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Review Article

Machine Fault Signature Analysis

Pratesh Jayaswal,[1] A. K. Wadhwani,[2] and K. B. Mulchandani[3]

[1] *Department of Mechanical Engineering, Madhav Institute of Technology and Science, Gwalior 474005, India*
[2] *Department of Electrical Engineering, Madhav Institute of Technology and Science, Gwalior 474005, India*
[3] *Department of Mechanical and Industrial Engineering, Indian Institute of Technology Roorkee, Roorkee 247667, India*

Correspondence should be addressed to Pratesh Jayaswal, pratesh_jayaswal@yahoo.co.in

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The objective of this paper is to present recent developments in the field of machine fault signature analysis with particular regard to vibration analysis. The different types of faults that can be identified from the vibration signature analysis are, for example, gear fault, rolling contact bearing fault, journal bearing fault, flexible coupling faults, and electrical machine fault. It is not the intention of the authors to attempt to provide a detailed coverage of all the faults while detailed consideration is given to the subject of the rolling element bearing fault signature analysis.

1. INTRODUCTION

Machine fault problems are broad sources of high maintenance cost and unwanted downtime across the industries. The prime objective of maintenance department is to keep machinery and plant equipments in good operating condition that prevents failure and production loss. If the department organizes a predictive maintenance program, this goal as well as cost benefits can be achieved, while accurate information at the right time is a crucial aspect of a maintenance regimen [1]. The condition-based maintenance strategy is being employed for uninterrupted production process in industries. Condition-based maintenance (CBM) consists of continuously evaluating the condition of a monitored machine and thereby successfully identifying faults before catastrophic breakdown occurs. Numerous condition monitoring (cm) and diagnostics methodologies are utilizing to identify the machine faults to take corrective action. Machine fault identification can be done with different methodologies as vibration signature analysis, lubricant signature analysis, noise signature analysis, and temperature monitoring, with the use of appropriate sensors, different signal conditioning, and analyzing instruments.

Vibration signature analysis techniques for machine fault identification are the most popular among other techniques. Vibration monitoring is based on the principle that all the system produces vibration. When a machine is operating properly, the vibration is small and constant, however, when faults develop and some of the dynamic process in the machine changes, there will be changes in vibration spectrum observed. After the review of previous published work, it is concluded that gear fault, bearing fault, and coupling fault are studied for research purpose to fault signature analysis. The majority of industrial machines use ball or rolling elements bearings (REB). The vibration signals obtained from the vicinity of a bearing assembly contain rich information about the bearing condition. Most of the researchers have used vibration signature analysis techniques for rolling element bearing fault identification in case of single defect on bearing components. Time-domain and frequency-domain vibration analysis techniques were tested but effective identification of bearing condition is, however, not so straightforward. Several researchers have used artificial intelligence techniques as well as time-frequency domain analysis and developed expert diagnostics system for bearing fault identification with the use of artificial neural network, fuzzy logic, wavelet transform, and hybrid techniques. In this paper, a review of need and different techniques of machine fault signature analysis are discussed. A special emphasis is given to rolling element bearing vibration signature analysis, while other techniques are also covered. This paper is divided into different sections, each dealing with various aspects of the subject. It begins with a summary of need of machine fault diagnosis followed by a general overview of the numerous means of signature analysis.

2. NECESSITY OF MACHINE FAULT IDENTIFICATION

Machine fault can be defined as any change in a machinery part or component which makes it unable to perform its function satisfactorily or it can be defined as the termination of availability of an item to perform its intended function. The familiar stages before the final fault are incipient fault, distress, deterioration, and damage, all of them eventually make the part or component unreliable or unsafe for continued use [2]. Classification of failure causes are as follows:

(i) inherent weakness in material, design, and manufacturing;
(ii) misuse or applying stress in undesired direction;
(iii) gradual deterioration due to wear, tear, stress fatigue, corrosion, and so forth.

Antifriction bearings failure is a major factor in failure of rotating machinery. Antifriction bearing defects may be categorized as localized and distributed. The localized defects include cracks, pits, and spalls caused by fatigue on rolling surfaces. The distributed defect includes surface roughness, waviness, misaligned races, and off-size rolling elements. These defects may result from manufacturing and abrasive wear [3].

Modern manufacturing plants are highly complex. Failure of process equipments and instrumentation increased the operating costs and resulted in loss of production. Undetected or uncorrected malfunctions can induce failures in related equipments and, in extreme cases, can lead to catastrophic accidents. Early fault detection in machines can save millions of dollars on emergency maintenance and production-loss cost. Gearbox and bearings are essential parts of many machineries [4]. The early detection of the defects, therefore, is crucial for the prevention of damage and secondary damage to other parts of a machine or even a total failure of the associated large system can be triggered [5].

There are certain objectives of machine fault identification:

(i) prevention of future failure events;
(ii) assurance of safety, reliability, and maintainability of machineries.

Machineries failures reveal a reaction chain of cause and defect. The end of the chain is usually a performance deficiency commonly referred to as the symptom, trouble, or simply the problem. The machine fault signature analysis works backwards to define the elements of the reaction chain and then proceeds to link the most probable failure cause based on failure analysis with a root cause of an existing or potential problem. Accurate and complete knowledge of the causes responsible for the breakdown of a machine is necessary to the engineer, similarly, as knowledge of a breakdown in health is to the physician. The physician cannot assure a lasting cure unless he knows what lies at the root of the trouble, and the future usefulness of a machine often depends on correct understanding of the causes of failure. The proper maintenance can be done only after the knowledge of root cause of failure.

Table 1: Timings of action for maintenance.

Timings of action	Maintenance
Operating to failure	Shutdown or breakdown
Fixed time based	Preventive
Condition based	Predictive or diagnostic

Edwards et al. [6] present a review on fault diagnosis of rotating machinery to provide a broad review of the state of the art in fault diagnosis techniques. The early fault detection and diagnosis allow preventive maintenance and condition-based maintenance to be arranged for the machine during scheduled period of downtime caused by extensive system failures that improves the overall availability, performance and reduces maintenance cost. For the fault diagnosis problem, it is not only to detect fault in system, but also to isolate the fault and find out its causes.

3. CONDITION-BASED MAINTENANCE

Maintenance is a combination of science, art, and philosophy. The rationalization of maintenance requires a deep insight into what maintenance really is. Efficient maintenance is a matter of having the right resources in the right place at the right time. Maintenance can be defined as the total activities carried out in order to restore or renew an item to working condition, if fault is there. Maintenance is also defined as combination of action carried out to return an item to or restore it to an acceptable condition. The classification of maintenance according to timings of action for maintenance is shown in Table 1.

Every machine component behaves as an individual. Failure can take place earlier or later than recommended in case of preventive maintenance. It can be improved by condition-based maintenance. Dileo et al. [7] present a review on the classical approaches to maintenance and then compare them with condition-based maintenance (CBM).

The prevention of potential damage to machinery is necessary for safe, reliable operation of process plants. Failure prevention can be achieved by sound specification, selection, review, and design audit routines. When failures do occur, accurate definition of root cause is an absolute prerequisite to the prevention of future failure events [2].

Condition-based maintenance is defined as "maintenance work initiated as a result of knowledge of the condition of an item from routine or continuous checking." It is carried out in response to a significant deterioration in a unit as indicated by a change in a monitored parameter of the unit condition or performance. Condition reports arise from human observations, checks, and tests, or from fixed instrumentation or alarm systems grouped under the name condition monitoring. It is here that one can make use of predictive maintenance by using a technique called signature analysis. Signature analysis technique is intended to continually monitor the health of the equipment by recording systematic signals or information derived from the form of mechanical vibrations, noise signals, acoustic and thermal emissions, change in chemical compositions, smell, pressure, relative displacement, and so on [8]. Mann et al. [9] present an article explores the benefits of condition-based preventive maintenance compared to the traditional statistical reliability approach. Nandi and Toliyat [10] present a review on condition monitoring and fault diagnosis of electrical machines. Marcus [11] proposed condition-based maintenance to rail vehicle for more effective maintenance.

Condition-based maintenance differs from both failure maintenance and fixed-time replacement. It requires monitoring of some condition-indicating parameter of the unit being maintained. This contrasts with failure maintenance, which implies that no successful condition monitoring is undertaken and with fixed-time replacement which is based on statistical failure data for a type of unit. In general, condition-based maintenance is more efficient and adaptable than either of the other maintenance actions. On indication of deterioration, that unit can be scheduled for shutdown at a time chosen in advance of failure, yet, if the production policy dictates, the unit can be run to failure. Alternatively, the amount of unnecessary preventive replacement can be reduced, while if the consequences of failure are sufficiently dire, the condition monitoring can be employed to indicate possible impending failure well before it becomes a significant probability. The trend monitoring method for one or group of similar machines is possible if sufficient data of monitored parameters are available. It relates the condition of machine(s) directly to the monitored parameters. On the other hand, condition checking method is employed for a wide range of diagnostics instruments apart from human senses. Some of the recent developments in the form of CBM are proactive maintenance, reliability centered maintenance (RCM) and total productive maintenance (TPM).

4. MACHINE CONDITION MONITORING

When a fault takes places, some of the machine parameters are subjected to change. The change in the machine parameters depends upon the degree of faults and the interaction with other parameters. In most cases, more than one parameter are subjected to change under abnormal condition. Condition monitoring can be carried out when the equipment is in operation, which known as on-line, or when it is off-line, which means when it is down and not in the operation. While on-line, the critical parameters that are possible to monitor are speed, temperature, vibration, and sound. These may be continuously monitored or may be done periodically. Off-line monitoring is carried out when the machine is down for whatever reason. The monitoring in such would include crack detection, a thoroughly check of alignment, state of balancing, the search for tell-tale sign of corrosion, pitting, and so on.

The International Standards Organization's Technical Committee 108 (ISO/TC108) produces standards in the area of mechanical vibration, shock, and machine condition monitoring. ISO/TC108's Subcommittee 5 (ISO/TC108/SC5) has focused on standards for the condition monitoring and diagnostic of machines. This subcommittee has published ISO 13374-1:2003 which establishes general guidelines for software specifications related to data processing, communication, and presentation of machine condition monitoring and diagnostic information. This standard defines the data processing and information flow needed between processing blocks in condition monitoring systems. Machine condition monitoring (MCM) is a vital component of preventive and predictive maintenance programs that seek to reduce cost and avoid unplanned downtime. MCM also contributes to health and safety by recognizing faults which may give rise to pollution or health hazards, and also by indication of incipient faults which could produce danger conditions. MCM setups include measurement hardware and software that acquire and interpret signals generated by the machine being monitored. Condition monitoring is taken to mean the use of advanced technologies in order to determine equipment condition, and to predict potential failure. It includes, but is not limited to, technologies such as visual inspection, vibration measurement and analysis, temperature monitoring, acoustic emission analysis, noise analysis, oil analysis, wear debris analysis, motor current signature analysis, and nondestructive testing.

4.1. Visual inspection

visual monitoring can sometimes provide a direct indication of the machine's condition without the need for further analysis. The available techniques can range from using a simple magnifying glass or low-power microscope. Other forms of visual monitoring include the use of dye penetrants to provide a clear definition of any cracks occurring on the machine surface, and the use of heat-sensitive or thermographic paints. The condition of many transmission components can readily be checked visually. For example, the wear on the surfaces of gear teeth gives much information. Problems of overload, fatigue failure, wear and poor lubrication can be differentiated from the appearance of the teeth.

4.2. Vibration analysis

Modern condition monitoring techniques encompass many different themes; one of the most important and informative is the vibration analysis of rotating machinery. Using vibration analysis, the state of a machine can be constantly monitored and detailed analysis may be made concerning the health of the machine and any faults which may arise or have already arisen. Machinery distress very often manifests itself in vibration or a change in vibration pattern. Vibration analysis is therefore, a powerful diagnostic and troubleshooting tool of major process machinery.

On-load monitoring can be performed mainly in the following three ways.

(i) Periodic field measurements with portable instruments; this method provides information about long-term changes in the condition of plant. The portable instruments are employed with a high load factor and can often be placed in the care of only one man. Use of life curves and the LEO approach assist the decision making.

(ii) Continuous monitoring with permanently installed instruments; it is employed when machine failures are known to occur rapidly and when the results of such failure are totally unacceptable as in the case of turbine generator units.

(iii) Signature analysis: scientific collection of information, signals or signatures, diagnosis and detection of the faults by a thorough analysis of these signatures based on the knowledge hitherto acquired in the field, and judging the severity of faults for decision making, all put together, is called signature analysis. The technique involves the use of electronic instrumentation especially designed for the purpose of varied capacities, modes of application and design features.

Vibration signals are the most versatile parameters in machine condition monitoring techniques. Periodic vibration checks reveal whether troubles are present or impending. Vibration signature analysis reveals which part of the machine is defective and why. Although a number of vibration analysis techniques have been developed for this purpose, still a lot of scope is there to reach a stage of expertise.

4.3. Temperature monitoring

Temperature monitoring consists of measuring of the operational temperature and the temperature of component surfaces. Monitoring operational temperature can be considered as a subset of the operational variables for performance monitoring. The monitoring of component temperature has been found to relate to wear occurring in machine elements, particularly in journal bearings, where lubrication is either inadequate or absent. The techniques for monitoring temperature of machine components can include the use of optical pyrometers, thermocouples, thermography, and resistance thermometers.

4.4. Acoustic emission analysis

Acoustic emission refers to the generation of transient waves during the rapid release of energy from localized sources within a material. The source of these emissions is closely associated with the dislocation accompanying plastic deformation and the initiation or extension of fatigue cracks in material under stress. The other sources of acoustic emission are melting, phase transformations, thermal stress, cool-down cracking, and the failure of bonds and fibers in composite materials. Acoustic emissions are measured by piezoelectric transducers mounted on the surface of the structure under test and loading the structure. Sensors are coupled to the structure by means of a fluid couplant or by adhesive bonds. The output of each piezoelectric sensor is amplified through a low-noise preamplifier, filtered to remove any extraneous noise and furthered processed by suitable electronic equipment.

Traditionally, acoustic emissions as a technique has been restricted to the monitoring of high cost structures due to the expenses of the monitoring equipment. However, as equipment costs steadily fall, the range of viable applications expands rapidly. Olsson et al. present a frame work for fault diagnosis of industrial robots using acoustic signals and case-based reasoning [12]. This frame work utilizes the case-based reasoning for fault identification based on sound recording in robot fault diagnosis. Wue et al. have developed experimental setup for online fault detection and analysis of modern water hydraulic system [13], and suggested that the incorporation of wavelet transformation into the analysis of acoustic emission opens up the door for future research, which can prove to be very relevant toward condition monitoring. Choe et al. [14] worked on neural pattern identification of railroad wheel-bearing faults from audible acoustic signals by comparison of FFT, continuous wavelets transform (CWT) and discrete wavelets transform (DWT) features.

4.5. Noise analysis

Noise signals are utilized for condition monitoring because noise signals measured at regions in proximity to the external surface of machines can contain vital information about the internal processes, and can provide valuable information about a machine’s running condition. When machines are in a good condition, their noise frequency spectra have characteristic shapes. As faults begin to develop, the frequency spectra change. Each component in the frequency spectrum can be related to a specific source within the machine. This is the fundamental basis for using noise measurement and analysis in condition monitoring. Sometimes the signal which is to be monitored is submerged within some other signal and it cannot be detected by a straightforward time history or spectral analysis. In this case, specialized signal processing techniques have to be utilized.

4.6. Wear debris analysis

It is not possible to examine the working parts of a complex machine on load, nor is it convenient to strip down the machine. However, the oil which circulates through the machine carries with it evidence of the condition of parts encountered. Examination of the oil, any particle it has carried with it, allows monitoring of the machine on load or at shutdown. A number of techniques are applied, some very simple, other involving painstaking tests and expensive equipments. Presently, available lubricant sampling or monitoring techniques like rotary particles depositor (RPD), spectrophotometer oil analysis programme (SOAP), Ferrographic oil analysis and recent software used techniques are available to distinguish between damage debris and normal wear debris. Every machine ever designed undergoes a process of wear and tear in operation, yet a battery of modern condition monitoring techniques is available to monitor this process and trigger preventive maintenance routines which depend on identifying any problem before it has the chance to develop to the point of final breakdown. Now recently, engineers have been able to extend their knowledge of conditions within operating machinery by studying the particles of metallic debris which can be found in lubricating oil from engines, gearboxes, final drive units and transmissions, or in hydraulic fluid, and recording the number, size, and type of these fragments of debris.

4.7. *Motor current signature analysis*

Motor current signature analysis (MCSA) is a novel diagnostic process for condition monitoring of electric motor-driven mechanical equipment (pumps, motor-operated valves, compressors, and processing machinery). The MCSA process identifies, characterizes, and trends overtime the instantaneous load variations of mechanical equipment in order to diagnose changes in the condition of the equipment. It monitors the instantaneous variations (noise content) in the electric current flowing through the power leads to the electric motor that drives the equipment. The motor itself thereby acts as a transducer, sensing large and small, long-term and rapid, mechanical load variations, and converting them to variations in the induced current generated in the motor windings. This motor current noise signature is detected, amplified, and further processed as needed to examine its time-domain and frequency-domain (spectral) characteristics. Korde [15] demonstrates that the spectrum analysis of the motors current and voltage signals can hence detect various faults without disturbing its operation using FFT transformation.

4.8. *Nondestructive testing*

The principle of nondestructive testing (NDT) is to be able to use the components or structure after examination. The inspection should not affect the item involved, and must therefore, be nondestructive. NDT includes many different technologies, each suitable for one or more specific inspection tasks, with many different disciplines overlapping or complimenting others. Thus the best technique(s), for any one application, should be decided by an expert eddy current testing, electrical resistance testing, flux leakage testing, magnetic testing, penetrant testing, radiographic testing, resonant testing, thermographic testing, ultrasonic testing, and visual testing are some of the different NDT techniques.

5. VIBRATION SIGNATURE ANALYSIS

The word signature has been coined to designate signal patterns which characterize the state or condition of a system from which they are acquired. Signatures are extensively used as a diagnostic tool for mechanical system. In many cases, some kind of signal processing is undertaken on those signals in order to enhance or extract specific features of such vibration signatures. It is very important to consider the type and range of transducers used as pickup for capturing vibration signal. Signature-based diagnostic makes extensive use of signal processing techniques involving one or more methods to deal with the problem of improvement in the signal to noise ratio.

Vibration-based monitoring techniques have been widely used for detection and diagnosis of bearing defects for several decades. These methods have traditionally been applied, separately in time and frequency domains. A time-domain analysis focuses principally on statistical characteristics of vibration signal such as peak level, standard deviation, skewness, kurtosis, and crest factor. A frequency domain approach uses Fourier methods to transform the time-domain signal to the frequency domain, where further analysis is carried out, conventionally using vibration amplitude and power spectra. It should be noted that use of either domain implicitly excludes the direct use of information present in the other. These techniques have been broadly classified in three areas, namely, the following.

5.1. *Time-domain analysis*

The time domain refers to a display or analysis of the vibration data as a function of time. The principal advantage of this format is that little or no data are lost prior to inspection. This allows for a great deal of detailed analysis. However, the disadvantage is that there is often too much data for easy and clear fault diagnosis. Time-domain analysis of vibration signals can be subdivided into the following categories: time-waveform analysis, time-waveform indices, time-synchronous averaging, negative averaging, orbits, and probability density moments.

5.2. *Frequency domain*

The frequency domain refers to a display or analysis of the vibration data as a function of frequency. The time-domain vibration signal is typically processed into the frequency domain by applying a Fourier transform, usually in the form of a fast Fourier transform (FFT) algorithm. The principal advantage of this format is that the repetitive nature of the vibration signal is clearly displayed as peaks in the frequency spectrum at the frequencies where the repetition takes place. This allows for faults, which usually generate specific characteristic frequency responses, to be detected early, diagnosed accurately, and trended overtime as the condition deteriorates. However, the disadvantage of frequency-domain analysis is that a significant amount of information (transients, nonrepetitive signal components) may be lost during the transformation process. This information is nonretrievable unless a permanent record of the raw vibration signal has been made. The various methods of frequency-domain vibration signature analysis are bandpass analysis, shock pulse (spike energy), enveloped spectrum, signature spectrum, and cascades (waterfall plots).

5.3. *The quefrency domain*

The quefrency is the abscissa for the cepstrum which is defined as the spectrum of the logarithm of the power spectrum. It is used to highlight periodicities that occur in the spectrum in the same manner as the spectrum is used to highlight periodic components occurring in the time domain [16]. One of the ways the expert system detects bearing tones is by looking at the spectrum of a spectrum. This process is called cepstrum analysis, "cepstrum" being a play on the word "spectrum."

6. FAULT DETECTION FROM VIBRATION ANALYSIS

Renwick and Babson [1] demonstrate that the predictive maintenance using vibration analysis has achieved meaningful results in successfully diagnosis machinery problems. The benefits of such programs include not only evident-cost benefits such as reducing machinery downtime and production losses, but also the more subtle long-term cost benefits which can result from accurate maintenance scheduling.

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 2 [17].

Weqerich et al. developed a nonparametric modeling technique by smart signal and demonstrate the use of this approach for detecting faults in rotating machinery via extracted features from vibration signals [18]. Lei et al. [19] present damage diagnosis approach using time series analysis of vibration signals for structural health monitoring benchmark problem.

Sohn and Farrar [20] have presented a procedure for damage detection and localization within a mechanical system solely based on the time series analysis of vibration data. Sahinkaya et al. [21] have worked on fault detection and tolerance in synchronous vibration control of rotor magnetic bearing system. A simple and effective algorithm has been developed to build fault detection and tolerances capabilities into the open-loop adaptive control of the synchronous vibration of flexible rotors supported or equipped with magnetic bearings.

Lebold et al. [22] have presented review of vibration-analysis methods for gearbox diagnostics and prognostics. This review listed some of the most traditional features used for machinery diagnostics and presented some of the signal processing parameters that impact their sensitivity.

Verma and Balan [23] present a fundamental study on the vibration behavior of electrical machine stators using an experimental model analysis and suggested that vibration level even at resonance can be reduced by designing the electromagnetic forces to have circumferential mode associated with corresponding resonance. Ocak and Loparo [24] present algorithms for estimating the running speed and the bearing-key frequencies of an induction motor using vibration data that can be used for failure detection and diagnosis.

Table 2: 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
Journal bearing	Oil whirl Oval or barreled journal Journal/bearing rub
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

Plenge et al. [25] developed optical inspection techniques for vibration analysis and defect indication in railway.

Vibration signals from gearboxes and roller bearings share many common characteristics. First, the signals are usually noisy. This is because the accelerometers for signals collection are mounted on the outer surface of gearbox. The signals obtained from these accelerometers include vibrations from meshing gears, bearings, and the equipment's many other parts. Second, symptoms from faulty bearings are very similar to those from faulty gears. For example, periodic impulses may indicate either cracked teeth of gears or damaged races or rollers of roller bearings. Such periodic impulses, however, cannot be detected easily with the frequency spectrum because of the heavy noise distributed in the low-frequency area [4].

Lin et al. [4] have obtained excellent results for mechanical fault detection based on the wavelet denoising technique. The method has performed excellently when used to denoise mechanical vibration signals with a low signal-to-noise ratio.

7. REB FAILURE AND ITS VIBRATION ANALYSIS

Each of the rolling element bearings used in industries consists of two rings, one inner and the other outer. A set of balls or rolling elements placed in raceways rotate inside these rings. Even when properly applied and maintained, the bearing will still be subjected to one cause of failure, fatigue of bearing material. Fatigue is the result of shear stresses cyclically applied immediately below the load-carrying surfaces and is observed as spalling away of surface metal. However, material fatigue is not the only cause of spalling. There are causes of premature spalling. So, although the observer can identify spalling, he must be able to discern between spalling produced at the normal end of bearing's useful life and that triggered by causes found in the three major classifications of premature spalling as lubrication, mechanical damage, and material defects. Most bearing failures can be attributed to one or more of the following causes as defective bearing seats on shafts and in housings, misalignment, faulty mounting practice, incorrect shaft and housing fit, inadequate lubrication, ineffective sealing, and vibration, while the bearing is not rotating, passage of electric current through the bearing [2]. As one of the most essential parts in rotating machinery rolling element bearings are often subjected to high stress and operate under severe conditions, Their integrity becomes an issue particularly in key machinery. A machine could be seriously jeopardized, if defects occur to those rolling element bearing during service [5]. A new approach for the categorization of bearing faults was introduced by Stack et al. [26]. A common way in which bearing faults are often classified according to the location of the fault (an inner race/outer race/ball/cage fault). In this research, bearing faults were grouped into one of two categories, as single point defects and generalized roughness. The single point defects are defined as visible defects that appear on the raceways, rolling elements, or cage.

A single point defect produces one of the four characteristics fault frequencies depending on which surface of the bearing contains the fault. In spite of the name, a bearing can possess multiple single point defects. The other group of bearing faults, generalized roughness, refers to an unhealthy bearing whose damage is not apparent to the unaided eye. Example of this failure mode includes deformation or warping of the rolling elements or raceways and overall surface roughness due to heating, contaminated lubricant, or electric discharge machining. The effects produced by this failure mode are difficult to predict, and there are no characteristics fault frequencies with this type of fault.

In rolling element bearing failure analysis, the low-frequency phenomenon is the impact caused by a defect of a bearing. The high-frequency carrier is a combination of the natural frequencies of the associated rolling element or even of the machine [27]. There are a number of factors that contribute to the complexity of the bearing signature. First, variation of bearing geometry and assembly make it impossible to precisely determine bearing characteristics frequencies. Secondly, locations of bearing defects cause different behavior in the transient response of the signal, which is easily buried in wide band response and noisy signals. Thirdly, signature appears to be very different with the same type of defect at different stages of damage, severity. Finally, operating speed and loads of the shaft greatly affect the way and the amount a machine vibrates.

Several researchers worked on the subject of rolling element bearing 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. Time-domain analysis focuses on dealing directly with the time-domain waveform of vibration signals. The indices RMS, peak value, and crest factor are often used to quantify the time signal. The statistical parameters such as kurtosis and skewness values are robust to varying bearing operating condition and are good indicators of incipient defects. The disadvantage, however, is that as the defect spreads across the bearing surfaces the values of these parameters drop back to normal [28].

The frequency domain, spectrum of the vibration signal reveals frequency characteristics of vibration. If the frequencies of the impulse occurrence are close to one of the bearing characteristic frequencies, such as ball pass inner race frequency, ball pass outer race frequency, ball spin frequencies, it may indicate a defect related fault in the bearing. Fast Fourier transform is used in conventional frequency-domain signature analysis techniques for conversion of time-domain signal in frequency-domain signal. Other frequency-domain techniques are generally used are the calculation of power spectral density, bandpass analysis, envelope analysis. The effectiveness of bandpass-analysis method relies on a suitable choice of narrow-band frequencies around the selected resonance. In envelope analysis, signals are filtered through bandpass filter and filtered signal is demodulated with the help of full-wave rectification or via Hilbert transform and then spectrum analyzed. The passband and envelope analysis techniques are useful to detect rolling element bearing faults when signals are noisy due to severity of fault or due to associated noise from other sources as shaft misalignment, unbalance, and looseness.

The fast Fourier transform has drawback, when signal is nonstationary or noisy, even in FFT, time information is lost. Many researchers have used short-time Fourier transform (STFT) to overcome the time information problem but low-resolution problem exists in STFT. The wavelets transform is currently used to overcome both the time information and low resolution problems. A major advantage of the wavelets transform is that this method can exhibit the local features of the signals and give account of how energy is distributed over frequencies changes from one instant to the next.

The confidence of bearing fault diagnosis can be improved by using a range of failure indicators including performance indices, oil analysis, thermography, and motor current readings in conjunction with vibration analysis. These indicators are generally assimilated and analyzed by human expert but a computational expert system, based on neural network, fuzzy logic, and rule based logic, as well as hybrid techniques containing elements of all three methods, is being used and continually improved in order to automate the process.

The neural network technology provides an attractive complement to traditional vibration analysis because of the potential of neural networks to operate in real-time mode and to handle data that may be distorted or noisy [29]. Neural networks have proven the ability in the area of nonlinear pattern classification and can correctly identify the different causes of bearing vibration [30]. The fuzzy logic has proven ability in mimicking human decisions, and the bearing fault diagnosis problem has typically been solved by an experienced engineer. The fuzzy logic is promising for automation in the area of bearing vibration diagnosis, if the input data is well processed [31]. The advantages of the fuzzy logic approach include the possibility to change the linguistic rules into decisions by copying the procedure and thinking of a human analyzer. The rules that include uncertainty and inaccuracy are changed into numbers describing the severity or the probability of fault. The rules and membership functions can be tuned to find the good sensitivity of the diagnostic system.

8. ADVANCED SIGNAL PROCESSING TECHNIQUES IN VIBRATION ANALYSIS

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. These systems gained popularity over other methods, as they are model free estimators capable of synthesizing nonlinear and noisy systems. The fuzzy logic was developed as a mean for representing, manipulating, and utilizing uncertain information (information that is usually expressed in linguistic terms). The recent surge of interest is in merging or combining NN and fuzzy logic system into a functional system to overcome their individual weaknesses.

Wavelet analysis is an emerging field of mathematics that has provided new tool and algorithms for the type of problems encountered in process monitoring. Wavelet transform (WT) is a mathematical approach that decomposes a time-domain signal into different frequency groups. Wavelet algorithms process data at different scales and resolutions

The monitoring and diagnosis of machinery is a well-established discipline, but much progress remains to be made in automating diagnosis as well as developing low-cost reliable technologies which can be applied cost-effectively in the majority of production environment. Developments in microtechnology and artificial intelligence have driven the trends toward more extensive onboard diagnostics. 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 [9]. 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 rolling element bearings.

Shikari and Sadiwala worked on automation in condition-based maintenance using vibration analysis [32]. In this work, importance of intelligent system in CBM is focused. Dyke [33] describes an example of the application of the DLI engineering ExpertAlert expert automated diagnostics system to successful diagnosis of machine tool spindle bearing problems. Sima [34] proposes a strictly neural expert system architecture that enables the creation of the knowledge base automatically by learning from example inferences. Bandyopadhya et al. [35] have developed an expert system for real-time condition monitoring using vibration analysis for turbine bearing. Poyhonen et al. [36] have applied support vector classification to fault diagnostics of an electrical machine.

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 [37]. The rolling element bearing signals are investigated accordingly to the principle that the wavelet can extract the signal envelope by Jun and Liao. A wavelet-based self-information extracting envelope method was applied, application of the method demonstrates that the method is effective to extract the rolling bearing signal envelope and is useful to analysis the bearing faults [27].

Four approaches based on bispectral and wavelet analysis of vibration signals are investigated as signal processing techniques for application of a number of induction motor rolling element bearing faults by Yang et al. [38]. A general methodology for machinery fault diagnosis through a pattern recognition technique is developed by Sun et al. [28], this involves data acquisition, feature extraction, mapping for feature fusion, and piecewise-linear classification and diagnosis. They conclude, to increase the sensitivity and reliability of pattern recognition, one is encouraged to include as many feature parameters as possible without concern the redundancy or numerical singularities.

Satish and Sharma [39] demonstrate a novel and cost-effective approach for diagnosis and prognosis of bearing faults in small and medium-size induction motor. In this work, a fuzzy back-propagation network was developed by combining neural network with fuzzy logic to identify the present condition of the bearing and to estimate the remaining life of the motor.

Fan and Zuo [40] proposed an effective method to extract modulating signal and to detect the early gear fault. In this new fault detection method, combination of Hilbert transform and wavelet-packet transform were used. Both simulated signals and real vibration signals collected from a gearbox dynamics simulator were used to verify the proposed method

Duraisamy et al. [41] have described a comparative study of membership functions for design of fuzzy logic fault diagnosis system for single-phase induction motor.

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. Intelligent systems, including neural networks, fuzzy logic, and wavelet 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].

9. CONCLUSIONS

In this paper, authors have been presented a brief review of art of machinery fault detection, different conventional and recent techniques were discussed for machine fault signature analysis with particular regard to rolling contact bearing fault diagnosis through vibration analysis. After the review of literature on machine fault signature analysis, the following points are concluded.

(i) Prevention of potential failure is required for reliable and safe operations of machineries and the prevention of catastrophic failure can be done by appropriate maintenance. Condition-based maintenance is the best suitable technique to avoid unwanted futuristic failures through condition monitoring or signature analysis for rotating machineries. Vibration signature analysis is the best suitable technique available for fault identification.

(ii) Among all machine components rolling contact bearing is needed more attention towards signature analysis. The lot of scope is available in bearing fault signature analysis through vibration data for multiple points or generalized faults.

(iii) Vibration analog signal can be converted in discrete data for further investigation and various time-domain and frequency-domain features can be used for further investigations. The Hilbert and wavelets transform have tremendous scope in machine fault signature analysis.

(iv) Expert system based on ANN and fuzzy logic can be developed for robust fault categorization with the use of extracted features from vibration signal.

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

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