Journal of Petroleum Science and Engineering 165 (2018) 444–452

Contents lists available at ScienceDirect

Journal of Petroleum Science and Engineering

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

Data-driven dynamic risk analysis of offshore drilling operations

Sunday A. Adedigba, Olalere Oloruntobi, Faisal Khan*, Stephen Butt

Centre for Risk, Integrity and Safety Engineering (C-RISE), Faculty of Engineering and Applied Science, Memorial University of Newfoundland, St. John's, NL A1B 3X5, Canada

ARTICLE INFO

Keywords:
Dynamic failure probability
Risk analysis
Blowouts
Drilling
Bayesian tree augmented naive Bayes (TAN)

ABSTRACT

A data-driven dynamic risk analysis methodology is proposed here. The methodology is applied to offshore drilling operations. Modern drilling rigs are highly instrumented to monitor real time operational data. This provides sufficient data for time dependent risk analysis of drilling operations. The probabilistic relationships (structure) among the primary operational (drilling) parameters are modelled using the Bayesian Tree Augmented Naïve Bayes (TAN) algorithm. The developed model is used to predict time dependent probability of kick, and is continuously updated based on the current state of the key drilling parameters. The real-time probability of kick is used to model blowout risk as a function of time. The dynamic risk profile generated from the model is useful in operational decision making to prevent accidents and enhance the safety of drilling operations. The proposed dynamic risk methodology is tested and verified using actual drilling operational data.

1. Introduction

The complexity and sophistication of the current process systems have greatly improved their productivity. However, this advancement in modern process systems presents a significant risk of failure along with their versatility and productivity (Yu et al., 2015; Adedigba et al., 2017a). Risk analysis is defined as "the process of characterizing, managing and informing others about the existence, nature, magnitude, prevalence, contributing factors and uncertainties of the potential losses" (Modarres, 2006). The static nature of conventional quantitative risk assessment (QRA) methods has limited their application in modelling and predicting risk variations during the operation of process systems (Yang et al., 2015). However, dynamic risk analysis provides a framework that captures risk variation during the operation. Khan et al. (2016) defined dynamic risk assessment "as a method that updates estimated risk of a deteriorating process according to the performance of the control system, safety barriers, inspection and maintenance activities, the human factors and procedure". Various methods have been applied for executing a dynamic risk analysis of process systems. Detailed information about these methods can be found in (Al-shanini et al., 2014; Aven, 2016; Durga Rao et al., 2009; Kalantarnia et al., 2010; Khakzad et al., 2012; Khan and Abbasi, 1998; Khan et al., 2016; Paltrinieri et al., 2013; Adedigba et al., 2016a,b).

An accident model offers thorough information about how and why process accidents occur and is a very important tool for implementing process risk assessment. Different types of process accident models have been developed over the years. (Attwood et al., 2006; Adedigba et al., 2016a,b; Qureshi, 2007; Rathnayaka et al., 2010). However, most of these models do not take into consideration the dependency of the process variables and these process monitoring data are not used in these models.

Offshore drilling, and in particular deep water drilling operations, is associated with high risk and a high cost of operation. One of most devastating accidents with severe consequences in the offshore oil and gas industry is a blowout, such as the Macondo blowout accident. Accident records have revealed that the majority of offshore blowouts have occurred during the drilling phase (Xue et al., 2013).

A blowout is an unrestrained flow of gas and oil (hydrocarbons) to the environment (Khakzad et al., 2013). Many blowout accidents have occurred in offshore drilling operations around the globe. The most recent and most devastating environmental disaster in U.S history is the Macondo blowout of 20 April 2010. This accident was caused by a series of technical factors (Rathnayaka et al., 2013).

Safety management of offshore drilling operations demands continuous monitoring of the safety performance and safety indicators of the system. Safety indicators provide information about the level of safety in a system to decision makers so the decision makers can activate safety systems whenever the level of safety in the system is below the acceptable range (Skogdalen et al., 2011). Most of the approaches adopted in risk analysis of offshore drilling operations are analytical methods (Khakzad et al., 2013; Kujath et al., 2010; Skogdalen et al.,

* Corresponding author.
E-mail address: fikhan@mun.ca (F. Khan).

https://doi.org/10.1016/j.petrol.2018.02.049
Received 6 November 2017; Received in revised form 16 February 2018; Accepted 20 February 2018
Available online 23 February 2018
0920-4105/

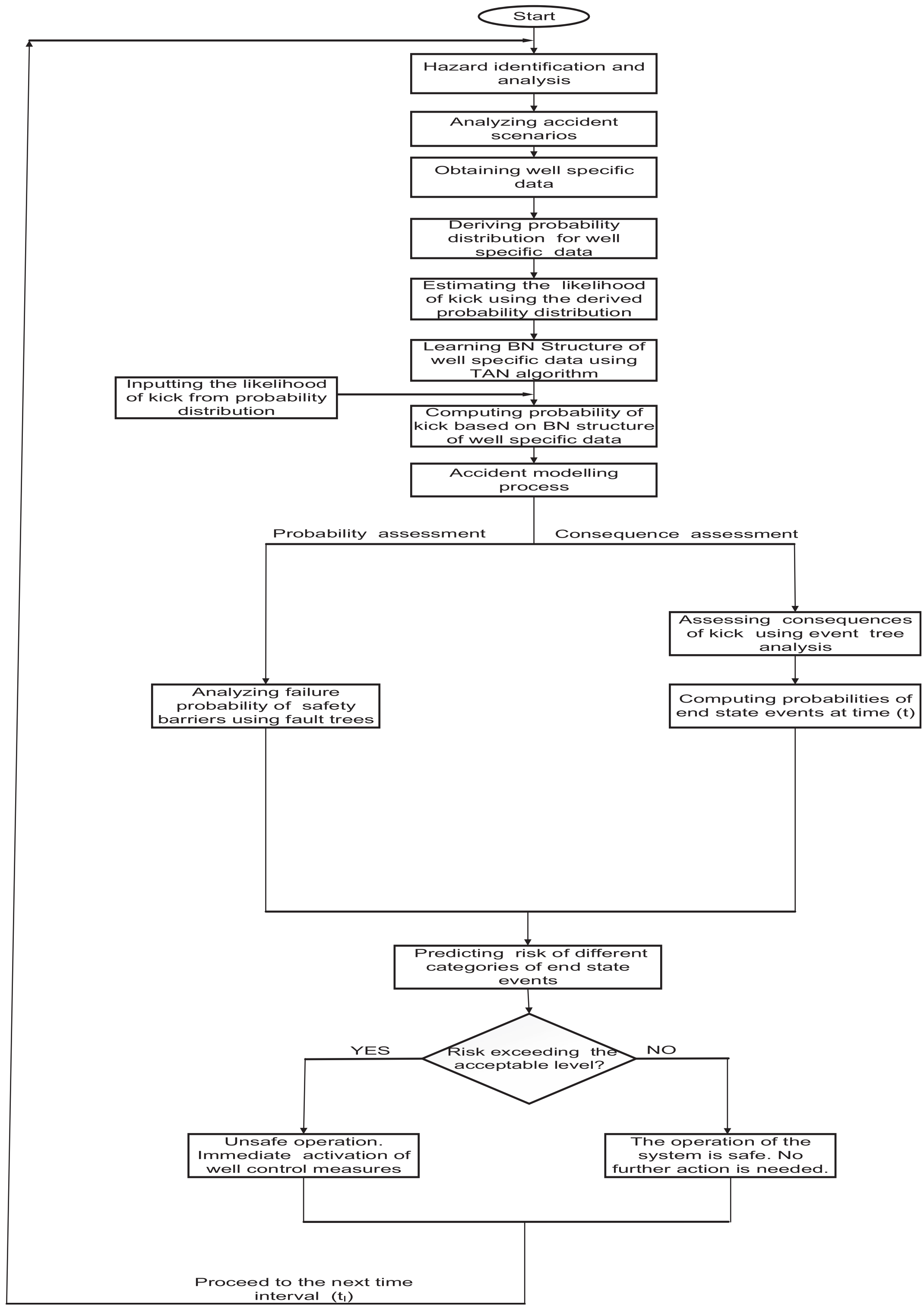

Fig. 1. The flowchart for the proposed methodology.

2011; Xue et al., 2013). However, analytical techniques do not take into consideration the probabilistic dependencies (structure) among well specific data.

The primary objective of the study is to develop a data-driven dynamic model for dynamic risk assessment. The developed model is demonstrated on an offshore drilling operation using the probabilistic relationships (structure) among actual industrial well-specific data such as bottom hole pressure (BHP), pore pressure (P_P) and fracture pressure (F_P). Also, management and organizational error are adequately accounted for in the model.

This paper is organised as follows. Section 2 discusses monitoring, prevention and control of well blowout. Section 3 presents the data driven dynamic risk analysis methodology. Section 4 provides the testing and verification of the proposed data driven risk assessment methodology with actual well specific data. The results and discussion are presented in section 5. Finally, the conclusion is given in Section 6.