



LJMU Research Online

Wang, YF, Liu, ZM, Jiang, JC, Khan, F and Wang, J

Blowout fire probability prediction of offshore drilling platform based on system dynamics

<http://researchonline.ljmu.ac.uk/id/eprint/11630/>

Article

Citation (please note it is advisable to refer to the publisher's version if you intend to cite from this work)

Wang, YF, Liu, ZM, Jiang, JC, Khan, F and Wang, J (2019) Blowout fire probability prediction of offshore drilling platform based on system dynamics. Journal of Loss Prevention in the Process Industries, 62. ISSN 0950-4230

LJMU has developed **LJMU Research Online** for users to access the research output of the University more effectively. Copyright © and Moral Rights for the papers on this site are retained by the individual authors and/or other copyright owners. Users may download and/or print one copy of any article(s) in LJMU Research Online to facilitate their private study or for non-commercial research. You may not engage in further distribution of the material or use it for any profit-making activities or any commercial gain.

The version presented here may differ from the published version or from the version of the record. Please see the repository URL above for details on accessing the published version and note that access may require a subscription.

For more information please contact researchonline@ljmu.ac.uk

<http://researchonline.ljmu.ac.uk/>

Blowout Fire Probability Prediction of Offshore Drilling Platform Based On System Dynamics

Yan-fu WANG^{1,4}, Zi-Mo LIU¹, Jun-Cheng JIANG², Faisal KHAN³, Jin WANG⁴

¹Department of Safety Science and Engineering, College of Mechanical and Electronic Engineering, China University of Petroleum, Qingdao, China

²School of Environment & Safety Engineering, Changzhou University, Changzhou, China

³Centre 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

⁴Department of Maritime and Mechanical Engineering, Liverpool John Moores University, Liverpool, UK

Abstract: A Barrier Failure Model of offshore platform fire is proposed based on the analysis of historical accidents. On this basis, a fault tree is built to analyze the causes of fire accidents and the Fussell Vesely importance method is used to compare the contributions degree of the basic events. However, it is known that the traditional fault tree method has some limitations on predicting the dynamic probabilities of accidents. To improve the situation, a dynamic probability prediction model is proposed by integrating fault tree with a system dynamics model. Firstly, the dynamic probability of blowout fire for offshore drilling is predicted using the proposed model. Secondly, sensitivities of causal factors are analyzed based on mutual information to find out the key contributory factors to blowout fire. The research results provide safety managers with reliable and effective risk control strategies for preventing the occurrence of accidents.

Key words: Offshore drilling platform; Probability of blowout fire; System dynamics; Sensitivity analysis

1. Introduction

Oil and gas drilling operations have accounted for the highest rate of critical accidents compared to other domains in the petroleum industry (Vandenbussche et al., 2012). Geological uncertainties, high pressure flammable fluids in the presence of ignition sources, complicated structural layouts, limited response time allowance and the difficulties of communication are some of the critical factors that pose clear threats toward safety operations and may result in serious consequence events (Nafiz et al., 2017). Under such environments, the leakage of oil and gas may cause uncontrollable fire accidents, not only causing casualties and great economic losses, but also leading to serious pollution and ecological damage (Wang et al., 2015).

Many accident modelling methods, such as System Hazard Identification, Prediction and Prevention (SHIPP) (Rathnayaka et al., 2011), Functional Resonance Accident Model (Hollnagel, 2004), simulator-based simulation (Chen et al., 2018), Systems-Theoretic Accident Model (Leveson, 2004) and Fault tree and Bayesian Network (BN) have been developed over the last several decades. SHIPP is a systematic methodology to identify, evaluate, and model the accident process, thereby predicting and preventing accidents in a process facility (Rathnayaka et al., 2011). In this methodology, process hazard accidents were modeled using safety barriers rather than causal factors. The fault tree and event tree analysis techniques enhance the accident model. They gave researchers a holistic picture on the cause-consequence mechanism of the accident process. Quantitative analysis of BN has two aspects: updating and prediction. The Bayesian theory updates failure probability and consequence occurrence probability when there is a new observation. Traditional accident models normally use a fault and event tree sequential approach to predict cause-consequence relationships, which are unable to capture the real nonlinear interactions of several

1. Corresponding author: Yan Fu Wang (Tel: +86-13698651195), E-mail: wangyanfu@upc.edu.cn.

accident contributory factors.

Recently, some studies have been carried out in dynamic risk assessment of offshore drilling. Safety and reliability assessment of a managed pressure drilling operation by investigating the kick control operation of the constant bottom hole pressure technique is explored (Sule et al., 2018). Abimbola introduced the loss function approach into the risk analysis of drilling operations to address the drawbacks of static consequence analysis (Abimbola and Khan, 2016). Perez proposed an Accident Precursor Probabilistic Method that aims to overcome the usual limitations of existing Quantitative Risk Analyses and assessing the risk of blowouts in offshore hydrocarbon drilling projects (Perez and Tan, 2018). Adedigba presented a data driven risk assessment methodology for offshore drilling operation, from which the dynamic risk profile generated is useful in operational decision making to prevent accidents and enhance the safety of drilling operations (Adedigba et al., 2018).

Some researchers attempted to analyze the effect of human factor in quantitative risk analysis for drilling operation. Strand and Lundteigen presented a human reliability analysis (HRA) method for the qualitative and quantitative analysis of human factor influences on the blowout risk (Strand and Lundteigen, 2016). Strand and Lundteigen presented a novel method that combines the well accident report reviews and analysis with the probabilistic well risk assessment (Strand and Lundteigen, 2017). Zhang presented a method for the dynamic and quantitative risk assessment of MPD operations in the offshore oil and gas field by translating the Bow Tie model to Dynamic BNs (Zhang et al., 2018). Sun applied the hybrid method of Analytic Network Process and Structural Equation Modelling to evaluate the importance of human factors in an oil drilling work system (Sun et al., 2018).

Existing methods have their own strengths and weakness which depend mainly on the areas of their application. What is missing in the literature is a simplified time dependent blowout fire accident modelling approach considering holistic view of causal and non-causality-based factors. In this paper, a dynamic probability prediction model is proposed by integrating Fault Tree (FT) with System Dynamic (SD) theory to handle both the complexity and changes in a system over time. The methodology is grouped into two main activities including system dynamic modeling of a sociotechnical system and a dynamic probability analysis. The objective is to provide theoretical support for safety managers to reduce the probability of blowout fire accidents and to improve the overall safety of offshore drilling platforms. The novelty is proposing a simplified time dependent blowout probability prediction model, which can be used to predict the dynamic probability of blowout fire on offshore drilling platforms.

2 Causal analysis of blowout fire and importance analysis

2.1 Methodology

Firstly, the fire accidents of offshore drilling platforms are statistically analyzed. Secondly, a Barrier Failure Model for blowout fire is proposed based on the above analysis of historical accidents. This model can be used to define the causal relationship among factors, which is useful to draw a complex causal relationship of FT and SD. Thirdly, a fault tree is established to analyze the causes of blowout fire and provide guidance to define the hierarchical structure diagram of System Dynamics model. The root causes of the offshore platform blowout fire could be determined. Based on this, the causal loop diagrams of SD model is built to predict the dynamic probabilities of blowout fire.

2.2 Barrier failure model of blowout fire

A blowout is the uncontrolled release of crude oil and/or natural gas from a well after pressure control systems failed (Westergaard, 1987). The down-hole fluid pressures are controlled in modern wells through the balancing of the hydrostatic pressure provided by the mud column. Should the balance of the drilling mud pressure be incorrect, the formation fluids may start flowing into the wellbore and filling up the annulus or going inside the drill pipe. This is commonly called a kick. Ideally, mechanical barriers, such as blowout preventers, can be closed to isolate the well while the hydrostatic balance is regained through circulation of fluids in the well. Improper handling of kicks in oil well control can result in blowouts with very serious consequences. A blowout fire is an accident that the formation fluids is ejected from the wellbore and subsequently ignited.

The occurrence of an accident is not only a reaction chain of time itself, but also in a penetrated set of organization defects (Vinnem et al., 2010). If the organization defects at different levels are triggered by an accident factor at the same time or in sequence, entire multi-level blocking barriers will fail and an accident will potentially occur. According to the process of blowout fire, the barrier failure model of blowout fire for offshore drilling platforms is constructed as shown in Fig. 1. The four large rectangles represent physical or operational barriers to reduce hazards.

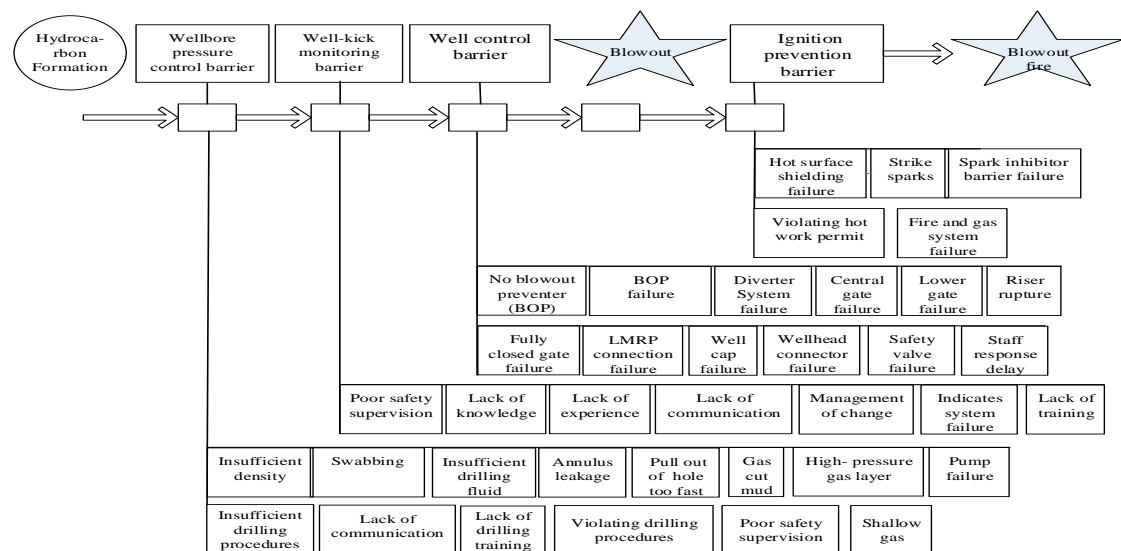


Fig. 1 Barriers Failure model of blowout fire accident

From Fig. 1, it can be seen that safety measures to prevent blowout fire are divided into four levels, which consist of wellbore pressure control barrier, well kick monitoring barrier, well control barrier and ignition prevention barrier. The first barrier is mainly used to balance the pressure inside the wellbore and prevent the occurrence of the well kick. The well kick monitoring barrier is used to timely detect the precursors of well kick before the occurrence of the blowout. The well control barrier is the emergency response measures after blowout. The last level of the model is the ignition prevention barrier, which is used to eliminate the potential ignition source and prevent the blowout from escalating to blowout fire.

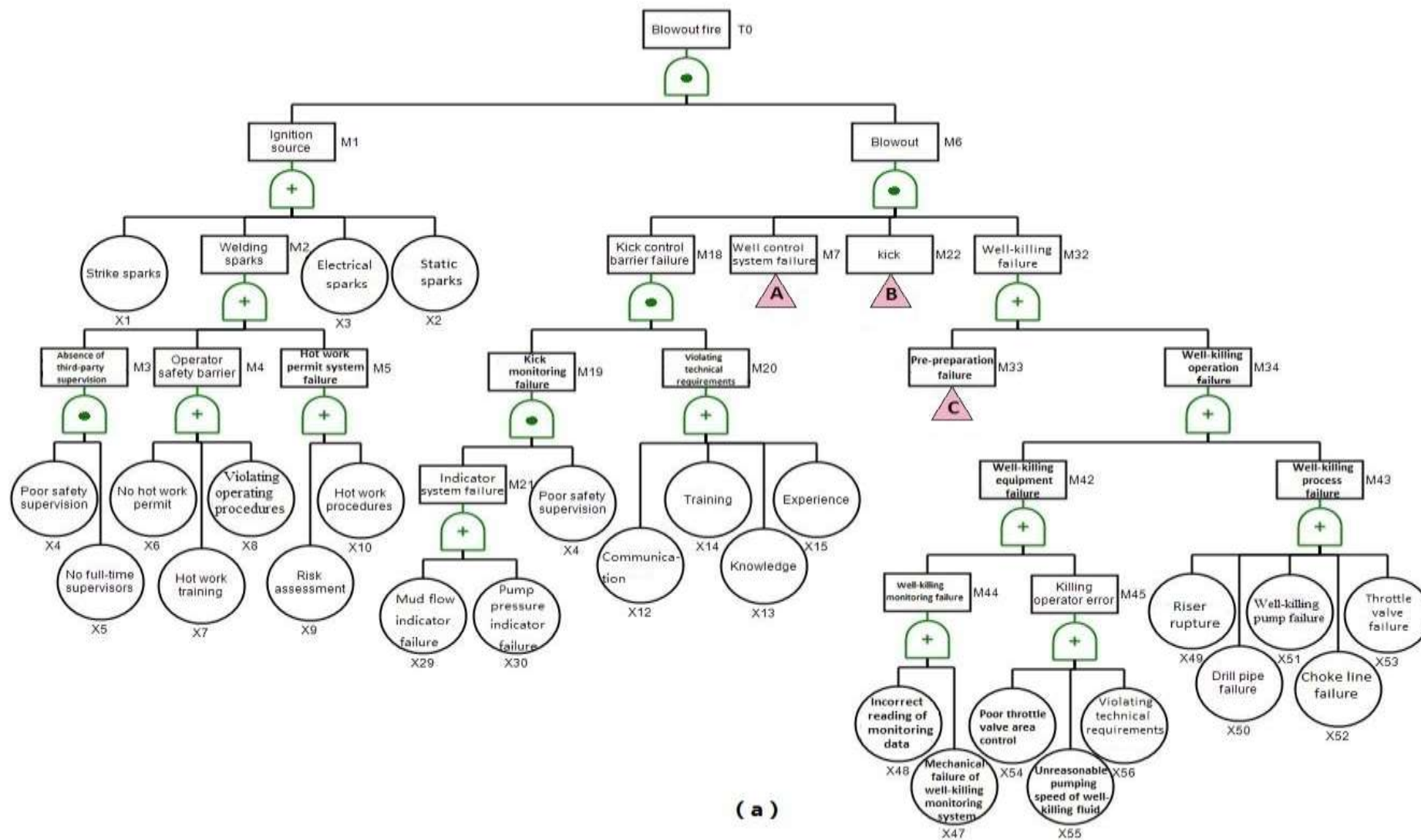
2.3 Fault tree model of blowout fire

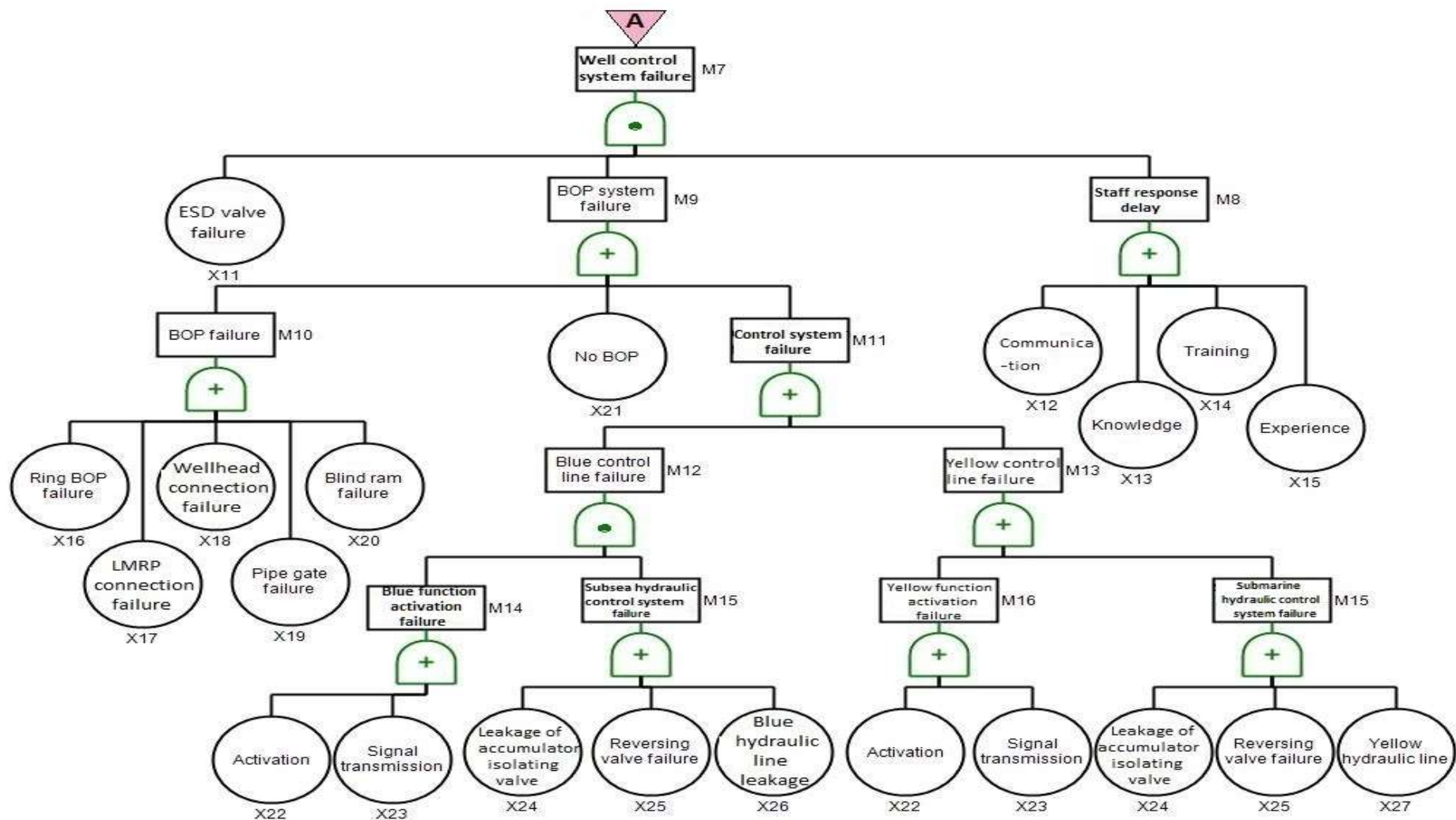
The 2837 fire accidents of offshore platforms in the Gulf of Mexico during the period from 1976 to 2015 are analyzed to determine the main causes and processes of fire accidents [18]. The FT of blowout fire is proposed as shown in Fig. 2, which is constructed based on the above barrier failure model and the statistical analysis of historical accident. There are 58 basic events that contribute to the occurrence of blowout fire accidents. Their occurrence probabilities are determined

according to the statistics of historical data from Offshore Reliability Data, Health and Safety Executive and Bureau of Safety and Environment as shown in Table 1(Holland, 1997; Engevik, 2007; Jyoti et al., 2015; BSEE, 2019).

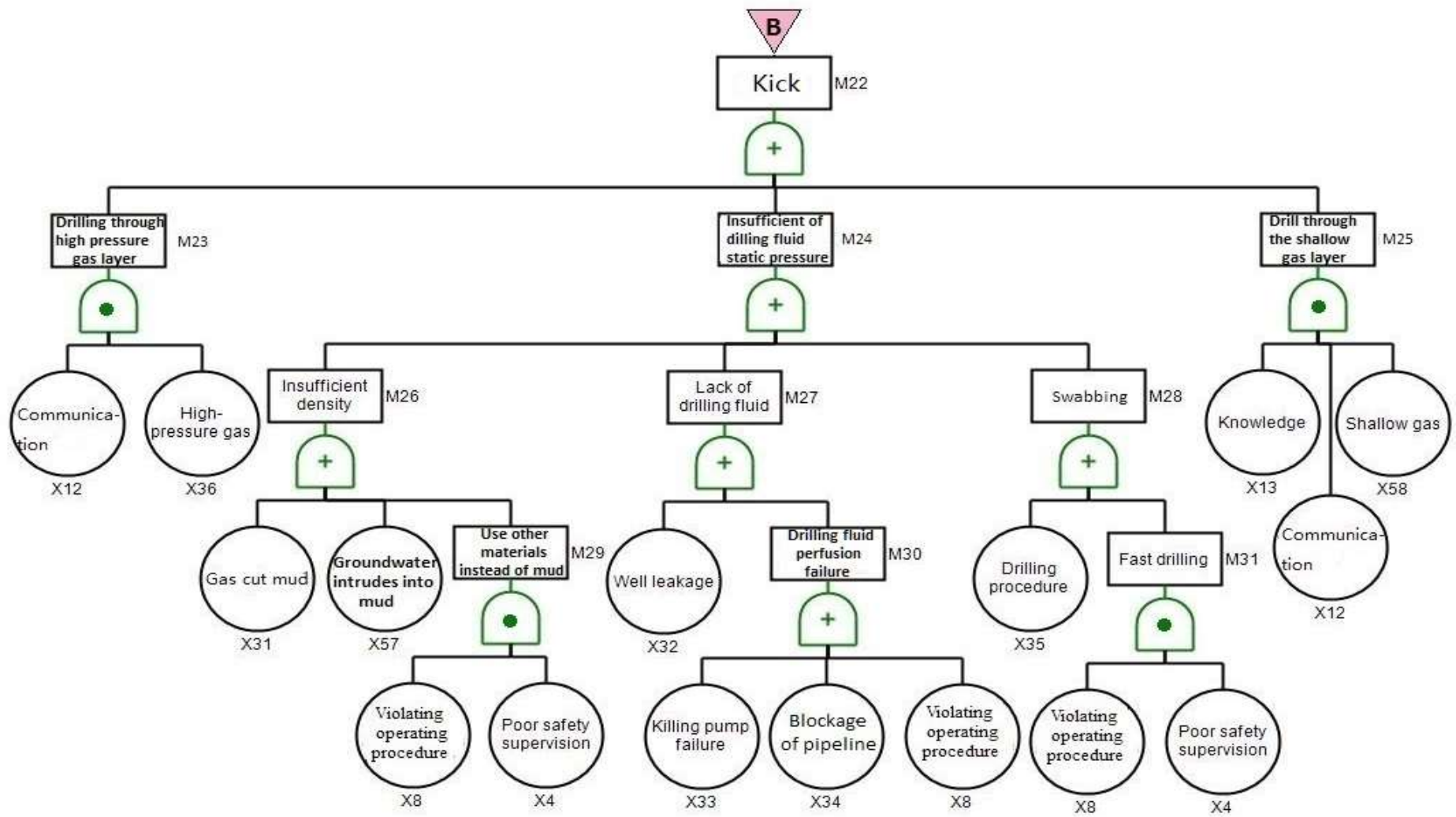
Table 1 Probability of basic events (Holland, 1997; Engevik, 2007; Jyoti et al., 2015; BSEE, 2019)

Basic events	Probability (10 ⁶ hour)	Basic events	Probability (10 ⁶ hour)
Strike sparks (X1)	6.3E-3	Well leakage (X32)	2.7E-3
Static sparks(X2)	1.1E-3	Killing pump failure(X33)	4.3E-3
Electrical spark(X3)	1.1E-3	Clogged pipeline (X34)	5E-5
Poor safety supervision(X4)	4.6E-4	Drilling procedure (X35)	7E-4
No full-time supervisor(X5)	7.4E-4	High-pressure gas layer (X36)	1.5E-2
No hot work permit(X6)	5.5E-3	Insufficient technical handover(X37)	6.3E-3
Hot work training(X7)	8.6E-3	Insufficient equipment safety check(X38)	2.5E-2
Violating operating procedures (X8)	1.7E-4	Unfamiliar with wellbore(X39)	5.6E-3
Risk assessment(X9)	1.8E-4	Lack of well-killing experience(X40)	1.25E-3
Hot work procedures (X10)	3E-6	Insufficient reserve plan (X41)	3.5E-3
ESD valve failure(X11)	1.3E-4	No periodic inspection of well-killing material(X42)	2.5E-2
Communication(X12)	1.89E-3	Invalid daily record(X43)	5.6E-3
Knowledge(X13)	1.2E-3	Inadequate well-killing technology(X44)	1.25E-3
Training(X14)	1.89E-3	Inadequate emergency well-killing plan (X45)	5E-4
Experience(X15)	1.1E-3	Design error of operator(X46)	2.2E-3
Ring BOP failure(X16)	3E-5	Killing monitoring system failure (X47)	5E-4
LMRP connection failure(X17)	1E-6	Fail to read the monitoring data correctly (X48)	2.5E-3
Wellhead connection failure(X18)	3E-5	Riser rupture(X49)	1.25E-3
Pipe gate failure(X19)	3E-5	Drill pipe failure(X50)	1.25E-3
Blind ram failure(X20)	1E-5	Well-killing pump failure (X51)	3.5E-3
No BOP (X21)	3E-5	Choke line failure(X52)	2.2E-3
Activation(X22)	2.37E-5	Throttle failure(X53)	1E-2
Signal transmission (X23)	3.35E-5	Poor throttle valve area control(X54)	5E-4
Leakage of accumulator isolating valve(X24)	1.03E-5	Unreasonable pumping speed of well-killing fluid(X55)	4.3E-3
Reversing valve failure (X25)	1.32E-5	Failed to follow the technical requirements (X56)	1.92E-4
Blue hydraulic line leakage(X26)	2.08E-5	Groundwater intrudes into mud (X57)	3E-5
Yellow hydraulic line leakage(X27)	2.08E-5	Shallow gas (X58)	3E-5
Display wrong mud flow (X29)	2E-3	Violating the technical requirements (X59)	1.92E-4
Display wrong pump pressure (X30)	2E-3		
Gas gut mud (X31)	3E-5		





(b)



(c)

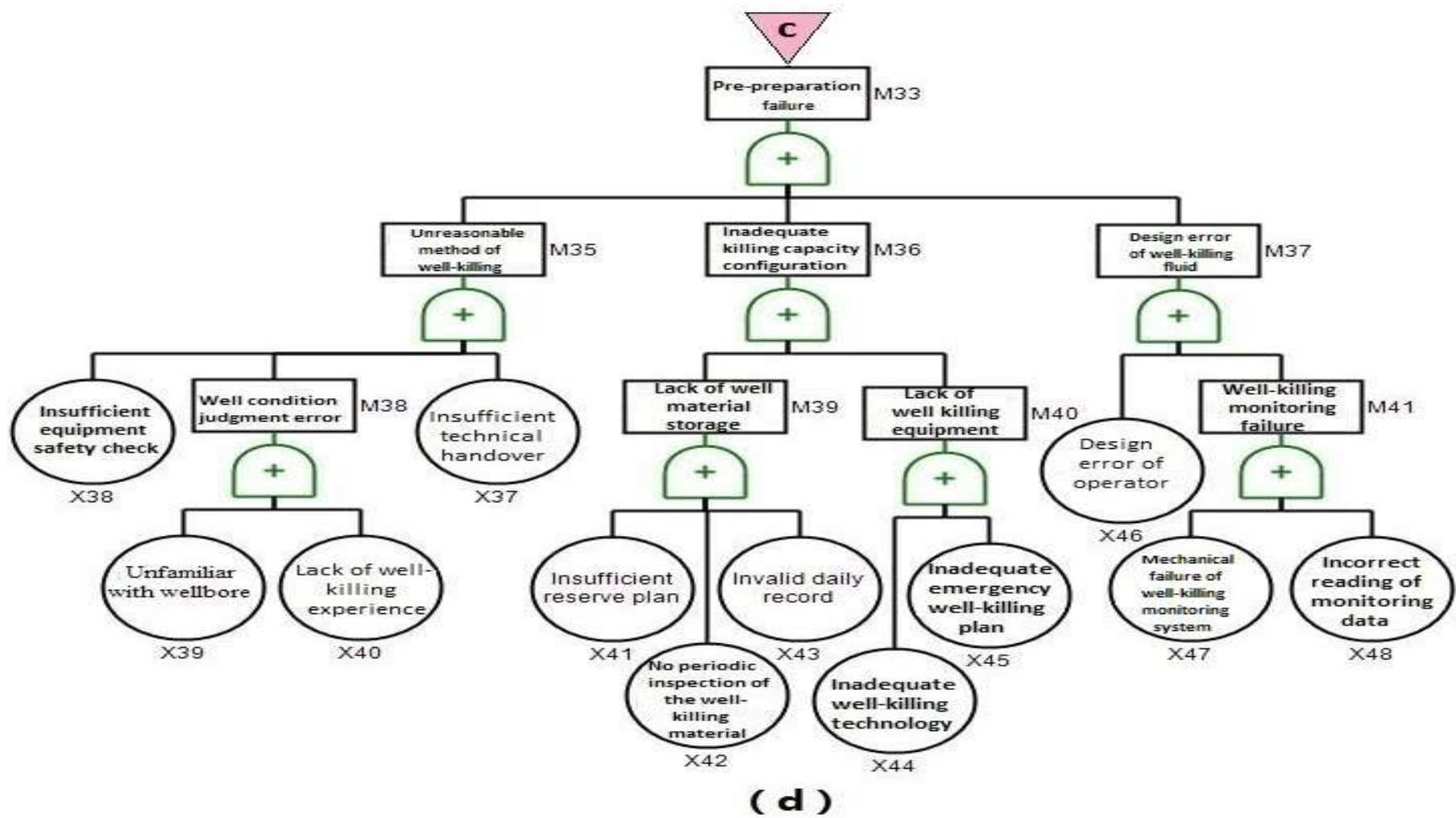


Fig. 2 Fault Tree of blowout fire on offshore drilling platforms

Seen from Fig. 2, both blowout and ignition source are the coupling interactions of human errors, organizational defects and equipment failures. There are 60 basic events contributing to the blowout fire as shown in Table 1. There are 57 minimal cut sets as shown in Table 2. The probability of blowout fire is estimated as $4.748E-10$.

2. 4 Fussel-Vesely measure of importance

In this section, the Fussel-Vesely method is adopted to measure the importance of the basic events and minimum cut sets. Fussel-Vesely measure of importance for basic events is defined as the ratio of the occurrence probability of the union of the minimum cut sets containing event X_i over the occurrence probability of the top event.

The importance of X_i is represented by $I(X_i)$.

$$I(X_i) = P(U(\text{cut sets containing } X_i)) / P(\text{top event}) \quad (1)$$

where, U stands for “union” or “OR” operation.

The importance of minimum cut sets is defined as the ratio of the occurrence probability of minimum cut set i (i.e. MC_i) over the occurrence probability of the top event (Andrews, 1993).

The importance of MC_i is represented by $I(MC_i)$:

$$I(MC_i) = P(MC_i) / P(\text{top event}) \quad (2)$$

The Fussell-Vesely importance order of the minimal cut sets are listed as follows:
 $IFV(43) > IFV(53) > IFV(9) = IFV(42) > IFV(54) = IFV(13) > IFV(44) > IFV(55) > IFV(46) > IFV(25) > IFV(29) = IFV(35) > IFV(51) > IFV(47) = IFV(2) > IFV(48) > IFV(4) = IFV(20) > IFV(26) > IFV(5) > IFV(41) > IFV(49) > IFV(3) = IFV(57) > IFV(56) > IFV(37) > IFV(52) > IFV(16) > IFV(38) > IFV(33) > IFV(18) > IFV(50) > IFV(10) > IFV(12) > IFV(14) > IFV(39) > IFV(6) > IFV(27) > IFV(45) > IFV(8) > IFV(23) > IFV(1) > IFV(34) > IFV(17) > IFV(32) > IFV(19) > IFV(28) > IFV(24) > IFV(56) > IFV(21) > IFV(11) > IFV(15) > IFV(30) > IFV(22) > IFV(31) > IFV(7)$.

The Fussell Vesely importance order of the main basic events are listed in descending order as follows:
 $I(X_{12}) > I(X_{38}) > I(X_8) > I(X_{14}) > I(X_{36}) > I(X_7) > I(X_{33}) > I(X_1) > I(X_{13}) > I(X_{49}) > I(X_6) > I(X_{15}) > I(X_{32}) > I(X_{37}) > I(X_{39}) > I(X_{51}) > I(X_{47}) > I(X_3) > I(X_{42}) > I(X_{35}) > I(X_{48}) > I(X_2) = I(X_{43}) = I(X_{44}) = I(X_{40}) > I(X_{41}) = I(X_{45}) = I(X_{52}) = I(X_9) > I(X_{46}) = I(X_{54}) = I(X_{55}) = I(X_{56}) = I(X_{34}) = I(X_{53}) = I(X_{31}) = I(X_{57}) > I(X_{50}) = I(X_{10}) = I(X_4) = I(X_5) > I(X_{58}) > I(X_{29}) = I(X_{30}) = I(X_{11}) > I(X_{23}) = I(X_{21}) = I(X_{16}) = I(X_{18}) = I(X_{19}) = I(X_{22}) = I(X_{25}) = I(X_{24}) = I(X_{20}) > I(X_{17}) > I(X_{26}) = I(X_{27})$.

3 Dynamic probability analysis of blowout fire based on System Dynamics

3.1 System Dynamics Method

A SD is an analytical method of combining qualitative analysis, quantitative analysis and synthesis reasoning, which is regarded as an effective approach for nonlinear complex systems and scientific decision-making. The SD modeling is useful for understanding the underlying behavior of complex systems over time, taking into account time delays and feedback loops (Calvo and García, 2013). Unlike traditional approaches that place an emphasis on linear cause-and-effect, the SD focuses on feedback between variables in a system. The focus on feedback enables a more holistic view of the real world and places emphasis on the complex dynamics that invariably exist within systems. Some of the reported benefits of SD include dynamic and nonlinear analysis (Schade and Rothengatter, 2003) and a platform for policy makers and stakeholders to understand the possible impacts of policies and strategies over a period of time (Maalla and Kunsch, 2008). In this section, the dynamic relationship among the equipment, organizational function and human behavior is studied through the establishment of the SD model using Vensim software. Vensim is a simulation software tool developed by Ventana Systems (Vensim, 2019). It primarily supports continuous simulation (SD), with some discrete event and agent-based modelling capabilities. Vensim provides a graphical modeling interface with stock and flow and causal loop diagrams, on top of a text-based system of equations in a declarative programming language. It includes a patented method for interactive tracing of behavior through causal links in model structure, as well as a language extension for automating quality control experiments

on models called Reality Check (Peterson and David, 1994). Sensitivity analysis options provide a variety of ways to test and sample models, including Monte Carlo simulation with Latin Hypercube sampling.

3.2 Dynamic probability prediction model of blowout fire

It is difficult to directly build the causal loop diagrams of the SD model of blowout fire due to the complexity of offshore drilling and the complicated causality between their technical, human, and organizational factors. However, it is easier to draw the causal loop diagrams of a SD model by integrating FT with the SD (Mohaghegh et al., 2009). The SD model is proposed, as shown in Fig. 3, according to the causal relationship of FT in Section 2.2. The occurrence probabilities of causal factors are presented in Table 1.

4. Simulation Results and Analysis

4.1. Dynamic Probability of Blowout Fire

The time boundary condition is set to display the dynamic change trend of blowout fire probability for each month within 48 months: INITIAL TIME=0; FINAL TIME=48; TIME SETP=1; Units for Time=month. The occurrence probability of each basic event in Table 1 is put into the established simulation model. Thereafter, time series data sets can be generated through the dynamic analysis of the simulation model. The dynamic probability of blowout fire for an offshore drilling platform is shown in Fig. 4.

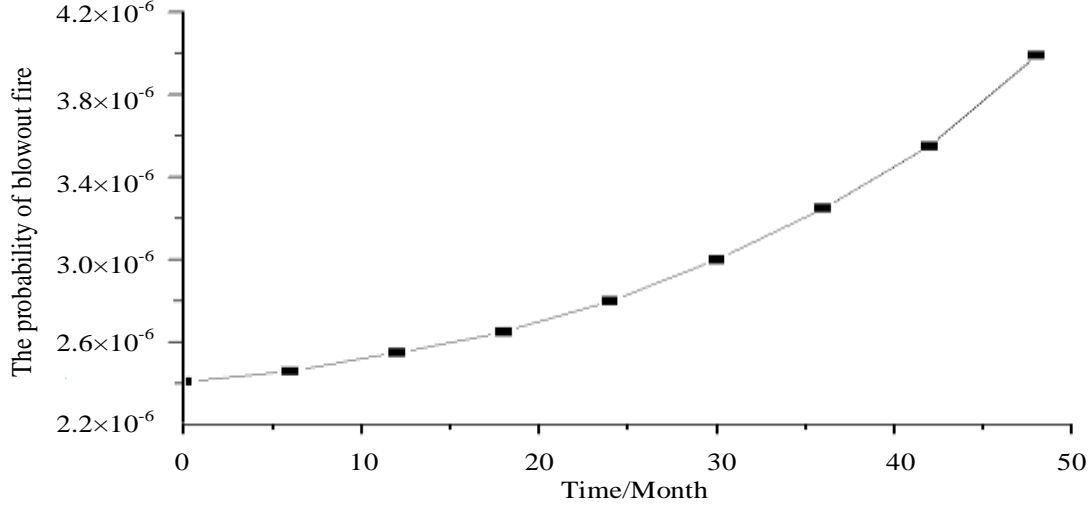


Fig. 4 Dynamic blowout fire probability of an offshore drilling platform

As shown in Fig. 4, the blowout fire probability of an offshore drilling platform is between 2.41E-6 and 3.997E-6 within four years. The corresponding historical data from the statistics of the Bureau of Safety and Environmental Enforcement (BSEE, 2019) is around 3.18E-6 (Wang et. al, 2016). From the comparison of simulation results with the real data, it can be seen that the proposed model can be used to reliably predict the dynamic probability of blowout fire. The fire probability in 48 months will increase with time due to the ignorance of safety management. This is because the fire probability is predicted without considering the effect of strengthening safety management. If the above identified contributing factors of the blowout fire are managed to a reasonable level, the fire probability should be reduced correspondingly.

4.2. Sensitivity Analysis Based on Mutual Information

In probability theory and information theory, the mutual information of two variables is a measure of the mutual dependence between the two variables. More specifically, it quantifies the "amount of information" obtained about one variable, through the other variable. The concept of mutual information is intricately linked to that of entropy of a variable, a fundamental notion in information theory that defines the "amount of information" held in a variable. The information entropy is the expected value of the information contained in each message, which can be used to characterize the uncertainty about the source of information. The entropy is expressed by Eq. (3) (Borda and Monica, 2011).

$$H(Y) = -\sum_i P(y) \log P(y) \quad (3)$$

where, $P(y)$ is the probability mass function.

The mutual information of two discrete variables X and Y can be defined as:

$$H(X:Y) = \sum_{y \in Y} \sum_{x \in X} P(x,y) \log_2 \left(\frac{P(x,y)}{p(x)p(y)} \right) \quad (4)$$

where, $P(x, y)$ is the joint probability distribution function of X and Y , while $P(x)$ and $P(y)$ are the respective marginal probability distribution functions of X and Y .

The sensitivity analysis is carried out to determine the impact of the contributory factors on blowout fire. The results of sensitivity analysis for well kick, the failure of the well control barrier, the failure of the well control system, blowout and fire are shown from Fig. 5 to Fig. 9 respectively.

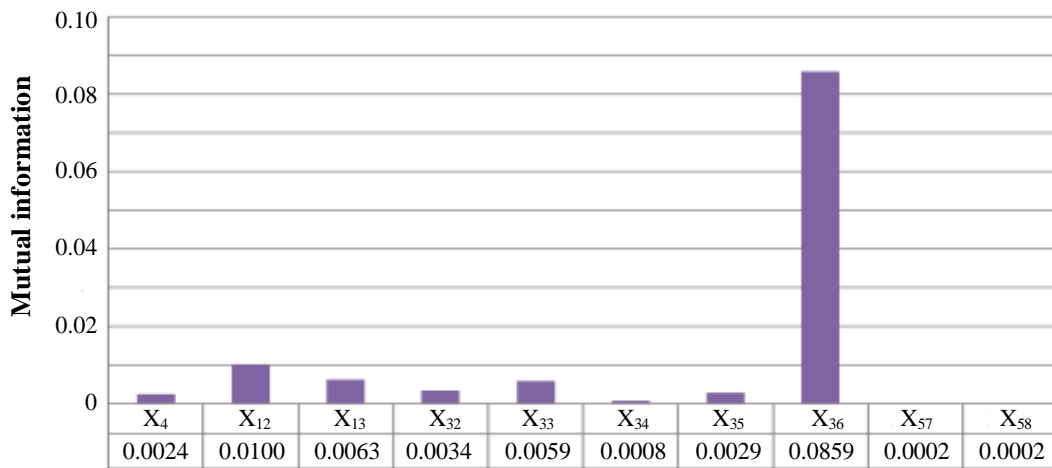


Fig. 5 Mutual information of basic events and well kick

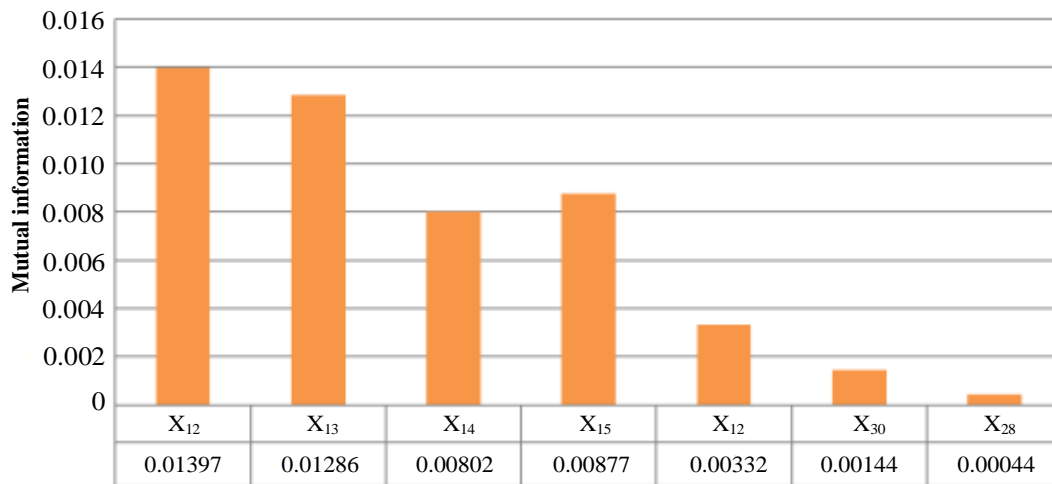


Fig. 6 Mutual information of basic events and well kick control barrier failure

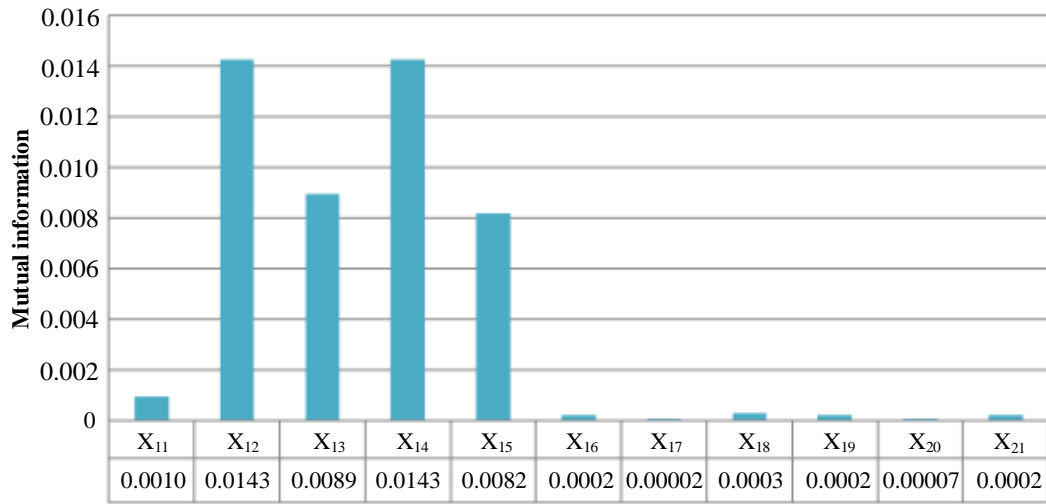


Fig. 7 Mutual information of basic events and well-control system failure

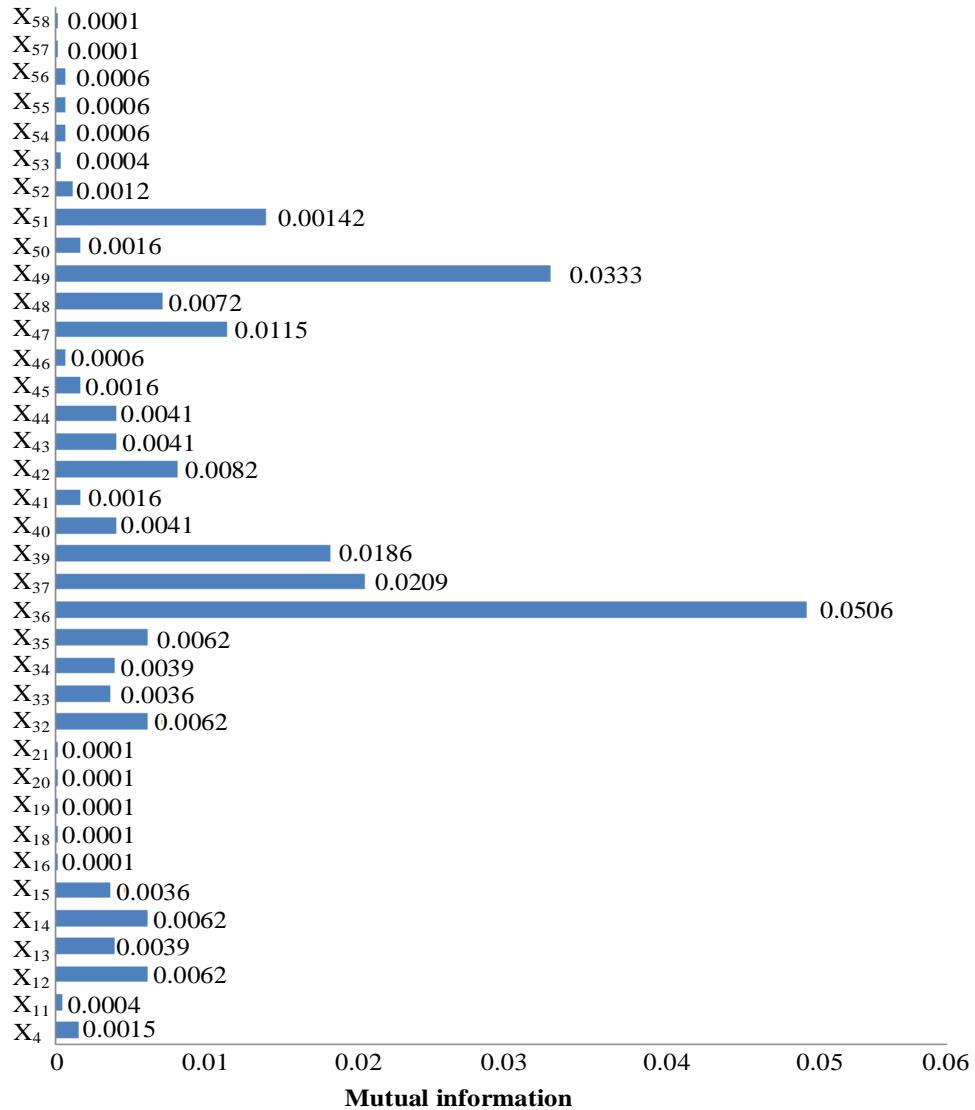


Fig. 8 Mutual information of basic events and blowout

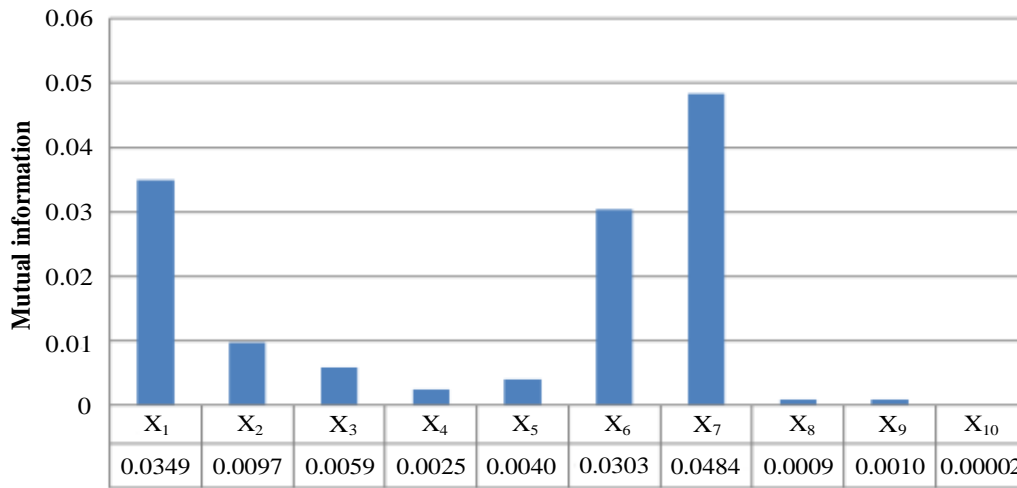


Fig. 9 Mutual information of basic events and fire

From Fig. 5, it can be seen that X36 High-pressures gas, X12 Communication, X13 Knowledge and X33 Drilling pump failure are the main contributing factors of well kick.

Seen from Fig. 6, the sensitivity of node variable in descending order are X12 Communication, X13 Knowledge, X15 Experience, X14 Training and X30 Pump pressure indicator failure. Insufficient communication, knowledge, experience and training contribute more to the failure of well kick control barrier.

As shown in Fig. 7, the sensitivity of node variables in descending order are X12 Communication, X14 Training, X13 Knowledge, X15 Experience, X11 ESD valve failure, X18 Wellhead connection failure, X16 Annular BOP failure, X19 Pipe gate failure, X21 No BOP, X20 Blind ram failure and X17 LMRP connection failure. The result shows that insufficient communication, training, knowledge and experience are the main contributing factors that lead to the delay response of personnel. The failure of ESD valve and wellhead connection contribute more to the failure of well-control system.

From Fig. 8, it can be seen that X36 High-pressure gas, X49 Riser rupture, X37 Insufficient technical handover, X39 Unfamiliar with the wellbore, X51 Well-killing pump failure, X47 Mechanical failure of well-killing monitoring system are the main contributing factors of blowout.

As shown in Fig. 9, the sensitivity of variables in descending order are X7 Hot work training, X1 Strike sparks, X6 No hot work permit, X2 Electrical sparks, X3 Static sparks, X5 Lack of supervisors, X4 Poor safety supervision, X9 Risk assessment, X8 Violating standard operation procedures and X10 Hot work procedures separately. Therefore, hot work training, Strike sparks, No hot work permit, Electrical sparks, Static sparks and Lack of supervisors are the main contributing factors for blowout fire.

5. Conclusions

1) The Barrier Failure Model is constructed to analyze the process and the potential pathways of blowout fire. The FT model of blowout fire for offshore drilling platforms is built based on the statistics analysis of historical data. The probability of blowout fire is estimated as 4.748E-6 using the built FT model.

2) The dynamic probability prediction model of blowout fire is proposed by integrating FT with a SD model.

From the simulation results of SD, it can be seen that the probability of blowout fire increases from 2.41E-6 to 3.997E-6 within 48 months. The comparison results between the simulation data and historical data show that the proposed model can be used to predict the dynamic probability of blowout fire on offshore drilling platforms.

3) The proposed methodology can be used to develop some targeted safety precautions to prevent the occurrence of similar accidents because the main contributing factors can be identified. X36 High-pressure gas, X7 Hot work training, X1 Strike, X49 Riser rupture, X6 No hot work permit, X37 Insufficient technical handover, X39 Unfamiliar with the wellbore, X12 Communication, X13 Knowledge, X47 Mechanical failure of well-killing monitoring system, X15 Experience and X14 Training are the main contributing factors of blowout fire.

4) By comparing sensitivity analysis with importance analysis, the Fussell Vesely importance method can be used to compare the basic events in terms of their contribution to the accident.

Acknowledgments

This work is supported by Shandong Provincial Natural Science Foundation (Project No. ZR2019MEE080), “Key R&D program projects in Shandong Province (Project No.2018GSF120021) and “the Fundamental Research Funds for the Central Universities” (Project No. 17CX02062 and No.19CX02025A)”. This research has received funding from the EU H2020 research and innovation program under the Marie Skłodowska-Curie grant agreement– 840425. This research is also partially supported by EU H2020 RISE 2016 RESET – 730888.

References

- Abimbola, M., Khan, F., 2016. Development of an integrated tool for risk analysis of drilling operations. *Process Safety & Environmental Protection*. 102, 421-430.
- Adedigba, S., Oloruntobi, O., Khan, F., et al., 2018. Data-driven dynamic risk analysis of offshore drilling operations. *Journal of Petroleum Science & Engineering*. 165, 444-452.
- Andrews, J.D., Moss, T.R., 1993. *Reliability and Risk Assessment*, Longman Scientific and Technical, John Wiley in U.S.A.
- Borda, Monica, 2011. *Fundamentals in Information Theory and Coding*. Springer, ISBN 978-3-642-20346-6.
- BSEE, Bureau of safety and environmental enforcement, 2019, Offshore Incident Investigations. <http://www.bsee.gov/Inspection-and-Enforcement/Accidents-and-Incidents/Incident-Investigations>.
- Calvo, G. S., García, E. Z., 2013. Norwegian Oil and Gas Industry Project to Reduce the Number of Hydrocarbon Leaks with emphasis on Operational Barriers Improvement. *Revista De Patología Respiratoria*. 14(4), 147–149.
- Chen, L.J., Yan, X.P., Huang, L.W., et al., 2018. A systematic simulation methodology for LNG ship operations in port waters: A case study in Meizhou Bay. *Journal of Marine Engineering and Technology*. 17(1), 12-32.
- Engevik, M.O., 2007. Risk Assessment of Underbalanced and Managed Pressure Drilling Operations. tesis de Maestría. NTNU.
- Goh, Y. M., Peter, E.D., Love, 2012. Methodological application of system dynamics for evaluating traffic safety policy. *Safety Science*. 50, 1594–1605.
- Holland, P., 1997. *Offshore Blowouts: Causes and Control*. Gulf Professional Publishing.
- Hollnagel, E., 2004. *Barriers and accident prevention*, Aldershot, Ashgate.
- Jyoti, B., Rouzbeh, A., Vikram, G., Khan, F., 2015. Risk analysis of deep water drilling operations using Bayesian network. *Journal of Loss Prevention in the Process Industries*. 38, 11-23.
- Leveson, N., 2004. A new accident model for engineering safer systems. *Safety Science*. 42, 237-270.
- Maalla, B.M.E., Kunsch, P.L., 2008. Simulation of micro-CHP diffusion by means of system dynamics. *Energy Policy*. 36, 2308–2319.
- Mohaghegh, Z., Kazemi, R., Mosleh, A., 2009. Incorporating organizational factors into Probabilistic Risk Assessment (PRA) of complex socio-technical systems: A hybrid technique formalization. *Reliability Engineering & System Safety*. 94(5), 1000-1018.
- Tamim, N., Laboureur, D. M., Mentzer, R. A., RashidHasan, A., Sam Mannan, M., 2017. A framework for developing leading indicators

for offshore drill well blowout incidents. *Process Safety and Environmental Protection*. 106, 256–262.

OREDA. (2002). *Offshore reliability data handbook* (4th ed.). SINTEF.

Perez, P., Tan, H., 2018. Accident Precursor Probabilistic Method (APPM) for modeling and assessing risk of offshore drilling blowouts – A theoretical micro-scale application. *Safety Science*. 105, 238-254.

Peterson, David W.; Eberlein, Robert L., 1994. "Reality check: A bridge between systems thinking and system dynamics". *System Dynamics Review*. 10 (2–3): 159–174.

Rathnayaka, S., Khan, F., Amyotte, P., 2004. SHIPP methodology: Predictive accident modeling approach, Part II. Validation with case study. *Process Safety and Environmental Protection*. 89, 2011, 75-88.

Rathnayaka, S., Khan, F., Amyotte, P., 2011. SHIPP methodology: Predictive accident modeling approach, Part I- Methodology and model description. *Process Safety and Environmental Protection*. 89(3), 151-164

Schade, W., Rothengatter, W., 2003. Improving assessment of transport policies by dynamic cost–benefit analysis. *Transportation Finance, Economics and Economic Development 2003 – Planning and Administration*. Transportation Research Board Natl Research Council, Washington.

Strand, G. O., Lundteigen, M. A., 2016. Human factors modelling in offshore drilling operations. *Journal of Loss Prevention in the Process Industries*. 43, 654-667.

Strand, G. O., Lundteigen, M. A., 2017. On the role of HMI in human reliability analysis of offshore drilling operations. *Journal of Loss Prevention in the Process Industries*. 49, 191-208.

Sule, I., Khan, F., Butt, S., et al., 2018. Kick control reliability analysis of managed pressure drilling operation. *Journal of Loss Prevention in the Process Industries*. 52, 7-20.

Sun, Z. Y., Zhou, J. L., Gan, L. F. , 2018. Safety assessment in oil drilling work system based on empirical study and Analytic Network Process. *Safety Science*. 105(6), 86-97.

Vandenbussche, V., Bergsli, A., Brandt, H., Brude, O. W. W., Nissen-lie, T.R., 2012. Well-specific blowout risk assessment. In: *International Conference on Health, Safety and Environment in Oil and Gas Exploration and Production*.

Vensim, <https://vensim.com/>, 2019.

Vinnem, J. E., Hestad, J. A., Kvaløy, J. T., et al., 2010. Analysis of root causes of major hazard precursors (hydrocarbon leaks) in the Norwegian offshore petroleum industry. *Reliability Engineering & System Safety*. 95(11), 1142-1153.

Wang, Y. F., Li, Y. L., Zhang, B., et al., 2015. Quantitative Risk Analysis of Offshore Fire and Explosion Based on the Analysis of Human and Organizational Factors. *Mathematical Problems in Engineering*. 2015 (2), 1-10.

Wang, Y. F., LI, Y.L., ZHANG, B., YAN, P.N., 2016. Probability analysis on the offshore platform fire based on the logic tree and Bayesian network model (in Chinese). *Journal of Safety and Environment*. 16(5), 66-72.

Westergaard, R., 1987, *All about Blowout*, Norwegian Oil Review, ISBN 82-991533-0-1.

Zhang, L., Wu, S., Zheng, W., et al, 2018. A dynamic and quantitative risk assessment method with uncertainties for offshore managed pressure drilling phases. *Safety Science*. 104, 39-54.