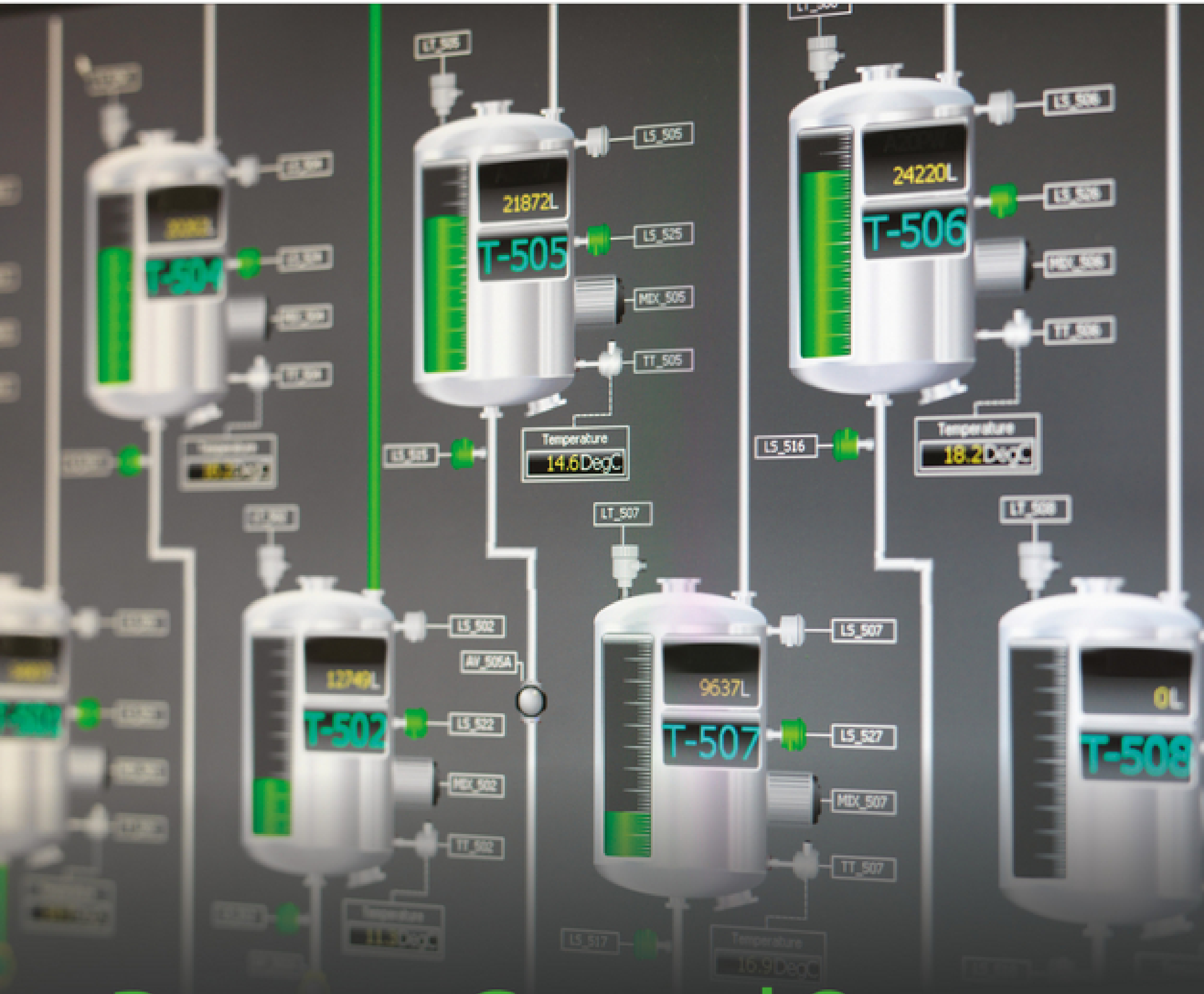
Ruben Gonzalez | Fei Qi | Biao Huang



Process Control System Fault Diagnosis

a Bayesian Approach

WILEY

PROCESS CONTROL SYSTEM FAULT DIAGNOSIS

PROCESS CONTROL SYSTEM FAULT DIAGNOSIS

A BAYESIAN APPROACH

Ruben Gonzalez

Fei Qi

Biao Huang

WILEY

This edition first published 2016

First edition published in 2016

Registered office
John Wiley & Sons Ltd, The Atrium, Southern Gate, Chichester, West Sussex, PO19 8SQ, United Kingdom

For details of our global editorial offices, for customer services and for information about how to apply for permission to reuse the copyright material in this book please see our website at www.wiley.com.

Library of Congress Cataloging-in-Publication Data

Names: Gonzalez, Ruben, 1985- author. | Qi, Fei, 1983- author | Huang, Biao, 1962- author.
Title: Process control system fault diagnosis : a Bayesian approach / Ruben Gonzalez, Fei Qi, Biao Huang.
Description: First edition. | Chichester, West Sussex, United Kingdom : John Wiley & Sons, 2016. | Includes bibliographical references and index.
Identifiers: LCCN 2016010340| ISBN 9781118770610 (cloth) | ISBN 9781118770597 (epub)
Subjects: LCSH: Chemical process control–Statistical methods. | Bayesian statistical decision theory. | Fault location (Engineering)
Classification: LCC TP155.75 .G67 2016 | DDC 660/.2815–dc23 LC record available at https://lccn.loc.gov/2016010340

A catalogue record for this book is available from the British Library.

Set in 10/12pt, TimesLTStd by SPi Global, Chennai, India.

1 2016

Contents

Preface

Background

Control performance monitoring (CPM) has been and continues to be one of the most active research areas in the process control community. A number of CPM technologies have been developed since the late 1980s. It is estimated that several hundred papers have been published in this or related areas. CPM techniques have also been widely applied in industry. A number of commercial control performance assessment software packages are available off the shelf.

CPM techniques include controller monitoring, sensor monitoring, actuator monitoring, oscillation detection, model validation, nonlinearity detection and so on. All of these techniques have been designed to target a specific problem source in a control system. The common practice is that one monitoring technique (or monitor) is developed for a specific problem source. However, a specific problem source can show its signatures in more than one monitor, thereby inducing alarm flooding. There is a need to consider all monitors simultaneously in a systematic manner.

There are a number of challenging issues:

1. There are interactions between monitors. A monitor cannot be designed to just monitor one problem source in isolation from other problem sources. While each monitor may work well when only the targeted problem occurs, relying on a single monitor can be misleading when other problems also occur.
2. The causal relations between a problem source and a monitor are not obvious for industrial-scale problems. First-principles knowledge, including the process flowchart, cannot always provide an accurate causal relation.
3. Disturbances and uncertainties exist everywhere in industrial settings.
4. Most monitors are either model-based or data-driven; it is uncommon for monitor results to be combined with prior process knowledge.

Clearly, there is a need to develop a systematic framework, including theory and practical guidelines, to tackle the these monitoring problems.

Control Performance Diagnosis and Control System Fault Diagnosis

Control systems play a critical role in modern process industries. Malfunctioning components in control systems, including sensors, actuators and other components, are not uncommon in industrial environments. Their effects introduce excess variation throughout the process, thereby reducing machine operability, increasing costs and emissions, and disrupting final product quality control. It has been reported in the literature that as many as 60% of industrial controllers may have some kind of problem.

The motivation behind this book arises from the important task of isolating and diagnosing control performance abnormalities in complex industrial processes. A typical modern process operation consists of hundreds or even thousands of control loops, which is too many for plant personnel to monitor. Even if poor performance is detected in some control loops, because a problem in a single component can invoke a wide range of control problems, locating the underlying problem source is not a trivial task. Without an advanced information synthesis and decision-support system, it is difficult to handle the flood of process alarms to determine the source of the underlying problem. Human beings' inability to synthesize high-dimensional process data is the main reason behind these problems. The purpose of control performance diagnosis is to provide an automated procedure that aids plant personnel to determine whether specified performance targets are being met, evaluate the performance of control loops, and suggest possible problem sources and a troubleshooting sequence.

To understand the development of control performance diagnosis, it is necessary to review the historical evolution of CPM. From the 1990s and 2000s, there was a significant development in CPM and, from the 2000s to the 2010s, control performance diagnosis. CPM focuses on determining how well the controller is performing with respect to a given benchmark, while CPD focuses on diagnosing the causes of poor performance. CPM and CPD are of significant interest for process industries that have growing safety, environmental and efficiency requirements. The classical method of CPM was first proposed in 1989 by Harris, who used the minimum variance control (MVC) benchmark as a general indicator of control loop performance. The MVC benchmark can be obtained using the filtering and correlation (FCOR) algorithm, as proposed by Huang et al. in 1997; this technique can be easily generalized to obtain benchmarks for multivariate systems. Minimum variance control is generally aggressive, with potential for poor robustness, and is not a suitable benchmark for CPM of model predictive control, as it does not take input action into account. Thus the linear quadratic Gaussian (LQG) benchmark was proposed in the PhD dissertation of Huang in 1997. In order to extend beyond simple benchmark comparisons, a new family of methods was developed to monitor specific instruments within control loops for diagnosing poor performance (by Horch, Huang, Jelali, Kano, Qin, Scali, Shah, Thornhill, etc). As a result, various CPD approaches have appeared since 2000.

To address the CPD problem systematically, Bayesian diagnosis methods were introduced by Huang in 2008. Due to their ability to incorporate both prior knowledge and data, Bayesian methods are a powerful tool for CPD. They have been proven to be useful for a variety of monitoring and predictive maintenance purposes. Successful applications of the Bayesian approach have also been reported in medical science, image processing, target recognition, pattern matching, information retrieval, reliability analysis and engineering diagnosis. It provides a flexible structure for modelling and evaluating uncertainties. In the presence of noise and disturbances, Bayesian inference provides a good way to solve the monitoring and diagnosis problem, providing a quantifiable measure of uncertainty for decision making. It is one of the most widely applied techniques in statistical inference, as well being used to diagnose engineering problems.

The Bayesian approach was applied to fault detection and diagnosis (FDI) in the mechanical components of transport vehicles by Pernestal in 2007, and Huang applied it to CPD in

2008. CPD techniques bear some resemblance to FDI. Faults usually refer to failure events, while control performance abnormality does not necessarily imply a failure. Thus, CPD is performance-related, often focusing on detecting control related problems that affect control system performance, including economic and environmental performance, while FDI focuses on the failure of components. Under the Bayesian framework, both can be considered as an abnormal event or fault diagnosis for control systems. Thus control system fault diagnosis is a more appropriate term that covers both.

Book Objective, Organization and Readership

The main objectives of this book are to establish a Bayesian framework for control system fault diagnosis, to synthesize observations of different monitors with prior knowledge, and to pinpoint possible abnormal sources on the basis of Bayesian theory. To achieve these objectives, this book provides comprehensive coverage of various Bayesian methods for control system fault diagnosis. The book starts with a tutorial introduction of Bayesian theory and its applications for general diagnosis problems, and an introduction to the existing control loop performance-monitoring techniques. Based upon these fundamentals, the book turns to a general data-driven Bayesian framework for control system fault diagnosis. This is followed by presentation of various practical problems and solutions. To extend beyond traditional CPM with discrete outputs, this book also explores how control loop performance monitors with continuous outputs can be directly incorporated into the Bayesian diagnosis framework, thus improving diagnosis performance. Furthermore, to deal with historical data taken from ambiguous operating conditions, two approaches are explored:

- Dempster–Shafer theory, which is often used in other applications when ambiguity is present
- a parametrized Bayesian approach.

Finally, to demonstrate the practical relevance of the methodology, the proposed solutions are demonstrated through a number of practical engineering examples.

This book attempts to consolidate results developed or published by the authors over the last few years and to compile them together with their fundamentals in a systematic way. In this respect, the book is likely to be of use for graduate students and researchers as a monograph, and as a place to look for basic as well as state-of-the-art techniques in control system performance monitoring and fault diagnosis. Since several self-contained practical examples are included in the book, it also provides a place for practising engineers to look for solutions to their daily monitoring and diagnosis problems. In addition, the book has comprehensive coverage of Bayesian theory and its application in fault diagnosis, and thus it will be of interest to mathematically oriented readers who are interested in applying theory to practice. On the other hand, due to the combination of theory and applications, it will also be beneficial to applied researchers and practitioners who are interested in giving themselves a sound theoretical foundation. The readers of this book will include graduate students and researchers in chemical engineering, mechanical engineering and electrical engineering, specializing in process control, control systems and process systems engineering. It is expected that readers will be acquainted with some fundamental knowledge of undergraduate probability and statistics.

Acknowledgements

The material in this book is the outcome of several years of research efforts by the authors and many other graduate students and post-doctoral fellows at the University of Alberta. In particular, we would like to acknowledge those who have contributed directly to the general area of Bayesian statistics that has now become one of the most active research subjects in our group: Xingguang Shao, Shima Khatibisepehr, Marziyeh Keshavarz, Kangkang Zhang, Swanand Khare, Aditya Tulsyan, Nima Sammaknejad and Ming Ma. We would also like to thank our colleagues and collaborators in the computer process control group at the University of Alberta, who have provided a stimulating environment for process control research. The broad range of talent within the Department of Chemical and Materials Engineering at the University of Alberta has allowed cross-fertilization and nurturing of many different ideas that have made this book possible. We are indebted to industrial practitioners Aris Espejo, Ramesh Kadali, Eric Lau and Dan Brown, who have inspired us with practical relevance in broad areas of process control research. We would also like to thank our laboratory support from Artin Afacan, computing support from Jack Gibeau, and other supporting staff in the Department of Chemical and Materials Engineering at the University of Alberta. The support of the Natural Sciences and Engineering Research Council of Canada and Alberta Innovates Technology Futures for this and related research work is gratefully acknowledged. Last, but not least, we would like to acknowledge Kangkang Zhang, Yuri Shardt and Sun Zhou for their detailed review of and comments on the book.

Some of the figures presented in this book are taken from our previous work that has been published in journals. We would like to acknowledge the journal publishers who have allowed us to re-use these figures:

Figures 3.1 and 14.1 are adapted with permission from *AIChE Journal*, Vol. 56, Qi F, Huang B and Tamayo EC, ‘A Bayesian approach for control loop diagnosis with missing data’, pp. 179–195. ©2010 John Wiley and Sons.

Figures 4.4 and 13.2 are adapted with permission from *Automatica*, Vol. 47, Qi F and Huang B, ‘Bayesian methods for control loop diagnosis in the presence of temporal dependent evidences’, pp. 1349–1356. ©2011 Elsevier.

Figures 4.1, 4.3, 4.5–4.7, 13.1 and 13.3 are adapted with permission from *Industrial & Engineering Chemistry Research*, Vol. 49, Qi F and Huang B, ‘Dynamic Bayesian approach for control loop diagnosis with underlying mode dependency’, pp. 8613–8623. © 2010 American Chemical Society.

Figures 8.1–8.4 are adapted with permission from *Journal of Process Control*, Vol. 24, Gonzalez R and Huang B, ‘Control loop diagnosis using continuous evidence through kernel density estimation’, pp. 640–651. ©2014 Elsevier.

List of Figures

List of Tables

Nomenclature

Symbol	**Description**
α	Frequency parameter for the Dirichlet distribution
$\boldsymbol{\alpha}\{\frac{\bullet}{\boldsymbol{m}_k}\}$	Frequency parameters pertaining to the ambiguous mode $\boldsymbol{m}_k$
μ	Population mean
Σ	Population covariance
σ	Population standard deviation
Θ	Complete set of probability/proportion parameters
$\Theta\{\frac{\bullet}{\boldsymbol{m}_k}\}$	The set of elements in Θ pertaining to the ambiguous mode $\boldsymbol{m}_k$
$\hat{\Theta}$	Informed estimate of Θ
$\boldsymbol{\Theta}$	Complete set of probability/proportion parameters (matrix form)
$\boldsymbol{\Theta}^*$	Inclusive estimate of Θ (matrix form)
$\boldsymbol{\Theta}_*$	Exclusive estimate of Θ (matrix form)
θ	A probability/proportion parameter
$\theta\{\frac{m}{\boldsymbol{m}}\}$	Proportion of data in ambiguous mode $\boldsymbol{m}$ belonging to mode m
$Bel(M)$	Lower-bound probability of mode M
C	State of the component of interest (random variable)
c	State of the component of interest (observation)
$\mathcal{C}(M)$	The event where mode M was diagnosed
$\mathcal{C}(M)\vert M$	The event where mode M was diagnosed and M was true
$\mathcal{C}(\bar{M})\vert M$	The event where a mode other than M was diagnosed and M was true
$\mathcal{D}$	Historical record of evidence
D_i	ith element of historical evidence data record $\mathcal{D}$
E	Evidence (random variable)
e	Evidence (observation)
F_N	False negative diagnosis rate
$\boldsymbol{G}$	Generalized BBA
$\boldsymbol{G}[:, m]$	mth column of $\boldsymbol{G}$ (MATLAB notation)
$\boldsymbol{G}[k, :]$	kth row of $\boldsymbol{G}$ (MATLAB notation)
H	Bandwidth matrix (Kernel density estimation)
$\boldsymbol{H}$	Hessian matrix
i.i.d.	Independent and identically distributed
$\boldsymbol{J}$	Jacobian matrix

Symbol	Description
K	Support for conflict (Dempster–Shafer theory)
K	Kernel function (kernel density estimation)
M	Operational mode (random variable)
$\boldsymbol{M}$	Potentially ambiguous operational mode (random variable)
m	Operational mode (observation)
$\boldsymbol{m}$	Potentially ambiguous operational mode (observation)
MIC	Mutual information criterion
CMIC	Conditional mutual information criterion
$n(E)$	Number of times evidence E has been observed
$n(E, M)$	Number of times evidence E and mode M have been jointly observed
$n(M)$	Number of times mode M was observed
ODE $[f(x)]$	Ordinary differential equation solver applied to $f(x)$
$p(E)$	Normalization over evidence (probability of evidence)
$p(E\|M)$	Likelihood (probability of evidence given the mode)
$p(M)$	Prior (prior probability of the mode)
$p(M\|E)$	Posterior (probability of mode given the evidence)
$Pl(M)$	Upper bound probability of mode M
P	Posterior state covariance (Kalman filter)
Q	Model error covariance (Kalman filter)
R	Observation error covariance (Kalman filter)
S	Sample covariance matrix
$S(E\|\boldsymbol{M})$	Support for evidence E given potentially ambiguous mode $\boldsymbol{M}$
$S(\boldsymbol{M})$	Support for potentially ambiguous mode $\boldsymbol{M}$
$S(E\|\boldsymbol{M})$	Support for potentially ambiguous mode $\boldsymbol{M}$ given evidence E
UCEM	Underlying complete evidence matrix
UKF $[f(x)]$	Unscented Kalman filter with a model $f(x)$

Part One

Fundamentals

1

Introduction

1.1 Motivational Illustrations

Consider the following scenarios:

Scenario A

You are a plant operator, and a gas analyser reading triggers an alarm for a low level of a vital reaction component, but from experience you know that this gas analyser is prone to error. The difficulty is, however, that if the vital reaction component is truly scarce, its scarcity could cause plugging and corrosion downstream that could cost over $120 million in plant downtime and repairs, but if the reagent is not low, shutting down the plant would result in $30 million in downtime. Now, imagine that you have a diagnosis system that has recorded several events like this in the past, using information from both upstream and downstream, is able to generate a list of possible causes of this alarm reading, and displays the probability of each scenario. The diagnosis system indicates that the most possible cause is a scenario that happened three years ago, when the vital reagent concentration truly dropped, and by quickly taking action to bypass the downstream section of the plant a $120-million incident was successfully avoided. Finally, imagine that you are the manager of this plant and discover that after implementing this diagnosis system, the incidents of unscheduled downtime are reduced by 60% and that incidents of false alarms are reduced by 80%.

Scenario B

You are the head of a maintenance team of another section of the plant with over 40 controllers and 30 actuators. Oscillation has been detected in this plant, where any of these controllers or actuators could be the cause. Because these oscillations can push the system into risky operating regions, caution must be exercised to keep the plant in a safer region, but at the cost of poorer product quality. Now, imagine you have a diagnosis tool that has data recorded from previous incidents, their troubleshooting solutions, and the probabilities of each incident.

Process Control System Fault Diagnosis: A Bayesian Approach, First Edition. Ruben Gonzalez, Fei Qi and Biao Huang.

With this tool, we see that the most probable cause (at 45%) was fixed by replacing the stem packing on Valve 23, and that the second most probable cause (at 22%) was a tank level controller that in the past was sometimes overtuned by poor application of tuning software. By looking at records, you find out that a young engineer recently used tuning software to re-tune the level controller. Because of this information, and because changing the valve packing costs more, you re-tune the controller during scheduled maintenance, and at startup find that the oscillations are gone and you can now safely move the system to a point that produces better product quality. Now that the problem has been solved, you update the diagnosis tool with the historical data to improve the tool's future diagnostic performance. Now imagine, that as the head engineer of this plant, you find out that 30% of the most experienced people on your maintenance team are retiring this year, but because the diagnostic system has documented a large amount of their experience, new operators are better equipped to figure out where the problems in the system truly are.

Overview

These stories paint a picture of why there has been so much research interest in fault and control loop diagnosis systems in the process control community. The strong demand for better safety practices, decreased downtime, and fewer costly incidents (coupled with the increasing availability of computational power) all fuel this active area of research. Traditionally, a major area of interest has been in detection algorithms (or *monitors* as they will be called in this book) that focus on the behaviour of the system component. The end goal of implementing a monitor is to create an alarm that would sound if the target behaviour is observed. As more and more alarms are developed, it becomes increasingly probable that a single problem source will set off a large number of alarms, resulting in an alarm flood. Such scenarios in industry have caused many managers to develop alarm management protocols within their organizations. Scenarios such as those presented in scenarios A and B can be realized and in some instances have already been realized by research emphasizing the best use of information obtained from monitors and historical troubleshooting results.

1.2 Previous Work

1.2.1 Diagnosis Techniques

The principal objective in this book is to diagnose the operational mode of the process, where the mode consists of the operational state of all components within the process. For example, if a system comprises a controller, a sensor and a valve, the mode would contain information about the controller (e.g. well tuned or poorly tuned), the sensor (e.g. biased or unbiased) and the valve (e.g. normal or sticky). As such, the main problem presented in this book falls within the scope of *fault detection and diagnosis*.

Fault detection and diagnosis has a vast (and often times overwhelming) amount of literature devoted to it for two important reasons:

1. The problem of fault detection and diagnosis is a legitimately difficult problem due to the sheer size and complexity of most practical systems.

2. There is great demand for fault detection and diagnosis as it is estimated that poor fault management has cost the United States alone more than $20 billion annually as of 2003 (Nimmo 2003).

In a three-part publication, Venkatasubramanian et al. (2003b) review the major contributions to this area and classify them under the following broad families: quantitative model-driven approaches (Venkatasubramanian et al. 2003b), qualitative model-driven approaches (Venkatasubramanian et al. 2003a), and process data-driven approaches (Venkatasubramanian et al. 2003c). Each type of approach has been shown to have certain challenges. Quantitative model-driven approaches require very accurate models that cover a wide array of operating conditions; such models can be very difficult to obtain. Qualitative model-driven approaches require attention to detail when developing heuristics, or else one runs the risk of a spurious result. Process data-driven approaches have been shown to be quite powerful in terms of detection, but most techniques tend to yield results that make fault isolation difficult to perform. In this book, particular interest is taken in the quantitative model-driven and the process data-driven approaches.

Quantitative Model-driven Approaches

Quantitative model-driven approaches focus on constructing the models of a process and using these models to diagnose different problems within a process (Lerner 2002) (Romessis and Mathioudakis 2006). These techniques bear some resemblance to some of the monitoring techniques described in Section 1.2.2 applied to specific elements in a control loop. Many different types of model-driven techniques exist, and have been broken down according to Frank (1990) as follows:

1. *The parity space approach* looks at analytical redundancy in equations that govern the system (Desai and Ray 1981).
2. *The dedicated observer and innovations approach* filters residual errors from the Parity Space Approach using an observer (Jones 1973).
3. *The Fault Detection Filter Approach* augments the State Space models with fault-related variables (Clark et al. 1975; Willsky 1976)
4. *The Parameter Identification Approach* is traditionally performed offline (Frank 1990). Here, modeling techniques are used to estimate the model parameters, and the parameters themselves are used to indicate faults.

A popular subclass of these techniques is deterministic fault diagnosis methods. One popular method in this subclass is the parity space approach (Desai and Ray 1981), which set up parity equations having analytical redundancy to look at error directions that could correspond to faults. Another popular method is the observer-based approach (Garcia and Frank 1997), which uses an observer to compare differences in the predicted and observed states.

Stochastic techniques, in contrast to deterministic techniques, use fault-related parameters as augmented states; these methods enjoy the advantage of being less sensitive to process noise (Hagenblad et al. 2004), being able to determine the size and precise cause of the fault, but are very difficult to implement in large-scale systems and often require some excitement

(Frank 1996). Including physical fault parameters in the state often requires a nonlinear form of the Kalman filter (such as the extended Kalman filer (EKF), unscented Kalman filter (UKF) or particle filter) because these fault-related parameters often have nonlinear relationships with respect to the states. Such techniques were pioneered by Isermann (Isermann and Freyermuth 1991), (Isermann 1993) with other important contributions coming from Rault et al. (1984). The motivation for including fault parameters in the state is the stochastic Kalman filter's ability to estimate state distributions. By including fault parameters in the state, fault parameter distributions are automatically estimated in parallel with the state. Examples of this technique include that of Gonzalez et al. (2012), which made use of continuous augmented bias states, while Lerner et al. (2000) made use of discrete augmented fault states.

Process Data-driven Approaches

A popular class of techniques for process monitoring are data-driven modeling methods, where one of the more popular techniques is principal component analysis (PCA) (Ge and Song 2010). These techniques create black-box models assuming that the data can be explained using a linear combination of independent Gaussian latent variables (Tipping and Bishop 1998); a transformation method is used to calculate values of these independent Gaussian variables, and abnormal operation is detected by performing a significance test. The relationship between abnormal latent variables and the real system variables is then used to help the user determine what the possible causes of abnormality could be. There have also been modifications of the PCA model to include multiple Gaussian models (Ge and Song 2010; Tipping and Bishop 1999) where the best local model is used to calculate the underlying latent variables used for testing.

All PCA models assume that the underlying variables are Gaussian, but more recent methods (Lee et al. 2006) do away with this assumption by first using independent components analysis (ICA) to calculate values of independent latent variables (which are not assumed to be Gaussian under ICA) and then using a kernel density estimation to evaluate the probability density of that value. Low probability densities indicate that the process is behaving abnormally. Even more recent work (Gonzalez et al. 2015) uses Bayesian networks instead of PCA/ICA to break down the system into manageable pieces; this allows the user to define variables of interest for monitoring and determine the causal structures used to help narrow down causes. Abnormality is detected if key process variables take on improbable values or if groups of key process variables take on improbable patterns. Results from this approach are generally easier to interpret than PCA/ICA-based methods.

Bayesian Data-driven Approaches

This book focuses on using the Bayeisan data-driven approach, which is distinct from other fault detection and diagnosis methods, mainly for the reason that the Bayesian approach is a *higher-level diagnosis method* (Pernestal 2007; Qi 2011). This type of approach is not meant to compete with previously mentioned fault detection and diagnosis methods; instead, the Bayesian approach provides a unifying framework to simultaneously use many of these methods at once. As such, it can take input from many different fault detection and diagnosis techniques in order to make a final decision. In this book, other diagnosis methods and even instruments themselves are treated as input sources and are referred to as *monitors*; this term is chosen mainly because previous work (Qi 2011) focused heavily on using input from control loop monitoring techniques (described in Section 1.2.2).

For Bayesian diagnosis, data from monitors must be collected for every scenario that one would wish to diagnose. In this book, such scenarios are referred to as operational *modes*. When new monitor information arrives, the new information is compared to historical data in order to determine which historical mode best fits the new information. The Bayesian diagnosis technique ranks each of the modes based on posterior probability, which is calculated using Bayes' theorem (Bayes 1764/1958):

$$p(M|E) = \frac{p(E|M)p(M)}{p(E)}$$

$$P(E) = \sum_i p(E|m_i)p(m_i)$$

where

- $p(M|E)$ is the posterior probability, or probability of the mode M given evidence E
- $p(E|M)$ is the likelihood of the evidence E given the historical mode M
- $p(M)$ is the prior probability of the historical mode M
- $p(E)$ is the probability of the evidence E (which is a normalizing constant).

In the Bayesian diagnosis technique, the historical data and mode classifications are used to construct the likelihood $p(E|M)$, and prior probabilities of modes are assigned to $p(M)$ using expert knowledge. While collecting data for historical modes may be a challenge, the Bayesian method at least allows us to collect data in a way that is not necessarily representative of the true mode occurrence rate. For example, if mode 1 occurs 90% of the time, then representative sampling would require that 90% of the data come from mode 1. Bayesian methods (which use prior probabilities to cover mode representation) allow us to collect an arbitrary amount of data for each mode, giving us a lot more flexibility in data collection than other methods.

1.2.2 Monitoring Techniques

Much of this work focuses on monitoring and diagnosing control-loops (a schematic for a typical control loop is given in Figure 1.1); for this area of research, there exists abundant

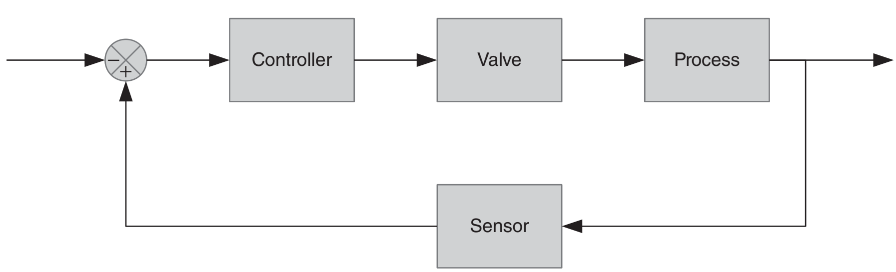


Figure 1.1 Typical control loop

Table 1.1 List of monitors for each system

Simulated	Bench-scale	Industrial-scale
Control performance	Sensor bias	Raw sensor readings
Valve stiction	Process operation	
Process model		

literature on assessing the performance of the entire loop as well as diagnosing problems within the loop's core components. These methods (defined as monitors in this book) can be directly used to create alarms or notification statuses which alert operators and engineers about risky or inefficient operation.

Monitors tend to focus on one or more of the main components in a control system: for example, the controller, the actuator (often a valve), the process and the sensor. The following monitors will be considered in this book as examples but the diagnosis approach as proposed in this book can be applied to other monitors as well.

- **Control performance monitors** are intended to monitor the performance of the controller, but are often affected by other parts of the control loop.
- **Sensor bias monitors** focus on sensor performance.
- **Valve stiction monitors** focus on valve performance, but can sometimes be affected by other sources of oscillation.
- **Process model monitors** evaluate the correctness of the process model, which has utility in diagnosing controller performance and process performance. Deviation from the model can indicate a change in the system operation, and perhaps even a fault. In addition, because control tuning is performed with a model in mind, changes in the model may indicate that the current controller configuration is not suitable for current operation.
- **Process operation monitors** tend to fall under the category of fault detection, and aim to diagnose abnormalities and faults within a process.

The methods in this book are tested on three particular testbed systems: a simulated system, a bench scale system and an industrial scale system. Each type of monitor has been used in at least one of the testbed systems; a summary of monitors for each system is presented in Table 1.1. The simulated system makes use of three monitors (control performance monitors, valve stiction monitors and process model monitors) while the bench scale system makes use of the two remaining monitor types (a process operation monitor and two sensor bias monitors). The industrial-scale system uses no monitors, but instead directly uses data from the various sensors within the facility.

Control Performance Monitoring

Control performance assessment is concerned with the analysis of available control loop performance against certain benchmarks, while control performance monitoring is concerned with monitoring control performance change with respect to certain references. Due to their similarity, the two terminologies have often been used interchangeably and it is commonly accepted that they can represent each other. Research in this areas was pioneered by Harris et al. 1999 for proposing the minimum variance control (MVC) benchmark. Huang et al. (1995) developed a