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A dynamic and quantitative risk assessment method with uncertainties for offshore managed pressure drilling phases

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ABSTRACT

Drilling into offshore oil and gas fields often meets many challenges and uncertainties, such as a narrow window of drilling fluid density and shallow gas zones. Managed pressure drilling (MPD) techniques are increasingly used as alternatives to conventional drilling operations to manage such extreme conditions and reduce drilling costs and risks. Many safety and operational issues related to MPD process need to be investigated more thoroughly. Well kick is considered a typical hazardous event that may occur at different drilling phases, and such an event is prone to develop into a blowout. During offshore drilling phases, the risk of accidents may change with time, and such a dynamic characteristic should be recorded in risk assessment. This study presents a method for the application of dynamic Bayesian networks (DBNs) in conducting accident scenario analysis and dynamic quantitative risk assessment for MPD safety. This method can model the influence of uncertain risk factors, which have been ignored in existing research, by introducing an additional probability parameter. The effects of degradation are also taken into account. DBN inference is adopted to perform quantitative risk analysis and dynamic risk evolution. Then, the vulnerable root causes are identified by sensitivity analysis for accident prevention and mitigation measures. Well kick for four drilling cases is analyzed as a case study to demonstrate the feasibility of the proposed method. Three-step analysis partially validates the correctness and rationality of the proposed DBN model.

1. Introduction

Offshore oil and gas drilling operations are complicated and hazardous because of significant uncertainties and extreme operating conditions. Drilling safety is a major concern, and such operations are vulnerable to numerous challenges from the harsh marine environment, complicated geological conditions, and human and equipment factors (Skogdalen and Vinnem, 2012; Yang and Haugen, 2016). The narrow window of drilling fluid density is a challenge in oil and gas wells, which results in either direct or indirect well control implications. In comparison with less demanding oil and gas fields, uncontrolled influx to well ("kick"), loss of drilling fluid, and blowouts to the environment are among the hazardous incidents that can result in unplanned downtime or may develop into catastrophic accidents. For example, in the Deepwater explosion in the Gulf of Mexico, prior to the blowout of the Macondo well on April 20, 2010, several kicks and lost circulations were experienced during the drilling phase in February, March, and April 2010; the blowout ultimately occurred during the cementing stage and caused 11 fatalities and the largest oil spill in the history of the offshore oil and gas industry (Bly, 2011; Khakzad et al., 2016; Skogdalen et al., 2011). Predicting early kick or lost circulation and taking necessary precautions are necessary to avoid such disastrous accidents.

Kick is the first warning of a blowout. Thus, detecting a kick as early as possible and implementing efficient measures in due time are important. Drilling fluid column is a primary barrier to prevent the development of disastrous accidents. Further attention must be paid to manage this situation (Holand and Awan, 2012; Holand and Skalle, 2001). Well kick occurs when the bottom hole pressure (BHP) in the wellbore is lower than the formation pressure, thereby allowing the formation fluid to flow into the bottom hole. Managed pressure drilling (MPD) technology has been widely used to control the BHP for the enhancement of well control. MPD use can also especially reduce the likelihood of drilling incidents, as well as drilling cost in oil and gas wells with narrow downhole pressure limits. However, compared with conventional drilling operations, additional equipment, higher expertise for well control, and higher risks are involved. Therefore, the risks related to MPD should be included in quantitative risk assessments (Abimbola et al., 2014; Abimbola et al., 2015; Hannegan, 2013).

Quantitative risk analysis techniques have strengthened the safety

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of offshore oil and gas exploration and development activities. Such techniques have also been useful in reducing the occurrence possibility of incidents to ensure a safe operating state. Some of these techniques have been developed for accident scenario modeling and risk assessment. Among these techniques the fault tree analysis (FTA), event tree analysis (ETA), bow-tie analysis (BTA), Markov chain analysis (MCA) (Wu et al., 2018), fuzzy-based analysis (FA) (Ataallahi and Shadizadeh, 2015), and Bayesian networks (BNs) (Cai et al., 2017) are well-known. Drilling safety has been emphasized for blowout preventer (BOP) reliability analysis by relevant studies (Holand and Rausand, 1987; Holand and Skalle, 2001; Kim et al., 2014) using FTA and Markov modeling. Compared with other methods, BN is a graphical probabilistic technique with a flexible structure and a robust reasoning engine based on Bayes' theorem (Cai et al., 2014, 2016a). BNs have been widely used in risk assessment to overcome the weaknesses (Khakzad et al., 2013a) from FTA, ETA, and BTA, in which the modeling of data scarcity, correlations between risk influence factors, risk updating from new evidence, and uncertainty issues cannot be effectively addressed. BNs are also integrated with other frequently used models (Khakzad et al., 2013a; Zarei et al., 2017). Some researchers (Abimbola et al., 2015; Bhandari et al., 2015) have presented the risk assessment approaches on the basis of the application of BNs to analyze the effects of risk influencing factors with different offshore drilling technologies with respect to potential accident scenarios. Other approaches have been presented for offshore drilling risk assessment, among which a human reliability analysis method (Strand and Lundteigen, 2016, 2017) is a typical example.

The main limitations of the above BN models are their incapability to treat explicitly temporary relationships between model parameters or time-varying parameters; that is, they do not account for the fact that relationships of parameters may change from one phase to the next. Several efforts have focused on the development of dynamic risk assessment (DRA) approaches (Khan et al., 2016; Paltrinieri and Khan, 2016; Paltrinieri and Reniers, 2017; Villa et al., 2016), among which coupling of DRA and dynamic procedure for atypical scenarios identification (Paltrinieri et al., 2014), risk barometer (Hauge et al., 2015), Bayesian inference-based DRA (Scarponi and Paltrinieri, 2016), and real-time-based analysis (Islam et al., 2017), are mainly used for identifying potential accident scenarios, monitoring risk picture changing, estimating dynamic probabilities, and decision making. In addition, dynamic BNs (DBNs) have been introduced to handle systems with complex dynamics (with behavior highly dependent on the time) (Hu et al., 2017; Wu et al., 2016) by considering the evolution of conditions that affect risks. DBNs are extended from BNs but have additional features that allow the incorporation of events, conditions, and interrelationships that may change over time. Therefore, they are suitable to capture the dynamic behaviors of a drilling operation in a real ever-changing environment, such as changes in well conditions and the release of new information for the state of equipment. Multiphase DBN methodologies (Cai et al., 2016b) have been explored to determine safety integrity levels. Wu et al. (2016) proposed a DBN-based risk assessment model to predict and diagnose offshore drilling incidents.

Several issues, however, need to be further investigated when DBNs are applied to offshore MPD phases. The effects of uncertain risk influence factors that cannot be modeled are usually ignored given an investigation of a hazardous event. The challenges of parameters of conditional probability based on prior knowledge from existing literature are not considered. In addition, the effects of degradation for mechanical equipment in the current DBN-based models are missing because failure rates are usually assumed constant. Therefore, the potential contribution of the current study is to present a new method that can model the influence of uncertain risk factors by introducing an additional probability parameter. Conditional probability is calculated by integrating uncertainties of prior knowledge. The failures are assumed to use an increasing failure rate to model degradation in an ocean environment in practice. This approach can systematically perform quantitative risk assessment, dynamic risk evolution, and sensitivity analysis under accident scenario identification and cause-consequence relationship analysis.

The rest of this paper is organized as follows. Section 2 presents a method for dynamic and quantitative risk assessment of offshore MPD phases by translating a bow-tie (BT) model to a DBN. An additional probability parameter is introduced to model uncertain risk factors, and the effect of degradation is considered for the risk evolution during drilling. In Section 3, a case study of drilling well kick is conducted to demonstrate the application of the proposed method. Section 4 provides the conclusion and research perspectives of this study.

2. Proposed method

2.1. BT approach

As an effective graphical approach, BT models can provide a visual explanation of the complete accident scenario evolution from root causes to consequences. The model is widely applied in hazard identification and risk analysis. A typical BT model consists of a fault tree (FT) and an event tree (ET). The left side of the BT is a FT that identifies the root causes of an unwanted event which is placed in the middle. The right side of the BT is an ET that depicts the possible outcomes derived from failures of safety barriers. Once hazards have been identified, a BT model can be applied to further build causal relationships. This process for hazard identification is considered a difficult task for complex offshore wells, especially during drilling with high temperature and high pressure. However, the application of BT models in risk analysis suffers the limitation of updating the probability of events due to the incapability of capturing new information and considering uncertainties (Abimbola et al., 2014; Badreddine and Amor, 2013). Furthermore, BT models have not been widely recognized in the context of dynamic analysis due to its static nature. To consider dynamic behavior over time, a BT model must be transformed into DBNs for DRA.

2.2. Overview of DBNs

A DBN is a BN that introduces relevant temporal dependencies to model the dynamic behavior of random variables. A BN, which consists of a directed acyclic graph and an associated joint probability distribution (Nielsen and Jensen, 2009), is widely used for quantitative risk assessment. In a BN, nodes, including parent and child nodes, represent random variables, and links determine probabilistic dependences between variables. A conditional probability table (CPT) for discrete variables is defined for the relationship among parent nodes to demonstrate marginal probability. Assume that $Pa(X_i)$ is the parent node of X_i. The CPT of X_i is denoted by $P(X_i|Pa(X_i))$. Therefore, the joint probability $P(X_1,...,X_N)$ can be rewritten as Eq. (1).

$$P(X_1,...,X_N) = \prod P(X_i|Pa(X_i)) \tag{1}$$

A DBN consists of a sequence of time slices and temporal links (Murphy, 2002a). Each slice represents a static BN to describe variables in the corresponding time step, and temporal links between variables in different time slices represent a temporal probabilistic dependence. A DBN can model probability distribution over a semi-infinite collection of random variables. It can also be defined by a pair of BNs (B_1, $B_{\rightarrow}$), where B_1 is a BN that defines the prior $P(X_1)$, and $B_{\rightarrow}$ is a two-slice temporal Bayesian net (2TBN) that defines the transition and observation models as a product of the CPTs in the 2TBN. The nodes in the first time-slice of a 2TBN have unconditional initial state distribution, $P(X_1^{1:N})$, whereas each node in the second time-slice has an associated CPT. For a DBN with T slices, the joint distribution can then be obtained by "unrolling" the network, as shown as follows