1

Mathematical Modeling and Fault Description

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1.1. 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 large number of methods can be found in current literature based on the use of the mathematical models of the process under investigation and on exploiting modern control theory.

Model-based fault detection methods use residuals that indicate changes between the process and the model. One general assumption is that the residuals are changed significantly so that 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 fault detection and isolation (FDI) techniques related to the applications described in this book.

For all of the methods considered, it is essential that the process can be described by a mathematical model. As there is almost never an exact agreement between the

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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 concerns the accuracy of the model describing the behavior of the monitored system. This issue has become a central research theme over recent years, as modeling uncertainty has risen from the impossibility of obtaining complete knowledge and understanding of the monitored process.

The main focus of this chapter is the modeling 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, because, 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 is presented.

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

1.2. Model-based FDI Techniques

According to the definitions given in the literature, 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 terms of 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 1.1 shows the general and logic block diagram of the model-based FDI system.

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

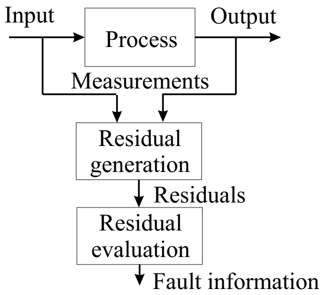

Figure 1.1. *Structure of the model-based FDI system*

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, while indistinguishably 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 1.1, 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 1.1, 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, for example, generalized 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 1.3 presents a number of different strategies for solving the quantitative residual generation problem.

1.3. Modeling of faulty systems

This chapter is mainly concerned with multi-input single-output (MISO) and multi-input multi-output (MIMO) dynamic systems.

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

The detailed scheme for the FDI techniques presented here is depicted in Figure 1.2.

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*.

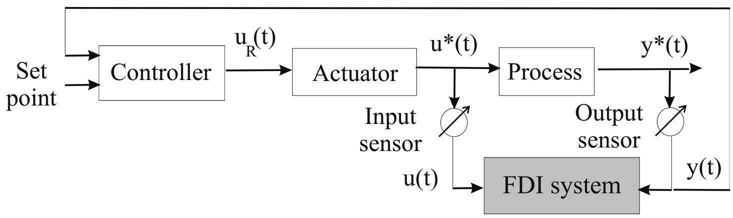

Figure 1.2. *Closed-loop FDI system*

In the following, the system working conditions will be monitored by means of its input $u(t)$ and output $y(t)$ measurements and signals from the controller $u_R(t)$, which are supposedly completely available for FDI purposes. Also, as shown in Figure 1.3, the behavior of any controller that drives the system is inherently taken into consideration.

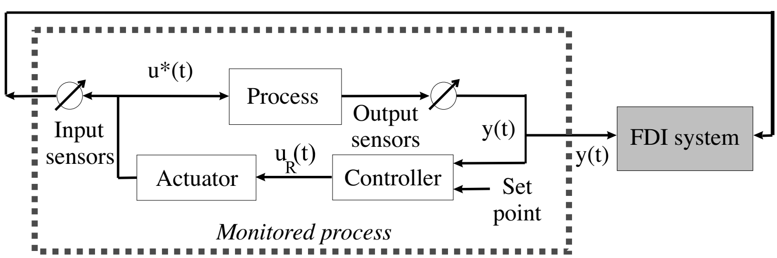

Figure 1.3. *The rearranged FDI scheme*

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

Once the actual process inputs and outputs $u^*(t)$ and $y^*(t)$ (usually unavailable) are measured by the input and output sensors, FDI theory can be treated as an observation problem of $u(t)$ and $y(t)$. The monitored system considered for FDI purpose can be therefore rearranged, as illustrated in Figure 1.3.

1.3.1. *Fault modeling and description*

Concerning the occurrence of malfunctions, the *location of faults* and their modeling, 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;

– controllers.

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

Figure 1.3 shows that the input and output signals $u^*(t)$ and $y^*(t)$ are acquired in order to obtain the measurements $u(t)$ and $y(t)$ from the sensors. This fault scenario can be summarized by the diagram shown in Figure 1.4.

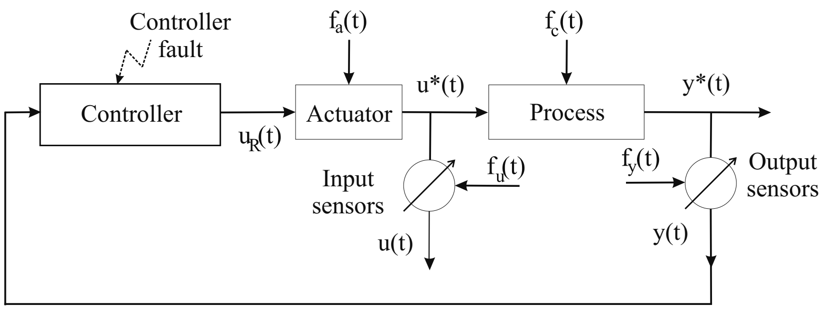

Figure 1.4. *Monitored system and fault topology*

Figure 1.4 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 a subsystem where faults are likelier to occur, while the latter remains free from faults.

Under these assumptions, as depicted in Figure 1.5, when the system is considered in view of fault location, since input and output measurements are supposedly completely available for FDI purposes, the controller behavior in the design of a fault diagnosis scheme can be neglected, as well as the interconnection between the control system and the process.

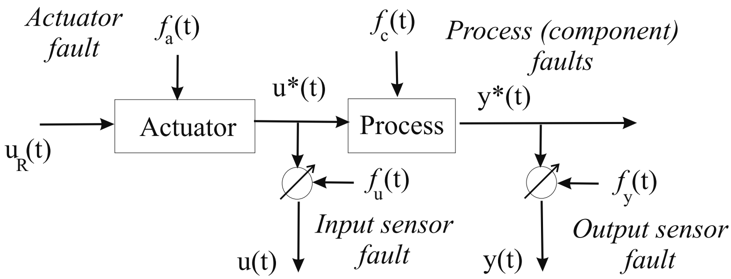

Figure 1.5. *The monitored system and fault typology*

1.3.2. *Mathematical description*

Under the hypothesis of linearity, the process dynamics considered in this chapter are described by the following discrete-time, time-invariant, linear dynamic system in the state–space form

$$\begin{cases} x(t+1) = Ax(t) + Bu^*(t) \\ y^*(t) \quad = Cx(t) \end{cases} \quad [1.1]$$

where $x(t) \in \Re^n$ is the system state vector, $u^*(t) \in \Re^r$ is the input signal vector driven by actuators and $y^*(t) \in \Re^m$ is the real system output vector, which is not directly available. A, B and C are system matrices with appropriate dimensions obtained by a modeling or identification procedure.

With reference to Figure 1.5, a component fault vector $f_c(t)$ affects process dynamics as follows:

$$x(t+1) = Ax(t) + Bu^*(t) + f_c(t) \quad [1.2]$$

In some cases, component faults come from a change in the system parameters, for example, a change in the entries of the A matrix. For example, a change in the ith row and the jth column of the A matrix leads to a fault vector $f_c(t)$ described as

$$f_c(t) = I_i \Delta a_{ij} x_j(t) \quad [1.3]$$

where $x_j(t)$ is the jth element of the vector $x(t)$ and I_i is an n-dimensional vector with all zero, except a “1” in the ith element.

As stated previously, as the actual process output $y^*(t)$ is not directly available, a sensor is used to acquire a measure of the system outputs. Moreover, generally speaking, a sensor can also be used to measure the system inputs $u^*(t)$ (e.g. for an uncontrolled system).

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

$$\begin{cases} u(t) = u^*(t) + f_u(t) \\ y(t) = y^*(t) + f_y(t) \end{cases} \tag{1.4}$$

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

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

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

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 $u(t)$ and $y(t)$ with additive noise can be modeled as:

$$\begin{cases} u(t) = u^*(t) + \tilde{u}(t) \\ y(t) = y^*(t) + \tilde{y}(t) \end{cases} \tag{1.5}$$

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

In this case, taking into account the effects of faults and noise, [1.4] has to be replaced by:

$$\begin{cases} u(t) = u^*(t) + \tilde{u}(t) + f_u(t) \\ y(t) = y^*(t) + \tilde{y}(t) + f_y(t) \end{cases} \tag{1.6}$$

By neglecting the actuator block, Figure 1.6 shows the structure of the measurement process.

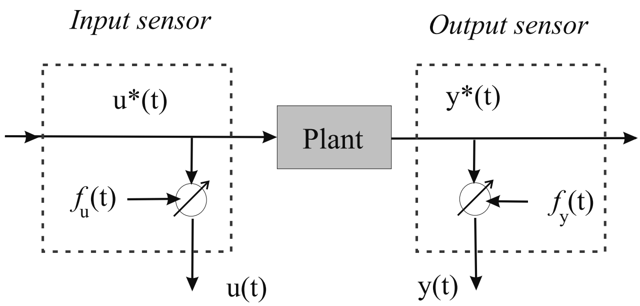

Figure 1.6. *The structure of the plant sensors*

Model descriptions of the types of equations [1.1] and [1.5] are also known as Errors-In-Variables models (Kalman 1982b, 1990). They will be briefly recalled later in this chapter.

With reference to a controlled system, according to Figure 1.5, signals $u^*(t)$ are the actuator response to the command signals $u_R(t)$.

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

$$u^*(t) = u_R(t) + f_a(t) \tag{1.7}$$

where, similarly to the input–output sensor fault situation, $f_a(t) \in \Re^r$ is the actuator fault vector.

In general, as shown in Figure 1.5, if the actuation signals $u^*(t)$ 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:

$$\begin{cases} x(t+1) = Ax(t) + f_c(t) + Bu^*(t) \\ y(t) \quad\quad = Cx(t) + f_y(t) \\ u(t) \quad\quad = u^*(t) + f_u(t) \end{cases} \tag{1.8}$$

On the other hand, Figure 1.7 represents the case where the 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 1.5.

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

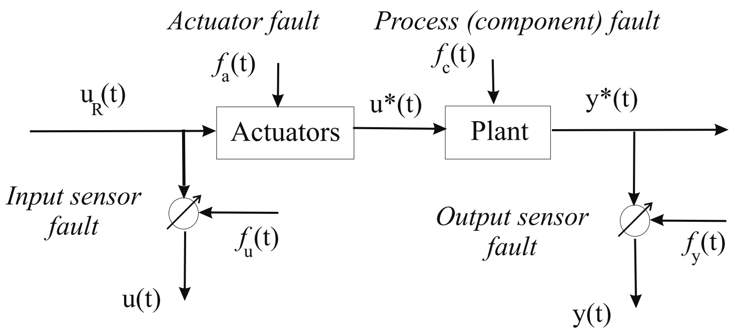

Figure 1.7. *Fault topology with actuator input signal measurement*

By also taking into account actuator faults $f_a(t)$, the below description is obtained:

$$\begin{cases} x(t+1) = Ax(t) + f_c(t) + Bf_a(t) + Bu^*(t) \\ y(t) \quad = Cx(t) + f_y(t) \\ u(t) \quad = u^*(t) + f_u(t) \end{cases} \quad [1.9]$$

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

$$\begin{cases} x(t+1) = Ax(t) + Bu^*(t) + L_1 f(t) \\ y(t) \quad = Cx(t) + L_2 f(t) \\ u(t) \quad = u^*(t) + L_3 f(t) \end{cases} \quad [1.10]$$

where the entries of the vector $f(t) = [f_a^T,\ f_u^T,\ f_c^T,\ f_y^T]^T \in \Re^k$ correspond to specific faults.

In practice, it is reasonable to assume that the fault signals are described by *unknown* time functions. The matrices L_1, L_2, L_3 are known as faulty entry matrices, which describe how the faults enter the system.

The vectors $u(t)$ and $y(t)$ are the available and measurable inputs and outputs, respectively. Both vectors are supposedly known for FDI purposes.

The distribution of the fault in the system, depicted in Figure 1.5, can be described as an input–output transfer matrix representation in the following form:

$$y(z) = G_{yu^*}(z)u^*(z) + G_{yf}(z)f(z) \quad [1.11]$$

with z being the unitary advance operator while the transfer matrices $G_{yu^*}(z)$ and $G_{yf}(z)$ are defined as:

$$\begin{cases} G_{yu^*}(z) = C(zI - A)^{-1}B \\ G_{yf}(z) \ = C(zI - A)^{-1}L_1 + L_2 \end{cases} \qquad [1.12]$$

Both of the general models for FDI described by equations [1.10] and [1.11] in the time and frequency domain, respectively, have been widely accepted in the fault diagnosis literature (Patton *et al.* 1989, 2000; Chen and Patton 1999; Gertler 1998).

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

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 modeling and robust residual generation, both for the deterministic case (noise free measurements) and the stochastic case (measurements affected by noises), the system matrices A, B and C, [1.10], 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 known from the system identification framework, 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, in connection with the model-based residual generation problem.

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

There is certainly an increasing interest in the use of nonlinear methods (nonlinear 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 behavior can be used to monitor system performance changes, as well as component malfunctions.

1.4. Residual generation

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

The most frequently used FDI methods exploit the *a priori* knowledge of the 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 the unknown working conditions of the system under diagnosis are the 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 1.1 can be interpreted as illustrated in Figure 1.8 (Basseville 1988).

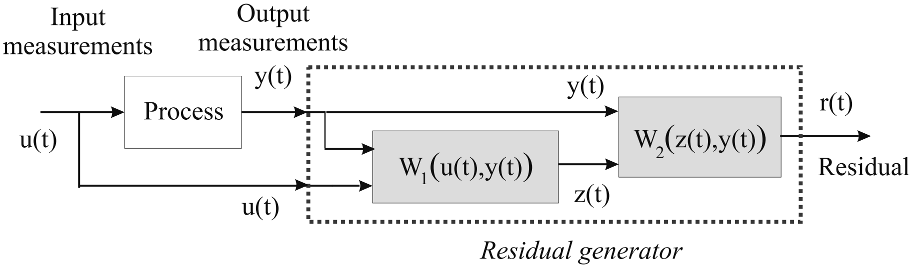

Figure 1.8. *Residual generator general structure*

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

In the fault-free case, the following relations are satisfied:

$$\begin{cases} z(t) = W_1\big(u(\cdot), y(\cdot)\big) \\ r(t) = W_2\big(z(\cdot), y(\cdot)\big) = 0. \end{cases} \qquad [1.13]$$

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

The simplest residual generator is depicted in Figure 1.9 and it is obtained when the system W_1 is a plant identical model $z(t) = W_1\big(u(\cdot)\big)$, or it is an input–output description for the actual process obtained from the system identification procedure (e.g. an Auto-Regressive eXogenous (ARX) model).

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

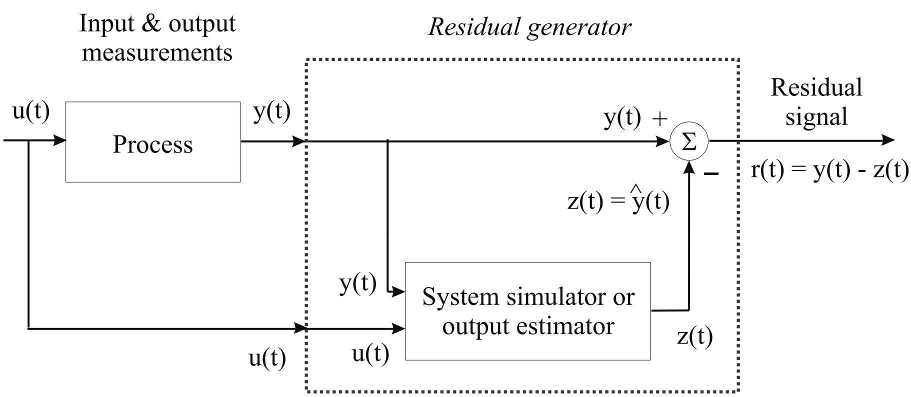

Figure 1.9. *System simulator or output estimator for residual generation*

An extension to the model-based residual generation is to replace $W_1\big(u(\cdot)\big)$ by $W_1\big(u(\cdot), y(\cdot)\big)$, that is, 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 $W_1\big(u(\cdot), y(\cdot)\big) = My(t)$, while function W_2 can be defined as $W_2\big(z(\cdot), y(\cdot)\big) = W\big(z(t) - My(t)\big)$, with W as a weighting matrix.

Therefore, 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 1.10 represents a general structure for all residual generators using the input–output transfer matrix description presented in Patton and Chen (1991a).

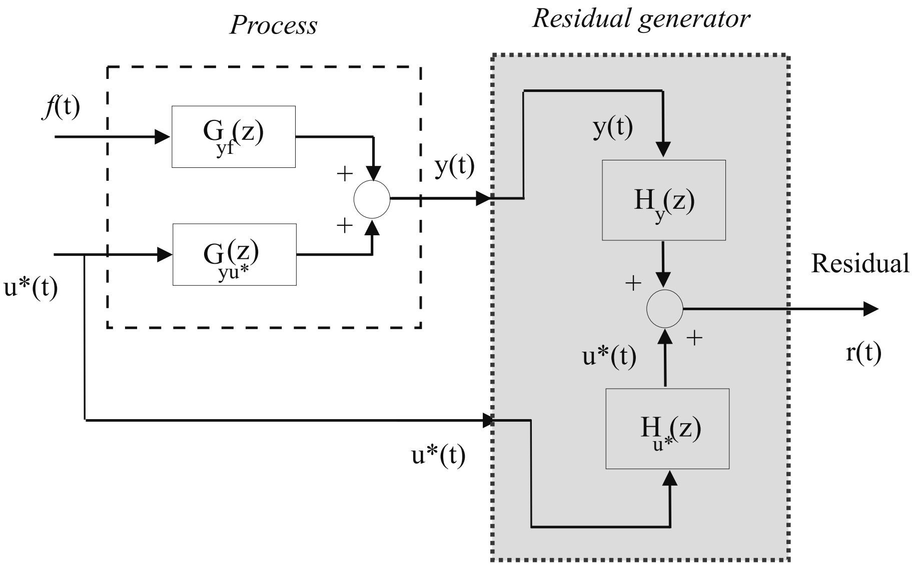

Figure 1.10. *Transfer function residual generator*

With reference to equations [1.11] and [1.12], the residual generator structure is expressed mathematically by the generalized representation:

$$r(z) = \left[H_{u^*}(z) \; H_y(z) \right] \begin{bmatrix} u^*(z) \\ y(z) \end{bmatrix} = H_{u^*}(z)u^*(z) + H_y(z)y(z) \qquad [1.14]$$

where $H_{u^*}(z)$ and $H_y(z)$ are discrete transfer matrices that can be designed using stable discrete-time linear systems. The functions $u^*(z)$, $y(z)$, $r(z)$ and $f(z)$ are the Z-transform of the corresponding discrete-time signals.

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

$$r(t) = 0 \text{ if and only if } f(t) = 0 \qquad [1.15]$$

In order to satisfy equation [1.15], the design of the transfer matrices $H_{u^*}(z)$ and $H_y(z)$ must satisfy the constraint conditions

$$H_{u^*}(z) + H_y(z)G_{yu^*} = 0 \quad [1.16]$$

It is worth noting that different residual generators can be obtained by using different parameterizations of $H_{u^*}(z)$ and $H_y(z)$ (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 the residual signal $r(t)$ or the residual function $J\left(r(t)\right)$ with a fixed threshold ϵ or a threshold function $\varepsilon(t)$ as follows:

$$\begin{cases} J\left(r(t)\right) \leq \varepsilon(t) \text{ for } f(t) = 0 \\ J\left(r(t)\right) > \varepsilon(t) \text{ for } f(t) \neq 0 \end{cases} \quad [1.17]$$

where $f(t)$ is the general fault vector defined in equation [1.10]. If the residual exceeds the threshold, a fault may have occurred.

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

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

1.5. 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 briefly presents 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 on discrete-time dynamic linear models.

The following process model-based fault detection schemes will be considered and summarized (Isermann and Ballé 1997; Patton *et al.* 2000):

1) fault detection via parameter estimation (Isermann 1984, 1993; Isermann and Freyermuth 1992; 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).

1.5.1. *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 $u(t)$ and $y(t)$, 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 online 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 modeling the input–output behavior of the monitored system.

1.5.1.1. *Equation error methods*

The SISO process discrete-time model of order n is written in the vector form:

$$y(t) = \Psi^T \Theta \qquad [1.18]$$

where

$$\Theta^T = [a_1 \dots a_n,\ b_1 \dots b_n] \qquad [1.19]$$

is the parameter vector, and

$$\Psi^T = [y(t-1) \dots y(t-n)\ \ u(t-1) \dots u(t-n)] \qquad [1.20]$$

is the discrete-time data vector.

According to Figure 1.11, for parameter estimation, the EE $e(t)$ is introduced:

$$e(t) = y(t) - \Psi^T \Theta \qquad [1.21]$$

or, if

$$\frac{y(t)}{u(t)} = \frac{B(z)}{A(z)} \qquad [1.22]$$

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

$$e(t) = \hat{B}(z)u(t) - \hat{A}(z)y(t) \qquad [1.23]$$

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

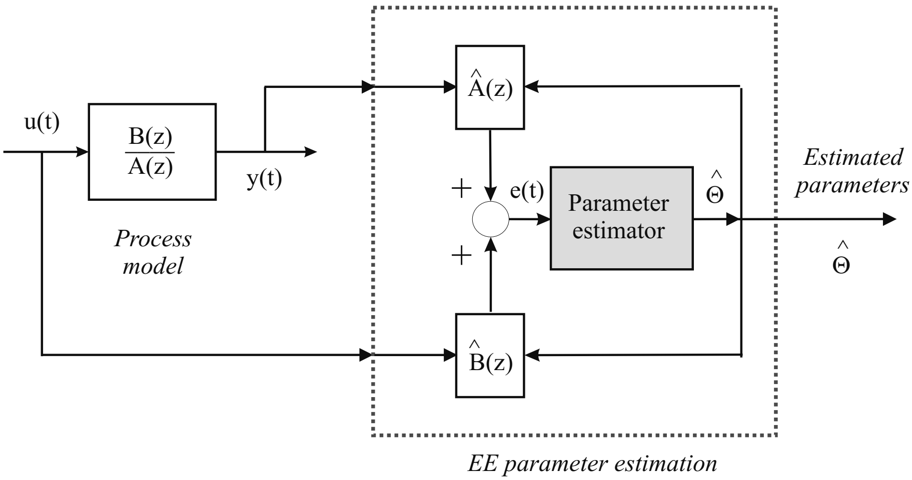

Figure 1.11. *Parameter estimation Equation Error (EE)*

The least-squares (LS) estimate

$$\hat{\Theta} = [\Psi^T\ \Psi]^{-1}\Psi^T y \qquad [1.24]$$

is obtained if the minimization of the sum of LS is computed

$$\begin{cases} J(\Theta) & = \sum_t e^2(t) = e^T e \\ \frac{d\ J(\Theta)}{d\ \Theta} & = \qquad 0. \end{cases} \qquad [1.25]$$

As described in Patton *et al*. (2000) and Isermann (1992), the LS estimate can also be computed via a recursive least square (RLS) algorithm in real-time form, with respect to the estimates at the instant t, with $t = 0,\ 1,\ 2, \cdots$:

$$\hat{\Theta}(t+1) = \hat{\Theta}(t) + \gamma(t)\left[y(t+1) - \Psi^T(t+1)\hat{\Theta}(t+1)\right] \quad [1.26]$$

where

$$\begin{cases} \gamma(t) & = \frac{1}{\Psi^T(t+1)P(t)\Psi(t+1)+1} P(t)\Psi(t+1) \\ P(t+1) = & \left[I - \gamma(t)\Psi^T(t+1)\right] P(t). \end{cases} \quad [1.27]$$

For improved estimates, filtering methods can be exploited. In particular, when measurements are affected by noise, a Kalman filter can be used for the parameter estimation (Jazwinski 1970).

1.5.1.2. *Output error methods*

Instead of the EE computed in equation [1.21], the Output Error (OE)

$$e(t) = y(t) - \hat{y}(\Theta, t) \quad [1.28]$$

where

$$\hat{y}(\Theta, z) = \frac{\hat{B}(z)}{\hat{A}(z)} u(z) \quad [1.29]$$

which is the model output, can also be used, as depicted in Figure 1.12.

Unfortunately, a direct calculation of the parameter estimate Θ is not possible, because $e(t)$ is nonlinear in the parameters.

Therefore, the loss function of equation [1.28] as equation [1.21] has to be minimized by numerical optimization methods. The computational effort is then much larger and online real-time application is generally impossible. However, relatively precise parameter estimates may be obtained.

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

$$\Delta y(t) = \Psi^T(t)\Delta\Theta(t) + \Delta\Psi^T(t)\Theta(t) + \Delta\Psi^T(t)\Delta\Theta(t) \quad [1.30]$$

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

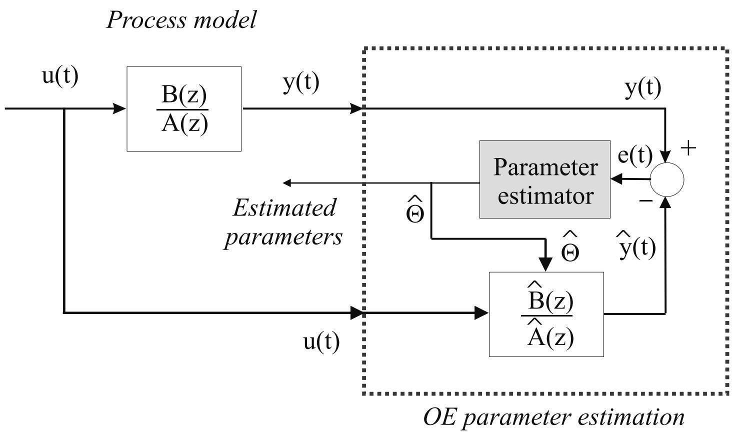

Figure 1.12. *Parameter estimation Output Error (OE)*

Generally, the process parameters Θ depend on physical process coefficients p (such as stiffness, damping factor and resistance):

$$\Theta = f(p) \quad [1.31]$$

via nonlinear algebraic equations. If the inversion of the relationship

$$p = f^{-1}(\Theta) \quad [1.32]$$

exists (Patton *et al*. 2000; Isermann 1992), changes Δp 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 Δp facilitates the fault diagnosis problem, it is not necessary for fault detection only. Parameter estimation can also be applied to nonlinear static process models (Isermann 1993).

1.5.2. *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, while 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 (generalized) observer, the discrete-time, time-invariant, linear dynamic model for the process under consideration in a state–space form is considered:

$$\begin{cases} x(t+1) = Ax(t) + Bu(t) \\ y(t) \quad\quad = Cx(t) \end{cases} \qquad [1.33]$$

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

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

$$\begin{cases} \hat{x}(t+1) = A\hat{x}(t) + Bu(t) + He(t) \\ e(t) \quad\quad = y(t) - C\hat{x}(t). \end{cases} \qquad [1.34]$$

The observer scheme described by equation [1.34] is depicted in Figure 1.13.

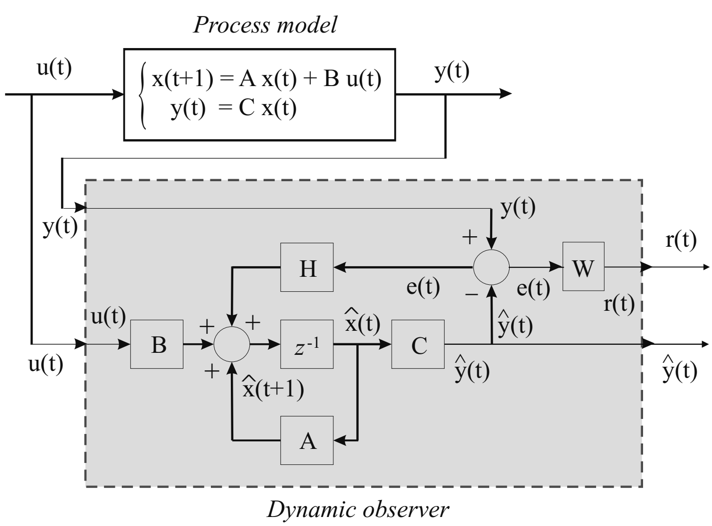

Figure 1.13. *State and output dynamic observer*

For the state estimation error $e_x(t)$, it follows from equations [1.34] that

$$\begin{cases} e_x(t) & = x(t) - \hat{x}(t) \\ e_x(t+1) & = (A - HC)e_x(t). \end{cases} \qquad [1.35]$$

The state error $e_x(t)$ (and the error $e(t)$) vanishes asymptotically)

$$\lim_{t\to\infty} e_x(t) = 0 \qquad [1.36]$$

if the observer is stable, which can be achieved by proper design of the observer feedback H.

If the process is influenced by disturbance and faults, by comparing Figure 1.14 and equations [1.10] it is described by the following system:

$$\begin{cases} x(t+1) & = Ax(t) + Bu(t) + Qv(t) + L_1 f(t) \\ y(t) & = Cx(t) + Rw(t) + L_2 f(t) \end{cases} \qquad [1.37]$$

where $v(t)$ is the non-measurable disturbance vector at the input, $w(t)$ is the non-measurable disturbance vector at the output and$f(t)$ are the 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.

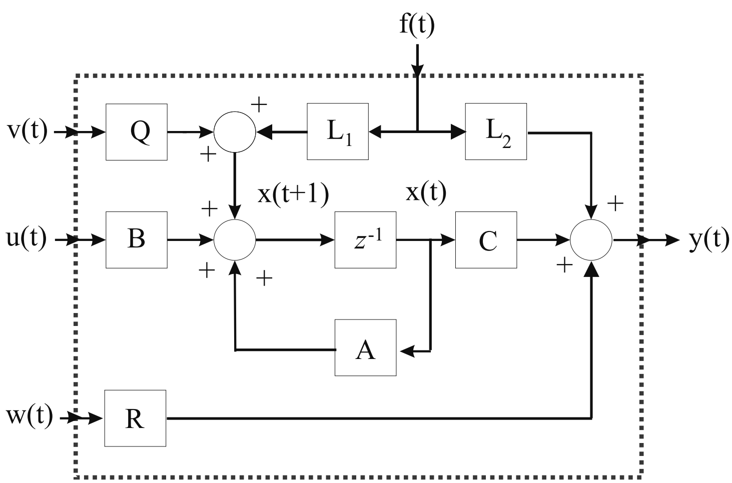

Figure 1.14. *MIMO process with faults and noises*

For the state estimation error, the following equations hold if the disturbances $v(t) = 0$ and $w(t) = 0$:

$$e_x(t+1) = (A - HC)e_x(t) + L_1 f(t) - HL_2 f(t) \quad [1.38]$$

and the OE $e(t)$ becomes

$$e(t) = Ce_x(t) + L_2 f(t). \quad [1.39]$$

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

When sudden and permanent faults $f(t)$ occur, the state estimation error will deviate from zero. $e_x(t)$ and $e(t)$ show dynamic behaviors, which are different for $L_1 f(t)$ and $L_2 f(t)$. Both $e_x(t)$ or $e(t)$ can be taken as residuals.

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

For the generation of a residual with special properties, the design of the observer feedback matrix H is of interest (Chen and Patton 1999; Liu and Patton 1998).

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

If faults appear as changes ΔA or ΔB of the parameters, the process behavior becomes:

$$\begin{cases} x(t+1) = (A + \Delta A)x(t) + (B + \Delta B)u(t) \\ y(t) \qquad\ \ = Cx(t) \end{cases} \quad [1.40]$$

while the state $e_x(t)$ and the output estimation $e(t)$ errors are given as:

$$\begin{cases} e_x(t+1) = (A - HC)e_x(t) + \Delta A x(t) + \Delta B u(t) \\ e(t) \qquad\ \ = Ce_x(t). \end{cases} \quad [1.41]$$

The changes ΔA and ΔB 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 $f(t)$.

The following observer-based fault detection schemes and configurations are briefly summarized and recalled (Isermann 1997; Willsky 1976; Patton *et al*. 1989, 2000; Chen and Patton 1999).

1) **Dedicated observers for MIMO processes**

- *Observer excited by one output*: one observer is driven by one sensor output. The other outputs $\hat{y}(t)$ are reconstructed and compared with measured outputs $y(t)$. 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 are detected by a hypothesis test (Willsky 1976).

- *Bank of observers, excited by single outputs*: several observers for single sensors outputs are used. The estimated outputs $\hat{y}(t)$ are compared with the measured outputs $y(t)$. this allows the detection of multiple sensor faults (Dedicated Observer Scheme) (Clark 1978).

- *Bank of observers, excited by all outputs except one*: as previously mentioned, but each observer is excited by all outputs except one sensor output, which is supervised (Generalized Observer Scheme) (Wünnenberg and Frank 1987; Frank 1993).

2) **Fault detection filters for MIMO processes**

- The feedback H of the state observer in equation [1.34] is chosen so that particular fault signals $L_1 f(t)$ change in a definite direction and fault signals $L_2 f(t)$ change in a definite plane (Beard 1971; Jones 1973; Chen and 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 (1971) and Jones (1973) to generate directional residual vectors. Many more straightforward methods have followed, including methods to achieve a "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 with 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 the internal analytical redundancy of multivariable systems. Recently, it was proposed to improve their robustness with respect to process parameter changes and unknown input signals $v(t)$ and $w(t)$ (Patton and Chen 1994; Chen *et al*. 1996b; Chung and Speyer 1998; Chen and Speyer 1999).

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

$$r(t) = We(t) \qquad [1.42]$$

together with a special design of the observer feedback matrix H.

3) **Output observers**

Another possibility is the use of output observers, or the so-called generalized observers, for example, the unknown input observers (UIO), in the reconstruction of the output signals, if the estimate of the state variable $\hat{x}(t)$ is not of primary interest.

In this context, it is worth mentioning the paper by Chen *et al.* (1996b) concerning the design of output observers for robust FDI using the eigenstructure assignment method.

Through a linear transformation

$$z(t) = Tx(t) \qquad [1.43]$$

the state–space representation of the observer becomes

$$\hat{z}(t+1) = F\hat{z}(t) + Ju(t) + Gy(t) \qquad [1.44]$$

and the residual is determined by

$$r(t) = W_z\hat{z}(t) + W_y y(t). \qquad [1.45]$$

This situation is depicted in Figure 1.15.

The state estimation error

$$e_x(t) = \hat{z}(t) - z(t) = \hat{z}(t) - Tx(t) \qquad [1.46]$$

and the residuals $r(t)$ are then designed, such that they are independent of the process states $x(t)$, the known input $u(t)$ and the unknown inputs $v(t)$ and $w(t)$, as depicted in Figure 1.14.

In this way, the residuals are dependent only on fault signals $f(t)$ (Chen and Patton 1999; Patton and Chen 1994; Chen *et al.* 1996b; Gertler 1998; Patton *et al.* 2000).

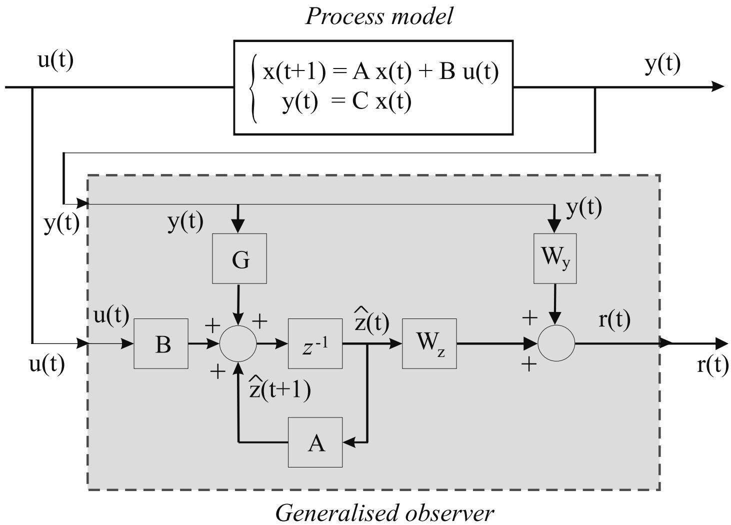

Figure 1.15. *Process and output observer*

1.5.3. *Fault detection via 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), this section is focused on analytical forms of redundancy.

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

$$r(z) = \left(\frac{A(z)}{B(z)} - \frac{\hat{A}(z)}{\hat{B}(z)}\right) u(z). \quad [1.47]$$

The methodology described here is depicted in Figure 1.16.

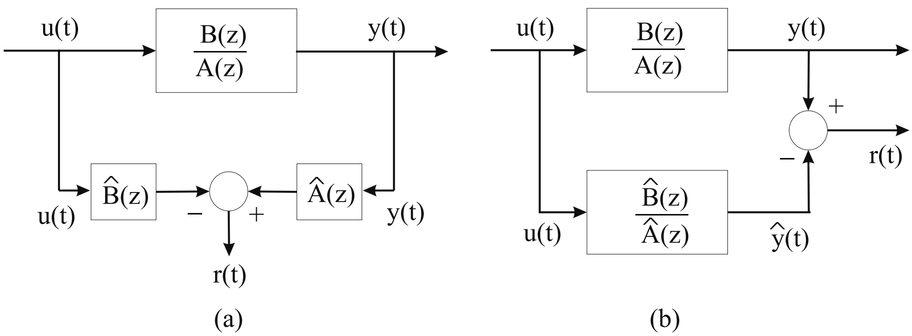

Figure 1.16. *Parity equation methods: (a) EE and (b) OE*

However, as for observers, the model parameters and structure of the monitored process have to be known *a priori*.

With reference to Figure 1.5, if

$$G_M(z) = G_P(z) \text{ i.e. } \frac{\hat{A}(z)}{\hat{B}(z)} = \frac{A(z)}{B(z)} \quad [1.48]$$

for additive input $f_u(z)$ and output $f_y(z)$ faults, the $r(z)$ error then becomes

$$r(z) = \frac{A(z)}{B(z)} f_u(z) + f_y(z). \quad [1.49]$$

According to Figure 1.16, another possibility is to generate a polynomial error:

$$\begin{aligned} r(z) &= \hat{A}(z)y(z) - \hat{B}(z)u(z) \\ &= B(z)f_u(z) + A(z)f_y(z). \end{aligned} \quad [1.50]$$

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

Moreover, the error vector $r(z)$ computed by equation [1.49] corresponds to the OE of the parameter estimation method computed by equation [1.28].

On the other hand, $r(z)$ in equation [1.50] concerns the equation error of equation [1.21].

Equations [1.49] and [1.50] 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 $\hat{A}(z)$ and $\hat{B}(z)$ in order to minimize the residuals.

Moreover, for the generation of specific characteristics of the parity vector $r(z)$ and for obtaining fault detection and isolation properties, the residuals can be filtered according to matrix $G_f(z)$ to compute the vector $r_f(z)$ (Gertler 1991; Patton and Chen 1994; Patton *et al*. 2000):

$$r_f(z) = G_f(z)r(z). \tag{1.51}$$

Equations [1.49]–[1.51] can therefore be used to implement and design the residual generation system, in order to meet fault detection and isolation specifications (Gertler 1998).

However, only one residual can be generated for SISO processes 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 intermediate signals can be measured for SISO processes, as shown in Figure 1.5, or for MIMO systems.

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

The redundancy relations are now specified mathematically as follows.

Given the system

$$\begin{cases} x(t+1) &= Ax(t) + Bu(t) \\ y(t) &= Cx(t) \end{cases} \tag{1.52}$$

by substituting the second of equations [1.52] into the first one and delaying several times, the following system is obtained:

$$\begin{bmatrix} y(t) \\ y(t+1) \\ y(t+2) \\ \vdots \end{bmatrix} = \begin{bmatrix} C \\ CA \\ CA^2 \\ \vdots \end{bmatrix} x(t) + \begin{bmatrix} 0 & 0 & 0 \dots \\ CB & 0 & 0 \dots \\ CAB & CB & 0 \dots \\ \vdots & \vdots & \vdots \ddots \end{bmatrix} \begin{bmatrix} u(t) \\ u(t+1) \\ u(t+2) \\ \vdots \end{bmatrix} \qquad [1.53]$$

$$Y_f(t) = Tx(t) + QU_f(t). \qquad [1.54]$$

In order to remove the non-measurable states $x(t)$ and obtain a parity vector useful for FDI, equation [1.53] is multiplied by W, such that

$$WT = 0. \qquad [1.55]$$

This leads to residuals

$$r(t) = WY_f - WQU_f(t) \qquad [1.56]$$

as shown in Figure 1.17.

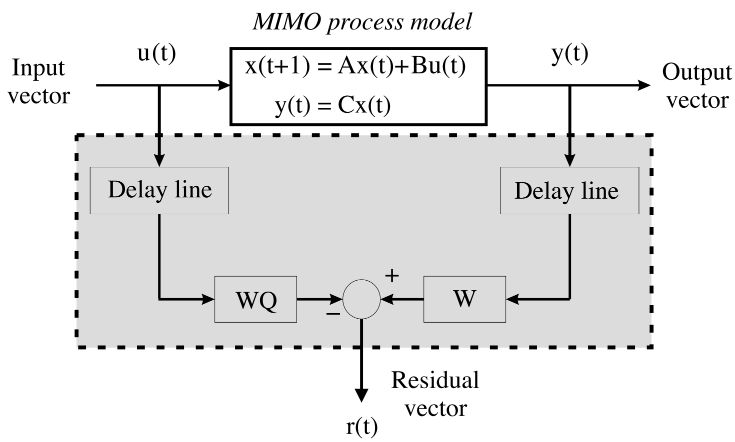

Figure 1.17. *Parity EE methods for a MIMO model*

The filtered input and output vectors U_f and Y_f are obtained by delaying the corresponding signals.

The design of the matrix W gives some freedom to generate a structured set of residuals.

One possibility is to select the elements of 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 1994; Chen and Patton 1999).

Finally, because of the previous results, it is clear that some correspondence exists between the parity relation and observer-based methods. This aspect was first pointed out by Massoumnia (1986) and was later demonstrated by Wünnenberg (1990) and Patton *et al*. (1989).

The problem was re-examined in detail by Patton and Chen (1994), 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 of 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 the MIMO systems described by the estimated input–output discrete-time forms (e.g. ARX or Auto Regressive Moving Average eXogenous [ARMAX] models) of equations [1.49] and [1.50], leads to a representation in which parameter redundancy cannot be avoided. To overcome this drawback, Delmaire *et al*. (1999) proposed to use observers designed from identified canonical state-space forms (Guidorzi 1975). Moreover, in the case of parameter redundancy, multiple identifications of some parameters may occur, leading to inconsistent estimations that 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.

1.6. 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 in equation [1.17], a decision process may consist of a simple threshold test on the instantaneous values of the 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 exploit statistical methods.

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

$$\bar{r}_i = E\{r_i(t)\}; \qquad \bar{\sigma}_i^2 = E\{[r_i(t) - \bar{r}_i]^2\} \tag{1.57}$$

as normal values for the fault-free process.

Analytic symptoms are then obtained as changes:

$$\Delta r_i = E\{r_i(t) - \bar{r}_i\}; \qquad \Delta\sigma_i = E\{\sigma_i(t) - \bar{\sigma}_i\} \tag{1.58}$$

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 behavior from faulty behavior, a fixed threshold Δr_{tol} usually defined as

$$\Delta r_{tol} = \epsilon\bar{\sigma}_r, \qquad \epsilon \geq 2 \tag{1.59}$$

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, such 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

$$\Delta r = [\Delta r_1 \; \Delta r_2 \; \cdots \; \Delta r_q] \tag{1.60}$$

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 Δr from the origin. Geometrical distance methods (Carpenter and Grossberg 1987; Tou and Gonzalez 1974) or artificial neural networks (NNs) (Himmelblau *et al.* 1991; Meneganti *et al.* 1998) can hence be applied.

The generation and evaluation of analytic symptoms concludes the task of fault detection within the framework of model-based fault diagnosis, as shown in Figure 1.8.

1.7. Residual generation robustness problem

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

The main problem regarding the reliability of FDI schemes is the modeling uncertainty, which is due, for example, to process noise, parameter variations and nonlinearities.

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 modeling uncertainty is unavoidable.

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

Several papers addressed this problem. For example, optimal robust parity relations were proposed (Chow and Willsky 1984; Chung and Speyer 1998; Chen and 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 1994; Chen *et al.* 1996b). Patton and Chen's approach is an interesting contrast to Chow and Willsky's method, which seems to minimize the modeling 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 1994; 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 behavior of the system, the better the FDI precision will be. If an FDI method can be developed, which is insensitive to modeling uncertainty, a very accurate model is not necessarily needed.

All uncertainties are summarized 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 summarize the approach to the robustness problem, the state–space model of the monitored system should be considered (Patton and Chen 1993):

$$\begin{cases} x(t+1) = (A + \Delta A)\, x(t) + (B + \Delta B)\, u(t) + E_1 \varepsilon(t) + R_1 f(t) \\ y(t) \qquad\;\; = Cx(t) + E_2 \varepsilon(t) + R_2 f(t) \end{cases} \qquad [1.61]$$

where $\varepsilon(t)$ is the disturbance vector, and E_1 and E_2 are the known and unknown input distribution matrices. The matrices ΔA and ΔB are the parameter errors or variations that represent modeling errors.

The discrete transfer matrix description between the output $y(t)$ and input $u(t)$ of the system [1.61] is then

$$y(z) = (G_u(z) + \Delta G_u(z))\, u(z) + G_\varepsilon(z)\varepsilon(z) + G_f(z) f(z) \qquad [1.62]$$

where $\Delta G_u(z)$ is used to describe modeling errors, while both $\Delta G_u(z)$ and $G_\varepsilon(z)$ represent modeling uncertainty.

With reference to the residual generator in Figure 1.10 and described by equation [1.14], the z-domain residual vector is rewritten as

$$r(z) = H_y(z) G_f(z) f(z) + H_y(z) G_\varepsilon(z) \varepsilon(z) + H_y(z) \Delta G_u(z) u(z). \qquad [1.63]$$

With respect to equation [1.14], the terms $H_y(z)G_\varepsilon(z)$ and $H_y(z)\Delta G_u(z)$ cannot be deleted.

Both faults and modeling uncertainty (disturbance and modeling 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

$$H_y(z) G_\varepsilon(z) = 0 \qquad [1.64]$$

in order to achieve total de-coupling between residual $r(z)$ and disturbance $\varepsilon(z)$.

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, 2000; Liu and Patton 1998; Duan *et al.* 2002).

These approaches can be integrated with different system identification tools for achieving robust residual generation schemes. Hence, for disturbance de-coupling approaches in FDI, the aim is to completely eliminate the disturbance effects 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 modeling error and faults. There is a tradeoff between sensitivity to faults and robustness to modeling uncertainty, and hence robust residual generation can be considered as a *multi-objective optimization problem* (Chen and Patton 1999, Chapter 6). It consists of the maximization of fault effects and the minimization of uncertainty effects (Wünnenberg 1990; Frank *et al.* 2000).

1.7.1. *FDI H_∞ approach*

Therefore, the approach to the design of optimal residuals requires the satisfaction of a set of objectives. These objectives are essential for achieving a robust diagnosis of incipient faults. If such joint optimization 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, 1997; Hou and Patton 1997; Chen and Patton 1999, 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 minimization 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 also be exploited (Hou and Patton 1996, 1997; Frank *et al.* 2000; Chen and Patton 2000).

Among the many ways of eliminating or minimizing disturbance and modeling error effects on the residual, and hence achieving robustness in FDI (Patton *et al.*

2000), H_∞ optimization is a robust design method with the original motivation firmly rooted in the consideration of various uncertainties, especially the modeling errors. It is reasonable to seek an application of this technique in the robust design of FDI systems. Therefore, the H_∞ optimization method can be successfully exploited for a robust residual generation of FDI.

The early work of using H_∞ optimization techniques for robust FDI was based on the use of the factorization approach (Ding and Frank 1990; Ding *et al.* 2000). The factorization-based H_∞ optimization technique is useful in solving FDI problems. However, the more elegant and advanced H_∞ optimization methods are based on the use of the Algebraic Riccati Equation (ARE) (Zhou *et al.* 1996). Mangoubi *et al.* (1992) first solved the robust FDI estimation problem using the ARE approach, via the use of the H_∞ and μ robust estimator synthesis methods developed by 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.* (1997). To deal with modeling errors as well as disturbances in robust FDI design, Niemann and Stoustrup (1996) introduced modeling 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 nonlinear systems, where the nonlinearity is treated in the same way as a modeling 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, that is, the design objective is to minimize the effect of disturbances and modeling 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 while the effect of disturbance is minimized. 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 modeling errors was studied extensively by 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, that is, 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 that provides the maximum ratio between fault sensitivity and disturbance sensitivity.

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

In case the condition of equation [1.64] is not satisfied, only an approximate de-coupling can be obtained. In particular, the performance index (Ding and Frank 1991)

$$J_d = \frac{\| H_y(w)G_\varepsilon(w) \|}{\| H_y(w)G_f(w) \|} \qquad [1.65]$$

can be defined by considering the w-transformation in the frequency domain for discrete-data systems (Kuo 1995).

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 minimization of performance index (Frank *et al.* 2000)

$$J = \frac{\|\frac{\partial r}{\partial d}\|}{\|\frac{\partial r}{\partial f}\|} \text{ or } J = \|\frac{\partial r}{\partial d}\| \text{ with } \|\frac{\partial r}{\partial f}\| > \alpha \qquad [1.66]$$

is widely recognized as a suitable design objective. Associated with the norm used, the type of the residual generator and the mathematical tool adopted, a number of optimization approaches have been developed (Frank *et al.* 2000). Recently, Ding *et al.* (2000) derived a unified solution for a number of optimization problems, and thus provided a satisfactory solution to the above-defined optimization problem 10 years after it was first proposed. In Frank *et al.* (2000), a brief review of the state of art of the solutions can be found, whereas in Hou and Patton (1996, 1997) and Frank *et al.* (2000), the H_∞/H_- method is detailed.

By minimizing the performance index of [1.66] over a specified range in the w-transformed plane (Kuo 1995), 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).

According to the norm selected, by minimizing the performance index of [1.66] 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).

1.7.2. *Active and passive disturbance de-coupling*

Regarding this issue, 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 modeling errors in equation [1.63], represented by the term $\Delta G_u(z)$, 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 1994).

One attempts to take into account the uncertainty in the design of the residual (see, e.g. Chen *et al.* 1993; Frank 1996); it is known as *active robustness*.

The active way of achieving a robust solution is to approximate uncertainties, that is, by approximately representing modeling errors as disturbances (Chen and Patton 1999):

$$\Delta G_u(z)u(z) \approx G_d(z)d(z) \qquad [1.67]$$

where $d(z)$ is an unknown vector and $G_d(z)$ is an estimated transfer function. When this approximate structure is exploited to design disturbance de-coupling residual generators, robust FDI can be achieved.

The second approach called *passive robustness* makes use of a residual evaluator with an adaptive threshold. As a simple example, it is assumed that the residual generation uncertainty [1.63] is only represented by modeling errors.

The fault-free residual $r(z)$ is given as

$$r(z) = H_y(z)\Delta G_u(z)u(z). \qquad [1.68]$$

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

$$\| \Delta G_u(w) \| \leq \delta \quad [1.69]$$

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

$$\varepsilon(t) = \delta H_y(z)u(z) \quad [1.70]$$

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

$$\| r(t) \| > \| \varepsilon(t) \| \quad [1.71]$$

A robust FDI technique with a 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 have been studied extensively, their effectiveness regarding real problems has not been fully demonstrated.

The main difficulty arises as most of the disturbances 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 modeling errors.

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

This chapter provides some considerations on different approaches for representing modeling errors and other uncertain factors via the disturbance term with an estimated distribution matrix. As addressed in a system identification framework, this identified distribution matrix will be used for the design of the disturbance de-coupled residual, in order to solve the robust FDI problem.

1.8. Fault diagnosis technique integration

Several FDI techniques have been developed and their application shows different properties with respect to 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 advantage of the different procedures (Isermann 1994; 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.

1.8.1. *Fuzzy logic for residual generation*

As stated in section 1.2, 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 nonlinear (Chen and Patton 1999; Gertler 1998; Patton and Chen 1997) and cannot be modeled by using a single model for all operating conditions.

Since a mathematical model is a description of system behavior, accurate modeling for a complex nonlinear system is very difficult to achieve in practice. Sometimes, for some nonlinear 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 nonlinear models obtained by modeling techniques, it is also possible to describe the plant by a collection of local affine fuzzy and non-fuzzy models (Leontaritis and Billings 1985a, 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, 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 facts, and is therefore well 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, 2000). Fault diagnosis using rule-based systems needs a database of rules, and the accuracy of diagnosis depends 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 again using fuzzy logic (Dexter and Benouarets 1997; Isermann 1998).

1.8.2. *Neural networks for 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, that is, 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, the pattern recognition method can provide a convenient approach to solve the fault identification problem, that is, to determine the size of the fault (Himmelblau 1978; Pau 1981).

In recent years, NNs have been used successfully in pattern recognition, as well as system identification, and they have been also been proposed as a possible technique for fault diagnosis.

NN can handle nonlinear behavior and partially known processes because they learn the diagnostic requirements by means of the information of the training data.

NNs are noise tolerant and their ability to generalize the knowledge, as well as 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*. 1990). Some example processes were considered, in which FDI was performed by an NN using input and output measurements. In these works, the NN is trained to identify the fault from measurement patterns, however the classification of the individual measurement pattern is not always unique in dynamic situations, therefore the straightforward use of NN in fault diagnosis of dynamic plants is not practical and other approaches should be investigated.

An 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 a pattern classifier or nonlinear function approximator. In fact, artificial NNs are capable of approximating a large class of functions for the fault diagnosis of an industrial plant.

Under these considerations, this book also considers the identification of fuzzy and non-fuzzy models for the system under diagnosis, as well as the application of NN as function approximators.

Quantitative and qualitative approaches have a lot of complementary characteristics, which can be suitably combined together to exploit their advantages and increase the robustness of quantitative techniques. The suggested combination can also minimize 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 is to find a way to properly combine these two approaches together to provide highly reliable diagnostic information.

1.8.3. *Neuro-fuzzy approaches to FDI*

The 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 modeling errors, parameter variation, noise and disturbance (Chen and Patton 1999; Patton *et al*. 2000). Process modeling has limitations, especially when the system is complex and uncertain, and the data are ambiguous and not rich in information.

As previously stated, NNs are known to approximate any nonlinear even dynamic function, given suitable weighting factors and architecture. Moreover, online training makes it possible to change the FDI system easily in cases where changes are made in the physical process or the control system. NNs can generalize 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. An NN can operate simultaneously on qualitative and quantitative data. NN can be very useful when no mathematical model of the system is available, that is, analytical models cannot be applied.

Almost all of the physical processes are dynamic in nature. Combining dynamic elements, such as filters and delays, yields a powerful modeling technique. But the NN operates as a “black box” with no qualitative/quantitative information available about the model it represents. Usually, engineers and operators want to visualize 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 situations (Korbicz *et al*. 1999).

Fuzzy logic systems, on the other hand, have the ability to mimic the sensing, generalizing, 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 NNs (Chiang *et al*. 2001). 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 NN is built on fuzzy neurons or on standard neurons dealing with fuzzy data. A fuzzy NN 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; Nelles 2001).

Different neuro-fuzzy (NF) structures can therefore be designed to combine the advantages of both NNs and fuzzy logic (Patton *et al*. 1999; 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 modeling, application to complex and uncertain systems, inherent nonlinear 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 NNs with fuzzy logic:

1) fuzzification of the inputs or outputs of the NNs;

2) fuzzification of the interconnections of conventional NNs;

3) using NNs in fuzzy models where neurons provide the necessary membership functions and rule base.

Research effort has also been focused also on NF networks making use of B-spline functions, which can be used to identify the process using NN architecture and at the same time extract some qualitative knowledge of the system being modeled. Applications of the B-spline NNs show how to successfully integrate the approximation techniques of NNs and the qualitative approach of fuzzy logic. The operator can also include any heuristic knowledge about the plant. Unlike many other NF approaches, B-spline networks offer a simple and easy to build framework (Uppal and Patton 2000).

Once the NF network structure and parameters are identified, such network can be useful in general FDI schemes, which consists of residual generation and decision making (classification). In residual generation, the residual vector is determined in order to characterize each fault. The residual vector is then processed to determine the location and occurrence time of the faults, which is called decision making. Ideally, the models identify all classes of system behavior (Uppal and Patton 2000).

Therefore, the NF network is used to classify process faults that are assumed to be known *a priori*. Their corresponding data are available to the designer. The network then has as many outputs as classes of behavior. Hence, for a system with M classes of faults, the output of the network will be a vector of dimension $M+1$; this includes the models associated with the M faults, as well as the one corresponding to the healthy case.

To train the network, it is necessary to decompose it into a set of $(M+1)$ MIMO sub-models, if M is the number of faulty classes, and find the set of optimal weighting coefficients with each sub-model. When the network is used to classify a test point

$\{u(t), y(t)\}$, the network's output is a real vector of dimension $(M+1)$. Under these assumptions, each component of that output vector (from 1 to M) is identified with a class of behavior, which can represent either the ith fault ($i = 1, \ldots, M$) or the nominal model. When the system is operating in its nominal condition, all of the network outputs are zero except the last one. However, when a specific fault develops in the system, the corresponding output will deviate from zero, whereas the output $i+1$ becomes zero, confirming that the system is no longer healthy.

1.8.4. *Fault detectability and isolability*

A successful detection of a fault is obtained if a residual has the maximal sensitivity to its occurrence. Fault *detectability* conditions were stated in Chen and Patton (1999). Such a stage is followed by the fault isolation procedure, which allows us to distinguish a particular fault from others. While a single residual signal is sufficient to detect faults, a vector of residuals is usually required for fault isolation. Faults are distinguishable or *isolable* using the residual set if each residual is sensitive to a subset of faults, while remaining insensitive to the remaining faults. The design technique to obtain the so-called *structured residual set* will be shown briefly in the following sections.

All of the NF modeling 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 1994; Jang and Sur 1995). For example, an NF model of a nonlinear dynamical system can be identified from the empirical data. This modeling approach can give us some insight about the nonlinearity 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; 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 NN (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 NF 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 modeling, application to complex and uncertain systems, inherent nonlinear 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. Here, transparency corresponds to a more meaningful description of the process, that is, less rules with appropriate membership functions. In the Adaptive Neuro-Fuzzy Inference System (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 LS estimates and gradient-based methods, the so-called *hybrid learning rule*. This method is fast and easy to implement for low-dimensional input spaces. It is more prone to losing transparency and local model accuracy because of the use of *error back-propagation*, which is a global and not locally nonlinear optimization procedure. One possible method to overcome this problem can be to find the antecedents and rules separately, for example, by clustering and constraining the antecedents, and then applying optimization.

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 NF models are built 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, that is, pre-processing data, identification, (residual generation) or classification (decision making/fault isolation). For example, an 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, an NF network with more transparency is required.

1.8.5. *NF model structure identification*

For complexity reduction and transparency, structure identification methods can be applied to find appropriate input partitions, rules and membership functions (MFs). Methods such as 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, that is, the rules and input membership functions, the consequent parameters can be identified by optimization 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 nonlinear dynamic system with p inputs, the product space $X \times Y \subset \Re^{p+1}$ is divided into subspaces in which linear models can approximate the nonlinear system. The locally linear model tree LOLIMOT algorithm developed by 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 problem may be to initialize the algorithm with a large number of clusters.

The transparency of the NF models can be enhanced by tuning rules and MFs (Babuška 1998). This type of method is referred to as a structure simplification/optimization technique. 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 and Kaymak (1998) used a supervised fuzzy clustering algorithm that uses input–output data, orthogonal techniques and tuning for complexity reduction.

1.8.6. *NF residual generation for FDI*

Figure 1.18 describes an FDI scheme in which several NF models are constructed to identify the faulty and the fault-free behavior of the system.

$$r_i(t) = f\big(u(t), \ldots, u(t-n), y(t), \ldots, y(t-n)\big), \quad i = 1, \ldots, m \qquad [1.72]$$

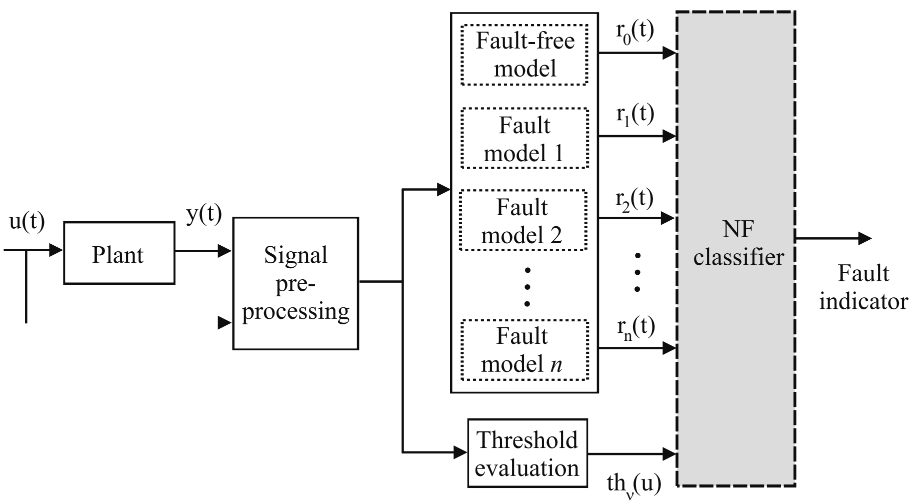

Figure 1.18. *Neuro-fuzzy-based FDI scheme*

Each residual $r_i(t)$ in [1.72] 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 an NF classifier. A linguistic style (Mamdani) NF network is used that processes the residuals to indicate the fault.

This NF model is constructed with the following set of rules:

$$\textbf{If } r_1 \text{ is small } \ldots r_j \text{ is large, } r_m \text{ is small } \textbf{then } \text{fault}_r \text{ is large} \qquad [1.73]$$

Fuzzy threshold evaluation in equation [1.74] is employed to take into account the imprecision of the residual generator at different regions in the input space

$$\text{th}_\nu(u) = \frac{\sum_{i=1}^{C} \text{th}_i \, \eta_i(u)}{\sum_{i=1}^{C} \eta_i(u)} \qquad [1.74]$$

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 ith 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 nonlinear dynamic model of the plant that approximates a nonlinear 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 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:

$$y = \frac{\sum_{i=1}^{C} \alpha_i(u_s) \, f_i}{\sum_{i=1}^{C} \alpha_i(u_s)} \qquad [1.75]$$

where f_i is the ith local linear model given by:

$$f_i = \sum_{k=0}^{n} b_{i,k} \, u(t-k) + \sum_{k=0}^{n} a_{i,k} \, y(t-k) + c_i \qquad [1.76]$$

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

From $a_{i,k}$, $b_{i,k}$ and c_i, physical parameters such as time constants, static gains, offsets, and so on (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 nonlinear dynamic model described above. Also, the OE should be minimum when operated in parallel to the system. Moreover, this method requires that there is sufficient excitation at each operating point for the online estimation of parameters. The TSK NF-based FDI scheme is depicted in Figure 1.19.

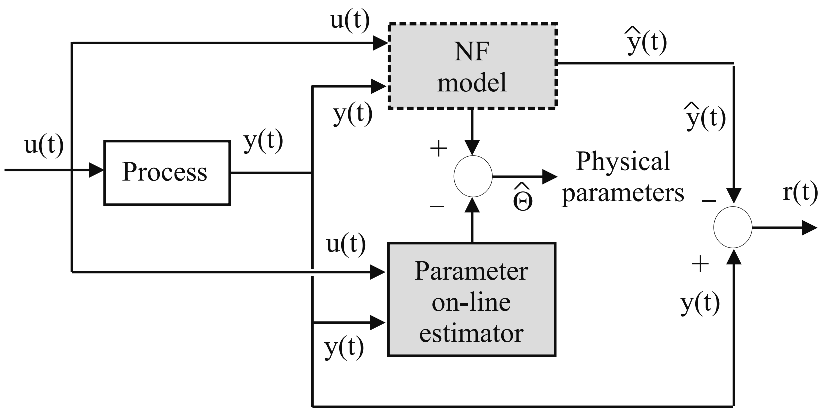

Figure 1.19. *TSK NF-based FDI scheme*

1.9. Conclusion

This chapter has presented a tutorial treatment on the basic principles of model-based FDI.

The FDI problem has been formalized 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 summarized 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 that should be robust with respect to modeling uncertainty. The robust FDI problem has also been discussed in this chapter and the implementation of a robust residual generator will be shown in the following chapters.

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

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