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Alarm management via temporal pattern learning

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ABSTRACT

Industrial plant safety involves integrated management of all the factors that may cause accidents. Process alarm management can be formulated as a pattern recognition problem in which temporal patterns are used to characterize different typical situations, particularly at startup and shutdown stages. In this paper we propose a new approach of alarm management based on a diagnosis process. Assuming the alarms and the actions of the standard operating procedure as discrete events, the diagnosis step relies on situation recognition to provide the operators with relevant information on the failures inducing the alarm flows. The situation recognition is based on chronicle recognition where we propose to use the hybrid causal model of the system and simulations to generate the representative event sequences from which the chronicles are learned using the Heuristic Chronicle Discovery Algorithm Modified ($HCDAM$). An extension of this algorithm is presented in this article where the expertise knowledge is included as temporal restrictions which are a new input to $HCDAM$. An illustrative example in the field of petrochemical plants is presented.

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1. Introduction

The operation of many industrial processes, especially in the petrochemical sector, involves inherent risks due to the presence of dangerous material such as gases and chemicals which in specific conditions can cause emergencies (Stauffer et al., 2000). Safety in industrial processes is supplied by layers of protection as illustrated by Fig. 1. These layers initiate with a safe design and an effective process control (Layers 1 and 2), followed by an "*alarm*" display to the operators (Layer 3) that may trigger manual operator actions. The next layer corresponds to the automatic (Safety Instrumented System) prevention layer (Layer 4), continuing with the layers (Layers 5, 6, and 7) to mitigate the consequences of an event (in safety theory an "event" corresponds to a dangerous situation that happens, for example an explosion). Our work focuses on Layer 3. In the process state transitions such as startup and shutdown stages, the alarm flood increases and generates critical conditions in which the operator does not respond efficiently then, a dynamic alarm management is required (Beebe et al., 2013). The dynamics of a process can be represented by an approach that depicts the process behavior using the events that occur. In this context, the chronicle approach has been applied in many diagnosis applications. Applications such as diagnosis of network telecommunication (Cordier and Dousson, 2000), cardiac arrhythmia detection (Carrault et al., 1999) and intrusion detection systems (Morin and Debar, 2003) can be mentioned. Another application of the chronicles is the recognition in the setting of unmanned aircraft systems and unmanned aerial vehicles operating over road and traffic networks (Fessant et al., 2004). Chronicles are designed to provide temporal patterns of total and partial order. While chronicles consider temporal constraints between event type occurrences, one of the main difficulties of chronicle discovery is to guarantee robustness to variations. Another difficulty is to obtain automatically a base of chronicles that represents each situation. To obtain relevant chronicles from a set of event sequences representing a given situation, it is often necessary to incorporate expert knowledge. This paper enhances the results of the chronicle learning algorithm proposed in Subias et al. (2014) by incorporating expert knowledge in the form of temporal restrictions, as well as additional information that allows us to limit the conservatism of chronicles.

The paper is divided into 6 sections. Section 2 gives an overview on the relevant literature of alarm management. Section 3 presents the problem statement and overviews the new method Chronicle Based Alarm Management (CBAM). Section 4 provides a background on chronicles including the *HCDAM* description. Section 5 indicates the formal framework for this analysis with the representation of the hybrid causal model and the qualitative abstraction of continuous behavior. Finally, a

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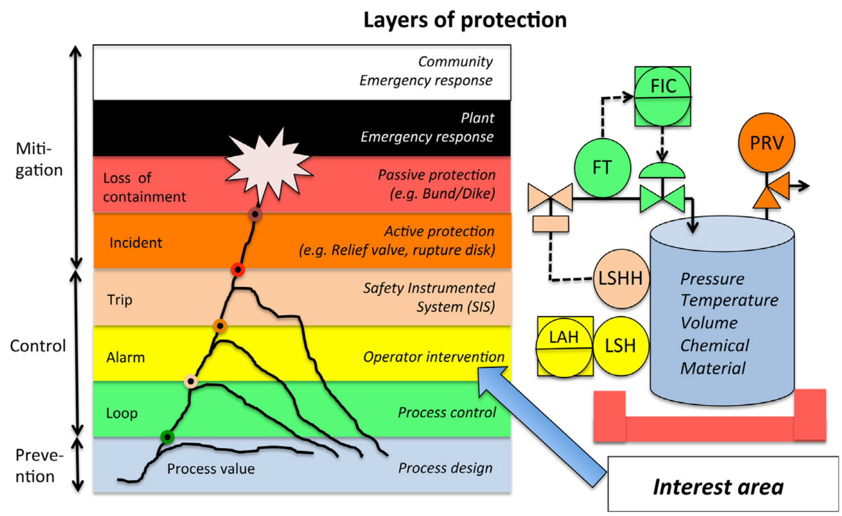

Fig. 1. Safety layers of protection from Stauffer et al. (2000).

case study is given in Section 6 where an illustrative application in the petrochemical sector is presented.

2. Alarm management review

An *alarm* aims to alert the operator of deviations in the process variables from normal operating conditions, i.e. abnormal operating situations. ISA-18.2 defines an alarm as "An audible and/or visible means of indicating to the operator an equipment malfunction, process deviation, or abnormal condition requiring a response". From this definition it appears clearly that an alarm is not a simple message or event but rather a condition directing the operator's attention to plant functioning in order to generate a timely assessment or action. Because of the fundamental role of an alarm management, the attention of many researchers has recently focused in themes such as alarm history visualization and analysis, process data based alarm system analysis and plant connectivity and causality analysis that are further presented below.

2.1. Alarm historian visualization and analysis

A combined analysis of plant connectivity and alarm logs to reduce the number of alerts in an automation system is presented in Schleburg et al. (2013); the aim of the work is to reduce the number of alerts presented to the operator. If alarms are related one to another, those alarms should be grouped and presented as one alarm problem. Graphical tools for routine assessment of industrial alarm systems are proposed by Kondaveeti et al. (2012); two new alarm data visualization tools for the performance evaluation of the alarm systems are presented. These tools are called the high density alarm plot and the alarm similarity color map. In Higuchi et al. (2009), event correlation analysis and two-layer cause–effect model are used to reduce the number of alarms and a Bayesian method is introduced for multimode process monitoring in Ge and Song (2009). These approaches allow to recognize alarm chattering, to group many alarms or to estimate the alarm limits in transition stages, but the dates of the alarm occurrences and the procedure actions are not considered.

2.2. Data based analysis of alarm system

In Liu et al. (2010) an operator model is used as a virtual subject to evaluate plant alarm systems under abnormal situations. Another proposal (Yang et al., 2012) introduced a technique for optimal design of alarm limits by analyzing the correlation between process variables and alarm variables. In 2009 a framework based on the receiver operating characteristic curve was proposed to optimally design alarm limits, filters, dead bands, and delay timers; this work was presented in Izadi et al. (2009) and a dynamic risk analysis methodology that uses alarm databases to improve process safety and product quality was presented in Pariyani et al. (2012). In Liu and Chen (2010), the Gaussian mixture model is employed to extract a series of operating modes from the historical process data. Then local statistics and its normalized contribution chart are derived for detecting abnormalities early and for isolating faulty variables. These approaches require numerous simulations and/or historical data, and are not well suited in case of new plants for which historical data is not yet available.

2.3. Plant connectivity and causality analysis

In the literature, transition monitoring of chemical processes has been reported by many researchers. In Zhu et al. (2014) a dynamic alarm management strategy is presented for chemical process transitions in which the artificial immune system-based fault diagnosis method and a Bayesian estimation based dynamic alarm management method are integrated. In another proposal (Jing et al., 2013), a fault diagnosis strategy for startup process based on standard operating procedures is presented. This approach proposes a behavior observer combined with dynamic PCA (Principal Component Analysis) to estimate process faults and operator errors at the same time. One can also mention the work related to direct causality detection via a transfer entropy approach in Duan et al. (2013). Yang and Xiao (2012) overviews the modeling methods for capturing process topology and causality. Bhagwat et al. (2003) proposes fault detection during process transitions: a model-based approach in which extended Kalman filters, Kalman filters, and open-loop observers are used to estimate process states during the transition and to generate residuals. Srinivasan et al. (2005) presents a framework for managing transitions in chemical plants where a trend analysis-based approach for locating and characterizing the modes and transitions in historical data is proposed. Finally, in Xu et al. (2014) a hybrid model-based framework is used for alarm anticipation where the user is preparing for the possibility of a single alarm occurrence. For transition monitoring, these types of techniques are used in industrial processes and the hybrid model based framework is a possible representation of a petrochemical system. A causal model allows to identify the root of the failures and to check the correct evolution in a transitional stage. Our proposal is closer to this third type of approach as it seeks to exploit the causal relationships between process variables and procedure actions as explained in the next sections.

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