ONLINE FAULT DETECTION AND ISOLATION OF INDUSTRIAL PLANTS - AN ALGEBRAIC AND ARTIFICIAL INTELLIGENCE ANALYSIS

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Abstract

On-line fault detection and isolation techniques have been developed for automated processes during the last few years. These methods include algebrical methods artificial intelligence methods or combinations of the two methodologies. This paper includes a reference to recent research work on algebrical methods, an extensive presentation of artificial intelligence methods used for the fault detection process in technical systems and relevant survey material. Special reference is made to the on-line expert systems development where specific resent research work is illustrated.

Keywords: Fault detection, diagnosis, artificial intelligence techniques, on line systems

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 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, generationof hypotheses about the fault behaviour and fault explanation.

Mathematical modelling techniques that come from classical algebrical fault detection methods have the advantage of permitting fault prediction or detection of faults in an early stage. Fault prediction has both safety and economical benefits by preventing future process failures and improving process maintenance schedules. Isermann (1984) pointed out thatan essential prerequisite for further development of automatic supervision is an earlyprocess fault detection. A lot of methods of fault detection in technical processes permit recognition when limit values of measurable output signals have already been exceeded.

New methods for predicting and compensating faults are needed. For this purpose mathematical modelling techniques should be combined with artificial intelligence techniques and methodologies should be improved for effective coupling ofalgebrical and symbolic information. The implementation of these coupled techniques toon-line processes for fault detection is characterised by Zhang and Morris (1994) as a strategically important research topic due to the increasing demands for economic and safe operation of industrial processes. For on-line systems future controllers should interpret the signals as well as deliver the required control action, conduct tests and recommend diagnostic procedures. According to Frank (1990) these systems open a new dimension onfault diagnosis for complex processes with incomplete process knowledge as the quantitative analytical models of the algorithmical and analytical methods of fault detection are combined with the qualitative models of knowledge-based methods.

II ALGEBRICAL METHODS

The classical way for detecting faults consists of checking the measurable variables of a system in regard to a certain tolerance of the normal values and triggering alarm message if the tolerances are exceeded or taking an appropriate action when they exceed a limit value which signifies a dangerous process.

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. Fault detection using algebrical techniques based on mathematical system models is a well established subject and a lot ofsurvey papers and books have been written, such as Isermann (1984), Himmelblau (1988), Frank (1990), Patton (1991), Basseville and Nikiforov(1993), Frank (1996), Frank and Ding (1997),Gertler J. (1998), Chen and Patton (1999), Patton, Frank and Clark (2000),Basseville (2003).

Among the underlying strategies, the analytical redundancy (model-based) approach is characterised as the most capable one by Basseville (2003) due to the emergence of powerful techniques of mathematical modelling. In thiscase faults can be detected by comparing the data collected with the appropriate valid mathematical models. The use of models enables the estimation of variables and parameterswhich are influenced by the fault. A survey on model-based fault diagnosis can be found inDavis and Hamscher (1988). An important wide coverage of the various diagnostic techniques in dynamic systems is presented in the multi-authored book of Patton, Frank and Clark (1989).

III. ARTIFICIAL INTELLIGENCE METHODS IN FAULT DETECTION

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 by researchers. These methods come from the area of Artificial Intelligence and allow the development of new approaches to fault detection in dynamical systems.

These diagnostic approaches include the knowledge based approach (Angeli and Chatzinikolaou 2002), the qualitative simulation based approach (Calado and Roberts 1998), and the neural network based approach (Papadimitropoulos et al 2003).

A.1 Expert Systems technology in Fault Detection

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. In the 1980's, expert systems emerged from the laboratories and developed commercial applications due to the powerful new software for expert systems development as well as the new possibilities of hardware.

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". Differences from conventional programs include facts such as: An expert system simulates human reasoning about aproblem domain as the main focus is the expert's problem solving abilities and how toperform relevant tasks, as the expert does. An expert system performs reasoning overrepresentations of human knowledge in addition to doing algebrical calculations or dataretrieval using the knowledge base and the inference engine separately. An expert system solves problems using heuristic knowledge rather than precisely formulated relationships informs that reflect more accurately the nature of most human knowledge dealing with symbolic values and procedures.

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 as Tzafestas (1989) pointed out. The first diagnostic expert systems for technical fault diagnosis were developed in the early 1970's at MIT as is reported by Scherer and White (1989). Since then numerous systems have beenbuilt. Surveys of the first diagnostic expert systems of technological processes are providedby Pau (1986), Tzafestas (1989), Scherer and White (1989).

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. The empirical association between premisesand conclusions in the knowledge base is their main characteristic. These associations describe cause-effect relationships to determine logical event chains that were used to represent the propagation of complex phenomena. Heuristic-based expert systems canguide efficient diagnostic procedures but they lack in generality. Widman et al (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.

The main limitations of the early expert systems may be eliminated by using model-based methods. 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 independent diagnostic procedures. These systems offer more robustness in diagnosis because they can deal with unexpected cases that are not covered by heuristic rules. The knowledge bases of such systems are less expensive to develop because they do not require field experience for their building. In addition, they are more flexible in case of design changes. Model-based diagnosis systems offer flexibility and accuracy but they are also domain dependent.

Recently, several investigators have started combining algebrical with qualitative methods. Relevant recent research work is reported by Forbus and Falkenhainer (1990), Dvorak and Kuipers (1991), Milne and Trave-Massuyes (1998), Manders and Biswas(2003). In these knowledge-driventechniques, although the governing elements are symbolic, numeric computations still play an important role in providing certain kinds of information for making decisions. Various methodologies have been proposed for the combination of knowledge-based techniques with algebrical techniques. Frank (1990, 1996), Patton (1996) consider that the combination of both approaches in an effective way offers an appropriate solution for most situations.

A.2 Neural Networks in on-line Fault detection

Neural networks find application in fault detection due to their main ability of pattern recognition. The network is trained to learn, from the presentation of the examples, to forman internal representation of the problem. For diagnosis it is needed to relate the sensor measurements to the causes of faults, and distinguish between normal and abnormal states. Input vectors are introduced to the network and the weights of the connections are adjustedto achieve specific goals. An adaptive algorithm automatically adjusts the weightings of theinputs to the combiner so that the mean square of the error between the actual output value and the desired output value is brought to a minimum.

A significant feature of neural networks is that good models are not required in order to reach the decision. The process model may be only approximate because the neural networks are able to internally map the functional relations that represent the process. Compared to other systems there is no need to develop complex rules or algorithms. Research work on neural networks in on-line fault detection processes has been developed during the few last years. Recent work includes Hoskins and Himmelblau (1988), Kramer and Leonard (1990), Fossand Johansen (1993), Zhang and Morris (1994), Fujiwara et al (1996), Yu et al (1998), Boudaoud and Masson (1998), Rzepiejewski et al (2003).

Scientists have pointed out drawbacks of neural networks especially of the back propagation network that make them undesirable for on-line fault diagnosis applications (Kramer and Leonard 1990, Lee 1991).

One of their limitations in the on-line fault detection process is the high accuracy of the measurements needed in order to calculate the evolution of faults. Fault detection usually makes use of measurements taken by instruments that may not be sensitive enough or that may produce noisy data. In this case the neural network may not be successful in identifying faults. It is nearly always necessary to pre-process the data so that only meaningful parameters are presented to the net.

Neural networks are able to learn diagnostic knowledge from process operation data. However, the learned knowledge is in the form of weights which are difficult to comprehend. Another limitation compared to expert systems is their inability to explain the reasoning. This is because neural networks do not actually know how they solve problems or why in a given pattern recognition task they are able to recognise some patterns but not others. They operate as “black boxes” using unknown rules and are unable to explain the results.

A.3 Qualitative simulation in on-line Fault Detection

In this method fault detection is performed by comparing the predicted behaviour of a system based on qualitative models with the actual observation. Qualitative models of normal and faulty equipment are simulated to describe the range of possible behaviours of the operation of a system without numeric models. The modelling of physical situations contains a set of qualitative equations derived from a set of quantitative equations or from qualitative descriptions about relationships among the process variables and contains knowledge about structure, function and behaviour. Sensor data from actual processes are used to select between the different developed models. The fault diagnosis is realised by matching between predicted and observed behaviour.

Research work on this method includes the qualitative reasoning of De Kleer and Brown (1984), the qualitative process theory of Forbus (1984), the qualitative simulation of Kuipers (1990) and a lot of research work in diagnosis as Weld and De Kleer (1990),Zhang Roberts and Ellis (1990), Whiteley and Davis (1993), Coghill et al (1998), Zhuang and Frank (1998).

The main advantage of this approach is that accurate numerical knowledge and time consuming mathematical models are not needed. On the other hand this method only offers solutions in cases where high numerical accuracy is not needed.

A.4 On-line Expert systems in Fault Detection

On-line diagnostic systems emerging from recent research areas usually combine quantitative methods of fault detection with qualitative methods. This combination allows the evaluation of all available information and knowledge about the system for fault detection. The basic structure of an on-line expert system is illustrated in Figure 1.

One of the main characteristics of this system is that in parallel to the knowledge base of the traditional expert system a data base exists with information about the present state of the process. This information is derived on-line from the sensors. The data base is in a state of continuous change. The knowledge base of the system contains both analytical knowledge and heuristic knowledge about the process. The knowledge engineering task comprises different knowledge sources and structures. The inference engine combines heuristic reasoning with algorithmic operation in order to reach a specific conclusion.

Response time is a critical issue for on-line expert systems because they are operating in parallel with a dynamic industrial process. Calculations and fault detection must be performed in a specific time in order to perform fault diagnosis and control in a suitable time.

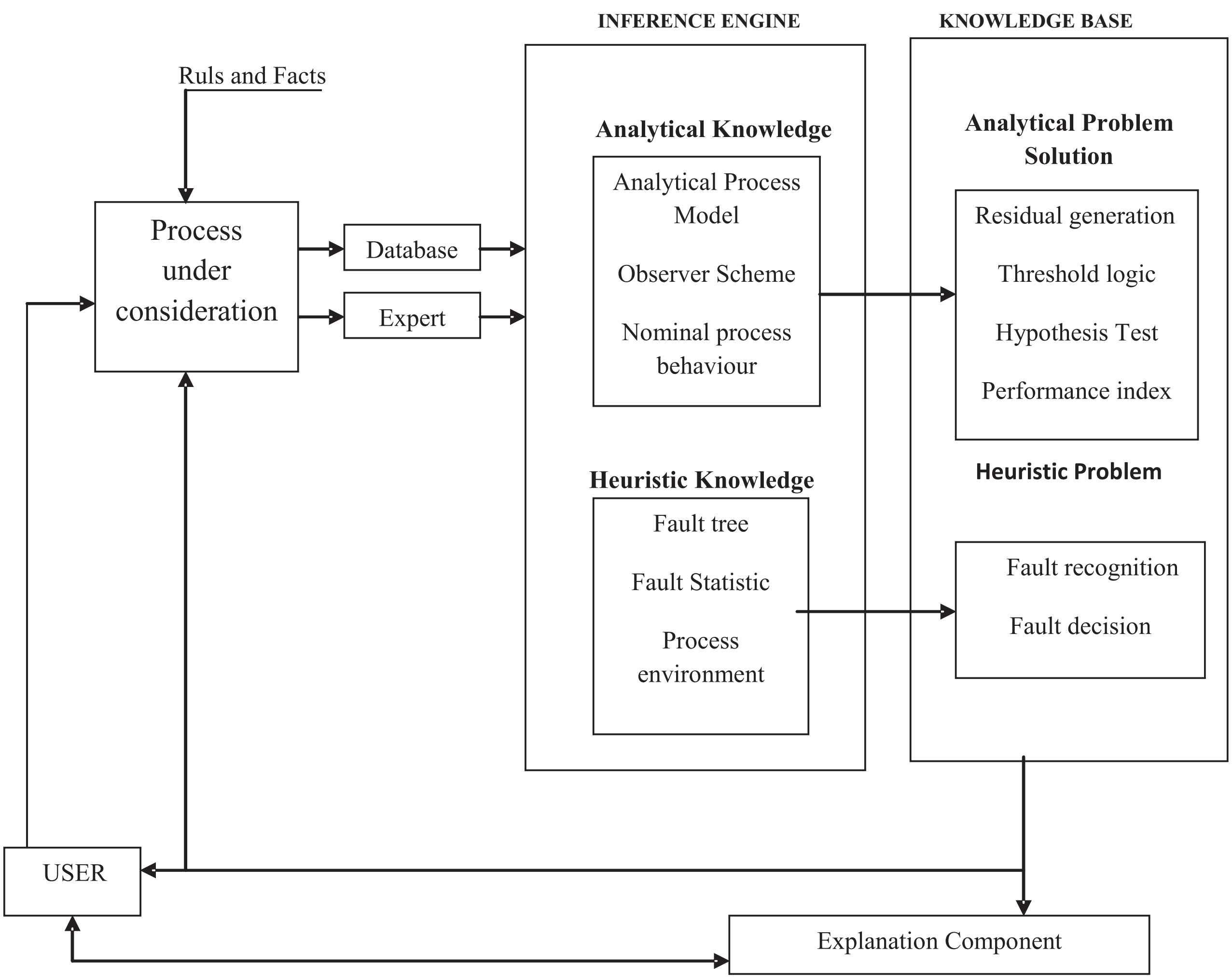

Fig. 1. Basic Structure of an on -line Expert System

An on-line expert system has to interface with the external environment for gathering the incoming data. In case the data is of poor validity due to the time variation or sensor performance, the system should be able to recognize and appropriately process these data.

On-line knowledge driven techniques have been developed in the last few years. A survey paper on the early attempts of applying on-line knowledge-based systems to solve problems in domains such as aerospace, communications, finance, medicine, process control and robotic systems, is published by Laffey et al (1988). The authors emphasise that the surveyed applications have not progressed beyond the prototype state. The main reason for this situation was the lack of suitable tools specifically built for real-time monitoring as well as the limitations of inference engines in high performance to guarantee response times. They conclude that a substantial amount of research is needed to improve the performance of on-line knowledge-based systems.

Kramer M. (1991) also reported that in the first international workshop on principles of diagnosis the need for new model-based frameworks for efficient interaction of behavioral knowledge and diagnostic inference was pointed out.

More recent research work in on-line diagnostic knowledge based systems is conducted mainly in domains such as the chemical industry and nuclear reactors. Relevant research work and applications are reported by the following researchers:

Sachs P., A. Paterson and M. Turner (1986) developed an expert system that provides advice on plant crises and presents them in a simple manner to reduce the problem of cognitive overload on the operators of process plant where they had to deal with 500 analogue and 2500 digital signals, a cognitive overload that is critical when problems occur.

D'Ambrosio B., et al (1987) developed an expert system using the Lisp programming language that provides tools for monitoring, examining and controlling a chemical manufacturing process control.

Fathi Z., et al (1993) present a diagnostic methodology in which the knowledge-based approach is combined with statistical decision methods and adaptive Kalman filtering in order to detect faults in process plants. It also performs various statistical analyses to determine the process conditions and check the validity of the models. The inputs to the system are not real but simulated and statistically tested.

Pfau-Wagenbauer M., and T. Brunner presented in the Workshop an expert system that acts as part of a supervisory control and data acquisition system and diagnoses network disturbances and device malfunctions. Relevant work is published by Barachini F. (1993). The system includes hierarchical diagnosis levels using heuristic rules and compiled model based knowledge. The expert system does not guarantee response time and the whole system needs 8 minutes to scan and filter its inputs.

Surgenor B., and P. Jofriet (1993) presented two real-time prototype expert system examples of a process fault analysis technique. The first one deals with the feedwater system of a nuclear power plant and the second one with the steam supply system of an oil refinery. Both systems have been tested off-line with simulations of the process.

Rengaswamy R., and V. Venkatasubramanian (1993) discuss a conceptual framework for monitoring, diagnosis and control of plants. They use a back propagation-based neural network to identify primitives in noisy sensor data and an expert system to make decisions on the normal or abnormal behaviour of the plant and to propose actions. Control actions are not included in this framework. The system has been implemented on a simulated reactor and the performance of the integrated expert system was tested on a number of simulated faults.

Terpstra V. et al (1993) have developed an expert system for a continuous stirred reactor which uses deep-knowledge fuzzy logic and hierarchical oriented sub models/objects. The fault detection method is independent of the actual process. The model represents the domain knowledge and can be described with three differential equations for the state of variables of the process. The system can detect the faults that can occur in the process simulation and cannot respond to dynamically changing states.

Addanki N., and R. Sethuraman (1993) have reported an on-line diagnostic expert system in the field of water chemistry for thermal power plants that assists the plant personnel in maintaining the chemistry levels in the water within acceptable limits. The system monitors parameter values in engineering units continuously, compares them with set limits and indicates corrective actions to the operator.

Kordon A., and P. Duhrjati (1996) have proposed an expert system for process supervision of a crude unit that uses model-based reasoning to analyse the static behaviour of the unit, monitoring module to collect the current set of process and laboratory data, what-if module that includes the rules reflecting the influence of some selected process variables on the unit's performance and an advisory module that suggests moves from the current operating point of the unit.

Harris T., et al (1996) have reported an expert system that diagnoses the underlying cause of poor behaviour in control loops. The system collects sets of data from a plant, analyses and evaluates their performance based on a statistical index of previous performance, and diagnoses problems in control loops using experiential knowledge.

Shen L. C., and Hsu P. L. (1998) have presented an intelligent supervision system that has a hardware interface to directly extract features from 2-D analogue image signals of a beam map. A qualitative model for the beam scanning is then obtained and the symptoms of abnormal operations are analysed to achieve on-line diagnosis. Furthermore, a fuzzy expert system is developed to advice operators taking appropriate adjustment for the beam scanning.

Heiming B., and I. Lunze (1998) have reported an expert system for complex industrial plants that is applied to a local power station plant. The process description consists of a large number of logical implication. By using graph decomposition, the diagnostic task is decomposed into several subtasks which can be solved in parallel on a multicomputer system.

Li I., and K. Kwok (1998) have presented the development of an expert system that prevents sheet breaks of a pulp-machine from happening. Using the PLS modelling technique it was found that the breaks can be modelled with 3 latent variables that are used for the process monitoring and fault diagnosis instead of using numerous process variables. The expert systems performs diagnosis of the process and identify the cause of sheet breaks by analysing information from major operating variables as well as operators inputs.

Norvilas A., et al (1998) have reported an intelligent diagnostic system where the fault detection is implemented in the form of multivariable statistical process monitoring and fault diagnosis is based on a expert system. Faults are diagnosed by determining the process variables that have made significant contribution to the faulty signal and relating these variables the specific process equipment faults.

Angeli C., and D. Atherton (2001) have developed an on-line expert system to detect faults in electro-hydraulic systems using on line connections with sensors, signal analysis methods, model-based strategies and deep reasoning techniques. Expert knowledge is contained primarily in a model of the expert domain. The final diagnostic conclusions will be conducted after interaction among various sources of information.

Koscielny J., and M. Syfer (2003) presented main problems that appear in diagnostics of large scale processes in chemical, petrochemical, pharmaceutical and power industry and propose an algorithm for decomposition of a diagnostic system, dynamical creation of fault isolation threads and multiple fault isolation assuming single fault scenarios.

IV. PROBLEMS AND RESTRICTIONS IN ON-LINE EXPERT SYSTEM DEVELOPMENT

Researchers in on-line fault detection techniques have pointed out some problems and difficulties that arose in the development of on-line systems. These difficulties can be summarised as follows:

1. Traditional, theoretical modelling techniques that are usually used for the detailed modelling of faults and are incorporated in systems are not suitable for on-line performance of a system. These techniques need a lot of time for the running of the models of faults and in on-line systems it is required to reduce the best possible time response within the given deadline.
2. On-line systems use a lot of sensors for the measurements needed for the data acquisition process. These sensors are expensive and researchers wonder about the increasing cost applications in real industrial environments.
3. Traditional techniques in knowledge base development are not useful for on-line systems as the knowledge base requires on-line updating from the sensor measurements and possibilities for the interaction of different sources of knowledge.
4. Researchers conclude that new methodologies are needed to be developed for the further evolution of on-line expert systems. It is pointed out that suitable new tools are also needed to be developed for efficient interaction of numeric and symbolic computing. In consequence new methodologies are needed to be developed that would be able to propose effective solutions to these problems.

V. CONCLUSION

On line fault detection techniques have been developed the last years for the intelligent problem solving process in technical systems. In this paper, recent research work on online intelligent fault detection techniques has been presented including the expert systems approach the neural network approach and the qualitative simulation approach. In addition, the main advantages and disadvantages of each technology regarding the diagnostic process for technical systems have been discussed. Particular emphasis has been posed on the on-line expert system paradigm for technical systems. In this case the main characteristics of the technology as well as a detailed description of specific expert system applications of the last years for the on-line fault detection process have been illustrated. Difficulties and main problems in on-line expert systems development as well as future directions of the research in these systems have been also highlighted.

REFERENCES

[1] Addaki N. and R. Sethuraman, 1992, On-line diagnosis of water chemistry in thermal power plant, In IFAC symposium, *On-line fault detection and supervision in the chemical process industries*, Newark, Delaware, USA, April 22-24 pp. 299-303.

[2] Angeli C., and D.P Atherton, 2001, A model based method for an on-line diagnostic knowledge-based system, *Expert Systems* Vol. 18, Nr. 3, pp. 150-158.

[3] Angeli C. and A. Chatzinikolaou, 2002, Fault Prediction and Diagnosis in Hydraulic Systems, *Journal of Engineering Manufacture*, Vol. 216, Nr. B2, pp. 293-297.

[4] Angeli C. and A. Chatzinikolaou, 2004, 13th IASTED International Conference Applied Simulation and Modelling, ASM 2004, Intelligent Monitoring and Control of Proportional Valves, Rhodes, Greece, June 28-30, pp. 365-370

[5] Basseville M. and I. Nikiforov, 1993*, Detection of Abrupt Changes: Theory and Application*, Prentice Hall.

[6] Basseville M., 2003, Model-based statistical Signal Processing and Decision Theoretic Approaches to Monitoring, In Proceedings Safeprocess 03, Washington, U.S.A. pp. 1- 12.

[7] Boudaoud A. and M. Masson, 1998, On-line Adaptive Fuzzy Diagnosis System: Fusionand Supervision, In IFAC Symposium, *Fault Detection, Supervision and Safety for Technical Processes*, Kingston Upon Hull, UK, 26-28 August 1997, pp. 1195-1200.

[8] Calado J. and P. Roberts, 1998, Fault detection and Diagnosis Based on Fuzzy Qualitative Reasoning, In IFAC Symposium, *Fault Detection, Supervision and Safety for Technical Processes*, Kingston Upon Hull, UK, 26-28 August 1997, pp. 513-518.

[9] Chen J and R. Patton, 1999, Robust Model Based Fault Diagnosis For Dynamic Systems, Kluwer Academic Publishers.

[10] Coghill G., M. Chantler, Q. Shen and R. Leitch, 1998, Towards Model Switching for Diagnosis of Dynamic Systems, In IFAC Symposium, *Fault Detection, Supervision and Safety for Technical Processes*, Kingston Upon Hull, UK, 26-28 August 1997, pp. 545-552.

[11] D' Ambrosio B., M. Fehling, S. Forrest, P. Raulefs and B. Wilbur, 1987, Real-Time Process Management for Materials Composition in Chemical Manufacturing. *IEEE Expert* 2(2), pp. 80-89.

[12] .Dvorak D. and B. Kuipers, 1991. Process monitoring and diagnosis. *IEEE Expert*, 6, No.4.

[13] Fathi Z., Ramirez W.F., A.P. Tavares, G. Gilliland and J. Korbicz, 1993, A Knowledgebased system with embedded estimation components for fault detection and isolation in process plants. In IFAC symposium, *On-line fault detection and supervision in the chemical process industries*, Newark, Delaware, USA, April 22-24 pp. 43-49.

[14] Feigenbaum E., 1981, *Handbook of Artificial Intelligence*, Heuris Tech Press, W.Kaufman Inc.

[15] Feigenbaum E., 1982, *Knowledge Engineering in 1980's*. Dep. of Computer Science, Stanford University, Stanford CA.

[16] Forbus K., 1984, Qualitative process theory, *Artificial Intelligence*, 24, pp. 85-186.

[17] Forbus K.D. and B. Falkenhainer, 1990, Self-explanatory simulations: an integration of qualitative and quantitative knowledge. *IJCAI*, 380-387.

[18] Foss B.A. and T.A. Johansen, 1993, An integrated approach to on-line fault detection and diagnosis - including artificial neural networks with local basis functions. IFAC symposium in *On-line fault detection and supervision in the chemical process industries*. Delaware, USA, USA, April 22-24 pp. 207-213.

[19] Frank, P., 1990, Fault Diagnosis in Dynamic Systems Using Analytical and Knowledgebased Redundancy - A Survey and Some New Results. *Automatica*, Vol. 26, No. 3. pp.459-474.

[20] Frank P.M. and X. Ding, 1997, Survey of robust residual generation and evaluation methods in observer-based fault detection systems. *Journal of Process Control*.

[21] Fujiwara T., T. Tsushi and H. Nishitani, 1996, Failure Detection by Auto-Associative Neural

Networks, In IFAC Workshop, *On-line Fault Detection and Supervision in the Chemical Process Industries*, Newcastle, 12-13 June 1995, pp. 33-38.

[22] Gertler J., 1998, Fault Detection and Diagnosis in Engineering Systems, Marcal Dekker.

[23] Harris T., C. Seppala, P. Jofriet and B. Surgenor, 1996, Plant-wide feedback control performance assessment using an expert system framework. In IFAC *On-line fault detection and supervision in the chemical process industries*, Newcastle, 12-13 June1995, Pergamon, pp.149-154.

[24] Heiming B. and J. Lunze, 1998, Parallel Knowledge-Based Process Diagnosis Applied to a Local Power Station Plant, In IFAC Symposium, *Fault Detection, Supervision and Safety for Technical Processes*, Kingston Upon Hull, UK, 26-28 August 1997, pp. 1113-1118.

[25] Himmelblau D. M., 1988, Fault detection and diagnosis - Today and tomorrow, Proc. Of the 1st *IFAC Workshop on fault detection and safety in chemical plants*, Kyoto, 28th Sept - 1st Oct, pp. 95-105.

[26] Isermann, R., 1984, Process Fault Detection Based on Modelling and Estimation Methods - A Survey. *Automatica*, Vol 20, N. 4. pp 387-404.

[27] Kordon A. and P. Dhurjati, 1996, An expert system for crude unit process supervision. IFAC International federation of automatic control. *On-line fault detection and supervision in the chemical process industries 1995,* Newcastle, 12-13 June1995, Pergamon, pp. 143-148.

[28] Koscielny J. and Syfert M., 2003, Fuzzy Logic Application to Diagnostics of Industrial Processes, In Proceedings Safeprocess 03, Washington, U.S.A. pp.711-717.

[29] Kramer, M. A. and J. A. Leonard, 1990, Diagnosis using backpropagation neural networks; analysis and criticism. *Computer and Chemical Engineering*, 14, pp. 1323-1338.

[30] Kuipers B., 1990, Qualitative simulation. In *Readings in Qualitative Reasoning about physical systems* Ed. Weld D. and J. De Kleer, M. Kaufmann Publ. pp. 236-260.

[31] Laffey T., P. Cox, J. Schmidt, S. Kao & J. Read, 1988, Real-Time Knowledge-Based Systems, *AI Magazine*, Vol. 9, No. 1, pp. 27-45.

[32] Lee, Y., 1991, Handwritten Digit Recognition using K Nearest-Neighbor, Radial-Basis Function, and Backpropagation Neural Networks, *Neural Computation*, 3, pp. 440-449.

[33] Li I.S., K. Kwok and J. Zurcher, 1998, Prediction and Prevention of Sheetbreak Using PLS and an Expert System, In IFAC Symposium, *Fault Detection, Supervision and Safety for Technical Processes*, Kingston Upon Hull, UK, 26-28 August 1997, pp. 1159-1164.

[34] Manders E. and G. Biswas, 2003, FDI of Abrupt Faults with Combined Statistical Detection and Estimation and Qualitative Fault Isolation, In Proceedings Safeprocess 2003, Washington, U.S.A. pp.339-344

[35] Milne and Trave-Massuyes, 1998, Model Based Aspects of the TIGER Gas Turbine Condition Monitoring System, In IFAC Symposium, *Fault Detection, Supervision and Safety for Technical Processes*, Kingston Upon Hull, UK, 26-28 August 1997, pp. 405-410.

[36] Norvilas A., A. Negiz, J. DeCicco and A. Cinar, 1998, Intelligent Process Monitoring by Interfacing Knowledge-Based Systems and Multivariate SPC Tools, In IFAC Symposium, *Fault Detection, Supervision and Safety for Technical Processes*, Kingston Upon Hull, UK, 26-28 August 1997, pp. 43-48.

[37] Papadimitropoulos A., G. Rovithakis and T. Parasini, 2003, Fault Detection in Mechanical systems with Friction Phenomena: An On-line Neural Approximation Approach, In Proceedings Safeprocess 03, Washington, U.S.A. pp.705-711.

[38] Patton R., 1991, Fault detection and diagnosis in aerospace systems using analytical redundancy, *IEE Computing and Control Journal*, 2 (3), 127-136.

[39] Patton R., Frank P and Clark R., 2000 Issues in Fault Diagnosis For Dynamic Systems, Springer-Verlag, New York.

[40] Rengaswamy R. and V. Venkatasubramanian, 1993, An integrated framework for process monitoring, diagnosis, and control using knowledge-based systems and neural networks. In IFAC symposium*, On-line fault detection and supervision in the chemical process industries,* Newark, Delaware, USA, April 22-24 pp. 49-55.

[41] Rzepiejewski P., M. Syfert and S. Jegorov, 2003, On-line Actuator Diagnosis Based on eural Models and Fuzzy Resoning: The DAMADICS Benchmark Study, In Proceedings Safeprocess 03, Washington, U.S.A. pp.981-986.

[42] Sachs P., A. Paterson and M. Turner, 1986, Escort-An Expert System for Complex Operations in Real Time. *Expert Systems* 3(1), pp. 22-29.

[43] Shen L.C., and P.L. Hsu, 1998, An Intelligent Supervision System for the Ion Implementation in IC Fabrication Processes, In IFAC Symposium, *Fault Detection, Supervision and Safety for Technical Processes*, Kingston Upon Hull, UK, 26-28 August 1997, pp. 611-616.

[44] Scherer W. and C. White, 1989. A Survey of Expert Systems for Equipment Maintenance and Diagnostics. In *Knowledge-based system Diagnosis, Supervision*, and Control eds. S. Tzafestas, Plenum Publishing Inc.

[45] Surgenor B. and P. Jofriet, 1993, Thermal fault analysis and the diagnostic model processor. In IFAC symposium, *On-line fault detection and supervision in the chemical process industries* , Eds. Dhurjati P. and G. Stephanopoulos. No.1, Pergamon Press.

[46] Terpstra V., H. Verbruggen, M. Hoogland and R. Ficke, 1993, A real-time, fuzzy, deepknowledge based fault-diagnosis system for a CSTR. In IFAC symposium, *On-line fault detection and supervision in the chemical process industries,* Newark, Delaware, USA, April 22-24 pp. 73-79.

[47] Tzafestas S.G., 1989, System Fault Diagnosis Using the Knowledge-Based Methodology, Eds. Patton R.J., Frank, P.M. and Clark, R.N. (1989), *Fault diagnosis in dynamic systems, Theory and application*, Prentice Hall.

[48] Weld D. and J. De Kleer, 1990, *Qualitative Reasoning about Physical Systems*, M. Kaufmann Publishers Inc.

[49] Whiteley J. and J. Davis, 1993, Qualitative interpretation of sensor patterns using a similariy-based approach, *On-line fault detection and supervision in the chemical process industries,* Newark, Delaware, USA, April 22-24 pp. 115-121.

[50] Yu D., J. Gomm and D. Williams, 1998, Diagnosing Sensor Faults in a Chemical Process Via RBF Network, In IFAC Symposium, *Fault Detection, Supervision and Safety for Technical Processes*, Kingston Upon Hull, UK, 26-28 August 1997, pp. 893-898.

[51] Zhang J., P. Roberts and J. Ellis, 1990, Fault diagnosis of a mixing process using deep qualitative knowledge representation of physical behaviour. *Journal of Intelligent and Robotic Systems*, 3, 103-115.

[52] Zhang J. and A. Morris, 1994, On-line process fault diagnosis using fuzzy neural networks. *Intelligent Systems Engineering*, 3. 37-47.

[53] Zhuang Z. and P. Frank, 1998, Fault Detection and Isolation with Qualitative Models. In IFAC Symposium, *Fault Detection, Supervision and Safety for Technical Processes*,Kingston Upon Hull, UK, 26-28 August 1997, pp. 663-668.

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