PRINCIPLES OF MODEL-BASED FAULT DETECTION

P.M. Frank

Fachgebiet Mess- und Regelungstechnik, Universität-GH-Duisburg, Bismarckstr. 81, 4100 Duisburg, Germany

Abstract. The paper outlines the principles of fault detection and isolation (FDI) in dynamic systems using a mathematical model of the system. Implemented on a digital computer, these model-based algorithms can efficiently be applied to signal validation, on-line detection of abrupt faults and early fault diagnosis in a long-term system supervision. The basic concept of the model-based approach to fault detection and isolation is described, and the different methods of residual generation developed in the past two decades are reviewed. Among the methods considered are the parameter identification approach, the different observer-based concepts, the parity space approach and the knowledge-based strategy. It is also shown how structured residuals for the localization of the faults can be generated with the aid of observer schemes. As an issue of great practical relevance the robustness with respect to modeling errors is taken into consideration. Here emphasis is placed upon the unknown input observer approach and its application to instrument, actuator and component fault detection.

Keywords. Fault detection, diagnosis, model-based fault detection, analytical redundancy, observer-based fault detection, robustness

Introduction

The need for an effective fail-safe management in modern automation systems calls for powerful fault detection and isolation (FDI) techniques. Evoked by these needs and supported by the advances of modern control theory and computer technology, a number of sophisticated FDI strategies have been developed in recent years.

Among these strategies the *model-based* is by nature the most capable one. Actually, if one could acutely understand the dynamic processes arising in any physical plant, and precisely and reliably measure every process variable of interest, one could detect, locate and identify any fault in the plant, almost immediately, by comparing the data collected with those of a functional mathematical model of the plant. This is the fundamental idea of the model-based FDI strategy, which is also known as the *functional* or *analytical* redundancy approach. In contrast the *physical* redundancy approach that performs the comparison on the basis of physical replica.

Unfortunately, the prerequisites for the model-based approach formulated above do generally not hold in real technical processes. Neither are the models perfectly known nor are all the necessary measurements reliable enough or available at all.

Inspite of this deficiency, the model-based methodology remains basically practicable even under such restricted conditions. However, it requires skillful treatment and proper arrangements, and can only provide more or less reduced efficiency depending upon the special type of plant and the given restrictions. This gives evidences why a comprehensive theory of model-based FDI for real plants does not exist but, instead, a number of different methods have been proposed.

In this paper we outline the principles of the model-based FDI methods known so far. They can roughly be divided into two major categories, the *analytical redundancy* approach using analytical mathematical models and the *knowledge-based* approach using qualitative (deep or shallow) models associated with heuristic reasoning. All these methods are implemented on digital computers.

The *analytical* approach is tailored for *information rich* systems that, by definition, provide enough sensor information and can satisfactorily be described by analytical models.

Note that even in this case model uncertainty and incompleteness of measurements to a certain degree can still be tolerated. Depending upon the degree of uncertainty, robust or adaptive strategies have to be used.

In the case of *information poor* systems where unsatisfactory information and only poor models are available, only the knowledge-based approach comes into question. Logically, less can be achieved in such situations. It is then reasonable to employ the techniques built around artificial intelligence which at least allow to exploit as much knowledge of the process as available. In the extreme case where only a bare minimum of sensors is at hand and the process is extremely uncertain, as for example in complex chemical processes, only a *common sense* strategy may be practicable, a method that is still in its infancy (Howell 1991). In all these cases, expert systems, neural nets and fuzzy logic may be best suited to solve the FDI problems. At the same time, these techniques, eventually combined with Petri nets, can be used to implement the general fail-safe management for the overall supervision of the system.

In many practical situations, a combination of both the analytical and knowledge-based methodology may be the most appropriate solution to the FDI problem. Clearly, the inclusion of the analytical model, if available, provides the most condensed expertise of the plant possible and its inclusion helps a lot to overcome the known difficulties of filling the knowledge-base of the expert system and to simplify the reasoning program of the inference engine of the expert system. The general configuration of an expert system combining the analytical and knowledge-based strategy for FDI is shown in Fig. 1.

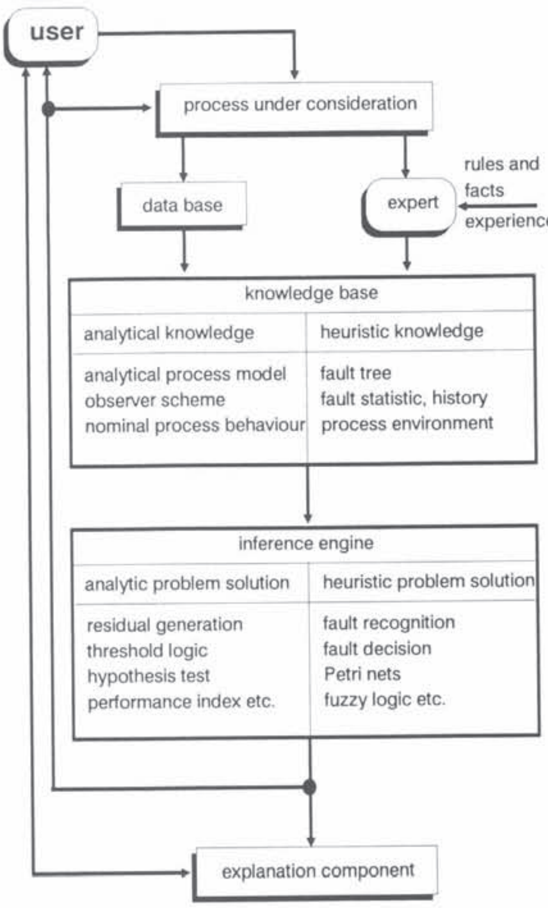

Figure 1: FDI Expert-system combining the analytical and knowledge-based approach

There exists quite a number of expert systems for fault diagnosis, especially in medicine and engineering systems. From the theoretical point of view, however, the analytical redundancy approach has so far reached the highest degree of maturity, especially as far as linear systems with little model uncertainty are concerned. This applies primarily to electrical, mechanical, pneumatic and hydraulic systems. For the latest state of the art and more references the reader is refered to the survey papers of Frank (1990, 1991), Gertler (1991), Patton and Chen (1991), Isermann (1984, 1991), the books of Patton, Frank, Clark (1989), Brunet, Jaume, Labarrere, Rault, Vergé (1990), and the PhD thesis of Sauter (1991).

Because of its maturity we focus our attention in this paper upon the analytical redundancy approach to FDI with due regard of the techniques to enhance the robustness with respect to modeling uncertainty. Only the basic ideas of the most important concepts are outlined because of the limitations in space. For more detailed description the reader is referred to the literature mentioned above and the literature cited therein.

General Concept of Analytical Model-based FDI

The basic concept of model-based FDI is illustrated in Fig. 2. In general, three kinds of models are required: A model of the nominal process as a reference, a model of the faulty process carrying information about the effect of faults, and

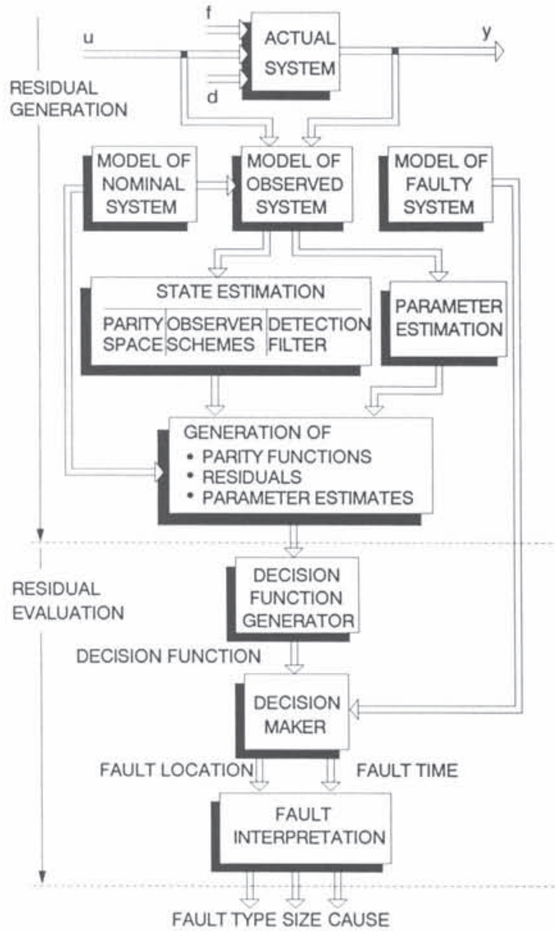

Figure 2: Basic concept of model-based FDI

a model of the observed process defined by the inputs and outputs taken from the actual process. To achieve a high quality of fault detection with a low false-alarm rate, the nominal model should be tracked with high precision by the unfaulted observation model.

The first step of FDI consits of generating estimates of the outputs and/or parameters of the actual process. The estimates are then compared with the corresponding quantities of the nominal model in order to generate residuals or parameter error signals, respectively, or they are used to form fault effected textures such as likelihood functions. The basis for the decision on a fault is a signal obtained from a model of the faulty process defining the effects of faults to be discovered. The final step is to diagnose the fault location and, if desired, its size and cause.

Concerning the model, one has to admit that the process with input u and output y can in general be nonlinear and may be subject to process disturbances, d_1, measurement noise, d_2, parameter variations, d_3 (due to modelling uncertainties and process parameter changes), and faults, f, that we want to detect. After linearizing the process around an operating point and grouping d_1, d_2 and d_3 to the so-called vector of unknown inputs $d = [d_1^T \quad d_2^T \quad d_3^T]^T$, the mathematical model takes the form:

$$\dot{x} = A\,x + B\,u + E\,d + K\,f \tag{1}$$
$$y = C\,x + F\,d + G\,f \tag{2}$$

Here, x denotes the state vector and A, B, C, E, F, K, and G are known matrices of proper dimensions. Actuator faults are reflected in changes in B, sensor faults in changes in C, and component faults in changes in A. They can all be represented by f when K and G are chosen properly. Note that, in general, no assumption can (and should!) be made on the mode (type and size) of d and f.

For the case of nonlinear models see Frank (1992) and Seliger and Frank (1991 a,b).

Principles of Residual Generation

The key problem of model-based FDI is the generation of residuals, i.e., signals which are accentuated by the faults. The residuals should be sensitive to faults and insensitive to the known and unknown inputs which may lead to false alarms.

In the widest sense, a residual generator is therefore defined as a dynamic system which, fed by the inputs and available outputs of the process under consideration, attenuates all influences except those caused by the faults to be detected. In connection with the decision logic, such a system may, in general, be termed a fault detection filter FDF.

The different approaches to residual generation can be grouped into two major categories:

- Parameter identification approach
- Observer-based approach.

Parameter Identification Approach

This approach makes use of the fact that faults in functional units of a process are reflected by changes in the physical parameters, p, *as*, for example, friction, mass, viscosity, resistance, capacitance, inductance, etc.. On the other hand, the physical parameters affect the parameters of the mathematical model of the observed system, i.e., A, B, C in Eqns. (1) and (2). The idea of the parameter identification approach is to detect the faults via estimation of the physical model parameters, due to the following procedure illustrated in Fig. 3:

1. Choice of a parametric model of the process, $y(t) = G[u(t), \theta]$ mostly by theoretical modelling. Normally one uses linear models with lumped parameters in the form of input/output differential equations:

$$a_n y^{(n)}(t) + \ldots + a_1 \dot{y}(t) + y = b_o u(t) + \ldots + b_m u^{(m)}(t) \quad (3)$$

   instead of the state-space representations, Eqns. (1) and (2).

2. Determination of the relationships between the vector of the mathematical model parameters θ_i and of the physical parameters p_j:

$$\theta = f(p) \quad (4)$$

3. Identification of the vector of model parameters θ using the inputs u and outputs y of the observed process.

4. Determination of the corresponding vector of physical parameters

$$p = f^{-1}(\theta) \quad (5)$$

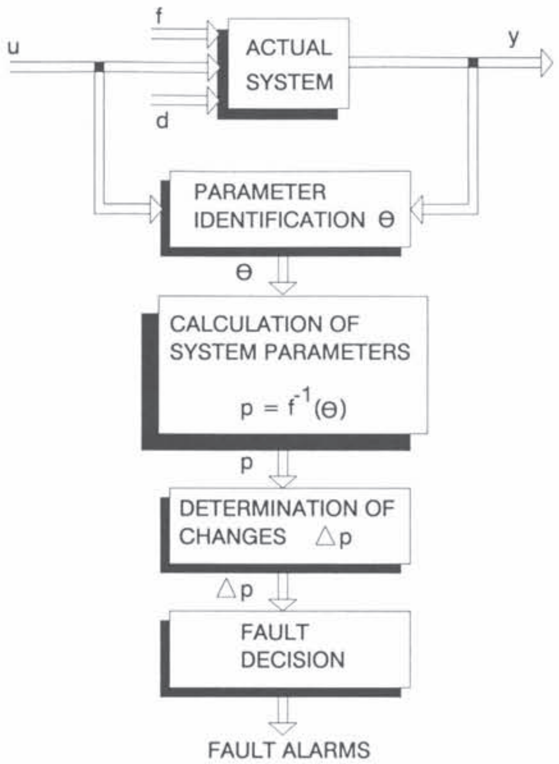

Figure 3: Parameter estimation approach to FDI

5. Calculation of the deviations, Δp, from their nominal values, p_0, determined from θ_0 of the nominal model of the process. Δp plays the role of the residual.

6. Decision on a fault by exploiting the relationships between faults and changes in the physical parameters, Δp_i. For this task one can also use catalogues in which the relationships between process faults and changes Δp_i have been established.

For the identification of θ one can make use of well established methods of the theory of parameter estimation. Problems may arise from the fact that the inversion f^{-1} in Eqn. (5) is in general not unique and only little is known about the robustness to model uncertainties, parameter variations, disturbances and noise. Moreover, the identification problem may become difficult to solve in the case of high-order systems that are not decomposeable into small units and/or systems that are nonlinear in the parameters. But under favourite conditions a powerful fault diagnosis is possible with this technique (Isermann 1991).

Observer-based Residual Generation

The basic idea of the observer-based approach is to reconstruct the outputs of the process with the aid of observers or Kalman filters and to use the estimation error or innovation, respectively, as a residual for the detection of the faults. The procedure of fault detection then consists of the following two steps:

1. Generation of residuals via output observation
2. Evaluation of the residuals by a decision logic.

It is well known from observer theory that for the task of observation one can use linear or nonlinear, ful or reduced-order observers (in the deterministic case) or Kalman filters (when noise is considered). In either case a mathematical model of the process is needed. The basic configuration of a full-order observer is shown in Fig. 4. In this case the observer simply consists of a parallel model of the process with a feedback of the estimation error, $e = y - \hat{y}$. The feedback is important for several reasons:

1. to compensate for differences in the initial conditions
2. to stabilize the parallel model in the case of an unstable process
3. to provide freedom for the design of the observer, for example, to decouple the desired effects of faults, f, from the effects of unknown inputs, d ("unknown input observers").

In the case of a process with the state Eqns (1) and (2), the state, $\hat{x}$, and output, $\hat{y}$, of a full-order observer obey the equations:

$$\dot{\hat{x}} = (A - H\ C)\hat{x} + B\ u + H\ y \tag{6}$$
$$\hat{y} = C\ \hat{x} \tag{7}$$

where H denotes the feedback gain matrix. With Eqns. (1),(2),(6) and (7) the relations for the state estimation error $\epsilon = y - \hat{y}$, become:

$$\dot{\epsilon} = (A - H\ C)\epsilon + E\ d + K\ f \tag{8}$$
$$e = C\ \epsilon + F\ d + G\ f \tag{9}$$

It is seen from Eqns. (8) and (9) that the output estimation error, e, is a function of both, f and d. Hence, e can be used as the *residual*, r, for FDI. If no fault occurs, i.e., $f = 0$, the observer will track the process so that r only depends on the unknown input, d. If, however, $f \neq 0$, the observer does no longer model the process precisely and r will be increased. Hence, a fault can be detected by checking the increment of r caused by f. In the simplest case this can be done by a threshold logic where the threshold is surpassed as f occurs. The objective of the observer design is to choose the feedback gain matrix, H, such that the fault signature in the residual is decoupled from that of the unknown input and becomes large enough to be detected.

In a similar way one can derive residuals using reduced-order observers, or Kalman filters, or even nonlinear observers in the case of nonlinear systems (Frank 1991, 1992).

Generation of structured residuals

For the task of fault isolation one needs structured residuals. They can be generated by observers or Kalman filters that are arranged as observer *schemes* or *banks* of observers. The goal of the observer schemes is to generate structured sets of residuals that enable a unique fault isolation. To this end, each observer may be made sensitive to a different fault and insensitive to the rest of faults. This may be accomplished by driving the observers by different sets of inputs or outputs of the process depending on the type of desired fault detection, i. e. actuator fault detection AFD, instrument fault detection IFD or general type component fault detection CFD. The most important types of observer schemes for FDI are briefly outlined in this section.

Innovation Test

A very simple observer configuration for FDI is that of using a *single Kalman filter* driven by all outputs of the process. The innovation vector, i.e., the difference between the measurement vector and its estimate is taken as the residual. In normal operation the residual is white noise with zero mean

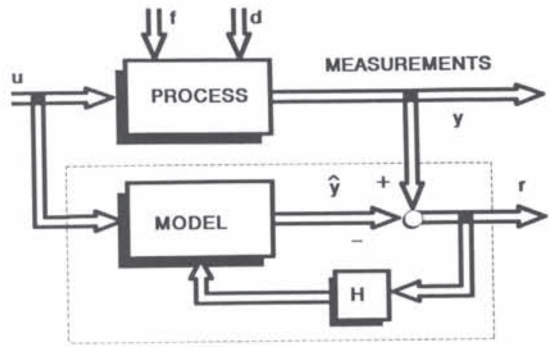

Figure 4: Basic concept of observer-based FDI: Identity observer

and known covariance. With the occurrence of a fault in the process the character of the noise and the covariance change. Hence, a fault can be detected by statistical tests of whiteness, mean and covariance of the innovation. Examples are the Chi-squared test, the bad data suppression concept and the general likelyhood ratio (GLR) test. The latter approach includes a hypothesis test based on different modes of the faults (Willsky 1976). More robustness of the covariance matrix test with respect to parameter variations can be achieved by a proper time shifting of the components of the innovation vector, i.e., by inclusion of correlation (Frank 1987).

Fault Detection Filter (FDF)

The so-called fault detection filter (or fault sensitive filter) is a full order observer of Kalman filter designed for the decoupling of the effects of different faults f_i in the process (Willsky 1976). Let the process be given by

$$\dot{x} = A\ x + B\ u + K\ f \tag{10}$$
$$y = C\ x \tag{11}$$

instead of Eqns. (1) and (2), i.e., no unknown input vector d be considered. The corresponding observer equations are

$$\dot{\hat{x}} = (A - H\ C)\hat{x} + B\ u + H\ y \tag{12}$$
$$\hat{y} = C\ \hat{x} \tag{13}$$

with the same meaning of the symbols as in Eqns. (6) and (7). Defining the state estimation error as $\epsilon = x - \hat{x}$ and the residual as $r = y - \hat{y}$, the state equation of the residual becomes:

$$\dot{\epsilon} = (A - H\ C)\epsilon + +K\ f \tag{14}$$
$$r = C\ \epsilon \tag{15}$$

Typical for the fault detection filter is that H is chosen such that the residual r due to a *particular fault*, f_i, is constrained to a single direction or plane in the residual space independent of the *mode* of f_i. This is often not possible unless the state x is accordingly enlarged.

Since the important information about the fault is in the *direction* of the residual rather than in its time function, the use of a fault detection filter does not require any knowledge of the fault *mode* $f_i(T)$, i.e., on the size or time history. Hence, a fault is detected when one or more of the residual projections along the known fault direction or in the known fault plane are sufficiently large. Since unknown inputs are not considered in the design, this approach does not account for the effects of disturbances, model uncertainty, parameter variations or measurement noise. This can, however, be achieved by treating the disturbances of concern like faults to be decoupled.

Parity Space Approach

The parity space approach provides a systematic exploitation of the analytical redundancy relations defined by the mathematical model of the process. This is associated with (generalized) parity checks (Chow and Willsky 1984). Parity functions are functions of the time histories of the measured outputs that are small (ideally zero) if and only if the process operates normally.

Following the state space representation of Chow and Willsky (1984), consider the system equations in discrete form

$$x(k+1) = A\ x(k) + B\ u(k), \quad (16)$$
$$y(k) = C\ x(k) + D\ u(k). \quad (17)$$

A redundancy relation for this model is some linear combination of present and shifted values of u and y that is identically zero if and only if no faults occur. For the mathematical specification, consider the subspace of $(m+1)q$ dimensional vectors given by

$$P = \left\{ y | y^T \begin{bmatrix} C \\ C\ \ A \\ \vdots \\ C\ \ A^m \end{bmatrix} = 0 \right\}$$

This is called the parity space of order m with q being the dimension of the measurement matrix C. At any time instant k, every vector y in Eqn. (18) can be associated with a parity check, $r_{(k)}$:

$$r_{(k)} = y^T \left[\begin{bmatrix} y_{(k-m)} \\ \vdots \\ y_{(k)} \end{bmatrix} - H \begin{bmatrix} u_{(k-m)} \\ \vdots \\ u_{(k)} \end{bmatrix} \right]$$

with

$$H = \begin{bmatrix} D & & & & \bigcirc \\ CB & D & & & \\ CAB & CB\ \ D & & & \\ \vdots & & & & \\ CA^{m-1}\ \ B & \dots & CAB & CB & D \end{bmatrix}$$

It is evident from Eqns. (19) and (20), that a redundancy relation is simply an input-output model for a part of the dynamics of the process.

Robustness can now be achieved by using primarily the relations of the certain part of the model, which can, e.g., be found by a minimax optimization (Lou et al. 1986).

Note that the resulting observer due to Eqn. (19) has all poles in the origin and can thus be interpreted as a deadbeat observer, i.e., a special form of an observer (Frank and Wuennenberg 1989). Gertler (1991) has discussed the parity space method from the ARMA and MA model point of view and has illustrated its crossconnections with the observer-based methodology (see also Patton and Chen (1991) and Frank 1992).

Unknown Input Observer Scheme (UIOS)

A most efficient way of creating robustness with respect to modeling errors is to apply unknown input observers UIO. Unknown input observers are therefore gaining increasing importance in FDI schemes. Here the feedback gain matrix H in Fig. 4 is assigned to make the residual invariant to unknown input signals d_i whilst being sensitive to faults f_k. The resulting state equation of the UIO for a process described by Eqns. (1) and (2) is:

$$\dot{z} = F\ z + G\ y + J\ u \quad (18)$$

with the residual

$$r = L_1\ z + L_2\ y \quad (19)$$

and with r having the following properties

$$\lim_{t\to\infty} r = 0 \quad \text{for } f = 0$$

and for all K, d and initial conditions $x(0)$ and $z(0)$ and

$$r \neq 0 \qquad \text{for } f \neq 0$$

Moreover, the states z of the UIO are linear combinations of the system states according to the following similarity transformation:

$$z = T\ x \quad (20)$$

which holds in the no-fault case after the transients due to the initial conditions have died out.

The resulting estimation error, $e = Tx - z$, is governed by:

$$\dot{e} = TAx + TBu + TEd + TKf - Fz - Ju - Gy \quad (21)$$

Evidently, to guarantee that e only depends on the faults f, the following relations have to be fulfilled

$$\begin{aligned} T\ A - F\ T &= G\ C \\ J &= T\ B \\ T\ E &= 0 \\ T\ K &\neq 0 \\ L_1 T + L_2 C &= 0 \end{aligned} \quad (22)$$

Solutions can be found under certain conditions, as for example, if the number of measurements is at least as large as the number of unknown inputs (Frank and Wuennenberg 1989, Wuennenberg 1990).

If the prerequisites for the existence of a UIO are not given, the best one can do is to design an *optimal approximation* such that a norm of the sensitivity with respect to the unknown inputs related to a norm of the sensitivity with respect to faults becomes minimal (Frank and Wuennenberg 1989).

In order to configure robust observer schemes using UIOs that allow the isolation of multiple faults in the face of unknown inputs, one has to partition the faults into subsets of f, specified by vectors f_i, with corresponding matrices K_i and G_i. Each UIO of the observer scheme is then assigned to be sensitive to a particular subset of faults and invariant to the rest of faults. The remaining design freedom can be used to provide invariance to unknown inputs. This is done, in turn, to such an extent that a properly structured set of residuals is obtained which enables a unique decision on the appearance and isolation of the faults. Such an observer scheme is shown in Fig. 5.

Depending on the given circumstances, this *unified design philosophy* covers a number of established FDI schemes:

- When the system is considered undisturbed and simultaneous faults in all sensors are to be detected, the design procedure leads to the *dedicated observer scheme DOS* as shown in Fig. 6 (Clark 1978). Here the ith observer ($i = 1, ..., p$) is driven only by the ith measured variable.

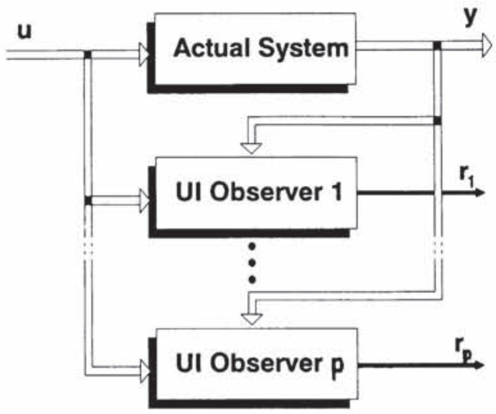

Figure 5: Generation of structured residuals using an observer scheme

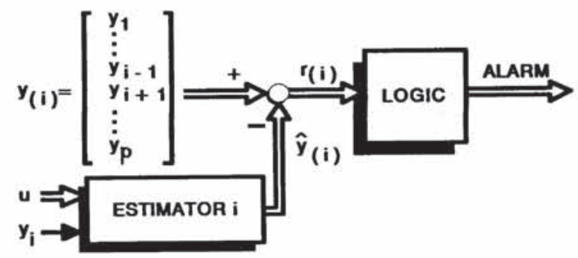

Figure 6: Dedicated observer scheme DOS

- When simultaneous sensor faults, component faults or actuator faults are to be detected and no disturbances have to be considered one arrives at the fault detection filter FDF as described earlier in this paper.
- When disturbances are considered and only a single sensor fault at a time is to be detected, the design procedure leads to the *generalized observer scheme GOS* (Frank 1987) as shown in Fig. 7. Suppose, for example, a process has p measurable outputs. Then an IFD scheme with p observers is used. The ith observer ($i = 1, 2, ..., p$) is driven by all but the ith output. In this case one fault at a time in one of the p sensors can be detected and isolated and the IFD scheme can be made invariant to $p-1$ unknown inputs. If, instead, two faults at a time are to be detected and isolated, the IFD scheme can be made invariant to only $p-2$ unknown inputs, etc.

In the widest sense the *simplified observer scheme SOS* (Clark 1978) can also be seen as a special case of this approach. Here, only a single fault at a time can be detected

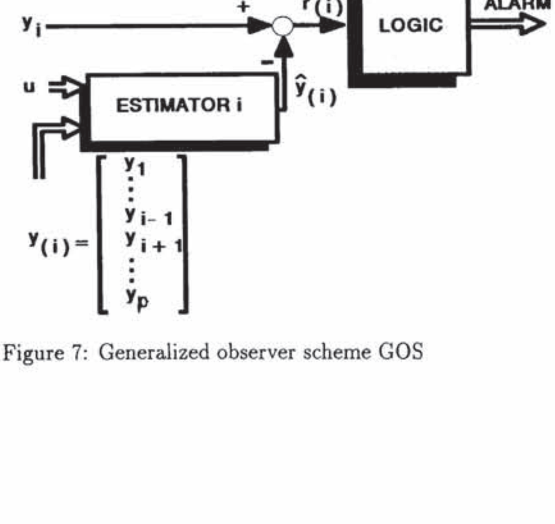

Figure 7: Generalized observer scheme GOS

and no disturbances can be considered. However, only a single observer is needed that is driven by one of the measured variables.

Whilst Wuennenberg (1990) has used the Cronecker form to design UIOS, an alternative approach for the decoupling of the effects of d and f using an *eigenstructure design* was proposed by Patton et al. (1987). In the no-fault case, the observer can be designed to have an invariant subspace (Patton 1988). Motions in the invariant sub-space are rendered completely insensitive to disturbances, whilst the residual signal departs substantially from zero during a fault - thus allowing a low threshold to be set for robust and rapid fault detection. The methods of Wuennenberg and Frank and of Patton differ in the design approaches adopted but lead to similar results.

The observer-based approach can readily be extended to nonlinear systems (Frank 1992). For a certain class of nonlinear systems an unknown input observer approach was proposed by Seliger and Frank (1991 a,b).

For frequency domain design procedures of FDI observers see Ding and Frank (1991) and Frank (1991).

Multiple Hypotheses Tests

The idea of FDI by multiple hypotheses test is to define a hypothesis for each fault, i.e., H_0 : ,,no fault", H_1 : ,,fault in sensor 1", ..., H_q : ,,fault in sensor q", and to test these hypotheses by using Bayesian decision theory. Each hypothesis is associated with a Kalman filter and a likelihood computation from the innovations, see Fig. 8. Hence, a bank of parallel Kalman filters is needed. The erroneous sensor is detected with the aid of m-array hypothesis testing. A moving window of the innovation of each Kalman filter drives a detector that calculates the likelihood ratio for each hypothesis of a possible failure mode.

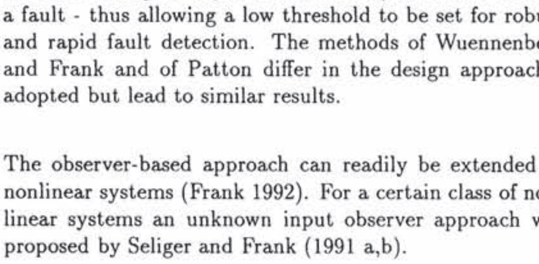

Figure 8: Multiple hypothesis test

Combined Hardware-Software Redundancy

Instead of pure software or hardware redundancy, one can also combine both of them. In the most simple case of e *duplex sensor system* one uses two sets of sensors, each set being supervised by an IFD scheme. Once a fault in one of the sensor sets is detected, the decision logic provides that the system is further operated with the unfaulted sensor. Using duplicated sensor sets complemented by dedicated observer schemes leads to the quality of a triplex hardware redundancy system.

Hierarchical Observer Scheme (HOS)

The isolation of component faults requires more structural insight in the process than the isolation of sensor or actuator faults. If no assumption on the fault mode can be made, a reasonable approach is to decompose the process and apply a hierarchical scheme of local observers or Kalman filters

(Frank 1987), see Fig. 9. The difficulty of local state obser-

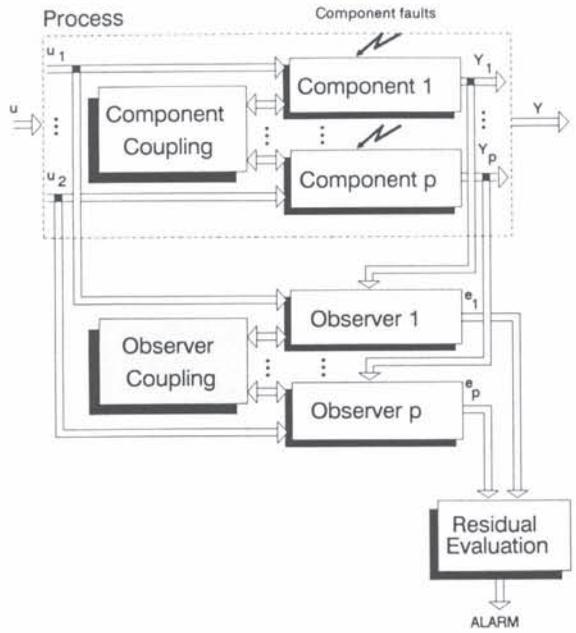

Figure 9: Local observer scheme

vation lies in the couplings among the components. If the couplings are sufficiently weak or measurable, malfunctions in the components affect only the estimates of the corresponding local observers. A unique fault isolation is then possible. However, if there are substantial non-measurable interactions, then the effect of a fault in a component propagates to observers of other components, and the observer scheme fails to isolate the fault. What could, however, be isolated is a fault in a subsystem of coupled components, which has only known interconnections to other similar subsystems.

The hierarchical observer scheme permits the division of the whole system into an upper level of interconnected subsystems with either weak or measurable couplings among the subsystems, and a lower level comprising only components with strong and uncertain couplings. For each of the resulting configurations in both levels a local observer scheme can be applied. In the upper level the so-called available state coupled observer scheme ASCOS, Fig. 10, can be used. Here the intercouplings of the original system are taken to feed the observers.

In the lower level a coupling network is required to generate the unavailable coupling signals among the observers. As coupling signals one can take the estimated states including the estimation errors. The resulting estimated state coupled observer scheme ESCOS is shown in Fig. 11.

The coupling of the local observers can completely be avoided by using local unknown input observers that are made invariant to the non-measurable coupling signals, see Fig. 12.

Decision and Monitoring

The final step in any FDI procedure is the fault *decision* and *monitoring*. The decision logic operates either directly on the residuals generated by the residual generator or on decision functions built of there, as, for example, likelihood functions. The final goal is then to maximize the detection probability while minimizing the false alarm rate. In general the decision procedure includes either threshold logic or

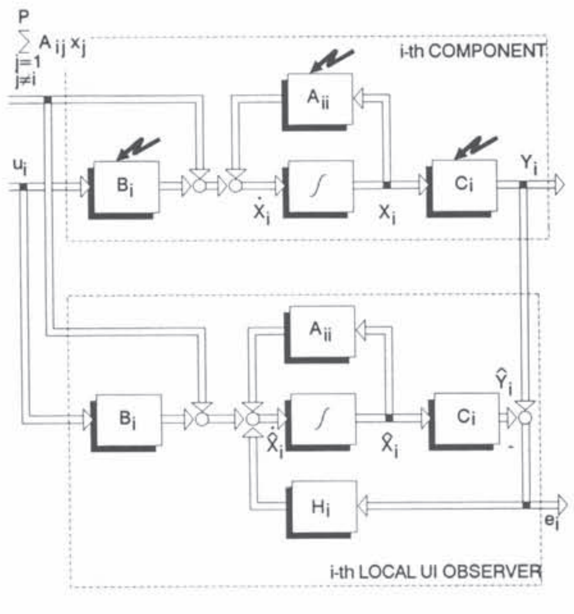

Figure 10: ASCOS

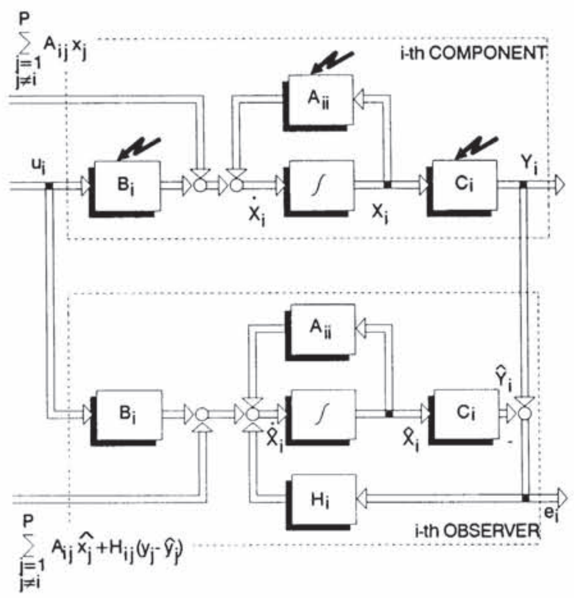

Figure 11: ESCOS

more sophisticated deterministic or probabilistic tests with an increasing tendency towards the application of adaptive strategies, fuzzy logic and artificial intelligence (Frank 1992).

Our view is that the use of natural intelligence should increasingly be used. This means that the evaluation of the residuals should preferably be done by the operators using the residual generator as a proper tool to support their decision in combination with their expert knowledge of the process and the process environment. This strategy may be of particular relevance in connection with lean production.

Conclusions

The paper has outlined the principles and various techniques of FDI in dynamic systems based on analytical system models. Attention has been focused upon the observer-based methodology with due regard to a unified approach

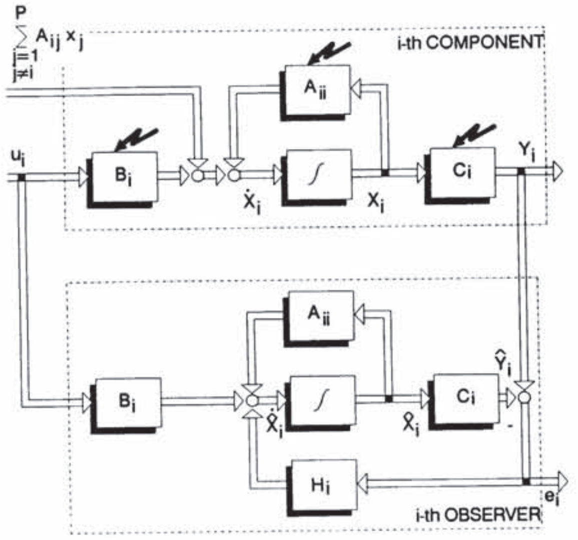

Figure 12: Local Unknown Input Observer Scheme LUIOS

known as the unknown input observer scheme UIOS which can provide a maximum of robustness with respect to unknown inputs.

Though much research is still going on in this field some of the methods described have already reached a rather high degree of maturity and there are a number of encouraging applications of model-based FDI schemes, especially in electrical, mechanical, pneumatic and hydraulic systems as, for example, aircrafts or advanced transportation systems. Yet in cases where only poor analytical models are available, as, for example, in complex chemical processes, the analytical model-based FDI approach is still facing difficulties and restrictions, and it seems that here it is the knowledge-based method that will have the best chance to be used for model-based FDI in combination with or as an alternative to the analytical model-based approach.

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