

HANDLING MODELLING UNCERTAINTY IN FAULT DETECTION AND ISOLATION SYSTEMS

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Abstract: *The paper deals with the treatment of modelling uncertainties in model-based fault detection and isolation (FDI). Essential for the practical implementation of model-based FDI algorithms is to make accurate fault decisions despite the unavoidable deviations between the model and the actual system under consideration. When analytical models are used, robustness of the FDI algorithms is an important factor, which, however, is usually achieved on the cost of increased complexity and often a reduction of the quality of FDI. A powerful alternative is the use of qualitative models which allow accurate FDI under even imprecise observations and at reduced complexity. In the first part we describe in some detail the basic concept of the analytical approach – to lay the grounds - and in the second part we briefly outline the recent attempts to employ non-analytical models while referring to the relevant literature for detail.*

Keywords: *Fault detection and isolation, modeling uncertainty, robustness, qualitative models.*

1. INTRODUCTION

All real systems in nature – physical, biological and engineering systems – can malfunction and fail due to faults in their components. The chances for failures are increasing with the systems' complexity. The complexity of engineering systems is permanently growing due to the growing size of the systems and the degree of automation, and accordingly increasing are the chances for faults and aggravating their consequences for man and environment.

Therefore, increased attention has to be paid to the reliability, safety and fault tolerance in the design and operation of engineering systems. But obviously, compared to the high standard of perfection that nature has achieved with its self-healing and self-repairing mechanisms in complex biological organisms, the fault management in engineering systems is far behind the standards of their technological capabilities and is still in its infancy, and much work is left to be done.

In automatic control systems, defects may happen in sensors, actuators, components of the controlled object, or within the hardware or software of the control framework. A fault in a

component may develop into a failure of the whole system. This effect can easily be amplified by the closed loop, but the closed loop may also hide an incipient fault from being observed until a situation is reached in which failing of the whole system is unavoidable. Even making the closed loop *robust* or *reliable* through *robust* or *reliable* control, respectively, can not solve the problem in full. It may help to make the closed loop continue its mission with the desired or a tolerable degraded performance, despite the presence of faults, but when the faulty device continues to miss-function, it may cause damage to man and environment due to the persistent impact of the faults (i.e., leakage in gas tanks or in oil pipes etc.). So, both robust control and reliable control using the available hard- or soft-ware redundancy of the system may be efficient ways to maintain the functionality of the control system, but it can not guarantee safety or environmental compatibility of the whole system.

A realistic fault management has to provide *dependability* which includes both reliability and safety. Dependability is a fundamental requirement in industrial automation, and a cost-effective way to provide dependability is *fault-tolerant control* (FTC) [9, 53]. The key issue of FTC is to prevent local faults from developing into system failures that can end the mission of the system and cause safety hazards for man and environment. Because of its increasing importance in industrial automation, FTC has become an emerging topic in control theory.

Automation for *safety-critical* systems, where no failure can be tolerated, requires redundant hardware to accomplish fault recovery. *Fail-operational* systems are made insensitive to any single component fault. *Fail-safe* systems perform a controlled shut-down to a safe state with graceful degradation when a sensor indicates a critical fault. *Reliable* and *robust* control ensure stability or pre-assigned performance of the control system even in the presence of *discrete* or, resp., *continuous* faults. *Fault-tolerant* control supervises online the system behaviour and causes appropriate remedial actions in order to prevent faults from developing into a failure of the whole system. In advanced FTC systems, this is achieved by *fault detection and isolation* (FDI) to detect the faulty components, followed by appropriate system reconfiguration [9, 53].

But fault detection and isolation has not only become a key issue in FTC, it is also the core of

fault-tolerant measurement (FTM). In this case the task of the FDI system is to make sure that the measurements in a sensor platform are reliable and to replace erroneous sensor readings with the aid of the existing analytical redundancy. Finally, FDI is a basic tool for offline tasks such as condition-based maintenance and repair, which is carried out according to the information obtained from early fault detection.

The backbone of modern FDI systems is the *model-based* approach [22, 26, 30, 31, 34, 64]. Making use of dynamic models of the system under consideration allows us to detect small faults and perform high-quality fault diagnosis by determining time, size and cause of a fault, and it is also applicable during dynamic system operation. The classical approach to model-based FDI is to utilize *analytical*, i.e. parametric mathematical models.

A fundamental difficulty with analytical models is that there are always unmodelled disturbances and modelling errors due to simplifications, idealizations and parameter variations which are basically unavoidable in the mathematical modelling of a real system. They are subsumed under the term *unknown inputs*. These are not mission-critical, but if they are miss-interpreted as faults, they cause false alarms which can make an FDI system useless. Therefore, the most essential requirement for an analytical model-based FDI algorithm is to provide *robustness* to the different kinds of unknown inputs. This problem is well recognized in the control community and there is a good deal of relevant literature on *robust* FDI techniques [12, 21, 22, 23, 24, 25, 30, 31, 33, 51, 52, 54, 55, 56, 58, 64].

Surprisingly, much less attention has been paid to the use of *qualitative* models in FDI systems, in which case the parameter uncertainty problem does not arise at all. The attractiveness of the qualitative approach is that qualitative models permit accurate decision making even under imperfect system knowledge and imprecise measurements. Moreover, qualitative models may be less complex than comparably powerful analytical models. At present, increased research is going on in the field of FDI using qualitative modelling and computational intelligence, and there is a good deal of publications with most encouraging results [3, 20, 22, 26, 28, 39, 41, 44, 45, 62, 68, 69].

In this paper, we briefly review the

fundamentals of model-based FDI and focus our attention on how to cope with modelling uncertainty, in-complete system knowledge and imprecise measurements. Included in the consideration are analytical (quantitative), knowledge-based (qualitative) and data-based models. It is our intention to stress the point that increasing the modelling abstraction will enable us to make accurate decisions for FDI with less complexity even in the face of high uncertainty and imprecision.

2. ANALYTICAL MODEL-BASED APPROACH TO FDI

2.1. Diagnostic strategy

The basic idea of the model-based approach to FDI is to compare the behaviour of the actual system with that of a functional system model. Any kind of model reflecting the occurrence of a fault can be used. The traditional approach is to use *analytical* models and to check the model outputs for consistency with the measured outputs of the actual system. The model provides the *functional redundancy* of the system. Since it is realized via software on a computer, one speaks of *software redundancy*, and when using analytical models of *analytical redundancy*. The diagnostic strategy is as follows:

If the measurements of inputs and outputs are inconsistent with the behaviour of the fault-free model, this means that a fault has occurred.

If the measurements are consistent with the behaviour corresponding to a certain fault scenario, f_i , then the fault scenario, f_i is declared.

Hence, there are two different strategies concerning the kinds of models used: One of them is to simulate the *nominal*, i.e., *fault-free* behaviour, and any inconsistency of the actual system behaviour with this model indicates a fault. Alternatively one can model the *faulty* behaviour for a particular pre-assigned fault scenario; then the consistency of the actual system with the model indicates that the assumed faults have occurred. In this paper we will only discuss the common approach of using *fault-free* reference models.

In general, the FDI task is accomplished by the following two-step procedure (Figure 1):

1) *Residual/symptom generation*. This means to generate residuals/symptoms that reflect the

faults of interest from the measurements or observations of the actual system. If the individual faults in a set of faults are to be *isolated*, one has to generate properly *structured* residuals or *directed* residual vectors.

2) *Residual/symptom evaluation*. This is a logical decision making process to determine the time of occurrence of faults (*fault detection*) and to localize them (*fault isolation*). If, in addition, faults are to be identified, this requires the determination of the type, size and cause of a fault (*fault analysis*).

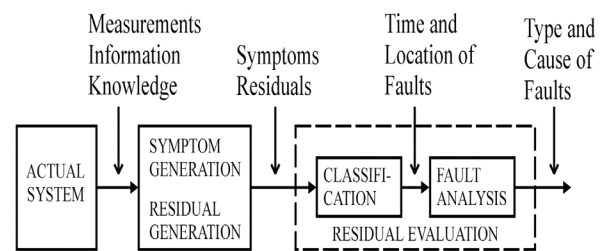


Fig. 1. The two-step process of residual generation and evaluation.

The basic block diagram of the model-based residual generator for the case of a MIMO system with multiple faults possible is as shown in Figure 2. Note that the core of the residual generator is a system model which has to be *accurate*, otherwise false alarms occur that falsify the results and make the FDI system useless.

The task of the residual evaluator is, according to Figure 1, to infer the occurrence of faults from the residuals/symptoms. This is a decision making or classification problem which requires the pre-assignment of the faulty behaviour in terms of a *faulty model*.

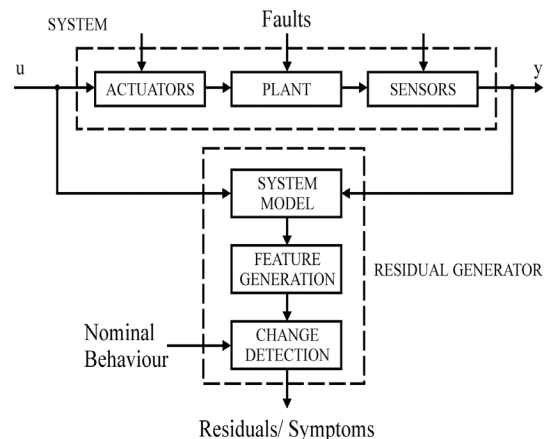


Fig. 2. General scheme of a model-based residual generator for FDI.

2.2. Analytical model representation

In case of using *analytical* models they may be given either in input-output or state space format. For linear continuous systems the state equations used for FDI are given by:

$$\dot{x}(t) = Ax(t) + Bu(t) + F_1 f(t), \quad (1)$$

$$y(t) = Cx(t) + F_2 f(t), \quad (2)$$

where:

- $x(t) \in \mathfrak{R}^n$ is the system state vector,
- A - the system matrix,
- $u(t) \in \mathfrak{R}^p$ is the known input vector,
- B - the input distribution matrix,
- $f(t) \in \mathfrak{R}^s$ is the vector of (additive) actuator, sensor and component faults,
- F_1 and F_2 the corresponding fault distribution matrices,
- $y(t) \in \mathfrak{R}^q$ the measurement vector and
- C - the output matrix.

According difference equations apply in the case of discrete time systems.

The corresponding input-output model, with p the differential or shift operator (depending on whether the system is continuous or discrete) is given by

$$y(t) = [G_u(p) + \Delta G_u(p)]u(t) + G_f(p)f(t), \quad (3)$$

where:

- $G_u(p)$ is the transfer matrix operator from u to y ,
- $G_f(p)$ is the fault transfer matrix operator from f to y , and
- $\Delta G_u(p)$ denotes the parameter deviation operator reflecting parametric faults in the system.

For the mathematical treatment of faults it makes a big difference whether the faults are additive or multiplicative. Additive faults can be treated as external inputs. $f(t)$ in (1)-(3) represents the set of *additive* faults such as actuator faults, sensor faults and some kinds of component faults (e.g., leaks). In contrast, faults that are reflected by system parameter variations (parametric faults), are represented by $\Delta G_u(p)$. They are of *multiplicative* nature, because $\Delta G_u(p)$ multiplies with $u(t)$. It can be shown that multiplicative faults can easily be approached by additive faults but with time-variant coefficients; they are therefore not as

easy to handle as genuine additive faults.

2.3. Uncertainty of analytical models

In (1)-(3) modelling uncertainties have not been taken into account. Under modelling uncertainties in the widest sense we understand all kinds of discrepancies between the mathematical model and the actual system caused by *imperfect modelling*. Typical examples are parameter deviations, unmodeled dynamics and non-linearities, neglected system disturbances, system noise, measurement noise and actuator noise. They are taken into account in the model equations as *unknown inputs* denoted by the vector $d(t)$ [64].

Note that since unknown inputs are not mission-critical, they have to be distinguished from faults in that they are tolerable with no need to be detected, but if they are misinterpreted as faults, they cause false alarms, and already small false alarm rates can make an FDI system totally useless.

According to the way of their mathematical treatment, the unknown inputs can be divided into two groups: *additive* and *multiplicative*. All kinds of unmodelled disturbances and noise act like additive external inputs. But parameter deviations multiply with state variables $x(t)$ or input variables $u(t)$ and are therefore termed *multiplicative*. Figure 3 illustrates the difference, where for simplicity a scalar gain factor a is considered. Note that the uncertainty $u(t)\Delta a$ can be interpreted as a (usually time constant) parameter variation Δa with a time variant coefficient $u(t)$. Another difficulty is that Δa affects the stability of the system.

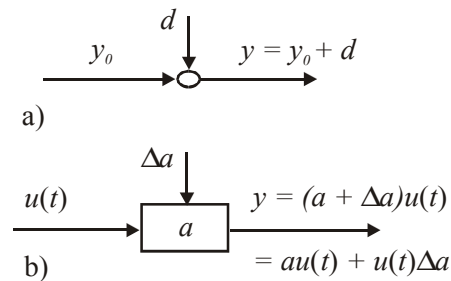


Fig. 3. a) additive uncertainties, b) multiplicative uncertainties.

Taking the modelling uncertainties into account, the complete state space model used

for residual generation becomes:

$$\dot{x}(t) = (A + \Delta A)x(t) + (B + \Delta B)u(t) + F_1 f(t) + E_1 d(t), \quad (4)$$

$$y(t) = (C + \Delta C)x(t) + F_2 f(t) + E_2 d(t), \quad (5)$$

where: $d(t)$ denotes the vector of the additive un-known inputs, with E_1 and E_2 the corresponding distribution matrices (constant and usually known), and $\Delta Ax(t)$, $\Delta Bu(t)$ and $\Delta Cx(t)$ de-note the parameter errors of the model which appear as multiplicative unknown inputs.

The corresponding input-output model becomes

$$y(t) = [G_u(p) + \Delta G_u(p)]u(p) + G_f(p)f(t) + G_d(p)d(t), \quad (6)$$

where:

- $G_d(p)$ is the transfer matrix operator from d to y and
- $\Delta G_u(p)$ here comprises both the parametric faults of the system and the parameter errors of the model.

Note that G_u , G_f and G_d can be easily calculated from (4)-(5). If the matrices E_1 , E_2 and $G_d(p)$ are known, we speak of *structured* uncertainties, which means that ΔG_u , and ΔG_d , are given. If they are unknown, the uncertainties are *unstructured*, but ΔG_u has usually at least a bounded frequency response

$$|\Delta G_u(j\omega)| \leq \delta_u(\omega). \quad (7)$$

2.4. General form of the residual generator

In its most general form, the residual generator is defined as a dynamic system with the input-output relation

$$r(t) = P(s)u(t) + Q(p)y(t), \quad (8)$$

where: P and Q are realizable transfer matrix operators.

In order to make the residual $r(t)$ become zero for the fault-free case, P and Q must satisfy the condition

$$P(p) + Q(p)G_u(p) = 0. \quad (9)$$

Different forms of the residual generator can be obtained by using different forms of P and Q . Substituting (9) into (8) gives the residual generator in the *output equation form*

$$r(t) = Q(p)[y(t) - G_u(p)u(t)], \quad (10)$$

where $Q(p)$ is a filter matrix operator yet free to select. By using the left coprime factorization,

$$G_u(p) = M_u^{-1}(p)N_u(p)$$

the residual generator can also be given in the unified, most general *equation error form*

$$r(t) = R(p)[M_u(p)y(t) - N_u(p)u(t)], \quad (11)$$

where: $R(p)$ is the so-called parameterisation matrix which can be arbitrarily chosen from the set of stable systems RH_∞ .

Substituting (6) into (10) yields the general form of the residual relation

$$r(t) = Q(p)[\Delta G_u(p)u(t) + G_f(p)f(t) + G_d(p)d(t)], \quad (12)$$

which considers all kinds of possible model uncertainty, $\Delta G_u(p)u(t)$ and $G_d(p)d(t)$.

2.5. Principles of residual generation

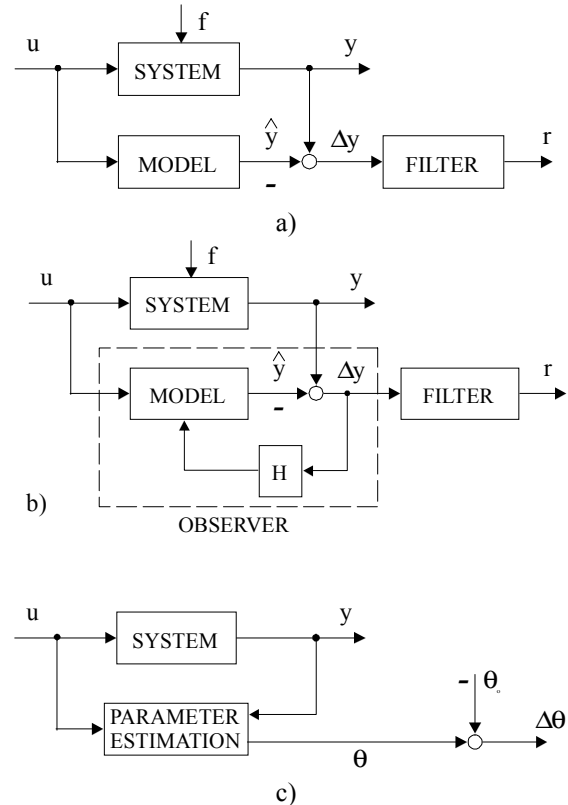


Fig. 4. Principles of different analytical residual generators: a) parity equation approach, b) observer-based approach, c) parameter estimation approach.

Based on this general definition, a number of different residual generation concepts can be derived. They may be classified into three major

categories, namely the *parity equation* (or “parity space”) approach, the *observer-based* approach and the *parameter estimation* approach [22, 23, 24, 28, 34, 52, 53]. The principles are outlined in Figure 4, a)-c). In the different approaches the residuals are defined as follows:

- *Parity equation approach*: Output or equation error (or modifications of them) with respect to a parallel model
- *Observer-based approach*: Output estimation error of output observer, e.g., Luenberger observer, or innovation of Kalman filter, or modifications of them
- *Parameter estimation approach*: Variations of the actual parameters from their nominal values.

Though conceptually different, intensive investigations during recent years have shown that there are close relationships among these approaches. It is easy to see that the parity space approach leads to a parallel model which can be interpreted as a special class of observer, namely the so-called ‘dead-beat’ observer with all poles at the origin [22, 64]. This means that the residual generator resulting from the parity equation approach can be subsumed, as a special case, under the group of diagnostic observers. Hence the residual can be given for both of them in the unified form of (10) or (11).

2.6. Treating modelling uncertainty in the residual generation stage

An important issue of any analytical residual generation procedure is to ensure *robustness* with respect to the *model uncertainties* defined above in order to keep the false alarm rate of the FDI system zero or at least extremely small. It should though be noted that this is often in conflict with the quality of FDI, that is to say, with fault detection and isolation sensitivity.

The strategies of creating robustness in analytical residual generators fall into three categories:

- 1) Perfect decoupling of the residuals from uncertainties (without making use of any knowledge of the time or frequency characteristics of the uncertainties)
- 2) Approximate decoupling of the residuals from the uncertainties (making use of some knowledge of the time or frequency characteristics of the uncertainties).

- 3) Knowledge-based selection of the partial models that reflect the faults and are not or minimally affected by model uncertainties.

2.6.1. Perfect residual decoupling

Perfect decoupling from unknown inputs is the most powerful way of creating robustness. From (12) we see that in order to decouple the fault vector F from the model uncertainties, the matrix $Q(p)$ has to be chosen so that

$$Q(p) [\Delta G_u(p)u(t) + G_d(p)d(t)] = 0 \quad (13)$$

whilst $Q(p)G_f(p) \neq 0$. Note that to make the term $Q(p)\Delta G_u(p)u(t)$ zero requires a time-variant filter matrix $Q(p)$. It is easier to solve this problem by threshold adaptation in the phase of residual evaluation, as will be seen later, and restrict the choice of $Q(p)$ to satisfy

$$Q(p)G_d(p) = 0. \quad (14)$$

The decoupling condition is a structural property of the system and can thus be described independent of the special type of residual generator used. Suppose that the transfer matrix $G_d(p)$ in (6) is known; then a fault f_i (element of the fault vector f) is detectable independent of d if

$$\text{rank} [G_d(p) \ G_{f_i}(p)] > \text{rank} [G_d(p)], \quad (15)$$

and f is isolable *and* decouplable from d if

$$\begin{aligned} \text{rank} [G_d(p) \ G_f(p)] &= \text{rank} [G_d(p)] + \\ &+ \text{rank} [G_f(p)]. \end{aligned} \quad (16)$$

Conditions (15)-(16) can be equivalently expressed for the state space model (4)-(5):

$$\text{rank} \begin{bmatrix} pI - A & E_1 & F_{1f_i} \\ -C & E_2 & F_{2f_i} \end{bmatrix} > \text{rank} \begin{bmatrix} pI - A & E_1 \\ -C & E_2 \end{bmatrix} \quad (17)$$

$$\text{rank} \begin{bmatrix} pI - A & E_1 & F_1 \\ -C & E_2 & F_2 \end{bmatrix} =$$

$$\text{rank} \begin{bmatrix} pI - A & E_1 \\ -C & E_2 \end{bmatrix} + \text{rank} \begin{bmatrix} pI - A & F_1 \\ -C & F_2 \end{bmatrix}. \quad (18)$$

Even though perfect decoupling is practicable in many real systems, namely all those which meet the conditions given above, there are severe limitations in practice. It can easily be shown [22, 64] that the number of unknown inputs from which the residuals can be decoupled, depends upon the number of independent

residuals, i.e., the number of sensors. Let the number of sensors be m , then

$$\text{rank} [G_d(p) \ G_j(p)] = m. \quad (19)$$

So, for fault *detection* (i.e. detection of a single fault) we have [31]

$$\text{rank} [G_d(p)] \leq m - 1, \quad (20)$$

and for the *isolation* of a fault

$$\text{rank} [G_d(p)] \leq m - 2. \quad (21)$$

The freedom given by the number m of independent measurements has to be shared among unknown input decoupling and fault isolation.

The conditions under which full decoupling exists are known and there are many methods for the solution of the problem in the frequency domain and in the time domain, where similar rank conditions hold; there are also extensions to certain classes of non-linear systems [2, 24, 27, 59, 64, 65, 66, 67].

2.6.2 Approximate residual decoupling

It can be seen from the decoupling conditions (16) -(18) that the number of unknown inputs from which the residuals can be perfectly decoupled, reduces accordingly the number of faults that can be isolated. Since in practical applications the number of uncertainties may be quite high, there is usually not enough design freedom for perfect decoupling from all uncertainties and only approximate decoupling can be achieved.

The approximation of perfect decoupling can be seen as an optimization process. The variety of different optimization techniques can be classified into the following three categories:

- Making use of some kind of knowledge of $r(t)$, deterministic [23] or statistic [6]. A typical example is the Kalman filter approach, in which it is assumed that the unknown inputs are white Gaussian noise;
- Approximating $G_d(p)$ by a transfer function matrix $G_d^*(p)$ which satisfies the existence conditions for full unknown input decoupling and provides an optimum approximation (in some sense) to $G_d(p)$ [12];
- Solving the approximate decoupling problem under a certain robustness performance index [6, 22, 24, 51, 56, 64].

We concentrate our consideration on the last

category due to its important role in the theoretical foundation of FDI and its close correspondence to residual evaluation and the integrated design of FDI systems. Since the goal of residual generation is to enhance the robustness of the residual to model uncertainty with minimum loss of sensitivity to the faults, the minimization of the performance index

$$J = \frac{\left\| \frac{\partial r}{\partial d} \right\|}{\left\| \frac{\partial r}{\partial f} \right\|} \rightarrow \min \text{ or} \quad (22)$$

$$J = \left\| \frac{\partial r}{\partial d} \right\| \rightarrow \min \text{ with } \left\| \frac{\partial r}{\partial f} \right\| > 0 \quad (23)$$

is widely recognized as a suitable design objective [22, 64]. Depending on the norm and type of the residual generator used, a number of optimization techniques have been applied. The most important ones are the rank reduced approximation by singular value decomposition, constrained least squares optimization, H-infinity optimization, μ -synthesis and LMI techniques. Recently, Ding et al. [18] have derived a unified solution for a number of optimization criteria and provided thus a useful theoretical platform to tackle the various approximation problems.

From a practical point of view, the above mentioned optimization strategies should not be overestimated. Even if an optimum has been achieved, this does not necessarily mean that the result is *satisfactory*; the number of false alarms may still be too high due to the number and size of model uncertainties.

A more practice-oriented definition of the optimization problem is to minimize the missed detection rate for a given pre-assigned false alarm rate. This leads to a *weighted* consideration of all model relations rather than the selection of subsets of relations. Recently this problem has been solved by Ding et al. [19].

In addition, there is a high potential for a further reduction of the effects of uncertainties in the residual *evaluation* stage. This is especially important for unstructured parameter errors which can in general not be decoupled with satisfaction in the residual *generation* stage.

2.6.3 Knowledge-based decoupling

The analytical decoupling methods discussed above lead to subsets of (modified) model relations, i.e. partial models with the following

properties: They are affected by the faults of interest but not or only weakly by parameter errors. In practice, this result can often be achieved intuitively based on inspection of the architecture of the system and the sensor configuration. The model relations have then simply to be selected with respect to their degree of dependence on faults and critical model uncertainties.

2.7. Robust residual evaluation

Due to the great number of uncertainties and the limited measurements available in practical applications, the decoupling method at the residual generation stage does often not lead to satisfactory robustness. This is especially true for unstructured modelling errors, and it is then necessary to use the residual evaluation stage for further enhancement of robustness.

The goal of *robust residual evaluation* is to minimize the false-alarm and missed-faults rates due to the remaining effects of unknown inputs on the residuals. The two main approaches to residual evaluation are

- Classification (or pattern recognition)
- Inference (or reasoning).

Traditionally, statistical methods such as maximum likelihood ratio tests have been widely used with great success [6, 31, 32]. But they are primarily tailored for disturbances and noise with given statistical characteristics (probability distributions etc.). This does not apply to modelling errors which are usually constants multiplying with the time function of the input vector u (6). In this case, threshold adaptation is a very useful tool [24, 26, 28, 52, 58].

2.7.1 Threshold adaptation

A threshold test is the final step in any decision making process. That is, residuals $r(t)$, or functions of them, $J(r)$, or resulting signatures have to be checked against thresholds. Traditionally, one uses constant thresholds. In this case, the decision is largely affected by parameter mismatches. If the threshold is chosen too small, the uncertainties cause false alarms, if too large, small faults cannot be detected. The situation can be strongly improved if the threshold is adapted to the time evolution of the residual in the fault-free case [24]. This idea of threshold adaptation is illustrated in Figure 5.

Suppose there is a mismatch between the system and the model in the residual generator. Then

any input, $u(t)$, of the system produces a residual unlike zero even if there is no fault. Figure 6 shows such a typical time evolution of the residual (or decision function) in the case of a model mismatch ΔG_u . If now a fault occurs at, say t_F , this causes an according additional change of the residual. Evidently, if we use a fixed threshold (broken lines), a false alarm occurs at t_{FA} and, on the other hand, the fault at t_F can not be detected. If an adaptive threshold is used (solid line) which follows in some way the residual caused by the input in the fault-free case, both the false alarm can be avoided and the fault at t_F can be detected.

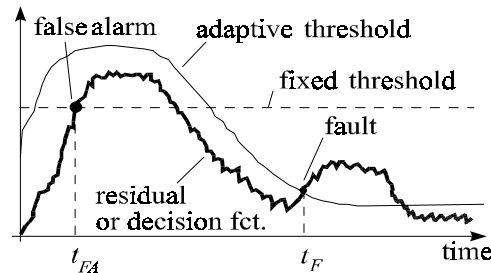


Fig. 5. Illustration of the concept of adaptive threshold.

The shape of the adaptive threshold can be found empirically by inspection of the shape of the residual under fault-free system operation [24, 28]. An analytical solution can be found as follows. If $y(t)$ of (6) is substituted in (10), and Q is chosen so that $QG_d = 0$ (decoupling of r from d), and f is set to zero (no fault present), then the residual due to the modelling errors becomes (with $Q = R M_u$)

$$r(t) = R(p)M_u(p)\Delta G_u(p)u(t). \quad (24)$$

From this, the threshold can be defined as

$$T(t) > \delta_u R(p)M_u(p)u(t), \quad (25)$$

where $\delta_u \geq \|\Delta G_u\|$.

A fault is declared if $|r(t)| \geq |T(t)|$. Note that the threshold $T(t)$ is no longer a constant in time. Its time function depends on the time function of the input, $u(t)$, and its size on the uncertainty, δ_u .

The block diagram of the resulting threshold selector for robust residual evaluation is shown in Figure 6. If the residual is evaluated in terms of a measure $J(r)$, (instead of r) e.g., the r.m.s. value of r , the threshold J_{th} can accordingly be found.

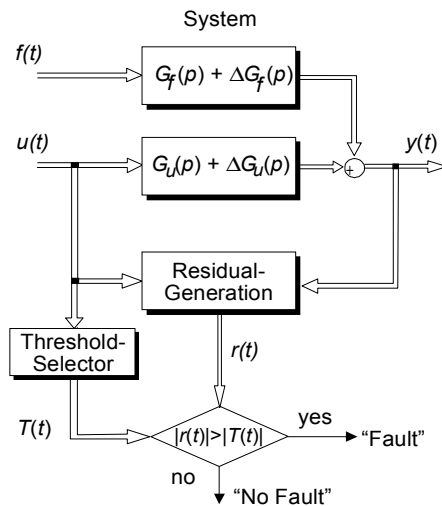


Fig. 6. Residual evaluation with adaptive threshold test.

It is important to note that, using this concept of a test with a time variant (“adaptive”) threshold, relatively small faults can still be detected without false alarms in face of structured or unstructured modelling uncertainties. This concept has, for example, been successfully applied to the fault detection of the bearings of robots with unmodelled operation-dependent friction [28].

3. FDI WITH NON-ANALYTICAL MODELS

3.1. Types of models for residual generation

It has been mentioned earlier that any kind of model that reflects the faults can be used for residual generation. From the methodological point of view the most appropriate model under the given circumstances is the one which allows a correct fault decision at a minimum false alarm rate and low complexity. There is a variety of different kinds of non-analytical models that come into question. They can be roughly classified into four categories:

- quantitative (analytical),
- qualitative (knowledge-based),
- data-based,
- structural.

The classification of the corresponding residual generation approaches is shown in Figure 7.

Concerning the modelling uncertainties, it has become apparent from our earlier discussion that

the crux with quantitative models is that they are usually inaccurate due to uncertain, imprecise or incomplete knowledge of the system. Hence, under those circumstances analytical modelling is most problematic and not appropriate, and it is practically useless for FDI unless one can renounce the parts with substantial uncertainty and delete them with the aid of robust FDI strategies, i.e., concentrate on the certain part of the model, as was described in the previous chapter

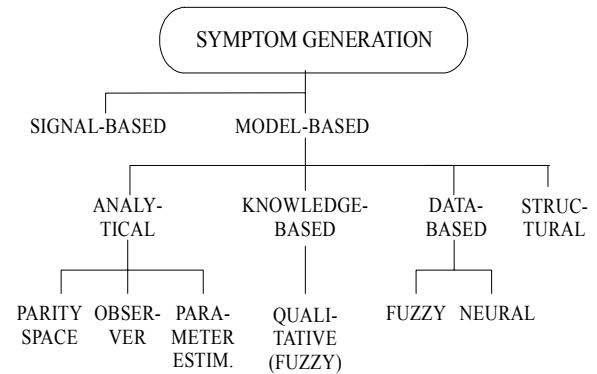


Fig. 7. Classification of different model-based approaches to residual generation.

3.2. The power of abstraction

The best way to fight model uncertainties is to avoid them from the very beginning. That is to say, to use such kinds of models that need not to be precisely defined in terms of parameters to describe the relevant system behaviour that reflects the faults, so that accurate FDI becomes possible despite incompleteness of the model and use of imprecise information. Under certain circumstances this can indeed be achieved with qualitative (knowledge-based) models that describe the system behaviour in terms of sets or symptoms rather than signals, or with data-based models (including fuzzy and neuro techniques), or with structural models. Their additional benefit is that they allow us to include available heuristic knowledge of the system and to apply artificial intelligence. Such techniques are applicable in all three stages of fault diagnosis: residual generation, residual evaluation and fault analysis.

Note that the use of qualitative models (in conjunction with symptoms) or structural models means an increase of the degree of *abstraction*, which plays a fundamental role in reaching correct results. Logically, achieving correctness in FDI implies that the check of the reference model must be accurate, i.e., it must

ensure that the symptoms are in agreement with the observations of the fault-free actual system even if those are imprecise. This is only possible, at reasonable complexity of the FDI system, with an according degree of *abstraction* of the model.

Figure 8 shows the typical relationship between model complexity, measurement imprecision and modelling uncertainty of an *accurate* model for FDI. It can be seen that the required complexity is maximum for precise, i.e. quantitative analytical models, and it decreases considerably with the degree of abstraction obtained by the use of non-analytical models. This means that accurate decisions are possible even in case of imprecise observations if abstract (non-analytic) modelling is applied, or, in other words:

A reduction of complexity of robust FDI algorithms can be obtained by increasing the degree of abstraction of the model.

To implement qualitative and knowledge-based FDI algorithms, one can stay with the described observer-based or parity relation strategies as a conceptual basis and replace the analytical models by non-analytical ones as well as the analytical signal processing algorithms by symptom processing algorithms. The resulting residual generators take the form of *qualitative observers, knowledge observers, fuzzy observers, neural observers, or diagnosis expert systems*, often supported by artificial intelligence. These approaches are most useful for FDI to cope with uncertainty in case of uncertain, poorly defined, complex and non-linear systems.

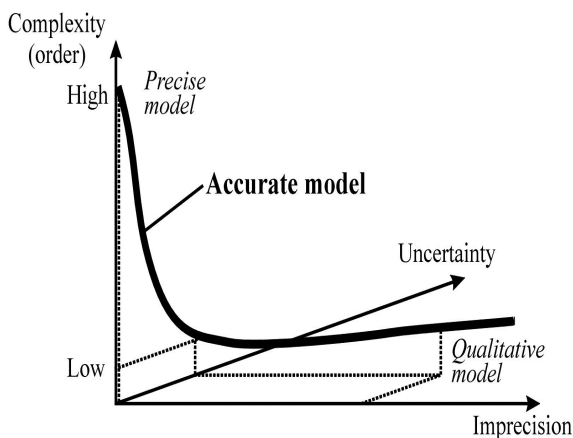


Fig. 8. Complexity of an accurate model for FDI versus uncertainty and imprecision.

3.3. FDI based on qualitative models

3.3.1 Qualitative approaches to FDI

Qualitative models reduce the resolution of the representations by introducing tolerances in order to emphasize relevant distinctions and ignore unimportant or unknown details. At imprecise observations this description represents the systems accurately if a *set* of values rather than a single value becomes a primitive representation.

In the last decade, the study of applying qualitative models to system monitoring and FDI received much attention, see, e.g., [20, 39, 41, 68, 68], and the concept of *qualitative (knowledge-based) observer* was born [26]. Typical qualitative descriptions of variables are signs [15], intervals [38], [41] and fuzzy sets [59]. As a fuzzy set can be divided into a series of intervals, the use of the α -cut identity principle proposed by Nguyen [49] allows to reduce fuzzy mappings into interval computations. Therefore, intervals are the most fundamental representations in qualitative modelling. The rough representations of variables lead to the imprecision in a qualitative model that relates the variables with each other. Qualitative simulation reconstructs the qualitative behaviour using such a model and retains or even enlarges the imprecision.

According to the available information about a system, there are several different possibilities to qualitatively represent the information of the dynamic process, each of which is associated with an appropriate simulation method. Basically, a qualitative simulation method should be responsible for retaining the accuracy of the represented system behaviour (so called soundness property following the definition of Kuipers [38], thus the FDI approaches based on them could avoid false alarms. The types of representation relevant to the FDI approaches presented in this section are:

- Qualitative differential equations (QDE) [38, 59]
- Envelope behaviour (e.g., [10, 36])
- Stochastic qualitative behaviour [41, 69].

Other relevant methods to qualitative models for fault diagnosis are e.g. signed directed graphs [40], logical based diagnosis [42] and structural analysis [60]. Dynamic behaviours are not emphasized in these methods, their main

concern is the causality or correlativity among various parts of systems, which are especially useful for performing fault isolation and analysis.

3.3.2 FDI using qualitative observers based on QDE

Conceptually, a qualitative differential equation can be considered as the extension of an ordinary differential equation

$$\dot{x} = g(x, u, \theta), \quad (26)$$

where x , u and θ denote the vectors of state variables, known inputs and parameters with the dimension of n , r and s , respectively. However, in a QDE, the variables take intervals as their values and the variant of the non-linear function $g(\cdot)$ is allowed to include various imprecise representations: e.g., interval parameters, non-analytical functions empirically represented by IF-THEN rules and even, in the algorithm QSIM of Kuipers [36], unknown monotonic functions. If the non-linear function $g(\cdot)$ is rational, its corresponding QDE can be readily derived from it by using the natural interval extension of the real function [47].

Through qualitative simulation procedures that are composed of the two main steps “generation” and “test/exclusion” are basically different from the numerical ones, the behaviour of continuous variables is discretely represented by a branching tree of qualitative states.

The qualitative observer (QOB) based on QDE is an extension of a qualitative simulator, and it functions in further reducing the number of irrelevant behaviours (including spurious solutions) to the system under consideration [68] as illustrated in Figure 9. The principle of observation filtering is that the simulated qualitative behaviour of a variable must cover its counterpart of the measurements obtained from the system itself; otherwise the simulated behavioural path is inconsistent and can be eliminated. Since these procedures do not lead to the violation of the accuracy of the qualitative behaviour under fault free condition, the output of QOB is the refined prediction behaviour in this case.

However, when a fault occurs which causes a significant deviation of the system output such that no consistent predicted counterpart of the output could be generated, the output of the QOB becomes an empty set, which indicates the fault occurrence. Following this principle, fault

detection and sensor fault isolation can be implemented [68]. It is important to note that, in exchange with the advantage of requiring weaker process knowledge in this method, one has to put up with an increase in computational complexity and less sensitivity to small faults.

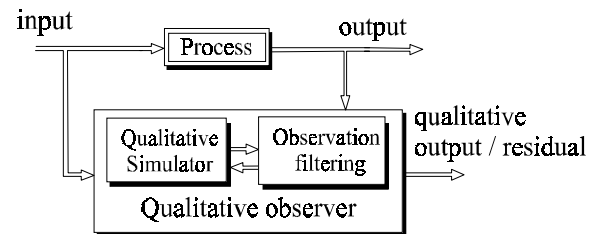


Fig. 9. Qualitative observer.

3.3.3 Fault detection based on envelope behaviours

A key issue on improving the small fault detectability when applying qualitative methods is that the qualitative system behaviour should be predicted as precisely as possible. Different from the qualitative model and the simulation method presented above, the model considered in this and the next sections is of less ambiguity, i.e. imprecision in (26) is caused only by interval parameters and interval initial states, the structure of $g(\cdot)$ is fully known.

While qualitative behaviours here are interval values of system variables against time; qualitative simulation, aiming at producing all possible dynamic behaviours, means the generation of their envelope. Once the envelope is generated, the scheme for fault detection is nothing else than a direct comparison between the envelope and the measurements. In fault-free cases, the measurements are always contained in the envelope; otherwise, it indicates fault occurrence. Therefore, a well designed simulation method is most important in this case for detecting small faults.

Recently, many efforts have been made to increase the precision of classical qualitative simulation, i.e., to avoid unnecessary conservativeness. More quantitative information is brought into a model representation [7], and simulation methodologies tend to be more constructive. Kay and Kuipers [36] and Verscovi et al. [63] propose approaches based on standard numerical methods to obtain the bounding behaviour. In [10, 37] Bonarini and Keller et al. treat the interval parameters and the state variables as a super-cube, whose evolution at any time is specified by its external surface.

Armengo et al. [3] present the computation of envelopes by means of modal interval analysis.

3.3.4 Residual generation via stochastic qualitative behaviours

Another qualitative representation of system behaviours is the stochastic distribution under partitioned state and output spaces. Beginning with the similar model assumptions as in section 3.3.1, the parameter vector is in θ and the initial state is uniformly distributed within a prescribed area, say cell 0 . $X_i(t)$ and $Y_i(t)$ denote the probabilities that the trajectories of the respective state and output variables, which start from all initial states in cell 0 , fall into the i -th cell at any time t . The behaviour can be approximately represented by a Markov chain [69]. It turns out that the new state and output variables X and Y can be described by the following discrete hidden Markov model (HMM):

$$X(k+1) = A(u, \theta) X(k) + V(k), \quad (27)$$

$$Y(k+1) = C(\theta) X(k+1), \quad (28)$$

where V represents the influence of spurious solutions.

A fault detection scheme based on the HMM is shown in Fig. 10 [69]. A qualitative observer (QOB) aiming at attenuating the effect of V and watching over the possible abnormal behaviour of measurements is applied. The residual r and its credibility v can be calculated, the latter reflects the degree of spurious solutions.

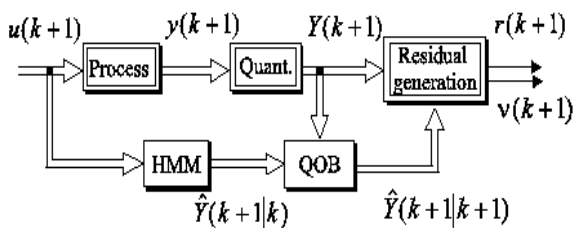


Fig. 10. Observer-based residual generation using HMM.

3.4. Residual generation employing computational intelligence

In the case of fault diagnosis in complex systems, one is faced with the problem that no or insufficiently accurate mathematical models are available. The use of knowledge-model-based or data-model-based techniques, either in the framework of diagnosis expert systems or in combination with a human expert, is then a

much more appropriate way to proceed. The concepts presented in the following section employ computational intelligence techniques such as

- Neural networks
- Fuzzy logic
- Genetic algorithms

and/or combinations of them in order to cope with the problem of uncertainty, lacking analytical knowledge and non-linearity. The latest developments in this area are briefly summarized in the following four sections.[28]:

3.4.1 Neural observer-based residual generation

Neural networks can be used as non-linear multi-input single-output (MISO) models of ARMA type to set up different kinds of observer schemes in the neural observer-based approach [28, 46]. Thereby the neural networks replace the analytical models which are usually necessary for observer-based FDI. If instead of a single multi-input multi-output structure a separate neural network is identified for each output, a set of smaller neural networks can be used for each class of system behaviour.

The type of neural network employed for this task is of a mixed structure called *dynamic multi-layer perceptron (DMLP-MIX)* integrating three generalized structures of a DMLP [44]. These three are: the DMLP with synaptic generalized filters, which have each synapse represented by an ARMA filter with different orders for denominator and numerator, the DMLP with internal generalized filters [5] integrating an ARMA filter within the neurons before the activation function, and the DMLP with a connectionist hidden layer, which has a partially recurrent structure interconnecting only the hidden units. The mixed structure is implemented in such a way that one can select either a basic architecture or a combination of them.

The training of the DMLP-MIX neural network is performed by applying dynamic back propagation while the problem of structural optimisation is solved with the help of a genetic algorithm [45].

Two types of observer schemes have been proposed by Marcu et al. [46] for actuator, component and instrument fault detection: the neural single observer scheme (NSOS) and the

neural dedicated observer scheme (NDOS). While the first one is driven by all system inputs and outputs, the second one is only driven by the system inputs and the output of the component to be supervised. Therefore the first scheme consists only of a single observer which is composed of a bank of MISO neural nets each estimating one output in contrast to the second scheme, which consists of a number of observers assigned to each component of the plant. These neural observers in turn consist of a number of MISO neural nets each estimating one system output. In both cases the training is based on fault free process data reflecting the normal behaviour. The residual evaluation part can then be performed by a well-known static MLP neural network.

3.4.2 Fuzzy observer-based residual generation

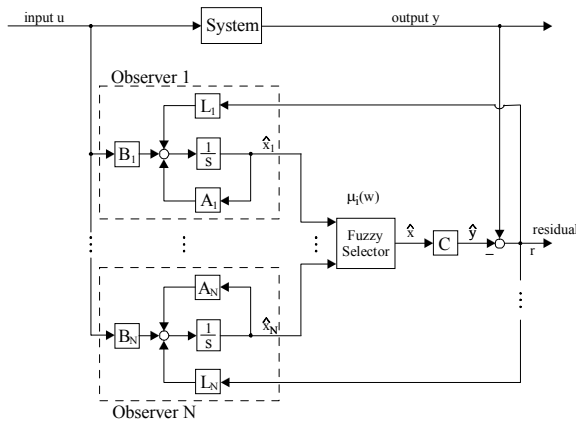


Fig. 11. Fuzzy functional observer scheme [12].

There are many ways of using fuzzy logic to cope with uncertainty in observer-based residual generation [28]. The resulting type of fuzzy observer depends upon the type of the fuzzy model used. Fuzzy modelling can roughly be classified into four categories: fuzzy rule-based, fuzzy qualitative, fuzzy relational and fuzzy functional (Tagaki-Sugeno type).

As an example of a fuzzy functional observer consider the observer configuration proposed by Chen et al. [12] (Figure 11). It consists of a set of analytical linear observers on whose outputs a fuzzy fusion is performed based on the idea of Tagaki-Sugeno [61]. Using this approach a non-linear dynamic system is described by a number of locally linearized models. For the fuzzy observer scheme the linear models are implemented in a bank of linear observers. The final state estimation is given by a fuzzy fusion of all local observer outputs. The difference between the measured output and the estimated

output produces the residual for further diagnostic evaluation.

Although all local observers can be designed stable, the overall fuzzy observer is not necessarily stable. The linear matrix inequality (LMI) method can be employed to analyse and ensure stability of the fuzzy observer scheme. The technique of eigenvalue assignment is used to ensure a certain diagnostic performance such as speed or robustness.

3.4.3 Residual generation with hierarchical fuzzy neural networks

Here the fault diagnosis system is designed by a knowledge-based approach and organized as a hierarchical structure of fuzzy neural networks (FNN) [11]. FNNs combine the advantage of fuzzy reasoning, i.e. being capable of handling uncertain and imprecise information, with the advantage of neural networks, i.e. being capable of learning from examples. The neural nets consist of a fuzzification layer, a hidden layer and an output layer. Fault detection is performed through the knowledge-based system, where the detection rules are generated from knowledge obtained from the structural decomposition of the overall system into subsystems and operational experience. After detecting a fault the diagnostic module is triggered which consists of a hierarchical structure (usually three layers) of FNNs. The number of FNNs is determined by the number of faults considered. The lower level only contains one FNN, which processes all measured variables. The FNNs on the medium level are fed by all measurements but also by the outputs of the previous level. The upper level consists of an OR operation on the outputs of the medium level. This hierarchical structure can cope with multiple simultaneous faults under highly uncertain conditions.

3.4.4 Fuzzy residual evaluation

Fuzzy logic is especially useful for decision making under considerable uncertainty. The three main categories of current residual evaluation methods are: classification (clustering) or pattern recognition, inference or reasoning, and threshold adaptation. Although all approaches employ fuzzy logic, the first one is actually data-based while the other two are knowledge-based.

Fuzzy clustering

The approach of fuzzy clustering actually consists of a combination of statistical tests to

evaluate the time of occurrence of the fault and the fuzzy clustering to provide isolation of the fault [14]. The statistical tests are based on the analysis of the mean and the variance of the residuals, e.g., the CUSUM test [32]. The subsequent fault isolation by means of fuzzy clustering consists of the two following steps: In an online phase the characteristics of the different classes are determined. A learning set which contains residuals for all known faults is necessary for this online phase. In the online phase the membership degree of the current residuals to each of the known classes is calculated. A commonly used algorithm is the fuzzy C-means algorithm [8].

Fuzzy reasoning

The basic idea behind the application of fuzzy reasoning for residual evaluation is that each residual is declared as *normal*, *high* or *low* with respect to the nominal residual value [14, 62]. These linguistic attributes are defined in terms of fuzzy sets, and the rules among the fuzzy sets are derived from the dynamics of the system. For fault detection, the only relevant information is whether or not the residual has deviated from the fault free value, and hence it is only necessary to differentiate between normal and abnormal behaviour. However, if isolation of faults is desired, it may be necessary to consider both the direction and magnitude of the deviation.

The rules for evaluating the residuals can be written down based on knowledge of the system or from inspection of simulated residuals. The rules are derived in an iterative algorithm starting with a small number of input membership functions for each input and a single output membership function for each fault, and the number of inputs and/or input membership functions is increased until satisfactory fault detection and isolation is achieved.

Fuzzy reasoning has been applied with great success to threshold adaptation [26, 56].

Fuzzy threshold adaptation

In case of poorly defined systems it is difficult or even impossible to determine adaptive thresholds on the basis of (25). In such situations the fuzzy logic approach is much more efficient. The relation for the adaptive threshold can be defined as a function of input u and output y by

$$T(u, y) = T_0 + \Delta T(u, y). \quad (29)$$

Here $T_0 = T_0(u_0, y_0)$ denotes a constant threshold for nominal operation at the operational point (u_0, y_0) where only the effects of the stationary disturbances including measurement noise are taken into account. The increment $\Delta T(u, y)$ represents the effects of $u(t)$ and $y(t)$ caused by the modelling errors. These effects are described in terms of IF-THEN rules and the variables by fuzzy sets (e.g. SMALL, MIDDLE, LARGE, etc.) that are characterized by proper membership functions.

As a typical example of an industrial application we consider the residual evaluation via fuzzy adaptive threshold of a six-axis industrial robot (Manutec R3) [26, 56]. Let the goal be to detect a collision of the robot by checking the moments of the drives. A model of the robot is available, but without knowledge of the friction of the bearings, which is highly uncertain. It is known, however, that the residual of the moment is heavily distorted by the friction which strongly depends on the arm acceleration. This knowledge can be formulated by rules. For example for the third axis the following rules apply:

- IF {*speed small*}, THEN {*threshold middle*}
- IF {*acceleration high*}, THEN {*threshold large*}
- IF {*acceleration very high*}, THEN {*threshold very large*}
- IF {*acceleration of any other axis very high*}, THEN {*threshold middle*}.

The linguistic variables *small*, *middle*, *high*, *very high*, *large*, *very large* are defined by proper membership functions [56], they are assigned intuitively based on the experience of the operators or the manufacturers of the robot.

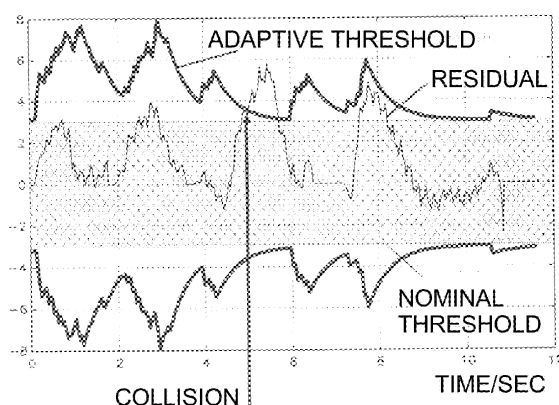


Fig. 12. Obstacle detection of a robot with fuzzy adaptive threshold.

Figure 12 shows the time shape of the thresh-old together with the shape of the residual of axis 3 for a particular manoeuvre of the robot. Note that at $t = 4,5$ sec the heavy robot which can handle 15 kg objects in its gripper, hits an obstacle which causes a momentum of about 5 Nm. As can be seen, this small fault can be detected at high robustness to the uncertainty caused by the unknown friction that is neglected in the model.

3.5 FDI using structural models

The use of structural system models together with structural analysis is another way of abstraction of the modelling of the system behaviour in order to increase the robustness of the FDI algorithm to model uncertainties. Here we only consider the *structure* of the constraints, i.e., the existence of links between variables and parameters rather than the constraints themselves [60]. The links are usually represented by a *bi-partite graph*, which is independent of the nature of the constraints and variables (quantitative, qualitative, equations, rules, etc.) and of the values of the parameters. Structural properties are true almost everywhere in the system parameter space.

This represents indeed a very low-level easy-to-obtain model of the system behaviour, which is logically extremely insensitive to changes in the system parameters but, of course, also to parametric faults. Despite their simplicity, structural models can provide much useful information for FDI and FTC, because a structural analysis is able to:

- identify those components of the system which are monitorable,
- provide design approaches for analytical redundancy-based residuals
- suggest alarm filtering strategies
- identify those components whose failure can be tolerated or not through re-configuration.

Important tasks of structural analysis are

- Identification of the monitorable part of the system, i.e., of the subset of components whose faults can be detected and isolated
- Generation of residuals which meet some specific FDI requirements, namely to be *robust*, i.e. insensitive to disturbances and uncertainties, and *structured*, i.e. sensitive to certain faults whilst insensitive to others

- Estimation of some variables of interest for system reconfiguration in case of sensor, actuator or component faults.

This is achieved with the aid of the analysis of the system structural graph and its canonical decomposition. An important factor in the canonical decomposition is the property of causality which provides the bi-partite graph with an orientation. FDI is performed with the aid of analytical redundancy relations based on structural analysis and the generation of structured residuals.

It is important to note that the use of structural models together with the strong decoupling approach solves automatically the robustness problem in structurally observable systems. This is easy to see, because strong decoupling exhibits analytical redundancy relations which only depend on known variables. On the other hand, the price to pay for the structural approach is that faults reflected in parameter changes can not be detected. Structural analysis is of primary importance for system reconfiguration in FTC, since the results correspond to graph properties whose changes due to switching off some components after a fault has occurred are analysed.

4. CONCLUSION

The paper reviews the methods of handling modelling uncertainties and incomplete system knowledge in model-based fault detection and isolation. It is pointed out that the general strategy to solve this problem is to restrict oneself to that part of any kind of functional system model which reflect the faults of interest without being considerably affected by modelling uncertainties. In the case of using quantitative models, proper sub models can be determined by well elaborated robust FDI techniques. From the uncertainty point of view and with respect to the complexity of the FDI system more abstract non-analytical models are superior, and the paper outlines the relevant on-going research in the field of approaching the modelling uncertainty problem in FDI with various types of non-analytical models.

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