SERIES EDITORS' FOREWORD

The series *Advances in Industrial Control* aims to report and encourage technology transfer in control engineering. The rapid development of control technology has an impact on all areas of the control discipline. New theory, new controllers, actuators, sensors, new industrial processes, computer methods, new applications, new philosophies..., new challenges. Much of this development work resides in industrial reports, feasibility study papers and the reports of advanced collaborative projects. The series offers an opportunity for researchers to present an extended exposition of such new work in all aspects of industrial control for wider and rapid dissemination.

As many technological systems become more complex, widespread and integrated, the effects of system failure can be simply devastating to the infrastructure of modern society. Feedback control is just one important component of total system supervision. Fault detection and isolation (FDI) is a second component with extensive commercial, industrial and societal implications if only we could work out how to do it in a reliable and inexpensive manner. Hardware or physical redundancy is the usual solution of the practical FDI problem, but as the authors Simani, Fantuzzi and Patton note in this monograph it is capital and maintenance costly. The search for reliable and inexpensive FDI methods has been active since the early 1970s. Since 1991, the International Federation of Automatic Control (IFAC) has created the SAFEPROCESS Steering Committee to promote research, developments and applications in the FDI field. The last decade has seen the formalisation of several theoretical approaches accompanied by some attempts to standardise nomenclature in the field.

The monograph series *Advances in Industrial Control* does not have many entries from this important research area but the monograph by Mangoubi, *Robust Estimation and Failure Detection* (ISBN 3-540-76251-5; 1998) and that by Russell, Chiang and Braatz, *Data-driven Techniques for Fault Detection and Diagnosis in Chemical Processes* (ISBN 1-85233-285-1; 2000) both make contributions even if they use quite different ideas. To these we can now add this monograph by S. Simani, C. Fantuzzi and R.J. Patton. Key features of this text include useful survey material (Chapter 2), a new approach based on model identification and an extended application study using a single shaft industrial gas turbine (Chapter 5). Different groups of readers ranging from industrial engineers wishing to gain insight into the applications potential of new FDI methods, to the academic control community looking for new problems to tackle (Chapter 6) will find much to learn from this monograph.

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PREFACE

Control devices, which are nowadays exploited to improve the overall performance of industrial processes, involve both sophisticated digital system design techniques and complex hardware (input-output sensors, actuators, components and processing units). Such complexity results in an increased probability of failure. As a direct consequence of this, control systems must include automatic supervision of the closed-loop operation to detect and isolate malfunctions as early as possible.

Since the early 1970s, the problem of fault detection and isolation (FDI) in dynamic processes has received great attention, and a large variety of methodologies have been studied and developed based upon both physical and analytical redundancy. In the first case, the system is equipped with redundant physical devices, like sensors and actuators, so that if a fault occurs, the redundant device replaces the functionality of the faulty one.

The analytical redundancy approach is based on a completely different principle. The basic idea consists of using an accurate model of the system to mimic the real process behaviour. If a fault occurs, the residual signal (i.e. the difference between real system and model behaviours) can be used to diagnose and isolate the malfunction. This approach has some advantages with respect to physical (hardware-software) redundancy, mainly in economical and practical aspects. The analytical redundancy approach does not require additional equipment, but also suffers from some potential disadvantages, which are principally related to the need of an accurate model of the real system.

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. As model-based fault diagnosis methods are designed to detect any discrepancy between real system and model behaviours, it is assumed that a 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 can be (erroneously) detected as a fault, giving rise to a "false alarm" in detection. 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. On the other hand, the availability of a "good" model of the monitored system can significantly improve the performance of diagnostic tools, minimising the probability of false alarms.

This monograph focuses on the explanation of what is a "good" model suitable for robust diagnosis of system performance and operation. The book also describes carefully how "accurate models" can be obtained from real data. A large amount of attention is paid to the "real system modelling problem", with reference to either linear-non-linear 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 a system identification approach that produces a reliable model of the plant under investigation as well as the variances of the inputoutput noises affecting the data.

After the discussion of identification procedures given in the first two chapters, the monograph focuses on the residual generation problem and fault diagnosis and identification for several cases, namely sensors, actuators and system faults.

The purpose of the monograph is to provide guidelines for the modelling and identification of real processes for fault diagnosis. Hence, significant attention is paid to practical application of the methods described to real system studies, as reported in the last chapters.

Both theoretical and practical arguments have been presented and discussed in a homogenous manner and the book targets both professional engineers working in industry and researchers in academic and scientific institutions.

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