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Alarm management practices in natural gas processing plants

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ABSTRACT

In industrial data sets, groups of variables often move together. Monitoring all these variables may result in many nuisance alarms. However, it is possible to take advantage of redundant information to design and reduce the size of alarm sets. The present work reports the application of an alarm management protocol based on alarm priorization to three large Natural Gas Processing Plants, during a three year period, and also investigates the use of different correlation analyses techniques as tools to assist in the further reduction of the number of alarms. The results show that the adopted practices enable the reduction of alarms.

1. Introduction

An alarm system is the collection of hardware and software that can provide alarm states, communicating them to operators and recording state changes. Alarm systems are critically important for safe and efficient operations of modern industrial plants, including oil refineries, petrochemical facilities and power plants (Bransby & Jenkinson, 1997; Rothenberg, 2009). These systems are used primarily as tools for detection of near misses, which can be defined as departures from normal operating ranges that are followed by subsequent returns to the desired process operation conditions (Pariyani, Seider, Oktem, & Soroush, 2010). Therefore, these systems are indeed safeguards to prevent the deterioration of near misses to accidents. Retrospective investigations over a large number of accidents support the important roles played by alarm systems during process operation (Venkatasubramanian, Rengaswamy, Yin, & Kavuri, 2003).

Alarm systems also play prominent roles in maintaining the high efficiency of plant operation. It is a well-known fact that deviations of process variables from normal/optimal operating zones usually imply negative effects on the process performance, leading for example to off-spec products and excessive consumption of raw materials and energy. In spite of that, these systems may suffer from poor performance when too many alarms have to be handled by the operators (EEMUA, 2013). For all these reasons, industrial alarm systems are receiving increasing attention from both industrial and academic communities.

The importance of this issue in the industrial field can be measured by the enormous amount of standards and guidelines regarding the design and use of alarm systems published by industrial societies and professional organizations, including the Nuclear Regulatory Commission, the Engineering Equipment and Materials Users' Association, the Standardization Association for Measurement and Control in Chemical Industries, the Electric Power Research Institute, the Abnormal Situations Management Consortium, the International Society of Automation, the International Electrotechnical Commission, the American Petroleum Institute, among many others (Wang, Fan, Chen, & Shah, 2015a).

All of these standards and guidelines impose specific requirements on the performance of alarm systems and suggest the use of indicators based on frequency analyses, alarm rates, pattern distributions, operator response times, reaction times, among others (ISA, 2009; EEMUA, 2013).

Alarm occurrences can be classified into two major groups: true alarms and nuisance alarms. A true alarm indicates an abnormal condition associated with the process or equipment requiring an action in a limited time. A nuisance alarm does not require a specific action or response from operators as it does not affect the process operation (Rothenberg, 2009). Thus, the key point to distinguish correct alarms from nuisance alarms regards the requirement of operator response (EEMUA, 2013). In contrast to nuisance alarms, a true alarm requires operators to pay attention or to take action in a prompt manner; otherwise, abnormal situations associated with true alarms will exert negative effects on operation safety and/or efficiency.

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Chattering alarms are the mostly encountered nuisance alarms and may account for 70% of alarm occurrences (Rothenberg, 2009; Hollifield & Habibi, 2010). A chattering alarm can be defined as the alarm that transitions between the alarmed state and the normal state with undesired high frequency or with a constant time period. These types of alarms are typically generated by random noise and/or frequent disturbances on process variables, especially when the process operates in the vicinities of the alarm setpoint. Chattering alarms can also be induced by repeated on-off actions of badly-tuned control loops (Bransby & Jenkinson, 1998; ISA, 2009; Wang & Chen, 2013; Wang & Chen, 2014).

Nuisance alarms often lead to occurrence of alarm overloading, while the simultaneous occurrence of a large number of true alarms can lead to alarm floods. Occurrence of alarm overloading can be extremely detrimental to the confidence and usefulness of alarm systems. First, if significant number of alarms can be regarded as nuisance, the alarm system may provide no useful information and only serve as distractions to plant operators. As a result, a true alarm may be overlooked by process operators among the many active nuisance alarms. Second, even if all active alarms are correct, the alarm rate may be too high to be manageable by operators. When the alarm rate is too high, operators may have no other choice but to ignore some of the active alarms. In this case, the designed functionality of the alarm systems can be completely discredited (Hollifield & Habibi, 2010; ISA, 2009; Yang, Duan, Shah, & Chen, 2014).

Many different techniques can be used for improvement of alarm system performance, including: (automatic) adjustment of setpoint and dead bands; use of filtering, transient suppression and de-bounce timers to repeating alarms; combination and simplification of redundant sets of alarms; eclipsing of multi-level alarms (such as high and high-high); application of counters and auto-shelving to repeating alarms; dynamic alarm re-prioritization; grouping of alarms that demand similar operator responses; automatic suppression of alarms according to the operating mode of the plant; development of intelligent logics for identification of the most important alarms; among others (EEMUA, 2013). However, while one may possibly say that many strategies have been devised to improve the performance of an alarm system, strategies proposed for reduction of the number of alarms configured in an industrial plant are scarcer. Perhaps this can be linked to a conservative operation approach, as it is frequently assumed that reduction of the number of alarms can somehow compromise the safety of the process operation.

The technical literature indicates that different techniques can be used to investigate correlations among variables (EEMUA, 2013). However, when one concentrates specifically on the behavior of alarm states, analysis and comparison of distinct variable correlation methods are seemingly scarce. This is particularly true when one is interested in reducing the number of alarm activations in real industrial plants, as a tool of alarm management. Xie et al. (2006a, 2006b) presented a multivariate statistical approach to detect and diagnose faults in industrial plants with complex dynamics. Their work pointed the difficulties related to monitoring correlated variables. Lieftucht, Kruger, and Irwin (2006) proposed multivariate statistical methods to remove auto-correlation and cross correlation between variables, reducing the number of false alarms.

Natural Gas Processing Plants are treatment plants that operate under severe pressure (often above 9000 kPa) and temperature (range from −70 °C to 300 °C) conditions. Their products are mostly flammable and explosive. The process is dynamic and can change dramatically depending on the composition of the gas processed. Furthermore, they are usually the "bottleneck" of the production/operation fields, so that their stop can mean total loss of the activities of these fields, either at sea (offshore) or ground (onshore), with great economical losses. Because of all these reasons, the monitoring of the process in these units is extremely important.

This paper aims to contribute to alarm management practices by combining a theoretical statistical framework with long-term industrial implementation. With that purpose, the results of a long-term (3-year) alarm management program to 3 identical Natural Gas Processing Plant based on alarm priorization are presented. Additionally, correlation methods - namely Correlation Analysis (Yang, Shah, & Xiao, 2010), Cluster Analysis (Higuchi, Yamamoto, Takai, Noda, & Nishitani, 2009; Yang, Shah, Xiao, & Chen, 2012; Kondaveeti, Izadi, Shaha, Black, & Chen, 2012) and Principal Component Analysis (Izadi, Shah, Shook, & Chen, 2009; Chen, 2010) − are applied, compared and investigated with the intent of further reducing the number of alarms. Insights and recommendations for industrial application arising from this analysis are presented.

This text is organized as follows. Section 2 introduces the fundamentals on correlation analyses. Section 3 presents and discusses the results of the industrial application of the proposed alarm management protocol and of the correlation analyses. Finally, the conclusions are described in Section 4.

2. Fundamentals

2.1. Correlation analysis

Alarms can be represented in terms of binary sequence of zeros and ones, where zero (0) represents no alarm or no information and one (1) represents an alarm annunciation. Thus, each alarm tag name is represented by a sequence of 0's and 1's sampled over a given period of time. Most part of the binary sequence is filled with 0's, except for time instants when an alarm is presented to the operator (Chen, 2010; Kondaveeti et al., 2012; Wang, Li, Huang, & Chong, 2015b). This can be represented mathematically by,

$$x_a(t) = \begin{cases} 1, \text{if} x_a(t) \geq (\leq) \text{ alarm setpoint} \\ 0, \text{if} x_a(t) < (>) \text{ alarm setpoint} \end{cases} \tag{1}$$

Alarm sequences can be analyzed statistically. Two numbers are often used to summarize a probability distribution for a random variable X. The mean (μ_X) is a measure of the center or middle of the probability distribution, and the variance ($\sigma^2{}_{XX}$) is a measure of the dispersion, or variability of the distribution. These two measures do not uniquely identify a probability distribution; that is, two different distributions can have the same mean and variance. Still, these measures are simple, useful summaries of the probability distribution of X (Montgomery, 2005). As the variance unit is the square of the variable unit, the standard deviation is usually employed to represent data scattering (σ_X).

$$\mu_X = \frac{1}{N} \sum_{i=1}^{N} X_i \tag{2}$$

$$\sigma_{XX}^2 = \frac{1}{N-1} \sum_{i=1}^{N} \left(X_i - \mu_X\right)^2 \tag{3}$$

$$\sigma_X = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} \left(X_i - \mu_X\right)^2} \tag{4}$$

When two or more random variables are defined on a probability space, it is useful to describe how they vary together; that is, it is useful to measure the relationship between the variables. A common measure of the relationship between two random