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Developing a dynamic model for risk analysis under uncertainty: Case of third-party damage on subsea pipelines

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A B S T R A C T

Third-party damage is an important factor leading to subsea pipelines failure, and risk analysis an efficient approach to mitigate and control such events. However, available crisp probabilities for input events are usually limited, missing or unknown, which introduces data uncertainty. Furthermore, conventional risk analysis methods are known to have a static structure, which introduces model uncertainty. This paper presents a dynamic model for risk analysis under uncertainty and illustrates it by a case of third-party damage on subsea pipelines. Proposed model makes use of fuzzy set theory and evidence theory to handle data uncertainty, and utilizes Bayesian network (BN) to address model uncertainty. Primary accident scenario is developed by the FT-ESD approach, and it is transformed into BN to circumvent model uncertainty by relaxing the limitations of conventional methods. Expert elicitation is integrated into fuzzy set theory and evidence theory to obtain the crisp probabilities of input events in BN. Based on the model, a robust probability reasoning is conducted, through which the most probable factors contributing to the occurrence of unexpected consequence are identified. As new observations become available, potential accident probabilities are updated over time to produce a dynamic risk profile. The case study demonstrates the applicability and effectiveness of the model, which indicates that it is an alternative approach for risk analysis in the process industries under uncertainty.

1. Introduction

Subsea pipelines are main transportation way of ocean oil and gas, suffering from complex environment loads. Third-party damage is one of the important causes resulting in subsea pipelines failure. As per OGP (2010), about 38% accidents of subsea pipelines are induced by third-party damage. Safety and risk analysis is a systematic and scientific way to avoid the undesired events, and develop effective mitigation measures (Khan and Abbasi, 2001; Apostolakis, 2004). Some qualitative and quantitative methods such as FMEA, HAZOP, Fault tree (FT) and Event tree (ET) are widely applied in risk analysis of process industries (Li et al., 2016). FT, ET and their combination, i.e., Bowtie (BT) are well-established techniques that can describe the relationships among basic events, safety barriers and consequences (Khakzad and Khana, 2012). BT not only can give a qualitative analysis by presenting undesired events from causes to consequences but also can render a quantitative probability analysis for undesired events and their consequences.

All these methods use probabilities of basic events and safety barriers as a quantitative input to determine the probabilities of undesired events and consequences. The probabilities of basic events are required to be crisp values or probability density functions (PDFs) (Markowski et al., 2009; Ferdous et al., 2012). However, the precise crisp probabilities or PDFs are often difficult to obtain. In the real world, the objective data available to estimate probabilities of specific events is often missing or sparse, and even if available, is subject to incompleteness (partial ignorance) and imprecision (vagueness) (Ferdous et al., 2012). In particular, there are a number of fresh events emerging in a new process, facility or environmental condition, which usually have unknown failure data. Besides, even for precise probabilities or PDFs, inherent uncertainties may still exist due to variant failure modes, poor understanding of failure mechanisms, as well as the vagueness of system phenomena (Sadiq et al., 2008). These issues will generate data uncertainty in quantitative risk analysis.

Since available objective failure data of events are often limited, incomplete or imprecise, the expert judgment becomes an alternative approach to obtain the occurrence probabilities of events under uncertain condition. Fuzzy set theory and evidence theory have been proven to be efficient in handling uncertain information, and estimating occurrence probabilities of events using expert knowledge (Ferdous et al., 2013; Yazdi and Kabir, 2017; Chang et al., 2018; Hong et al., 2016). However, previous studies generally only consider the data

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uncertainty arisen from imprecision and subjectivity in expert knowledge, whereas the data uncertainty due to ignorant, conflict, and incomplete information is seldom mentioned. Furthermore, a comprehensive consideration of data uncertainty resulting from different types of information can be found sporadically in literature.

On the other hand, conventional methods are known to have a static structure, they are not able to capture the variation of risk as changes in the system take place. Furthermore, conventional methods consider that input events are independent and fail to include multi-states of input events and common cause failure. These issues introduce so-called model uncertainty in risk analysis. To circumvent the model uncertainty induced by the limitations of convention methods, Ferdous et al. (2013) proposed a dependency coefficient method to consider interdependences of events in ET and FT. Yu et al. (2017) developed a joint likelihood function in the hierarchical Bayesian framework to model the interdependences among events in ET and FT. Hashemi et al. (2015, 2016) utilized a copula function based technique to model the dependency among variables and improve uncertainty analysis.

In recent years, BN has become a popular method and is widely applied in risk analysis of process industries, such as risk analysis of leakage, fire, explosion, drilling operations, maintenance activities (Li et al., 2016; Bhandari et al., 2015; Pui et al., 2017). BN is a probabilistic inference technique for reasoning under uncertainty, which uses d-separation and chain rule to represent causal relationships among a set of random variables considering local dependencies (Nielsen and Jensen, 2009). It has a flexible structure and is able to relax the limitations of conventional methods well. A number of studies have shown the parallels between BT and BN and discussed how the limitations of BT are addressed by mapping into BN (Khakzad et al., 2013a; Li et al., 2017a; Bhandari et al., 2015). Due to the flexible structure, the interdependences of events can be easily achieved by linking with directed arcs. Multi-states of the input events, as well as common cause failure, can be considered in BN modeling. In addition to coping with model uncertainty, the main advantage of BN making it be a superior technique for risk analysis is the ability to perform probability updating. Applying Bayes' theorem, the initial beliefs of events can be updated as new information about system becomes available over time (Khakzad et al., 2013a), and these features of BN contribute to its application to a dynamic risk analysis.

This paper develops a dynamic methodology for risk analysis under uncertainty, which is illustrated by a case of third-party damage on subsea pipelines. This methodology intends to address data and model uncertainties. Multi-expert knowledge is integrated into fuzzy set theory and evidence theory to acquire probabilities of input events with unknown, imprecise and incomplete failure data. The failure scenario of subsea pipelines resulting from third-party damage is developed by BN, accounting for interdependences among input events, as well as common cause failure. Applying the developed model, the most probable third-party factors contributing to subsea pipelines failure are identified. As new observations are available, a dynamic risk profile can be derived from probability adapting.

The rest of paper is organized as follows: Section 2 presents an uncertainty analysis in risk modeling of process industries to clarify the characteristics of uncertainty. Section 3 shows the modeling techniques that are used in this paper to develop failure scenario and handle uncertainties. Proposed methodology framework is provided in Section 4. Application of proposed methodology is illustrated using a case study in Section 5. Section 6 gives the conclusions of this paper.

2. Uncertainty in risk analysis

Some critical consideration of representation and description of uncertainty in risk analysis can be seen in the literature (Zio, 2013; Zio and Aven, 2013). Uncertainties usually stem from physical variability of a system and data unavailability about system due to lack of knowledge or limited information, which are inherent and unavoidable in risk analysis (Ferdous et al., 2012). In most situations, a system under consideration cannot be easily described perfectly due to incomplete knowledge, which contributes to the uncertainties in parameters and models.

Table 1
Uncertainty types and handling approaches (Ferdous et al., 2012; Chang et al., 2015).

Types	Characteristics	Handling approaches
Aleatory uncertainty	Stochastic, objective, irreducible, random	Probability theory and evidence theory
Epistemic uncertainty (including data, model and completeness uncertainties)	Imprecise, incomplete, ambiguous, ignorance, inconsistent, vague	Possibility theory, fuzzy set theory, and evidence theory

Uncertainty can be divided into two types: the randomness due to natural variation of the physical system is called as aleatory uncertainty, whereas the imprecision due to lack of knowledge or incompleteness is termed as epistemic uncertainty (Aven and Zio, 2011). These two uncertainties commonly exist in risk analysis of oil and gas industries. In particular, the likelihood of many risk factors cannot be quantified properly since they are rare to occur or unknown. A number of alternative approaches have been proposed to address these uncertainties, including probabilistic or non-probabilistic methods, e.g. probabilistic analysis, imprecise probability, probability bound analysis, random sets and possibility theory (Chang et al., 2015). The uncertainty types and corresponding handling approaches are stated in Table 1.

In reality, epistemic uncertainty can be reduced if more knowledge about the system is available, whereas aleatory uncertainty cannot be reduced due to inherent nature of a system. This study mainly focuses on epistemic uncertainty. As stated in Table 1, epistemic uncertainty can be further divided into data, model and completeness uncertainties from different generation causes. Data uncertainty also named parameter uncertainty, is often expressed by PDFs of parameters values. Probability theory based Monte Carlo Simulation is used in previous studies to cope with such uncertainty (Abrahamsson, 2002; Li et al., 2017b), which is a kind of sampling based technique that requires definite PDFs. However, the PDFs are usually difficult to obtain. In addition, it is unable to address uncertainty properly for highly subjective, vague, incomplete or inconsistent knowledge.

In this paper, fuzzy set theory and evidence theory are utilized to cope with data uncertainty. Probabilities of input events are treated as fuzzy numbers in fuzzy set theory and basic probability assignments in evidence theory, which are derived from expert knowledge. In practice, expert knowledge is a significant and available way to obtain objective failure data of input events when crisp values or PDFs are not accurately available. In this process, fuzzy set theory is used to address the vagueness, imprecision, and subjectivity in expert knowledge, whereas evidence theory is employed to handle the uncertainty arisen from ignorant, conflict, and incomplete information.

Model uncertainty exists since a model is subjected to certain simplifications or assumptions. In practice, it becomes related to the fact that several different models may be used to analyze the same system (Jin et al., 2012). This study focuses on the model uncertainty of former type arisen from the assumptions of independence among events in conventional methods. To address such type of uncertainty, BN is employed in this study to develop failure scenario and conduct a quantitative analysis, which not only can overcome the limitations of conventional methods and but also account for more characteristics of the system.

Completeness uncertainty arises from the same sources with model uncertainty, i.e., some simplifications and assumptions, which is further divided into known and unknown one. The details of completeness uncertainty can be seen in Jin et al. (2012). Completeness uncertainty is