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Detection of Natural Crack in Wind Turbine Gearbox

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Abstract

One of the most challenging scenarios in bearing diagnosis is the extraction of fault signatures from within other strong components which mask the vibration signal. Usually, the bearing vibration signals are dominated by those of other components such as gears and shafts. A good example of this scenario is the wind turbine gearbox which presents one of the most difficult bearing detection tasks. The non-stationary signal analysis is considered one of the main topics in the field of machinery fault diagnosis. In this paper, a set of signal processing techniques has been studied to investigate their feasibility for bearing fault detection in wind turbine gearbox. These techniques include statistical condition indicators, spectral kurtosis, and envelope analysis. The results of vibration analysis showed the possibility of bearing fault detection in wind turbine high-speed shafts using multiple signal processing techniques. However, among these signal processing techniques, spectral kurtosis followed by envelope analysis provides early fault detection compared to the other techniques employed. In addition, outer race bearing fault indicator provides clear indication of the crack severity and progress.

1. Introduction

Wind energy is one of the growing renewable energy industries. In recent years, hundreds of wind farms, frequently in unmanned and remote areas, have been built. As the size of wind power projects keeps increasing, the need for reducing the downtime and making the best use of availability is essential. Wind turbines are becoming more established as an economically viable alternative to fossil-fueled power generation. The potential of the wind turbine could meet the demand in two times over in many places around the word (Nie & Wang 2013). The continuous monitoring and fault diagnosis of wind turbine systems (generators, blades, and drive trains) can be the most effective way to reduce the operational and maintenance costs of these systems and increase their reliability. With good data acquisition and appropriate signal processing, faults can thus be detected while components are operational and appropriate actions can be planned in time to prevent damage or failure of components. Maintenance tasks can be planned and scheduled more efficiently, resulting in increased reliability, availability, maintainability and safety (RAMS) whilst downtime, maintenance and operational costs are reduced (Wenxian et al. 2010). The gearbox steps up the speed from the input shaft (approx. 20 rpm.) to the high-speed shaft (approx. 1500+ rpm.). The high-speed bearings, which support both radial and thrust loads, are highly susceptible to failure, being subjected to continue variable speed, load and misalignment, see Figure 1. The high-speed shaft is supported by the high-speed stage bearings located on the front and back ends of the shaft. If there is any misalignment between the high-speed shaft and the connected generator, unexpected minor vibrations will occur and may cause damage to the bearings. Therefore, as the wind turbine gearbox is virtually inaccessible since it is situated atop a high tower, once a bearing roller has broken, it could lead to breaking of another component of the gearbox, with the consequential need to replace several parts inside the gearbox (Musial et al. 2007; Wenxian Yang 2014).

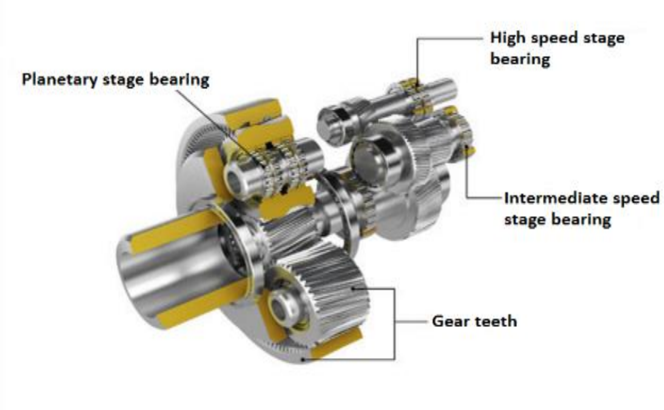

Figure 1: Wind turbine gearbox arrangement (olympus-ims.com)

Acquired vibration data followed by processing for fault diagnosis of rotating machinery with multiple bearings, such as wind turbine gearbox, can be a challenging task, as data are usually required in three perpendicular directions for a reliable diagnosis. Also, the extracted data are typically masked by another signals. Consequently the task of diagnosing faults on such systems may be daunting for even an experienced specialist (Wenxian Yang et al. 2014). Wind turbine condition monitoring and fault diagnosis were the central points of many types of research, which has been covered in the past literature (Patil et al. 2008; Hamilton & Quail 2011; Lu et al. 2009; Lu et al. 2012; Elasha et al. 2016; Cibulka et al. 2012; Uma Maheswari & Umamaheswari 2017). Modern wind turbines are usually fitted out with some method of condition monitoring systems, including subsystem-level or system-level fault detection. Subsystem-level fault detection systems are typically based on monitoring parameters such as the vibration of the wind turbine drive train, bearing temperature, and oil particulate content (Kusiak & Li 2011). A number of works have focused on fault diagnosis of rotating machinery by using vibration measurement techniques for bearings and gears of wind turbine gearboxes. In vibration measurement techniques, vibration signals are collected by means of vibration analyser equipped with sensor in time domain then this is converted into the frequency domain by using FFT analyser.

Several attempts have been made to improve advanced signal processing techniques for vibration signals to obtain useful information in recent years. Wavelet analysis, as one of the time-frequency analysis methods, has been developed to describe the change of frequencies in the signal over a period of time. A number of wavelet formulations have also been employed to remove non-stationary noise from the recorded vibration signals. Among them, continuous wavelet transform, discrete wavelet transform as well as harmonic wavelet transform have been accepted as key signal processing methods for wind turbine gearbox monitoring (Lu et al. 2012; Yang et al. 2008; Anon 2010; Str & Barszcz 2016). Igba et al. 2016, studied novel techniques for wind turbine faults detection using the RMS and peak values of vibration signals. They proposed techniques based on three models (signal correlation, extreme vibration, and RMS intensity), and validated the proposed techniques with time domain data driven approach using condition monitoring data from wind turbine. Their results showed that signal correlation with RMS values are good for detecting progressive failure such as bearing pitting in its insipient stage (Igba et al. 2016). Ruiz-Carcel and others proposed a technique based on merging process and vibration data with the objective of improving the detection of mechanical faults in industrial systems working under variable operating condition. They tested the capability of Canonical Variate Analysis (CVA) for detecting faults using experimental data acquired from a test rig where different process faults were introduced. The results showed that the combination of process and vibration data can effectively improve the detectability of mechanical faults in systems working under variable operating conditions (Ruiz-Carcel et al 20016). Elasha and others presented a comparative study of adaptive filters in detecting a naturally degraded bearing within a gearbox. They compared the effectiveness of four different techniques in diagnosing a bearing defects within a gearbox employed for endurance tests of an aircraft control system. The techniques investigated include the least mean square (LMS), self-adaptive noise cancellation (SANC) and the fast block LMS (FBLMS). All three techniques were applied to measured vibration signals taken throughout the endurance test. The results of this study showed that the LMS technique is able to detect the bearing failure earlier (Elasha et al 2017). Sonawane experimentally investigated defects prediction in a wind turbine drive train. In this study diagnosis techniques focusing on ball bearing defects for non-linear and non-stationary fault signals were investigated using vibration monitoring and spectral analysis as the predictive maintenance tools. The results showed that sequential regression SER algorithm was successful in detecting the gearbox defect and also demonstrated which gear contained the damage (Sonawane 2014). Gray and Watson 2010, have proposed a new approach for calculation of damage accumulation using standard turbine performance parameters and physics of failure methodology. They concluded that the proposed approach can be used to calculate all critical failure modes in real time on the basis of standard measured performance parameters (Gray & Watson 2010). Mohanty and Kar studied fault detection of the multistage gearbox by applying discrete wavelet transformation to demodulate the current signal. The results showed that the input shaft frequency is a good indicator of defects at a different load condition (Mohanty & Kar 2006). Amirat and others provided an assessment of a failure detection technique based on the homopolar component of the generator stator current and highlighted the use of the Ensemble Empirical Mode Decomposition, EEMD, as a tool for failure detection in wind turbine generators for stationary and non-stationary cases (Amirat et al. 2013). Elasha applied various vibration analysis techniques including statistical measures, spectral kurtosis and enveloping to diagnose the presence of naturally developed faults within a worm gearbox. The results showed that diagnosis of faults is feasible as long as the appropriate analysis technique is employed. Additionally, the results showed sensitivity to the direction of vibration measurement(Elasha et al. 2015).

Zhang and others applied data mining algorithms and statistical methods to analyse the jerk data obtained from monitoring the gearbox of a wind turbine and identify failed stages of the gearbox. They applied the correlation coefficient analysis and clustering analysis for the component failure identification (Zhang et al. 2012). Elforjani experimentally investigated condition monitoring of slow speed bearing and applied linear regression classifier and multilayer artificial neural network model. Elforjani used a new fault indicator which is signal intensity estimator (SIE) for analysing data and estimate remaining useful life (RUL) for bearing while in operation. The results demonstrated the applicability of proposed models in locating and discriminating the faulty bearings from the healthy bearings. Therefore the results showed the reliability and sensitivity of SIE to detecting of incipient cracks and defects (Elforjani 2016). Minh Zhao proposed Tach-less envelope order method (TLEO) and used vibration signals collected from locomotive roller bearing to demonstrate the effectiveness of the proposed method. They illustrated the effectiveness of the proposed method by simulation and experimental work. The analysed results showed that the TLEO could identify different bearing faults effectively and accurately under speed varying conditions (Zhao et al. 2014). Yuh-Tay Sheen proposed an envelope estimation algorithm based on the resonance modes of the mechanical system. The results showed that the envelope estimation algorithm could be applied for signal processing for bearing vibration. Furthermore, the results of the envelope spectra showed acceptable consistency of the proposed method to the high-frequency resonance technique (Sheen 2010). Litreature review shows there is a lack of real world application data and especially for detecting of bearing degradation within gearboxes where the bearing fault is masked with noise and components of gear meshing. Therefore this paper will employ a series of signal processing techniques to improve bearing fault detection. In addition it will employ a new condition indicator, Energy Index (EI), to detect high speed shaft bearing failure in wind turbine gearbox. In this paper, a crack fault in the high-speed bearing has been investigated using vibration analysis. The analysis has been performed using newly developed energy index and outer race fault indictors, as well as conventional condition indicators such as rms and kurtosis. In addition, the demodulation analysis was performed to detect the crack and evaluate the progress.

2. Vibration Measurements

The dataset used in the current study was extracted from the high-speed shaft of a two MW commercial wind turbine with measurements taken for fifty consecutive days by using the vibration-based method. The accelerometers were microelectromechanical systems (MEMS) based. The component under examination was the high-speed bearing which is housed on the tail of the gearbox. The bearing defect was detected by a sensor which has been mounted radially on the bearing support ring. Figure 2 shows the defect in the high-speed shaft bearing.

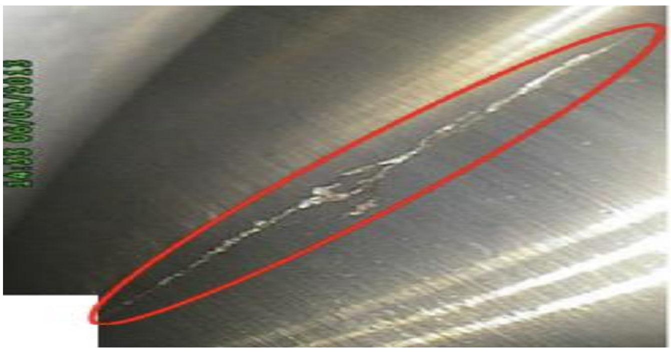

Figure 2: Wind turbine high-speed shaft bearing defect (Bechhoefer et al. 2013)

Data was collected over the 50 days in 10-minute intervals. The database consisted of 50 waveforms, which were recorded at 1800 rpm. The data was sampled at 97656 sps for 6 seconds (Bechhoefer et al. 2013). Bearing envelope analysis was performed by a band passing the signal between 9 to 11 KHz. The Fast Kurtogram Matlab code and other codes were used on the heterodyned signal. Statistical parameters such as kurtosis, crest factor, and energy index were calculated. The table 1 below lists the operation details of the wind turbine which has been monitored until the high-speed shaft bearing failed.

Table 1. Wind turbine operating details

Nominal Machine Health:	Increasing inner race bearing fault		
Power rating:	2 MW		
Nominal speed:	1800 rpm		
Bearing Information:			
	FTF:	0.42 x (shaft speed)	
	BPFO:	6.72 x (shaft speed)	
	BPFI:	9.47 x (shaft speed)	
	BSF	1.435 x (shaft speed)	
Measurement Channels			
	Channel: 1	Sensor	
		Sample rate:	97656 Hz
		Record length:	6 Seconds
		Sensor type:	Accelerometer

3. Result and Discussion

To correlate the impulsive presence on vibration signals with the component and its failure, many analyses were undertaken. This includes time domain, frequency domain and envelope analysis, see figure 3. The extracted signals from the faulty rolling elements can be processed using different indicators to obtain features of the measured vibration and to identify the health condition of the component. The statistical analysis techniques employed are commonly applied for time domain signal analysis, in which descriptive statistics such as rms, crest factor, kurtosis and energy index are used to detect the faults. To provide different ways for analysing measuring the signals deviations from the normal conditions, several of fault index extraction and signal processing techniques were applied to the measured data, include enveloping and spectrum analyses. Statistical tools such as Crest factor (CF), energy index (EI), and kurtosis (KU) have been employed for bearing defect detection.

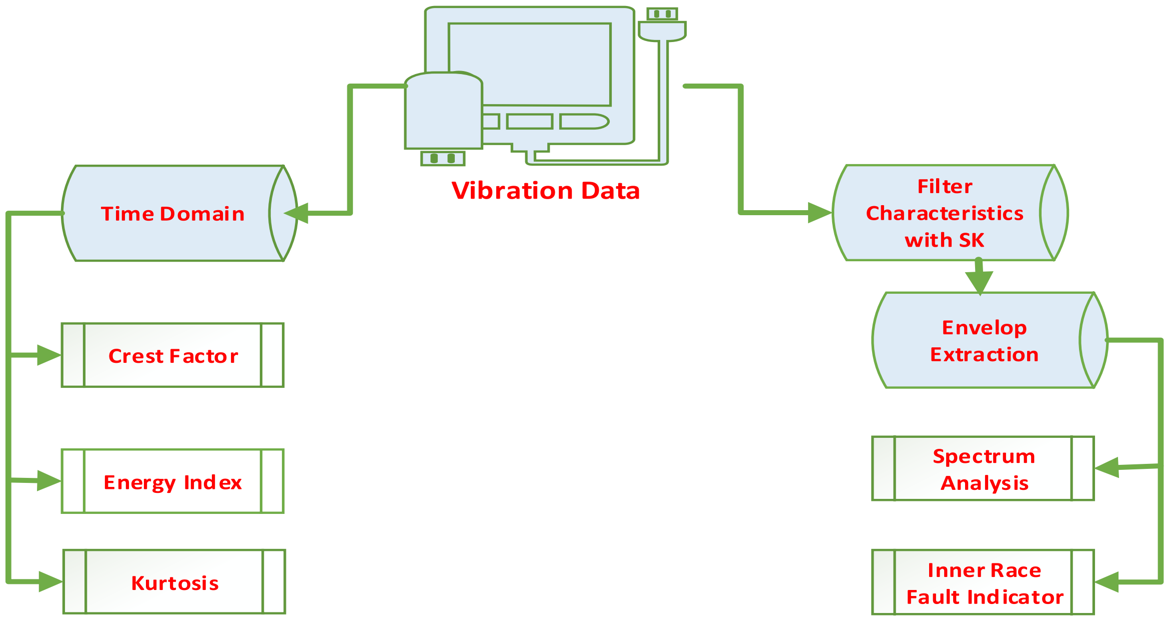

Figure 3: Proposed signal processing scheme

3.1. Time domain analysis

The extracted data, in general, have a tendency to be high noisy because of overlapping signals of the system components, such as the case of vibration data, and for that reason, it is required to be filtered before any future processing. However, an excess in reduction, may lead the extracted data to losing some important information. Figure 4, shows the waveform of the data on day 1, 10, 20, 30, 40, and 50 respectively. Visual examination of the waveforms showed no distinctive difference between the signals acquired on different days, therefore this kind of analysis is not useful for fault detection. Full records of all days have been examined. First, it can be seen that the collected vibration signals are dominated by other vibration components, which is mainly induced by the gearbox components (such as shafts and gears).

The results showed that as the runnning of the wind turbine progressed with time, waveform showed a noisier trend in the variation in bearing signals occurred, see figure 4.

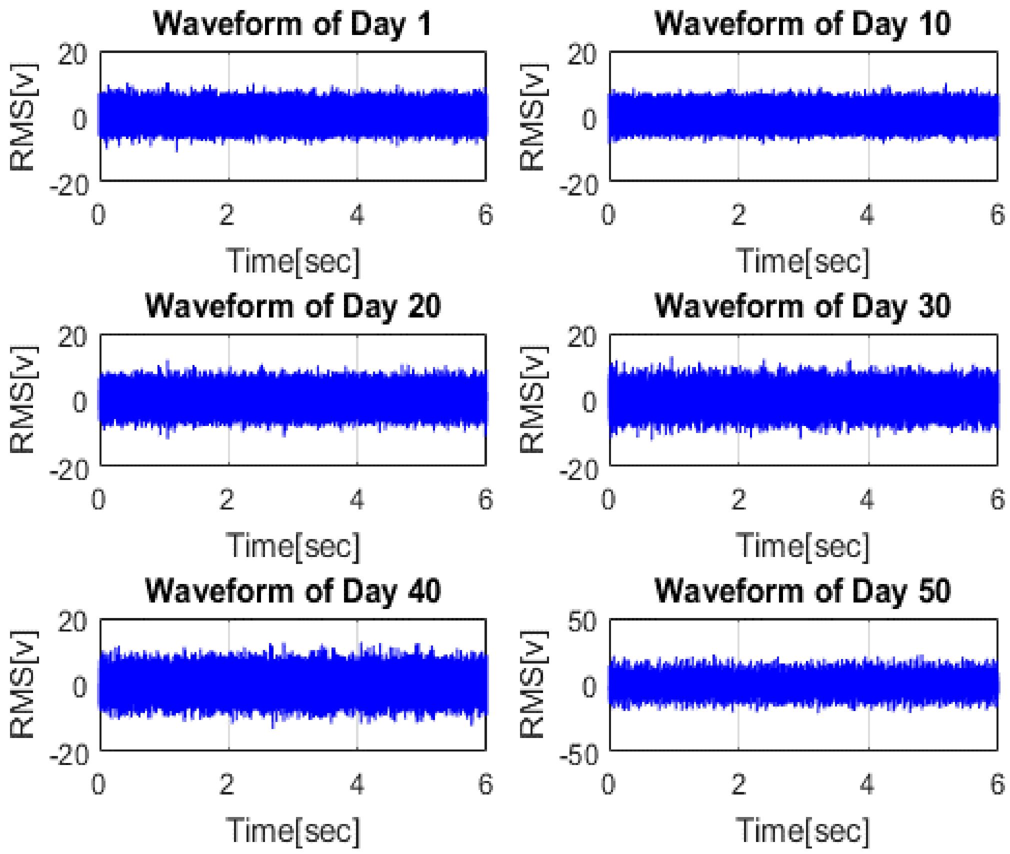

Figure 4: Vibration Data Collected at different days of Monitoring

3.2. Condition Fault Indicators

Condition monitoring systems based on vibration analysis can monitor all parts of gearboxes, for example, gears, bearings and shafts. For a better signal to noise ratio, a raw vibration signal is filtered and pre-amplified. Consequently, the signal is processed in two different ways and the overall vibration level is monitored. The time domain signal is synchronously averaged and consequently filtered to focus only on the important part of the vibration signal. Then some condition indicators are computed. Finally, the computed condition fault indicators are compared to provide useful information about the bearing condition.

3.2.1. Kurtosis

One of the most effective means to detect bearings failure from vibrational data is to monitor the value of the kurtosis of the acquired signal. The kurtosis is defined as the fourth statistical moment of a given signal and describes how peaky or flat the distribution is. It is known that KU is a measure of the peakness of a signal and on the basis that a signal will contain impulsive transient events during the onset of degradation (Zhu et al. 2014). A kurtosis value close to 3 indicates a Gaussian signal. Kurtosis greater than 3 indicates a sharp peak signal. Whereas, signals with relatively flat peaks have a kurtosis less than 3. In some applications, other sources of vibration signals or background noise frequently mask the bearing fault features in the signal and as a result of that, the kurtosis may not be able to capture the peaks of the faulty signal. In such cases, the kurtosis as an indicator is not useful; however, better results could be obtained if the kurtosis value was calculated across different frequency bands (Eftekharnejad et al. 2011). The kurtogram, developed by Antoni and Randall (Antoni 2007), is a representation of the kurtosis value as a function of the frequency and the bandwidth of the different frequency bands where it is calculated. Using the kurtogram, it is possible to identify the frequency band where the kurtosis is maximum. This information can be used to design a filter which extracts the part of the signal with the highest level of impulsiveness, enhancing the bearing fault signal from the raw signal. This technique has been already applied successfully by different researchers in bearing fault detection and diagnosis (Barszcz & Randall 2009). Kurtosis values for a given signal can be estimated using the equation:

$$KU = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{Xi-\mu}{\sigma}\right)^4 \qquad (1)$$

3.2.2. Crest Factor

One of the frequently used parameter to characterised obtained data is Crest factor. Crest factor is defined as a ratio of the signal side peak value of the input signal to the root mean square level (Večeř et al. 2005). Crest factor calculated using the equation:

$$CF = \frac{S_{peak}}{S_{rms}} \qquad (2)$$

3.2.3. Energy Index

Energy Index (EI) is defined as the square of the ratio of the root mean square of a defined segment ($RMS_{segment}$) in a given signal to the overall root mean square ($RMS_{overall}$) of the same signal. The technique was effectively applied to simulate an experimental data of bearing (Al-Balushi et al. 2010). In application, an Energy Index value of one is associated with non-transient type waveforms and greater than one where transient characteristics are present. EI was calculated using the equation:

$$EI = \left(\frac{\mathrm{RMSsegment}}{\mathrm{RMSoverall}}\right)^2 \qquad (3)$$

To understand the trend of the degradation signals, originating from bearings, linear or exponential models were widely employed to fit the features extracted for the acquired signals. In this research work, the following exponential model could fit the different fault indicators.

$$f = y_0 + \frac{a(e^{bt}-1)}{b} \qquad (4)$$

In the above function (***f***) is the value of any of the fault indicators (KU or EI and/or CF), (***a*** and ***b*****)** are the model constants, and (***t***) is the time. The constant ($\boldsymbol{y_o}$) is used here to indicate the value when the degradation time is almost equal to zero. To find the optimal values for the above function constants ***a***, ***b*** and $\boldsymbol{y_o}$, the popular least-square method was applied to the bearing case; figures **5** shows the fitted bearing case for 50 days of measurements. Table 2 also summarizes the general optimal estimated constants and global goodness of fit (**R^2**) for the exponential model.

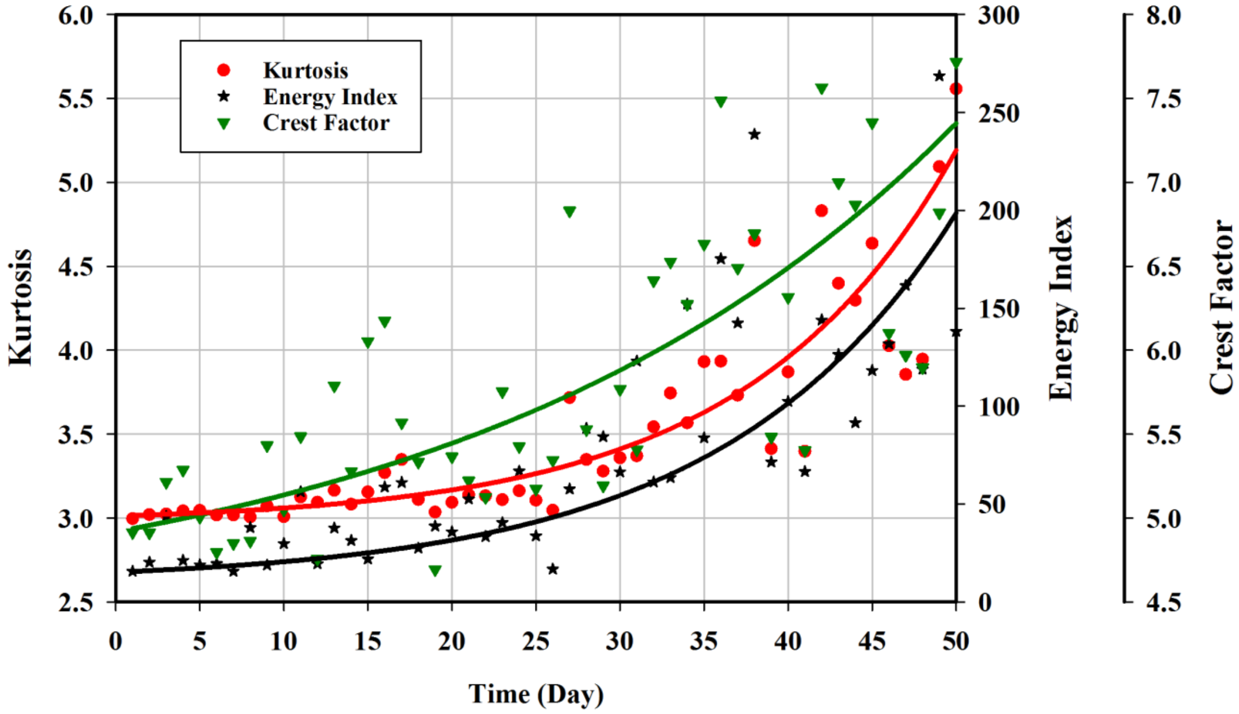

Figure 5: Condition indicators

Table 2. general optimal estimated constants

f	y_0	*a*	*b*	R^2
Kurtosis	3.0116	0.0031	0.0811	0.9336
Energy Index	15.2174	0.364	0.0725	0.9996
Crest Factor	4.9187	0.0183	0.0342	0.8697

While the operating days passed 25 days of measurement, results indicated that the three indicators EI, CF and KU have relatively high values of about 122.95, 5.41 and 3.37 respectively. It is worth mentioning that after 40 days of operating significant increase in calculated KU and EI values was observed. As the operating days progressed the KU and EI values were very sensitive to the variation in bearing signals, see figure 5. On the termination of measurements (50 days running) EI recorded a maximum value of 268.68, whereas KU recorded maximum values of 5.6, shown in figure 5. However, the CF result showed an inconsistant pattern and therefore CF is not fitting with the degradation pattern shown in figure 5.

It can be concluded that KU and IE are reliable indicators in detecting bearing failure, their detection sensitivity depends on the presence of incipient defects and on defect size. The observations from the results presented in figure 4, show also that the EI is a sensitive tool to a high transient vibration activity in rotary machines, typical for natural degrading bearings. Hence the continuous monitoring of bearings employing techniques such as the EI would offer the operator a relatively sensitive method for observing high transient type activity.

3.3.Demodulation analysis

The time series data has further been processed using Fast Fouriet Transform FFT to obtain frequency spectrum. Figure 6 depicted the power spectrum of the vibration signal collected on the day 15. Observations from this figure show multiple peaks at 3500 Hz and 10 KHz. However, no fault frequencies can be identified due to high noise level and existence of strong signal from gears and shafts. Thus, the vibration signal was further studied to reduce the noise level and extract bearings fault frequency.

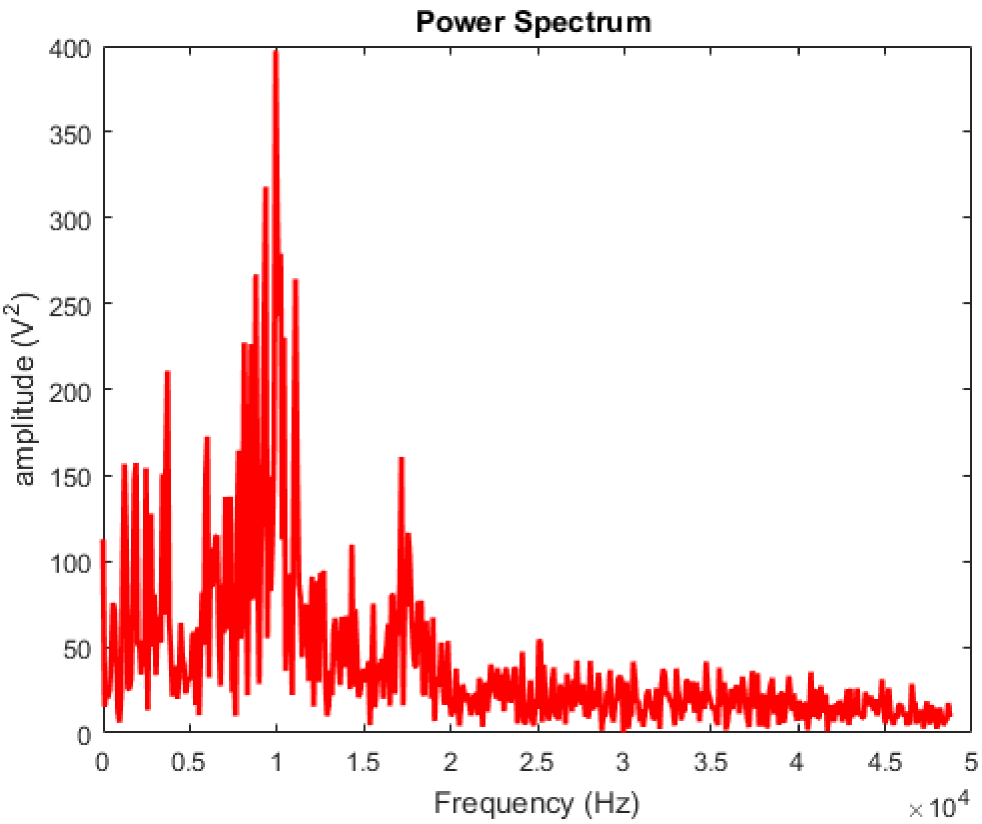

Figure 6: Power Spectrum for the fifteenth day

To achieve this task, the authors employed the envelop analysis. In envelope analysis, the vibration signal is filtered at high frequency band to extract bearing impacts. The frequency band characteristic has been obtained using spectral kurtosis (SK). The filtered signal then processed using frequency analysis. Figures 7 presents kurtogram obtained using the original algorithm developed by Antonio and others (Antoni 2007), the result shows the frequency band and central frequency of the filter for the vibration data collected on day 20 and day 50. Then this band has been used to flitter out the vibration signal.

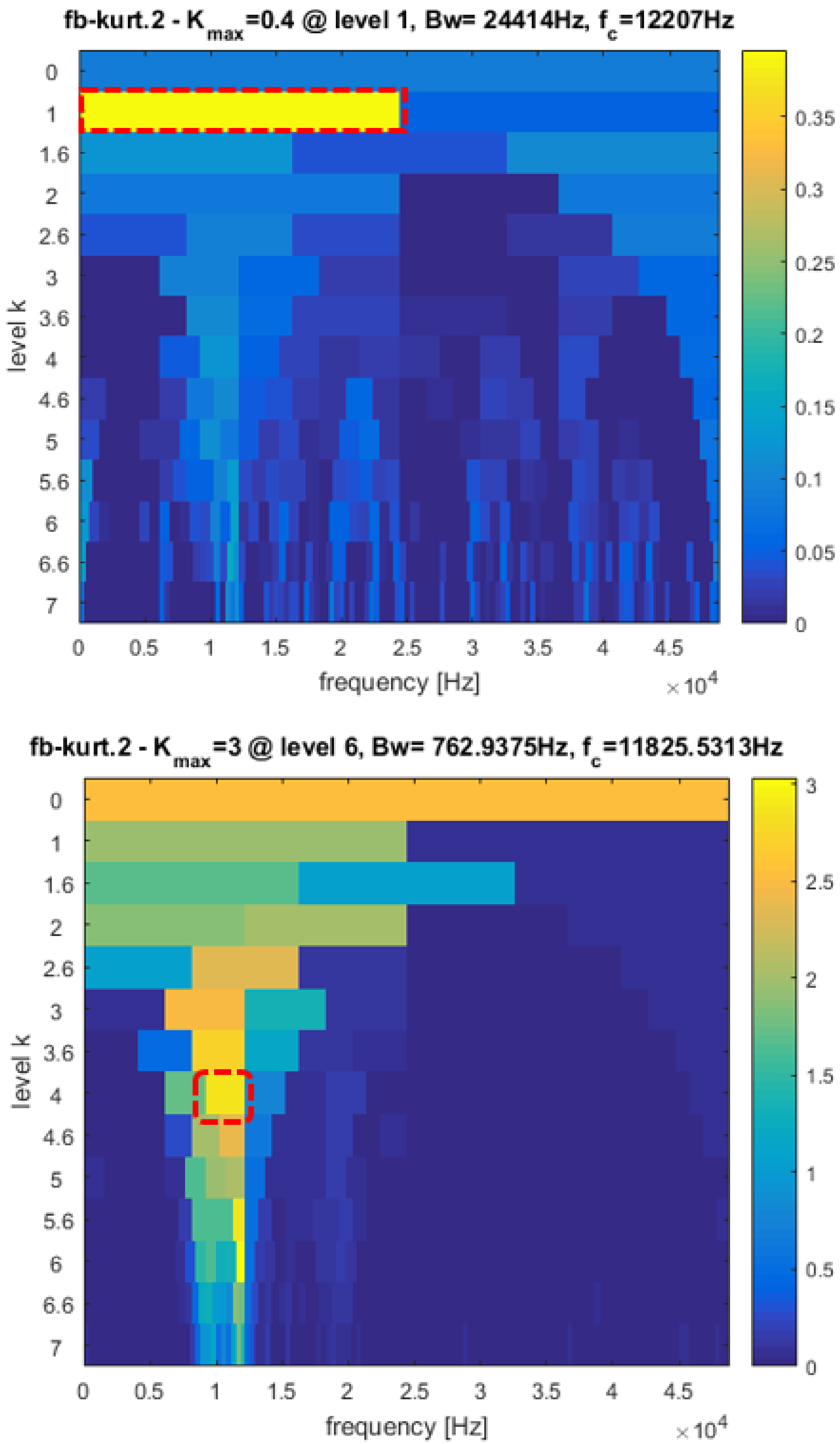

Figure 7: Kurtogram plot obtained from vibration data collected on day 20 (up) and day 50 (down)

To obtain the frequency spectrum, the filtered signal has further been processed; samples of the selected signals are presented in figures [8-13]. Observations from figure 8, for instance, show an inner race fault frequency at 284 Hz. It is worth mentioning that though the noise level was very high, the speed shaft frequency and its harmonics can obviously be observed. Analysis of the acquired signals throughout the days 10 and 20 show almost the same results, see figures 9 and 10.

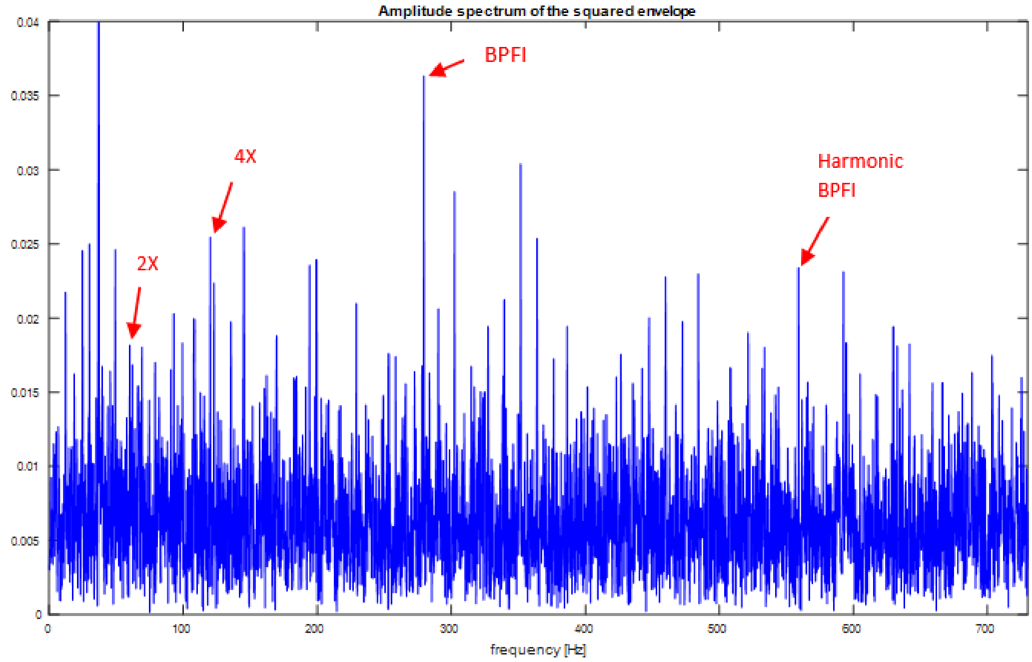

Figure 8: Amplitude spectrum of the squared envelope first day

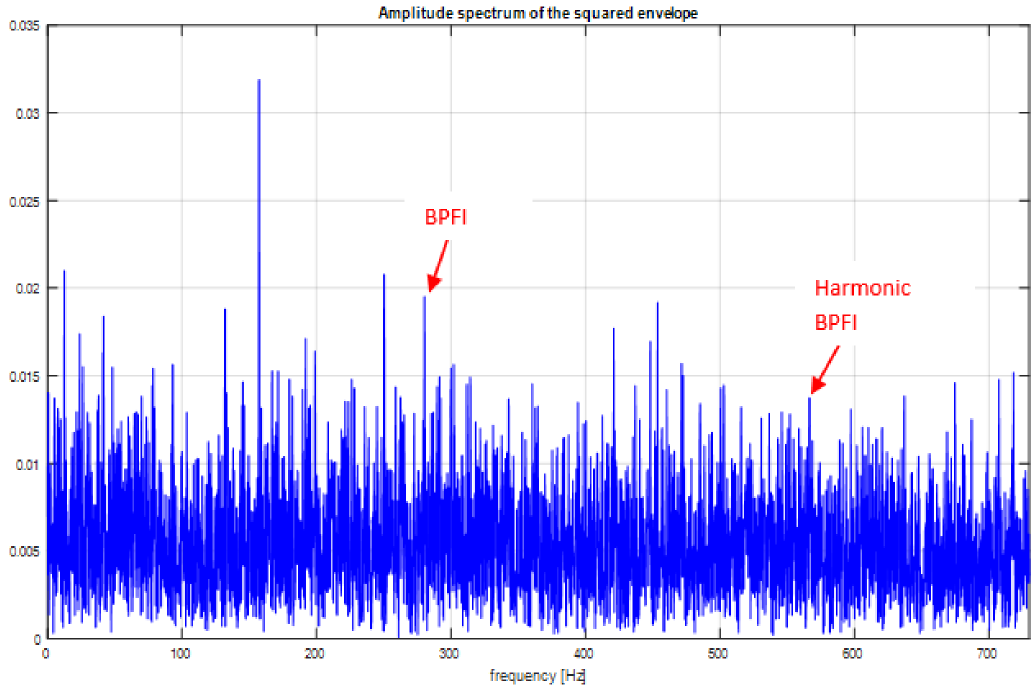

Figure 9: Amplitude spectrum of the squared envelope day 10

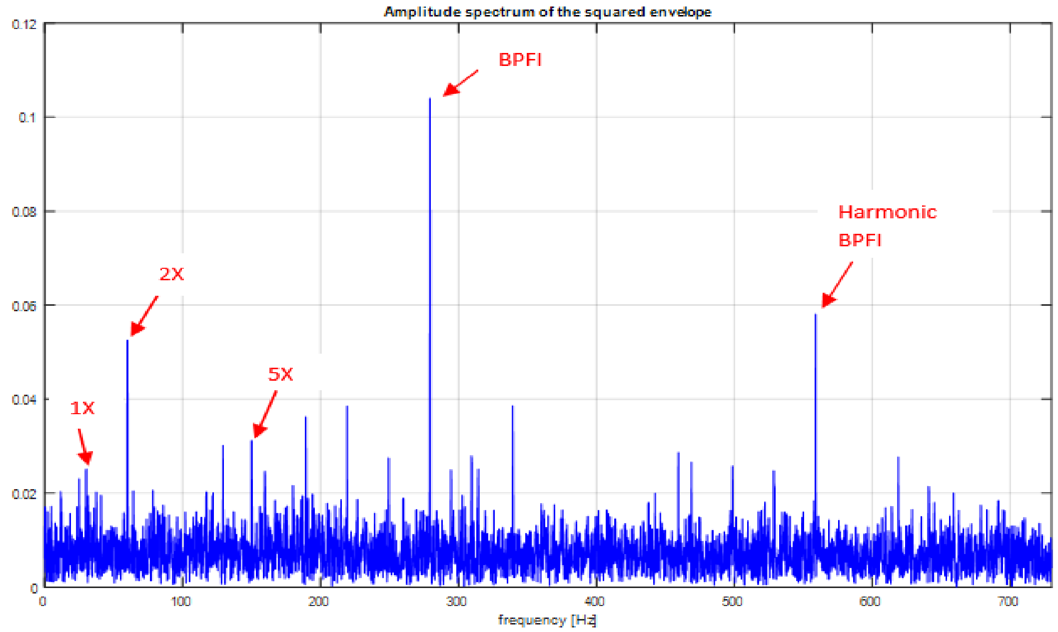

Figure 10: Amplitude spectrum of the squared envelope day 20

Interestingly, significant increase in the amplitude of the bearing inner race fault frequency was noted in the enveloped signal for day 30. The amplitude increased from 0.017 in day 20 to 0.11 in the day 30, shown in figure 11. For the data collected on day 40, similar remark was observed, and harmonic of the bearing fault was also detected. On the termination of measurements (day 50) the harmonics of the faulty bearing recorded higher level than the noted on day 30, see figure 13.

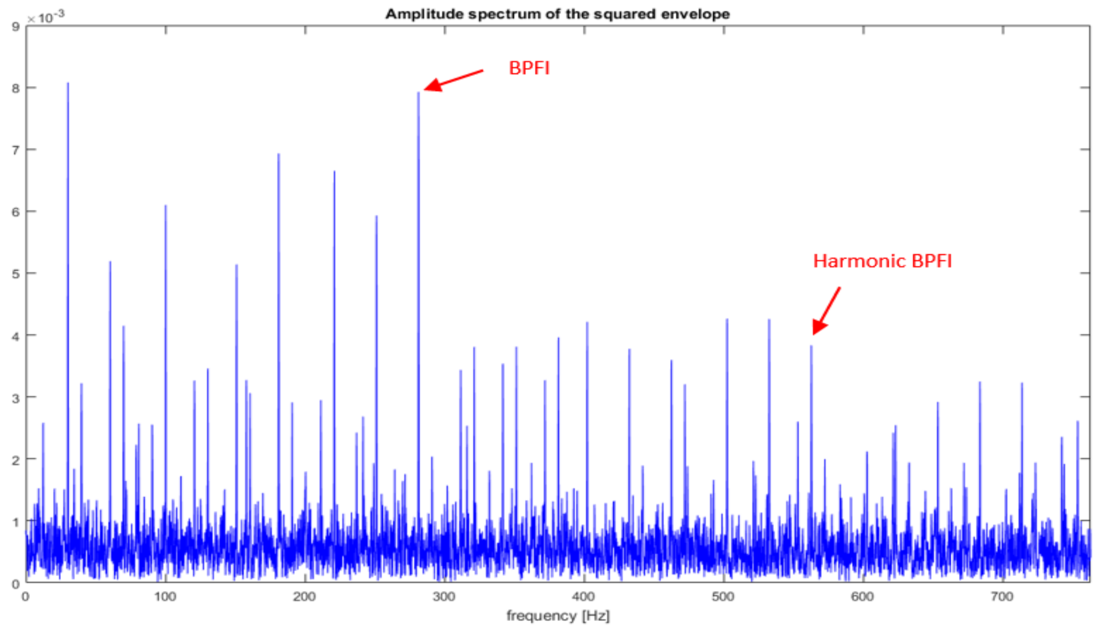

Figure 11: Amplitude spectrum of the squared envelope day 30

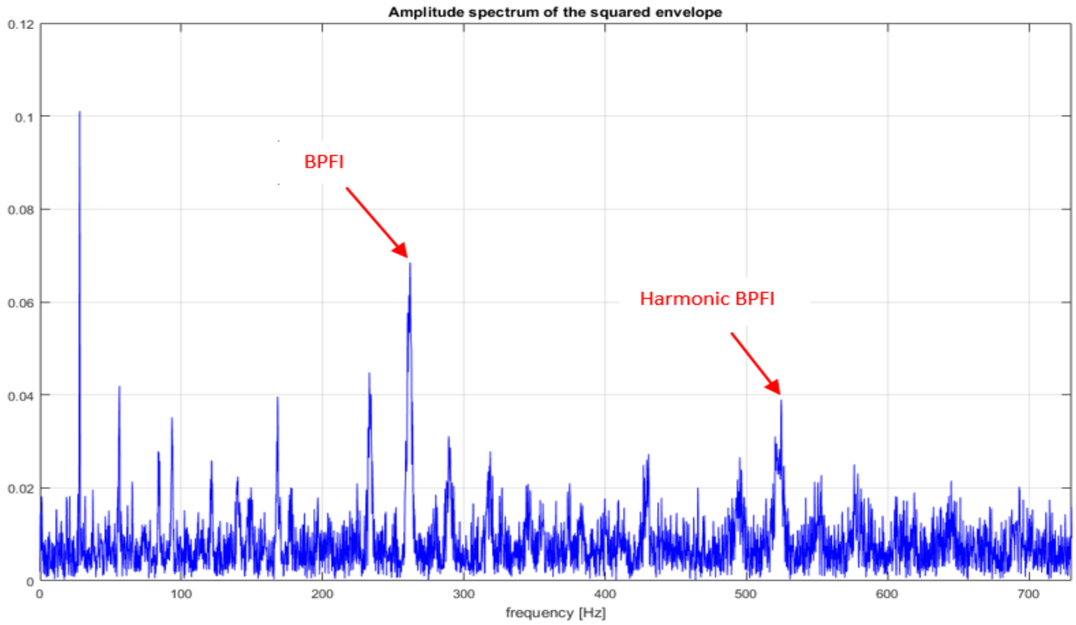

Figure 12: Amplitude spectrum of the squared envelope day 40

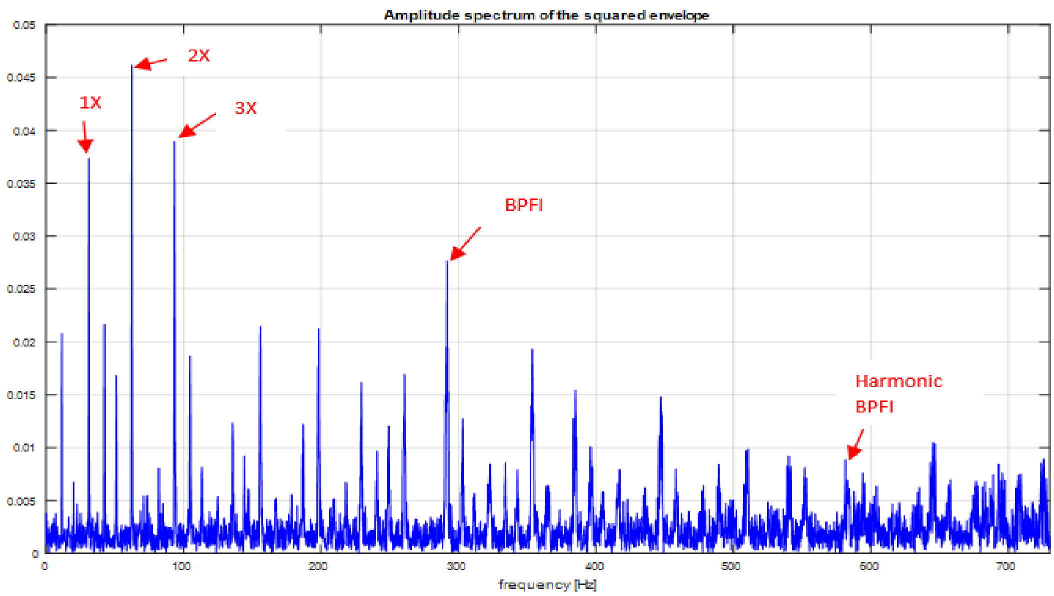

Figure 13: Amplitude spectrum of the squared envelope day 50

Another analysis was undertaken using the fault frequency indicator. Results of the inner race fault indicator, presented in figure 14, showed an increase in the fault frequency amplitude after 14 days of measurements. The highest amplitude of this indicator was recorded between day 28 and day 41, and it eventially decreased to its level prior to day14. This was attributted to the high noise level as a result of the formation of fully developed crack on the bearing race. The use of this indicator could also provide another way to measure how the bearing deviates from its normal health conditions.

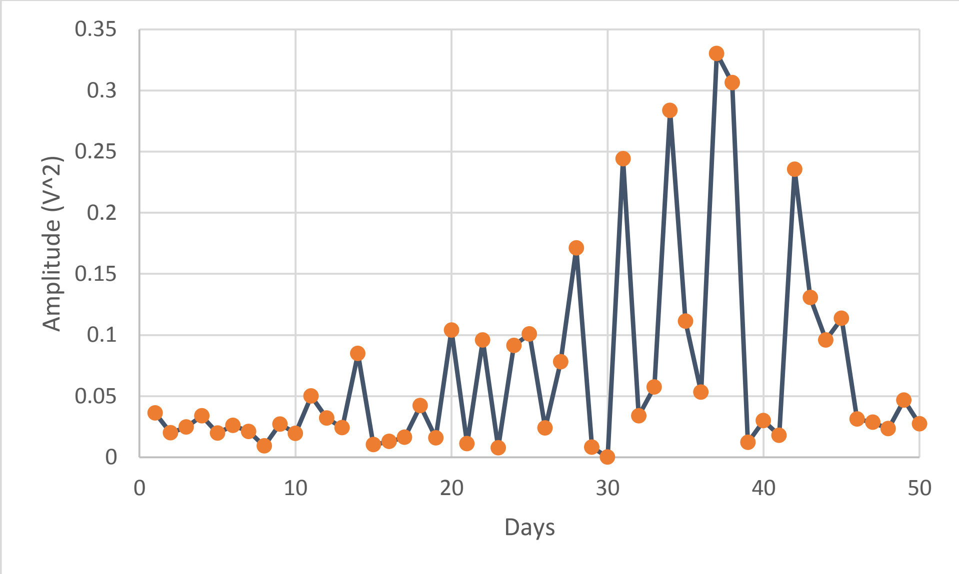

Figure 14: Outer race fault indicator

4. Discussion and Conclusion

The techniques used in this paper are typically used for applications where strong background noise masks the defect signature of interest within the measured vibration signature. this paper motivated by a lack of real world application data and especially for detecting of bearing degradation within gearboxes where the bearing fault is masked with noise and components of gear meshing. Therefore this paper has employed a series of signal processing techniques to improve bearing fault detection. In addition it has employed a new condition indicator, Energy Index (EI), to detect high speed shaft bearing failure in wind turbine gearbox. The use of Energy Index is relatively recent and this paper enhances the understanding of this technique as means of obtaining condition information in these intricate conditions.

Results from statistical indicators showed both kurtosis and EI are reliable indicators and increased as fault severity increases. In addition these indicators provide a clear exponential trend, which is very useful to fault prognosis. However, the CF showed poor results with no clear trend, therefore such indicator was not useful in this case.

Frequency analysis using Fast Fourier Transform should no fault frequency exist. However, Results from frequency analysis using Spectral Kurtosis and envelope analysis showed the possibility to identify the fault defect frequency at early stage. The fault frequency was identified from the first day of the test and the fault frequency amplitude increases as crack progress.

By comparing the results of statistical condition indicators with frequency analysis; it is clear that the frequency analysis can be considered as a superior tool in detection of the bearing fault at early stages though the statistical indicators were sensitive as the fault on the bearing race was well advanced. Further, the use of the spectral kurtosis could exactly identify the location of the fault within the bearing components. The fault severity was assessed using inner race fault indicator, and the results showed a significant increase in the amplitude as the crack progressed with time. However, this was not the case throughout the measurement period in the last days where a sharp drop in the indicator levels was noted. This is due to an increase of the clearance within the bearing which led to less vibration levels.

Results obtained from the analysis of condition indicators showed that the energy index as a consistent fault measure of the fault severity, and it had less drops as the fault progressed. On contrary crest factor, kurtosis and inner race bearing fault showed some level variation with progress of the crack. Thus, energy index can be used to provide a good severity measure of the bearing fault.

Overall, the signal processing techniques used in this study proved their ability in detection of crack fault within wind turbine gearbox. In addition, combination use of these techniques will in turn provide the analyst with more reliable diagnosis tools for online monitoring of wind turbines.

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Declaration of conflicting interests

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Detection of natural crack in wind turbine gearbox

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