



VIBRATION ANALYSIS TECHNIQUES FOR GEARBOX

DIAGNOSTIC: A REVIEW

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Review Article

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ABSTRACT

Gears are important element in a variety of industrial applications such as machine tool and gearboxes. An unexpected failure of the gear may cause significant economic losses. For that reason, fault diagnosis in gears has been the subject of intensive research. Vibration signal analysis has been widely used in the fault detection of rotation machinery. The vibration signal of a gearbox carries the signature of the fault in the gears, and early fault detection of the gearbox is possible by analyzing the vibration signal using different signal processing techniques. In this paper, a review is made of some current vibration analysis techniques used for condition monitoring in gear fault.

KEYWORDS Condition Monitoring; Vibration Analysis; Fault Diagnosis; Gearbox.

1. INTRODUCTION

All machines with moving parts give rise to sound and vibration. Each machine has a specific vibration signature related to the construction and the state of the machine. If the state of the machine changes the vibration signature will also change. A change in the vibration signature can be used to detect incipient defects before they become critical. This is the basics of many condition monitoring methods. Condition monitoring can save money through increased maintenance efficiency and by reducing the risk of serious accidents by preventing breakdowns. The use of vibration analysis as one of the fundamental tools for condition monitoring has been developed extensively over a period of approximately 35 years. With the parallel developments in electronic equipment, transducers, computers and software nowadays machine supervision is almost completely automated. In the present work the authors present a review of a variety of diagnosis techniques for gearbox fault identification with particular regard to vibration analysis. The vibration techniques were developed with two main purposes. The first purpose is to separate the gearbox related signal from other components and to minimize the noise that may mask the gearbox signal, especially in the early stages of the fault. The second purpose is to identify the status of the gearbox, to distinguish the good and the faulty gear and to indicate the defective components. Examples of widely used techniques for gearbox are such as Waveform analysis, Time-Frequency analysis, Faster Fourier Transform (FFT), Spectral analysis, Order analysis, Time Synchronous Average, and probability density moments. These vibration based diagnosis techniques has been the most popular monitoring technique because of ease of measurement. Vibration analysis was used former mainly to determine faults and critical operation conditions. Nowadays the demands for condition monitoring and vibration analysis are no more limited trying to minimize the consequences of machine failures, but to utilize existing resources more effectively.

2. FAULT DETECTION AND DIAGNOSIS FROM VIBRATION ANALYSIS

Diagnostics is understood as identification of a machine's condition/faults on the basis of symptoms. Diagnosis requires a skill in identifying machine's

condition from symptoms. The term diagnosis is understood here similarly as in medicine. It is generally thought that vibration is a symptom of a gearbox condition. Vibration generated by gearboxes is complicated in its structure but gives a lot of information. We may say that vibration is a signal of a gearbox condition. To understand information carried by vibration one have to be conscious/ aware of a relation between factors having influence to vibration and a vibration signal. In order to detect (and diagnosis) an impending failure, a good understanding of the evidence relating to the failure mode and methods of collecting and quantifying the evidence is needed. Although many faults may be easily detectable by physical examination of a component, using techniques such as microscopy, X-ray, dye penetrates, magnetic rubber, etc., these methods usually cannot be performed without removal of, and in some cases physical damage to, the component. Whilst physical examination techniques still play a critical role during manufacture, assembly and overhaul, they are impractical in an operational large transmission system and other (non-intrusive) fault detection methods need to be employed for routine monitoring purposes. Most modern techniques for gear diagnostics are based on the analysis of vibration signals picked up from the gearbox casing. The common target is to detect the presence and the type of fault at an early stage of development and to monitor its evolution, in order to estimate the machine's residual life and choose an adequate plan of maintenance. It is well known that the most important components in gear vibration spectra are the gear meshing frequency (GMF) and its harmonics, together with sidebands due to modulation phenomena. The increment in the number and amplitude of such sidebands may indicate a fault condition. Moreover, the spacing of the sidebands is related to their source. source identification and fault detection from vibration signals associated with items which involve rotational motion such as gears, rotors and shafts, rolling element bearings, journal bearings, flexible couplings, and electrical machines depend upon several factors: (i) the rotational speed of the items, (ii) the background noise and/or vibration level, (iii) the location of the monitoring transducer, (iv) the load sharing characteristics of the item, and

(v) the dynamic interaction between the item and other items in contact with it. The main causes of mechanical vibration are unbalance, misalignment, looseness and distortion, defective bearings, gearing and coupling in accuracies, critical speeds, various form of resonance, bad drive belts, reciprocating forces, aerodynamic or hydrodynamic forces, oil whirl, friction whirl, rotor/stator misalignments, bent rotor shafts, defective rotor bars, and so on. Some of the most common faults that can be detected using vibration analysis are summarized in Table 1

Table 1: Some typical faults and defects that can be detected with vibration analysis

Item	Fault
Gears	Tooth missing faults, misalignment, cracked and/or worm teeth, eccentric gear
Rotors and shaft	Unbalance Bent shaft Misalignment Eccentric journals Loose components Rubs Critical speed Cracked shaft Blade loss Blade resonance
Rolling element bearings	Pitting of race and ball/roller Spalling Other rolling elements defect
Flexible coupling	Misalignment Unbalance
Electrical machines	Unbalanced magnetic pulls Broken/damaged rotor bars Air gap geometry variations Structural and foundation faults Structural resonance Piping resonance

Ebersbach et al, (2005) [1], has investigated the effectiveness of combining both vibration analysis and wear debris analysis is an integrated machine condition monitoring maintenance program. Decker Harry. J (2002) [2], has proposed two new detection techniques. The time synchronous averaging concept was extended from revolution-based to tooth engagement based. The detection techniques are based on statistical comparisons among the averages for the individual teeth. These techniques were applied to a series of three seeded fault crack propagation tests. Polyshchuk V.V et al (2002) [3], has presents the development of a novel method in gear damage detection using a new gear fault detection parameter based on the energy change in the joint time-frequency analysis of the vibration analysis of the vibration signal. Choy F. K et al, (2003) [4], demonstrates the use of vibration signature analysis procedures for health monitoring and diagnostics of a gear transmission system. Lin J. and Zuo M. J (2003) [5], has introduced an adaptive wavelet filter based on Morlet Wavelet, the parameters in the Morlet wavelet function are optimized based on the kurtosis maximization principle. The wavelet used is adaptive because the parameters are not fixed. The adaptive wavelet filter is found to be very effective in detection of symptoms from vibration signals of a gearbox with early fatigue tooth crack.

3. GEARBOX FAILURE AND ITS VIBRATION ANALYSIS TECHNIQUES

The principle causes for gear failure are given here -
a) An error of design, b) An application error, c) It is

likely that there is a manufacturing error. Design errors may be due to causes like improper gear geometry, use of wrong materials, quality, lubrication and other specifications. Application errors can be due to problems like vibration, mounting and installation, cooling and maintenance while manufacturing errors can be in the form of mistakes in machining or problems in heat treating. Summary of safety critical failure modes (Table 2), several researchers worked on the subject of gearbox defect detection and diagnosis through vibration analysis. Time domain, frequency domain, time frequency domain based on short time Fourier transform (STFT) and wavelet transform and advanced signal processing techniques have been implemented and tested.

Table 2 Safety critical failure modes

Failure	Failure Mode	Cause	Contributing factors
Shaft fracture	Fatigue	Unbalance	
		Misalignment	Coupling Bearing failure
		Bent shaft	
	Overload	Interference	Incorrect assembly Bearing failure
		Operational	
Gear fracture	Fatigue	Life limit exceeded Surface damage	
	Resonance	Design	
Tooth fracture	Bending fatigue	Life limit exceeded	
		Surface damage	Process related Excessive wear Destructive scoring
		Thin tooth	
	Random fracture	Surface damage	Process related Foreign object Pitting/Spalling
		Overload	Interference
		Operational	
Over-heating	Lubrication	Insufficient oil	
		Loss of oil	Oil line failure Filter bowl failure
	Insufficient cooling	Cooling fan failure	Shaft/gear fracture

3.1 Time Domain Analysis: The time domain methods try to analyze the amplitude and phase information of the vibration time signal to detect the fault of gear-rotor-bearing system. The time domain is a perceptive that feels natural, and provides physical insight into the vibration [6]. It is particularly useful in analyzing impulsive signals from bearing and gear defects with non-steady and short transient impulses [7].

3.1.1 Time Waveform Analysis: Prior to the commercial availability of spectral analyzers, almost all vibration analysis was performed in the time domain. By studying the time domain waveform using equipment such as oscilloscopes, oscillographs, or 'vibrographs', it was often possible to detect changes in the vibration signature caused by faults. However, diagnosis of faults was a difficult task; relating a change to a particular component required the manual calculation of the repetition frequency based on the time difference observed between feature points. Waveform analysis can also be useful in identify vibrations that are non synchronous with shaft speed. In machine cost down analysis waveform can indicate the occurrence of resonance. A typical vibration waveform is shown in figure-3.1 for a gearbox. This waveform shows the anomalous behavior of the gear after certain intervals with large magnitude. The peak level, RMS, level, and the crest factor are often used to quantify the time signal.

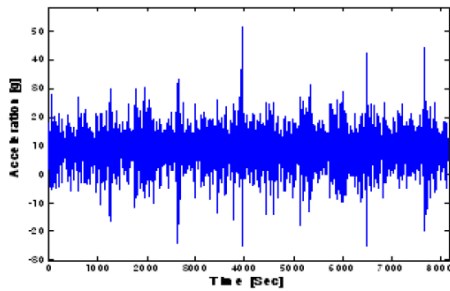


Figure 3.1: A typical waveform of defected gear vibration signal.

3.1.2 Indices: Indices have also been used in vibration analysis [8, 6]. The peak value, RMS level and their ratio crest factor are often used to quantify the time signal. The peak level is not a statistical quantity and hence may not be reliable in detecting damage continuously operating systems. The RMS value, however, is more-satisfactory for steady-state applications. The crest factor, defined as the ratio of the peak value to RMS level, has been proposed as a trending parameter as it includes both parameters. Crest factors are reliable only in the presence of significant impulsiveness.

Peak: The peak level of the signal is defined simply as half the difference between the maximum and minimum vibration levels:

$$peak = Max(A) \dots\dots\dots (3.1)$$

RMS: The RMS (Root Mean Square) value of the signal is the normalized second statistical moment of the signal (standard deviation):

$$RMS = \sqrt{\frac{\sum_{n=1}^N [A(n)]^2}{N}} \dots\dots\dots (3.2)$$

Where, $A(n)$ is the amplitude of the n th digitized point in the time domain, and N is the number of point in time domain.

The RMS of the signal is commonly used to describe the ‘steady-state’ or ‘continuous’ amplitude of a time varying signal.

Crest Factor: The crest factor is defined as the ratio of the peak value to the RMS of the signal:

$$Crest\ Factor = \frac{Peak\ Level}{RMS\ Level} \dots\dots\dots (3.3)$$

3.1.3 Statistical Methods: Statistical analysis can also be carried out on time domain data.

Kurtosis: Kurtosis is the normalized fourth statistical moment of the signal [8]. For continuous time signals this is defined as:

$$K = \frac{\sum_{n=1}^N [y(n) - \mu]^4}{N \times (\sigma^2)^2} \dots\dots\dots (3.4)$$

Where $y(n)$ is the data; $n = 1, 2, 3, \dots, N$; N is the total number of data samples, μ is the mean; and σ is the standard deviation.

The kurtosis level of a signal is used in a similar fashion to the crest factor that is to provide a measure of the impulsive nature of the signal. Raising the signal to the fourth power effectively amplifies isolated peaks in the signal.

Skewness: Skewness is a measure of symmetry, or more precisely, the lack of symmetry. A distribution of data set is symmetric if it looks the same to the left
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and right of the centre point. Equation (3.5) is used to calculate the values of skewness.

$$S = \frac{\sum_{n=1}^N [y(n) - \mu]^3}{N \times (\sigma)^3} \dots\dots\dots (3.5)$$

3.2 Frequency Domain Analysis: The frequency domain methods include Fast Fourier Transform (FFT), Hilbert Transform Method and Power Cepstrum Analysis, etc. They are using the difference of power spectral density of the signal due to the fault of gear and/or bearing to identify the damage of elements [8]. Any real world signal can be broken down into a combination of unique sine waves. Every sine wave separated from the signal appears as a vertical line in the frequency domain. Its height represents its amplitude and its position represents the frequency. The frequency domain representation of the signal is called the signal. The frequency domain completely defines the vibration. Frequency domain analysis not only detects the faults in rotating machinery but also indicates the cause of the defect [6].

Theoretically, time domain can be converted into frequency domain using the Fourier Transforms and vice versa. The Fourier transform is a generalization of the complex Fourier series in the limit as $L \rightarrow \infty$. Replace the discrete A_n with the continuous $F(k)dk$ while letting $n/L \rightarrow k$. Then change the sum to an integral, and the equations become

$$f(x) = \int_{-\infty}^{\infty} F(k) e^{2\pi i k x} dk \dots\dots\dots (3.6)$$

$$F(k) = \int_{-\infty}^{\infty} f(x) e^{-2\pi i k x} dx \dots\dots\dots (3.7)$$

Here, equation (3.7) is called forward (-i) Fourier Transform and the (3.6) is called the inverse Fourier Transform.

3.2.1 Fast Fourier Transformation: The Fast Fourier Transform (FFT) is simply a class of special algorithms which implement the discrete Fourier transform with considerable savings in computational time. It must be pointed out that the FFT is not a different transform from the DFT, but rather just a means of computing the DFT with a considerable reduction in the number of calculations required. The Fast Fourier transform (FFT) is a discrete Fourier transform algorithm which reduces the number of computations needed for N points from $2N^2$ to $2N \log N$, where \log is the base-2 logarithm.

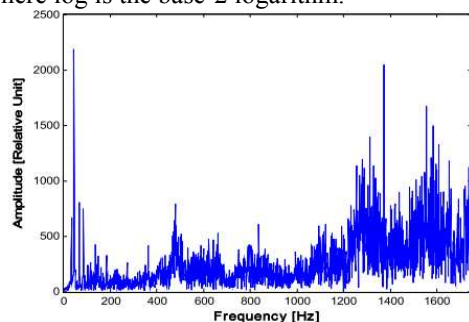


Figure 3.2: A typical FFT Spectrum of defected gear vibration signal.

The vibration characteristics of any rotating machine are to some extent unique, due to the various transfer

characteristics of the machine. In the FFT plot various peaks with large and small are presented corresponding to characteristic frequencies shows the origin of defects. Or we can say FFT shows the frequencies in terms of shaft harmonics. For gear problems, special attention must be given to gear's FFT spectrum's bearing defect frequencies. The spectra of FFT may produce peaks at identified fault frequencies. These peaks may or may not represent the indicated fault. One must look for harmonics to determine if the identified frequencies were generated from the indicated fault.

- If peaks appear at the fundamental fault frequency and also at frequency two times of fundamental frequency, it shows strong indication of reality of fault.
- If no peak appears at the fundamental fault frequency but peaks are present at two, three, and maybe four times of fundamental fault frequency, then this also represents a strong indication that the indicated fault is valid.

FFT for determination of the severity of the fault:

- One way to determine the fault's severity is to compare its amplitude with the past readings taken under consistent conditions.
- Another way is to compare the amplitude to the other readings obtained by similar machines running under same conditions. A higher than normal reading indicates a problem.

3.2.2 Frequency band analysis

Often, the fault detection capability using overall vibration level and/or wave shape metrics can be significantly improve by dividing the vibration signal into a number of frequency bands prior to analysis. This can be done with a simple analogue band-pass filter between the vibration sensor and the measurement device. The rationale behind the use of band-pass filtering is that, even though a fault may not cause a significant change in overall vibration signal (due to masking by higher energy, non-fault related vibrations), it may produce a significant change in a band of frequencies in which the non-fault related vibrations are sufficiently small. For a simple gearbox, with judicious selection of frequency bands, one frequency band may be dominated by shaft vibrations, another by gear tooth-meshing vibrations, and another by excited structural resonances; providing relatively good coverage of all gearbox components.

3.2.3 Spectral Analysis

Spectral (or frequency) analysis is a term used to describe the analysis of the frequency domain representation of a signal. Spectral analysis is the most commonly used vibration analysis technique for condition monitoring in geared transmission systems and has proved a valuable tool for detection and basic diagnosis of faults in simple rotating machinery [26]. Whereas the overall vibration level is a measure of the vibration produced over a broad band of frequencies, the spectrum is a measure of the vibrations over a large number of discrete contiguous narrow frequency bands. The fundamental process common to all spectral analysis techniques is the conversion of a time domain representation of the vibration signal into a frequency domain representation. This can be achieved by the use of

narrow band filters or, more commonly in recent times, using the discrete Fourier Transform (DFT) of digitized data. The vibration level at each 'frequency' represents the vibration over a narrow frequency band centered at the designated 'frequency', with a bandwidth determined by the conversion process employed. For machines operating at a known constant speed, the frequencies of the vibrations produced by the various machine components can be estimated therefore, a change in vibration level within a particular frequency band can usually be associated with a particular machine component. Analysis of the relative vibration levels at different frequency bands can often give an indication of the nature of a fault, providing some diagnostic capabilities. The frequency domain spectrum of the vibration signal reveals frequency characteristics of vibrations if the frequencies of the impulse occurrence are close to one of the gear characteristic frequencies, such as gear frequency, pinion frequency, gear mesh frequency, as shown in equations (3.7 to 3.9). Then it may indicate a defect related fault in the gearbox.

The Gear frequency (F_{rg}) is given by

$$F_{rg} = R_g / 60 \text{ (Hz)} \text{ ----- (3.7)}$$

The Pinion frequency (F_{rp}) is given by

$$F_{rp} = R_p / 60 \text{ (Hz)} \text{ ----- (3.8)}$$

The Tooth Mesh Frequency (F_{rm}) is given by

$$F_{rm} = F_{rp} \times N_p \text{ (Hz) or } F_{rg} \times N_g \text{ (Hz)} \text{ ----- (3.9)}$$

Where: R_g is the speed of gear in rpm, R_p is the speed of pinion in rpm, N_p is the number of teeth on the pinion and N_g is the number of teeth on gear

3.2.4 Conversion to the frequency domain

The frequency domain representation of a signal can be described by the Fourier Transform [9] of its time domain representation

$$X(f) = \int_{-\infty}^{\infty} x(t) e^{-j2\pi ft} dt. \text{ ----- (3.10)}$$

Where $x(t)$ is the original function in time domain, $X(f)$ is the Fourier transform of the function $x(t)$.

The inverse process (Inverse Fourier Transform [9]) can be used to convert from a frequency domain representation to the time domain

$$x(t) = \int_{-\infty}^{\infty} X(f) e^{-j2\pi ft} df. \text{ ----- (3.11)}$$

Where j is the square root of -1 and e denotes the natural exponent. In the above equation, t stands for time, f stands for frequency, and x denotes the signal in frequency domain.

There are a number of limitations inherent in the process of converting vibration data from the time domain to the frequency domain.

3.2.5 FFT Analyzers

Most modern spectrum analyzers use the Fast Fourier Transform (FFT) [10], which is an efficient algorithm for performing a Discrete Fourier Transform (DFT) of discrete sampled data.

The Discrete Fourier Transform is defined as [27]

$$X(m) = \frac{1}{N} \sum_{n=0}^{N-1} x(n) e^{-j2\pi \frac{mn}{N}} \text{ ----- (3.12)}$$

and the Inverse Discrete Fourier Transform [36] is

$$x(n) = \sum_{m=0}^{N-1} X(m)e^{j2\pi \frac{mn}{N}} \text{-----} (3.13)$$

The sampling process used to convert the continuous time signal into a discrete signal can cause some undesirable effects.

3.3 Order Analysis

Order analysis is a technique for analyzing noise and vibration signals in rotating or reciprocating machinery. Some examples of rotating or reciprocating machinery include aircraft and automotive engines, compressors, turbines, and pumps. Such machinery typically has a variety of mechanical parts such as a shaft, bearing, gearbox, blade, coupling, and belt. Each mechanical part generates unique noise and vibration patterns as the machine operates. Each mechanical part contributes a unique component to the overall machine noise and vibration. When performing vibration analysis many sound and vibration signal features are directly related to the running speed of a motor or machine such as imbalance, misalignment, gear mesh, and bearing defects. Order analysis is a type of analysis geared specifically towards the analysis of rotating machinery and how frequencies change as the rotational speed of the machine changes. It resamples raw signals from the time domain into the angular domain, aligning the signal with the angular position of the machine. This negates the effect of changing frequencies on the FFT algorithm, which normally cannot handle such phenomena.

Table 3: Noise or Vibration Characteristics of mechanical faults

Mechanical faults	Vibration components
Imbalance	1x component
Misalignment	1x and 2x components.
Mechanical looseness	Harmonics of 1x and 0.5x components
Resonance	High vibration amplitude and large phase change at certain speed range
Gear defect	Gear mesh <i>n</i> x components (<i>n</i> is the number of gear teeth); usually modulated by rotational speed components.
Rolling-element bearing defect	Non-synchronous vibration components, usually modulated by rotational speed components.

Note: 1x means 1st order component and *n*x means *n*th order component.

A common order analysis application is usually comprised of 5 steps:

- Acquire noise or vibration signals and tachometer signal.
- Preprocess the noise or vibration signals.
- Process the tachometer signal to get the rotational speed profile.
- Perform order analysis with the noise or vibration signals and speed profile.
- Display the analysis results in different formats.

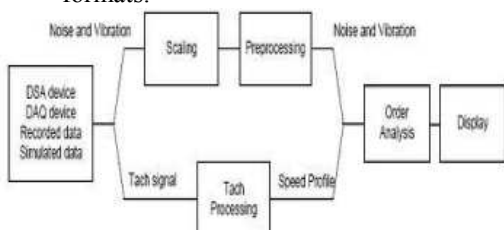


Figure 4.1 Common Order Analysis Application Process

3.4 Time synchronous Averaging

Stewart [11] showed that with ‘time synchronous averaging’ the complex time-domain vibration signal from a transmission could be reduced to estimates of the vibration for individual shafts and their associated gears. The synchronous average for a shaft is then treated as if it were a time domain vibration signal for one revolution of an individual, isolated shaft with attached gears. Time Synchronous Averaging (TSA) is a fundamentally different process than the usual spectrum averaging that is generally used in FFT analysis. While the concept is similar, TSA results in a time domain signal with lower noise than would result with a single sample. An FFT can then be computed from the averaged time signal. The signal is sampled using a trigger that is synchronized with the signal. The averaging process gradually eliminates random noise because the random noise is not coherent with the trigger. Only the signal that is synchronous and coherent with the trigger will persist in the averaged calculation, as shown below. Traditional spectrum based averaging records a frame of data in the time domain, computes the FFT and then adds the FFT spectrum to the averaged spectrum. The time signal is discarded and then the process is repeated until the averaging number is complete. The result is a spectrum with very low noise, but if you examine each time record that is used to compute the FFT spectra, each time record will include the signal of interest plus random noise because the averaging is performed in the frequency domain, not the time domain. Another important application of time synchronous averaging is in the waveform analysis of machine vibration, especially in the case of gear drives. In this case, the trigger is derived from a tachometer that provides one pulse per revolution of a gear in the machine. This way, the time samples are synchronized in that they all begin at the same exact point related to the angular position of the gear. After performing a sufficient number of averages, spectrum peaks that are harmonics of the gear rotating speed will remain while non-synchronous peaks will be averaged out from the spectrum. Two kinds of time synchronous average: time synchronous linear average and time synchronous exponential average.

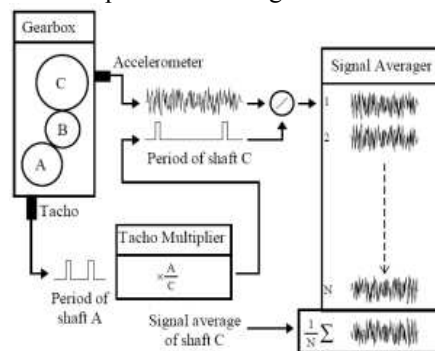


Figure 4.2 Synchronous signal averaging

For time synchronous linear average the spectrum will stop updating when the average number is reached.

T_n = *n*th frame of the time block signal

A_n = *n*th average of the time block signal

N = average number given

For *n* = 1~*N*, *A*1 = *T*1.

A_n = (*A_{n-1}* * (*n-1*) + *T_n*)/*n*

nth frame of the spectrum is calculated from AN .
When the average number N is reached, the averaged time block signal is
 $AN = (AN-1 * (N-1) + TN) / N = (A1 + A2 + A3 + \dots + AN-1 + AN) / N$

The averaged spectrum is calculated from AN .
For time synchronous exponential average: spectrum keeps updating and never stops.

$\alpha = 1/N =$ inverse of the average number N
 T_{cur} = current frame of the time block signal
 A_{cur} = current average of the time block signal
 A_{pre} = previous average of the time block signal

The averaged time block signal is

$$A_{cur} = (1 - \alpha) * A_{pre} + \alpha * T_{cur}$$

The averaged spectrum is calculated from A_{cur} .

Stewart developed a number of non-dimensional parameters based on the synchronous signal average, which he termed 'Figures of Merit' [38]. These were originally defined as a hierarchical group, with which Stewart described a procedure for the detection and partial diagnosis of faults.

3.4.1 FM0

The parameter FM0 was developed by Stewart in 1977 as a robust indicator of major faults in a gear mesh [11]. Major changes in the meshing pattern are detected by comparing the maximum peak-to-peak amplitude of the signal to the sum of the amplitudes of the mesh frequencies and their harmonics. FM0 is given as

$$FM0 = \frac{PPx}{\sum_{n=0}^H P_n} \text{-----} (3.14)$$

where PPx is the maximum peak-to-peak amplitude of the signal x ; P_n is the amplitude of the n th harmonic, and H is the total number of harmonics in the frequency range. Notice that in cases where PPx increases while P_n remains relatively constant, FM0 increases. Also, if P_n decreases while PPx remains constant, FM0 also increases.

3.4.2 FM4

Developed by Stewart in 1977, the parameter FM4 was designed to complement FM0 by detecting faults isolated to only a limited number of teeth [11]. This is accomplished by first constructing the difference signal, d ; given in Eq. (5). The normalized kurtosis of d is then computed. FM4 is given as

$$FM4 = \frac{N \sum_{i=1}^N (d_i - \bar{d})^4}{\left[\sum_{i=1}^N (d_i - \bar{d})^2 \right]^2} \text{-----} (3.15)$$

Where \bar{d} is the mean of the difference signal, and N is the total number of data points in the time signal. FM4 is nondimensional and designed to have a nominal value of 3 if d is purely Gaussian. When higher-order sidebands appear in the vibration signal, FM4 will deviate from this value.

3.4.3 NA4

The parameter NA4 was developed in 1993 by Zakrajsek, Townsend, and Decker at the NASA Lewis Research Center as a general fault indicator which reacts not only to the onset of damage as FM4 does, but also to the continuing growth of the fault [12]. The residual signal r ; given in Eq. (6), is first constructed. The quasi-normalized kurtosis of the residual signal is then computed by dividing the

fourth moment of the residual signal by the square of its run time averaged variance. The run time averaged variance is the average of the residual signal over each time signal in the run ensemble up to the point at which NA4 is currently being calculated. NA4 is given as

$$NA4(M) = \frac{N \sum_{i=1}^N (r_{iM} - \bar{r}_M)^4}{\left\{ \frac{1}{M} \sum_{j=1}^M \left[\sum_{i=1}^N (r_{ij} - \bar{r}_j)^2 \right] \right\}^2} \text{-----} (3.16)$$

Where \bar{r} is the mean of the residual signal, N is the total number of data points in the time signal, M is the number of the current time signal, and j is the index of the time signal in the run ensemble. Like FM4, NA4 is nondimensional and designed to have a nominal value of 3 if r is purely Gaussian.

3.4.4 M6A

The parameter M6A was proposed by Martin in 1989 as an indicator of surface damage on machinery components [13]. The underlying theory is the same as that of FM4. However, it is expected that M6A will be more sensitive to peaks in the difference signal due to the use of the sixth moment. M6A is given as

$$M6A = \frac{N^2 \sum_{i=1}^N (d_i - \bar{d})^6}{\left[\sum_{i=1}^N (d_i - \bar{d})^2 \right]^3} \text{-----} (3.17)$$

Note that in this case, the moment is normalized by the cube of the variance.

3.4.5 M8A

The parameter M8A, also proposed by Martin in 1989, is designed to be yet more sensitive than M6A to peaks in the difference signal [13]. M8A uses the eighth moment normalized by the variance to the fourth power and is given as

$$M8A = \frac{N^3 \sum_{i=1}^N (d_i - \bar{d})^8}{\left[\sum_{i=1}^N (d_i - \bar{d})^2 \right]^4} \text{-----} (3.18)$$

3.4.6 NB4

The parameter NB4 was developed by Zakrajsek, Handschuh and Decker in 1994 as an indicator of localized gear tooth damage [14]. The theory behind NB4 is that damage on just a few teeth will cause transient load fluctuations different from those load fluctuations caused by healthy teeth, and that this can be seen in the envelope of the signal. As with NA4, NB4 uses the quasi-normalized kurtosis. However, instead of the difference signal, NB4 uses the envelope of the signal band-pass filtered about the mesh frequency. The envelope, s is computed using the Hilbert transform and is given by

$$s(t) = \left[[b(t) + i[H(b(t))]] \right] \text{-----} (3.19)$$

Where $b(t)$ is the signal band-pass filtered about the mesh frequency, $H(b(t))$ is the Hilbert transform of $b(t)$; and i is the sample index.

3.4.7 NA4*

The parameter NA4* was developed in 1994 by Decker, Handschuh and Zakrajsek as an enhancement to NA4 [15]. In this case, the denominator of NA4 is statistically modified, i.e. when the variance of the residual signal exceeds a certain statistically

determined value, the averaging stops and the denominator is locked. This modification was made based on the observation that as damage progresses from localized to distributed, the variance of the signal increases significantly, causing the kurtosis to settle back to nominal values after the initial indication of the onset of damage. By normalizing the fourth moment by the variance of a baseline signal from the transmission operating under nominal conditions, NA4* is provided with enhanced trending capabilities. Since it was observed that the variance of a damaged transmission signal is greater than that of a healthy transmission signal, the decision to lock the denominator is made based on an upper limit, L; given by

$$L = \bar{v} + \frac{Z}{\sqrt{N}} \sigma \text{-----} (3.20)$$

Where v is the mean value of previous variances, Z is the probability coefficient usually chosen for a normal distribution, s is the standard deviation of the previous variances, and N is the number of samples. Z for a normal distribution can be found in any introductory statistics text. However, the actual choice of Z should be made based on experimentation as too small a value could lead to an over abundance of false alarms.

3.4.8 Demodulation

The original observation made by Stewart [11] that gear tooth damage causes an increase in the amplitude of the sidebands about the regular meshing components led to further investigations into the nature of the amplitude and phase modulation functions. It was proposed that the vibration signal could be demodulated to obtain separate approximations of the amplitude and phase modulation functions and that these approximations could subsequently be inspected to find early indications of gear damage [16, 17]. This work was further refined by Blunt and Forrester [18] to produce a useful damage indicator referred to as a bulls-eye plot which indicates both amplitude and phase demodulations simultaneously.

4. ADVANCED SIGNAL PROCESSING TECHNIQUES IN VIBRATION ANALYSIS

An overall schema for intellectual diagnostics is presented in Figure 5. Intelligent diagnosis begins with the act of data collection which is followed by feature extraction usually employing the frequency spectra. Feature extraction techniques are widespread and can range from statistical to model based techniques and comprises a variety of signal processing algorithms which includes wavelet transforms. Fault detection and identification is a subsequent step and is further classified in this review into the four categories shown in the figure - these will now be treated separately.

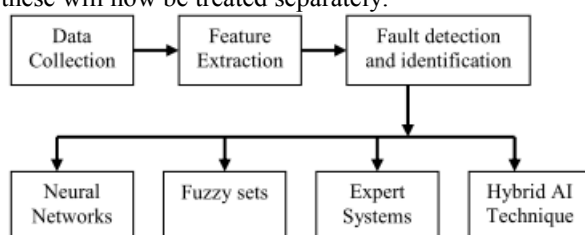


Figure 5: Intelligent fault diagnosis

With the development of soft computing techniques such as artificial neural network (ANN) and fuzzy logic, there is a growing interest in applying these approaches to the different areas of engineering. Artificial Neural Networks (ANN) have become the outstanding method in the recent decades exploiting their non-linear pattern classification properties, offering advantages for automatic detection and identification of gearbox failure conditions, whereas they do not require an in-depth knowledge of the behavior of the system. Recent systems have relied on artificial intelligence techniques to strengthen the robustness of diagnostics systems. Four artificial techniques have been widely applied as expert system, neural networks, fuzzy logic, and model-based systems [16]. Different kinds of artificial intelligence method have become common in fault diagnosis and condition monitoring. For example, fuzzy logic and neural networks have been used in modeling and decision making in diagnostics schemes. Neural networks-based classifications are used in diagnosis of gearbox. Rafiee. J et al, proposed fault detection and identification of gearboxes using a new feature vector extracted from standard deviation of wavelet packet coefficients of vibration signals of various faultless and faulty conditions of a gearbox using ANN. Over and above the structure of ANN, an appropriate feature vector plays a vital role in training a high performance ANN. Ultimately a MLP (Multi-Layer Perceptron) network with a 16:20:5 structure has been used that not only is small in size but also with a 100% perfect accuracy and performance to identify gear failures and detect bearing defects [19].

ANN-based research to carry out the task can be categorized into two distinct groups: fault identification systems with low efficiency which was presented by Kazlas et al [20] to recognize gears and bearings failures of a helicopter gearbox and fault detection systems with high efficiency which is illustrated by Samanta et al. [52] to detect roller-bearing elements defects. Precisely speaking, fault identification proves effective in the case of particular fault classification systems, whereas this may be in conflict with a situation that there is a requirement to a comprehensive fault detection system to provide accordingly precision and promptness. The objective of this research was to develop an ANN-based system with high efficiency and the lowest erroneous outcome to identify faulty gears and detect faulty bearing of a gearbox which has a lot of applications for preventing from fatal breakdowns in rotary machineries. Zhenya et al. proposed a multilayer feed forward network-based machine state identification method. They represent certain fuzzy relationship between the fault symptoms and causes, with highly nonlinearity between the input and the output of the network [21]. Fuzzy logic-based fault diagnosis methods have the advantages of embedded linguistic knowledge and approximate reasoning capability. The Fuzzy logic proposed by Zadeh [22] performs well at qualitative description of knowledge. However, the design of such a system depends heavily on the intuitive experience acquired from practicing operators thus resulting in subjectivity of diagnosed faults. The

fuzzy membership function and fuzzy rules cannot be guaranteed to be optimal in any case. Furthermore, fuzzy logic systems lack the ability of self learning, which is compulsory in some highly demanding real-time fault diagnosis cases [25]. Rough set based intelligence diagnostic systems have been constructed and used in diagnosing valves in three-cylinder reciprocating pumps [24] and turbo generators [25]. Intelligent systems cover a wide range of techniques related to hard science such as modeling and control theory, and soft science such as the artificial intelligence. Intellectual systems, including neural networks, fuzzy logic, and hybrid techniques, utilize the concepts of biological systems and human cognitive capabilities. These three systems have been recognized as a robust and alternative to some of the classical modeling and control methods [24].

5. CONCLUSION

In this paper, authors have been presented a brief review of some current vibration based techniques used for condition monitoring in geared transmission systems. After the review of literature on gear fault analysis, the following points are concluded.

- (i) Gearbox vibration signals are usually periodic and noisy. Time-frequency domain average technique successfully removes the noise from the signal and captures the dynamics of one period of the signals.
- (ii) Time domain techniques for vibration signal analysis as waveform generation, Indices (RMS value, Peak Level value, and crest factor) and overall vibration level do not provide any diagnostic information but may have limited application in fault detection in simple safety critical accessory components. The statistical moment as kurtosis is capable to identify the fault condition but skewness trend has not shown any effective fault categorization ability in this present gear fault condition.
- (iii) Spectral analysis may be useful in the detection and diagnosis of shaft faults.
- (iv) In frequency domain analysis, it is concluded that FFT is not a suitable technique for fault diagnosis if multiple defects are presents on gearbox. The envelope analysis and Power Spectrum Density techniques have shown a better representation for fault identification. The Hilbert Transform and PSD techniques are suitable for multiple point defect diagnostics for condition monitoring.
- (v) Synchronous signal averaging has the potential of greatly simplifying the diagnosis of shaft and gear faults (i.e., the safety critical failures) by providing significant attenuation of non-synchronous vibrations and signals on which ideal filtering can be used. Further development needs to be done on the implementation of synchronous averaging techniques and the analysis of results.
- (vi) Expert system based on ANN and fuzzy logic can be developed for robust fault categorization with the use of extracted features from vibration signal.
- (vii) The results further show that the waveform generation in case of multiple faults at gear

contact surfaces is only useful to find the healthy or faulty condition but not capable to identify the categories of fault.

These conclusions motivate further research to incorporate other parameters and symptoms with vibration features to develop more robust expert systems for diagnose the problem of gear faults signature analysis.

It has been shown that using these ways of vibration signal analysis there are possibilities to detect signal faults and distributed faults in gearboxes. A signal fault is caused by a tooth crack/fracture and breakage, a spall in a gearing or in an inner or outer race of a bearing, a spall on a rolling element of a bearing; distributed faults are caused by uneven wear (pitting, scuffing, abrasion, erosion).

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