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Fault Diagnosis in Rotating System Based on Vibration Analysis

Mohamed B. Abd-Elbary, Ahmed G. Embaby and Fawkia R. Gomaa

Department of Production Engineering and Mechanical Design, Shebin Alkoum Faculty of Eng., Menoufia University, Egypt.
(Corresponding author: e.mohamed.badr@gmail.com)

ABSTRACT
Vibration is one of the major parameters to consider in condition monitoring of rotating systems. If an undetected fault is noticed in the rotating system, then, at best, the issue will not be too significant and can be remedied cheaply and quickly; at worst case, it may result in down-time, expensive damage, injury, or even life loss, therefore early fault identification is a critical factor in ensuring and extending the working life of the rotating systems. By measurement and analysis of the vibration of rotating machinery, it is possible to detect and locate important faults such as mass unbalance, misalignment, bearing failure, gear faults and rotor cracks. This article is aimed to guide the researchers to implement identification, diagnosis and remedy techniques of common fault types using vibration analysis and outlines many important techniques used for condition monitoring of rotating systems such as fast Fourier transform, frequency domain decomposition method, wavelet transform, stochastic subspace identification and deep learning.

Keywords: *fault diagnosis; vibration analysis; rotating system.*

1. Introduction

The necessity of using small and large rotating machinery in industrial systems imposes monitoring, maintenance, and reparation. The main function of condition monitoring of rotating machines is to provide knowledge about machines condition at each moment without stopping the line of production. Vibration monitoring is one of the most common techniques of condition monitoring and this is for its ability to detect, locate and distinguish different types of faults since its inception before they become critical and dangerous, these faults which may be distributed or localized. The bearings are the most essential mechanical elements of rotating machinery. They are employed to support the rotating shafts in rotating machinery. On the other hand, several studies showed that the main source of most mechanical faults in rotating machinery is the bearing fault. Therefore, any bearings fault may influence the level of production and equipment working life as well as having an unsafe environment for workers. For these reasons, condition monitoring, early fault detection and fault diagnosis of these bearings is one of the major fundamental axes of development and industrial research.

There are many techniques that can be used to detect and diagnosis the bearing faults such as Fast Fourier Transform (FFT), Short Time Fourier Transform (STFT), Envelope analysis (EA), Empirical Mode Decomposition (EMD), Frequency Domain Decomposition method (FDD), Enhanced Frequency Domain Decomposition method (EFDD), Frequency-Spatial Domain Decomposition method (FSDD), Wavelet Transform (WT), Stochastic Subspace Identification (SSI), Artificial Neural-Network approach for fault detection (ANN), Adaptive Neuro-Fuzzy Inference System (ANFIS) and Deep Learning for Fault Diagnosis. The purpose of this article is to review these techniques and explore their capabilities, advantages, and drawbacks in monitoring bearings.

2. Fault in Rotating Machines

Turbomachinery, or generally speaking rotating systems, are used in almost all industry sectors and plays a major role .

Rotating machines can create propulsion (propellers), extract energy (turbines), convoy fluids (fans and pumps) and convert the state of working fluids (compressors or pumps). In such cases, performance, reliability, efficiency, and rapid delivery are important factors that must be achieved.

Each rotating system type has one or more key design challenges. In gas turbines, high temperatures is a problematic, so cooling is a challenge. In aeroengine fans, there are space limitations in designing automotive fans, so noise is a challenge. In pumps, non-ideal gas attitude in refrigerant compressors and steam turbines must be considered, so cavitation is a challenge.

A fault is an irregularity in the functioning of the equipment which results in component damage, energy losses and reduced efficiency of the machine .

Common types of machine faults are mass unbalance, misalignment, bearing failure, gear faults, rotor cracks and bent shafts. The relation of the predominant vibration frequencies with the forcing frequency (input force frequency) gives us an idea about the source of the fault. The increased amplitude of the predominant frequencies indicates the severity of the fault. Standard relations between common faults and corresponding fault signatures are available [1, 2].

2.1 Rotor Unbalance

Unbalance always appears in the form of noticeable vibrations which endangers people, machines, and the environment when it exceeds permissible tolerances [3]. It shortens the service life of machinery and reduces their utility value. In practice, there's no perfectly balanced rotors because of manufacturing errors, tolerances and rotor geometric changes during operation in the field [4]. This requires the rotor to be balanced usually by adding or removing correction masses at certain positions.

Edwards et al. [5] detected unbalance experimentally from data obtained from just a single run-up or run-down of the rotor rig and attempted to balance the rotor. Janik and Irretier [6] proposed a method for the unbalance identification of elastic rotors based on the rotor dynamic theory mutual with experimental modal analysis. Park et al. [7] used an on-line weighted-incremental least square method and conducted experiments to detect mass unbalance and high order sensor runout in a turbo molecular pump having active magnetic bearings. Tiwari and Chakravarthy [8] used impulse response measurements for calculating residual mass unbalances and bearing dynamic characteristics and validated the developed method experimentally in a flexible rotor-bearing test-rig. DE Queiroz [9] simulated identification of rotor unbalance parameters using the resulting disturbance calculations.

Various balancing techniques includes influence coefficient methods [10, 11], modal balancing [12, 13], unified balancing approach [14], balancing using amplitude only [15-17], balancing using phase only [18], automatic balancing of rigid rotors [19, 20] and virtual Balancing [21, 22].

2.2 Misalignment

Misalignment can be the second most common fault after unbalance. Misalignment can cause over 70% of the vibration issues of rotating machinery [23]. Misalignment exists because of improper machine assembly, thermal distortion, and asymmetry in the applied load. Misalignment in rotating machinery results reaction forces and moments acting on the coupling which cases vibration in the rotating system. Practically we cannot achieve perfectly balanced aligned rotor system. However, it can be within an acceptable level. [24, 25].

Sinha et al. [26] studied misalignment from a single run of flexible rotating system, while Taradai and Don [27] developed a combined experimental and computational method to estimate the shaft alignment without couplings disassembly. Bachschmid and Pennacchi [28], Sekhar [29, 30] has successfully identified coupling misalignment by using model-based methods. Pennacchi and Vania [31] identified misalignment through orbit shape analysis and subsequently used model-based method for the fault identification. Some recent works include failure of the misaligned flexible rotor was studied by Hili et al. [32], and while on-line prediction of motor shaft misalignment was investigated by Omitaomu et al. [33] using FFT generated spectra data and support vector regression. Patel and Darpe [34] proposed a method for using the full spectra to identify misalignment fault in rotor systems. And later, in [35] they made experimental investigations in a laboratory test rig and found that the misalignment causes coupling phenomenon in the axial, bending, and torsional vibrations.

They identified coupling misalignment fault using full spectra and orbit plots of the vibration response.

The study of shaft misalignment is still inadequate. Few researchers have given attention to shaft misalignment due to complexity in modeling. Also, most of the past studies on misalignment were theoretical [36-38]. experimental investigations were relatively limited. Furthermore, the theoretical studies often attempted with several assumptions and simplifications [39-41].

2.3 Bearing Failure

Bearings are the most critical components of any rotating system. They are used to support the rotating shafts in rotating machinery. Thus, any fault or malfunction in the bearings can result losses on the production level and equipment as well as having unsafe working environment for humans [42]. Therefore, the fault diagnosis of bearings has got large attention from the researchers in the recent years [43-45]. Time domain analysis [46], frequency domain analysis [47] and spike energy analysis [48] are applied to detect different bearing faults.

2.4 Damaged Gears

Gear vibrations are mainly produced by the shock between the teeth of the two meshed gears. The vibration monitored on a faulty gear generally exhibits a significant level of vibration at the tooth meshing frequency [49-53].

Gear faults can be generally classified into two major categories: distributed faults and local faults [54]. Distributed faults are those faults that results from poor gear mounting, or manufacturing inaccuracies such as eccentricities, varying gear tooth spacing, etc. Meanwhile, local faults are those resulting from localizing defects that may occur in gear teeth such as tooth surface wear, cracks in gear teeth, and loss of part of the tooth due to breakage or loss of the whole teeth.

2.5 Cracked Rotor

Undetected cracks in a shaft can lead to catastrophic failure in the rotating system. This problem may be monitored by observing the vibration signature and behavior of cracked rotor systems [55].

Generally, there are two different methods are employed to detect and locate cracks in rotating systems. The first approach is depends on the exitance of a cracked shaft in a rotating system which results in decreasing the structure stiffness [56, 57]. Therefore, decreasing the natural frequencies of the original uncracked shaft. The second approach considers the effectiveness of a transverse active crack on the response of a rotor system [58, 59].

2.6 Bent Shafts

Bends in shafts may be caused in several ways, for example due to creep, thermal distortion, or a large residual unbalance force. The forcing caused by a bend is similar, though slightly different to that caused by conventional mass unbalance. The response of shaft bow is a function of shaft rotating speed and results different phase angle and amplitude relationships than is measured with mass unbalance, which is a function of the square of the rotating speed. It is important to be able to diagnose shaft bow from vibration measurements and Thus, distinguish between it and mass unbalance.

Parkinson et al. [60] described the differences in whirl resulting from a rotating shaft subjected to shaft bow and mass unbalance. After shaft balancing, it’s found that the net whirl showed conventional resonance behavior considering amplitude and phase angle. Experimental results were included, which confirmed the above findings and showed the balancing of net whirl to be an extremely effective method of balancing a bent shaft.

3. Vibration Analysis Techniques for Fault Detection

3.1 Fast Fourier Transform (FFT)

Frequency analysis is considered to be the most traditional method which can be employed for analyzing the vibration signals [61-63]. Fourier analysis transforms a signal from its original domain (usually space or time) into frequency domain and vice versa. Results showed that it is difficult to detect and identify the fault at bearings using FFT [64], because of limitations of the spectral analysis found in the non-stationary signal analysis.

3.2 Short Time Fourier Transform (STFT)

Short-Time Fourier Transform (STFT) is the most widely used technique for time frequency (TF) analysis of non-stationary signals. The aim of STFT is to analyze the signal into segment by segment (or window by window) [65]. It uses a window function to slide on the signal studied and then divide it into several equal length segments (or window). The inside signal of the segments is supposed to be stationary. After that Fourier transform is applied in each segment to find out the frequencies contained in that segment. Hence, the signal will be represented by two elements of time and frequency [66, 67].

3.3 Envelope Analysis (EA)

The envelope analysis is an important signal processing technique which is applied to extract the defect features from modulation signals.

The envelope analysis can be divided into three procedures: signal filtering, applying Hilbert transform (HT) [68] to envelope extraction of the filtered signal, and at last, the spectrum estimation of the envelope by the applying the Fast Fourier transform (FFT) [69-71]. The identification of the bearing faults is possible by using envelope analysis. However, a critical limitation of this approach is that it needs a pre-knowledge of the filtering band and frequency at resonance.

3.4 Empirical Mode Decomposition (EMD)

Empirical Mode Decomposition (EMD) is an adaptive time-frequency technique for analyzing non-stationary and nonlinear signals, which applies time domain signals and divides it into a group of oscillatory functions, called intrinsic mode functions (IMF) [72]. EMD is a superb technique used for bearing fault diagnosis [73-75]. Unfortunately, there are two problems in EMD, which are the selection of the suitable decomposition level and its intrinsic mode functions (IMF) which contains the necessary information for faults diagnosis.

3.5 Frequency Domain Decomposition Method (FDD)

Frequency Domain Decomposition (FDD) is a non-Bayesian approach for operational modal analysis of rotating systems [76]. Applying FDD in the frequency domain, it gives the natural frequencies, the associated mode shapes and damping coefficients as output, given a sufficient number of measurement channels as input [77-79]. The most important requirements of the method are the following:

The equations of motion of the structure are linear.

The structure is lightly damped, e.g., modal damping coefficients do not exceed 10%–15%.

The external load on the structure, though unknown, can be regarded as a white noise over the frequency range of interest.

3.6 Enhanced Frequency Domain Decomposition method (EFDD)

Enhanced Frequency Domain Decomposition method (EFDD) approach is an expansion of FDD approach described earlier. In this approach, modes are simply selected locating the peaks in singular value decomposition plots calculated from the spectral density spectra of the responses [80]. As FDD approach is based on using a single frequency line from the Fast Fourier Transform (FFT) analysis, the accuracy of the evaluated natural frequency depends on the FFT resolution, and no modal damping is determined. However, EFDD gives an improved calculation of both the mode shapes and the natural frequencies including damping calculation [81].

3.7 Frequency-Spatial Domain Decomposition Method (FSDD)

The spatial and frequency domain decomposition (FSDD) method was introduced in 2005, in which the damping ratios and modal frequencies are calculated from the enhanced power spectrum density (PSD) [82] directly, without the necessity to perform inverse fast Fourier transform (IFFT). FSDD greatly improves the performance of FDD type algorithms and has been widely applied in various engineering fields [83-85]. However, problems like being unable to differentiate between repeated modes, presence of computational modes, and even less capacity of calculating damping ratios are still big obstacles encountered in many applications of these kind of methods.

3.8 Wavelet Transform (WT)

A wavelet is defined as a small wave (the sinusoids used in Fourier analysis are big waves) and in brief, a wavelet is an oscillation that decays quickly [86-88]. The wavelet analysis is done like the short-time Fourier transform analysis. In STFT, the signal is multiplied with a window function; and wavelet transform follows a similar process to study the signal but with multiplying with a wavelet function, and then the signal is estimated for each result segment. However, unlike STFT, in Wavelet transform, with each spectral component results in changing the wavelet function width [89-91]. Advantages of Wavelet Theory can be summarized as:

Wavelets offer localization in frequency and time domain simultaneously.

A wavelet transform can be used to decompose a signal into multiple wavelets.

Wavelets can often compress or de-noise a signal without appreciable degradation.

3.9 Stochastic Subspace Identification (SSI)

SSI technique works directly with time data, without needing to convert them to correlations or spectra; also, SSI is an output-only time domain technique.

This technique is applied especially in operational modal parameter identification [82], but it is a difficult technique to clarify in detail for civil engineers. The model of vibration structures can be defined by a set of linear, constant coefficient and second-order differential equation (1):

$$[M]\{\ddot{U}(t)\} + [C_2]\{\dot{U}(t)\} + [K]\{U(t)\} = \{(F(t))\} \qquad (1)$$

Where $[M]$, $[C_2]$, $[K]$ are the mass, damping and stiffness matrices, $\{(F(t))\}$ is the excitation force vector, and $\{U(t)\}$ is the displacement vector depending on time t. Solution of Equation (1) is given in detail in the literature [92-95].

3.10 Intelligent Fault Diagnosis Techniques Based on Vibration

Traditionally, the framework of intelligent fault diagnosis includes four main steps: signal acquisition, feature selection, feature extraction, and fault sorting [96-98]. This method needs to obtain the signals in normal and various abnormal states for learning prior to performing diagnosis. Besides, in order to improve its universality, for example, further tests on a larger sample size should be conducted.

3.11 Artificial Neural-Network Approach for Fault Detection (ANN)

An artificial neural network (ANN) is a pattern of information processing similar to the way processing information for humans [99, 100]. Due to the ability of ANNs in generalizing and studying nonlinear relationships between output data and input data, they provide a flexible mechanism for learning and recognizing system faults. They have been established as a powerful intelligence technique in the fault diagnosis of rotating machinery. Fault diagnosis using ANN classifiers may largely increase the reliability of fault diagnosis methods.

3.12 Adaptive Neuro-Fuzzy Inference System (ANFIS)

Adaptive Neuro-Fuzzy Inference System (ANFIS) is an integration technique in which neural networks are applied to make the best or most effective use of the fuzzy inference system. ANFIS forms a series of fuzzy if–then rules with appropriate membership functions to make the stipulated input–output pairs. The initial fuzzy rules and membership functions are first set by using experienced humans about the outputs to be modeled. Then, ANFIS can modulate these fuzzy if–then rules and membership functions to minimize the error percentage in output functions, measure or explain the input–output relationship of a complex system [101, 102].

3.13 Deep Learning for Fault Diagnosis

Deep learning can be applied for fault diagnosis [103]. Deep learning is a real time online plan or scheme that can improve the accuracy of identification, classification, prediction, and efficient for initial faults that cannot be identified by traditional statistic techniques. In machine learning, we can choose features manually and a classifier to arrange and investigate images while in deep learning, modeling steps and feature extraction are done automatically. Deep learning had formed a hot topic mostly in image application and object recognition. It is also suitable for large system with multiple variables and fault diagnosis [104-107].

4. Conclusion

Vibration experts and developers have done great efforts to create functions that solve the few limitations of vibration analysis, however, there are still some issues that we are unable to see through vibration analysis such as;

- **Very High frequency**: Common sensors have a maximum frequency of 10 to 15 kHz. If one does not invest in special sensors, higher frequencies will be invisible to the equipment.

- **Ultra-low frequencies:** Although it is possible to measure very low frequencies, they are often ignored because they require long samples which are not done in a normal route.

- **Lubricant condition:** This is one of the biggest limitations of vibration analysis. The condition of the lubricant cannot be evaluated by this technique, you can only suspect the lack of it.

Many vibration analysis techniques are presented to explore their capabilities, advantages, and disadvantage in diagnosing and monitoring rotating systems. The following points can be concluded:

1. The identification of the bearing faults by using frequency analysis is difficult because, it is not suitable for non-stationary signal analysis.

2. The identification of the bearing faults is possible by using envelope analysis. However, the envelope analysis has a major drawback consisting of the requirement of a preliminary research of the resonance frequencies.

3. The identification of the bearing faults is possible by using Short Time Fourier Transform (STFT). However, the problem with STFT is that it provides constant resolution for all frequencies since it uses the same window for the entire signal. Therefore, once the window function is chosen, the time and frequency resolution are fixed. So, there is a trade-off to choose a proper window function between the time resolution and the frequency resolution: a longer window will lead to a higher frequency resolution with a lower time frequency and vice versa.

4. The identification of the bearing faults is possible by using Empirical Mode Decomposition (EMD). Unfortunately, there are two problems in EMD, which are the selection of the suitable decomposition level and its intrinsic mode functions (IMF) which contains the necessary information for faults diagnosis.

5. Deep learning for fault diagnosis had been paid less attention. Because of these difficulties:(1) for images, the characteristics of recognition objects are relatively fixed, but faults are changeable, such as patterns variability and shape variability;(2) as fault has no fixed pattern, whether deep learning can capture a useful "hierarchical grouping" or" part-whole decomposition" of the fault data is unknown; (3) the detection mechanism and ability based on deep learning is not yet well explored, especially for the incipient faults not any observable changes, which is a bottle neck that traditional methods suffering.

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