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Fault Diagnosis Methods and their Applications in the Process Industry

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Abstract: Global competition is forcing the process industry to optimize the production processes. One key factor in optimization is effective process state monitoring and fault diagnosis. Another motivator to improve process monitoring systems is the substantial losses of revenue resulting from abnormal process conditions. In recent years there has been an increasing interest in applying different process monitoring and fault diagnosis systems and as a result a large number of successful applications have been reported. In this paper the model and data-based FDD methods and their applications in the process industry are reviewed and discussed. The paper ends with the large scale case studies from the mineral processing, oil refining and pulp and paper industry.

Keywords: Process Monitoring, Fault Diagnosis, Industrial Application, Large Scale Systems.

1. INTRODUCTION

Tightened global competition, higher final product quality requirements, and environmental and safety regulations have forced the process industry to continuously optimize the efficiency and profitability of its plants. Profitability can generally be enhanced through process optimization, by cutting costs and by reducing the duration of unplanned and planned shutdowns. Optimization can be further enhanced by focusing on preventing off-spec production caused by process disturbances and faults. In recent years, there has been increasing interest in applying different process monitoring and fault diagnosis methods in process industry. A large number of applications have been reviewed, e.g. by Isermann (2011) and Patton, Uppal, and Lopez-Toribio (2000).

Process knowledge has always played a key role when developing the fault diagnosis systems for process industries. Thereby the FDD methods are also classified into three categories: Quantitative model-based, qualitative model based and process history based methods as reported by Venkatasubramanian, et al. (2003). Each of these methods has various strengths and weaknesses and lately hybrid methods have been suggested by either combining the results of individual methods or using the method which combines incomplete process knowledge from different categories. These methods are, however, sufficient for unit operations or small sized processes, but they become in most cases inefficient for large scale processes due to their size-related characteristics. This has driven diagnosis of large-scale processes to process decomposition-based strategies: the top-down and the bottom-up strategies. The decomposition methods mostly apply structural or functional decomposition, and Prasad, et al. (1998) have suggested a decomposition methodology based on the structure of the chemical plant. However, there is no well-defined criterion to evaluate the optimality of these decomposition schemes.

When developing the FDD system for industrial use, the most important phase is the fault analysis. The aim of the fault analysis is to find out the main reasons for the production losses and thus the main focus areas for the system development. Identification of the most common faults, their characteristics, locations, causes and the faulty devices decides eventually the selection of the suitable FDD methods to be used in the system under development.

Economic demand for high plant availability has introduced the Fault Tolerant Control (FTC) concept also to process industries. This is an emerging area where several disciplines are combined to prevent the faults from developing into failures and production losses. Traditionally, the most actively studied fault detection and diagnosis (FDD) components of the FTC strategies have been based on model-based approaches. In the modern process industries, however, there is need for the data-based FDD components due to the complexity and limited availability of mechanistic models. Recently, active FTC strategies using fault accommodation and controller reconfiguration have become popular due to the increased computation capacity, easier adaptability and lower overall implementation costs of the active FTC strategies.

In this paper, methodology for the industrial FDD system development is described. The different development phases are presented and briefly discussed. The paper ends with the FDD case studies from the different fields of the process industry.

2. METHODOLOGY FOR THE FDD SYSTEM DEVELOPMENT

Development of the FDD strategy for the large scale system involves the following main four phases: process decomposition, fault analysis, constructing a diagnostic technique for each subsystem and combining the diagnostic results of each subsystem to determine the fault. The final phase of the methodology consists of algorithms validation and industrial implementation.

2.1 Process decomposition

When developing the FDD system application for process industries, a decomposition methodology based on the structure of the chemical plant is recommended. Based on the plant main production objectives, the plant is decomposed first to unit processes, second equipment and finally to field instruments. Plant topology, PI-diagrams and expert knowledge are used for specifications.

2.2 Fault analysis

The aim of the fault analysis is to find out the main reasons for the production losses and thus the main focus areas for the FDD system development. The production and maintenance long-term data is collected and used for the study. First the analysis of the shutdowns, planned and unplanned ones are categorized. Next the unplanned shutdowns are further classified; maintenance and operational. The operational data of the unplanned shutdown is the main information source for the development of the FDD algorithms.

The aim of the fault analysis is also to identify the most common faults, fault locations, fault causes, and the faulty devices. The fault types in the process industries can be listed f.ex as follows: equipment malfunctioning, leakages in valves, pipes and pumps, clogging or jamming of pipes, breakage, vibration of pumps and drives, fouling etc. Faults locations and their propagations are further studied using the decomposition results.

2.3 User requirements and system specifications

The second phase of the methodology is to define the specifications of the target application and the user requirements for the FDD system. The background information is acquired by interviewing experienced personnel at the production plant. In order to obtain as wide a perspective as possible to the problem, persons working in the different operational sectors are interviewed: operators, engineers, and management personnel. The following information is acquired through the interviews: (1) detailed description of the required functionality of the FDD system, (2) description of the process conditions under which the system will be used. (3) end-users' attitudes toward false alarms and missed detections, (4) specifications of the environment in which the system is implemented, and (5) specification of the user-interface. The first two items are required in setting up the system, the third is related to the tuning of the system, and last two concern the external restrictions. The results of the fault analysis are used for background information for the interviews.

2.4 Selection of the FDD methods

Most of the FDD methods in the process industries are implemented as advanced supervision methods. Surveys of the analytical fault-detection methods and the fault – diagnosis methods are presented f.ex. by Isermann (2011). He classifies detection and diagnosis as separate tasks. Detection methods are classified by the type of elements used to detect an abnormal state, while diagnosis methods are classified by the type of the decision methodology used.

The basis of the fault detection classification is signals employed by the methods. Detection performed with single signals encapsulates methods like limit and trend checking. The detection performed with the use of multiple signals is composed of methods that make use of multivariate analysis. The detection methods, which use models, can be grouped with single signal methods, if the signal behaviour is the modelled element, or with multiple signals, if the process is being modelled.

There are two main categories for classification of fault diagnosis methods: The first category uses classifiers to evaluate the symptoms in order to achieve its diagnosis decision. Classification methods are used in absence of any structural information on the process related to the symptoms and the faults, a classifier maps the relationship between the symptoms and the faults. Pattern recognition, statistical classification approximation methods, density based methods and artificial intelligence methods belong to the methods listed here. The second category contains the inference methods like binary reasoning and approximate reasoning.

Selection of the most suitable methods for a specific FDD problem from these classifications depends on many factors f. ex. intended use of the method, the process and its dynamics, faults and their characteristics. One way to present f.ex. the suitability of the modelling methods for different process types is described in Table.1. Similar tables can be further built based on the other factors listed above.

2.5 Implementation and testing

The FDD algorithms are usually implemented and tested both in off-line and online. The offline testing is done in the simulation environment utilizing the collected plant data: one data set for training and one for validation. Recommendation for the online testing is to embed the FDD algorithms in the different process control hierarchy level and to test using the plant automation facilities.

3. CASES

In the following three process monitoring /FDD systems will be presented. The first one is the feed type identification system using Self Organizing Map (SOM) in the minerals processing industry; the second describes application the dynamic causal digraph reasoning method in the board machine. The third case study is the FTC application for a dearomatisation process in the oil refinery. Each application has been selected based on the fault analysis done in the factory.

Table 1. Characteristics of data-driven fault detection methods

Model characteristics	Data similarity										Regression							Classification	
	PCA	Multi-way PCA	Moving PCA	Multi scale PCA	Robust multi scale PCA	Recursive PCA	Dynamic PCA	Nonlinear PCA	ICA	DISSIM	PLS	Nonlinear PLS	Multi-way PLS	Recursive PLS	SMI	MLP	RBFN	SOM	ART
Suitability for linear processes	X	X	X	X	X	X	X	x	X	X	X	X	X	X	X	x	x	x	x
Suitability for nonlinear processes								x				x				X	X	X	X
Suitability for steady state processes	X	X	X	X	X	X	X	x	X	X	X	X	X	X	X	x	x	x	x
Suitability for non-steady state processes			X			X	X	x						X	X			X	X
Suitability for batch processes		X											X					X	X
Ability to identify faults																		X	X
Ability to detect new fault types	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	x	x
Ability to detect simultaneous faults																		x	x
Heavy calculations during online use			x	x	x	x		x						x					
Easy interpretation of results	x	x	x			x	x	x	x	x	X	X	X	X	X	X	X	X	X
Good updatability			x			x								x					
Strict requirements for training data								x								X	X	X	X
Robustness against noise in training data	x	x	x	x	X		x		x	x	x		x	x	x			x	

The small 'x' denotes that the property describes a method, capital 'X' denotes that the property describes a method very well.

5.1 Feed type identification using SOM

The heterogeneous characteristics of ore deposits pose a problem to achieve profitable production, since different ores require diverse optimal treatments at the concentrator. The monitoring system developed by Jämsä-Jounela et al (2001) uses SOM for on-line identification of the feed ore type and a knowledge database that contains information about how to handle a determined ore type. A self-learning algorithm scans historical data to suggest the best control strategy.

The system was first tested at the Hitura Concentrator. The Hitura Mine is a nickel mine located in central Finland. The mine capacity is 530 000 t/a ore and production currently is 38 000 t/a of NiCu concentrates with a grade of 6.5 % Ni, 1,7 % Cu and 10-12% MgO. At the Hitura mine changes in the mineralogy of the concentrator feed caused problems in process control. After a change in the feed type new process control method had to be found. This was done by experiment because the new type was often unknown. These experiments took time and the resulting treatment method might not be optimal.

5.1.1 On-line variables for classification

The on-line information available at the plant was studied and a search was made for useful on-line measurements. The domain experts of the Hitura concentrator recommended the use of measurements related to grinding, the consumption of sulphuric acid and the channel intensities of the on-line XRF analyser. The grinding measurements reflect the specific energies required to grind the ore, which in turn reflect the host rock mineralogy; the relevant measurements were the power draw of the mills, the feed rate of ore to the rod mill, the particle size distribution at the hydrocyclone overflow and the pulp density at the hydrocyclone feed. The set related to the consumption of sulphuric acid reflects the content of serpentine in the feed; the relevant measurements were the channel intensities of the Courier 30 analyzer relevant to the analysis of the concentrator feed.

The online SOM was trained using the five combinational variables describing the feed type: NIMO, NISU, CUFE, GRIN and ACID.

The variable NIMO estimates the nickel content of the feed. It indicates the amount of pentlandite in the feed and is a good indicator of the feed type. The nickel content is estimated by two Courier 30 channel intensities:nickel and molybdenum.

$$NIMO = OINI / OIMO \quad (1)$$

OINI is concentrator feed Courier 30 intensity foe nickel and OIMO concentrator feed Courier 30 intensity for molybdenum.

The variable NISU estimates the nickel content in the sulphide phase of the ore which reflects both the sulphide phase and the host rock mineralogy.

$$NISU=a - b^* CICU/CINI+c^*OICU/OINI \quad (2)$$

CINI, OINI are concentrate and feed Courier 30 intensities for nickel and CICU,OICU concentrate and feed Courier 30 intensities for copper.

The CUFE variable is the ratio between the copper and iron channels of the Courier 30 analyser analyzing the concentrator feed.

$$CUFE = OICU / OIFE \quad (3)$$

The variable GRIN reflects the grindability of the ore.

$$GRIN = (P / feed) ^*R \quad (4)$$

P is powerdraw of the mills, feed massflow to the rodmill and R is ratio of the pulp densities (cyclone feed density/grinding feed density).

The classification variable ACID represents the consumption of sulphuric acid. The mineralogical justification is the presumed dissolution and/or adsorption of sulphuric acid by serpentine. As talc, amphibole and chlorite are rather insoluble in sulphuric acid the consumption can be used to estimate the proportion of serpentine.

$$ACID=(m_{H2SO4}/feed)/(pH-8) \quad (5)$$

M_{H2SO4} is the mass flow of sulphuric acid and feed is the massflow to the rod mill.

5.1.2 Online SOM

The pre-processed data were classified using the Kohonen Self-organising map. The bubble algorithm was used to train a hexagonal SOM with 8 rows and 12 columns.

The locations of the ore types in the on-line SOM were studied. The high values of variable NISU were on the right side and the low values on the left side of the map. Thus the serpentinized ore types are on the right side and the talc-amphibole types on the left. The average and high values of variable NIMO were found at two locations: in the left-top corner and in the right-mid area of the map. They represent the variations in the nickel content within the major feed types. The result of the study on the on-line SOM is presented in Fig.1.

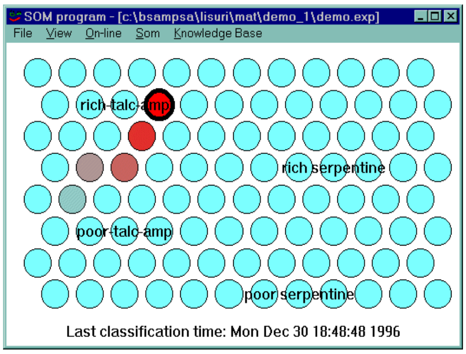

Fig. 1. The online SOM.

5.1.3 Results

The system has been in use at the Hitura concentrator since 1996. During this period, the Hitura personnel have maintained the system. According to the users, the system is capable of approximately indicating the feed type. The economical benefits of the system were mostly due to the faster and more accurate adaptation for the ore type changes. The commercial system has found since 1996 several implementations.

The detailed description of the system is presented by Laine et al (2000).

5.2 Fault diagnosis of the paper machine short circulation process using novel dynamic causal digraph reasoning

The enhanced dynamic causal digraph method employs the process knowledge formalized as a causal digraph model in order to perform the ordinary monitoring tasks. Fault detection in the EDCDG method is performed with the residuals of the nodes in the graph, while the isolation is carried out by applying a set of rules to the residuals in order to extract the fault propagation path. The diagnosis is based on identification of those arcs in the digraph that explain the faulty behaviour. The EDCDG method has been described in detailed by Hui et al (2011).

5.2.1 Board Machine Process

The board making process begins with the preparation of raw materials in the stock preparation section. Different types of pulp are refined and blended according to a specific recipe in order to achieve the desired properties and composition for the board grade to be produced.

The consistency of the stock is controlled with dilution water. The blended stock passes from the stock preparation to the short circulation. First, the stock is diluted in the machine chest to the correct consistency for web formation. The diluted stock is then pumped with a fan pump, which is used to control the basis weight of the board, to cleaning and screening. Next, the stock passes to the head box, from where the stock is sprayed onto the wire in order to form a solid board web. The excess water is first drained through the wire and later by pressing the board web between rollers in the press section. The rest of the water is evaporated off in the drying section using steam-heated drying rolls. In a board machine producing three-layered boards, such as the one examined in this study, the stock is prepared in two different stock preparations (top and bottom layers have a similar composition which, however, differs from that of the middle layer) and then passed to three short circulations—one for each layer. After web forming the layers are combined to form the end product. In these test scenarios the process is limited to the two stock preparations, the three short circulations and the forming sections of the board machine.

5.2.2 Dynamic Causal Digraph Modelling and Fault scenarios

The dynamic causal digraph model of the board machine was obtained by constructing the causal structure of the process and then identifying the cause-effect models representing the relationships between variables. Also, the interarc knowledge matrix was constructed based on the process knowledge.

Two fault scenarios were selected for the study: a sensor fault in a consistency sensor in the stock preparation and a retention drop fault in the short circulation of the layer 2.

5.2.3 Fault Diagnosis Results

In the first case study the only detected variable was pcon2, pine consistency, and the fault isolation rules inferred that the fault was local, and the fault nature rules that it was a sensor fault. The fault propagation path for the fault period is shown as the result of fault diagnosis in Fig2.

For the second scenario, the detection set was performed by the variables: acceptcon2 (consistency of accept flow from the hydrocyclone), headcon2 (headbox consistency) and wpcon2 (wire pit consistency). The origin of the fault was located on the variable wpcon2, while the nature of the fault was identified as a process fault. Since the identified fault was a process fault, the approach for separating fault effects was applied. The final propagation path is shown as the result of the fault diagnosis in Fig. 3.

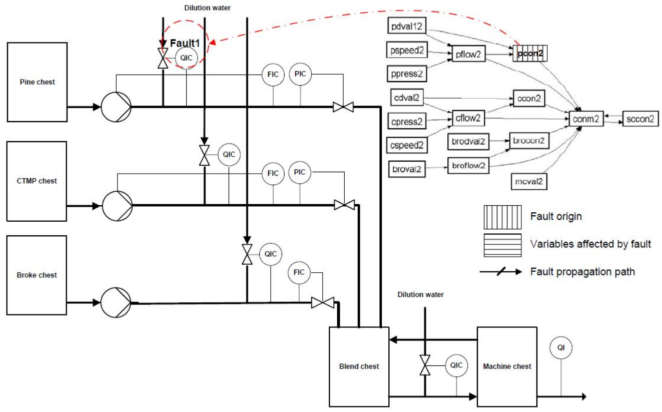

Fig. 2 Fault diagnosis results for the fault scenario 1.

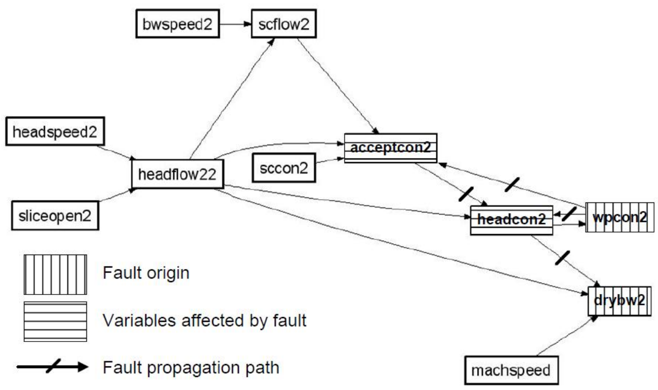

Fig. 3 Fault propagation path of the fault scenario 2.

5.3 Fault-Tolerant Control for a Dearomatization Process

5.3.1 General description of the dearomatization unit

The dearomatization process unit is used for the production of special oil refining products; low-aromatic solvents. The purpose of the dearomatization process is to remove aromatic compounds from the solvent feedstock through catalytic hydrogenation in a continuous process. The process itself is divided in two parts: the reactor part and distillation part. In the reactor part exothermic saturation reactions take place in two trickle-bed reactors, which remove aromatic compounds from the feed. The distillation part is composed of primary distillation column and side-stripper , which are used for adjusting the quality parameters, such as flashpoint (FP) or initial boiling point (IBP) of the low-aromatic product. The more detailed process description can be found in Sourander et al. (2005).

5.3.2 Description of the dearomatization process faults

Vermasvuori et al (2005) have studied the common fault types present in the dearomatization process. Most of the faults are located in the quality analysers that analyse the quality, such as flash point, of the final products. In addition to the analysers, faults are located in temperature, flow and pressure measurements and control valves of the unit. Therefore, the fault types that are taken into account with the FTMPC strategy are narrowed down to bias- and drift-shaped faults for analysers and sensors of controlled variables and disturbance variables , bias-shaped faults for the manipulated variables , and a stuck valve fault for the actuators.

5.3.3 Control of the Dearomatisation Process and its FTMPC

The overall dearomatization process control objectives are based on maximisation of profitability and stability by using the low-level control strategies and an MPC. The overall control strategy affects the distillation part of the dearomatization process as the final quality of the product is adjusted in that section of the process unit. In order to fulfil the tight product specifications, the primary control strategy keeps the distillation column bottom product above the grade specific IBP or FP limit. The secondary control strategy involves minimisation of losses by minimising the primary distillation column overhead flow rate. This is achieved by minimising both the column bottom product FP or IBP and the side-stripper bottom product FP.

The FTMPC is composed of three FTC strategies for reducing the effects of the faults and an FDD component for detecting and isolating faults.(Kettunen and Jämsä-Jounela, 2011). The first FTC strategy is based on fault accommodation and it was designed to reduce the effects of the faults in process analysers and measured disturbances. The second FTC strategy is based on fault accommodation and controller reconfiguration and it is capable of reducing effects of faults in the manipulated variable measurements. The third FTC strategy is based on controller reconfiguration and it has been configured to reduce the effects of faults in the control elements of the manipulated variables.

The FTC strategies 1 and 2 utilise partial least squares (PLS) algorithm with nonlinear iterative partial least squares (NIPALS) regression by Wold et al. (1983) as an FDD. PLS is used for estimating the measurement values, which were then compared to the actual measurements forming root mean square error of prediction (RMSEP) index. This index is then evaluated by comparing it to a detection threshold. If the index value is higher than the threshold for several time steps, a fault was declared. With strategy 1 the fault was compensated with estimated fault value and in strategy 2 the faulty measurement is compensated with the estimated fault value and the faulty actuator was given an opposite step change with the same magnitude as the fault.

In Strategy 3 the failure of an actuator is detected by calculating the root mean square error (RMSE) index from the actual measurement and the MPC reference trajectory. In this case the fault is compensated by setting the faulty actuator as a disturbance and by enabling a secondary actuator to compensate for the loss of controllability.

Based on the testing results, the FTMPC was able to reduce the duration of faults more than 70 % in all cases. Profitability of the FTMPC was also tested in this study and based on the profitability calculations, the FTMPC produced savings of USD 143,000 during one year and from one specific grade alone. Further FTMPC testing results can be found from the study by Kettunen and Jämsä-Jounela (2011).

4. CONCLUSIONS

A methodology for the FDD system development is presented in this paper. Especially the development phases for the large scale system are described in detailed. Three case studies from the different sectors of the process industries are presented and evaluated.

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