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VIBRATION EVENT DETECTION: A MONITORING METHOD FOR SLOW SPEED BEARINGS.

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Abstract

Traditional signal analysis methods appear to fail in their ability to provide consistent meaningful information when presented with data from large slow moving slew bearings. A number of reasons for this are presented. Statistics obtained from vibration data collected from a large Coal Reclaimer and an experimental test-rig is discussed. The Coal Reclaimer rotates at 4.3 rpm about two vertically mounted, large, slew bearings. The experimental test-rig rotates at 1 rpm in the horizontal plane. These statistics are compared to the results obtained using a simple event detection algorithm. The event detection algorithm is detailed and its strengths discussed relative to other methods. It is found that the event detection method provides a consistent statistical view of the condition of the slew bearing but not necessarily better than simple statistical measures. The event detection algorithm is now being used as a condition monitoring tool on the test-rig designed to specifically condition monitor horizontally mounted slow speed (1 rpm) bearings to failure.

1. INTRODUCTION

The use of vibration data from slow-speed slew-bearings has been notoriously unsuccessful in predicting bearing failure. There are a number of reasons for this. Primarily, the very slow speeds involved (1 - 4 rpm) lead to very low rotational energy release. The operation of a slew bearing is often intermittent and non-cyclic. The data used in this paper is from a Coal Reclaimer and an experimental test-rig. The Coal Reclaimer has 2 large (4.2m diameter), vertically mounted, slew bearings supporting the reclaiming buckets and rotates at approximately 4.3 rpm in one direction in a continuous mode. The test-rig slew bearing is horizontally mounted, small (0.3m diameter) and rotates nominally at 1 rpm under a 15 tonne load.

Current condition monitoring methods for the Coal Reclaimer provide a short sample (4098 max) of acceleration data at 240samples/sec. Data from the test-rig can be sampled across a broad frequency range from 1 to10million samples/sec. The ICP type piezoelectric accelerometers used on the Coal Reclaimer and the test-rig are from the same manufacturer with the same frequency response characteristics.

Demodulation/Fourier type data analyses of vibration from slew bearings have been unsuccessful in determining the useful life and /or time to replace. After examining some thirty different statistics for the history of raw acceleration data obtained from the Bridge Reclaimer we obtained no statistic that produced a significant trend. This result forced us to consider the use of acoustic emission methods and in particular the simple idea of an event.

The definition of the term 'event' as used in this paper is 'a thing that happens; a result, an outcome that includes measured events and or calculated events from measured events'. The science of Acoustic Emission is primarily concerned with the measurement of ultrasonic events and their categorisation [1]. Pollock [2] says 'Acoustic Emissions are the stress waves produced by sudden movement in stressed materials. The classic sources of acoustic emissions are defect related deformation processes such as crack growth and plastic deformation.' He goes on to say 'The source of the acoustic emission energy is the elastic field in the material'. In acoustic emission the term 'ringdown counts' is a dominant measure. Tandon and Choudhury [3] say 'Ringdown counts involve counting the number of times the amplitude exceeds a preset voltage level (threshold level) in a given time'. They go on to say 'An event consists of a group of ringdown counts and signifies a transient wave'. Choudhury and Tandon [4] say 'The method of ringdown counts has been found to be a very good parameter for the detection of defects in both the inner race and roller of the bearings tested'. They go on to say 'that as the defect size increases, more events are emitted with higher values of peak amplitude and ringdown counts'. However, they qualify these results by stating 'emission has not been detected for some cases of good bearings running at low speeds of 100 and 250 rpm' which of course is a highly desirable result. In this paper we are dealing with bearings at 1 to 4.3 rpm which raises the likelihood of extremely low acoustic emissions and/or no significant change at all.

In this work we count the number of times a threshold is reached and or exceeded within a fixed length dataset. We introduce two operators that extract an amplified view of the events embedded in any data. The algorithm to produce the event statistics is outlined and we then illustrate the use of these operators on raw acceleration data obtained from both the machines previously described.

2. EVENTS

Every element of a dataset can be considered to be an event. We require a means of categorising each event. This is usually done by examining the value of the element and placing the value in a bin (a memory location) that represents the value. This can be done quite easily given that we have defined a bin to receive the value. Defining the bins to receive the value is the problem. If the number of bins is too large then some of the bins will be empty and if the number of bins is too small we may miss out on some subtle change that has taken place at some value level and the effect is absorbed along with values less than or greater than the value itself. This is typically what happens in statistical analysis. The user has to define a range of values and the number of bins based on some fixed interval that represents the range. Although there are two main methods that we employ, we briefly describe one of them as it is quite simple.

Initially, we find the maximum and minimum of our data and decide if the data is best described in one of the following rules in Table 1. We assume that the data x takes both positive and negative values and in our case because we are measuring acceleration; either in g's or milli-Volts (mV), we restrict the maximum to a value of 1000.0 as we do not normally detect values above this range in operating conditions on slow speed slew bearings. Notice in

Table 1 that we also adopt a variable number of bins (steps) depending on the category that the top value finds a match. Note also that all the bins take a positive value. That is, we establish the absolute maximum value and define the categorization rule.

Rule	If abs(max (value))	steps	comment
1	>0.001 and <=0.01	100	0 to 0.01 in steps of 0.0001
2	>0.01 and <=0.1	100	0 to 0.1 in steps of 0.001
3	>0.1 and <=1.0	100	0 to 1 in steps of 0.01
4	>1.0 and <=10.0	100	0 to 10 in steps of 0.1
5	>10.0 and <=1000.0	1000	0 to 1000 in steps of 1

Table 1. Categorisation rules.

Now that we have our events all categorised into bins we can calculate the fraction of all events (or probability of an event) taking that binned value.

We will now discuss some operators that allow us to take a particular view of the data other than the raw values.

3. EMBEDDED EVENTS

It is implicit that we are looking at the data x from start to finish in event order. Within x is a range of events from slow (low frequency) to very fast events (high frequency). We now describe a very simple novel transformation that highlights all the short duration events s that are contained in a n length dataset x. We deliberately do not consider the concept of time in the definitions as these transforms also apply to data that is not sampled at recorded time intervals. More generally the approach is based on an event precedence paradigm. That is, this event occurred before that event. The quantity being measured has no impact on the paradigm.

We define stability as, the amplification of change in the neighbourhood of an observer. The observer in a one dimensional space can have, at most, a neighbour on the left and on the right. From this we define stability as $s = uv$ where $u = (x_{i+1} - x_i)$ and $v = (x_{i+2} - x_{i+1})$ for $i = 0,1,2...m = n-1$. Both u and v are changes that when multiplied amplify or attenuate the raw data. If the object x is given a unit of mass, v and u can be considered as representing momenta. From this Newtonian description we obtain a related 'cousin', the work done of x defined as $w = 0.5(v^2 - u^2)$. For most purposes we can ignore the factor 0.5. It is interesting to note these two operators s and w are related via the complex number $z = v + iu$ where $i = \sqrt{-1}$. The units of the measures are to the power two, like energy. Hence mV transforms to mV² and g transforms to g².

The operators s and w behave like high pass non-linear filters in the time/frequency domain.

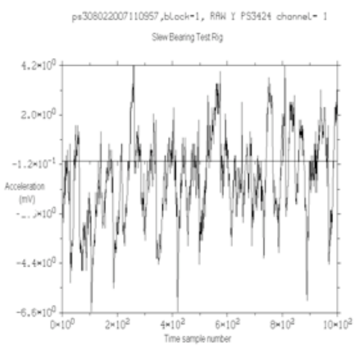

Figure 1. x Time-series.

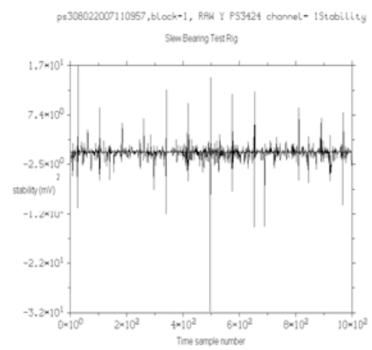

Figure 2. s Time-series.

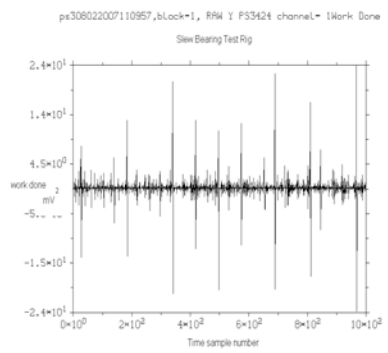

Figure 3. w Time-series.

Figures 1, 2 and 3 are short samples (1000) of the time domain for the raw signal x, s and w and illustrate the highlighting of events that occurs with these transforms. Notice how more distinct the data becomes. These transforms extract the very fast significant events from all the slowly changing data.

4. THRESHOLD COUNTS

For the same particular dataset x we can produce counts for the various threshold categories defined in Table 1. Figures 4, 5 and 6 all represent the data from the experimental test-rig slew bearing at the beginning of its useful life. The thresholds are in units of mV or mV².

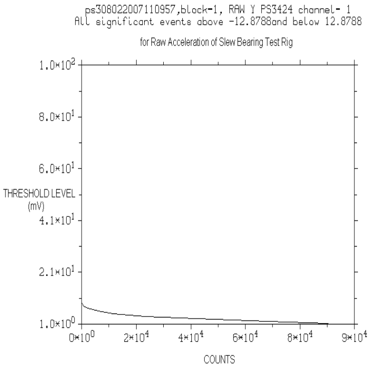

Figure 4. x Thresholds versus counts.

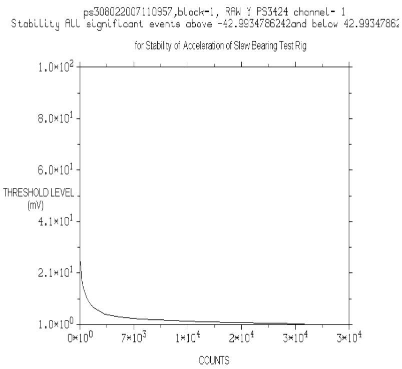

Figure 5. s Thresholds versus counts.

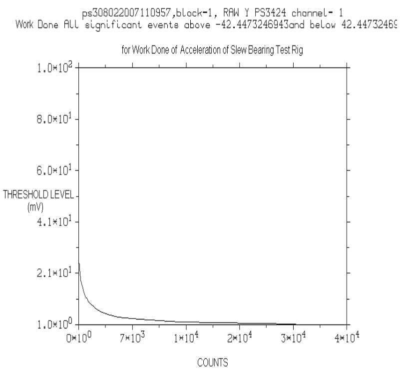

Figure 6. w Thresholds versus counts.

Note the relative insensitivity of the plot for the raw data x (Figure 4) compared to s and w (Figures 5 and 6). Both s and w give very similar results demonstrating their close relationship.

5. THRESHOLDS COUNTS AND HISTORY

5.1 Ultrasonic (≥20kHz)

We now examine the collection of datasets obtained over a period of 2 months from the test-rig and plot the combinations of threshold versus counts to produce Figures 7, 8. Figure 7 displays the history of counts at a threshold of 10 mV. Similarly Figure 8 displays the history of counts at a threshold of 15 mV. Note that the threshold level to adopt for evaluating the future performance of the bearing is very sensitive.

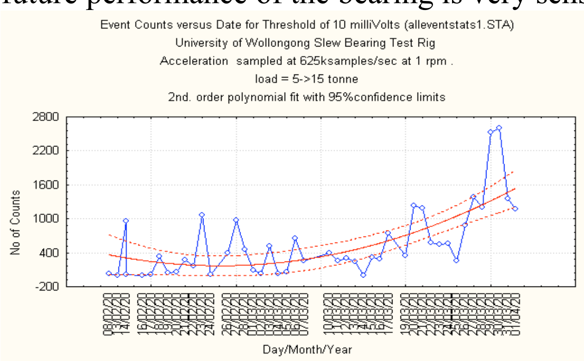

Figure 7. x threshold=10mV. Date versus counts.

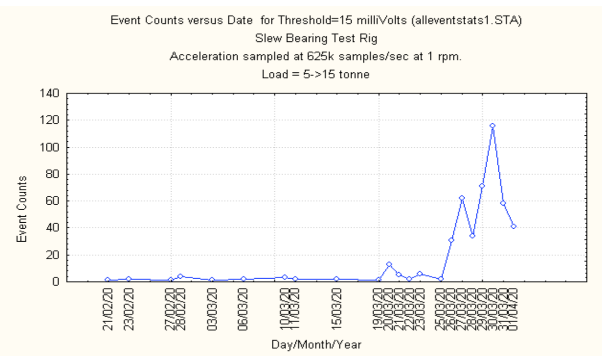

Figure 8. x threshold=15mV. Date versus counts.

If we adopt the lower threshold (10) then we could say that the bearing started to exhibit increased vibration activity at approximately half way through the first month of its life. If we adopt the higher threshold (15) then we could say that the increase in bearing vibration activity started at approximately half way through the second month of its life. This is very significant for bearing life prediction. As an example, this gap of 1 month on the experimental test-rig equates to 4.7 years of actual life on a continuous casting machine operating under equivalent conditions.

We need to find an indicator that is robust and relatively insensitive to the threshold level. When we plot w (Figures 9, 10) we see that a larger range of thresholds ($15mV^2$, $45mV^2$) essentially indicates that the bearing started to become 'active' at approximately half way through the first month in both instances.

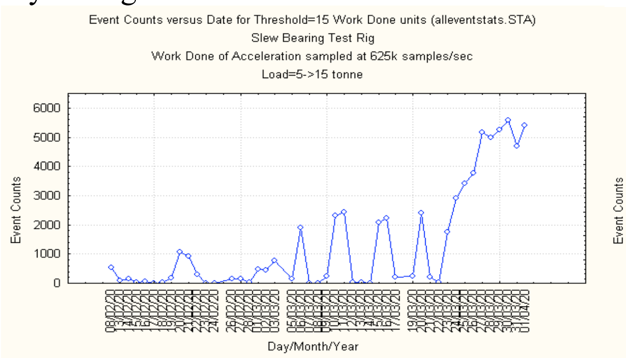

Figure 9. w threshold $=15mV^2$.
Date versus counts.

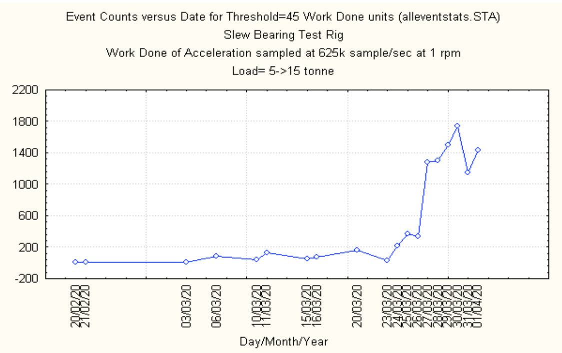

Figure 10. w threshold$=45mV^2$.
Date versus counts.

When we plot s (Figures 11) we note Figure 10 is similar to Figure 11. Secondly, a larger threshold ($= 50mV^2$) again indicates that the bearing started to become 'active' at approximately half way through the first month.

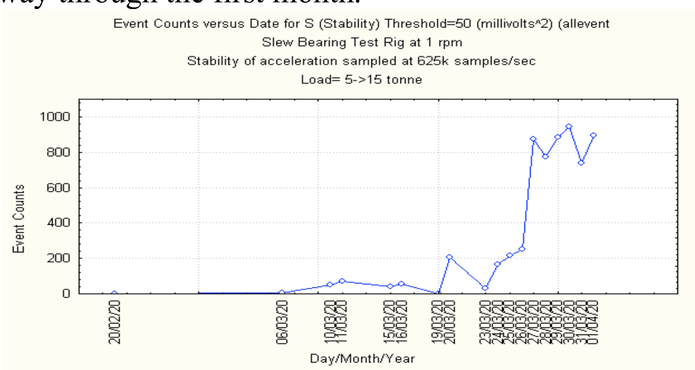

Figure 11. s threshold$=50mV^2$.
Date versus counts.

Now the accelerometer used is a 100mV/g device and consequently for a threshold $\overset{>}{s} = 50mV^2 = 0.0004998\ (g^2)$.

5.2 Sonic(<20kHz)

We now turn our attention to the datasets collected at sonic sampling rates from a large bearing on the Bridge Reclaimer. Figures 12, 13 and 14 are the event count histories of the acceleration x, the w transform and s transform. Figure 12 indicates that x is a poor indicator although it does indicate that towards the most recent end of the history the bearing was changing significantly.

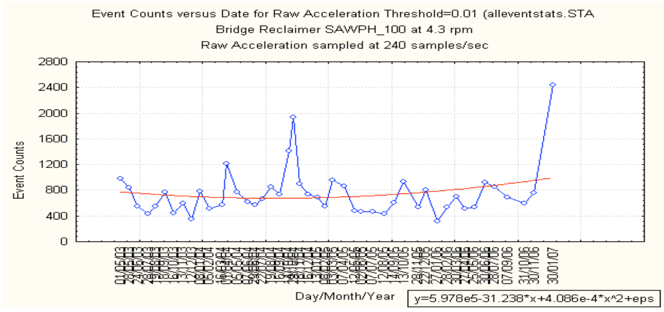

Figure 12. x threshold =0.01g. Date versus counts.

However, both the w transform and s transform indicate that the bearing started to experience problems much earlier. Interestingly the w transform says at February 2005 the bearing started to get more active and the s transform goes one better by saying that the bearing started to get more active in June 2004. The difference of 8 months is significant suggesting that the s transform is a prime candidate for indicating when a replacement bearing should be ordered.

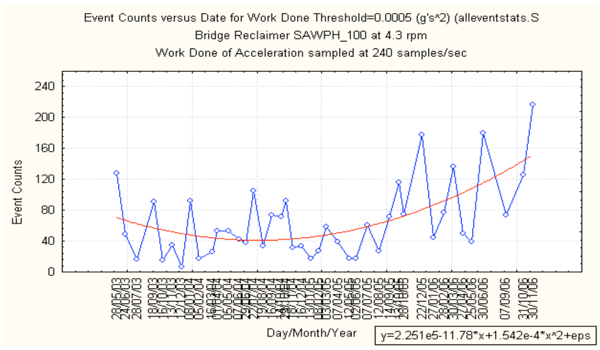

Figure 13. w threshold=0.0005g². Date versus counts.

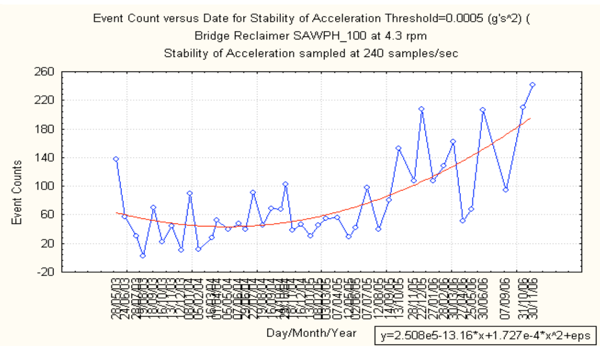

Figure 14. s threshold=0.0005g². Date versus counts.

When we compare the t.wo different bearings, Figure 11 and Figure 14, you may note that Figure 14 is significantly more irregular. It is our suspicion that this effect is due to the large differences in the sampling rates and the number of samples as well as the operating environment which is considerably more exposed to active vibration sources than the test rig.

6. OTHER STATISTICS

There are many possible indicators that may also be useful in determining the end state of a slow speed slew bearing. For any statistic to be useful we require it to be able to indicate consistent changes throughout the life of a bearing. We are also required to establish an 'end of life' value. This is similar to the 'end of life' for event counts that still needs to be established. Initially, we briefly discuss the statistics of the 'raw' acceleration x off the experimental test-rig. From every dataset we calculate 30+ different statistics. One of the most promising is the mean higher order autocorrelation [6] of a signal x defined as $A_{xx} = 1/n \sum_{i=0}^{i=n-1} abs(x_i x_{i+1}^2 - x_i^2 x_{i+1})$ 'which measures time asymmetry, a strong signature of nonlinearity'. Figure 15 indicates that quite a reasonable ($R^2 = 0.7169$) second order polynomial can be fitted to the raw data. The R^2 is an indicator of how well the model fits the data (e.g., a R^2 close to 1.0 indicates that the model accounts for almost all of the variability in the respective variables).

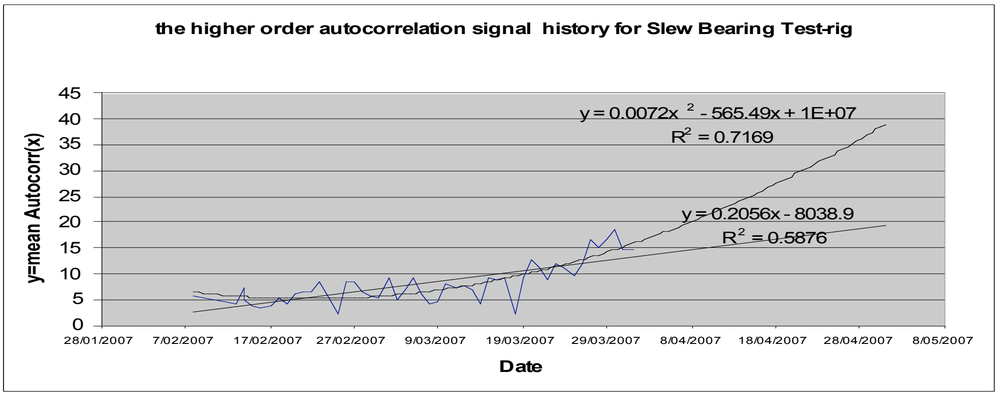

Figure 15. Mean higher autocorrelation of x versus Date.

A much weaker candidate appears to be the sum of absolute values of the signal x defined as $S_x = \sum_{i=0}^{i=n-1} abs(x_i)$. Notice the much lower $R^2 = 0.4115$ in Figure 16.

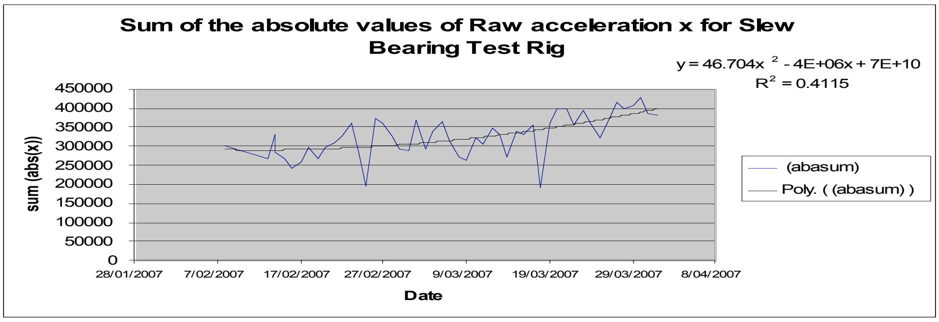

Figure 16. Sum of absolute values of x versus Date.

These potential indicators show considerable instability. This detracts from their ability to provide a confident prediction (a low R^2). However, we can transform x into w or s or some other time series via various filters. There is no shortage of possibilities. When we transform the data using the stability transform we obtain an improved result using the sum of the absolute stability values $S_s = \sum_{i=0}^{i=n-1} abs(s_i)$. In Figure 17 we achieve a $R^2 = 0.8416$.

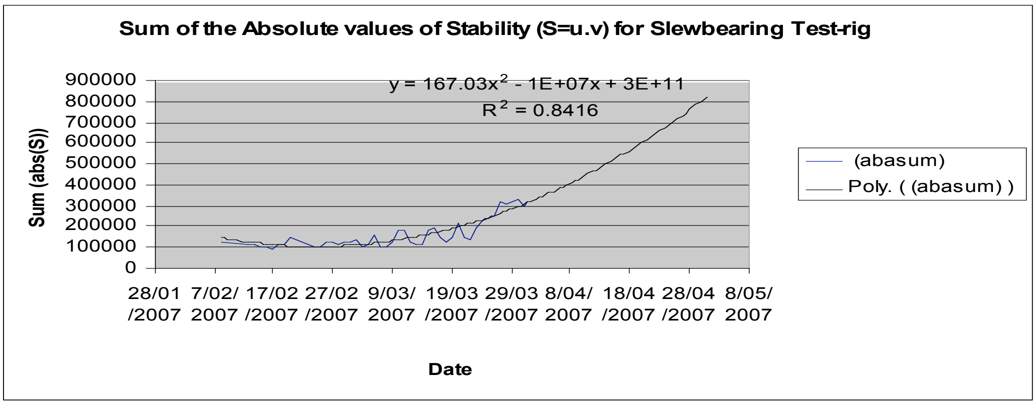

Figure 17. Sum of the absolute values of s versus Date.

Using the mean higher order autocorrelation $A_{ss} = 1/n \sum_{i=0}^{i=n-1} abs(s_i s_{i+1}^2 - s_i^2 s_{i+1})$ we obtain a second order fit with $R^2 = 0.7255$ (see Figure 18). This appears to be inferior to the sum of the absolute stability value.

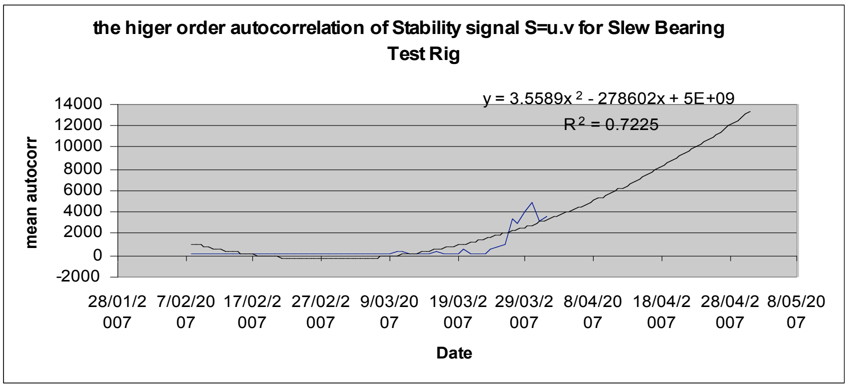

Figure 18. Mean higher autocorrelation of s versus Date.

7. CONCLUSIONS

Event count detection is a simple measure of bearing activity both in the sonic and ultrasonic vibration frequency ranges. Event counts are not yet established to be superior to simple statistics.

Both the w transform and s transform are superior to x; the raw acceleration data, in enabling the prediction of bearing behaviour. The stability transform s provides the earliest indicator of unstable bearing behaviour. The s transform will be used as one of the primary indicators for bearing life estimates on the experimental test-rig.

The threshold to use for the test-rig is 50mV^2=0.0004998 g^2. The threshold to use for the Bridge Reclaimer is 0.0005 g^2.These two thresholds are essentially the same indicating that 0.0005 g^2 is perhaps a good value to use for all very slow speed slew bearings.

It remains to establish the acceptable level of event counts that indicate a slew bearing should be replaced. The intention of the experimental test-rig is to establish this.

The statistic, the sum of absolute values of the stability s, appears to offer the most stable; second order polynomial, bearing behaviour indicator. This statistic may also enable a bearing replacement strategy.

It still remains to establish acceptable 'end of life' vibration levels for a slew bearing. This is the goal for the experimental slew bearing test-rig.

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