SCIENCES

SYSTEMS AND INDUSTRIAL ENGINEERING

Reliability, Diagnosis, Safety and Maintenance of Systems

Diagnosis and Fault-tolerant Control 1

Data-driven and Model-based Fault Diagnosis Techniques

Coordinated by
Vicenç Puig and Silvio Simani

iSTE

WILEY

Diagnosis and Fault-tolerant Control 1

SCIENCES

Systems and Industrial Engineering,
Field Director – Jean-Paul Bourrières

Reliability, Diagnosis, Safety and Maintenance of Systems,
Subject Head – Jean-Marie Flaus

Diagnosis and Fault-tolerant Control 1

Data-driven and Model-based Fault Diagnosis Techniques

Coordinated by
Vicenç Puig
Silvio Simani

iSTE

WILEY

First published 2021 in Great Britain and the United States by ISTE Ltd and John Wiley & Sons, Inc.

ISTE Ltd
27-37 St George's Road
London SW19 4EU
UK

www.iste.co.uk

John Wiley & Sons, Inc.
111 River Street
Hoboken, NJ 07030
USA

www.wiley.com

Library of Congress Control Number: 2021943898

British Library Cataloguing-in-Publication Data
A CIP record for this book is available from the British Library
ISBN 978-1-78945-058-3

ERC Code:
PE7 Systems and Communication Engineering
PE7_1 Control engineering

Contents

Introduction ix
Vicenç PUIG and Silvio SIMANI

Chapter 1. Mathematical Modeling and Fault Description 1
Silvio SIMANI

1.1. Introduction 1
1.2. Model-based FDI techniques 2
1.3. Modeling of faulty systems 3
1.3.1. Fault modeling and description 5
1.3.2. Mathematical description 6
1.4. Residual generation 11
1.5. Residual generation techniques 14
1.5.1. Residual generation via parameter estimation 15
1.5.2. Observer-based approaches 18
1.5.3. Fault detection via parity equations 24
1.6. Change detection and symptom evaluation 28
1.7. Residual generation robustness problem 30
1.7.1. FDI H_∞ approach 32
1.7.2. Active and passive disturbance decoupling 35
1.8. Fault diagnosis technique integration 36
1.8.1. Fuzzy logic for residual generation 37
1.8.2. Neural networks for fault diagnosis 38
1.8.3. Neuro-fuzzy approaches to FDI 40
1.8.4. Fault detectability and isolability 42

1.8.5. NF model structure identification 43
1.8.6. NF residual generation for FDI 44
1.9. Conclusion 46
1.10. References 47

Chapter 2. Structural Analysis 57
Mattias KRYSANDER and Erik FRISK

2.1. Introduction 57
2.2. Background 58
2.2.1. Structural models 58
2.2.2. Dulmage–Mendelsohn decomposition and matchings 60
2.2.3. Dulmage–Mendelsohn decomposition and simulation 63
2.3. Fault isolability analysis 64
2.3.1. Fault detectability analysis 64
2.3.2. Fault isolability analysis 65
2.3.3. Canonical isolability decomposition of the overdetermined part . 67
2.4. Testable submodels 69
2.4.1. Basic definitions 69
2.4.2. MSO algorithm 71
2.4.3. Residual generation based on matching 72
2.5. Sensor placement 74
2.5.1. The basic sensor placement problem 74
2.5.2. A structural approach 75
2.6. Summary and discussion 80
2.7. References 81

Chapter 3. Set-based Fault Detection and Isolation 83
Ye WANG and Vicenç PUIG

3.1. Introduction 83
3.2. Notations, definitions and properties 84
3.3. Problem statement 86
3.3.1. Uncertain discrete-time linear systems 86
3.3.2. Set-based methods 86
3.3.3. FDI problem statement 88
3.4. Proposed techniques 89
3.4.1. Set-membership approach 89
3.4.2. Zonotopic observer 90
3.4.3. Relationship between set-based methods 91
3.5. Design methods 92
3.5.1. Robustness conditions 92
3.5.2. Fault sensitivity condition 96

3.6. Fault detection and isolation procedures 99
3.6.1. Fault detection 99
3.6.2. Fault isolation 100
3.7. Application example: quadruple-tank system 101
3.7.1. Results with robustness condition 105
3.7.2. Results with robustness and fault sensitivity conditions 105
3.8. Conclusion 105
3.9. References 109

Chapter 4. Diagnosis of Stochastic Systems 111
Gregory PROVAN

4.1. Introduction 111
4.2. Stochastic diagnosis task 113
4.2.1. Notation 113
4.2.2. Problem formulation 113
4.2.3. Representing uncertainty 115
4.3. Inference methods for diagnosis task 116
4.3.1. Difference with other tasks 116
4.4. Model-based approach 117
4.4.1. Traditional FDD methods 117
4.4.2. Bayesian inversion/filtering 120
4.5. Data-driven approaches 122
4.5.1. ML methods 123
4.5.2. Statistical methods 124
4.6. Hybrid approaches: surrogate methods 125
4.6.1. Fitting surrogate models via sampling 125
4.7. Comparative analysis of approaches 126
4.8. Summary and conclusions 127
4.9. References 128

Chapter 5. Data-Driven Methods for Fault Diagnosis 131
Silvio SIMANI

5.1. Introduction 131
5.2. Models for linear system fault diagnosis 133
5.3. Parameter estimation methods for fault diagnosis 135
5.3.1. Data-driven method in ideal conditions 135
5.3.2. Data-driven methods in real scenarios 138
5.3.3. Algebraic Frisch scheme 139
5.3.4. Dynamic Frisch scheme 141
5.3.5. MIMO case Frisch scheme 145
5.4. Nonlinear dynamic system identification 146
5.4.1. Piecewise affine model 147
5.4.2. Hybrid model structure 148
5.4.3. Nonlinear system approximation 149

5.4.4. Model continuity and domain partitioning 151
5.4.5. Local affine model estimation 154
5.4.6. Multiple-model estimation 158
5.5. Fuzzy data-driven approach to fault diagnosis 164
5.5.1. Fuzzy model identification 165
5.5.2. Takagi–Sugeno prototypes 167
5.5.3. Data-driven fuzzy modeling 170
5.5.4. Clustering methods 170
5.5.5. Fuzzy c-means clustering algorithms 172
5.5.6. Gustafson–Kessel clustering algorithm 174
5.5.7. Optimal number of clusters 176
5.6. Fuzzy model identification 176
5.6.1. Nonlinear model identification 178
5.6.2. Product space clustering identification 181
5.6.3. Fuzzy clustering model identification 183
5.6.4. Antecedent membership function estimation 183
5.6.5. Estimating consequent parameters 185
5.7. Conclusion 189
5.8. References 189

Chapter 6. The Artificial Intelligence Approach to Model-based Diagnosis 197
Belarmino PULIDO, Carlos J. ALONSO-GONZÁLEZ and Anibal BREGON

6.1. Introduction 197
6.2. Case studies 199
6.3. Knowledge-based diagnosis systems 201
6.3.1. Diagnosis task and system model 203
6.3.2. Diagnosis of physical devices 206
6.3.3. Limits of KBS for diagnosis of physical devices 207
6.4. Model-based diagnosis 208
6.4.1. Formalization of consistency-based diagnosis and its first implementation, GDE 209
6.5. CBD for dynamic systems 217
6.5.1. Different approaches for CBD of dynamic systems 219
6.5.2. PCs for the three-tank system case study 222
6.6. Conclusion 224
6.7. References 226

List of Authors 231

Index 233

Summary of Volume 2 237

Introduction

Vicenç PUIG[1] and Silvio SIMANI[2]

[1] *Institute for Robotics and Industrial Informatics, Polytechnic University of Catalonia, Barcelona, Spain*

[2] *Department of Engineering, University of Ferrara, Emilia-Romagna, Italy*

I.1. Introduction

There is an increasing interest in the theory and applications of model-based fault detection and fault diagnosis methods, because of economical and safety-related matters. In particular, well-established theoretical developments can be seen in many contributions published in the IFAC (International Federation of Automatic Control) Congresses and IFAC Symposium SAFEPROCESS (Fault Detection, Supervision and Safety of Technical Processes) since the seminal editions (Isermann and Ballé 1997; Isermann 1997; Patton 1999; Frank *et al*. 2000).

The developments began at various places in the early 1970s. Beard (1971) and Jones (1973) reported, for example, the well-known "failure detection filter" approach for linear systems.

A summary of this early development is given by Willsky (1976). Then, Rault *et al*. (1971) considered the application of identification methods to the fault detection of jet engines. Correlation methods were applied to leak detection (Siebert and Isermann 1976).

The first book on model-based methods for fault detection and diagnosis with specific application to chemical processes was published by Himmelblau (1978).

Sensor failure detection based on the inherent analytical redundancy of multiple observers was shown by Clark (1978).

The use of parameter estimation techniques for fault detection of technical systems was demonstrated by Hohmann (1977), Bakiotis *et al.* (1979), Geiger (1982) and Filbert and Metzger (1982).

The development of process fault detection methods based on modeling, parameter and state estimation was then summarized by Isermann (1984, 1997).

Parity equation-based methods were developed initially by Chow and Willsky (1984) and then further developed by Patton and Chen (1994), Gertler (1991) and Höfling and Pfeufer (1994).

Frequency domain methods are typically applied when the effects of faults as well as disturbances have frequency characteristics that differ from each other and thus the frequency spectra serve as criterion to distinguish the faults (Massoumnia *et al.* 1989; Ding and Frank 1990; Ding *et al.* 2000; Frank *et al.* 2000).

The developments of fault detection and isolation (FDI) methods to the present time are summarized in books by Pau (1981), Patton *et al.* (2000), Basseville and Nikiforov (1993), Chen and Patton (1999), Gertler (1998) and Isermann (1994b) as well as in survey papers by Gertler (1988), Frank (1990) and Isermann (1994a).

Within IFAC, the increasing interest in this field was taken into account by creating first in 1991 a SAFEPROCESS (Fault Detection Supervision and Safety for Technical Processes) Steering Committee, which then became a Technical Committee in 1993. The first IFAC SAFEPROCESS Symposium was held in Baden–Baden (Germany) in 1991 (Isermann and Freyermuth 1992). The last edition was organized in 2018 in Warsaw (Poland). Another triennial series of IFAC workshops exist for “Fault detection and supervision in the chemical process industries”. Many other thematic workshops have been organized between 1992 and 2020.

Most contributions in fault diagnosis rely on the analytical redundancy principle. The basic idea consists of using an accurate model of the system to mimic the real process behavior. If a fault occurs, the residual signal (i.e. the difference between the real system and model behavior) can be used to diagnose and isolate the malfunction.

Model-based method reliability, which also includes false alarm rejection, is strictly related to the “quality” of the model and measurements exploited for fault diagnosis, as model uncertainty and noisy data can prevent an effective application of analytical redundancy methods.

This is not a simple problem, because model-based fault diagnosis methods are designed to detect any discrepancy between the real system and model behaviors. It is assumed that this discrepancy signal is related to (has a response from) a fault. However, the same difference signal can respond to model mismatch or noise in real measurements, which are erroneously detected as a fault. These considerations have led to research in the field of "robust" methods, in which particular attention is paid to the discrimination between actual faults and errors due to model mismatch.

However, the availability of a "good" model of the monitored system can significantly improve the performance of diagnostic tools, minimizing the probability of false alarms.

This book explains what a good model is, one that is suitable for robust diagnosis of system performance and operation. The book also explains how robust models can be obtained from real data. A large amount of attention is paid to the "real system modeling problem", with reference to either linear or nonlinear model structures. Special treatment is given to the case in which noise affects the acquired data. The mathematical description of the monitored system is obtained by means of a system identification scheme based on equation error and errors-in-variables models. This is an identification approach that leads to a reliable model of the plant under investigation, as well as the estimation of the variances of the input–output noises affecting the data.

The purpose of this book is also to provide guidelines for the modeling and identification of real processes for fault diagnosis and fault-tolerant control (FTC). Hence, significant attention is paid to the practical application of the methods describing real system studies, as reported in the last chapters of Volume 2.

In particular, this introduction of the book outlines a new common terminology in the fault diagnosis framework and provides some discussion and a summary of developments in the field of fault detection and diagnosis as well as FTC based on papers selected during 1991–2020.

I.2. Nomenclature

By going through the literature, one immediately recognizes that the terminology in this field is not consistent. This makes it difficult to understand the goals of the contributions and to compare the different approaches.

The IFAC SAFEPROCESS Technical Committee therefore discussed this matter and tried to find commonly accepted definitions. Some basic definitions can be found, for example, in the RAM (Reliability, Availability and Maintainability) dictionary (Omdahl 1988) and in contributions to the IFIP (International Federation for Information Processing) (IFI 1983).

Some of the terminology used in this book is given below. These are based on information obtained from the IFAC SAFEPROCESS Technical Committee and are considered "on-going" in the sense that new definitions and updates are still being made.

1) ***States and signals***

- **Fault**: an unpermitted deviation of at least one characteristic property or parameter of the system from the acceptable, usual or standard condition.

- **Failure**: a permanent interruption of a system's ability to perform a required function under specified operating conditions.

- **Malfunction**: an intermittent irregularity in the fulfillment of a system's desired function.

- **Error**: a deviation between a measured or computed value of an output variable and its true or theoretically correct value.

- **Disturbance**: an unknown and uncontrolled input acting on a system.

- **Residual**: a fault indicator based on a deviation between measurements and model-equation-based computations.

- **Symptom**: a change of an observable quantity from normal behavior.

2) ***Functions***

- **Fault detection**: determination of faults present in a system and the time of detection.

- **Fault isolation**: determination of the kind, location and time of detection of a fault. It follows fault detection.

- **Fault identification**: determination of the size and time-variant behavior of a fault. It follows fault isolation.

- **Fault diagnosis**: determination of the kind, size, location and time of detection of a fault. It follows that fault diagnosis includes fault detection and identification.

- **Monitoring**: a continuous real-time task of determining the conditions of a physical system by recording information, recognizing and indicating anomalies in the behavior.

- **Supervision**: monitoring a physical system and taking appropriate actions to maintain the operation in the case of a fault.

3) ***Models***

- **Quantitative model**: use of static and dynamic relationships among system variables and parameters in order to describe a system's behavior in quantitative mathematical terms.

- **Qualitative model**: use of static and dynamic relationships among system variables in order to describe a system's behavior in qualitative terms such as causalities and IF–THEN rules.

- **Diagnostic model**: a set of static or dynamic relationships that link specific input variables, the *symptoms*, to specific output variables, the *faults*.

- **Analytical redundancy**: use of more (not necessarily identical) ways to determine a variable, where one way uses a mathematical process model in an analytical form.

4) ***System properties***

- **Reliability**: ability of a system to perform a required function under stated conditions, within a given scope, during a given period of time.

- **Safety**: ability of a system to operate without causing danger to persons, equipment or the environment.

- **Availability**: probability that a system or equipment will operate satisfactorily and effectively at any point of time.

5) ***Time dependency of faults***

- **Abrupt fault**: fault modeled as step-wise function. It represents bias in the monitored signal.

- **Incipient fault**: fault modeled by using ramp signals. It represents drift of the monitored signal.

- **Intermittent fault**: combination of impulses with different amplitudes.

6) ***Fault terminology***

- **Additive fault**: it influences a variable by an addition of the fault itself. It may represent, for example, offsets of sensors.

- **Multiplicative fault**: it is represented by the product of a variable with the fault itself. It can appear as parameter changes within a process.

I.3. Fault diagnosis methods based on analytical redundancy

A traditional approach to fault diagnosis in the wider application context is based on *hardware* or *physical redundancy* methods, which use multiple sensors, actuators and components to measure and control a particular variable. Typically, a voting technique is applied to the hardware redundant system to decide if a fault has occurred and its location among all the redundant system components. The major problems encountered with hardware redundancy are the extra equipment and maintenance costs, as well as the additional space required to accommodate the equipment (Isermann 1997; Isermann and Ballé 1997).

In view of the conflict between reliability and the cost of adding more hardware, it is possible to use the dissimilar measured values together to cross-compare with each other rather than replicating each hardware individually. This is the meaning of *analytical* or *functional redundancy*. It exploits redundant analytical relationships among various measured variables of the monitored process (Patton *et al*. 1989; Chen and Patton 1999). Figure I.1 illustrates the concepts of hardware and analytical redundancy.

In the analytical redundancy scheme, the resulting difference generated from the comparison of different variables is called a *residual* or *symptom signal*. The residual should be zero when the system is in normal operation and should be different from zero when a fault has occurred. This property of the residual is used to determine whether faults have occurred (Patton *et al*. 1989; Chen and Patton 1999).

Consistency checking in analytical redundancy is normally achieved through a comparison between a measured signal and estimated values. The estimation is generated by a mathematical model of the plant considered. The comparison is done using the residual quantities that are computed as differences between the measured signals and the corresponding signals generated by the mathematical model (Patton *et al*. 1989; Chen and Patton 1999).

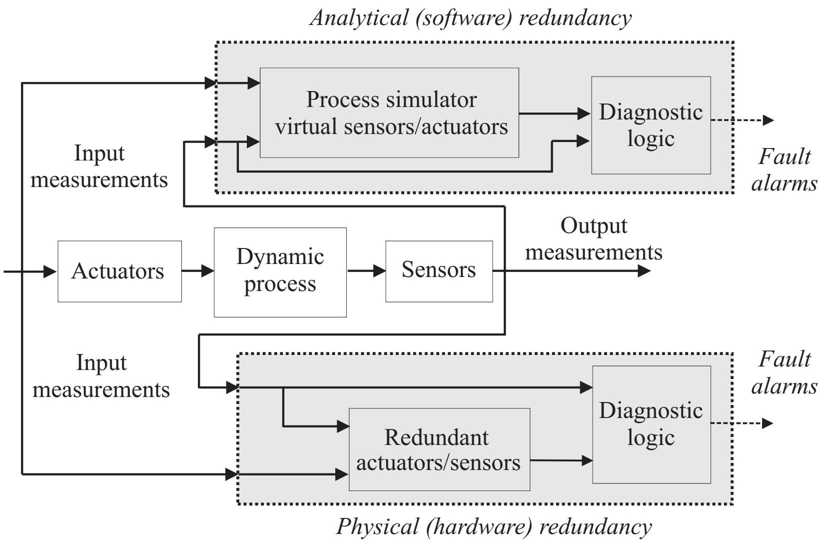

Figure I.1. *Comparison between hardware and analytical redundancy schemes*

In practice, the most frequently used diagnosis method is to monitor the level (or trend) of the residual and take action when the signal reaches a given threshold. This method of *geometrical analysis*, while simple to implement, has a few drawbacks. The most important is that, in the presence of noise, input variations and change of operating point of the monitored process, false alarms are possible.

The major advantage of the model-based approach is that no additional hardware components are required to implement an FDI algorithm as well as FTC. A model-based FDI algorithm can be implemented via software on a process control computer. In many cases, the measurements necessary to control the process are also sufficient for the FDI algorithm, so no additional sensors have to be installed (Patton *et al*. 1989; Basseville and Nikiforov 1993; Chen and Patton 1999).

Analytical redundancy uses a mathematical model of the system under investigation and therefore it is often referred to as the *model-based approach* to fault diagnosis.

I.4. Model-based fault diagnosis

This diagnosis task detects faults in the technical process, including actuators, components and sensors by measuring the available input and output variables $u(t)$ and $y(t)$. The principle of model-based fault diagnosis is depicted in Figure I.2.

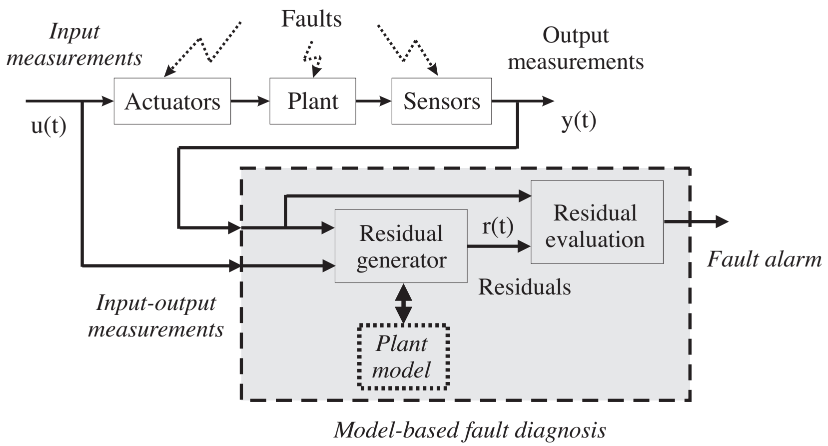

Figure I.2. *Scheme for the model-based fault diagnosis*

Basic process model-based FDI methods have been described by Patton *et al.* (1989, 2000), Basseville and Nikiforov (1993), Gertler (1998) and Chen and Patton (1999), which include the following steps:

1) output observers (OO, estimators, filters);

2) parity equations;

3) identification and parameter estimation.

These methods generate residuals for output variables with fixed parametric models using step 1, fixed parametric or non-parametric models using step 2 and adaptive non-parametric or parametric models using step 3.

An important aspect of these methods is the kind of fault to be detected. As noted above, one can distinguish between *additive faults*, which influence the variables of the process by summation, and *multiplicative faults*, which are products of the process variables. The basic methods show different results, depending on the type of fault.

If only output signals $y(t)$ can be measured, *signal model-based methods* can be applied, for example, vibrations can be detected, which are related to rotating machinery or electrical circuits. Typical signal model-based methods of fault detection are as follows:

1) bandpass filters;

2) spectral analysis (FFT);

3) maximum-entropy estimation.

The characteristic quantities or features from fault detection methods show stochastic behavior with mean values and variances. Deviations from the normal behavior must then be detected by methods of *change detection* (residual analysis, Figure I.2), such as:

1) mean and variance estimation;

2) likelihood-ratio test, Bayes decision;

3) run-sum test.

I.5. Model uncertainty and fault detection

Model-based FDI makes use of mathematical models of the system. However, a perfectly accurate mathematical model of a physical system is not possible. Usually, the parameters of the system may vary with time, and the characteristics of the disturbances and noises are unknown, so they cannot be modeled accurately. Hence, there is always a mismatch between the actual process and its mathematical model, even under no fault conditions. Such discrepancies cause difficulties in FDI applications, in particular, since they act as sources of false alarms and missed alarms. Therefore, the effect of modeling uncertainties, disturbances and noise is the most crucial point in the model-based FDI concept, and the solution to this problem is the key for its practical applicability (Chen and Patton 1999).

To overcome these problems, a model-based FDI scheme has to be insensitive to modeling uncertainty. Sometimes, a reduction of the sensitivity to modeling uncertainty does not solve the problem, because the sensitivity reduction may be associated with a reduction of the sensitivity to faults (Gertler 1998; Chen and Patton 1999). A more meaningful formulation of the FDI problem is to increase the insensitivity to modeling uncertainty in order to provide increasing fault sensitivity.

The difficulties introduced by model uncertainties, disturbances and noises in model-based FDI have been widely considered during the last 10 years by both academia and industry (Gertler 1998). A number of methods have been proposed to tackle this problem, for example, the Unknown Input Observer (UIO), eigenstructure assignment and parity relation methods.

An important task of the model-based FDI scheme is to be able to diagnose *incipient faults* in a system. With respect to *abrupt faults*, incipient faults may have a small effect on residuals and can be hidden by disturbances. On the other hand, hard faults can be detected more easily because their effects are usually larger than modeling uncertainties and a simple fixed threshold is usually enough to diagnose their occurrence by residual analysis.

The presence of incipient faults may not necessarily degrade the performance of the plant, however, they may indicate that the component should be replaced before the probability of more serious malfunctions increases. The successful detection and diagnosis of incipient faults can therefore be considered a challenge for the design and evaluation of FDI algorithms.

I.6. Robust fault diagnosis

In the context of automatic control, the term robustness is used to describe the insensitivity or invariance of the performance of control systems with respect to disturbances, model–plant mismatches or parameter variations. Fault diagnosis schemes, on the other hand, must, of course, also be robust to the mentioned disturbances, but, in contrast to automatic control systems, they must not be robust to actual faults. On the contrary, while generating robustness to disturbances, the designer must maintain or even enhance the sensitivity of fault diagnosis schemes to faults. Furthermore, the robustness, as well as the sensitivity properties, must be independent of the particular fault and disturbance mode. Generally, the problem of robust FDI can be divided into the tasks of *robust residual generation* followed by *robust residual evaluation*.

In many cases, the disturbances and model–plant mismatches to which robustness must be generated are due to the use of linear models for describing dynamic behavior of nonlinear processes. Modeling errors can be avoided from the very beginning by focusing on robust residual generation methods using linear and nonlinear process models. This, in turn, simplifies the problem of residual evaluation without reducing the sensitivity to actual faults.

Effective tools for robust residual generation and even complete decoupling from external disturbances and unknown system parameters can be provided, for example, by UIOs, which are introduced and applied to industrial processes. It is shown that the proposed solution to the disturbance decoupling problem also provides the solution to both the fault detection and fault isolation problems.

On the other hand, many dynamic processes can only be described effectively using nonlinear mathematical models. However, most of the existing observer-based FDI techniques are limited to the use of linear process models. The methods that can be found in the literature are based on the assumption that the system under supervision stays, during normal operation, in a neighborhood of a certain known operating point (Chen and Patton 1999; Patton *et al*. 2000)

It is clear that, as almost every process system is nonlinear, the modeling errors almost always reduce the accuracy of the linear model and therefore the performance of the FDI algorithm is compromised. Various methods for generating robustness to linearization have been proposed in the literature and the reader is referred to (Patton *et al*. 2000, Chapter 7) for a comprehensive treatment of this subject.

This book also surveys the state of the art of robustness methods and presents some important ideas concerning the development of the use of nonlinear models and predictors for FDI. For example, observer-based approaches to robust FDI and FTC for dynamic systems are considered in more detail. The available model-based approaches are generalized, and thus extended to a wider class of dynamic systems.

In order to accommodate the application of robust FDI concepts, disturbances and parameter uncertainties of the monitored plants, as well as faults, are modeled in the form of unknown input signals. It is shown that, provided certain conditions can be met, complete decoupling of the residual from disturbances as well as from the parameter uncertainties of the process model can be achieved, while the sensitivity of the residual to faults is maintained. As the faults are also modeled in the form of external signals, this method additionally provides tools for the purpose of fault isolation. Fault isolation requires the decoupling of the effects of different faults from the residual (Chen and Patton 1999) and this, in turn, allows for decisions on which fault or faults out of a given set of possible faults has actually occurred.

These residual properties must be completely independent of the magnitude or frequency of the unknown inputs and the faults. This is crucial in cases where no *a priori* knowledge about these properties is available. For systems where the complete decoupling of the remaining unknown inputs or faults from the residual proves impossible, a threshold selection method, employing functional analytic methods and appropriate vector and operator norms, can be exploited. This technique provides a tool for the robust evaluation of the residuals, which have been generated by UIOs. Using the same functional analysis methods as employed for threshold selection, a performance index can be defined that allows for performance evaluation and, to a certain degree, also allows for optimal residual generator design (Patton *et al*. 2000).

I.7. Data–driven approaches to robust FDI

In previous sections, we have seen that model-based FDI methods formally require a high accuracy mathematical model of the monitored system. The better the model is as a representation of the dynamic behavior of the system, the better the FDI performance will be. It is difficult to develop a highly accurate model of a complex system and hence the interesting question is: "what is a reasonable model to enable good performance in FDI to be guaranteed?".

It would be attractive to develop a robust FDI technique which is insensitive to modeling uncertainty, that is, so that a highly accurate mathematical model is no longer required. However, in order to design a robust FDI scheme, we should have a description (i.e. some information) about the uncertainty, for example, its *distribution matrix* and spectral bandwidth, and so on. Furthermore, this description should provide assistance for a robust FDI design, that is, it can be handled in a systematic manner. This book will show how a typical uncertainty description makes use of the concept of "unknown inputs" acting upon a nominal linear model of the system. These unknown disturbances describe the uncertainties acting upon the system but disturbance distribution matrices are assumed to be known since they can be estimated by identification schemes.

It is clear that disturbances and faults act on the system in the same way, and thus we cannot easily discriminate between these excitation signals unless we know the structure of the disturbance distribution matrix. Once the disturbance distribution matrix is known, we can generate the residual with the disturbance decoupling (robust) property, that is, the residual is decoupled from the disturbance (uncertainty). The robust residual can then be used to achieve reliable FDI and FTC.

The theories underlying robust FDI approaches have been very well developed, but for real applications the following problems remain unsolved:

– estimation of the reliable model for the monitored process;

– modeling accuracy of the real uncertainty by means of identified disturbance terms when no knowledge of the uncertainty is available;

– estimation of the disturbance terms and the structure of distribution matrices.

This book addresses these unsolved problems. Some simulation and real examples are given to test some of the theoretical results. These problems have to be addressed, otherwise the application domain of the disturbance decoupling approach for robust FDI is very limited. In fact, few researchers and contributions have presented the application results of robust fault diagnosis to real processes.

As mentioned above, a primary requirement for model-based and disturbance decoupling approaches to robust FDI is that both the system model and disturbance distribution matrices must be known. It is interesting that, within the framework of international research on this subject, there have been few attempts to address the problem by means of the *identification approach*. This lack of information has obstructed the application of robust FDI in real engineering systems. Therefore, we present the research developments surrounding the joint estimation of system and disturbance matrices in order to solve the robust fault diagnosis problem.

Concerning the data-driven schemes developed and exploited throughout the book, when all observed variables of a dynamic process are affected by uncertainties, the parameter estimation task can be performed by the so-called *errors-in-variables* methods. On the other hand, *equation error* methods can be developed in the case of exactly known plant variables (Simani *et al*. 2000). It is worthwhile noting that less attention has been paid to errors-in-variables schemes.

Under these considerations, this book presents the robust FDI results concerning the description of monitored plants by means of equation error and error-in-variables identified models in the presence of variable uncertainties. Moreover, for the examples presented, estimates obtained by the proposed data-driven approaches and parameter estimates will be computed and compared.

I.8. Data-driven methods for fault diagnosis

If several symptoms change differently for certain faults, an initial way of determining them is to use classification methods which indicate changes of symptom vectors.

Some classification methods are as follows (Patton *et al*. 1989; Basseville and Nikiforov 1993; Babuška 1998; Gertler 1998; Chen and Patton 1999):

1) geometrical distance and probabilistic methods;

2) artificial neural networks;

3) fuzzy clustering.

When more information about the relations between symptoms and faults is available in the form of diagnostic models, methods of reasoning can be applied. Diagnostic models then exist in the form of symptom–fault causalities, for example, in the form of symptom–fault trees. The causalities can be expressed as IF–THEN rules.

Then analytical as well as heuristic symptoms (from operators) can be processed. By considering these symptoms as vague facts, probabilistic or fuzzy set descriptions lead to a unified symptom representation. By using forward and backward reasoning, probabilities or possibilities of faults are obtained as a result of diagnosis. Typical approximate reasoning methods are as follows (Basseville and Nikiforov 1993; Chen and Patton 1999):

1) probabilistic reasoning;

2) possibilistic reasoning with fuzzy logic;

3) reasoning with artificial neural networks.

This very short consideration shows that many different methods have been developed over the last 30 years. It is also clear that many combinations of them are possible.

On the basis of different contributions during the last 30 years, it can be stated that parameter estimation and observer-based methods are the most frequently applied techniques for fault detection, especially for the detection of sensor and process faults. Nevertheless, the importance of neural network-based and combined methods for fault detection is steadily growing. In most applications, fault detection is supported by simple threshold logic or hypothesis testing. Fault isolation is often carried out using classification methods. For this task, neural networks are being more and more widely used.

The number of applications using nonlinear models is growing, while the trend of using linearized models is diminishing. It seems that analytical redundancy-based methods have their best application areas in mechanical systems where the models of the processes are relatively precise. Most nonlinear processes under investigation belong to the group of thermal and fluid dynamic processes. The field of applications to chemical processes has few developments, but the number of applications is growing. The favorite linear process under investigation is the DC motor. In general, the trend is changing from applications to safety-related processes with many measurements, as in nuclear reactors or aerospace systems, to applications in common technical processes with only a few sensors. For diagnosis, classification and rule-based reasoning methods are the most important, and the use of neural network classification as well as fuzzy logic-based reasoning is growing.

I.9. FDI application report

Because of the many publications and increasing number of applications (IFAC Congress and IFAC Symposia SAFEPROCESS) between 1991 and 2018, it is of interest to show some trends (Patton *et al*. 1989; Basseville and Nikiforov 1993; Gertler 1998; Chen and Patton 1999; Frank *et al*. 2000). Therefore, a literature study is briefly presented as follows. Contributions taking into account the applications reported in Table I.1 were considered. The type of faults considered is distinguished according to Table I.2. Among all contributions, the fault detection methods were classified as in Table I.3. The change detection and fault classification methods are indicated in Table I.4. The reasoning strategies for fault diagnosis are reported in Table I.5. The contributions considered are summarized in Table I.6. The evaluation has been limited to the fault detection and diagnosis (FDD) of laboratory, pilot and industrial processes.

Application	Number of contributions
Simulation of real processes	105
Large-scale pilot processes	94
Small-scale laboratory processes	68
Full-scale industrial processes	98

Table I.1. *FDI applications and number of contributions*

Fault type	Number of contributions
Sensor faults	129
Actuator faults	111
Process faults	123
Control loop or controller faults	48

Table I.2. *Fault type and number of contributions*

Method type	Number of contributions
Observer	123
Parity space	74
Parameter estimation	101
Frequency spectral analysis	57
Neural networks	79

Table I.3. *FDI methods and number of contributions*

Evaluation method	Number of contributions
Neural networks	89
Fuzzy logic	65
Bayes classification	54
Hypothesis testing	48

Table I.4. *Residual evaluation methods and number of contributions*

Reasoning strategy	Number of contributions
Rule based	40
Sign directed graph	33
Fault symptom tree	32
Fuzzy logic	66

Table I.5. *Reasoning strategies and number of contributions*

FDD	Number of contributions
Milling and grinding processes	91
Power plants and thermal processes	106
Fluid dynamic processes	67
Combustion engine and turbines	96
Automotive	68
Inverted pendulum	63
Miscellaneous	102
DC motors	121
Stirred tank reactor	77
Navigation system	75
Nuclear process	50

Table I.6. *Applications of model-based fault detection*

Table I.6 shows that among mechanical and electrical processes, DC motor applications are mostly investigated. Parameter estimation and observer-based methods are used in the majority of applications in these kind of processes, followed by parity space and combined methods. Thermal and chemical processes are investigated less frequently.

Table I.3 shows that parameter estimation and observer-based methods are used in nearly 70% of all applications considered. Neural networks, parity space and combined methods are applied notably less often.

More than 50% of sensor faults are detected using observer-based methods, while parameter estimation, parity space and combined methods play a less important role. For the detection of actuator faults, observer-based methods are mostly used, followed by parameter estimation and neural network methods.

Parity space and combined methods are rarely applied. In general, there are fewer applications for actuator faults than for sensor or process faults. The detection of process faults is mostly carried out with parameter estimation methods. Nearly 50% of all the applications considered use parameter estimation-based methods for detection of process faults. Observer-based, parity space and neural network-based methods are used less often for this class of faults.

Among all the described processes, linear models have been used much more than nonlinear models. In processes with nonlinear models, observer-based methods are mostly applied, but parity equations and neural networks also play an important role. In processes with linear or linearized models, parameter estimation and observer-based methods are mostly used. Parity space and combined methods are also used in several applications but not to the same extent as observer-based and parameter estimation methods.

Taking into account the system considered, the number of nonlinear process applications using nonlinear models is decreasing. For linear processes, no significant change can be stated. The applications of fault-detection methods for nonlinear processes used mostly observer-based and parameter estimation, more than parity space methods. Also, the use of neural networks and combinations are important.

Concerning the fault diagnosis methods, in recent years, the field of classification approaches, especially with neural networks and fuzzy logic, has steadily been growing. Also, rule-based reasoning methods are increasingly being based on fault diagnosis. A growing application of fuzzy rule-based reasoning can be stated. Applications using neural networks for classification are increasing and the trends are analogous to the increasing number of nonlinear process investigations. Nevertheless, the classification of generated residuals seems to remain the most important application area for neural networks.

I.10. From FDI to FTC

A conventional feedback control design for complex systems may result in unsatisfactory performance in the event of malfunction in input–output sensors, actuators and system components. A fault-tolerant closed-loop control system is very attractive because it can tolerate faults while also maintaining desirable performance.

The conventional approach to the design of an FTC includes different steps and separate modules: modeling or identification of the controlled system, design of the controller, FDI scheme and a method for re-configuring the control system. Identification and design of the controller can be performed separately or using combined methods. Hence, the FDI and controller are linked through the reconfiguration module. The fundamental problem with such a system lies in the identification stage in the independent design of the control and FDI modules. Significant interactions occurring among these modules can be neglected. There is therefore a need for a research study into the interactions between system identification, control design, the FDI stage and the FTC design strategy.

Fault identification is the most important of all the fault diagnosis tasks. When a fault is estimated, detection and isolation can be easily achieved since the fault nature can improve the diagnosis process. However, the fault identification problem itself has not gained enough research attention.

Most fault diagnosis techniques, such as parameter identification, parity space and observer-based methods, cannot be directly used to identify faults in sensors and actuators. Very little research has been done to overcome the fault identification problem. The Kalman filter for statistical testing and fault identification was proposed in Chen and Patton (1999). However, the statistical testing methods can impose a high computational demand. A fault identification scheme solving a system inversion problem was proposed in Chen and Patton (1999); Simani *et al*. (2003) and Simani and Farsoni (2018).

In the scheme, depicted in Figure I.3, fault identification is performed by estimating the nonlinear relationship between residuals and fault magnitudes. This is possible because robust residuals should only contain fault information.

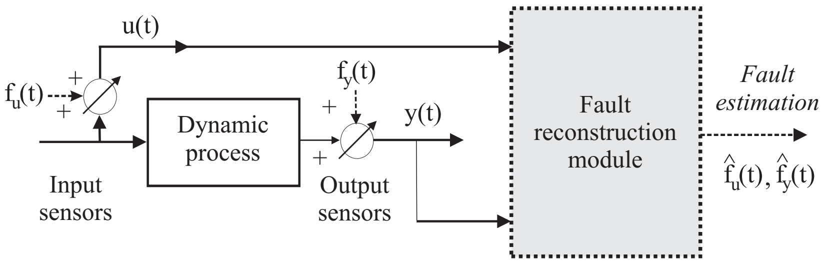

Figure I.3. *Fault estimation scheme FTC*

Such a nonlinear function approximation and estimation can be performed by using fuzzy systems, neural networks or an inversion of the transfer matrix between residuals and faults (Simani *et al*. 2003; Simani and Farsoni 2018). The central task in model-based fault detection is the residual generation. Most residual generation techniques are based on linear system models. For nonlinear systems, the traditional approach is to linearize the model around the system operating point. However, for systems with high nonlinearity and a wide dynamic operating range, the linearized approach fails to give satisfactory results.

One solution is to use a large number of linearized models corresponding to a range of operating points. This means that a large number of FDI schemes corresponding to each of the operating points is needed. Hence, it is important to study residual generation techniques that tackle nonlinear dynamic systems directly. There are some research studies on the residual generation of nonlinear dynamic systems, for example using nonlinear observers (Chen and Patton 1999; De Persis and Isidori 2001). There have been some attempts to use nonlinear observers to solve nonlinear system FDI problems, (Chen and Patton 1999; De Persis and Isidori 2001), for example, nonlinear UIOs, including adaptive observers and sliding mode observers. If the class of nonlinearities can be restricted, observers for bilinear systems were also proposed (Chen and Patton 1999).

On the other hand, the analytical models that the nonlinear observer approaches are based on are not easy to obtain in practice. Sometimes, it is impossible to model the system using an explicit mathematical model. To overcome this problem, it is desirable to find a universal approximate model that can be used to represent the real system with an arbitrary degree of accuracy. Different approaches were proposed and they are currently under investigation: neural networks, fuzzy models and hybrid models.

As shown in Simani *et al*. (2003) and Simani and Farsoni (2018), fuzzy systems and neural networks are a powerful tool for handling nonlinear problems. One of the most important advantages of neural networks is their ability to implement nonlinear transformations for functional approximation problems. Therefore, neural networks can be used in a number of ways to tackle fault diagnosis problems for nonlinear dynamic systems. In existing publications, they were mainly exploited as fault classifier with steady-state processes, whereas neural networks have been used as residual generators and for modeling nonlinear dynamic systems for FDI purposes (Chen and Patton 1999).

Fuzzy models can be used both as a residual classifier and as a nonlinear system parametric model (Chen and Patton 1999). In the second case, the main idea is to build an FDI scheme based on fuzzy observers. Estimated outputs and residuals are computed as fuzzy fusion of local observer output and residuals. The main problem of this approach concerns the stability of the global observer. A linear matrix inequality method was proposed in Chen and Patton (1999) using Lyapunov theorem, but this solution can be quite conservative.

Hybrid models can describe the behavior of any nonlinear dynamic process if they are described as a composition of several local affine models, selected according to the process operating conditions (Chen and Patton 1999; Simani *et al*. 2003). Instead of exploiting complicated nonlinear models obtained by modeling techniques, it is possible to describe the plant by a collection of affine models. Such a compound system requires the identification of the local models from data. Several works (Chen and Patton 1999; Simani *et al*. 2003) addressed a method for the identification and the optimal selection of the local affine models from a sequence of noisy measurements acquired from the process. Application of these results to model-based fault diagnosis for safety critical systems is another research area worthy of mention.

I.11. Structure of the book

To detect and isolate faults in a dynamic system, based on the use of an analytical model, a residual signal has to be used. It is derived from a comparison between real measurements and the relative estimates (generated by the model). The modeling uncertainty problem can be tackled by designing FDI and FTC schemes, whose residuals are insensitive to uncertainties while sensitive to faults. On the other hand, a model with satisfactory accuracy can be estimated using identification procedures (Norton 1986; Söderström and Stoica 1987; Ljung 1999).

The aim of the design of FDI and FTC schemes is to reduce the effects of uncertainties on the residuals and to enhance the effects of faults acting on the residuals. The *main aim of this book* is to develop a residual generator for model-based fault diagnosis and to design an effective FTC strategy for a dynamic process by means of input and output signals. An accurate model of the process under investigation will be estimated using identification procedures from data affected by noises and acquired from simulated and/or actual plants. The book consists of an Introduction and six chapters in Volume 1 and eight chapters in Volume 2 and the main contributions are summarized in the following.

The Introduction, provides a brief overview and critical discussion of the state of the art of the most recent literature from 2015 to 2020, thereby introducing the field of fault detection, fault diagnosis and fault-tolerant systems with methods, which have proven their significance in practical applications.

Chapter 1 addresses the mathematical modeling and description of the faults most commonly exploited for providing a proper description of the process under diagnosis, in connection with the strategy proposed for the diagnosis and FTC designs.

By taking into account these aspects, Chapter 2 is focused on structural analysis issues. In particular, this chapter addresses the standard tool used to identify submodels that can be used to design model-based and data-driven diagnostic modules. Structural approaches typically operate on models described by a set of equations, which can also be obtained from model-free approaches.

With reference to FDI, Chapter 3 considers set-based methods. The set-membership and interval observer approaches are introduced to deal with the robustness problem in fault detection. The design conditions to guarantee robustness, and at the same time fault sensitivity, are presented. Next, the extension to fault isolation using unknown-input observer schemes is described.

Chapter 4 describes stochastic methods for FDI. In particular, the chapter revises the existing methods for FDI using stochastic modeling of uncertainty, using both models and data.

As an alternative to analytical approaches, Chapter 5 proposes data-driven schemes. It is therefore devoted to the problem of fault detection in technical systems described by nonlinear dynamical models containing non-smooth nonlinearities. The so-called "model-free" or "data-driven" solutions can be exploited to solve the considered FTD and FTC problems. The feature of this method is that parameters of the system under consideration may be unknown.

Among data-driven solutions, Chapter 6 considers the artificial intelligence (AI) approach to fault diagnosis. After revising the evolution of fault diagnosis methods in the AI domain, the chapter focuses on the model-based approach rooted in the logic theory of diagnosis.

When considering analytical approaches, Chapter 1 of Volume 2 proposes the development of nonlinear methods. This chapter gives a review of the principal model-based fault diagnosis and fault-tolerant approaches for nonlinear systems. Some schemes extending the well-known diagnosis methods for linear systems to the nonlinear case are considered. The robustness of these schemes in the presence of uncertainty is discussed. Similarities between the approaches considered are also pointed out.

With reference to Volume 2, the problem of the FTC is addressed. In particular, Chapter 2 of Volume 2 considers the use of linear parameter varying (LPV) methods. In particular, this chapter considers FDI and FTC for descriptor LPV systems with unmeasurable decision variables under actuator faults and perturbations.

A different approach is considered in Chapter 3 of Volume 2, where fuzzy Takagi–Sugeno and neural network methods for FDI and FTC are revised. After introducing the different types of models, their application to fault diagnosis and estimation is presented. The extension to FTC is then described.

Chapter 4 of Volume 2 presents the model predictive control (MPC) techniques to deal with robustness and nonlinearity. To this aim, the use of neural networks is considered.

Chapter 5 of Volume 2 considers nonlinear methods for FTC. This chapter presents a methodology for detecting, isolating and accommodating faults in a class of nonlinear dynamic systems. On the basis of the fault information obtained by the fault-diagnosis procedure, an FTC component is designed to compensate for the effects of faults.

Chapter 6 of Volume 2 proposes virtual sensor and actuator development. The problem of FTC for dynamic processes is considered by using virtual sensor/actuator approaches to deal with sensor and actuator faults. This chapter also presents the extension to LPV systems using the Linear Matrix Inequality (LMI) approach.

Finally, Chapters 7 and 8 of Volume 2 complete the book by providing some concluding remarks and open research directions.

In particular, Chapter 7 of Volume 2 summarizes the main achievements of the book by highlighting the key features of the proposed diagnosis and fault-tolerant solutions when applied to safety critical systems.

Finally, Chapter 8 of Volume 2 analyzes some perspectives in the field of diagnosis and FTC by exploring open problems and future issues that could require further investigation. Future possible research directions are also outlined.

Therefore, the book reviews the state of the art of the data-driven and model-based FDI and FTC. The FDI and FTC problems are formalized in an uniform framework by presenting the mathematical description and definitions. The fundamental issue of model-based methods is the generation of residuals using the mathematical model of the monitored system. By analyzing residuals, fault diagnosis and FTC can be performed. Some structures of the residual generator are recalled to give ideas as to how to implement the residual generation. A residual generator can be designed for achieving the required diagnosis performances, for example, fault isolation and disturbance decoupling.

In order to design the residual generator, some assumptions about the modeling uncertainties need to be made. The most frequently used hypothesis is that the modeling uncertainty is expressed as a disturbance term in the system dynamic equation. The disturbance vector is unknown, while its distribution matrix can be estimated by using identification procedures. On the basis of this assumption, the disturbance decoupling residual generator can be designed by using UIO methods Chen and Patton (1999); Liu and Patton (1998).

The book also demonstrates how to apply dynamic system identification methods and more general data-driven approaches in order to estimate an accurate model of the monitored system.

The FDI and FTC methods presented can, in fact, require a mathematical model of the process under investigation, either in a state–space or an input–output form.

In particular, since state–space descriptions provide general and mathematically rigorous tools for system modeling, they may be used in the residual generator design, both for the deterministic case (generalized observers, such as UIOs and output dynamic observers) (Chen and Patton (1999); Frank (1990); Luenberger (1979); Watanabe and Himmelblau (1982)) and the stochastic case (such as Kalman filters and unknown input Kalman filters) (Jazwinski (1970); Xie *et al*. (1994); Xie and Soh (1994)).

In such a manner, the suggested FDI and FTC tools may not require any physical knowledge of the process under observation since the linear models are obtained by means of an identification scheme, which can, for example, exploit equation error (EE) and errors-in-variables (EIV) models. In this situation, the identification technique is based on the rules of the Frisch scheme (Frisch 1934), traditionally exploited to analyze economic systems. This approach, modified to be applied to dynamic system identification (Kalman 1982b, 1990; Beghelli *et al*. 1990), gives a reliable model of the plant under investigation, as well as the variances of the input–output noises affecting the data.

For the nonlinear case, fuzzy models and neural networks can be used as prototypes for the identification. In particular, the multiple-model approach, using several local affine submodels each describing a different operating condition of the process, is exploited.

Under these considerations, this book aims to define a comprehensive methodology for actuator, process component and sensor fault detection. It is based on an output estimation approach, in conjunction with residual processing schemes, which include simple threshold detection, in a deterministic case, as well as statistical analysis when data are affected by noise. The final result consists of a strategy based on fault diagnosis methods well known in the literature for generating redundant residuals.

In particular, this work studies different approaches to residual generation and fault compensation with the aid of several methodologies. In general, the residual is defined as the *output estimation error*, obtained by the difference between the measurement of one output and the relative estimate. This work also presents the design of such estimators both in the deterministic and stochastic environment.

The diagnosis procedure may be further specialized for actuators, input or output sensors and process components. In fact, the fault diagnosis of input sensors and actuators uses banks of estimators in high signal-to-noise ratio conditions, or filters, otherwise. The general principle designs the ith reconstructor to be insensitive to the ith signal of the system. On the other hand, output sensor and process component faults affecting a single residual can be detected by means of output observer or filters, driven by a single output and all the inputs of the system.

The book shows how the proposed algorithms can be applied to the FDI and FTC of actuators, process components and input–output sensors of industrial plants.

In particular, the different techniques presented in this book have been tested on time series of data acquired from different simulated and realistic industrial processes, energy conversion systems, power plants, and more general safety critical systems, whose linear mathematical description is obtained by using data-driven and model-based procedures.

Results from simulation show that minimum detectable faults are perfectly compatible with the industrial target of this application.

Finally, the book concludes the proposed research and application topics by summarizing its contributions and achievements, providing some suggestions for possible further research topics as an extension of this work.

I.12. Summary

This Introduction has provided a common terminology in the fault diagnosis framework in order to comment on some developments in the field of fault detection and diagnosis based on papers selected from the last 30 years. The structure of the 14 chapters and their main contributions have also been outlined briefly.

I.13. References

Babuška, R. (1998). *Fuzzy Modeling for Control*. Kluwer Academic Publishers. Boston, MA, USA.

Bakiotis, C., Raymond, J., Rault, A. (1979). Parameter identification and discriminant analysis for jet engine mechanical state diagnosis. *IEEE Conference on Decision and Control, Fort Lauderdale*, Fort Lauderdale, FL, USA.

Basseville, M. and Nikiforov, I.V. (1993). *Detection of Abrupt Changes: Theory and Application*. Prentice-Hall, Inc., Upper Saddle River, NJ, USA.

Beard, R.V. (1971). Failure accomodation in linear systems through self-reorganisation. Technical Report MVT-71-1, Man Vehicle Lab, Cambridge, MA, USA.

Beghelli, S., Guidorzi, R.P., Soverini, U. (1990). The Frisch scheme in dynamic system identification. *Automatica*, 26(1), 171–176.

Chen, J. and Patton, R.J. (1999). *Robust Model–Based Fault Diagnosis for Dynamic Systems*. Kluwer Academic Publishers, Boston, MA, USA.

Chow, E.Y. and Willsky, A.S. (1984). Analytical redundancy and the design of robust detection systems. *IEEE Transactions Automatic Control*, 29(7), 603–614.

Clark, R.N. (1978). Instrument fault detection. *IEEE Transactions on Aerospace & Electronic Systems*, 14(3), 456–465.

De Persis, C. and Isidori, A. (2001). A geometric approach to non-linear fault detection and isolation. *IEEE Transactions on Automatic Control*, 45(6), 853–865.

Ding, X. and Frank, P.M. (1990). Fault detection via factorization approach. *Syst. Contr. Lett.*, 14(5), 431–436.

Ding, S.X., Jeinsch, T., Frank, P.M., Dind, E.L. (2000). A unified approach to the optimisation of fault detection systems. *International Journal of Adaptive Control and Signal Processing*, 14(7), 725–745.

Filbert, D. and Metzger, K. (1982). Quality test of systems by parameter estimation. *9th IMEKO Congress*, Berlin, Germany.

Frank, P.M. (1990). Fault diagnosis in dynamic systems using analytical and knowledge based redundancy: A survey of some new results. *Automatica*, 26(3), 459–474.

Frank, P.M., Ding, S.X., Köpper-Seliger, B. (2000). Current developments in the theory of FDI. *SAFEPROCESS'00: Preprints of the IFAC Symposium on Fault Detection, Supervision and Safety for Technical Processes*, vol. 1, Budapest, Hungary, 16–27.

Geiger, G. (1982). Monitoring of an elecrical driven pump using continuous-time parameter estimation models. *6th IFAC Symposium on Identification and Parameter Estimation*, Washington, Pergamon Press, Oxford, UK.

Gertler, J. (1988). Survey of model-based failure detection and isolation in complex plants. *IEEE Control System Magazine*, 8(6), 3–11.

Gertler, J. (1991). Generating directional residuals with dynamic parity equations. *IFAC/IMACS Symposium Proceedings: SAFEPROCESS'91*, Baden-Baden, Germany.

Gertler, J. (1998). *Fault Detection and Diagnosis in Engineering Systems*. Marcel Dekker, New York, USA.

Himmelblau, D.M. (1978). *Fault Diagnosis in Chemical and Petrochemical Processes*. *Elsevier*, Amsterdam, The Netherlands.

Höfling, T. and Pfeufer, T. (1994). Detection of additive and multiplicative faults – Parity space vs. parameter estimation. *IFAC Symposium Proceedings: SAFEPROCESS'94*, Espoo, Finland.

Hohmann, H. (1977). Automatic monitoring and failure diagnosis for machine tools. Dissertation, T.H. Darmstadt, Germany [in German].

IFI (1983). Reliable computing and fault tolerance. Meeting, IFI, Como, Italy.

Isermann, R. (1984). Process fault detection based on modeling and estimation methods: A survey. *Automatica*, 20(4), 387–404.

Isermann, R. (1994a). Integration of fault detection and diagnosis methods. *IFAC Symposium Proceedings SAFEPROCESS'94*, Espoo, Finland.

Isermann, R. (1994b). Supervision and fault diagnosis. Paper, VDI-Verlag, Düsseldorf [in German].

Isermann, R. (1997). Supervision, fault detection and fault diagnosis methods: An introduction. *Control Engineering Practice*, 5(5), 639–652.

Isermann, R. and Ballé, P. (1997). Trends in the application of model-based fault detection and diagnosis of technical processes. *Control Engineering Practice*, 5(5), 709–719.

Isermann, R. and Freyermuth, B. (eds) (1992). *Fault Detection, Supervision and Safety for Technical Processes*. Pergamon Press, Oxford, UK.

Jazwinski, A.H. (1970). *Stochastic Processes and Filtering Theory*. Academic Press, New York, USA.

Jones, H.L. (1973). Failure detection in linear systems. PhD Thesis, Department of Aeronautics, M.I.T., Cambridge, MA, USA.

Kalman, R.E. (1982). System identification from noisy data. In *Dynamic Systems II, a University of Florida International Symposium*, Bednarek, A.R., Cesari, L. (eds). Academic Press, New York, USA.

Kalman, R.E. (1990). Nine lectures on identification. In *Lecture Notes on Economics and Mathematical System*, Fandel, G. and Trockel, W. (eds). Springer, Berlin, Germany.

Liu, G.P. and Patton, R.J. (1998). *Eigenstructure Assignment for Control System Design*. John Wiley & Sons, Chichester, UK.

Ljung, L. (1999). *System Identification: Theory for the User*, 2nd edition. Prentice Hall, Englewood Cliffs, N.J, USA.

Luenberger, D.G. (1979). *Introduction to Dynamic Systems: Theory, Models and Application*, John Wiley & Sons, New York, USA.

Massoumnia, M., Verghese, G.C., Willsky, A.S. (1989). Failure detection and identification. *IEEE Transactions on Automatic Control*, 34, 316–321.

Norton, J. (1986). *An Introduction to Identification*. Academic Press, London, UK.

Omdahl, T.P. (1988). *Reliability, Availability and Maintainability Dictionary*. ASQC Quality Press, Milwaukee, WI, USA.

Patton, R.J. (1999). Preface to the papers from the 3rd IFAC Symposium SAFEPROCESS'97. *Control Engineering Practice*, 7(1), 201–202.

Patton, R.J. and Chen, J. (1994). A review of parity space approaches to fault diagnosis for aerospace systems. *AIAA Journal of Guidance, Control & Dynamics*, 17(2), 278–285.

Patton, R.J., Frank, P.M., Clark, R.N. (eds) (1989). *Fault Diagnosis in Dynamic Systems, Theory and Application*, Prentice Hall, London, UK.

Patton, R.J., Frank, P.M., Clark, R.N. (eds) (2000). *Issues of Fault Diagnosis for Dynamic Systems*. Springer-Verlag, London, UK.

Pau, L.F. (1981). *Failure Diagnosis and Performance Control*. Marcel Dekker, New York, USA.

Rault, A., Richalet, A., Barbot, A., Sergenton, J.P. (1971). Identification and modelling of a jet engine. *IFAC Symposium od Digital Simulation of Continuous Processes*, Gejör.

Siebert, H. and Isermann, R. (1976). Fault diagnosis via online correlation analysis. Technical Report 25-3, VDI/VDE Darmstadt, Germany [In German].

Simani, S. and Farsoni, S. (2018). *Fault Diagnosis and Sustainable Control of Wind Turbines: Robust Data–driven and Model–based Strategies*, 1st edition. Butterworth–Heinemann, Elsevier, Oxford, UK.

Simani, S., Fantuzzi, C., Beghelli, S. (2000). Diagnosis techniques for sensor faults of industrial processes. *IEEE Transactions on Control Systems Technology*, 8(5), 848–855. DOI: 10.1109/87.865858.

Simani, S., Fantuzzi, C., Patton, R.J. (2003). *Fault Diagnosis in Dynamic Systems Using Identification Techniques*, 1st edition. Springer–Verlag, London, UK.

Watanabe, K. and Himmelblau, D.M. (1982). Instrument fault detection in systems with uncertainties. *International Journal of System Science*, 13(2), 137–158.

Willsky, A.S. (1976). A survey of design methods for failure detection in dynamic systems. *Automatica*, 12(6), 601–611.

Xie, L. and Soh, Y.C. (1994). Robust Kalman filtering for uncertain systems. *Systems and Control Letters*, 22, 123–129.

Xie, L., Soh, Y.C., de Souza, C.E. (1994). Robust Kalman filtering for uncertain discrete-time systems. *IEEE Transaction on Automatic Control*, 39, 1310–1314.