IOSR Journal of Electrical and Electronics Engineering (IOSR-JEEE)
e-ISSN: 2278-1676,p-ISSN: 2320-3331, Volume 10, Issue 6 Ver. II (Nov – Dec. 2015), PP 16-22
www.iosrjournals.org

Embedded Condition Based Maintenance A New Modeling Approach

Eid Muhammad Al-Hajri
Jubail Industrial College, Al Jubail 31961

Abstract: *The types of faults that can be detected using the proposed scheme are tank leaks, pump failure, valve failure… etc. In the first step of the proposed scheme, the data will be collected at the normal mode of the process. These data will be clustering according to its source. This stage directs these data to the second-stage that comprises local models. The Fault Diagnostic and Detection [FDD] stage will detect and isolate faults (if any) and recommend the solution for the detected fault. The existing maintenance methods used nowadays are planned maintenance, corrective maintenance, preventive maintenance, fault reporting, condition-based-maintenance (CBM), etc. CBM may be the best one used in recent years. The FDD proposed to the Embedded Condition Based Maintenance [ECBM] will use the existing modules in DCS and/or SCADA systems to improve the CBM used today. Compared with the CBM, the proposed ECBM scheme will be lower in cost, and will be faster in fault detection. The Scheme used in the proposed ECBM performs on-line maintenance instead of planned maintenance or CBM. The usage of Embedded technology within CBM raises lots of challenges to be explored and new methods to deduced*

Key Words: *Diagnostics and Prognostics Signals, Petri nets, Clustering Techniques, Online Fault Detection [OFD], CBM, ECBM, FDI, FDD, AEM and CMMS*

I. Introduction

Keeping physical assets in proper working order is essential to any industry especially petrochemical, oil and mining industries. Today, most maintenance is still performed either according to a set calendar schedule or according to the most ancient procedure: “if it breaks, fix it.” It means billions of Dollars loss. Traditional maintenance is based on asset run-hours, cycle times, equipment starts/stops, and meters sourced directly from plant floor data and fed automatically into computerized maintenance management systems (CMMS) to drive plant’s maintenance schedule. Expecting one step ahead of breakdowns, avoids equipments failures, and efficiently plans scheduling maintenance. The preventive maintenance can be automated and remove the need to manually collect readings and enter results into computerized maintenance management systems (CMMS).

Now with a giant step, in this modern, data-intensive industrial environment, we can do much better and take plant performance to the next level with condition-based maintenance (CBM).

Frequent shutdown for the petrochemical, oil and mining industries leads to loss of billions of Dollars each year. In industries much of the cost of maintenance is incurred unnecessarily due to bad planning for maintenance, overtime-cost, misused preventive maintenance, shutdown-time cost and so on. Again, CBM considered as the solution for a more effective maintenance. Unplanned downtime kills plant’s capacity that necessitates emergency parts and labor, and major failures present substantial health, safety and environmental risks. CBM program takes real-time data and gives it the predictive power to add capacity, reliability, and profitability to the operation of the plants. It is a maintenance program that recommends maintenance decisions based on the information collected through condition monitoring. It consists of three main steps: data acquisition, data processing and maintenance decision-making. Diagnostics and prognostics are two important aspects of a CBM program.

This paper is an attempt to summarize and review CBM with emphasis on models, algorithms and technologies for data processing and maintenance decision-making. The ECBM as an improvement of existing CBM also will be discussed. Instead of using separate sensors and equipment in condition monitoring, our motto is to enhance and improve existing advanced control technologies using the diagnostics and prognostics signals, which already embedded in industrial control systems.

Compared with the CBM, the proposed Embedded Condition Based Maintenance [ECBM] will be lower in cost, and faster in fault detection. Basically our ECBM will be employing clustering approaches, intelligent schemes, and Petri nets tools to construct a simpler, but effective, hybrid fault detector and isolation (FDI) scheme for detecting and isolating faults on-line to enhance the existing CBM. Unlike CBM that is performed after one or more indicators show that equipment is going to fail or that equipment performance is deteriorating, the proposed ECBM performs on-line maintenance instead of planned maintenance or CBM. Our main goal is doing a specific leap from the scheduled preventive maintenance to an effective on-line immediate maintenance.

II. Reducing The Cost Of Plant Maintenance

The economic, political and cultural realities have forced managers to reduce the costs and energy expenditures in their organizations. For instance, these can be achieved, with respect to maintenance, by replacing a reactive repair-focused attitude by a proactive reliability-focused culture. Thereby far less (i) human effort is expended and (ii) energy would be wasted, both of which lead to increased profitability.

A. The current Scenario of Condition Based Maintenance [CBM]

CBM was introduced to try to maintain the correct equipment at the right time. It is based on using real-time data to prioritize and optimize maintenance resources. Such a system will determine the equipment's health, and act only when maintenance is actually necessary. Developments in recent years have allowed extensive instrumentation of equipment, and together with better tools for analyzing condition data, the maintenance personnel of today are more than ever able to decide what is the right time to perform maintenance on some piece of equipment. Ideally condition-based maintenance will allow the maintenance personnel to do only the right things, minimizing spare parts cost, system downtime and time spent on maintenance.

The advantages of the use of CBM are:

a) Preventing unplanned downtime
b) Making better use of maintenance resources
c) Maximizing the operational life of the assets

A condition-based maintenance program takes real-time asset data and gives it the predictive power to add capacity, reliability, and profitability to the operation. Since CBM consists of three main steps: data acquisition, data processing and maintenance decision-making, it is implemented with the help of additional models, algorithms and technologies for data acquisition, processing and maintenance decision-making.

B. Challenges of CBM

As discussed above, despite its usefulness, there are several challenges to the use of CBM. First and most important of all, the initial cost of CBM is high. It requires improved instrumentation of the equipment. Often the cost of sufficient instruments can be quite large, especially on equipment that is already installed. Therefore, it is important for the installer to decide the importance of the investment before adding CBM to all equipment.

C. A New Dimension to CBM : Embedded Condition Based Maintenance

Definition 1: An embedded maintenance means a special-purpose arrangement in which the system is completely encapsulated by the device it controls

Definition 2: Condition-based maintenance (CBM) is the maintenance-scheme when the need arises. This scheme is performed just before the edge of failure. In CBM, the maintenance is done when one or more indicators show that the equipment is going to fail or that the performance is deteriorating

Definition 3: Diagnostic Signal is a signal in the process to identify or characterize some un-natural/irregular behaviors or being a precise indication for that.

Definition 4: Prognostic Signal is a signal in the process for predicting the future behavior depending upon current situation

Definition 5: Pattern Recognition uses, "Fault-Signatures" as the observed symptoms of a problem and compares them to a set of known-symptoms for each possible problem, looking for the best match

Definition 6: Embedded Condition-based maintenance (ECBM) is a special CBM using diagnostic- and prognostic-signals without using additional sensors. The faults-signatures

One more step ahead to existing CBM, our proposal is about to use, enhance and improve existing advanced control technologies, which already embedded in industrial control systems, to detect and predict maintenance requirements. This is added value point that needs no real additional cost. In addition, we are trying to create a new method to adopt the advanced embedded CBM.

The proposed method will offer tremendous cost-saving opportunities through elimination of issues related to CBM system installation cost, system maintenance, and training issues. It will also enhance the error alerting, increase safety and better maintenance, and it will enhance customers' competitive advantage and present new opportunities. It will enhance the efficiency of operations by enabling unprecedented adjustment to the system. For example, you can slow down worn-out pumps while speeding up more healthy ones, thus avoiding unplanned shutdowns. And it reduces vulnerability to unforeseen operational changes through continuous monitoring.

Often the cost of deploying CBM systems has been too high to justify. In some situations, there hasn't been a technology that could solve the technical challenges. There are a number of factors that have limited the adoption of condition-based maintenance besides the fact that it is a relatively new strategy:

- CBM is expensive to be justified for implementation.
- Difficulty in connecting some equipment's to the CBM.
- Maintaining the CBM after installation.
- Trainings needed to reconfigure CBM to add new instruments

The proposed Embedded-CBM (ECBM) model should be solving all the four issues listed above and in addition to that will be lowering the costs in five primary areas, compared to other maintenance schemes, as follows:

- Reduced outages because of early warnings;
- Replacement deferral;
- Substitution of current manual processes;
- Operational efficiencies; and
- Safety improvements

The cost is getting lower because of lot of factors for example using the existing diagnostic- and prognostic-signals

III. Fault Detection

3.1) Introduction

Fault detection and diagnosis (FD) is an important problem in process engineering as a condition-based-maintenance. It is the central component of abnormal event management (AEM) which has attracted a lot of attention recently. AEM deals with the timely detection, diagnosis and correction of abnormal conditions of faults in a process. Early detection and diagnosis of process faults while the plant is still operating in a controllable region can help avoid abnormal event progression and reduce productivity loss. Hence, there is considerable interest in this field now from industrial practitioners as well as academic researchers. There is an abundance of literature on process fault diagnosis ranging from analytical methods to knowledge-based and data driven approaches [1].

The main components in a diagnosis classifier can be distinguished based on the type of knowledge and the type of search strategy. The latter strongly depends on the type of a priori knowledge available, hence the type of an available knowledge employed is the most important distinguished feature in a diagnosis scheme. Based on a priori knowledge, diagnostic methods can be mainly classified into three categories: Qualitative model– based methods, Quantitative model-based methods, and Process history based methods that are further classed into many other schemes [2, 3, and 4].

Process history based method as a main category of the above diagnostic methods, is classed into qualitative and quantative feature extraction. The former is also classed into two important methods; expert systems that solve problems in a narrow domain of expertise, and trend modelling approaches that can be used to explain the various important events happening in the process, and predict future states. Fig. 1 shows the most important diagnoses methods.

Other elements of AEM related to diagnosis include the associated system and user interfaces, and procedural support for the overall process. Procedural support steps that might be manual or automated include notifications, online instructions, growth procedures if problems are ignored, fault improvement actions, direct corrective actions, and steps to return to normal once repairs are complete.

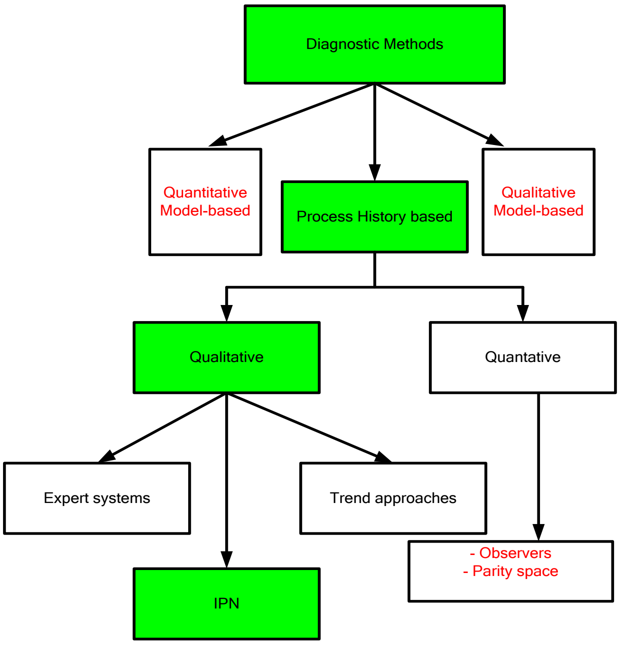

Fig.1: Diagnostic methods

Automated fault detection and diagnosis depends heavily on input from sensors. In many applications, such as those in the process industries, sensor failures are among the most common equipment failures. So a major focus in those industries has to be on recognizing sensor problems as well as process problems. Distinguishing between sensor problems and process problems is a major issue in these applications.

Our usage of the term "sensors" includes process monitoring instrumentation for flow, level, pressure, temperature, power, and so on. We are not trying to improve the fault detection of sensors. However, we are looking for a fault detection system that can find faults in a machine, equipments and process and recommend maintenance requirement for that equipment as shown in Fig. 2. The existing condition-based-maintenance (CBM) is a standalone system which is very costly and cannot take all sensors. New model should use the existing control methods and programs in DCS/SCADA and PLC to create a FD program to overcome most of the existing CBM problems. On-line process monitoring and fault diagnosis are key factors that ensure product quality and operation safety. So, we focus mainly on online monitoring systems or other automated inputs, but possibly including on some manual input from end users such as plant operators (expertise).

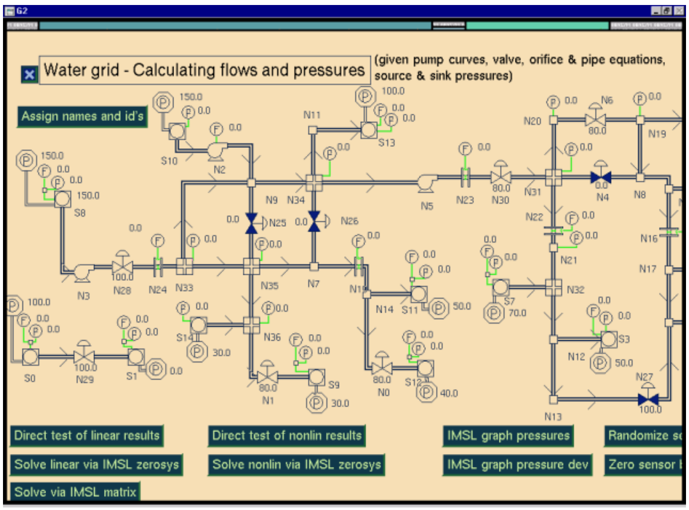

Fig. 2: A part of industrial process

Accordingly, expert systems-based, clustering techniques, and may be Petri nets are employed to enhance the existing CBM in the sense of computational cost by using the modules included in distributed control systems (DCS) and programmable logic controllers (PLC). The proposed FDD will convert the routinely maintenance to on-line maintenance before the fault propagation.

3.2) Robust detection and isolation

Due to the increasing complexity of modern control systems, and the growing demand for safety, quality and cost efficiency, the last two decades have witnessed a growing interest for automatic failure diagnosis. Isermann and Balle[5] reviewed the literature published on the subject, and suggested the following nomenclature:

i. ***Failure***: A permanent interruption of a system's ability to perform a required function under specific operating conditions.
ii. ***Failure detection***: Determination of the failures present in a system, and the time of detection.
iii. ***Failure isolation***: Determination of a kind, location and time of detection of a failure.

Failure detection and isolation typically performs two steps, which are reviewed hereafter:

i. ***Generation of residuals***, which are functions that are accentuated by specific failures (failure signature).
ii. ***Residual interpretation***, which leads to failure isolation.

Once the failure is detected in a part of an industrial process, subsequent steps focused on its propagation and avoidance. The general structure of a diagnostic system is shown in Fig.3 [6].

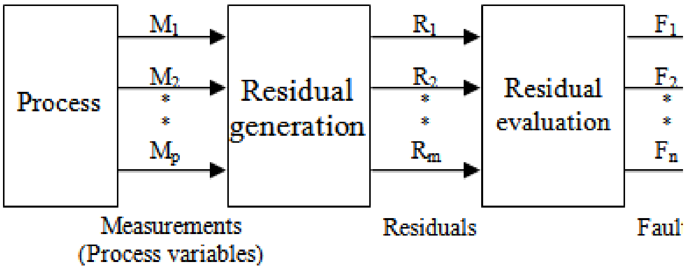

Fig. 3: The general structure of a diagnostic system

3.2.1) Residual generation

The goal of residual generation is to combine all the information available to create signals which are accentuated by specific failures. Furthermore, robust residuals are not (or weakly) affected by modelling errors and disturbances. The exiting failure detection and isolation methods can be divided into four categories:

i. Observer-based methods
ii. Parity space methods
iii. Parameter estimation methods
iv. Artificial intelligence, or knowledge-based methods

It has been recently shown that the first three methods are closely related. However, we will employ the fourth one. Failure diagnosis based on knowledge, or qualitative representation of the system has recently considered as a potential replacement of the traditional quantitative-model based approaches [7]. The conventional approaches suffer from the need for accurate models of the system. For practical applications, such models might not be available, especially for large scale, complex and uncertain systems. The advantage of knowledge-based methods is that the signals used for the diagnosis are not restricted to output signals; instead any 'symptoms' can be used.

Robustness of the diagnosis can be obtained using only those symptoms, which are not dependent upon the uncertainties. Knowledge-based diagnosis techniques fall into two categories:

i) Symptoms-based.
ii) Qualitative-model based.

The first group uses heuristics symptoms and statistical or historical knowledge about the system to evaluate the system's status. The main drawback of this approach resides in the knowledge acquisition. In the qualitative-model based approach, the system is represented by a set of rules and facts, which describe the system structure and behaviour.

3.2.2) Residual interpretation

Residual interpretation is basically a decision making process, that uses the information provided by the residuals to detect and isolate the failure(s). Ideally, residuals should be zero in the absence of failures. In practice, however, due to disturbances and un-modelled processes, the residuals deviate from zero even during failure-free operations (the methods discussed above for the design of robust residuals enhance residual robustness, but do not provide absolute robustness). Therefore, the goal of robust residual interpretation is to

DOI: 10.9790/1676-10621622

provide reliable decisions, namely to limit the rate of false alarms while retaining acceptable failure sensitivity (i.e. acceptable detection time with a small number of missed failures).

The simplest decision logic consists of fixed thresholds checking: whenever one or several residual(s) are above pre-set thresholds, an alarm is declared. The simplest way to determine the thresholds is by inspecting the effects of the unknown inputs in the failure-free case. A significant improvement was contributed by [8], who presented a method for determining the optimal thresholds (and the size of the smallest detectable failure, and classes of reference and failure signals). However, it is intuitively clear that for non-linear systems, the effect of a failure on the system depends on the operating point. In such case, fixed thresholds lead either to a high rate of false alarms, or a large number of missed failures. Recently, adaptive thresholds based on fuzzy-logic have also been developed. The adaptive fuzzy threshold is described as a constant (nominal) threshold to which is added an increment which is expressed as IF-THEN rules of the working conditions [9].

The use of artificial intelligence tools for residual interpretation has been steadily growing over the last three decades. While fuzzy-logic and expert systems have also been used, neural networks (NNs) remain the most frequently used tool [7]. Failure detection and isolation is treated as a classification problem, for which neural networks are particularly well adapted. In most applications that use neural networks to detect and isolate failures, the distinction between residual generation and residual interpretation is not clearly defined. In many applications, the NN is trained to detect and isolate the failures from the available measurements, without the generation of intermediate signals as residuals.

While this greatly simplifies the design of the diagnosis system, the robustness which could be achieved by an analytical design is not exploited. Although neural networks have the ability to learn, its structures are opaque. Unlike neural networks, fuzzy systems are transparent, but have not the ability to learn. Fuzzy neural networks could be employed to eliminate the disadvantages of the two schemes and maximize their advantages [10].

3.3) Clustering Techniques

Pattern recognition techniques can be classified into two broad categories: unsupervised techniques and supervised techniques. An unsupervised technique does not use a given set of unclassified data points, whereas a supervised technique uses a data set with known classifications. These two types of techniques are complementary. For example, unsupervised clustering can be used to produce classification information needed by a supervised pattern recognition technique. In this proposal, the unsupervised clustering schemes; "C-Means"- and "Fuzzy C-Means"-algorithm (FCM), are employed as pattern recognition. Pattern recognition is a general approach that directly uses the observed symptoms of a problem and compares them to a set of known symptoms for each possible problem, looking for the best match. We can represent the “pattern”, or “fault signature”, as a vector (1 dimensional array) of symptoms for each defined fault.

3.4) Petri nets as fault detector

In general, tools for the specification and analysis of discrete event systems can be classed into three main groups: Graphical, algebraic, and formal language-based tools. The former that includes automata, reactive flow diagrams, ladder diagrams, Grafcet, and Petri nets is the main graphical modeling group used in industry. This is due to the transparency and ability of graphical tools to provide rich visual information to operators and engineers. Out of these graphical tools, ladder diagram (LD) and Grafcet are the major programming languages of industrial programmable logic controllers (PLC) [11]. It can be used as a plant wide control system or as an emergency shutdown system (ESD).

Ladder diagram programs, on one hand, are difficult to debug and modify because their graphical representation of switching logic obscures state-dependent logics inherent in the program design. As this method is intuitive and experiential, the LD program is written through trial and error in many cases. LD is suitable for representing sequential process control, but it is difficult to analyze and model the system with it. Grafcet, on the other hand, represents a process model that is safe or binary module that is a special case of Petri nets [12] [13] [14] [15].

A PLC can be also programmed using any of the three languages which are: Instruction List (IL), Structured Text (ST), and Function Blocks Diagrams (FBD) [11]. Using these languages, the semantics of these languages is not strictly defined; certain definitions are missing or contain ambiguities.

For simple systems, it is easy to write down PLC programs using the heuristic or ad hoc above programming languages. However, as a system gets more complex it becomes very difficult to handle its problems effectively. When the bugs or faults occur during real-time operations, it is difficult for engineers to trace them. Also, verifications of PLCs programs are made through exhaustive testing. This method takes a long time to be executed and some errors may pass unnoticed in complex systems. These shortcomings direct us to search for powerful FDD tools such as Petri nets.

Many FDD schemes for single fault detection and isolation are available nowadays. FDD techniques for multiple faults detecting and isolating are seldom addressed in current research. Introducing a diagnoser for detecting and isolating multiple faults that were not possible in other FDD schemes is an issue in this paper.

Emergency shutdown (ESD) system scan time is very important and critical [16]. Some companies do not accept any ESD system if the scan time execution exceed 100 msec. and some companies stick to 300 msec. So low scan time is something very important in industry. Some of the control parameters or blocks such as proportional plus integral plus derivative (PID), Timer etc. will increase the scan time which will exceed the required time. That is why PID and other blocks are not recommended in ESD PLC systems which will increase the scan time. Some of the PLC companies tried to solve this issue by dividing the programs in different hardware controllers that will run by themselves and then will reduce the scan time. However, this costs more money. Reducing the scan time using small computation cost unified framework represents a challenge in this project.

In short, based on the above issues and challenges, using multi technology to design control narrative for industrial processes increases the cost, difficult to learn, difficult to follow, and increases the scan time. So, developing a unified scheme using one technology is one of the main challenges in this paper to be employed in the FDD problem. Also, the intended scheme should be compatible with other technologies used in industry as mentioned above.

IV. Recommendations and Future Work

The question is how to implement the Embedded-CBM (ECBM) with low cost and without any impact to the operation of the plants and can include most of the equipments. To answer this issue, our research will be focusing on the development of low cost and reliable methods for the primary cause for component degradation and failures. Operators may use the information to prioritize their inspection and maintenance schemes. One of the most important sources of information for health determination is operational data from SCADA and DCS systems, e.g. the number of starts and stops, development of temperatures over time, or occurrence of alarms. In short, instead of using separate sensors and equipment in condition monitoring, our motto is to enhance and improve existing advanced control technologies, which already embedded in industrial control systems, to detect and predict maintenance requirements.

The questions that arise in this situation are: Is it possible to develop FDI for industrial processes to overcome the complexity and the high cost of the use of CBM? Can this be done using intelligent systems and/or Petri Nets? If so, what are the benefits of these methods and technologies compared with the sequential tools discussed above? All these queries represent the cornerstone for our future work

References

[1]. Elshenawy, Lamiaa, and Hamdi A. Awad, (2012) "Recursive fault detection and isolation approaches of time-varying processes ", *Industrial & Engineering Chemistry Research*, vol. 51, Issue 29, pp. 9812-9824, 2012. **DOI:** 10.1021/ie300072q, http://pubs.acs.org/doi/abs/10.1021/ie300072q

[2]. Venkatasubramanian, V., Rengaswamy, R., Kavuri, S.N., and Yin, K., (2003). "A Review of Process Fault Detection and Diagnosis. Part II: Qualitative model-based methods", *Computers and Chemical Engineering*, vol. 27, pp. 313-326.

[3]. Venkatasubramanian, V., Rengaswamy, R., Kavuri, S.N., and Yin, K., (2003). "A Review of Process Fault Detection and Diagnosis. Part III: Process history based methods", *Computers and Chemical Engineering*, vol. 27, pp. 327-346.

[4]. Venkatasubramanian, V., Rengaswamy, R., Kavuri, S.N., and Yin, K., (2003). "A Review of Process Fault Detection and Diagnosis. Part I: Quantitative model-based methods", *Computers and Chemical Engineering*, vol. 27, pp. 293-311.

[5]. Iserman, R. and Balle, P. (1997). Trends in the application of model-based fault detection and diagnosis of technical processes. Control Engineering Practice, vol. 5, pp. 709-719.

[6]. Palade, V., Patton. R.J., Uppal, F.J., Quevedo, J. and Daley, S. (2002). Fault diagnosis of an industrial gas turbine using neuro-fuzzy methods. IFAC.

[7]. Frank, P.M. and Koppen-Seliger, B. (1997). New developments using AI in fault diagnosis. Engineering Applications of Artificial Intelligence, vol. 10, pp. 3-14.

[8]. Emami-Naeini, A., Akhter, M.M. and Rock, S.M. (1988). Effect of model uncertainty on failure detection: The threshold selector. IEEE Transactions on Automatic Control, vol. 33, pp. 1106-1115.

[9]. Schneider, H. and Frank, P.M. (1996). Observer-based supervision and fault detection in robots using nonlinear and fuzzy logic residual evaluation. IEEE Transactions on Control Systems Technology, vol. 4, pp. 274-282.

[10]. Hamdi A. Awad, (2001). Fuzzy Neural Networks for Modelling and Controlling Dynamic Systems, Cardiff University, Wales, England.

[11]. Bolton, W., (2006). *Programmable Logic Controllers.* ISBN-13: 978-0-7506-8112-4, W. Bolton. Published by Elsevier Newnes.

[12]. Al-Hajri, E.M, Rossiter, J.A., (2009). "Enhanced Interpreted Petri Nets for Industrial Processes", *The 4th IFAC workshop on Discrete-Event System Design*,Gandia Beach, Valencia, Spain, pp.102-108.

[13]. Al-Hajri, E.M, Rossiter, J.A., (2010). "Industrial Oil Producing Stations: Modeling and Analysis using Petri nets and Intelligent Schemes", *Conference on Control and Fault-Tolerant Systems, (SysTol'10), no. 105, October 6-8, 2010,* Nice, France.

[14]. Murata, T., (1989). "Petri Nets: Properties, Analysis and Applications", *Proceedings of IEEE,* vol. 77, pp.541-580.

[15]. David, R.,Alla, H., (2005). *Discrete, Continuous, and Hybrid Petri Nets*NBSI: 3-540-22480-7, Springer-Verlag, Berlin Heidelberg.

[16]. Zhang, P., (2008). *Industrial Control Technology: A handbook for engineers and researchers*, ISBN: 978-0-8155-1571-5, William Andrew Inc.