Gear Fault Analysis using MATLAB Approach

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Abstract— A vibration analysis is about the art of looking for changes in the vibration pattern, and then relating those changes back to the machines mechanical design. The level of vibration and the pattern of the vibration tell us some-thing about the internal condition of the rotating component. The vibration pattern can tell us if the machine is out of balance or out of alignment. Al-so faults with the rolling elements and coupling problems can be detected. This paper presents a approach for gear fault analysis using signal processing schemes. The data has been taken from university of ohio, united states. The analysis has done using matlab 7.8.0.

Keywords— Gear Fault, IMD, EMF, signal processing, MATLAB

I. INTRODUCTION

Maintenance can be described as fixing or replacing something that is broken. Also is defined as performing routine actions in order to keep a machine running or preventing any further problem.

Maintenance includes:

- Operation: Process control, use of machines, small component changes
- Keeping machine running: Cleaning, lubrication, monitoring
- Logistics: Selection, procurement and delivery of resources
- Improvement: Without changing the object's original action
- Changes: Changes to the original function
- Factory service: e.g. security, fire protection, sanitation, waste- and snow removal .

Why do we perform maintenance services? “Failure” is the answer. When a machine does not perform a required function as a result of an incident, this can be described as a failure. In most of the cases failures can be anticipated through a good maintenance plan, but the possibility of unpredictable critical failures is always present.

1.2.1 Common reasons for failures:

- Equipment is not used in the right way
- Too much focus on repairing instead of checking and analyzing
- The operating conditions are not optimal
- The design does not adequately take into account the actual use or the conditions of use.

Equipment operators detect symptomatic defects, but they don’t take any action or reports.

1.3 Importance of vibration analysis

Vibration measurements give us the information needed to understand why problems have occurred. If we can interpret the data obtained in a correct way and perhaps change the way a machine is operated or maintained, the machine will become more reliable in the future making the overall process more profitable.

Therefore by including vibration measurements into our maintenance plan we can save money and in most of the cases improve the product quality.

1.4 Vibration in a Rotating Machine

Rotating machines are the most common type of machines found in different industry fields and they have to work with high performances. An unscheduled stop due to the machine’s failure leads to high maintenance and production costs risks. High costs are initiated through the production stops, losses, and urgent procurements of spare parts. High risks are associated with the possibilities of workers’ injuries and secondary damages of neighboring machines. To avoid such a scenario, several maintenance strategies have been developed, from the breakdown maintenance to condition based and proactive maintenance. The implementation of condition-based maintenance implies monitoring of machine operating condition based on the physical parameter that is sensitive to machine degradation. Among many possible parameters, mechanical vibration acquired at the bearing’s housing is one of the best parameter for early detection of a developing fault inside a machine. Methods of vibration signal analysis enable the extraction of type and severity of a fault. Despite the fact that the information on type and severity of a fault is contained in the vibration signal, due to the:

a) ***Existence of multiple faults on a machine,***

b) ***Dependence of vibration signal content on operating conditions,***

c) ***Existence of vibration components from neighboring machines,*** Derivation of incorrect vibrodiagnostical conclusions and wrong estimation of machine criticality in the plant, is a very common situation.

To avoid this, there are two approaches:

a. ***Engagement of highly skilled and trained vibration analysts or***

b. ***Application of artificial intelligence (AI) methods for reliable extraction of an existing fault.***

Engagement of certified vibration analysts can be a problematic issue due to the following reasons: there are not many of them, in many cases they don't have a substitution when absent and they are often engaged in other maintenance tasks so they cannot be fully focused on the analysis of acquired data from the machine. In such an environment, implementation of AI methods through previously developed and validated fault identification algorithm has a huge potential.

The monitoring of a Gearbox condition is a vital activity because of its importance in power transmission in any industry. Techniques such as wear and debris analysis, and acoustic emissions require accessibility to the Gearbox either to collect samples or to mount the transducers on or near the Gearbox. Vibration analysis is one of the most important condition monitoring technique that are applied in real life. Most of the defects encountered in the rotating machinery give rise to a distinct vibration pattern (vibration signature) and hence mostly faults can be identified using vibration signature analysis techniques. Vibration Monitoring is the ability to record and identify vibration "Signatures" which makes the technique so powerful for monitoring rotating machinery.

II. BACKGROUND AND LITERATURE SURVEY

Due to the industrial importance of gears in power transmission systems, the effective CM of gearboxes is essential. There is constant pressure to improve measuring techniques and tools for the early detection and diagnosis of gearbox faults. The gears themselves are the most important elements in the gearbox, and the degree of wear and fatigue to which they are subjected even under normal operating conditions means that they are often subject to premature failure. Ma and Li claim that up to two-thirds of gearbox failures are due to faults which develop in the gears, and almost all of these are due to localised defects such as fatigue induced fractures [1].

Increased demand for lower production and maintenance costs means that the CM of gear transmissions has become an important area of research. The severe conditions under which gears operate relative to other machine components, means that they deteriorate quite rapidly, especially their teeth [2]. Fakhfakh et al have defined three general types of gear defects that cause transmission error and gearbox failure:

a. ***Manufacturing defects (e.g. error in the tooth profile),***

b. ***Installation defects (e.g. the alignment of the gears)***

c. ***Defects which occur during the work process (e.g. cracking of teeth) [2].***

Sudden loading of the gear teeth during operation is the main factor causing fatigue cracks that appear at the root of the tooth and weaken the structural integrity of the gear.

Lin and Zuo have described tooth breakage as the most serious problem for gears because it can lead to complete failure of the gearbox [3]. Initially a fatigue crack at the base of a tooth will not be considered a serious problem, but as the crack propagates, damage will accelerate and may result in catastrophic tooth failure. If the crack can be detected and its development tracked, the gear can be replaced before the tooth breaks.

Much effort has gone into developing reliable methods for fault detection in gearboxes. Proven techniques include oil analysis [4], temperature distribution within the gearbox, the noise produced by the gearbox when in operation, motor current analysis [5] and, most popular today, vibration analysis [6]. Unfortunately, no single technique has been found that is able to detect all machine faults. Vibration measurement, which is the most widely used CM technique in industry, because of its proven ability to detect the early presence of faults, can identify only 60% to 70% of machine faults [7,8].

Vibration analysis is now usually performed online via a computer-based machine CM system and does not require shutdown of the machinery.

Analysis of vibration signals is very appropriate for monitoring gearboxes because any change in the vibration signature of the gearbox is most likely a result due a change in gearbox condition. This is because as defects on a gear will alter both the amplitude and phase modulations of the gear's vibrations. Thus, any changes in vibration signal can be analyzed to provide an indication of possible faults [9, 10]. Most natural phenomena are non-linear and the majority of these signals have varying frequency content. The vibrations of multi-stage gearboxes contain non-stationary transients, e.g. the short periodic impulsive components produced by impacts between components. Typically, vibration signals generated in gearboxes will contain three main components,

(1) ***Periodic components such as those resulting from interactions between the gears during meshing,***

(2) ***Transient components caused by short duration events, such as repeated impacts due to a tooth having broken off, and***

(3) ***Broad-band background noise.***

In the early stages of damage and fault initiation, the resulting low amplitude vibration signal will be masked by other sources present in the gearbox and cannot therefore be used directly for damage detection. However, it is precisely at this stage that detection of these faults is important. As a result, more effective signal processing methods are required to better analyse vibration measurements and more reliable gearbox condition monitoring and health diagnosis.

Analysis of the time-domain signal uses statistical parameters such as peak value, root mean square (RMS), kurtosis and Crest factor (CF) and their use is well established in assessing the condition of gears [9]. Stevens et al have claimed that these measures are suitable for detection and diagnosis when mechanical faults take the form of impulses which impose periodic pulses of short time duration (wide frequency bandwidth) onto the base vibration signal [11].

However, the most common method used for detection and diagnosis of gear failure is spectral analysis of the vibration signal in the frequency-domain. This is because the most important CM elements in the vibration spectra of gears are: the tooth meshing frequency, harmonics and sidebands (due to modulation phenomena) located on either side of the gear tooth meshing frequency. The sidebands are separated by integer multiples of the gear rotation frequency. The behaviour of these sidebands can be strongly indicative of the presence of a fault, e.g., through an increase in the number of sidebands and their relative amplitudes. Randall found that the first three gear meshing harmonics and their sidebands provided sufficient information for gear fault identification [12].

Thus tracking and monitoring changes in the amplitude of particular sidebands in the spectrum can provide a good predictor of gear failure. In practice, it is often difficult to extract meaningful information from vibration spectra based on a simple Fourier Transform (FT) of time-domain to frequency-domain. In the early stages of fault development, important defining frequencies have low amplitude and can be masked by other vibration sources or buried in background noise [13]. This is particularly relevant because the individual vibration impulses generated by gear defects typically tend to be of short duration causing the corresponding frequency pulse to spread over a wide frequency band with low amplitude [12]. It can also be very difficult to identify a particular frequency indicative of a defect when a large number of spectral components are present.

Today, combined time and frequency analysis is increasingly used in gear fault diagnosis and is gradually replacing conventional time-domain analysis and frequency-domain analysis. Representing the signal in the time and frequency-domains simultaneously is a powerful tool for examining non-stationary vibration signals and the results can be easily interpreted. Wang and McFadden claim that it is relatively easy to characterise the local features of the signal, and all distinctive components in the frequency range of interest, their sequences causality and changes with time can be displayed on a single chart [14].

During the past twenty years, a number of time-frequency signal processing techniques have proved to be suitable for analysis of vibration signals and have gained acceptance in the field of CM [15]; such approaches as the Short-Time Fourier Transform (STFT) [14], Wigner-Ville Distribution (WVD) [16] and Wavelet Transforms (WTs) [17, 18, 19] are widely used. Peng and Chu have claimed that the WT technique has proved eminently suitable for analysis of vibration signals because most signals contain instantaneous impulse trains and other elements which are transient and non-stationary in nature [19]. The WT decomposes a signal into different frequencies with different resolutions i.e. it provides time-scale (frequency) representation of a signal [18].

2.1 Time-domain Analysis

Time domain analysis of vibration signals is one of the simplest and cheapest fault detection approaches. Conventional time-domain analysis attempts to use the amplitude and temporal information contained in the gear vibration time signal to detect gear faults. The amplitude of the signal can be used to signal that a fault is present and the periodicity of the vibration can then indicate a likely source for the fault [11].

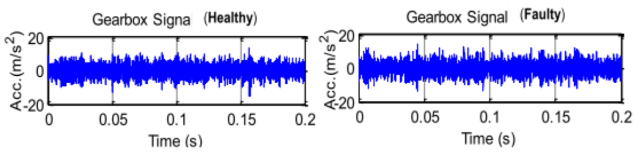

Figure 2.1-Waveform of the vibration signal for a gearbox with healthy and faulty gears

Time domain approaches are appropriate when periodic vibration is observed and faults produce wideband frequencies due to periodic impulses [11]. Use of the waveform enables changes in the vibration signature caused by faults to be detected, but it is difficult to diagnose the source of faults. Figure 2.1 (from section 4.2.1) shows the gearbox vibration waveform for healthy and faulty gear systems.

Some mechanical systems generate high vibration levels throughout their operation. When these systems develop a progressive fault, the resulting vibration level is likely to increase consistently with time but the increase in vibration may be very small and difficult to identify. If the rate of development of the fault vibration is small, it may not be possible to clearly determine a fault symptom from variations in the waveform of the signal [20].

Mechanical systems are termed deterministic if their properties such as displacement, acceleration, etc. can be predicted over time. Mechanical systems such as a gearbox with a localised fault reveal characteristics which cannot be estimated over time. The characteristics of such systems, termed random or non-deterministic, cannot be accurately predicted, but they can be estimated by statistical parameters and these parameters can be used to predict fault progression [21].

Statistical indicators, which are commonly used for mechanical fault detection and based on the time-domain waveform include: the Peak Value (PV), Root Mean Square (RMS), Kurtosis and Crest Factor (CF) [22, 23]. These indicators are also referred to as "condition indices", [24]. The vibration signal from a gearbox is processed and a single value returned to indicate whether its condition is within normal operating parameters or not.

The condition index should increase as the fault increases; indicating the deteriorating condition of the gearbox. Sometimes this analysis can be performed by simple visual observation of the vibration time-domain waveform, but it is more likely that the time-domain signal will be processed to provide a statistical parameter (feature) which bears a known relation to the severity of the vibration.

2.2 Frequency (Spectral) Domain Analysis

Frequency-domain analysis is a powerful conventional technique for vibration analysis and has been demonstrated as a useful tool for detection and diagnosis of faults in simple rotating machinery [22, 23]. Using this technique, the time-domain of the vibration signal is transformed into its frequency equivalent. It has been found that the spectral content of the measured signal is often much more useful than the time-domain for determining gear condition because the complex time-domain signal can be broken down into several frequency components. It is therefore easy for analysts to focus on these frequencies which are valuable in fault diagnosis [22], whereas the overall vibration is a measure of the vibration produced over a broadband of frequencies; the spectrum is a measure of the vibrations over a large number of discrete contiguous narrow frequency bands. Thus the common approach to vibration CM is use the Fast Fourier Transform (FFT) to transform the vibration signal to the frequency domain. This approach is perfectly acceptable if the measured signal does not vary in spectral content over time (i.e. no variations in the rotational speed of the machine).

For machines operating with known constant speed, the vibration frequencies of the vibrations produced by each component in the machine can be estimated therefore, any change in vibration level within a particular frequency band can be related to a particular component. Analysis of relative vibration levels at different frequency bands can provide some diagnostic information.

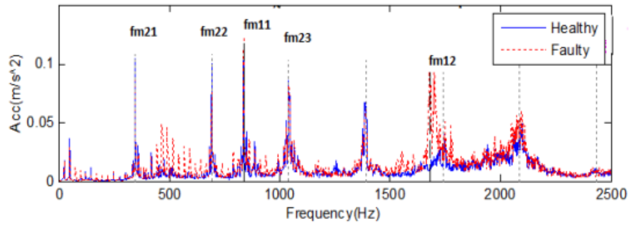

Figure 2.3-Spectrum of Gearbox Vibration Signal for Healthy (blue) and Faulty (red) gears

Sidebands generated by either amplitude modulation or frequency modulation of the vibration signal often provide useful information. Amplitude modulation is attributed to tooth fracture or eccentricity of the gear or shaft with a damaged tooth

generating pulses at a rate equal to the gear speed. Frequency modulation, on the other hand, is caused by errors generated during gear manufacture (e.g. non-uniform tooth spacing). As previously stated, Randall has claimed that the first three gear meshing harmonics and their sidebands provide sufficient information for the successful identification of gear faults [22].

Therefore, changes in the amplitude of a particular frequency peak or sidebands of a signal can provide a good indicator of potential gear failure. In practice, the spacing of the sidebands depends on periodic properties of the loading and on the transmission path, it can be difficult therefore to extract useful features directly from vibration spectra based solely on a FFT. When the signal to noise (S/N) is low and the vibration spectrum has a large number of frequency components due to the complexity of the system, it becomes almost impossible to distinguish the peaks due to faults from peaks from other sources. This is the most difficult problem associated with the FFT based fault detection approach.

2.3 Joint Time-Frequency Approaches

Analysis of the vibration signals in the time-domain and the frequency-domain produces signal characteristics for their respective domains only. The time-domain contains no spectral information and when a time-domain signal is transformed to the frequency-domain, the detailed information about the time-domain is lost.

Consequently, both methods have their limitations. Additionally, it must be remembered that there are limits on the results of the Fourier Transform (FT) which are strictly only valid for stationary signals. FT can be used for analysis of non-stationary signals, to identify which spectral components exist within the signal. However, the time or interval at which these occur cannot be determined. If time information is required, then FT is not a suitable method of analysis.

It is often difficult to detect clear symptoms of any defect in the gear if Time Synchronous Averaging (TSA) is used in isolation [23]. The technique may also fail to detect and differentiate between faults, particularly if multiple faults are present simultaneously in multiple gears within the gearbox. A wide variety of different techniques have been explored over the years to further process the TSA method to make it more sensitive to early fault detection [24].

Recently, much work has been carried out on the analysis of vibration signals in the time-frequency domain, with a view to combining this with frequency domain analysis to give a full representation of a vibration signal [19].

Time-frequency analysis provides information on the evolution of spectral content of the signal with time, allowing investigation of transient features such as impacts [25, 26]. In recent years, joint time-frequency representations such as the Short-Time Fourier Transform (STFT) [14], Wigner-Ville Distribution (WVD) [24, 23, 10], and Wavelet Transform (WT) [17, 18, 19], have become popular in an attempt to address the lack of either time domain or frequency domain analysis. An overview of the joint time frequency application for the machine diagnostics can be found in Atles et al., [27]

The major differences between these transforms are their respective time and frequency resolutions. WT analysis has been shown as an ideal tool for condition monitoring of gears. In contrast to the STFT, the WT method uses narrow time windows at high frequencies and wide time windows at low frequencies [28, 29]. It is therefore a very effective method for the analysis of transient and non-stationary signals. Abnormal transients generated by early stage gear faults can be detected using discrete [9] and continuous [23] wavelet transformation. It has been found that even though the discrete WT offers a very efficient signal representation with no redundancies, the resulting time-scale map is limited, and not very informative. Lin et al. introduced a linear wavelet transform concept, whereby the wavelet map was normalized according to the signal amplitude instead of energy [3]. Boulahbal et al [30] applied both the WT amplitude and phase simultaneously to study cracked and chipped tooth faults and proposed polar representation as a useful tool for pinpointing the location of the gear damage in WT maps.

2.4 Wavelet Transform

The Wavelet Transform method can be used as an alternative technique to the STFT. Where STFT is used to measure the local frequency content of the signal, the WT method compares several components of the vibration signal at different resolutions.

The basis of the STFT approach is multiplication of the sine and cosine signals by a fixed sliding resolution. In the case of the WT method, the window is already oscillating and is called a mother window. The mother wavelet, rather than being multiplied by sine and cosine, is expanded and contracted depending on the value of the dilation parameter. Other wavelets are then generated by the mother wavelet, and it is this which forms the basis of wavelet analysis. The Wavelet Transform can be seen as decomposition of a signal into a set of basis functions called wavelets, obtained from a signal prototype wavelet by dilations, scaling and shifts [21].

In recent years, several WT analyses have been accepted as suitable signal processing techniques for machine CM and failure diagnosis. By decomposing a time series into time-frequency space, it is possible to determine not only the existing frequencies in the signal but also the duration of each individual frequency in time [18, 19]. This is highly advantageous in examining vibration signals from faulty rotating machinery, where either large or small scale changes in the vibration may occur whether the fault is distributed or local [9]. When monitoring gearbox condition, WTs are used primarily to identify all possible transients in vibration signals which are generated by faults. WTs possess multiple resolutions for localization of short time components, enabling all possible types of gear fault to be displayed by a single time-scale distribution resulting from the transform [15].

III. PROPOSED WORK

3.1 Empirical mode decomposition

Huang et al [58]. Presented the use of EMD for decomposition of any temporal signal into a finite set of amplitude and frequency modulated components known as IMFs. This decomposition is independent of the properties of the signal like stationary, linearity etc. The following two conditions are the necessary conditions for the IMF:

(1) The number of extrema and the number of zero-crossing must either equal or differ maximum by one.

(2) At any point, the mean value of the envelope defined by local maxima and the envelope defined by local minima is zero.

The EMD algorithm can be summarized as follows:

(1) Extract all extrema of x(t).

(2) Interpolate between minima (resp. maxima) to obtain two envelopes $X_{min}(t)$ and $X_{max}(t)$.

(3) Compute the average

$a(t)=(X_{min}(t) + X_{max}(t))/2.$

(4) Extract the detail $h(t) = x(t) – a(t)$.

(5) Repeat the step (4) to reduce the required extracted signal to an IMF.

(6) Test if h(t) is an IMF:

a. If yes, repeat the procedure to get residual signal $r(t) = x(t) – h(t)$.

b. If not, replace x(t) with h(t), and repeat the procedure from step (1).

The IMFs IMF_1 (t), IMF_2 (t), ….. IMF_N (t) includes different frequency bands of x(t) from high to low. The central tendency of a signal *x(t)* is represented by its residual. By summing up all IMF and residual, we should be able to reconstruct the original signal *x(t).*

3.2 Variable window based analysis

The commonly used windows in signal processing are Tukey window (Tapered Cosine Window). These can be defined as following in the interval $0 \leq n \leq M-1$, where M can be any Rational Integer [59].

Tukey Window:

$$h(n) = \frac{1}{2}\left[1 + \cos\left(\frac{n - \frac{(1+\alpha)(M-1)}{2}}{(1-\alpha)\frac{M-1}{2}}\pi\right)\right] \qquad (3)$$

Where M is a variable which controls the time span of the middle portion of the window. The value of this window varies as the value of M varies. The selection of the value of M is dependent on the data, and to reduce the boundary distortion this M should be kept as accurate as possible on the basis of data.

3.3 Methodology Adopted

The work presented in this paper is based on the EMD, Hilbert transform, and variable window for bearing fault diagnosis has been divided into the following steps:

Step 1: Empirical mode decomposition: Extract the IMF for a given bearing vibration signal using the algorithm presented in section 2. The IMFs consists of a set of narrow-band non-stationary signals.

Step 2: Variable Tukey window (Tapered Cosine Window): Designing of the window of appropriate size depends on the frequency band of each IMF has been done in this step using the formula presented in section 2.2. The IMF under observation is multiplied by a respective designed window in order to reduce the boundary distortions present at both the ends of the IMFs.

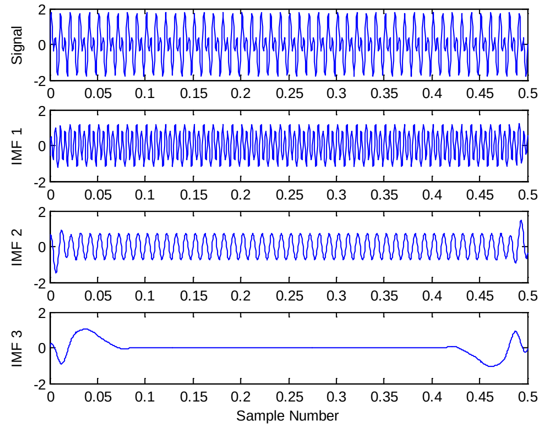

Fig 3.1. Empirical mode decomposition of the simulated signal x[n]

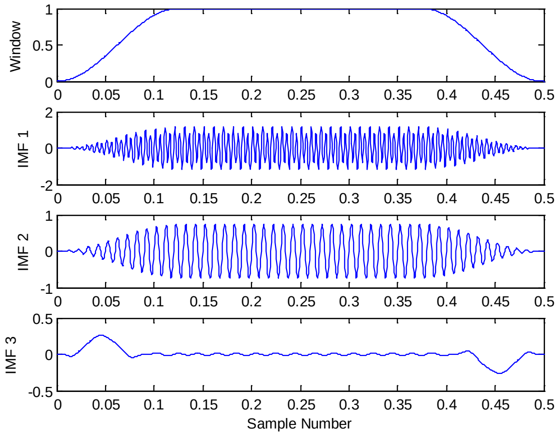

Fig 3.2. Windowing of IMFs of the signal x[n]

Step 3: Kurtosis analysis: Kurtosis analysis has been done in this step for the IMF before applying window, and for window applied IMF. The expression for kurtosis is written below:

$$K = \frac{1}{\sigma^4}\sum_{i=1}^{N} (x(i) - x')^4 / N \qquad (4)$$

Where σ^4 is the variance square, N is the number of samples, x' is the mean values of samples, and x_i is an individual sample. A normal distribution has a kurtosis value of 3 and it shows the good condition. The computation of Kurtosis for without applying the window leads to very high value, which are misleading the interpretation due to the boundary distortion presence.

IV. RESULT AND DISCUSSION

The recordings of vibration signal were carried out at CE-TIM, France on a gear system with a train of gearing with a ratio of 20/21 functioning continuously until its destruction. These signals are publically available in [60]. The test was of 13 days length with a daily mechanical appraisal; measurements were collected every 24 h. A fault was found on day 10. The signals are decomposed by EMD method as described earlier. First three IMFs of each days vibration signal has been taken for investigation of fault.

Only first three IMFs were taken, since the defect frequency lies in the second IMF. After having the IMFs, each IMF has been windowed by variable cosine window as explained in Section 2. Kurtosis, S_r and S_a of each IMF from day 4 to day 12 have been calculated. Further, Kurtosis value of each windowed IMF from day 4 to day 12 have been calculated. The kurtosis value of raw signal (i.e. original signal or signal without decomposition) have also been calculated. Kurtosis value of original signals from day 4 to day 12 has been given in Table 5.1. The Table 5.1 also shows percentage increase in the parameters from previous day.

Statistical Analysis of data

Day	IMF	Kurtosis	
		Without Window	With window
Four	IMF1	4.0530	4.3827
	IMF2	2.8881	2.8554
	IMF3	3.4415	3.5063
Five	IMF1	2.7532	3.0009
	IMF2	2.6187	2.7678
	IMF3	3.2677	3.3975
Six	IMF1	4.0745	4.5459
	IMF2	2.7247	2.7660
	IMF3	4.2510	4.3618
Seven	IMF1	2.8578	3.1305
	IMF2	2.6894	2.8569
	IMF3	3.1591	3.3015
Eight	IMF1	4.5176	4.8209
	IMF2	3.0510	3.1482
	IMF3	4.9592	5.1249
Nine	IMF1	2.9256	3.1732
	IMF2	2.8914	3.0758
	IMF3	3.1488	3.2773
Ten	IMF1	4.6374	4.8333
	IMF2	3.3553	3.4293
	IMF3	3.5562	3.6438
Eleven	IMF1	2.8899	3.1667
	IMF2	3.0740	3.2830
	IMF3	3.4115	3.3774
Twelve	IMF1	4.2183	4.5547
	IMF2	3.5007	3.6978
	IMF3	3.0122	3.1591

The results which have been plotted in Figs. 5.1–5.2 are discussed in this section. It can be seen that there is no significant change in the kurtosis value of the original signal, IMF1, and windowed IMF1 from day 4 to day 10. The kurtosis value of the original signal increases drastically on day 11. Similarly kurtosis value of IMF1 and windowed IMF1 also increases significantly.

Since first IMF contains very high frequency component (similar to noise), IMF1 is unable to give any information about fault on day 10 (when the fault has just started). Moreover, on day 11 the kurtosis values are very high for original signal, IMF1, and windowed IMF1. This indicates that kurtosis parameter for IMF1 is very unreliable for fault diagnosis.

In Fig 5.2 kurtosis value of the IMF2 does not change sigificantly from day 4 to day 9. On day 10, kurtosis value of the original signal remains almost same but in case of IMF2 it increases drastically, and for windowed IMF2 it increases marginally. Since on day 10 fault has just initiated, very high kurtosis value for IMF2 is misleading. The very high value of kurtosis parameter for IMF2 is due to boundary distortion of IMF as shown in Fig. 14. In windowed IMF2, the boundary distortion problem is minimized and kurtosis value has increased which may be due to initiation of fault. Since on day 10 fault magnitude is very less, increase in kurtosis value is marginal. It suggest that windowed IMF2 gives more reliable information about the fault. On day 11, IMF 2 and windowed IMF2 give almost same kurtosis values, since the magnitude of boundary distortion is very less as compared to the magnitude of the fault.

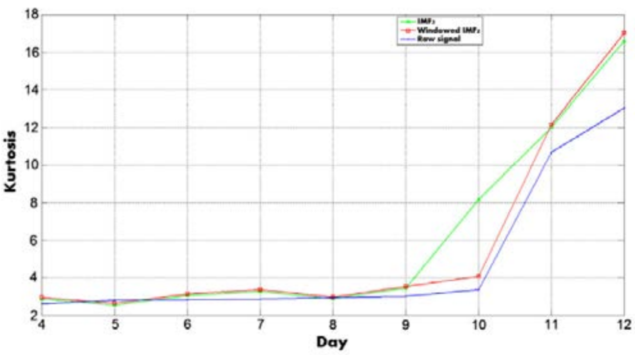

Fig 5.1 Kurtosis computation of IMF2, windowed IMF2, and original signal.

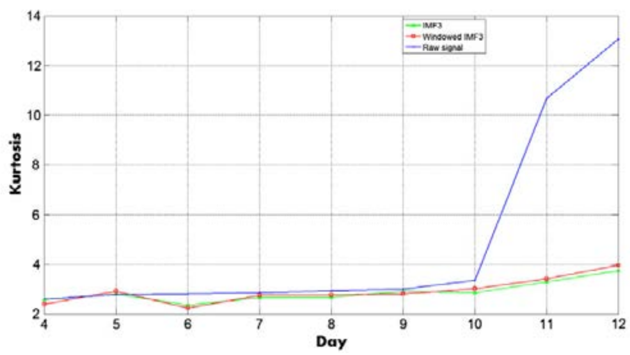

Fig 5.2 Kurtosis computation of IMF3, windowed IMF3, and original signal.

V. CONCLUSION

This paper presents a study of various approaches for the analysis of faults presents in the gears. These approaches has been classified in to the categories; time domain analysis, frequency domain analysis, time-frequency domain analysis. proposed a new method based on empirical mode decomposition for improved fault diagnosis. A serious problem of boundary distortion in IMFs extracted from MD process, has been addressed in this paper by using variable cosine window. The statistical parameters (kurtosis) have been computed for original signal, IMFs, and windowed IMFs. It has been observed that all the IMFs are not suitable for fault detection. The second IMF which carry characteristic defect frequency is suited for fault detection. The kurtosis parameter is a better fault indicator if calculated for windowed second IMF. Kurtosis of IMF without windowing may give misleading indication of fault present in the gear.

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