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A quantitative risk analysis model considering uncertain information

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ABSTRACT

Bayesian network (BN) has been proven to be an excellent method that can describe relationships between different parameters and consequences to mitigate the likelihood of accidents. Nevertheless, the application of BN is limited due to the subjective probability and the static structure. In reality, available crisp probabilities for BN are generally insufficient, the system under consideration cannot be precisely described since the knowledge of the underlying phenomena is incomplete, which introduces data uncertainties. Furthermore, conventional BN have static structures, which results the model to have structure uncertainties. This paper presents a Dynamic BN-based risk analysis model to characterize the epistemic uncertainty and illustrates it through a case on the offshore kick failure. Linguistic variables are transformed into probabilities to represent data uncertainties by applying fuzzy sets and evidence theory. Structural uncertainties caused by conditional dependencies and static models were addressed by utilizing dynamic BN. Based on the model, a robust probability updating and dynamic risk analysis are conducted, through which critical events with potential risks of causing accidents are identified and a dynamic risk profile is obtained. The case study indicates that it is a comprehensive approach for quantitative risk analysis in offshore industries under uncertainties.

1. Introduction

Risk analysis is a systematic and scientific method to predict risk in industrial systems. Several qualitative and quantitative techniques, such as HAZOP analysis, Fault tree analysis (FTA), Event tree analysis (ETA), and Failure mode effect analysis (FMEA) have been widely used in chemical processes and offshore oil and gas industries (Khan and Abbasi, 1998; Abimbola et al., 2015). If there are enough accident precursors, the possibility of accidents can be estimated through conventional statistical methods such as maximum likelihood estimation (MLE) (Yu et al., 2017). However, due to the penurious knowledge and scarcities, the system data will become unavailable and uncertain (Markowski et al., 2009). When unavailable, conventional approaches will lead to biased and inconsistent estimates (Khakzad et al., 2014). Accordingly, an alternative approach need to be developed to evaluate the probability of significant accidents under uncertainties.

In recent years, several researchers concentrated on utilizing Bayesian models for quantitative risk analysis. For the researches of Bayesian inference, Kalantarnia et al. (2009) defined the failure probability of barriers obeys *Beta* distribution and then updated accidental possibilities and posterior probabilities of barriers by Monte Carlo model and Bayesian inference. Khakzad et al. (2013a) mapped BN from Bow-tie models (BT) to overcome the difficulties for BT in considering the feasibility of updating probabilities of accident precursors. Li et al. (2016) constructed an BT-based object-oriented BN with a more clarified structure to specify common causes and conditional dependencies in the accident evolution. However, the probability updating performance of BN depends on the accuracy of prior distributions and conditional probability tables (CPTs) (Yu et al., 2017). Taking into account the inherent uncertainty of expert judgments and estimation parameters, a hierarchical Bayesian analysis (HBA) technique was proposed to cope with source-to-source variability in data samples (Yang et al., 2013; Yu et al., 2017; Khakzad et al. 2014). HBA adds a new level of estimation to the basic distribution of parameters, taking into account the prior parameters sampled from a set of prior distributions controlled by hyper-parameters. Real-time information obtained from facilities can be exploited by these techniques to update prior beliefs (Khakzad et al., 2013a). Conditional probability distributions are adapted using cumulative information collected from time intervals, but it has not been commonly used in the accident scenario modeling and process safety assessment (Khakzad et al., 2013a). Besides, similar technologies use generic failure data,

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which makes them non-case-specific and introduces uncertainties into results (Li et al., 2016).

The uncertainty can be classified as the aleatory uncertainty and the epistemic uncertainty (Aven and Zio, 2013). The aleatory uncertainty cannot be reduced due to its inherent nature, while the epistemic uncertainty can be decreased through dividing into the data uncertainty and structural uncertainty (Ferdous et al., 2012). The structural uncertainty caused by conditional dependencies can be solved by mapping BT to BN. However, conventional BN has a static structure, they are unable to capture the variation of risk when system changes occur. Thus, the structural uncertainty caused by model variations still consists in quantitative risk analysis (Mi et al., 2018). On the other hands, available failure data for risk analysis is usually limited and insufficient, expert judgments become an effective approach to obtain failure probabilities under data uncertainties. To deal with the ambiguities in accidental datasets, fuzzy sets and evidence theory were introduced to address uncertainties in risk analysis (Huang et al., 2001; Lin and Wang, 1997; Ferdous et al., 2012). Fuzzy sets and evidence theory utilize linguistic variables to represent the boundaries between system states and state probabilities, suitable for situations in which state boundaries cannot be defined in the form of probability data (Wilcox and Ayyub, 2003). Ferdous et al. (2013) developed a framework based on fuzzy sets and evidence theory to address the uncertainty caused by expert knowledge and to determine the likelihood and dependence on input events. The critical problem for similar uncertainty approaches is the static structure, which results the method can only take into account the static data uncertainties while ignore the data dynamic regulation. Accordingly, a comprehensive risk analysis method needs to be proposed to address data uncertainties and structural uncertainties simultaneously in process industries.

Present works proposes a dynamic methodology for quantitative risk analysis under uncertainties. Fuzzy sets and evidence theory are introduced to transform the linguistic variables into probabilities to address data uncertainties in risk analysis. Dynamic BN is applied to resolve the structural uncertainty from conditional dependencies and static structures in the accident chain network. The uncertainty caused by imprecise information and scarce information, is handled respectively with fuzzy sets and evidence theory. A case on the offshore kick was conducted to demonstrate the proposed method. The risk updating and dynamic risk analysis for a drilling operation were conducted through this approach, evolution processes for a kick failure from causes to consequences was also presented. This study can provide compelling support for the risk decision-making and prevention under uncertainties.

The structure of paper is organized as follows: A brief description of risk analysis method including fuzzy sets, evidence theory, and BN is presented in Section 2. A proposed method framework of risk analysis under uncertain information is as shown in Section 3. The accident evolution process modeling for drilling operation using BT approaches, as well as the process of risk updating and dynamic risk analysis are as presented in Section 4, and the conclusion is made in Section 5.

2. Methodology for uncertainty management

2.1. Fuzzy set theory

With the published paper "fuzzy sets" by Zadeh (1965), fuzzy set theory was widely considered as a new way for modeling more realistic decision models (de Gusmão et al., 2016). Fuzzy set theory provides a language with syntax and semantics. It translates qualitative knowledge or judgments into numerical reasoning or probabilities to capture the subjective, vague and uncertain information (Silva et al., 2014; Ferdous et al., 2012; Arunraj et al., 2013).

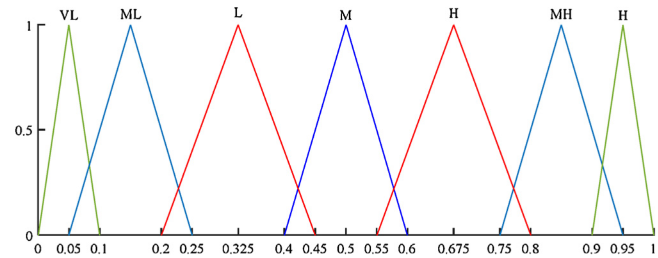

Fig. 1. Fuzzy membership functions.

Due to the vagueness, imprecision, and subjectivity in expert knowledge, fuzzy set theory is explored to deal with uncertainties (Ferdous et al., 2012). The fuzzy number is used in fuzzy sets to handle uncertain or ambiguous information on expert evaluations (Lin and Wang, 1997). Triangular fuzzy numbers (TFN) or trapezoidal fuzzy numbers (ZFN) are applied for representing linguistic variables (Ferdous et al., 2011; Mardani et al., 2015). In this paper, TFN is utilized to quantify the subjectivity of expert knowledge. A TFN can be described by a vector (P_l, P_m, P_u) representing the lower boundary, most likely value, and the upper boundary (Huang et al., 2001).

Seven linguistic variables, *Very Low* (VL), *Moderately Low* (ML), *Low* (L), *Moderate* (M), *High* (H), *Moderately High* (MH) and *Very High* (VH) have been proposed to describe expert knowledge for defining the probability of input events (Ferdous et al., 2012). TFNs of these variables are represented in Fig. 1.

Fuzzy boundaries of a TFN may also be determined through the point of the most likely value if the rigid fuzzy scale, developed in Fig. 1, is unable to map the subjective uncertainty for an expert (Ferdous et al., 2009). The fuzzy boundary of a TFN can be determined by Eqs. (1) and (2).

$$\begin{cases} P_l = P_m \times 0.5 \\ P_u = P_m \times 1.5 \end{cases} \quad 0 \le P_m < 0.5 \tag{1}$$

$$\begin{cases} P_l = \dfrac{3P_m - 1}{2} \\ P_u = \dfrac{P_m + 1}{2} \end{cases} \quad 0.5 \le P_m < 1.0 \tag{2}$$

The sum of aggregation processes can be represented by the weighted average method shown in Eq. (3) to summarize the knowledge of multiple experts.

$$P_i = \frac{\sum_{j=1}^{m} w_j P_{i,j}}{\sum_{j=1}^{m} w_j} i = 1, 2, 3, \cdots, n \tag{3}$$

Where, P_{ij} is the linguistic expression of expert j for event i, w_j is the weighting factor of expert j, n is the number of input events, m is the number of experts, P_i is the aggregated fuzzy number.

Subsequently, the right and left score of fuzzy sets can be computed, and the fuzzy possibility score (FPS) of the aggregated fuzzy number can be obtained by the following Eq. (4) (Yazdi and Kabir, 2017).

$$FPS(P_i) = [FPS_{Right}(P_i) + 1 - FPS_{Left}(P_i)]/2 \tag{4}$$

Finally, the FPS are converted to a failure probability by using the analogous Eq. (5) proposed by Onisawa (1990).

$$PF_i = 1/10^k \tag{5}$$

Where, $k = 2.301 \times [(1 - FPS)/FPS]^{1/3}$.

The process of transferring linguistic variables into failure probabilities considering α-cut methods is completed at this point.