Intelligent Alarm Management

Carlos Agudelo
Instituto Colombiano del Petroleo – Ecopetrol S.A.
Bucaramanga, Colombia
carlos.agudelo@ecopetrol.com.co

Eduardo Quiles Cucarella
Universidad Politecnica de Valencia
Valencia, 46022, Spain
equiles@isa.upv.es

Francisco Morant Anglada
Universidad Politecnica de Valencia
Valencia, 46022, Spain
fmorant@isa.upv.es

Emilio García Moreno
Universidad Politecnica de Valencia
Valencia, 46022, Spain
emilio@isa.upv.es

***Abstract*— An ergonomic problem for the plant operators has appeared in the modern electronic control systems, in which configure an alarm is very easy. We present a methodology and an intelligent software tool to manage alarms and make early fault detection and diagnosis in industrial processes, integrating three techniques to detect and diagnose faults. The three techniques use available information in industrial environments: The alarms of the electronic control system; the fault knowledgebase of the process, formulated in terms of rules; and a simplified model used to detect disturbances in the process. A prototype in a Fluid Catalytic Cracking process is shown.**

Keywords- Fault detection, diagnosis, knowledge engineering, alarm systems, Fluid Catalytic Cracking.

I. Introduction

The fault detection and diagnosis techniques measured with criteria that define the early fault detection and diagnosis, the discrimination between different faults, robustness in the presence of noise and uncertainty, new faults identification, multiple faults identification, ease of explanation for the faults detected, and adaptability, suffer of one of these criteria, necessitating of a new approach. In [1] a new alternative is shown, the extended fault dictionary, in which through an inference rule engine makes the integration of various early fault detection and diagnosis techniques. In the present article we show the integration of early fault detection and diagnosis techniques with the purpose of getting the best of each one of them to detect the wrong behavior in industrial processes. The early fault detection and diagnosis allows to assist the operational personnel in an industrial plant about the best actions to take during the real state of the process, avoiding that incipient faults scale to critical situations where there is risk of economical and human lives loses.

Through this work is shown the use of the detection and diagnosis techniques that make use of the available information in industrial environments, its strengths and weaknesses, and the fusion mechanisms to integrate them. On this article we describe the information needed for the construction of a prototype software tool applied to a Fluid Catalytic Cracking unit in a petroleum refinery. A process diagram is shown in the next figure.

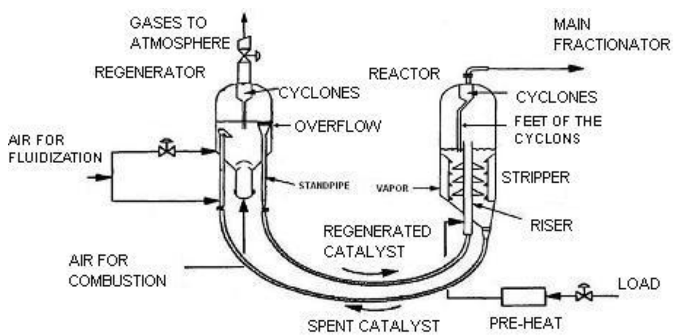

Fig. 1. Process diagram of the FCC process

II. The Methodology for Alarm Management

There are international norms (EEMUA 191; ISA 18.2; etc.) to deal with the problem of alarm flooding (so many alarms triggering in the electronic control system). An alarm is a visual (and sound) indication that an abnormal situation is present in the process, and the operations personnel must implement some immediate action, and whose implications are well known for all the personnel involved. Alarms are typically associated with acceptable limits for the state variables of the process, being configured into the electronic control system for low limits violation and high limits violation. Also there are alarms configured in the emergency shutdown system warning the operations personnel about an imminent emergency stop.

Alarms must address the operator`s attention in order to evaluate the appropriate actions to respond to the actual process conditions, avoiding unnecessary information, to reduce the risk on the people, the environment and equipments [2]. Unfortunately it is common to find alarms that confuse the operator instead of helping him, flooding the system with too many events, not only during emergency situations but also during normal operation. Because of this, it´s mandatory to optimize the information from the process alarms, to prioritize applying a methodology analyzing hazardous operations [3], [4]. To do so, we applied international standards (EEMUA Publication No. 191 “A guide to design, management and procurement of Alarms Systems”) defining criteria for alarm optimization and criteria for performance measurement and benchmarks during normal operation and fault scenarios.

We´ve applied this methodology for several plants at the refineries of Barrancabermeja and Cartagena (Colombia). We have divided the methodology in three phases: Phase 1 has to do with the Bad Actors of Alarms, which are the alarms that trigger the most in an industrial plant. We detected these Bad Actors using statistical tools. With an interdisciplinary people equipment (integrated for the electronic engineer responsible of the control system, the chemical engineer responsible for the process, the expert operators and supervisors of the plant, and the alarms facilitator), we detect why those alarms are triggering. Sometimes it´s because of configuration problems (such as wrong parameter configuration), sometimes it´s because of control loop tuning problems, sometimes it´s because of limit problems. Phase 2 has to do with alarm rationalization, applying the analysis to the whole alarm set of the plant, eliminating redundant alarms, and alarms that are not really alarms but maintenance activities. Phase 3 is intelligent alarm management, which is the application of advanced software tools to make besides alarm management, early fault detection and diagnosis. Plant performance monitoring, early fault detection and diagnosis, can be assisted with advanced software tools to increase reliability. We used what is called causal inhibition [5]. We don´t inhibit alarms in the control system, but we show in the software tool only the alarms associated with faults that haven´t been detected or diagnosed.

Several fault detection and diagnosis techniques have been developed and probed in industrial environments, showing their strengths and weaknesses. We have studied the integration of early fault detection and diagnosis techniques to incorporate the best of each to detect abnormal situations in complex processes. Early fault detection and diagnosis techniques assist the operations personnel to take the best actions, avoiding incipient faults scale to critical situations. The integrated fault detection and diagnosis techniques use the available information in industrial environments. We have collected the information and developed the methodology to build a prototype in a FCC unit. It is important to note that the different phases of the project assume that the previous ones have been successfully executed.

III. WHY INTEGRATION IS IMPORTANT

Several lost of human lives and economic impact have been documented in the petrochemical industry because of inappropriate abnormal situation management [6]. The desired attributes for a fault detection and diagnosis system have been defined previously [6]: Early fault detection and diagnosis; discrimination between different faults; robustness in the presence of noise and uncertainty; new faults identification; multiple fault identification; ease of results explanation and adaptability. Comparing different methods for fault detection and diagnosis according to these criteria, the results showed that none of the techniques used until now fulfill all the performance evaluation attributes [7], [8]. As a result, a new approach is needed to use these techniques. In this work we propose one possible solution using an integrated architecture combining some methods, using artificial intelligence tools.

It`s well known the use of different techniques for knowledge representation to describe the structure and behavior of complex processes, which are compared against the observed behavior of the real system, and if inconsistent this might help to probe hypothesis about faults and its root causes [9]. We reviewed the existent techniques for fault detection and diagnosis. We were especially interested in those techniques using the available information in industrial processes: The alarms associated to the allowed operational limits for process variables; the operations personnel experience on common faults, and compiled in rules; and a simplified model (step response of the process) of the unit which allows to predict the dynamic behavior during normal operation and fault scenarios. We`ve developed an extended fault dictionary and implemented a logic inference system to integrate the symptoms and the results of each fault detection and diagnosis technique.

An inference logic system has been used to incorporate the best of the different kind of techniques, compiling the expert knowledge in rules of the form if –antecedent is true- then –consequent is true-, to capture the causal relations in the process. The inference process to validate fault hypothesis is done through backward chaining. The model used to detect disturbances (an early way faults show in the process) is a step-test model, used in multivariable predictive control to predict the behavior of the controlled variables based on the calculated movements for the manipulated variables.

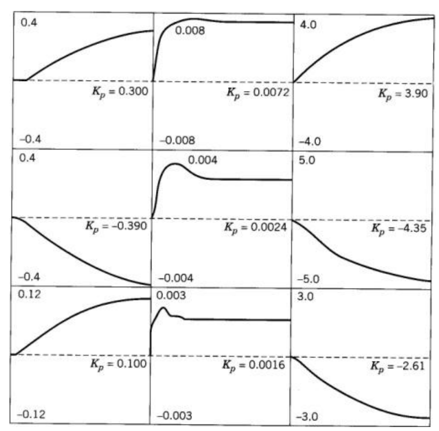

Fig. 2. Step-test model used to detect disturbances in the process

The available information (from the alarms and the other techniques) is incorporated in an extended fault dictionary [10]. This information is: Disturbances detected using the step-test model of the process; similarity between the observed alarm sequence and the previous sequences identified during fault scenarios; observed symptoms during fault scenarios (from the expert fault knowledgebase).

We have centered our work in those techniques that use the most relevant information available in a typical industrial process: The alarms associated to the process variables, which are design to warn the operator when those operational limits are violated; the available experience for fault detection and diagnosis, and formulated in terms of rules that resemble the inference mechanism used for operational personnel in abnormal situations in the unit; a simplified model to detect disturbances in the process.

Alarms must be seen as tools for fault detection and diagnosis. In the next figure, the alarm sequences for the main faults of the process have been represented.

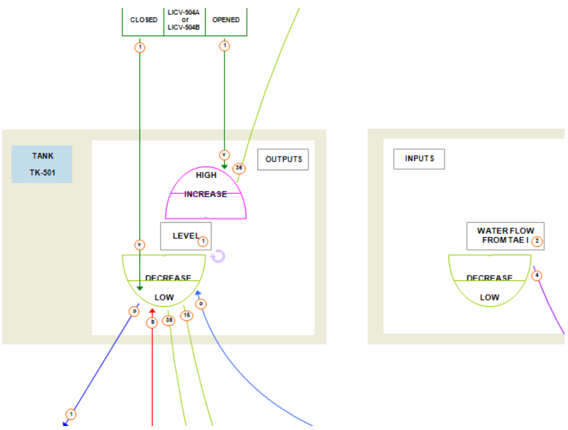

Fig. 3. Alarm sequences for the main faults in the process.

Knowledge engineering has methodologies to build knowledge bases with the operations personnel experience [11]: Terms definition to include in the model, variables influencing them; qualitative and quantitative codification of variables dependency; special cases; queries to inference procedures to validate answers from the experts; and sensibility analysis to establish robustness in the presence of disturbances.

Forward chaining (data driven inference) allows process monitoring, and backward chaining allows fault hypothesis validation during the diagnosis process.

IV. EXTENDED FAULT DICTIONARY

The integration of the fault detection and diagnosis techniques must solve conflicts when results from each technique don´t match. Each technique doesn´t detect all possible faults.

Diagnosis information coming from different sources must be fused correctly (ordered timestamps for the events of the system, upgraded results from every diagnosis technique, equipment performance monitoring to hypothesis validation, etc.).

The available information (from the alarms and the other techniques) is incorporated in an extended fault dictionary [10]. This information is: Disturbances detected using the simplified model; similarity between the observed alarm sequence and previously known fault alarm sequences; observed symptoms during fault scenarios (from expert knowledge on the process).

	t_1	t_2	t_3	…	t_r	Mode
f_0	S_{10}	S_{20}	S_{30}		S_{r0}	m_0
f_1	ϕ	S_{21}	S_{31}		S_{r1}	m_1, m_2
f_2	S_{12}	S_{22}	ϕ		S_{r2}	m_2
⋮	⋮	⋮	⋮		⋮	
f_n	S_{1n}	S_{2n}	S_{3n}	…	S_{rn}	m_m

Fig. 4. Extended fault dictionary

The software tool resembles the inference process through rules' backward chaining. These rules register the possible fault hypothesis and are built from the extended fault dictionary. The rule ij will be:

$$S_{ij} \wedge Mode(m) \Rightarrow f_j \quad (1)$$

Where the fault hypothesis (f_j) is on the consequent side and the validation symptoms (S_{ij}) are on the antecedent side of the rule with the operation mode in which this hypothesis is valid. There are five modes used to represent the conditions of the process: Initial mode, starting mode, production with defects mode, stopping mode, and emergency mode. The transition between the modes is estimated monitoring the operational conditions of the process, as shown in [12].

V. PROTOTYPE

An intelligent software tool for alarm management is being built using the previous concepts in a Fluid Catalytic Cracking unit, located at the refinery of Barrancabermeja (Colombia). The knowledge database required to build the application was gathered through interviews with the operators, supervisors and engineers, experts in the process, using the proper methodology. The software tool is being built using Jess[1], a tool for building intelligent software, based on rules and facts. A prototype tool to connect with the electronic control system, the real-time database of the refinery and the laboratory results database is being built using C++ compiler. The connection between these two platforms is achieved through a SQL Server[2] database.

The faults detected by the software tool include (but are not limited to): Catalyst circulation; catalyst losses; coking/fouling; flow reversal; high regenerator temperature; after burn; hydrogen blistering; and product quantity and quality problems. The main causes of these problems were classified as: Operations conditions; mechanical problems; feed characteristics; and catalyst characteristics, as described in [13].

One rule for the fault "Catalyst circulation limitation and reversal flow" due to a mechanical failure, in the intelligent software tool has the symptoms:

Decrease in PDIC27149

Decrease in ZI27100

Decrease in ZI27101

[1]Jess has been developed at Sandia National Laboratories.

[2]SQL Server is a trademark of Microsoft Corporation.

Increase in PIC27116

Decrease in ZI27103

Increase in ZI27104

Where PDIC27149 is the tag for the differential pressure between reactor and regenerator, which indicates that a low differential pressure between the reactor and regenerator has been caused due to clogging in the tap of the reactor pressure transmitter. ZI27100 and ZI27101 are the position of the slide valves of the regenerator flue gas lines, which indicates that the control system wants to press the regenerator. PIC27116 is the pressure controller of the regenerator. ZI27103 and ZI27104 are the positions of the slide valves for the regenerated catalyst and spent catalyst lines between the reactor and the regenerator, respectively, and the control system decreases the position of the ZI27103 valve in order to decrease the reactor pressure, due to a decrease in temperature.

The cause of the fault is "clogging in the pressure taps in the reactor pressure transmitter". If there is a clogging in the tap of the reactor pressure transmitter, the control system is going to close the slide valves to press the regenerator, increasing the differential pressure between the regenerator and the reactor, increasing the risk that the air blower decreases its flow. The recommendation to the operator is: To put the PDIC27149 in manual and to adjust its output in the value it had just before the disturbance.

Once the software tool detects a fault, it warns the operator, and gives him/her the recommendations needed to prevent an incident to happen or to recover from the fault state in the best way. The software architecture is shown in the next figure.

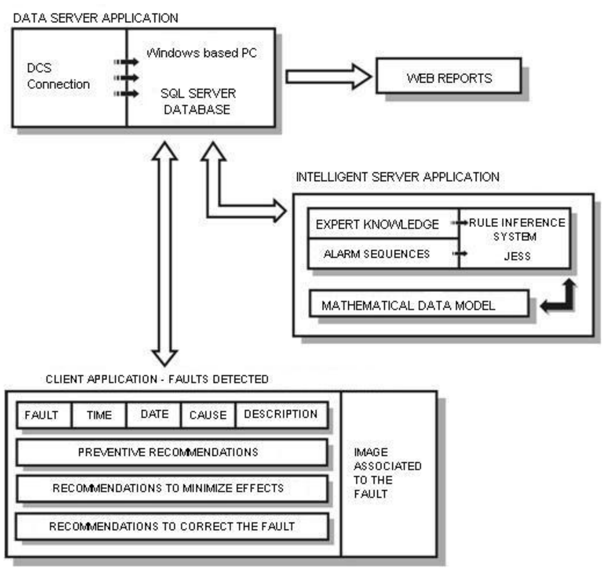

Fig. 5. Software tool architecture.

Several tests were performed using an Operator Training System (OTS) for the process plant, and the installation on the real process at the refinery has been approved.

VI. CONCLUSION

Important recommendations on alarm management were reviewed. The use of advanced software tools to aid the operations personnel in early fault detection and diagnosis tasks was supported. Integration of three techniques using the alarms of the electronic control system, the fault knowledgebase of the expert operations personnel, and a simplified model to detect disturbances in the controlled variables of the process was reviewed. A prototype of the software tool in a FCC process is shown.

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Carlos Agudelo is an advanced process control specialist in the oil and gas industry, working for the Colombian Petroleum Institute (the R&D center of the Colombian Petroleum Company, Ecopetrol S.A.) for more than ten years. He studied his bachelor of Design and Electronic Automation Engineering at Universidad De La Salle in Bogota (Colombia), and his Master of Automation and Industrial Informatics from Universidad Politecnica de Valencia, at Valencia (Spain). He is

currently finishing his PhD of Automation and Industrial Informatics at Universidad Politecnica de Valencia.

Francisco Morant received the B.S and the Ph. D. degree from the Universidad Politecnica de Valencia. He is a professor of Electrical Engineering at Universidad Politecnica de Valencia. His theorical research interest include: adaptive control and the application of Artificial Intelligence Techniques to continuous process control. His theorical work has been applied in process control industry.

Eduardo Quiles Cucarella was born in Valencia, Spain, in May 1967. He received the M.Sc in Electrical Engineering from Universidad Politecnica de Valencia in 1993, and the Ph.D. in the same University in 1998. In 1996 he joined the Systems and Control Engineering Department of the Universidad Politecnica de Valencia, where he is Associate Professor. His current research areas are Fault Detection and Diagnosis and System Reliability.

Emilio García Moreno is in the Department of Systems Engineering and Control of the Universidad Politecnica de Valencia (Spain) since 1989. Actually he is Associate Professor of Electrical and Automation Engineering. His research interest covers discrete-event and hybrid systems control, failure diagnosis and predictive supervision and applications in Factory Automation and Process Control Systems. At the moment, he is the main researcher in a subproject of Eolia Project, focused on the predictive supervision, fault diagnosis and maintenance of offshore farms of Power Wind Generators.