A DBN-based risk assessment model for prediction and diagnosis of offshore drilling incidents

Abstract:

Drilling operations of offshore oil and gas fields are characterized by high reliance on advanced technology, high risk, and high costs due to operating in harsh ocean environments, under complicated geological factors, and extreme operating condition. Lost circulation or well "kick" are examples of hazardous events that may occur while drilling wells and such events may develop into a blowout accident if not handled. Identification and analysis of root causes and consequences are effective measures to prevent serious accidents from happening. The risk of having a blowout may change with time, depending on the stage of the drilling operation, and such kind of dynamics should be captured in risk assessment. This paper presents an approach for determining the conditional probabilities of hazardous events and their consequences. The approach includes models that take into account the influence of degradation and (if used in operation) new real-time information which represents the change in a state of a model parameter (such as state change of mud density) that can be captured while the drilling operation is ongoing. The approach presents a newly-developed model based on the basic theory of Dynamic Bayesian network (DBN) and this proposed model can incorporate some additional nodes to handle the uncertainty issues involving the model uncertainty and relevant parameters' uncertainty and also consider the effect of degradation, which are missed in other papers when using the DBN method for risk assessment of similar systems and operations. The main objective of this newly-developed model is to demonstrate how dynamic risk assessments can be used for incident prediction evolution as well as root cause reasoning during offshore drilling operation, given that a specific event has occurred. A bowtie model is established firstly to link the potential incident scenarios with pressure regimes and formation load capacity, and then the model is translated into a DBN. DBN inference is adapted to perform predictive and diagnostic analysis in different time slices for risk assessment and root cause reasoning. A sensitivity analysis is carried out to find the relative importance of each root cause in generating the potential drilling incidents. A case study with focusing on lost circulation during three drilling scenarios is used to illustrate and verify the feasibility of the proposed approach.

Key words: Dynamic Bayesian network (DBN); drilling incidents; dynamic risk assessment; prediction of incident evolution; root cause reasoning

Highlights:

- Potential incident scenarios with pressure regimes and weak formation are presented.
- A newly-developed model based on Dynamic Bayesian Network is proposed for offshore

drilling incidents.

- Effects of model and parameter uncertainty are taken into account.
- Prediction of risk evolution and root cause reasoning are performed based on the influence of degradation and occurred events.

1 Introduction

Drilling into offshore oil and gas fields with high pressure, temperature, H_2S-gases, and weak formations such as sand, limestone and fissures will often face challenges such as narrow safe drilling fluid density window, multiple pressure systems in vertical direction, and high pressure zones. Drilling operations at such fields are more prone to serious problems (here referred to as drilling incidents), such as lost circulation and uncontrolled influx to well ("kick"), and blowouts (to environment) compared to (less demanding) oil and gas fields. These drilling incidents can result in unplanned downtime (which are costly) or may develop into large accidents, with the potential to cause fatalities, environmental damages, and full or partially loss of drilling facility and well (Crichton et al., 2005; Holland, 1997; Skogdalen et al., 2011). For example, the well-known Macondo blowout that occurred during the last stage of a drilling operation resulted in 11 fatalities and the largest oil spill in the history of offshore oil and gas industry. Predicting early kick or lost circulation, and taking necessary precautions, have been regarded as key measures to avoid such kind of disastrous accidents (Khan and Abbasi, 1999; Skogdalen and Vinnem, 2012).

Kick is the first warning and step towards a blowout, and it is therefore important to detect a kick as early as possible and to implement efficient measures in due time. Mud weight and circulation is the primary barrier to prevent kicks, and lost circulation is an early indication of a kick under development. It is reported that drilling operations often experience loss of circulation, and it is therefore important to direct the attention to avoid and manage this situation. A loss of circulation occurs when the bottom hole pressure in the wellbore is higher than the formation pressure, allowing (or forcing) the drilling fluid to flow into the formation. Several researchers have focused on the effects of lost circulation (Shen, 2015; Yan et al., 2015), and proposed measures to reduce such effects (Alexander, 1989; Sheremetov et al., 2008). Lost circulation is usually accompanied by wellbore stability problems, damage of reservoir near well bottom, and stuck pipe, and these are the main reasons why kick and even blowout can occur as a consequence. Managed pressure drilling (MPD) technology is developed to avoid flow of drilling fluid into the formation, and MPD is therefore an important measure to avoid loss of circulation and eliminate lost circulation-kick incidents (Hannegan, 2006; Hannegan & Fisher, 2005). Consequently, the effects of MPD should be included in risk assessments associated with loss of circulation.

Bayesian networks (BNs) is a flexible approach to include the effects of drilling systems along with other risk influencing factors like well conditions and physical measurements. Abimbola et al. (2015) have, for example, proposed a BN-based risk model that considers potential scenarios for different pressure regimes. BNs may be derived from other frequently used models, such as bow-ties (BTs), fault trees (FTs) and event trees (ETs), for example with basis in the BTs, FTs and ETs developed by Khakzad et al. (2013). Bhandari et al. (2015) applied BN method to investigate different risk factors associated with MPD and underbalanced drilling deep water drilling technologies with respect to blowout accidents. Other approaches for modeling risk also exist: Xue et al. (2013) have proposed a safety barrier-based accident model for blowouts which is consider the effects of three-level well control (i.e. control using drilling fluid, control using circulation and shut-in). Ataallahi and Shadizadeh (2015) have introduced Delphi and fuzzy approach into a risk analysis model, and used this model to find and compare the main risk influencing factors in exploration drilling, of well completion, and workover of wells after the well has been put into production phase.

The main weakness of the mentioned risk assessment approaches is their inability to capture dynamic effects of a drilling operation, such as change of well conditions, new information about events that have occurred, and new estimates or measurement of technical state of equipment. FT, ET and BT models (which constitute the main elements of most methods proposed) are all unable to account for correlation and dependencies between mentioned factors, and the models cannot be easily updated under changing conditions and handle the uncertainty issues (Khakzad et al., 2011). Models based on BN can overcome these modeling deficiencies, but cannot explicitly treat temporary relationships between model parameters (Cai et al., 2015; Hu et al., 2015), i.e. account for the fact that relationships of parameters may change from one drilling phase to the next. These limitations have already been resolved by introducing dynamic BNs (DBN). DBN builds on BNs, but have additional features that allow the incorporation of events, conditions, and interrelationships that may change over time. Cai et al. (2013) have explored the use of DBN in performance evaluation of subsea blowout preventer BOP considering imperfect repair. DBNs have also been introduced for the same purpose in other industry sectors, such as for monitoring the risk of tunnel-induced road surface damage (Wu et al., 2015) and for studying the risk of life extension of fire water pump (Ramírez and Utne, 2015).

The application of DBN is an alternative to the traditional risk techniques in terms of applying the conditional dependencies, and updating initial failure probabilities of root causes when additional information is available. What seems to be missing is the possibility to incorporate the effects of both model uncertainty and parameter uncertainty. Parameter uncertainty may exist due to prior knowledge being from existing literature, while model uncertainty may relate to uncertainty about the logical relationship between model parameters. Both of these are relevant in situations where experience is limited and the causal relationship is not well understood. In addition, current DBN based models assume that parameters of conditional probability and failure rates are time-invariant (Cai et al., 2013; Hu et al., 2011) , but in practices many failures in mechanical equipment follow other probability distribution, e.g. Weibull. The main motivation for this paper is therefore to present a newly-developed approach based on DBN theory for risk modeling, by integrating parameter uncertainty of prior knowledge, by introducing failure probability distribution according to the Weibull rules, and by allowing that causal relationships may be uncertain. The modeling techniques by (Kjaerulff and Madsen, 2008) are used to handle the model uncertainty issues. The proposed approach may be used to systematically perform the predictive, diagnostic and sensitivity analysis for risk assessment. A case study is introduced to demonstrate the application of the proposed risk models for lost circulation during three drilling operations.

The rest of this paper is organized as follows. Section 2 presents three drilling scenarios with the MPD technology. In section 3, the fundamental theory of BN and DBN will be briefly introduced. In section 4, a DBN-based risk assessment model is developed by incorporating some additional nodes to handle the uncertainty issues involving the model uncertainty and relevant parameters' uncertainty and the effect of degradation is also considered for the drilling incidents.

The proposed method is applied for incident prediction evolution as well as root cause reasoning regarding lost circulation in the case study of section 5. Section 6 provides the conclusion and research perspectives of this study.

2. Manage pressure drilling (MPD) technology

MPD is regarded as a powerful drilling hazard mitigation technique for offshore drilling and is defined by International Association of Drilling Contractors (IADC) Underbalanced Operations Committee as “an adaptive drilling process used to precisely control the annual pressure profile throughout the wellbore”. The aim of MPD is to ascertain the down hole pressure environment limits and to manage the annular hydraulic pressure profile accordingly (Stamnes et al., 2008). An MPD system consists of the following main systems: a rotating control device (RCD), an automated dynamic annular pressure control (DAPC) system, a backpressure pump, a DAPC choke manifold, a flowmeter (Elliott et al., 2011). The RCD is also regarded as first barrier to seal between the annulus and drillstring by creating a closed circulation system different from normally open circulation system, and therefore the flow of mud out from the annulus can be controlled by an automated choke. The DAPC system is used to maintain the constant bottom hole pressure (BHP) through providing the backpressure on the annulus by continuously adjusting the DAPC chocks and backpressure pump. A flowmeter provides the flow-out data and kick detection is predicted by monitoring flow-in data (Vajargah and van Oort, 2015). MPD drilling techniques include constant bottom hole pressure (CBHP), pressurized mud-cap drilling, and dual gradient drilling (Rehm et al., 2013). The case study selected for this paper focuses on the use of CBHP as a measure to prevent or mitigate drilling hazards, such as differential sticking, lost circulation and kicks, on a development well in a pressurized, fractured basement with narrow downhole environmental limitation. The MPD system can also optimize the rate of penetration, reduce non-productive time and the number of casing strings relative to conventional drilling techniques, and deepen casing set points. The typical offshore MPD system is illustrated in Fig.1.

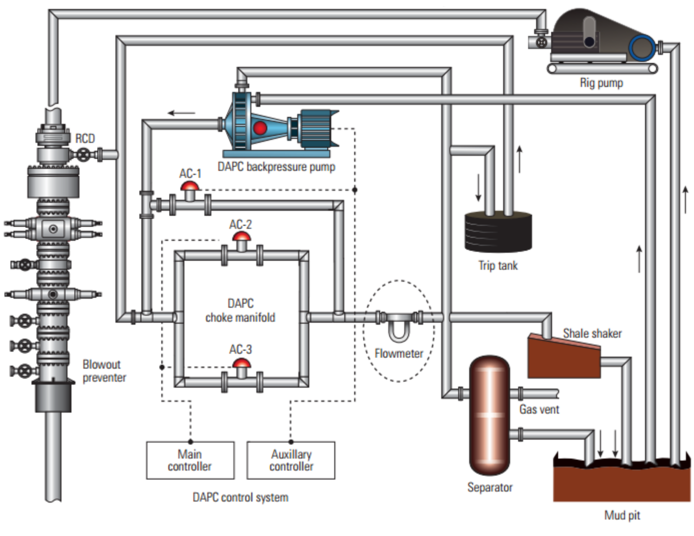


Fig.1 MPD system (Elliott et al., 2011)

During a drilling operation, it is required to always maintain two functioning well barriers: The primary barrier, which is the active balancing of drilling fluid (i.e. mud) to avoid hydrocarbons escaping from the well, and the secondary barrier, which is the BOP. The BOP consists mainly of BOP control system and BOP stack, used to seal, control and monitor oil and gas wells to prevent blowout, the uncontrolled release of crude oil and/or natural gas from well. The MPD system can be regarded as being part of the primary barrier, as the system applies backpressure control to maintain control with BHP (Patel et al., 2013). The hydrostatic pressure of the drilling fluid column must take into account the correct balance between BHP and formation fracture pressure (FFP).

The formula for determining the BHP (Rehm et al., 2013) varies for different types of drilling operations. Three types of drilling operations have been considered in this paper: not circulating, tripping in, and circulating. When the rig pump is not circulating the drilling fluid, the static BHP is defined as:

$$\mathrm{BHP}_{static} = P_{dfc} = \rho_d g h + P_b \tag{1}$$

where P_{dfc} is the hydrostatic pressure of the drilling fluid column, ρ_d is the density of drilling fluid and, g stands for gravitational acceleration, h is drilling fluid height, and P_b is the backpressure of wellhead.

When the drillstring is tripping in the wellbole, the dynamic BHP is defined as:

$$\mathrm{BHP}_{dynamic} = P_{dfc} + P_{sg} = \rho_d g h + P_{sg} + P_b \tag{2}$$

where P_{sg} is the surging pressure caused by drillstring tripping in the wellbore, and P_b is the backpressure of wellhead.

When the rig pump is on and circulating the drilling fluid, the dynamic BHP is defined as:

$$\mathrm{BHP}_{dynamic} = P_{dfc} + P_{fc} = \rho_d g h + P_{fc} + P_b \tag{3}$$

where P_{fc} is the frictional pressure due to pumping the drilling fluid through the drillstring, and P_{fc} is the backpressure of wellhead.

In this paper, the main focus is on the control a CBHP to avoid drilling fluid loss. If the MPD system fails to perform this function, the result may be serious, such as differential sticking and lost circulation. Lost circulation does not simply means the loss of a few dollars of drilling mud, but it can be disastrous as a blowout. Drilling crew therefore pays close attention to monitoring of tanks, pits, and flow from the well, to quickly assess and control the lost circulation. This paper studies the causes and effects of lost circulation for the three mentioned, considering the performance of the MPD system and other influencing factors.

3 Theoretical basis for Dynamic Bayesian Networks

Dynamic Bayesian Networks (DBNs) is an extension of Bayesian Network (BNs). This section highlights some selected points about the theoretical of BNs as well as DBNs.

3.1 Bayesian Networks

A BN is a combination of graph model and probability theory, consisting of a directed acyclic graph (DAG) and an associated joint probability distribution (JPD) (Nielsen and Jensen, 2009). In a DAG, nodes including parent nodes and child nodes represent random variables, and links determine probabilistic dependences between variables. A conditional probability table (CPT) for discrete variables is defined for the relationship among parent nodes to demonstrate marginal probability. Assuming $Pa(X_i)$ is the parent node of X_i, the CPT of X_i is denoted by $P(X_i \mid Pa(X_i))$. Therefore, the JPD,$\mathrm{P}(X_1, \dots, X_N)$, can be rewritten as Eq. (4).

$$\mathrm{P}(X_1, \dots, X_N) = \prod P(X_i \mid Pa(X_i)) \tag{4}$$

The quantification of probabilities in BNs includes to two steps: assigning prior probabilities to the parent nodes, and defining CPT of child nodes by combining a priori knowledge. Such knowledge can be from expert judgment, or observations.

3.2 Dynamic Bayesian Networks

A DBN is a type of BN which is used to model time-series data by introducing relevant temporal dependencies, so as to describe the dynamic behavior of random variables (Hu et al., 2011). A DBN consists of a sequence of time slices and temporal links. Each slice represents a static BN to describe variables in the corresponding time step and temporal links between variables in different time slices represent a temporal probabilistic dependence. A DBN is an extension of BN to model probability distribution over semi-infinite collection of random variables. The CPT of each variable in DBN can be calculated independently, facilitating the interpretation of DBN.

In general, there are two assumptions for a DBN construction interconnected time slices of static BNs. Firstly, the system is considered as the first-order Markovian (i.e.,$\mathrm{P}(X_t|X_1, \dots, X_{t-1}) = \mathrm{P}(X_t| \ X_{t-1})$. Secondly the transition probability $\mathrm{P}(X_t| \ X_{t-1})$ is the same for all the t. Therefore, a DBN can be defined by a pair of BNs (B_1, B→): where B_1 is a BN which defines the prior $P(X_1)$, and *B*→ is a two-slice temporal Bayesian net (2TBN) that defines the transition and observation models as a product of the CPTs in the 2TBN (Murphy, 2002), as seen in Eq. (5).

$$\mathrm{P}(X_t| \ X_{t-1}) = \prod_{i=1}^{N} P(X_t^i \mid Pa(X_t^i)) \tag{5}$$

where

- X_t^i is the i^{th} node in time-slice *t*,
- $Pa(X_t^i)$ denotes the parent of X_t^i, which may be in the same time-slice *t* or previous time-slice *t-1*, and
- *N* indicates the number of random variables in X_t^i.

The nodes in the first time-slice of a 2TBN have unconditional initial state distribution, $\mathrm{P}(X_1^{1:N})$, while each node in the second time-slice has an associated CPT. Then, for a DBN with *T* slices, the joint distribution can be obtained by "unrolling" the network as expressed in Eq. (6).

$$\mathrm{P}(X_{1:T}^{1:N}) = \prod_{i=1}^{N} P_{B1}(X_1^i \mid Pa(X_1^i)) \times \prod_{t=2}^{T} \prod_{i=1}^{N} P_{B\rightarrow}(X_t^i \mid Pa(X_t^i)) \tag{6}$$

Several inference algorithm (Murphy, 2002; Neapolitan, 2004) have been proposed for DBN modeling. In this paper, the forwards-backwards inference and mutual information are used for Bayesian inference. The main benefit of introducing DBN for risk assessment may be summarized as follows:

- A DBN as an excellent tool for many types of probabilistic inference can make all relevant qualitative and quantitative analysis in a full probabilistic model, including a broad variety of modeling schemes in a single framework and a large collection of exact and approximate inference techniques from the BN applied to dynamical process.

- A DBN is more acceptable for predicting values of variables and capable of revealing the system state at any time. At a time slice new information about model parameters may be incorporated into the model, the value of a variable can be calculated based on probabilistic inference. This information may be in the format of:
  1) Updated probabilities, updated only on the basis of the associated probability distribution and the elapsed time.
  2) Updated probabilities, considering new real-time information, such as a change in a state of a model parameter.
  3) A combination of the two above, using Bayesian update.

4 Development of a DBN-based risk assessment model

DBN is in this paper introduced as an approach to enhance the safety and reliability of drilling activities of complex offshore wells. The DBN is used as basis to set up a risk assessment model consisting of factors that may lead to drilling incidents, the causal relationship between them, and the effects of measures available to prevent the escalation. The model is used to perform the prediction for occurrence probability of drilling incidents over time and compare risk among the different drilling processes. The overall workflow needed to derive the model and apply it for risk assessment is shown in Fig. 2. As seen in the figure, there are three main steps: Hazard identification, DBN establishment, and DBN-based risk assessment.

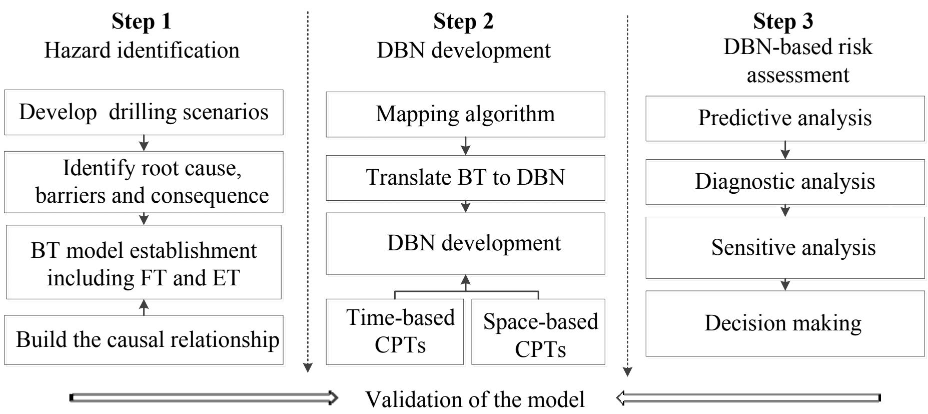


Fig. 2. DBN-based risk assessment model for drilling incidents

The particulars of the presenting model are specified as:

- Step 1: A BT model is integrated, so that the cause-consequence chain or causal relationships can be easily identified and evolvement of drilling incidents can be foreseen.
- Step 2: Uncertainties related to DBN model construction and failure data are considered. The parameters of CPTs from the previous time to the current time used in the proposed model are assumed both time-variant and time-homogeneous.
- Step 3: Estimation does not only focus on forward analysis, but also dynamics given any event occurring drilling process. In addition, the occurrence probability of a top event as a

function of time will be evaluated. The root cause reasoning and the development trend of underlying consequence are discussed given the occurrence of top event in diagnostic analysis.

4.1 Step 1: Hazard identification

A BT model can provide visual explanation of a complete accident scenario evolution and are widely applied in hazard identification and risk analyses (De Dianous and Fiévez, 2006). A simplified BT is shown in Fig. 3(a), with three main parts: The left side, the middle, and the right side. On the left side is a FT, identifying the causes of an unwanted event (which is placed in the middle), and on the right side there is an ET, identifying the possible outcomes given the effects of mitigating measures.

The following notations will be used in the rest:

- Root causes (RC), the basic events of the FT,
- Intermediate event (IE), which can be substructures of the FT,
- Top event (TE), the unwanted event that is placed in the middle of the BT,
- Safety barriers (SB), mitigation measures to reduce the severity of potential consequences (C).

Once hazards have been identified, the bow-tie model can be applied to further build the causal relationships. This process for hazards identification is considered a difficult task for complex offshore wells, especially the drilling with high temperature and pressure information.

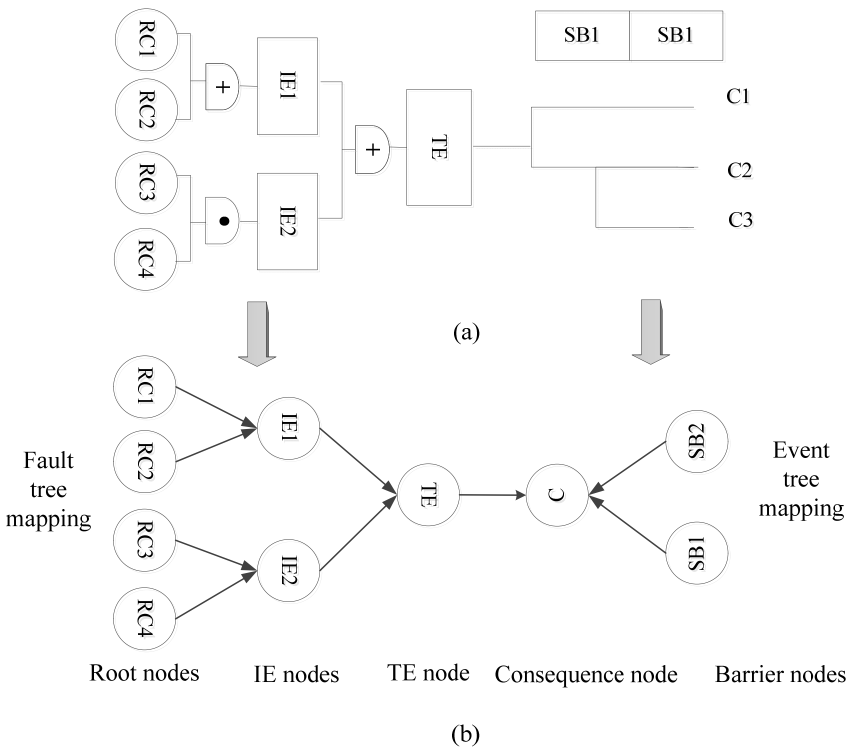


Fig. 3. Translating from BT to BN (a) simplified BT model (b) simplified BT model

The detailed steps for hazard identification are explicitly illustrated as follows.

(1) Develop drilling incidents scenarios based on the drilling operations and pressure regime

in section 2.

(2) Collect available safety-based information about hazards including ocean environment factors, geological factors, drilling technology, and human factors ect.., incidents (kick, lost circulation ect.) or underlying consequences (blowout ect.) associated with the drilling operation in question, using the relative standards, literature, accident reports and experts input.

(3) Develop BT based on the FT and ET theory for drilling incidents, and the BT should be reviewed by relevant personnel from operations, maintenance, safety and management, etc.

(4) Describe the explicit causal relationships among the root causes, target incidents and consequences and define the state of each root cause and the corresponding failure data.

But the application of BT in the risk analysis suffers the limitation of updating probability and cannot take uncertainty into consideration (Khakzad et al., 2011). More importantly, because of being composed of static structures such as FT and ET, BT has not widely been recognized in the context of dynamic analysis. To consider dynamic behavior over time, the BT model needs to be transformed into DBN for dynamic risk assessment. The dynamic behavior over time consists of three aspects as follows:

- The evolution tendency of the TE can be predicted over time after the actual evidences of root causes are collected in different time-slices.
- The occurrence probability of having TE and experiencing corresponding consequences will be predicted given the current status of root causes detected at any time.
- The failure probabilities of any root cause at previous time can be calculated when the status of this cause at current time is detected.

4.2 Step 2: DBN development

4.2.1 Mapping BT to BN

The translating algorithm from BT to BN consists of FT mapping and ET mapping(Khakzad et al., 2013). First, the mapping from FT into BN includes a graphical and probability translation based on the previous work (Bobbio et al., 2001). Fig. 3(b) illustrates the simplified procedure of mapping FT and ET into BN. In the graphical translation phase, each root cause, intermediate event and top event of FT is translated into a corresponding root node, intermediate event (IE) node and top event (TE) node of BN, respectively. The nodes of BN are linked in the same way as the corresponding events in the FT. In the probability translation phase, the failure probabilities of the root causes are assigned to the corresponding parents nodes as prior probabilities. The connections between events such as "AND gate" and "OR gate" are translated into equivalent conditional probability tables (CPT) in BN.

Bearfield and Marsh (2005) present a mapping algorithm from ET into DBN, which includes safety barriers and consequence translation. Each safety barrier of ET is translated into a corresponding barrier node with two states (functioning and failure) and the consequences of ET are translated into a corresponding consequence node with multiple states as the number of the event tree consequences. The state probability of the consequence node is influenced by the state of the barrier node. The failure probability of safety barriers is assigned to the prior probabilities of corresponding barrier nodes. It is noted that the CPTs of the corresponding consequence node are assigned base on the expert judgment.

4.2.2 Simplified DBN model development

As state of the node or the occurrence probability of the node e.g. failure is changing over time, a simplified DBN is established by extending the BN formalism within three time-slices from at time $t=0$, $t=t_1$ to at time $t=t_2$, as presented in Fig. 4(a). The time interval is the same between 0 and t_1 or t_1 and t_2. As indicated in Fig. 4(a), the root nodes RC1, RC2, RC3 and RC4, and barrier nodes SB1 and SB2 are extended from 0^{th} to t_1 or from t_1 to t_2 with inter-slice arcs, respectively. There are no inter-slice arcs assigned for other nodes except for root nodes and barrier nodes because the inter relationship over time is not discussed in this paper. Each root nodes of DBN can take two states, YES and NO. The state YES denotes that a root cause occurs, while NO means that the root cause doesn't occur. IE/TE can take states True or False. The state True and False refers to the IE/TE occur and do not occur, respectively. Each barrier nodes of DBN also involve two states, namely, Success and Failure. The state Success and Failure refers whether or not the barrier is able to carry out its safety function or not.

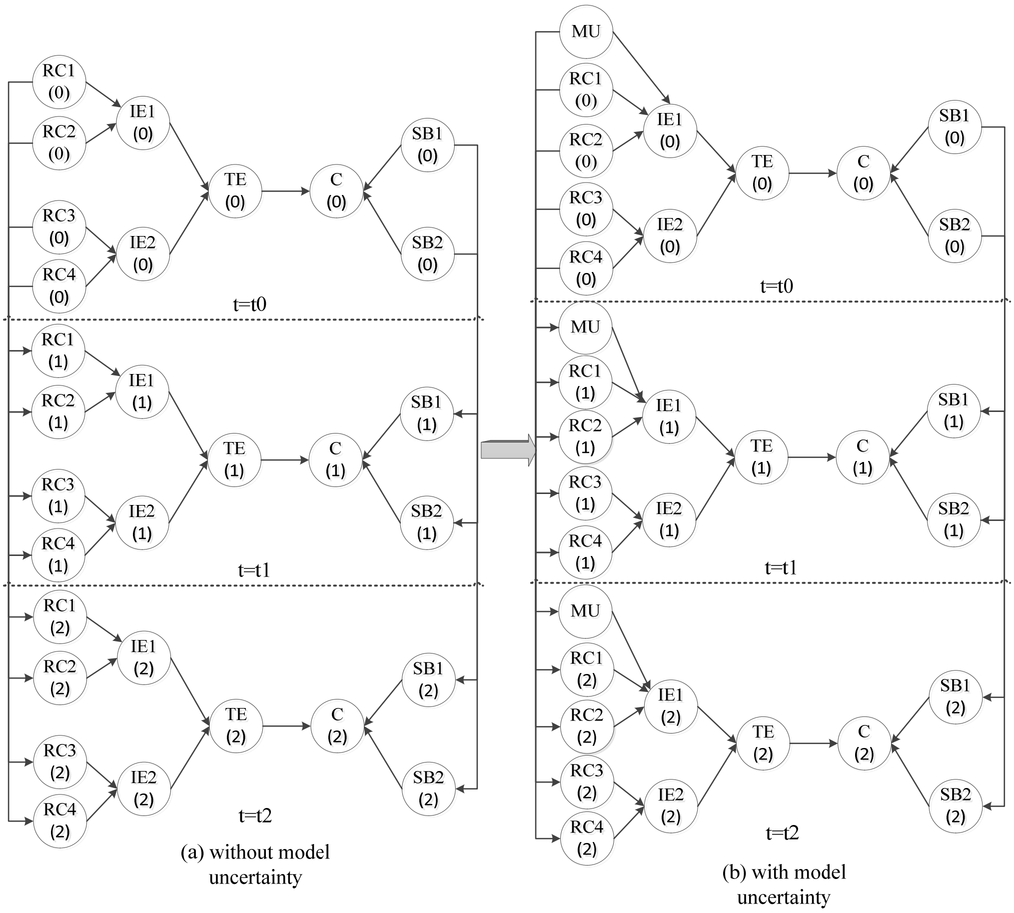


Fig. 4. Simplified DBN modeling (a) without model uncertainty and (b) with model uncertainty for three time-slices

This proposed model can handle the uncertainty issues involving the model uncertainty and parameters uncertainty.

(1) Modeling uncertainty is necessary due to the lack of the accurate determination of a causal relationship between the nodes and their parents, e.g. the relationship between the nodes RC1 and RC2 cannot completely follow the OR-gate. To handle the model uncertainty, the nodes denoted as MU as shown in Fig.5 (b) is introduced by modifying its CPT and constant with different time-slices. MU can take the states OR and AND, which refers to the IE follow the OR-gate or the AND-gate. The CPT of IE1 can be assigned as seen Table 1, e.g. $\mathrm{P(IE1 = True|RC1 = YES, RC2 = YES, MU = OR) = 1}$.

Table 1 CPT for IE1 node

RC1		RC2		MU		IE1	
YES	NO	YES	NO	OR	AND	True	False
1	0	1	0	1	0	1	0
1	0	1	0	1	0	1	0
1	0	0	1	1	0	1	0
0	1	0	1	1	0	0	1
1	0	1	0	0	1	1	0
0	1	1	0	0	1	0	1
1	0	0	1	0	1	0	1
0	1	0	1	0	1	0	1

(2) Parameters uncertainty can be split into the space-based and the time-based.

- The space-based parameters uncertainty occurs when linking the root nodes (R_i) to IE nodes (IE_j), which is based on the uncertainty of the root causes itself, e.g. the node RC3 and RC4 which represent the formation fracture pressure and formation porosity are influenced by uncertainty effect of geology information for offshore drilling operation. We can handle this uncertainty by using Noisy AND-gate or Noisy OR-gate algorithm (Neapolitan 2004). If we assume that $\mathrm{P(IE2 = True|RC3 = YES, RC4 = NO) = 0.04}$ and $\mathrm{P(IE2 = True|RC3 = NO, RC4 = YES) = 0.05}$, we can get $\mathrm{P(IE2 = True|RC3 = YES, RC4 = YES) = 0.088}$. The CPT can be assigned as seen Table 2.

Table 2 CPT for IE2 node

RC3		RC4		IE2	
YES	NO	YES	NO	True	False
1	0	1	0	0.088	0.912
0	1	1	0	0.04	0.96
1	0	0	1	0.05	0.95
0	1	0	1	0	1

- The time-based parameters uncertainty occurs when linking the root nodes (R^i_{tj-1}) at the previous time t_{j-1} to the root nodes (R^i_{tj}) at the current time t_j. The CPTs are assumed time-invariant if prior knowledge is usually obtained in accordance with accident statistic and literature reviews, e.g. the occurrence probability of for a specific change in density is P which is prior probability and assumed to be constant over time. We assumed when the root cause occurs at time t-1, the root cause will not occur at time t. It means that the root cause can be adjusted in a perfect state in the current time interval. The CPTs is therefore assigned as shown in Table 3, when $\mathrm{P}(R^i_{tj} = \mathrm{YES}|\ R^i_{tj-1} = \mathrm{YES}) = 0$ and $\mathrm{P}(R^i_{tj} = \mathrm{NO}|\ R^i_{tj-1} = \mathrm{YES}) = \mathrm{P}(R^i_{tj})$.

Table 3 CPT for two time slices

t_{j-1}	t_j

	YES	NO
YES	0	1
NO	$P(R^i_{tj})$	$1-P(R^i_{tj})$

The CPTs are regarded as the time-variant if failures for root causes such as equipment failure and safety barrier failure follow the Weibull distribution. The degradation influence is considered to estimate the parameters of CPTs. If $P(R^i_{tj} = \text{YES}|\ R^i_{tj-1} = \text{YES}) = 1 - e^{-(\lambda t_{j-1})^\alpha}$ and $P(R^i_{tj} = \text{YES}|\ R^i_{tj-1} = \text{NO}) = 1 - e^{-(\lambda t_j)^\alpha}$, we have CPTs which is assigned as listed in Table 4, where λ and α denote the scale parameter and shape parameter, respectively.

Table 4 CPT for two time slices

t_{j-1}	t_j	
	YES	NO
YES	$1 - e^{-(\lambda t_{j-1})^\alpha}$	$e^{-(\lambda t_{j-1})^\alpha}$
NO	$1 - e^{-(\lambda t_j)^\alpha}$	$e^{-(\lambda t_j)^\alpha}$

4.3 Step 3:DBN-based risk assessment

In this step it is proposed to utilize DBN for the three mentioned decision-support scenarios:

- Predictive analysis, meaning to estimate the risk evolution of drilling operation over time and forecast development in the risk of a drilling operation given the current state of knowledge.
- Diagnostic analysis, meaning to detect and investigate the most likely causes of a drilling incident using backward analysis when the top event occurs.
- Sensitivity analysis, meaning to check to what extent the results of the predictive or diagnostic analysis is influenced by specific parameters which are regarded as uncertain.

4.3.1 Predictive analysis

Predictive analysis aims to predict the future risk evolution tendency of drilling operation over time and forecast development in the risk of a drilling operation given the current state of knowledge, using the forward inference technical in DBN. The occurrence probability distribution of a top event at time t under the combination of root causes $(R^1_t, \cdots R^i_t)$ and the occurrence probability distribution of the corresponding consequence (C) under the combination TE and safety barriers $(B^1_t, \cdots B^i_t)$. The state of each root cause or safety barrier is treated as input by CPTs into DBN model. Probability distribution of TE/C, represented by *P* $(TE_t{=}te)/\ P(C_t{=}c)$, is calculated by Eq. (7) and Eq. (8).

$$P(TE_t = te) = P\left(TE_t = te \middle| IE^1_t = ie_1, \cdots, IE^i_t = ie_j\right) \\ \times P\left(IE^1_t = ie_1, \cdots, IE^i_t = ie_j, R^1_t = r_1, \cdots, R^i_t = r_j\right) \quad (7)$$

where, *te* stands for the state of a top event TE_t; ie_j stands for the state of intermediate event IE_t and r_j stands for the state of root nodes R^i_t; $P(TE_t = te|IE^1_t = ie_1, \cdots, IE^i_t = ie_j)$ refers to the conditional probability distribution of TE_t; $P(IE^1_t = ie_1, \cdots, IE^i_t = ie_j, R^1_t = r_1, \cdots, R^i_t = r_j)$ refers to the joint probability distribution of IE nodes and root nodes.

$$P(C_t = c) = P\left(C_t = c \middle| TE_t = te, B^1_t = b_1, \cdots, B^i_t = b_j\right) \times \\ P(TE_t = te) \times P(B^1_t = b_1, \cdots, B^i_t = b_j) \quad (8)$$

where, *c* stands for the state of consequence C_t; and *bi* stands for the state of root nodes B_i;

$P\left(C_t = c \middle| TE_t = te, B_t^1 = b_1, \cdots, B_t^i = b_j\right)$ refers to the conditional probability distribution of C_t; $P(B_t^1 = b_1, \cdots, B_t^i = b_j)$ refers to the joint probability distribution of barrier nodes.

The risk of a drilling operation given the occurrence of root causes ($R_t^m = r_m$), represented by $P\left(TE_t = te | R_t^1 = r_1, \cdots, R_t^m = r_m, \cdots, R_t^i = r_j\right)$, can also be calculated by Eq.(9)

$$P(TE_t = te | R_t^m = r_m) = P\left(TE_t = te \middle| IE_t^1 = ie_1, \cdots, IE_t^i = ie_j\right)$$
$$\times P(IE_t^1 = ie_1, \cdots, IE_t^i = ie_j,\ R_t^1 = r_1, \cdots, R_t^m = r_m, \cdots, R_t^i = r_j) \quad (9)$$

where, $P(TE_t = te | IE_t^1 = ie_1, \cdots, IE_t^i = ie_j)$ refers to the conditional probability distribution of *TE*; $P(IE_t^1 = ie_1, \cdots, IE_t^i = ie_j\ R_t^1 = r_1, \cdots, R_t^m = r_m, \cdots, R_t^i = r_j)$refers to the joint probability distribution of IE nodes and root causes given the occurrence of root causes ($R_t^m = r_m$).

Generally, $P(TE_t=te)$,$P(C_t=c)$ *or* $P(TE_t = te | R_t^m = r_m)$ can serve as an indicator to evaluate the risk, informing decision makers to take proper measures.

4.3.2 Diagnostic analysis

Diagnostic analysis aims to obtain the posterior probability distribution of each root causes when a TE occurs at certain time, which is performed through backward analysis of DBN. The underlying causes with the largest occurrence probability or the occurrence probability above the acceptable safety level can then be detected by means of posterior probability distribution, reminding engineers to pay more attention for these causes. Posterior probability distribution of root nodesR_t^i, represented by $P\left(R_t^i = r_i | TE_t = te\right)$, can be calculated by Eq. (10).

$$P\left(R_t^i = r_i | TE_t = te\right) = \frac{P\left(TE_t = te \middle| R_t^i = r_i\right) \times P(R_t^i = r_i)}{P(TE_t = te)} \quad (10)$$

Normally, R_t^i is more likely to become the key root cause at time t leading to the occurrence of the TE when $P\left(R_t^i = r_i | TE_t = te\right)$ is close to 1.

4.3.3 Sensitivity analysis

Sensitivity analysis, meaning to check to what extent the results of the predictive or diagnostic analysis is sensitive to specific parameters regarded as uncertain. The important degree of root cause to the top event can be analyzed by applying Shannon's mutual information (entropy reduction), which is one of the most commonly used measurement for ranking information sources(Kjærulff and Madsen, 2006). The mutual information is the total uncertainty-reducing potential of R, given the original uncertainty in R_i prior to consulting R_j. Intuitively, mutual information can measure how much knowing one of these variables reduces our uncertainty about the other. The mutual information of R_i and R_j is given by:

$$I\left(R_i, R_j\right) = -\sum_i \sum_j P\left(R_i, R_j\right) \log \frac{P\left(R_i, R_j\right)}{P\left(R_i\right) P\left(R_j\right)} \quad (10)$$

where $P(R_i, R_j)$ is the joint probability distribution function of root cause R_i and R_j, and $P(R_i)$ and $P(R_j)$ is the probability distribution of root cause R_i and R_j, respectively.

4.4 Validation of the model

Validation for a newly-develop model is a significant process of checking whether it will provide a reasonable amount of confidence to meet its specification and produce the required results in a sound, defensible and well-grounded way. It seems to become an impractical exercise to gather the all monitored data to perform a fully comprehensive validation for a newly-develop model because it ideally requires to cover the complete range of possibilities. The validation in this paper including the model development process, the model usability and results comparison has been therefore carried out to partially verify the proposed model.

- Validation of model development process means to verify the newly-develop model to be constructed in a reasonably, defensibly and realistically way.
- Validation of model usability means to check sensitivities of results by modeling the change of inputs data by three-axiom-based validation method by Jones et al. (2010).
- Validation of model results means to evaluate the results generated from a developed model involving model parameters inputs, and make the result more reasonable by a comparison with that of another approach such as fault tree and static Bayesian network using existing data.

1) The proposed model is developed based on a Bowtie model illustrated in Fig. 3 that is also used for translating to meet the requirement for dynamic risk assessment. Examination of development process, illustrated in Fig. 4, consists of checking both effect of uncertainty and degradation. As an example, it is not clear whether the relationship between RC1 and RC2 follows rule of OR-gate or AND-gate and what kind of effect it will bring. Uncertainty effect about model and parameters is therefore to be validated by comparing the model without MU nodes and that with MU nodes by taking probabilities range of OR-gate [0, 1]. The results, seen as in Fig. 5, reveal that the occurrence probability of the top event will be revised from 1.9×10^{-3} to 3.61×10^{-2} given every root cause taking the initial probabilities 0.1 in YES state under not considering effect of parameter uncertainty, while that will be changed from 9×10^{-5} to 1.7×10^{-3} under considering that. The validation for degradation effect given MU nodes probabilities (0.3, 0.7) is carried out by comparing the occurrence probability not taking degradation effect (time-invariant CPT) with that taking degradation effect (time-variant CPT) as listed as in Table 3 and Table 4. The results (seen as in Table 5) also indicate that the occurrence probability of the top event will change slightly former and increase later. The change of occurrence probability can be explained reasonably due to the consideration of the causal relationship and parameters uncertainty and degradation effect.

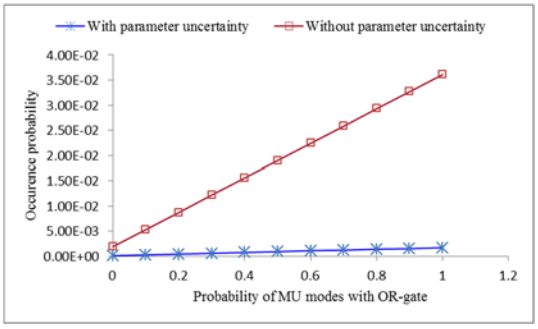


Fig. 5 Occurrence probability under MU nodes with OR-gate taking different probabilities

Table 5 Comparison for degradation

Time slice	DBN without degradation effect	DBN with degradation effect

0	0	0
1	5.7E-04	5.7E-04
2	5.6E-04	9.7E-04

2) Validation of model usability as illustrated in Fig. 4, is to check whether sensitivities of results by modeling parameters inputs is expected. At the initial time, the prior probabilities for all root causes are set to 0.1, and probability of MU nodes is taken by (0.3, 0.7). When the probabilities of root causes including RC1, RC2, RC3, and RC4 are set to 1 in sequence and keep the probability of MU nodes constant, the occurrence probability of the top event will gradually increase from 5.7×10^{-4} to 3.3×10^{-3}, 9×10^{-3}, 4.48×10^{-2} and 8.8×10^{-2}, respectively. The exercise of increasing the failure probability of each root cause one after another will meet the axiom specification and produce the required results, thus giving a partial verification to the newly-developed model.
3) The results have been validated by the special case with "lost circulation" in not circulating scenario using the existing partial data seen as Fig. . The results from the fault tree (FT), BN with average probability failure on demand (PFDavg)(Rausand, 2014) and DBN with probability failure on demand (PFD(t)) and PFDavg (Rausand, 2014) are compared for a period with 4 time slices, which is seen as in Table 6. The basic event with these of the occurrence probability is listed as Table 7 and Table 8. The results has indicated that the magnitude of occurrence probabilities almost keep the same. The difference of results between FT and BN is caused by the uncertainty issues, while that between BN and DBN can be explained by the effect of degradation. This part can make the final results from the newly-developed model more reasonable.

Table 6 Comparison final results of for different methods

Time	FT	BN	DBN with PFD(t)	DBN with PFDavg
t=0	8.00E-05	5.00E-05	0	0
t=360	8.00E-05	5.00E-05	2.00E-05	9.40E-07
t=720	8.00E-05	5.00E-05	7.00E-05	2.60E-05
t=1080	8.00E-05	5.00E-05	1.40E-04	5.00E-05

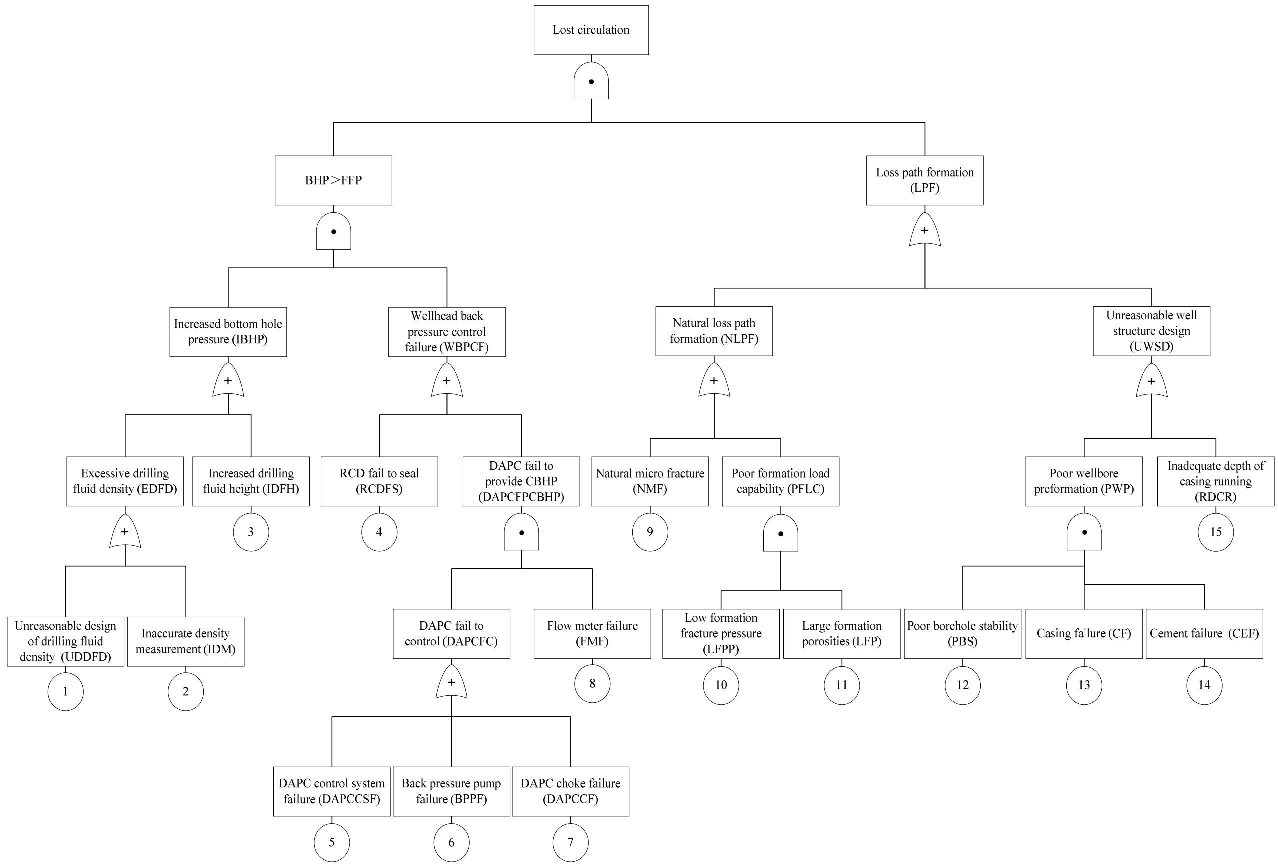
5 Case study

A case study for an offshore well related to lost circulation is carried out in this section. An offshore drilling well in BD oil and gas field in Madura is considered as the equipment under protection. The highest wind events (thunderstorms) will result in maximum wave heights that are relatively small according the statistics. The interface of the target oil and gas reservoir pressure is approximately 8090 psi, which is equivalent to the pressure coefficient 1.68, and formation temperature is about 151.7℃, belonging to the high-temperature and high-pressure system. Lost circulation or kick is likely caused by the very light gray and low-density limestone reservoir with narrow drilling fluid density window and high pressure. Therefore, the MPD technology is adapted in this application.

5.1 Risk identification for lost circulation

A BT model is firstly developed for risk identification of lost circulation in the three drilling operations. Fig.6 and Fig.7 show the fault tree and event tree of lost circulation in BT model. Considering well lost circulation as an undesired event among such drilling incidents, the potential causes and consequences have to be determined. As indicated in Fig.6 (a), (b) and (c), three fault trees are established for modeling different drilling operations involving not circulating, tripping in and circulating process. The root causes of lost circulation are collected and investigated. According to the section 2, the overbalanced drilling condition is likely to result in the loss of mud. As drilling encountering limestone and fissures formation, the likelihood of lost circulation will be increased. So, two main reasons could be identified including the larger BHP than the FFP and leakage path. The increasing BHP and the MPD system failing to maintain a constant BHP will make larger BHP than the FFP possible. The others leading to lost circulation may include excessive drilling fluid density in not circulating process, the surging effect caused by tripping activities and high pump pressure in circulating process. The formation condition and well structure design can also be taken into consideration in terms of the contribution to the lost circulation. Therefore, totally 21 potential root causes in fault tree was found based on the work of Fuh et al. (1992), Skogdalen and Vinnem (2012) and Abimbola et al. (2015).

Safe operation, collapse stuck, kick and blowout as potential consequences are emphasized for a weak formation as depicted in Fig. 5 (d). To forestall the occurrence of these consequences, three safety barriers are installed: plugging barrier, kick detection system and BOP system. Plugging barriers should be used when massive volume of drilling mud into the formation is losing. The successful plugging to the lost circulation plays a critical role in reducing the downtime loss and preventing the wellbore collapse and pipe sticking through the utilizing of plugging materials, tools and a series shut or kill operations. Kick detection system has the function to detect the occurrence of kick if the plugging barriers fail to control the loss of mud. The BOP system can prevent the formation fluid into external environment and it will be highlighted when kick cannot be detected and controlled.


Lost circulation
BHP＞FFP
Loss path formation (LPF)
Increased bottom hole pressure (IBHP)
Wellhead back pressure control failure (WBPCF)
Natural loss path formation (NLPF)
Unreasonable well structure design (UWSD)
Excessive drilling fluid density (EDFD)
Increased drilling fluid height (IDFH)
RCD fail to seal (RCDFS)
DAPC fail to provide CBHP (DAPCFPCBHP)
Natural micro fracture (NMF)
Poor formation load capability (PFLC)
Poor wellbore preformation (PWP)
Inadequate depth of casing running (RDCR)
Unreasonable design of drilling fluid density (UDDFD)
Inaccurate density measurement (IDM)
DAPC fail to control (DAPCFC)
Flow meter failure (FMF)
Low formation fracture pressure (LFPP)
Large formation porosities (LFP)
Poor borehole stability (PBS)
Casing failure (CF)
Cement failure (CEF)
DAPC control system failure (DAPCCSF)
Back pressure pump failure (BPPF)
DAPC choke failure (DAPCCF)
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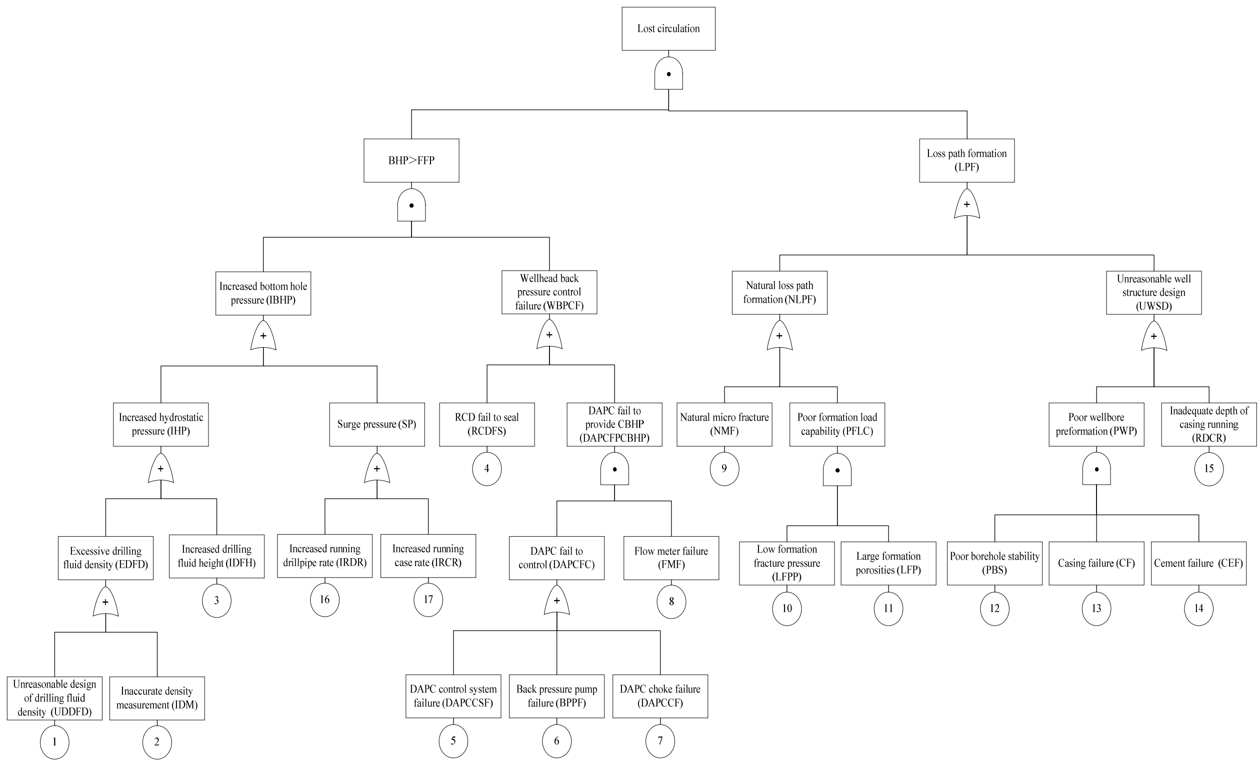
（a）


Lost circulation
BHP＞FFP
Loss path formation (LPF)
Increased bottom hole pressure (IBHP)
Wellhead back pressure control failure (WBPCF)
Natural loss path formation (NLPF)
Unreasonable well structure design (UWSD)
Increased hydrostatic pressure (IHP)
Surge pressure (SP)
RCD fail to seal (RCDFS)
DAPC fail to provide CBHP (DAPCFPCBHP)
Natural micro fracture (NMF)
Poor formation load capability (PFLC)
Poor wellbore preformation (PWP)
Inadequate depth of casing running (RDCR)
Excessive drilling fluid density (EDFD)
Increased drilling fluid height (IDFH)
Increased running drillpipe rate (IRDR)
Increased running case rate (IRCR)
DAPC fail to control (DAPCFC)
Flow meter failure (FMF)
Low formation fracture pressure (LFPP)
Large formation porosities (LFP)
Poor borehole stability (PBS)
Casing failure (CF)
Cement failure (CEF)
Unreasonable design of drilling fluid density (UDDFD)
Inaccurate density measurement (IDM)
DAPC control system failure (DAPCCSF)
Back pressure pump failure (BPPF)
DAPC choke failure (DAPCCF)
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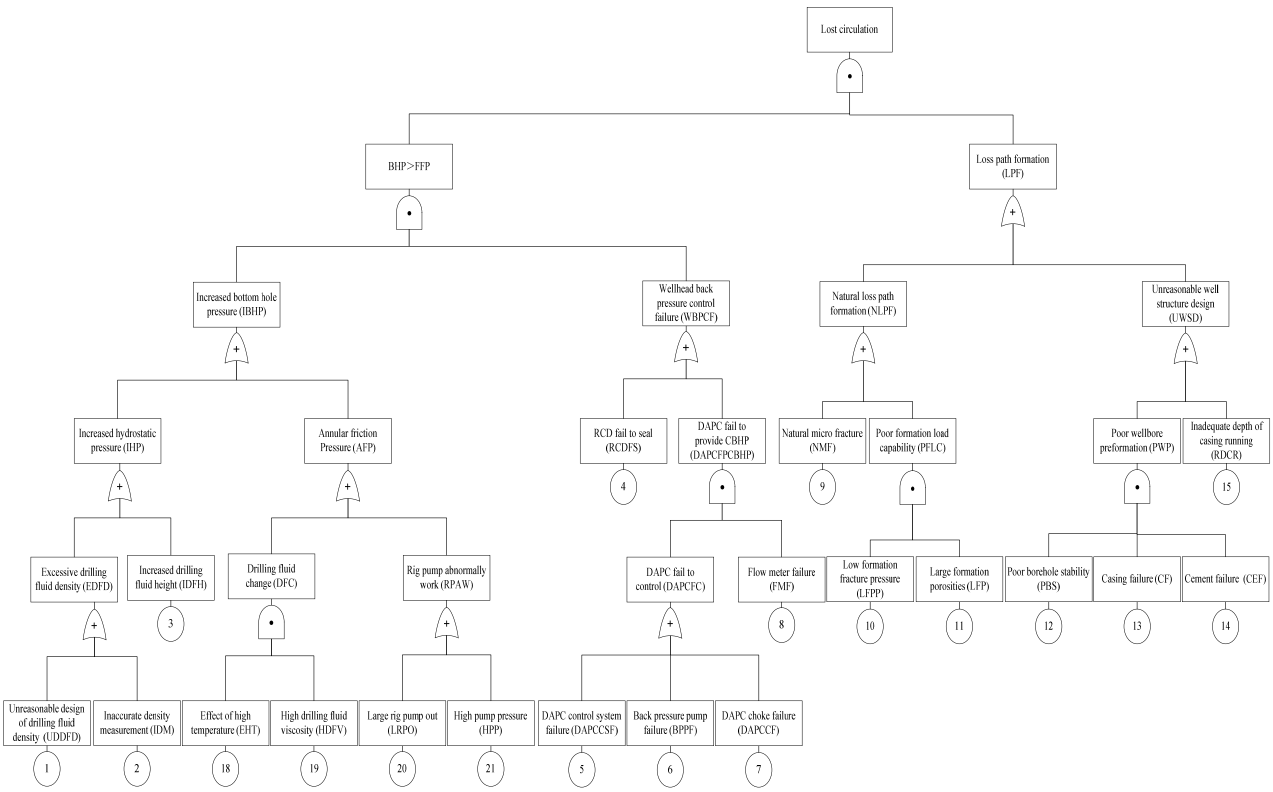
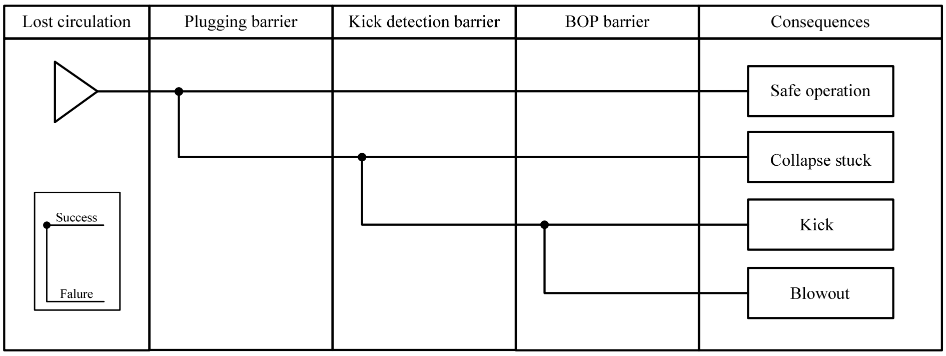
(b)



(c)

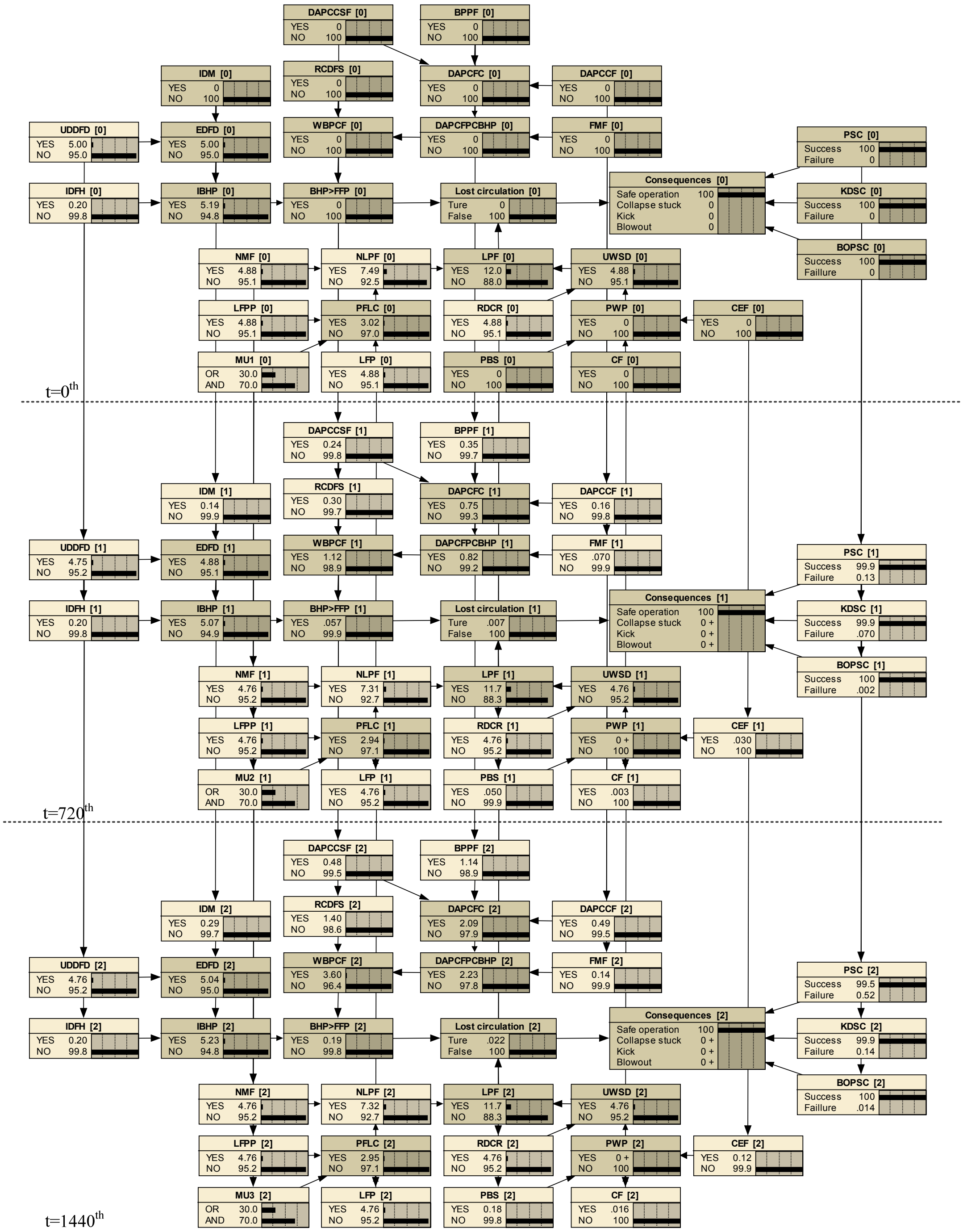


(d)

Fig. 6. BT model for (a) fault tree of Not circulating, (b) fault tree of Tripping in and (c) fault tree of Circulating (d) event tree

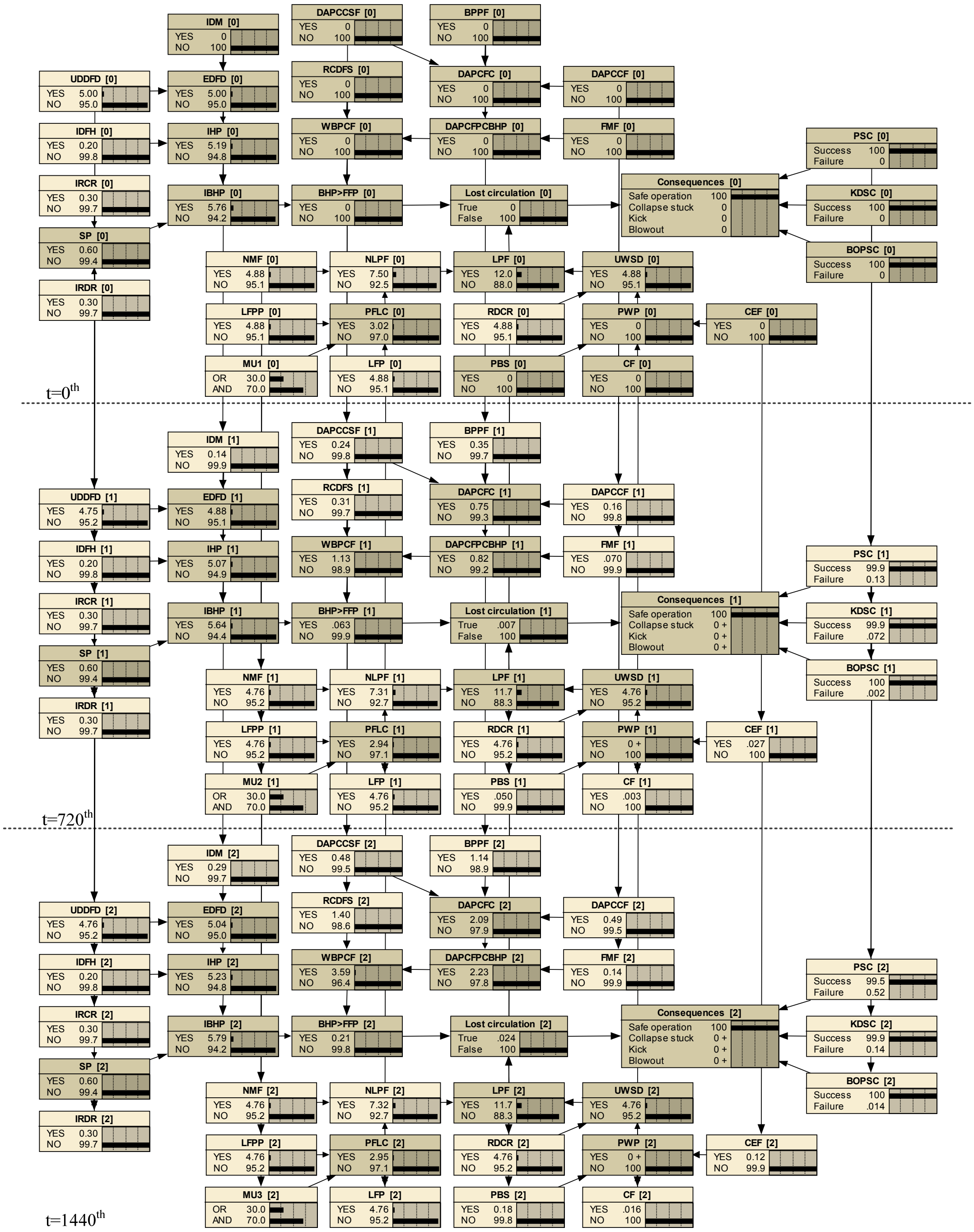
5.2 DBN modeling for the case

The DBNs for drilling lost circulation in this study are established using Netica (2015) software that can use the networks to perform various kinds of inference with the fastest and most modern algorithms. According to the mapping algorithm described in Section 4.2.1, BTs of "lost circulation" combining the root causes and consequences for three drilling operations are translated into corresponding DBN with three time-slices as presented in Fig. 7, which is extended from time at t=0th , t=720th to t=1440th hour during drilling days for modeling.



DAPCCSF [0] YES 0 NO 100
BPPF [0] YES 0 NO 100
IDM [0] YES 0 NO 100
RCDFS [0] YES 0 NO 100
DAPCFC [0] YES 0 NO 100
DAPCCF [0] YES 0 NO 100
UDDFD [0] YES 5.00 NO 95.0
EDFD [0] YES 5.00 NO 95.0
WBPCF [0] YES 0 NO 100
DAPCFPCBHP [0] YES 0 NO 100
FMF [0] YES 0 NO 100
PSC [0] Success 100 Failure 0
Consequences [0] Safe operation 100 Collapse stuck 0 Kick 0 Blowout 0
IDFH [0] YES 0.20 NO 99.8
IBHP [0] YES 5.19 NO 94.8
BHP>FFP [0] YES 0 NO 100
Lost circulation [0] Ture 0 False 100
KDSC [0] Success 100 Failure 0
BOPSC [0] Success 100 Faillure 0
NMF [0] YES 4.88 NO 95.1
NLPF [0] YES 7.49 NO 92.5
LPF [0] YES 12.0 NO 88.0
UWSD [0] YES 4.88 NO 95.1
LFPP [0] YES 4.88 NO 95.1
PFLC [0] YES 3.02 NO 97.0
RDCR [0] YES 4.88 NO 95.1
PWP [0] YES 0 NO 100
CEF [0] YES 0 NO 100
MU1 [0] OR 30.0 AND 70.0
LFP [0] YES 4.88 NO 95.1
PBS [0] YES 0 NO 100
CF [0] YES 0 NO 100
t=0th
DAPCCSF [1] YES 0.24 NO 99.8
BPPF [1] YES 0.35 NO 99.7
IDM [1] YES 0.14 NO 99.9
RCDFS [1] YES 0.30 NO 99.7
DAPCFC [1] YES 0.75 NO 99.3
DAPCCF [1] YES 0.16 NO 99.8
UDDFD [1] YES 4.75 NO 95.2
EDFD [1] YES 4.88 NO 95.1
WBPCF [1] YES 1.12 NO 98.9
DAPCFPCBHP [1] YES 0.82 NO 99.2
FMF [1] YES .070 NO 99.9
PSC [1] Success 99.9 Failure 0.13
Consequences [1] Safe operation 100 Collapse stuck 0 + Kick 0 + Blowout 0 +
IDFH [1] YES 0.20 NO 99.8
IBHP [1] YES 5.07 NO 94.9
BHP>FFP [1] YES .057 NO 99.9
Lost circulation [1] Ture .007 False 100
KDSC [1] Success 99.9 Failure .070
BOPSC [1] Success 100 Faillure .002
NMF [1] YES 4.76 NO 95.2
NLPF [1] YES 7.31 NO 92.7
LPF [1] YES 11.7 NO 88.3
UWSD [1] YES 4.76 NO 95.2
LFPP [1] YES 4.76 NO 95.2
PFLC [1] YES 2.94 NO 97.1
RDCR [1] YES 4.76 NO 95.2
PWP [1] YES 0 + NO 100
CEF [1] YES .030 NO 100
MU2 [1] OR 30.0 AND 70.0
LFP [1] YES 4.76 NO 95.2
PBS [1] YES .050 NO 99.9
CF [1] YES .003 NO 100
t=720th
DAPCCSF [2] YES 0.48 NO 99.5
BPPF [2] YES 1.14 NO 98.9
IDM [2] YES 0.29 NO 99.7
RCDFS [2] YES 1.40 NO 98.6
DAPCFC [2] YES 2.09 NO 97.9
DAPCCF [2] YES 0.49 NO 99.5
UDDFD [2] YES 4.76 NO 95.2
EDFD [2] YES 5.04 NO 95.0
WBPCF [2] YES 3.60 NO 96.4
DAPCFPCBHP [2] YES 2.23 NO 97.8
FMF [2] YES 0.14 NO 99.9
PSC [2] Success 99.5 Failure 0.52
Consequences [2] Safe operation 100 Collapse stuck 0 + Kick 0 + Blowout 0 +
IDFH [2] YES 0.20 NO 99.8
IBHP [2] YES 5.23 NO 94.8
BHP>FFP [2] YES 0.19 NO 99.8
Lost circulation [2] Ture .022 False 100
KDSC [2] Success 99.9 Failure 0.14
BOPSC [2] Success 100 Faillure .014
NMF [2] YES 4.76 NO 95.2
NLPF [2] YES 7.32 NO 92.7
LPF [2] YES 11.7 NO 88.3
UWSD [2] YES 4.76 NO 95.2
LFPP [2] YES 4.76 NO 95.2
PFLC [2] YES 2.95 NO 97.1
RDCR [2] YES 4.76 NO 95.2
PWP [2] YES 0 + NO 100
CEF [2] YES 0.12 NO 99.9
MU3 [2] OR 30.0 AND 70.0
LFP [2] YES 4.76 NO 95.2
PBS [2] YES 0.18 NO 99.8
CF [2] YES .016 NO 100
t=1440th

(a)



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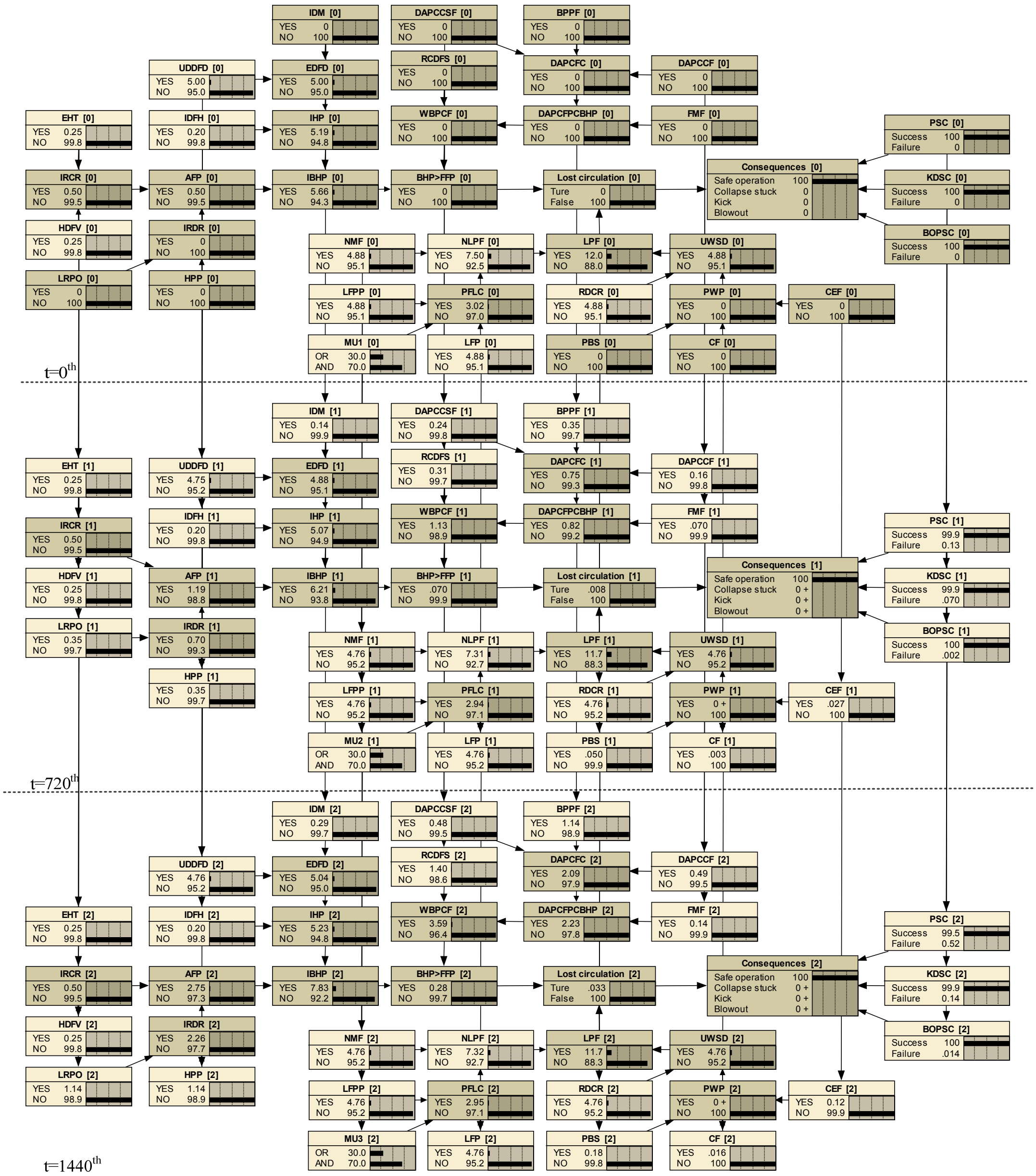


(c)

Fig. 7 DBN modeling with three time-slices for different drilling scenarios (a) Not circulating (b) Tripping in and (c) Circulating

It is noted that model uncertainty issues can be handled by adding the MU node with two states "OR" and "AND" in the proposed DBN-based model. The states of root/IE nodes, TE nodes and barriers nodes are assigned "YES/NO", "True/False" and "Success/Failure" respectively, as indicated in Fig.8. Similarly, consequences states are achieved from "safe operation to blowout" according to the availability and reliability performance of safety barriers. The CPTs of nodes considering the parameters uncertainty should be assigned to model the DBNs. In the initial time at t=0, the value of the prior probability needs to be assigned to each state of root nodes. If the prior knowledge of root causes such as UDDFD and IDFH is obtained by taking advantage of the available literature (Abimbola et al., 2014; Holland, 1997; Participants, 2002) and also the expert inputs if necessary, the prior probabilities of these root causes are assigned as listed in column 4 of Table 7. If the probabilities of failure on demand for the equipment and safety barriers such as

RCDFS and BOPS are assumed to follow the Weibull distribution, the initial states of these root causes are considered to in its perfect functioning state, and the value of failure probability is assigned to 0. The values of scale parameter λ and shape parameter α in Weibull distribution are provided in Table 8, which are determined by the expert's inputs.

Table 7 Prior and posterior probability for root causes

No.	Basic event	Description	Prior probability		posterior probability t=1440th		
			t=0	t=1440th	Not circulating	Tripping in	Circulating
1	UDDFD	Unreasonable design of drilling fluid density	5.00E-02	4.76E-02	9.15E-01	8.29E-01	6.2E-01
2	IDM	Inaccurate density measurement	0	2.90E-03	5.31E-02	4.81E-02	3.59E-02
3	IDFH	Increased drilling fluid height	2E-03	2.00E-03	3.66E-02	3.32E-02	2.48E-02
4	ACDFS	RCD fail to seal	0	1.40E-02	3.89E-01	3.89E-01	3.89E-01
5	DAPCCSF	DAPC control system failure	0	4.8E-03	1.33E-01	1.33E-01	1.33E-01
6	BPPF	Back pressure pump failure	0	1.14E-02	3.16E-01	3.16E-01	3.16E-01
7	DAPCCF	DAPC choke failure	0	4.9E-03	1.36E-02	1.36E-02	1.36E-02
8	FMF	Flow meter failure	0	1.4E-03	3.89E-02	3.89E-02	3.89E-02
9	NMF	Natural micro fracture	4.88E-02	4.76E-02	4.79E-01	4.79E-01	4.79E-01
10	LFPP	Low formation fracture pressure	4.88E-02	4.76E-02	8.41E-02	8.41E-02	8.41E-02
11	LFP	Large formation porosities	4.88E-02	4.76E-02	8.8E-02	8.8E-02	8.8E-02
12	PBS	Poor borehole stability	0	1.80E-03	1.80E-03	1.80E-03	1.80E-03
13	CF	Casing failure	0	1.56E-04	1.56E-04	1.56E-04	1.56E-04
14	CEF	Cement failure	0	1.15E-03	1.15E-03	1.15E-03	1.15E-03
15	RDCR	Inadequate depth of casing running	3.00E-03	3.00E-03	4.88E-01	4.88E-01	4.88E-01
16	IRDR	Increased running drillpipe rate	3.00E-03	3.00E-03	-	4.97E-02	-
17	IRCR	Increased running case rate	3.00E-03	3.00E-03	-	4.97E-02	-
18	EHT	Effect of high temperature	2.50E-03	2.50E-03	-	-	3.1E-02
19	HDFV	High drilling fluid viscosity	2.50E-03	2.50E-03	-	-	3.1E-02
20	LRPO	Large rig pump out	0	1.14E-03	-	-	1.4E-01
21	HPP	High pump pressure	0	1.14E-03	-	-	1.4E-01

Table 8 Parameters of the Weibull distribution

Basic event	Description	Shape parameter (α)	Scale parameter (λ)
IDM	Inaccurate density measurement	1.0	2.00E-06
RCDFS	RCD fail to seal	2.2	1.00E-04
DAPCCSF	DAPC control system failure	1	3.33E-06
BPPF	Back pressure pump failure	1.7	5.00E-05
DAPCCF	DAPC choke failure	1.6	2.50E-05
FMF	Flow meter failure	1.0	1.00E-06
PBS	Poor borehole stability	1.9	2.50E-05
CF	Casing failure	2.5	2.08E-05
CEF	Cement failure	2.1	2.78E-05
LRPO	Large rig pump out	1.7	5.00E-05
HPP	High pump pressure	1.7	5.00E-05

The parameters of CPTs should also be assigned to model DBNs. The approach of CPTs calculation considering the parameters uncertainty is following the discussion in section 4.2.2. There are two examples to illustrate the space-based parameters of CTPs and two examples to explain the time-based parameters of CPTs, respectively. Taking the "DAPC fail to control" as example, the occurrence of this event is caused by the DAPC system failure, back pressure pump failure and DAPC choke failure. With the use of Boolean logic relationships, the CPTs can be calculated as listed in Table 9. Taking the "NLPF" as example, the CPT is calculated from the nodes "NMF" and "PFLC" to the node "NLPF" based on experts knowledge and Noisy-OR filling-up algorithm in this study, as presented in Table 10. The presence of NLPF is caused by NMF and PFLC in the YES state at respective probability of 0.02 and 0.05, but not 1 due to the effect of uncertainty. The time-based CPTs, namely the CPTs for two time-slices of root causes follow the rules as depicted in Table 3 and Table 4. Taking the "UDDFD" as example, the prior probability of UDDFD is 0.05, and the CPT is assigned as listed in Table 11. Taking the "BPPF" as example, the failure probability of BPPF is 0.07 and 0.014 at $t=720^{th}$ and $t=1440^{th}$ hour respectively, and the CPT is assigned as listed in Table 12.

Table9 CPT for DAPCFC

DAPCCF		BPPF		DAPCCSF		P_{DAPCFC}	
YES	NO	YES	NO	YES	NO	YES	NO
1	0	1	0	1	0	1	0
1	0	1	0	1	0	1	0
1	0	0	1	1	0	1	0
0	1	0	1	1	0	1	0
1	0	1	0	0	1	1	0
0	1	1	0	0	1	1	0
1	0	0	1	0	1	1	0
0	1	0	1	0	1	0	1

Table 10 CPT for NLPF

NMF		PFLC		NLPF	
YES	NO	YES	NO	YES	NO
1	0	1	0	0.999	0.001
0	1	1	0	0.98	0.02
1	0	0	1	0.95	0.05
0	1	0	1	0	1

Table 911 CPT of UDDFD for two time slices

t_{j-1}	t_j	
	YES	NO
YES	0	1
NO	0.05	0.95

Table 12 CPT of BPPF for two time slices

t_{j-1}	t_j	
	YES	NO
YES	0.007	0.993
NO	0.014	0.986

5.3 Results and discussion

5.3.1 DBN-based predictive analysis

Fig. 7 shows DBNs modeling results for the three drilling scenarios contributing to lost circulation within three time-slices. The predictive results indicate that the occurrence probability of lost circulation at time t=720th hour and at time t=1440th hour for not circulating, tripping in and circulating scenario is 7.0E-05, 7E-05 and 8E-05, and 2.2E-04, 2.4E-04 and 3.3E-04, respectively. Fig. 8 shows the risk comparison for three drilling scenarios and tendency of the risk evolution within 9 time-slices. We assume that the time slice interval is the same as 360 hours. It is clear that the occurrence probability of lost circulation is highest and is growing fastest in the scenario of circulating process meaning that lost circulation is much more likely to occur in circulating process when the rig pump is on. Compared to the static operation, dynamic operations is more vulnerable due to the effect of the surging pressure and the annual friction pressure. In addition, the reliability of wellhead back pressure control is decreasing over time and it has a great effect on the occurrence probability of lost circulation. Dynamic operation and the reliability of wellhead back pressure control therefore needs to be paid more attention when drilling.

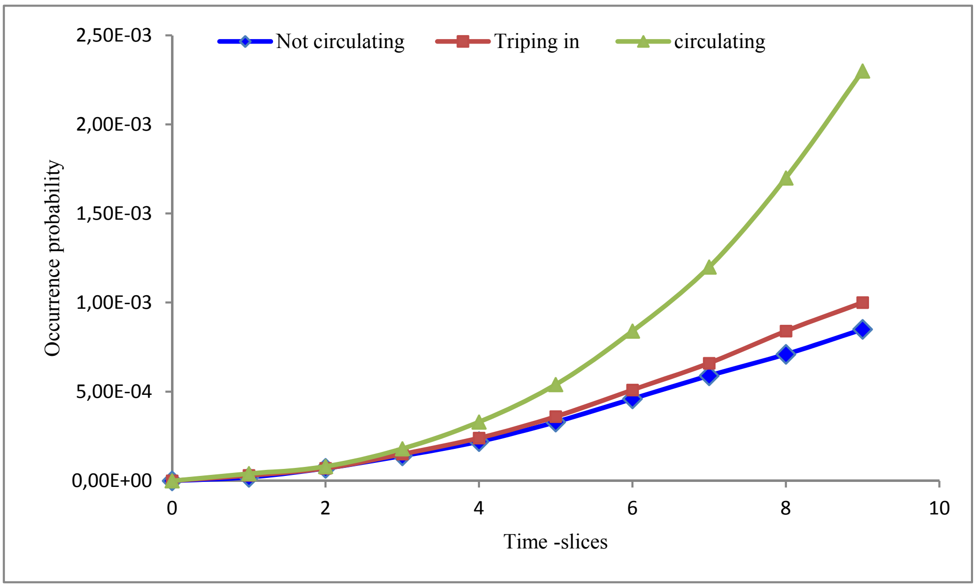


Fig. 8 Risk comparison for three drilling scenarios

When drilling encounters the formation with the narrow mud density window, the small change of mud density will have a great impact on the occurrence of lost circulation. Fig. 9 shows the occurrence probability of lost circulation at the different time (at 3rd time-slice, 4th time-slice and 7th time-slice) given the mud density in abnormal state in circulating scenarios. It is clear that the occurrence probability of lost circulation increases fast given the unreasonable change of mud density at 3rd time-slice, 4th time-slice and 7th time-slice and will decrease at their next time-slice. The occurrence probability of lost circulation increases from 1.8×10^{-4} to 2.6×10^{-3} when the mud density changed at 3rd time-slice. According the assumption in Section 4.2.2, when $P(UDDFD_t = \text{YES}|UDDFD_{t-1} = \text{YES}) = 0$, the occurrence probability of lost circulation decreases from 3.3×10^{-4} to 1.4×10^{-4} at 4th time-slice given the mud density changed at 3rd time-slice. The ratio is largest at 7th time-slice compared that of 3rd time-slice and 4th time-slice. As a matter of fact, the drilling well went exactly through more narrow density window as the depth is growing over time, and the 7th time-slice was mostly considered as dangerous period during the drilling progress. The likelihood of lost circulation can be estimated with the unreasonable change of mud density.

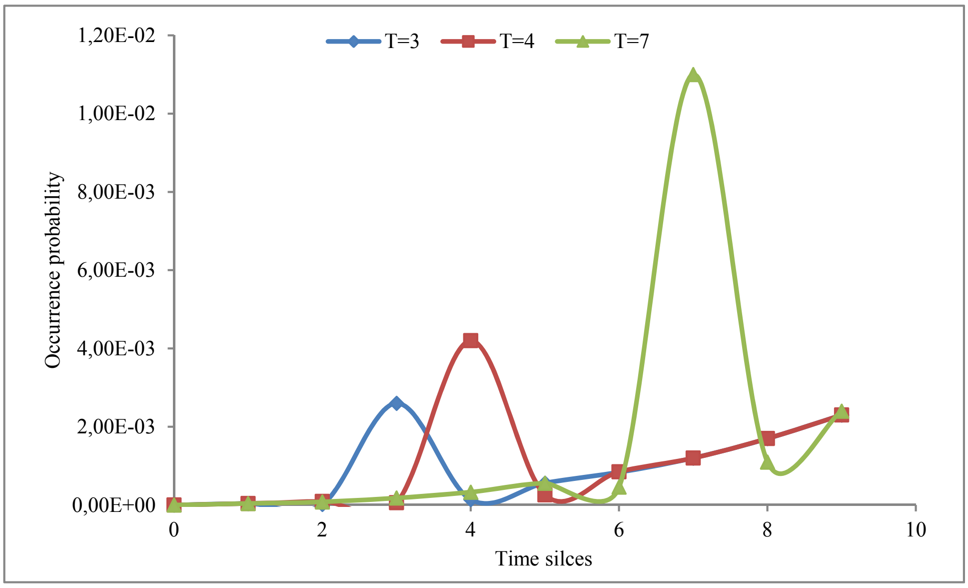


Fig. 9 Occurrence probability of lost circulation given mud density change at different time-slices

5.3.2 DBN-based root cause reasoning

Assuming the occurrence of lost circulation for three drilling scenarios by 1440th hours with setting the state of lost circulation node to true, a diagnostic analysis is conducted. The prior and posterior probabilities of these root causes for not circulating, tripping in and circulating scenarios are listed in column 4 and column 5 of Table 9, which indicate updated failure probability available given the occurrence of lost circulation from backward propagation. The comparison of prior probabilities and posterior probabilities by using the ratio as presented in Fig. 10 shows that the posterior probabilities are more than10- 200 times as much as their prior probabilities. In the above diagnostic analysis using DBN probability inference algorithm, the critical roles of drilling fluid density should be highlighted because the ratio of UDDFD (1) is the largest. It is worth noting that the root causes such as UDDFD (1) and RDCD (15) which would have been totally dominating as other factors in causing lost circulation in three scenarios. The other main contributing factors identified are LRPO (20) and HPP (22) in circulating process. Therefore the practical diagnosis and checking should then focus on the availability of these root causes until the high risk was controlled in real time.

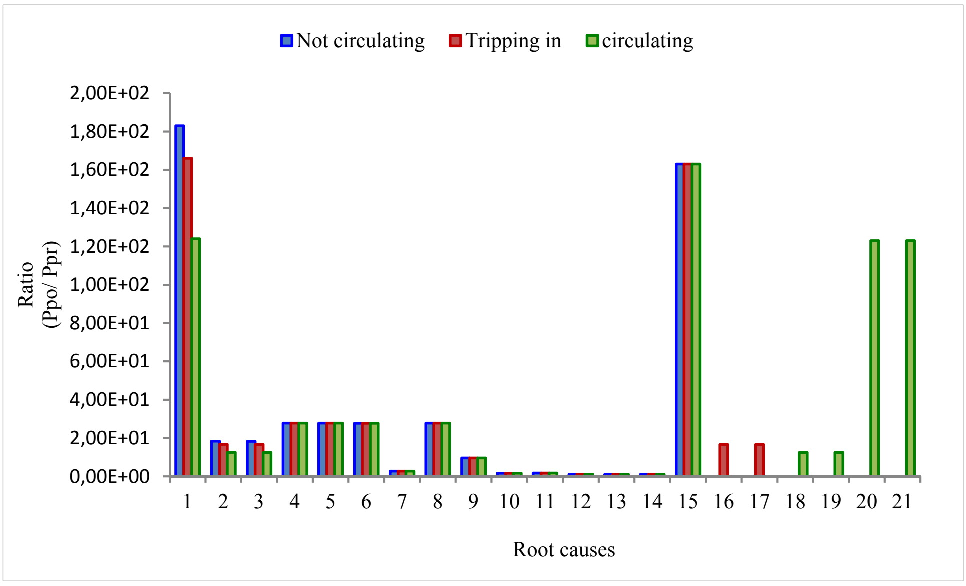
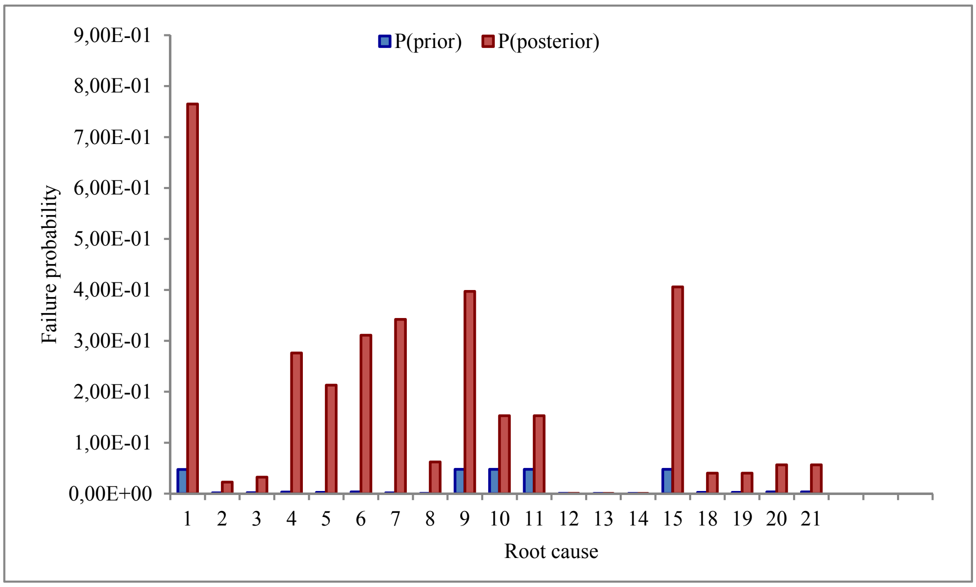
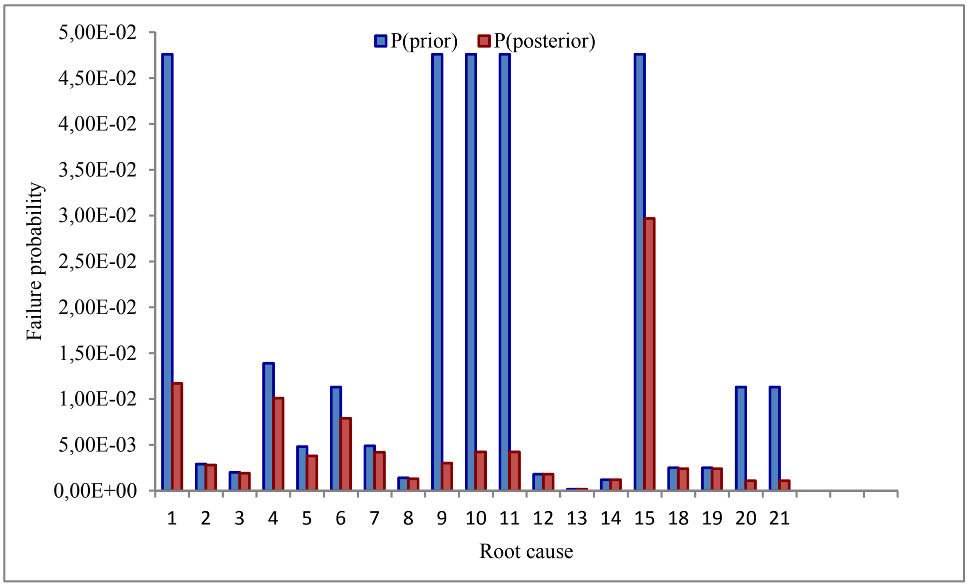


Fig. 10. Ratio of Posterior probability and prior probability in (a) Not circulating (b) Tripping in and (c) Circulating

The occurrence probability of lost circulation at current time can be calculated by the proposed model when the loss of circulation occurred at previous time. Taking the circulating scenario as example, the occurrence probability of lost circulation (LC) at time t=1440th given the LC occurred at time t=720th is calculated, namely$P(LC_{t=1440th} = Ture|\ LC_{t=720th} = True) =$ 0.00009, which become lower than that (0.00033) of no occurrence of lost circulation at time t=720th. There is a change for root cause (RC) state between at time t=720th and t=1440th, the $P(RC_{t=720th} = YES|\ LC_{t=720th} = True)$ becomes larger and $P(RC_{t=1440th} = YES|\ RC_{t=720th} = YES)$ become smaller based on the Eq. (10) and Eq. (6), as shown in Fig.11 (a) and Fig.11 (b). As a result, the posterior probabilities can provide new evidential information for diagnosis analysis, and the values of root causes can be updated in a dynamic manner.



(a)



(b)

Fig. 11 Prior probability (P (prior)) and posterior probability (P (posterior)) of root causes at time (a) t=720th and (b) t=1440th

The blowout may happen at the same time when encountering the weak formation with gas-layers. The occurrence probability is mostly close to 0 in Fig.7 due to the lower probability of the lost circulation and failure of safety barriers. Based on the failure of safety barriers following the Weibull rules, the reliability of barriers in different time is decreasing. Taking the circulating scenarios as example, the consequence probabilities when lost circulation occurred are calculated starting from collapse stuck to blowout as shown in Fig.12. Hence, collapse stuck has the higher likelihood than other consequences. Plugging barrier should be therefore given more concern to meet high level reliability. It is also worth noting that there is a small change for kick and blowout in occurrence probability because of the higher reliability of kick detection barrier and BOP barrier in the whole drilling.

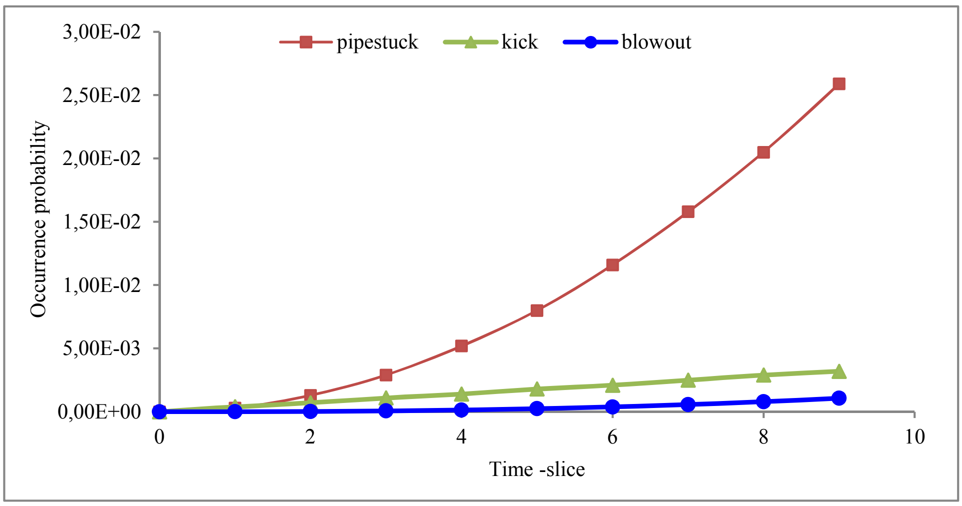
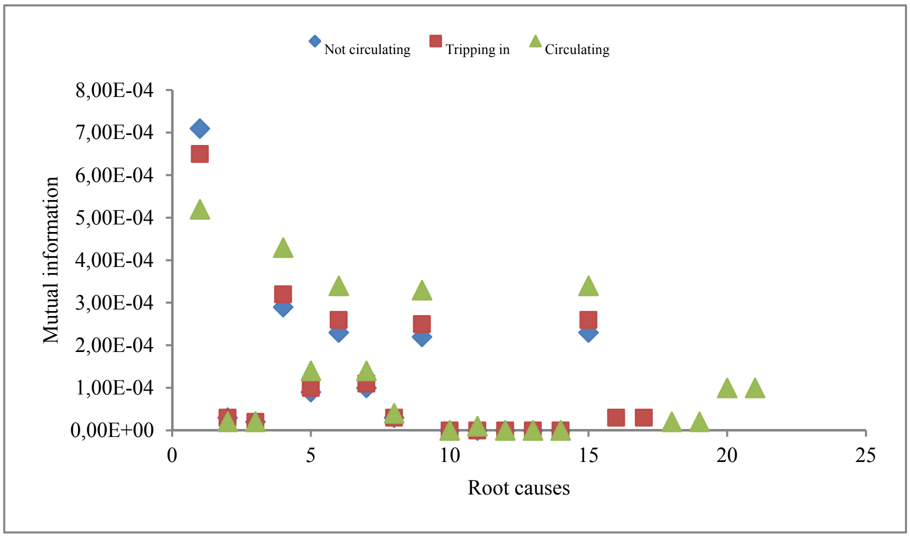


Fig. 12 Occurrence probability of collapse stuck, kick and blowout at different time-slices

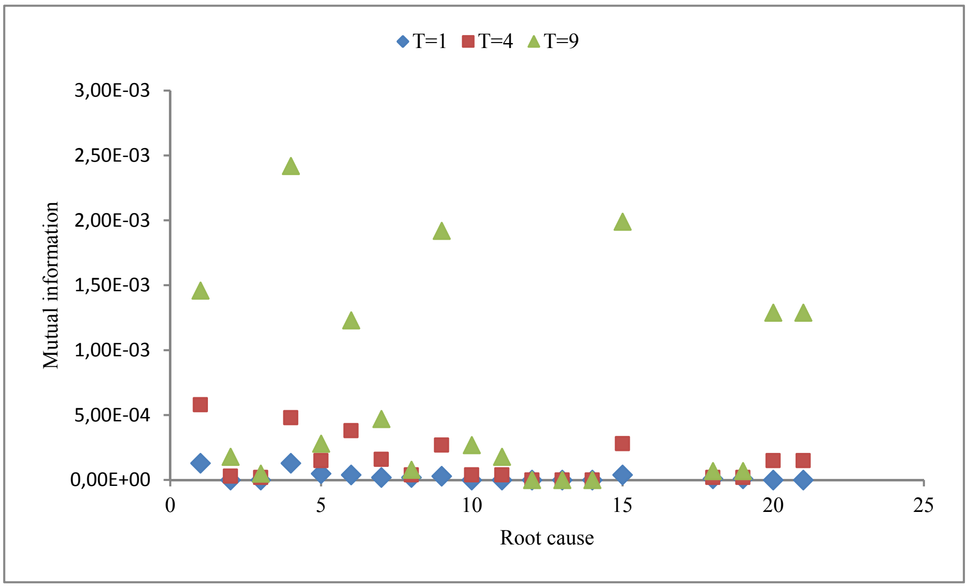
5.3.3 Sensitivity *analysis*

Importance factors degree sequence of root causes for lost circulation is also calculated by using mutual information, which can measure the information that two variables share and how much uncertainty about one variable is reduced by knowing the other. The individual contribution of each root cause towards lost circulation at time slice T=4 is calculated by comparing three drilling scenarios as shown in Fig. 13(a). It is seen that, for three types of operations, UDDFD (1) contributes much to the lost circulation, which is regard as the most fatal weakness. In Fig. 13(a), UDDFD (1) in not circulating scenario has a higher contribution for lost circulation comparing with other scenarios, whereas ACDFS (4), BPPF (6), NMF (9), and RDCR (15) in circulating scenario also have higher contributions than those of other scenarios.

The individual contribution of each root cause towards lost circulation in circulating scenarios is calculated by comparing the time slice T=1, and T=4 and T=9 as shown in Fig. 13(b). It is found that, UDDFD (1) and RCDFS (4) at time slice T=1, UDDFD (1) at time slice T=4 and RCDFS (4) at time slice T=9 make the highest contribution to the lost circulation, which indicates that these root causes are sensitive to the lost circulation and should be given more attention in order to guarantee the safe drilling operation at different time. In Fig. 13(b), the value of mutual information at time slice t=9 has a higher contribution for lost circulation comparing with other time slices, such as UDDFD (1), BPPF (6), NMF (9), and RDCR (15). Therefore, the different root causes should be give more attention focused on at different time of drilling.



(a)



(b)

Fig. 13. Sensitivity analysis of root causes for (a) different scenarios and (b) different slices

6 Conclusions and research perspectives

This paper focuses on the safe drilling operations given the special geological environment with high temperature and high pressure, where the MPD technology which is adopted to avoid the drilling incidents. According to the close relationship between hazard factors and the dynamic variance of bottom hole pressure during drilling, a risk assessment model based on DBN for predict analysis, diagnostic analysis and sensitivity analysis is proposed.

The application of the proposed model has been presented with a case study on the offshore lost circulation. In order to provide graphical symbols for the logical causal relationship between factors and effect of lost circulation, a BT model is establish to map different drilling operation scenarios. All potential root causes contributing to lost circulation and the corresponding possible outcomes identified given the occurrence of this incident are analyzed carefully. Then the DBN is established from the BT. Finally by the inference mechanism of DBN, the risk evolution tendency of drilling operations can be predicted comparing the not circulating, tripping in and circulating scenarios over time and given the current state of root causes. The root cause reasoning and the development trend of underlying consequence are discussed given the occurrence of top event in diagnostic analysis. The root causes most important for the top event occurrence have been identified with sensitivity analysis on the basis of mutual information for different drilling scenarios and different time. The occurrence probability is highest in the scenario of circulating process, which indicates that lost circulation is much more likely to occur in circulating process. Drilling fluid density and availability of rotating control device have made the highest contribution to the lost circulation for this scenario, and they may for this reason be regarded as the most important weaknesses to give attention. The overall safety can be ensured by taking effective corrective measures on circulating process. The direction of our subsequent work is to extend our model to improve the robustness of probability distribution of root causes from the prior knowledge by logging data and apply the method to other oil and gas operations such as production and overwork.

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