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Predicting the frequency of abnormal events in chemical process with Bayesian theory and vine copula

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ABSTRACT

Chemical accidents, such as an explosion, are of low frequency and high consequence (e.g. casualties, significant economic losses, pollution). Due to the shortage of accident data, recently, precursor data have received much attention in chemical risk analysis. Usually, in chemical processes, an abnormal event can be seen as a precursor, which can propagate into near-miss, incident or even accident. The abnormal event frequency (AEF) is defined as the number of abnormal events in a time interval, which can be an early indicator of risk. In this paper, an AEF predicting model based on Bayesian theory and D-vine copula is proposed. Generally, a chemical process is managed in shifts by several teams. The AEFs vary with different experience and operational skills of the operator teams. Furthermore, the previous operating team has an effect on the following operator teams and the effects are asymmetric between two teams, hence, D-vine copula is employed to describe the dependence with much flexibility. Finally, the proposed method is applied to a case study of 4-group-3-shift, and the simulation result shows that it has a better performance compared to conventional approaches.

1. Introduction

Chemical process systems are prone to devastating accidents because they deal with hazardous material at high temperature and/or high pressure. Chemical plants are also characterized as complex systems with a dense cluster or pipes and facilities, therefore an accident in a given facility is likely to cause loss in neighboring facilities, leading to a chain of accidents (Khakzad et al., 2013). Although advanced control and monitor systems, such as DCS and ESD systems, have been used, chemical catastrophes still occur continuously, which will cause asset loss, reduced public confidence in the company, even human casualties. For example, the explosion and fire occurred at the BP Texas City refinery on 23 March 2005 caused 15 deaths and more than 170 injuries (CSB, 2007). On April 17, 2013, an ammonium nitrate explosion occurred at the West Fertilizer Company storage and distribution facility in West, Texas, which killed 14 people and wounded more than 160 people (Xinhuanet, 2013). And the oil pipeline blast on November 22, 2013 in Qingdao, China, killed 62 and injured 136 people (Chinadaily, 2013).

To analyze the risk and reduce potential accidents in process industry, conventional methods (Sales et al., 2007; Meel et al., 2007; Kamarizan and Markku, 2013) are always used, which are based on major accident data. However, the shortage of accident data has weakened their performance. Realizing the limitation, in recent years, the precursors receive more and more attention and several precursor-based risk analysis methods have been put forward. For example, Nima Khakzad and Majeed Abimbola et al. (Khakzad et al., 2014; Abimbola et al., 2014) performed dynamic risk analysis of offshore drilling based on precursor data (near accident data). Seider and his co-workers (Meel and Seider, 2006; Pariyani et al., 2010, 2012a, b) developed a dynamic risk assessment method based on precursor data in chemical process and Kalantarnia et al. (2010) applied this approach to model the BP Texas City refinery accident, which demonstrated its applicability.

Abnormal event in chemical process is seen as a precursor of a chemical accident. The abnormal event will not cause damage or casualties unless it propagates into an accident (e.g. toxic gas leak, fire, explosion) because of further safety barrier failures (Jones et al., 1999; Meel et al., 2007). Abnormal event frequency (AEF) is the rate of occurrence of the abnormal event in a time interval. When the production process is in bad condition, such as pipeline break or machine aging, the AEF will increase, which means the increased probability of accidents. Knowing the AEF in the chemical

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process in advance can give an alarm to the operators, so that the operators have enough time to take effective actions (e.g. inspect the safety systems) to reduce the probability of accidents. AEF can be an early indicator of chemical accidents. Furthermore, reducing the AEF can improve the product quality, because an abnormal event also spoils the product quality (Kleindorfer et al., 2012). Meel and Seider (2006) have used a Bayesian model to predict the AEF in the next time interval. But the operator teams have not been considered in the Bayesian model as well as other risk analysis methods, which are directly related to the abnormal event (Alireza et al., 2013).

Generally, a chemical process is operated by teams in a multi-shift form. For example, the majority of chemical plants in China operate on 4-team-3-shift basis, that is, every team alternately works for 8 h and rests for 24 h. Due to the differences of operating experience and skills, the AEF varies from team to team. The team with expert operators can regulate the process in a stable condition with less AEF than other teams. Besides, the operation of pre-team will affect the performance of the other teams who take over the duty and the effects are asymmetric between any two teams. A further explanation will be given in Section 4.2.

As an alternative to dependence modeling between multivariate variables, the standard multivariate copulas, such as the multivariate Gaussian or Student-*t* as well as exchangeable Archimedean copulas (Whelan, 2004), are always used. Vine copula is a pair-copula-based (Aas et al., 2009) copula which is more flexible than standard multivariate copulas in modeling complex patterns, such as conditional dependence, asymmetries and tail dependence. This has been demonstrated by the good performance in many applications. For example, Czado (2009) illustrated the model flexibility of vine copula by considering a D-vine tree in 3 dimensions and showed that vine copulas can describe asymmetries well by using different kinds of copulas, along with their parameters. Berg and Aas (2009) tested the good performance of vine copulas (pair copula constructions) in computational complexity and fitting capability compared with those nested Archimedean constructions, one group of relatively flexible multivariate Archimedean copula extensions.

In this paper, a novel AEF predicting model is proposed considering the operator teams. A Bayesian model is used to formulate the AEFs of different teams and the inter-dependence between the AEF sequences of each team is described by D-vine copula. Based on historical AEF data in the alarm database of DCS and ESD, the AEF in the next time interval can be calculated from the joint posterior distribution of AEFs of all the teams. To show the predicting process, a chemical process operated on 4-team-3-shift basis is performed as an application of the Bayesian predicting method.

The rest of this article is structured as follows. Abnormal event is addressed in details in Section 2. Section 3 provides a review of Bayesian theory and vine copula. The predicting model of AFEs is established in Section 4. In this Section, the predicting process, such as data collection, modeling process, predicting result analysis, is demonstrated by an application. Finally, the conclusions are given in Section 5.

2. Abnormal event in production

Before defining abnormal event, it is necessary to introduce the control chart of variables and alarm zones as shown in Fig. 1. The chart consists of four zones, green-belt zone, yellow-belt zones, orange-belt zones and red-belt zones, ranking based on the level of risk. Green-belt zone is normal zone, where the variable fluctuation is acceptable despite the configuration of the variable as a fixed value. When the production process is disturbed or there is

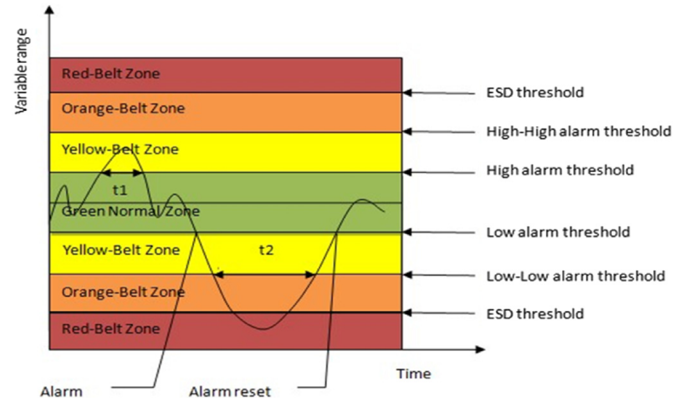

Fig. 1. Control chart of variables and alarm zones.

something wrong with the based control system, a variable will probably deviate from its normal zone into the yellow-belt zones, triggering high/low alarm. Entering the orange-belt zones will trigger High–High/Low–Low alarm. ESD system will be triggered if the variable moves into red-belt zone.

An abnormal event begins with the departure of a variable from its normal zone and triggering an alarm. Obviously, the departures are the omen signals of accidents. In the actual production, the abnormal event which propagates into an accident is very rare. For most of abnormal events, the variables return to the green-belt zone, ending up with different alarms or shutdowns, which are recognized as near-misses. In the present study, we use an event-tree to depict the paths of abnormal events traced by the variables. To prevent the abnormal event from developing into an undesired consequence, several safety barriers (Phimister et al., 2003) are used. According to the control result of the safety barriers, an abnormal event can evolve into three end-states: CO (Continual Operation), SD (Shut Down), and accident. A simplified development process of abnormal event is given in Fig. 2 with three safety barriers. Assuming during the time interval *t*, the consequences CO1, CO2, SD, and accident have occurred $n1$, $n2$, $n3$, and $n4$ times, respectively. Thus, the number of occurred abnormal events, N, can be deserved in time interval *t*: $N = n1 + n2 + n3 + n4$, which is defined as an abnormal event frequency (AEF). In this paper, time of a shift *t* is set as 8 h.

3. The theoretical background

In this section, a brief review of Bayesian statistical method is given, along with vine copula modeling the correlation between random variables, which is used in Bayesian modeling in Section 4.

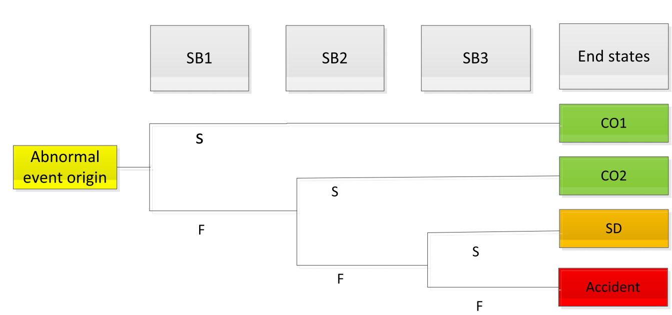

Fig. 2. Event tree for abnormal event with three barriers.