An investigation on gearbox fault detection using vibration analysis techniques: A review *

Article *in* Australian Journal of Mechanical Engineering · November 2012

DOI: 10.7158/M11-830.2012.10.2

Amit Aherwar
Madhav Institute of Technology & Science Gwalior

An investigation on gearbox fault detection using vibration analysis techniques: A review*

A Aherwar†
Department of Mechanical Engineering, Madhav Institute of Technology & Science, Gwalior, India

ABSTRACT: *Gears are critical 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 analysis has been used as a predictive maintenance procedure and as a support for machinery maintenance decisions. As a general rule, machines do not breakdown or fail without some form of warning, which is indicated by an increased vibration level. By measuring and analysing the machine's vibration, it is possible to determine both the nature and severity of the defect, and hence predict the machine's failure. 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 analysing the vibration signal using different signal processing techniques. This paper presents a review of a variety of diagnosis techniques that have had demonstrated success when applied to rotating machinery, and highlights fault detection and identification techniques based mainly on vibration analysis approaches. The paper concludes with a brief description of a new approach to diagnosis using neural networks, fuzzy sets, expert system and fault diagnosis based on hybrid artificial intelligence techniques.*

KEYWORDS: Condition monitoring; vibration analysis; fault diagnosis; gearbox.

REFERENCE: Aherwar, A. 2012, "An investigation on gearbox fault detection using vibration analysis techniques: A review", *Australian Journal of Mechanical Engineering*, Vol. 10, No. 2.

1 INTRODUCTION

The ubiquitous of gears in rotating machinery has made the study of vibration a more interesting subject. One study found that 65% of gear box damage is due to faults in the gears (Allianz Versicherungs-AG, 1978). In engineering, they show a considerable number of different forms of damage. The common types of gear damage mainly consist of pitting, scuffing, spalling, cracking and wear (Michel & Miller, 1983). One of the major reasons for gear faults is excessive vibration. Vibration can be thought of as a ratio of the forces acting on the gear to its dynamic stiffness. The backlash, the error of the gear transmission, the unbalanced inertia mass, the time varying mesh stiffness of tooth, the friction between tooth faces and the time varying support stiffness of geared system, change the ratio, ie. vibration which characteristics can reflect symptoms of a lot of faults or defects. The benefit of using vibration analysis for their monitoring and diagnosis has been demonstrated to be successful since the early time because of the ease of measurement. The approaches of gear vibration analysis are mainly subdivided into three categories according to analysis domains. They are time domain, frequency domain and time-frequency domain. The time domain methods include time synchronous average and statistical analysis. The former is a signal averaging process over a large number of cycles, synchronous with the running speed of a specific shaft in the gearbox. It can remove not only the background noise but also periodic events that are not exactly synchronous with the gear being monitored (McFadden, 1989; 1991). The latter consists of many descriptive statistics such as sample skewness, kurtosis and so on. The frequency domain methods include spectral

* Paper M11-830 submitted 13/11/11; accepted for publication after review and revision 5/09/12.

† Corresponding author Amit Aherwar can be contacted at amit22141982@yahoo.com.

analysis based ones such as power spectral density and Cepstrum analysis (Randal, 1982), and higher-order statistics and spectra (Zhang et al, 1999). The time-frequency domain methods are composed of the short-time Fourier transform (STFT), Wigner-Ville, Cohen distribution and wavelet analysis (Wang & McFadden, 1993; Lai et al, 2003). Feature extraction methods play an important role in machine condition monitoring and fault diagnosis, from which the diagnostic information can be obtained. Through gear vibration analysis, a lot of features are acquired, and the next step is optimisation and classification. 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 minimise 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. Nowadays the demands for condition monitoring and vibration analysis are no more limited trying to minimise the consequences of machine failures, but to utilise 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. While 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 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 summarised in table 1.

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

Item	Fault
Gears	Tooth messing 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, vortex shedding

Ebersbach et al (2005) investigated the effectiveness of combining both vibration analysis and wear debris analysis is an integrated machine condition monitoring maintenance program. Decker (2002) proposed two new detection techniques. The time synchronous averaging (TSA) 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 et al (2002) presented 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 et al (2003) demonstrated the use of vibration signature analysis procedures for health monitoring and diagnostics of a gear transmission system. Lin & Zuo (2003) introduced an adaptive wavelet filter based on the Morlet wavelet; the parameters in the Morlet wavelet function are optimised based on the kurtosis maximisation 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: (i) error of design; (ii) application error; and (iii) 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 are presented in table 2. Several researchers have worked on the subject of gearbox defect detection and diagnosis through vibration analysis. Time domain, frequency domain, time frequency domain based on STFT, wavelet transform and advanced signal processing techniques have been implemented and tested.

3.1 Time domain analysis

The time domain methods try to analyse 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 (Forrester, 1996). It is particularly useful in analysing impulsive signals from bearing and gear defects with non-steady and short transient impulses (McFadden, 1987). Time domain vibration signals, if understood properly, can yield enormous amount of information. Identify some characteristics which are not readily observed can be highlighted by this technique. Various time-domain techniques can be used in machine condition monitoring and these are as follows.

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
		Thin tooth	Excessive wear, destructive scoring
	Random fracture	Surface damage	Process related, foreign object, pitting/spalling
	Overload	Interference	Incorrect assembly, bearing failure
		Operational	
Over-heating	Lubrication	Insufficient oil	
		Loss of oil	Oil line failure, filter bowl failure
	Insufficient cooling	Cooling fan failure	Shaft/gear fracture

3.1.1 *Waveform analysis*

Waveform analysis consists of recording the time history of the event on a storage oscilloscope or a real time analyser. Apart from an obvious fundamental appreciation of the signal, it is useful in the study of non-steady conditions and short transient impulses. Waveform analysis can also be useful in identify vibrations that are non-synchronous with shaft speed and in machine coast down analysis waveform can indicate the occurrence of resonance. In machine cost down analysis waveform can indicate the occurrence of resonance. The digitised data of 8202 samples is used to transfer in time domain signature with the help of MATLAB algorithms of 1.934 seconds time length. Figure 1 shows the waveform (sample time record) of vibration signals of defected gearbox.

3.1.2 *Indices*

Indices are also used in vibration analysis (Braun, 1986; Forrester, 1996). The peak value, root-mean-square (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. Typical values of crest factors for gear in a good condition range from 3.5 to 4.0, and values for gear with impulsive defects are higher, ranging up to ~10.0. Generally crest factors higher than 4.5 are indicative of damage. Crest factor values of a vibration signal are relatively insensitive to operating speed and gear load, provided that sufficient speed is maintained to generate a gear vibration which is above the background noise level, and sufficient load is applied to maintained full contact. At higher operating speed, both the peak and RMS values increase proportionally, giving a relatively constant crest factor. In the absence of significant impulsiveness, the reliability of the crest factor technique to detect gear damage breaks down.

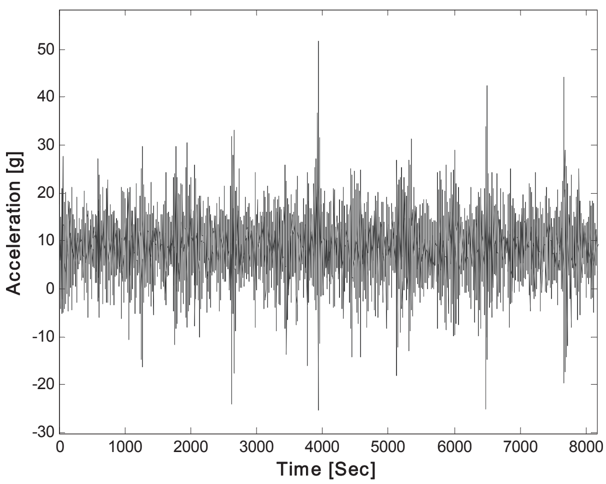

Figure 1: A typical waveform of vibration for duration of 1.934 seconds of defected gearbox.

$$\text{Peak value} = A_{\max} \tag{1}$$

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

Here $A_{\max}$ = maximum amplitude value in the time domain; $A(n)$ = amplitude of the n^{th} digitised point in the time domain; and N = number of points in the time domain.

The simplest approach to measuring defects in the time domain is using the RMS approach. However, the RMS level may not show appreciable changes in the early stages of gear and bearing damage. A better measure is to use "crest factor", which is defined as the ratio of the peak level of the input signal to the RMS level. Therefore, peaks in the time series signal will result in an increase in the crest factor value. This feature is used to detect changes in the signal pattern due to impulsive vibration sources such as tooth breakage on a gear or a defect on the outer race of a bearing. The crest factor feature is not considered a very sensitive technique. Below is the equation for the crest factor:

$$\text{Crest factor} = \text{Peak level}/\text{RMS level} \tag{3}$$

3.13 *Statistical methods*

Statistical analysis can also be carried out on time domain data. The probability density is the probability of finding instantaneous values within a certain amplitude interval, divided by the size of the interval. All signals will have a characteristic probability density curve. These curves if derived from machinery vibration signals can subsequently be used in machine condition monitoring.

3.1.3.1 Probability density moments

The shape of the probability density curve can be described by a series of single-number indices. These are the moments of the curve and are analogues to mechanical moment about the centroid of a plane.

3.1.3.2 Kurtosis (*K*)

Kurtosis, as explained in equation (4), is defined as the fourth moment of the distribution and measures the relative peakedness or flatness of a distribution as compared to a normal distribution (Braun, 1986). Kurtosis provides a measure of the size of the tail of distribution and is used as an indicator of major peaks in a set of data. As a gear wears and breaks this feature should indicate an error due to the increased level of vibration. The equation for kurtosis is given by:

$$K = \frac{\sum_{n=1}^{N}\left[y(n)-\mu\right]^4}{N\sigma^4} \tag{4}$$

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

3.1.3.3 Skewness (*S*)

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 and right of the centre point. Equation (5) is used to calculate the values of skewness.

$$S = \frac{\sum_{n=1}^{N}\left[y(n)-\mu\right]^3}{N\sigma^3} \tag{5}$$

3.2 Frequency domain analysis

The frequency domain methods include fast Fourier transform (FFT), Hilbert Transform Method and Power Cepstrum Analysis. They use the difference of power spectral density of the signal due to the fault of gear and/or bearing to identify the damage of elements (Braun, 1986). 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 (Forrester, 1996).

3.2.1 Fourier transform

Fourier transform is a mathematical approach used to express any deterministic periodic and non-periodic function by an infinite series of sum of periodic exponential functions. The purpose of using Fourier transform is to obtain the frequency components of the vibration signal and to present it in frequency domain. The Fourier transform can be expressed by equation (6):

$$X(f) = \int_{-\infty}^{\infty} x(t)e^{-j2\pi ft}dt \tag{6}$$

where $x(t)$ is the original function in time domain; $X(f)$ is the Fourier transform of the function $x(t)$; j is the square root of –1; and e denotes the natural exponent.

The inverse transform is:

$$x(t) = \int_{-\infty}^{\infty} X(f)e^{j2\pi ft}df \tag{7}$$

In the above equations, t stands for time, f stands for frequency and x denotes the signal at hand. Note that x denotes the signal in time domain and the X denotes the signal in frequency domain. This conversion is used to distinguish the two representations of the signal. Equation (6) is called the Fourier transform of $x(t)$, and equation (7) is called the inverse Fourier transform of $X(t)$, which is $x(t)$.

The signal $x(t)$ is multiplied with an exponential term $e^{-2\pi ft}$, at some certain frequency f and then integrated over all times.

The exponential term $e^{-2\pi ft}$ can also be written as equation (8):

$$\cos(2\pi ft) + j\sin(2\pi ft) \tag{8}$$

The above expression has a real part of cosine of frequency f, and an imaginary part of sine of frequency f. In equation (6), multiplication of the original signal with a complex expression, which has sins and cosines of frequency f, is done. Then this product is integrated. In other words, addition of all the points in this product is done. If the result of this integration (which is nothing but some sort of infinite summation) is a large value then, the signal $x(t)$, has a dominant spectral component at frequency f. This means that, a major portion of this signal is composed of frequency f. If the integration result is a small value, than this means that the signal does not have a major frequency component of f in it. If this integration result is zero, then the signal does not contain the frequency f at all.

3.2.1.1 Discrete Fourier transform

If the signal (function) is in discrete time form, the discrete Fourier transform (DFT) process can be used to analyse it. DFT can be expressed by equation (9):

$$X(m) = \frac{1}{N}\sum_{n=0}^{N-1} x(n)e^{-j2\pi mn/N} \tag{9}$$

For $m = 0, 1, 2, ..., N–1$. This is the N-point DFT for the time series $x(n)$ for $n = 0, 1, 2, ..., N–1$, where N is the total number of sample in a given time record, $x(n)$ is the discrete time function and $X(m)$ is the DFT of the function.

The DFT algorithm is the basis of digital signal analysis with N^2 complex multiplications required to establish a single N-point transform. If averaging is required over M time signals, then MN^2 calculations are required. The FFT algorithm significantly reduces the number of computations that are required; it is essentially a more efficient procedure for evaluating a DFT. While the DFT transform above can be applied to any complex valued series, in practice for a large series it can take considerable time to compute, the time being proportional to the square of the number of points in the series. The much faster FFT algorithm was developed by Cooley & Tukey (1965). The only requirement of the most popular implementation of this algorithm (Radix-2 Cooley-Tukey) is that the number of points in the series be a power of 2. The computing time for the FFT is proportional to $N\log_2(N)$. So, for example, a transform on 1024 points using the DFT takes about 100 times longer than using FFT, a significant speed increase.

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 large and small peaks 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 the 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 peak appears at the fundamental fault frequency and another peak appears at two times the fundamental frequency, it is a very strong indication that the fault is real.
- If no peak appears at the fundamental fault frequency, but peaks are present at two, three and maybe four times the fundamental fault frequency, then this also represents a strong indication that the indicated fault is valid.

Figure 2(a) shows the spectrum of defected gear vibration signal. In this figure, the peaks are found at F_m and its second multiple frequencies, but there are some other peaks due to modulation effect of the signal. In figure 2(b) the peaks are found at Fr_g and Fr_p, and its second and third multiple frequency, but there are some other peaks due to modulation effect of signal. These peaks show a strong indication that the gear is in faulty condition and the nature of fault is chipped tooth pitch to the top at 2% thickness.

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*

Pass band analysis is yet another technique of reducing the quantity of data made available in a spectrum to manageable proportions. The technique involves monitoring only a band of frequencies either broad or narrow, in which defect frequencies

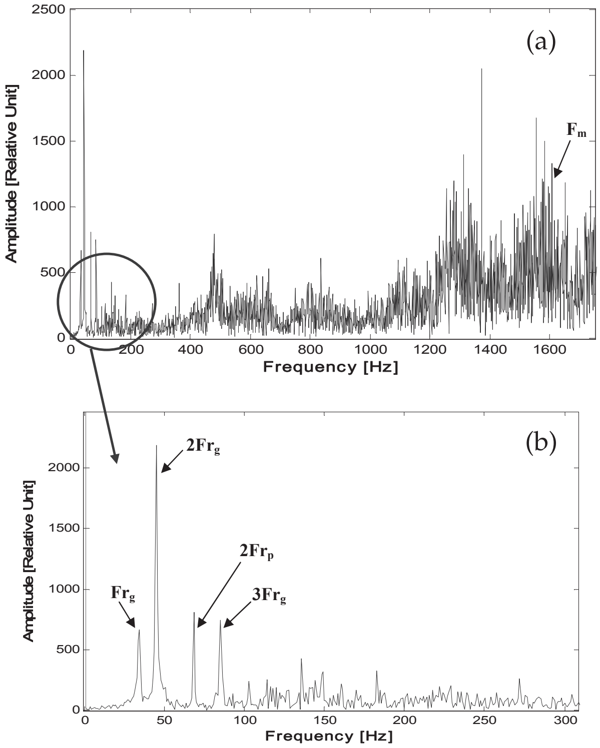

Figure 2: (a) A typical FFT spectrum of defected gear vibration signal. (b) Zoom view of a typical FFT spectrum of defected gear vibration signal.

of components are anticipated known as discrete frequency monitoring. The frequency of interest in the detection of bearing faults is the modulating frequencies because the resonant frequency of housing is high and the number of spectral lines typically limited, it is difficult if not possible to resolve sidebands. Pass band technique allow one to get a direct measure of the frequency of the modulating signal. The purpose of band pass filtering is to reject the low frequency high amplitude signals associated with unbalance, misalignment, looseness and to eliminate random noise. The filter design can be design by defining the transfer function. Filtering in the frequency domain is an operation in which the frequency components to be further analysed is multiplied by unity and other frequency components are multiplied by zero. Mathematically, we can define filter function as follows by equation (10):

$$H(\omega) = \begin{cases} 1, & \omega_1 < \omega < \omega_2 \\ 0, & \text{otherwise} \end{cases} \qquad (10)$$

Therefore band pass filtering technique is employed in this section to extract the features of the defected gearbox for further fault categorisation. There are various types of filters are available, such as Bessel, Butterworth, Chebyshev and Elliptic. The Elliptic filters offer steeper roll-off characteristics than then Butterworth or Chebyshev filters, but are equi-ripple in both the pass and stop bands. In general, Elliptic filters meet given performance specifications with the lowest order of any filter type.

3.2.3 Spectral analysis

The simple spectral analysis is generally unable to detect gear failures at an early stage; for this reason, many researchers have proposed the application of other vibration analysis techniques for the early detection of fault symptoms. 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 (Dalpiaz et al, n.d.). 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 DFT of digitised data. The vibration level at each "frequency" represents the vibration over a narrow frequency band centred 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 (11) to (13). Then it may indicate a defect related fault in the gearbox.

The gear frequency (Fr_g) is given by:

$$Fr_g = R_g/60 \text{ [Hz]} \tag{11}$$

The pinion frequency (Fr_p) is given by:

$$Fr_p = R_p/60 \text{ [Hz]} \tag{12}$$

The tooth mesh frequency (Fr_m) is given by:

$$Fr_m = Fr_p N_p \text{ [Hz] or } Fr_g N_g \text{ [Hz]} \tag{13}$$

where R_g is the speed of gear [rpm], R_p is the speed of pinion [rpm], N_p is the number of teeth on the pinion, and N_g is the number of teeth on the gear.

3.3 Order analysis

Order analysis is a technique for analysing 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. This technique is suitable for analysing noise and vibration signals when the rotational speed changes over time. Order is defined as the normalisation of the rotational speed. The first order is the rotational speed and order n is n-times the rotational speed. Order components are the vibration harmonics of the rotational speed. In the case of the PC fan, the shaft vibration is the first order vibration. The coil and blade vibrations are the fourth and seventh order vibrations, respectively. In general, order analysis techniques relate noise and vibration signals the rotational speed. Order analysis techniques also reduce these signals into characteristic components, associate these components to mechanical parts, and provide repeatable noise and vibration measurements. You can obtain information about individual mechanical parts as well as the entire machine with order analysis. 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.

Rotating or reciprocating machines are comprised of a variety of mechanical parts like shaft, bearing, gearbox, coupling etc. The conditions of the mechanical parts mainly determine the overall machine conditions. If the mechanical parts of the machine are well tuned, ideally the machine will generate very low vibrations. On the contrary, the existing flaws in mechanical parts will usually cause the machine to vibrate significantly. Therefore, the machine vibrations can be used as good indicators of the mechanical faults. Common mechanical faults like imbalance, misalignment, mechanical looseness, bearing fault, resonance, gearbox defects have specific vibration characteristics. Table 3 summarises the relationships between the common mechanical faults and vibration components.

Table 3: Noise or vibration characteristics of mechanical faults.

S. No.	Mechanical faults	Vibration components
1	Imbalance	$1x$ component
2	Misalignment	$1x$ and $2x$ components.
3	Mechanical looseness	Harmonics of $1x$ and $0.5x$ components
4	Resonance	High vibration amplitude and large phase change at certain speed range
5	Gear defect	Gear mesh nx components (n is the number of gear teeth), usually modulated by rotational speed components
6	Rolling-element bearing defect	Non-synchronous vibration components, usually modulated by rotational speed components
Note: $1x$ means first-order component and nx means n^{th} order component.		

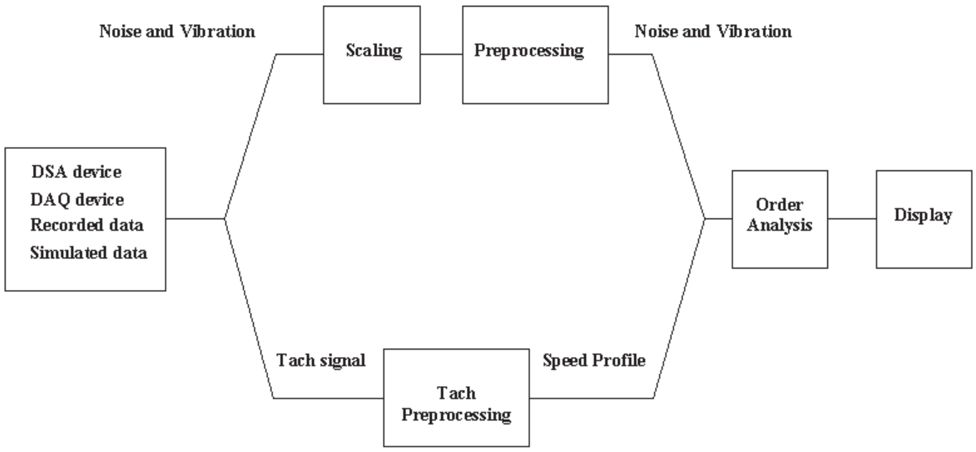

Figure 3: Common order analysis application process.

The noise and vibration components of the possible mechanical faults are usually the most important information of the machine. The key tasks in noise and vibration analysis in most applications are to extract the patterns from the noise and vibrations signals and evaluate the condition of the mechanical parts with the patterns. The order analysis can help you to get those characteristic components.

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

1. acquire noise or vibration signals and tachometer signal
2. pre-process the noise or vibration signals
3. process the tachometer signal to get the rotational speed profile
4. perform order analysis with the noise or vibration signals and speed profile
5. display the analysis results in different formats.

3.4 Time synchronous averaging

Stewart (1977) showed that with TSA 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. 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 fundamental principle behind synchronous signal averaging is that all vibration related to a shaft, and the gears on that shaft, will repeat periodically with the shaft rotation. By dividing the vibration signal into contiguous segments, each being exactly one shaft period in length, and ensemble averaging a sufficiently large number of segments, the vibration which is periodic with shaft rotation will be reinforced and vibrations which are not periodic with the shaft rotation will tend to cancel out; leaving a signal which represents the average vibration for one revolution of the shaft. Figure 4 illustrates how this process might be performed on a continuous time signal from a gearbox, using a tacho multiplier to calculate each rotational period of the shaft. The process illustrated in figure 4 assumes the vibration signal being averaged is a continuous time signal. In practice, the signal averaging process

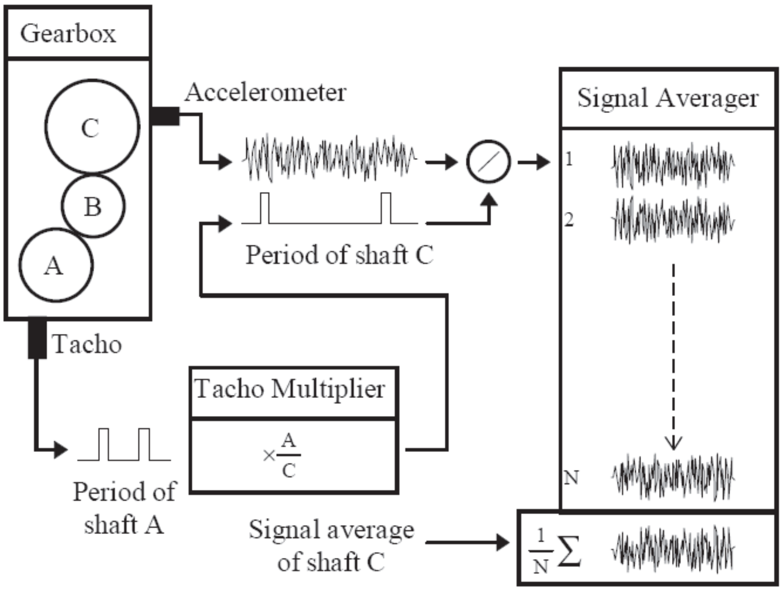

Figure 4: Synchronous signals averaging.

usually takes place on a discrete sampled signal (eg. via an analogue-to-digital converter in a PC) and, in addition to defining the start and end points of the shaft rotation, some mechanism is needed to ensure that the sample points are at equally spaced angular increments of the shaft and that these are at the same angular position for each revolution of the shaft. That is, the sampling must be coherent with the rotation of the shaft. Originally, Stewart (1977) used a phase-locked frequency multiplier, however, McFadden (1986c) showed that far greater accuracy and flexibility could be achieved using digit resampling of time-sampled vibration based on a reference derived from a simultaneously time sampled tacho signal.

The principle of synchronising the averaging with some other process (in this case the rotational frequency of a shaft) is fundamental to the technique; whether it is per formed on continuous or discrete signals. As was seen above, when the process is performed on discrete signals the sampling must be coherent with the rotation of the shaft (hence the term "coherent rotational signal averaging" used by Swansson et al). Note that the process can be performed in the time or frequency domain (as long as the frequency domain averaging is performed on the complex frequency domain representation). The term "time domain averaging" (McFadden, 1986b; Braun, 1975) was used to distinguish the technique from that of averaging of amplitude or power spectra to reduce variance in spectral analysis (Randall, 1987). To properly describe the process when applied to discrete signals, it should probably be referred to as "rotationally coherent synchronous signal averaging". However, this is quite clumsy and therefore the technique will normally be referred to as "synchronous signal averaging" (the rotational coherency being implied when the technique is applied to discrete data).

The signal is sampled using a trigger that is synchronised 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 TSA 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 synchronised 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.

For time synchronous linear average, the spectrum will stop updating when the average number is reached. The n^{th} frame of the spectrum is calculated from A_n.

$$A_n = (A_{n-1}(n-1) + T_n)/n \tag{14}$$

for $n = 1 \sim N$ and $A_1 = T_1$, where $A_n = n^{th}$ average of the time block signal, $T_n = n^{th}$ frame of the time block signal, and N = average number given.

When the average number N is reached, the averaged time block signal is:

$$A_N = (A_{N-1}(N-1) + T_N)/N = (A_1 + A_2 + A_3 + \ldots + A_{N-1} + A_N)/N \tag{15}$$

The averaged spectrum is calculated from A_N.

For time synchronous exponential average, the spectrum keeps updating and never stops. The averaged time block signal is:

$$A_{cur} = (1-\alpha)A_{pre} + \alpha T_{cur} \tag{16}$$

The averaged spectrum is calculated from A_{cur}, which is the current average of the time block signal. $\alpha = 1/N$ = inverse of the average number N, T_{cur} = current frame of the time block signal, and A_{pre} = previous average of the time block signal.

Stewart (1977) developed a number of non-dimensional parameters based on the synchronous signal average, which he termed "Figures of Merit" (McFadden, 1986b). 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 FM*0*

The parameter *FM*0 was developed by Stewart (1977) as a robust indicator of major faults in a gear mesh. 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. *FM*0 is given as:

$$FM0 = \frac{PP_x}{\sum_{n=0}^{H} P_n} \tag{17}$$

where PP_x 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 PP_x increases while P_n remains relatively constant, FM0 increases. Also, if P_n decreases while PP_x remains constant, *FM*0 also increases.

3.4.2 FM*4*

Developed by Stewart (1977), the parameter *FM*4 was designed to complement *FM*0 by detecting faults isolated to only a limited number of teeth. This is accomplished by first constructing the difference signal, d, given in equation (18). The normalised kurtosis of d is then computed. *FM*4 is given as:

$$FM4 = \frac{N\sum_{i=1}^{N}(d_i - \bar{d})^4}{\left[\sum_{i=1}^{N}(d_i - \bar{d})^2\right]^2} \tag{18}$$

where $\bar{d}$ is the mean of the difference signal and N is the total number of data points in the time signal. *FM*4 is non-dimensional and designed to have a nominal value of 3 if d is purely Gaussian. When higher-order sidebands appear in the vibration signal, *FM*4 will deviate from this value.

3.4.3 NA*4*

The parameter *NA*4 was developed by Zakrajsek (1994) as a general fault indicator that reacts not only to the onset of damage as *FM*4 does, but also to the continuing growth of the fault. The residual signal r, given in equation (19), is first constructed. The quasi-normalised 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 *NA*4 is currently being calculated. *NA*4 is given as:

$$NA4(M) = \frac{N\sum_{i=1}^{N}(r_{iM} - \bar{r}_M)^4}{\left\{\frac{1}{M}\sum_{j=1}^{M}\left[\sum_{i=1}^{N}(r_{ij} - \bar{r}_j)^2\right]\right\}^2} \tag{19}$$

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 *FM*4, *NA*4 is non-dimensional and designed to have a nominal value of 3 if r is purely Gaussian.

3.4.4 M6*A*

The parameter *M6*A was proposed by Martin (1989) as an indicator of surface damage on machinery components. The underlying theory is the same as that of *FM*4. However, it is expected that *M6*A will be more sensitive to peaks in the difference signal due to the use of the sixth moment. *M6*A is given as:

$$M6A = \frac{N^2\sum_{i=1}^{N}(d_i - \bar{d})^6}{\left[\sum_{i=1}^{N}(d_i - \bar{d})^2\right]^3} \tag{20}$$

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

3.4.5 M8*A*

The parameter *M8*A, also proposed by Martin (1989), is designed to be yet more sensitive than *M6*A to peaks in the difference signal. *M8*A uses the eighth moment normalised by the variance to the fourth power and is given as:

$$M8A = \frac{N^3\sum_{i=1}^{N}(d_i - \bar{d})^8}{\left[\sum_{i=1}^{N}(d_i - \bar{d})^2\right]^4} \tag{21}$$

3.4.6 NB*4*

The parameter *NB*4 was developed by Zakrajsek (1994) as an indicator of localised gear tooth damage.

The theory behind *NB*4 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 *NA*4, *NB*4 uses the quasi-normalised kurtosis. However, instead of the difference signal, *NB*4 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:

$$s(t) = \left\| \left[b(t) + i\left[H(b(t)) \right] \right] \right\| \tag{22}$$

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 *NA*4* was developed in by Decker et al (1994) as an enhancement to *NA*4. In this case, the denominator of *NA*4 is statistically modified, ie. 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 localised 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 normalising the fourth moment by the variance of a baseline signal from the transmission operating under nominal conditions, *NA*4* 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:

$$L = \overline{v} + \frac{Z}{\sqrt{N}}\sigma \tag{23}$$

where $\overline{v}$ is the mean value of previous variances, Z is the probability coefficient usually chosen for a normal distribution, σ is the standard deviation of the previous variances, and N is the number of samples. For a normal distribution, Z 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 overabundance of false alarms.

3.4.8 Demodulation

The original observation made by Stewart (1977) 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 (McFadden, 1986a; Cempel & Staszewski, 1992). This work was further refined by Blunt & Forrester (1985) 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.

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. ANNs 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 behaviour 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 (McFadden, 1986a). 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 modelling and decision making in diagnostics schemes. Neural networks-based classifications are used in diagnosis of gearbox. Rafiee et al (2007) proposed fault detection and identification of gearboxes using a new feature vector extracted from

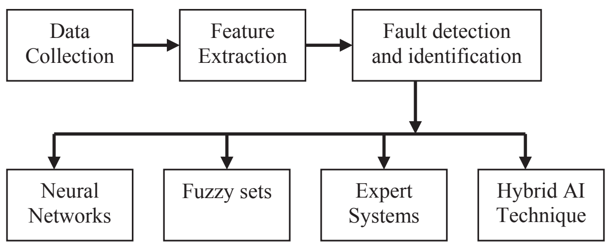

Figure 5: Intelligent fault diagnosis.

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 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 (Rafiee et al, 2007).

ANN-based research to carry out the task can be categorised into two distinct groups: fault identification systems with low efficiency, which was presented by Kazlas et al (1993) to recognise gears and bearings failures of a helicopter gearbox; and fault detection systems with high efficiency, which was illustrated by Samanta & Al-Balushi (2003) 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 (1992) proposed a multilayer feed-forward network-based machine state identification method. They represented certain fuzzy relationships between the fault symptoms and causes, with highly non-linearity between the input and the output of the network (Zhenya et al, 1992). Fuzzy logic-based fault diagnosis methods have the advantages of embedded linguistic knowledge and approximate reasoning capability. The fuzzy logic proposed by Zadeh (1965) 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 (Hu et al, 2000). Rough set-based intelligence diagnostic systems have been constructed and used in diagnosing valves in three-cylinder reciprocating pumps (Liu & Shi, 2001) and turbo generators (Hu et al, 2000).

Intelligent systems cover a wide range of techniques related to hard science, such as modelling and control theory, and soft science, such as the artificial intelligence. Intellectual systems, including neural networks, fuzzy logic, and hybrid techniques, utilise the concepts of biological systems and human cognitive capabilities. These three systems have been recognised as a robust and alternative to some of the classical modelling and control methods (Liu & Shi, 2001).

5 CONCLUSIONS

This paper has 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:

- 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.
- 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 categorisation ability in this present gear fault condition.
- Spectral analysis may be useful in the detection and diagnosis of shaft faults.
- In frequency domain, FFT was able to show the impulses at fault characteristics frequencies and its multiple frequencies but other peaks are also presents due to signal modulation effect. By this technique identification of fault categories is difficult.
- In band pass analysis of gear vibration signals it is found that the technique is feasible for feature extraction for fault diagnostics. It has been concluded that RMS value of filtered signal in three frequency bands can be valuable feature to develop intelligent system with the use of TSA.
- Synchronous signal averaging has the potential of greatly simplifying the diagnosis of shaft and gear faults (ie. 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 done on the implementation of synchronous averaging techniques and the analysis of results.
- Expert system based on ANN and fuzzy logic can be developed for robust fault categorisation with the use of extracted features from vibration signal.
- 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).

ACKNOWLEDGEMENTS

The author is pleased to acknowledge the support of Madhav Institute of Technology and Science (MITS), Gwalior, India, for providing the facility of literature review. A special thanks to Prof Pratesh Jayaswal, Reader, Mechanical Engineering Department, MITS Gwalior, India, for the motivation and guidance throughout the study.

REFERENCES

Allianz Versicherungs-AG, 1978, *Handbook of Loss Prevention*, Springer-Verlag, Berlin.

Blunt, D. M. & Forrester, B. D. 1995, "Health monitoring of blackhawk and seahawk main transmissions using vibration analysis", *Proceedings of the Sixth Australian Aeronautical Conference/Second Pacific International Conference on Aerospace Science and Technology*, Melbourne, Australia.

Braun, S. 1975, "The Extraction of periodic waveforms by Time domain Averaging", *Acustica*, Vol. 32, pp. 69-77.

Braun, S. (editor), 1986, *Mechanical Signature Analysis – Theory and applications*, Academic Press Inc., London, UK.

Cempel, C. & Staszewski, W. J. 1992, "Signal demodulation techniques in vibroacoustical diagnostics of machinery", *Machine Dynamics Problems*, Vol. 5, pp. 161-173.

Choy, F. K. et al 2003, "Damage Identification of a Gear Transmission Using Vibration Signatures", *Journal of Mechanical Design*, Vol. 125, pp. 394-403.

Cooley, J. W. & Tukey, J. W. 1965, "An Algorithm for the Machine Calculation of Complex Fourier Series", *Mathematics of Computing*, Vol. 19, pp. 297-301.

Dalpiaz, G. et al n.d., "Gear fault monitoring comparison of vibration analysis techniques", *Italian National Research Council*, pp. 623-632.

Decker, H. J. 2002, "Gear crack detection using tooth analysis at NASA Research Center".

Decker, H. J., Handschuh, R. F. & Zakrajsek, J. J. 1994, "An enhancement to the NA4 gear vibration diagnostic parameter", Technical Report NASA TM-106553, ARL-TR-389, NASA and the US Army Research Laboratory, July.

Ebersbach et al, 2005, "The investigation of the condition and faults of a spur gearbox using vibration and wear debris analysis techniques", *International Conference on Wear of Materials*, Vol. 260, pp. 16-24.

Forrester, B. D. 1996, "Advanced Vibration Analysis Techniques for Fault Detection and Diagnosis in Geared Transmission Systems", PhD Thesis, Swinburne University of Technology, Australia.

Gao, X. Z. & Ovaska, S. J. 2001, "Soft computing methods in motor fault diagnosis", *Applied Soft Computing*, Vol. 1, No. 1, pp. 73-81.

Hu, T., Lu, B.C. & Chen, G. J. 2000, "A Rotary Machinery Fault Diagnosis Approach Based on Rough Set Theory", *3rd World Congress on Intelligent Control and Automation*, Hefei, China, pp. 589-685.

Kazlas, P. T., Monsen, P. T. & LeBlanc, M. J. 1993, "Neural network-based helicopter gearbox health monitoring system", *Neural Networks for Signal Processing, Proceedings of the IEEE-SP Workshop*, 6-9 September, pp. 431-440.

Lai, W., Xuan, J., Shi, T. & Yang, S. 2003, "Research of Vigner-Ville Time Frequency and Application in Detecting Gear Pinion Fault", *Journal of Vibration Engineering*, Vol. 16, pp. 247-250.

Lin, J. & Zuo, M. J. 2003, "Gear box fault diagnosis using adaptive wavelet filter", *Mechanical Systems and Signal Processing*, Vol. 17, No. 6, pp. 1259-1269.

Liu, S. & Shi, W. 2001, "Rough set based intelligence diagnostic system for valves in reciprocating pumps", *IEEE International Conference on Systems, Man, and Cybernetics*, Dept. of Mech. Eng., Daqing Pet. Inst., Heilongjiang, China, Vol. 1, pp. 353-358.

Martin, H. R. 1989, "Statistical moment analysis as a means of surface damage detection", *Proceedings of the Seventh International Modal Analysis Conference*, Society for Experimental Mechanics, Schenectady, NY, pp. 1016-1021.

McFadden, P. D. 1986a, "Detecting fatigue cracks in gears by amplitude and phase demodulation of the meshing vibration", *Journal of Vibration, Acoustics, Stress, and Reliability in Design*, Vol. 108, pp. 165-170.

McFadden, P. D. 1986b, "A model for the extraction of periodic waveforms by time domain averaging", Aero Propulsion Technical Memorandum 437, Department of Defence, Aeronautical Research Laboratory, March.

McFadden, P. D. 1986c, "Interpolation techniques for the time domain averaging of vibration data with application to helicopter gearbox monitoring", Aero Propulsion Technical Memorandum 437, Department of Defence, Aeronautical Research Laboratory, September.

McFadden, P. D. 1987, "A revised model for the extraction of periodic waveforms by time domain averaging", *Mechanical Systems and Signal Processing*, Vol. 1, No. 1, pp. 83-95.

McFadden, P. D. 1989, "Interpolation Techniques for Time Domain Averaging of Gear Vibration", *Mechanical Systems and Signal Processing,* Vol. 3, pp. 87-97.

McFadden, P. D. 1991, "A Technique for Calculating the Time Domain Averages of the Vibration of the Individual Planet Gears and Sun Gear in an Epicyclic Gearbox", *Journal of Sound and Vibration*, Vol. 144, pp. 163-172.

Michel, A. N. & Miller, R. K. 1983, *Gears and Their Vibration*, Marcel Dekker, Inc.

Oppenheim, A. V. & Schafer, R. W. 1975, *Digital Signal Processing*, Prentice Hall International.

Polyshchuk, V. V. et al 2002, "Gear fault detection with time frequency based parameter NP4", *International Journal of Rotating Machinery*, Vol. 8, No. 1, pp. 57-70.

Rafiee, J. et al 2007, "Intelligent condition monitoring of a gearbox using artificial neural network", *Mechanical Systems and Signal Processing*, Vol. 21, pp. 1746-1754.

Randal, R. B. 1982, "A New Method of Modeling Gear Faults", *Journal of Mechanical Design*, Vol. 104, pp. 259-267.

Randall, R. B. 1987, *Frequency Analysis*, 3rd edition, Brüel and Kjær.

Samanta, B. & Al-Balushi, K. R. 2003, "Artificial neural network based fault diagnostics of rolling element bearings using time-domain features", *Mech. Systems and Signal Processing*, Vol. 17, No. 2, pp. 317-328.

Stewart, R. M. 1977, "Some useful analysis techniques for gearbox diagnostics", Technical Report MHM/R/10/77, Machine Health Monitoring Group, Institute of Sound and Vibration Research, University of Southampton, July.

Wang, W. J. & McFadden, P. D. 1993, "Early Detection of Gear Failure by Vibration Analysis I. Calculation of the Time-Frequency Distribution", *Mechanical Systems and Signal Processing*, Vol. 7, pp. 82-192.

Zadeh, L. A. 1965, "Fuzzy sets", *Information and Control*, Vol. 8, pp. 338-353.

Zakrajsek, J. J. 1994, "A review of transmission diagnostics research at NASA Lewis Research Center", Technical Report NASA TM-106746, ARL-TR-599, NASA and the US Army Research Laboratory, December.

Zhang, G., Shi, T., Xuan, J. & Yang, S. 1999, "Classification of Gear Faults Using RBF Network Combined with Higher-order Statistics", *China Mechanical Engineering*, Vol. 11, pp. 1250-1252.

Zhenya, H., Meng, W. & Bi, G. 1992, "Neural network and its application on machinery fault diagnosis", *Proceedings of the IEEE International Conference on Systems Engineering*, Kobe, Japan, September, pp. 576-579.

AMIT AHERWAR

Amit Aherwar received his BE degree in Mechanical Engineering and M-Tech degree in Production Engineering from the Rajiv Gandhi Technical University, Bhopal, Madhya Pradesh, India, in 2006 and 2010, respectively. He is currently an Assistant Professor in the Department of Mechanical Engineering, Anand Engineering College (SGI) Agra (UP), India. His current research interests are condition monitoring, machine fault signature analysis, and application of AI and fuzzy techniques in mechanical systems.