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Symbols and Abbreviations

The symbols and abbreviations listed here are used unless otherwise stated.

ARMAX	autoregressive moving average exogenous
ARX	autoregressive exogenous
BFDF	Beard fault detection filter
DOS	dedicated observer scheme
EE	equation error
EIV	errors-in-variables
FDD	fault detection and diagnosis
FDI	fault detection and isolation
FFT	fast Fourier transform
GK	Gustafson-Kessel
GOS	generalized observer scheme
IGV	inlet guided vane
KF	Kalman filter
LS	least-squares
MIMO	multiple-input multiple-output
MISO	multiple-input single-output
MLP	multiLayer perceptron
NN	neural network
OO	output observer
OLS	ordinary least-squares
RBF	radial basis function
RLS	recursive least-squares
SISO	single-Input single-Output
TS	Takagi-Sugeno
UIKF	unknown input Kalman filter
UIO	unknown input observer

1. Introduction

There is an increasing interest in 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) [Isermann and Ballé, 1997, Isermann, 1997, Patton, 1999, Frank *et al.*, 2000].

The developments began at various places in the early 1970s. Beard [Beard, 1971] and Jones [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 [Willsky, 1976]. Then Rault and his staff [Rault *et al.*, 1971] have 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 [Himmelblau, 1978]. Sensor failure detection based on the inherent analytical redundancy of multiple observers was shown by Clark [Clark, 1978].

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

The development of process fault detection methods based on modelling, parameter and state estimation was then summarised by Isermann [Isermann, 1984] and [Isermann, 1997]

Parity equation-based methods were treated early [Chow and Willsky, 1984], and then further developed by Patton and Chen [Patton and Chen, 1994b], Gertler [Gertler, 1991], Höfling and Pfeufer [Höfling and Pfeufer, 1994].

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

The developments of fault detection and isolation methods to the present time is summarised in the books of Pau [Pau, 1981], then Patton *et al.* [Patton *et al.*, 2000], Basseville and Nikiforov [Basseville and Nikiforov, 1993], Chen and Patton [Chen and Patton, 1999], Gertler [Gertler, 1998], Isermann [Isermann, 1994b] and in survey papers by Gertler [Gertler, 1988], Frank [Frank, 1990] and Isermann [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], and the second in Espo, Finland in 1994. The third symposium was scheduled at Hull, UK in 1997 and the fourth one was held in Budapest, Hungary in June 2000. The fifth is expected at Washington DC in July 2003.

Another tri–ennial series of IFAC Workshop exist for "Fault detection and supervision in the chemical process industries". Workshops were held in Newark, Delaware, Newcastle UK, Lyon and Korea between 1992 and 2001.

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 behaviour. If a fault occurs, the residual signal (*i.e.* the difference between real system and model behaviour) 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 real system and model behaviours. 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.

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 is devoted to the explanation of what is a "good" model 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 modelling problem", with reference to either linear and 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 an identification approach which 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 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.

In particular, this first chapter of the book outlines a new a common terminology in the fault diagnosis framework and gives some discussion and summary of developments in the field of fault detection and diagnosis based on papers selected during 1991–2001.

1.1 Nomenclature

By going through the literature, one recognises immediately 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 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 [RAM, 1988], in contributions to 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 SAFEPROCESS Technical Committee and are considered "on–going" in the sense that new definitions and updates are 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 fulfilment 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 one.

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 behaviour.

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. Follows fault detection.
Fault identification
Determination of the size and time-variant behaviour of a fault. Follows fault isolation.
Fault diagnosis
Determination of the kind, size, location and time of detection of a fault. Follows fault detection. Includes fault detection and identification.
Monitoring
A continuous real-time task of determining the conditions of a physical system, by recording information, recognising and indication anomalies in the behaviour.
Supervision
Monitoring a physical and taking appropriate actions to maintain the operation in the case of fault.

3. ***Models***
Quantitative model
Use of static and dynamic relations among system variables and parameters in order to describe a system's behaviour in quantitative mathematical terms.
Qualitative model
Use of static and dynamic relations among system variables in order to describe a system's behaviour in qualitative terms such as causalities and IF–THEN rules.
Diagnostic model
A set of static or dynamic relations which 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 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 not to cause danger to persons or 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 modelled as stepwise function. It represents bias in the monitored signal.
   Incipient fault
   Fault modelled by using ramp signals. It represents drift of the monitored signal.
   Intermittent fault
   Combination of impulses with different amplitudes.

6. ***Fault terminology***
   Additive fault
   Influences a variable by an addition of the fault itself. They may represent, *e.g.*, offsets of sensors.
   Multiplicative fault
   Are represented by the product of a variable with the fault itself. They can appear as parameter changes within a process.

1.2 Fault Detection and Identification 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, 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 cost, as well as the additional space required to accommodate the equipment [Isermann and Ballé, 1997, Isermann, 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 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].

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 or not 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 with estimated values. The estimation is generated by a mathematical model of the considered plant. The comparison is done using the residual quantities which 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 1.1 illustrates the concepts of hardware and analytical redundancy.

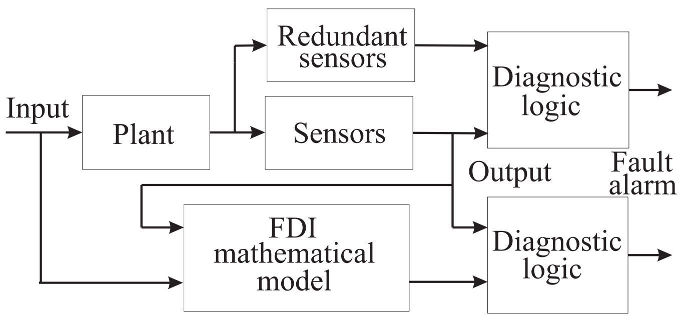


Fig. 1.1. Comparison between hardware and analytical redundancy schemes.

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*, whilst simple to implement, has a few drawbacks. The most serious 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 in order to realize a Fault Detection and Isolation (FDI) algorithm. 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 that no additional sensors have to be installed [Patton *et al.*, 1989, Chen and Patton, 1999, Basseville and Nikiforov, 1993].

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

1.3 Model-based Fault Detection Methods

The task consists of the detection of faults on the technical process including actuators, components and sensors by measuring the available input and output variables $\boldsymbol{u}(t)$ and $\boldsymbol{y}(t)$. The principle of the model–based fault detection is depicted in Figure 1.2.

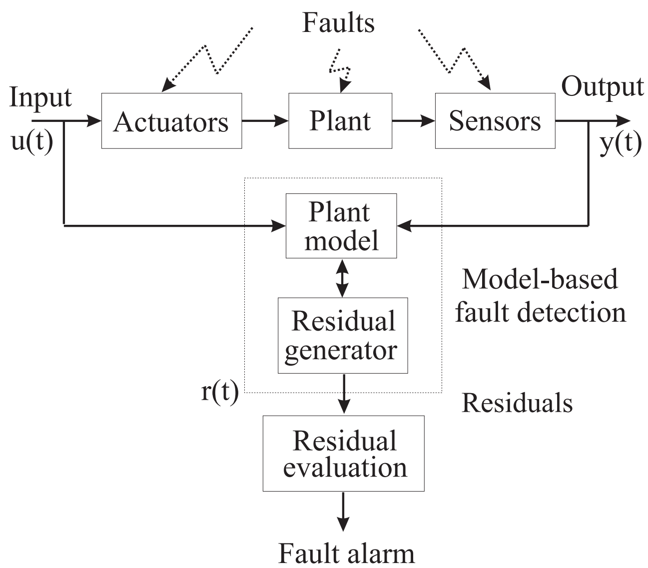


Fig. 1.2. Scheme for the model–based fault detection.

Basic process model–based FDI methods have been described by Patton *et al.* [Patton *et al.*, 1989], Basseville and Nikiforov [Basseville and Nikiforov, 1993], Gertler [Gertler, 1998] and Patton *et al.* [Chen and Patton, 1999, Patton *et al.*, 2000]:

1. Output observers (OO, estimators, filters);
2. Parity equations;
3. Identification and parameter estimation.

They generate residuals for output variables with fixed parametric models under method 1, fixed parametric or nonparametric models under method 2 and adaptive nonparametric or parametric models under method 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 a summation and *multiplicative faults* which are products of the process variables. The basic methods show different results, depending on these types of faults.

If only output signals $\boldsymbol{y}(t)$ can be measured, *signal model–based methods* can be applied, *e.g.* vibrations can be detected, which are related to rotating machinery or electrical circuits. Typical signal model–based methods of fault detection are:

1. Bandpass filters;
2. Spectral analysis (FFT);
3. Maximum-entropy estimation.

The characteristic quantities or features from fault detection methods show stochastic behaviour with mean values and variances. Deviations from the normal behaviour must then be detected by methods of *change detection* (residual analysis, Figure 1.2) like:

1. Mean and variance estimation;
2. Likelihood-ratio test, Bayes decision;
3. Run-sum test.

1.4 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 never available. Usually, the parameters of the system may vary with time and the characteristics of the disturbances and noises are unknown so that they cannot be modelled 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. The effect of modelling uncertainties, disturbances and noise is therefore 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 modelling uncertainty. Sometimes, a reduction of the sensitivity to modelling uncertainty does not solve the problem since the sensitivity reduction may be associated with a reduction of the sensitivity to faults [Chen and Patton, 1999, Gertler, 1998]. A more meaningful formulation of the FDI problem is to increase insensitivity to modelling 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 they can be hidden by disturbances. On the other hand, hard faults can be detected more easily because their effects are usually larger than modelling 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.

1.5 The Robustness Problem in Fault Detection

In this monograph, observer–based approaches to robust FDI in industrial dynamic systems are summarised and applied to simulated and real plants. 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 behaviour of non–linear processes. In this contribution, modelling errors are avoided from the very beginning by focusing on robust residual generation methods using linear and non–linear 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, *e.g.*, by unknown input observers which are introduced and applied to industrial processes. It is shown that the proposed solution to the disturbance de–coupling problem provides, in addition, the solution to both the fault detection and fault isolation problems.

On the other hand, many dynamic processes can only be described effectively using non–linear mathematical models. Most of the existing observer–based FDI techniques, however, 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 neighbourhood of a certain known operating point [Chen and Patton, 1999, Patton *et al.*, 2000]

It is clear that, as almost every process system is non–linear, the modelling 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 linearisation have been proposed in the literature and the reader is referred to [Patton *et al.*, 2000, Chap. 7] for a comprehensive treatment of this subject.

This monograph also surveys the state of the art of robustness methods and it presents some important ideas concerning the development of the use of non–linear models and predictors for FDI. In Chapter 4 observer–based approaches to robust FDI for dynamic systems are considered in more detail. In this contribution, the available model–based approaches are generalised, 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 modelled 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, whilst the sensitivity of the residual to faults is maintained. As the faults are also modelled in the form of external signals, this method additionally provides tools for the purpose of fault isolation. Fault isolation requires the de-coupling of the effects of different faults on 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 unknown input observers. Using the same functional analysis methods as employed for threshold selection, a performance index can be defined which allows for performance evaluation and, to a certain degree, also allows for optimal residual generator design [Patton *et al.*, 2000].

1.6 System Identification for Robust FDI

In earlier sections of this monograph, we have seen that model–based FDI methods formally require a high accuracy mathematic model of the monitored system. The better the model is as a representation of the dynamic behaviour of the system, the better will be the FDI performance. 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 modelling uncertainty, *i.e.*, 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, *e.g.*, its *distribution matrix* and spectral bandwidth, etc. Furthermore, this description should provide assistance for robust FDI design, *i.e.*, it can be handled in a systematic manner. Chapters 2 and 4 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 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 excitations 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 de-coupling (robust) property, *i.e.*, the residual is de-coupled from the disturbance (uncertainty). The robust residual can then be used to achieve reliable FDI.

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

– estimation of reliable model for the monitored process;
– modelling 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 seeks to answer the above questions. 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 de–coupling 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 de-coupling 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. Chapters 3 and 4 present the research developments surrounding the joint estimation of system and disturbance matrices in order to solve the robust fault diagnosis problem.

Concerning the identification schemes developed and exploited in Chapters 3, 4 and 5, 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.*, 2000a]. It is worthwhile noting that less attention has been paid to errors–in–variables schemes.

Under these considerations, Chapters 3, 4 and 5 present the robust FDI results concerning the description of monitored plants by means of equation error and error–in–variables identified models in the presence variable uncertainties. Moreover, for the examples presented, estimates obtained by the errors–in–variables approach and equation error estimates are computed and compared in Chapter 5.

1.7 Fault Identification Methods

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

Some classification methods are [Patton *et al.*, 1989, Basseville and Nikiforov, 1993, Gertler, 1998, Babuška, 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, *e.g.* in the form of symptom-fault tree. 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 [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 during the last 20 years. It is also clear that many combinations of them are possible.

Based on more than 100 publications during the last 5 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 non–linear models is growing, while the trend of using linearised 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 non–linear 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 favourite 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.

1.8 Report on FDI Applications

Because of the many publications and increasing number of applications (IFAC Congress and IFAC Symposia SAFEPROCESS) between 1991–2000, 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 of IFAC FDI–related Conferences is briefly presented in the following. Contributions taking into account the applications reported in Table 1.1 were considered. The type of faults considered are distinguished according to Table 1.2. Among all contributions, the fault detection methods were classified as in Table 1.3. The change detection and fault classification methods are indicated by Table 1.4. The reasoning strategies for fault diagnosis are reported in Table 1.5. The contributions considered are summarised in Table

1.6. The evaluation has been limited to the Fault Detection and Diagnosis (FDD) of laboratory, pilot and industrial processes.

Table 1.1. FDI applications and number of contributions.

Application	Number of contributions
Simulation of real processes	55
Large-scale pilot processes	44
Small-scale laboratory processes	18
Full-scale industrial processes	48

Table 1.2. Fault type and number of contributions.

Fault type	Number of contributions
Sensor faults	69
Actuator faults	51
Process faults	83
Control loop or controller faults	8

Table 1.3. FDI methods and number of contributions.

Method type	Number of contributions
Observer	53
Parity space	14
Parameter estimation	51
Frequency spectral analysis	7
Neural networks	9

Table 1.4. Residual evaluation methods and number of contributions.

Evaluation method	Number of contributions
Neural networks	19
Fuzzy logic	5
Bayes classification	4
Hypothesis testing	8

Table 1.6 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 on these kind of

Table 1.5. Reasoning strategies and number of contributions.

Reasoning strategy	Number of contributions
Rule based	10
Sign directed graph	3
Fault symptom tree	2
Fuzzy logic	6

Table 1.6. Applications of model–based fault detection.

FDD	Number of contributions
Milling and grinding processes	41
Power plants and thermal processes	46
Fluid dynamic processes	17
Combustion engine and turbines	36
Automotive	8
Inverted pendulum	33
Miscellaneous	42
DC motors	61
Stirred tank reactor	27
Navigation system	25
Nuclear process	10

processes, followed by parity space and combined methods. Thermal and chemical processes are investigated less frequently.

Table 1.3 shows that parameter estimation and observer-based methods are used in nearly 70% of all application considered. Neural networks, parity space and combined methods are significantly less often applied.

More than 50% of sensor faults are detected using observer-based methods, while parameter estimation and 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 networks 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 networks-based methods are used less often for this class of faults.

Among all the described processes, linear models have been used much more than non–linear ones. On processes with non–linear models, observer-based methods are mostly applied, but parity equations and neural networks also play an important role. On processes with linear or linearised 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 non–linear process applications using non–linear models are decreasing. For linear processes, no significant change can be stated.

The use of neural networks and combinations seems to be increasing.

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 non–linear process investigations. Nevertheless, the classification of generated residuals seems to remain the most important application area for neural networks.

1.9 Outline 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 modelling uncertainty problem can be tackled by designing a FDI scheme, whose residuals are insensitive to uncertainties whilst 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 a FDI scheme 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 monograph* is to develop a residual generator for model–based fault diagnosis of a 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 monograph consists of 6 chapters and the main contributions are presented in Chapters 3, 4 and 5. Chapters are devoted to the particular problem in residual generation and the are organised as follows.

Chapter 2 reviews the state of the art of the model–based FDI. The FDI problem is formalised 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 analysing residuals, fault diagnosis can be performed. Some structures of the residual generator are presented in this Chapter in order to give ideas how to implement the residual generation. A residual generator can be designed for achieving the required diagnosis performances, *e.g.* fault isolation and disturbance decoupling.

In order to design the residual generator, some assumptions about the modelling uncertainties need to be made. The most frequently used hypothesis is that the modelling uncertainty is expressed as a disturbance term in the system dynamic equation. The disturbance vector is unknown whilst its distribution matrix can be estimated by using identification procedures. Based on this assumption, the disturbance decoupling residual generator can be design by using unknown input observer methods [Chen and Patton, 1999, Liu and Patton, 1998].

Chapter 3 demonstrates how to apply dynamic system identification methods in order to estimate an accurate model of the monitored system.

The FDI methods presented require, in fact, a linear mathematical model of the process under investigation, either in state space or input-output form.

In particular, since state space descriptions provide general and mathematically rigorous tools for system modelling, they may be used in the residual generator design, both for the deterministic case (UIO and OO) [Chen and Patton, 1999, Frank, 1990, Luenberger, 1979, Watanabe and Himmelblau, 1982] and the stochastic case (Kalman filters (KF) and unknown input Kalman filters (UIKF)) [Jazwinski, 1970, Xie *et al.*, 1994, Xie and Soh, 1994].

In such a manner, the suggested FDI tool does not require any physical knowledge of the process under observation since the linear models are obtained by means of an identification scheme which exploits 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 analyse economic systems. This approach, modified to be applied to dynamic system identification [Kalman, 1982b, Kalman, 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 non–linear case, piecewise affine and fuzzy models will 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.

Chapter 4 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 a simple threshold detection, in 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 Chapter studies the approach to residual generation with the aid of OO, UIO, KF and UIKF. The residual is defined as the *output estimation error*, obtained by difference between the measurement of one output and the relative estimate. This Chapter also presents the design of such estimators both in the deterministic and stochastic environment.

The diagnosis procedure may be further specialised for actuators, input or output sensors and process components. In fact, the fault diagnosis of input sensors and actuators uses a bank of UIO in high signal to noise ratio conditions or a bank of UIKF, otherwise. The i–th UIO or UIKF is designed to be insensitive to the i–th input of the system. On the other hand, output sensor and process component faults affecting a single residual can be detected by means of a OO or a classical KF, driven by a single output and all the inputs of the system.

Chapter 5 shows how the proposed algorithms can be applied to the FDI of actuators, process components and input-output sensors of industrial plants.

In particular, the FDI techniques presented in this book have been tested on time series of data acquired from different simulated and real industrial gas turbine working in parallel with electrical mains, whose linear mathematical description is obtained by using identification procedures.

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

Chapter 6 summarises the contributions and achievements of the monograph providing some suggestions for possible further research topics as an extension of this work.

1.10 Summary

Chapter 1 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 during the last 10 years.

The structure of the six chapters of this monograph and the main contributions presented have also been outlined briefly.

2. Model-based Fault Diagnosis Techniques

2.1 Introduction

The model–based approach to fault detection in dynamic systems has been receiving more and more attention over the last two decades, in the contexts of both research and real plant application.

Stemming from this activity, a great variety of methods are found in current literature, based on the use of mathematical models of the process under investigation and exploiting modern control theory.

Model–based fault detection methods use residuals which indicate changes between the process and the model. One general assumption is that the residuals are changed significantly so that a detection is possible. This means that the residual size after the appearance of a fault is large and long enough to be detectable.

This chapter provides an overview on the various fault detection methods, with particular attention to the FDI techniques related to the applications described in this book.

All the methods considered require that the process can be described by a mathematical model. As there is almost never an exact agreement between the model used to represent the process and the process itself, the model–reality discrepancy is of primary interest.

Hence, the most important issue in model–based fault detection is concerned with the accuracy of the model describing the behaviour of the monitored system. This issue has become a central research theme over recent years, as modelling uncertainty arises from the impossibility of obtaining complete knowledge and understanding of the monitored process.

The main focus of this Chapter is the modelling aspects of the process whose faults are to be detected and isolated. The Chapter also studies the general structure of a controlled system, its possible fault locations and modes. Residual generation is then identified as an essential problem in model–based FDI, since, if it is not performed correctly, some fault information could be lost. A general framework for the residual generation is also recalled.

Residual generators based on different methods, such as state and output observers, parity relations and parameter estimations, are just special cases in this general framework. In the following, some commonly used residual generation and evaluation methods are discussed and their mathematical formulation presented.

Finally, the chapter presents and summarises special features and problems regarding the different methods.

2.2 Model-based FDI Techniques

According to the definitions given in Section 1.1, model–based FDI can be defined as the *detection*, *isolation* and *identification* of faults on a system by means of methods which extract features from measured signals and use *a priori* information on the process available in term of a mathematical models.

Faults are thus detected by setting fixed or variable thresholds on residual signals generated from the difference between actual measurements and their estimates obtained by using the process model.

A number of residuals can be designed with each having sensitivity to individual faults occurring in different locations of the system. The analysis of each residual, once the threshold is exceeded, then leads to fault isolation.

Figure 2.1 shows the general and logic block diagram of model–based FDI system.

It comprises two main stages of residual generation and residual evaluation. This structure was first suggested by Chow and Willsky in [Chow and Willsky, 1980] and now is widely accepted by the fault diagnosis community.

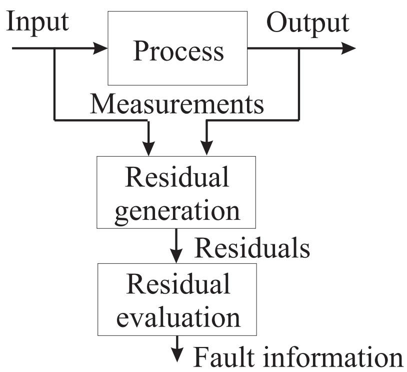


Fig. 2.1. Structure of model-based FDI system.

The two main blocks are described as follows:

1. **Residual generation:** this block generates residual signals using available inputs and outputs from the monitored system. This residual (or fault symptom) should indicate that a fault has occurred. It should normally be zero or close to zero under no fault condition, whilst distinguishably different from zero when a fault occurs. This means that the residual is characteristically independent of process inputs and outputs, in ideal conditions. Referring to Figure 2.1, this block is called *residual generation*.
2. **Residual evaluation:** This block examines residuals for the likelihood of faults and a decision rule is then applied to determine if any faults have occurred. The *residual evaluation* block, shown in Figure 2.1, may perform a simple threshold test (geometrical methods) on the instantaneous values or moving averages of the residuals. On the other hand, it may consist of statistical methods, *e.g.*, generalised likelihood ratio testing or sequential probability ratio testing [Isermann, 1997, Willsky, 1976, Basseville, 1988, Patton *et al.*, 2000].

Most contributions in the field of quantitative model–based FDI focus on the residual generation problem, since the decision–making problem can be considered relatively straightforward if residuals are well–designed.

Section 2.3 presents a number of different strategies for solving the quantitative residual generation problem.

2.3 Modelling of Faulty Systems

This book is concerned with Multi–Input Single–Output (MISO) and Multi–Input Multi–Output (MIMO) dynamic systems.

The first step in FDI model–based approach consists of providing a mathematical description of the system under investigation which shows all the possible fault cases, as well.

The detailed scheme for FDI techniques here presented is depicted by Figure 2.2.

The main components are the *Plant* under investigation, the *Actuators* and *Sensors*, which can be further sub–divided as *input* and *output* sensors, and finally the *Controller*.

In the following, the system working conditions will be monitored by means of its input $\boldsymbol{u}(t)$ and output $\boldsymbol{y}(t)$ measurements and signals from the controller $\boldsymbol{u}_R(t)$ which are supposed completely available for FDI purposes. Also, as shown in Figure 2.3, the behaviour of any controller that drives the system is inherently taken into consideration.

It is worth noting that, when the signals $\boldsymbol{u}_R(t)$ from the controller or measurements of plant inputs $\boldsymbol{u}(t)$ are not available, the controller plays an important role in the design of the FDI scheme, as a robust controller may desensitise faults effects and make diagnosis difficult.

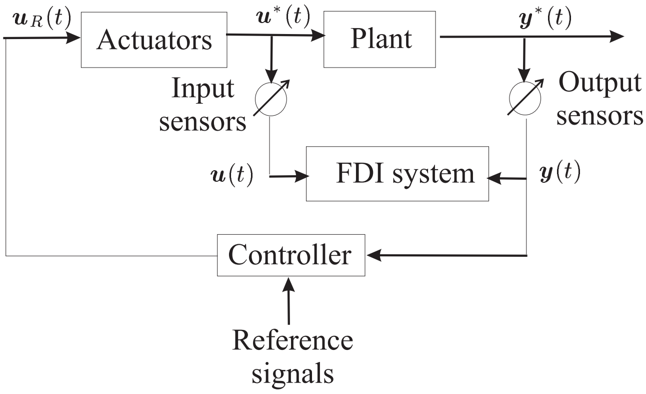


Fig. 2.2. Fault diagnosis in a closed-loop system.

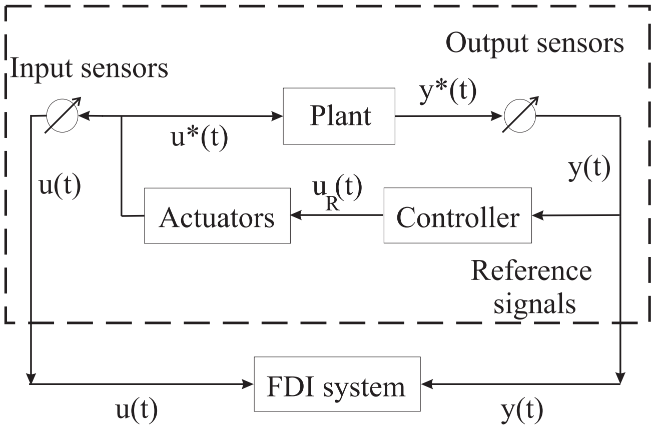


Fig. 2.3. The rearranged fault diagnosis scheme.

Once the actual process inputs and outputs $\boldsymbol{u}^*(t)$ and $\boldsymbol{y}^*(t)$ (usually not available) are measured by the input and output sensors, FDI theory can be treated as an observation problem of $\boldsymbol{u}(t)$ and $\boldsymbol{y}(t)$. The monitored system considered for FDI purpose can be therefore rearranged as illustrated in Figure 2.3.

Concerning the occurrence of malfunctions, the *location of faults* and their modelling, the system under diagnosis can be separated into the following different parts which can be affected by faults:

– Actuators,
– Process or system components,
– Input sensors,

– Output sensors,
– Controller.

With respect to previous work (see, *e.g.*, in the References [Patton *et al.*, 1989, Gertler, 1998, Patton *et al.*, 2000]), it is necessary to distinguish between input and output sensors.

Figure 2.3 shows that the input and output signals $\boldsymbol{u}^*(t)$ and $\boldsymbol{y}^*(t)$ are acquired in order to obtain the measurements $\boldsymbol{u}(t)$ and $\boldsymbol{y}(t)$ from the sensors.

This fault scenario can be summarised by the diagram shown in Figure 2.4.

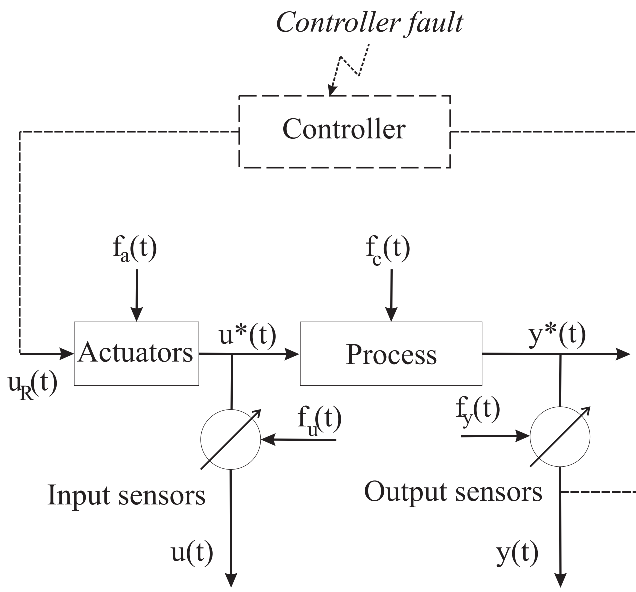


Fig. 2.4. The controlled system and fault topology.

Figure 2.4 also shows the situation where the controller can be affected by faults, since the monitored process consists of a closed-loop system. However, because of technological reasons (*e.g.*, the control action is performed by a digital computer), when the actuator is considered as a part or a component of the whole controller device, the former can be treated as subsystem where faults are likelier to occur whilst the latter remains free from faults.

Under these assumptions, as depicted in Figure 2.5 when system is considered in view of fault location, since input and output measurements are supposed completely available for FDI purposes, hence the controller behaviour in the design of a fault diagnosis scheme can be neglected as well as the interconnection between control system and the process.

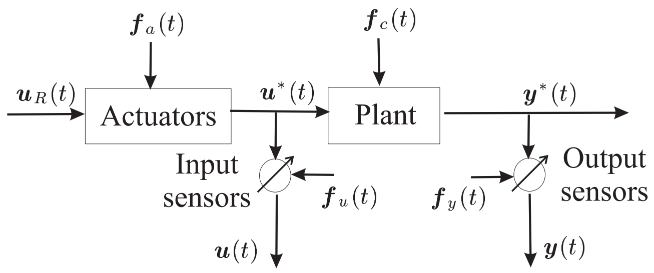


Fig. 2.5. The monitored system and fault topology.

Under the hypothesis of linearity, process dynamics can be described by the following discrete–time, time–invariant, linear dynamic system in the state–space form

$$\begin{cases} \boldsymbol{x}(t+1) & = & \boldsymbol{A}\boldsymbol{x}(t) + \boldsymbol{B}\boldsymbol{u}^*(t) \\ \boldsymbol{y}^*(t) & = & \boldsymbol{C}\boldsymbol{x}(t) \end{cases} \tag{2.1}$$

where $\boldsymbol{x}(t) \in \Re^n$ is the system state vector, $\boldsymbol{u}^*(t) \in \Re^r$ is the input signal vector driven by actuators, and $\boldsymbol{y}^*(t) \in \Re^m$ is the real system output vector, not directly available.

$\boldsymbol{A}$, $\boldsymbol{B}$, and $\boldsymbol{C}$ are system matrices with appropriate dimensions obtained by modelling or identification procedure.

With reference to Figure 2.5, a component fault vector $\boldsymbol{f}_c(t)$ affects process dynamics as follows:

$$\boldsymbol{x}(t+1) = \boldsymbol{A}\boldsymbol{x}(t) + \boldsymbol{B}\boldsymbol{u}^*(t) + \boldsymbol{f}_c(t) \tag{2.2}$$

In some cases, component faults come from a change in the system parameters, *e.g.*, a change in entries of the $\boldsymbol{A}$ matrix. For example, a change in the i-th row and the j-th column of the $\boldsymbol{A}$ matrix, leads to a fault vector $\boldsymbol{f}_c(t)$ described as

$$\boldsymbol{f}_c(t) = I_i \Delta a_{ij} x_j(t) \tag{2.3}$$

where $x_j(t)$ in the j-th element of the vector $\boldsymbol{x}(t)$ and I_i is a n-dimensional vector with all zero except a “1” in the i-th element.

As stated previously, as the actual process output $\boldsymbol{y}^*(t)$ is not directly available, a sensor is used to acquire a measure of the system outputs.

Moreover, generally speaking, a sensor can be also used to measure the system inputs $\boldsymbol{u}^*(t)$ (*e.g.*, for uncontrolled system).

By neglecting sensor dynamics, faults on input and output sensors are modelled with additive signals, respectively, as

$$\begin{cases} \boldsymbol{u}(t) & = & \boldsymbol{u}^*(t) + \boldsymbol{f}_u(t) \\ \boldsymbol{y}(t) & = & \boldsymbol{y}^*(t) + \boldsymbol{f}_y(t) \end{cases} \tag{2.4}$$

where the vectors $\boldsymbol{f}_u(t) = [f_{u_1}(t) \ldots f_{u_r}(t)]^T$ and $\boldsymbol{f}_y(t) = [f_{y_1}(t) \ldots f_{y_m}(t)]^T$ are chosen to describe a fault situation.

For example, if the sensor outputs are stuck at a fixed value $\bar{\boldsymbol{u}}$ because of a malfunction, the measurement vector is $\boldsymbol{u}(t) = \bar{\boldsymbol{u}}$ and the fault can be written as $\boldsymbol{f}_u(t) = -\boldsymbol{u}^*(t) + \bar{\boldsymbol{u}}$.

On the other hand, when the sensors are affected by a multiplicative fault δ, the measurements become $\boldsymbol{u}(t) = (1+\delta)\boldsymbol{u}^*(t)$, and the fault vector can be written as $\boldsymbol{f}_u(t) = \delta \boldsymbol{u}^*(t)$.

Usually, as shown in the following, fault modes can be described by step and ramp signals in order to model abrupt and incipient (hard to detect) faults, representing bias and drift, respectively.

Moreover, for technical reasons, sensor output signals are generally affected by measurement noise. Fault–free sensor signals $\boldsymbol{u}(t)$ and $\boldsymbol{y}(t)$, with additive noise can be modelled as:

$$\begin{cases} \boldsymbol{u}(t) &= \boldsymbol{u}^*(t) + \tilde{\boldsymbol{u}}(t) \\ \boldsymbol{y}(t) &= \boldsymbol{y}^*(t) + \tilde{\boldsymbol{y}}(t) \end{cases} \tag{2.5}$$

in which the sequences $\tilde{\boldsymbol{u}}(t)$ and $\tilde{\boldsymbol{y}}(t)$ are usually described as white, zero–mean, uncorrelated Gaussian processes.

In this case, taking into account the effects of faults and noise, 2.4 has to be replaced by:

$$\begin{cases} \boldsymbol{u}(t) &= \boldsymbol{u}^*(t) + \tilde{\boldsymbol{u}}(t) + \boldsymbol{f}_u(t) \\ \boldsymbol{y}(t) &= \boldsymbol{y}^*(t) + \tilde{\boldsymbol{y}}(t) + \boldsymbol{f}_y(t) \end{cases} \tag{2.6}$$

By neglecting the actuator block, Figure 2.6 shows the structure of the measurement process.

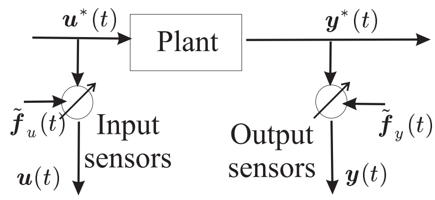


Fig. 2.6. The structure of the plant sensors.

Model descriptions of types of Eqs. 2.1 and 2.5 are also known as Error–In–Variable (EIV) models [Kalman, 1982b, Kalman, 1990]. They will be briefly presented in Chapter 3.

With reference to a controlled system, according to Figure 2.5, signals $\boldsymbol{u}^*(t)$ are the actuator response to the command signals $\boldsymbol{u}_R(t)$.

A purely algebraic actuator (*i.e.* with gain equal to 1) can be described by:

$$\boldsymbol{u}^*(t) = \boldsymbol{u}_R(t) + \boldsymbol{f}_a(t) \tag{2.7}$$

where, similarly to input-output sensor fault situation, $\boldsymbol{f}_a(t) \in \Re^r$ is the actuator fault vector.

In general, as shown in Figure 2.5, if the the actuation signals $\boldsymbol{u}^*(t)$ are assumed to be measurable, by neglecting input and output sensor noises, the process model with fault can be described by the following system equation:

$$\begin{cases} \boldsymbol{x}(t+1) & = & \boldsymbol{A}\boldsymbol{x}(t) + \boldsymbol{f}_c(t) + B\boldsymbol{u}^*(t) \\ \boldsymbol{y}(t) & = & \boldsymbol{C}\boldsymbol{x}(t) + \boldsymbol{f}_y(t) \\ \boldsymbol{u}(t) & = & \boldsymbol{u}^*(t) + \boldsymbol{f}_u(t) \end{cases} \tag{2.8}$$

On the other hand, Figure 2.7 represents the case where the $\boldsymbol{u}_R$ signals are measured only by the input sensors.

Such a configuration represents a critical situation with respect to the input sensor connection depicted in Figure 2.5.

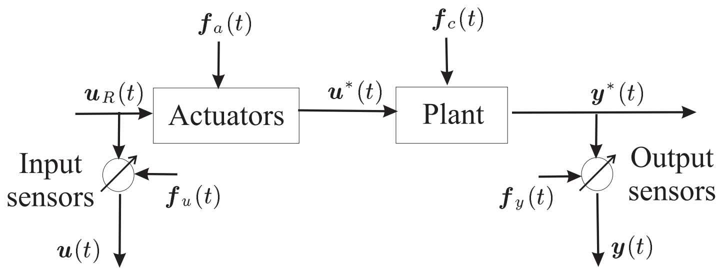


Fig. 2.7. Fault topology with actuator input signal measurement.

In this situation, actuator faults cannot be directly related to the input measurements $\boldsymbol{u}(t)$ but their effects can only be detected by means of output signals $\boldsymbol{y}(t)$.

By taking into account also actuator faults $\boldsymbol{f}_a(t)$, the description below is obtained:

$$\begin{cases} \boldsymbol{x}(t+1) & = & \boldsymbol{A}\boldsymbol{x}(t) + \boldsymbol{f}_c(t) + \boldsymbol{B}\boldsymbol{f}_a(t) + \boldsymbol{B}\boldsymbol{u}^*(t) \\ \boldsymbol{y}(t) & = & \boldsymbol{C}\boldsymbol{x}(t) + \boldsymbol{f}_y(t) \\ \boldsymbol{u}(t) & = & \boldsymbol{u}^*(t) + \boldsymbol{f}_u(t) \end{cases} \tag{2.9}$$

Moreover, considering the general case, a system affected by all possible faults can be described by the the following state–space model:

$$\begin{cases} \boldsymbol{x}(t+1) & = & \boldsymbol{A}\boldsymbol{x}(t) + \boldsymbol{B}\boldsymbol{u}^*(t) + \boldsymbol{L}_1\boldsymbol{f}(t) \\ \boldsymbol{y}(t) & = & \boldsymbol{C}\boldsymbol{x}(t) + \boldsymbol{L}_2\boldsymbol{f}(t) \\ \boldsymbol{u}(t) & = & \boldsymbol{u}^*(t) + \boldsymbol{L}_3\boldsymbol{f}(t) \end{cases} \tag{2.10}$$

where entries of the vector $\boldsymbol{f}(t) = [\boldsymbol{f}_a^T,\ \boldsymbol{f}_u^T,\ \boldsymbol{f}_c^T,\ \boldsymbol{f}_y^T]^T \in \Re^k$ correspond to specific faults.

In practice, it is reasonable to assume that the fault signals are described by *unknown* time functions. The matrices $\boldsymbol{L}_1, \boldsymbol{L}_2, \boldsymbol{L}_3$ are known as faulty entry matrices which describe how the faults enter the system.

The vectors $\boldsymbol{u}(t)$ and $\boldsymbol{y}(t)$ are the available and measurable inputs and outputs, respectively. Both vectors are supposed known for FDI purpose.

The distribution of the fault in the system depicted in Figure 2.5 can be described as input–output transfer matrix representation in the following form:

$$\boldsymbol{y}(z) = \boldsymbol{G}_{yu^*}(z)\boldsymbol{u}^*(z) + \boldsymbol{G}_{yf}(z)\boldsymbol{f}(z) \tag{2.11}$$

z being the unitary advance operator whilst the transfer matrices $\boldsymbol{G}_{yu^*}(z)$ and $\boldsymbol{G}_{yf}(z)$ are defined as:

$$\left\{ \begin{array}{lcl} \boldsymbol{G}_{yu^*}(z) & = & \boldsymbol{C}(zI - \boldsymbol{A})^{-1}\boldsymbol{B} \\ \boldsymbol{G}_{yf}(z) & = & \boldsymbol{C}(zI - \boldsymbol{A})^{-1}\boldsymbol{L}_1 + \boldsymbol{L}_2 \end{array} \right. \tag{2.12}$$

Both the general models for FDI described by Equations 2.10 and 2.11 in the time and frequency domain, respectively, have been widely accepted in the fault diagnosis literature [Patton *et al.*, 1989, Patton *et al.*, 2000, Chen and Patton, 1999, Gertler, 1998].

Under these assumptions, the general model–based FDI problem here treated can be performed on the basis of the knowledge only of the measured sequences $\boldsymbol{u}(t)$ and $\boldsymbol{y}(t)$.

Frequency domain descriptions are typically applied when the effects of faults as well as the disturbances have frequency characteristics which differ from each other and thus information in the frequency spectra serve as criteria to distinguish the faults [Ding and Frank, 1990, Massoumnia *et al.*, 1989].

On the other hand, since state–space descriptions provide general and mathematically rigorous tools for system modelling and robust residual generation, for both the deterministic (noise free measurements) and the stochastic case (measurements affected by noises), the system matrices $\boldsymbol{A}$, $\boldsymbol{B}$ and $\boldsymbol{C}$, 2.10, in canonical forms can be obtained by multivariable identification procedures [Guidorzi, 1975, Norton, 1986, Söderström and Stoica, 1987, Ljung, 1999].

Moreover, in the case of a MIMO system, the choice of state–space representations in canonical form [Guidorzi, 1975] instead of parity space methods [Gertler, 1995] may avoid unexpected false alarm problems [Delmaire *et al.*, 1999].

As shown in Chapter 3, the FDI methods proposed here do not require any physical knowledge of the processes under observation, since the mathematical description of the monitored system is obtained by means of a system identification scheme based on Equation Error (EE) and EIV models.

It is worthy to note how this approach represents a novel point of view of the model–based fault diagnosis. The new aspect consists of exploiting linear system identification procedures, presented in Chapter 3, in connection with the model–based residual generation problem, shown in Chapter 4.

Although most systems to be monitored are actually non–linear, linear system modelling and identification methods are described here to avoid the complexities that would otherwise be inevitable when non–linear models are used.

There is certainly an increasing interest in the use of non–linear methods (non–linear observers, extended Kalman filters, fuzzy-logic methods, etc). However, as the feature of system supervision is to monitor the operation and performance of the system with respect to an expected point of operation, linear system methods are still very valid. Deviations from expected behaviour can be used to monitor system performance changes as well as component malfunctions.

2.4 Residual Generator General Structure

In this section, a review is given on fault detection methods based on *process models* and *signal models*. The basic methods are described briefly whilst their presentation and application are shown in Chapter 4 and 5, respectively.

The most frequently used FDI methods exploit the *a priori* knowledge of characteristics of certain signals. As an example, the spectrum, the dynamic range of the signal and its variations may be checked.

However, the necessity of *a priori* information concerning the monitored signals and the dependence of the signal characteristics on unknown working conditions of the system under diagnosis are main drawbacks of such a class of methods.

The most significant contribution in modern model–based approaches is the introduction of the *symptom or residual signals*, which depend on faults and are independent of system operating states.

They represent the inconsistency between the actual system measurements and the corresponding signals of the mathematical model.

The residual generator block introduced in Figure 2.1 can be interpreted as illustrated in Figure 2.8 [Basseville, 1988].

In the above structure, the auxiliary redundant signal $\boldsymbol{z}(t)$ is generated by the function $W_1\big(\boldsymbol{u}(\cdot), \boldsymbol{y}(\cdot)\big)$ and, together with the measurement $\boldsymbol{y}(t)$, the symptom signal $\boldsymbol{r}(t)$ is computed by means of $W_2\big(\boldsymbol{z}(\cdot), \boldsymbol{y}(\cdot)\big)$.

In the fault–free case, the following relations are satisfied

$$\left\{ \begin{array}{lcll} \boldsymbol{z}(t) & = & W_1\big(\boldsymbol{u}(\cdot), \boldsymbol{y}(\cdot)\big) & \\ \boldsymbol{r}(t) & = & W_2\big(\boldsymbol{z}(\cdot), \boldsymbol{y}(\cdot)\big) & = \mathbf{0}. \end{array} \right. \tag{2.13}$$

When a fault occurs in the plant, the residual $\boldsymbol{r}(t)$ will be different from zero.

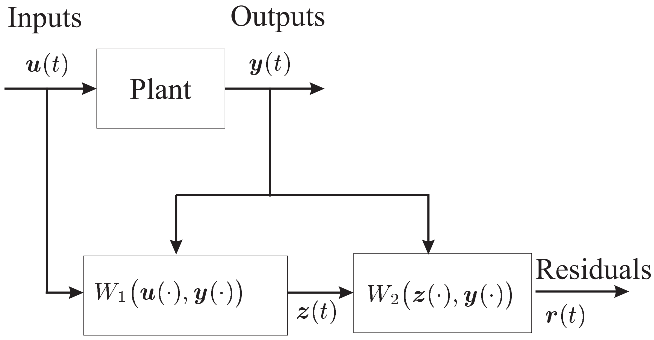


Fig. 2.8. Residual generator general structure.

The simplest residual generator is depicted in Figure 2.9 and it is obtained when the system W_1 is a plant identical model $\boldsymbol{z}(t) = W_1\big(\boldsymbol{u}(\cdot)\big)$ or it is an input–output description for the actual process obtained from system identification procedure (*e.g.*, an Auto Regressive eXogenous (ARX) model, see Chapter 3).

In the former case, the measurement $\boldsymbol{y}(t)$ is not required in W_1 because it is a *system simulator*. The signal $\boldsymbol{z}(t)$ represents the simulated output and the residual is computed as $\boldsymbol{r}(t) = \boldsymbol{z}(t) - \boldsymbol{y}(t)$. Since it is an open–loop system, the process simulation may become unstable.

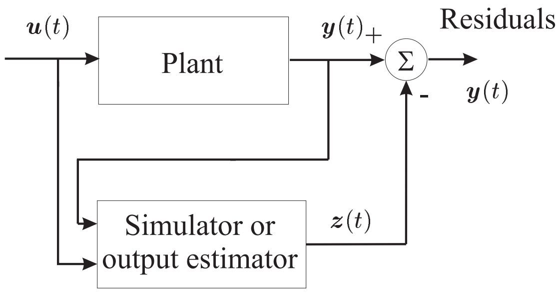


Fig. 2.9. Residual generation via system simulator.

An extension to the model–based residual generation is to replace $W_1\big(\boldsymbol{u}(\cdot)\big)$ by $W_1\big(\boldsymbol{u}(\cdot), \boldsymbol{y}(\cdot)\big)$, *i.e.* an *output estimator* fed by both system input and output.

In such a case, function W_1 generates an estimation of a linear function of the output $W_1\big(\boldsymbol{u}(\cdot), \boldsymbol{y}(\cdot)\big) = \boldsymbol{M}\boldsymbol{y}(t)$ whilst function W_2 can be defined as $W_2\big(\boldsymbol{z}(\cdot), \boldsymbol{y}(\cdot)\big) = \boldsymbol{W}\big(\boldsymbol{z}(t) - \boldsymbol{M}\boldsymbol{y}(t)\big)$, $\boldsymbol{W}$ being a weighting matrix.

Concluding, no matter which type of method is used, the residual generation process is nothing but a liner mapping whose inputs consist of process inputs and outputs.

As an example, Figure 2.10 represents a general structure for all residual generators using the input–output transfer matrix description was presented by Patton and Chen in [Patton and Chen, 1991a].

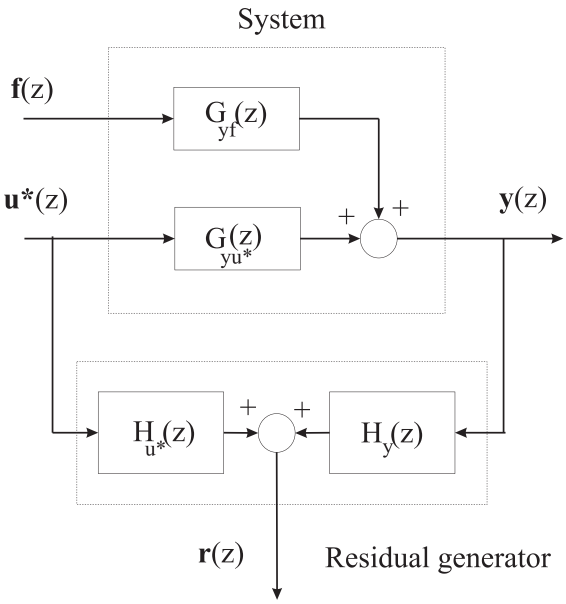


Fig. 2.10. Residual generator general structure.

With reference to Equations 2.11 and 2.12, the residual generator structure is expressed mathematically by the generalised representation:

$$\boldsymbol{r}(z) = \left[\begin{array}{cc} \boldsymbol{H}_{u^*}(z) & \boldsymbol{H}_y(z) \end{array} \right] \left[\begin{array}{c} \boldsymbol{u}^*(z) \\ \boldsymbol{y}(z) \end{array} \right] = H_{u^*}(z)\boldsymbol{u}^*(z) + \boldsymbol{H}_y(z)\boldsymbol{y}(z) \quad (2.14)$$

where $\boldsymbol{H}_{u^*}(z)$ and $\boldsymbol{H}_y(z)$ are discrete transfer matrices which can be designed using stable discrete–time linear systems. The functions $\boldsymbol{u}^*(z)$, $\boldsymbol{y}(z)$, $\boldsymbol{r}(z)$ and $\boldsymbol{f}(z)$ are the Z-transform of the corresponding discrete–time signals.

According to the definition, the residual $\boldsymbol{r}(t)$ has to be designed to become zero for for fault–free case and different from zero in case of failures. This means that

$$\boldsymbol{r}(t) = \mathbf{0} \text{ if and only if } \boldsymbol{f}(t) = \mathbf{0} \quad (2.15)$$

In order to satisfy the Equation 2.15, the design of the transfer matrices $\boldsymbol{H}_{u^*}(z)$ and $\boldsymbol{H}_y(z)$ must satisfy to the constraint conditions

$$\boldsymbol{H}_{u^*}(z) + \boldsymbol{H}_y(z)\boldsymbol{G}_{yu^*} = \mathbf{0} \tag{2.16}$$

It is worth noting that different residual generators can be obtained by using different parametrisations of $\boldsymbol{H}_{u^*}(z)$ and $\boldsymbol{H}_y(z)$ [Patton and Chen, 1991a, Chen and Patton, 1999].

After generating the residual, the simplest and most widely used way to fault detection is achieved by directly comparing residual signal $\boldsymbol{r}(t)$ or a residual function $J(\boldsymbol{r}(t))$ with a fixed threshold ϵ or a threshold function $\varepsilon(t)$ as follows

$$\begin{cases} J(\boldsymbol{r}(t)) \leq \varepsilon(t) & \text{for} \quad \boldsymbol{f}(t) = \mathbf{0} \\ J(\boldsymbol{r}(t)) > \varepsilon(t) & \text{for} \quad \boldsymbol{f}(t) \neq \mathbf{0} \end{cases} \tag{2.17}$$

where $\boldsymbol{f}(t)$ is the general fault vector defined in Equation 2.10. If the residual exceeds the threshold, a fault may be occurred.

This test works especially well with fixed thresholds ε if the process operates approximately in a steady state and it reacts after relatively large feature, *i.e.* after either a large sudden or a long-lasting gradually increasing fault.

On the other hand, adaptive thresholds $\varepsilon(t)$ can be exploited which depend on plant operating conditions, for example when $\varepsilon(t)$ is expressed as a function of plant inputs [Clark, 1989, Chen and Patton, 1999].

2.5 Residual Generation Techniques

The generation of symptoms is the main issue in model–based fault diagnosis.

A variety of methods are available in literature for residual generation and this section presents briefly some of the most common methods.

Most of the residual generation techniques are based on both continuous and discrete system models, however, in this book, the attention is focused only on discrete–time dynamic linear models.

The following process model–based fault detection schemes will be considered and summarised [Isermann and Ballé, 1997, Patton *et al.*, 2000]:

1. Fault detection via parameter estimation [Isermann, 1984, Isermann and Freyermuth, 1992, Isermann, 1993, Isermann and Ballé, 1997, Patton *et al.*, 2000].
2. Observer–based approaches [Beard, 1971, Frank, 1993, Frank and Ding, 1997, Patton and Chen, 1997, Willsky, 1976, Basseville, 1988],

3. Parity vector (relation) methods [Chow and Willsky, 1984, Gertler and Singer, 1990, Patton and Chen, 1991a, Gertler and Monajemy, 1993, Delmaire *et al.*, 1999].

2.5.1 Residual Generation via Parameter Estimation

In most practical cases, the process parameters are not known at all, or they are not known exactly enough. Then, they can be determined with parameter estimation methods, by measuring input and output signals, $\boldsymbol{u}(t)$ and $\boldsymbol{y}(t)$, if the basic structure of the model is known [Isermann, 1997, Patton *et al.*, 2000].

This approach is based on the assumption that the faults are reflected in the physical system parameters and the basic idea is that the parameters of the actual process are estimated on–line using well–known parameter estimations methods.

The results are thus compared with the parameters of the reference model; obtained initially under fault–free assumptions. Any discrepancy can indicate that a fault may have occurred.

Now we compare two different approaches for modelling the input–output behaviour of the monitored system.

Equation Error Methods. The SISO process discrete–time model of order n is written in the vector form

$$y(t) = \boldsymbol{\Psi}^T \boldsymbol{\Theta} \tag{2.18}$$

where

$$\boldsymbol{\Theta}^T = [a_1 \dots a_n,\ b_1 \dots b_n] \tag{2.19}$$

is the parameter vector and

$$\boldsymbol{\Psi}^T = [y(t-1) \dots y(t-n) \quad u(t-1) \dots u(t-n)] \tag{2.20}$$

the discrete–time data vector.

According to Figure 2.11, for parameter estimation, the equation error $e(t)$ is introduced

$$e(t) = y(t) - \boldsymbol{\Psi}^T \boldsymbol{\Theta} \tag{2.21}$$

or, if

$$\frac{y(t)}{u(t)} = \frac{B(z)}{A(z)} \tag{2.22}$$

is the transfer function of the process, the equation error via Z-transformation becomes

$$e(t) = \hat{B}(z)u(t) - \hat{A}(z)y(t). \tag{2.23}$$

in which $\hat{A}(z)$ and $\hat{B}(z)$ correspond to the estimates of $A(z)$ and $B(z)$.

The least–squares (LS) estimate

$$\hat{\boldsymbol{\Theta}} = [\boldsymbol{\Psi}^T\ \boldsymbol{\Psi}]^{-1}\boldsymbol{\Psi}^T y \tag{2.24}$$

is obtained if the minimisation of the sum of least–squares is computed

$$\begin{cases} J(\boldsymbol{\Theta}) & = & \sum_t e^2(t) = \boldsymbol{e}^T\boldsymbol{e} \\ \frac{d\ J(\boldsymbol{\Theta})}{d\ \boldsymbol{\Theta}} & = & \mathbf{0}. \end{cases} \tag{2.25}$$

As described in *e.g.*, [Patton *et al.*, 2000, Isermann, 1992], the least–squares estimate can be also expressed in recursive form (RLS) with respect to the estimates at the instant t, with $t = 0,\ 1,\ 2, \cdots$

$$\hat{\boldsymbol{\Theta}}(t+1) = \hat{\boldsymbol{\Theta}}(t) + \gamma(t)\left[y(t+1) - \boldsymbol{\Psi}^T(t+1)\hat{\boldsymbol{\Theta}}(t+1)\right] \tag{2.26}$$

where

$$\begin{cases} \gamma(t) & = & \frac{1}{\boldsymbol{\Psi}^T(t+1)\boldsymbol{P}(t)\boldsymbol{\Psi}(t+1)+1}\boldsymbol{P}(t)\boldsymbol{\Psi}(t+1) \\ \boldsymbol{P}(t+1) & = & \left[I - \gamma(t)\boldsymbol{\Psi}^T(t+1)\right]\boldsymbol{P}(t). \end{cases} \tag{2.27}$$

For improved estimates, filtering methods can be exploited. In particular, as shown in Section 4.8, when measurements are affected by noise, a Kalman filter can be used for the parameter estimation [Jazwinski, 1970].

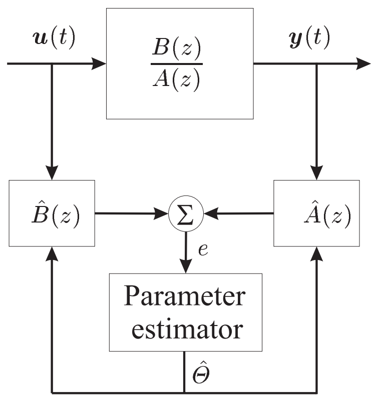


Fig. 2.11. Parameter estimation equation error.

Output Error Methods. Instead of the equation error computed in Equation 2.21, the output error

$$e(t) = y(t) - \hat{y}(\boldsymbol{\Theta}, t) \tag{2.28}$$

where

$$\hat{y}(\boldsymbol{\Theta}, z) = \frac{\hat{B}(z)}{\hat{A}(z)} u(z) \tag{2.29}$$

is the model output, can also be used, as depicted in Figure 2.12.

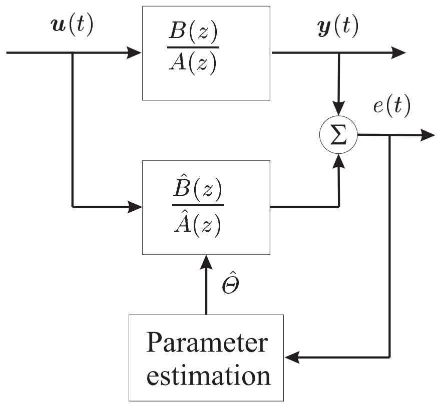


Fig. 2.12. Parameter estimation output error.

Unfortunately, direct calculation of the parameter estimate $\boldsymbol{\Theta}$ is not possible, because $e(t)$ is non–linear in the parameters.

Therefore, the loss function 2.28 as Equation 2.21 has to be minimised by numerical optimisation methods. The computational effort is then much larger and on-line real-time application is in general impossible. However, relatively precise parameter estimates may be obtained.

If a fault within the process changes one or several parameters by $\Delta\boldsymbol{\Theta}$, the output signal changes for small deviations according to

$$\Delta y(t) = \boldsymbol{\Psi}^T(t)\Delta\boldsymbol{\Theta}(t) + \Delta\boldsymbol{\Psi}^T(t)\boldsymbol{\Theta}(t) + \Delta\boldsymbol{\Psi}^T(t)\Delta\boldsymbol{\Theta}(t) \tag{2.30}$$

and the parameter estimator indicates a change $\Delta\boldsymbol{\Theta}$.

Generally, the process parameters $\boldsymbol{\Theta}$ depend on physical process coefficients $\boldsymbol{p}$ (like stiffness, damping factor, resistance, ...)

$$\boldsymbol{\Theta} = f(\boldsymbol{p}) \tag{2.31}$$

via non–linear algebraic equations. If the inversion of the relationship

$$\boldsymbol{p} = f^{-1}(\boldsymbol{\Theta}) \tag{2.32}$$

exists [Patton *et al.*, 2000, Isermann, 1992], changes $\Delta\boldsymbol{p}$ of the process coefficients can be calculated. These changes in the coefficients are in many cases directly related to faults.

Thus, although the knowledge of $\Delta\boldsymbol{p}$ facilitates the fault diagnosis problem, it is not necessary for fault detection only. Parameter estimation can also be applied to non–linear static process models [Isermann, 1993].

2.5.2 Observer-based Approaches

The basic idea behind the observer or filter–based techniques is to estimate the outputs of the system from the measurements by using either Luenberger observers in a deterministic setting or Kalman filters in a noisy environment. The output estimation error (or its weighted value) is therefore used as residual.

It is worth noting that when an observer is exploited for FDI purpose, the estimation of the outputs is necessary, whilst the estimation of the state vector is usually not needed [Chen and Patton, 1999]. Moreover, the advantage of using the observer is the flexibility in the selection of its gains which leads to a rich variety of FDI schemes [Frank, 1994b, Frank and Ding, 1997, Chen *et al.*, 1996b, Liu and Patton, 1998].

In order to obtain the structure of a (generalised) observer, the discrete-time, time-invariant, linear dynamic model for the process under consideration in a state-space form is considered

$$\begin{cases} \boldsymbol{x}(t+1) & = & \boldsymbol{A}\boldsymbol{x}(t) + \boldsymbol{B}\boldsymbol{u}(t) \\ \boldsymbol{y}(t) & = & \boldsymbol{C}\boldsymbol{x}(t). \end{cases} \tag{2.33}$$

being $\boldsymbol{u}(t) \in \Re^r$, $\boldsymbol{x}(t) \in \Re^n$ and $\boldsymbol{y}(t) \in \Re^m$.

Assuming that all matrices $\boldsymbol{A}$, $\boldsymbol{B}$ and $\boldsymbol{C}$ are perfectly known, an observer is used to reconstruct the system variables based on the measured inputs and outputs $\boldsymbol{u}(t)$ and $\boldsymbol{y}(t)$

$$\begin{cases} \hat{\boldsymbol{x}}(t+1) & = & \boldsymbol{A}\hat{\boldsymbol{x}}(t) + \boldsymbol{B}\boldsymbol{u}(t) + \boldsymbol{H}\boldsymbol{e}(t) \\ \boldsymbol{e}(t) & = & \boldsymbol{y}(t) - \boldsymbol{C}\hat{\boldsymbol{x}}(t). \end{cases} \tag{2.34}$$

The observer scheme described by Equation 2.34 is depicted in Figure 2.13.

For the state estimation error $\boldsymbol{e}_x(t)$, it follows from Equations 2.34 that

$$\begin{cases} \boldsymbol{e}_x(t) & = & \boldsymbol{x}(t) - \hat{\boldsymbol{x}}(t) \\ \boldsymbol{e}_x(t+1) & = & (\boldsymbol{A} - \boldsymbol{H}\boldsymbol{C})\boldsymbol{e}_x(t). \end{cases} \tag{2.35}$$

The state error $\boldsymbol{e}_x(t)$ (and the error $\boldsymbol{e}(t)$) vanishes asymptotically

$$\lim_{t\to\infty} \boldsymbol{e}_x(t) = \boldsymbol{0} \tag{2.36}$$

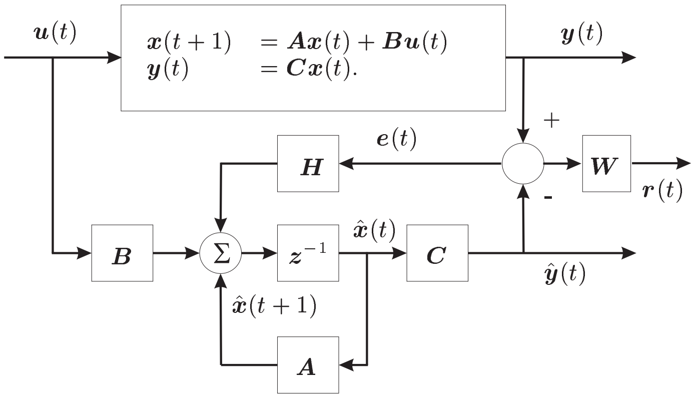


Fig. 2.13. Process and state observer.

if the observer is stable, which can be achieved by proper design of the observer feedback $\boldsymbol{H}$.

If the process is influenced by disturbance and faults, by comparing Figure 2.14) and Equations 2.10 it is described by the following system

$$\left\{ \begin{array}{lcl} \boldsymbol{x}(t+1) & = & \boldsymbol{A}\boldsymbol{x}(t) + \boldsymbol{B}\boldsymbol{u}(t) + \boldsymbol{Q}\boldsymbol{v}(t) + \boldsymbol{L}_1 \boldsymbol{f}(t) \\ \boldsymbol{y}(t) & = & \boldsymbol{C}\boldsymbol{x}(t) + \boldsymbol{R}\boldsymbol{w}(t) + \boldsymbol{L}_2 \boldsymbol{f}(t) \end{array} \right. \tag{2.37}$$

where $\boldsymbol{v}(t)$ is the non–measurable disturbance vector at the input, $\boldsymbol{w}(t)$ the non–measurable disturbance vector at the output, $\boldsymbol{f}(t)$ fault signals at the input and output acting through L_1 and L_2, respectively.

They can represent actuator, process, input and output sensor additive faults.

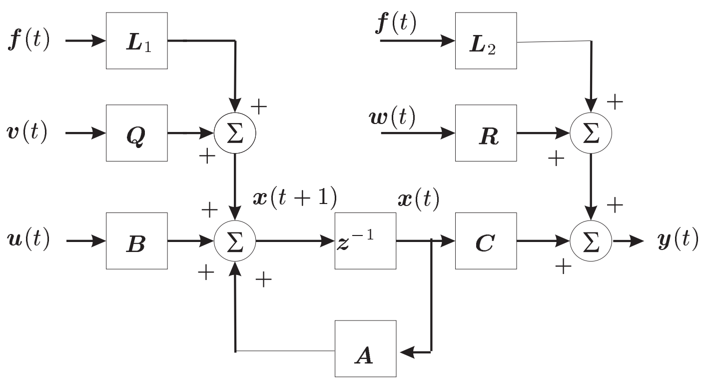


Fig. 2.14. MIMO process with faults and noises.

For the state estimation error, the following equations hold if the disturbances $\boldsymbol{v}(t) = \mathbf{0}$ and $\boldsymbol{w}(t) = \mathbf{0}$

$$\boldsymbol{e}_x(t+1) = (\boldsymbol{A} - \boldsymbol{H}\boldsymbol{C})\boldsymbol{e}_x(t) + \boldsymbol{L}_1\boldsymbol{f}(t) - \boldsymbol{H}\boldsymbol{L}_2\boldsymbol{f}(t) \tag{2.38}$$

and the output error $\boldsymbol{e}(t)$ becomes

$$\boldsymbol{e}(t) = \boldsymbol{C}\boldsymbol{e}_x(t) + \boldsymbol{L}_2\boldsymbol{f}(t). \tag{2.39}$$

The vector $\boldsymbol{f}(t)$ represents *additive faults* because they influence $\boldsymbol{e}(t)$ and $\boldsymbol{x}(t)$ by a summation.

When sudden and permanent faults $\boldsymbol{f}(t)$ occur, the state estimation error will deviate from zero.

$\boldsymbol{e}_x(t)$ as well as $\boldsymbol{e}(t)$ show dynamic behaviour which are different for $\boldsymbol{L}_1\boldsymbol{f}(t)$ and $\boldsymbol{L}_2\boldsymbol{f}(t)$. Both $\boldsymbol{e}_x(t)$ or $\boldsymbol{e}(t)$ can be taken as residuals.

In particular, the residual $\boldsymbol{e}(t)$ is the basis for different fault detection methods based on output estimation.

For the generation of residual with special properties, the design of the observer feedback matrix $\boldsymbol{H}$ is of interest [Chen and Patton, 1999, Liu and Patton, 1998].

Limiting conditions are the stability and the sensitivity against disturbances $\boldsymbol{v}(t)$ and $\boldsymbol{w}(t)$. If the signals are affected by noise, the Kalman filter must be used instead of classical observers [Jazwinski, 1970].

If faults appear as changes $\Delta\boldsymbol{A}$ or $\Delta\boldsymbol{B}$ of the parameters, the process behaviour becomes

$$\begin{cases} \boldsymbol{x}(t+1) & = & (\boldsymbol{A} + \Delta\boldsymbol{A})\boldsymbol{x}(t) + (\boldsymbol{B} + \Delta\boldsymbol{B})\boldsymbol{u}(t) \\ \boldsymbol{y}(t) & = & \boldsymbol{C}\boldsymbol{x}(t) \end{cases} \tag{2.40}$$

while the state $\boldsymbol{e}_x(t)$ and the output estimation $\boldsymbol{e}(t)$ errors

$$\begin{cases} \boldsymbol{e}_x(t+1) & = & (\boldsymbol{A} - \boldsymbol{H}\boldsymbol{C})\boldsymbol{e}_x(t) + \Delta\boldsymbol{A}\boldsymbol{x}(t) + \Delta\boldsymbol{B}\boldsymbol{u}(t) \\ \boldsymbol{e}(t) & = & \boldsymbol{C}\boldsymbol{e}_x(t). \end{cases} \tag{2.41}$$

The changes $\Delta\boldsymbol{A}$ and $\Delta\boldsymbol{B}$ are then *multiplicative faults* [Isermann, 1997, Patton *et al.*, 2000].

In this case, the changes in the residuals depend on the parameter changes, as well as input and state variable changes. Hence, the influence of parameter changes on the residuals is not as straightforward as in the case of the additive faults $\boldsymbol{f}(t)$.

The following observer–based fault detection schemes and configurations are briefly summarised and recalled [Isermann, 1997, Willsky, 1976, Patton *et al.*, 1989, Chen and Patton, 1999, Patton *et al.*, 2000].

1. **Dedicated observers for MIMO processes**
   – *Observer excited by one output*: one observer is driven by one sensor output. The other outputs $\hat{\boldsymbol{y}}(t)$ are reconstructed and compared with measured outputs $\boldsymbol{y}(t)$. This allows the detection of single output sensor faults [Clark, 1978].
   – *Bank of observers, excited by all outputs*: several observers are designed for a definite fault signal and detected by hypothesis test [Willsky, 1976].
   – *Bank of observers, excited by single outputs*: several observers for single sensors outputs are used. The estimated outputs $\hat{\boldsymbol{y}}(t)$ are compared with the measured outputs $\boldsymbol{y}(t)$. This allows the detection of multiple sensor fault (DOS, Dedicated Observer Scheme) [Clark, 1978].
   – *Bank of observers, excited by all outputs except one*: as before, but each observer is excited by all outputs except one sensor output, which is supervised (GOS, Generalised Observer Scheme) [Wünnenberg and Frank, 1987, Frank, 1993].

2. **Fault detection filters for MIMO processes**
   – The feedback $\boldsymbol{H}$ of the state observer in Equation 2.34 is chosen so that particular fault signals $\boldsymbol{L}_1\boldsymbol{f}(t)$ change in a definite direction and fault signals $\boldsymbol{L}_2\boldsymbol{f}(t)$ in a definite plane [Beard, 1971, Jones, 1973, Speyer, 1999].

With directional residual vectors, the fault isolation problem consists of determining which of the known fault signature directions the residual vector lies the closest to. The original form of the "failure detection filter" was proposed by Beard [Beard, 1971] and Jones [Jones, 1973] to generate directional residual vectors. Many more straightforward methods have followed, including methods to achieve "robust fault detection filter" [Chen *et al.*, 1996b].

The fault (or failure) detection is a class of Luenberger observers with a specially designed feedback gain matrix. It allows output estimation errors having directional characteristics associated with some known fault directions, to be obtained.

These fault detection methods mostly require several measurable output signals and make use of internal analytical redundancy of multivariable systems. Recently it was proposed to improve their robustness with respect to process parameter changes and unknown input signals $\boldsymbol{v}(t)$ and $\boldsymbol{w}(t)$ [Patton and Chen, 1994a, Chen *et al.*, 1996b, Chung and Speyer, 1998, Speyer, 1999].

This can be reached, for example, through filtering the output error of the observer by

$$\boldsymbol{r}(t) = \boldsymbol{W}\boldsymbol{e}(t) \tag{2.42}$$

together with a special design of the observer feedback matrix $\boldsymbol{H}$.

3. **Output observers**
   Another possibility is the use of output observers (or UIO, see Section 4.3) in the reconstruction of the output signals, if the estimate of the state variable $\hat{\boldsymbol{x}}(t)$ is not of primary interest.
   In this context, it is worthy to mention the paper by Chen, Patton and Zhang [Chen *et al.*, 1996b] concerning the design of output observers for robust FDI using eigenstructure assignment method.
   Through a linear transformation

$$\boldsymbol{z}(t) = \boldsymbol{T}\boldsymbol{x}(t) \tag{2.43}$$

the state–space representation of the observer becomes

$$\hat{\boldsymbol{z}}(t+1) = \boldsymbol{F}\hat{\boldsymbol{z}}(t) + \boldsymbol{J}\boldsymbol{u}(t) + \boldsymbol{G}\boldsymbol{y}(t) \tag{2.44}$$

and the residual is determined by

$$\boldsymbol{r}(t) = \boldsymbol{W}_z\hat{\boldsymbol{z}}(t) + \boldsymbol{W}_y\boldsymbol{y}(t). \tag{2.45}$$

This situation is depicted in Figure 2.15.

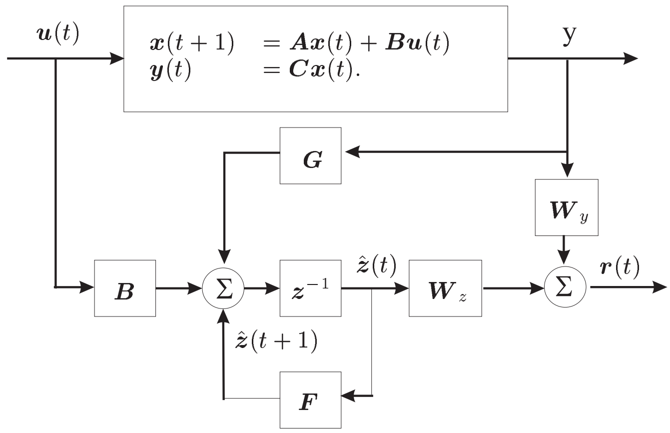


Fig. 2.15. Process and output observer.

The state estimation error

$$\boldsymbol{e}_x(t) = \hat{\boldsymbol{z}}(t) - \boldsymbol{z}(t) = \hat{\boldsymbol{z}}(t) - \boldsymbol{T}\boldsymbol{x}(t) \tag{2.46}$$

and the residuals $\boldsymbol{r}(t)$ are then designed, such that they are independent of the process states $\boldsymbol{x}(t)$, the known input $\boldsymbol{u}(t)$ and the unknown inputs $\boldsymbol{v}(t)$ and $\boldsymbol{w}(t)$, as depicted in Figure 2.14.

In this way, the residuals are dependent only on fault signals $\boldsymbol{f}(t)$ [Patton and Chen, 1994a, Chen *et al.*, 1996b, Gertler, 1998, Patton *et al.*, 2000].

2.5.3 Fault Detection with Parity Equations

The basic idea of the parity relations approach is to provide a proper check of the parity (consistency) of the measurements acquired from the monitored system.

In the early development of fault diagnosis, the parity vector (relation) approach was applied to static or parallel redundancy schemes [Potter and Suman, 1977] which may be obtained directly from measurements (hardware redundancy) or from analytical relations (analytical redundancy). A survey of these methods can be found in [Ray and Luck, 1991].

In the case of hardware redundancy, two methods can be exploited to obtain redundant relations. The first requires the use of several sensors having identical or similar functions to measure the same variable. The second approach consists of dissimilar sensors to measure different variables but with their outputs being relative to each other.

Even if these techniques have been successfully applied for fault diagnosis [Potter and Suman, 1977, Daly *et al.*, 1979], the attention of this section is focused on analytical forms of redundancy.

A straightforward model–based method of fault detection is to take a model $G_M(z) = \frac{\hat{\boldsymbol{A}}(z)}{\hat{\boldsymbol{B}}(z)}$ and to run it in parallel to the process described by $G_P(z) = \frac{\boldsymbol{A}(z)}{\boldsymbol{B}(z)}$, thereby forming an error vector $\boldsymbol{r}(z)$

$$\boldsymbol{r}(z) = \left(\frac{\boldsymbol{A}(z)}{\boldsymbol{B}(z)} - \frac{\hat{\boldsymbol{A}}(z)}{\hat{\boldsymbol{B}}(z)} \right) \boldsymbol{u}(z). \tag{2.47}$$

The methodology here described is depicted in Figure 2.16(a).
However, as for observers, the model parameters and structure of the monitored process have to be known *a priori*.

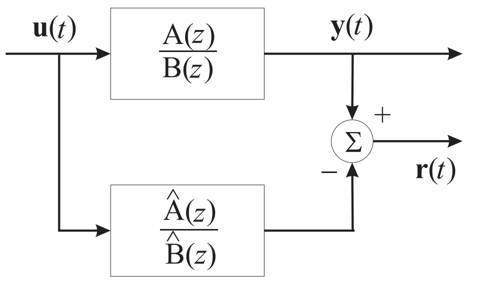
With reference to Figure 2.5, if

$$\boldsymbol{G}_M(z) = \boldsymbol{G}_P(z) \;\; i.e. \;\; \frac{\hat{\boldsymbol{A}}(z)}{\hat{\boldsymbol{B}}(z)} = \frac{\boldsymbol{A}(z)}{\boldsymbol{B}(z)} \tag{2.48}$$

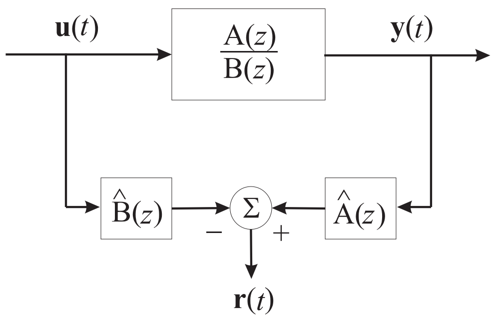
for additive input $\boldsymbol{f}_u(z)$ and output $\boldsymbol{f}_y(z)$ faults, the $\boldsymbol{r}(z)$ error then becomes

$$\boldsymbol{r}(z) = \frac{\boldsymbol{A}(z)}{\boldsymbol{B}(z)} \boldsymbol{f}_u(z) + \boldsymbol{f}_y(z). \tag{2.49}$$

According to Figure 2.16(b), another possibility is to generate a polynomial error



(a) Output error



(b) Equation error

Fig. 2.16. Parity equation methods.

$$
\begin{aligned}
\boldsymbol{r}(z) &= \hat{\boldsymbol{A}}(z)\boldsymbol{y}(z) - \hat{\boldsymbol{B}}(z)\boldsymbol{u}(z) \\
&= \boldsymbol{B}(z)\boldsymbol{f}_u(z) + \boldsymbol{A}(z)\boldsymbol{f}_y(z).
\end{aligned}
\tag{2.50}
$$

In both cases, different time responses are obtained for an additive input or output fault.

Moreover, the error vector $\boldsymbol{r}(z)$ computed by Equation 2.49 corresponds to the output error of parameter estimation method computed by Equation 2.28.

On the other hand, $\boldsymbol{r}(z)$ in Equation 2.50 concerns the equation error of Equation 2.21.

Equations 2.49 and 2.50 generate residuals and are called *parity equations* [Gertler, 1991] under the assumptions of fault occurrence and of exact agreement between process and model.

However, within the parity equations, the model parameters are assumed to be known and constant, whereas the parameter estimations can vary the parameters of $\hat{\boldsymbol{A}}(z)$ and $\hat{\boldsymbol{B}}(z)$ in order to minimise the residuals.

Moreover, for the generation of specific characteristics of the parity vector $\boldsymbol{r}(z)$ and for obtaining fault detection and isolation properties, the residuals can be filtered according to matrix $\boldsymbol{G}_f(z)$ to compute the vector $\boldsymbol{r}_f(z)$ [Gertler, 1991, Patton and Chen, 1994c, Patton *et al.*, 2000]:

$$\boldsymbol{r}_f(z) = \boldsymbol{G}_f(z)\boldsymbol{r}(z). \tag{2.51}$$

Equations 2.51, 2.49 and 2.50 can be therefore used to implement and design the residual generation system, in order to meet fault detection and isolation specifications, as well [Gertler, 1998].

However, for SISO processes only one residual can be generated and it is therefore not easy to distinguish between different faults.

On the other hand, more freedom in the design of parity equations can be obtained when for SISO processes intermediate signals can be measured (see Figure 2.5), or for MIMO systems.

As an extension of the parity equation method, the parity relation concept presented here can be generalised [Chow and Willsky, 1984, Lou *et al.*, 1986, Patton and Chen, 1994c] and then extended to state–space descriptions, as shown in [Gertler, 1998] for discrete–time models.

The redundancy relations are now specified mathematically as follow.

Given the system

$$\begin{cases} \boldsymbol{x}(t+1) & = & \boldsymbol{A}\boldsymbol{x}(t) + \boldsymbol{B}\boldsymbol{u}(t) \\ \boldsymbol{y}(t) & = & \boldsymbol{C}\boldsymbol{x}(t) \end{cases} \tag{2.52}$$

by substituting the second of Equations 2.52 in the first one and delaying several times, the following system is obtained

$$\begin{bmatrix} \boldsymbol{y}(t) \\ \boldsymbol{y}(t+1) \\ \boldsymbol{y}(t+2) \\ \vdots \end{bmatrix} = \begin{bmatrix} \boldsymbol{C} \\ \boldsymbol{CA} \\ \boldsymbol{CA}^2 \\ \vdots \end{bmatrix} \boldsymbol{x}(t) + \begin{bmatrix} \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} & \dots \\ \boldsymbol{CB} & \boldsymbol{0} & \boldsymbol{0} & \dots \\ \boldsymbol{CAB} & \boldsymbol{CB} & \boldsymbol{0} & \dots \\ \vdots & \vdots & \vdots & \ddots \end{bmatrix} \begin{bmatrix} \boldsymbol{u}(t) \\ \boldsymbol{u}(t+1) \\ \boldsymbol{u}(t+2) \\ \vdots \end{bmatrix} \tag{2.53}$$

$$\boldsymbol{Y}_f(t) = \boldsymbol{T}\boldsymbol{x}(t) + \boldsymbol{Q}\boldsymbol{U}_f(t). \tag{2.54}$$

In order to remove the non–measurable states $\boldsymbol{x}(t)$, and to obtain a parity vector useful for FDI, Equation 2.53 is multiplied by $\boldsymbol{W}$, such that

$$\boldsymbol{W}\boldsymbol{T} = \boldsymbol{0}. \tag{2.55}$$

This leads to residuals

$$\boldsymbol{r}(t) = \boldsymbol{W}\boldsymbol{Y}_f - \boldsymbol{W}\boldsymbol{Q}\boldsymbol{U}_f(t) \tag{2.56}$$

as shown in Figure 2.17.

The filtered input and output vectors $\boldsymbol{U}_f$ and $\boldsymbol{Y}_f$ are obtained by delaying the corresponding signals.

The design of the matrix $\boldsymbol{W}$ gives some freedom to generate a structured set of residuals.

One possibility is to select the elements of $\boldsymbol{W}$ such that one measured variable has no impact on a specific residual. Then, this residual remains small in the case of an additive fault on this variable, and the other residuals increase [Patton and Chen, 1994c, Chen and Patton, 1999].

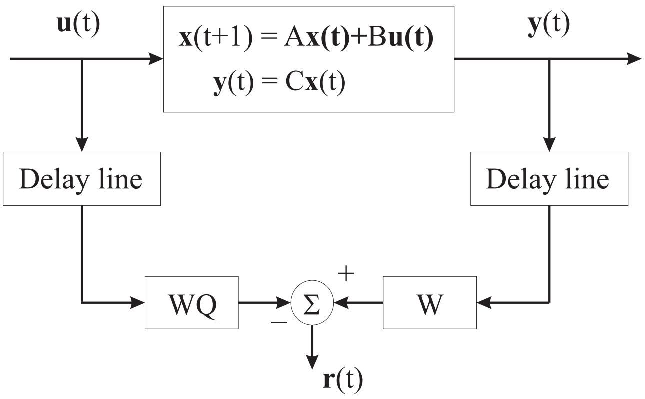


Fig. 2.17. Parity equation methods for a MIMO model.

Finally, because of the previous results, it is clear therefore that some correspondence exists between parity relation and observer–based methods. This aspect was firstly pointed out by Massoumnia [Massoumnia, 1986] and later was demonstrated by Frank and Wunnenberg [Wünnenberg, 1990, Patton *et al.*, 1989].

The problem was re–examined in detail by Chen and Patton [Patton and Chen, 1994c] and the equivalence under different conditions and in different meanings was discussed. It was shown that the parity relation approach is equivalent to the use of a dead–beat observer.

This implies that the parity relation scheme provides less design flexibility when compared with methods which are based on observers without any restriction.

More recently, a comparison between observer–based and parity space techniques was proposed [Delmaire *et al.*, 1999]. Both the methods were first explored for SISO systems and therefore extended the comparison to MIMO systems. The comparison was performed using linear discrete-time models.

In particular, considering MIMO systems described by estimated input–output discrete–time forms (*e.g.*, ARX or Auto Regressive Moving Average eXogenous (ARMAX) models) of Equations 2.49 and 2.50 leads to a representation in which parameters redundancy can not be avoided. To overcome this drawback Delmaire *et al.* proposed in [Delmaire *et al.*, 1999] to use observers designed from identified canonical state–space forms [Guidorzi, 1975]. Moreover, in the case of parameters redundancy, multiple identification of some parameters may occur, leading to inconsistent estimations which might produce inconsistent FDI decisions [Delmaire *et al.*, 1999].

This states again the FDI capabilities of the observer–based methods with respect to parity relation schemes.

2.6 Change Detection and Symptom Evaluation

When the residual generation stage has been performed, the second step requires the examination of symptoms in order to determine if any faults have occurred.

As shown by Equation 2.17, a decision process may consist of a simple threshold test on the instantaneous values of moving averages of residuals.

On the other hand, because of the presence of noise, disturbances and other unknown signals acting upon the monitored system, the decision making process can exploits statistical methods.

In this case, the measured or estimated quantities, such as signals, parameters, state variables or residuals are usually represented by stochastic variables $\boldsymbol{r}(t) = \{r_i(t)\}_i^q$, with mean value and variance [Willsky, 1976]

$$\bar{r}_i = E\{r_i(t)\}; \qquad \bar{\sigma}_i^2 = E\{[r_i(t) - \bar{r}_i]^2\} \tag{2.57}$$

as normal values for the fault-free process.

Analytic symptoms are then obtained as changes

$$\Delta r_i = E\{r_i(t) - \bar{r}_i\}; \qquad \Delta\sigma_i = E\{\sigma_i(t) - \bar{\sigma}_i\} \tag{2.58}$$

with reference to the normal values. Usually, the time instant $t > t_f$ represents the unknown instant of the fault occurrence.

In order to separate normal from faulty behaviour, usually a fixed threshold Δr_{tol} defined as

$$\Delta r_{tol} = \epsilon\bar{\sigma}_r, \qquad \epsilon \geq 2 \tag{2.59}$$

has to be selected.

By a proper choice of ϵ, a compromise has to be made between the detection of small faults and false alarms.

Another class of methods can be exploited for detecting residual changes due to faults. Therefore, techniques of change detection, *e.g.*, as a likelihood–ratio–test or Bayes decision, a run–sum test are commonly used [Isermann, 1984, Basseville and Benveniste, 1986, Basseville and Nikiforov, 1993].

Moreover, fuzzy or adaptive thresholds may improve the binary decision [Chen and Patton, 1999, Patton *et al.*, 2000].

Finally, when several variables change, classification methods are used. In a multidimensional space, the symptom vector

$$\Delta \boldsymbol{r} = [\Delta r_1 \ \Delta r_2 \ \cdots \ \Delta r_q] \tag{2.60}$$

belongs to a q–dimensional space and its direction depends on the fault occurrence.

In this case, the process of residual evaluation consists of determining the direction as well as the distance of $\Delta \boldsymbol{r}$ from the origin. Geometrical distance methods [Carpenter and Grossberg, 1987, Tou and Gonzalez, 1974] or artificial neural networks [Himmelblau *et al.*, 1991, Meneganti *et al.*, 1998] can be hence applied.

The generation and evaluation of analytic symptoms concludes the task of fault–detection within the framework of model–based fault diagnosis of Figure 2.8.

2.7 The Residual Generation Problem

Although the analytical redundancy method for residual generation has been recognised as an effective technique for detecting and isolating faults, the critical problem of unavoidable modelling uncertainty has not been fully solved.

The main problem regarding the reliability of FDI schemes is the modelling uncertainty which is due, for example, to process noise, parameter variations and non–linearities.

On the other hand, all model–based methods use a model of the monitored system to produce the symptom generator. If the system is not complex and can be described accurately by the mathematical model, FDI is directly performed by using a simple geometrical analysis of residuals. In real industrial systems however, the modelling uncertainty is unavoidable.

The design of an effective and reliable FDI scheme for residual generation should take into account of the modelling uncertainty with respect to the sensitivity of the faults. Therefore, the task of the design of an FDI system is thus to generate residuals which are *robust* [Chow and Willsky, 1984, Ding and Frank, 1990, Frank, 1994b, Frank and Ding, 1997, Patton and Chen, 1994c].

Several papers addressed this problem. For example, optimal robust parity relations were proposed [Chow and Willsky, 1984, Chung and Speyer, 1998, Speyer, 1999, Lou *et al.*, 1986] and the threshold selector concept was introduced [Emami-Naeini *et al.*, 1988]. Robust FDI using the disturbance decoupling technique was also used [Patton and Chen, 1994c, Chen *et al.*, 1996b]. The Patton and Chen approach is an interesting contrast to the Chow and Willsky method which seems to minimise the modelling uncertainty over several points of operation. Patton and Chen deal directly with this problem by estimating the optimum unknown input distribution matrix over a range of operating points and exploiting the eigenstructure assignment approach [Patton and Chen, 1994c, Chen and Patton, 1999].

The model–based FDI technique requires a high accuracy mathematical description of the monitored system. The better the model represents the dynamic behaviour of the system, the better will be the FDI precision. If a FDI method can be developed which is insensitive to modelling uncertainty, a very accurate model is not necessarily needed.

All uncertainties can be are summarised as disturbances acting on the system. Although the disturbance vector is unknown, its distribution matrix can be obtained by an identification procedure. Under this assumption, the "disturbance de–coupling" principle can be exploited to design a robust FDI scheme.

In order to summarise the approach to the robustness problem, the state–space model of the monitored system should be considered [Patton and Chen, 1993]:

$$\left\{ \begin{array}{lcl} \boldsymbol{x}(t+1) & = & (\boldsymbol{A} + \Delta\boldsymbol{A})\,\boldsymbol{x}(t) + (\boldsymbol{B} + \Delta\boldsymbol{B})\,\boldsymbol{u}(t) + \boldsymbol{E}_1\boldsymbol{\varepsilon}(t) + \boldsymbol{R}_1\boldsymbol{f}(t) \\ \boldsymbol{y}(t) & = & \boldsymbol{C}\boldsymbol{x}(t) + \boldsymbol{E}_2\boldsymbol{\varepsilon}(t) + \boldsymbol{R}_2\boldsymbol{f}(t) \end{array} \right. \tag{2.61}$$

where $\boldsymbol{\varepsilon}(t)$ is the disturbance vector, and $\boldsymbol{E}_1$ and $\boldsymbol{E}_2$ are the known or unknown input distribution matrices. The matrices $\Delta\boldsymbol{A}$ and $\Delta\boldsymbol{B}$ are the parameter errors or variations which represent modelling errors.

The discrete transfer matrix description between the output $\boldsymbol{y}(t)$ and input $\boldsymbol{u}(t)$ of the system 2.61 is then

$$\boldsymbol{y}(z) = (\boldsymbol{G}_u(z) + \Delta\boldsymbol{G}_u(z))\,\boldsymbol{u}(z) + \boldsymbol{G}_\varepsilon(z)\boldsymbol{\varepsilon}(z) + \boldsymbol{G}_f(z)\boldsymbol{f}(z) \tag{2.62}$$

where $\Delta\boldsymbol{G}_u(z)$ is used to describe modelling errors, whilst both $\Delta\boldsymbol{G}_u(z)$ and $\boldsymbol{G}_\varepsilon(z)$ represent modelling uncertainty.

With reference to the residual generator of Figure 2.10 and described by Equation 2.14, the z–domain residual vector has to be rewritten as

$$\boldsymbol{r}(z) = \boldsymbol{H}_y(z)\boldsymbol{G}_f(z)\boldsymbol{f}(z) + \boldsymbol{H}_y(z)\boldsymbol{G}_\varepsilon(z)\boldsymbol{\varepsilon}(z) + \boldsymbol{H}_y(z)\Delta\boldsymbol{G}_u(z)\boldsymbol{u}(z). \tag{2.63}$$

With respect to Equation 2.14, the terms $\boldsymbol{H}_y(z)\boldsymbol{G}_\varepsilon(z)$ and $\boldsymbol{H}_y(z)\Delta\boldsymbol{G}_u(z)$ cannot be deleted.

Both faults and modelling uncertainty (disturbance and modelling error) affect the residual and hence discrimination between these two effects is difficult.

The principle of disturbance de–coupling for robust residual generation requires that the residual generator satisfies

$$\boldsymbol{H}_y(z)\boldsymbol{G}_\varepsilon(z) = \boldsymbol{0} \tag{2.64}$$

in order to achieve total de–coupling between residual $\boldsymbol{r}(z)$ and disturbance $\boldsymbol{\varepsilon}(z)$.

This property can be achieved by using the unknown input observer [Watanabe and Himmelblau, 1982, Wünnenberg and Frank, 1987, Chen *et al.*, 1996b, Frank *et al.*, 2000], optimal (robust) parity relations [Chow and Willsky, 1984, Lou *et al.*, 1986, Wünnenberg, 1990, Wünnenberg and Frank, 1990, Frank *et al.*, 2000] or alternatively the eigenstructure assignment approach [Patton *et al.*, 1986, Patton and Chen, 1991b, Liu and Patton, 1998, Patton and Chen, 2000, Duan *et al.*, 2002].

These approaches are presented in detail in Chapter 4 where the design of a robust residual generator is also achieved in connection with different identification tools summarised in Chapter 3.

Hence, for disturbance de–coupling approaches in FDI, the aim is to completely eliminate the disturbance effect from the residual. However, the complete elimination of disturbance effects may not be possible due to the lack of degree of freedom. Moreover, it may be problematic, in some cases, because the fault effect may also be eliminated. Hence, an appropriate criterion for robust residual design should take into account the effects of both modelling error and faults. There is a trade–off between sensitivity to faults and robustness to modelling uncertainty and hence robust residual generation can be considered as a *multi–objective optimisation problem* [Chen and Patton, 1999, chapt. 6]. It consists of the maximisation of fault effects and the minimisation of uncertainty effects [Wünnenberg, 1990, Frank *et al.*, 2000].

Therefore, the approach to the design of optimal residuals can require the satisfaction of a set of objectives. These objectives are essential for achieving robust diagnosis of incipient faults. If such joint optimisation problems, which can be also expressed in the frequency domain, were reformulated for satisfying a set of inequalities on the performance indices, Genetic Algorithms (GA) [Goldberg, 1989, Davis, 1991] and Linear Matrix Inequalities (LMI) [Boyd *et al.*, 1994] can be successfully exploited to search the optimal solution [Chen *et al.*, 1996a, Hou and Patton, 1997, Chen *et al.*, 1997], [Chen and Patton, 1999, Chen and Patton, 2001].

Disturbance de–coupling can also be achieved using frequency domain design techniques. As an example, the robust fault detection problem can be managed by using the standard H_∞ filtering formulation [Ding and Frank, 1990, Hou and Patton, 1996, Frank and Ding, 1997].

With this method, the minimisation of the disturbance effect on the residual is formulated as a standard H_∞ filtering problem [Chen and Patton, 2000, Frank *et al.*, 2000]. On the other hand, the so–called H_∞/H_- approach can be also exploited [Hou and Patton, 1996, Hou and Patton, 1997, Frank *et al.*, 2000, Chen and Patton, 2000].

Among the many ways for eliminating or minimising disturbance and modelling error effects on the residual and hence for achieving robustness in FDI [Patton *et al.*, 2000] H_∞ optimisation is a robust design method with the original motivation firmly rooted in the consideration of various uncertainties, especially the modelling errors. It is reasonable to seek an application of this technique in the robust design of FDI systems. Therefore, the H_∞ optimisation method can be successfully exploited for robust residual generation of FDI.

The early work of using H_∞ optimisation techniques for robust FDI was based on the use of factorisation approach [Ding and Frank, 1990, Ding *et al.*, 2000]. The factorisation–based H_∞ optimisation technique is useful in solving FDI problems. However, the more elegant and advanced H_∞ optimisation methods are based on the use of the Algebraic Riccati Equation (ARE) [Zhou *et al.*, 1996]. Mangoubi *et al.* [Mangoubi *et al.*, 1992] first solved the robust FDI estimation problem using the ARE approach via the use of H_∞ and μ robust estimator synthesis methods developed by Appleby *et al.* [Appleby *et al.*, 1991]. A direct formulation of the FDI problem as a robust H_∞ filter design problem with the solution of an ARE was given in Edelmayer *et al.* [Edelmayer *et al.*, 1997]. To deal with modelling errors as well as disturbances in robust FDI design, Niemann and Stoustrup [Niemann and Stoustrup, 1996] introduced modelling error blocks into the standard H_∞ observer design. The weighting factors are then introduced in the problem formulation for finding an optimal FDI solution. This is further extended to non–linear systems where the non–linearity is treated in the same way as a modelling error block [Stoustrup and Niemann, 1998, Stoustrup *et al.*, 1997].

The majority of studies discussed so far involve the use of a slightly modified H_∞ filter for the residual generation, *i.e.* the design objective is to minimise the effect of disturbances and modelling errors on the estimation error and subsequently on the residual. However, robust residual generation is different from the robust estimation because it does not only require the disturbance attenuation. The residual has to remain sensitive to faults whilst the effect of disturbance is minimised. Sauter et at. [Sauter *et al.*, 1997] studied this problem where the fault sensitivity is enhanced by applying an optimal post–filter to the "primary residual". The problem of enhancing fault sensitivity while increasing robustness against disturbances and modelling errors was studied extensively by Sadrnia *et at.* [Sadrnia *et al.*, 1997]. The essential idea is to reach an acceptable compromise between disturbance robustness and fault sensitivity. In the beginning, an observer with very small disturbance sensitivity bound is designed via an ARE. Then, the fault sensitivity is checked. If the fault sensitivity is too small, the disturbance robustness requirement should be relaxed, *i.e.* to design another optimal observer with an increased disturbance sensitivity bound. This procedure is likely to be repeated several times. The final goal is to find a design which provides the maximum ratio between fault sensitivity and disturbance sensitivity.

Recently, Chen and Patton [Chen and Patton, 1999, Chen and Patton, 2000] have formulated the robust residual generation problem within the standard H_∞ filtering framework, *i.e.* to generate the residual whose sensitivity to disturbances is minimised. To facilitate reliable FDI, the residual sensitivity to faults has to be maintained (or maximised) in addition to the minimisation of the disturbance sensitivity. This problem was solved via the minimisation of the difference between the residual and the fault against the disturbance and the fault, *i.e.* the objective is to replicate the fault using the residual. In this way, the residual sensitivity to the fault is indirectly maximised. The residual sensitivity to the modelling error can be minimised if the modelling error is approximately represented by the disturbance vector with the estimated distribution matrix [Chen and Patton, 1999]. However, the modelling error can be handled directly using standard H_∞. In [Chen and Patton, 1999, Chen and Patton, 2000] the way of including the modelling error in the robust residual design within the standard H_∞ framework was shown.

Generally speaking, the robust FDI approach can be approached in different ways. It is therefore important to mention the design principle of residual generators under a certain performance index [Basseville, 1997, Frank *et al.*, 2000]. This is indeed a reasonable extension of the unknown input residual generator design, in which, instead of full de–coupling, a compromise between the robustness and sensitivity is made.

It is worth focusing the attention to this scheme, due to its important role in theoretical studies and its relationship to the residual evaluation and integrated design of FDI systems. Since the goal of residual generation is to enhance the robustness of the residual to the model uncertainty without loss of its sensitivity to the faults, the minimisation of performance index [Frank *et al.*, 2000]

$$J = \frac{\|\frac{\partial r}{\partial d}\|}{\|\frac{\partial r}{\partial f}\|} \text{ or } J = \|\frac{\partial r}{\partial d}\| \text{ with } \|\frac{\partial r}{\partial f}\| > \alpha \tag{2.65}$$

is widely recognised as a suitable design objective. Associated to the norm used, the type of the residual generator and the mathematical tool adopted, a number of optimisation approaches have been developed [Frank *et al.*, 2000]. Recently, [Ding *et al.*, 2000] derived a unified solution for a number of optimisation problems and provided thus a satisfactory solution to the above–defined optimisation problem ten years after it was first proposed. In [Frank *et al.*, 2000] a briefly review the state of art of the solutions can be found whilst [Hou and Patton, 1996, Hou and Patton, 1997, Frank *et al.*, 2000] address the H_∞/H_- method.

According to the norm selected, by minimising the performance index 2.65 over a specified range, an approximate de–coupling design can be achieved [Ding and Frank, 1990, Patton and Hou, 1997, Frank and Ding, 1997, Ding *et al.*, 1999].

Moreover, the approximated design for optimal disturbance de–coupling can also be solved in the time domain [Wünnenberg, 1990, Chen *et al.*, 1993].

On the other hand, with reference to the modelling errors in Equation 2.63, represented by the term $\Delta \boldsymbol{G}_u(z)$ the robust problem is more difficult to solve.

Two main techniques have been described by Patton and Chen. In the first case, the uncertainty is taken into account at the residual design stage [Chen *et al.*, 1996b]; this is known as *active robustness* in fault diagnosis [Patton and Chen, 1994c].

The active way of achieving a robust solution is to approximate uncertainties, *i.e.* representing approximately modelling errors as disturbances [Chen and Patton, 1999]

$$\Delta \boldsymbol{G}_u(z)\boldsymbol{u}(z) \approx \boldsymbol{G}_d(z)\boldsymbol{d}(z) \tag{2.66}$$

where $\boldsymbol{d}(z)$ is an unknown vector and $\boldsymbol{G}_d(z)$ is an estimated transfer function. When this approximate structure is exploited to design disturbance de–coupling residual generators, robust FDI can be achieved. This disturbance approximation technique will be presented in Section 4.7.

The second approach called *passive robustness* makes use of a residual evaluator with adaptive threshold. As a simple example, it is assumed that the residual generation uncertainty 2.63 is only represented by modelling errors.

The fault–free residual $\boldsymbol{r}(z)$ is

$$\boldsymbol{r}(z) = \boldsymbol{H}_y(z)\Delta \boldsymbol{G}_u(z)\boldsymbol{u}(z). \tag{2.67}$$

Under the assumption that the modelling errors are bounded by a value δ, such that

$$\| \Delta \boldsymbol{G}_u(w) \| \leq \delta \tag{2.68}$$

an adaptive threshold $\varepsilon(t)$ can be generated by a linear system

$$\varepsilon(t) = \delta \boldsymbol{H}_y(z)\boldsymbol{u}(z) \tag{2.69}$$

In such case, the threshold $\varepsilon(t)$ is no longer fixed but depend on the input $\boldsymbol{u}(t)$, thus being adaptive to the system operating point. A fault is then detected if

$$\| \boldsymbol{r}(t) \| > \| \varepsilon(t) \| \tag{2.70}$$

A robust FDI technique with the threshold adaptor or selector is therefore briefly recalled [Clark, 1989], [Emami-Naeini *et al.*, 1988], [Ding and Frank, 1991]. This method represents a passive approach since no effort is made to design a robust residual.

Even if disturbance de–coupling methods for robust FDI has been studied extensively, their effectiveness regarding real problems has not been fully demonstrated.

The main difficulty arises as most of the disturbance only account for a small percentage of the uncertainty in the real system. The presented disturbance decoupling methods cannot be directly applied to the systems with other uncertainties such as modelling errors.

The estimation and approximate representation of modelling errors as well as other uncertain factors as the disturbance term provides a practical way to tackle the robustness issue for real plants.

Chapter 4 provides a study of a different approach for representing modelling errors and other uncertain factors via the disturbance term with an estimated distribution matrix. As presented in Chapter 3, this identified distribution matrix will be used for the design of the disturbance de–coupled residual in order to solve the robust FDI problem.

2.8 Fault Diagnosis Technique Integration

Several FDI techniques have been developed and their application shows different properties with respect of the diagnosis of different faults in a process. In order to achieve a reliable FDI technique, a good solution consists of a proper integration of several methods which take advantages of the different procedures [Isermann, 1994a, Isermann and Ballé, 1997].

Furthermore, a comprehensive approach to fault diagnosis should exploit a knowledge–based treatment of all available analytical and heuristic information. This successful approach can be performed by an integrated method to knowledge–based fault diagnosis.

2.8.1 Fuzzy Logic for Residual Generation

As stated in Section 2.2, model–based FDI consists of two stages, residual generation and decision making.

The first block is exploited to generate residuals by means of the available inputs and outputs from the monitored system.

For the first step, classical fault diagnosis model–based methods can exploit state–space of input–output dynamic models of the process under investigation. Within this framework, faults are supposed to appear as changes on the system state or output caused by malfunctions of the components as well as of the sensors. Such fault indices are often monitored using estimation techniques.

The main problem with these techniques is that the precision of the process model affects the accuracy of the detection and isolation system as well as the diagnostic sensibility.

On the other hand, the majority of real industrial processes are non–linear [Chen and Patton, 1999, Gertler, 1998, Patton and Chen, 1997] and cannot be modelled by using a single model for all operating conditions.

Since a mathematical model is a description of system behaviour, accurate modelling for a complex non–linear system is very difficult to achieve in practice. Sometimes for some non–linear systems, it can be impossible to describe them by analytical equations. Moreover, sometimes the system structure or parameters are not precisely known and if diagnosis has to be based primarily on heuristic information, no qualitative model can be set up

Because of these assumptions, fuzzy system theory seems to be a natural tool to handle complicated and uncertain conditions [Babuška, 1998].

Instead of exploiting complicated non–linear models obtained by modelling techniques, it is also possible to describe the plant by a collection of local affine fuzzy and non–fuzzy models [Leontaritis and Billings, 1985a, Leontaritis and Billings, 1985b, Takagi and Sugeno, 1985], whose parameters are obtained by identification procedures.

The second stage of model–based FDI consists of a logic decision process that transforms residual signal information (quantitative knowledge) into qualitative statements (faulty or normal working conditions). Therefore, the problem of decision–making can be treated in a novel way by means of fuzzy logic.

As noise contamination and uncertainty affect the residuals even in fault–free conditions, so that they fluctuate and become unequal to zero. This common situation, which may hide the fault effects, can be handled by means of the fuzzy logic framework.

The interesting feature of fuzzy logic is that it represents a powerful tool for describing vague and imprecise fact and is therefore suited for applications where complete information about fault and system is not available to the designer.

Even if much effort has been spent on trying to decrease the uncertainty associated with quantitative residual generation, it is impossible to fully eliminate the effect of uncertainty. On the basis of this limitation, the residual evaluation problem consists of making the correct decision with respect to uncertain information. Fuzzy logic can be a suitable tool for this task. For instance, a lot of processes can be managed by humans heuristically since an analytical description is impossible to use. Fuzzy logic can express expert knowledge in the form of a rule–based knowledge format.

The introduction of fuzzy logic can improve the decision making in order to provide reliable FDI methods which are applicable for real industrial systems.

As an example, fuzzy logic can be exploited for residual evaluation mainly in the decision making stage for releasing the final yes–no decision [Ulieru and Isermann, 1993, Frank, 1994a, Meneganti *et al.*, 1998].

Rule–based expert systems have therefore been investigated very intensively for fault detection and diagnosis problems [Rich and Venkatasubramanian, 1987, Kramer, 1987, Patton *et al.*, 1989, Patton *et al.*, 2000]. Fault diagnosis using rule–based system needs a database of rules and the accuracy of diagnosis depend on the rules. Moreover, creating a rich and detailed database of rules is usually a time-consuming task and many process experts are needed.

It should finally be pointed out how the fuzzy approach in FDI can solve the problem at two levels: first, fuzzy descriptions are used to generate symptoms and then, the fault detection and isolation is achieved using again fuzzy logic [Dexter and Benouarets, 1997, Isermann, 1998].

2.8.2 Neural Networks in Fault Diagnosis

Quantitative model–based fault diagnosis generates symptoms on the basis of the analytical knowledge of the process under investigation. In most cases however, this does not provide enough information to perform an efficient FDI, *i.e.*, to indicate the location and the mode of the fault.

A typical integrated fault diagnosis system uses both analytical and heuristic knowledge of the monitored system. The knowledge can be processed in terms of residual generation (analytical knowledge) and feature extraction (heuristic knowledge). The processed knowledge is then provided to an inference mechanism which can comprise residual evaluation, symptom observation and *pattern recognition*.

In particular, when the process model is only known to a certain extent of precision, pattern recognition method can provide a convenient approach to solve the fault identification problem, *i.e.* to determine the size of the fault [Himmelblau, 1978, Pau, 1981].

In recent years, neural networks (NN) have been used successfully in pattern recognition as well as system identification, and they have been proposed as a possible technique for fault diagnosis, too.

NN can handle non–linear behaviour and partially known process because they learn the diagnostic requirements by means of the information of the training data.

NN are noise tolerant and their ability to generalise the knowledge as well as to adapt during use are extremely interesting properties [Hoskins and Himmelblau, 1988, Dietz *et al.*, 1989, Venkatasubramanian and Chan, 1989, McDuff and Simpson, 1990, Chen *et al.*, 1990a]. Some example processes were considered in which FDI was performed by a NN using input and output measurements. In these works the NN is trained to identify the fault from measurement patterns, however the classification of individual measurement pattern is not always unique in dynamic situations, therefore the straightforward use of NN in fault diagnosis of dynamic plant is not practical and other approaches should be investigated.

A NN could be exploited in order to find a dynamic model of the monitored system or connections from faults to residuals. In the latter case, the NN is used as pattern classifier or non–linear function approximator. In fact, artificial neural networks are capable of approximating a large class of functions, for fault diagnosis of an industrial plant.

Under these considerations, in Chapter 4, the identification of fuzzy and non–fuzzy models for the system under diagnosis as well as the application of NN as function approximator will be shown.

Quantitative and qualitative approaches have a lot of complementary characteristics which can be suitably combined together to exploit their advantages and to increase the robustness of quantitative techniques. The suggested combination can also minimise the disadvantages of the two procedures; in particular, it is important that partial knowledge deriving from qualitative reasoning is reduced by quantitative methods. Hence, the main aim of further research on model–based fault diagnosis consists of finding the way to properly combine these two approaches together to provide highly reliable diagnostic information.

2.8.3 Neuro-fuzzy Approaches to FDI

Identification of multivariable processes can be interpreted as a problem of approximation to an input–output mapping. The mathematical model used in traditional methods is sensitive to modelling errors, parameter variation, noise and disturbance [Chen and Patton, 1999, Patton *et al.*, 2000]. Process modelling has limitations, especially when the system is complex and uncertain and the data are ambiguous and not information rich.

As previously stated, NN are known to approximate any non–linear even dynamic function, given suitable weighting factors and architecture. Moreover, on–line training makes it possible to change the FDI system easily in cases where changes are made in the physical process or the control system. NN can generalise when presented with inputs not appearing in the training data and make intelligent decisions in cases of noisy or corrupted data. They are also readily applicable to multivariable systems and have a highly parallel structure, which is expected to achieve a higher degree of fault tolerance. A NN can operate simultaneously on qualitative and quantitative data. NN can be very useful when no mathematical model of the system is available, *i.e.* analytical models cannot be applied. 152

Almost all the physical processes are dynamic in nature. Combining dynamic elements such as filters and delays yield a powerful modelling technique. But the NN operates as a "black box" with no qualitative/quantitative information available of the model it represents. Usually, engineers and operators want to visualise how the system is working and what rules govern its operation. There is also ambiguity about the performance of the NN in case of unexpected situation [Korbicz *et al.*, 1999].

Fuzzy logic systems, on the other hand, have the ability to mimic the sensing, generalising, processing, operating and learning abilities of a human operator. They offer a linguistic model of the system dynamics which can be easily understood by certain rules. They also have inherent abilities to deal with imprecise or noisy data.

Fuzzy logic can be used with neural networks [Chiang *et al.*, 2001, chapt. 12]. A fuzzy neuron has the same basic structure as the artificial neuron, except that some or all of its components and parameters may be described through fuzzy logic. A fuzzy neural network is built on fuzzy neurons or on standard neurons but dealing with fuzzy data. A fuzzy neural network is a connectionist model for the implementation and inference of fuzzy rules. There are many different ways to fuzzify an artificial neuron, which results in a variety of fuzzy neurons and fuzzy networks [Chiang *et al.*, 2001, chapt. 12], [Nelles, 2001].

Different neuro–fuzzy structures can be therefore designed to combine the advantages of both neural networks and fuzzy logic [Patton *et al.*, 1999b, Calado *et al.*, 2001]. These structures have been successfully applied to a wide range of applications from industrial processes to financial systems, because of the ease of rule base design, linguistic modelling, application to complex and uncertain systems, inherent non-linear nature, learning abilities, parallel processing and fault–tolerance abilities [Wu and Harris, 1996, Ayoubi, 1995]. However, successful implementation depends heavily on prior knowledge of the system and the training data. There are three common methods of combining neural networks with the fuzzy logic.

1. Fuzzification of the inputs or outputs of the neural networks.
2. Fuzzification of the interconnections of conventional neural networks.
3. Using neural networks in fuzzy models where neurons provide the necessary membership functions and rule base.

All of the Neuro–fuzzy (NF) modelling structures combine, in a single framework, both numerical and symbolic knowledge about the process. Automatic linguistic rule extraction is a useful aspect of NF especially when little or no prior knowledge about the process is available [Brown and Harris, 1994a, Jang and Sur, 1995]. For example, a NF model of a non–linear dynamical system can be identified from the empirical data. This modelling approach can give us some insight about the non–linearity and dynamical properties of the system.

The most common NF systems are based on two types of fuzzy models TSK [Takagi and Sugeno, 1985, Sugeno and Kang, 1988] and [Mamdani, 1976, Mamdani and Assilian, 1995] combined with NN learning algorithms. TSK models use local linear models in the consequents, which are easier to interpret and can be used for control and fault diagnosis [Füssel *et al.*, 1997, Isermann and Ballé, 1997]. Mamdani models use fuzzy sets or rules as consequents and therefore give a more qualitative description.

The B–spline neural network (with triangular basis functions) is the simplest of all of the Mamdani NF structures, but the large consequent rule set means that the method is not easy to use due to low transparency.

Many neuro–fuzzy structures have been successfully applied to a wide range of applications from industrial processes to financial systems, because of the ease of rule base design, linguistic modelling, application to complex and uncertain systems, inherent non-linear nature, learning abilities, parallel processing and fault-tolerance abilities. However, successful implementation depends heavily on prior knowledge of the system and the empirical data [Ayoubi, 1995].

NF networks by their intrinsic nature can handle a limited number of inputs and can usually be identified in a not very transparent way from the empirical data. Transparency corresponds here to a more meaningful description of the process *i.e.* less rules with appropriate membership functions. In ANFIS [Jang, 1993, Jang and Sur, 1995] a fixed structure with grid partition is used. Antecedent and consequent parameters are identified by a combination of least-squares estimates and gradient based methods, the so–called called *hybrid learning rule*. This method is fast and easy to implement for low dimensional input spaces. It is more prone to losing the transparency and the local model accuracy because of the use of *error back-propagation* that is a global and not locally non–linear optimisation procedure. One possible method to overcome this problem can be to find the antecedents and rules separately *e.g.* clustering and constrain the antecedents, and then apply optimisation.

Hierarchical NF networks can be used to overcome the dimensionality problem by decomposing the system into a series of MISO and/or SISO systems called *hierarchical systems* [Tachibana and Furuhashi, 1994]. The local rules use subsets of input spaces and are activated by higher level rules.

The criteria on which to build a NF model are based on the requirements for fault diagnosis and the system characteristics. The function of the NF model in the FDI scheme is also important *i.e.* pre–processing data, identification (residual generation) or classification (decision making/fault isolation). For example, a NF model with high approximation capability and disturbance rejection is needed for identification so that the residuals are more accurate. Whereas, in the classification stage, a NF network with more transparency is required.

2.8.4 Structure Identification of NF Models

For complexity reduction and transparency, structure identification methods can be applied to find appropriate input partition, rules and membership functions (MFs). Methods like Evolutionary Algorithms (EA), Classification and Regression Trees CART [Jang, 1994], Clustering and unsupervised NN (*e.g.* like the Kohonen feature maps) can be used. Once the structure is determined *i.e.* the rules and input membership functions, the consequent parameters can be identified by optimisation techniques like Least–Squares Estimation. The Product Space Clustering approach can be used [Babuška, 1998] for structure identification of TSK and Mamdani fuzzy models. For a MISO non–linear dynamic system with p inputs, the Product Space $X \times Y \subset \Re^{p+1}$ is divided in subspaces in which linear models can approximate the non–linear system. The locally linear model tree LOLIMOT algorithm developed by Nelles and Isermann [Nelles and Isermann, 1996] can be used to identify a TSK fuzzy model with dynamic linear models as consequent. When using such structure identification techniques, a major issue is the sensitivity to uneven distribution of data. For example in most clustering algorithms, more clusters are created in regions with more data. A possible solution to this is problem may be to initialise the algorithm with large number of clusters.

Transparency of the NF models can be enhanced by tuning rules and MFs [Babuška, 1998]. This type of method is referred to as structure simplification/optimisation techniques. To find the optimal number of rules, different cluster validity measures and methods like Compatible Cluster Merging CCM [Krishnapuram and Freg, 1992] can be used. At the NF model level the rules are further simplified by merging similar fuzzy sets and removing fuzzy sets similar to the universal set. Setnes *et al.*, [Setnes and Kaymak, 1998] used a supervised fuzzy clustering algorithm that uses input–output data, orthogonal techniques and tuning for complexity reduction.

2.8.5 NF Residual Generation Scheme for FDI

Fig. 2.18 describes a FDI scheme in which several NF models are constructed to identify the faulty and the fault–free behaviour of the system.

$$r_i(t) = f\big(\boldsymbol{u}(t), \ldots, \boldsymbol{u}(t-n), \boldsymbol{y}(t), \ldots, \boldsymbol{y}(t-n)\big), \quad i = 1, \ldots, m \qquad (2.71)$$

Each residual $r_i(t)$ in 2.71 is ideally sensitive to one particular fault in the system. In practice however, as a consequence of noise and disturbances, residuals are sensitive to more than one fault.

To take into account the sensitivity of residuals to various faults and noise we apply a NF classifier. A linguistic style (Mamdani) NF network is used which processes the residuals to indicate the fault.

This NF model is constructed with following set of rules:

$$\textbf{If } r_1 \text{ is small } \ldots r_j \text{ is large } r_m \text{ is small } \textbf{then } \text{fault}_r \text{ is large} \qquad (2.72)$$

Fuzzy threshold evaluation in Equation 2.73 is employed to take into account the imprecision of the residual generator at different regions in the input space

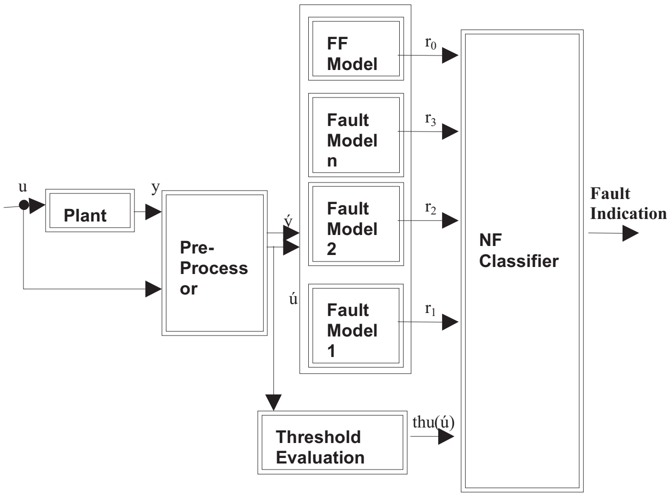


Fig. 2.18. Neuro–fuzzy based FDI scheme.

$$\mathrm{th}_{\nu}(\boldsymbol{u}) = \frac{\sum_{i=1}^{C} \mathrm{th}_i \; \eta_i(\boldsymbol{u})}{\sum_{i=1}^{C} \eta_i(\boldsymbol{u})} \tag{2.73}$$

where C is the total number of I/P regions with different sensitivity to faults and a multidimensional fuzzy set η_i defines the fuzzy boundary of i–th such region. This approach depends heavily on the availability of the faulty and fault–free data and it is more difficult to isolate faults that appear in the dynamics.

Residuals can also be generated by a non–linear dynamic model of the plant that approximates a non–linear dynamic system by local linear models. Such a model can be obtained by *Product space clustering* [Babuška, 1998], or tree–like algorithms (LOLIMOT algorithm by Nelles *et al.*, [Nelles and Isermann, 1996]). Each local model is a linear approximation of the process in an I/P subspace and the selection of the local model is fuzzy. The output of such a model can be described by:

$$y = \frac{\sum_{i=1}^{C} \alpha_i(\boldsymbol{u}_s) \; f_i}{\sum_{i=1}^{C} \alpha_i(\boldsymbol{u}_s)} \tag{2.74}$$

where f_i is the i–th local linear model given by:

$$f_i = \sum_{k=0}^{n} b_{i,k} \; \boldsymbol{u}(t-k) + \sum_{k=0}^{n} a_{i,k} \; \boldsymbol{y}(t-k) + c_i \tag{2.75}$$

$a_{i,k}$, $b_{i,k}$ and c_i are the parameters of the i–th model, $\boldsymbol{u}_s$ is the I/P subspace defining the operating point, α_i is the degree to which the i–th local model is valid at this operating point.

From $a_{i,k}$, $b_{i,k}$ and c_i, physical parameters like time constants, static gains, offsets, *etc.* [Füssel *et al.*, 1997] can be extracted for each operating point and can be compared with the parameters estimated online. This approach heavily depends on the accuracy of the non-linear dynamic model described above. Also the output error should be minimum when operated in parallel to the system. Moreover, this method requires that there is sufficient excitation at each operating point for online estimation of parameters. The TSK NF based FDI scheme is depicted in Figure 2.19.

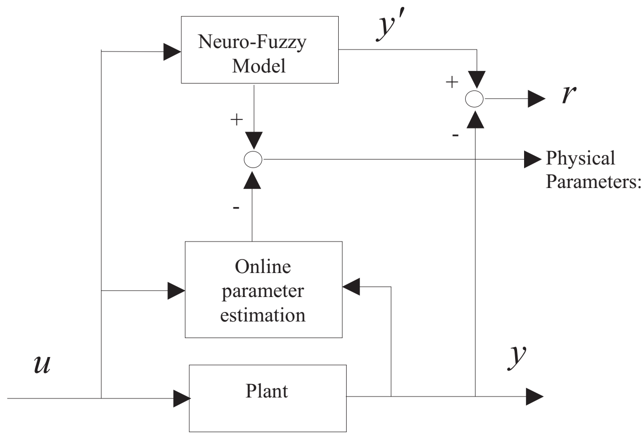


Fig. 2.19. TSK NF based FDI scheme.

2.9 Summary

This Chapter has presented a tutorial treatment on the basis principles of model-based FDI.

The FDI problem has been formalised in a uniform framework by presenting a mathematical description and definition. Within this framework, the residual generation has been identified as a central issue in model–based FDI. By choosing the proper design approach, the FDI task can be performed.

The residual generator has been summarised in different residual generation structures. The ways of designing residuals for isolation have also been discussed. The most commonly used residual generation techniques have been introduced by presenting related problems and discussing the applicability of model-based FDI methods.

It is worth noting that the success of fault diagnosis depends on the quality of the residuals. Successful diagnosis requires residual signals which should be robust with respect to modelling uncertainty. The robust FDI problem has been also discussed in this chapter and the implementation of a robust residual generator will be shown in the following chapters of the book.

Other FDI methods such as fuzzy logic, qualitative modelling and NN have been briefly discussed and the concept of integrated knowledge–based fault diagnosis, utilising both analytical and heuristic information has been presented.

[IFI, 1983] (1983). *Reliable computing and fault tolerance*, meeting in Como, Italy. IFIP working group 10.4.

[RAM, 1988] (1988). Reliability, Availability and maintainability Dictionary. ASQC Quality press. Milwaukee.

[Mat, 1990] (1990). *MATLAB User's Guide*. MathWorks Inc. South Natick, MA, U.S.A.

[Hyb, 1998] (1998). Special issue on hybrid control systems. IEEE Trans. on Automatic Control, vol. 43, n. 4.

[Akaike, 1974] Akaike, H. (1974). A new look at the statistical model identification. *IEEE Trans. Automatic Control*, 19(6):716–723.

[Alexandru *et al.*, 2000] Alexandru, M., Combastel, C., and Gentil, S. (2000). Diagnostic decision using recurrent neural network. In *Proc. of the 4th IFAC Symposium on Fault Detection, Supervision and Safety for Technical Processes*, volume 1, pages 410–415, Budapest, Hungary.

[Appleby *et al.*, 1991] Appleby, B., Dowdle, J., and Vander Velde, W. (1991). Robust estimator design using μ synthesis. In *Proc. of the 30th Conf on Decision & Control*, pages 640–644, Brighton, UK.

[Ayoubi, 1995] Ayoubi, M. (1995). Neuro–Fuzzy Structure for Rule Generation and Application in the Fault Diagnosis of Technical Processes. In *Proc. of the American Control Conference, ACC'95*, pages 2757–2761, Washington, USA.

[Babu and Murty, 1994] Babu, G. and Murty, M. (1994). Clustering with evolution strategies. *Pattern Recognition*, 27(2):321–329.

[Babuška, 1998] Babuška, R. (1998). *Fuzzy Modeling for Control*. Kluwer Academic Publishers.

[Babuška, 2000] Babuška, R. (2000). *Fuzzy Modelling and Identification Toolbox*. Control Engineering Laboratory, Faculty of Information Technology and Systems, Delft University of Technology, Delft, The Netherlands, version 3.1 edition. (Available at http://lcewww.et.tudelft.nl/ ˜babuska).

[Babuška *et al.*, 1997] Babuška, R., Keizer, R., and Verhaegen, M. (1997). Identification of nonlinear dynamic systemsas a composition of local linear parametric or state space models. In *Proc. of SYSID'97*, Fukuoka, Japan.

[Babuška and Verbruggen, 1995] Babuška, R. and Verbruggen, H. B. (1995). Identification of composite linear models via fuzzy clustering. In *Proc. 3rd ECC'95*, pages 1207–1212, Rome, Italy.

[Backer, 1995] Backer, E. (1995). *Computer–assisted reasoning in cluster analysis*. Prentice Hall, New York.

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

[Banks and Kathur, 1989] Banks, S. and Kathur, S. (1989). Structure and control of piecewise linear system. *Int. J. of Control*, 50:346–358.

[Basseville, 1988] Basseville, M. (1988). Detecting changes in signals and systems: A survey. *Automatica*, 24(3):309–326.

[Basseville, 1997] Basseville, M. (1997). Information criteria for residual generation and fault detection and isolation. *Automatica*, (33):783–803.

[Basseville and Benveniste, 1986] Basseville, M. and Benveniste, A. (1986). Detection of abrupt changes in signals and and dynamical systems. In *Lecture Notes in Control and Information Sciences*, volume 77, London. Springer–Verlag.

[Basseville and Nikiforov, 1993] Basseville, M. and Nikiforov, I. V. (1993). *Detection of Abrupt Changes: Theory and Application*. Prentice–Hall Inc.

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

[Beghelli *et al.*, 1994a] Beghelli, S., Castaldi, P., Guidorzi, R. P., and Soverini, U. (1994a). A comparison between different model selection criteria in Frisch scheme identification. *Systems Science Journal*, 20(1):77–84. Wroclaw, Polonia.

[Beghelli *et al.*, 1994b] Beghelli, S., Castaldi, P., and Soverini, U. (1994b). Dynamic Frisch scheme identification: time and frequency domain approaches. In *IFAC'94*. 10th IFAC Symposium on System Identification.

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

[Beghelli *et al.*, 1997] Beghelli, S., Guidorzi, R. P., and Soverini, U. (1997). A frequencial approach to the dynamic Frisch scheme identification. In *ECC'97*, Brussels, Belgium. 4th European Control Conference.

[Beghelli and Soverini, 1992] Beghelli, S. and Soverini, U. (1992). Identification of linear relations from noisy data: Geometrical aspects. *System and Control Letters*, 18(5):339–346.

[Bemporad and Morari, 1999] Bemporad, A. and Morari, M. (1999). Control od systems integrating logic, dynamics, and constraints. *Automatica*, 35(3):407–428.

[Benvenuti *et al.*, 1993] Benvenuti, E., Bettocchi, R., Cantore, G., and Negri di Montenegro, G. Spina, P. R. (1993). Gas Turbine Cycle Modelling Oriented to Component Performance Evaluation from Limited Design or Test Data. In *Proceeding of 7th ASME COGEN–TURBO*, pages 327–337, Bournemouth, UK.

[Bettocchi *et al.*, 1996] Bettocchi, R., Spina, P. R., and Fabbri, F. (1996). Dynamic Modelling of Single–Shaft Gas Turbine. In *ASME Paper 96–GT–332*, pages 1–9.

[Bezdek, 1980] Bezdek, J. (1980). A convergence theorem for the fuzzy isodata clustering algorighms. *IEEE Trans. Pattern Anal. Machine Intell.*, PAMI–2(1):1–8.

[Bezdek, 1981] Bezdek, J. (1981). *Pattern recognition with fuzzy objective function*. Plenum Press, New York.

[Bezdek *et al.*, 1987] Bezdek, J., Hathaway, R., Howard, R., Wilson, C., and Windham, M. (1987). Local convergence analysis of a grouped variable version of coordinate descendent. *Journal of Optimization Theory and Applications*, 54(3):471–477.

[Bezdek and Pal, 1992] Bezdek, J. and Pal, S. (1992). *Fuzzy models for pattern recognition*. IEEE Press, New York.

[Billings and Voon, 1983a] Billings, S. and Voon, W. (1983a). Structure detection and model validity test in the identification of nonlinear systems. *IEE Proceedings*, 130D(4):193–199.

[Billings and Voon, 1983b] Billings, S. and Voon, W. (1983b). Structure detection and model validity tests in the identification of nonlinear systems. *IEE Proc.*, 130(4):193–200.

[Billings and Voon, 1986] Billings, S. A. and Voon, W. (1986). Correlation based model validity test for non–linear models. *International Journal of Control*, 44(1):235–244.

[Blotenberg, 1993] Blotenberg, W. (1993). A model for the dynamic simulation of a two–shaft industrial gas turbine with dry low NOx combustor. In *ASME*, number 93–GT–355, pages 1–11. ASME.

[Boyd *et al.*, 1994] Boyd, S., Ghaoui, L., Feron, E., and Balakrishnan, V. (1994). *Linear Matrix Inequalities in System and Control Theory*. SIAM, Philadelphia.

[Brown and Harris, 1994a] Brown, M. and Harris, C. (1994a). *Neurofuzzy adaptive modelling and control*. Prentice Hall.

[Brown and Harris, 1994b] Brown, M. and Harris, C. (1994b). *Neurofuzzy Adaptive Modelling and Control*. Prentice Hall.

[Calado *et al.*, 2001] Calado, J., Korbicz, J., Patan, K., Patton, R., and Sá da Costa, J. (2001). Soft computing approaches to fault diagnosis for dynamic systems. *European Journal of Control*, 7(2–3):248–286.

[Carpenter and Grossberg, 1987] Carpenter, G. and Grossberg, S. (1987). A massively parallel architecture for a self-organizing neural pattern recognition machine. *Computer Vision, Graphics and Image Processing*, 37:54–115.

[Castaldi and Soverini, 1998] Castaldi, P. and Soverini, U. (1998). Identification of errors-in-variables models and optimal output reconstruction. In Beghi, A., Finesso, L., and Picci, G., editors, *Proc. of the MNST'98 Symposium*, pages 727–730, Padova, Italy. Il Poligrafo.

[Chang and Hsu, 1995] Chang, S. K. and Hsu, P. L. (1995). A novel design for the unknown input fault detection observer. *Control Theory and Advanced Technology*, 10(4).

[Chen and Patton, 1999] Chen, J. and Patton, R. J. (1999). *Robust Model–Based Fault Diagnosis for Dynamic Systems*. Kluwer Academic.

[Chen and Patton, 2000] Chen, J. and Patton, R. J. (2000). Standard H_∞ filter formulation of robust fault detection. In Edelmayer, A. M., editor, *SAFEPROCESS2000, 4th IFAC Symposium on Fault Detection, Supervision and Safety for Technical Processes*, volume 1, pages 256–261, Budapest, Hungary. IFAC 2000, IFAC 2000.

[Chen and Patton, 2001] Chen, J. and Patton, R. J. (2001). Fault–tolerant control systems design using the linear matrix inequality method. In *European Control Conference, ECC'01*, pages 1993–1998, Porto, Portugal.

[Chen *et al.*, 1996a] Chen, J., Patton, R. J., and Liu, G. P. (1996a). Optimal residual design for fault–diagnosis using multiobjective optimisation and genetic algorithms. *Int. J. Sys. Sci.*, 27(6):567–576.

[Chen *et al.*, 1993] Chen, J., Patton, R. J., and Zhang, H. Y. (1993). A multi–criteria optimization approach to the design of robust fault detection algorithm. In *Proc. of Int. Conf. on Fault Diagnosis: TOOLDIAG'93*, Toulouse, France.

[Chen *et al.*, 1996b] Chen, J., Patton, R. J., and Zhang, H. Y. (1996b). Design of unknown input observer and robust fault detection filters. *Int. J. Control*, 63(1):85–105.

[Chen *et al.*, 1990a] Chen, S., Billings, A. S., Cowan, C. F. N., and Grant, P. M. (1990a). Practical identification of NARMAX models using radial basis function. *Int. J. Control*, 52:1327–1350.

[Chen and Billings, 1989] Chen, S. and Billings, S. (1989). Representation of non–linear systems: the NARMAX model. *Int. J. Control*, 49:1013–1032.

[Chen *et al.*, 1990b] Chen, S., Billings, S., Cowan, C. F., and Grant, P. (1990b). Practical identification of NARMAX model using radial basis functions. *Int. J. Control*, 52:1327–1350.

[Chen *et al.*, 1991] Chen, S., Cowan, C., and Grant, P. (1991). Orthogonal least squares learning algorithm for radial basis function networks. *IEEE Trans. Neural Networks*, 2(2):302–309.

[Chen *et al.*, 1997] Chen, Z., Patton, R. J., and Chen, J. (1997). Robust fault-tolerant system synthesis via LMI. In *Proc. of IFAC Symposium on Fault Detection, Supervision and Safety for Technical Processes: SAFEPROCESS'97*, volume 1, pages 347–352, The University of Hull, UK.

[Chiang *et al.*, 2001] Chiang, L. H., Russel, E. L., and Braatz, R. D. (2001). *Fault Detection Diagnosis in Industrial Systems*. Advanced Textbooks in Control and Signal Processing. Springer–Verlag London Limited, London, Great Britain.

[Chow and Willsky, 1980] Chow, E. Y. and Willsky, A. S. (1980). Issue in the development of a general algorithm for reliable failure detection. In *Proc. of the 19th Conf. on Decision & Control*, Albuquerque, NM.

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

[Chowdhury and Aravena, 1998] Chowdhury, F. N. and Aravena, J. L. (1998). A modular methodology for fast fault detection and classification in power systems. *IEEE Trans. of Control System Technology*, 6(5).

[Chung and Speyer, 1998] Chung, W. H. and Speyer, J. L. (1998). A game theoretic fault detection filter. *IEEE Trean. on Automatic Control*, 43(2):143–161.

[Clark, 1978] Clark, R. N. (1978). Instrument fault detection. *IEEE Trans. Aero. & Electronic Systems*, 14(3).

[Clark, 1989] Clark, R. N. (1989). *Fault Diagnosis in Dynamic Systems: Theory and Application*, chapter 2, pages 21–45. Prentice Hall.

[Cottle, 1982] Cottle, R. (1982). Minimal triangulation of the 4-cube. *Discrete Mathematics*, 40:25–29.

[Daly *et al.*, 1979] Daly, K. C., Gai, E., and Harrison, J. V. (1979). Generalized likelihood test for FDI in redundancy sensor configurations. *J. of Guidance, Control & Dynamics*, 2(1):9–17.

[Davis, 1991] Davis, L. (1991). *Handbook of Genetic Algorithms*. Van Nostrand Reinhold, New York.

[de Boor, 1978] de Boor, C. (1978). *A practical guide to splines*. Springer–Verlag, New York.

[De Persis and Isidori, 2001] 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.

[Delmaire *et al.*, 1999] Delmaire, G., Cassar, P., Staroswiecki, M., and Christophe, C. (1999). Comparison of multivariable identification and parity space techniques for FDI purpose in M.I.M.O. systems. In *ECC'99*, Karlsruhe, Germany.

[Demuth and BealeDemuth, 1997] Demuth, H. and BealeDemuth, M. (1997). *Neural Network Toolbox For Use with MATLAB*. The MathWorks Inc., Version 3.0 edition. South Natick, MA, U.S.A.

[DeSarbo, 1982] DeSarbo, W. (1982). Gennclus: New models for general nonhierarchical clustering analysis. *Psychometrika*, 47(4):449–476.

[Dexter and Benouarets, 1997] Dexter, A. L. and Benouarets, M. (1997). Model–based fault diagnosis using fuzzy matching. *IEEE Trans. on Sys. Man. and Cyber. Part A: Sys. & Humans*, 27(5):673–682.

[Dietz *et al.*, 1989] Dietz, W. E., Kiech, E. L., and Ali, M. (1989). Jet and rocket engine fault diagnosis in real time. *J. of Neural Network Computing*, 1:5–18.

[Ding *et al.*, 1999] Ding, S. X., Jeinsch, T., Ding, E. L., Zhou, D., and Wang, G. (1999). Application of Observer–Based FDI Schemes to the Three Tank System. In *European Control Conference, ECC'99*, Karlsruhe, Germany.

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

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

[Ding and Frank, 1991] Ding, X. and Frank, P. M. (1991). Frequency domain approach and threshold selector for robust model–based fault detection and isolation. In *Preprint of IFAC/IMACS Symposium SAFEPROCESS'91*, volume 1, pages 307–312. Baden–Baden.

[Diversi and Guidorzi, 1998] Diversi, R. and Guidorzi, R. P. (1998). Filtering–oriented identification of multivariable errors-in-variables models. In Beghi, A., Finesso, L., and Picci, G., editors, *Proc. of the MNST'98 Symposium*, pages 775–778, Padova, Italy. Il Poligrafo.

[Diversi *et al.*, 2002] Diversi, R., Simani, S., and Soverini, U. (2002). Robust residual generation for dynamic processes using de–coupling technique. In *CCA'02. Proc. of the Conference on Control Applications*, Glasgow, Scotland. IEEE Control Systems Society.

[Drag and Patton, 2001] Drag, G. R. and Patton, R. J. (2001). Robust fault detection using Luenberger–type unknown input observers: a parametric approach. *Int. J. Systems Science*, 32(4).

[Duan *et al.*, 2002] Duan, G., How, D., and Patton, R. (2002). Robust Fault Detection in Descriptor Systems via Generalised Unknown Input Observers. *Int. J. Systems Science.*

[Duda and Hart, 1973] Duda, R. and Hart, P. (1973). *Pattern classification and scene analysis.* John Wiley & Sons, New York.

[Dunn, 1974] Dunn, J. (1974). A fuzzy relative of the ISODATA process and its use in detecting compact well–separated clusters. *International Journal of Cybernetics and Systems*, 3(3):32–57.

[Edelmayer *et al.*, 1997] Edelmayer, A., Bokor, J., and Keviczky, L. (1997). A scaled L_2 optimisation approach for improving sensitivity of $H_i nfty$ detection filters for LTV systems. In Bányász, C., editor, *Preprints of the 2nd IFAC Symp. on Robust Control Design: RECOND97*, pages 543–548, Budapest, Hungary.

[Edwards and Spurgeon, 1994] Edwards, C. and Spurgeon, S. (1994). On the development of discontinuous observers. *International Journal of Control*, 59(1):1211–1229.

[Edwards *et al.*, 2000] Edwards, C., Spurgeon, S. K., and Patton, R. J. (2000). Sliding mode observers for fault detection and isolation. *Automatica*, 36(1):541–553.

[Emami-Naeini *et al.*, 1988] Emami-Naeini, A., Akhter, M., and Rock, M. (1988). Effect of model uncertainty on failure detection: the threshold selector. *IEEE Trans. on Automatic Control*, 33(2).

[Fantuzzi and Rovatti, 1996] Fantuzzi, C. and Rovatti, R. (1996). On the approximation capabilities of the homogeneous Takagi–Sugeno model. *Proceedings of the Fifth IEEE International Conference on Fuzzy Systems*, pages 1067–1072.

[Fantuzzi *et al.*, 1998] Fantuzzi, C., Rovatti, R., Simani, S., and Beghelli, S. (1998). Fuzzy modeling with noisy data. In *EUFIT'98*, volume 3, pages 1615–1619, Aachen, Germany. The 6th European Congress on Intelligent Techniques and Soft Computing.

[Fantuzzi and Simani, 2002] Fantuzzi, C. and Simani, S. (2002). Parametric identification in robust fault detection. In *IFAC'02*, Balcelona, Spain. 15th IFAC World Congress on Automatic Control. Invited paper, accepted.

[Fantuzzi *et al.*, 2001a] Fantuzzi, C., Simani, S., and Beghelli, S. (2001a). Parameter identification for eigenstructure assignment in robust fault detection. In *ECC'01*, pages 149–154, Porto, Portugal. European Control Conference 2001.

[Fantuzzi *et al.*, 2001b] Fantuzzi, C., Simani, S., and Beghelli, S. (2001b). Robust fault diagnosis of dynamic processes using parametric identification with eigenstructure assignment approach. In CSS, I., editor, *CDC'01*, pages 155–160, Orlando, Florida, U.S.A. 2001, 40th IEEE Conference on Decision and Control.

[Fantuzzi *et al.*, 2002] Fantuzzi, C., Simani, S., Beghelli, S., and Rovatti, R. (2002). Identification of piecewise affine models in noisy environment. *International Journal of Control.* accepted.

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

[Frank, 1990] 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, 1993] Frank, P. M. (1993). Advances in observer-based fault diagnosis. *Proc. TOOLDIAG'93 Conference*. CERT, Toulose (F).

[Frank, 1994a] Frank, P. M. (1994a). Application of fuzzy logic process supervision and fault diagnosis. In *SAFEPROCESS'94: Preprints of the IFAC Symposium on Fault Detection, Supervision and Safety for Technical Processes*, volume 2, pages 531–538, Espoo, Finland.

[Frank, 1994b] Frank, P. M. (1994b). Enhancement of robustness on observer-based fault detection. *International Journal of Control*, 59(4):955–983.

[Frank *et al.*, 2000] Frank, P. M., Ding, S. X., and Köpper-Seliger, B. (2000). Current Developments in the Theory of FDI. In *SAFEPROCESS'00: Preprints of the IFAC Symposium on Fault Detection, Supervision and Safety for Technical Processes*, volume 1, pages 16–27, Budapest, Hungary.

[Frank and Ding, 1997] Frank, P. M. and Ding, X. (1997). Survey of robust residual generation and evaluation methods in observer-based fault detection system. *Journal of Process Control*, 7(6):403–424.

[Friedmann, 1991] Friedmann, J. (1991). Multivariable adaptive regression Splines. *The Annal of Statistics*, pages 1–141.

[Frisch, 1934] Frisch, R. (1934). *Statistical Confluenece Analysis by Means of Complete Regression Systems*. University of Oslo, Economic Institute, publication n. 5 edition.

[Funahashi, 1989] Funahashi, K. (1989). On the approximate realization of continous mappings by neural networks. *Neural Networks*, 2:183–192.

[Füssel *et al.*, 1997] Füssel, D., Ballé, P., and Isermann, R. (1997). Closed loop fault diagnosis based on a non-linear process model and automatic fuzzy rule generation. In *Proc. of IFAC Symposium on Fault Detection, Supervision and Safety for Technical Process SAFEPROCESS'97*, The University of Hull, UK.

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

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

[Gertler, 1991] Gertler, J. (1991). Generating directional residuals with dynamic parity equations. *Proc. IFAC/IMACS Symp. SAFEPROCESS'91*. Baden Baden (G).

[Gertler, 1995] Gertler, J. (1995). Diagnosing Parametric Faults: from Parameter Estimation to Parity Relations. In *ACC'95*, pages 1615–1620, Seatle, Washingtown.

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

[Gertler and Monajemy, 1993] Gertler, J. and Monajemy, R. (1993). Generating directional residuals with dynamic parity equations. *Proc. of the 12th IFAC World Congress*, 7:505–510. Sydney.

[Gertler and Singer, 1990] Gertler, J. and Singer, D. (1990). A new structural framework for parity equation–based failure detection and isolation. *Automatica*, 26(2):381–388.

[Goldberg, 1989] Goldberg, D. E. (1989). *Genetic Algorithms in Search, Optimisation and Machine Learning*. Addison Wesley Publishing Company.

[Guidorzi, 1975] Guidorzi, R. P. (1975). Canonical Structures in the Identification. *Automatica*, 11:361–374.

[Guidorzi, 1981] Guidorzi, R. P. (1981). Invariants and canonical forms for system structural and parametric identification. *Automatica*, (17):117–133.

[Guidorzi, 1996] Guidorzi, R. P. (1996). On the use of minimal parametrisations in multivariable ARMAX identification. In *IFAC'96*, pages 31–36, S. Francisco, USA. 13th IFAC World Congress.

[Guidorzi *et al.*, 1982] Guidorzi, R. P., Losito, P., and Muratori, T. (1982). The range error test in the structural identification of linear multivariable systems. *IEEE Transactions on Automatic Control*, 27(5):1044–1054.

[Gustafson and Kessel, 1979] Gustafson, D. E. and Kessel, W. C. (1979). Fuzzy clustering with a variance covariance matrix. In *Proc. IEEE CDC'79*, pages 161–166, San Diego, CA, USA.

[Hadamard, 1964] Hadamard, J. (1964). *La theorie des equations aus derivees partielles.* Editions Scientifiques, Pekin.

[Haiman, 1991] Haiman, M. (1991). A simple and relatively efficient triangulation of the n-cube. *Discrete Computational Geometry*, 6:287–289.

[Hathaway and Bezdek, 1983] Hathaway, R. and Bezdek, J. (1983). Switching regression models and fuzzy clustering. *IEEE Trans. of Fuzzy Systems*, 1(3).

[Hermans and Zarrop, 1996] Hermans, F. and Zarrop, M. (1996). Sliding mode observers for robust sensor monitoring. In *Proceedings 13th IFAC World Congress*, pages 211–216, San Francisco, USA.

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

[Himmelblau *et al.*, 1991] Himmelblau, D. M., Barker, R. W., and Suewatanakul, W. (1991). Fault classification with the aid of artificial neural networks. In *IFAC/IMACS Symposium SAFEPROCESS '91*, volume 2, pages 369–373, Baden Baden, Germany.

[Höfling and Pfeufer, 1994] Höfling, T. and Pfeufer, T. (1994). Detection of additive and multiplicative faults - Parity space vs. parameter estimation. In *Proc. IFAC SAFEPROCESS Symposium '94*, Espoo, Finland.

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

[Hoskins and Himmelblau, 1988] Hoskins, J. C. and Himmelblau, D. M. (1988). Artificial neural network models of knowledge representation in chemical engineering. *Comp. chem. Engng*, 12:881–890.

[Hou and Patton, 1996] Hou, M. and Patton, R. J. (1996). An LMI approach to H_-/H_∞ fault detection observers. In *CONTROL'96*, pages 305–310, University of Exter, UK. IEE.

[Hou and Patton, 1997] Hou, M. and Patton, R. J. (1997). An $\mathrm{H}_\infty/\mathrm{H}_-$ approach to the design of robust fault diagnosis observers based upon LMI optimisation. In *Proceedings of the 4th European Control Conference, ECC'97*, Brussels.

[Hunt *et al.*, 1992a] Hunt, J., Lee, M., and Price, C. (1992a). An introduction to qualitative model-based reasoning. In *Preprints IFAC/IFIP/IMACS Int. Sym. on Artificial Intelligence in Real-Time Control*, Delft (The Nederland).

[Hunt *et al.*, 1992b] Hunt, K., Sbarbaro, D., Zbikowki, R., and Gawthrop, P. (1992b). Neural networks for control system: a survey. *IEEE Trans. Neural Networks*, 28:1083–1112.

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

[Isermann, 1992] Isermann, R. (1992). Estimation of physical parameters for dynamic processes with application to an industrial robot. *Int. J. of Control*, 55:1287–1298.

[Isermann, 1993] Isermann, R. (1993). Fault diagnosis via parameter estimation and knowledge processing. *Automatica*, 29(4):815–835.

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

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

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

[Isermann, 1998] Isermann, R. (1998). On fuzzy logic applications for automatic control, supervision and fault diagnosis. *IEEE Trans. on Sys. Man. and Cyber. Part A: Sys. & Humans*, 28(2):221–235.

[Isermann and Ballé, 1997] 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 and Freyermuth, 1992] Isermann, R. and Freyermuth, B., editors (1992). *Fault Detection, Supervision and Safety for Technical Processes*, volume 6 of *IFAC Symposia Series*. SAFEPROCESS'91, Pergamon Press.

[Isermann and Füssel, 1999] Isermann, R. and Füssel, D. (1999). Knowledge-based fault detection and diagnosis systems. Tutorial workshop in ECC 1999, Karlsruhe,Germany.

[Jackson, 1991] Jackson, J. E. (1991). *A user's guide to principal components*. Wiley-Interscience, N.J.

[Jager, 1995] Jager, R. (1995). *Fuzzy logic in control*. PhD thesis, Delft University of Technology, Delft, The Netherlands.

[Jain and Dubes, 1988] Jain, A. and Dubes, R. (1988). *Algorithms for clustering data*. Englewood Cliffs: Prentice Hall.

[Jang, 1993] Jang, J. (1993). ANFIS: Adaptive network based fuzzy inference system. *IEEE Transactions on Systems, Man., & Cybernetics*, 23(3):665–684.

[Jang, 1994] Jang, J. (1994). Structure determination in fuzzy modelling: a fuzzy CART approach. In *Proc. of IEEE International Conf. on Fuzzy Systems*.

[Jang and Sur, 1995] Jang, J. and Sur, R. (1995). Neuro–fuzzy modeling and control. *Proc. IEEE*, 83(3):378–405.

[Jazwinski, 1970] Jazwinski, A. H. (1970). *Stochastic processes and filtering theory*. Academic Press, New York.

[Johansen and Foss, 1993] Johansen, T. and Foss, B. (1993). Constructing NARMAX models using ARMAX models. *Int. J. Control*, 58(5):1125–1153.

[Johansen, 1996] Johansen, T. A. (1996). Robust identification of takagi-sugeno-kang fuzzy models using regularization. In *Fifth IEEE International Conference on Fuzzy Systems*, New Orleans, USA.

[Jones, 1973] Jones, H. L. (1973). *Failure detection in linear systems*. PhD thesis, Dept. of Aeronautics, M.I.T., Cambridge, Mass.

[Juditsky *et al.*, 1995] Juditsky, A., Hjalmarsson, H., Beneviste, A., Delyon, B. Ljung, L., Sjöberg, J., and Zhang, Q. (1995). Nonlinear black–box modelling in system identification: a mathematical foundation. *Automatica*, 31(12):1691–1724.

[Kalman, 1982a] Kalman, R. E. (1982a). Identification from real data. In Hazewinkel, M. and Rinnoy Kan, A. H. G., editors, *Current Developments in the Interface: Economics, Econometrics, Mathematics,*, pages 161–196. D. Reidel, Dordrecht, The Netherlands.

[Kalman, 1982b] Kalman, R. E. (1982b). System Identification from Noisy Data. In Bednarek, A. R. and Cesari, L., editors, *Dynamical System II*, pages 135–164. Academic Press, New York.

[Kalman, 1984] Kalman, R. E. (1984). Identification of noisy systems. In *50th Anniversary Symp. Steklov Institute of Mathematics, U.S.S.R. Academy of Sciences*, Moskva.

[Kalman, 1990] Kalman, R. E. ((Springer-Verlag, Berlin, 1990)). Nine lectures on identification. *Lecture Notes on Economics and Mathematical System*.

[Kavuri and Venkatasubramanian, 1994] Kavuri, S. N. and Venkatasubramanian, V. (1994). Neural network decomposition strategies for large-scale fault diagnosis. *Int. J. of Control*, 59(3):767–792.

[Klir and Yuan, 1995] Klir, G. J. and Yuan, B. (1995). *Fuzzy Sets and Fuzzy Logic: Theory and Applications*. Prentice Hall.

[Korbicz *et al.*, 1999] Korbicz, J., Patan, K., and Obuchowicz, A. (1999). Dynamic neural network for process modelling in fault detection and isolation systems. *Applied Mathematics and Computer Science*, 9(2):519–546. Technical University of Zielona Gora, Poland.

[Korbicz and Obuchowitcz, 1999] Korbicz, J. anf Patan, K. and Obuchowitcz, K. (1999). Dynamic neural networks for process modelling in fault detection and isolation systems. *Journal of Applied Mathematics and Computer Science*, 9(3):519–546.

[Koscielny *et al.*, 1999] Koscielny, J., Syfert, M., and Bartys, M. (1999). Fuzzy–logic fault diagnosis of industrial process actuators. *Journal of Applied Mathematics and Computer Science*, 9(3):637–652.

[Kosko, 1994] Kosko, B. (1994). Fuzzy systems as universal approximators. *IEEE Transactions on Computers*, 43:1329–1333.

[Kramer, 1987] Kramer, M. A. (1987). Malfunction diagnosis using quantitative models with non-boolean reasoning in expert systems. *AIChE*, (33):130–140.

[Krishnapuram and Freg, 1992] Krishnapuram, R. and Freg, C. (1992). Fitting an unknown number of lines and planes to image data through compatible cluster merging. *Pattern Recognition*, 25(4):385–400.

[Lee *et al.*, 1994] Lee, Y., Hwang, C., and Shih, Y. (1994). A combined approach to fuzzy model identification. *IEEE Trans. Sys. Man, Cybern.*, 24(5):736–744.

[Leonard and Kramer, 1991] Leonard, J. A. and Kramer, M. A. (1991). Radial basis function for calssifying process faults. *IEEE Control System Magazine*, 11(3):31–38.

[Leontaritis and Billings, 1985b] Leontaritis, I. and Billings, S. A. (1985b). Input-output parametric models for non–linear systems part II: stochastic non-linear systems. *Int. J. Control*, 41(2):329–344.

[Leontaritis and Billings, 1985a] Leontaritis, I. and Billings, S. A. (1985a). Input-output parametric models for non-linear systems part I: deterministic non-linear systems. *Int. J. Control*, 41(2):303–328.

[Leshno *et al.*, 1993] Leshno, M., Lin, V. Y., Pinkus, A., and Shocken, S. (1993). Multilayer feedforward networks with a non polynomial activation function can approximate any function. *Neural Networks*, 6:861–867.

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

[Ljung, 1999] Ljung, L. (1999). *System Identification: Theory for the User*. Prentice Hall, Englewood Cliffs, N.J., second edition.

[Lou *et al.*, 1986] Lou, X., Willsky, A., and Verghese, G. (1986). Optimal robust redudancy relations for failure detection in uncertainty systems. *Automatica*, 22(3):333–344.

[Luenberger, 1971] Luenberger, D. G. (1971). An introduction to observers. *IEEE Transactions on Automatic Control*, AC-16(6):596–602.

[Luenberger, 1979] Luenberger, D. G. (1979). *Introduction to Dynamic System: Theory, Models and Application*. John Wiley and Son, New York.

[Mamdani, 1976] Mamdani, E. (1976). Advances in the linguistic synthesis of fuzzy controllers. *Int. J. Man–Machine Studies*, 8:669–678.

[Mamdani and Assilian, 1995] Mamdani, E. and Assilian, S. (1995). An experiment in linguistic synthesis with fuzzy logic controller. *Int. J. Man–Machine Studies*, 7(1):1–13.

[Mangoubi *et al.*, 1992] Mangoubi, R., Appleby, B. D., and Farrell, J. R. (1992). Robust estimation in fault detection. In *Proc. of the 31st Conf. on Decision & Control*, pages 2317–2322, Tucson, AZ, USA.

[Mara, 1976] Mara, P. (1976). Triangulation for the cube. *Journal of Combinatorial Theory (A)*, 20:170–177.

[Marcu and Mirea, 1997] Marcu, T. and Mirea, L. (1997). Robust detection and isolation of process faults using neural networks. *IEEE Control System Magazine*, pages 72–79.

[Marcu *et al.*, 1999] Marcu, T., Mirea, L., and Frank, P. (1999). Development of dynamic neural networks with application to observer–based fault detection and isolation. *Journal of Applied Mathematics and Computer Science*, 9(3):547–570.

[Massoumnia *et al.*, 1989] Massoumnia, M., Verghese, G. C., and Willsky, A. S. (1989). Failure detection and identification. *IEEE Trans. Automat. Contr.*, 34:316–321.

[Massoumnia, 1986] Massoumnia, M. A. (1986). *A geometric appoach to failure detection and identification in linear systems*. PhD thesis, Massachusetts Institute of Technology, Massachusetts, USA.

[MathWorks, 1998] MathWorks (1998). *Neural Network Toolbox: User's Guide*. MathWorks Inc. South Natick, MA, U.S.A.

[McDuff and Simpson, 1990] McDuff, R. J. and Simpson, P. K. (1990). An adaptive reasonance diagnostic system. *J. of Neural Network Computing*, (2):19–29.

[McGraw and Harbisson-Briggs, 1989] McGraw, K. and Harbisson-Briggs, K. (1989). *Knowledge Acquisition: Principles and Guidelines*. Englewood Cliffs: Prentice Hall.

[Meneganti *et al.*, 1998] Meneganti, M., Saviello, F., and Tagliaferri, R. (1998). Fuzzy neural networks for classification and detection of anomalies. *IEEE Trans. on Neural Networks*, 9(5):848–861.

[Morozov, 1984] Morozov, V. (1984). *Methods for Solving Incorrectly Posed Problems*. Springer, Berlin.

[Murray-Smith and Johansen, 1997] Murray-Smith, R. and Johansen, T. A. (1997). *Multiple model approaches to nonlinear modelling and control*. Taylor & Frencis, London, UK.

[Napolitano *et al.*, 1998] Napolitano, M. R., Widon, D. A., Casanova, J. L., Innocenti, M., and Silvestri, G. (1998). Kalman filters and neural–networks schemes for sensor validation in flight control system. *IEEE Trans. on Control System Technology*, 6(5):596–611.

[Nauck and Kruse, 1998] Nauck, D. and Kruse, R. (1998). Nefclass – a soft computing tool to build readable fuzzy classifiers. *BT Technol. Journal*, 16(3).

[Nelles, 2001] Nelles, O. (2001). *Nonlinear System Identification*. Springer–Verlag Berlin Heidelberg, Germany.

[Nelles and Isermann, 1996] Nelles, O. and Isermann, R. (1996). Basis function networks for interpolation of local linear models. In *Proc. of the 35th IEEE Conference on Decision and Control*, volume 4, pages 470–475, Kobe, Japan.

[Niemann and Stoustrup, 1996] Niemann, H. and Stoustrup, J. (1996). Filter design for failure detection and isolation in the presence of modelling errors and disturbances. In *Proc. of the 35th IEEE Conf. on Decision and Contr.*, pages 1155–1160, Kobe, Japan.

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

[Palade *et al.*, 2002] Palade, V., Patton, R. J., Uppal, F. J., Quevedo, J., and Daley, S. (2002). Fault diagnosis of an industrial gas turbine using neuro–fuzzy methods. In *IFAC'02*, Balcelona, Spain. 15th IFAC World Congress on Automatic Control.

[Patton and Chen, 1993] Patton, R. and Chen, J. (1993). Optimal selection of unknown input distribution matrix in the design of robust observers for fault diagnosis. *Automatica*, 29(4):837–841.

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

[Patton *et al.*, 1992] Patton, R., Chen, J., and Zhang, H. (1992). Modelling methods for improving robustness in fault diagnosis of jet engine system. In *31*-st *IEEE Conference on Decision and Control*, pages 2330–2335.

[Patton *et al.*, 1999a] Patton, R., Lopez-Toribio, C., and Uppal, F. (1999a). Artificial Intelligence Approaches to fault diagnosis for dynamic systems. *Journal of Applied Mathematics and Computer Science*, 9(3):471–518.

[Patton *et al.*, 1986] Patton, R., Willcox, S., and Winter, J. (1986). A parameter insensitive technique for aircraft sensor fault diagnosis using eigenstructure assignment and analytical redundancy. In *Proc. of the AIAA Conference on Guidance, Navigation & Control*, number 86–2029–CP, Williamsburg, VA.

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

[Patton and Chen, 1991a] Patton, R. J. and Chen, J. (1991a). A review of parity space approaches to fault diagnosis. In *IFAC Symposium SAFEPROCESS '91*, Baden-Baden.

[Patton and Chen, 1991b] Patton, R. J. and Chen, J. (1991b). Robust fault detection using eigenstructure assignment: a tutorial consideration and some new results. *30*–th *IEEE Conference on Decision and Control*, pages 2242–2247.

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

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

[Patton and Chen, 1997] Patton, R. J. and Chen, J. (1997). Observer–based fault detection and isolation: Robustness and applications. *Control Eng. Practice*, 5(5):671–682.

[Patton and Chen, 2000] Patton, R. J. and Chen, J. (2000). On eigenstructure assignment for robust fault diagnosis. *Int. J. of Robust & Non–Linear Control*, 10(9).

[Patton *et al.*, 1989] Patton, R. J., Frank, P. M., and Clark, R. N., editors (1989). *Fault Diagnosis in Dynamic Systems, Theory and Application*. Control Engineering Series. Prentice Hall, London.

[Patton *et al.*, 2000] Patton, R. J., Frank, P. M., and Clark, R. N., editors (2000). *Issues of Fault Diagnosis for Dynamic Systems*. Springer–Verlag, London Limited.

[Patton and Hou, 1997] Patton, R. J. and Hou, M. (1997). h_∞ estimation and robust fault detection. In *Proc. of the 1997 European Control Conference*, Brussels, Belgium. ECC'97. (CD-ROM).

[Patton and Hou, 1998] Patton, R. J. and Hou, M. (1998). Design of fault detection and isolation observers: a matrix pencil approach. *Automatica*, 34:1135–1140.

[Patton *et al.*, 2001a] Patton, R. J., Lopez-Toribio, C. J., and Simani, S. (2001a). Robust fault diagnosis in a chemical process using multiple model identification. In CSS, I., editor, *CDC'01*, pages 149–154, Orlando, Florida, U.S.A. 2001, 40th IEEE Conference on Decision and Control.

[Patton *et al.*, 2001b] Patton, R. J., Lopez-Toribio, C. J., Simani, S., Morris, J., Martin, E., and Zhang, J. (2001b). Actuator fault diagnosis in a continuous stirred tank reactor using identification techniques. In *ECC'01*, pages 2729–2734, Porto, Portugal. European Control Conference 2001.

[Patton *et al.*, 1999b] Patton, R. J., Lopez-Toribio, C. J., and Uppal, F. I. (1999b). Artificial Intelligence Approaches to Fault Diagnosis. *Applied Mathematics and Computer Science*, 9(3):471–518.

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

[Pettit and Wellstead, 1995] Pettit, N. and Wellstead, P. (1995). Analyzing piecewise linear dynamical systems. *IEEE Control System*, pages 43–50.

[Potter and Suman, 1977] Potter, I. E. and Suman, M. C. (1977). Thresholdless redundancy management with array of skewed instruments. Technical Report AGARDOGRAPH-224, AGARD, Integrity in Electronic Flight Control Systems.

[Priestly, 1988] Priestly, M. (1988). *Non–linear non–stationary time series analysis*. Academic press.

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

[Ray and Luck, 1991] Ray, A. and Luck, R. (1991). An introduction to sensor signal validation in redundant measurement systems. *IEEE Contr. Syst. Mag.*, 11(2):44–49.

[Rich and Venkatasubramanian, 1987] Rich, S. H. and Venkatasubramanian, V. (1987). Model-based reasoning in diagnostic expert system for chemical process plant. *Comp. chem. Engng*, 11:111–122.

[Rissanen, 1978] Rissanen, J. (1978). Modelling by shortest data description. *Automatica*, (14):465–471.

[Rovatti, 1996] Rovatti, R. (1996). Takagi–sugeno models as approximators in sobolev norms: the siso case. In *Fifth IEEE International Conference on Fuzzy Systems*, New Orleans (Louisiana).

[Rovatti *et al.*, 1998a] Rovatti, R., Borgatti, M., and Guerrieri, R. (1998a). A geometric approach to maximum-speed n-dimensional linear interpolation in rectangular grids. *IEEE Transactions on Computers*, 47:894–899.

[Rovatti *et al.*, 2000] Rovatti, R., Fantuzzi, C., and Simani, S. (2000). High–speed DSP–based implementation of piecewise–affine and piecewise–quadratic fuzzy systems. *The Signal Processing Journal*, 80(6):951–963.

[Rovatti *et al.*, 1998b] Rovatti, R., Fantuzzi, C., Simani, S., and Beghelli, S. (1998b). Parameter Identification for Piecewise Linear Model with Weakly Varying Noise. In *CDC'98*, volume 4, pages 4488–4489, Tampa, Florida. 1998 IEEE Conference on Decision and Control.

[Sadrnia *et al.*, 1997] Sadrnia, M. A., Chen, J., and Patton, R. J. (1997). Robust H_∞/μ observer–based residual generation for fault diagnosis. In Pergamon, ., editor, *Proc. of the IFAC Symp. on Fault Detection, Supervision and Safety for Technical Processes: SAFEPROCESS'97*, pages 155–162, Univ. of Hull, UK.

[Sallee, 1982] Sallee, J. (1982). A triangulation of the n-cube. *Discrete Mathematics*, 40:81–86.

[Sallee, 1984] Sallee, J. (1984). Middle-cut triangulations of the n-cube. *SIAM Journal on Algebraic and Discrete Methods*, 5:407–419.

[Sauter *et al.*, 1997] Sauter, D., Rambeaux, F., and Hamelin, F. (1997). Robust fault diagnosis in a H_∞ setting. In Pergamon, ., editor, *Proc. of the IFAC Symp. on Fault Detection, Supervision and Safety for Technical Processes: SAFEPROCESS'97*, pages 867–874, Univ. of Hull, UK.

[Schilling *et al.*, 2001] Schilling, R., Carroll, J.J., J., and Al-Ajlouni, A. (2001). Approximation of non–linear systems with radial basis function neural networks. *IEEE Transactions on Neural Networks*, 12(1):1–15.

[Seber and Wild, 1989] Seber, G. and Wild, C. (1989). *Nonlinear regression*. John Wiley & Sons, New York.

[Setnes and Kaymak, 1998] Setnes, M. and Kaymak, U. (1998). Extended fuzzy c–means with volume prototypes and cluster merging. In *Proceedings EUFIT'98*, volume 3, pages 1360–1364, Aachen, Germany.

[Shann and Fu, 1995] Shann, J. and Fu, H. (1995). A fuzzy neural network for rule acquiring on fuzzy control systems. *Fuzzy Sets and Systems*, 71(1):345–357.

[Shapiro, 1977] Shapiro, A. H. (1977). *The Dynamics and Thermodynamics of Compressible Fluid Flow*. John Wiley and Sons;, London.

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

[Simani, 1999a] Simani, S. (1999a). Fuzzy multiple inference identification and its application to fault diagnosis of industrial processes. In *ISAS'99/SCI'99*, volume 7, pages 185–191, Orlando, FL, USA. The Fifth Conference of the ISAS (Information Systems Analysis and Synthesis)/The Third Conference of the SCI (Systemics, Cybernetics and Informatics).

[Simani, 1999b] Simani, S. (1999b). Sensor fault diagnosis of a power plant: an approach based on state estimation techniques. In Mastorakis, N. E., editor, *IMACS-IEEE'99*, volume Recent Advances in Signal Processing and Communications, pages 274–281, Athens. International Conference on Computer Engineering in System Applications, World Scientific Engineering Society.

[Simani, 2000a] Simani, S. (2000a). Fault Diagnosis of a Power Plant at Different Operating Points using Neural Networks. In *SAFEPROCESS2000*, volume 1, pages 192–196, Budapest, Hungary. 4th Symposium on Fault Detection Supervision and Safety for Technical Processes. Invited session.

[Simani, 2000b] Simani, S. (2000b). Multi Model Based Fault Diagnosis of a Sugar Cane Crushing Process. In *SAFEPROCESS2000*, volume 2, pages 657–662, Budapest, Hungary. 4th Symposium on Fault Detection Supervision and Safety for Technical Processes.

[Simani and Fantuzzi, 2000] Simani, S. and Fantuzzi, C. (2000). Fault diagnosis in power plant using neural networks. *International Journal of Information Sciences*, 127(3–4):125–136. Special Issue: Applications to Intelligent Manufacturing and Fault Diagnosis: PART 1 - Fault Diagnosis.

[Simani and Fantuzzi, 2002] Simani, S. and Fantuzzi, C. (2002). Neural networks for fault diagnosis and identification of industrial processes. In *ESANN'02*, pages 489–494, Bruges, Belgium. Proc. of the 10th European Symposium on Artificial Neural Networks. Invited paper.

[Simani *et al.*, 1999a] Simani, S., Fantuzzi, C., and Beghelli, S. (1999a). Improved observer for sensor fault diagnosis of a power plant. In *MED99. The 7th IEEE Mediterranean Conference on Control & Automation*, pages 826–834, Haifa, Israel.

[Simani *et al.*, 2000a] Simani, S., Fantuzzi, C., and Beghelli, S. (2000a). Diagnosis techniques for sensor faults of industrial processes. *IEEE Transactions on Control Systems Technology*, 8(5):848–855.

[Simani *et al.*, 2002] Simani, S., Fantuzzi, C., and Patton, R. (2002). Identification and fault diagnosis of a simulated model of an industrial gas turbine. *IEEE Transactions on Control Systems Technology*. (under revision).

[Simani *et al.*, 1998a] Simani, S., Fantuzzi, C., Rovatti, R., and Beghelli, S. (1998a). Noise rejection in parameters identification for piecewise linear fuzzy models.

In *WCCI'98, FUZZ-IEEE'98*, pages 378–383, Ancorage, Alaska. 1998 IEEE International Conference on Fuzzy Systems.

[Simani *et al.*, 1999b] Simani, S., Fantuzzi, C., Rovatti, R., and Beghelli, S. (1999b). Non–linear algebraic system identification via piecewise affine models in stochastic environment. In *CDC'99*, pages 1083–1088, Phoenix, AZ, U.S.A. 1999 IEEE Conference on Decision and Control.

[Simani *et al.*, 1999c] Simani, S., Fantuzzi, C., Rovatti, R., and Beghelli, S. (1999c). Parameter identification for piecewise linear fuzzy models in noisy environment. *International Journal of Approximate Reasoning*, 1–2(22):149–167.

[Simani *et al.*, 1998b] Simani, S., Fantuzzi, C., and Spina, P. R. (1998b). Application of a neural network in gas turbine control sensor fault detection. In *CCA'98*, volume 1, pages 182–186, Trieste, Italy. 1998 IEEE Conference on Control Applications.

[Simani *et al.*, 1999d] Simani, S., Marangon, F., and Fantuzzi, C. (1999d). Fault diagnosis in a power plant using artificial neural networks: analysis and comparison. In *ECC'99*, pages 1–6, Karlsruhe, Germany. European Control Conference 1999.

[Simani and Patton, 1999] Simani, S. and Patton, R. J. (1999). Identification and fault diagnosis of a simulated model of an industrial gas turbine. Technical Report 1, Department of Electronic Engineering at the University of Hull, Hull, U.K.

[Simani and Patton, 2002a] Simani, S. and Patton, R. J. (2002a). Model–based data–driven approaches to robust fault diagnosis in chemical processes. In *IFAC'02*, Balcelona, Spain. 15th IFAC World Congress on Automatic Control. Invited paper.

[Simani and Patton, 2002b] Simani, S. and Patton, R. J. (2002b). Neural networks for fault diagnosis of industrial plants at different working points. In *ESANN'02*, pages 495–500, Bruges, Belgium. Proc. of the 10th European Symposium on Artificial Neural Networks. Invited paper.

[Simani *et al.*, 2000b] Simani, S., Patton, R. J., Daley, S., and Pike, A. (2000b). Fault diagnosis of a simulated model of an industrial gas turbine prototype using identification techniques. In *SAFEPROCESS2000*, volume 1, pages 518–524, Budapest, Hungary. 4th Symposium on Fault Detection Supervision and Safety for Technical Processes.

[Simani *et al.*, 2000c] Simani, S., Patton, R. J., Daley, S., and Pike, A. (2000c). Identification and fault diagnosis of an industrial gas turbine prototype model. In CSS, I., editor, *CDC'00*, pages 2615–2620, Sydney, Australia. 2000, 39th IEEE Conference on Decision and Control.

[Simani and Spina, 1998] Simani, S. and Spina, P. R. (1998). Kalman filtering to enhance the gas turbine control sensor fault detection. In *6th IEEE Med '98*, pages 443–450, Alghero, Sardinia, Italy. The 6th IEEE Mediterranean Conference on Control and Automation.

[Simani *et al.*, 1998c] Simani, S., Spina, P. R., Beghelli, S., Bettocchi, R., and Fantuzzi, C. (1998c). Fault detection and isolation based on dynamic observers applied to gas turbine control sensors. In *ASME TURBO EXPO LAND, SEA & AIR '98*, number 98-GT-158 in ASME, pages 1–11, Stockholm, Sweden. The 43rd ASME Gas Turbine and Aeroengine Congress, Exposition and Users Symposium, STOCKHOLM INTERNATIONAL FAIR.

[Sjöberg *et al.*, 1995] Sjöberg, J., Zhang, Q., Ljung, L., Beneviste, A., Delyon, B., Glorennec, P.-Y., Hjalmarsson, H., and Juditsky, A. (1995). Nonlinear black–box modelling in system identification: a unified overview. *Automatica*, 31(12):1691–1724.

[Skeppstedt *et al.*, 1992] Skeppstedt, A., Ljung, L., and Millnert, M. (1992). Construction of composite models from observed data. *Int. J. Control*, 55:141–152.

[Slotine *et al.*, 1987] Slotine, J., Hedrick, J., and Misawa, E. (1987). On sliding observers for nonlinear systems. *Transactions of the ASME: Journal of Dynamic Systems, Measurement and Control*, 109:245–252.

[Sneider and Frank, 1996] Sneider, H. and Frank, P. (1996). Observer–based supervision and fault detection in robots using nonlinear and fuzzy logic residual evaluation. *IEEE Transactions on Control Systems Technology*, 4(3):274–282.

[Söderström and Stoica, 1987] Söderström, T. and Stoica, P. (1987). *System Identification*. Prentice Hall, Englewood Cliffs, N.J.

[Sontag, 1981] Sontag, E. (1981). Nonlinear regulation: The piecewise linear approach. *IEEE Trans. on Automatic Control*, 26:346–358.

[Speyer, 1999] Speyer, J. L. (1999). Residual sensitive fault detection filters. In *MED'99*, pages 835–851, Haifa, Israel.

[Sreedhar *et al.*, 1993] Sreedhar, R., Fernandez, B., and Masada, G. (1993). Robust fault detection in nonlinear systems using sliding mode observers. In *Proceedings of the IEEE Conference on Control Applications*, pages 715–721.

[Stoustrup and Niemann, 1998] Stoustrup, I. and Niemann, H. (1998). Fault detection for nonlinear systems - a standard problem approach. In *Proc. of the 37th IEEE Conf. on Decision & Control*, pages 96–101, Tampa, Florida, USA.

[Stoustrup *et al.*, 1997] Stoustrup, J., Grimble, M. J., and Niemann, H. (1997). Design of integrated systems for the control and detection of actuator/sensor faults. *Sensor Review*, 17(2):138–149.

[Strang and Fix, 1973] Strang, G. and Fix, G. (1973). *An Analysis of the Finite Element Method*. Prentice-Hall.

[Sugeno and Kang, 1988] Sugeno, M. and Kang, G. (1988). Structure identification of fuzzy model. *Fuzzy Set and Systems*, 28:15–33.

[Tachibana and Furuhashi, 1994] Tachibana, K. and Furuhashi, T. (1994). A hierarchical fuzzy modelling method using genetic algorithm for identification of concise submodels. In *Proc. of 2nd Int. Conference on Knowledge–Based Intelligent Electronic Systems*, Adelaide, Australia.

[Takagi and Sugeno, 1985] Takagi, T. and Sugeno, M. (1985). Fuzzy identification of systems and its application to modeling and control. *IEEE Transaction on System, Man and Cybernetics*, SMC-15(1):116–132.

[Tan and Edwards, 2001] Tan, C. P. and Edwards, C. (2001). An LMI approach for designing sliding mode observers for fault detection and isolation. In *European Control Conference, ECC'01*, pages 481–486, Porto, Portugal.

[The MathWorks Inc, 1990] The MathWorks Inc (1990). *MATLAB User's Guide*. The MathWorks, Inc, Natick, Massachusetts, USA.

[The MathWorks Inc, 1991] The MathWorks Inc (1991). *SIMULINK User's Guide*. Mathworks Inc, Natick, Massachusetts, USA.

[Tikhonov and Arsenin, 1977] Tikhonov, A. and Arsenin, V. (1977). *Solution of Ill-posed Problems*. Winston and Wiley, Washington.

[Tou and Gonzalez, 1974] Tou, J. T. and Gonzalez, R. C. (1974). *Pattern recognition principles*. Addison–Wesley Publishing.

[Ulieru and Isermann, 1993] Ulieru, M. and Isermann, R. (1993). Design of fuzzy–logic based diagnostic model for technical process. *Fuzzy Set and Systems*, 58(3):249–271.

[Uppal and Patton, 2002] Uppal, F. J. and Patton, R. J. (2002). Fault diagnosis of an electro–pneumatic valve actuator using neural networks with fuzzy capabilities. In *ESANN'02*, Bruges, Belgium. Proc. of the 10th European Symposium on Artificial Neural Networks. Invited paper.

[Uppal *et al.*, 2002] Uppal, F. J., Patton, R. J., and Palade, V. (2002). Neuro-fuzzy based fault diagnosis applied to an electro–pneumatic valve. In *IFAC'02*, Balcelona, Spain. 15th IFAC World Congress on Automatic Control.

[Utkin, 1977] Utkin, V. (1977). Variable structure with sliding modes. *IEEE Trans. AC*, 22:212–222.

[Utkin, 1992] Utkin, V. (1992). *Sliding modes in control and optimisation*. Springer–Verlag, Berlin, 3rd edition.

[van Huffel and Vandewalle, 1991] van Huffel, S. and Vandewalle, J. (1991). The Total Least Squares Problem: Computational Aspects and Analysis. *Frontiers in Applied Mathematics*. Philadelphia, USA.

[Venkatasubramanian and Chan, 1989] Venkatasubramanian, V. and Chan, K. (1989). A neural network methodology for process fault diagnosis. *AIChE J.*, (35):1993–2002.

[Verhaegen and Dewilde, 1992] Verhaegen, M. and Dewilde, P. (1992). Subspace model identification. Part I: the output error state space model identification class of algorithms. *International Journal of Control*, 56(1):1187–1210.

[Walcott and Żak, 1988] Walcott, B. and Żak, S. (1988). Combined observer–controller synthesis for uncertain dynamical systems with applications. *IEEE Transactions on Systems, Man. and Cybernetics*, 18:88–104.

[Wang, 1992] Wang, L. (1992). Fuzzy systems are universal approximators. In *Proc. first IEEE Int. Conf. on Fuzzy Syst.*, S. Diego (CA).

[Wang, 1995] Wang, L.-X. (1995). The design and analysis of fuzzy identifiers of nonlinear dynamic systems. *IEEE Transaction on Automatic Control*, 40(1):11–23.

[Wang *et al.*, 1975] Wang, S. H., Davison, E. J., and Dorato, P. (1975). Observing the state of systems with unmeasurable disturbance. *IEEE Trans. on Automatic Control*, 20:716–717.

[Watanabe and Himmelblau, 1982] Watanabe, K. and Himmelblau, D. M. (1982). Instrument fault detection in systems with uncertainties. *Int. J. System Sci.*, 13(2):137–158.

[Weerasinghe *et al.*, 1998] Weerasinghe, M., Gomm, J., and Williams, D. (1998). Neural network for fault diagnosis of a nuclear fuel processing plant at different operating points. *Control Engineering Practice*, 6:281–289.

[Werbos, 1990] Werbos, P. J. (1990). Backpropagation through time: what it does and how to do it. *Proc. IEEE*, 78(10):1550–1560.

[Widrow and Lehr, 1990] Widrow, B. and Lehr, M. A. (1990). 30 years of adaptive neural networks: Perceptron, madaline, and backpropagation. *Proc. IEEE*, 78(9):1415–1442.

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

[Wu and Harris, 1996] Wu, Z. Q. and Harris, C. J. (1996). Neuro–fuzzy modelling and state estimation. In *IEEE Medit. Symp. on Control and Automation: Circuits, Systems and Computers '96*, pages 603–610, Hellenic Naval Academy, Piraeus, Greece.

[Wünnenberg, 1990] Wünnenberg, J. (1990). *Observer–based fault detection in dynamic systems*. PhD thesis, University of Duisburg, Duisburg, Germany.

[Wünnenberg and Frank, 1987] Wünnenberg, J. and Frank, P. M. (1987). Sensor fault detection via robust observer. In *System Fault Diagnosis, Reliability, and Related Knowledge-Based Approaches*, volume 1, pages 147–160. S. Tzafestas et al edition.

[Wünnenberg and Frank, 1990] Wünnenberg, J. and Frank, P. M. (1990). Robust observer–based detection for linear and non–linear systems with application to robot. In *Proc. of IMACS Annals on Computing & Applied Mathematics MIM–S^2:90*, Brussels.

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

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

[Ying, 1994] Ying, H. (1994). Sufficient conditions on general fuzzy systems as function approximators. *Automatica*, 30:521–525.

[Yu *et al.*, 1999] Yu, D., Gomm, J., and Williams, D. (1999). Sensor fault diagnosis in a chemical process via RBF Neural Networks. *Control Engineering Practice*, 7:49–55.

[Zeng and Singh, 1996] Zeng, X.-J. and Singh, M. (1996). Approximation accuracy analysis of fuzzy systems as function approximators. *IEEE Transactions on Fuzzy Systems*, 4:44–63.

[Zhang and Morris, 1996] Zhang, J. and Morris, J. (1996). Process modeling and fault diagnosis using fuzzy neural networks. *Fuzzy Sets and Systems*, 79(1):127–140.

[Zhou *et al.*, 1996] Zhou, K., Doyle, J. C., and Glover, K. (1996). *Robust and Optimal Control*. Prentice Hall, New Jersey.

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