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Fault Detection and Diagnosis-A Review

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***Abstract*— The operation of technical processes requires increasingly advanced supervision and fault diagnosis to improve reliability, safety and economy. This paper gives an introduction to the field of fault detection and diagnosis. It begins with a consideration of a knowledge-based procedure that is based on analytical and heuristic information. Then different methods of fault detection are considered, which extract features from measured signals and use process and signal models. These methods are based on parameter estimation, state estimation and parity equations. By comparison with the normal behaviour, analytic symptoms are generated. Human operators are another source of information, and support the generation of heuristic symptoms. For fault diagnosis, all symptoms have to be processed in order to determine possible faults. This can be performed by classification methods or approximate reasoning, using probabilistic or possibility (fuzzy) approaches based on if-then-rules.**

***Index Terms*— Distributed Control System (DCS); Fault detection and diagnosis; Gas Pressure Reduction Station.**

I. INTRODUCTION

There has been an increasing interest in fault detection in recent years, as a result of the increased degree of automation and the growing demand for higher performance,
efficiency, reliability and safety in industrial systems. Diagnosis can be a complex reasoning activity, which is currently one of the domains where Artificial Intelligence
techniques have been successfully applied. The reason is that these techniques use association, reasoning and decision making processes as would the human brain in solving
diagnostic problems. Classical fault detection methods are based on limit value checking of some important
measurable variables and a lot of valuable research work has been done in this direction. These methods do not allow an in-depth fault diagnosis and do not simulate the human
reasoning activity. Modelling the human problem solving process using sensors for inputs, knowledge bases for data record, reasoning and experience for the final decision, provides ***C. Angeli, A. Chatzinikolaou.***
Powerful new techniques that have the ability to reason about deep models and to operate with a wide range of information. Artificial Intelligence experiments with models of human intelligence by building systems that can exist autonomously in their respective environment and are able to act intelligently.
Applications such as expert systems, neural networks and intelligent signal processing are
used as fault detection techniques. Current trends include coupling of these applications in order to produce more effective tools. For diagnosis, these knowledge-driven techniques involve the interpretation of sensors' signals, detection of abnormal situations, generation of hypotheses about the fault behaviour and fault explanation.

I.THEORY

Most of the processes in the industry are multivariable and the process variables are highly correlated in many cases. The conventional monitoring method is found to be inefficient and thus cannot properly identify the fault conditions. Multivariate SPC (MSPC) has been developed to monitor the multivariable processes. T2 Hotelling statistics is one of the first proposed SPC Methods. The multivariate T2 statistic takes into account the correlations between the variables [1]. Nevertheless, ill conditioning or co-linearity problems can be caused when the system dimension increases.

As discussed earlier, multivariate methods could analyse all the process variables to present the process condition. Accordingly, system operators could easily be informed of the exact conditions of the process. On the other hand, the conventional and dominant automation systems in the industry such as DCSs do not provide such explicit monitoring tool.
Moreover, DCS monitoring tools such as WinCC [13] and Citect [14] are designed based on the univariate monitoring methods and they usually have no ability for execution of Multivariate and advanced monitoring techniques. Consequently, developing methods to implement the advanced monitoring techniques in DCSs seems to be an essential task.

II. FAULT DETECTION

Fault detection and fault diagnosis in a plant is illustrated. The station model is presented. The station dynamic model includes three main parts which are the heater, the first and the second regulators, respectively (Fig. 1). The input variables of the model are the heat generated by the heater and the input gas flow and pressure. The output variables include the temperatures of the output water and output gas of the heater as well as the temperature and the pressure of the output gas of the station.

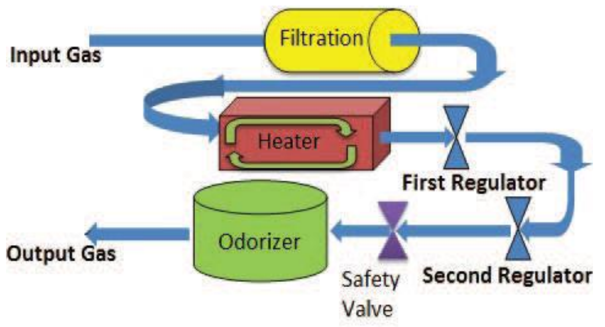


Figure 1:- DCS VIEW OF GAS PLANT

II.1 IMPLEMENTATION

This section first presents the proposed method for online fault detection and fault diagnosis. Subsequently, one explicit solution for implementation of the proposed method in DCS PCS7 is illustrated.In the presented solution, the whole or a part of the calculations of the monitoring algorithm are fulfilled through interface software and the processed results are then transferred to PCS7.

II .2 **GENERATING DATA FOR MODELLING**

The normal region is easily created with data recorded during the normal operation of the station. In order to model different fault occasions, the gas station data under different abnormal conditions are required. Such faults are very dangerous and can make the process unstable. Hence, the station model is first developed and then utilized to record the required data of the process under abnormal conditions. The abnormal conditions of the process are imposed to the system through sudden disturbance occurrence in the inputs.

II.3 **FAULT DIAGNOSIS**

The PCA algorithm is applied to the normal data extracted from the station and two loading vectors associated with the two largest singular values are selected for the PCA model. Afterward, the projection of the new observations into specified 2-dimensional space are calculated and plotted versus one another. In this paper the singular value of the first principal component is equal to 3.9 and for the second principal component, the singular value is equal to 0.02 and hence, dimension of the first principal component is dominant.

Normal region of the operation is obtained by means of the projection of data recorded from the station under normal operation conditions to the 2-dimensional space and is shown in Fig. 2.

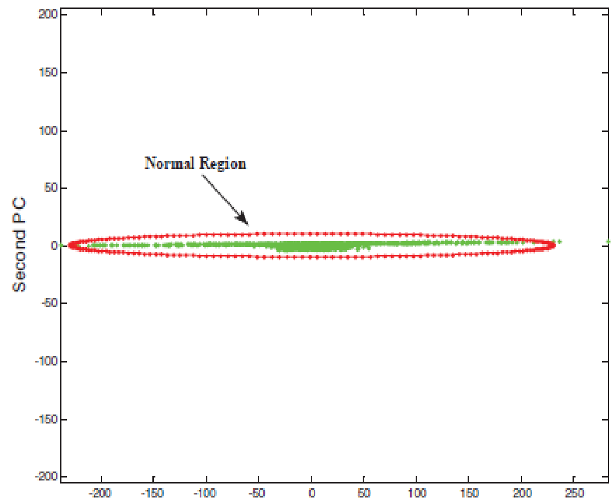


FIGURE 2 :- SPECIFIED NORMAL OPERATION REGION

The direction of the data leaving the ellipsoid determines the fault source. In this paper, four different abnormal states are studied.That have been explained in the below section.

When the input heat of the heater is decreased and/or the flow of the input gas is increased, the direction of the data leaving the normal region is depicted in Fig. 3. Similarly, Fig. 4 shows the direction of the data leaving the normal region for another case in which the input heat of the heater is increased and/or the flow of the input gas is decreased.

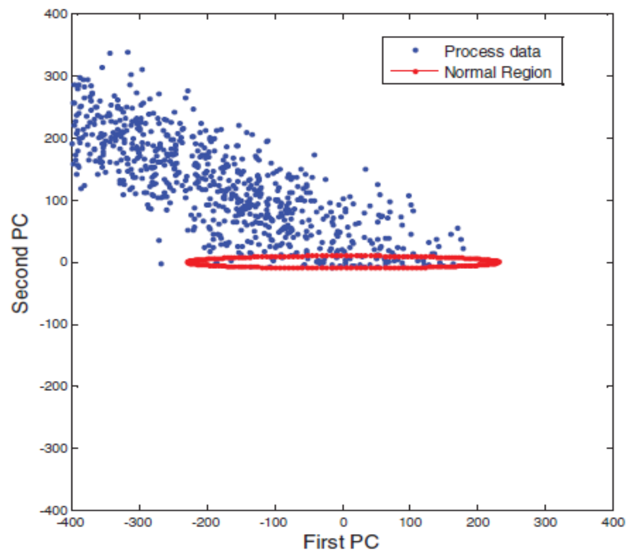


FIGURE 3:- DATA POINTS EXCEEDED THE NORMAL REGION

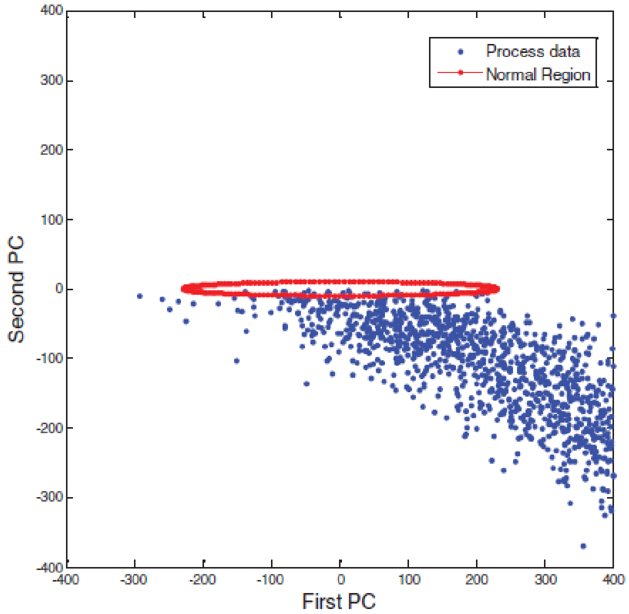


FIGURE 4:- DATA POINTS EXCEEDED THE NORMAL REGION

FIG. 5 Shows the advanced monitoring results including the fault detection and fault diagnosis of the gas station. Fault diagnosis algorithm is applied to every new observation and the fault source can be distinguished according to the coordination of the data point in the two dimensional diagram.

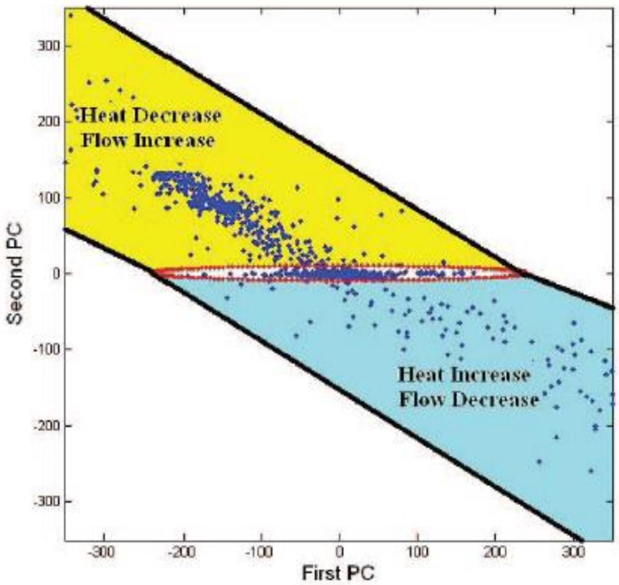


Figure 5:- FAULT DIAGNOSIS

In accordance with Fig. 5, it is evident that the variations along the axis correspondent to the first principal component is greater which demonstrates the abovnt e discussion.

II.4 **IMPELEMETATION OF ALGORITHM IN PCS7**

This section presents the implementation of the online fault detection and fault diagnosis algorithm in DCS PCS7. It is necessary to mention that the proposed method is applicable for all other algorithms in PCS7. The process of implementation is classified into three different sections which are described below:

1) CONNECTING MATLAB SOFTWARE

The configuration process includes the construction of a new channel, addition of a new device, definition of the required tags and etc. MATLAB OPC Toolbox offers an OPC client to Simulink which should be appropriately configured to provide connection between MATLAB and OPC Server.

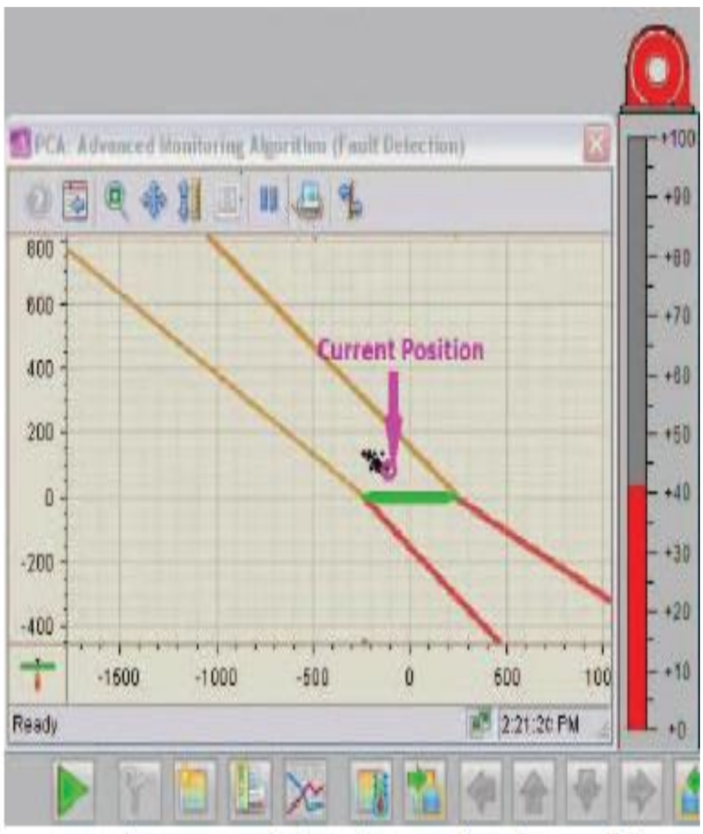
Thus, the results calculated by means of MATLAB can be transferred to OPC Server.

2) CONFIGURING AND CREATING PICTURES

Designer By using "New Project" Wizard in SIMATIC PCS7, a multiproject could be automatically created. After the software and hardware necessary configurations related to AS, ES and OS are completed, they should be compiled and downloaded.WinCC Explorer also enables the user to access the graphic designer tool to provide required pictures and graphics.

3) CONNECTING SERVER

PCS7 can also be used to exchange the data with external systems such as the plant management and production control level or ERP level via the OPC interface. Where several clients are used to transfer the data. Client like WinCC is used to access this data. Hence this data is processed using Matlab.



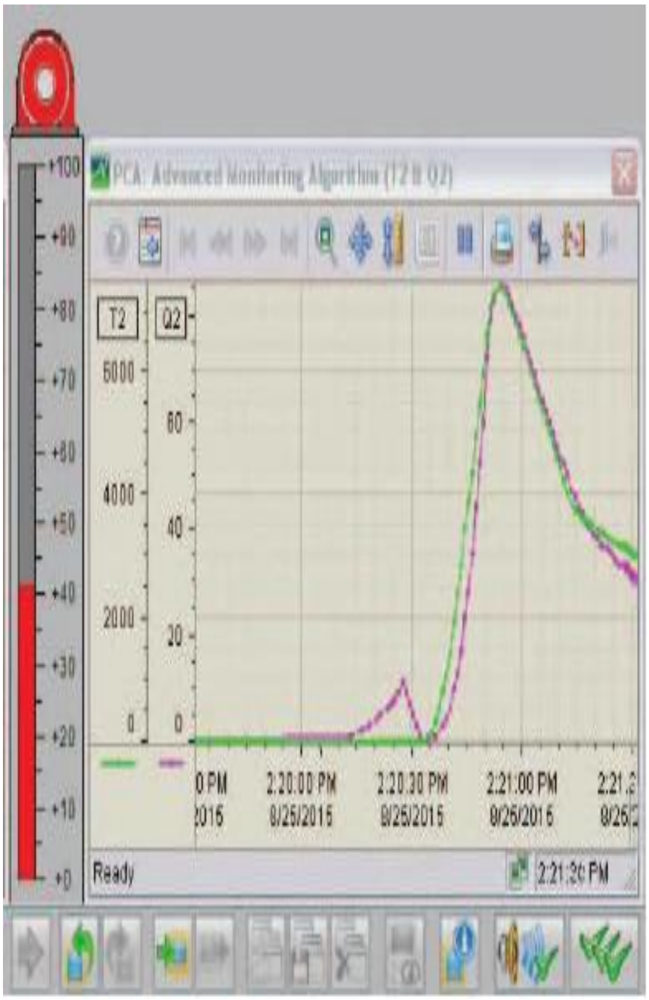


Figure 7
(a) The input heat of the heater is decreased.
(b) The input heat of the heater is decreased

The implementation demo of the proposed monitoring method in PCS7 software is depicted in Fig. 6. The right hand side plot in Fig. 6 shows the Hotelling and Q statistics. Based on the values of these statistics, when these curves rise above zero, the system abnormal conditions can be distinguished. The left hand side plot of Fig. 6, shows the process conditions in the two dimensional diagram under the environment of PCS7 which is achieved by implementing the fault diagnosis algorithm on the system data.

III FAULT DETECTION TECHNIQUE

In any circuit composed of logic gates there is the possibility of the occurrence of a fault. A fault is defined to have occurred when any circuit variable assumes a value (1, 0, or X) which differs from that expected.

III.1 MASKING FAULT

The presence of an internal or input fault may not be observable at the circuit output, in which case, the fault is considered to be masked. A single fault may be masked as a result of
1) ReConvergent fan-out, where unequal parity changes have occurred
2) Circuit redundancy;
3) Previous occurrence of an undetectable fault.
Masked faults are undetectable by their definition since the observed circuit behaviour is correct. However, the occurrence of a second fault may uncover a previously undetectable fault. To be complete, the test set must include tests for this case.

III.2 Fault Types

Faults may be indeterminate in value (suspended between logical "1" and logical "0"), or determinate in value (exhibiting a "0" or a "1").
Faults may be transient (indeterminate, time-varying), in which case they are elusive and difficult to detect.
Faults may be permanent (considered "hard" or "solid"), in which case they are easy to detect if they are not masked and if a proper test is used.
Faults may be multiple in occurrences, which have always been considered a rare event. (With higher circuit densities, this event has increased somewhat in probability.
Faults may occur singly, which is considered to be the most likely event. Further, multiple faults can occur in such a manner that there is an equivalent single fault for them. A test which detects the presence of this equivalent [single] will be sufficient to detect the presence of multiple faults. Thus detection of fault to such extent is not possible.

FAULT DETECTION

There has been an increasing interest in fault detection in recent years, as a result of the increased degree of automation and the growing demand because of this parameter like Efficiency, Reliability, Safety, Higher-performance etc. Diagnosis can be a complex reasoning activity, which is currently one of the domains where Artificial Intelligence techniques have been successfully applied. The reason is that these techniques use association, reasoning and decision making processes as would the human brain in solving diagnostic problems. These methods do not allow an in-depth fault diagnosis and do not simulate the human reasoning activity. Modelling the human problem solving process using sensors for inputs, knowledge bases for data record, reasoning and experience for the final decision, provides powerful new techniques that have the ability to reason about deep models and to operate with a wide range of information. Fault prediction has both safety and economic benefits by preventing future process failures and improving process maintenance schedules. Several methods are used for this purposes that are illustrated as follows that are explained below.

NUMERICAL METHOD

The Suitable way for detecting faults consists of checking the measurable variables of a system in regard to a certain tolerance of the normal values. And if these tolerances values are exceeded then alarm will be triggered. Fault detection and isolation schemes are basically signal processing techniques employing state estimation, parameter estimation, adaptive filtering, variable threshold logic, statistical decision theory and analytical redundancy methods.

ARTIFICIAL INTELLIGENCE

As a result of increasing competition in the industry and the requirement for quality power supply, adequate fault detection is becoming vitally important to both companies and consumers. One of the strategies to ensure low running cost is the general avoidance of supply interruption. In the case of very complex time-varying and non-linear systems, where reliable measurements are very complicated and valid mathematical models do not exist, a number of different methods have been proposed.

EXPERT TECHNOLOGY

In the late 1960's to early 1970's, expert systems began to emerge as a branch of Artificial Intelligence. Feigenbaum (1981) published the best single reference for all the early systems.

E. Feigenbaum (1982), defined an expert system as "an intelligent computer program that uses knowledge and inference procedures to solve problems that are difficult enough to require significant human expertise for their solution".
An expert system simulates human reasoning about a problem domain as the main focus is the expert's problem solving abilities and how to perform relevant tasks, as the expert does. An expert system performs reasoning over representations of human knowledge in addition to doing numerical calculations or data retrieval using the knowledge base and the inference engine separately.

NEURAL NETWORK

Diagnosis is one of the major areas where expert systems find application from their early stages. The knowledge-based approach for fault detection and isolation, over the past decade has received considerable attention

Early diagnostic expert systems are rule-based and use empirical reasoning whereas new model-based expert systems use functional reasoning. In the rule-based systems knowledge is represented in the form of production rules.

Widmanetal (1989) have counted the limitations of the early diagnostic expert systems as follows:
1). Inability to represent accurately time-varying and spatially varying phenomena.
2). Inability of the program to detect specific gaps in the knowledge base.
3). Difficulty for knowledge engineers to acquire knowledge from experts reliably.
4). Difficulty for knowledge engineers to ensure consistency in the knowledge base.
5). Inability of the program to learn from its errors.
The rule-based approach has a number of weaknesses such as lack of generality and poor handling of novel situations but it also offers efficiency and effectiveness.

Expert knowledge is contained primarily in a model of the expert domain. Such models can be used for simulation to explore hypothetical problems. Model-based diagnosis uses knowledge about structure, function and behaviour and provides device in dependent diagnostic procedures. These systems offer more robustness in diagnosis because they can deal with unexpected cases that are not covered by heuristic rules

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