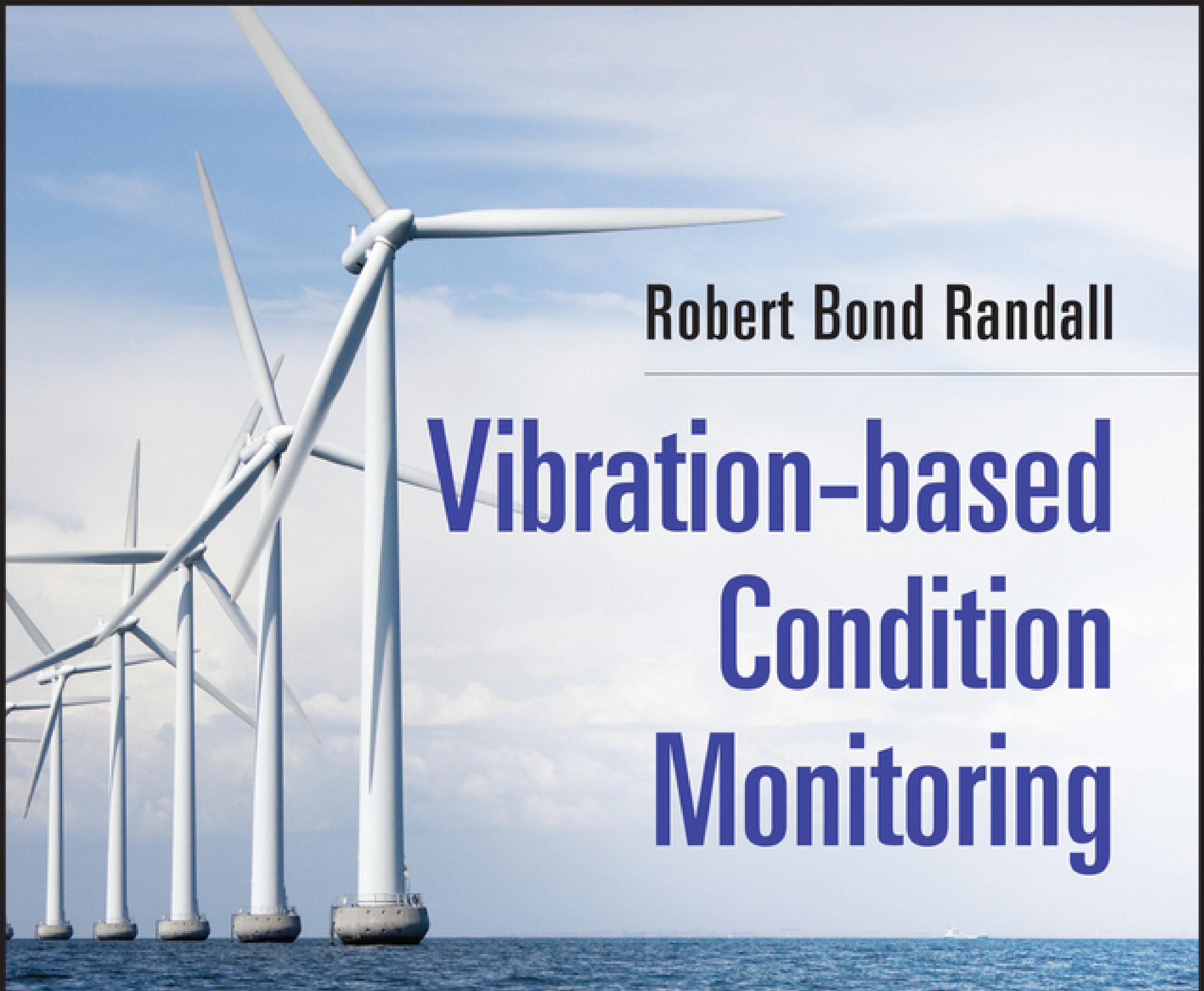

Robert Bond Randall

Vibration-based Condition Monitoring

Industrial, Automotive and Aerospace Applications

Second Edition

WILEY

VIBRATION-BASED CONDITION MONITORING

VIBRATION-BASED CONDITION MONITORING

INDUSTRIAL, AUTOMOTIVE AND AEROSPACE APPLICATIONS

Second Edition

Robert Bond Randall

University of New South Wales
Australia

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Dedicated to the memory of Professor Simon Braun, 1933–2020.

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Foreword

About 10 years ago, when the first edition of Prof Randall's *Vibration-based Condition Monitoring* was published, I enthusiastically welcomed it, because a book was finally published that presented a systematic approach to a subject, 'Condition-Based Monitoring', which had grown in complexity over the years, with contributions from many important scholars, but in a non-systematic way.

There were already books that dealt with partial aspects (e.g. *Vibration and Acoustic Measurement Handbook* (1972) by Michael P. Blake and William S. Mitchell, *A Practical Vibration Primer* (1979) by Charles Jackson and *Fundamentals of Noise and Vibration Analysis for Engineers* (1989) by Michael P. Norton), or they dealt with specific fields (including, among the many, Maurice L. Adams Jr.'s *Rotating Machinery Vibration from Analysis to Troubleshooting* in 2001). There was already a reference journal (i.e. *Mechanical Systems and Signal Processing*, founded in 1987 with foresight by the late and recently deceased Simon Braun), but it lacked an organic work, a book that presented a systematic approach and introduced both methods and techniques.

Certainly, in twenty-first century society, one could reflect and debate for a long time whether ***a book*** still represents 'the instrument' for the transmission of knowledge. Today we have different ***media***, but I remain personally convinced that, in the scientific field, ***the book*** is still a fundamental tool; what has certainly changed is the way it is used: probably many readers of ***this book*** are not doing it, right now, on paper media, but on a digital medium.

The scientific community and engineers were lucky because this book was written by Prof Randall. I do not think there is any need to present him, because he has a long career of research, of development of signal processing techniques, of case study analysis and of teaching. I was lucky enough to meet him in person 20 years ago, and my esteem for him has always grown, as a monotonic function, not only for its scientific aspects, but also human.

Now, this second edition fills in some inevitable gaps (when writing for the first time a wide-ranging work like this, it is impossible to delve into all the topics or not neglect some, which appeared secondary at that time), but above all introduces and deepens new methods and techniques that have been fully developed in the last ten years, such as tacho-less techniques.

Why is Condition Monitoring so important in engineering and, more generally, in today's world? Prof Randall explains very well the reasons in the introduction of this book: it is a fundamental component for some of the so-called pillars of the technology paradigm of Industry 4.0, at least for IoT ('Internet of Things'), but also for Big Data analytics. Condition Monitoring allows the full implementation of Condition-Based Maintenance (CBM), with remarkable economic advantages, from a single machine to entire plants and industrial facilities, from manufacturing, to services and utilities. Finally, Condition Monitoring is the basis of a predictive – i.e. prognostic – approach to determining the residual useful life (RUL) of a component or a system.

It is certainly ambitious to define what the purpose of science is, and illustrious minds have applied themselves to this: from Greek philosophers to Galileo, from Descartes to Gödel, from Cantor to Popper. If we limit ourselves to the narrow sphere of Engineering and to its purpose, it is not possible to fail to recognise that it must explain *'how'* one does something and *'why'* it is done. In this case, in his book, Prof Randall explains very clearly the *'how'*, that is, the most well-established methods and techniques for condition monitoring are analysed in detail and implemented. To do this, he uses one of the most natural signals generated by mechanical systems: vibrations, inextricably linked to the dynamic behaviour of the mechanical systems themselves. Prof Randall also explains in detail *'why'* applying Condition Monitoring is so important.

There is also, however, another interesting '*why'* to analyse, by limiting the scope to the foreword to a book: it concerns Condition Monitoring's rapid development in recent years and its pervasiveness in the modern world. Condition Monitoring is certainly a technological innovation, and as such, its genesis and evolution can be analysed by means of the mechanisms of generating innovation, starting from the more traditional ones, such as the 'Technology-Push', theorised by Joseph A. Schumpeter way back in 1911, and the 'Demand-Pull' most recently introduced by Jacob Schmookler in 1966.

Certainly, the 'epic' and 'primordial' phase of Condition Monitoring (we could call it the 'Proto-Condition Monitoring') was governed by technology-push: without the microprocessors (introduced in the Cold War, not so much for the space race as it is commonly believed, but for the guidance and control of intercontinental missiles), without the invention of miniaturised and reliable sensors (the switch from the strain-gage to the piezoelectric accelerometer happened between the 1940s and the 1950s, with the starting up of manufacturers such as Brüel & Kjær, Columbia Research Laboratories, Endevco, Gulton Manufacturing and Kistler Instruments – some of which are still firmly on the market – or the introduction of the eddy-current proximity probe in 1961 for rotary machines by Bently Nevada), without the personal computers and without the low-cost storage systems, Condition Monitoring would have remained confined to laboratories. Very often, the hardware manufacturer also produced the necessary software and supplied the brainware: for example, minicomputers to collect data and run signal processing methods and rule-based systems for the implementation of condition monitoring. Think, for example, to Hewlett-Packard and Sohre's tables of 1968 or to Bently Nevada and their ADRE systems, and the signal processing methods developed by Donald Bently himself and Agnes Muszynska.

This phase was followed by a 'maturity' phase, governed mainly by the demand-pull, which we could call the 'Meso-Condition Monitoring', during which some large players immediately realised the benefits of Condition Monitoring and implemented it within a CBM approach, as an economic driver for cost reductions. At this stage, the leading roles were big companies and operators of 'big fleets', both in a physical and figurative sense, in various sectors: from the military (think the US Navy) to the transport and aerospace (as in the case of NASA), from the energy (first of all GE and Siemens) to the manufacturing.

However, the two traditional technology-push and demand-pull models do not explain, as it is often the case in technology, why what we might call the 'Neo-Condition Monitoring' is growing so rapidly, in more recent years. The explanation, from a technological innovation point of view, is given by an interactive vision: on the one hand, technological evolution introduces new tools (hardware in the broadest sense: sensors, wireless systems, computers and memory) and new signal processing techniques are proposed, with a frequency if not weekly, at least monthly. On the other hand, as we said, the condition monitoring market, thanks in part to the IoT, has become immense.

In light of these considerations, it is clear how important it is that we have a reference and authoritative text for ‘Vibration-based Condition Monitoring’ and all of us who work in science and technology should be grateful to Bob Randall (I now allow myself to move to a more confidential tone) for writing this second updated and expanded edition, which will certainly become a new milestone.

Paolo Pennacchi
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October 2020

About the Author

Bob Randall is a visiting Emeritus Professor in the School of Mechanical and Manufacturing Engineering at the University of New South Wales (UNSW), Sydney, Australia, which he joined as a Senior Lecturer in 1988, and where he is still active in research. Prior to that, he worked for the Danish company Brüel and Kjær for 17 years, after 10 years' experience in the chemical and rubber industries in Australia, Canada and Sweden. His research and publication record while with Brüel and Kjær was treated as PhD equivalent when he joined UNSW. He was promoted to Associate Professor in 1996 and to Professor in 2001, retiring in 2008. He has degrees in Mechanical Engineering and Arts (Mathematics, Swedish) from the Universities of Adelaide and Melbourne, respectively. He is the invited author of chapters on vibration measurement and analysis in a number of handbooks and encyclopedias, including *Shock and Vibration Handbook* (McGraw-Hill) and *Handbook of Noise and Vibration* Control (Wiley). He is a member of the Advisory Board of *Mechanical Systems and Signal Processing* and of the Editorial Board of *Trans. IMechE Part C*. He is the author of more than 350 cited papers in the fields of vibration analysis and machine diagnostics, and has supervised seventeen PhD and three Master's projects to completion in those and related areas. From 1996 to 2012, he was Director of the Defence Science and Technology Organisation (DSTO) Centre of Expertise in Helicopter Structures and Diagnostics at UNSW. He has an interest in languages and has lectured in English, Danish, Swedish, French, German, and Norwegian.

Preface to The Second Edition

In the 10 years since the first edition was published, there have been a very large number of developments in vibration-based machine condition monitoring, not only in the techniques applied, but also in its much wider acceptance in industry, as the most efficient basis for maintenance. This has, for example, changed the relative importance of intermittent manual monitoring and permanent online monitoring. The former approach covered, and still does cover, a much larger number of (simpler) machines, but the latter now represents a much larger investment in monitoring equipment and systems.

Where online monitoring was previously confined largely to expensive and critical machines in say a chemical or power generation plant, which often ran at constant speed and almost constant base load, the huge growth in development of renewable energy sources in the last decade, in particular wind turbines, first onshore, and then offshore, has prompted the development of techniques that can cope with widely dispersed smaller machines, often multiple units in large wind farms, with widely varying speed and load. Such techniques could then also be applied to other machines with difficult access, and variable speed and load, such as automated machines in manufacturing plants, and mobile equipment in mines, etc, the latter often being driverless and remotely controlled. Industry 4.0 and the associated Internet of Things (IoT) recognise the importance of including more transducers in autonomous machines, not only for automatic control, but also for optimised condition-based maintenance (CBM), and the economic benefits of CBM.

The new edition contains nine chapters instead of the original six. Chapters 1, 2, and 4 only have minor updates. Because of the need to process signals with varying speed, considerable advances have been made in order tracking, involving resampling time signals at uniform spacings in rotation angle of a machine. The accuracy of doing this has been greatly improved, allowing multiple transformations back and forth between the time and angle domains. This was found very useful to cope with the fact that shaft speed related signals, such as gearmesh frequencies, are made more periodic in the angle domain, while structural response properties, such as impulse responses, retain constant time scales in the time domain, independent of speed. It is now often possible to extract the speed information from the response signal itself, avoiding the need for a tachometer signal. A related topic is the accurate determination of the machine speed, often from the vibration signals as well. A new Chapter 5, called *Some special signal processing techniques* has thus been added to address this, but it also includes carry-over of some updated topics from the original Chapter 3, *Basic signal processing techniques*. Significant new material has been added to the remaining topics in the updated Chapter 3.

Shortly after the publication of the first edition there was a breakthrough in cepstrum analysis, which meant that time signals could be obtained by editing the cepstrum of continuous signals. This was not previously thought to be possible, since the complex cepstrum, which can be reversed back to time signals, requires continuous phase spectra, which are a property of transients only. However, there are many applications where the real cepstrum can be edited, to obtain an edited log amplitude spectrum, which can then be combined with the original non-continuous phase spectrum, to give edited time signals with very little error. Just one example of this is where the editing removes families of harmonics from the spectrum (and time signals) by notching in the cepstrum. The phase will be in error at the frequencies of the removed components, but these have been greatly reduced (to the same level as adjacent noise components) and are widely spaced, so the effect of the residual phase errors is usually negligible. This new possibility gives rise to so many new applications, including extraction of separated gear and bearing signals under varying speed conditions, and pre-processing of machine vibration signals as a precursor to operational modal analysis (OMA), that a new Chapter 6, devoted to *Cepstrum analysis applied to machine diagnostics*, has been added. It should be mentioned that OMA is now recognised as being an important part of advanced condition monitoring, to allow the extraction of force signals from measured vibration responses.

The new Chapter 7, *Diagnostic Techniques for particular applications*, is a substantially updated version of the old Chapter 5, *Diagnostic techniques*, even though many of the headings are the same. Quite recently, it has been discovered that the analysis of gear transmission error (TE) is much more powerful as a diagnostic tool than originally thought, and though introduced in the first edition, it was then thought that the required mounting of shaft encoders would restrict it to being a laboratory tool. However, with the rapid progress of Industry 4.0 and the IoT, it is becoming more common to build such transducers into machines at the design phase, also because of their benefits in control, in particular of variable speed machines. This topic has thus been considerably expanded, and important new applications developed. There have also been many other improvements in the diagnostics of gears and bearings, not least under variable speed and load conditions. While still being a very important tool, the main approach to bearing diagnostics in the first edition, based on spectral kurtosis and the kurtogram, has been shown to sometimes fail, for example when impulsive signals from other sources, such as EMI (electromagnetic interference) dominate the kurtosis, so a number of alternative approaches can now be chosen, which have benefits in many situations. Diagnostics of internal combustion (IC) engines has also been greatly improved, for example to include mechanical faults such as piston slap and bearing knock.

Another area which has become much more practicable is the ability to make realistic detailed simulation models of machine components, and even complete complex machines, using CAD, FEM, and multi-body dynamics. This has become a standard part of the machine development process, greatly reducing the number of intermediate prototypes. It has led to the adaptation of such models to individual machines (known as ‘digital twins’), for example to compensate for tolerance variations, and even changes in performance with time, in particular in the now much more common situation where manufacturers are responsible for the whole-life performance and maintenance of machines. For the latter application, it would be advantageous to simulate faults in components, using substructuring techniques to incorporate them in the overall models, in place of the original healthy components. A new Chapter 8 has thus been added, entitled *Fault simulation*, giving typical approaches for the cases of gears, bearings and IC engines, largely developed since the publication of the first edition. It is particularly with dynamic machine models that OMA is required to update the simulation models, not only because they vary more with operating conditions than static structures, but also because the forcing functions are much more complex in general. Extraction of these forces, using the modal models, is also much more important in machine condition monitoring than in structures, where the condition is indicated primarily by modal properties.

Simulation is also now a very important part of prognostics, because of the impossibility of experiencing fully documented failures in sufficient quantities to use purely data driven methods, so the new Chapter 9, replacing the old Chapter 6 on *Fault trending and prognostics*, has been considerably updated, even though the ideal solution to this problem has still not been found. The sometimes blind faith in 'Big data' as a future solution is misplaced, although such techniques will play a large part in compensating for the effects of wide variations in operating conditions, for machines in normal, or near normal, condition, for which big data does exist. This will greatly increase the reliability of detection of departures from normal condition, and at least aid prediction of developments into the near future. The first advances will most likely be made in fleets of similar machines, e.g. wind turbines and helicopter gearboxes, where increasing numbers of documented cases will be incorporated into predictive systems, based initially on physics-based fault development models, including simulation of various degrees of sophistication, right up to digital twins. Watch this space.

Because of the large amount of new material, a large number of additional acknowledgements are required, not only for new work, but also because some earlier work has now increased in importance for machine condition monitoring. In that category must now be added Dr Yujin Gao, whose pioneering work on cepstral methods of modal analysis, forms the basis of much of the added material of Chapter 6, and Dr Yuejin Li, whose work, still not widely published, on the weighting of responses at a fixed point on the casing to faults in rotating planet bearings led to the first application of the log envelope of a bearing signal, and will almost certainly assist in the diagnostics of planet gears and their bearings in the future.

I would like to acknowledge the contributions of all the many co-authors of the large number of new papers by our group at UNSW, from 2011 to the present, but in particular would like to thank my colleagues in that period including Dr Wade Smith, Dr Pietro Borghesani, and Prof. Zhongxiao Peng, as well as my former PhD students Dr Jian Chen, Dr Lav Deshpande, and Dr Michael Coats, whose doctoral works make substantial contributions to the new edition. I am very sad to report that Dr Chen tragically passed away in July 2019, at a very young age, after a short illness. It is also with great sadness that I have to report the passing in June 2015, of Dr Peter McFadden, many of whose contributions are reported in both editions.

One of the greatest losses to the machine diagnostic community was the passing, in March 2020, of Professor Simon Braun, founder of the journal *Mechanical Systems and Signal Processing*. I would like to reiterate my acknowledgement, from the first edition, of his continued support and mentorship over many years. It is perhaps worth mentioning that over 50% of the references in the new material of the new edition were published in MSSP.

A special thanks is again due to Professor Jérôme Antoni, who moved to INSA Lyon, France, several years ago, and who has continued to be a steady inspiration and collaborator in many of the new developments.

To the list of international academic institutions, with whom collaboration has enhanced much of the new material, must be added Vrije Universiteit Brussel (VUB), Belgium, on OMA and wind turbine monitoring, and Professor Paolo Pennacchi's group at Politecnico di Milano, on bearing diagnostics, initiated by the visit to UNSW in 2011 of Pietro Borghesani, during his PhD studies. SpectraQuest Inc., Richmond USA, supported work on bearing diagnostics and system modelling, while the former Leuven Measurement Systems (LMS, now Siemens), Belgium, supported the groundbreaking PhD project of Dr Jian Chen.

Once again, I would like to acknowledge the support of my wife, Helen, who encouraged me to keep writing at all times, even when it threw a greater load on her.

About the Companion Website

This book is accompanied by a companion website.

www.wiley.com/go/randall/vibration

This website includes:

Exercises and tutorial questions

1

Introduction and Background

1.1 Introduction

Machine Condition Monitoring is an important part of Condition-based Maintenance (CBM), which is becoming recognised as the most efficient strategy for carrying out maintenance in a wide variety of industries. Machines were originally ‘run to break’, which ensured maximum operating time between shutdowns, but meant that breakdowns were occasionally catastrophic, with serious consequences for safety, production loss, and repair cost. The first response was ‘Preventive Maintenance’, where maintenance is carried out at intervals such that there is a very small likelihood of failure between repairs. However, this results in much greater use of spare parts, as well as more maintenance work than necessary.

Even at the time of the first edition of this book, there was a considerable body of evidence that CBM gave economic advantages in most industries. An excellent survey of the development of maintenance strategies was given by Rao in a Keynote paper at a Comadem (Condition Monitoring and Diagnostic Engineering Management) conference in 2009 [1]. Maintenance is often regarded as a Cost Centre in many companies, but Al-Najjar [2–4] has long promoted the idea that CBM can convert maintenance to a Profit Centre. Jardine et al. [5, 6] from the University of Toronto documented a number of cases of savings given by the use of CBM. The case presented in [6], from the Canadian pulp and paper industry, is discussed further in Chapter 9, in connection with their approach to prognostics.

Since the first edition of this book was written, the value of CBM has been even more accepted, and for example a recent report [7] indicates that the global value of the machine condition monitoring market will rise from USD 2.6 to 3.9 billion from 2019 to 2025. This is in part due to the increasing general acceptance of Industry 4.0, or the Fourth Industrial Revolution, which according to Wikipedia ‘is the trend towards automation and data exchange in manufacturing technologies and processes which include cyber-physical systems (CPSs), the internet of things (IoT), industrial internet of things (IIoT), cloud computing, cognitive computing and artificial intelligence’. CBM is expected to be part of the ‘Smart factory’, and this is evidence that it is starting to be more extensively applied in manufacturing plants, for example on complex automated machine tools, whose operations have rapid changes in speed and load. This was just not possible in the early days of condition monitoring, where the monitored machines tended to run for long periods at constant speed and loads, for example in power generation and chemical plants. Some of the newer techniques to

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cope with variable speed and loads have been developed in the intervening 10 years and are described in this new edition.

To base maintenance on the perceived condition of operating machines (many of which are required to run continuously for 12 months or more) requires that methods are available to determine their internal condition whilst they are in operation. The two main ways of getting information from the inside to the outside of operating machines are vibration analysis and lubricant analysis, although a few other techniques are also useful.

This chapter includes a description of the background for, and methods used in, condition monitoring, while most of the rest of the book is devoted primarily to the methods based on vibration analysis, which are the most important. This chapter describes the various types of vibration measurement used in condition monitoring, and the transducers used to provide the corresponding vibration signals. It also describes the basic problem in interpretation of vibration signals, in that they are always a compound of forcing function effects (the source) and transfer function effects (the structural transmission path), and how the two effects may be separated.

1.2 Maintenance Strategies

As briefly mentioned above, the available maintenance strategies are broadly:

1. Run-to-break
   This is the traditional method where machines were simply run until they broke down. This in principle gives the longest time between shutdowns, but failure when it does occur can be catastrophic, and can result in severe consequential damage, for example of components other than the ones that failed, and also of connected machines. As a result, the time to repair can be greatly increased, including the time required to obtain replacement parts, some of which might be major items and take some time to produce. In such a case, the major cost in many industries would be production loss, this often being much greater than the cost of individual machines. There is still a place for run-to-break maintenance, in industries where there are large numbers of small machines, e.g. sewing machines, where the loss of one machine for a short time is not critical to production, and where failure is unlikely to be catastrophic.
2. (Time-based) Preventive Maintenance
   Maintenance is done at regular intervals which are shorter than the expected 'time-between-failures'. It is common to choose the intervals to be such that no more than 1–2% of machines will experience failure in that time. It does mean that the vast majority could have run longer by a factor of two or three [8]. The advantage of this method is that most maintenance can be planned well in advance, and that catastrophic failure is greatly reduced. The disadvantages, in addition to the fact that a small number of unforeseen failures can still occur, are that too much maintenance is carried out, and an excessive number of replacement components consumed. It has been known to cause reduced morale in maintenance workers (who are aware that most of the time they are replacing perfectly good parts) so that their work suffers and this can give rise to increased 'infant mortality' of the machines, by introducing faults which otherwise never would have happened. Time-based preventive maintenance is appropriate where the time to failure can be reasonably accurately predicted, such as where it is based on well-defined 'lifing' procedures, which can predict the fatigue life of crucial components on the basis of a given operational regime. Some components do tend to wear or fatigue at a reasonably predictable rate, but with others, such as rolling element bearings, there is a large statistical spread around the mean, leading to estimates such as the one given above, where the mean time to failure is two to three times the minimum [8].

3. Condition-based Maintenance (CBM)
This is also called 'predictive maintenance' since the potential breakdown of a machine is predicted through regular condition monitoring, and maintenance is carried out at the optimum time. It has obvious advantages compared with either run-to-break or preventive maintenance, but does require having access to reliable condition monitoring techniques, which are not only able to determine current condition, but also give reasonable predictions of remaining useful life. It has been used with some success for 35–45 years, and for example the abovementioned report [8] by Neale and Woodley predicted back in 1978 that maintenance costs in British industry could be reduced by approximately 65% by appropriate implementation in a number of industries that they identified. However, the range of monitoring techniques was initially quite limited, and not always correctly applied, so it is perhaps only the last 20 years or so that it has become recognised as the best maintenance strategy in most cases. Initially the greatest successes were attained in industries where machines were required to run for long periods of time without shutting down, such as the power generation and (petro-) chemical industries. The machines in such industries typically run at near constant speed, and with stable load, so the technical problems associated with the condition monitoring were considerably reduced. As more powerful diagnostic techniques have become available, it has been possible to extend condition monitoring to other industries in which the machines have widely varying speed and load, and are perhaps even mobile (such as ore trucks in the mining industry). Refs. [9, 10] discuss the potential benefits given by CBM applied to hydroelectric power plants and wind turbines, respectively.

This book aims at explaining a wide range of techniques, based on vibration analysis, for all three phases of machine condition monitoring, namely, fault detection, fault diagnosis, and fault prognosis (prediction of remaining useful life).

1.3 Condition Monitoring Methods

Condition monitoring is based on being able to monitor the current condition and predict the future condition of machines while in operation. Thus, it means that information must be obtained externally about internal effects while the machines are in operation.

The two main techniques for obtaining information about internal condition are:

1. Vibration Analysis
A machine in standard condition has a certain vibration signature. Fault development changes that signature in a way that can be related to the fault. This has given rise to the term 'Mechanical Signature Analysis' [11].
2. Lubricant Analysis
The lubricant also carries information from the inside to the outside of operating machines in the form of wear particles, chemical contaminants etc. Its use is mainly confined to circulating oil lubricating systems, although some analysis can be carried out on grease lubricants.

Each of these is discussed in a little more detail along with a couple of other methods, performance analysis and thermography, that have more specialised applications.

1.3.1 Vibration Analysis

Even in good condition, machines generate vibrations. Many such vibrations are directly linked to periodic events in the machine's operation, such as rotating shafts, meshing gear teeth, rotating electric fields, etc. The frequency with which such events repeat often gives a direct indication of the source, and thus many powerful diagnostic techniques are based on frequency analysis. Some vibrations are due to events that are not completely phase-locked to shaft rotations, such as combustion in IC (internal combustion) engines, but where a fixed number of combustion events occur each engine cycle, even though not completely repeatable. As will be seen, this can even be an advantage, as it allows such phenomena to be separated from perfectly periodic ones. Other vibrations are linked to fluid flow, as in pumps and gas turbines, and these also have particular, quite often unique, characteristics. The term 'vibration' can be interpreted in different ways, however, and one of the purposes of this chapter is to clarify the differences between them, and the various transducers used to convert the vibration into electrical signals that can be recorded and analysed.

One immediate difference is between the absolute vibration of a machine housing, and the relative vibration between a shaft and the housing, in particular where the bearing separating the two is a fluid film or journal bearing. Both types of vibration measurement are used extensively in machine condition monitoring, so it is important to understand the different information they provide.

Another type of vibration which carries diagnostic information is torsional vibration, i.e. angular velocity fluctuations of the shafts and components such as gears and rotor discs.

All three types of vibration are discussed in this chapter, and the rest of the book is devoted to analysing the resulting vibration signals, though mainly from accelerometers (acceleration transducers) mounted on the machine casing.

It should perhaps be mentioned that a related technique, based on the measurement of 'acoustic emission' (AE), has received some attention and is still being studied. The name derives from high frequency solid-borne rather than airborne acoustic signals from developing cracks and other permanent deformation, bursts of stress-waves being emitted as the crack grows, but not necessarily otherwise. The frequency range for metallic components is typically 100 kHz–1 MHz, this being detected by piezoelectric transducers attached to the surface.

One of the first applications to machine diagnostics was to detection of cracks in rotor components (shafts and blades) in steam turbines, initiated by the Electric Power Research Institute (EPRI) in the USA [12]. Even though they claimed some success in detecting such faults on the external housing of fluid film bearings, the application does not appear to have been developed further. AE monitoring of gear fault development was reported in [13], where it was compared with vibration monitoring. The conclusion was that indications of crack initiation were occasionally detected a day earlier (in a 14 day test) than symptoms in the vibration signals, but the latter persisted because they were due to the presence of actual spalls, while the AE was only present during crack growth. Because of the extremely high sampling rate required for AE, huge amounts of data would have to be collected to capture the rare burst events, unless recordings were based on event triggering. In [14], AE signals are compared with vibration signals (and oil analysis) for gear fault diagnostics and prognostics, but the AE sensors had to be mounted on the rotating components and signals extracted via slip rings.

There is some evidence that AE measurements on rolling element bearings can detect very small incipient faults a little earlier than vibration measurements (e.g. [15]), but it is almost certain that the frequency range of the excitation will fall below 100 kHz as the faults become physically larger, after which the AE transducers could not be relied upon to follow the fault development. In the author's opinion, other methods which can detect resonant responses in the frequency range 40–100 kHz, are likely to detect bearing faults almost as early as AE transducers, and would still give sufficient advance warning to allow prognostics of the fault development as the frequency range of the excitation reduces with increase in fault size.

One such method is the proprietary 'PeakVue' method incorporated in Emerson CSI analysers [16], where the signal used to generate the envelope is down-sampled from the original rate of 102.4 kHz in such a way that envelope information is not lost. If the sample rate is to be reduced by a factor of 50, for example, to give an envelope spectrum range of about 1 kHz, instead of simply retaining every 50th sample (which might completely miss short high frequency pulses) the absolute peak value in every 50 samples is retained. Because the signal is not lowpass filtered before down-sampling, this of course gives aliasing (see Chapter 3), but only of the high frequency carrier, which does not contain diagnostic information. The important information about the repetition frequency of the response pulses (from a bearing fault, for example), is contained in the envelope signal, which is retained, as explained in [17]. The down-sampling approach in [15] is based on the same principle. The high frequency signals (up to the original lowpass filter frequency of about 40 kHz) containing the bearing fault pulses, are almost certainly dominated by the accelerometer mounting resonance, which as pointed out in [16] varies considerably based on the mounting method. It is therefore unlikely that the PeakVue method will give repeatably scaled measurements, suitable for trending, but it will often give a very early detection and diagnosis of a bearing fault. The same accelerometer as used for the PeakVue method is also used for conventional vibration analysis in the lower frequency range where the accelerometer response is linear and more repeatable.

Another somewhat similar approach, the Shock Pulse Method (SPM), specifically uses the accelerometer resonance to carry information about high frequency fault pulses, such as from bearings, and uses the demodulated signal for a range of diagnostic purposes, including envelope spectrum analysis. In this case the accelerometer mounted resonance is specified as 32 kHz, and is ensured by tight control of the mounting method, including the use of steel rod wave guides to carry the signal from the machine casing to where it can more easily be measured. The conventional SPM techniques use only this resonant response, but from 2015, a new ‘DuoTech’ transducer has been made available which can cover the conventional lower frequency vibration range as well ([18]).

Because of the difficulty of application of AE monitoring to machine condition monitoring there are only limited further discussions in this book, although new developments may change the situation.

1.3.2 Oil Analysis

This can once again be divided into a number of different categories:

1. **Chip detectors**. Filters and magnetic plugs are designed to retain chips and other debris in circulating lubricant systems, and these are analysed for quantity, type, shape, size, etc. Alternatively, suspended particles can be detected in flow past a window.
2. **Spectrographic Oil Analysis Procedures (SOAPs).** Here, the lubricant is sampled at regular intervals and subjected to spectrographic chemical analysis. Detection of trace elements can tell of wear of special materials such as alloying elements in special steels, white metal, or bronze bearings, etc. Another case applies to oil from engine crankcases, where the presence of water leaks can be indicated by a growth in NaCl or other chemicals coming from the cooling water. Oil analysis also includes analysis of wear debris, contaminants and additives, and measurement of viscosity and degradation. Simpler devices measure total iron content.
3. **Ferrography.** This represents the microscopic investigation and analysis of debris retained magnetically (hence the name), but which can contain non-magnetic particles caught up with the magnetic ones. Quantity, shape, and size of the wear particles are all important factors in pointing to the type and location of failure.

Successful use of oil analysis requires that oil sampling, changing, and top-up procedures are all well-defined and documented. It is much more difficult to apply lubricant analysis to grease lubricated machines, but grease sampling kits are now available to make the process more reliable.

Since the first edition of this book was published, more advanced online techniques have been developed ([19, 20]). Ref. [19] describes online measurement of oil viscosity and other parameters such as different particle concentration levels, while Ref. [20] uses online image analysis to obtain particle quantity, size, shape, and colour. This does help to remove some of the problems involved in sending out oil samples to external organisations for analysis, including much more extensive sampling, and greatly reduces the time involved.

1.3.3 Performance Analysis

With certain types of machines, performance analysis (e.g. stage efficiency) is an effective way of determining whether a machine is functioning correctly.

One example is given by reciprocating compressors, where changes in suction pressure can point to filter blockage, valve leakage could cause reductions in volumetric efficiency, etc. Another is in gas turbine engines, where there are many permanently mounted transducers for process parameters such as temperatures, pressures, and flowrates, and it is possible to calculate various efficiencies and compare them with the normal condition, so-called 'flow path analysis'.

With modern IC engine control systems, e.g. for diesel locos, electronic injection control means that the fuel supply to a particular cylinder can be cut off, and the resulting drop in power compared with the theoretical.

1.3.4 Thermography

Sensitive instruments are now available for remotely measuring even small temperature changes, in particular in comparison with a standard condition. At this point in time, thermography is still used principally in quasi-static situations, such as with electrical switchboards, to detect local hot spots, and to detect faulty refractory linings in containers for hot fluids such as molten metal.

So-called 'hot box detectors' have been used to detect faulty bearings in rail vehicles, by measuring the temperature of bearings on trains passing the wayside monitoring point. These are not very efficient, as they must not be separated by more than 50 km or so, because a substantial rise in temperature of a bearing only occurs in the last stages of life, essentially when 'rolling' elements are sliding. Monitoring based on vibration and/or acoustic measurements appears to give much more advance warning of impending failure.

1.4 Types and Benefits of Vibration Analysis

1.4.1 Benefits Compared with Other Methods

Vibration analysis is by far the most prevalent method for machine condition monitoring because it has a number of advantages compared with the other methods. It reacts immediately to change, and can therefore be used for permanent as well as intermittent monitoring. With oil analysis for example, several days often elapse between the collection of samples and their analysis, although some online systems do exist. Also in comparison with oil analysis, vibration analysis is more likely to point to the actual faulty component, as many bearings, for example, will contain metals with the same chemical composition, whereas only the faulty one will exhibit increased vibration. There is some development towards the combined use of wear debris analysis and vibration analysis, the first indicating the type and total amount of wear, and the second the detailed distribution of the wear, but this book concentrates on the vibration analysis part.

Most importantly, many powerful signal processing techniques can be applied to vibration signals to extract even very weak fault indications from noise and other masking signals. Most of this book is concerned with these issues.

1.4.2 Permanent vs Intermittent Monitoring

Critical machines often have permanently mounted vibration transducers, and are continuously monitored so that they can be shut down very rapidly in the case of sudden changes, which might be a precursor to catastrophic failure. Even though automatic shutdown will almost certainly disrupt production, the consequential damage that could occur from catastrophic failure would usually result in much longer shutdowns and more costly damage to the machines themselves. Critical machines are often 'spared', so that the reserve machines can be started up immediately to continue production with a minimum of disruption. Most critical high speed turbo-machines in, for example, power generation plants and petro-chemical plants, have built-in proximity probes (Section 1.5.2) which continuously monitor relative shaft vibration, and the associated monitoring systems often have automatic shutdown capability. Where the machines have gears and rolling element bearings, or to detect blade faults, the permanently mounted transducers should also include accelerometers, as explained in Section 1.5.4.

Note that 'permanent' or 'online' monitoring is not synonymous with 'real-time' monitoring, which is rarely required in machine monitoring, as compared, for example, with automatic control. Real-time processing implies causal signal processing, which has severe disadvantages compared with non-causal processing, as typified by the use of the Fast Fourier Transform (FFT), which is perhaps the dominant signal processing tool in machine monitoring. As shown in Chapter 3, use of the FFT involves batch processing of time records selected out of a continuous record, but individually treated as though repeated periodically. This means that the second half of each time record is implicitly treated as negative time (thus non-causal), but gives huge advantages in that it allows for almost ideal filters, with no phase distortion, which can completely exclude adjacent strong frequency components, not possible with causal filters, which have a much more gentle 'roll-off', and introduce phase shifts over relatively wide frequency ranges. The delay involved in the non-causal processing is just the processing time of one such time record, and would rarely be more than a second or so, this normally being negligible compared with the time constants associated even with real-time processing. Even if a large turbomachine were automatically tripped (that would be rare because a human would normally have to make that decision) the speed (which is normally reduced over a period of many hours) would not change significantly in the few seconds difference between causal and non-causal processing. Another example where real-time processing is of no advantage is if the machine being monitored were, say, an aircraft engine, what would be the difference between the warning 'this engine will self-destruct in two seconds', compared with two milliseconds? Neither would be of much use.

The **advantages** of permanent, or online, monitoring are:

- It reacts very quickly to sudden change, and gives the best potential for protecting critical and expensive equipment.
- It is the best form of protection for sudden faults that cannot be predicted. An example is the sudden unbalance that can occur on fans handling dirty gas, where there is generally a build-up of deposits on the blades over time. This is normally uniformly distributed, but can result in sudden massive unbalance when sections of the deposits are dislodged.

- It is sometimes more economical to have permanently mounted transducers on widely distributed and difficult-to-access machines, such as wind turbines, and automated manufacturing machines, and then the additional cost of transmitting the collected signals back to a centralised monitoring system is economically justified. This approach is now being applied also for mobile equipment, such as mining trucks and machines, many of which are autonomous.

The **disadvantages** of permanent monitoring are:

- The cost of having permanently mounted transducers is very high, so previously could only be justified for the most critical machines in a plant, or where it is difficult for operators to access the machines. However, the cost of transducers such as accelerometers is continuously being reduced, and with the increased development of autonomous machines, more in-built transducers are required anyway, in conformity with the 'Internet of Things'. Because of the increasing realisation of the benefits of CBM, online monitoring is being extended to more and more machines.
- Where the transducers are proximity probes, they virtually have to be built in to the machine at the design stage, as modification of existing machines would often be prohibitive.
- Since the reaction has to be very quick, permanent monitoring is normally based on relatively simple parameters, such as overall RMS or peak vibration level, and the phase of low harmonics of shaft speed relative to a 'key phasor', a once-per-rev pulse at a known rotation angle of the shaft. In general, such simple parameters do not give much advance warning of impending failure; it is likely to be hours or days, as opposed to the weeks or months lead time that can be given by the advanced diagnostic techniques detailed in later chapters in this book.

Of course, if transducers are mounted permanently, it is still possible to analyse the signals in more detail, just not continuously. It gives the advantage that intermittent monitoring can be carried out in parallel with the permanent monitoring, and updated at much more frequent intervals, typically once per day instead of once per week or once per month, to give the best of both worlds. In order to take advantage of the powerful diagnostic techniques, the permanently mounted transducers would have to include accelerometers, for the reasons discussed below in Section 1.5.4.

For the vast majority of machines in many plants, it is not economically justified to have them equipped with permanently attached transducers or permanent monitoring systems. On the other hand, since the major economic benefit from condition monitoring is the potential to predict incipient failure weeks or months in advance, so as to be able to plan maintenance to give the minimum disruption of production and acquire replacement parts etc., it is not always important to do the monitoring continuously. The intervals must just be sufficiently shorter than the minimum required lead times for maintenance and production planning purposes. A procedure for determining the optimum intervals is described in [21]. A very large number of machines can then be monitored intermittently with a single transducer and data logger, and the data downloaded to a monitoring system capable of carrying out detailed analysis.

The **advantages** of intermittent monitoring are:

- Much lower cost of monitoring equipment.
- The potential (through detailed analysis) to get much more advance warning of impending failure, and thus plan maintenance work and production to maximise availability of equipment.
- It is thus applied primarily where the cost of lost production from failure of the machine completely outweighs the cost of the machine itself.