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Introduction to Machine Condition Monitoring

1.1 Background

The need for an effective condition monitoring (CM) and machinery maintenance program exists wherever complex, expensive machinery is used to deliver critical business functions. For example, manufacturing companies in today's global marketplace use their best endeavours to cut costs and improve product quality to maintain their competitiveness. Rotating machinery is a central part of the manufacturing procedure, and its health and availability have direct effects on production schedules, production quality, and production costs. Unforeseen machine failures may lead to unexpected machine downtime, accidents, and injuries. Recently it has been stated that machine downtime costs UK manufacturers £180bn per year (Ford 2017; Hauschild 2017). Moreover, Mobley stated that based on the specific industry, maintenance costs can represent between 15% and 60% of the cost of goods produced. For instance, in food-related production, average maintenance costs represent approximately 15% of the cost of goods produced, whereas for iron and steel and other heavy industries, maintenance costs represent up to 60% of total production costs (Mobley 2002).

Components including motors, bearings, gearboxes, etc. are engaged to operate effectively to keep the rotating machine in a stable, healthy condition. For that reason, maintenance is performed by repairing, modifying, or replacing these components in order to ensure that machines remain in a healthy condition. Maintenance can be accomplished using two main approaches: corrective and preventive maintenance (Wang et al. 2007). Corrective maintenance is the most basic maintenance technique and is performed after machine failure, which is often very expensive particularly for large-scale applications of rotating machines. Preventive maintenance can be applied to prevent a failure using either time-based maintenance (TBM) or condition-based maintenance (CBM), which can be localised CBM or remote CBM (Higgs et al. 2004; Ahmad and Kamaruddin 2012). TBM uses a calendar schedule that is set in advance to perform maintenance regardless of the health of the machine, which makes this approach expensive in some large and complex machines. In addition, TBM may not prevent machines from failing.

With regard to CBM, it has been reported that 99% of rotating equipment failures are preceded by nonspecific conditions indicating that such a failure is going to happen (Bloch and Geitner 2012). Hence, CBM is regarded as an efficient maintenance approach that can help avoid the unnecessary maintenance tasks of the TBM approach. Numerous studies have shown the economic advantages of CBM in several applications of rotating machines (e.g. McMillan and Ault 2007; Verma et al. 2013; Van Dam and Bond 2015;
In CBM, decisions about maintenance are made based on the machine’s current health, which can be identified through the CM system. Once a fault occurs, an accurate CM technique allows early detection of faults and correct identification of the type of faults. Thus, the more accurate and sensitive the CM system, the more correct the maintenance decision that is made, and the more time available to plan and perform maintenance before machine breakdowns.

Condition monitoring of rotating machine components can minimise the risk of failure by identifying machine health via early fault detection. The main aim of condition monitoring is to avoid catastrophic machine failures that may cause secondary damage, machine downtime, potentially safety incidents, lost production, and higher costs associated with repairs. The CM techniques in rotating machinery encompass the practice of monitoring measurable data (e.g. vibration, acoustic, etc.), which can be used individually or in combination to identify changes in machine condition. This allows the CBM program to be arranged, or other actions to be taken to prevent machine breakdowns (Jardine et al. 2006). Based on the types of sensor data acquired from rotating machines, CM techniques can be grouped into the following: vibration monitoring, acoustic emission (AE) monitoring, electric current monitoring, temperature monitoring, chemical monitoring, and laser monitoring. Of these techniques, vibration-based condition monitoring has been widely studied and has become a well-accepted technique for planned maintenance management (Lacey 2008; Randall 2011). In the real world, different fault conditions generate different patterns of vibration spectrums. Thus, vibration analysis in principle allows us to examine the inner parts of the machine and analyse the health of the operating machine without physically opening it (Nandi et al. 2013). Moreover, various characteristic features can be observed from vibration signals that make this one of the best selections for machine CM.

This chapter describes maintenance approaches for rotating machines failures and applications of machine condition monitoring (MCM). It also provides a description of various CM techniques used for rotating machines.

1.2 Maintenance Approaches for Rotating Machines Failures

As briefly just described, maintenance can be accomplished using two main types: corrective and preventive maintenance. In this section, we will discuss these two types of maintenance in detail.

1.2.1 Corrective Maintenance

Corrective maintenance, also called run-to-failure, is the most basic maintenance technique, performed after a machine breakdown. In this way, when failure happens, it can be catastrophic and result in a long downtime. The procedure of corrective maintenance involves actions, activities, or tasks that are undertaken to restore the machine from breakdown status. This often can be performed by repairing, modifying, or replacing the components that are responsible for the overall system failure, e.g. bearings replacement, gear replacement, etc. Companies that use run-to-failure maintenance, i.e. corrective maintenance, do not need to perform maintenance or spend any money on maintenance while waiting for a machine to fail to operate. However, this type of maintenance is very expensive, particularly for large-scale applications of rotating machines.
1.2.2 Preventive Maintenance

Preventive maintenance is an alternative approach to corrective maintenance. The basic idea of preventive maintenance is to prevent machine breakdowns. This approach consists of actions, activities, or tasks that can be applied to prevent machine failure. Preventive maintenance can be accomplished using either TBM or CBM. These are described as follows.

1.2.2.1 Time-Based Maintenance (TBM)

TBM, also called periodic-based maintenance, uses a calendar schedule that is set in advance and performs maintenance regardless of the health of the machine, which makes this approach expensive for some large, complex machines. In addition, TBM may not prevent machine failures. In TBM, maintenance decisions are determined based on failure-time analysis. In fact, TBM assumes that the failure characteristics of equipment are predictable based on failure-rate trends, which can be grouped into three stages: burn-in, useful life, and wear-out (Ahmad and Kamaruddin 2012).

1.2.2.2 Condition-Based Maintenance (CBM)

As described by Higgs et al. (2004), a CBM system is able to understand and makes decisions without human involvement. CBM is an efficient maintenance approach that can help avoid the unnecessary maintenance tasks of the TBM approach. As described earlier, decisions regarding maintenance are made based on the machine’s current health, which can be identified through the CM system. There are two types of CBM systems: localised CBM and remote CBM. Localised CBM is an independent predictive maintenance practice, which is likely to be done by a maintenance engineer or operator. The procedure of localised CBM starts by acquiring and recording CBM data from a component of interest at periodic intervals in order to recognise its current status and then decide whether that status is satisfactory. On the other hand, a remote CBM system can be independent or networked to another business system. Remote CBM monitors the condition of a component at remote areas through wireless sensors networks. Various studies have shown the economic advantages of CBM in several applications of rotating machine (for example, McMillan and Ault 2007; Verma et al. 2013; Van Dam and Bond 2015; Kim et al. 2016).

1.3 Applications of MCM

Having discussed the role of CM in CBM, in this section we present the use of CM in various rotating machine applications including a wind turbine, oil and gas, aerospace and defense, automotive, marine, and locomotive.

1.3.1 Wind Turbines

Wind turbines have become one of the fastest growing renewable energy sources. A major issue of a wind turbine is the relatively high cost of operation and maintenance (O&M). Wind turbines are usually hard-to-access structures, as they are located at remote onshore and offshore places with richer wind sources (Lu et al. 2009; Yang et al. 2013). Hence, they are subject to tough environmental conditions over their
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lifetime. Accordingly, major failures in wind turbines are expensive to repair and cause loss of revenue due to long downtimes (Bangalore and Patriksson 2018).

Compared to conventional power-generation techniques, wind turbines do not have resource energy costs. However, their O&M costs are high. Hence, CM of wind turbine is utilised as a tool for reducing O&M costs and improving wind farm electricity production by the wind power industry (Zhao et al. 2018). A considerable amount of literature has been published on wind turbine CM. Several systematic reviews of wind turbine CM have been undertaken (Lu et al. 2009; Hameed et al. 2009; Tchakoua et al. 2014; Yang et al. 2014; Qiao and Lu, 2015 2015a,b; Salameh et al. 2018. Gonzalez et al. 2019).

1.3.2 Oil and Gas

The oil and gas industry comprises procedures for exploration, extraction, refining, transporting, and marketing petroleum products, e.g. fuel, oil, and gasoline. Onshore and offshore oil and gas projects are capital-intensive investments with the possibility for serious financial and environmental consequences when a catastrophic failure happen (reza Akhondi et al. 2010; Telford et al. 2011). In their study of multimodel-based process CM of offshore oil and gas production process, Natarajan and Srinivasan stated that offshore oil and gas production platforms are uniquely hazardous, in that the operating personnel have to work in a perilous environment surrounded by extremely flammable hydrocarbons. Therefore, a fault in a piece of equipment may possibly spread to others, resulting in leaks, fires, and explosions, and causing loss of life, capital, and production downtime (Natarajan and Srinivasan 2010). Hence, a technique to monitor equipment in oil and gas production platforms is needed to prevent such failures in these platforms.

Condition monitoring plays an important role in monitoring the condition of equipment while operating and is utilised to predict failure in the mechanical system using a fault-diagnosis technique. Thus far, several studies have investigated the use of CM in the oil and gas industry (e.g. Thorsen and Dalva 1995; reza Akhondi et al. 2010; Natarajan and Srinivasan 2010; Telford et al. 2011).

1.3.3 Aerospace and Defence Industry

An aircraft is an extremely dynamic system where all flight-critical components within the vehicle are exposed to extreme dynamic loads and continuous vibratory and impulsive loads. Hence, to ensure rotorcraft safety and reliability, maintenance inspections, repairs, and parts replacement must be performed regularly. However, this is an expensive and time-consuming task. Even with these measures, early failure due to fatigue leads to many helicopter accidents, resulting in a fatal accident rate per mile flown for rotorcraft (Samuel and Pines 2005). Accordingly, both operating costs and safety are motivating factors for the development of health-monitoring systems. Hence, advanced fault diagnostics and prognostics for aircraft engines are required. Also, the availability and reliability of military spacecraft and aircraft are of vital importance (Keller et al. 2006).

As far as aerospace health management is concerned, Roemer et al. (2001) developed diagnostic and prognostic techniques for aerospace health management applications. Moreover, a survey of aircraft engine health monitoring systems is presented
in (Tumer and Bajwa 1999). In terms of helicopter transmission diagnostics, Samuel and Pines reviewed the state of the art in vibration-based helicopter transmission diagnostics (2005).

1.3.4 Automotive

Modern vehicle systems software and hardware are complex, so their maintenance is challenging. Thus, predictive maintenance has become more important. The literature on automotive CM has highlighted several studies focused on vehicle fault diagnosis. For example, Abbas et al. (2007) presented a method for fault diagnosis and failure prognosis of vehicle electrical power generation and storage (EPGS) that includes a battery, a generator, electrical loads, and a voltage controller. Moreover, Shafi et al. (2018) introduced an approach for fault prediction of four main subsystems of a vehicle: fuel system, ignition system, exhaust system, and cooling system.

1.3.5 Marine Engines

The marine diesel engine is one of the most important sources in marine power systems. Therefore, its health and availability are vital to normal operation and efficacy of marine vessels and ships. Unforeseen failures in marine diesel engines may result in substantial economic loss and severe accidents. The problems relating to marine diesel engines, especially medium- and high-speed engines, are due primarily to their large size, which does not allow the use of trial-and-error techniques (Kouremenos and Hountalas 1997; Li et al. 2012a,b). Therefore, CM of marine diesel engines in a ship is very important to ensure vessel safety.

1.3.6 Locomotives

Railway transportation has played an important role in most countries’ economic and social development. Thus, the continuous operation of trains is very important in these countries. Unforeseen failure of train components may result in unexpected breakdowns. For instance, locomotive bearings that often rotate at high speeds when the train is running need to be kept in healthy condition to ensure the safety of the locomotive (Shen et al. 2013). Hence, CM of locomotive bearings is very important to ensure the safety of people on trains.

1.4 Condition Monitoring Techniques

Based on the types of sensor data acquired from rotating machines, MCM techniques can be grouped into the following: vibration monitoring, acoustic emission monitoring, a fusion of vibration and acoustic, electric motor current monitoring, oil analysis, thermography, visual inspection, performance monitoring, and trend monitoring.

1.4.1 Vibration Monitoring

As described earlier, vibration-based bearing CM has been extensively used and has become a well-accepted technique for planned maintenance management (Lacey 2008; Randall 2011). In fact, different fault conditions generate different patterns of vibration
spectrums. Thus, vibration analysis in principle allows us to examine the inner parts of the machine and analyse the health of the operating machine without physically opening it (Nandi et al. 2013). In addition, various characteristic features can be observed from vibration signals, which makes this one of the best selections for machine CM. In this book, we will describe various techniques for MCM using vibration signals.

1.4.2 Acoustic Emission

Acoustic emission (AE) is a technology for CM of machines such as gearboxes. Emitted sound waves are caused by faults or discontinuities. In electrical machines, sources of AE include impacting, cyclic fatigue, friction, turbulence, material loss, cavitation, leakage, etc. (Goel et al. 2015). AE is often propagated on the surface of the material as Rayleigh waves; and the displacement of these waves is measured by AE sensors, which are usually piezoelectric crystals. Compared to vibration monitoring, AE monitoring can provide a higher signal-to-noise ratio (SNR) in a high-noise environment. However, it has two main drawbacks: (i) it experiences high system costs, and (ii) it requires specialised expertise to acquire AE (Zhou et al. 2007). The application of AE for bearing CM is studied by Li and Li (1995). The results of this study showed that AE is found to be a better signal than vibrations when transducers have to be placed remotely from the bearing. Also, its application for bearing fault detection in another study verified that AE is more sensitive for detecting incipient faults than vibration (Eftekharnejad et al. 2011). Moreover, Caesarendra used AE for low-speed slewing bearing CM (Caesarendra et al. 2016).

1.4.3 Fusion of Vibration and Acoustic

In an attempt to obtain informative features, one may use a fusion of vibration signals and AE. This technique has been used for CM in several studies of MCM (e.g. Loutas et al. 2011; Khazaee et al. 2014; Li et al. 2016).

1.4.4 Motor Current Monitoring

Motor current monitoring also can be used for CBM. No additional sensors are needed to implement current monitoring for electric machines. Here, the basic electrical measures associated with electromechanical plants are readily measured by tapping into the existing voltage and current transformers that are often installed as part of the protection system. The two main advantages of current monitoring are as follows: (i) it provides significant economic benefits, and (ii) an overall MCM package is possible (Zhou et al. 2007). Several studies have used current monitoring (Schoen et al. 1995; Benbouzid et al. 1999; Li and Mechefske 2006; Blodt et al. 2008).

1.4.5 Oil Analysis and Lubrication Monitoring

In electrical and mechanical machines, lubrication oil is used to reduce friction between moving surfaces. The lubrication oil is an important source of information for early diagnosis of machine failures, similar to the role of testing human blood samples in order to detect diseases. Compared to vibration-based machine health monitoring techniques, lubrication oil CM is able to provide warnings about machine failure approximately
10 times earlier (Zhu et al. 2013). Moreover, it has been stated that incorrect lubrication, either over-lubrication or under-lubrication, is one of the main reasons for bearing defects (Harris 2001).

1.4.6 Thermography

As described by Garcia-Ramirez et al. (2014), thermographic analysis has been considered a technique that can be used in fault diagnosis with the advantages of being non-invasive and having a wide range of analysis. This technique can be performed through thermographic images that can be captured using a thermographic camera sensor: an infrared detector that absorbs both the energy emitted by the object and the temperature of the surface to be measured, and converts it into a signal called a thermogram. Each pixel of a thermogram has a specific temperature value, and the image contrast can be derived from the differences in temperature of the object surface. Bagavathiappan et al. (2013) presented a comprehensive review of infrared thermography for CM that focused on the advances of infrared thermography as a non-invasive CM tool for machinery, equipment, and processes. Moreover, the most recent contributions related to the application of infrared thermography to different industrial applications have been reviewed in Osornio-Ríos et al. (2018).

1.4.7 Visual Inspection

Given high-resolution cameras and advancements in computer hardware and software, visual inspection is considered an alternative technique for MCM, which can be performed by visually inspecting the surface of the components in a machine. The procedure of automated visual inspection involves image acquisition, preprocessing, feature extraction, and classification. The applications of machine vision extract a feature from 2D digital images of a 3D scene. The main aim of an industrial machine vision system is to replace human inspectors with automated visual inspection procedures. Machine vision systems can be categorised into three groups (Ravikumar et al. 2011):

1. **Measurement systems.** The aim of the measurement system is to find the dimensions of an object through digitisation and manipulation of the image of the object.
2. **Guidance systems.** The guidance system instructs a machine to perform specific actions based on what it sees.
3. **Inspection systems.** The inspection system defines whether an object or a scene matches a predefined description.

Various studies have assessed the efficacy of visual inspection in MCM (e.g. Sun et al. 2009; Ravikumar et al. 2011; Chauhan and Surgenor 2015; Liu et al. 2016; Karakose et al. 2017.).

1.4.8 Performance Monitoring

The basic idea here is that a machine’s condition can be identified using the information obtained from performance monitoring. This technique requires two predefined conditions to ensure a successful application: (i) the system should be stable in a normal condition, and its stability is reproduced in the parameters under investigation;
and (ii) measurements are taken either manually or automatically. If these conditions are met, any changes from the normal behaviours of the system indicate abnormality (Rao 1996).

1.4.9 Trend Monitoring

Trend monitoring involves continuous or regular measurements of a parameter, e.g. temperature, noise, electric current, etc. It includes the selection of a suitable and measurable indication of machine or component weakening and the study of the trend in this measurement with a running time to indicate when weakening exceeds a critical rate. For instance, the measured data is recorded and plotted on a graph as a function of time. Then, it is compared with other measured data that represent the normal condition of a machine. Here, the difference between the measured data and the predefined data that represent the normal condition is used to recognise any machine abnormality (Davies 2012).

1.5 Topic Overview and Scope of the Book

MCM is a crucial technique for guaranteeing the efficiency and quality of any production process. When machine failure happens, the correct monitoring data analysis helps the engineers to locate the problem and repair it quickly. In an ideal situation, we could predict machine failure in advance and carry out maintenance before the failure happens, and thus machines would always run in a healthy condition and provide satisfactory work.

Given the importance of MCM in various sensitive applications of rotating machines, such as power generation, oil and gas, aerospace and defence, automotive, marine, etc., CM techniques for rotating machinery encompass the practice of monitoring measurable data (e.g. vibration, acoustic, etc.), which can be used individually or in combination to identify changes in a machine’s condition. The increased level of complexity in modern rotating machines requires more effective and efficient CM techniques. For that reason, a growing body of literature has resulted from efforts in research and development by many research groups around the world. These publications have a direct impact on the present and future development of MCM. The nature of the MCM problem requires multiple directions for solutions and motivates continuous contributions from generations of researchers.

First, there are various type of CM techniques. As described earlier, based on the types of sensor data acquired from rotating machines, MCM techniques can be grouped into the following: vibration monitoring, acoustic emission monitoring, a fusion of vibration and acoustic, electric motor current monitoring, oil analysis, thermography, visual inspection, performance monitoring, and trend monitoring.

Second, instead of processing the originally acquired signals, a common approach is to compute certain attributes of the raw signal that can describe the signal in essence. In the machine learning community, these attributes are referred to as features. At times, multiple features are computed to form a feature set. Depending on the number of features in the set, one may need to perform further filtering of the set using a feature-selection algorithm. Various techniques of feature extraction and feature selection can be used in MCM.
Third, the core objective is to categorise the acquired signal into the corresponding machine condition correctly, which is generally a multiclass classification problem. A number of classification algorithms can be used to deal with the classification problem.

In this book, we attempt to bring together many techniques in one place and outline a complete guide, from the basics of rotating machines to the generation of knowledge using vibration signals. We will provide an introduction to rotating machines and the vibration signals they produce, at a level that can be easily understood by readers such as post-graduate students, researchers, and practicing engineers (Chapter 2). The introduction will help those readers become familiar with the basic knowledge needed to appreciate the specific applications of the methods in this book. Based on the stages of the MCM framework and the aim to design effective techniques for fault detection and classification of rotating machines, we will cover feature extraction (Chapters 3–8), feature selection (Chapter 9), and classification methods (Chapters 10–13) as well as their applications to machine vibration datasets. Moreover, this book will describe recent trends of deep learning in the field of MCM and provide an explanation of commonly used techniques and examples of their applications in machine fault diagnosis (Chapter 14). Additionally, to assess the efficiency of the classification algorithms introduced in this book, we will describe different validation techniques that can be used to validate the efficiency of classification algorithms in terms of classification results (Chapter 15).

Furthermore, we will present new methods including machine learning and compressive sampling. These offer significant improvements in accuracy, with reduced computational costs. It is important that these are made available to all researchers as well as practitioners and new people coming into this field to help improve safety, reliability, and performance (Chapters 16 and 17). Finally, we will provide conclusions and recommendations for the application of the different methods studied in this book (Chapter 18).

1.6 Summary

In this chapter, we briefly introduced the commonly used maintenance approaches for rotating machines failures as well as the applications of MCM in various sensitive applications of rotating machines such as power generation, oil and gas, aerospace and defence, automotive, marine, etc. In addition, we provided a description of various CM techniques that can be used for rotating machines, including vibration monitoring, acoustic emission monitoring, a fusion of vibration and acoustic, electric motor current monitoring, oil analysis, thermography, visual inspection, performance monitoring, and trend monitoring.

References


