INTEGRATION OF HUMAN FACTORS IN OFFSHORE BLOWOUT RISK ASSESSMENT

A Thesis

by

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ABSTRACT

Human factors (HFs) are important factors to the Macondo well blowout, but traditional risk assessment has not addressed them. Some common methodologies for offshore drilling risk assessment are fault tree, event tree and Bow-tie analysis, which are static structure and cannot consider common causes or conditional dependent factors. The Hybrid Causal Logic (HCL) model is a multi-layered, dynamic ever green model that can incorporate human factors. The HCL model enables the prediction of the probability of human errors and explains the reasons of human errors occurrence. This research applied the HCL model to offshore blowout risk assessment by using swabbing induced kick as a case study.

The contribution of human factors to accidents in offshore industry has been identified based on literature review. They were categorized as individual factors, group factors and organization factors. The sub-heading human factors was considered as influencing factors in the HCL model.

In the HCL model, an event tree was developed to display the links between kick and blowout. The safety barriers were identified as kick detection, kick control and shear ram. Basic events that could contribute to kick scenario, failure of kick detection, kick control and shear ram to seal the well were developed in fault trees. Then, the fault trees and event tree were mapped into Bayesian networks (BN). The human factors that could contribute to causal events in fault trees were also linked with BN. Objected-oriented

BN was applied to link the fault trees models into a higher-level model with input and output nodes.

This higher-level model was able to evaluate the impact of different HFs' levels on the probability of kick and blowout. The most influencing factors could also be tracked in this model for risk control and mitigation. Based on the assumptions and structure of this model, competence, pressure, communication and management were identified as the most influencing factors for blowout escalating by swabbing induced kick. The blowout probability could be decreased four times if the competence level of an operator was increased from a low level to a high level.

DEDICATION

To my family: parents, husband, and daughter.

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NOMENCLATURE

APJ	Absolute probability judgment
BBN	Bayesian belief network
BN	Bayesian network
BOP	Blowout preventer
BORA	Barrier and operational risk analysis
CPT	Conditional probability table
CSB	Chemical Safety Board
DHSG	Deepwater Horizon Study Group
ET	Event tree
FT	Fault tree
HAZOP	Hazard and operability study
HCL	Hybrid causal logic
HEART	Human error assessment and reduction technique
HFs	Human factors
HMI	Human machine interface
HRA	Human reliability analysis
HSE	Health and Safety Executive
NPRT	Negative pressure test
NPT	Node probability table
OGP	Oil & Gas Producers

OOBNs	Object-oriented BNs
POOH	Pull out of hole
QRA	Quantitative risk analysis
RIF	Risk influencing factors
SHERPA	Systematic human error reduction and prediction approach
THERP	Technique for human error rate prediction
TNormal	Truncated normal distribution

TABLE OF CONTENTS

Page

LIST OF FIGURES

LIST OF TABLES

Page

1 INTRODUCTION

1.1 Background

On April 20th, 2010, 11 people were killed and 17 were injured in the Deepwater Horizon Blowout accident. Hydrocarbon released from the Macondo well because of an uncontrolled blowout, resulting in fire and explosions on the Deepwater Horizon offshore oil platform. Figure 1 shows the Deepwater Horizon after the explosion and the sinking platform. It is considered the worst and largest oil spill in the U.S. history. After this accident, the offshore industry focused new attention on human factors (HFs) because HFs is considered one of the ultimate sources of the resulting consequences of these events. According to a comprehensive study of more than 600 well failures from 1988 to 2005, 80% of major failures in offshore structures were due to human factors (HFs) [1].

Figure 1 Deepwater Horizon after the explosion [2]

1.2 Offshore drilling and blowout

With the increasing demand for oil and gas all over the world and new developing technologies of oil exploration and drilling, the global offshore industry is expected to continuing increase in the coming years. According to Global Business Intelligence (GBI) estimation, the offshore drilling spending has increased dramatically during the last 15 years and it is estimated that the offshore drilling activity will still increase.

The sub-operations of drilling involve drilling, tripping out, tripping in, casing and cementing. Figure 2 shows a simplified sequence of drilling operations.

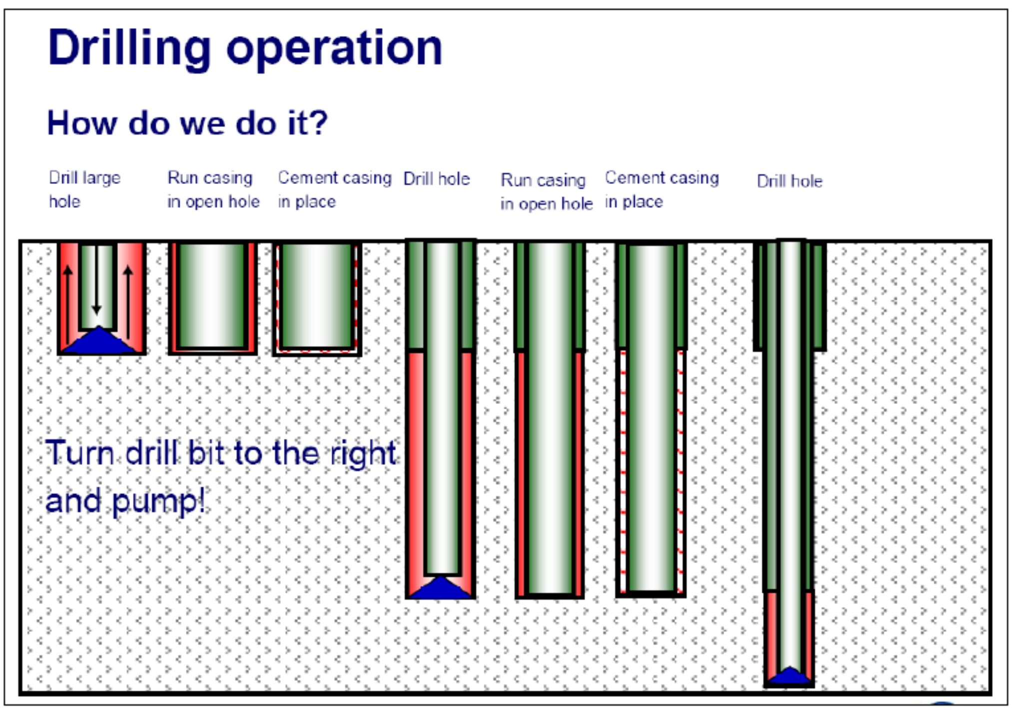


Figure 2 Simplified sequence of drilling [3]

Offshore drilling activities are among the highest risk because of the special working environment and complex characters of drilling operation. Offshore drilling is trending to deeper depth, with ever larger and more complex drilling rigs, which will increase the safety risk. One serious event in offshore drilling is blowout. Blowout is the uncontrolled release of oil and/or gas after pressure control systems have failed. Once the oil or gas is ignited, fire and explosion could result in a catastrophic disaster. Blowout accidents statistics show that most of blowouts happened in the drilling phase [4]. In order to prevent blowout, some safety barriers are established and each barrier relies on human to interact with the system.

1.3 Human factors and human errors

1.3.1 Human factors

There is no uniform definition about human factors so far. When it comes to safety, Health and Safety Executive (HSE) and International Association of Oil & Gas Producers (OGP) give their definition and explanation about human factors.

HSE definition [5]: Human factors refer to environmental, organizational and job factors, and human and individual characteristics that influence behavior at work in a way that can affect health and safety. HSE addressed three aspects, including the job, individual and organization factors. The job factor includes task, workload, environment, display & controls, procedures, and so on. The individual factor includes competence, skills, personality, attitudes, risk perception and so on. The organization factor includes safety culture, leadership, resources, work patterns, communications and so on.

OGP definition [6]: Human factor is the term used to describe the interaction of individuals with each other, with facilities and equipment, and with management systems". The detailed explanations are shown in Figure 3.

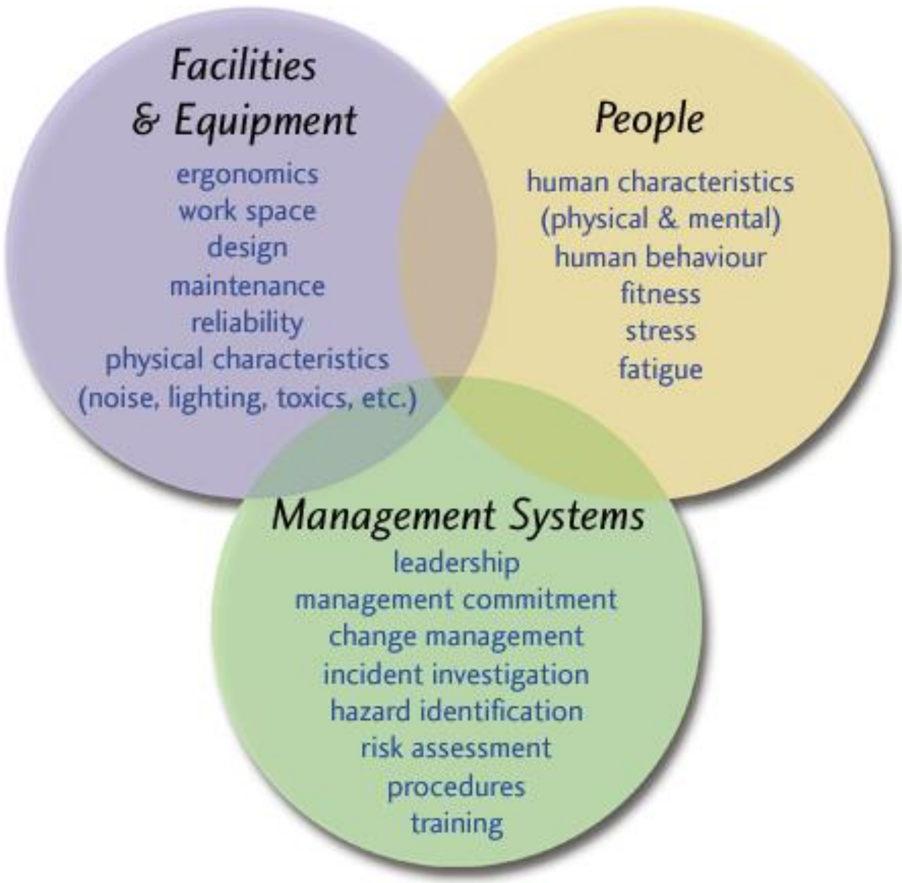


Figure 3 Human factors definition from OGP [6]

1.3.2 Human errors

Rasmussen developed an influential classification system to classify human performance into three levels, which is Skill, Rule and Knowledge (SRK) based behaviors [7]. The skill-based behaviors refer to highly practiced and automatic actions without conscious thought or attention. Rule-based behaviors apply learned rules or procedures to control activities in a familiar situation. Knowledge based behaviors are those in unfamiliar situation and in which a novel problem need to be solved. The distinction between skill-based behaviors and rule-based behaviors rely on individual's attention and training level.

Reason [8] categorized human failures based on the SRK model. The basic error types are described as slips, lapses and mistakes. He distinguishes rule-based mistakes and knowledge-based mistakes. Violations are also included in his taxonomy of human error, which used when people break the rule intentionally. The detail classification of human errors by Reason is shown in Figure 4.

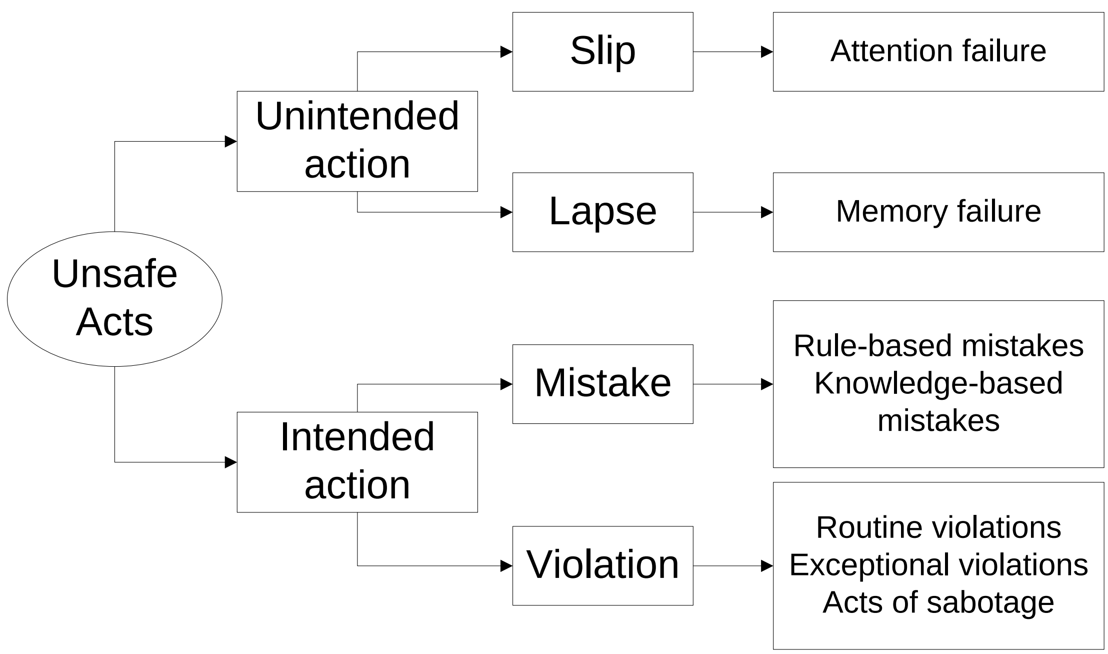


Figure 4 Reason's taxonomy of human errors [8]

Taxonomy of human error - slips, lapses, mistakes and violations are active errors, which can cause immediate adverse effects by front-line operators. Another kind of error is latent errors that are often hard to foresee and may lie dormant in the system for many years to trigger the accident. Most latent errors could be caused by designers, decision makers and maintenance person in the organizational and management aspects [8].

In offshore industry, the terms “human factors” and “human error” are often used interchangeably [9]. Rachael proposed a framework of the relationships between the underlying causes of human factors and the active human errors, which is shown in Figure 5. Human factors categories can be used to identify the underlying causes of accidents in the offshore oil industry. In his study, he defined the underlying human factors as individual, group and organization factors. Individual factors are competence, stress and motivation. Group factors are management, supervision and crew. Organization factors are company policies, company standards and systems and procedures. An improved categorization based on his work will be discussed later.

1.4 Contribution of HFs on the Macondo well blowout

After the Macondo Well blowout, many investigation reports have been published by different agencies, such as BP [10], CSB [11], DHSG [12] and National Commission on the BP Deepwater Horizon Oil Spill and Offshore Drilling [13]. Some reports addressed the contribution of human factors in the failure of several safety barriers.

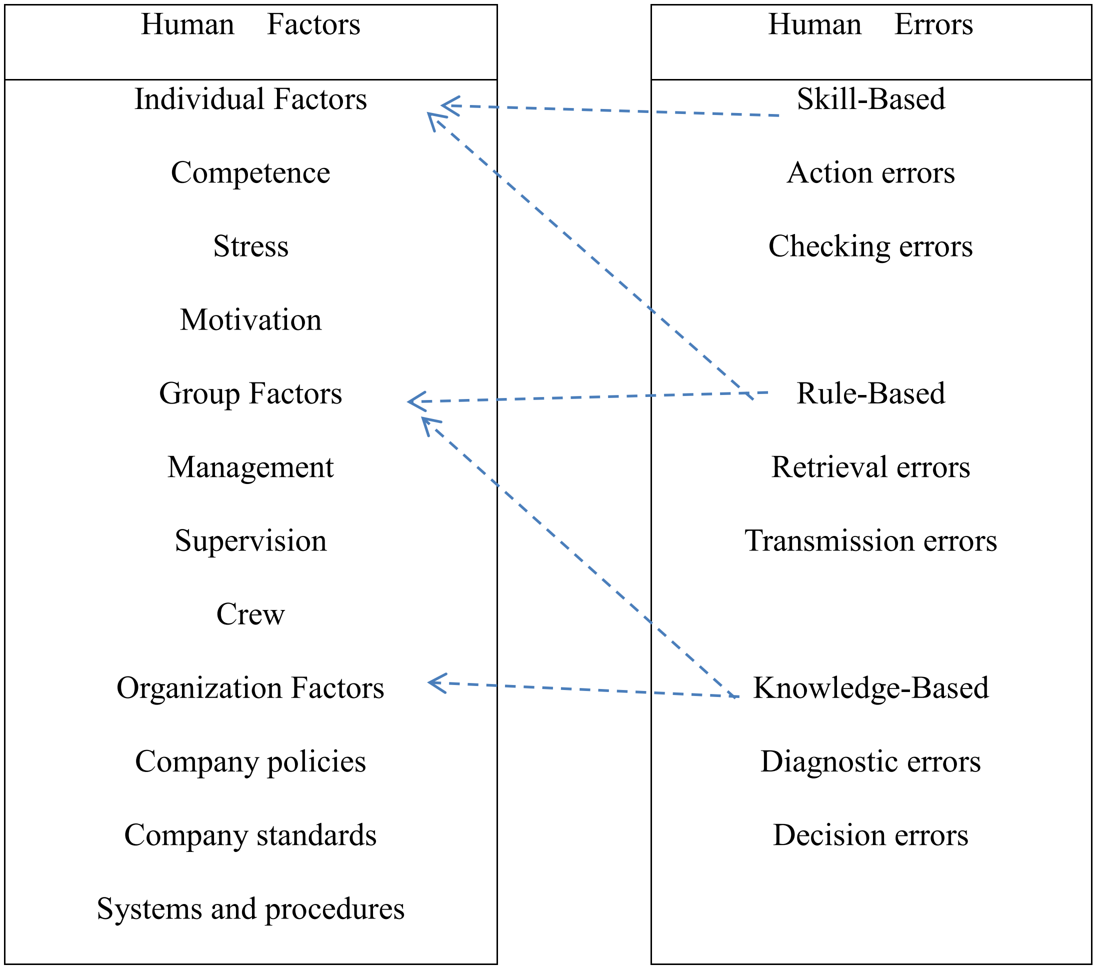


Figure 5 Relationship between human factors and human errors [9]

The BP accident investigation team released a report on this accident on Sep. 2010, in which eight defensive physical and operational barriers were identified. Najmedin Meshkati attacked BP's report stating that their investigation did not address human performance issues, organizational factors, and decision-making issues. The information about shift duration, worker fatigue and safety culture are not included in this report. BP's head of safety and operations also admitted that errors in human judgment contributed to three of the safety barriers' failures. A pressure test should have revealed problems, but people from BP and the Transocean rig interpreted it as successful by incorrect judgment. The pipe pressure was expected to drop, which some indicators had shown the pipe pressure had increased and were unrecognized for about 40 minutes, which shorten the emergency response time. The rig crew may have been distracted by simultaneous operations. The root cause of distraction was not identified in the report, which may be long shift duration and fatigue [14].

In kick detection, the operator did not detect kick at the early stage. The Chief Counsel's report from National Commission on the BP Deepwater Horizon Oil Spill and Offshore Drilling [13] pointed out that kick detection instrumentation was highly depend on human's abilities and attention.

The final report from the Deepwater Horizon Study group on the investigation of the Macondo Well blowout disaster also addressed the organization factors. This report [12] pointed out the malfunctions and shortsightedness of BP's organization. Poor decision making when choosing production over system protection was a key factor in the accident causation. Other factors such as not following required guidelines, poor maintenance, inadequate communications, unawareness of risks and no appropriate management of change were pointed out in the report. Also, the offshore oil and gas industry did not learn lessons from previous accidents, for example, another blowout happened just eight months before this accident in Montara well. Ultimately, it is not just the company that stands to benefit from learning lessons from accidents, but rather the entire offshore industry. This requires a good balance between operating companies, government and environmental organizations to prevent barriers failures.

Patrick Smith et al. [15] analyzed human error of the Macondo well blowout. He identified 25 human errors and developed an error classification system, which is divided into eight categories. The eight categories include design, maintenance/testing, policies/procedures, training, decision making, organization/management, risk perception/acceptance and communication. Their analysis shows the factor with the most contribution is organization or management.

1.5 Risk assessment methodology

Risk assessment is the process of identifying hazards, evaluating the levels of risk that related to the hazards quantitatively or qualitatively, and determining ways to reduce or eliminate the hazards to level of acceptable risk. The level of risk distribution is the product of the probability distribution and the consequences distribution. This study will focused on the probability of blowout scenarios. The risk assessment approaches that will be used are fault tree (FT), event tree (ET) and Bayesian Network (BN).

1.5.1 Fault tree analysis

Fault tree analysis [16] is a deductive approach to identify the hazards that could lead to accidents. Fault tree begins with a top event and works backwards towards different intermediate events or basic events that could contribute to that event. The basic events are marked with a circle symbol and intermediate events are marked with a rectangles symbol. These events can be hardware failure, software failure, and human and environment factors.

Logic diagrams with gates are used to construct a fault tree. A detailed list of logic transfer components are shown in Figure 6. The most important two gates are 'AND' and 'OR' gate. The output state of an AND gate is active only when all the input states are active. The output state of an OR gate is active when at least one of its input sates is active.

The fault tree can be used both for qualitative or quantitative risk assessment. The qualitative risk assessment can express the casual relationship between basic event, intermediate events and top events. If their probabilities are available, quantitative risk assessment could be achieve. Assuming P(F) is the probability of top events, P(A), P(B) and P(C) are basic events and they are independent, the probability of the output state obtained from the AND gate is expressed as following

$$P(F) = P(A) \times P(B) \times P(C)$$

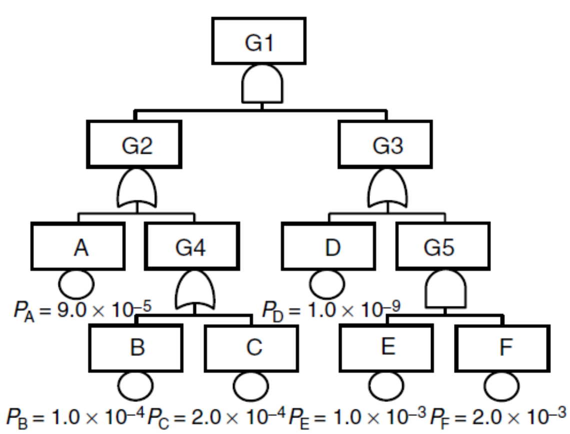
OR gate is given by the expression

$$P(F) = P(A) + P(B) + P(C)$$

Symbol	GateType	Description
G / A B	AND Gate	The output occurs only if all of the inputs occur together. $P = P_A \bullet P_B = P_A P_B$ (2 input gate) $P = P_A \bullet P_B \bullet P_C = P_A P_B P_C$ (3 input gate)
G / A B	OR Gate	The output occurs only if at least one of the inputs occurs. $P = P_A + P_B - P_A P_B$ (2 input gate) $P = (P_A + P_B + P_C) - (P_{AB} + P_{AC} + P_{BC}) + (P_{ABC})$ (3 input gate)
G / A B	Priority AND Gate	The output occurs only if all of the inputs occur together, and A must occur before B. The priority statement is contained in the Condition symbol. $P = (P_A P_B) / N!$ Given $\lambda_A \approx \lambda_B$ and N = number of inputs to gate
G / A B	Exclusive OR Gate	The output occurs if either of the inputs occurs, but not both. The exclusivity statement is contained in the Condition symbol. $P = P_A + P_B - 2(P_A P_B)$
G / Y / A	Inhibit Gate	The output occurs only if the input event occurs and the attached condition is satisfied. $P = P_A \bullet P_Y = P_A P_Y$

Figure 6 List of logic functions in fault tree [17]

Figure 7 is an example of the quantitative calculations of a fault tree.



$P_{G4} = P_B + P_C - P_B P_C$
$P_{G4} = 1.0 \times 10^{-4} + 2.0 \times 10^{-4} - (1.7 \times 10^{-4})\ (2.1 \times 10^{-4})$
$P_{G4} = 3.0 \times 10{-4}$

$P_{G5} = P_E \bullet P_F$
$P_{G5} = 1.0 \times 10^{-3} + 2.0 \times 10^{-3}$
$P_{G5} = 2.0 \times 10^{-6}$

$P_{G2} = P_A + P_{G4} - P_A P_{G4}$
$P_{G2} = 9.0 \times 10^{-5} + 3.0 \times 10^{-6} - (1.7 \times 10^{-6})\ (3.0 \times 10^{-6})$
$P_{G2} = 3.9 \times 10^{-4}$

$P_{G3} = P_D + P_{G5} - P_D P_{G5}$
$P_{G3} = 1.0 \times 10^{-9} + 2.0 \times 10^{-6} - (1.7 \times 10^{-9})\ (2.0 \times 10^{-6})$
$P_{G3} = 2.0 \times 10^{-6}$

$P_{G1} = P_{G2} \bullet P_{G3}$
$P_{G1} = 3.9 \times 10^{-4} + 2.0 \times 10^{-6}$
$P_{G1} = 7.8 \times 10^{-10}$

Figure 7 Example of fault tree calculations [17]

1.5.2 Event tree analysis

Event tree analysis is an inductive approach to determine accident event sequences that start from an initiating event. It provides information about all possible consequences that following a specified failure mode. In the offshore industry, there are some safety functions or safety barriers existing to prevent or mitigate the accident from propagating if an initiating event occurs. The success or fail of these safety systems will determine the consequences of initiating event. Conventionally, event trees are constructed from left-to-right with the initiating event located in the center of the page on the left. A line is drawn from the initiating event to two branches with success of the first safety function upward and failure of the function downward. The two lines are horizontal lines and the analysis proceeds to the next applicable operation. This process continues until an end state is reached. The ET analysis concept is shown in Figure 8.

For constructing an event tree, the first step is to identify an initiating event of interest. After that, safety functions or safety barriers that are assigned to deal with the initiating event are identified. Then, event tree are constructed beginning with the initiating event and processing with failure of the safety functions or safety barriers. The last step is to describe the resulting event sequences.

Event tree can be used in risk assessment qualitatively or quantitatively. We can quantify the final outcomes if data are available on the probabilities of the initiating event and each safety functions.

There are some drawbacks of ET analysis. It can only consider one initiating event for each event tree. If an engineer considers a specified outcome, the initiating event could not be the only reason and the one that the engineer is interested. Another is the data availability if quantitative analysis is required. Data gathering is always challenging in offshore industry.

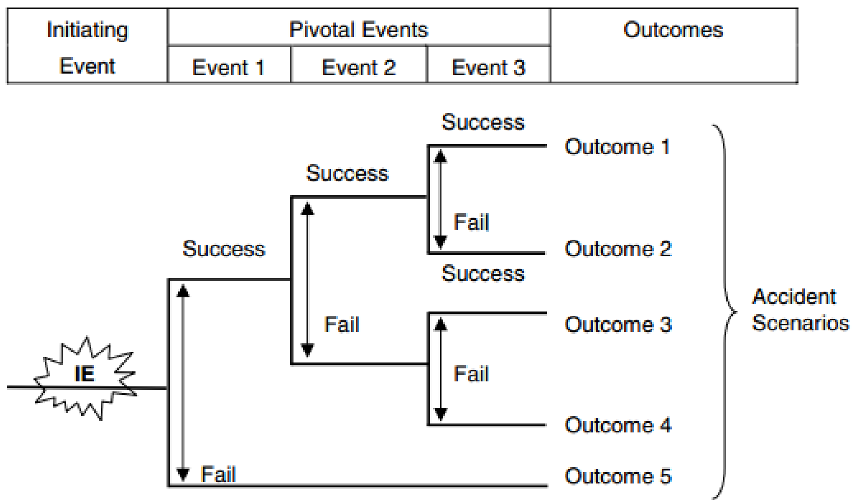


Figure 8 The event tree concept [17]

1.5.3 Bayesian network

One limitation of fault tree and event tree is that they are not applicable for scenarios with common causes or conditional dependence. Another limitation is that they are not applicable in dynamic safety analysis. If the probability of event is updated, the consequence risk is difficult to be updated due to the static structure.

Bayesian network (BN) is a popular method used in dynamic risk assessment that can overcome these limitations due to its flexibility. Nodes and arrows are used to link the causal-effects relationships in a graph. Nodes represent variables and arrows represent the relationships among these variables. If two nodes are affected by a common cause, they will be connected with arrows to the common cause node, which can show the relationship clearly and solve the limitation in FT or ET.

BN can be used qualitatively or quantitatively. The network with nodes and arrows can be used for qualitative analysis. If the conditional probabilities between nodes are available, BN can be used for quantitative risk assessment. The probabilities of variables can be updated if new data are available through observation or other ways. Bayes' theorem is the fundamental knowledge to update the prior probability given the evidence in the BN. Suppose the prior probability of variable H has i possible states $h_1, h_2, \dots, h_i$, where they represent i different outcomes and they are mutually exhaustive and exclusive. If E represent new evidence, the posteriors probability can be represented by Equation 1 [18].

$$\boldsymbol{P(h_i|E) = \frac{P(E|h_i)P(h_i)}{\sum P(E|h_i)P(h_i)}} \qquad \textbf{Equation 1}$$

A simple example with CPT in BN is shown in Figure 9. The Rain or sprinkler could cause the grass to be wet. When it is raining, the probablitiy of turning on the sprinkle is small as 0.01, so the sprinkle and rain are not independent and an arrow is connected to shown their depenency [19].

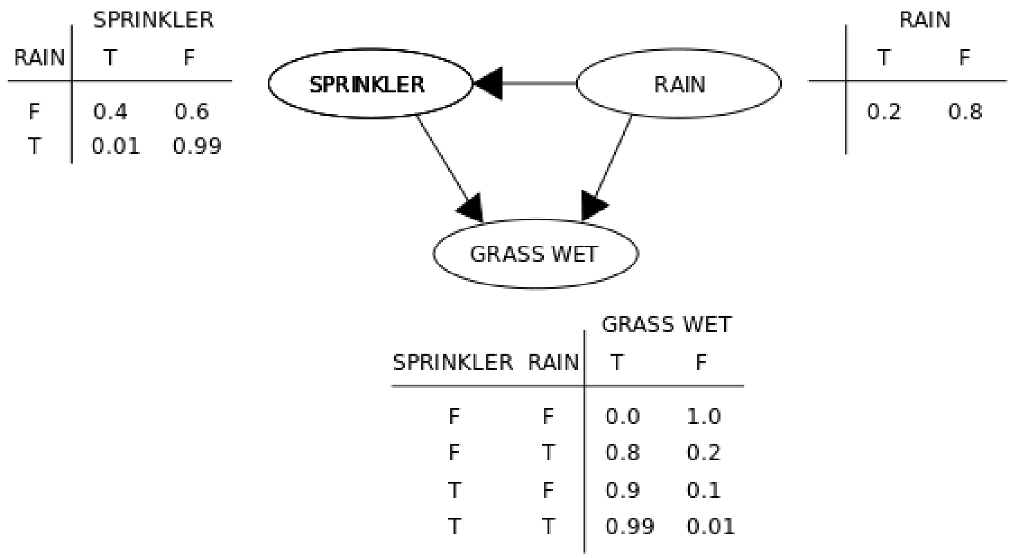


Figure 9 An example of Bayesian network with CPT [19]

BN is also useful in situations with high uncertainty. In offshore drilling, HFs are highly uncertain due to the different environment, personality and organization. There are rare data collected for HFs in offshore industry, so it is difficult to define a certain probability for HFs variables.

2 LITERATURE REVIEW

In order to develop model that could take HFs into account in offshore drilling risk assessment, two areas of literature review have been conducted. The first part concludes the research that has been done in the offshore drilling risk assessment. Another part gives an overview of models that have incorporated human factors in offshore risk assessment.

2.1 Research about offshore drilling risk assessment

In offshore drilling, there are unexpected severe consequences due to its harsh environment, compact space for equipment and people. Blowout is the worst accidents that could threaten human lives and environment in offshore drilling. Risk assessment is a widely used tool to provide prevention and mitigation measures for accident and incident.

The most extensively used method in risk assessment of blowout is FT analysis. In 1978, Bercha et al. only used fault trees to analyze the blowout probability in Canadian artic waters [20], including human, environmental and equipment failures. In 1994, Kirwan [21] also developed a comprehensive fault tree for offshore blowout that focused on human errors. The results were quantified to five major top events, including drill-pipe blowout, blowout through the BOP, the choke system, at the mud-processing level and shallow gas blowout. As we mentioned above, FT can reflects the casual-effect relationship related to blowout scenarios, but it is a static method that cannot capture dynamic parameters in drilling, such as pressure in wellbore and weight of drilling mud. Also, it fails to consider the dependent failures and common cause failures.

Khakzad [22] demonstrated QRA of offshore drilling operations with a bow-tie model and Bayesian network. The bow-tie model consists of fault trees and event trees for potential blowout scenarios. Then, the bow-tie model is mapped into BN for its flexibility application in situation with common cause failures and conditional dependencies. The fault tree was used to investigate the causes of kick and kick detection. Event tree illustrated the safety barriers that prevent kick from propagating into blowout. Some common factors are considered with BN in his model. The mud density is the common cause failure for kick and kick detection. Also, the kick can be detected only if kick occurs, which shows their dependency. His method is very effective in decision making of well control safety. However, his work did not consider the well control regain scenarios, and the effect of organization factors on basic events of kick and safety barriers was not addressed in his model.

Cai [23] analyzed the effect of human factors safety barriers on offshore blowouts with the application of dynamic Bayesian networks and pseudo-fault tree. The pseudo-fault tree was introduced to eliminate the binary restriction of fault tree to build the structure of human factors barrier. He categorized the underlying human factors that contribute to offshore blowout into three parts, including individual, group and organization factors. He also investigated the effect of repair action on the human factors barrier failure and conducted sensitivity analysis in Bayesian networks. The results showed that repair action can improve the performance of human factors barriers.

Among the three categories of human factors, the important sequences are: group factors, organization factors and individual factors. This paper gave a comprehensive analysis of HFs, but it did not study the physical causal mechanisms related to the kick and blowout phenomenon. A system approach should identify how human factors affect multi-step procedures involved in drilling and well control operations.

In 2014, Tabibzadeh [24] developed a systematical risk analysis methodology in offshore drilling and emphasized the contribution of HFs on the negative pressure test (NPRT). This method could qualitatively and quantitatively analyze the interpretation of NPRT. NPRT is used to test whether cement barrier can seal off the hydrocarbons. It is the only method to test cement integrity during offshore drilling [13]. In Macondo Well blowout, the negative pressure test was misinterpreted, which was a major contribution to this accidents [10] and showed the problem of human factors. Three approaches were introduced and constituted in his risk analysis methodology. The first approach is a comparative analysis of the test conducted by Deepwater Horizon crew with “standard” negative pressure test to identify the discrepancies between the two tests procedures. The second approach is a conceptual assessment framework to identify the causes of the above discrepancies with three layers. The three layers are physical state of system or basic events level, decisions or actions level made by crew and root organizational factors level from bottom to top. Finally, he proposed a rational decision making model to quantify a section of the developed conceptual framework in the second step. His methodology is focused only on the NPRT. It could be applied in analysis of other single operation activity in offshore drilling, but it is too complex to analyze the whole picture of blowout scenarios in such detail steps.

2.2 Research about integrating HFs in offshore risk assessment

2.2.1 Human reliability analysis

The most well - known method to integrate human factors into risk assessment is Human Reliability Assessment (HRA) that proposed by Kirwan in 1994. HRA can identify human errors. The general HRA process is shown in Figure 10.

Numerous HRA approaches based on above process are developed in the last 40 years. Some major approaches include THERP, HEART, Human HAZOP Study, SHERPA, and APJ [24]. Some methods that have been used in offshore operations include THERP and APJ [24]. Tabibzadeh [24] mentioned that those methods are only focused on human performance analysis. The root organization factors, such as procedures, management are not addressed in them.

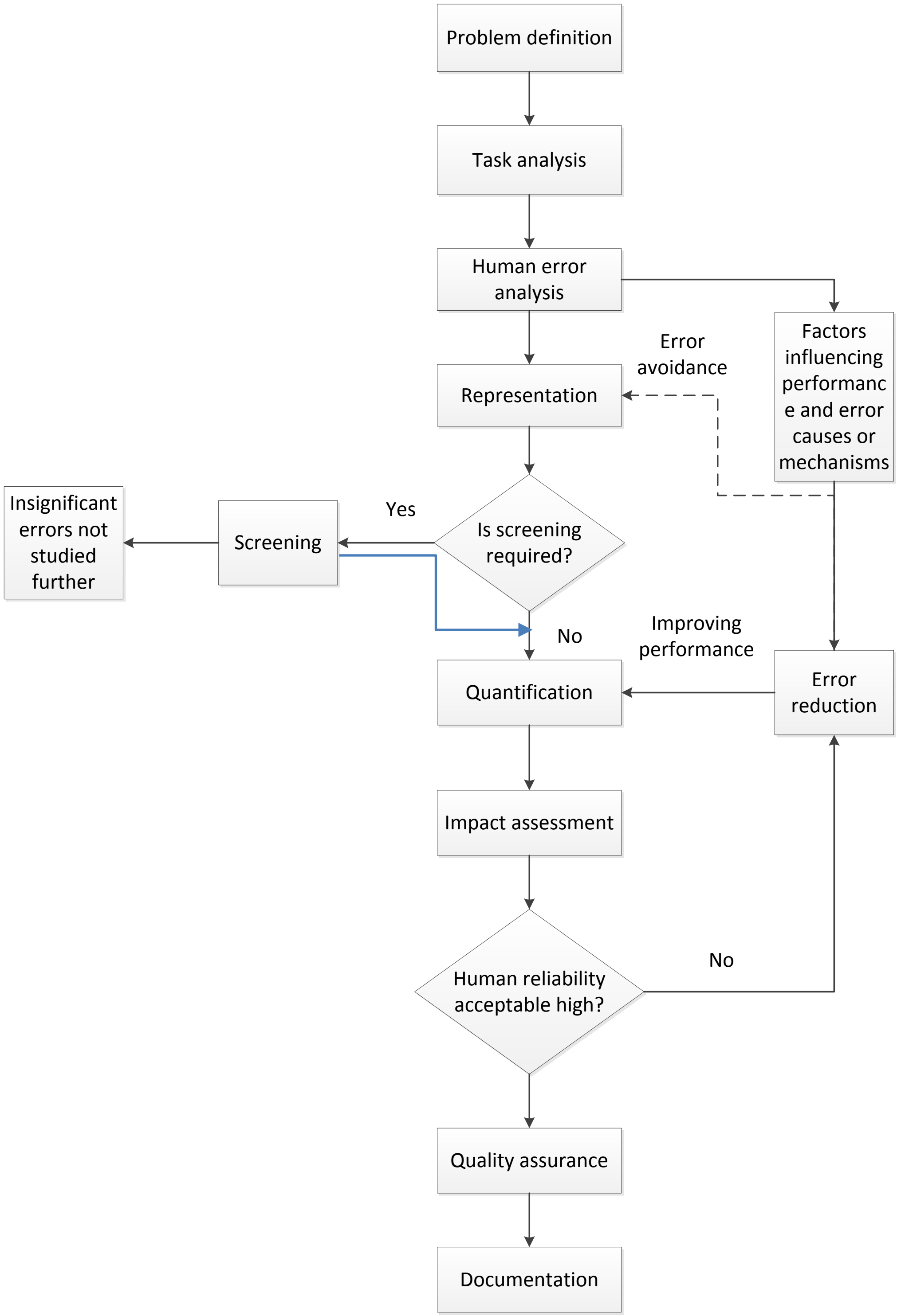


Figure 10 Process of HRA [21]

2.2.2 *Barrier and operational risk analysis*

Barrier and operational risk analysis (BORA) project was initiated to develop a method for analyzing the frequency of hydrocarbon release qualitatively and quantitatively by incorporating the effect of technical, operational, human and organizational factors in offshore industry. The method is called BORA-release, which is built by barrier block diagrams, fault trees, event trees and risk influencing diagrams [25]. The general model for the leak scenarios is illustrated in Figure 11. The first step is to identify initiating events, which are types of errors, or failures that may lead to a leak during the work operations or equipment failures due to corrosion, fatigue, or other technical causes. For certain work operation, generic frequency will be assigned to initiating events. This frequency is influenced by RIFs. The barrier block diagram is an event tree to model barrier systems to prevent the initiating events from developing to hydrocarbon release. The performances of safety barrier systems are modeled with fault tree analysis. The basic events in FT are also influenced by RIFs and their probabilities are identified by risk influencing diagrams. The main contribution of this model is that it introduces the term “Risk Influencing factors”, which include technical, operational, human and organizational factors.

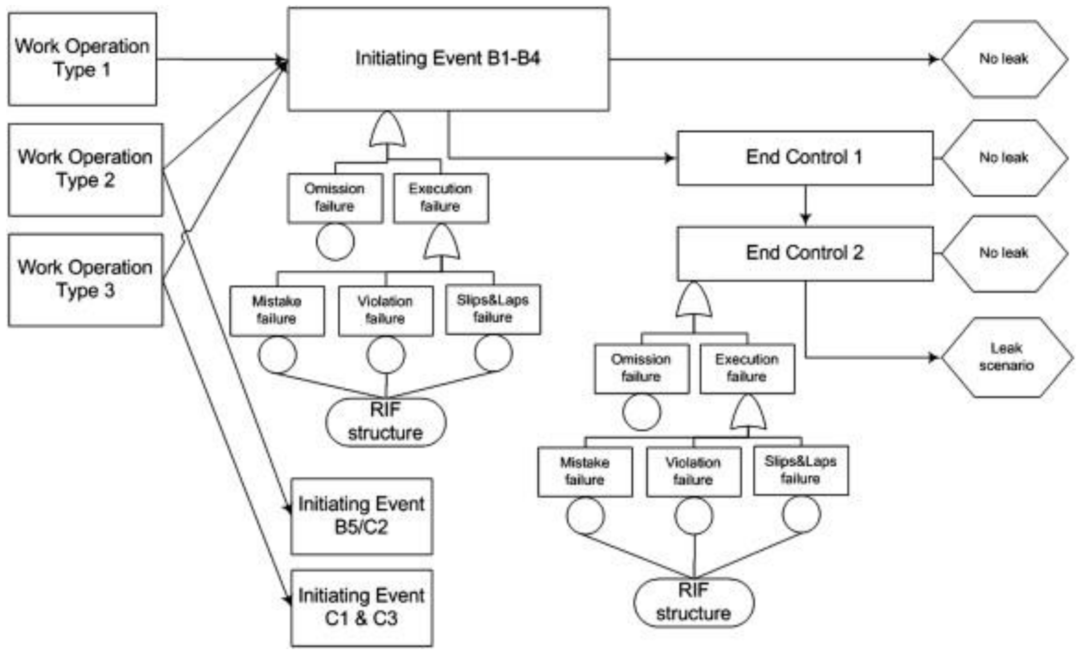


Figure 11 BORA general risk model [26]

OTS method is another project that based on the BORA to monitor the status of human and organizational factors with questionnaire survey, interview, HSE data analysis and documents review on [27]. Seven performance standards are comprised in OTS method, including work practice, competence, procedures and documentation, communication, workload and physical working environment, management, management of change.

The Risk modelling - Integration of Organizational, Human and Technical factors (Risk_OMT) is a further developed program built on BORA and OTS methods to provide quantitative risk analysis [26]. Bayesian Network is introduced in this model to consider the dependency of basic events, RIFs and common cause effects.

2.2.3 Hybrid causal logic

In 2005, Wang [28] developed a multi-layered model that could incorporate human factors and physical environments in addition to hardware failures, which is called the Hybrid Causal Logic (HCL) model. This model combines event trees or event sequence diagrams, fault trees and BN networks. The event trees and fault trees are input information in BN. The three major layers of HCL include:

- Develop event trees or event sequence diagrams to define the accident or incident scenarios and consequences.

- Develop fault trees to identify contribution factors to accidents or incidents in the above event trees or event sequence diagrams.

- Develop a model to link the human factors that are contributed to causal events in fault trees with BN.

The HCL has already been applied in aviation industry [29]. Roed [30] used this framework in offshore oil and gas industry and discuss its application in hydrocarbon release scenarios. The general HCL framework is illustrated in Figure 12.

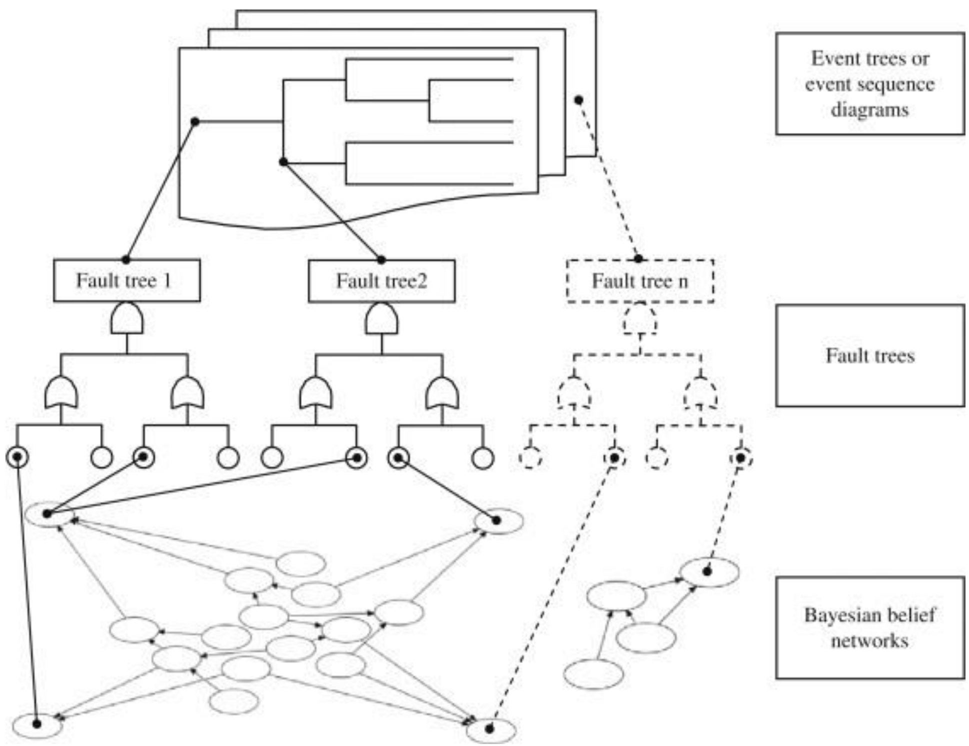


Figure 12 General HCL framework [30]

Wang.et al. [31] presented a similar method to analyze the probability of offshore fire by integration of HFs. Fault trees are used to identify the basic events that contribute to the fire scenarios. Then, fault trees are converted into BN and human factors are linked into the model by extended BN.

2.3 Gaps in research

It is important to identify HFs before developing models so that comprehensive influencing factors could be considered. However, there is no uniform definition about HFs so far. The category about human factors that developed 30 years ago did not consider about the new technology, environment and organization change.

Even though many methods have been developed to integrate human factors in risk assessment, they are not appropriate or applied in offshore drilling. The HRA methodologies are focused on human errors without considering organization factors. The BORA method is mainly focused on the hydrocarbon scenarios and it is not appropriate for situation where data is not enough.

Traditional offshore drilling risk assessment models did not comprehensively address HFs and dynamic parameters in complex drilling activities and environments. A model should be developed to have the following functions: 1) incorporate HFs; 2) dynamic risk assessment; 3) reflect dependency and common cause failures; 4) multi-step procedures in drilling and well control operations. HCL is a good method to have all above functions, but it has not been used in offshore drilling yet. Hence, this work will apply HCL framework in offshore blowout risk assessment.

2.4 Research objective

As offshore drilling is vulnerable to human factors in offshore oil and gas industry [21], this research will develop a model to incorporate human factors in offshore blowout risk assessment. The general research scope and methods are shown in Figure 13.

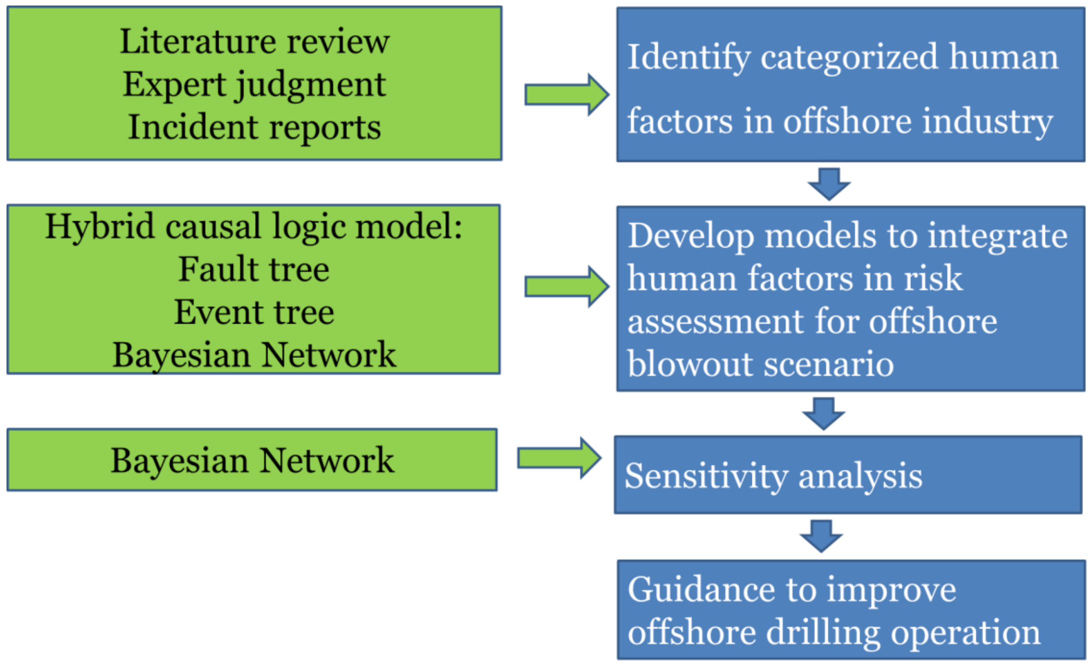


Figure 13 Scope and methodologies of research

The first step is to identify categorized human factors in offshore industry. General category of human factors includes individual, group and organization factors. More detail specification under the three categories will be concluded in this research.

Fault trees will be developed to identify human errors that could contribute to kick scenario, failure of kick detection, kick control and shear ram to seal the well. An event tree will display the links of kick into blowout. Then, the fault tree and event tree will be converted into Bayesian networks to consider the common cause failures, especially the common human factors. This methodology is a dynamic, ever green safety assessment by updating probability if new data is available.

3 IDENTIFY CATEGORIZED HFS IN OFFSHORE INDUSTRY

In 1996, Gordon [9] gave an overview of the contribution of human factors on accidents in the offshore oil industry. He suggested improved accident reporting forms by providing detailed categories of human factors accident causation. In order to make a clear explanation, three levels of category are divided as main - categories, subheadings and sub-categories. The main-categories are individual factors, group factors and organizational factors, which are illustrated in Table 1 [5,9].

Table 1 Explanation of human factors categories

Main categories of HFs	Explanation
Individual factors	Individual characteristics and external factors that affect a person's performance
Group factors	Factors that affect teamwork, including the role of middle management, supervision and crew factors
Organization factors	Factors in which behavior occurs and the basis of people's expectations

Gordon's categories gave a detailed structure of basic human factors that should be considered in the accident reporting forms. However, this paper did not provide an importance ranking of each factor in offshore industry. Some factors addressed in recent accident reports are also not covered in the categories, such as HMI. Factors, like communication, in sub-category can be important and contribute to many major accidents. It is very important to list these factors in subheading and specify them in detail.

In order to give a more comprehensive category and address the key factors, improved categorizations of human factors based on Gordon's paper [9], literature review [15,23,24,26,27] and expert judgment have been developed, which are shown in Figure 14, Figure 15 and Figure 16. As it is hard to consider all factors in the risk assessment, this research will consider the sub-heading factors.

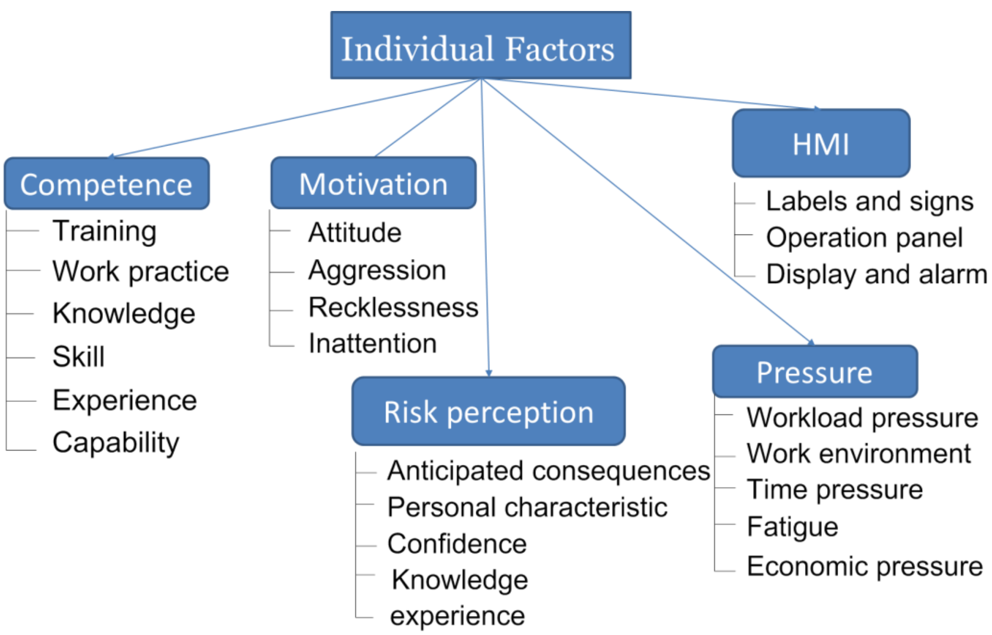


Figure 14 Individual factors [9,15,23,24,26,27]

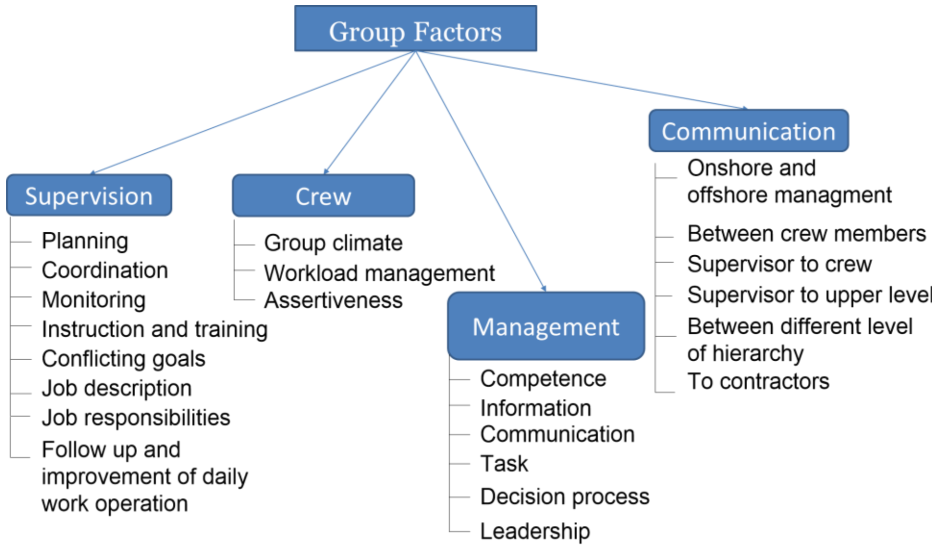


Figure 15 Group factors [9,15,23,24,26,27]

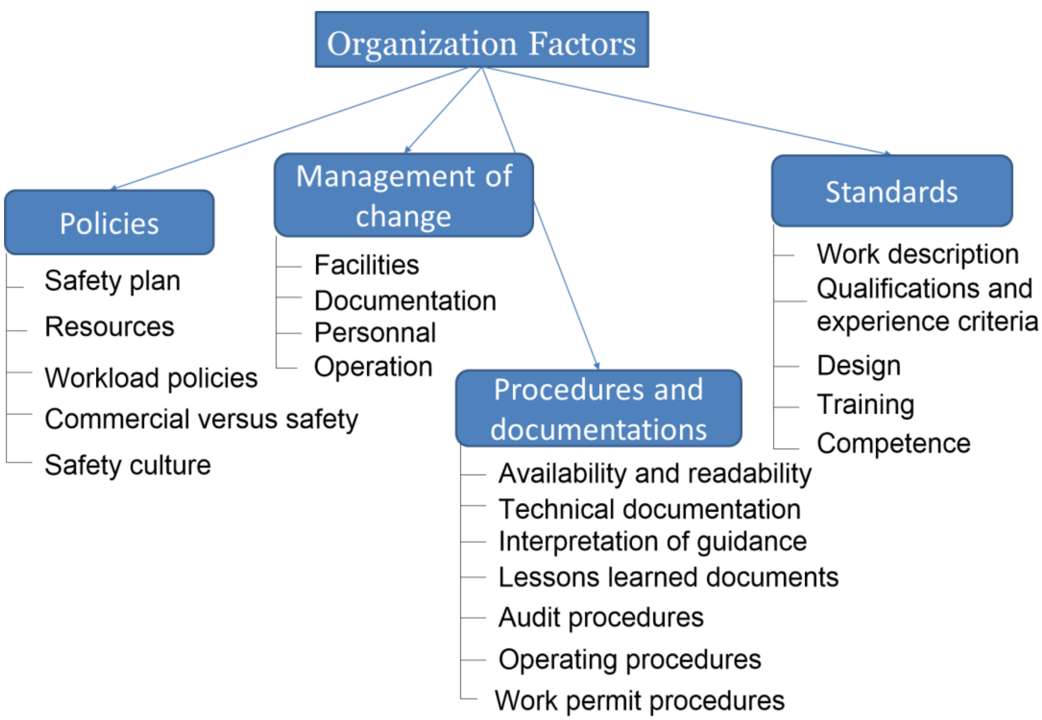


Figure 16 Organization factors [9,15,23,24,26,27]

4 INTEGRATE HFS IN BLOWOUT RISK ASSESSMENT WITH HCL FRAMEWORK

As we have identified sub-heading human factors in offshore drilling, we will discuss how to incorporate them into risk assessment with HCL framework. The steps to develop the HCL model for offshore blowout are illustrated as following.

1. As the kick is the initiating event for blowout, the first step is to define kick scenarios and safety barriers
2. Develop the event tree of kick escalation to blowout because of safety barriers' failure
3. Develop fault trees of kick and safety barriers
4. Identify HFs and causal relation for the basic events in fault trees
5. Map fault trees and causal relationship into Bayesian network with different fault tree mapping model
    - Build BN structure with nodes and arcs
    - Assign Node Probability Table to each node
6. Map the event tree in Bayesian network, import fault trees and connect them with OOBNs
7. Analyze the Bayesian networks and evaluate the results

Both the event tree and fault trees in this research are qualitative analysis, showing causal relationships. The quantitative analysis will be completed in Agenarisk [32], which is the software to build Bayesian network.

4.1 Kick scenarios

Kick is an unscheduled flow of formation fluids into the wellbore during drilling operations. An uncontrolled kick may result in a blowout. Kick could occur in any sub-operations of offshore drilling, such as drilling, tripping, making a connection, casing, logging and cementing.

To prevent a kick, the wellbore pressure should be greater than the rock pore pressure, but cannot exceed the fracture pressure, which could be expressed as Equation 2

$$P_p < P_b < P_f \qquad \text{Equation 2}$$

P_p is pore pressure, P_f is fracture pressure, P_b is wellbore pressure

Pore pressure is the pressure of fluids in the pores of a reservoir [33]. Fracture pressure is the pressure required to cause the rock formation to fail or split [34].

The wellbore pressure varies with different sub-operations. The wellbore pressures during sub-operations are expressed as following [22,35].

- Drilling: $P_b = P_h + \Delta P$
- Tripping out: $P_b = P_h + \Delta P - P_{sb}$
- Tripping in: $P_b = P_h + \Delta P + P_{sg}$
- Cementing: $P_b = P_h + \Delta P$

- Casing: $P_b = P_h + \Delta P + P_{sg}$

Where $P_h = 0.052 * \text{MW} * \text{vertical depth} + P_0$, is hydrostatic pressure and depends on the density and depth of drilling mud. MW is mud weight, the unit is pound per gallon (ppg).

ΔP is the frictional pressure losses

P_{sb} and P_{sg} are swabbing and surging pressures due to drillstring tripping out and tripping in the wellbore.

Kick causes could be insufficient wellbore fluid density, reduction of mud column height, excessive swab friction pressure, wellbore collision or cement hydration [35].

According to the SINTEF Blowout Database between 1980 and 1994, the most frequent activities performed when a deep drilling blowout initiated are drilling, tripping out and waiting on cement to harden [4]. The most common reasons are swabbing while tripping out, unexpected high well pressure and low mud weight while drilling

Due to the complexity of offshore drilling, it is hard to consider all kick scenarios in the same model. This would complicate the Bayesian network resulting in an impractical size and CPU time for calculation. Hence, the scenario of swabbing induced kick, which is one of the most common reason for blowout, will be used as a case study to analyze the effect of human factors on offshore blowout probability quantitatively in this research.

4.2 ET of kick into blowout

To construct an event tree for blowout scenarios, kick is the initiating event leading to a blowout.

Some kick detection equipment and tools are used to detect any signs of kick if kick occurs. If the operators observe some warning signs of kick, they will take some measures to control the well, which include shut-in the well according to shut-in procedure, operators' experience and judgment and kill the well after shut-in. If well control is failure, the last safety barrier is shear ram in BOP. The chain of events that lead to a blowout are: kick occurs, kick is detected, kick is controlled and blowout is prevented [21].

The HCL framework for offshore blowout is shown in Figure 17. The top part is the event tree for kick leading to blowout consequence. Kick is the initiating event, the safety barriers are kick detection, kick control and shear ram to seal the well. The bottom part is the fault tree general model for kick and safety barriers. The basic events that contribute to the top event will be emphasized on the unsafe acts. After the basic events are identified, the underlying causes (HFs) that affect the basic events will be linked with arrows in Bayesian networks.

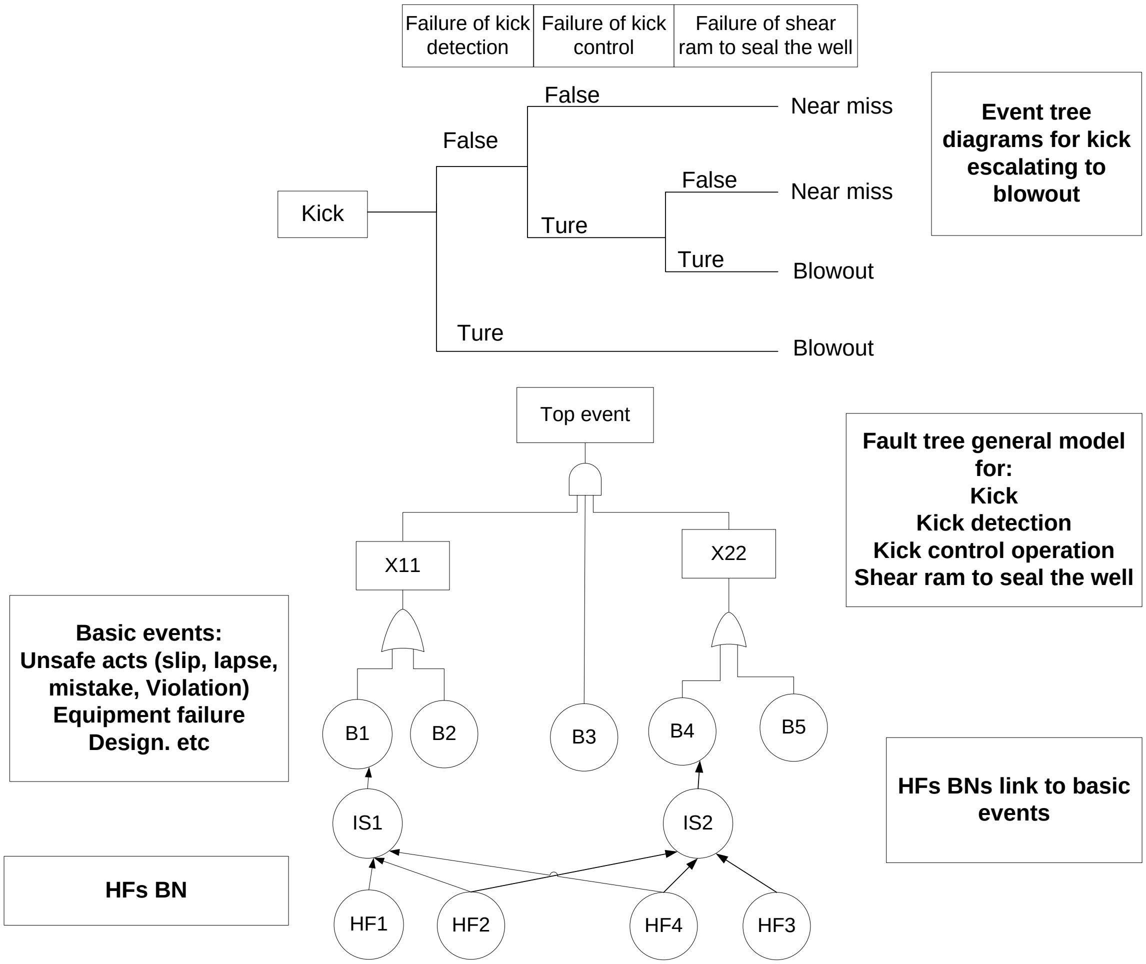


Figure 17 HCL framework for offshore blowout scenarios

4.3 FT of swabbing induced kick

Pulling the drill pipe out of the borehole (POOH) could cause swabbing pressure and lower the bottom hole pressure. During the tripping out, void space formed by the drill-pipe, drill-collar, or tubing must be filled by pumping mud into the space. If the rate of tripping out is greater than rate of pumping, then swab will occur. If the lower bottom hole pressure due to swabbing is below the pore pressure, a potential kick has developed [35] [36].

Kirwan [21] developed a large, human-error-based fault tree analysis of offshore drilling operations. Two basic events for swabbing induced kick are POOH too fast without sufficient check during tripping operation, so the fault tree of swabbing induced kick is shown in Figure 18 and the basic events are shown in Table 2.

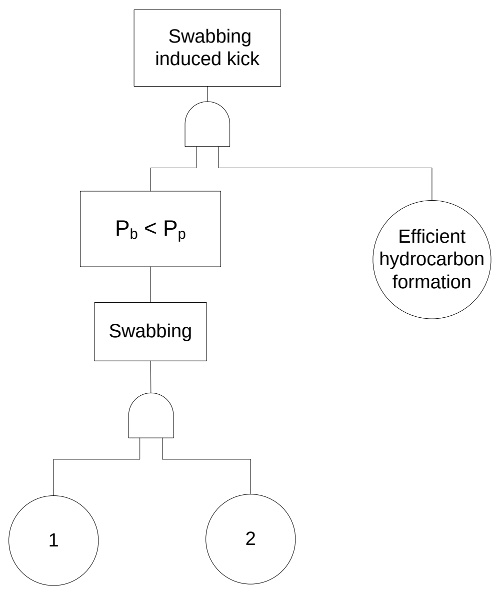


Figure 18 FT of swabbing induced kick

Table 2 Basic events of FT of swabbing induced kick

Swabbing induced kick	
Index	Basic events
1	POOH fast
2	Insufficient checks

4.4 FT of kick detection

It is crucial to detect the kick quickly because whether a kick develops into a blowout is highly dependent on whether a kick could be detected at early time [22]. When kick occurs, there are some warning signs for operators to detect the kick. These signs include [35]:

- Increase in mud return rate
- Pit gain
- Decrease in circulating pressure
- Increase in pump rate and decrease in pump pressure
- Mud property changes

Figure 19 shows FT analysis that could contributes to the failure of kick detection either by equipment failure or human response failure [21]. The basic events are shown in Table 3. Equipment of the kick detection are a tank level indicator, flow meter, pressure gage, displacement sensor, gas detector, density meter, resistivity sensor [22]. The alarm system failure could be caused by hardware failure, trip sensors miscalibrated or inhibited, isolated or blocked sensors [21]. Even if the warning sign are successful, the operator or mud engineer could not monitor the signal, or misinterpret the signal due to alarm saturation or distraction due to multi-tasking. Communication error can also occur between the rig crew or mud engineer to warn the driller [21].

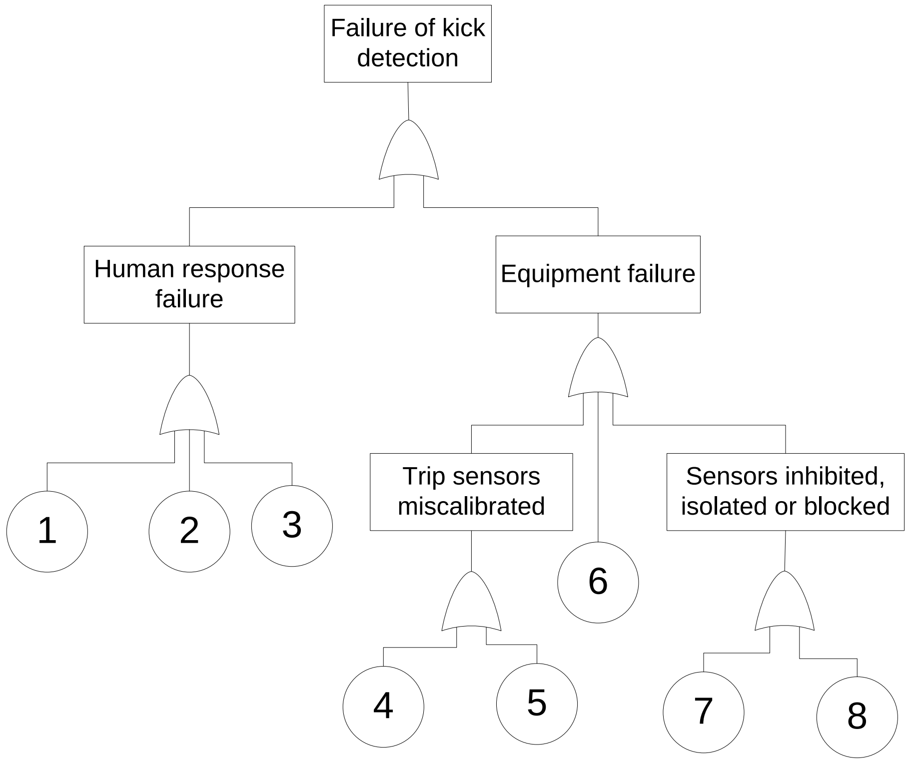


Figure 19 FT of kick detection

Table 3 Basic event of FT of kick detection

Index	Basic events
1	Signal is not monitored
2	Signal interpretation failure
3	Communication error
4	Setting error
5	Rule violation
6	Hardware failure
7	Maintenance/testing error
8	Inhibit alarm and forget to reset

4.5 FT of kick control

If any warning signs of kick are observed, shut-in the well and kill the well should be conducted to control the kick [35].

1. Shut-in procedures - close in a flowing well to reduce the kick influx and prevent a blowout from occurring

2. Well kill - circulate out any formation fluid already in the wellbore with circulating appropriate balanced mud into the well without allowing further fluid into the hole.

Two kind of shut-in procedures are “hard” and “soft”. In the shut-in procedure, the chock line valves are in the closed position. The BOP is closed immediately after the pumps are shut down. In soft shut-in procedures, the choke valves are in the opened position firstly. Then the BOP is closed. Choke valves are closed after the BOP is closed [36]. The hard shut-in can shut in the well faster than the soft shut-in. A shut-in procedure is a company-specific procedure, and the policy of a company will dictate how a well should be shut-in [35].

Shut-in procedures also vary with the type of rig and the drilling operations when the kick occurs[37]. Drilling rigs could be floating rig, land or bottom supported rig. For example, deep-water drilling rigs are mostly floating rig, and swabbing occurs during tripping operations. The specific procedures for tripping on a floating rig should be employed.

The most likely failure for well killing involves in an incorrect hydrostatic balance, caused by the mud weight, the pumping rate, or the choke control [21]. Gao also pointed out that equipment failure and operation error are major contributions to the failure well control in deep-water drilling [38]. A detailed FT of kick control is shown in Figure 20 and the basic events are shown in Table 4.

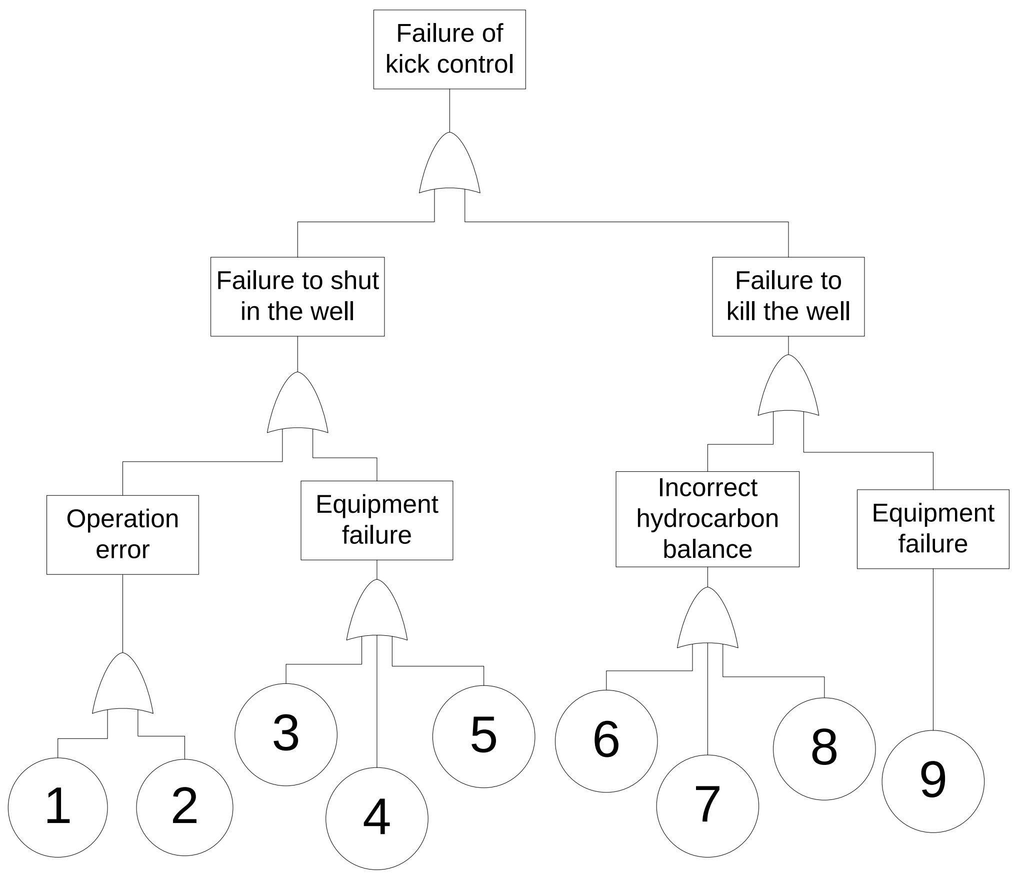


Figure 20 FT of kick control

Table 4 Basic event of FT of kick control

Index	Basic events
1	Not follow the shut-in procedure
2	Action inadequate or error for shut-in
3	BOP failure（pipe rams and annular preventer）
4	Choke valve failure
5	Blockage in choke system
6	Pump rate error
7	Choke control error
8	Incorrect mud weight
9	Mud pump failure

4.6 FT of shear ram to seal the well

The pipe and shear rams are effective barrier system when control is fail [21]. The blind shear ram is designed to cut the drill pipe and shut-in the well in am emergency situation. However, the shear ram could fail to seal the well for design limitations [39]. A study by a drilling consulting firm for Minerals Management Service (MMS) in 2002 [39] showed that only 71% shear rams were tested successfully. This percentage dropped to 50% under operational condition. This study also pointed out that many operators and drilling contractors had chosen not to perform actual shear testing when accepting new or rebuilding drilling rigs. Thereby, the evidence to show the shearing success of installed shear rams is lacking. In order to improve the accuracy of the shear tests, therefore improve the probability of shear operation success when required, consistent testing methodologies and standards should be considered.

FT of shear rams failing to seal the well is shown in Figure 21 and the basic events are shown in Table 5.

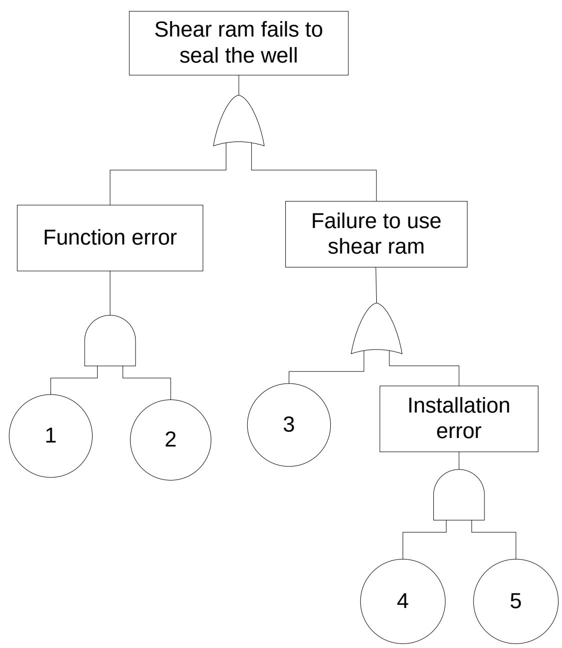


Figure 21 FT of the blind shear ram failing to seal the well

Table 5 Basic events of FT of shear ram failing to seal the well

Index	Basic events
1	Design limitation
2	Failure of shear ram test
3	Action error
4	Installation error occurs
5	No detection of error during Maintenance/testing

4.7 Methodologies to convert HCL model into BN

Agenarisk will be used to build the Bayesian network. It is a powerful but intuitive tool for modelling and analyzing risk and predicting about uncertain events. It combines the benefits of BNs, statistical simulations and spreadsheet-like analysis. Otherwise, it is easy to use and flexible [18]. The Agenarisk risk maps are used to model causal relationships in Bayesian networks by supporting both diagnostic and predictive reasoning about uncertainty.

4.7.1 Fault tree mapping into BN

FT is represented as a BN through a directed graph and a set of node probability tables (NPT). The directed graph consists of a set of nodes and arcs [18]. The top event, intermediate events and basic events are represented as a leaf node, intermediate nodes and root nodes in the equivalent Bayesian network [40]. These nodes are connected in the same way as the corresponding events in FT. Roots nodes, intermediate nodes and leaf nodes are Boolean nodes with states either True or False. The fault tree mapping into BN is shown in Figure 22.

4.7.2 Event tree mapping into BN

Bearfield and Marsh [41] used a train derailment case study to show how an event tree can be mapped into the Bayesian network. A safety node in BN represents corresponding safety barrier. The node is either success or failure, which is represented as true or false in BN. Consequence node in BN represents consequence in event tree and the states of consequence node are the same number of event tree consequences. The consequences here are near miss and blowout. Another state that is not reflected in event tree is safe state when there is no kick. Both the near miss and safe state are expressed as false blowout in BN.

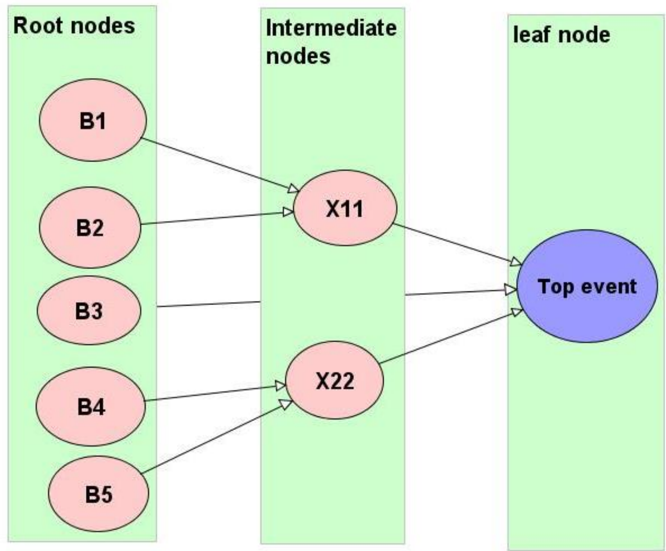


Figure 22 Fault tree mapping into BN

Two kinds of arcs need to complete the network, which are consequence arcs and causal arcs [41]. Consequence arcs connect each safety node to consequence node. Causal arcs connect each safe node to all safety nodes later in time. As the blowout and safety barriers are also influenced by initiating event "swabbing induced kick", the kick node should also be connected to safety nodes and the consequence node. Figure 23 shows the detail of event tree mapping into BN.

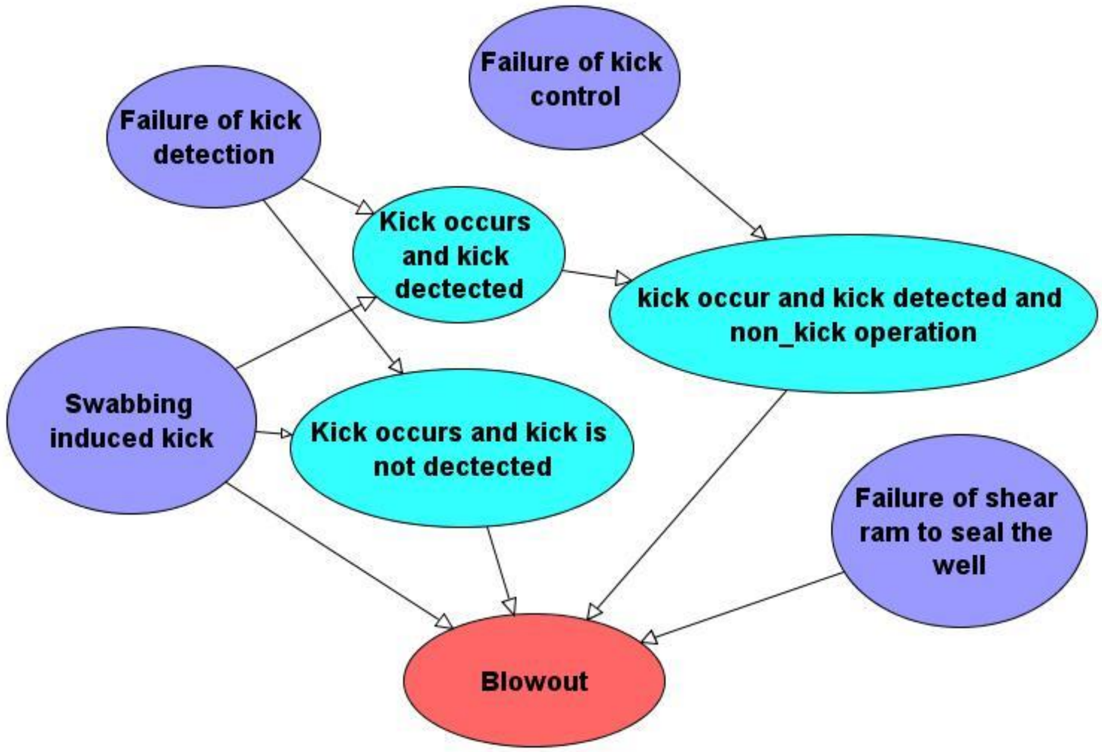


Figure 23 Event tree mapping into BN

4.7.3 BN for human factors

The human factors are represented as human factors (HFs) nodes in BN, such as nodes HF1, HF2 in Figure 24. In numerical step, the HF nodes are ranked nodes with TNormal distribution with 5 levels from "Very low" to "Very high." TNormal distribution is very flexible and can generate satisfactory NPTs for all ranked nodes with ranked parents [18]. Another power of TNormal distribution is that the child ranked node can be weighted by the importance of the parent nodes. When we input evidence of the parents, the mean value of the child nodes is equal to the weighted average of the parent nodes.

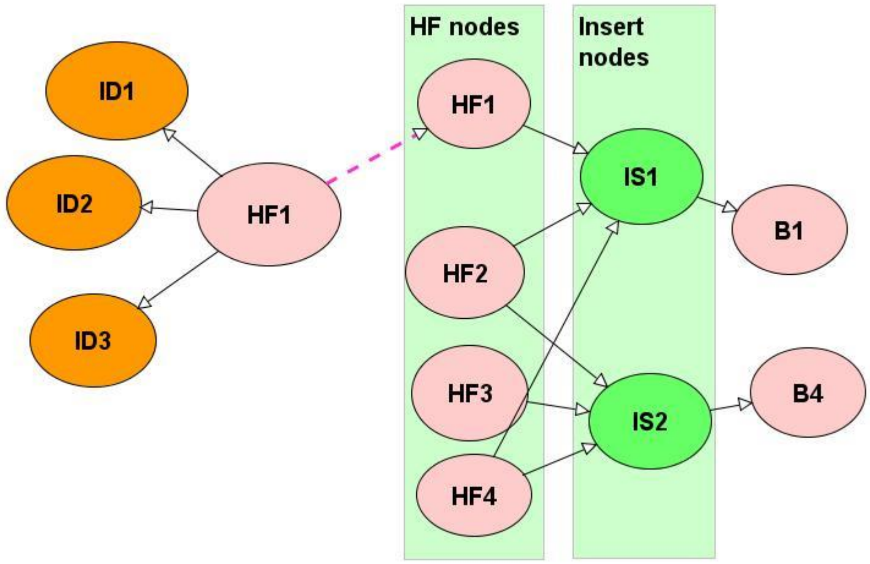


Figure 24 BN for human factors

In order to consider about the human factors, the fault tree structure is extended with linking the root nodes to their corresponding influencing HF nodes. If the root node is linked with *n* HF nodes (n≥2) directly, $2*5^n$ probabilities need to be assigned in NPT, which is large and complicated. Another shortage is that the weighted importance of human factors cannot be reflected. A solution is to insert a child ranked node of the influence HF nodes if parent nodes have 2 or more HF nodes, then the insert node (IS node) will link to the root node. The assigned probability number will reduce to 10 and the important of the HFs can be reflected with weighted functions for ranked node. Take Figure 24 for example, the root node B1 is influenced by the HF nodes HF1, HF2 and HF4, so IS1 is inserted as the child node of them and the parent node of B1.

A common cause human factor can also be considered in BN. For example, HF2 influences both the B1 and B4, so two links are connected with HF2 to B1 and HF2 to B4 indirectly, which shows common cause factors being considered here. One assumption is that subheading human factors are independent in this research.

The HFs can be evaluated with BN if the indicators information are available. Some human factors cannot be measured directly, but we can measure them indirectly by measured indicators. The indicator node is a child of the HF node. The NPT for the indicator node is defined as a TNormal distribution where the parameters are conditioned on the states of the HF node. Figure 25 shows the evaluation model of the competence factor. Training months and training frequency are indicators for the competence factor. The competence is likely to be very low in scenario 1 and to be high in scenario 2.

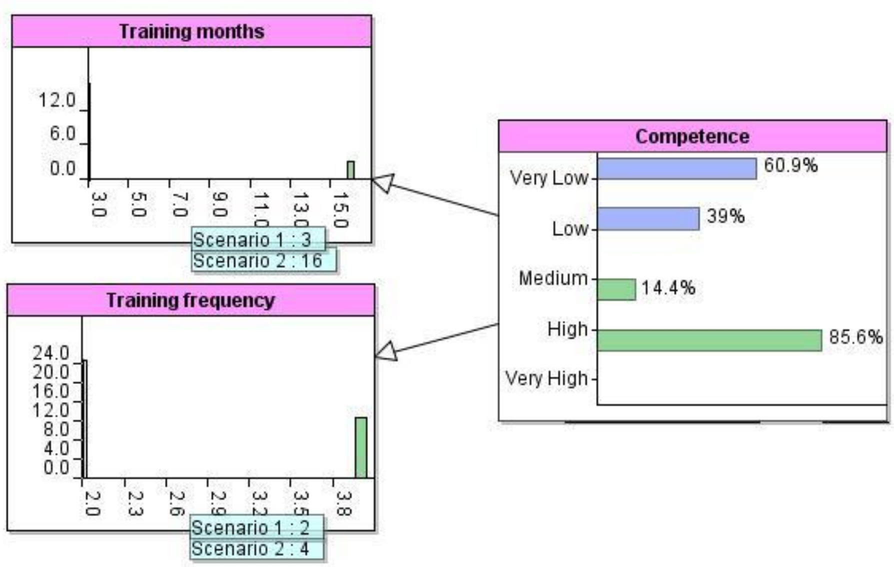


Figure 25 The impact of indicators on competence level

4.7.4 Object-oriented Bayesian networks

As we see from the HCL framework, we have four fault trees and one event tree. Kick is the initiating event in the event tree and the top event in the kick fault tree. Failure of kick detection, kick control and shear ram to seal the well are also top events in the fault tree and safety barriers in the event tree. If we build all nodes in the same BN, it will be very complicated and difficult to recognize the logic relationship in BN. In order to simplify the model and make it easier to understand, object-oriented Bayesian networks (OOBNs) is introduced.

OOBNs can decompose the model into smaller simple models. The individual OOBNs can be linked into a higher-level model with input and output nodes. The input and output nodes have the same type and the same probability values [18]. In other words, the event tree model and fault tree models are developed separately, and then they are combined together with OOBNs. This is illustrated in Figure 26.

All of the dashed pink arcs are used to connect the nodes by the OOBNs method. For example, if the probability of swabbing induced kick is updated in the BN of the fault tree, the probability of kick in the BN of event tree should also be updated as the same value. Hence, the kick node is assigned as an output node in the fault tree and an input node in the event tree.

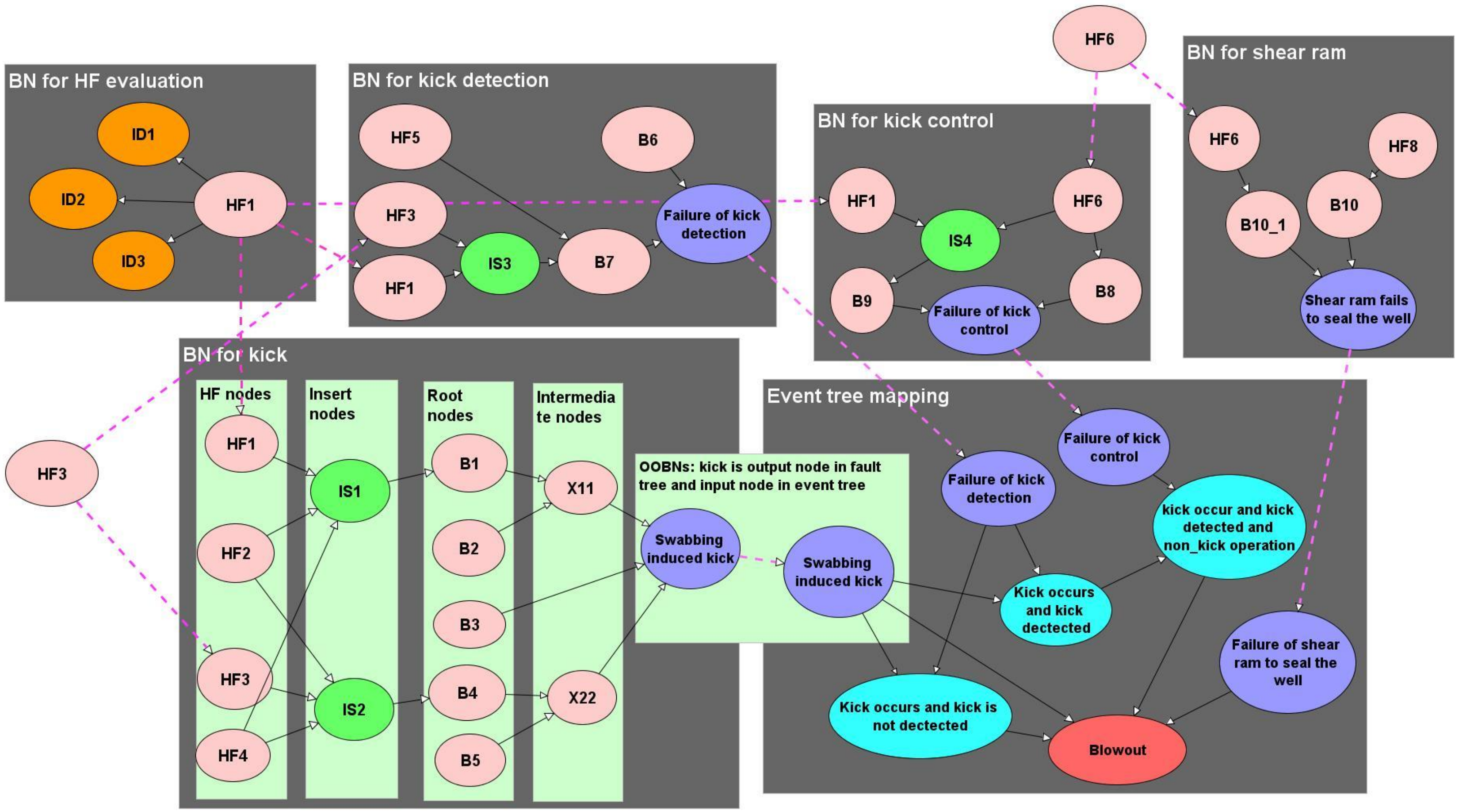


Figure 26 Mapping fault trees and event tree in BNs

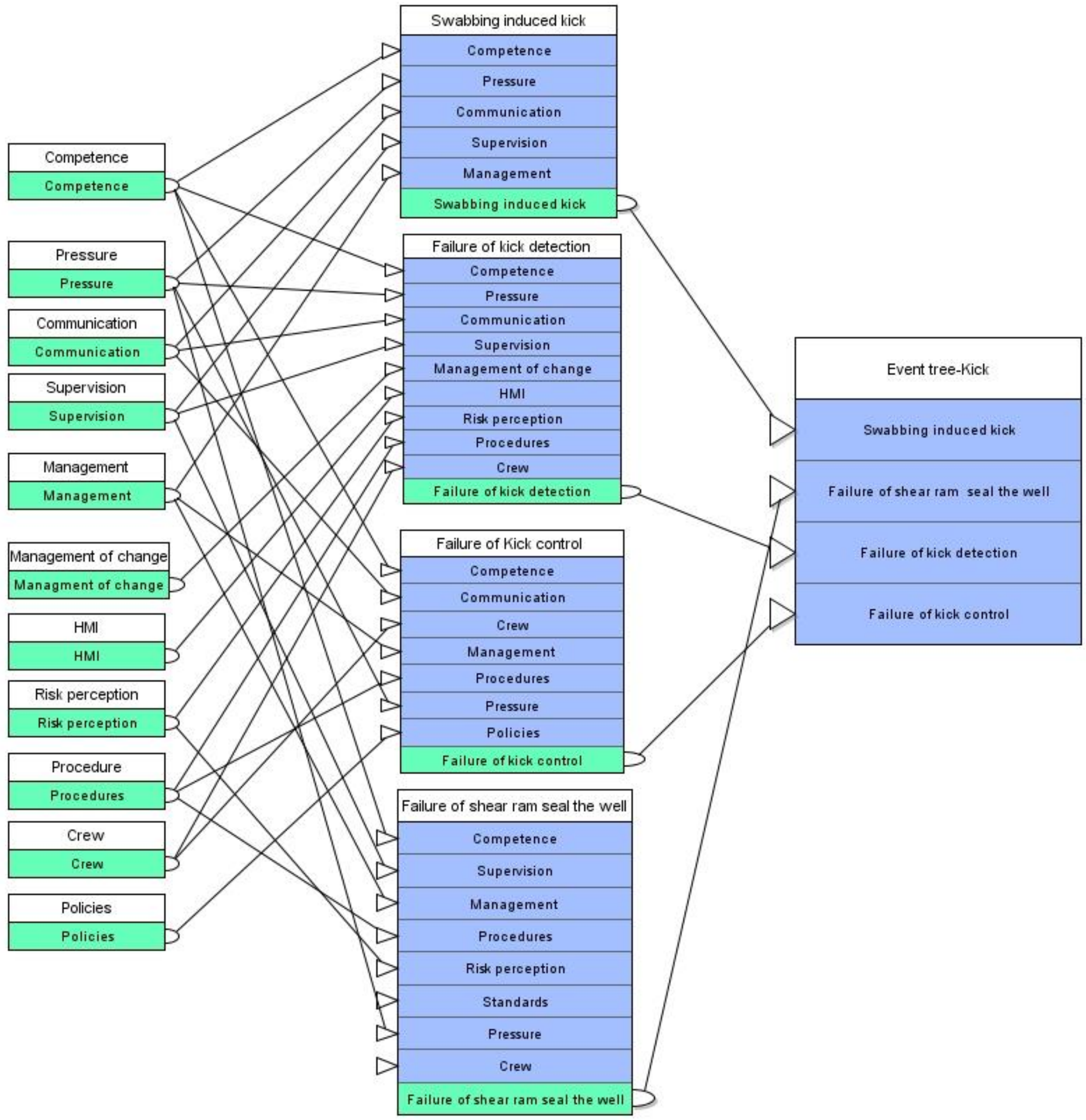


Figure 27 OOBNs in Agenarisk

The connections of different models in Agenarisk are illustrated in Figure 27.

Another application of the OOBN objective method is the influence of HFs. The BN allows the same HFs to have a connection to different safety barriers models. For example, the level of HF3 affects the probability of swabbing induced kick and failure of kick detection. If we assign the probability manually in each model, it is time-consuming. If we use OOBNs and assign HF3 as the output node in their evaluation model and the input node in fault trees BN, the information of HF3 will be updated simultaneously.

4.8 Mapping FTs and ET into BN

Before constructing the model in BN, some assumptions in the models include:

- All models consider the kick scenario due to swabbing in this research
- Some probabilities of basic events are assumed as the same value in literatures. If there is no information available, the value can be input by expert judgment.
- This research mainly focused on illustrating the methodology to incorporate HFs in offshore drilling risk assessment and analyze the results. The accuracy of the results depends on data information. The sensitivity analysis results in this research are only valid based on the assumptions in this paper.
- The same human factors that influence basic events are assumed to have the same distribution.

4.8.1 BN of swabbing induced kick

As we discussed above in section 4.7.3, the NPTs of human factors are TNormal distribution. They are quantified by mean and variance. The influencing importance rank of HFs nodes to basic events is assigned by weights. The scale of weights ranges from 1 to 5. If the human factor has the highest importance, the weight is assigned to 5. The mean of a child node is a weighted average of its parent nodes and calculated with a built-in *WeightedMean* expression in Agenarisk. The human factors that cause POOH fast includes [21]:

- Calculation error of pulling speed because of a low level of an engineer's competence
- Communication error
- Time pressure
- Insufficient data information about wells because of poor management of information

The HFs and their importance weights relevant to basic events are shown in Table 6.

Table 6 HFs and their weights to basic events in FT of swabbing induced kick

Basic events	Contributed human factors	Weights
POOH fast	Pressure	4
	Competence	3
	Communication	2
	Management	1
Insufficient check	Management	3
	Supervision	2

In offshore industry, the general probability of basic events is a certain value that is determined by generic data. However, the probability value could change on a certain specific platform due to different levels of influencing human factors. In order to reflect this consideration in the model, the probabilities of basic events are inputted as general probabilities when the conditions of the insert nodes are the “medium” level. The probabilities of basic events given by different parent node levels should be adjusted from the general probability. If the general probability is less than 0.1, the adjustment factors are suggested from the BORA method [30]. Otherwise, the adjusted probabilities are suggested by expert judgment. The suggested adjustment factors and the conditional probabilities of POOH fast for different levels of error are shown in Table 7.

Table 7 Probabilities of POOH fast for different levels of error

Level of error	Very Low	low	medium	High	Very high
Adjustment factors [30]	0.1	0.55	1	4	7
Probability of POOH fast	0.01	0.055	0.1	0.4	0.7

Figure 28 is the BN of swabbing induced kick. The prior probability of swabbing induced kick is 9.7%.

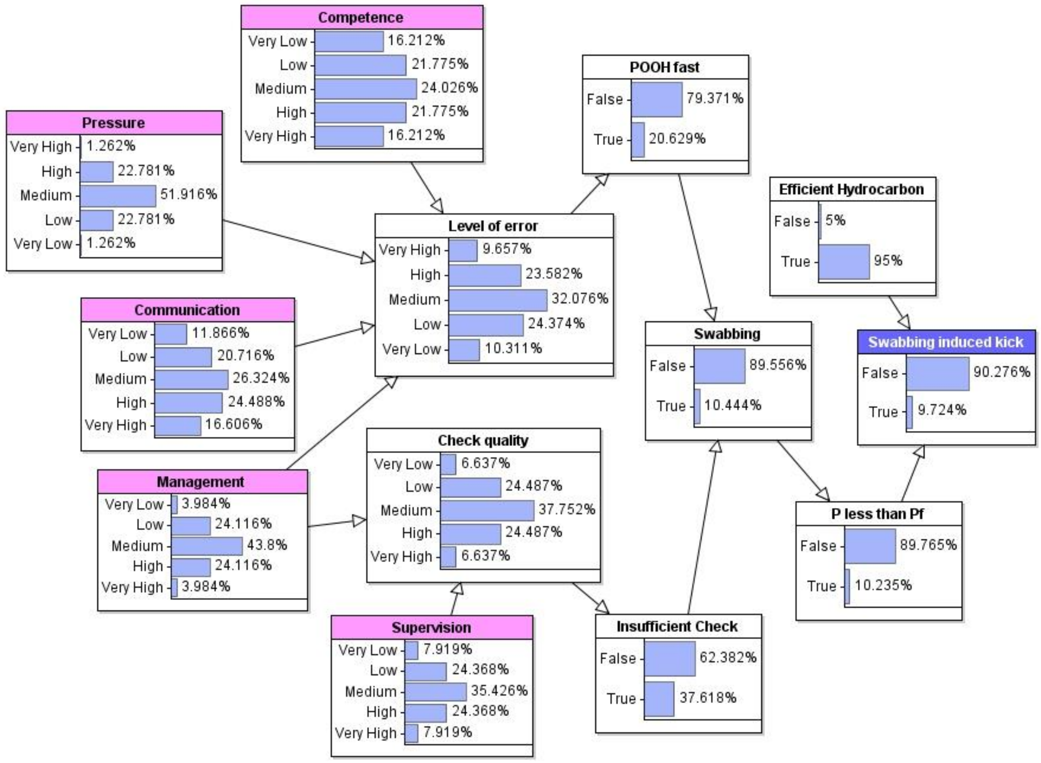


Figure 28 Swabbing induced kick by BN

4.8.2 BN of FT of kick detection

The HFs and their importance weights relevant to basic events in FT of kick detection are shown in Table 8.

With the same methodology as swabbing induced kick, the fault tree of kick detection is represented by BN in Figure 29. The prior probability of kick detection failure is 24.1%.

Table 8 HFs and their weights to basic events in FT of kick detection

Basic events	Contributed human factors	Weights
Signal is not monitored	HMI	5
	Pressure	3
Signal interpretation failure	Competence	-
Communication error	Communication	-
Setting error	Procedure	-
Rule violation	Risk perception	-
Hardware failure	-	-
Maintenance/testing error	Supervision	5
	Crew	2
	MOC	3
Inhibit alarm and forget to reset	Risk perception	4
	Pressure	2

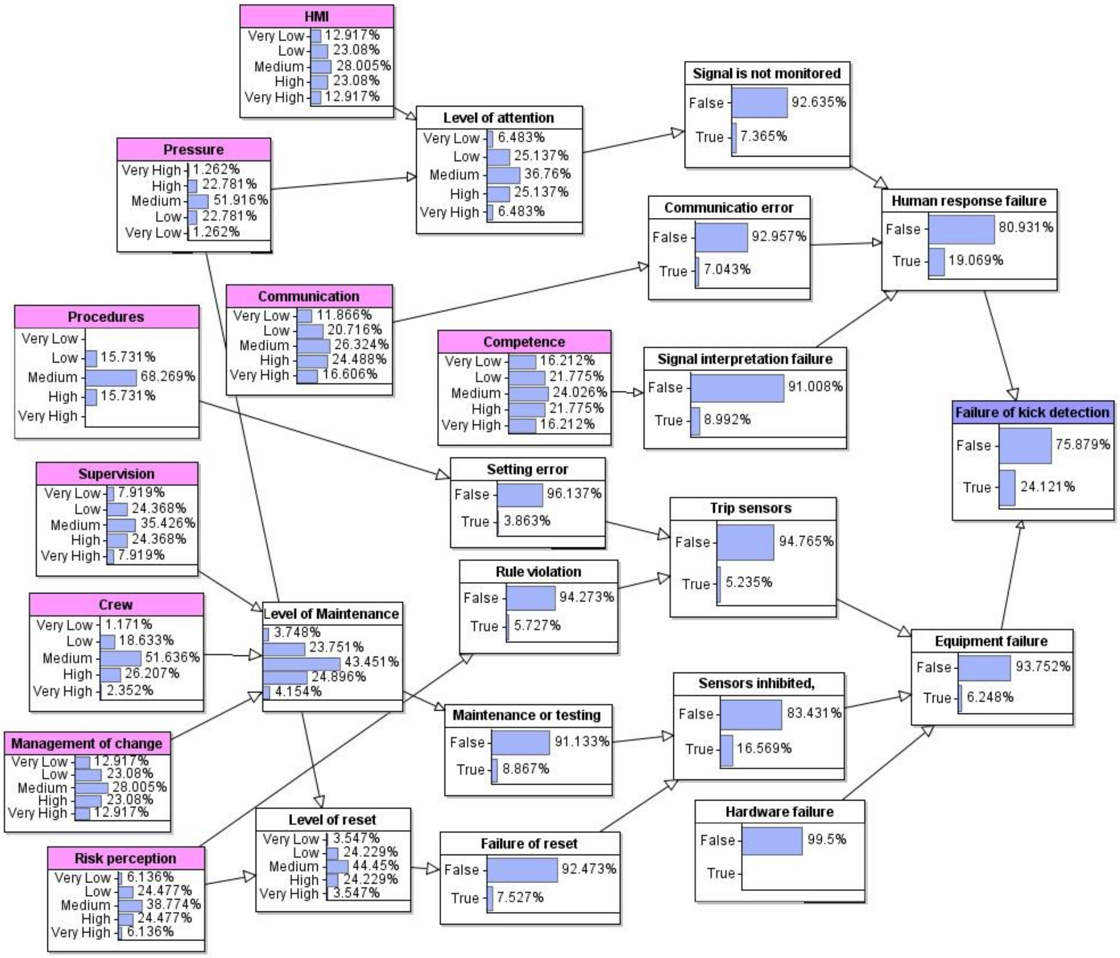


Figure 29 FT of kick detection by BN

4.8.3 BN of FT of kick control

The HFs and their importance weights relevant to basic events in FT of kick control are shown in Table 9.

The fault tree of kick control is represented by BN in Figure 30. The prior probability of kick detection failure is 22.6%.

Table 9 HFs and their weights to basic events in FT of kick control

Basic events	Contributed human factors	Weights
Not follow the shut-in procedure	Procedures	5
	Pressure	3
	Policies	3
Action inadequate or error for shut-in	Communication	4
	Crew	1
Failure of pipe rams and annular preventer in BOP	-	-
Choke valve failure	-	-
Blockage in choke system	Management	-
Pump rate error	Competence	-
Choke control error	Competence	-
Incorrect mud weight	Competence	3
	Communication	2
Mud pump failure	Management	-

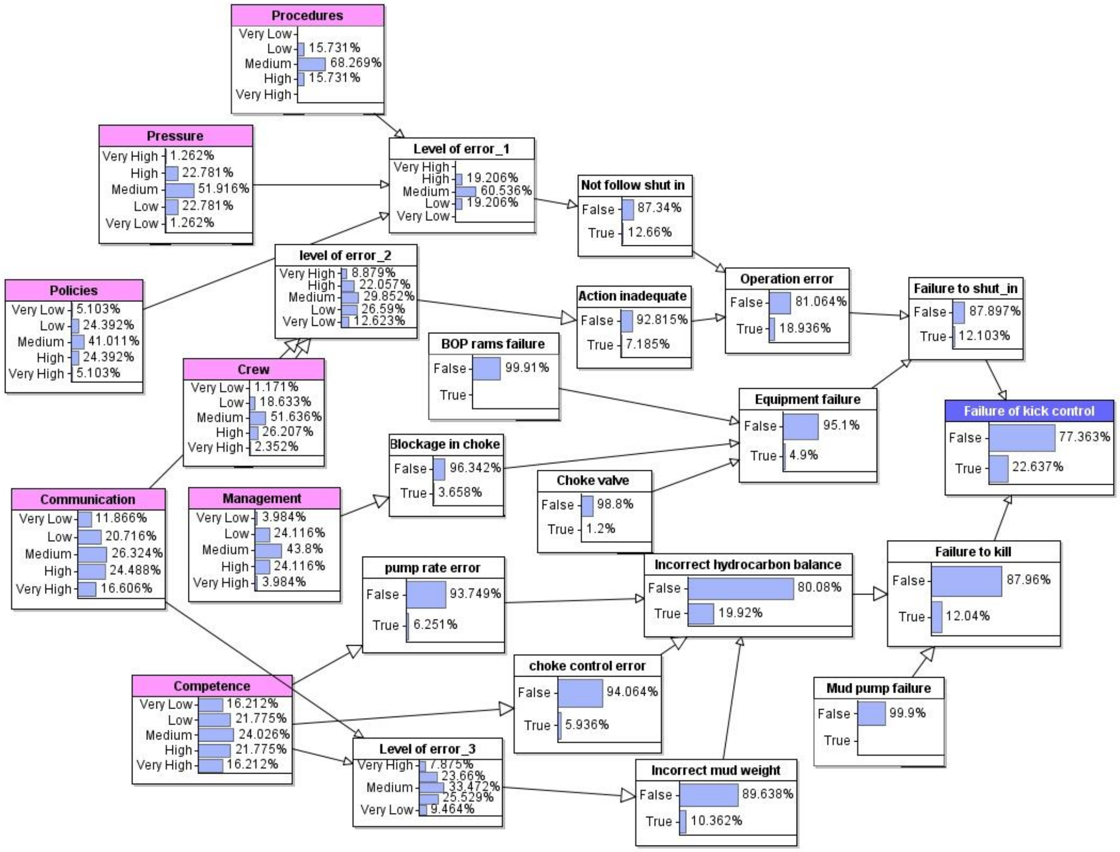


Figure 30 FT of kick control by BN

4.8.4 BN of FT of shear ram to seal the well

The HFs and their importance weights relevant to basic events in FT of shear ram to seal the well are shown in Table 10.

With the same methodology as swabbing induced kick, fault tree of shear ram to seal the well is represented by BN in Figure 31. The prior probability of kick detection failure is 16.8%.

Table 10 HFs and their weights to basic events in FT of shear ram to seal the well

Basic event	Contributed human factors	Weights
Design limitation	Standards	-
No shear ram test	Procedures	3
	Standards	4
Action error	Competence	2
	Risk perception	3
	Pressure	3
Installation error	Procedure	3
	Supervision	1
Maintenance/testing error	Management	3
	Supervision	1
	Crew	2

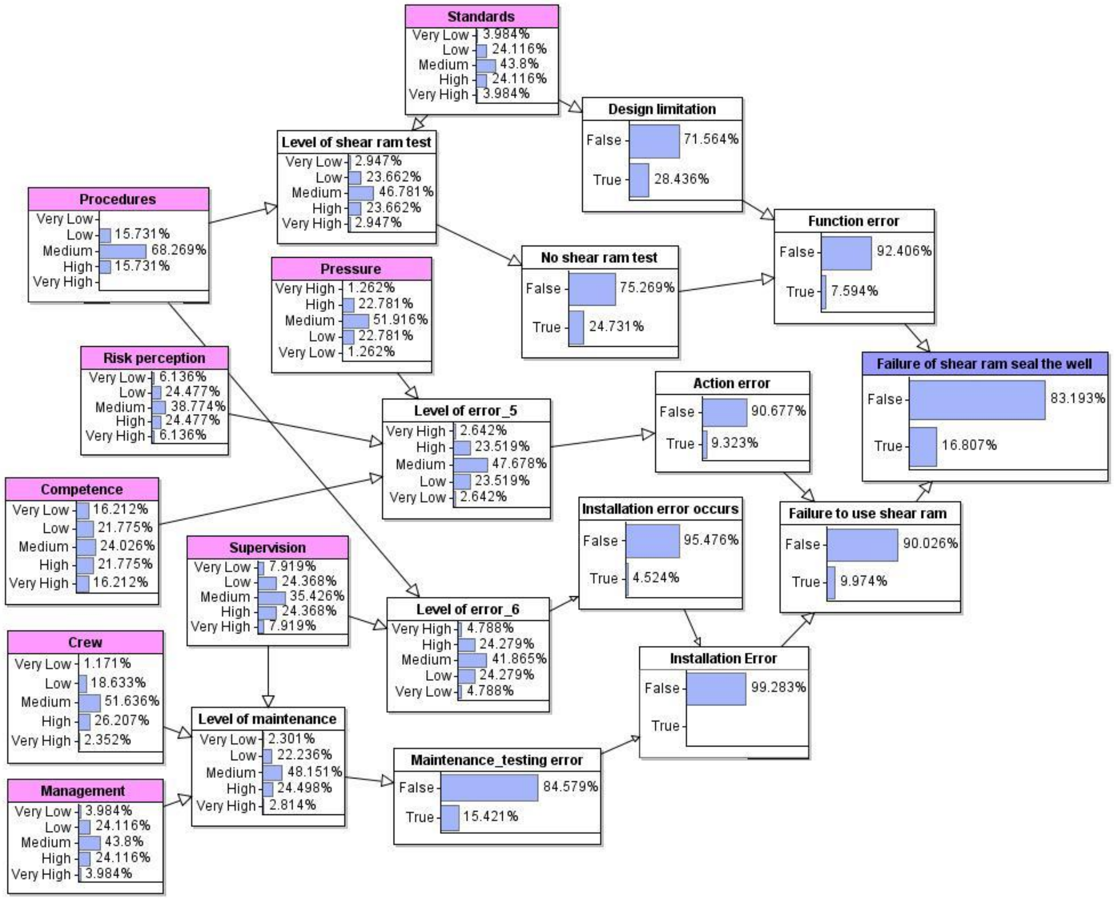


Figure 31 FT of shear ram to seal the well by BN

4.8.5 BN of ET

As we discussed above, the probabilities of swabbing induced kick, failure of kick detection, kick control and shear ram to seal the well are the same as the probabilities of top events in fault trees by OOBNs, which are shown in Figure 32. If any information is updated in the fault trees, the probabilities in this event tree model will be updated automatically. The prior probability of blowout is 2.6%.

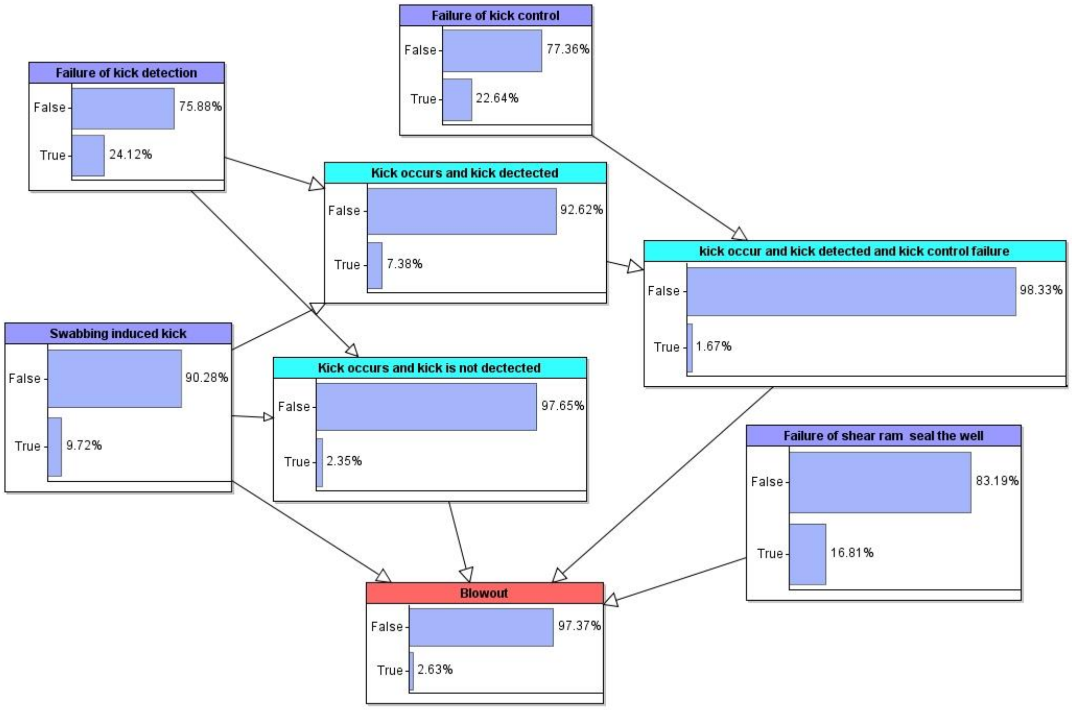


Figure 32 ET of kick into blowout by BN

4.9 Sensitivity analysis

The Agenarisk provides the function of sensitivity analysis. The length of the bars in Figure 33 correspond to each sensitivity node in the tornado graph as a measure of the impact of that node on the target node. The value shows the probability of the target node given the sensitivity node. For example, P (blowout= "True" | swabbing induced kick = "True") = 0.27. Thus, the node swabbing induced kick is by far the most impacted node on blowout and the kick detection is the second most impacted node. In industry, preventing the kick is the first and most important barriers for blowout, which prove that the model result is reasonable.

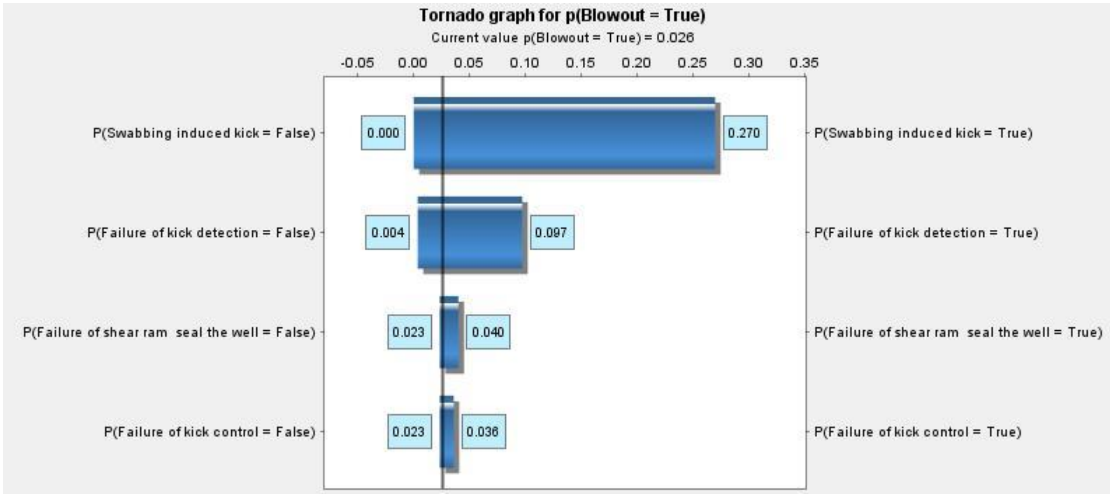


Figure 33 Sensitivity analysis of event tree

The important influencing HFs to kick, kick detection, kick control and shear ram function are shown in Figure 34 - Figure 37. For swabbing induced kick, the important HFs are pressure and management. For kick detection, they are competence and human-machine interface. For kick control, they are competence and management. For shear ram to seal the well, they are standards and pressure.

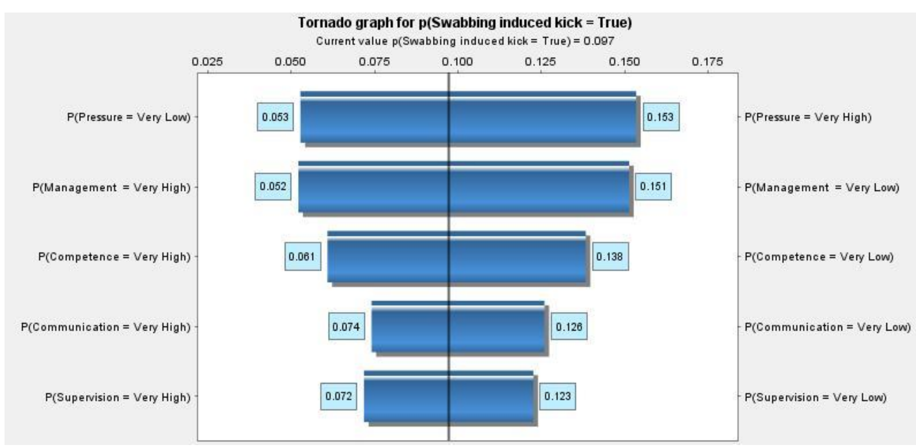


Figure 34 Sensitivity analysis of HFs' effect on kick

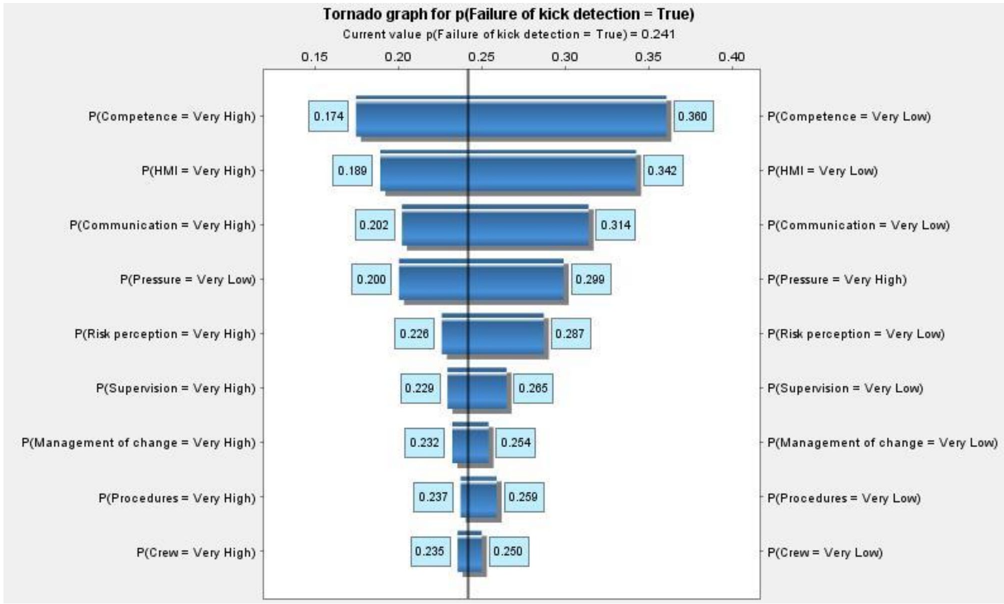


Figure 35 Sensitivity analysis of HFs' effect on kick detection

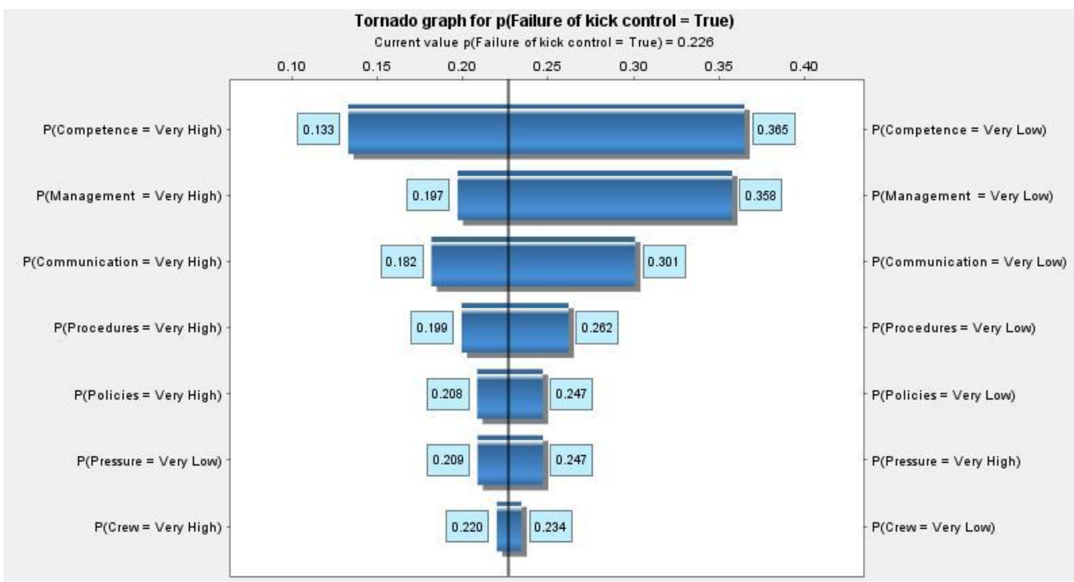


Figure 36 Sensitivity analysis of HFs' effect on kick control

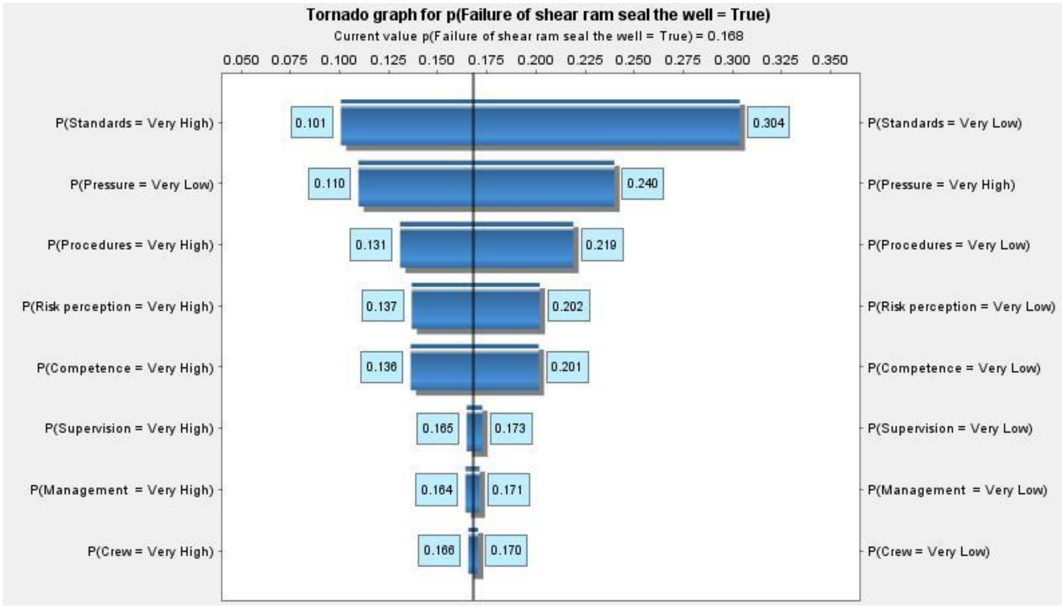


Figure 37 Sensitivity analysis of HFs' effect on shear ram

As the HFs nodes and blowout node are developed in different models and linked with OOBNs, the sensitivity function in Agenarisk cannot be achieved automatically. However, the blowout probability can be updated by assigning HFs information manually. Each human factor is assumed to be the lowest level and the probabilities of blowout are updated and compared. The results in Table 11 show that the most influencing human factors of blowout are competence, pressure, communication and management.

Table 11 Sensitivity analysis of HFs' effect on blowout

Human factors	**Blowout probabilities**
Prior probability	2.63%
Communication	4.39%
Pressure	5.22%
Management	4.35%
Competence	5.63%
Supervision	3.6%
Procedures	2.93%
HMI	3.57%
Management of change	2.74%
Risk perception	3.11%
Crew	2.72%
Policies	2.65%

As the most influencing factor is competence, the blowout probabilities for different competence levels (very low, medium, very high) are also studied. The input information of the three scenarios are shown in Figure 38. The very low, medium, and very high levels of competence are shown as blue, green and orange. The corresponding updated probabilities of blowout are 5.63%, 2.28% and 1.15% in Figure 39. The results show that the blowout probability decreases four times if the competence level of operators increases from a low level to a high level.

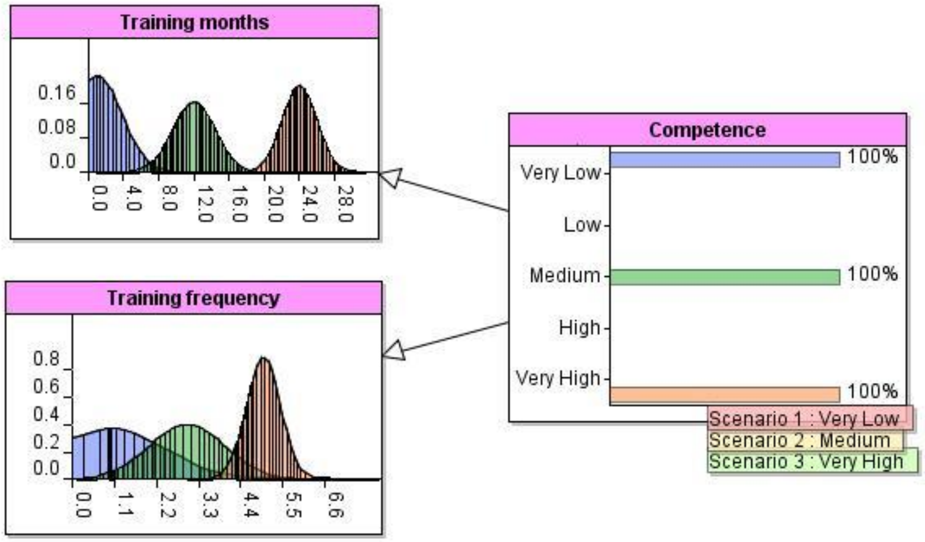


Figure 38 Input information of three scenarios

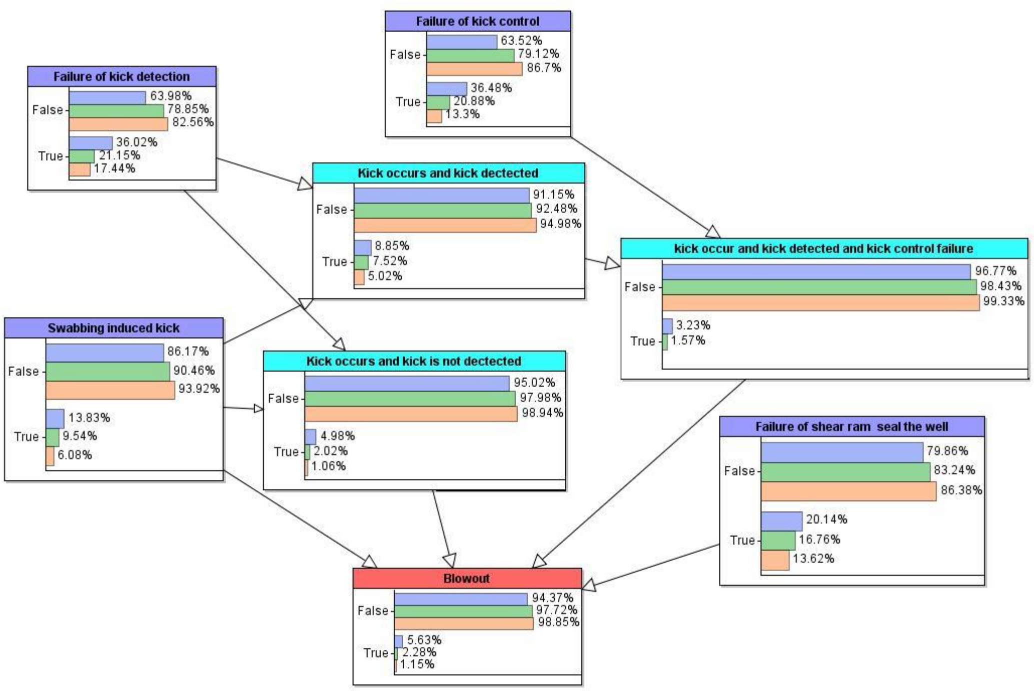


Figure 39 Updated blowout probabilities of different competence levels

The results show that the oil & gas companies should focus on the measures to improve the operators' competence, establish a balance between pressure and safety, improve management and improve communication between crews and different level of organization to mitigate the drilling risk due to swabbing.

5 CONCLUSION AND FUTURE WORK

5.1 Conclusion

As the offshore drilling is in a complex environment that depends on human factors, it is necessary to develop methodology to analyze the role of HFs. However, traditional risk assessment methodologies, such as FT, ET and bow-tie are static and not able to include soft evidence. HCL is a dynamic risk assessment model that capable of incorporating HFs together with common cause failures and casual relationships in drilling.

This research introduced the HCL framework for offshore blowout risk assessment to assess the contribution of human factors to offshore drilling safety with ET, FT and OOBNs. This work focused on a very common reason for kick – swabbing as a case study to illustrate how to apply these approaches to predict the blowout probability.

This work starts with identifying the HFs that should be considered in offshore industry. Only sub-heading human factors are considered in the model, including competence, motivation, risk perception, HMI, pressure, supervision, crew, communication, management, policies, management of change, standards, procedures and documentations.

Event tree is developed to describe how kick developed into blowout because of safety barriers' failure. Fault trees of swabbing induced kick and safety barriers are also developed to identify the basic events. The HFs is integrated to Bayesian network by linking arrows to basic events in fault trees mapping models. OOBNs is used to simply the model and connect all modes together for information updating.

The advantages of this model include:

- Evaluate the impact of HFs' levels on the probability of kick, kick detection, kick control, shear ram successful and blowout
- Track the most influencing factors for risk control and mitigation
- Update blowout probability by any accident precursor observations, such as kick
- Obtain more accurate result for specific platform and company

Result analysis of the BN in this research indicates that preventing the kick is the first and most important barriers for blowout. The most influencing human factors for blowout are competence, pressure, communication and management. The blowout probability decreases 4 times if the competence level of operators increases from a low level to a high level.

The developed models are only used to analyze the swabbing induced kick scenario. In offshore drilling, kick could be occurred by other reason during different sub-operations. The corresponding kick control methods could also varies, which will affect the detail information in fault trees. However, the methodologies are the same. It is expected to apply this work to other kick scenarios. In addition, human factors is a major contribution to other high-risk operations, either onshore or offshore, for which this model can be used.

5.2 Future work

In offshore drilling, another important performance factor is the respond time. whether a kick escalates into a blowout is highly dependent on how quickly it is detected and how properly and timely the mitigation measures are implemented [22]. In the Macondo Well, an important factor is that the operator did not detect the kick until more than 40 minutes later, which was too late for well control. This work only focused on human errors, so it could be improved by considering the time dependency.

Another limitation of this work is that human factors are assumed to be independent, which is not true in realistic. As the organization factors affect individual and group behavior, it is important to identify their dependent relationships.

The availability of date is important for the accuracy of blowout probability. Developing human factor indicators and establishing indictor databases are important tools to evaluate the effectiveness of HFs in human factors evaluation models.

Collaborate with a human factors expert to identify a more comprehensive structure of HFs categorization, such as perception and memories in cognition.

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