INDUSTRIAL APPLICATIONS OF FAULT DIAGNOSIS

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Contents

Summary

This chapter gives an overview about industrial applications of modern fault detection and diagnosis approaches. It will not cover all possible applications which is impossible because of the numerous applications in different areas. Instead, some examples will highlight the possible use of modern supervision systems. Future aspects will briefly be touched to give the reader a feeling of what trends will become important in the years to come.

The structure is as follows: In the introduction, some typical application areas and the methodologies used in these areas will be briefly mentioned. After that, the contribution will go into more details by showing exemplary applications in the fields of industrial processes and mechatronic devices in automotive applications. For a better

understanding of the examples, an introduction into the most important methods will be given first. Finally, a summary with future aspects will be given.

1. Introduction and Overview

Process supervision systems serve to indicate faulty states of a process and initiate appropriate counteractions. One can distinguish the following three functions:

- *Monitoring:* Measurable quantities are checked and threshold violations are displayed. Alarms are generated to trigger actions from the operator.

- *Automatic protection:* In addition to monitoring, appropriate actions are undertaken to avoid damage or possibly hazardous situations.

- *Supervision with fault diagnosis:* Using advanced mathematical methods, not only simple quantities are checked, but features are calculated, that serve as a basis for a diagnosis identifying different fault causes.

In most of today's supervision systems only monitoring is performed. This very simple and reliable way of process supervision has nevertheless some drawbacks: It can only be employed when the signals are in steady-state condition. Any dynamic operation would lead to false alarms. During set point changes, those systems are usually deactivated. Closed-loop control further hinders fault detection since fault effects are covered by control actions.

Modern supervision concepts allow not only monitoring and automatic protection but can also help to perform maintenance on demand or an earlier detection of gradually developing faults. They can be employed in closed-loop situations and work even under dynamic operation. That allows a supervision at more levels of technical processes.

1.1 Main Application Areas

If one considers the different application areas, one finds distinctively different requirements for supervision systems that lead to the use of the different methods to detect and diagnose faults.

Chemical industry and process industry applications are characterized by a large number of measurement values. The systems usually have relatively large time constants and are relatively robust, not meaning that serious faults can not lead to devastating problems. One finds many relatively simple systems that are sufficiently supervised by limit and plausibility checking. This includes system parts like flow controls, discrete event systems such as transportation devices, valves, etc. Many of these individual components are already equipped with simple diagnosis capabilities. Hydraulic pistons for instance that are used to transport and move parts of a production environment can be equipped with end-position switches to monitor the correct movement. Modern sensors are also equipped with diagnostic circuits that can discover failures and malfunctions. Most of these diagnostic capabilities, however, are limited: Usually they only make a binary decision, meaning they can only discover a total breakdown of the devices. Overall, one can state that monitoring is the main task in these applications.

Since there are usually numerous individual devices connected via industrial field bus, the central process control receives many diagnostic signals. The main task of such a process control is to manage this number, select the important, perform automatic protection and display them in appropriate form to the process operator. Consequently, modern methods include approaches like data mining or discrete event logic's; they are usually highly specific to the individual plant.

Still less frequently, supervision with fault diagnosis concepts is realized. They can connect the information from different sensors and actuators to monitor their correct behavior. They are, on the other hand, capable of detecting possibly hazardous situations early on and start appropriate counteractions. They also need an application to the individual process. Typically, only some main or highly critical parts of industrial or chemical factories are equipped with these supervision systems utilizing modern signal-processing techniques.

Mechatronic devices and automobiles are the other important application area of supervision and diagnosis approaches. Examples in automotive applications are the on-board diagnosis capabilities of modern vehicles. They allow us to inform the driver about problems requiring repair or advice him to use the vehicle only in a limited way. These diagnostics are usually driven either by laws for instance in the avoidance of excessive pollution due to malfunctions or by the effort to avoid unwanted stops. In the context of more and more replacements of mechanical by electro-mechanical or electrical components, the self-diagnostics becomes essential for the assurance of safety-critical operation.

Many individual components in vehicles can be described as mechatronic devices where a close connection of the mechanics with actuators and local computational resources is given. These devices are also frequent in modern production processes and they enter more and more areas of today's life. They have the capability to supervise their functionality to a higher degree than traditional devices with separate mechanical and electrical parts have. Hence, there is a strong tendency to design mechatronic devices with built-in supervision with fault detection.

2. Methods

To illustrate the use of modern fault detection and diagnosis capabilities, examples will be given in the following sections. They will be a thermal plant as common in many chemical plants and other examples will be from the automotive area where mechatronic devices are used.

For an easier understanding of the examples, some of the most important modern methods will be described first. They deal with the two problems of fault detection and fault diagnosis.

2.1 Fault Detection Methods

Different approaches for fault detection using mathematical models have been developed since the 1980s. In this section, some of these are briefly described.

Figure 1 displays the basic approach of model-based techniques: Using input and output measurements from the process, it can be judged whether or not the expected behavior is still present.

Any change in the system will lead to a deviation of certain signals (usually called symptoms or features) being calculated by the fault detection scheme. A change detection taking the statistical properties of the residuals into account, will identify abnormal situations and trigger the fault diagnosis which identifies the specific fault situation.

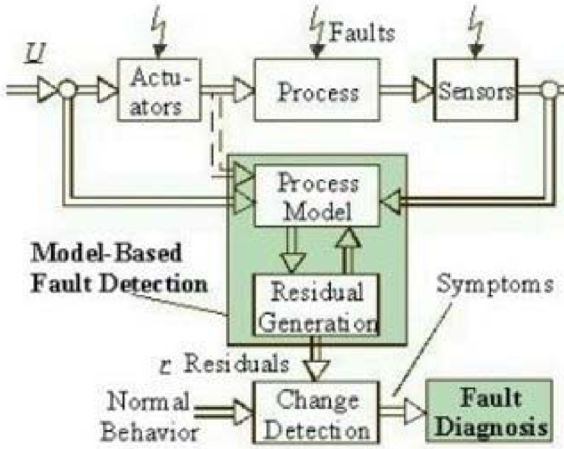

Figure 1: Model-Based Fault Detection and Diagnosis

2.1.1. Parameter Estimation Methods and Signal Models

Parameter estimation can be used to detect and isolate faults in a process if faults are reflected in parameters that can be gained from available measurements. The comparison of reference parameters of input-output models with the actual parameters determined by the measurements can indicate the appearance - and sometimes also the size - of the fault. If the process is sufficiently linear, its output $y(t)$ depending on the input $u(t)$ can be described by

$$y(t) = \boldsymbol{\psi}^{\mathrm{T}}(t)\boldsymbol{\theta} \tag{1}$$

$$\boldsymbol{\theta}^T = [a_1 \ldots a_n \; b_0 \ldots b_m] \qquad \boldsymbol{\psi} = \left[-y^{(1)}(t) \ldots - y^{(n)}(t) \;\; u(t) \ldots u^{(m)}(t)\right] \tag{2}$$

which leads to the following transfer function after Laplace transformation:

$$G_P(s) = \frac{y(s)}{u(s)} = \frac{B(s)}{A(s)} = \frac{b_0 + b_1 s + \ldots + b_m s^m}{1 + a_1 s + \ldots + a_n s^n} \tag{3}$$

Minimizing the equation error $e(t)$ of such a model in a least-square sense, see Figure 2a, leads to an estimate for the parameters given by

$$\hat{\boldsymbol{\theta}} = \left[\boldsymbol{\Psi}^{\mathrm{T}}\boldsymbol{\Psi}\right]^{-1}\boldsymbol{\Psi}^{\mathrm{T}}\mathbf{y} \qquad (4)$$

where the matrix $\underline{\boldsymbol{\Psi}}$ and vector $\mathbf{y}$ contain the measurements and their derivatives at the sample times. Similar estimation schemes can be used for discrete-time models and multi-input multi- output processes. The relationship between the physical parameters (like a stiffness, damping coefficient or resistance) of the process and the model parameters a_i, b_i must then be inverted to draw conclusions about the fault cause.

An alternative estimation approach is shown in Figure 2.b, where the parameters of the model are adopted to yield a minimal output error $e'(t)$. In this case, the necessary nonlinear optimization scheme of the estimation requires more computational effort.

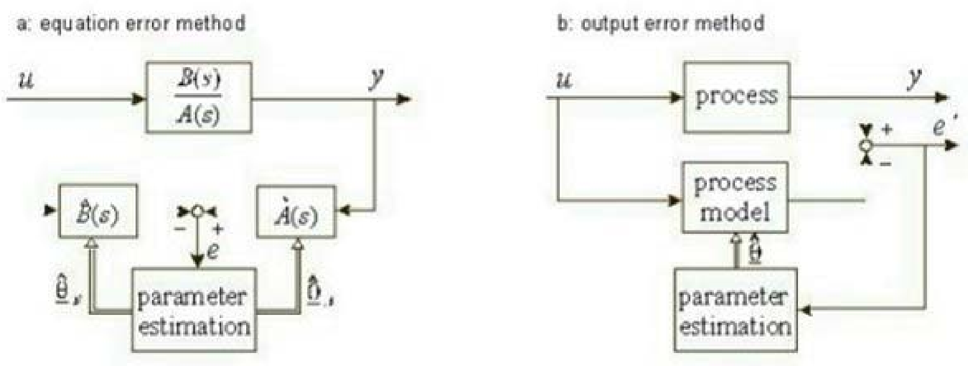

Figure 2: Model-based parameter estimation schemes for fault detection

The estimation will produce useful parameter deviations only if the signals are sufficiently excited. This situation is given during set-point changes or dynamic operation. One can also artificially excite the process or even run a special test-cycle on it (typical for end-of-line-testing). Generally speaking, the information gained from parameter estimation is very high, since even from a single-input/single-output process a number of different parameter deviations can be retrieved. A disadvantage is the necessary excitation of the process.

Parameter estimation can also be used in combination with *signal models* where no input is measured. This applies especially to periodic components where an estimation of characteristic values (like resonance frequencies) reveals insight into the process state.

2.1.2. Observers and State Estimation

The state space formulation for dynamic systems

$$\dot{\mathbf{x}}(t) = \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t) \qquad (5)$$

$$\mathbf{y}(t) = \mathbf{C}\mathbf{x}(t) \tag{6}$$

should be used when considering multi-input/multi-output systems. In state space form, a detailed modeling of fault can be done by distinguishing

- *Additive faults* that appear as an additional term either in 5 (additive to the states) or in 6 (added to the outputs $\mathbf{y}(t)$).
- *Multiplicative faults* are a variation of the system matrices $\mathbf{A}, \mathbf{B}, \mathbf{C}$ (usually modeled as additive terms like $\mathbf{A}_{\text{faulty}} = \mathbf{A} + \Delta\mathbf{A}$). These are faults on the *parameters* of the system. Their effect on the symptoms is formed by a multiplication of the parameter change with the corresponding signal amplitude.

By the use of state or output observers, different fault schemes can be constructed. The applicability of each of those methods depends heavily on the specific problem, especially on the degree of analytical redundancy provided by the process measurements. All schemes can be used to observe output signals or states of the system. The following methods are known:

- Observers, excited by one output. That way, the other outputs can be reconstructed and compared with the corresponding measurements. Especially suited for sensor faults. With a bank of observers (*dedicated observer scheme*), each driven by a different output, even the detection of multiple sensor faults becomes possible.
- Observers, excited by all but one output. This procedure is usually simpler to be implemented because the requirements for the observability of the process are less stringent. With a bank of observers (*generalized observer scheme*), a distinction of different faults can again be reached.
- Observers, excited by all outputs. This is suitable if the faults inflict changes on the internal states of the process.
- Kalman filters are used to find changes in the innovation indicating changes of the process.
- Fault detection filters can be observers that are designed to yield multi-dimensional residuals that point in a certain direction dependent on the specific fault.

Important improvements have been achieved in the extension to nonlinear systems and increased robustness.

2.1.3. Parity Equations

Parity equations are a simple and straight-forward approach to build residuals that indicate faulty systems. Figure 3 shows two basic approaches, the output-error method and the equation-error method. More sophisticated schemes with the ability to isolate different faults can be gained from MIMO processes.

Parity equations require a fixed parameterized model that serves as a reference for the measured behavior. They are closely related to observer methods but their design is sometimes more intuitive. A design from state space equations or directly from the Laplace-transformed differential equations of the process is possible.

2.2. Fault Diagnosis Methods

With the residuals or features computed by one (or more) of the approaches presented above, a *diagnostic system* can be driven. This system may either use traditional causal reasoning (like fault-symptom trees) or perform a classification task. The latter is usually based on reference examples (labeled by an expert) and automatically derived from measured data. Recently, combinations of neural network techniques and fuzzy logic have gained more attention since they promise to integrate both approaches.

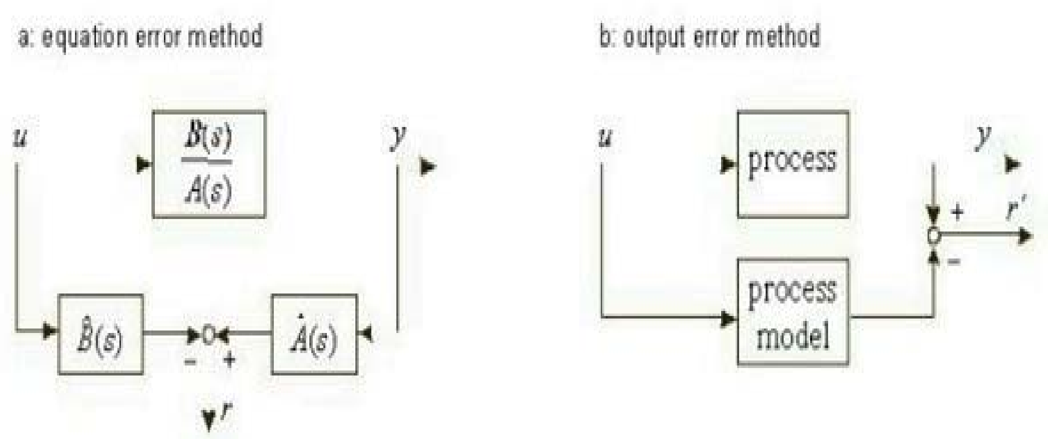

Figure 3: Parity equations for fault detection
(compare with the corresponding estimation schemes in Figure 2)

2.2.1. Classification Methods

Multilayer perceptron networks are frequently used to build diagnostic classification systems from reference data. Their advantage is the good software availability and high performance, provided complete data exists and no need for transparency of the diagnosis is present.

Simpler classification methods (like distance-based methods) are also employed.

2.2.2. Fuzzy and Neuro-Fuzzy Approaches

In addition to the symptoms from Figure 1, heuristic symptoms from an operator can augment the analytical ones. Since these are commonly expressed in linguistic terms, a fuzzy logic based system seems appropriate to perform the diagnostic task.

In addition, a-priori knowledge from experienced operators should be included, if present. That knowledge is preferably recovered as rules as well.

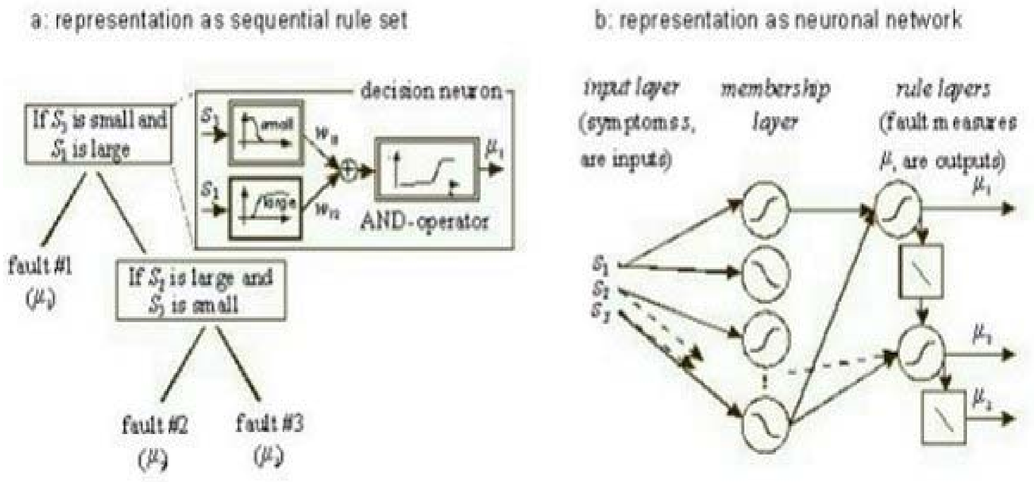

Figure 4: Example of a neuro-fuzzy scheme (SELECT, see) for fault diagnosis

This leads to completely rule-based systems; however, a better performance can be expected if a combination of a technique driven by data and human knowledge is applied. Figure 4 displays a diagnosis system resulting from such a technique. The SElf-Learning Classification Tree (SELECT) is a sequential set of fuzzy rules embedded in a neural network architecture.

That allows an automatic tuning of the system for optimal performance (membership functions, importance of symptoms or other parameters of the system). It has the ability to learn the relationship between the symptom appearance and the corresponding fault from given data. The resulting diagnostic system is transparent and can be understood by the engineer. In addition, rules can be added manually, if such *a-priori* known rules exist.

The rule set can be improved by a constrained optimization of some of system parameters (including the a-priori known rules).

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Biographical Sketches

Rolf Isermann was born in Stuttgart, Germany. He received the Dipl.-Ing. degree in mechanical engineering in 1962 from the University of Stuttgart. With a thesis on the multivariable control of steam generators he received the Dr.-Ing. degree in 1965. In 1968 he became "Privatdozent" for automatic control at the University of Suttgart and since 1972 "ausserplanmässiger Professor". In July - October 1971 he was visiting Professor at the Purdue-University, Lafayette, USA. Since 1977 he is Professor at the Darmstadt University of Technology and head of the Laboratory of Control Engineering and Process Automation at the Institute of Automatic Control. 1981/82 he served as Dean of the faculty. 1989 R. Isermann received the Dr. h.c. (honoris causa) from L'Université Libre de Bruxelles and 1996 from the Polythechnic University in Bucharest. In 1996 he received the VDE-Ehrenring, the highest scientific award from Verband der Elektrotechnik und Informationstechnik. In September 1998 he was invited as Russell Severance Springer Professor in the Department of Mechanical Engineering at the University of California at Berkeley.

R. Isermann has published books on Modeling of Industrial Processes (1971), Process Identification (1971, 1974, 1988), Digital Control Systems (1977, 1981, 1987) in different languages, Adaptive Control Systems (1992) together with K.-H. Lachmann and D. Matko, Supervision and Fault Diagnosis (1994) and Mechatronic Systems (1999)

Several papers appeared on the dynamics and control of heat exchangers and steam generators, on process modeling, process identification, parameter estimation, computer aided digital control systems design, adaptive control, steady-state optimization and process fault detection and diagnosis. Presently the work concentrates in the fields of identification with neural networks, non-linear digital control, intelligent control and model based methods of process fault diagnosis with applications for hydraulic and pneumatic servo systems, combustion engines, automobiles and mechatronic systems. At the Darmstadt University of Technology he chaired the special research project on Mechatronic Systems (IMES) from 1988 - 2001.

From 1976 - 1978 R. Isermann served as vice-president of the VDI/VDEGesellschaft Mess- und Regelungstechnik and from 1979 - 1987 he chaired the section "Operation of Automation Systems". Since 1973 he is member and from 1975 - 1978 he served as chairman of the IFAC-Technical Committee on Applications. From 1981 - 1986 he was a vice-chairman of the IFAC-Policy Committee. In the period 1987 - 1990 he served as IFAC-Technical Board Vice-Chairman. In 1996 he was elected as Vice-President of IFAC and chair for the Executive Board, followed by chair of the Technical Board in 1999.

In 1979 he organized the 5th IFAC-Symposium on Identification and System Parameter Estimation in Darmstadt. For the 6t^{h} IFAC/IFIP-Conference on Digital Computer Applications to Process Control 1980 in Düsseldorf, he chaired the International Program Committee. He acted as Chairman of the International Program Committee for the 10th IFAC-World-Congress in Munich, 1987. Furtheron he was Chairman for the 1st IFAC-Symposium Safeprocess, Baden-Baden, 1991 and the 1st IFAC-Conference on Mechatronic Systems, Darmstadt held in 2000.

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