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Dynamic Bayesian networks based performance evaluation of subsea blowout preventers in presence of imperfect repair

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ABSTRACT

This paper presents a quantitative reliability and availability evaluation method for subsea blowout preventer (BOP) system by translating fault tree (FT) into dynamic Bayesian networks (DBN) directly, taking account of imperfect repair. The FTs of series system and parallel system are translated into Bayesian networks, and extended to DBN subsequently. The multi-state degraded system is used to model the imperfect repair in the DBN. Using the proposed method, the DBN of subsea BOP system is established. The reliability and availability with respect to perfect repair and imperfect repair are evaluated. The mutual information is researched in order to assess the important degree of basic events. The effects of degradation probability on the performances are studied. The results show that the perfect and imperfect repairs can improve the performances of series, parallel and subsea BOP systems significantly, whereas the imperfect repair cannot degrade the performances significantly in comparison with the perfect repair. To improve the performances of subsea BOP system, eight basic events, involving LWHCO, LLPR, LCC, LLICV, SLPSV, LRPIL, PIHF and SVLPLE should given more attention, and the degradation probability of basic events, especially the ones with high sensitive to system failure, should be reduced as much as possible.

1. Introduction

A subsea blowout preventer (BOP) system plays an extremely important role in providing safe working conditions for drilling activities in 10,000 ft ultra-deepwater regions. Subsea BOP failures could cause catastrophic accidents such as the explosion of the deep-sea petroleum drilling rig *Deepwater Horizon* and the oil spill off the coast of Louisiana on April 20, 2010. It was concluded that the failure of the BOP to shear the drill pipe and seal the wellbore was caused directly by the physical location of the drill pipe near the inside wall of the wellbore, which was outside the blind shear ram cutting surface during activation (BOEMRE, 2011; Harlow, Brantley, & Harlow, 2011). In the wake of recent disasters in oil and gas exploration and production, the performance evaluation of subsea BOP systems is becoming recognized.

A few literatures involving the performance evaluation of subsea BOP systems were reported. Traditional analysis technique, such as fault tree, failure modes and effects analysis and Markov chain, were used for the purpose of reliability assessment. Shanks, Dykes, Quilici, and Pruitt (2003) studied the reliability of deepwater BOP control system and described a statistical process for determining the reliability and failure rate necessary to accomplish the maintenance goal. Holand and Rausand (1987) and Holand (1996) collected reliability data regarding subsea BOP failures and malfunctions, and calculated the failure rates of subsea BOP components and rig downtime. The availability of the subsea BOP systems was estimated using the fault tree analysis method. Fowler and Roche (1994) studied the system safety of well control equipment including BOPs and hydraulic control systems using failure modes and effects analysis and fault tree methods. The results showed that despite human errors, the ram BOP and its associated controls constituted a highly reliable system. Cai et al. (2012) assessed the performance of subsea BOP systems with respect to common-cause failures by merging the independent Markov models with the Kronecker product approach.

Recently, driven by the fact that Bayesian Networks (BN) and dynamic Bayesian networks (DBN) can perform forward or predictive analysis as well as backward or diagnostic analysis, BN and DBN techniques receive considerably increasing attention in the field of reliability analysis. In predictive analysis, the probability of occurrence of any node is calculated on the basis of the prior probabilities of the root nodes and the conditional dependence of each node. In diagnostic analysis, the posterior probability of any given set of variables is calculated given some observation (the evidence), represented as instantiation of some of the variables to one of their admissible values. Nordgard and Sand (2010) described a methodology for application of BN for risk analysis in

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electricity distribution system maintenance management. Khakzad, Khan, and Amyotte (2011) demonstrated the application of BN in safety analysis of process systems, and compared the approaches of fault tree and BN. Jones, Jenkinson, Yang, and Wangn (2010) applied BN modeling to a maintenance and inspection department, and established and modeled various parameters responsible for the failure rate of a carbon black producing system, in order to apply it to a delay-time analysis study. Mahadevan, Zhang, and Smith (2001) developed a methodology for the application of the BN to structural system reliability assessment.

BN models for reliability evaluation can be achieved by converting the traditional reliability models. Torres-Toledano and Sucar (1998) presented a general methodology for transforming a reliability structure represented as a reliability block diagram to a BN representation, and with this, the reliability of the system can be obtained using probability propagation techniques. Bobbio, Portinale, Minichino, and Ciancamerla (2001) presented an algorithm to convert a fault tree (FT) or a dynamic fault tree into a BN or DBN. A software tool named RADYBAN was also developed for automatic translation (Montani, Portinale, Bobbio, & Codetta-Raiteri, 2008). Webera and Jouffeb (2006) presented a methodology that help developing dynamic object oriented BN to formalize complex dynamic models as equivalent models to the Markov chains. Kim (2011) extended the research, and provided a method of mapping a reliability block diagram with general gates model into an equivalent BN model without losing the one to-one matching characteristic for quantitative analysis. Khakzad, Khan, and Amyotte (2013) presented a methodology to map bow-tie into BN for dynamic safety analysis of process systems.

Till now, BN and DBN are seldom used to evaluate the reliability of subsea BOP systems. The key issue in this thematic field is the integration of repair actions into a BN and DBN model. Flammini, Marrone, Mazzocca, and Vittorini (2009) presented both a failure model for voting architectures based on BN and a maintenance model based on continuous time Markov chains, and proposed to combine them according to a compositional multiformalism modeling approach in order to analyze the impact of imperfect maintenance on the system safety. Neil and Marquez (2012) presented a hybrid BN framework to model the availability of renewable systems. They used an approximate inference algorithm for hybrid BN that involves dynamically discretizing the domain of all continuous variables and used this to obtain accurate approximations for the renewal or repair time distributions for a system. Portinale et al. presented an approach to reliability modeling and analysis based on the automatic conversion of dynamic fault tree or series and parallel modules into BN taking repair into consideration (Codetta-Raiteri, Bobbio, Montani, & Portinale, 2012; Portinale, Raiteri, & Montani, 2010).

The work focuses on the translation from FT into DBN of series and parallel systems, taking account of imperfect repair. The paper is structured as follows: Section 2 presents the DBN modeling of series and parallel systems, and gives the reliability and availability results. Section 3 analyzes a case to demonstrate the application of DBN modeling with imperfect repair. Section 4 summarizes the paper.

2. Dynamic Bayesian networks with imperfect repair

2.1. Overview of BN and DBN

BN is widely used in quantitative risk assessment because the model can perform both of predictive and diagnostic analysis. A BN consists of qualitative and quantitative parts. The qualitative part is a directed acyclic graph in which the nodes represent the system variables and the arcs symbolize the dependencies or the cause–effect relationships among the variables. The quantitative part is the conditional probabilistic table, which gives the relations between each node and its parents.

BN models relationships between variables at a particular point in time or during a specific time interval. Although a causal relationship represented by an arc implies a temporal relationship, BN does not explicitly model temporal relationships between variables. The only way to model the relationship between the current value of a variable, and its past or future value, is by adding another variable with a different name.

DBN is a long-established extension to ordinary BN that allow explicit modeling of changes over time. Each time step is called a time-slice. Two time slices for each variable are considered in order to model the system temporal evolution. The relationships between variables in a time-slice are represented by intra-slice arcs. And the relationships between variables at successive time steps are represented by inter-slice arcs.

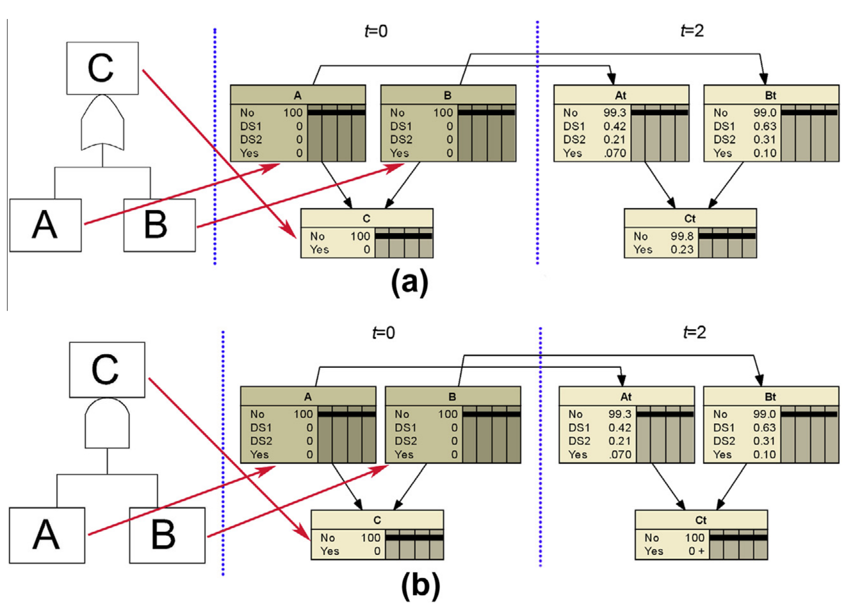

Fig. 1. DBN of (a) series and (b) parallel systems with two components.

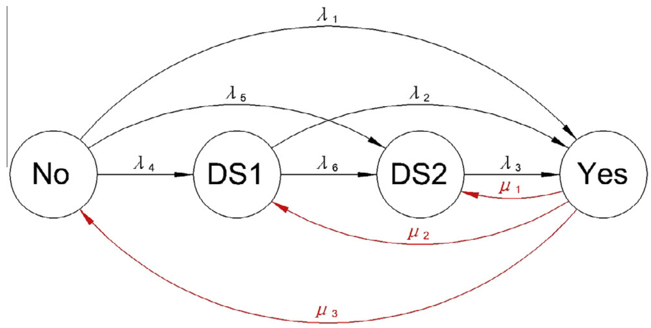

Fig. 2. State transition diagram of multi-state degraded components.

The important degree of basic event to the system failure can be assessed by using Shannon's mutual information (entropy reduction), which is one of the most widely used measurement for ranking information sources (Pearl, 1988). It is assumed that uncertainty of system can be represented by entropy function as given

$$H(T) = -\sum_{t} P(t)\log P(t) \tag{1}$$

where $P(t)$ is the probability distribution of random variable T.

The mutual information is the total uncertainty-reducing potential of X, given the original uncertainty in T prior to consulting X. Intuitively, mutual information measures the information that T and X share: it measures how much knowing one of these variables reduces our uncertainty about the other (Wang, Roohi, Hu, & Xie, 2011). The mutual information of T and X is given by

$$I(T,X) = -\sum_{x}\sum_{t} P(t,x)\log\frac{P(t,x)}{P(t)P(x)} \tag{2}$$

where $P(t,x)$ is the joint probability distribution function of T and X, and $P(t)$ and $P(x)$ are the marginal probability distribution functions of T and X, respectively.

2.2. DBN modeling of series and parallel systems

The fault tree (FT) of series system (OR-gate) and parallel system (ANG-gate) shown in left side of Fig. 1 can be translated into BN directly. Each basic event of FT is translated into a corresponding parent node of BN; and each top event of FT is translated into a corresponding child node of BN. The BN is extended to DBN subsequently.

DBN includes multiple copies of the same variables, where the different copies represent different states of the variables over time. The series and parallel systems are extended from 0th to 2nd week, as shown in the right side of Fig. 1. As indicated in series system shown in Fig. 1(a), the node A at time $t = 0$ is extended to node At at time $t = 2$ with an inter-slice arc, and the node B at time $t = 0$ is extended to node Bt at time $t = 2$ with another inter-slice arc. There is no relationship between node A and B, causing that no intra-slice arc is used to contact them. For the parent nodes A and B, there are four states, namely, No, DS1, DS2 and Yes. The child node C has two states, namely, No and Yes. The details of the states will be described in the following section. The parallel system shown in Fig. 1(b) has the same structure as series system, except that they have different conditional probability tables (CPT). Given the same data, it can be seen that parallel system has higher reliability value (99.999%) than series system (99.767%) in 2nd week.

Table 1
Transition relations between consecutive nodes without repair.

t	$t+\Delta t$			
	No	DS1	DS2	Yes
No	$e^{-(\lambda_1+\lambda_4+\lambda_5)\Delta t}$	$\frac{\lambda_4}{\lambda_1+\lambda_4+\lambda_5}\left(1-e^{-(\lambda_1+\lambda_4+\lambda_5)\Delta t}\right)$	$\frac{\lambda_5}{\lambda_1+\lambda_4+\lambda_5}\left(1-e^{-(\lambda_1+\lambda_4+\lambda_5)\Delta t}\right)$	$\frac{\lambda_1}{\lambda_1+\lambda_4+\lambda_5}\left(1-e^{-(\lambda_1+\lambda_4+\lambda_5)\Delta t}\right)$
DS1	0	$e^{-(\lambda_2+\lambda_6)\Delta t}$	$\frac{\lambda_6}{\lambda_2+\lambda_6}\left(1-e^{-(\lambda_2+\lambda_6)\Delta t}\right)$	$\frac{\lambda_2}{\lambda_2+\lambda_6}\left(1-e^{-(\lambda_2+\lambda_6)\Delta t}\right)$
DS2	0	0	$e^{-\lambda_3\Delta t}$	$1-e^{-\lambda_3\Delta t}$
Yes	0	0	0	1

Table 2
Transition relations between consecutive nodes with perfect repair.

t	$t+\Delta t$			
	No	DS1	DS2	Yes
No	$e^{-(\lambda_1+\lambda_4+\lambda_5)\Delta t}$	$\frac{\lambda_4}{\lambda_1+\lambda_4+\lambda_5}\left(1-e^{-(\lambda_1+\lambda_4+\lambda_5)\Delta t}\right)$	$\frac{\lambda_5}{\lambda_1+\lambda_4+\lambda_5}\left(1-e^{-(\lambda_1+\lambda_4+\lambda_5)\Delta t}\right)$	$\frac{\lambda_1}{\lambda_1+\lambda_4+\lambda_5}\left(1-e^{-(\lambda_1+\lambda_4+\lambda_5)\Delta t}\right)$
DS1	0	$e^{-(\lambda_2+\lambda_6)\Delta t}$	$\frac{\lambda_6}{\lambda_2+\lambda_6}\left(1-e^{-(\lambda_2+\lambda_6)\Delta t}\right)$	$\frac{\lambda_2}{\lambda_2+\lambda_6}\left(1-e^{-(\lambda_2+\lambda_6)\Delta t}\right)$
DS2	0	0	$e^{-\lambda_3\Delta t}$	$1-e^{-\lambda_3\Delta t}$
Yes	$1-e^{-(\mu_1+\mu_2+\mu_3)\Delta t}$	0	0	$e^{-(\mu_1+\mu_2+\mu_3)\Delta t}$

Table 3
Transition relations between consecutive nodes with imperfect repair.

t	$t+\Delta t$			
	No	DS1	DS2	Yes
No	$e^{-(\lambda_1+\lambda_4+\lambda_5)\Delta t}$	$\frac{\lambda_4}{\lambda_1+\lambda_4+\lambda_5}\left(1-e^{-(\lambda_1+\lambda_4+\lambda_5)\Delta t}\right)$	$\frac{\lambda_5}{\lambda_1+\lambda_4+\lambda_5}\left(1-e^{-(\lambda_1+\lambda_4+\lambda_5)\Delta t}\right)$	$\frac{\lambda_1}{\lambda_1+\lambda_4+\lambda_5}\left(1-e^{-(\lambda_1+\lambda_4+\lambda_5)\Delta t}\right)$
DS1	0	$e^{-(\lambda_2+\lambda_6)\Delta t}$	$\frac{\lambda_6}{\lambda_2+\lambda_6}\left(1-e^{-(\lambda_2+\lambda_6)\Delta t}\right)$	$\frac{\lambda_2}{\lambda_2+\lambda_6}\left(1-e^{-(\lambda_2+\lambda_6)\Delta t}\right)$
DS2	0	0	$e^{-\lambda_3\Delta t}$	$1-e^{-\lambda_3\Delta t}$
Yes	$\frac{\mu_3}{\mu_1+\mu_2+\mu_3}\left(1-e^{-(\mu_1+\mu_2+\mu_3)\Delta t}\right)$	$\frac{\mu_2}{\mu_1+\mu_2+\mu_3}\left(1-e^{-(\mu_1+\mu_2+\mu_3)\Delta t}\right)$	$\frac{\mu_1}{\mu_1+\mu_2+\mu_3}\left(1-e^{-(\mu_1+\mu_2+\mu_3)\Delta t}\right)$	$e^{-(\mu_1+\mu_2+\mu_3)\Delta t}$

Table 4
CPT for series system with two components.

A				B				C	
No	DS1	DS2	Yes	No	DS1	DS2	Yes	No	Yes
Yes	No	No	No	Yes	No	No	No	1.000000	0.000000
Yes	No	No	No	No	Yes	No	No	0.985000	0.015000
Yes	No	No	No	No	No	Yes	No	0.952000	0.048000
Yes	No	No	No	No	No	No	Yes	0.000000	1.000000
No	Yes	No	No	Yes	No	No	No	0.965000	0.035000
No	Yes	No	No	No	Yes	No	No	0.950525	0.049475
No	Yes	No	No	No	No	Yes	No	0.918680	0.081320
No	Yes	No	No	No	No	No	Yes	0.000000	1.000000
No	No	Yes	No	Yes	No	No	No	0.932000	0.068000
No	No	Yes	No	No	Yes	No	No	0.918020	0.081980
No	No	Yes	No	No	No	Yes	No	0.887264	0.112736
No	No	Yes	No	No	No	No	Yes	0.000000	1.000000
No	No	No	Yes	Yes	No	No	No	0.000000	1.000000
No	No	No	Yes	No	Yes	No	No	0.000000	1.000000
No	No	No	Yes	No	No	Yes	No	0.000000	1.000000
No	No	No	Yes	No	No	No	Yes	0.000000	1.000000

2.3. Imperfect repair modeling

The key issue of imperfect repair is modeled by assuming that each parent node is a multi-state degraded system. Four assumptions are made (Soro, Nourelfath, & Ait-Kadi, 2010):

(1) The system may have many levels of degradation, corresponding to discrete performance rates, which vary from perfect functioning to complete failure;
(2) The system might fail randomly from any operational state;
(3) All transition rates are constant and exponentially distributed;
(4) The current degradation is observable through some system parameters, and the time needed for inspection is negligible.

Each parent node of DBN involves four states, namely, No, DS1, DS2 and Yes. The state No refers to no failure or perfect functioning state. The state Yes refers to failure or failed state. The states DS1 and DS2 refer to the first and the second degraded states, respectively. Each parent node is initially in its perfect functioning state (No). As time progresses, it can either go to the first (DS1) or the second (DS2) degraded states, or it can go to a failed state (Yes).

When the node reaches the failed state, a repair is required. It can either only go to the perfect functioning state, which is considered to be perfect repair, or it can go to the perfect functioning state as well as the two degraded states, which is considered to be imperfect repair. The failure rates and repair rates are given above the state transition arcs. The state transition diagram of multi-state degraded components is shown in Fig. 2.

Assume that the current time is t, and the time interval between two successive trials is Δt. Then, the transition relations between consecutive nodes without repair, with perfect repair and with imperfect repair are given in Tables 1–3, respectively (Kohda & Cui, 2007).

For the sake of simplicity in the current study, given the failure rate λ and repair rates μ of each parent node, the failure rates λ_1, λ_2, λ_3, λ_4, λ_5, λ_6 and repair rates μ_1,μ_2, μ_3 between the states can be obtained from the following assumptive equations.

$$\lambda_2 = \lambda_5 \tag{3}$$
$$\lambda_3 = \lambda_4 = \lambda_6 \tag{4}$$
$$\lambda_1 + \lambda_4 + \lambda_5 = \lambda \tag{5}$$
$$\lambda_1 : \lambda_4 : \lambda_5 = 1 : 3 : 6 \tag{6}$$
$$\mu_1 + \mu_2 + \mu_3 = \mu \tag{7}$$
$$\mu_1 : \mu_2 : \mu_3 = 1 : 2 : 7 \tag{8}$$

For the parent nodes A and B in series and parallel systems described in Section 2.2, the failure rates are $\lambda_A = 3.118 \times 10^{-5}$ and $\lambda_B = 2.079 \times 10^{-5}$ and the repair rates are $\mu_A = 2.247 \times 10^{-2}$ and $\mu_B = 8.333 \times 10^{-2}$. Therefore, the failure rates and repair rates between the states of each node can be calculated using Eqs. (3)–(8). Subsequently, the transition relations between consecutive nodes can be calculated using Tables 1–3.

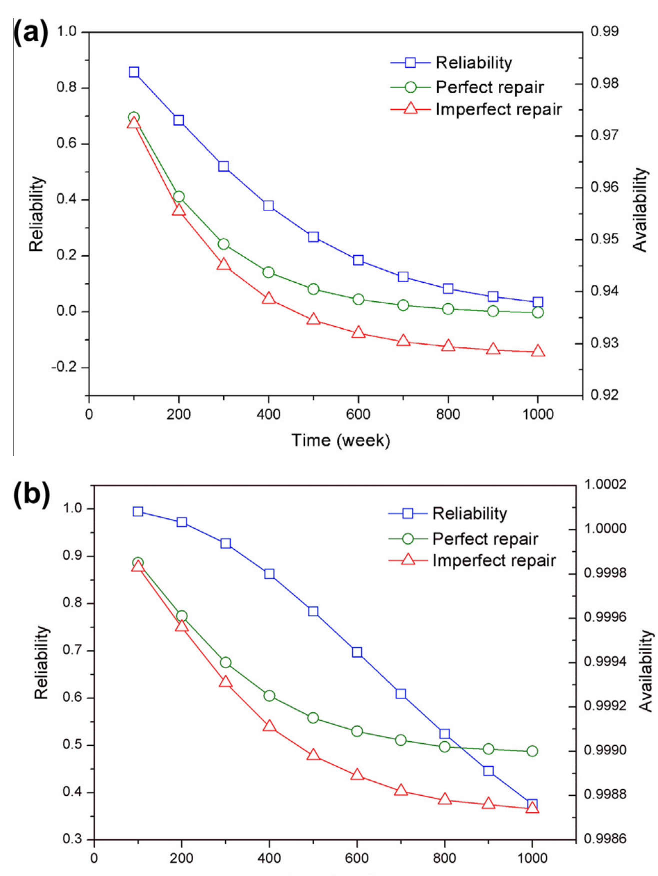

Fig. 3. Reliability and availability with respect to perfect and imperfect repair for (a) series and (b) parallel systems.

Table 5
CPT for parallel sYstem with two components.

A				B				C	
No	DS1	DS2	Yes	No	DS1	DS2	Yes	No	Yes
Yes	No	No	No	Yes	No	No	No	1.000000	0.000000
Yes	No	No	No	No	Yes	No	No	1.000000	0.000000
Yes	No	No	No	No	No	Yes	No	1.000000	0.000000
Yes	No	No	No	No	No	No	Yes	1.000000	0.000000
No	Yes	No	No	Yes	No	No	No	1.000000	0.000000
No	Yes	No	No	No	Yes	No	No	0.999475	0.000525
No	Yes	No	No	No	No	Yes	No	0.998320	0.001680
No	Yes	No	No	No	No	No	Yes	0.965000	0.035000
No	No	Yes	No	Yes	No	No	No	1.000000	0.000000
No	No	Yes	No	No	Yes	No	No	0.998980	0.001020
No	No	Yes	No	No	No	Yes	No	0.996736	0.003264
No	No	Yes	No	No	No	No	Yes	0.932000	0.068000
No	No	No	Yes	Yes	No	No	No	1.000000	0.000000
No	No	No	Yes	No	Yes	No	No	0.985000	0.015000
No	No	No	Yes	No	No	Yes	No	0.952000	0.048000
No	No	No	Yes	No	No	No	Yes	0.000000	1.000000

2.4. Conditional probability table

For a DBN with n parent nodes and m states for each parent nodes, it requires m^n independent parameters to completely specify the CPT. It is unfeasible to specify so many parameters to quantify the relationship when n is large. To solve this problem, noisy OR-gate and noisy AND-gate models are used for series and parallel systems, respectively.

Three assumptions including causal inhibition, exception independence, and accountability are made in the models (Neapolitan, 2003). Assume that there are n causes $X_1, X_2, \ldots$ and X_n of Y, the variable I_j is the mechanism that inhibits X_j. The I_j are independent owing to exception independence assumption. The variable A_j is on if and only if X_j is present and is not being inhibited. And Y should be present if any one of the A_j is present owing to the causal inhibition assumption. Therefore, the noisy OR-gate model can be expressed as follows:

$$P(Y|X_1, X_2, \ldots X_n) = 1 - \prod_{1 \leqslant j \leqslant n} (1 - p_j) \tag{9}$$

Similar considerations can be made for variables in the parallel system, by taking into account the noisy AND-gate as follows:

$$P(Y|X_1, X_2, \ldots X_n) = \prod_{1 \leqslant j \leqslant n} p_j \tag{10}$$

The degradation probabilities (DS) of parent nodes A and B in series and parallel systems are P(C = Yes|DS1$_A$ = Yes) = 3.5%, P(C = Yes|DS2$_A$ = Yes) = 6.8%, P(C = Yes|DS1$_B$ = Yes) = 1.5%, and P(C = Yes|DS2$_B$ = Yes) = 4.8%. The DBNs have $n = 2$ parent nodes, and for each parent node, it has $m = 4$ states; therefore, the CPTs have $m^n = 16$ states. By using Eqs. (9) and (10), the CPTs for series and parallel systems can be calculated as shown in Tables 4 and 5, respectively.

2.5. Reliability and availability

Fig. 3 reports the reliability and availability with respect to perfect and imperfect repair for series and parallel systems. As indicated in Fig. 3(a), with the increasing of time, the reliability and

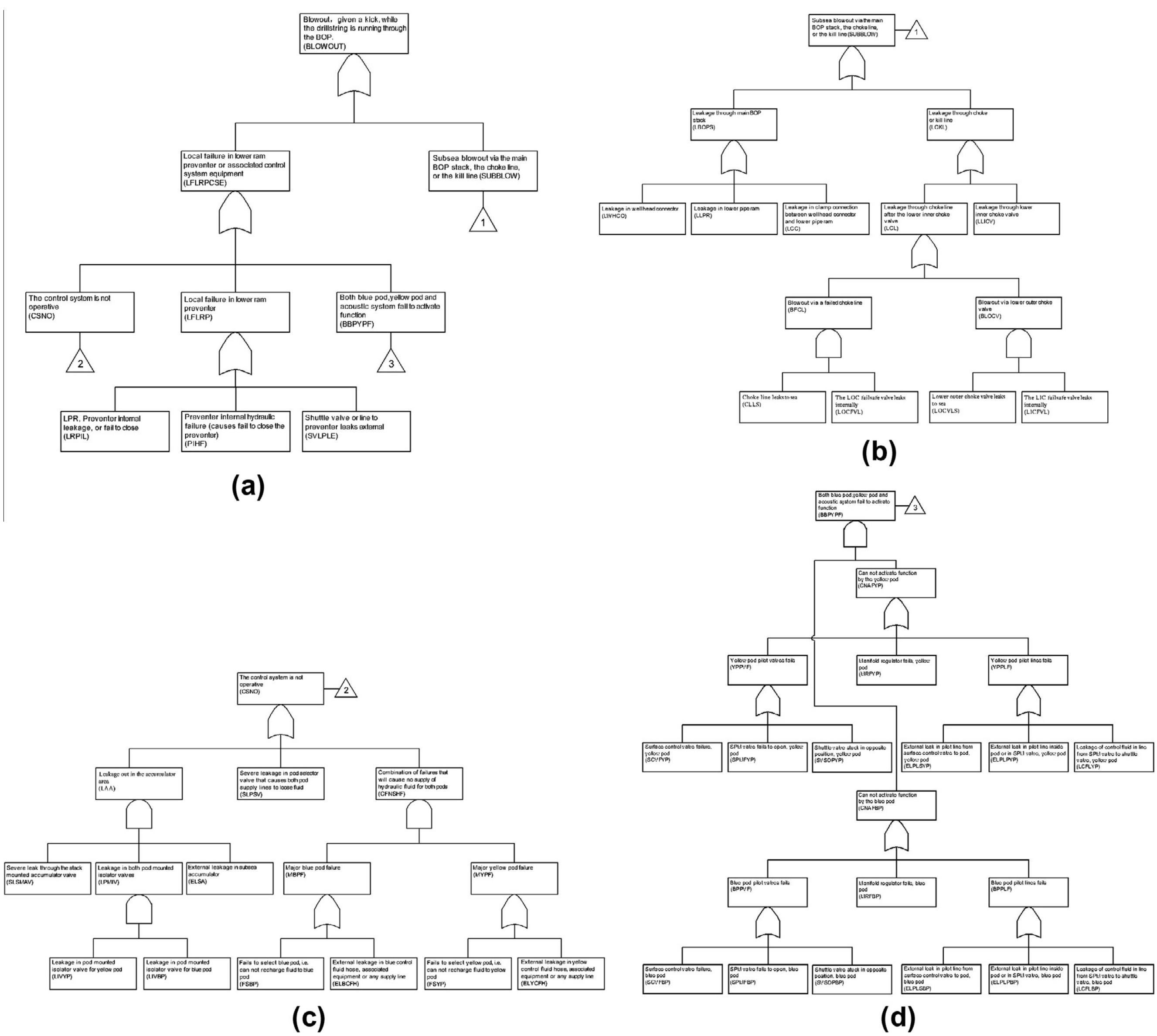

Fig. 4. Fault tree of "blowout, given a kick" (a) BLOWOUT, (b) SUBBLOW, (c) CSNO, and (d) BBPYPE.

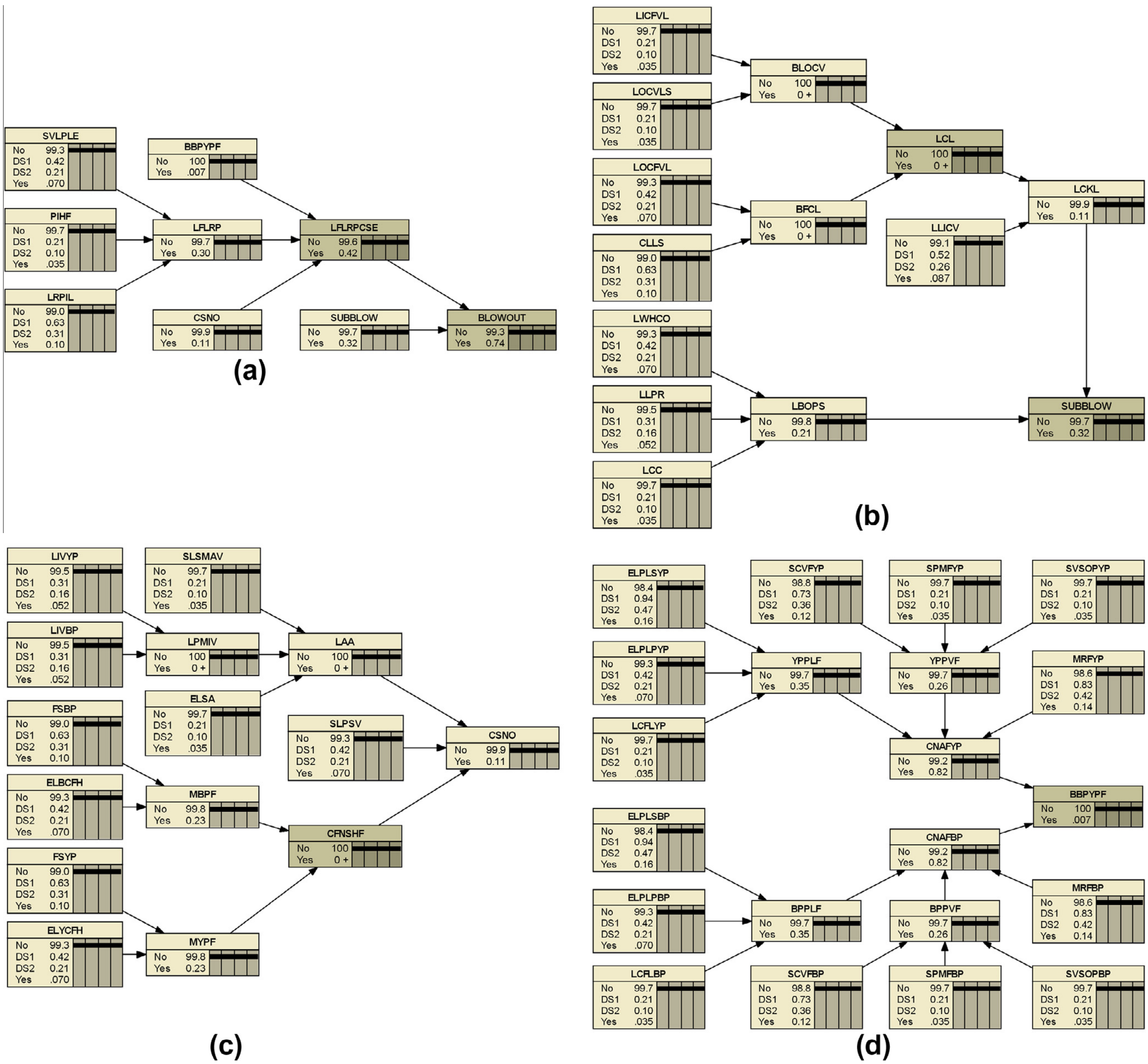

Fig. 5. Static BN in 2nd week (a) BLOWOUT, (b) SUBBLOW, (c) CSNO, and (d) BBPYPE.

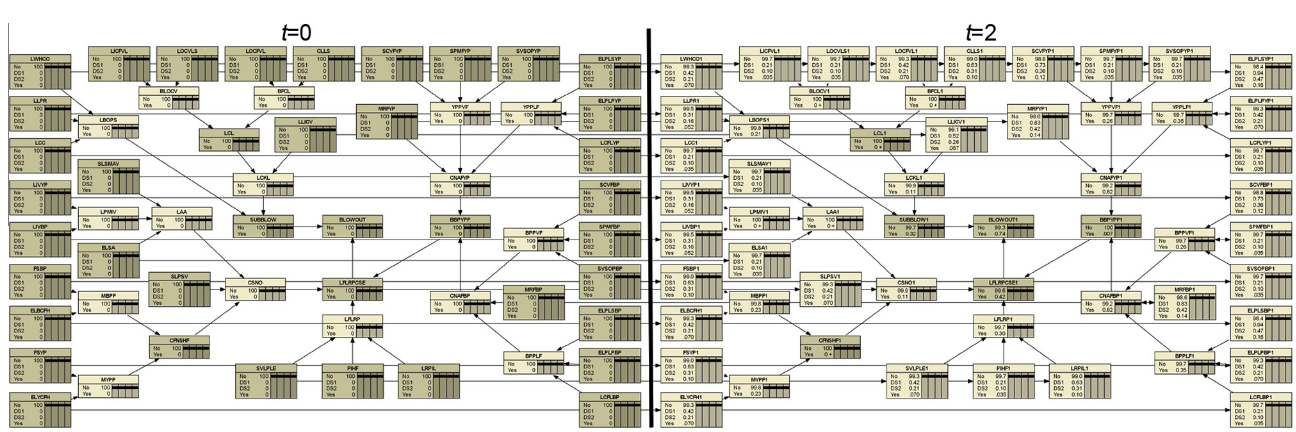

Fig. 6. Extended DBN of "blowout, given a kick" from 0th to 2nd week.

Table 6
List of basic events for ''blowout, given a kick''.

No.	Basic event	Description	Failure rate, λ	Repair rate, μ	DS1 (%)	DS2 (%)	Prior prob.[a]	Poste. prob.[a]
S1	LWHCO	Leakage in wellhead connector	2.07866E−05	0.08696	2.1	5.2	0.001009	0.016073
S2	LLPR	Leakage in lower pipe ram	1.55899E−05	0.00606	3.5	6.7	0.000806	0.012843
S3	LCC	Leakage in clamp connection between wellhead connector and lower pipe ram	1.03933E−05	0.00673	2.0	8.0	0.000480	0.007641
S4	CLLS	Choke line leaks to sea	3.11798E−05	0.06250	4.5	5.8	0.001719	0.001877
S5	LOCFVL	The LOC failsafe valve leaks internally	2.07866E−05	0.04348	2.7	4.8	0.001009	0.001195
S6	LOCVLS	Lower outer choke valve leaks to sea	1.03933E−05	0.05000	5.0	9.0	0.000430	0.000450
S7	LICFVL	The LIC failsafe valve leaks internally	1.03933E−05	0.04348	2.7	4.8	0.000430	0.000465
S8	LLICV	Leakage through lower inner choke valve	2.59832E−05	0.04000	1.8	5.8	0.001348	0.021482
C1	SLSMAV	Severe leak through the stack mounted accumulator valve	1.03933E−05	0.06667	4.0	6.0	0.000430	0.000430
C2	LIVYP	Leakage in pod mounted isolator valve for yellow pod	1.55899E−05	0.04000	3.5	6.5	0.000702	0.000702
C3	LIVBP	Leakage in pod mounted isolator valve for blue pod	1.55899E−05	0.04000	3.5	6.5	0.000702	0.000702
C4	ELSA	External leakage in subsea accumulator	1.03933E−05	0.02222	4.0	6.0	0.000430	0.000430
C5	SLPSV	Severe leakage in pod selector valve that causes both pod supply lines to loose fluid	2.07866E−05	0.05000	6.0	7.0	0.001009	0.016073
C6	FSBP	Fails to select blue pod, i.e. cannot recharge fluid to blue pod	3.11798E−05	0.02247	3.5	6.8	0.001719	0.002147
C7	ELBCFH	External leakage in blue control fluid hose, associated equipment or any supply line	2.07866E−05	0.08333	1.5	4.8	0.001009	0.001260
C8	FSYP	Fails to select yellow pod, i.e. cannot recharge fluid to yellow pod	3.11798E−05	0.02247	3.5	6.8	0.001719	0.002147
C9	ELYCFH	External leakage in yellow control fluid hose, associated equipment or any supply line	2.07866E−05	0.08333	1.5	4.8	0.001009	0.001260
C10	LRPIL	LPR, Preventer internal leakage, or fail to close	3.11798E−05	0.00738	2.3	7.0	0.001873	0.029835
C11	PIHF	Preventer internal hydraulic failure (causes fail to close the preventer)	1.03933E−05	0.01047	3.6	7.0	0.000443	0.007059
C12	SVLPLE	Shuttle valve or line to preventer leaks external	2.07866E−05	0.01325	6.4	8.1	0.001021	0.016260
Y1	SCVFYP	Surface control valve failure, yellow pod	3.63765E−05	0.04348	2.5	5.6	0.002117	0.003960
Y2	SPMFYP	SPM valve fails to open, yellow pod	1.03933E−05	0.02000	5.2	8.8	0.000431	0.000805
Y3	SVSOPYP	Shuttle valve stuck in opposite position, yellow pod	1.03933E−05	0.01325	2.6	6.3	0.000435	0.000814
Y4	MRFYP	Manifold regulator fails, yellow pod	4.15731E−05	0.08333	5.0	7.0	0.002542	0.004755
Y5	ELPLSYP	External leak in pilot line from surface control valve to pod, yellow pod	4.67698E−05	0.03922	2.0	5.5	0.002992	0.005597
Y6	ELPLPYP	External leak in pilot line inside pod or in SPM valve, yellow pod	2.07866E−05	0.02174	3.0	6.0	0.001010	0.001888
Y7	LCFLYP	Leakage of control fluid in line from SPM valve to shuttle valve, yellow pod	1.03933E−05	0.01667	5.0	6.2	0.000432	0.000807
B1	SCVFBP	Surface control valve failure, blue pod	3.63765E−05	0.04348	2.5	5.6	0.002117	0.003960
B2	SPMFBP	SPM valve fails to open, blue pod	1.03933E−05	0.02000	5.2	8.8	0.000431	0.000805
B3	SVSOPBP	Shuttle valve stuck in opposite position, blue pod	1.03933E−05	0.01325	2.6	6.3	0.000435	0.000814
B4	MRFBP	Manifold regulator fails, blue pod	4.15731E−05	0.08333	5.0	7.0	0.002542	0.004755
B5	ELPLSBP	External leak in pilot line from surface control valve to pod, blue pod	4.67698E−05	0.03922	2.0	5.5	0.002992	0.005597
B6	ELPLPBP	External leak in pilot line inside pod or in SPM valve, blue pod	2.07866E−05	0.02174	3.0	6.0	0.001010	0.001888
B7	LCFLBP	Leakage of control fluid in line from SPM valve to shuttle valve, blue pod	1.03933E−05	0.01667	5.0	6.2	0.000432	0.000807

[a] The prior and posterior probabilities are calculated in 52nd week with imperfect repair.

availability for series system decrease. The reliability drops to almost 0 in about 1000th week. Because of the repair, the availability decreases slowly. When perfect repair is considered, it reaches a stable level of approximately 0.936 in about 1000th week. When imperfect repair is considered, it reaches a lower value of 0.928 in about 1000th week. It can be seen that the imperfect repair does not affect the series system performances significantly.

Similar results for parallel system are obtained, as shown in Fig. 3(b). However, the reliability and availability values are higher than series system. The reliability drops to about 0.375 in about 1000th week, and the availability reaches the stable levels of approximately 0.9990 and 0.9987 for the system with perfect and imperfect repairs, respectively. Obviously, the availability values are almost the same, which suggests that imperfect repair does not affect the parallel system performances significantly.

3. Case study

3.1. Fault tree

The FT of ''Blowout, given a kick, while the drillstring is running through the BOP (BLOWOUT)'' is constructed according to references (Holand, 1999; Holand, 2001) as shown in Fig. 4. The blowout may occur via the main BOP stack or the upper, middle and lower pipe rams, blind shear ram, upper and lower annular BOPs. For the sake of simplicity, only one pipe BOP, that is subsea lower pipe ram, are modeled. The relationship between events is either AND or OR, and the events and their abbreviations are written in the blocks.

For example, the basic events ''Chock line leaks to sea (CLLS)'' and ''The LOC failsafe valve leaks internally (LOCFVL)'' are

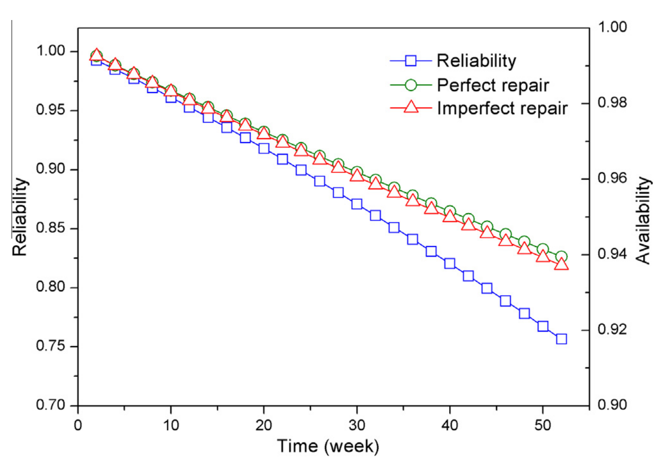

Fig. 7. Reliability and availability with respect to perfect and imperfect repair within one year.

connected to the top event ‘‘Blowout via a failed choke line (BFCL)’’ through a AND-gate. And the basic events ‘‘Fails to select blue pod, i.e. cannot recharge fluid to blue pod (FSBP)’’ and ‘‘External leakage in blue control fluid hose, associated equipment or any supply line (ELBCFH)’’ are connected to the top event ‘‘Major blue pod failure (MBPF)’’ through a OR-gate.

3.2. Corresponding DBN

According to the conversion algorithm from FT to DBN described in Section 2.2, the FTs of ‘‘Blowout, given a kick, while the drillstring is running through the BOP’’ are translated into corresponding DBN as shown in Fig. 5.

For example, the basic events CLLS and LOCFVL of FT are translated into two corresponding parent nodes CLLS and LOCFVL of BN, and the top event BFCL is translated into the corresponding child node BFCL of BN, as shown in Fig. 5(b). Similarly, the basic FSBP and ELBCFH are translated into two corresponding parent nodes FSBP and ELBCFH of BN, and the top event ELBCFH is translated into the corresponding child node MBPF of BN, as shown in Fig. 5(c). It is noted that only the primary parent nodes of BN, that is the corresponding basic events of FT, have four states, namely, No, DS1, DS2 and Yes. The other nodes have two states, namely, No and Yes.

The entire BN of BLOWOUT extended from 0th to 2nd week with imperfect repairs is shown in Fig. 6. As indicated, each parent node is initially in its perfect functioning state (No = 100%) in 0th week, and has different probabilities for four states in 2nd week because of failure and repair. The values of failure rate, repair rate, DS1 and DS2 are listed in the 4–7th columns of Table 6.

3.3. Evaluation and validation

The quantitative risk assessments of ‘‘Blowout, given a kick’’ are performed using Netica software, in which Junction Tree algorithm is used for exact inference. The reliability and availability of ‘‘BLOWOUT’’ with perfect repair and imperfect repair are evaluated via forward analysis, and the posterior probability given the ‘‘BLOWOUT’’ occurs with imperfect repair is evaluated via backward analysis. The mutual information is researched in order to assess the important degree of basic events. The analysis results can provide useful information to handle the risk incident or prevent the accident reoccurring. The effect of degradation probability on the reliability and availability of system with imperfect repair are also studied.

Validation is an important aspect of a proposed model because it provides a reasonable amount of confidence to the results of the model. Several approaches are applied appropriately to the different aspects of a particular model, including response analysis, response surface modeling, and external validation (Rathnayak, Khan, & Amyotte, 2012). In order to carry out a full validation of the model the parameters used would need to be closely monitored for a long period to time. For the offshore blowout, it is obviously an impractical exercise. In the current work, a three-axioms-based sensitivity analysis method is therefore used for partial validation of the proposed DBN modeling. The following three axioms should be satisfied (Jones, 2010).

(1). A slight increase/decrease in the prior subjective probabilities of each parent node should certainly result in the effect of a relative increase/decrease of the posterior probabilities of child nodes;

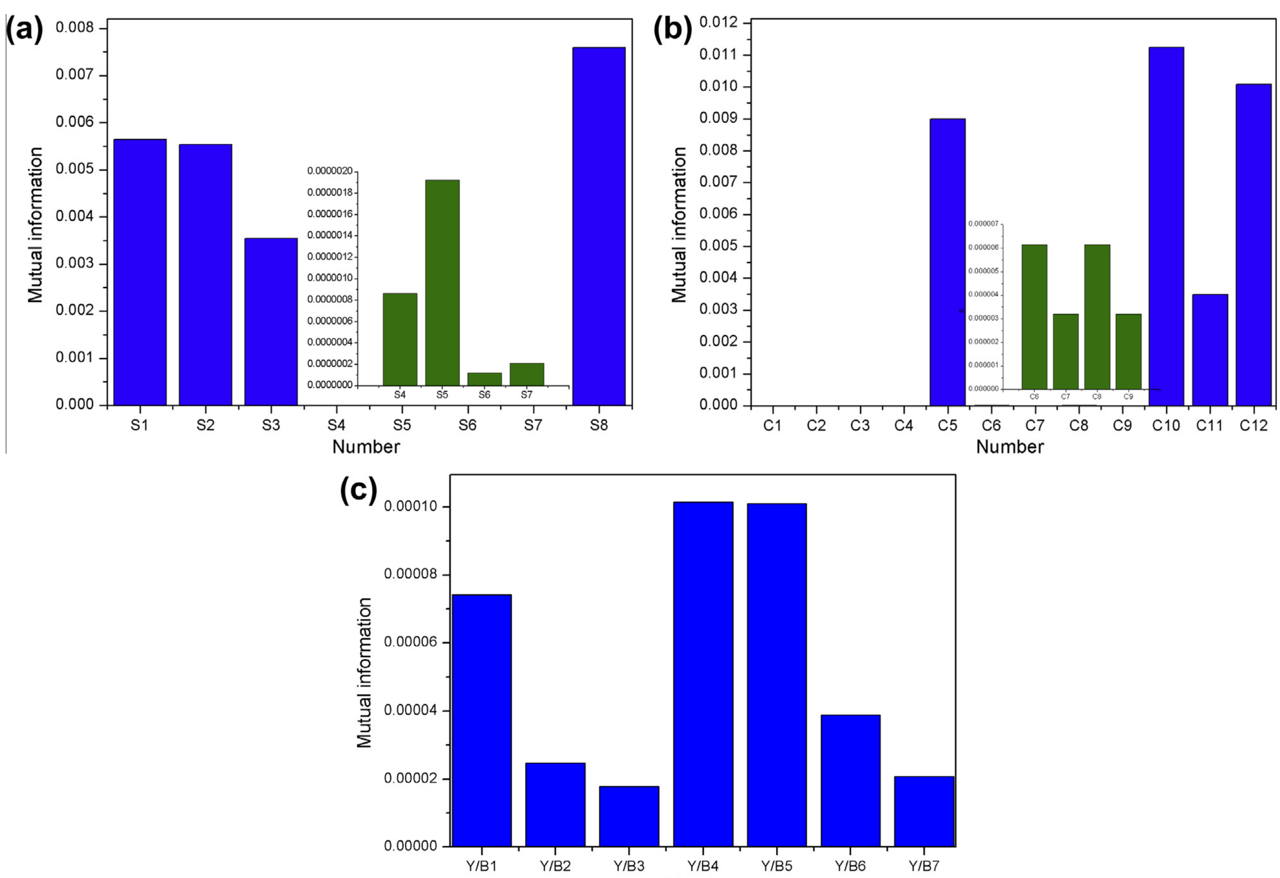

Fig. 8. Mutual information of basic events and BLOWOUT in 52nd week (a) S-series, (b) C-series and (c) Y/B-series.

(2). Given the variation of subjective probability distributions of each parent node, its influence magnitude to child node values should keep consistent;

(3). The total influence magnitudes of the combination of the probability variations from x attributes on the values should be always greater than the one from the set of x–y ($y \in x$) attributes.

3.4. Results and discussions

3.4.1. Reliability and availability

The quantitative risk assessments of ''Blowout, given a kick'' within one year (52 weeks) are investigated using DBN. The prior probability and posterior probability given BLOWOUT occurs in 52nd week with imperfect repair are given in the 8th and 9th columns of Table 6. The reliability and availability with perfect and imperfect repair are plotted in Fig. 7.

As indicated, as time progresses, the reliability and availability decrease. The reliability drops to about 0.756 in 52nd week, and the availability reaches the values of approximately 0.939 and 0.937 in 52nd week for the system with perfect repair and imperfect repair, respectively. Obviously, the availabilities with perfect and imperfect repair are almost the same, which are higher than the system reliability within one year. The results suggest that in a short period, the perfect and imperfect repairs can improve the system performances significantly, whereas the imperfect repair does not degrade the system performances significantly in comparison with the perfect repair.

3.4.2. Mutual information investigation

The individual contribution of each basic event to the system performances is described using mutual information, as shown in Fig. 8. As indicated in Fig. 8(a) and (b), among S-series events, S1 (LWHCO), S2 (LLPR), S3 (LCC), and S8 (LLICV) contribute much to BLOWOUT, among C-series events, C5 (SLPSV), C10 (LRPIL), C11 (PIHF), and C12 (SVLPLE) contribute much to BLOWOUT, whereas the other events contribute little. As indicated in Fig. 8(c), the Y/B-series events contribute little to BLOWOUT in comparison with S-series and C-series events, due to the facts that the yellow and blue subsea control pods provide completely redundant control of subsea functions. Therefore, the eight basic events are sensitive to subsea BOP system failure, which should given more attention in order to improve the performance of subsea BOP system and prevent the potential accident occurring.

3.4.3. Effect of degradation probability

Three basic events, LRPIL, SCVFYP, and LOCFVL, have different mutual information of 1.124×10^{-2}, 7.412×10^{-5} and 1.925×10^{-6}, respectively. Each degradation probability of DS1 and DS2 for the three basic events increases 5% from the values given in Table 6, the reliability and availability of subsea BOP system are calculated. The three-dimensional surface plots showing the effects of DS1 and DS2 of LRPIL, SCVFYP, and LOCFVL on the reliability and availability are shown in Fig. 9 and Fig. 10, respectively.

Clearly, for all of the three basic events with increasing degradation probability, the reliability decreases as shown in Fig. 9. For the LRPIL, that is sensitive to subsea BOP system failure, the reliability

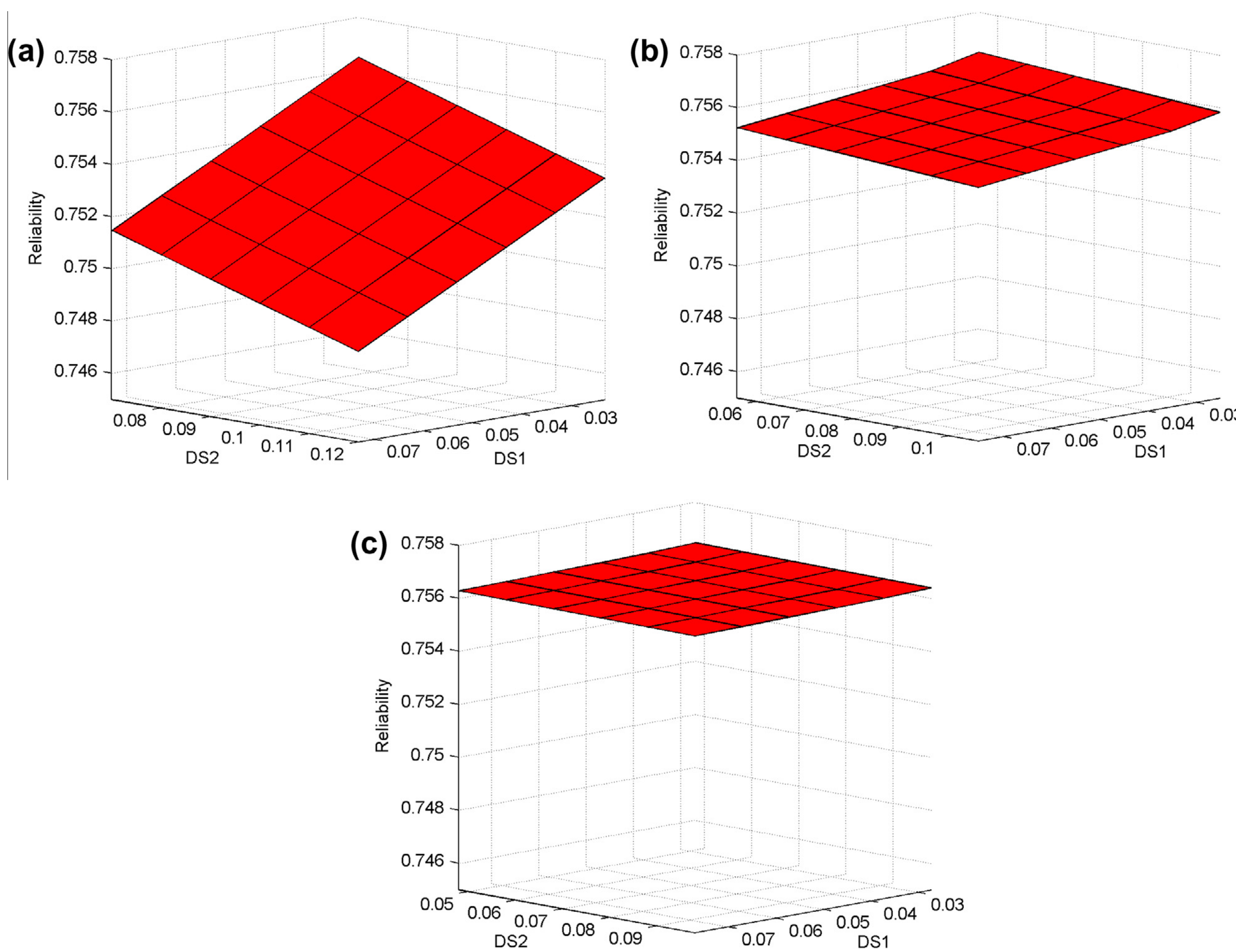

Fig. 9. Effect of degradation probability on the reliability (a) LRPIL, (b) SCVFYP, and (c) LOCFVL.

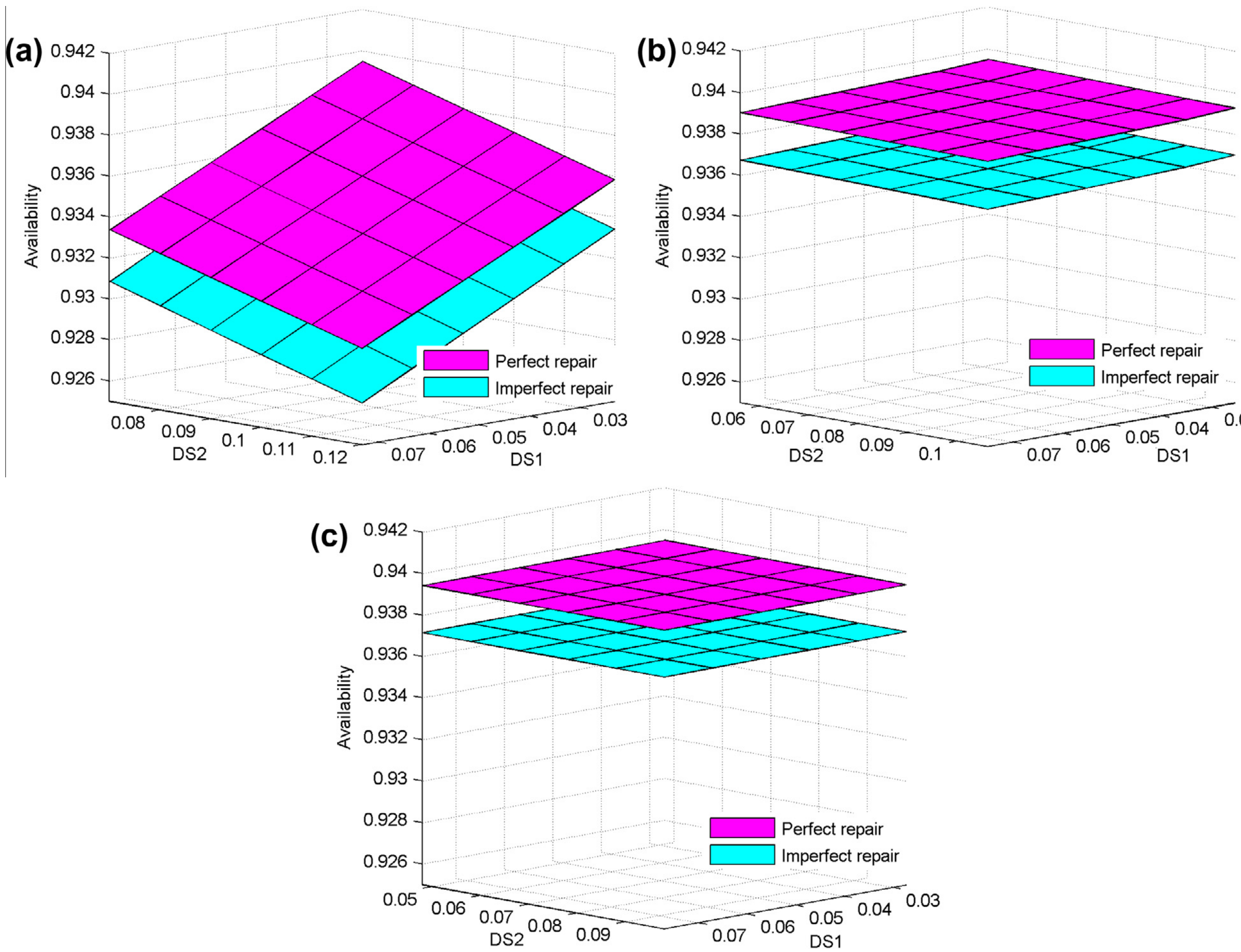

Fig. 10. Effect of degradation probability on the availability (a) LRPIL, (b) SCVFYP, and (c) LOCFVL.

decreases rapidly. The SCVFYP and LOCFVL are not sensitive to subsea BOP system failure, making their reliability decreases slowly with increasing degradation probability. Therefore, to improve the subsea BOP system performances, the degradation probability of events, especially the basic events with high sensitive to subsea BOP system failure, should be reduced as much as possible.

In addition, with increasing DS1 and DS2, the availability also decreases as shown in Fig. 10. As indicated, the availability of LRPIL decreases rapidly, and the ones of SCVFYP and LOCFVL decreases slowly. The availabilities with perfect repair are always higher than those with imperfect repair for the three events. The results also suggest that the degradation probability of events, especially the basic events with high sensitive to subsea BOP system failure, should be reduced as much as possible in order to improve the subsea BOP system performances.

3.4.4. Validation of the model

Validation is an important task of demonstrating that the model is a reasonable representation of an actual system. A sensitivity analysis has been carried out in order to give a partial validation of the model. The model should at least satisfy the three axioms described in Section 3.3. Taking the child nodes of LBOPS for example, when the state Yes of LWHCO is set to 50% from 0, the reliability of system decreases to 0.378 from 0.756, and the availability decreases to 0.933 from 0.937. When both the change plus the state Yes of LLRP are set to 50%, the reliability of system decreases to 0.189 and the availability decreases to 0.927. Finally, when the state Yes of last parent node LCC is set to 50% the reliability of system decreases to 0.095, and the availability decreases to 0.922. The exercise of increasing each influencing node satisfies the axioms, thus giving a partial validation to the model.

4. Conclusions

This paper presents a method of translating fault tree into dynamic Bayesian networks, taking account of imperfect repair. A case of subsea BOP system is analyzed to demonstrate the presented methods.

(1) The perfect and imperfect repairs can improve the performances of series and parallel system significantly, whereas the imperfect repair cannot degrade the system performances significantly in comparison with the perfect repair.
(2) Similarly, for the subsea BOP system, the repair improves the system performances, whereas imperfect repair does not degrade the system performances significantly in comparison with the perfect repair.
(3) Eight basic events, involving LWHCO, LLPR, LCC, LLICV, SLPSV, LRPIL, PIHF and SVLPLE are sensitive to subsea BOP system failure, which should given more attention in order to improve the performance of subsea BOP system and prevent the potential accident occurring.
(4) The degradation probability of basic events, especially the ones with high sensitive to subsea BOP system failure, should be reduced as much as possible in order to improve the subsea BOP system performances.

(5) The sensitivity analysis partially validate the proposed DBN modeling is correct and rational.

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References

Bobbio, A., Portinale, L., Minichino, M., & Ciancamerla, E. (2001). Improving the analysis of dependable systems by mapping Fault Trees into Bayesian Networks. *Reliability Engineering & System Safety, 71*, 249–260.

BOEMRE, (2011). Report regarding the causes of the April 20, 2010. The Bureau of Ocean Energy Management Regulation and Enforcement, September 14, 2011.

Cai, B. P., Liu, Y. H., Liu, Z. K., Tian, X. J., Zhang, Y. Z., & Liu, J. (2012). Performance evaluation of subsea blowout preventer systems with common-cause failures. *Journal of Petroleum Science and Engineering, 90–91*, 18–25.

Codetta-Raiteri, D., Bobbio, A., Montani, S., & Portinale, L. (2012). A dynamic Bayesian network based framework to evaluate cascading effects in a power grid. *Engineering Applications of Artificial Intelligence, 25*, 683–697.

Flammini, F., Marrone, S., Mazzocca, N., & Vittorini, V. (2009). A new modeling approach to the safety evaluation of N-modular redundant computer systems in presence of imperfect maintenance. *Reliability Engineering & System Safety, 94*, 1422–1432.

Fowler, J. H., & Roche, J. R. (1994). System safety analysis of well control equipment. *SPE Drilling & Completion, 9*, 193–198.

Harlow, W. F., Brantley, B. C., & Harlow, R. M. (2011). BP initial image repair strategies after the Deepwater Horizon spill. *Public Relations Review, 37*, 80–83.

Holand, P. (1996). Subsea blowout-preventer systems: Reliability and testing. *SPE Reprint Series, 42*, 29–32.

Holand, P. (1999). Reliability of subsea BOP systems for deepwater application, Phase II DW. Project report STF38 A99426.

Holand, P. (2001). Deepwater kicks and BOP performance, Project report STF38 A01419.

Holand, P., & Rausand, M. (1987). Reliability of subsea BOP system. *Reliability Engineering, 19*, 263–275.

Jones, B., Jenkinson, I., Yang, Z., & Wangn, J. (2010). The use of Bayesian network modelling for maintenance planning in a manufacturing industry. *Reliability Engineering & System Safety, 95*(3), 267–277.

Khakzad, N., Khan, F., & Amyotte, P. (2011). Safety analysis in process facilities: Comparison of fault tree and Bayesian network approaches. *Reliability Engineering & System Safety, 96*, 925–932.

Khakzad, N., Khan, Faisal, & Amyotte, P. (2013). Dynamic safety analysis of process systems by mapping bow-tie into Bayesian network. *Process Safety and Environment Protection, 91*, 46–53.

Kim, M. C. (2011). Reliability block diagram with general gates and its application to system reliability analysis. *Annals of Nuclear Energy, 38*, 2456–2461.

Kohda, T., & Cui, W. M. (2007). Risk-based reconfiguration of safety monitoring system using dynamic Bayesian network. *Reliability Engineering & System Safety, 92*, 1716–1723.

Mahadevan, S., Zhang, R. X., & Smith, N. (2001). Bayesian networks for system reliability reassessment. *Structural Safety, 23*(3), 231–251.

Montani, S., Portinale, L., Bobbio, A., & Codetta-Raiteri, D. (2008). Radyban: A tool for reliability analysis of dynamic fault trees through conversion into dynamic Bayesian networks. *Reliability Engineering & System Safety, 93*, 922–932.

Neapolitan, R. E. (2003). *Learning bayesian networks*. London: Prentice Hall.

Neil, M., & Marquez, D. (2012). Availability modelling of repairable systems using Bayesian networks. *Engineering Applications of Artificial Intelligence, 25*, 698–704.

Nordgard, D. E., & Sand, K. (2010). Application of Bayesian networks for risk analysis of MV air insulated switch operation. *Reliability Engineering & System Safety, 95*, 1358–1366.

Pearl, J. (1988). *Probabilistic reasoning in intelligent systems: Networks of plausible inference*. San Mateo: Morgan Kaufmann.

Portinale, L., Raiteri, D. C., & Montani, S. (2010). Supporting reliability engineers in exploiting the power of dynamic Bayesian networks. *International Journal of Approximate Reasoning, 51*, 179–195.

Rathnayak, S., Khan, F., & Amyotte, P. (2012). Accident modeling approach for safety assessment in an LNG processing facility. *Journal of Loss Prevention in the Process Industries, 25*, 414–423.

Shanks, E., Dykes, A., Quilici, M., & Pruitt, J. (2003). Deepwater BOP control systems-A look at reliability issues. *Offshore Technology Conference, OTC, 15194*, 1–10.

Soro, I. W., Nourelfath, M., & Ait-Kadi, D. (2010). Performance evaluation of multi-state degraded systems with minimal repairs and imperfect preventive maintenance. *Reliability Engineering & System Safety, 95*, 65–69.

Torres-Toledano, J. G., & Sucar, L. E. (1998). Bayesian networks for reliability analysis of complex systems. *Lecture Notes in Artificial Intelligence, 1484*, 195–206.

Wang, Y. F., Roohi, S. F., Hu, X. M., & Xie, M. (2011). Investigations of human and organizational factors in hazardous vapor accidents. *Journal of Hazardous Materials, 191*, 69–82.

Webera, P., & Jouffeb, L. (2006). Complex system reliability modelling with Dynamic Object Oriented Bayesian Networks (DOOBN). *Reliability Engineering & System Safety, 91*, 149–162.