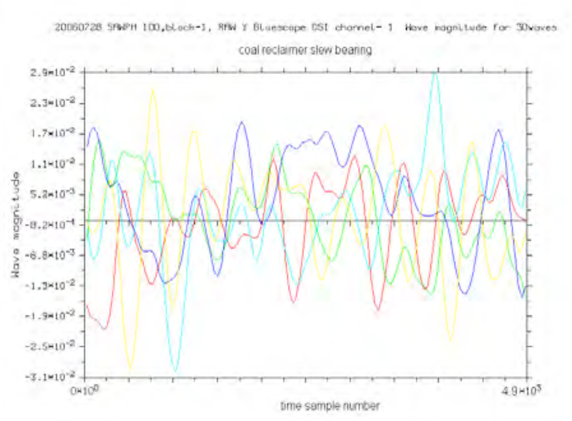


Figure5. SWD Accel'n vs. time at 01/05/2003. Figure6. SWD Accel'n vs. time at 28/07/2006.
For all waves in range max-3→max+3.

In Figures 5 and 6 we only show the 3 waves either side of the wave exhibiting the maximum energy. Note the number of waves whose peak magnitude exceeds $1.8*10^{-2}$.The increase from 2 to 5 waves is significant as a local effect and is probably caused by an external force. If the peaks were from an internal defect we would expect to see this effect in every wave as each wave would 'see' the defect. We do not see any more significant peaks in a field of 30 possible waves. To identify whether we have a global problem we produce for each wave, the ratio of the individual wave energy to the sum of all wave energies. In Figures 7 and 8, we see the energy probability $p_k = e_k / \mathrm{E}$ for each wave.

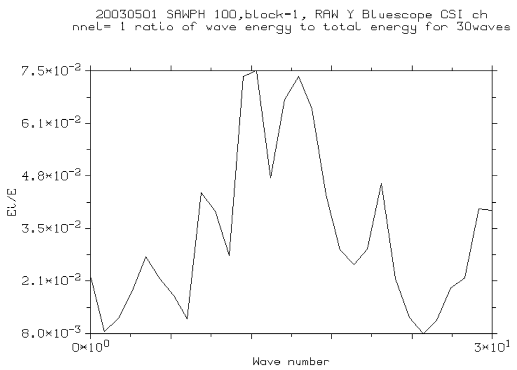


Figure7. p_k vs. wave number at 01/05/2003.

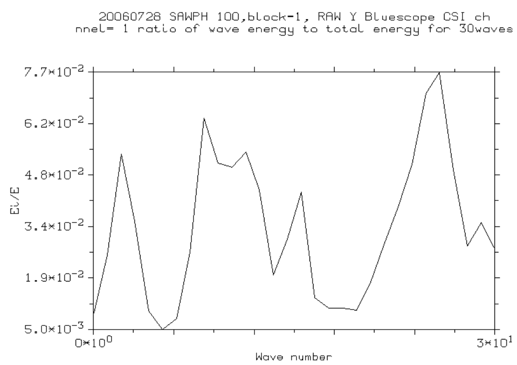
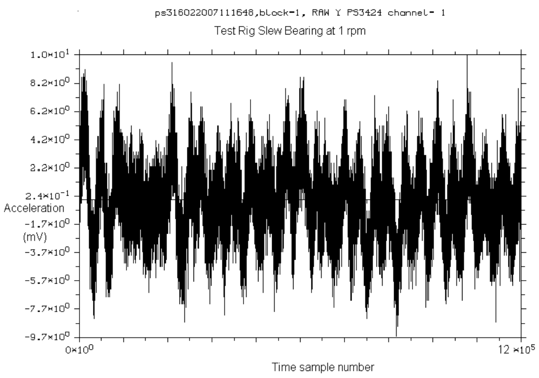


Figure8. p_k vs. wave number at 28/07/2006.

Note the number of waves whose peak value exceeds $4.0*10^{-2}$.The increase from 7 to 10 waves is significant but this still a lot smaller than 30 possible waves. This implies that things are still quite acceptable. Note that we cannot relate individual wave numbers between the two measurement periods because we have no reference marker at the start of each measurement. However, we can relate the cumulative behaviour by examining the cumulative energy and/or the entropy. For Figure 7 the cumulative energy is 0.00773 and for Figure 8 the cumulative energy is 0.02334 this is a significant overall change. However if we look at the change in entropy we go from 3.226 for Figure 7 to 3.34 for Figure 8. This is a much less significant movement. We can only conclude that 'things' are marginally worse. However, if we set a limit for damage at $p_k = 4.0*10^{-2}$ then 33.3% of the bearing is damaged.

6. SWD OF TEST-RIG DATA

Now for the test-rig bearing, we know that the bearing contains a total of 388 rolling elements or IGC's. We also have a substantial amount of data (125,000 values in mV) sampled at 625k samples/sec. Figures 9 and 10 are displays of the raw accelerometer data for the two dates 16/02/2007 and 21/02/2007.



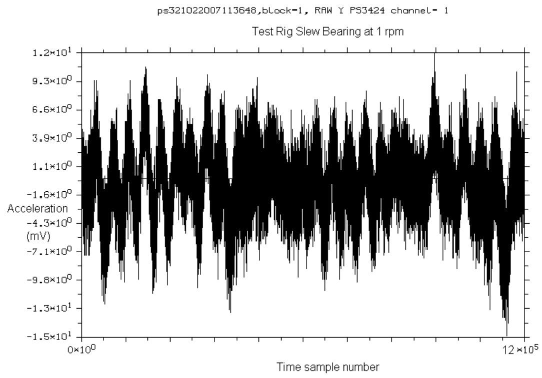
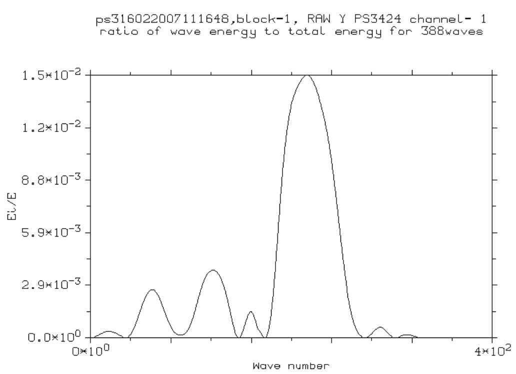


Figure9. $\hat{x}$ Accel'n vs. time at 16/02/2007. Figure10. $\hat{x}$ Accel'n vs. time at 21/02/2007.

When we run the SWD for this number of waves we get Figures 11 and 12. Both these figures say that there appears to be no wave energy above wave number 320. We do not see 388 waves.



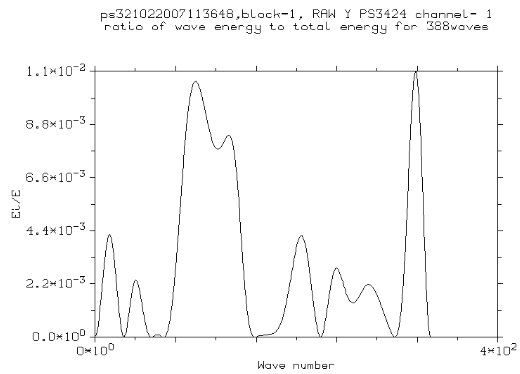
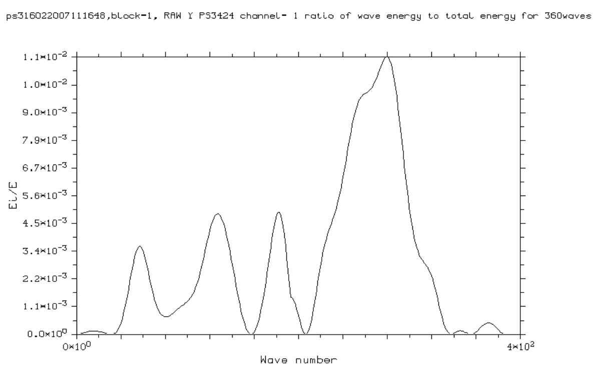


Figure11. p_k vs. wave number at 16/02/2007. Figure12. p_k vs. wave number at 21/02/2007.

If we re-run with 320 waves we get a result that indicates that there are more waves. After a few more iterations we arrive at 360 waves and get Figures 13 and 14.



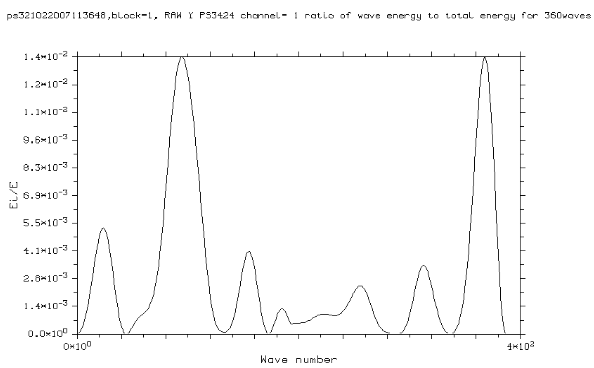
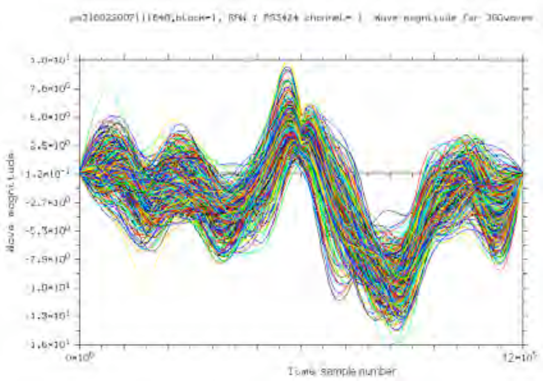


Figure13. p_k vs. wave number at 16/02/2007. Figure14. p_k vs. wave number at 21/02/2007.

Now that we have established the correct number of waves we can extract further information from the plots. At 16/02/2007 the cumulative energy is 4507.15 and the corresponding entropy is 5.27. For the 21/02/2007 measurement the cumulative energy has reduced to 4247.6 and the entropy has reduced to 5.205. The bearing is getting 'quieter'. This is characteristic for bearings in their early life stage.



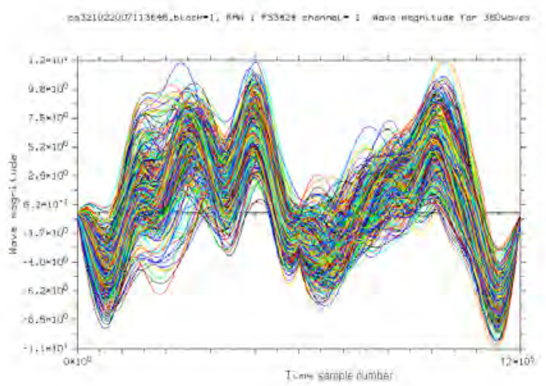
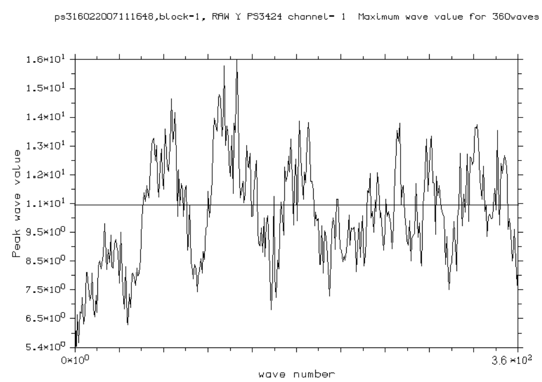


Figure15. SWD Accel'n vs. time at 16/02/2007. Figure16. SWD Accel'n vs. time at 21/02/2007.

Figures 15 and 16 display the wave forms resulting from SWD analysis at the two time instances of 16/02/2007 and 21/02/2007.



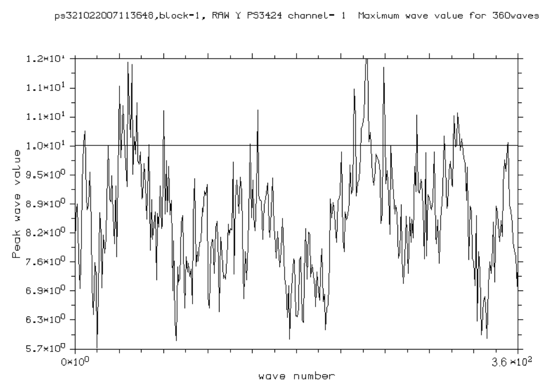


Figure17. Peak value of wave at 16/02/2007. Figure18. Peak value of wave at 21/02/2007. versus wave number.

Figures 17 and 18 shows a dramatic decrease in the number of waves where the peak value exceeds the horizontal line at 10 units (mV). In addition we also note that there appears to be more variability between successive waves for the date 21/02/2007. In this example we cannot use the 10mV level as the damage level because the bearing is getting 'quieter'. Obviously we have still to determine a damage level for this bearing. This is one of the goals for the experimental test-rig.

7. CONCLUSIONS

The SWD is a transform that allows individual wave-like vectors to be identified in correct time order. From the waves the wave energy and overall system entropy may be determined. The units of measurement and the number of data elements per wave determine the magnitude of the cumulative energy and associated entropy.

The maximum number of 'active' waves (components) can be established if sufficient data is available. If insufficient data is available the maximum waves can still be identified but they will not represent all the possible independent geometric components.

By examining local in time waves; either side of the maximum wave, we can identify the change and extent of impact peaks and consequently make some judgment about the location of a possible defect or source of excitation. This is particularly important when external forcing functions occur at the same frequency as an internal fault.

The extent of bearing damage can be determined by examining p_k versus the wave number plot and comparing it to previous history of similar plots. Given a value for p_k that represents damage, the number of damaged elements in a slow speed bearing can be determined. A goal of the slew bearing experimental test-rig is to determine the p_k level that represents a damaged element.

REFERENCES

1. C. Moodie, A. K. Tieu, S. Biddle. *De-convolution of time-series data using translational symmetry and eigenstate analysis*. — (to be published).
2. Z.K. Peng, Peter W. Tse, F. L. Chu. *A comparison study of improved Hilbert-Huang transform and wavelet transform: Application to fault diagnosis for rolling bearing.* Mechanical Systems and Signal Processing **19** (2005) 974-988.
3. Norden E. Huang, Man-Li C. Wu, Steven R. Long, Samuel S. P. Shen, Wendong Qu, Per Gloersen, Kuang L. Fan. *A confidence limit for the empirical mode decomposition and Hilbert spectral analysis.* Proc. R. Soc. Lond. A (2003) **459**, 2317-2345.
4. S.J. Loutridis. *Damage detection in gear systems using empirical mode decomposition.* Engineering Structures **26** (2004) 1833-1841.
5. Cheng Junsheng, Yu Dejie, Yang Yu. *Research on the intrinsic mode function (IMF) criterion in EMD method.* Mechanical Systems and Signal Processing **20** (2006) 817-824.
6. Yang Yu, Yu Dejie, Cheng Junsheng. *A roller bearing fault diagnosis method based on EMD energy entropy and ANN.* Journal of Sound and Vibration **294** (2006) 269-277.
7. Cheng Junsheng, Yu Dejie, Yang Yu. *A fault diagnosis approach for roller bearings based on EMD method and AR model.* Mechanical Systems and Signal Processing **20** (2006) 350-362
8. Christopher D. Blakely. *A Fast Empirical Mode Decomposition Technique for Nonstationary Nonlinear Time Series.* Preprint submitted to Elsevier Science 3 October 2005.
9. Norden E. Huang and Zhaohua Wu. *An adaptive data analysis for nonlinear & non-stationary time-series; The Empirical Mode Decomposition & Hilbert Spectral Analysis.*
10. The Concise Oxford Dictionary. Fifth Edition. Oxford at the Clarendon Press ISBN 0 19 861107 2 .pg 316.
11. Victor J Stenger. *The Comprehensible Cosmos.* Prometheus Books.2006. ISBN-13 978 1 59102 424 8. pp 97-144.
12. Victor J Stenger. *The Comprehensible Cosmos.* Prometheus Books.2006. ISBN-13 978 1 59102 424 8. pp 281-282.