Comprehensive bearing condition monitoring algorithm for incipient fault detection using acoustic emission

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HIGHLIGHTS

- Bearing fault detection at incipient stage.
- High frequency envelope detection is used for bearing fault detection.
- Two methods are adopted for envelope detection viz. Hilbert Transform and order analysis.
- Different frequency bands are studied using band pass filter.
- Compared the results of various frequency band band-pass filters.

ABSTRACT

The bearing reliability plays major role in obtaining the desired performance of any machine. A continuous condition monitoring of machine is required in certain applications where failure of machine leads to loss of production, human safety and precision. Machine faults are often linked to the bearing faults. Condition monitoring of machine involves continuous watch on the performance of bearings and predicting the faults of bearing before it cause any adversity. This paper investigates an experimental study to diagnose the fault while bearing is in operation. An acoustic emission technique is used in the experimentation. An algorithm is developed to process various types of signals generated from different bearing defects. The algorithm uses time domain analysis along with combination low frequency analysis technique such as fast Fourier transform and high frequency envelope detection. Two methods have adopted for envelope detection which are Hilbert transform and order analysis. Experimental study is carried out for deep groove ball bearing cage defect. Results show the potential effectiveness of the proposed algorithm to determine presence of fault, exact location and severity of fault.

Keywords:
- Bearing
- Time domain
- Frequency domain
- Enveloped analysis
- Hilbert transform

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1.0 INTRODUCTION

Rolling element bearings are a common component in machinery. Therefore, they have received great attention in the field of condition monitoring. A reliable online machinery condition monitoring system is very useful to a wide array of industries to recognize an incipient machinery defect so as to prevent machinery performance degradation, malfunctions, or even catastrophic failures (Kumar and Manuhar, 2003). Fault detection can be conducted based on information carriers such as the acoustic emission, stress waveform, oil analysis, temperature variation, sound and vibration, etc. Commonly used technique for fault detection is sound and vibration signature analysis. Sound and vibration monitoring and analysis in rotating machineries offer very important information about anomalies formed internal structure of the machinery. The information gained by sound and vibration analysis enables us to plan a maintenance action (Tandon and Choudhary, 1999).

Several techniques have been used to measure and analyse the vibration response of bearing defects. The time domain analysis is the simplest approach in which signal is represented in time verses amplitude chart. But by simply seeing the signal in time domain, one can’t say that whether signal is from healthy bearing or defective bearing. To extract some useful information from the signal in time domain, statistical parameters such as RMS, kurtosis, skewness, crest factor are used (Fabio et al., 2009; Sylvester, 2011; Dron et al., 2004; Vassa et al., 2008; Bo et al., 2007; Lorenzo et al., 2007; Yong-Han et al., 2006; Manish and Sulochana, 2011; Mustapha et al., 2011). The limitations of time domain analysis are it shows the presence of defect but it doesn’t give the location of the defect.

Another limitation of time domain analysis is inconsistency in statistical parameters such as the value of kurtosis increases with increase the size of the defect, but it starts decreasing when the width of the size exceeds the diameter of rolling element. To determine the exact location of bearing fault, the signal is further analysed in frequency domain. The signal from time domain is transformed into frequency domain by using Fast Fourier Transform. The principal advantage of the method is that the repetitive nature of the vibration signals is clearly displaced as peaks in the frequency spectrum at the frequency where the repetition takes place.

One of the main purposes in computing power spectra of vibrating data is to identify major frequency component which can be found in spectrum and then use these components and their amplitude for the trending purposes (Spyridon and Ioannis, 2009). There is risk involved in analyzing the signal in low frequency zone because there are chances of fault signal may get contaminated by surrounding noise in low frequency zone. Hence frequency study in low frequency zone may give deceiving results. The impact generated by a bearing fault distributes its energy over wide frequency range. The bearing characteristic frequencies lie in low frequency zone and it is often overlapped by
The interaction of the defect in the rolling element bearings produces pulses of very short duration, whereas the defect strikes the rotation motion of the system. These pulses excite the natural frequency of the bearing elements, resulting in the increase in the vibration energy at these high frequencies. The resonant frequencies can be calculated theoretically.

Each bearing element has a characteristic rotational frequency. With a defect on a particular bearing element, an increase in the vibration energy at this element rotational frequency may occur. This defect frequency can be calculated from the geometry of the bearing and element rotational speed. By using a method called high frequency resonance technique [HFRT], or envelope technique, these frequencies could be isolated and demodulated to give an indication of bearing condition (McFadden and Smith, 1984; Prasad et al., 1985). The envelope detection process is the heart of the HFRT diagnostic system. Two methods have used for envelope detection which are Hilbert transform (McInerny and Dai, 2003; Yuan and Zhang, 2010; Petr, 2009; Eric et al., 2011; Guillermo et al., 2007; Sunil, 2010) and order analysis toolkit (OAT) in Labview.

Cage defect is selected for this research work because whenever an external unbalanced load acts on the bearing, then there is every chance of cage to be damaged as a first reaction to the external unbalanced force (Howard, 1994). Cage defect do not initially cause a bearing to fail but there can be serious secondary effects of cage defect such as loosening of rivets. Defective cage allows the ball to move from its position which makes the bearing lose and induce ball spinning defect. This can cause serious mechanical damage to the bearing resulting in costly repair and production loss. Figure 1 shows dislocation of cage defect in bearing.

![Figure 1 Dislocation of cage link](image)

### 1.1 Statistical time domain parameters

Condition monitoring of any machine requires an easily interpreted and unambiguous condition indicator, or defect severity index, that can be calculated from the extracted vibration signature. Useful indicator should allow defect growth tracking and provide a
means to define indicator levels indicating acceptable and unacceptable machine conditions (Diagnostic book). Most defects in machinery develop where two surfaces meet in rolling and sliding contact. A normal healthy surface has a small-scaled roughness distribution whose deviation from the nominal ideal surface exhibits a Gaussian normal distribution over the surface. When two healthy surfaces repeatedly interact by a combined sliding and rolling contact the roughness distribution is successively changed. Defects like wear and fatigue cracks have been shown to produce a more narrow and peaked roughness distribution. Assuming that the roughness is directly correlated to the generated vibration, the vibration time history can be statistically analyzed to give information on the surface condition.

Defect severity index

The defect severity index measures the severity of the defect by comparing the overall background vibration level with the level at the characteristic defect frequency. For bearings experience has shown that a severity index equal to say 15% is suitable as a threshold value for early defect detection when the high frequent part of the vibration history is used. The defect severity indexes are:

(a) The RMS (Root Mean Square)

The RMS (Root Mean Square) value of the vibration acceleration can be used for primary health investigation of the machine. The root-mean-square (RMS) of a variant $X$, is the square root of the mean squared value of $x$:

$$ RMS = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (x_i - \mu)^2} $$

(1)

Where, $N$ is number of samples, $x(i)$ is the amplitude of individual sample and $\mu$ is the mean value of samples.

(b) Crest factor

The crest factor, is the ratio of peak value to the RMS value (maximum absolute value reached by the function representative of the signal during the considered period of time), yields a measure of spikiness of a signal. Crest factor of radial vibration signal is often used to indicate the rolling bearing faults. Crest factor for healthy bearing is more as compared to that of damaged bearing, in many cases.

$$ \text{Crest factor} = \frac{\text{Crest value}}{\text{RMS value}} = \frac{\sup|x(n)|}{\sqrt{\frac{1}{N} \sum_{i=1}^{N} [x(n)]^2}} $$

(2)
With $N$, number of samples taken within the signal; $x(n)$ the time domain signal. As the value of the crest factor of a signal whose amplitude distribution is Gaussian is between 3 and 6, this indicator can detect that kind of defects only if its value is at least 6.

(c) Skewness
Skewness is a measure of symmetry, or more precisely, the lack of symmetry about its mean. A distribution, or data set, is symmetric if it looks the same to the left and right of the center point of Gaussian distribution.

$$skewness = \frac{1}{N} \sum_{i=1}^{N} (x_i - \mu)^3 \sigma^3$$  (3)

Where $\sigma$ is the standard deviation of the time record. Negative values of Skewness indicate the data that are skewed left and positive values for right skewness.

(d) Kurtosis
It is a measure of whether the data are peaked or flat relative to a normal distribution. A uniform distribution would be the extreme case. High kurtosis indicates a "peaked" distribution and low kurtosis indicates a "flat" distribution near the mean value.

$$Kurtosis = \frac{1}{N} \sum_{i=1}^{N} (x_i - \mu)^4 \sigma^4$$  (4)

Kurtosis = 3 for Healthy bearing; increases on introduction of fault. Where $\bar{x}$ denotes the mean value of the discrete time signal $x(t)$ having $N$ data points. Crest factor is one of the important scalar parameter that is used to detect the defect in ball bearings. The crest factor value up to 5 shows the normal running of bearing but when crest factor increases greater than 5 then there could be a defect in the bearing. Kurtosis value for perfect Gaussian distribution shows value of 3. The kurtosis value of healthy bearing should be around 3 as healthy bearing signal shows perfect Gaussian behavior in time domain. If a localized defect develops within the bearing, the impulse content of the vibration signal will increase; hence, the kurtosis value, which is measure of the peakedness of the waveform, will also increase (McFadden and Smith, 1984).

1.2 High frequency envelope detection

Every time a rolling element comes in contact with the defect, an impulse is generated. The time duration of this impulse is extremely small as compared to the time interval between two impulses. The energy associated with the impulse is distributed over wide
range of low level frequency. It is difficult to locate this low level frequency as the signal is contaminated with noise disturbance from the surroundings sources. But this impact frequency is carried by the structural resonance frequency in high frequency zone. As a result of this some energy is concentrated near structural resonance frequency in narrow band. The signal produced is modulation of amplitude carried by resonance frequency. Envelope detection is nothing but amplitude demodulation, used in finding the repeated impulse signals.

The steps of envelope detection process are shown in Figure 2. The first step is to generate signal in time domain using transducer, then this time signal is filtered using Bandpass filter in high frequency zone which filters all the low frequency components including the noise disturbance from the surroundings. The high frequency zone for the Bandpass filter is carefully selected by studying the structural resonance frequency of the machine. Now this modulated distribution of energy in high frequency zone is enveloped and demodulated again in low frequency zone. The demodulation of filtered signal is carried out using Hilbert transform (Proakis and Salehi, 2000).

![Figure 2 Steps in envelope detection](image)

**Hilbert Transform**

There are several algorithms available to perform high frequency envelope detection effectively. One of the most used method is through the Hilbert transformation, a mathematical variation to the fast fourier transform which demodulated a vibration signal
and extracts high frequency, low amplitude data of interest. Hilbert transform is used to shift the phase by 90° from the original signal that means all the negative frequencies of the signal get the phase shifted by +90° and all the positive frequencies get phase shifted by -90° phase shift (Proakis and Manolakis, 1997). Following transformation, the data consists of a complex signal comprised of a real signal (original) and imaginary (transform) aspect. It can be mathematically described as $F(t) = f(t) + j^*h(t)$ where $t$ is in the time domain, $F$ is the analytical signal constructed from the input signal ($f$) and its Hilbert transform ($h$). If phase is a necessary component, then the expression becomes $F(t) = A(t)e^{j\theta(t)}$ where $A$ is the envelope or amplitude of the analytical signal and $\theta$ represents the phase of this analytical signal.

**Order analysis toolkit (OAT)**

Order analysis is more complex method of envelope detection. This is inbuilt algorithm available in National Instrument’s Sound & Vibration suit. An already filtered (using Bandpass filter) signal is feed to the virtual instrumentation (VI) and envelope spectrum is obtained as an output. This VI extracts the modulating signal from an amplitude modulated signal. This technique is particularly useful to identify the mechanical faults that have amplitude–modulating effect on the vibration signal of a machine (National Instrument).

### 2.0 EXPERIMENTAL

The experimental set up is designed to investigate bearing defects and acoustic characteristics of bearing as shown in Figure 3. Power is transmitted from AC induction motor of 0.5 hp, 1440 rpm, to the driven shaft with the help of belt drive. The driven shaft is supported at it ends by two bearings. The bearing used for the study is deep groove ball bearing NTN 204.

The acoustic signal are acquired with the help of microphone, Real-tech HD audio input, 16 bit resolution, impedance of 32 ohm at 1 KHz, 105 Db ± 3dB and frequency response of 20Hz- 44100Hz. The microphone is glued at the top of the bearing housing to remove any air in the gap between microphone and housing. Microphone converts sound waves into voltage signals and then passes them on to the sound card. Sound card acts like a data acquisition card (DAQ). It acquires the analog voltage signal from the microphone, digitizes it, and sends it to the software LabVIEW 12 for further processing and analysis. The sound card installed in the personal computer is having sampling resolution of 8 and 16 bit (Stereo or monaural) at sampling rate of 4.0kHz to 44.1 kHz. The dynamic range at 16 bits resolution is 65535 discrete levels. Frequency response 20 Hz - 20 kHz at 3dB and signal to noise ratio as 80 dB. LabVIEW 12.0 is a data acquisition software package commonly used with hardware acquisition boards LabVIEW has many features for data
acquisition and processing of either measured data or simulated signals. National Instruments make Sound and Vibration toolkit is used for the experimentation purpose, which provides enormous analyzing capabilities that would help in signal conditioning and signal processing and get most out of it. It also allows analyzing the frequency range of interest with improved resolution, and several other feature that would help in understanding the data in better way.

![Experimental setup](image)

**Figure 3 Experimental setup**

**Sampling rate selection**

1) Sampling rate selected = 44100 Hz (no. of samples per sec)
2) Block size for FFT = 4410 samples (\(\frac{1}{10}\)th of sampling rate)
3) Time taken by one block = \(\frac{1}{10}\)th of sec = 0.1 sec

So to take 4410 samples it takes 0.1 sec means, 0.1 sec recorded data is discretized into 4410 points. Cross check 4410 points are sufficient or not.

RPM of shaft at driven end = 2 \times 1440 = 2880 rpm
No. of rev. per min. = 2880
No. of rev. per sec = 2880/60 = 48
No. of rev. in 0.1 sec = 48/10 = 4.8 revolutions \approx 5 revolutions

So, for the block size of 4410 for FFT, there are 5 revolutions. Hence there are sufficient revolutions to identify the defect in the bearing.
3.0 RESULTS AND DISCUSSION

An algorithm is developed for determining the defects in the bearing as shown in the Figure 4. This algorithm works by calculating the fundamental frequencies of different components of the test bearing. Sensor is mounted on the test bearing. The signal from the sensor is analysed first in time domain and obtained the statistical parameters. Compare the statistical parameters with the benchmark values. The kurtosis and crest factor values for healthy signal are 3 and less than 5 respectively. If the statistical parameter values lie within the benchmark values then we can conclude that bearing is healthy. But, if the statistical parameter values deviates from the benchmark values that means presence of fault in the bearing and further analysis is required. To determine the exact location of the defect, the signal is analysed in frequency domain. Two approaches are adopted to analyse signal in frequency domain which are low frequency analysis and high frequency analysis. Low frequency analysis is done by using Fast Fourier Transform and high frequency analysis (envelope analysis) is carried out by Hilbert transform and Order analysis toolkit (OAT). And on the basis of results of low frequency and high frequency analysis, comment on the location has been made.

![Figure 4 Algorithm for experimentation](image-url)
3.1 Determination of presence of defect

The experimentation starts by obtaining the dimensions of the test bearing (NTN P204) (Table 1) and calculating the fundamental frequencies [Fundamental Train Frequency (FTF), Ball spinning defect (BSF), Ball pass outer race frequency (BPFO), Ball pass outer inner frequency (BPFI) and Rolling element defect frequency (REDF)] of different components of the bearing. The fundamental frequencies and its harmonics are shown in Table 2.

Table 1 Dimensions of NTN 204 bearing

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inner bore diameter (D_i), mm</td>
<td>20</td>
</tr>
<tr>
<td>Outer ring outside diameter (D_o), mm</td>
<td>45</td>
</tr>
<tr>
<td>Shaft speed</td>
<td>1440 rpm</td>
</tr>
<tr>
<td>Ball diameter (d_b), mm</td>
<td>7.9248</td>
</tr>
<tr>
<td>Pitch diameter (d_m), mm</td>
<td>34.4932</td>
</tr>
<tr>
<td>No. of balls (n)</td>
<td>08</td>
</tr>
<tr>
<td>Width (b), mm</td>
<td>12</td>
</tr>
<tr>
<td>Contact angle, θ˚</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 2 Fundamental frequencies and its harmonics

<table>
<thead>
<tr>
<th>FUN FREQ</th>
<th>1x</th>
<th>2x</th>
<th>3x</th>
<th>4x</th>
<th>5x</th>
<th>6x</th>
<th>7x</th>
<th>8x</th>
</tr>
</thead>
<tbody>
<tr>
<td>FTF</td>
<td>9.243</td>
<td>18.486</td>
<td>27.729</td>
<td>36.972</td>
<td>46.215</td>
<td>55.458</td>
<td>64.701</td>
<td>73.944</td>
</tr>
<tr>
<td>BSF</td>
<td>49.4738</td>
<td>98.9476</td>
<td>148.4214</td>
<td>197.8952</td>
<td>247.369</td>
<td>296.843</td>
<td>346.317</td>
<td>395.7904</td>
</tr>
<tr>
<td>BPFO</td>
<td>73.944</td>
<td>147.888</td>
<td>221.832</td>
<td>295.776</td>
<td>369.72</td>
<td>443.664</td>
<td>517.608</td>
<td>591.552</td>
</tr>
<tr>
<td>BPFI</td>
<td>118.056</td>
<td>236.112</td>
<td>354.168</td>
<td>472.224</td>
<td>590.28</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>REDF</td>
<td>98.4975</td>
<td>196.995</td>
<td>295.4925</td>
<td>393.99</td>
<td>492.4875</td>
<td>590.985</td>
<td>689.483</td>
<td>-</td>
</tr>
</tbody>
</table>

In order to investigate the presence of cage defect, a set of healthy bearings (deep groove ball bearings NTN 204) are installed and acquired the signal. Then cage defect is induced in one of the healthy bearing with the help of 6 mm hardened rotary burr. Initially, one cage link is damaged and observed the readings. The severity of the cage defect is analyzed by damaging one link in every step and observed the readings.

3.1.1 Time domain analysis

Overall condition monitoring of bearing can be done by studying statistical parameters extracted from signal in time domain. Figure 5 and 6 shows the time signal generated from the healthy and cage defected bearing respectively. Time domain statistical
parameters are RMS, Kurtosis, Variance, Standard deviation, skewness etc. Table 3 shows the scalar parameter readings for healthy and faulty bearings.

![Figure 5 Healthy bearing signal in time domain](image1)

![Figure 6 Faulty bearing signals in time domain](image2)

**Table 3 Assessment of statistical parameters in time domain**

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Healthy</td>
<td>0.00264732</td>
<td>0.00264731</td>
<td>7.01E-06</td>
<td>2.98017</td>
<td>0.058715</td>
<td>5.04</td>
</tr>
<tr>
<td>Faulty</td>
<td>0.0027443</td>
<td>0.00274429</td>
<td>7.53E-06</td>
<td>3.2469</td>
<td>0.708284</td>
<td>5.94</td>
</tr>
</tbody>
</table>

All the values of time domain statistical parameters of faulty bearing are showing upward swing as compare to the values of healthy bearing which shows the presence of fault in the bearing. Crest factor is one of the important scalar parameter that is used to detect the defect in ball bearings. When the crest factor up to 5 shows the normal running of bearing but when crest factor increases greater than 5 then there could be a defect in the bearing (Radoslav et al., 2010). Healthy bearing reading shows crest factor as 5.04 and faulty bearing shows crest factor as 5.94 which is in accordance with the findings of the previous researchers.

Kurtosis value for perfect Gaussian distribution shows value of 3 (Singh, 2007). The kurtosis value of healthy bearing should be around 3 as healthy bearing signal shows perfect Gaussian behavior in time domain (Mobley, 1999). If a localized defect develops within the bearing, the impulse content of the vibration signal will increase; hence, the
kurtosis value, which is measure of the peakedness of the waveform, will also increase. The pattern is similar to crest factor as kurtosis value of healthy bearing is 2.98 and that of faulty bearing is 3.24.

The ability of these time domain statistical parameters is limited in bearing fault indication. Because these parameters would show noticeable change in vibration signal generated from non-bearing faults such as shaft imbalance, pitting on gear tooth, misalignment etc. (McFadden and Smith, 1984). The other limitation is its inability to give the location of the fault in bearing.

3.2 Diagnosis of location of defect in bearing

3.2.1 Frequency domain analysis

Figure 5 shows the zoomed power spectrum in low frequency zone where ball spinning defect frequency (BSF) and its harmonics are expected to be present. The reason behind that rolling element is free to spin anywhere in absence of cage link, hence there is every chance of ball spinning defect to be present in the bearing. The theoretically calculated ball spinning frequency BSF is 49.4738 whereas frequency spectrum shows prominent peaks at 48.5 Hz, 100 Hz, 149 Hz 200 Hz as shown in Figure 7. These readings confirm the presence of ball spinning defect in the test bearing. The slight difference between theoretically calculated frequency and actual frequency is due to the belt slippage or voltage fluctuation.

Data for healthy and defected bearing, by comparing amplitude at fundamental frequency of bearing, has been compiled and analyzed. There is large fluctuation in the amplitudes of healthy and the cage defected bearing as shown in Figure 8. Change of amplitude by 1718.18% at BSF where as negligible change in amplitude at BPFO and BPFI by 19.69% and 7.27% respectively. Figure 9 shows the comparison between healthy and defective amplitudes at BSF and its harmonics. Vibration signal analysis has an edge over the other fault detection techniques in the sense that it doesn’t only identify the presence but also gives the exact location of the fault.

![Figure 7 Faulty bearing frequency domain plot in low frequency zone](image-url)
3.2.2 Envelope detection using Hilbert transform

The results of frequency domain analysis may be deceiving due contamination of signal with surrounding noise. This difficulty can be eliminated by analyzing the signal in high frequency zone (in structural resonance frequency zone) because whenever an impulse is generated due to bearing defect, it energizes the structural resonance of the system. As a result of this, defect frequency is carried by resonance frequency in high frequency zone (means signal is amplitude modulated in high frequency zone). This amplitude modulated signal is again demodulated using Hilbert transform to analyse it in low frequency zone as shown in Figure 10.

This process is accomplished by using FFT along with HFED for predicting bearing fault at incipient stage. HFED is implemented by applying a bandpass filter. This filter eliminates all the low frequency surrounding noise associated with the signal and selects a frequency band (with upper and lower frequency limits) in high frequency zone. The center frequency for bandpass filter is selected very carefully. The center frequencies are selected by seeing the frequency spectrum in structural resonance frequency zone.
Frequency ranges for bandpass filter are selected as per Table 4. The spectrum of Hilbert transform at various bandpass frequency range is shown in Figure 10. Results of HFED analysis can be interpreted by calculating the fundamental frequencies of bearing. Table 5 shows fundamental frequency (BSF) of bearing align with the peak frequency of envelope spectrum, hence the defect present in the bearing is ball spinning defect (BSF). Theoretically calculated fundamental frequency might slightly differ due to voltage fluctuation or belt slippage in the system (Prasad et al., 1985). The magnitudes of amplitudes might lead to deceiving at this stage because they might be affected by selection of signal processing technique.

<table>
<thead>
<tr>
<th>Bandpass frequency (a)</th>
<th>Hilbert band (b)</th>
<th>Diff. of Hilbert spectrum at prominent peak (c)</th>
<th>Peak Frequency $PF = \frac{a \times c}{b}$ Hz</th>
</tr>
</thead>
<tbody>
<tr>
<td>380-540</td>
<td>0.00875-0.01215</td>
<td>0.0109-0.0099</td>
<td>47.05882</td>
</tr>
<tr>
<td>1000-800</td>
<td>0.0181-0.02265</td>
<td>0.0187-0.01978</td>
<td>47.7</td>
</tr>
<tr>
<td>1200-1400</td>
<td>0.02703-0.03175</td>
<td>0.028936-0.03007</td>
<td>48.03</td>
</tr>
<tr>
<td>1600-1800</td>
<td>0.0362-0.0409</td>
<td>0.037519-0.03865</td>
<td>47.93</td>
</tr>
<tr>
<td>1800-2000</td>
<td>0.04065-0.0455</td>
<td>0.040107-0.04125</td>
<td>48.45</td>
</tr>
</tbody>
</table>
Healthy bearing at band 340-580 Hz

Healthy bearing at band 800-1000 Hz

Healthy bearing at band 1200-1400 Hz

Healthy bearing at band 1600-1800 Hz

Healthy bearing at band 1800-2000 Hz

Hilbert transform at band 2200-2400 Hz

Healthy bearing at band 2400-2800 Hz

Faulty bearing at band 340-580 Hz

Faulty bearing at band 800-1000 Hz

Faulty bearing at band 1200-1400 Hz

Faulty bearing at band 1600-1800 Hz

Faulty bearing at band 1800-2000 Hz

Hilbert transform at band 2200-2400 Hz

Faulty bearing at band 2400-2800 Hz

**Figure 10** Hilbert spectrums for healthy and faulty bearing at various bandpass frequency

### 3.2.3 Envelope detection using order analysis

Order analysis is inbuilt algorithm available in National Instrument’s Sound & Vibration suit. An already filtered (using Bandpass filter) signal is feed to the virtual
instrumentation (VI) and envelope spectrum is obtained as an output. This VI extracts the modulating signal of fault frequency which is amplitude modulated by the structural resonance frequency in high frequency zone. Figure 11 shows the demodulated spectrum of order analysis in low frequency zone. A prominent peak at frequency 48.5 Hz is shown in the spectrum observed at various bandpass frequency ranges. Figure 12 shows OAT analysis for healthy and faulty bearing at various bandpass frequency range.

**Table 6** Prominent peak frequency in OAT analysis

<table>
<thead>
<tr>
<th>Frequency Range (Hz)</th>
<th>Prominent peaks (Hz)</th>
</tr>
</thead>
<tbody>
<tr>
<td>380-540</td>
<td>48.2</td>
</tr>
<tr>
<td>800-1000</td>
<td>48.2</td>
</tr>
<tr>
<td>1200-1400</td>
<td>48.2</td>
</tr>
<tr>
<td>1600-1800</td>
<td>2.5</td>
</tr>
<tr>
<td>1800-2000</td>
<td>48.5</td>
</tr>
<tr>
<td>2200-2400</td>
<td>2.5,48.5</td>
</tr>
<tr>
<td>2400-2800</td>
<td>2.5,48.5</td>
</tr>
</tbody>
</table>

**Figure 11** Faulty bearing envelope spectrum using order analysis
3.2.4 Hilbert transform versus order analysis

Some similarities and differences can be observed while comparing the outputs of envelope detection using Hilbert transform and order analysis. The power spectrum from Hilbert transforms and order analysis show peak frequency at same fundamental frequency of the bearing fault. However the magnitude of amplitudes from the two methods is different. This difference can be related to the difference in signal processing technique used for envelope detection.

Figure 12 OAT analyses for healthy and faulty bearing at various bandpass frequency
3.3 Diagnosis of severity of bearing defect

The severity of the cage defect is analyzed by damaging one link in every step and observed the readings. Five bearings with damage levels from one cage link damage to four cage link damage are examined to analyse the severity of the bearing defect. At least four data sets for each condition are recorded. Then these data sets are analysed using time domain statistical parameters, using Hilbert transform and order analysis. Hilbert transform and order analysis is carried out using a band-pass filter. Two frequency bands are used for the band-pass filter viz 0-200 Hz and 380-540 Hz. Then compared the results of three methods and try to find the sensitivity of each method in detection of the severity of the bearing defect. Sensitivity of each frequency band in band-pass filter is also studied.

3.3.1 Time domain statistical parameters

RMS, skewness, kurtosis and crest factor were used to compare their effectiveness for condition monitoring of low speed bearings on the basis that they are commonly used parameters for condition monitoring of bearings. Table 7 shows the tabulated results of statistical parameter for at various severities of defects. Figure 13 shows the analysis of the results from Table 7. The RMS shows that there is linear rise in the RMS value as the severity of the defect increased. Similar to the RMS value, variance is also showing linear rise as the severity of the defect increased. It has found that kurtosis value of 2.98 for good bearing, then kurtosis value stats increasing and reached upto 3.31. But then it stats decreasing and reached the value of 3.23 for the largest defect.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Healthy</td>
<td>0.00264732</td>
<td>0.00264731</td>
<td>7.01E-06</td>
<td>2.98017</td>
<td>0.058715</td>
<td>5.04</td>
</tr>
<tr>
<td>Cage defect (1 link)</td>
<td>0.00310377</td>
<td>0.00310376</td>
<td>9.63E-06</td>
<td>3.08137</td>
<td>-0.01116</td>
<td>5.54</td>
</tr>
<tr>
<td>Cage defect (2 link)</td>
<td>0.00368653</td>
<td>0.00368653</td>
<td>1.36E-05</td>
<td>3.3128</td>
<td>0.093069</td>
<td>5.61</td>
</tr>
<tr>
<td>Cage defect (3 link)</td>
<td>0.00344117</td>
<td>0.00344116</td>
<td>1.18E-05</td>
<td>3.23613</td>
<td>0.004005</td>
<td>5.74</td>
</tr>
<tr>
<td>Cage defect (4 link)</td>
<td>0.00369558</td>
<td>0.00369557</td>
<td>1.36E-05</td>
<td>3.21298</td>
<td>0.043898</td>
<td>5.11</td>
</tr>
</tbody>
</table>
The reason for kurtosis value starting to decrease after a certain time is because when the damage becomes greater than the space among two consecutive rolling elements, it produces continuous, not impulsive, signal due to the fact that the first impulse doesn’t expire before the second one is produced; that causes the signal to produce a Gaussian distribution and kurtosis value starts decreasing. The Crest factor shows value of 5.04 for the healthy bearing. All defect bearings show crest factor greater than 5 with the highest being 5.94 for the largest defect of four link damaged. The ability of these time domain statistical parameters is limited in bearing fault indication. Because these parameters would show noticeable change in vibration signal generated from non-bearing faults such as shaft imbalance, pitting on gear tooth, misalignment etc. (McFadden and Smith, 1984). The other limitation is its inability to give the location of the fault in bearing.

During bearing condition monitoring, the increase in kurtosis value from 2.98 to 3.23, then it would be enough to underline a change in bearing running, it may not be necessary to get it stopped but keep watch frequently. An excessive increase of the kurtosis value up to 5.5 recommended a sudden stop of machinery and subsequent replacement of bearing. The crest factor values do not increase because they are based on the peak value of the time signal over the RMS level. The peak value of the time signal increases significantly along with RMS and the ratio of the two tends to remain the same and crest factor gives no indication of a defect. An increase of kurtosis value from 3 underline only a malfunction of the bearing but it does not give any information about defect type or its
location. A time domain method such as RMS is more suited for non-localized defect detection such as debris denting or insufficient lubrication. This information is to be related with the advance signal processing technique to underline the presence of cage defect in the bearing. But if we are satisfied to only to know if the bearing run well or not, kurtosis indicator is enough.

3.3.2 Envelope detection (Hilbert transform and Order analysis)

In the detection of a localized bearing defect, it is essential to determine the presence and the severity of the defect. Frequency domain technique has proven to be an efficient method of displaying bearing defect frequencies by having knowledge of characteristic frequencies. However, for automatic diagnosis of bearing defect it is necessary to extract a symptom of failure without any human involvement (Changting and Robert, 2000) suggested a peak ratio (PR) as an indicator to identifying the presence of bearing faults in the spectrum.

**Peak Ratio**

PR is defined as the sum of the peak values of the defect frequency and harmonics over the average value of the spectrum and is shown in Eq. (1).

\[
PR = \frac{N \sum_{j=1}^{n} P_j}{\sum_{k=1}^{N} S_k} \tag{5}
\]

Where, \( P_j \) is the amplitude value of the peak located at the defect frequency harmonics, \( S_k \) is the amplitude at any frequency, \( N \) is the number of points in the spectrum, and \( n \) is the number of harmonics in the spectrum.

**Modified Peak Ratio**

A modified PR is proposed in this study in order to make it more effective in showing the severity of the defects. The modified PR is defined in the following equation using the differences between the peak defect frequencies and the average value of the spectrum over the average of the spectrum.

\[
mPR_c = 20 \log_{10} \left( \frac{\sum_{j=1}^{n} (P_j - A_j)}{A_c} \right) \tag{6}
\]
\[ A_s = \frac{\sum_{k=a}^{b} S_k}{(b-a)} \] (7)

Where, \( A_s \) is an average spectrum amplitude in the frequency band from \( a \) to \( b \). By using a frequency band instead of whole spectrum band, PR can be a reliable indicator for earlier defect detection. In the case of an incipient bearing defect the amplitude of defect frequencies are often smaller than other peak frequencies.

### 3.3.2.1 OAT and Hilbert transform at 0-200 Hz

Peak ratio at defect frequency of 48.5 Hz in the frequency band of 0 to 200 Hz using order analysis toolkit (OAT) and Hilbert transform are shown in Table 8 and Table 9 respectively. The components of Table 8 and Table 9 are graphically represented in Figure 14.

**Table 8** Peak ratio at defect frequency of 48.5 Hz in the frequency band of 0 to 200 Hz using OAT

<table>
<thead>
<tr>
<th>Defects</th>
<th>(N)</th>
<th>( \sum_{k=1}^{N} S_k )</th>
<th>( A_s )</th>
<th>( \sum_{j=1}^{n} P_j )</th>
<th>PR (10^{-3})</th>
<th>( mPR_c )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Healthy</td>
<td>6785</td>
<td>0.0186</td>
<td>2.74E-06</td>
<td>4</td>
<td>0.000159</td>
<td>57.891371</td>
</tr>
<tr>
<td>Cage defect (1 link)</td>
<td>7692</td>
<td>0.0334</td>
<td>4.34E-06</td>
<td>4</td>
<td>0.000638</td>
<td>146.931018</td>
</tr>
<tr>
<td>Cage defect (2 link)</td>
<td>8056</td>
<td>0.0503</td>
<td>6.24E-06</td>
<td>4</td>
<td>0.001583</td>
<td>253.531769</td>
</tr>
<tr>
<td>Cage defect (3 link)</td>
<td>7197</td>
<td>0.0537</td>
<td>7.46E-06</td>
<td>4</td>
<td>0.00154</td>
<td>206.394413</td>
</tr>
<tr>
<td>Cage defect (4 link)</td>
<td>7524</td>
<td>0.0529</td>
<td>6.37E-06</td>
<td>4</td>
<td>0.001359</td>
<td>193.291418</td>
</tr>
</tbody>
</table>

**Table 9** Peak ratio at defect frequency of 48.5 Hz in the frequency band of 0-200 Hz using Hilbert transform

<table>
<thead>
<tr>
<th>Defects</th>
<th>(N)</th>
<th>( \sum_{k=1}^{N} S_k )</th>
<th>( A_s )</th>
<th>( \sum_{j=1}^{n} P_j )</th>
<th>PR (10^{-3})</th>
<th>( mPR_c )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Healthy</td>
<td>11521</td>
<td>7.86E-07</td>
<td>6.82E-11</td>
<td>1.87E-07</td>
<td>2.74E+03</td>
<td>6.88E+01</td>
</tr>
<tr>
<td>Cage defect (1 link)</td>
<td>8438</td>
<td>9.91E-07</td>
<td>9.80E-11</td>
<td>2.93E-07</td>
<td>2.49E+03</td>
<td>6.95E+01</td>
</tr>
<tr>
<td>Cage defect (2 link)</td>
<td>8838</td>
<td>1.26E-06</td>
<td>1.42E-10</td>
<td>3.37E-07</td>
<td>2.36E+03</td>
<td>6.75E+01</td>
</tr>
<tr>
<td>Cage defect (3 link)</td>
<td>7896</td>
<td>1.27E-06</td>
<td>1.60E-10</td>
<td>3.32E-07</td>
<td>2.06E+03</td>
<td>6.63E+01</td>
</tr>
<tr>
<td>Cage defect (4 link)</td>
<td>8254</td>
<td>2.22E-06</td>
<td>1.90E-10</td>
<td>3.54E-07</td>
<td>1.32E+03</td>
<td>6.54E+01</td>
</tr>
</tbody>
</table>
Figure 14 Comparing Hilbert and OAT at 0-200 Hz
### 3.3.2.2 OAT and Hilbert transform at 380-540 Hz

Peak ratio at defect frequency of 48.5 Hz in the frequency band of 380 to 540 Hz using order analysis toolkit (OAT) and Hilbert transform are shown in Table 10 and Table 11 respectively. The contents of Table 10 and Table 11 are graphically represented in Figure 15.

**Table 10** Peak ratio at defect frequency of 48.5 Hz in the frequency band of 380-540 Hz using OAT

<table>
<thead>
<tr>
<th>Defects</th>
<th>(N)</th>
<th>$\sum_{k=1}^{N} S_k$</th>
<th>$A_s$</th>
<th>n</th>
<th>$\sum_{j=1}^{n} P_j$</th>
<th>PR ($10^{-3}$)</th>
<th>$mPR_c$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Healthy</td>
<td>5120</td>
<td>8.76E-16</td>
<td>1.71E-19</td>
<td>4</td>
<td>2.36E-18</td>
<td>1.38E+01</td>
<td>2.21E+01</td>
</tr>
<tr>
<td>Cage defect (1 link)</td>
<td>3750</td>
<td>7.88E-16</td>
<td>2.10E-19</td>
<td>4</td>
<td>8.72E-18</td>
<td>4.15E+01</td>
<td>3.22E+01</td>
</tr>
<tr>
<td>Cage defect (2 link)</td>
<td>3927</td>
<td>1.28E-15</td>
<td>3.25E-19</td>
<td>4</td>
<td>1.09E-17</td>
<td>3.34E+01</td>
<td>3.02E+01</td>
</tr>
<tr>
<td>Cage defect (3 link)</td>
<td>3509</td>
<td>1.20E-15</td>
<td>3.41E-19</td>
<td>4</td>
<td>1.51E-17</td>
<td>4.42E+01</td>
<td>3.27E+01</td>
</tr>
<tr>
<td>Cage defect (4 link)</td>
<td>3668</td>
<td>1.15E-15</td>
<td>3.27E-19</td>
<td>4</td>
<td>2.51E-17</td>
<td>8.01E+01</td>
<td>3.76E+01</td>
</tr>
</tbody>
</table>

**Table 11** Peak ratio at defect frequency of 48.5 Hz in the frequency band of 380-540 Hz using Hilbert transform

<table>
<thead>
<tr>
<th>Defects</th>
<th>(N)</th>
<th>$\sum_{k=1}^{N} S_k$</th>
<th>$A_s$</th>
<th>$\sum_{j=1}^{n} P_j$</th>
<th>PR ($10^{-3}$)</th>
<th>$mPR_c$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Healthy</td>
<td>6912</td>
<td>3.25E-06</td>
<td>1.47E-10</td>
<td>7.21E-07</td>
<td>1.53E+03</td>
<td>7.38E+01</td>
</tr>
<tr>
<td>Cage defect (1 link)</td>
<td>7594</td>
<td>3.50E-06</td>
<td>2.61E-10</td>
<td>8.23E-07</td>
<td>1.79E+03</td>
<td>7.00E+01</td>
</tr>
<tr>
<td>Cage defect (2 link)</td>
<td>5302</td>
<td>3.67E-06</td>
<td>5.53E-10</td>
<td>8.67E-07</td>
<td>1.25E+03</td>
<td>6.39E+01</td>
</tr>
<tr>
<td>Cage defect (3 link)</td>
<td>5526</td>
<td>3.51E-06</td>
<td>6.36E-10</td>
<td>9.05E-07</td>
<td>1.42E+03</td>
<td>6.31E+01</td>
</tr>
<tr>
<td>Cage defect (4 link)</td>
<td>7428</td>
<td>3.86E-06</td>
<td>7.20E-10</td>
<td>9.72E-07</td>
<td>1.87E+03</td>
<td>6.26E+01</td>
</tr>
</tbody>
</table>
Figure 15 Comparing Hilbert and OAT at 380-540Hz
3.3.2.3 Comparing 0-200 Hz OAT & 380-540 Hz OAT

Peak ratio components are graphically represented for defect frequency of 48.5 Hz in the frequency band of 0 to 200 Hz and 380 to 540 Hz using order analysis toolkit (OAT) as shown in Figure 16.

*Figure 16* Comparing OAT Analysis at 0-200 Hz and 380-540 Hz
### 3.3.2.4 Comparing 0-200 Hz H.T. & 380-540 Hz H.T

Peak ratio components are graphically represented for defect frequency of 48.5 Hz in the frequency band of 0 to 200 Hz and 380 to 540 Hz using Hilbert transform as shown in Figure 17.

The peak ratio was the most reliable indicator of localised defect presence from the methods tested with kurtosis and RMS a close second in their reliability. Peak ratio and modified peak ratio are analysed for OAT and Hilbert transform at two frequency bands viz 0-200 Hz and 380-540 Hz. Results of order analysis shows better results in detection of the severity of bearing defect than Hilbert transform from the fact that peak ratio and modified peak ratio of Hilbert transform shows inconsistent results. Hence OAT analysis is better technique to diagnosis of severity. Out of the two frequency bands, 0-200 Hz band shows better results as the average $r^2$ value for 0-200 Hz is 0.7942 and that of 380-540 Hz shows $r^2$ value of 0.7618. Hence 0-200 Hz band is more sensitive to severity than the higher bands.

Moreover, after defect detection by the peak ratio, the peak value demonstrated a good correlation to defect size. A linear relationship between peak value and cage defect was outlined with $r^2$ correlation values of 0.795. Previous work has not attempted to establish such a relationship, instead focusing on the identification of the presence of a defect, with possible size differentiation based on categories such as light, medium and heavy. Statistical parameters are also showing good results in increasing defect severity condition. Out of the these scalar parameters RMS and crest factor being the most reliable parameters as they are showing linear trend with goo $r^2$ values of 0.75 and 0.835. Crest factor shows higher percentage change in values than RMS. So crest factor can be considered to be the most reliable statistical parameter in identification of the severity of the bearing defect.
Figure 17 Comparing 0-200 Hz H.T. & 380-540 Hz H.T
CONCLUSIONS

The results show that bearing envelope analysis and time domain statistical features appear the most promising for showing the progression of rolling element bearing failure. Using one or two features to monitor the health of rolling element bearings might not be sufficient. A comprehensive defect detection algorithm is incorporated which works on three stages. In first stage, it indicates the presence of defect in the bearing. In second stage, it gives the location of the defect whereas in third stage, it gives the severity of the fault in the bearing. These investigations reveal that whenever there is a cage defect in the bearing, then it is also associated with the ball spinning defect. A linear relationship between peak value and cage defect was outlined with $r^2$ correlation values of 0.795. The statistical measures could easily be calculated and evaluated by maintenance technicians. If there is a need for further consultation and investigation, a detailed frequency-based spectral technique could be applied by an expert. Therefore, study emphasizes the application steps to investigate the defect development using statistical and spectral methods.

The use of virtual instrumentation enables to make the vibration analysis inexpensive and can be analysed from any remote place. This system is also useful for the monitoring of machine running in adverse environmental conditions. Statistical parameters are also showing good results in increasing defect severity condition. Out of the these scalar parameters RMS and crest factor being the most reliable parameters as they are showing linear trend with good $r^2$ values of 0.75 and 0.835. Results of order analysis shows better results in detection of the severity of bearing defect than Hilbert transform from the fact that peak ratio and modified peak ratio of Hilbert transform shows inconsistent results. This algorithm can be applied to detect the fault in other component such as gearboxes, blowers, fans etc.

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