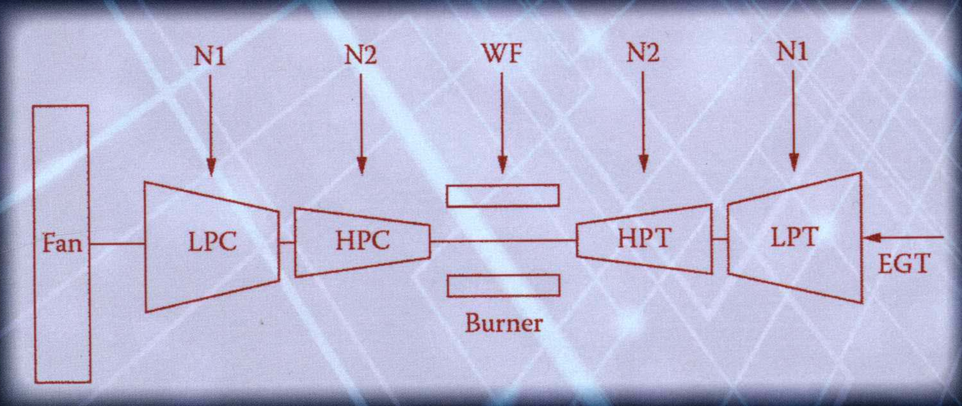
Gas Turbine Diagnostics

Signal Processing and Fault Isolation



RANJAN GANGULI

CRC Press
Taylor & Francis Group

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CRC Press
Taylor & Francis Group
Boca Raton London New York

CRC Press is an imprint of the
Taylor & Francis Group, an **informa** business

CRC Press
Taylor & Francis Group
6000 Broken Sound Parkway NW, Suite 300
Boca Raton, FL 33487-2742

Printed and bound in Great Britain by TJ International, Padstow, Cornwall
Version Date: 20121016

International Standard Book Number: 978-1-4665-0272-7 (Hardback)

Library of Congress Cataloging-in-Publication Data

Ganguli, Ranjan.
Gas turbine diagnostics : signal processing and fault isolation / Ranjan Ganguli.
pages cm
Includes bibliographical references and index.
ISBN 978-1-4665-0272-7 (hardback)
1. Aircraft gas-turbines--Testing--Data processing. 2. Fault location (Engineering) 3. Airplanes--Monitoring. I. Title.

TL709.G33 2013
629.134'3530287--dc23 2012027103

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Preface

Gas turbines are very important components of modern infrastructure and are widely used in power generation. In particular, gas turbines are used for propulsion in jet engines that power most commercial and military aircraft. Faults in gas turbine engines can result in major problems, such as delays and cancellations of flights. Engine in-flight shutdowns (IFSDs) are particularly problematic and can have an impact on flight safety. Unscheduled engine removals add to the cost of air transport.

A systematic analysis of engine data has shown that most engine malfunction is preceded by a so-called single fault, which is a fault in one engine module or component. These single faults occur as sharp changes in measurement deviations in the jet engine, when compared to a baseline good engine. In this book, we present and illustrate a number of algorithms for fault diagnosis in gas turbine engines. These methods focus on the aspects of filtering or cleaning the measurement data and on fault isolation algorithms that use simple engine models for finding the type of fault in the engine. Novel methods for detecting the damage by finding the time location of a sudden change in the signal are also given. These methods include those based on Kalman filters, neural networks, and fuzzy logic and a hybrid soft computing approach.

The book provides a discussion of the different methods in data filtering, trend shift detection, and fault isolation developed over the past decade. Each method is demonstrated through numerical simulations that can be easily done by the reader using worksheets such as MS Excel or through MATLAB®. The book provides a variety of new research tools for use in the condition monitoring of jet engines. Though the measurements and models are specific to a turbofan engine, the algorithms given in this book will be useful to all engineers and scientists working on fault diagnosis of gas turbine engines. The data cleaning algorithms based on nonlinear signal processing shown in this book are also applicable to condition and health monitoring problems in general, and as in all such problems, sharp changes in measurement data herald the onset of a fault.

This book will be useful for engineers and scientists interested in gas turbine diagnostics. It will also be of interest to researchers in signal processing and those working on the fault isolation of systems. The algorithms presented in this book have broad appeal and can be used for condition and health monitoring of a variety of systems.

I acknowledge Dr. Allan Volponi and Hans Depold, Pratt & Whitney, who introduced me to the field of gas turbine diagnostics. I am grateful to my students Rajeev Verma, Niranjan Roy, Buddhidipta Dan, Payuna Uday, V.N. Guruprakash, and V.P. Surendar for testing the algorithms and generating the numerical results. I am also grateful to K. Bhanu Priya for helping typeset the document. Finally, I am grateful to the Indian Institute of Science for furnishing an ambient atmosphere for doing research.

Prof. Ranjan Ganguli
Bangalore

About the Author

Dr. Ranjan Ganguli is a professor in the Aerospace Engineering Department of the Indian Institute of Science (IISc), Bangalore. He received his MS and PhD degrees from the Department of Aerospace Engineering at the University of Maryland, College Park, in 1991 and 1994, respectively, and his BTech degree in aerospace engineering from the Indian Institute of Technology in 1989. He worked in Pratt & Whitney on engine gas path diagnostics during 1998–2000. During his academic career at IISc since 2000, he has conducted sponsored research projects for companies such as Boeing, Pratt & Whitney, Honeywell, HAL, and others. He has published over 140 papers in refereed journals and has presented over 80 papers in conferences. He has published books entitled *Structural Health Monitoring Using Genetic Fuzzy Systems* and *Engineering Optimization*. He is a fellow of the American Society of Mechanical Engineers, a fellow of the Royal Aeronautical Society, an associate fellow of the American Institute of Aeronautics and Astronautics, and a fellow of the Indian National Academy of Engineering. He also received the Alexander von Humboldt Fellowship and the Fulbright Fellowship in 2007 and 2011, respectively. He is an associate editor of the *AIAA Journal* and of the *Journal of the American Helicopter Society*.

Contents

1

Introduction

Diagnostics of gas turbine engines is important because of the high cost of engine failure and the possible loss of human life. In this book, we will focus on aircraft or jet engines, which are a special class of gas turbine engines. Typically, physical faults in a gas turbine engine include problems such as erosion, corrosion, fouling, built-up dirt, foreign object damage (FOD), worn seals, burned or bowed blades, etc. These physical faults can occur individually or in combination and cause changes in performance characteristics of the compressors, and in their expansion and compression efficiencies. In addition, the faults cause changes in the turbine and exhaust system nozzle areas. These changes in the performance of the gas turbine components result in changes in the measurement parameters, which are therefore dependent variables. This chapter introduces some basic concepts that are necessary for an understanding of gas turbine diagnostics. First, the importance of signal processing in noise removal from measurements is highlighted. Next, the typical gas turbine diagnostic process is explained. The widely used linear filters and the median filter are then introduced. This is followed by an outline of the least-squares approach and the Kalman filter. Finally, the role of influence coefficients and the basics of vibration-based diagnostics are highlighted.

1.1 Background

Many problems in jet engines manifest themselves as changes in the gas path measurements [1–3]. Typical gas path measurements are exhaust gas temperature (*EGT*), low rotor speed (*N*1), high rotor speed (*N*2), and fuel flow (*WF*). These measurements are also called cockpit parameters, as they are displayed to the pilot. Some newer engines also have additional pressure and temperature probes between the compressors and turbines. However, the cockpit parameters are present in both newer and older engines, and therefore fault detection and isolation systems should be able to work for older engines, which are more susceptible to damage. Jet engine gas path analysis works on deviations in gas path measurements from an undamaged baseline engine to detect and isolate faults. These deviations in the measurements from baseline are known as measurement deltas and are plotted vs. time, and the resulting computer graphics (known as trend plots) are used by power plant engineers to visually analyze the condition of the engine and its different modules. Unfortunately, noise contaminates the measurement deltas, thereby reducing the signal-to-noise ratio. This can hide key features in the signal from a person observing the data. A key objective of gas turbine diagnostics is to make decisions about the existence and location of faults from the noisy data.

A typical measurement delta has two main features. The first is because of long-term deterioration that can be considered to vary in time as a low-degree polynomial, with a linear approximation being very satisfactory [4, 5]. The second feature of the measurement delta is sudden step-like changes due to so-called single faults. Depold and Gass [6] conducted a statistical study of airline data and discovered that the main cause of many engine in-flight shutdowns was these single faults, which were preceded by a sharp change in one or more of the measurement deltas. Such a sharp trend change can also happen if the engine is repaired and tested on the ground in a test cell. Therefore, a typical jet engine measurement delta signal can be assumed to be a linear long-term deterioration along with sudden step changes due to a single-fault or a repair event.

The power plant engineer does not solely rely on observing trend plots to monitor the engine condition. Various diagnostic algorithms have been developed to estimate engine condition and identify faults from the health signals using weighted least squares [7, 8], Kalman filter [9], neural network [6, 10–12], fuzzy logic [13], and Bayesian [14] approaches. However, while all these algorithms attempt to handle uncertainty in the measurement deltas, their performance is often degraded as the noise in the data increases. This is also true for system identification of jet engines [15] that is done to produce better control and diagnostics models. In addition, these estimation and pattern recognition algorithms are often optimal for Gaussian noise models and can degrade when non-Gaussian outliers are present in the data [16].

Classical signal processing has been dominated by the assumption of a Gaussian random noise model for defining the statistical properties of a real process. However, many real-world processes are characterized by impulsive noise that causes sharp spikes and outliers in the data. For example, data can be corrupted by impulsive noise during acquisition and transmission through communication channels [17]. Phenomena such as atmospheric noise is also impulsive in nature. Fault detection and isolation methods that are optimized for random Gaussian noise can suffer severe performance degradation under non-Gaussian noise. Therefore, signal processing of the measured data can be very useful for improving gas turbine diagnostics. In particular, impulsive noise should be removed.

1.2 Signal Processing

In signal processing, filtering methods are used to preprocess the data to reduce noise. The term *noise* here is used in a general sense and includes any corruption to the signal that hinders the pattern recognition or state estimation process or leads to false artifacts being observed during visualization. Traditionally, smoothing methods used by the gas turbine industry are moving averages and exponential smoothing [6]. The moving average is a special case of the finite impulse response (FIR) filter, and the exponential average is a special case of the infinite impulse response (IIR) filter. These filters will be explained later in this chapter. Depold and Gass [6] first addressed the problem of finding a filter that preserves the sharp trend shifts in gas path measurements due to a single fault. They showed that the exponential average filter has a faster reaction time than the widely used 10-point average and is therefore a better filtering method for processing data prior to trend detection and fault isolation. They also developed some rules of thumb to remove outliers from gas turbine measurements. These rules were based on the logic that a shift in any one measurement without shifts in the other measurements would indicate an outlier.

However, both the FIR and IIR filters are linear filters and remove noise while blurring the edges in the signal. In addition, the human visual system is acutely sensitive to high frequency in the spatial form of edges [18]. Most of the low frequency in an image is discarded by the visual system before it can even leave the retina. Unfortunately, the presence of sporadic high-amplitude impulsive noise in a signal can confuse the human visual system into seeing patterns where none are really present. Such noise can also trigger an automated trend detection system to give a false alarm. Therefore, it is necessary to remove any such high-amplitude noise while preserving edges from the measurement deltas before subsequent data processing operations for fault detection and isolation.

Substantial research efforts have been conducted in the field of image processing to find suitable alternatives to linear filters that are robust or resistant to the presence of impulsive noise. Among these works, the approach that has received the most attention is that of median filters. Median filters are a well-known and useful class of nonlinear filters in the image processing field [19–24]. They are useful for removing noise while preserving fine details in the signal. However, they are not well known in engineering health monitoring applications. Ganguli [25] used FIR-median hybrid (FMH) filters [20] for removing noise from gas turbine measurements while preserving trend shifts. In this study, step changes were considered in a constant signal as a representation of a single-fault event. Results showed that the FMH filter preserved the sharp trend shifts in the signal while the moving average and exponential average filter smoothed the trend shifts. The problem of deterioration was not addressed. Furthermore, the FMH filter used in this study required up to 10 points of forward data and therefore had a 10-point time lag. Since jet engines often get only 1 or 2 points in each flight, the 10-point time lag is very large and is more suitable for engines with online diagnostics systems or for systems where data are obtained rapidly. The cost of high-rate data acquisition remains quite high. In applications other than gas turbine engines, Nounou and Bakshi [26] used the FIR-median hybrid (FMH) filter to remove noise from chemical process signals. Manders et al. [27] used a median filter of length 5 to remove noise in temperature data for monitoring the cooling system of an automobile engine having installed thermocouples and pressure sensors. Ogaji et al. [28] used FMH filters to remove noise from data measured by a global positioning system (GPS) that directly measures relative displacement and position coordinates for a tall building.

Nonlinear filters are not limited to median type filters. A special class of neural networks called the autoassociative neural network (AANN) [29, 30] has been used for noise filtering, using sensor replacement and gross error detection and identification. Lu et al. [11, 31] used autoassociative neural networks for noise filtering gas path measurements. The AANN performs a unitary mapping, which maps the input parameters onto themselves. The AANN is also capable of removing any outliers in the data, and performed better at preserving trend shifts than the moving average or exponential average filter. To train the AANN, noisy data are input to it and mapped to noise-free data at the output nodes. The number of input nodes and output nodes is equal to the number of measurements. The AANN has an input and output layer, two hidden layers, and a bottleneck layer. Thus, the data go to the input layer, then a hidden layer, then a bottleneck layer, followed by a hidden layer and the output layer. Lu et al. [11] used eight measurement nodes for the hidden layer and five nodes for the bottleneck layer, resulting in an 8-9-5-9-8 AANN architecture. The neural network therefore learns the noise characteristics of the data and is trained to give noise-free data from noisy data. We will discuss the AANN in more detail in Chapter 9.

Many filtering algorithms use a fixed-noise detection threshold obtained at a presumed noise density level. For example, wavelet-based noise removal methods [26, 32, 33] use orthogonal wavelet analysis, which finds coefficients related to undesired features in the signal. Nounou and Bakshi [26] showed that wavelet-based noise removal methods could be superior to the FMH filter for processing signals with sharp trend shifts. The wavelet-based noise removal has three parts: (1) orthogonal wavelet transform, (2) thresholding of wavelet coefficients, and (3) inverse wavelet transform. By setting to zero the wavelet coefficients at the highest orthogonal level of decomposition, noise can be removed from the signal. However, finding a threshold depends on the noise level and nature of the noise and is a difficult problem. Neural network-based filtering methods are also sensitive to the noise levels in the training data. For example, the AANN used by Lu et al. [11] was trained with representative noisy data using simulated signals. However, when the noise characteristic becomes different from that used in algorithm development, which can happen in practical applications, the performance of these algorithms can show degradation.

1.3 Typical Gas Turbine Diagnostics

Urban [34] states the scope of gas turbine diagnostics in his research paper as follows: "Therefore, it follows that if physical problems result in degraded component performance, which in turn produce changes in the measurable engine parameter, then it is possible to utilize these measurable changes to isolate the degraded component characteristics, in whatever combination, and permit correction of the causative problems."

Figure 1.1 shows a schematic representation of the gas turbine diagnostics process. The measurement deltas are processed using smoothing algorithms based on moving or exponential averages [6]. In some cases, the diagnostics function may be completely performed by power plant engineers. In these cases, the measurement deltas are visualized using computer graphics and the power plant engineer uses his or her experience to detect engine deterioration or faults. In case a fault or severe performance degradation is detected, the power plant engineer may suggest prognostics and maintenance action. In other cases, the power plant engineer may also have access to automated fault detection and isolation software that can estimate the condition of the different modules and also detect and isolate other faults. In addition, expert systems may be available for interpreting

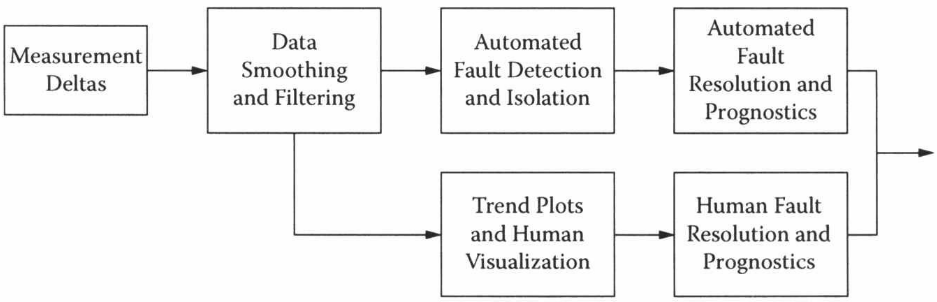

FIGURE 1.1
Schematic representation of gas turbine diagnostics process. (From Ganguli, R., *Journal of Propulsion and Power* 19(5):930–937, 2003. With permission.)

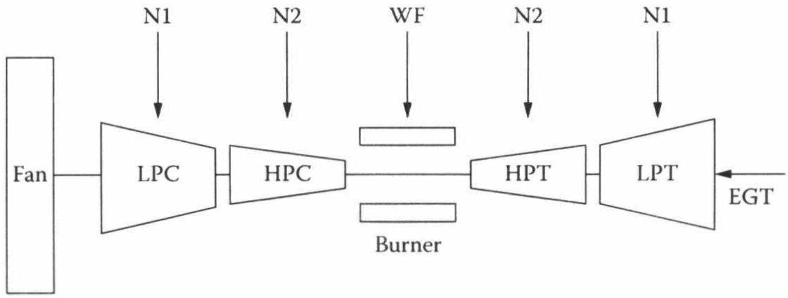

FIGURE 1.2
Schematic representation of gas turbine engine modules and sensor measurements. (From Ganguli, R., *Journal of Propulsion and Power* 19(5):930–937, 2003. With permission.)

the output of the fault detection and isolation algorithms for suggesting maintenance and prognostics action. In general, both the automated and human components of the diagnostics system should be used for the best possible decisions.

Figure 1.2 shows a schematic of a turbo engine that has five modules: fan, low-pressure compressor (LPC), high-pressure compressor (HPC), low-pressure turbine (LPT), and high-pressure turbine (HPT). Air is sucked into the engine through the fan and compressed in the LPC and HPC. Then, the compressed air is mixed with a fuel and burned in the burner. Following this, the hot gases are passed through the turbines and power is generated during this process. Finally, the hot gases are sent out through the exhaust.

Faults in the gas turbine engine cause efficiency deterioration for the engine modules. The engine state is monitored using at least the four basic sensors: exhaust gas temperature (EGT), fuel flow (WF), low rotor speed ($N1$), and high rotor speed ($N2$). The measurements that are taken at altitude at a given temperature are then converted to standard day sea level conditions, and then the baseline measurement of an undamaged engine at the same condition (usually from a thermodynamics-based performance model) is subtracted from the measurements to yield the measurement deltas ΔEGT, ΔWF, $\Delta N1$, and $\Delta N2$. The measurement deltas are then used for estimating the engine state. Various fault isolation algorithms are used to find the module where the fault has occurred. These include Kalman filter, neural networks, and fuzzy logic-based methods, some of which will be discussed in later chapters.

We can observe from Figure 1.1 that a key component of the diagnostics system is the smoothing or filtering function. While much research has been expended on the fault detection and isolation function, not much work has been done to improve the data smoothing and filtering function [6, 11, 25, 31]. The next two sections give a brief background on linear filters and the nonlinear median filter. Several variations of the median filter will be discussed in this book for application to gas turbine diagnostics.

1.4 Linear Filters

The finite impulse response (FIR) filter can be represented as

$$y(k) = \sum_{i=1}^{N} b(i)x(k-i+1) \tag{1.1}$$

where $x(k)$ is the kth input measurement and $y(k)$ is the kth output. N is the filter length and $\{b(i)\}$ is the sequence of weighting coefficients, which define the characteristics of the filter and sum to unity. When all the weights $\{b(i)\}$ are equal, the FIR filter reduces to the special case of the mean or average filter, which is widely used for data smoothing. For example, the 10-point moving average has the form

$$y(k) = \frac{1}{10}(x(k) + x(k-1) + x(k-2) + \cdots + x(k-9)) \tag{1.2}$$

Each of the 10 weights for this filter is equal to 1/10.

Exponentially Weighted Moving Average (EWMA) is a popular IIR filter that smoothes a measured data point $x(k)$ by exponentially averaging it with all previous measurements $y(k-1)$.

$$y(k) = ax(k) + (1 - a)y(k - 1) \tag{1.3}$$

The parameter a is an adjustable smoothing parameter between 0 and 1 with values such as 0.15 and 0.25 being routinely used in applications [6]. The exponential average filter has memory since it retains the entire time history by using the output of the last point. While linear filters are often used to smooth data before fault diagnosis, they can also smooth out important signal features. This problem is alleviated by the use of nonlinear filters such as the median filter.

1.5 Median Filters

Several median type filters are discussed in this book in Chapters 2–4, 6, and 7. Here, we introduce the standard median filter, which is well known in image processing.

Standard median (SM) filters are a popular and useful class of nonlinear filters. The success of median filters is based on two properties: edge preservation and noise reduction with robustness against impulsive type noise. Neither property can be achieved by traditional linear filtering without using