Journal of Loss Prevention in the Process Industries 52 (2018) 54–65

Contents lists available at ScienceDirect

Journal of Loss Prevention in the Process Industries

journal homepage: www.elsevier.com/locate/jlp

Risk analysis of subsea blowout preventer by mapping GO models into Bayesian networks

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ARTICLE INFO

Keywords:
Risk analysis
Subsea blowout preventer
GO methodology
Bayesian network

ABSTRACT

Bayesian network (BN) is commonly used in probabilistic risk quantification due to its powerful capacity in uncertain knowledge representation and uncertainty reasoning. For the formalization of BN models, this paper presents a novel approach on constructing a BN from GO model. The equivalent BNs of the seventeen basic operators in GO methodology are developed. Therefore, the existing GO model can be mapped into an equivalent BN on basis of these developed BNs of the operators. Subsea blowout preventer (BOP) system plays an important role in providing safety during the subsea drilling activities. A case of closing the subsea BOP in the presence of pump failures is used to illustrate the mapping process. First, its GO model is presented according to the flow chart of the case. Then, BN is obtained based on the presented GO model. The developed BN relaxes the limitations of GO model and is capable of probability updating and probability adapting. Sensitivity analysis is performed to find the key influencing factor. The three-axiom-based analysis method is used to validate the developed BN.

1. Introduction

Bayesian networks (BNs) can describe the dependencies between variables both qualitatively and quantitatively (Sanmiquel et al., 2015). It is a powerful tool in uncertain knowledge representation and uncertainty reasoning. BN is able to predict the probability of unknown variables by forward reasoning or update the probability of known variables given some new information by backward reasoning (Khakzad et al., 2011). Due to this ability, BN is widely used for safety analysis and risk assessment in various fields, such as natural gas pipeline network accident (Wu et al., 2017), gas explosion accidents (Huang et al., 2017), offloading process in floating liquefied natural gas platform (Yeo et al., 2016), maritime transportation systems (Goerlandt and Montewka, 2015), ship recycling sector (Garmer et al., 2015), offshore drilling operations (Khakzad et al., 2013a; Bhandari et al., 2015), human factor analysis (Musharraf et al., 2013, 2014; Akhtar and Utne, 2014), managed pressure drilling operation (Abimbola et al., 2015) and so on.

A BN is a directed acyclic graph composed of nodes and arcs, which is a graphical and qualitative illustration of relationships among different nodes using directed arcs. Nodes represent random variables and directed arcs between pairs of nodes denote dependencies between the variables (Cai et al., 2016, 2018). Conditional probability table (CPT) is specified at each node that has parents, while prior probability is specified at node that has no parents. A BN can be obtained by machine learning using data sets or deducing from expert knowledge (Zhao et al., 2013). These two methods can be used individually or jointly. A BN has higher uncertain inference capacity in dealing with multi sources of information like expert knowledge, empirical data, model output and so on (Cai et al., 2017). In order to make use of the powerful representation in uncertainty, BNs can be developed by converting the other reliability models, such as fault tree (Bobbio et al., 2001), dynamic fault tree (Boudali and Dugan, 2005; Montani et al., 2008), event tree (Bearfield and Marsh, 2005), bond graph model (Lo et al., 2011), reliability block diagram (Kim, 2011), bow-tie (Khakzad et al., 2013b), and so on.

GO methodology was originally developed to analyze the safety and reliability of nuclear systems (Williams and Gateley, 1977). It is a success-oriented system analysis technique and becomes an effective technique for system reliability analysis (Matsuoka and Kobayashi, 1988). With application of GO model, a new reliability analysis approach for repairable systems with multiple-input and multi-function component is presented (Yi et al., 2016). A new method for reliability of vehicle systems by taking into account of typical characteristics based on GO methodology is proposed (Yi et al., 2017). A supplemental algorithm for the repair system in GO methodology is developed (Shen

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https://doi.org/10.1016/j.jlp.2018.01.014
Received 5 December 2017; Received in revised form 25 January 2018; Accepted 28 January 2018
Available online 01 February 2018
0950-4230/

et al., 2006). The development of GO method is based on decision tree theory and its basic modeling way is to translate the schematic diagram, flow chart or engineering chart into GO chart according to some rules. Therefore, GO model is able to reflect the system structure, the relationship and effects among the components. Unlike Fault Tree Analysis, GO methodology can be used to model the system with multiple states and time-sequential signals. A GO model is created by representing the elements and logical features of a particular system based on the seventeen types of operators. The quantification calculation can be performed one by one along the sequence of the signal flows from the input operator to the final output signal of the system. However, GO method has its limitations. Too many operators makes the modeling process not easy. Besides, GO method is unable to construct hierarchical charts. Further, it is hard to describe the effects of uncertainty (Shen et al., 2000).

In this paper, a novel method on constructing BNs from GO models is presented. The proposed method can relax the mentioned limitations of GO model and enrich the ways of developing BN. Besides, constructing BN from GO model will have some improvements. The new model will be able to update the probability of known variables given some new evidences. Besides, various kinds of dependencies among system components can be accommodated. BN helps to incorporate the modeling aspects of handling multi-state variables, dependent failures, functional uncertainty and expert knowledge, which are common in safety analysis. Given the new evidences, BN can update the probabilities and then it will better reflect system safety characteristics (Khakzad et al., 2011). The corresponding BNs of classical operators in GO methodology are developed firstly. Then a case study of closing subsea blowout preventer (BOP) control system in the presence of pump failures is given to illustrate the proposed method. The reminder of this paper is organized as follows. In section 2, the equivalent BNs of operators in GO method are developed. Section 3 illustrates the method by a case study. Section 4 discusses the case study. Section 5 summarizes the paper.

2. Proposed methodology

This section introduces the seventeen basic operators in GO methodology. The equivalent BN of each operator is developed. Netica software (http://www.norsys.com/netica.html) is used to build the BNs. Because numbers are not allowed to be state names in Netica, state values of the signals such as 0, 1, 2 in GO methodology corresponds to s0, s1, s2 in BNs, respectively.

Type-1 operator is called two-state component (Shen and Huang, 2004). It has one input signal S and one output signal R. It is easily and commonly used, which simulates the element with two states (Success and Failure). "Success" denotes the signal can get through the operator, while "Failure" means the signal fails to pass. Type-1 operator can simulate switches, pipes and so on. Define V_s, V_o and V_R as the state values of input signal, operator and output signal, respectively. For V_o, two values are optional, where 1 denotes success state and 2 denotes failure state. V_s and V_R have N states. The logic rules are shown in Table 1.

For the operator in GO, the output signal R can be regarded as the consequence of input signal S_i and operator O. To map an operator into an equivalent BN, input of the operator S_i will be the parent node and output of the operator R will be the child node. Besides, if the logic rules

Table 1
Logic rules of type-1 operator.

V_s	V_o	V_R
0, …, N-1	1	0, …, N-1
N	1	N
0, …, N	2	N

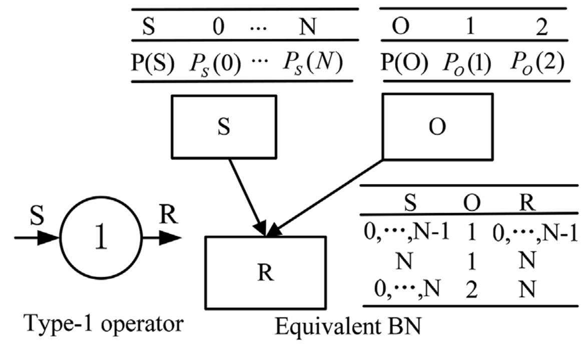

Fig. 1. Type-1 operator and its equivalent BN.

of the operator are related to the state values of the operator O, node O will also be the father parent node. Once the structure of the BN is established, the parameters need to specify. Prior probability of node S_i is defined according to the state values of the input signal. Similarly, if node O is present, its prior probability is specified based on the state values of operator. Therefore, the equivalent BN of type-1 operator is shown in Fig. 1. Nodes S, O, R represent the input signal S, operator and output signal, respectively. As output signal is related to the input signal and operator, nodes S and O are the parent nodes of node R. Prior probability of nodes S and O need to be specified. Conditional probability of node R will be established based on the logic rules listed in Table 1.

A case of type-1 operator is given to illustrate the mapping process. Assuming the input signal has two states, namely 1 and 2, so its equivalent BN is shown in Fig. 2. In the BN, s1 denotes state 1 and s2 means state 2. The probabilities of all the states are shown beside the state names in the BN. For nodes S and O, the probabilities are prior probabilities. According to the logic rules shown in Table 1, CPT of node R is defined. Fig. 2 shows that the probability of the output signal R $P_R(s1) = 0.72$ in the case. The probability of the output signal R can be calculated by

$$P_R(s1) = \sum P(S, O) \cdot P(R = s1|S, O) \tag{1}$$

Based on the Bayesian inference, $P_R(s1) = P_S(s1)\ P_O(s1)$, which is the same as value computed by the GO methodology.

Type-2 models an OR gate, which has more M input signal lines. The output signal is only related to the input signals. The output signal is determined by the minimum state value of the M input signals. The equivalent BN of type-2 operator is shown in Fig. 3. The input signal $S_i = (i = 0, 1,\ , N)$ node is the parent node of the output signal node. Prior probabilities of the input signal nodes need to be defined. The state value of the input signal is denoted by V_{si}. Based on the logic rule of the output signal, CPT of R is shown in the figure. Assuming there are two input signals S1 and S2 with two states, its equivalent BN is shown in Fig. 4. Prior probabilities of the input nodes are given. CPT of R can be defined as shown in the figure. It demonstrates that the probability of the output node R are correct according to the OR logic gate.

Type-3 operator is a triggered generator. It has one input signal and one output signal. It simulates an element with three states (premature, success and failure). In addition, the states "success" and "failure" has the same meanings with type-1 operator. The state "premature" means that the output signal is possible to be present even without an input signal. This state describes the output signal caused by inappropriate actions or unexpected external trigger. Premature, success and failure of operator is denoted by 0, 1, 2, respectively. Assuming input signal has N states, the logic rules of type-3 are shown in Table 2. Fig. 5 shows the type-3 operator and its equivalent BN. Nodes S, O and R represent input signal S, operator and output signal R, respectively. Node R is the child node of node S and O. CPT of node R can be defined based on the logic rules listed in Table 2.