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Probabilistic analysis of natural gas pipeline network accident based on Bayesian network

Jiansong Wu [a,*], Rui Zhou [b], Shengdi Xu [a], Zhengwei Wu [c]

[a] School of Resources and Safety Engineering, China University of Mining & Technology, Beijing 100083, China
[b] Institute for Public Safety Research, Tsinghua University, Beijing 100084, China
[c] Hefei Institute for Public Safety Research, Tsinghua University, Hefei 320601, China

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ABSTRACT

Natural gas pipeline network (NGPN) accident is a kind of catastrophic disaster as the hazard of natural gas may present a large-scale extension in NGPN that can easily result in cascading accidents. In this paper, the Bayesian network (BN) was employed to probabilistically analyze natural gas pipeline network accidents. On the basis of case-studies of typical NGPN accidents, eleven BN nodes were proposed to represent the evolution process of natural gas pipeline network accidents from failure causes to consequences. The conditional probabilities of every BN node were determined by expert knowledge with weighted treatments by the Dempster-Shafer evidence theory. Through giving evidences of some BN nodes with certain state values, the probabilities of evolution stages and consequences of the natural gas pipeline network accident can be estimated. The results indicate that the combination of Bayesian network and Dempster-Shafer evidence theory is an alternative method for evaluating NGPN accident, and the proposed framework can provide a more realistic consequence analysis since it could consider the conditional dependency in the evolution process of the NGPN accident. This study could be helpful for emergency response decision-making and loss prevention.

1. Introduction

Natural gas is one of the top consumed energies in modern society because of the economical and environmental advantages. Therefore, natural gas is widely used around the world, taking account for about a quarter of energy consumption in the United States, and about 20% of that in European Union every year (Liang et al., 2012). In China, 246 prefecture cities possess natural gas pipeline networks with the total length of over 10×10^4 km by the year 2015. With the increasing demand of transporting natural gas from long-distance districts, the natural pipelines tend to form complicated networks, particularly in city centers. In addition, the main component of natural gas is methane, which is highly flammable and explosive. If natural gas pipeline network accidents occur in urban area, it may not only lead to direct catastrophic losses, but also could result in cascading secondary accidents, such as large-scale urban fire, explosions, poisonous and harmful gas dispersion issues, etc. There were many disastrous events occurring around the world in the past decades, like a natural gas pipeline in Moscow leaked and exploded in 2009 causing the largest urban fire in Moscow since the end of World War II; the natural gas pipeline network explosion in 2010 in San Bruno, USA; Kaohsiung gas pipeline explosion accident in Taiwan in 2014 (Han and Weng, 2011; Girgin and Krausmann, 2016; Liaw, 2016).

As a result, many researchers have been concentrating on studying natural gas pipeline network (NGPN) problems. One of the most popular research focus is risk assessment of NGPN from qualitative and quantitative perspectives based on the conventional risk analysis methods (Fault Tree, Event Tree, Bow-Tie, Fuzzy Set theory, etc.) and relatively new methodologies (Petri Network and Bayesian Networks) (Cagno et al., 2000; Dong and Yu, 2005; Markowski and Mannan, 2009; Han and Weng, 2010, 2011; Hao et al., 2011; Ma et al., 2013; Baksh et al., 2015; Guo et al., 2016; Li et al., 2016; Kabir et al., 2016). The conventional risk analysis methods like Fault Tree, Event Tree, and Bow-Tie method can qualitatively determine the leading to any adverse event and can also quantitatively estimate the probability of the occurrence of

* Corresponding author.
E-mail address: jiansongwu@hotmail.com (J. Wu).

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the events. However, these traditional methods have some limitations: only discrete (binary) variables are used, and continuous or multi-state variables cannot be suitably modeled, and furthermore the conditional dependencies between the variables cannot be represented, which restricts these methods to diagnostic analysis (Martins et al., 2014). Moreover, these conventional risk analysis methods are known as static, and are unable to incorporate the uncertainties due to ignorance or lack of knowledge and unable to achieve probability updating in the analysis during the operation. Fuzzy Set method can relax the abovementioned limitations to some extent, but it also has restrictions. The membership function is not easy to determine, and it lies heavily on the researcher's rich professional knowledge and engineering experiences and the calculated risk results for some applications sometimes presents major errors (Liu et al., 2004). Compared with the conventional risk assessment methods, Bayesian network (BN) presents a couple of advantages. BN is a good cause-effect analysis tool for representing uncertain knowledge in probabilistic systems and has proven to be effective for capturing and integrating qualitative and quantitative information from various sources. Moreover, BN facilitates the modeling of continuous or multi-state variables and can perform the quantitative analysis in two ways: predictive analysis and diagnostic analysis taking advantage of the good representation of the conditional dependencies between the nodes (Joseph et al., 2010; Yuan et al., 2015). The key challenge in risk assessment of gas pipeline problems is dealing with the randomness, vagueness and ignorance-type uncertainties (Ferdous et al., 2011; Kabir et al., 2016). BN has been therefore becoming a popular tool to dynamic risk analysis of natural gas pipeline problems.

In the field of risk analysis of oil and gas pipeline problems based on Bayesian network, Hao et al. (2011) quantitatively examined the natural gas pipeline failure using BN and established a long transmission pipeline Bayes network quantitative analysis model. Yang et al. (2013) probabilistically analyzed the multi-factor and polymorphism failure of natural gas pipelines, and the proposed method can reflect the effects of different factors and predict the failure state of urban natural gas pipelines. Li et al. (2016) proposed a Bayesian network model for pipeline leakage through mapping from the Bow-tie model, and the model can provide a more case-specific analysis of the common cause failures and conditional dependency in accident evolution process of pipeline leakage. Kabir et al. (2016) incorporated fuzzy logic into Bayesian network for safety assessment of oil and gas pipelines, and found the most significant causes for the oil and gas pipeline failures. However, the studies above mainly adopt conventional risk analysis methods or relatively new BN method focusing on the risk assessment or probabilistic analysis of specific issues of oil and gas pipelines (leakage failure, safety barrier, etc.), but seldom involving probabilistic analysis of the comprehensive causes, the accident evolution process and consequences of natural gas pipeline accidents and additionally the cascading secondary disasters.

The present work is aimed at building a dynamic probabilistic analysis framework of natural gas pipeline network accident based on Bayesian network. Through the proposed framework, the evolution process of direct NGPN failures and serious accidents from causes to consequences is presented explicitly, and also, the impact of secondary accidents and the effects of emergency rescue on preventing loss can be evaluated. Bayesian network of NGPN accident is constructed on the basis of the investigation of many typical natural gas pipeline network accidents and expert judgements, which guarantees the universality of the model. Essentially, this study can provide supports for critical decision-making of pipelines operators and emergency response commanders.

2. Methodology

2.1. Bayesian network

Bayesian network can also be called belief network, which is a combination of Directed Acyclic Graph (DAG) and Probability Theory. It is composed of several nodes and directed edges, reflecting the information of analysis target and representing cause–effect relationships of different nodes respectively. BN is a probabilistic inference technology for reasoning under uncertainty by taking advantage of Conditional Probabilities Table (CPT) of BN nodes. Bayesian network was firstly presented by Pearl in 1985 (Pearl, 1985) and then has proven to be an effective cause-effect analysis tool for representing uncertain knowledge in probabilistic systems and have been applied to a variety of safety assessment and risk analysis problems (Khakzad et al., 2011; Hossain and Muromachi, 2012; Francis et al., 2014; Tan et al., 2014; Kabir et al., 2015; Wu et al., 2016).

The basic principles of Bayesian network are conditional independence and joint probability distribution:

$$P(V_1, V_2, \cdots, V_k/v) = \prod_{1}^{k} P(V_i/v) \quad (\mathrm{i} = 1, 2 \ldots \mathrm{k}) \tag{1}$$

$$P(V_1, V_2, \cdots, V_k) = \prod_{1}^{k} P(V_i/Parent(V_i)) \quad (\mathrm{i} = 1,\ 2 \ldots \mathrm{k}) \tag{2}$$

Where $V_1, V_2, \cdots, V_k$ represent various variables, v is the normal node, which facilitates the expression of the conditional probability, and $Parent(V_i)$ is the parent nodes of V_i. The basic process of building the Bayesian network is shown in Fig. 1.

2.2. Dempster-Shafer evidence theory

Demptster-Shafer evidence theory was first presented by Demptster, and then extended to Belief Function, which means that the Demptster-Shafer evidence theory has become a generalization of classic probability theory (Dempster, 1968). This theory had been successfully applied in information fusion and system uncertainty analysis. (Dempster, 2008; Neshat and Pradhan, 2015; Al-Abadi, 2015).

By defining the frame of discernment as Θ, which is a finite set including several limited and mutually exclusive elements of a particular proposition, the basic functions of Demptster-Shafer evidence theory are shown below:

$$m(A) = \begin{cases} \dfrac{1}{1-K} \sum\limits_{A_1 \cap A_2 \cap \ldots \cap A_N} m_1(A_1) \cdot m_2(A_2) \cdot \ldots m_N(A_N), A \neq \phi \\ 0, A = \phi \end{cases} \tag{3}$$

where, $m(A)$ is Mass function of object A, which is also the Basic Probability Assignment (BPA) of Demptster-Shafer evidence theory. $m(A)$ is a function of the power set 2^{Θ} to [0,1], and there are two conditions that $m(A)$ needs to meet:

$$\begin{cases} m(\phi) = 0 \\ \sum\limits_{A \subseteq \Theta} m(A) = 1 \end{cases} \tag{4}$$

where, $m(\phi)$ means there is no evidence supporting the empty set while $m(A)$ expresses the evidences supporting the object A. Therefore, $\sum_{A \subseteq \Theta} m(A) = 1$ shows that the total value of the reliability