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Failure probability analysis of the urban buried gas pipelines using Bayesian networks

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ABSTRACT

Failures of urban buried gas pipelines have caused significant fire and explosion accidents with tremendous losses. This work presents an advanced two-step approach to analyze failure probabilities of the urban buried gas pipeline. First, a logical failure model is developed with the operational, material and environmental parameters contributing to the failure (Fault Tree Analysis). Second, the logical model is transformed into a network model (Bayesian Network). This novel approach can better reveal the relationships among failure causal factors and can also update the failure probabilities as operational and environmental conditions evolve. The Bayesian network failure model is subsequently applied to a case study. The results indicate that this approach is feasible and reasonable which can assist in identifying safety critical factors. Improving reliability of these safety critical factors can be of great help in enhancing the safety of urban buried gas pipelines.

1. Introduction

As a major source of fuel consumption, gas is generally transported to the users through pipelines (Shahriar et al., 2012). The number of buried gas pipelines is growing rapidly in the world due to their advantages of mass transportation, high security and strong continuity. However, with the running time increasing, the wear and corrosion phenomenon of buried gas pipelines is very serious even though those buried pipelines were coated under cathodic protection (Wang et al. 2014, 2016). As the transported gas is usually combustible, explosive and diffusible, there have been vast amounts of urban buried gas pipeline leakage accidents causing considerable death toll, capital loss and environment damage (Dong and Yu, 2005). Table 1 listed some typical urban buried gas pipeline accidents in recent years.

Risk analysis is vital in order to improve the reliability of urban buried gas pipeline and prevent potential accidents. Although accidents cannot be fully avoided, the overall risk of urban buried gas pipeline can be reduced to an acceptable level by performing reasonable risk analysis and taking some effective risk prevention measures (Shahriar et al., 2012). While the consequence of pipeline failure can be modeled by using computational fluid dynamics, the probability of failure might be obtained through fault tree analysis or Bayesian approach (Joshi et al., 2016). Failure probability analysis is the key role of risk analysis and several studies have been carried out to analyze the failure probability of buried gas pipeline. Carr computed the failure probability of pipeline using First Order/Second Order Reliability Method (FORM/SORM) and Monte Carlo Simulation (MCS) (Carr, 2014). The operation speed of FORM/SORM is very fast with a low accuracy while MCS is an accurate method with a very long running time. Dong and Yu (2005) employed a fuzzy fault tree model to estimate the failure probability of oil and gas pipelines. In this study, expert elicitation and fuzzy set theories were combined to calculate the probabilities, which solved the problem of ambiguity and imprecision of basic events. Cagno et al. (2000) proposed a robust Bayesian approach to assess the

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Table 1 – Typical buried gas pipeline accidents in recent years.

Time	Location	Reason	Consequence
April 22, 1992	Mexico city	Pipe network leak explosion	More than 500 deaths and 7000 injuries
January 3, 1995	Tsinan, China	The leaked gas was filled with cable gutter and detonated	17 deaths, more than 100 injuries and loss of ¥4.29 million
December 11, 1999	Sian, China	Gas explosion caused by construction damage	More than 10 injuries, 2 of them were seriously injured
August 2, 2004	Asuncion, Paraguay	Fire caused by gas pipeline explosion	250 deaths
November 18, 2007	Kingdom of Saudi Arabia	Fire caused by gas leakage	28 injuries, and 12 were missing
June 11, 2013	Soochow, China	Gas leak explosion	11 deaths, 9 injuries, and 400 m^2 of three-story office building collapsed
August 1, 2014	Kaohsiung city	Gas leak explosion	32 deaths, 321 injuries
April 17, 2015	California, US	Gas explosion caused by construction damage	More than 14 injuries, 4 of them were seriously injured
July 20, 2016	Enshi, China	Gas explosion caused by geological hazard	2 deaths, 7 injuries, and 5 houses damaged

failure probability of low-pressure pipelines used in metropolitan gas networks. In their work, the prior probabilities of factors leading to gas pipeline failure were calculated by AHP and the integration of historical data and expert opinions was implemented by Bayesian inference to solve the problem of incomplete historical data. Han and Weng (2011) employed a modified empirical formula to derive the failure probability of urban natural gas pipeline network, which depended on some failure assumptions caused by risk factors. Guo et al. (2016) proposed a fuzzy Petri net approach for oil and gas pipeline, in which AHP model and EM model was combined to determine the weights of risk factors. The initial degrees of the risk factors were calculated by the cloud model and some parameters were optimized by fuzzy reasoning. This approach reflected the fuzziness and randomness of risk factors, reducing the impact of subjective and objective factors.

Most of the previous studies have some limitations. For example, they cannot handle data scarcity and relation uncertainties (Zarei et al., 2016), and cannot update the posterior probabilities of events (Duan and Zhou, 2012). In this paper, in order to overcome these limitations, a comprehensive analysis approach of failure probability was presented based on fault tree analysis and Bayesian networks (Rathnayaka et al., 2011a, 2011b). The fault tree model can reveal various risk factors on the failure of urban buried gas pipeline and their relations comprehensively and vividly. However, the calculation of failure probability is complex when the system of fault tree is large, and the fault tree model cannot describe multi-state variables and uncertain causal relationships (Khakzad et al., 2011, 2013a, 2013b). Bayesian network has an excellent ability in dealing with multi-state variables, uncertain causal relationships, updating probabilities, performing bidirectional reasoning and handling data scarcity (Dongiovanni and Iesmantas, 2016; Wu et al., 2015; Li et al., 2016). The combination of fault tree and Bayesian network in this work reduces the complexity of failure probability model and subjective factors in analysis and hence accurate results can be derived.

2. Methodology

2.1. *Bayesian network model based on fault tree*

Bayesian network, known as a graphical model of probability theory, is a directed acyclic graph comprising of many nodes representing stochastic variables and directed arcs symbolizing probabilistic conditional dependences between them (Khakzad et al., 2011; Wu et al., 2015; Tien and Der Kiureghian, 2016). Bayesian network is one of the most effective theoretical models in the field of reasoning based on uncertain knowledge, structure and parameter learning and updating probabilities given new observations, which can derive more accurate system failure probabilities and the posterior probabilities of root nodes (Hu et al., 2016). However, the construction of Bayesian network is the "bottleneck" for the application of it. Currently mapping fault trees to Bayesian networks is an efficient approach to solve this "bottleneck" problem (Duan and Zhou, 2012).

Fault tree is a deductive methodology describing the contributing causes of an undesired event. The fault tree starts with an undesired event (top event) and is conducted downward, dissecting the system for further details until basic events are known (Khakzad et al., 2011; Askarian et al., 2016). Since complete data of accidents is hard to obtain, the prior probabilities of basic events are usually determined by the data of historical accidents statistics, literature and expert opinions (Li et al., 2016; Weber et al., 2012). The rules of converting fault tree to Bayesian network is recapitulated as follows (Khakzad et al., 2013a; Bobbio et al., 2001; Lampis and Andrews, 2009):

(1) As the structure of Bayesian network corresponds to that of fault tree, basic events, intermediate events, and the top event in the fault tree are represented as root nodes, intermediate nodes, and the leaf node in the corresponding Bayesian network, respectively. For the basic event representing the same component, only one root node in Bayesian network is created.
(2) The nodes in Bayesian network are connected in the same way as the corresponding events in the fault tree such that the input events of gate in the fault tree are the child nodes of the Bayesian network while the output events are the parent nodes.
(3) The prior probabilities of root nodes in Bayesian network are assigned by the occurrence probabilities of the corresponding basic events in the fault tree.
(4) The conditional probability tables (CPTs) of intermediate nodes and the leaf node are assigned according to the type of gate. Fig. 1 shows the translation of an OR and an AND gate into the corresponding constructions of the Bayesian network and the corresponding CPTs are shown in Tables 2 and 3 (Dongiovanni and Iesmantas, 2016).

Table 2 – Conditional probability table of M1.

X 1		0		1	
X 2		0	1	0	1
M 1	0	1	0	0	0
	1	0	1	1	1