FAULT DIAGNOSIS IN CHEMICAL PROCESSES, ITS RELATION TO THERMAL DESALINATION SYSTEMS

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Contents

Summary

The basic principles for process diagnosis are outlined and the principal reported works are covered. A specific introduction to the subject is made focussing on the theoretical background needed for an application on thermal desalination processes.

1. Introduction

Since the beginnings of the chemical industry, the operator was the main agent in charge of the diagnosis task. Nevertheless, as the plant complexity increased, the amount of information to be analysed in critical situations consequently also increased, complicating the process fault diagnosis task.

The first operator support system, with the aim to recognize the normal or abnormal state of the process, was the control card (Himmelblau 1978). The following step was the alarm processing systems which perform a previous processing of the registered alarms so as to present classified information to the operator. In this way, the main alarms are highlighted from the rest (Lees 1983).

At the same time, studies for the validation of the sensor registration of the process variables were started. The principal methods were based on a mathematical model of the process. Among other things, these methods were useful for detecting sensor anomalies; thus minimizing false alarms during the process operation (Mah et al. 1976; Romagnoli and Stephanopoulos 1980; Wise and Ricker 1989).

On the other hand, the human operator is the best known supervisor, and it is natural that systems trying to simulate his own reasoning procedure have been developed. It is within this scope that works with artificial intelligence elements were started. The name of artificial intelligence is given to a new way of solving problems within which expert systems, robots control and handling, and natural language processors, among others, are included (Barr et al. 1989). The words *fault* and *malfunction* are used as synonyms to designate the deviation from an acceptable range of an observed variable or calculated parameter. *Fault diagnosis* refers to the determination (after detection of a fault) of the equipment, or component, that produces the fault(s) (Himmelblau 1978).

Due to the complex dynamics existing in most chemical processes (i.e. time delay, complicated interconnection between mass, momentum and energy flows, and the high dimension involved) it is impossible for human operators to detect and to diagnose faults in a limited time. Moreover, even with the help of the computer, diagnosis and supervision are difficult tasks. The necessity of optimal operation, safety and good conditions for batch and continuous operation of chemical processes became more evident.

After the fault is produced, it has to be identified as early as possible by detecting the fault *symptoms*, that is, the process-variable deviations motivated by the fault. The set of all the symptoms caused by a fault is the *fault pattern*. Symptoms analysis can be done by checking whether particular measurable variables are close to a certain tolerance to the normal value. If this check is not passed, a fault message is displayed. The functions up to this point are usually called monitoring or fault detection. If it is necessary, these are followed by the fault diagnosis: the fault is located and the fault origin is established. The next step is the fault evaluation, which means making an assessment of how the fault will affect the process. After the effect of the fault is known, a decision about the action to be taken can be made (Isermann 1984).

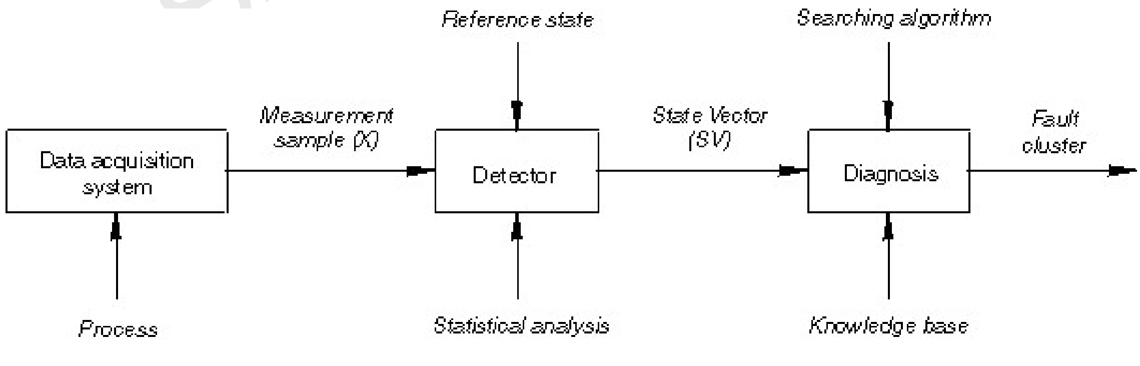

Figure 1. Diagnosis system.

Summarizing, the diagnosis process can be understood as illustrated in Figure 1. First, appropriate measurements are made, the results of which are termed measurement space. The measurements can be represented as a vector in which the elements: X_1, X_2, …, X_n represent numerical values (measured process variables). A computer (SCADA System Control and Data Acquisition) must be connected to the process. A statistical procedure checks if such values are normal or faulty by comparing measured values with a predetermined normal range for each variable. In this way, qualitative values can be assigned to each components - measured or estimated variables - determining the State Vector (SV). Possible values for the elements SV_j are (+1) higher than the normal value, (-1) lower than the normal value, and (0) normal value. SV components change according to the evolution of the measured variables. Then, the diagnostic system analyses each new state of the SV using some kind of knowledge about the process to locate the fault.

Due to the potential for deviation outside the normal or nominal state, a property that all processes have, it is of course very important to supervise them to prevent a serious impact on process economy, security and both process quality and environmental care. In general, added to the specific function, among others, a fault diagnosis system produces benefits such as minimization of lost production by faults, energy consumption; and improvements of product quality, productivity, plant life, etc.

Since the last decade, though at a small rate, many systems have been installed for process supervision and fault diagnosis.

On the other hand, there is a continuous growth in computer science. In fact, hardware and software continuously improve, implying a better platform to develop high performance and simultaneously friendly systems to help process operators. Thus, clearly in the future the tendency of adoption of such systems will be continuously growing at higher rates (Kramer and Fjelheim 1995).

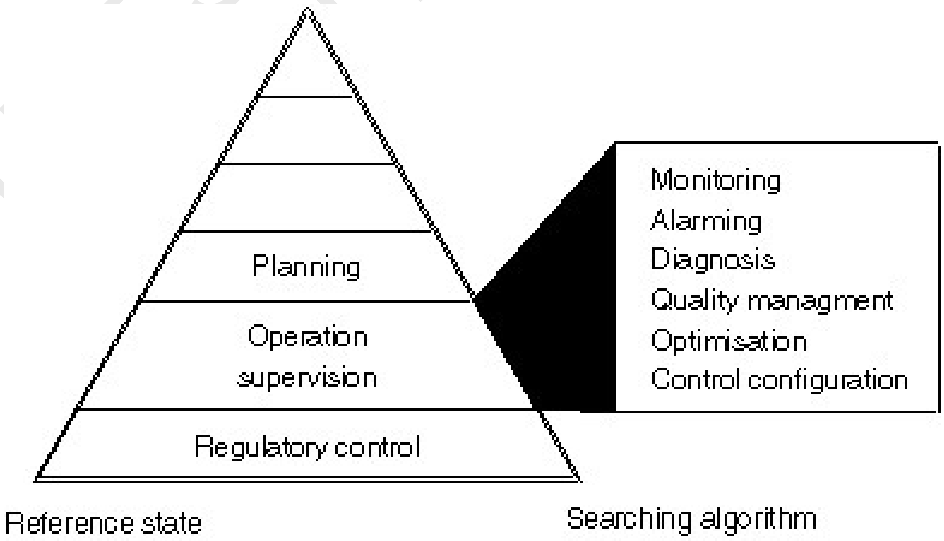

Figure 2. Fault diagnosis system position in a hierarchical level.

Hierarchically, the fault diagnosis system is placed above the regulatory control layer (see Figure 2), and below the process planning layer, in the decision support system or the management structure of the process.

2. Characteristics of a Diagnosis System

From the specific point of view, diagnostic tools can be classified according to the basic assumption made about the existence of a simple fault or a (simultaneous) multiple "faulty" state. Generally, each fault is assumed statistically independent of the others, and it is considered that only one fault is the origin of all the observed symptoms, because the probability of more than one fault (simultaneous faults) is very low. Nevertheless, it is also possible to find a multiple faulty-state, and then, an algorithm considering multiple, independent and simultaneous faults must be used. In this work, single-fault methods will be emphasised, because they are the most used.

It is common in the literature to emphasise the following characteristics as essentials for an ideal diagnosis system:

Exactness:

The right fault must always be included in the candidate set.

Resolution:

The candidate set must always be as small as it is possible (the minimum set).

Speed:

It is important to inform the operator the true fault after the minimum processing time.

Stability:

It is convenient to introduce only smooth changes in the candidate set during the diagnostic process.

Feasibility:

The cost and the effort for the implementation must be reasonable.

On the other hand, from the structural, functional or operation point of view, a diagnosis system can be divided in a series of modules (blocks or stages), each with a particular function.

Detector Module:

The detector module transforms quantitative information (the measured variables) in qualitative values. Once an anomaly is detected, the diagnostic module is activated.

Isermann (1984) presents a summary of the widely used detection methods. The general structure of this block is the following:

(a) Generally, it receives data from the SCADA (supervisory control and data acquisition system).
(b) Process variables (quantitative values) are filtered using different types of filters (generally without requiring a process model). If it is necessary to estimate state variables or parameters, an observer-process model is used.
(c) Using a model for the normal state of the process, variable deviations (qualitative values) are calculated for each variable (point b), using the following formula:

$$X_{dev} = X_{Observed} - X_{Normal} \quad (1)$$

where $X_{Observed}$ is the measured variable, and X_{Normal} is the expected value when the process is normally operating.

According to the value of X_{dev}, a decision about the process state is made using a model representing all the faulty process-states, classifying, for example, the state of each variable in {Low (-1), Normal (0), High (+1)}. In this stage, sensors can be validated. This means that faulty sensors, provided they do not belong to a control loop, can be identified.

If any anomaly has been detected, then the diagnosis block is activated to determine the location, size and cause of the fault.

Diagnosis Module:

This module uses the knowledge of the process-faulty states, which is generally contained in a knowledge data base. This information plus the actual state of the process are used for finding out the cause of the fault(s) (Kramer 1987; Dohnal 1983; Petti and Dhurjati 1991; Yu and Lee 1991). Once the fault is located, the diagnosis module starts the evaluation and exposition modules.

Evaluation Module:

It finds out all the interpretations for a given fault and predicts all the possible consequences of the detected fault.

Explanation Module:

It explains the reasoning chain to reach a given diagnosis.

Assistant Module:

It suggests the necessary actions to be carried out by the operator.

Finally, from the implementation point of view, the following steps are generally followed to carry out a diagnosis system:

OFF-LINE STEPS:

Model building:

A sort of process model must be implemented (quantitative, qualitative, etc).

Fault symptoms determination:
The model must be used to find out all the interpretations for each potential fault of the process (fault pattern characteristics, noises, vibration signals, other symptoms, etc).

Compilation of fault patterns

A sort of fault pattern data base must be carried out. For example all the fault patterns can be transformed in production rules (IF-THEN format) to build the knowledge data base for a real time expert system. Other tools like artificial neural networks, signal processing methods, etc., can be used.

ON-LINE STEPS:

Data acquisition

All measured variables must be processed. Quantitative values after filtration can be used directly or can be transformed in qualitative ones (detector module).

Fault searching

Using the process-symptoms database, they are matched with each fault pattern. A probability value is assigned to each potential fault to find the most probable candidate (diagnosis module).

At this point, given the desired properties and the general components that characterize a fault diagnosis system, the next question is the implementation. In the following section the basic nature of the diagnosis problem will be analysed, considering all the items and the desired characteristics above mentioned, to show and clarify the general difficulties to be overcome to implement such systems, and to relate them with the specific characteristics of desalination processes.

2.1. The Nature of the Diagnosis Problem

Considering that the analysis of the system is done by monitoring a set of predetermined process variables - so those that can be measured - the "measured space" is not complete. Thus, the resolution degree for the diagnosis procedure is limited. Generally, it is common to find a set of faults that corresponds to the same observed *pattern*. This set of faults is defined as a *cluster* of faults corresponding to this pattern. Then, to individualize the corresponding fault in the cluster, more resolution must be achieved using the knowledge of the process, the expertise of the operators, etc. The composition and dimension of the fault clusters depend strongly of the process measured variables proportion.

In qualitative simulation, the dimension of the real problems defines a combinatory space; and on the other hand, generally, inverse responses or compensatory responses (induced by controllers or by the nature of the system) are always present, and they must be handled by the diagnostic system during the fault propagation (fault pattern or symptoms). Also, the validation of the system and the necessity of real time responses are difficult challenges. All the difficulties previously analyzed are magnified in industrial processes. In fact, for large scale problems it is impossible to work with algorithms that are useful at unit level (e.g. unit operations). System theory suggests that a hierarchical approach may be more suitable for large or complex processes (Finch and Kramer 1988). *The problem is to find out a criterion for process division using a hierarchical approach for diagnosis*. Finch and Kramer (1988) introduce a model formalism to describe large and complex processes at a suitable level of detail for an early-stage diagnosis. They use a two-stage procedure to detect faulty systems and units. In the first stage, the potentially faulty systems of the plant are found out. The second stage involves the application of rules that further narrow the fault candidate space considering the adjacent system states to the faulty systems.

The process decomposition in units can be made using a structural or functional approach. The functional approach *emphasizes* the function of the unit in relation to the context or the full system, while the structural approach *is based on the structure* of the unit related to the full system structure.

Generally, modern plants are highly connected processes with many streams and recycles that imply a highly connected flow-sheet. The best choice for the process decomposition will be strongly dependent on the process particularities. This is the case of the thermal desalination plants, both single or dual purpose systems, for example.

3. Different Approaches for Fault Diagnosis

Different approaches or strategies have been developed for fault diagnosis, such as quantitative algorithms (Isermann 1984), fault tree methods (Lapp and Powers 1977), qualitative model and causal analysis approaches like directed signed graphs (Iri et al. 1979), expert system based approaches (Kramer 1987), pattern recognition methods and statistical approaches (Kvalhein 1988), (Nomikos and MacGregor 1995), fuzzy logic approaches (Chang and Yu 1990), (Yu and Lee 1991), Neural network approach (Venkatasubramanian et al. 1990), (Watanabe et al. 1994) (Kavuri and Venkatasubramanian 1993), analytical redundancy strategy, parameter and estimation approaches, hybrid approaches, etc. This state of the art seems to be a consequence of the nature of the diagnosis problem and the desired characteristics (above described) for a diagnostic system. Moreover, there is a high probability that, in the future, several new methodologies or strategies will be applied to build diagnostic tools.

As an introduction, in the following sections we will describe some strategies to carry out diagnostic systems. In general, we can mention model based approaches vs empirical ones, qualitative or quantitative approaches, fault diagnosis using binary or fuzzy logic, etc.

Generally, it is very difficult to classify diagnostic methodologies because we can use different points of view; for example the model used, the strategy, the mathematical basis, the implementation basis (neural nets, expert systems, statistical methods, etc).

Thus, given a diagnostic system, it can be probably classified in more than one of the previously mentioned classes.

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