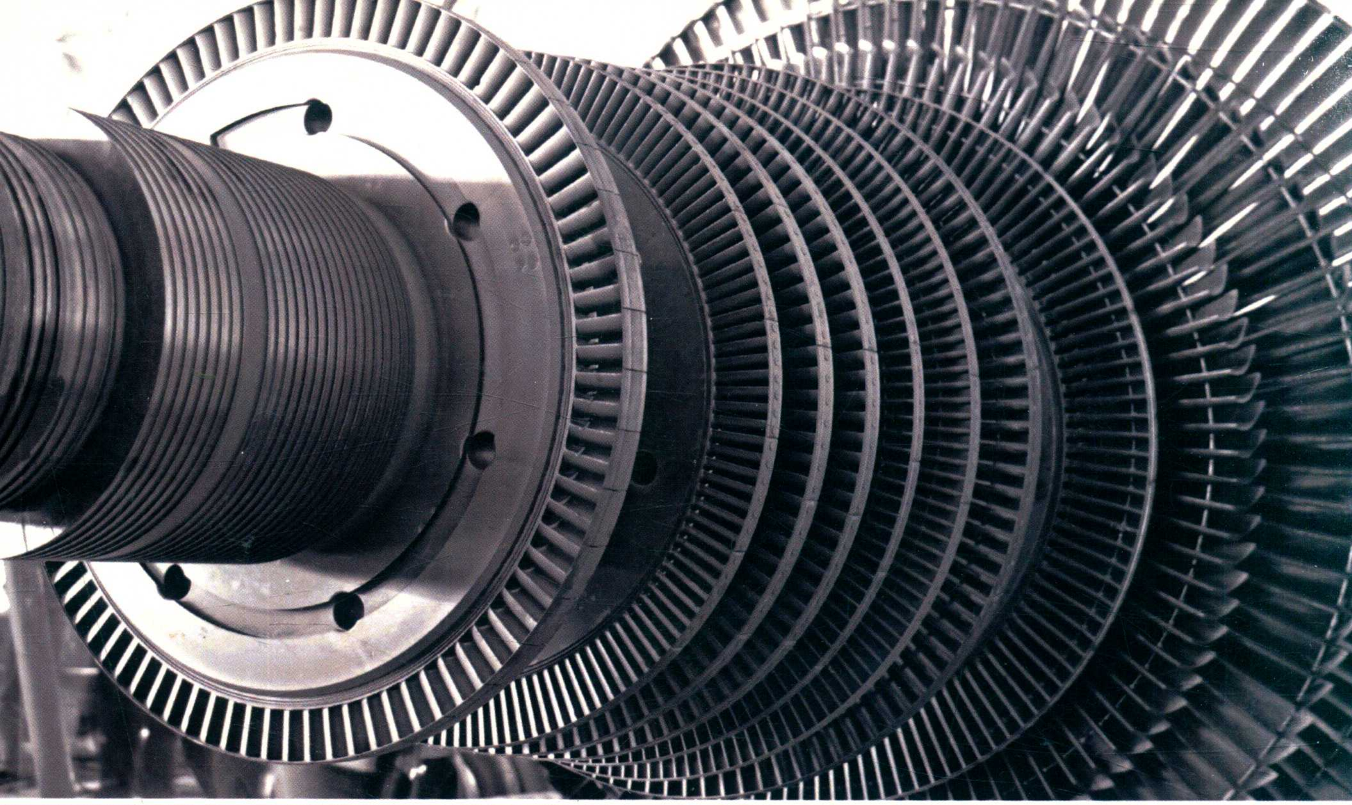


INTELLIGENT FAULT DIAGNOSIS AND REMAINING USEFUL LIFE PREDICTION OF ROTATING MACHINERY

旋转机械智能故障诊断与剩余寿命预测

（英文版）

雷亚国 著

西安交通大学出版社
XI'AN JIAOTONG UNIVERSITY PRESS

ELSEVIER

INTELLIGENT FAULT DIAGNOSIS AND REMAINING USEFUL LIFE PREDICTION OF ROTATING MACHINERY

旋转机械智能故障诊断与剩余寿命预测

Yaguo Lei

雷亚国 著

西安交通大学出版社
XI'AN JIAOTONG UNIVERSITY PRESS

ELSEVIER

图书在版编目(CIP)数据

旋转机械智能故障诊断与剩余寿命预测=Intelligent Fault Diagnosis and Remaining Useful Life Prediction of Rotating Machinery:英文/雷亚国著. —西安:西安交通大学出版社,2017.2
ISBN 978-7-5605-9400-2

Ⅰ.①旋… Ⅱ.①雷… Ⅲ.①旋转机构-故障诊断-英文 ②旋转机构-寿命-预测-英文 Ⅳ.①TH210.66

中国版本图书馆 CIP 数据核字(2017)第 024588 号

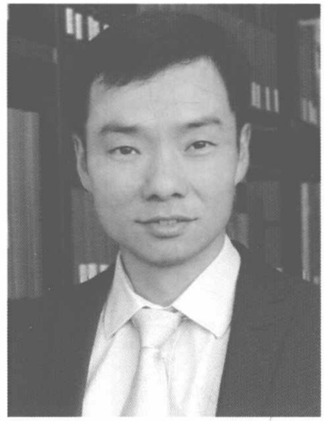
书　　名	旋转机械智能故障诊断与剩余寿命预测(英文版)
著　　者	雷亚国
策划编辑	秦茂盛　鲍　媛
责任编辑	鲍　媛

出版发行	西安交通大学出版社
地　　址	(西安市兴庆南路 10 号　邮政编码 710049)
电　　话	(029)82668357　82667874(发行中心) (029)82668315(总编办)
电子邮件	xjtupress@163.com
印　　刷	虎彩印艺股份有限公司

开　　本	787mm×1092mm　1/16　**印张** 23.25　**彩页** 1　**字数** 494 千字
版次印次	2017 年 4 月第 1 版　2017 年 4 月第 1 次印刷
书　　号	ISBN 978-7-5605-9400-2
定　　价	198.00 元

读者购书、书店添货、如发现印装质量问题,请与本社发行中心联系、调换。
订购热线:(029)82665248　(029)82665249
投稿热线:(029)82665380
读者信箱:banquan1809@126.com

ABOUT THE AUTHOR



Yaguo Lei is a Full Professor in the School of Mechanical Engineering at Xi'an Jiaotong University (XJTU), China, which he joined as an associate professor in 2010. Prior to that, he worked at the University of Alberta, Canada, as a postdoctoral research fellow. He also worked at the University of Duisburg-Essen, Germany, as an Alexander von Humboldt fellow in 2012. He was promoted to Full Professor in 2013. He received the BS degree and the PhD degree both in Mechanical Engineering from XJTU, in 2002 and 2007, respectively. He is a member of the editorial boards of nine journals, including *Neural Computing & Applications* and *Advances in Mechanical Engineering*. He is also a member of ASME and a member of IEEE. He has pioneered many signal processing techniques, intelligent diagnosis methods, and remaining useful life (RUL) prediction models for rotating machinery components, such as gearboxes, bearings, and rotor systems. He is the invited author of chapters on intelligent fault diagnosis. He has published more than 80 peer-reviewed papers on signal processing, fault diagnosis and RUL prediction.

PREFACE

Rotating machinery is commonly used and plays an important role in industrial applications. With rapid development of science and technology, rotating machinery in modern industry is growing larger and more precise. It has become a challenging task to enhance the availability, the reliability, and the security of rotating machinery. Prognostics and Health Management (PHM) is an effective tool for dealing with this task. Therefore, it has attracted considerable attention during the last few decades.

PHM of rotating machinery is composed of several modules, like signal acquisition, signal processing, diagnostics, prognostics, and maintenance decision. Some books have introduced many fault diagnostics and prognostics methods for rotating machinery. However, the earliest research achievements in the area of fault diagnostics and prognostics are not addressed, which is the motivation for writing this book. This book will provide an introduction of intelligent fault diagnostics and RUL prediction based on the current achievements appeared in academic journals, conference proceedings, and technical reports.

The book involves the fundamental theories and the advanced methods of intelligent fault diagnostics and RUL prediction for rotating machinery. These methods are paralleled by experimental investigations and real applications for rotors, rolling element bearings, and gears. It is able to provide a guide for the readers from the area of PHM to know the basic concepts, the fundamental theories, and the cutting edge research. It can be used as a text for master courses at both a fundamental and more advanced level. It also benefits engineers as well as researchers in the area of PHM of rotating machinery.

Most of the fault diagnostic and RUL prediction methods in this book were developed at Xi'an Jiaotong University (XJTU), China. So, I am grateful to my colleagues, Professor Jing Lin, Professor Yanyang Zi, Professor Xuefeng Chen, Professor Zhousuo Zhang, Professor Bing Li, etc., at XJTU, who have assisted me to conduct many theoretical and practical research projects about the subject of this book. I especially appreciate the guidance and the support of my PhD supervisor, Professor Zhengjia He, who died 3 years ago. I cherish the memory of the time when I was still his PhD student working with him together. The longer the time he leaves me, the more I miss him. This book is the best souvenir I can present to Professor He in the third year of his passing away.

Prior to joining XJTU, I worked at the University of Alberta, Canada, as a postdoctoral research fellow. In addition, I also worked at the University of Duisburg-Essen, Germany, as an Alexander von Humboldt fellow. Therefore, I have enjoyed a considerable amount of interaction and collaboration with overseas universities, which include the University of Alberta, University of Duisburg-Essen, Warsaw University of Technology, Carleton University, etc. Without the support and help from these overseas universities, I think that I could not finish writing this book.

Over many years I have received research support from the National Natural Science Foundation of China, Ministry of Education of China, Central Organization Department of China, and Provincial Natural Science Foundation research project of Shaanxi. The research supported by such grants has enriched the materials in this book. I have also received support from industrial partners, in particular Huadian Electric Power Research Institute, CRRC Zhuzhou Institute Co., LTD, Sinopec Jinan Company of China, etc. I acknowledge with thanks the permission given by these industrial partners to reuse the materials in this book. I also thank the Case Western Reserve University and the Institute of FEMTO-ST for sharing their bearing data generously.

Moreover, my PhD students at XJTU, those who worked with intelligent fault diagnosis and RUL prediction topics, supported and helped me to prepare materials and complete this book. I would like to acknowledge specially the help of Mr. Naipeng Li, Mr. Feng Jia, and Mr. Zijian Qiao.

Finally, I would like to thank the editors from Elsevier for their excellent cooperation.

Yaguo Lei

Xi'an, January, 2016

CONTENTS

1

INTRODUCTION AND BACKGROUND

1.1 Introduction

Rotating machinery is commonly used in mechanical systems and plays an important role in industrial applications (Lei et al., 2013). It generally operates under tough working environment and is therefore frequently subject to faults. Any fault of the rotating machinery possibly causes a breakdown of the entire mechanical system, which may reduce the reliability, security, and availability of the machinery. With the rapid development of science and technology, rotating machinery in modern industry is growing larger and more precise. The structure of rotating machinery is becoming more complex. As a result, its potential faults become more difficult to be detected. Therefore, how to maintain the normal operation of rotating machinery has attracted considerable attention in recent years.

There are various kinds of rotating machinery in various industry fields, such as the aeroengine in the field of aerospace, the gas turbine and wind turbine in the field of energy, and the automobile transmission in the field of traffic. Even though the rotating machinery is diversified, it generally includes some common essential rotating parts, such as rotors, rolling element bearings, and gears.

A rotor is defined as a rotating part of a machine that is generally supported by bearings. They are the indispensable components in rotating machinery. With the increasing requirement of reliability and precision of rotating machinery, rotors become more flexible and operate under tight clearances and harsh environment. Under such circumstances, one incipient fault possibly causes severe damages in other components and results in failures of the entire machine. For example, a little unbalance of a rotor might cause rub or serious impact between the rotating parts and the stationary parts under a high-speed condition. Severe thermal and mechanical stresses might lead to a fatigue crack in the rotors. The common fault types of rotors include mass unbalance, bent, misalignment, rub, resonance, and so on.

A rolling element bearing is a component that carries loads by placing rolling elements (such as balls or rollers) between two races. The relative motion of the rings causes the rolling elements to roll with little rolling resistance and little sliding. The rolling element bearing is developed from an ancient transportation strategy where sets of logs are laid on the ground with a large stone block on the top. As the stone is pulled, the logs roll along the ground with little sliding friction. A rolling element bearing generally includes three components: an outer race, an inner race, and several rolling elements. Rolling elements, such as balls or rollers, are able to reduce the friction forces between the contacting elements. A rolling element bearing is generally used to connect a shaft and a much larger hole with rollers tightly filling the space between the shaft and hole. As the shaft turns, each roller acts as the logs in the above example. Since the special position and function, rolling element bearings generally suffer from various attacks, such as improper mounting, mishandling, poor lubrication, entry of foreign matter, and abnormal heat generation. All of these may cause different types of faults on rolling element bearings. The common fault types include flaking, spalling, peeling, abrasion, scoring, corrosion, pitting, crack, material failure, and so on.

A gear is a rotating machine part having cut teeth, which meshes with another toothed part to transmit torque. Two or more gears working in a sequence (train) are called a gear train or, in many cases, a transmission. Such gear arrangements are able to produce a mechanical advantage through a gear ratio. Geared devices can change the speed, torque, and direction of a power source. Although, the most common situation is that a gear meshes with another gear. A gear meshes with a nonrotating toothed part, called a rack, thereby producing translation instead of rotation. The gears in a transmission are similar to the wheels in a crossed belt pulley system. An advantage of gears is that the teeth of a gear can prevent slippage. When two gears mesh, and one gear is bigger than the other, a mechanical advantage is produced, with the rotational speeds and the torques of the two gears differing in an inverse relationship. On account of the characteristics of the gears, they are widely used to transmit torque and rotation in mechanical systems.

Rotating machinery plays an important role in the industry applications because of its specific functions for mechanical systems. However, due to the specific function requirement, rotating machinery generally operates under tough working environment. Consequently, it always has a higher fault rate compared with other components, and most maintenance costs are directly or indirectly caused by the fault of rotating machinery. Here, we take the wind turbine system, for example, and give some reports about its fault rates and maintenance costs.

The worldwide wind markets have been dramatically developed in recent years because of its economic advantages and environmental protection compared with other sources of electricity. According to the half-year report in 2014 published by the World Wind Energy Association (WWEA) (The World Wind Energy Association, 2014), the total installed capability of the worldwide wind turbine presents a stable increasing trend from 2011 to 2014 as shown in Fig. 1.1. The worldwide wind turbine capacity reached 336,327 MW by the end of June 2014. The total worldwide installed wind turbine capacity by mid-2014 has generated around 4% of the world's electricity demand.

A major issue with the wind turbine system is the relatively high costs of operation and maintenance (OM). Wind turbines are hard-to-access structures, and they are often located in remote areas. These factors increase the OM costs for wind turbine systems. In addition, poor reliability directly reduces the availability of wind power due to the turbine downtime. For a turbine with over 20 years of operating life, the OM costs are estimated to be 10–15% of the total income for a wind farm, and the OM costs for offshore wind turbine are estimated to be 20–25% of the total income (Lu et al., 2009). The main fault types of the wind turbine are shown in Fig. 1.2, including imbalance, wear, fatigue, and impending cracks in rotor blades, bearings, shafts, the gearbox, the generator, the yaw, and the pitch angle mechanism. A study result for the causes of failures of wind turbines is shown in Fig. 1.3. It is seen that, the gearbox and generator are responsible for 17% of failures and 30% of the maintenance costs, which are clearly leading candidates for the causes of failures. Even in the wind turbine generators, most

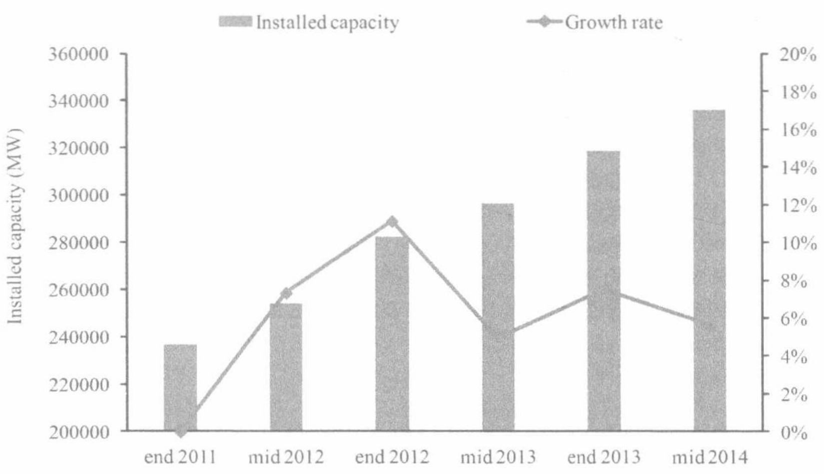


Figure 1.1. Total installed capacity of the worldwide wind turbine.

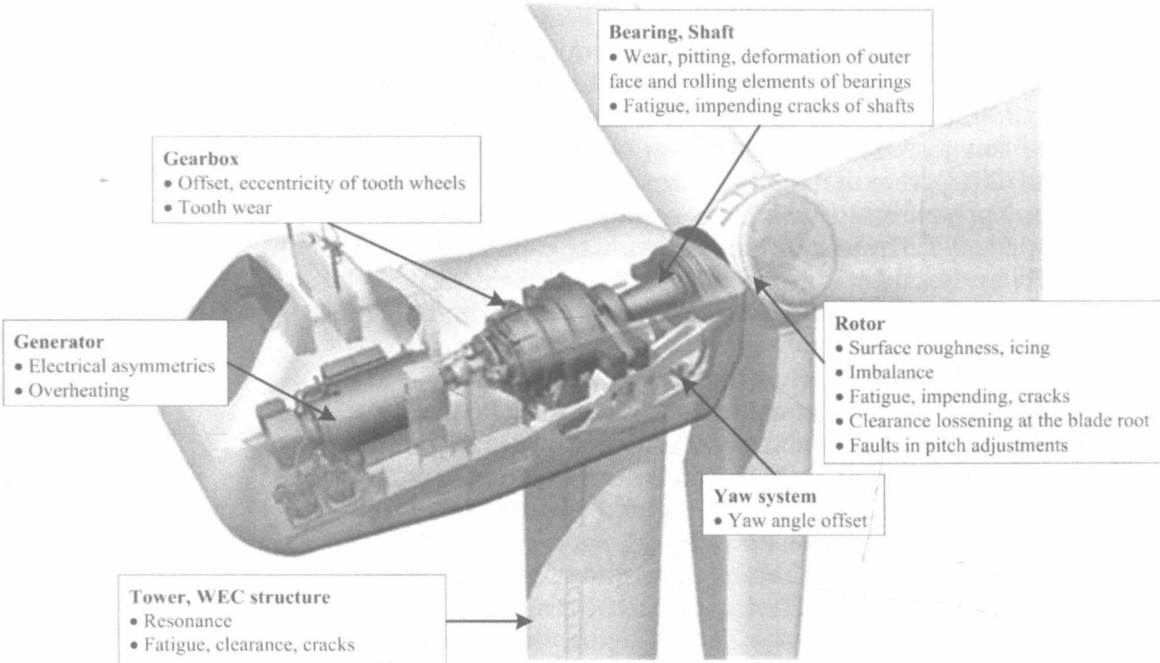


Figure 1.2. Overview of the main faults of wind turbines.

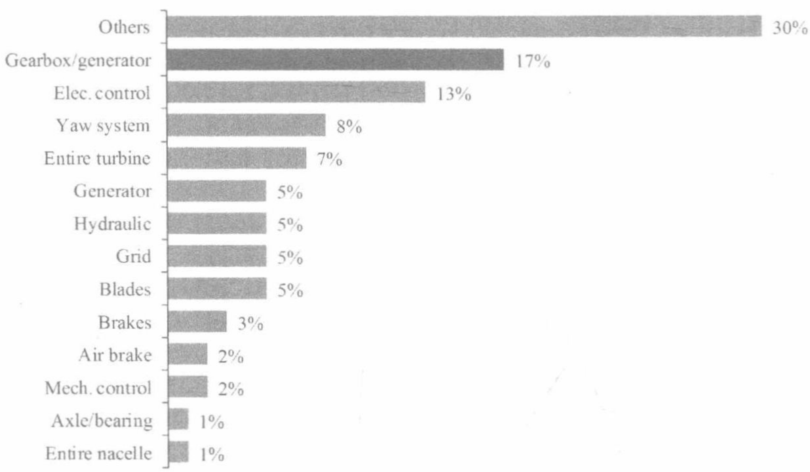


Figure 1.3. Statistic results for the causes of failure of wind turbines.

faults are still caused by the rotating machinery. For induction machines, about 40% failures are related to bearings, 38% to the stator and 10% to the rotor (Hyers et al., 2006).

It is concluded from the above reports that the fault of rotating machinery is the main cause of the failure of wind turbines. This trend is similar in many other mechanical systems. So the health management of rotating machinery is significant for reducing the OM costs of mechanical systems. Analysis of maintenance costs has shown that a repair made after failure always wastes lots of costs compared with the same maintenance when the failure has not occurred. A survey carried out by major organizations has revealed that with an investment of 10,000 – 20,000 dollars in health management, one can save up to 500,000 dollars annually (Saranga and Knezevic, 2001). Thus, it is apparent that an appropriate health management strategy is essential to sustain the inherent reliability of mechanical systems and reduce the OM costs.

The health management strategies of rotating machinery experienced the following three development stages (Randall, 2011) (Fig. 1.4).

1. Reactive maintenance (run-to-failure)
   This is a traditional maintenance strategy where machines keep running until they break down because of the final failure. This strategy in principle gives the longest operation time before failures. However, it only provides a passive reaction after a failure occurs, which may be catastrophic and result in severe damages or accidents. This strategy is acceptable in some cases where large numbers of machines are alternative even one machine has failed and the failure is not catastrophic. However, for machines like wind-turbine generator sets, steam-turbine generator sets, and heavy oil catalytic cracking units, the number of available machines is limited or the failure of a machine possibly leads to a great cost, making this strategy helpless to prevent the shutdown of the machines. Furthermore, if a failure would cause severe damages or catastrophes, this strategy is also invaluable.
2. Preventative maintenance (time-based)
   To prevent the happening of failures, machines are repeatedly checked at regular time intervals in the preventative maintenance, which is more conservative than reactive maintenance.

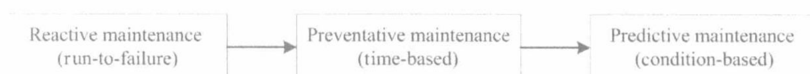


Figure 1.4. Development stages of the health maintenance strategies.

Once an incipient fault is detected, it is common to shut down the machine immediately and replace the fault components to avoid catastrophic consequences. An appropriate time interval for checking plays an important role in this strategy. If the time interval is too long, some unforeseen failures are still possible to occur. In contrast, if the time interval is too short, too much maintenance will be carried out and excessive replacement components will be consumed. This strategy is supposed to recognize the fault occurrence in time and plan the maintenance strategy in advance to reduce the catastrophic failure. However, it needs to shut down the machines frequently, which inevitably reduces the production efficiency and consumes a lot of maintenance costs. The preventative maintenance is appropriate when the failure time is reasonably accurately predicted according to the statistical properties of large numbers of the similar machines. However, for most rotating machines, such as rolling element bearings, there is a large statistical spread around the mean, leading to the estimates given by large numbers of machines severely deviating from the actual failure time of a single machine.

3. Predictive maintenance (condition-based)
Predictive maintenance, also called condition-based maintenance (CBM), is a maintenance strategy that recommends maintenance actions based on the information collected through condition monitoring. In this strategy, the degradation trend of the rotating machinery is first revealed through the analysis of condition monitoring data. Then the degradation trend in the future is predicted using some prediction models or techniques. With a prespecified failure threshold, the remaining useful life (RUL) of the rotating machinery is predicted. Based on the predicted RUL, an optimal maintenance strategy is scheduled before the real occurrence of the final failure. The predictive maintenance has obvious advantages compared with either reactive maintenance or preventative maintenance. It is able to predict the potential breakdown of a machine through regular condition monitoring thus preventing the happening of catastrophes. In addition, it schedules maintenance at an optimum time according to the predicted RUL. Therefore, it is able to make the machine have a maximum uptime with minimum maintenance costs. Thanks to the superiority of the predictive maintenance, it has attracted substantial attention in recent years.
Based on the predictive maintenance strategy, a new concept of prognostics and health management (PHM) has been developed in recent years. This book aims to provide an essential

guide to the PHM of rotating machinery, from the basic concepts and the fundamental theories to the latest techniques and their applications.

1.2 Overview of PHM

The flowchart of the PHM of rotating machinery is shown in Fig. 1.5. It is generally composed of five major processes, that is, data acquisition, signal processing, diagnostics, prognostics, and maintenance decision.

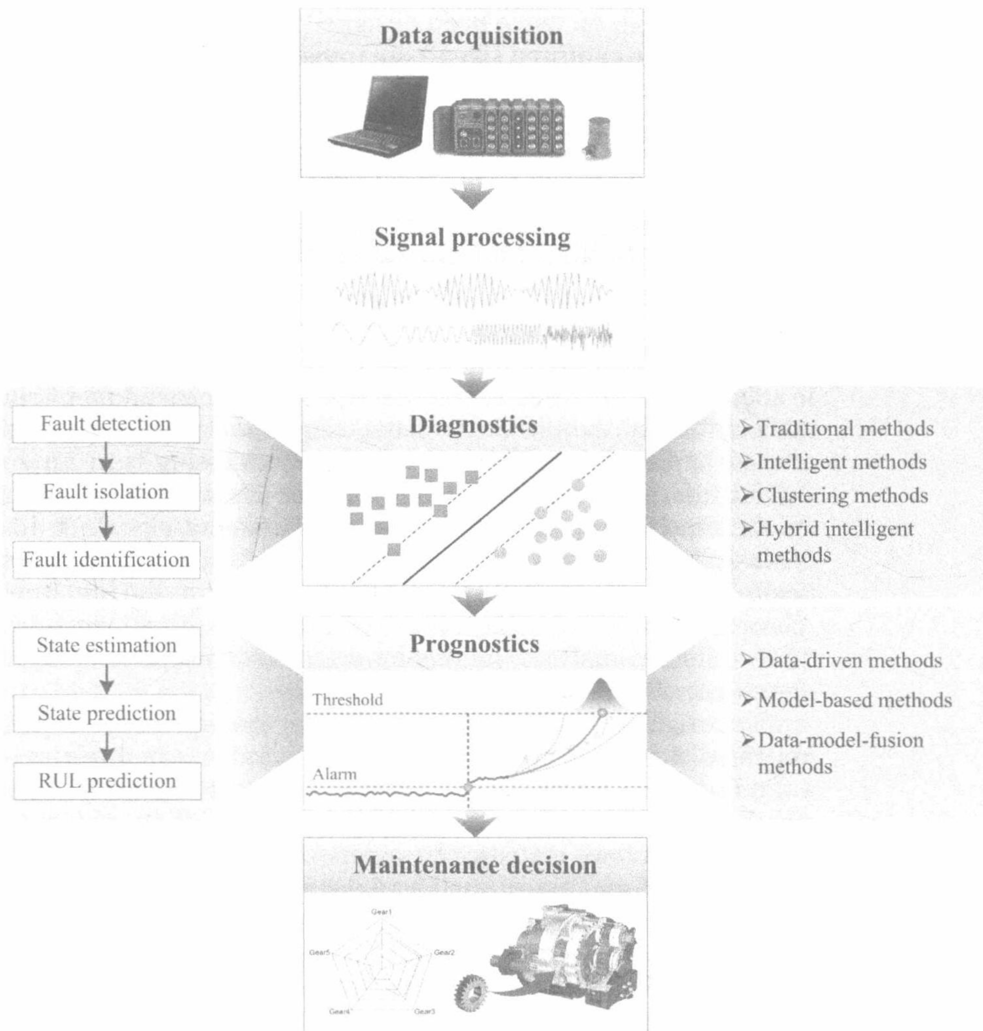


Figure 1.5. Flowchart of the PHM of rotating machinery.

1.2.1 Data Acquisition

Data acquisition is a process of capturing measurement signals using different kinds of sensors from monitored machines and storing the data into a computer. The measurement signals are supposed to be related to the health conditions of the monitored machines. In other words, the measurement signals incorporate some useful information, which reflects the health conditions of the machines. There are many different types of measurement signals, such as vibration signals, acoustic signals, temperatures, and electric currents. Various sensors including accelerometers, acoustic emission sensors, infrared thermometers, ultrasonic sensors, and so on, have been designed to collect different types of signals. The captured signals are transmitted into a PC through a data acquisition (DAQ) equipment and stored into a memory location for further analysis. With the rapid development of advanced computer and sensor technologies, lots of new data acquisition facilities and techniques have been designed and applied in modern industries. These powerful and versatile facilities have made data acquisition for PHM implementation more convenient and feasible.

1.2.2 Signal Processing

Signal processing is to analyze the stored measurement signals in the data acquisition process using signal processing techniques and methods. The task of signal processing is to extract useful information that is able to reveal the health conditions of the machines from the original measurement signals. It has been fully developed till now and numerous signal processing techniques and algorithms have been proposed in the literature. They are roughly classified into the following three categories: time–domain analysis, frequency–domain analysis, and time–frequency–domain analysis.

The original measurement signals that are generally sampled repeatedly between prespecified time intervals are in the form of time domain. Thus, the time-domain analysis is directly based on the original measurement signals. Traditional time-domain analysis calculates statistic characteristics describing the health conditions of machines, such as mean, peak, root mean square (RMS), kurtosis, and skewness. These statistic characteristics are named as time–domain features. Other commonly used time-domain analysis methods include time synchronous average (TSA), the autoregressive (AR) model, the autoregressive moving average (ARMA) model, principal component analysis (PCA), and so on.

Frequency–domain analysis is based on the transformed signals in frequency domain. The advantage of frequency–domain analysis over time–domain analysis is its ability to decompose the original signals into a series of frequency components. The most widely used frequency–domain analysis is the spectrum analysis by means of fast Fourier transform (FFT). The main idea of spectrum analysis is to isolate and locate certain frequency components of interest relating to the fault characteristics of machines. Power spectrum is a commonly used FFT-based method. Cepstrum is also widely used because of its capability to detect harmonics and sideband patterns in power spectrum. Some useful auxiliary tools for spectrum analysis include frequency filters, envelope analysis, side band structure analysis, and so on. Hilbert transform which is a useful tool in envelope analysis has also been used for machine fault detection and diagnostics.

One limitation of frequency–domain analysis is that it is only effective in handling stationary measurement signals and is unable to deal with nonstationary measurement signals. However, the measurement signals of machinery generally present nonstationary characteristics. Thus, time–frequency–domain analysis, which investigates measurement signals in both time and frequency domains, has been applied into the nonstationary measurement signal analysis. The time–frequency analysis describes the characteristics of measurement signals in two-dimensional functions of both time and frequency to better reveal the fault patterns of the machines. One of the commonly used time–frequency–domain analysis tools is short-time Fourier transform (STFT), which divides the measurement signals into different segments with short-time windows and then applies Fourier transform to each segment. Due to the signal segmentation, the frequency resolution is decreased inevitably. In addition, each signal segment is approximately considered to be a stationary process. Therefore, the STFT can only be applied to nonstationary signals with slow change in their rotating speeds. Another commonly used time–frequency–domain analysis tool is Wigner–Ville distribution. It is based on bilinear transform instead of signal segmentation. Therefore, it overcomes the frequency resolution limitation of STFT. However, due to the interference terms produced by the transformation itself, it is difficult to explain the estimated distribution. Another tool for time–frequency analysis is the wavelet transform. Different from the STFT, the wavelet transform can be used for multiscale analysis of a signal through dilation and translation, so it is able to extract time–frequency features of a signal effectively. Due to the multiscale analysis ability, the wavelet transform is able to produce a high frequency resolution at low frequencies and a