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An intelligent fault diagnosis system for process plant using a functional HAZOP and DBN integrated methodology

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ABSTRACT

Integration of a functional HAZOP approach with dynamic Bayesian network (DBN) reasoning is presented in this contribution. The presented methodology can unveil early deviations in the fault causal chain on line. A functional HAZOP study is carried out firstly where a functional plant model (i.e., MFM) assists in a goal oriented decomposition of the plant purpose into the means of achieving the purpose. DBN model is then developed based on the functional HAZOP results to provide a probability-based knowledge representation which is appropriate for the modeling of causal processes with uncertainty. An intelligent fault diagnosis system (IFDS) is proposed based on the whole integrated framework, and investigated in a case study of process plants at a petrochemical corporation. The study shows that the IFDS provides a very efficient paradigm for facilitating HAZOP studies and for enabling reasoning to reveal potential causes and/or consequences far away from the site of the deviation online.

1. Introduction

Modern technological advances are creating a rapidly increasing number of complex engineering systems, processes and products. It is their scale, nonlinearities, interconnectedness, and interactions with humans and the environment that can make these complex process plant systems fragile, when the cumulative effects of multiple abnormalities can propagate in numerous ways to cause systemic failures. One of the main reasons behind accidents is that it is often too late to correct the problems by the time they are detected. Given the size, scope, and complexity of the systems and interactions it is becoming difficult for plant personnel to anticipate, diagnose and control serious abnormal events in a timely manner. In a large process plant, there may be as many as 1500 process variables observed every few seconds leading to information overload. Furthermore, the measurements may be insufficient, incomplete and/or unreliable due to a variety of causes such as sensor biases or failures (Venkatasubramanian, 2005). Usually monitoring systems such as DCS have no 'understanding' of the actions required for changes in the process state, or of actions that an operator takes to correct the state. This often leads to alarms that many cases are inappropriate, and require interpretation from the operator.

Hazard studies provide a systematic methodology for identification, evaluation and mitigation of potential process hazards which can cause severe human, environmental and economic losses. However there exist nonlinear interactions among a large number of interdependent components and the environment. The nonlinear interactions can be further compounded by human errors, equipment failures, and dysfunctional interactions among components and subsystems, that make accident scenarios diversified, random and can also lead to "emergent" behavior (Pasman et al., 2013).

There exist considerable incentives in developing appropriate diagnostic methodologies for monitoring, analyzing, interpreting, and controlling such abnormal events in complex process plant systems. Effective diagnosis of the fault causes and prediction of their consequence can reduce investigation time of abnormal events and improve the effectiveness of accident prevention. Diagnosis methods for process system can be mainly divided into two categories: model-based diagnosis methods (Venkatasubramanian et al., 2003a, 2003b) and historical data-based diagnosis methods (Venkatasubramanian et al., 2003c; Wang et al., 2008). Data-based methods are usually used to detect abnormal event and set off alarms, but they are unable to reveal the underlying causes which is of capital importance for field operators. Whereas in order to present the cause-consequence relationship in complex process plant, various models have been put forward to identify potential hazard sometimes far away from the alarming position, such as Signed Directed Graph (SDG)

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(Chang and Chen, 2011; Ram et al., 2004; He et al., 2014), Petri network (Babaie et al., 2013), FSN (Gabbar et al., 2014) and a variety of methods are integrated for some typical complex systems (Zhang et al., 2005; Maurya et al., 2006).

The main advantages of model-based approaches consist in the causal models which capture more deep-level knowledge than a data-base method (Maurya et al., 2007). In general, models for the analysis of processes have been derived from expert or operator knowledge of the process or from known model equations that define the behavior of the system. The cornerstone of above modeling is fault propagation analysis (Gabbar, 2007). Yuan (2011) indicated that fault propagation and its cause–effect relationship in the system were of priority with regard to the fault diagnosis. Among qualitative reasoning methods, HAZard and OPerability (HAZOP) analysis is the preferred approach in the chemical process industry. HAZOP is a structured and systematic examination of a process operation so as to identify and evaluate the existing or impending problems (Baybutt, 2015). A typical HAZOP provides an identification of accidental events (top events, TEs) and operability problems by using logical sequences of cause-deviation-consequence of process parameters. Such method is usually used offline but can be helpful for the design of online FDI algorithms by identifying critical components to be monitored. Therefore the integration of model-based approaches and HAZOP analysis is of great interest as an interesting solution for fault diagnosis (Ruiz Diego et al., (2001); Venkatasubramanian et al., 2000).

Unfortunately, in spite of the abundant representation of specialized knowledge and expertise during HAZOP study, it is not possible to develop a systematic way to fully study all the fault propagation behavior. Some of the weaknesses that were addressed relate to the coupling of vulnerabilities of the method with the human limitations of practitioners; causes of deviations and the identification of initiating events (Baybutt, 2015). Rodríguez and de la Mata (2012) presented the use of D-higraphs to perform HAZOP studies to perform fault propagation analysis. Rossing et al. (2010) presented a HAZOP methodology where a functional plant model assisted in a goal oriented decomposition of the plant purpose into the means of achieving the purpose. This approach leaded to nodes with simple functions from which the selection of process and deviation variables followed directly. The method provided a good way for implementation into a computer aided reasoning tool to perform root cause and consequence analysis. However the rule based reasoning in functional model also may be combined with case based reasoning techniques (van Paassen and Wieringa, 1999). Another reason that limits functional model in online diagnosis for a real industrial plant lies in its qualitative reasoning capability rather than quantitative way. That is to say, it does not lend itself to quantitative analysis, to rank the effects of failures and to study the relative effectiveness of the proposed corrective actions (Giardina and Morale, 2015).

Therefore some disadvantages of above qualitative reasoning consist in the poor capability to handle uncertainties in the cause–effect structure, limited representation of observable node states, and only diagnosis of single faults is possible (Ould-Bouamama et al., 2012). Probabilistic graphical models are highly advantageous for analyzing the cause–effect relationship with uncertainty. The probabilistic graphical model consists of a graphical structure and a probabilistic description of the relationships among random variables under system uncertainty. Bayesian network is one of the major classes of graphical models and has been applied to various fields. Bayesian networks have been employed in order to identify the root cause of process variations and give a probabilistic confidence level of the diagnosis (Weidl et al., 2005; Alaeddini and Dogan, 2011; Mori et al., 2014; Hu et al., 2015). Nevertheless, for Bayesian network based process monitoring techniques, potential root causes need to be specified and added to hidden nodes in advance. The biggest problem with application of Bayesian network based methods is that they require the in-depth process knowledge to design the network structure for well-performed process diagnosis. In addition, it can be time-consuming to build precise graphical model for complex processes, and it is also challenging to check the accuracy of the inferred structure.

It is well known that, in general, no single method is sufficient for a wide range of problem-solving tasks. The paper presents a functional approach integrated with HAZOP study to hazard analysis and develops a functional model as a basis for dynamic Bayesian network (DBN) reasoning on causes and consequences of deviations monitored by condition monitoring system. In this paper, the use of multilevel flow modeling is proposed as a technique to obtain a representation of technical processes suitable for reasoning about goal oriented actions in complex and heterogeneous processes. While reasoning on the basis of a DBN model representing hazard cause–effect relationship to handle uncertainty should enable the construction of intelligent aids for the operator, that can function as a better assistant for presently used DCS based monitoring systems. The resulting tool is called intelligent fault diagnosis system (IFDS). By the reasoning system implemented using inherent DBN reasoning scheme, the most possible initial reason(s) when observable deviations are detected by condition monitoring system can be found out accurately, and also the future possible consequences can be predict timely for proactive maintenance or emergency decision making.

Section 2 presents a functional HAZOP study based on the qualitative MFM model of the process system with a few examples applied on a FCCU plant. Section 3 presents an intelligent fault diagnosis system (IFDS) based on the whole functional HAZOP and DBN integrated framework. In this section, after a brief presentation of basic DBN theory and its interest for quantitative causal reasoning, it is introduced how the functional HAZOP results are transformed to a DBN model for abnormal event identification and fault cause online diagnosis. The developed methodology is applied in Section 4 for online diagnosis of a FCCU process. Finally, Section 5 concludes the work.

2. MFM modeling and functional HAZOP study

In this paper multilevel flow modeling (MFM) as one of the main functional modeling method is used to represent the knowledge of plant functions. MFM combines the means-end dimension with the whole-part dimension, to describe the functions of the process under study and enable modeling at different abstraction levels. MFM is a modeling methodology which has been developed to support functional modeling of process plants involving interactions between material, energy and information flows (Lind, 1994). Along the means-end dimension MFM represents a system in terms of goals, objectives, functions and components each of which can be described at different levels of part-whole decomposition (see Fig. 1). This means that an MFM model consists of chunks of

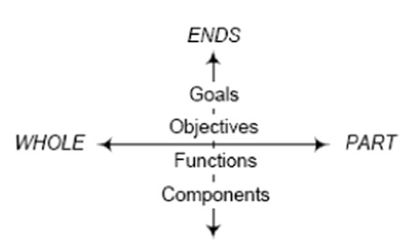

Fig. 1. Means-ends and part-whole dimensions in MFM.