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Dynamic Bayesian network modeling of reliability of subsea blowout preventer stack in presence of common cause failures

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ABSTRACT

A subsea blowout preventer (BOP) stack is used to seal, control and monitor oil and gas wells. It can be regarded as a series–parallel system consisting of several subsystems. This paper develops the dynamic Bayesian network (DBN) of a parallel system with n components, taking account of common cause failures and imperfect coverage. Multiple error shock model is used to model common cause failures. Based on the proposed generic model, DBNs of the two commonly used stack types, namely the conventional BOP and modern BOP are developed. In order to evaluate the effects of the failure rates and coverage factor on the reliability and availability of the stacks, sensitivity analysis is performed.

1. Introduction

A blowout preventer (BOP) is a specialized mechanical device, usually installed redundantly in stacks, used to seal, control and monitor oil and gas wells. It is developed to deal with extreme erratic pressures and uncontrolled flow gushing from a well reservoir during drilling. BOPs play an important role in the safety of crew, rig and environment, and they are critical to the monitoring and maintenance of well integrity. Once the BOP fails, kicks or blowout in the process of drilling will lead to serious consequences. For example, the semisubmersible drilling platform Deepwater Horizon in the Gulf of Mexico exploded and sank on April 20, 2010. This tragedy not only caused huge property losses and casualties, but also brought irreparable disaster to the ecological environment of the Gulf of Mexico (Skogdalen et al., 2011). One important cause of this accident is that the subsea BOP fails to function. Hence, reliability research of subsea BOP is of significance and it attracts more and more attentions recently.

Several methods have been proposed for reliability analysis of subsea BOP system. Fowler and Roche (1994) use failure modes and effects analysis (FMEA) and fault tree analysis (FTA) techniques for reliability analysis of a BOP and a hydraulic control system. Historical data about subsea BOP failures and malfunctions are collected and estimated by using the FTA method (Holand and Rausand, 1987; Holand and Awan, 2012). But, the two methods are only suitable for non-repair systems and lack of time element is their limitation (Sadou and Demmou, 2009). Besides, FMEA technique cannot differentiate situation of common failures or severe failure caused by compound failures (Globe, 2010). Owing to their flexibility, Markov methods are used for performance evaluation of subsea BOP stack configuration and mounting types for control pods (Cai et al., 2012). Due to the exponential growth of the state space with the number of components, Markov method is faced with state explosion problem (Boudali and Dugan, 2005). With Bayesian network (BN), there is no longer such a constraint since the number of parameters within the conditional probabilities table is considerable lower compared to a Markov model (Weber et al., 2012).

Recently, BNs have been popular for reliability and risk evaluation as a robust and viable alternative to most traditional methods such as fault tree, reliability block diagrams and so on (Khakzad et al., 2013). Martins and Maturana (2013) present a method based on BN for analyzing human reliability and apply this methodology to the operation of an oil tanker, focusing on the risk of collision accidents. Li et al. (2012) develop a fuzzy BN approach to improve the quantification of organizational influences in human reliability analysis frameworks. Morales-Napoles and Steenbergen (2014) have presented the potential of Hybrid BNs for modeling

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complex data such as the one generated by the Weigh-in-Motion system in the Netherlands. Doguc and Ramirez-Marquez (2012) develop a new method for estimating grid service reliability, which does not need prior knowledge about the grid system structure unlike the previous studies. Daemi et al. (2012) use BN for reliability assessment of composite power systems with emphasis on the importance of system components.

If a BN is involved with temporal factors, it is a dynamic network. Static BN can be extended into dynamic Bayesian network (DBN) by introducing relevant temporal dependencies between representations of the static network at different times, which allows modeling the dynamic behavior of the systems (Galán et al., 2002). Thus, DBN is more appropriate for monitoring and predicting values of random variables, and capable of representing the system states at any time with respect to BN (Weber and Jouffe, 2003). Several DBN models have been proposed for assessing reliability of technical systems. Portinale et al. (2010) present an approach to reliability modeling and analysis based on the automatic conversion of the dynamic fault tree into DBN, which is implemented in a software tool called RADYBAN (Montani et al., 2008). Cai et al. (2013) present a quantitative reliability and availability evaluation method for subsea BOP system by translating fault tree into DBN directly, taking account of imperfect repair. Boudali and Dugan (2005) propose a new reliability and analysis framework based on the BN formalism and the method is to investigate timed BNs and find a suitable reliability framework for dynamic systems.

Subsea BOP stack is composed of annular BOPs, ram BOPs, LMRP connector and wellhead connector. In order to improve the reliability of the BOP sack, several annular and ram BOPs are used for redundancy. Therefore, it can be regarded as a series–parallel system. This paper presents a method to develop the DBNs for reliability analysis of the subsea BOP stack. With common cause failures and imperfect coverage taken into account, two commonly used types, conventional BOP stack and modern BOP stack, are discussed. Sensitivity analysis is performed to research the influences of failure rates and imperfect coverage on system reliability and availability. The paper is structured as follows. Section 2 describes the subsea BOP stack in detail. Section 3 presents the method to develop DBNs of subsea BOP stacks. Section 4 covers the analytical results and discussions. Section 5 summarizes the paper.

2. Description of subsea BOP stack

BOPs come in two basic types, ram and annular. Both are often used together in drilling rig BOP stacks, typically with at least one annular BOP along with several ram BOPs. An annular-type BOP can close around the drill string or casing. Drill pipe including the larger-diameter tool joints (threaded connectors) can be "stripped" (i.e., moved vertically while pressure is contained below) through an annular preventer by careful control of the hydraulic closing pressure. Annular BOPs are also effective at maintaining a seal around the drill pipe even as it rotates during drilling. Regulations typically require that an annular preventer be able to completely close a wellbore, but annular preventers are generally not as effective as ram preventers in maintaining a seal on an open hole. Annular BOPs are typically located at the top of a BOP stack, with one or two annular preventers positioned above a series of several ram preventers. A ram-type BOP is similar in operation to a gate valve, but uses a pair of opposing steel plungers, rams. The rams extend toward the center of the wellbore to restrict flow or retract open in order to permit flow. The inner and top faces of the rams are fitted with packers that press against each other, against the wellbore, and around tubing running through the wellbore. Outlets at the sides of the BOP housing are used for connection to choke and kill lines or valves. Rams are of four common types: pipe, blind, shear, and blind shear. Pipe rams close around a drill pipe, restricting flow in the annulus (ring-shaped space between concentric objects) between the outside of the drill pipe and the wellbore, but do not obstruct flow within the drill pipe. Variable-bore pipe rams can accommodate tubing in a wider range of outside diameters than standard pipe rams, but typically with some loss of pressure capacity and longevity. Blind rams (also known as sealing rams), which have no openings for tubing, can close off the well when the well does not contain a drill string or other tubing, and seal it. Shear rams cut through the drill string or casing with hardened steel shears. Blind shear rams (also known as shear seal rams, or sealing shear rams) are intended to seal a wellbore, even when the bore is occupied by a drill string, by cutting through the drill string as the rams close off the well. The upper portion of the severed drill string is freed from the ram, while the lower portion may be crimped and the "fish tail" captured to hang the drill string off the BOP. Two hydraulic connectors are used to connect the BOP stack with the lower marine riser package (LMRP) and wellhead. LMRP connector joins the LMRP to the top of the lower BOP stack, while wellhead connector joins the stack to the subsea wellhead.

Fig. 1 demonstrates typical BOP configurations for a conventional and a modern BOP, respectively. However, these are representative sketches of BOPs as configuration may vary from rig to rig. A modern subsea BOP typically has six ram preventers, while a conventional subsea BOP has four ram preventers. As shown in Fig. 1, a conventional BOP configuration has two annular preventers, three pipe ram preventers, one blind shear ram preventer, one LMRP connector and wellhead connector. As a modern BOP configuration has two annular preventers, four pipe ram preventers, two blind shear ram preventers, one LMRP connector and wellhead connector. Compared with the conventional configuration, the modern BOP has one more pipe ram preventer and one more blind shear ram preventer.

According to the configuration, a BOP stack can be regarded as a series–parallel system composed of five subsystems, which is shown in Fig. 2. For conventional BOP, annular BOP subsystem is a parallel subsystem with two components and pipe ram BOP subsystem is a parallel subsystem with three components. For modern BOP, annular BOP subsystem and blind shear ram BOP subsystem are parallel subsystems with two components and pipe ram BOP subsystem is a parallel subsystem with four components.

3. Dynamic Bayesian network modeling

3.1. Dynamic Bayesian network

BNs are probabilistic models based on directed acyclic graphs which are used for representing and reasoning with uncertain knowledge (Ramírez and Utne, 2015). A BN is made up of a set of nodes representing the system variables and directed arcs representing the dependencies or influence among the variables. In BNs, a variable is defined over several mutually exclusive states and a probability is associated to each state. The probabilistic dependences are quantified by a conditional probability table for each node (Arsene et al., 2011). Each conditional probability table contains the probability of a node, given any possible combination of its parent nodes. Without parent nodes, root nodes only have prior probabilities. The nodes $(X_1, \ldots, X_N)$ in the network are labeled by related random variables. Assuming $Pa(X_i)$ is the parent node of X_i in the model, the conditional probability distribution of X_i is denoted by $P(X_i|Pa(X_i))$.The joint probability distribution $P(X_1, \ldots, X_N)$ can be written as Eq. (1).