CHAPTER 1

INTRODUCTION

1.1 Condition Monitoring and Fault Diagnosis of Gearbox

Machine condition monitoring and fault diagnostics of Gearbox is the activity in which selected physical parameters associated with machinery are observed for the purpose of determining machine condition and detecting the fault.

1.1.1 Importance of Gearbox

Gearbox [1] is one of the complex machinery and is a critical component in mechanical power transmission system. Gearboxes have wide applications in automobile, cement, petrochemical, power, paper & pulp, steel and sugar industries. The gear drives are the most effective means of transmitting power in machines due to their high degree of reliability and compactness. A gearbox is used in transmission systems [2] either for reducing or increasing of speeds. It consists of a set of gears, shafts and bearings that are mounted in an enclosed lubricated housing. Gearboxes [3] are available in broad range of sizes, capacities and speed ratios to convert input provided by a prime mover (usually an electric motor) into an output with lower speed and correspondingly higher torque or vice-versa.

1.1.2 Condition Monitoring and Fault Diagnosis

Machine condition monitoring and fault diagnostics [4] is one of the activities to reduce maintenance costs which account for approximately half of all costs of processing and manufacturing
operations. It motivates the researchers to concentrate on this potential activity. The ultimate goal with regard to maintenance activities is to schedule optimum storage of resources for shortest possible time.

Failure of Machinery is the inability of a machine to perform its required function and it is always machinery specific. The deficiencies could be in the original design, material or processing, improper assembly, inappropriate maintenance and excessive operational loads. These may lead to catastrophic failures which may happen suddenly and completely or incipient failures which may happen partially and gradually. In majority of instances, there is a distinct incipient phase which gives advanced warning of the onset of failure and forms the basis for machine condition monitoring. Fault diagnosis helps therefore in the identification, detection of this onset, diagnosis of the condition and trend its progression over time to avoid catastrophic failures excluding the ones caused by unforeseen and uncontrollable outside forces.

The potential advantages of fault diagnosis include increased machine availability and reliability, improved operating efficiency, improved risk management, reduced maintenance costs, reduced spare parts inventories, improved safety, in depth knowledge of the machine capability, extended operational life of the machine, improved customer relations, elimination of chronic failures and reduction of post-overhaul failures. The repercussions of these possible actions include reliability of monitoring equipment, operational costs, skilled personnel, strong management commitment, a significant run-in time to collect machine
histories and trends.

The goal of machine condition monitoring and fault diagnostics ensure that the useful data is collected, converted into information in a form required for useful diagnosis and provide to the condition monitoring personnel. This information includes parameters related to vibration, lubrication, wear, force, sound, temperature, machine output, product quality, odor and visual inspections. All these factors contribute to a complete assessment of the machine integrity in terms of existing

1.1.3 Condition Based Maintenance

Condition-Based Maintenance (CBM) is an alternative to the traditional maintenance philosophies of scheduled or preventive-maintenance and break-down maintenance [5]. It makes mandatory that the mechanical system must be instrumented with one or more sensors for monitoring. In addition, computer algorithms are required to make diagnostic inferences and estimate remaining useful life. In some systems, real-time decisions could then be made to shorten or extend the time between expensive system overhauls or modify real-time use of the system to minimize human or equipment damage. Thus, CBM is potential for improved safety, reduced costs and extended use of existing equipment. Indeed if properly implemented, smart CBM systems could be used to reduce the manpower required to operate and maintain large machinery.

CBM is becoming increasingly viable due to recent advances in sensors, digital signal processing, mechanical modeling and automated reasoning techniques. Sensors are placed in critical locations around the components of interest to gather the material and component level
variations during the operation of the system. This data is processed for various indicators related to faults of interest which enhance reliability of fault detection. Determination of the type of fault is done subsequently using appropriate fault classification techniques where some of the features could also be employed by prognostic models to produce time to failure indications. This information can then be interpreted for its impact on the current mission.

Typically, a CBM system is custom-designed and developed around a specific piece of machinery. Upgradability of CBM systems is another concern. Traditional time-based maintenance is being replaced by condition-based maintenance. Under condition-based maintenance, parts and components are replaced only when they can no longer operate at the desired capacity or when the machine is not able to operate long enough to complete its current mission. Automated machinery diagnostics promises huge cost savings per year in the form of decreased machinery downtime, unnecessary replacement of good parts and maintenance-induced failures.

The strategy for successful implementation of condition-based maintenance is the accurate diagnosis of component faults and the ability to predict when components are going to fail. The latter is the real key to successful condition-based maintenance. To reliably predict when components are going to fail, analysis techniques must be developed which can be implemented on embedded processing systems to automatically identify the remaining useful life of components without intervention from a human expert.
CBM uses sensors, algorithms, models, automated reasoning to monitor the operation of machinery and equipment, as well as determining appropriate maintenance tasks impending failure. Reducing life-cycle costs is the incentive for investing in CBM technology. And the maintenance cost is the largest controllable cost element in industry today. By understanding the working of machinery and equipment, industry can control costs through efficient planning of maintenance. CBM technology also provides significant savings compared to traditional preventive maintenance or break-down maintenance.

1.1.4 Gear Faults

There are many types of gear faults as represented in Figure 1.1, but they can be classified into two general groups as (i) tooth fracture like broken tooth, chipped tooth and (ii) surface defects like pitting, flank peeling, wear, surface cracks, corrosion[1-3]. Among the various faults, the most commonly occurring ones are broken tooth and tooth wear. In case of tooth fractures the gearbox cannot function effectively, because of shocks occurring in transmission. But in the case of surface defects, vibration increases and fault propagates with time resulting in fatigue failure.
1.1.5 Vibration Transmission from Gear Faults

Due to different types of existing faults in gears, vibrations [6] are excited in the transmission. These vibrations are transmitted through gear masses, stiffness of bearings, support structure, gear casing and finally transmitted to foundation of the gear box as shown in Figure 1.2. So, the vibration measured on the gearbox contains the vibration data of individual gear faults. As it is a complex signature, relating gearbox vibration signature to individual component vibrations is difficult. And we cannot measure individual component’s vibration signal.
Different Gear Faults

Faults in Pinion

Faults in Gear

Gear Masses
Support stiffness
Combined Damping
Internal Dynamic Response

Bearing Forces

Gear Masses
Support stiffness
Combined Damping

Gear Case Foot Vibrations

Anti vibration mounts

Transmitted Vibration to Structure

Figure 1.2 Vibration Excitation and Transmission Path
1.1.6 Importance of Vibration Signal and Analysis

The important parameter for routine condition monitoring [4] of rotating or reciprocating mechanical equipment is vibration. A properly implemented predictive maintenance program regularly monitors vibration at specific locations on each machine. A machine consists of a primary driver, intermediate drivers and driven components. Each component within a machine generates specific steady or dynamic forces during operation of the machine which leads to vibration with specific frequencies that uniquely identify the machine component. A gear set generates a unique set of vibration frequencies [5] that identify the actual and normal meshing of the gears. Any degradation of the gear set changes the amplitude of vibrations generated by the gear set. As all the individual components are mechanically linked with each other, the vibrations generated by each individual machine component are transmitted throughout the machine-train. Monitoring the vibration signals at specific points throughout the machine can be used to identify the degrading component.

Each gearbox has a unique vibration signature that identifies both normal and abnormal operations. It is a valuable tool for diagnosing problems but analysis or characterization of the vibration signature of a gearbox is difficult. Various difficulties like mounting vibration transducers close to individual gears, modulation and running speed frequencies do exist. The fact is that vibration produced by gearboxes contain important diagnostic and prognostic information about the operating condition of the gears, bearings, shafts, casing, seals etc. as
represented in Figure 1.3 and Table 1.1. The vibration signals produced by the various components may be different as shown in the above mentioned figure in terms of amplitudes and frequencies. As all the components are connected in the machine as an assembly, the various vibration signals generated from various components are combined in the overall vibration signature of the machine, which is a complex one as shown in the above mentioned Table.

![Figure 1.3 Vibration Signal from Machine Components](image)

**Table 1.1 Vibration Signature of the Machine**

<table>
<thead>
<tr>
<th>Machine Part</th>
<th>Vibration Signature due to Individual Part</th>
<th>Vibration Signature of the Machine</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coupling</td>
<td><img src="image" alt="Vibration Signature" /></td>
<td><img src="image" alt="Vibration Signature" /></td>
</tr>
<tr>
<td>Bearing</td>
<td><img src="image" alt="Vibration Signature" /></td>
<td><img src="image" alt="Vibration Signature" /></td>
</tr>
<tr>
<td>Gear</td>
<td><img src="image" alt="Vibration Signature" /></td>
<td><img src="image" alt="Vibration Signature" /></td>
</tr>
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</table>
So, vibration analysis must be clear on three aspects:

1. Analytical domain being used for data representation (time domain or frequency domain),
2. Metric being used (displacement or velocity or acceleration) and
3. Statistical form, generally a choice between instantaneous and energy-averaged amplitude.

1.2 Signal Processing Techniques

There are a large number of signal processing techniques [5] that can be used to extract defect information from a measured vibration signal. There are a large number of signal processing techniques like Time domain, Frequency-Domain, Cepstrum, Time-Frequency-Domain, Time Synchronous Averaging Technique and Demodulation which can be used. These techniques aim to extract on analytical form or metrics or statistical form of the signal whose value gives an indication of fault the monitored machine. Among the various signal processing techniques, the major challenge of condition monitoring is to find best suited technique for specific fault detection. In most cases to determine the condition of a machine requires study of more than one feature or a combination of several techniques. Implementation of such systems requires a combination of sensors, data fusion, features, classification methods and prediction algorithms.

1.2.1 Time Domain

The time domain represents display of the vibration magnitude as a function of time shown in Figure 1.4. The principal advantage of this
technique is that it allows a great deal of detailed analysis and no data is lost prior to inspection. Vibration amplitude increases from a new machine to faulty machine and also with respect to severity of the fault. Simple signal metrics applied to the measured time domain signal can give some information regarding the potential defects. The instrumentation of time domain metrics is cost effective and simple to implement.

![Time Domain Signal](image)

**Figure 1.4 Time Domain Signal**

In order to analyze the time domain signal, the amplitude of the vibration signal is converted into various forms using statistical formulae called features of the signal which will give some more useful information of the monitored machine.

### 1.2.2 Frequency Domain

The frequency domain spectrum is shown in Figure 1.5 which can give valuable information about potential defects of the machine. Application of Fast Fourier Transform (FFT) is a numerically efficient method to convert time-domain signal into frequency spectrum. All Digital Fourier Transform methods assume stationary signals as periodic in a time window. Practical use of the frequency spectrum in
fault detection often includes comparison of a measured spectrum to a reference spectrum measured from a healthy machine. Different faults are related to different frequencies in the spectrum and this information can be used to diagnose any specific fault. Due to this, it is often useful to consider relative amplitudes of different frequency components.

![Frequency Domain Signal](image)

**Figure 1.5 Frequency Domain Signal**

Local damages usually introduce non-stationary transient components in the vibration signal. When applying a Fourier method, which assumes a stationary signal, the power of the short transient signal gets averaged over the complete signal duration. This means that the average power of defect signal is small compared to the stationary part of the signal. Hence the spectral peaks related to the defect will be low. Fourier methods have limited use for detection of local damages. The frequency spectrum from a multispeed gearbox is very complex. This makes it hard to apply automated methods to perform the analysis.
1.2.3 Cepstrum

Cepstrum can be used for detection of periodicities in a frequency spectrum as shown in Figure 1.6. The Cepstrum is defined as the power spectrum of the logarithmic power spectrum [7,8]. The main benefit of the Cepstrum is its ability to highlight periodicities in complicated frequency spectra, which are not obvious at a first glance. Sidebands in gear and bearing vibration spectra are typical examples of such hidden periodicities.

A periodic component, such as a series of sidebands in the spectrum gives a peak at one single ‘quefrency’ in the cepstrum. Tracking the amplitude of the ‘quefrency’ peak can reveal sideband growth, which can be related to a defect. The logarithmic conversion performed when deriving the cepstrum gives more weight to low-level components. This is advantageous for detection of weak sidebands in the presence of strong gear meshing harmonics. The Cepstrum from both healthy and faulty gearboxes contain information of sidebands variation of certain degree in amplitude and spacing. It is difficult to
predict absolute sideband levels from the cepstrum, thus healthy reference measurements are needed to enable defect detection [9].

$$C(X(t)) = TF^{-1} \{\log X(\omega)\}$$

(1.1)

Where $X(t)$ is time domain signal, $X(\omega)$ is frequency domain signal.

**1.2.4 Time-Frequency Domain**

Conventional spectral methods such as the Fourier Transform assume stationary signals. However, localized defects generally introduce non-stationary signal components [10]. As mentioned above, these cannot be properly described by these spectral methods if they are of short duration in comparison to the time window. A time-frequency distribution describes the energy distribution of a signal in both the time and the frequency domain. Such distributions are suitable to represent signals with time-varying frequency content, e.g. transient resonances excited by localized damages. Time-frequency distributions can also be useful in cases where slightly varying rotational speeds cannot be measured. The Short-Time Fourier-Transform (STFT) can be used to produce a spectrogram, which is an energy density spectrum to detect fast variations. But a narrow time window gives poor frequency resolution which is the main disadvantage of the STFT. It is particularly difficult to analyze signals with both low and high frequency components. The Wigner-Ville Distribution (WVD), the Fourier transform of the instantaneous auto-correlation of the signal provides better resolution in the time-frequency plane compared to the STFT, but at the cost of severe interference terms.
1.2.5 Time-Synchronous Averaging (TSA)

The Time Synchronous Averaging (TSA) is a useful technique in many defect detection situations. For instance, it can be used to sort out the contribution from one individual shaft and its associated gears from the complex vibration signature of a multistage gearbox [11]. The output from the TSA denoted by Signal Average is the ensemble average of the angle domain signal, synchronously sampled with respect to the rotation of one particular shaft. The length of each segment should be exactly one revolution as shown in Figure 1.7. The averaging attenuates random noise as well as non-synchronous noise from shafts and gears whose rotational periods do not match the averaging period. Residual Signal is found to be especially sensitive as a general fault detector and it has been widely used in condition monitoring. The principle behind calculating the Residual Signal is by eliminating the gear meshing harmonics and its adjacent sidebands from the Signal Average spectrum and then transfers it back to the angle domain.

![Figure 1.7 Time Synchronous Average of Signal](image-url)
The main advantage of TSA is the possibility to divide the complex vibration signal from a gearbox into simple Signal Averages for each shaft. A drawback is the need for more complicated measurement equipment. Additional sensors are required to measure the rotational speed, and these sensors demand high sampling rates [12,14].

$$g(t) = \sum_{m=0}^{M} X_m (1 + a_m(t)) \cos(2\pi f_x t + \phi_m + b_m(t))$$  

where $M$ is the number of tooth-meshing harmonics, $f_x$ is the tooth-meshing frequency, $X_m$ and $\Phi_m$ are respectively, the amplitude and phase of the $m$th meshing harmonic, while the modulation effects concerning the same harmonic are given by the amplitude modulation function, $1 + a_m(t)$, and the phase modulation function, $b_m(t)$. These modulation functions are periodic with the considered gear rotation frequency.

**1.2.6 Demodulation**

High frequency vibrations measured from a gearbox are influenced by resonances in the transfer path between the vibration source and the sensor. The excitation can be seen as a modulation of the resonance signal. Demodulation can be used to extract information about the exciting signals hidden in the modulated signal [13, 14]. Finally, the envelope can be treated with ordinary time or frequency domain methods to extract a feature indicating the defect.

This technique is also efficient for detection of gear tooth cracks. A drawback with demodulation technique is involving band pass
filtering and the sensitivity to the pass band selection. A proper pass band gives good results, but a poor pass band can spoil the analysis. The pass band selection also requires a manual decision which can hardly be fully automated.

1.3 Specimen Vibration Signatures of a Gear

Gearbox is complicated machinery and each component of it influences its vibration. From the literature [15] some typical vibration signatures related to gear faults are collected and presented below.

The vibration signature of a normal gear without any fault is shown in Figure 1.8. As per the author [15] the peaks are related to rotational speeds of gears and gear mesh frequency. In this specimen all the peaks are of low magnitude and gear natural frequencies are not excited.

![Figure 1.8 Spectrum of Normal Gear](image)

The vibration signature of a gear tooth wear is shown in Figure 1.9 in which gear mesh frequency and its sidebands gets excited. Side bands
peaks are indication of gear wear. It may excite GMF or natural frequency.

![Figure 1.9 Spectrum of Gear Tooth Wear](image1)

**Figure 1.9 Spectrum of Gear Tooth Wear**

The vibration signature of a broken tooth is shown in Figure 1.10 which shows high amplitude at running speed of the faulty gear. It is best detected in time waveform which will show a pronounced spike every time the faulty tooth tries to mesh with teeth on the mating gear. Time between impacts (Δ) corresponds to 1/speed of gear having faulty tooth. Amplitudes of impact in time waveform will often be much higher than that of 1x Gear RPM in FFT.

![Figure 1.10 Spectrum of Broken Gear Tooth](image2)

**Figure 1.10 Spectrum of Broken Gear Tooth**
In condition monitoring and fault diagnosis of gears using vibration signatures the above mentioned spectrums can only guide us logically and these are not standard and widely accepted signatures. In the process of fault diagnosis the vibration spectrum is collected and maintenance instruction has to be given. So, the diagnosis is dependent on intelligence, interpretation and experience of the diagnostic engineer. In order to increase the accuracy of diagnosis, the help of artificial intelligence techniques like Artificial Neural Networks can be sought.

1.4 Introduction to Artificial Neural Networks

The field of Artificial Neural Networks (ANN) has a history of five decades but has found application only in the past fifteen years, and the field is developing rapidly. Thus, it is distinctly different from the fields of control systems or optimization where the terminology, basic mathematics, and design procedures have been firmly established and applied for many years. Neural networks have been trained to perform complex functions in various fields of application including pattern recognition, identification, classification, speech, vision and control systems. Today neural networks can be trained to solve problems that are difficult for conventional computers or human beings.

Artificial Neural Network [16] is an information processing paradigm inspired by the brain biological nervous systems for processing information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a
large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. ANNs, like people, learn by example. An ANN is configured for specific application, such as pattern recognition or data classification through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons. This is true of ANNs as well.

Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought of as an "expert" in the category of information it has been given to analyze. This expert can then be used to provide projections given new situations of interest and answer "what if" questions. Conventional computers use an algorithmic approach i.e. the computer follows a set of instructions in order to solve a problem. Unless the specific steps that the computer needs to follow are known the computer cannot solve the problem.

Neural networks learn by example. They cannot be programmed to perform a specific task. The examples must be selected carefully otherwise useful time is wasted or even worse the network might be functioning incorrectly. The disadvantage is that because the network finds out how to solve the problem by itself, its operation can be unpredictable. Neural networks and conventional algorithmic
computers are not in competition but complement to each other. But if used sensibly ANN can produce some amazing results.

1.5 Fault Diagnosis of Gearboxes – A Case Study

As per Case study [17], a failure survey of 134 investigations of damaged gearboxes, revealed the following interesting observations:

- Damage of a gearbox can be due to damage of shaft, casing, fasteners, bearings and gears. But this study clearly revealed that 60% of gearbox damages are due to faults in the gears as shown in Figure 1.11.

![Figure 1.11 Location of Damage](image)

Figure 1.11 Location of Damage
Failure of gears may be due to (i) product faults such as design, manufacturing, heat treatment, assembly etc., (ii) operational faults such as improper or insufficient lubrication, overloading, sudden load changes etc., and (iii) some extraneous influences. The study revealed that 40% of failures are due to product faults and 43% of failures are due operational faults as shown in Figure 1.12.

Figure 1.12 Causes of Damage