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Reliabilities analysis of evacuation on offshore platforms: A dynamic Bayesian Network model

Reliabilities analysis of evacuation on offshore platforms: A dynamic Bayesian Network model

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Abstract: An offshore platform is naturally vulnerable to accidents, such as the leakage of dangerous chemicals, fire and explosion because there are a lot of oil and gas, where all the equipment and pipes are squeezed into a limited area. Escape, Evacuation, and Rescue (EER) plans play a vital role as the last barrier to ensure the safety of personnel in the event of a major accident. As a result, the main contributors leading to evacuation failure are analyzed in this study to prioritize technology development needed to select a robust EER strategy. The scope of this research focuses on the quantitative analysis of various EER strategies on offshore platforms. In this research, a reliability prediction model of emergency evacuation is established for offshore platforms based on the K2 structure learning algorithm and a Bayesian network parameter learning method. The conditional probability tables of each node are determined by combining the Bayesian estimation method and a junction tree reasoning engine. The reliability of emergency evacuation on a platform is predicted using a dynamic Bayesian network model. The transition probability is determined through a Markov method. The main factors leading to evacuation failure are investigated using the diagnostic reasoning method of Bayesian Network.
Key words: K2 algorithm, Dynamic Bayesian network, Reliability prediction of successful evacuation, Analysis of influencing factors.

1 Introduction

There are a large number of leaking sources and flammable substances on offshore platforms. In the presence of ignition, material leakage may give rise to a catastrophic fire or an explosion. After the accidents, emergency evacuation plays a vital role in safeguarding the lives of personnel [1]. Unsuccessful evacuation would cause catastrophic consequences. Examples include the Piper Alpha platform disaster, the Alexander L. Kielland accommodation platform collapse and the Ocean Ranger tragedy [2-4]. Therefore, it is necessary to investigate the main factors influencing emergency evacuation and develop a model capable of predicting the probability of successful evacuation.

The studies about evacuation on offshore platforms can be broadly divided into qualitative and quantitative analysis. In qualitative analysis, the personnel evacuation process is usually researched in terms of route selection [5], moving speed and typical behaviors of participants [6]. The evacuation, escape and rescue (EER) system contains the entire process from the beginning of the movement due to an accident to a safe place, related works have been done to analyze the effectiveness of the system on offshore platforms [7-9]. Quantitative analysis of evacuation is also essential, mainly containing the effects of environmental conditions and human behaviors on the evacuation process. Related studies include evaluating the evacuation performance of each plan considering the total evacuation time [5][10] or the environmental conditions influencing the evacuation, such as smoke concentration [6], temperature, visibility and thermal radiation [11].

It is notable that there has been a growing research interests in Human and Organization Factors (HOFs), which contribute to the success/failure of evacuation in many offshore accidents [12]. Many qualitative studies have been conducted to investigate the effects of HOFs on the evacuation operation of offshore platforms [12-14]. Human error was quantitatively analyzed considering its probabilities [15] and risks [16] during the evacuation process on offshore platforms. Musharraf proposed a human behavioral model to simulate the response of general personnel during emergency situations [17]. Some software tools such as Pathfinder were used to analyze the flow rate and usage of each escape stairway during the evacuation process [11].
Among the methods used to carry out qualitative and quantitative analysis of evacuation on offshore platforms, Bayesian Network (BN) has been attracting particular attentions [8, 18-21] because of its backward diagnosis and forward prediction analysis ability [22]. Usually, BN is combined with other methods, such as HOFs [23], Reason's “Swiss cheese” model [24],

Binomial distribution [25], Human Reliability Analysis [26], or Analytic Hierarchy Process to satisfy different purposes. However, there has been no well-known approach for dealing with expert judgment [27]. This is particularly true when considering the increased complexity of systems and the subjective nature of expert opinions. Thus, it is required to deal with subjectivity during the expert elicitation process, and many researchers have made some explorations. For example, a Decision Making Trial and Evaluation Laboratory (DEMATEL) technique can deal with uncertainty during the expert elicitation process. Combining with fuzzy set theory, fuzzy DEMATEL has been used to deal with ambiguity and uncertainty of human thinking by many researchers [27,28]. A Fuzzy Bayesian Network methodology is developed to deal more effectively with uncertainty for overcoming the utilization of crisp probabilities in assessing uncertainty [29]. Usually, a Fuzzy Bayesian Network is combined with other models, such as the Human Factor Analysis and Classification System, to deal with data and model uncertainty [30].

In this research, the K-2 structure learning algorithm is used to build a BN model to avoid the subjectivity of expert judgments. Based on the historical data, the Conditional Probability Tables of a BN are determined by integrating a Bayesian estimation method with a junction tree inference engine. The remainder of this research is organized as follows. Section 2 briefly analyzes the main influencing factors of the emergency evacuation process on offshore platforms. In Section 3, the probabilistic prediction model of successful emergency evacuation is proposed through the structure learning and parameter learning of a BN model. In Section 4, the dynamic probability of emergency evacuation is predicted using a dynamic BN model followed by an analysis to prioritize the influential factors before the conclusions in Section 5.

2 Main influencing factors of evacuation process

2.1 Emergency evacuation process on offshore platforms

Safe and efficient evacuation on offshore platforms has been a significant concern between stakeholders and emergency professionals. Evacuation is defined as leaving an offshore installation during emergency in a systematic manner without directly entering the sea [31]. The emergency evacuation process on offshore platforms is shown in Fig. 1 [2, 15, 25,31].

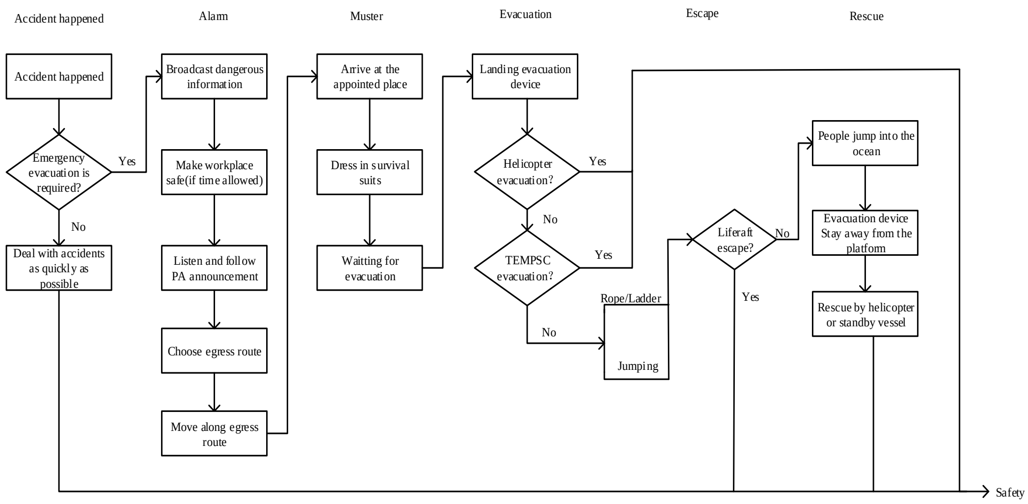

Fig. 1 The evacuation process on offshore platforms

After an accident happened, personnel should judge whether emergency evacuation is required and deal with accidents as quickly as possible. After the decision to muster is made, the personnel move along the egress route according to the PA instructions and assemble to the designated muster stations and register. After evaluating the state of sea and lifeboat, personnel leave the installation using the primary and preferred means, helicopter, or using the primary mainstay means.

2.2 Screening the factors influencing emergency evacuation

314 accidents in the Gulf of Mexico during 2003-2016 [32, 33] are statistically analyzed to identify the main factors influencing emergency evacuation. At the beginning, the influencing factors indices that affect the evacuation are selected as many as possible to make the index system comprehensive. However, too many indicators may cause redundancy and increase the model’s complexity. If there is a collinearity between the indicators, it may lead to redundancy. Therefore, it

is very important to analyze the correlation and screen the primary indices. All the accidents data is analyzed using the SPSS software to determine the correlation among the factors in the first column of Table 1. Some factors are eliminated to avoid the collinear effects between the factors. The main factors affecting evacuation are classified and screened as shown in the second column of Table 1.

Table 1 Classification of factors affecting safety evacuation

Classification	Influencing factors index	The factors after screened [31-34]
Human factors	Response delay	Response delay
	Forget	Forget
	Fatigue	Fatigue
	Unfamiliar environment	Unfamiliar environment
	Experience	Experience
	Lack of observation	Lack of observation
	Inattention	Inattention
	Bad mood	Bad mood
	Physical quality	Physical quality
	Absent relevant knowledge	Absent relevant knowledge
	Lack of safety awareness	Lack of safety awareness
	Misjudgment	Misjudgment
	Nervousness	Nervousness
	Panic	
	Pressure	
	Fluke mind	Fluke mind
	Energy saving psychology	Energy saving psychology
	Bravado	Bravado
	Ignore the alarm	Ignore the alarm
	Blind conformity	Blind conformity
	Inactive action	Inactive action
	Negligence	
	Evacuation procedures were not followed	Evacuation procedures were not followed
	Communication	Communication
	Improper evacuation path	Improper evacuation path
	Violation of rules and regulations	Violation of rules and regulations
	No protective equipment	No protective equipment
	Wrong operation	Wrong operation
	Dereliction of duty	Dereliction of duty
	Personnel attitude	Personnel attitude
	Human behavior	Human behavior
	Psychological quality	Psychological quality
Environmental factors	Noise	Noise
	Heavy fog	Heavy fog
	Strong wind	Strong wind
	Rain	Rain
	Temperature	Temperature
	Big waves	Big waves
	Ground slippery	Ground slippery
	Safety passage blocked	Safety passage blocked
	Crowd	Crowd
	Lighting	Lighting
	Smoke	Smoke
	Visibility	Visibility
	Stampede	Stampede
	Toxic gas	Toxic gas
	Vibration	Vibration
	Falling object	Falling object
	There are obstacles in the helicopter area	There are obstacles in the helicopter area
	Evacuation environment	Evacuation environment
Organizational factors	Lack of examination	Lack of examination
	Lack of supervision	
	Lack of field command	Lack of field command
	Lack of indication mark	Lack of indication mark
	Lack of monitoring	Lack of monitoring
	Lack of training exercise	Lack of training exercise
	Confusion in main control room	Confusion in main control room
	Insufficient safety culture	Insufficient safety culture

	Not evacuate to designated area	Not evacuate to the designated shelters
	Insufficient maintenance	Insufficient maintenance
	Lack of testing	Lack of testing
	Error indication	Error indication
	Emergency procedure	Emergency procedure
	Unreasonable workplace Layout	Unreasonable workplace Layout
	Organizational function	Organizational function
Equipment factors	Alarm failure	Alarm failure
	Communication equipment failure	Communication equipment failure
	Rescue equipment failure	Rescue equipment failure
	Protection equipment Failure	Protection equipment Failure
	Alarm delay	
	Improper location of rescue equipment	Improper location of rescue equipment
	Improper installation	Improper installation
	Lack of rescue equipment	Lack of rescue equipment
	Lack of protective equipment	Lack of protective equipment
	Other equipment failure	Other equipment failure

3 Modelling approach

The construction of a BN model usually includes three ways: (1) The structure of BN is determined subjectively according to experts' experience, which is usually called a naive Bayesian network; (2) The structure is determined by combining sample data with machine learning; (3) The structure is determined by combining the above two methods based on experts' experience. It is subjective if a BN structure is built completely relying on expert experience. The third way above is selected in this research.

3.1 Structure learning with K2-algorithm

A number of different methods are proposed for learning a structure of BN from a dataset, such as the Expectation-Maximization (EM) algorithm [35], Evolutionary algorithms [36] and Gibbs sampling-based algorithms [37]. A scored-based method proposed by Cooper et al. [38] is well-known as the K2 structure learning algorithm, which has become one of the most representative structural learning algorithms. The K2 algorithm [36] is a greedy search algorithm that can be used to determine the network structure of BNs from historical accident data. It attempts to select the network structure that maximizes the network's posterior probability. The K2 algorithm reduces computational complexity by requiring a prior ordering of nodes as input, from which the network structure will be determined. In the K2 algorithm, the candidate parent Pa_i for node X_i is initially set to be an empty set. Each node is visited according to the sequence specified in the prior ordering and Pa_i is added as the parent node of node X_i if the addition of the parent node maximizes the score of the network.

Given a database D, the K2 algorithm searches for the BN structure G with maximal P(G|D), where P(G|D) is the probability of network structure G given the database D. Let V(G) be a set of n random variables, where a variable Vi∈V(G) has ri possible value assignments vik where k=1, … ,ri . Let D be a database of m cases, where each case contains a value assignment for each variable. Let G denote a DAG representing the structure of a BN, and let GP be the associated set of conditional probability distributions (CPD). Each node Vi∈V(G) has a set of parents π(Vi). Let w_{ij} denote the j_{th} unique instantiation of $\pi(V_i)$ relative to D. Suppose there are q_i unique instantiations of $\pi(V_i)$. Define N_{ijk} to be the number of cases in D in which variable V_i has the value v_{ik} and π(Vi) is instantiated as w_{ij}. Let

$$N_{ij} = \sum_{k=1}^{r_i} N_{ijk} \tag{1}$$

Given a BN structure G, assuming that the cases occur independently and the conditional probability density function f (GP | G) is uniform, then it follows that [39]

$$P(G,D) = P(G)\prod_{i=1}^{n}\prod_{j=1}^{q_i}(r_i-1)!/(N_{ij}+r_i-1)!\prod_{k=1}^{r_i}N_{ijk}! \tag{2}$$

where, n is the number of the BN's nodes;

$$\mathrm{q_i} = \prod_{X_i \in \prod_{X_i}} r_i$$

The K2 algorithm looks for a network structure G that maximizes P (G, D). In particular, assuming that an ordering on the variables is available and that all structures are equally similar, it adopts a greedy method for maximizing P (G, D). This method consists of, for every node V_i, searching for the set of parent nodes that maximizes the function [39]:

$$g(i,\pi(V_i)) = \prod_{j=1}^{q_i} (r_i - 1)!/(N_{ij} + r_i - 1)! \prod_{k=1}^{r_i} N_{ijk}! \tag{3}$$

The K2 algorithm starts by assuming that a node lacks parents, after which in every step it adds incrementally the parent whose addition mostly increases g(i, π(Vi)).

The K2 algorithm stops adding parents to a node when any of the following conditions is met [37]:

1) The maximum number of parent nodes for that particular node is reached (This number is specified for each node. A suitable number for this is “n−1”).

2) There are no more possible parent nodes to add.

3) The addition of a single parent cannot increase the score.

3.2 Learning of the structure

The task of structure learning for BN refers to the determination of the directed acyclic graph (DAG) based on historical data. There are two major approaches for the structure learning: score-based approach and constraint-based approach [40]. For the score-based approach, a criterion is firstly defined to evaluate how well the BN model fits the data, and then a search is conducted over the space of the DAG for a structure with a maximal score. In this way, the score-based approach essentially for solving a search problem consists of two parts: the definition of a score metric and the search algorithm [41]. Based on the statistical analysis of the historical accidents data [31-34], the sequences of the screened factors are determined as shown in Table 2.

Table 2 Factors and their sequences

Factors	Status	Factors	Status
1 Violation of rules and regulations A23	Yes No	2 Blind conformity A18	Yes No
3 Evacuation procedures were not followed A20	Yes No	4 No protective equipment A24	Yes No
5 Ignore the alarm A17	Yes No	6 Inactive action A19	Yes No
7 Dereliction of duty A26	Yes No	8 Personnel attitude A27	Yes No
9 Lack of observation A6	Yes No	10 Inattention A7	Yes No
11 Absent relevant knowledge A11	Yes No	12 Unfamiliar environment A4	Yes No
13 Experience A5	Bad Good	14 Lack of safety awareness A8	Yes No
15 Lack of training exercise C5	Yes No	16 Wrong operation A25	Yes No
17 Noise B1	Yes No	18 Communication equipment failure D2	Yes No
19 Communication A21	Bad Good	20 Response delay A1	Yes No
21 Forget A2	Yes No	22 Fatigue A3	Yes No
23 Physical quality A10	Bad Good	24 Lack of testing C1	Yes No
25 Misjudgment A12	Yes No	26 Improper evacuation path A22	Yes No
27 Human behavior A28	Bad Good	28 Nervousness A13	Yes No
29 Bad mood A9	Bad Good	30 Bravado A16	Yes No
31 Fluke mind A14	Yes No	32 Energy saving psychology A15	Yes No
33 Psychological quality A29	Bad Good	34 Heavy fog B2	Yes No

35 Lighting B10	Yes No	36 Smoke B11	Yes No
37 Visibility B12	Yes No	38 Toxic gas B14	Yes No
39 Vibration B15	Yes No	40 Falling object B16	Yes No
41 There are obstacles in the helicopter area B17	Yes No	42 Safety passage blocked B8	Yes No
43 Crowd B9	Low High	44 Stampede B13	Yes No
45 Rain B4	Yes No	46 Ground slippery B7	Yes No
47 Temperature B5	Low High	48 Strong wind B3	Yes No
49 Big waves B6	Yes No	50 Evacuation environment B18	Bad Good
51 Lack of field command C2	Yes No	52 Confusion in main control room C6	Yes No
53 Insufficient safety culture C7	Yes No	54 Error indication C11	Yes No
55 Rescue equipment failure D3	Yes No	56 Improper location of rescue equipment D5	Yes No
57 Lack of rescue equipment D7	Yes No	58 Lack of monitoring C4	Yes No
59 Protection equipment failure D4	Yes No	60 Emergency procedure C12	Bad Good
61 Other equipment failure D9	Yes No	62 Alarm failure D1	Yes No
63 Lack of protective equipment D8	Yes No	64 Improper installation D6	Yes No
65 Unreasonable workplace layout C13	Yes No	66 Not evacuate to designated area C8	Yes No
67 Lack of examination C10	Yes No	68 Insufficient maintenance C9	Yes No
69 Lack of indication mark C3	Yes No	70 Organizational function C14	Yes No
71 Emergency evacuation E	Failure Success		

The K2 algorithm is used to carry out the structure learning of a BN model. A pseudo code representation of the K2 algorithm is shown in Appendix 1. By testing the number of parent nodes, it is found that the structure keeps stable when the maximum number of the parent nodes is larger than 10. After the sequences of the factors and the maximum number of parent nodes are determined, the structure of a BN model can be obtained using Full BNT-1.0.4 of MATLAB software as shown in Fig. 2. The number of the factors in Table3 is the same as the one in Fig. 2.

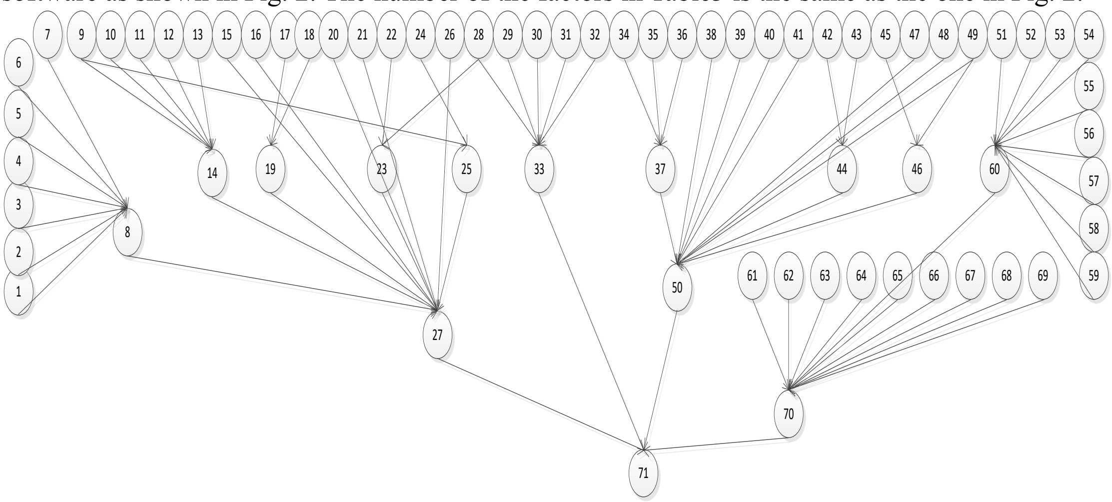

Fig. 2 Structure learning results of K2 algorithm

Based on the above structure learning results, a reliability prediction model of the evacuation process is built using the NETICA Software tool as shown in Fig. 3. The prior probability of each node is provided based on the statistics of the historical data [31-34].

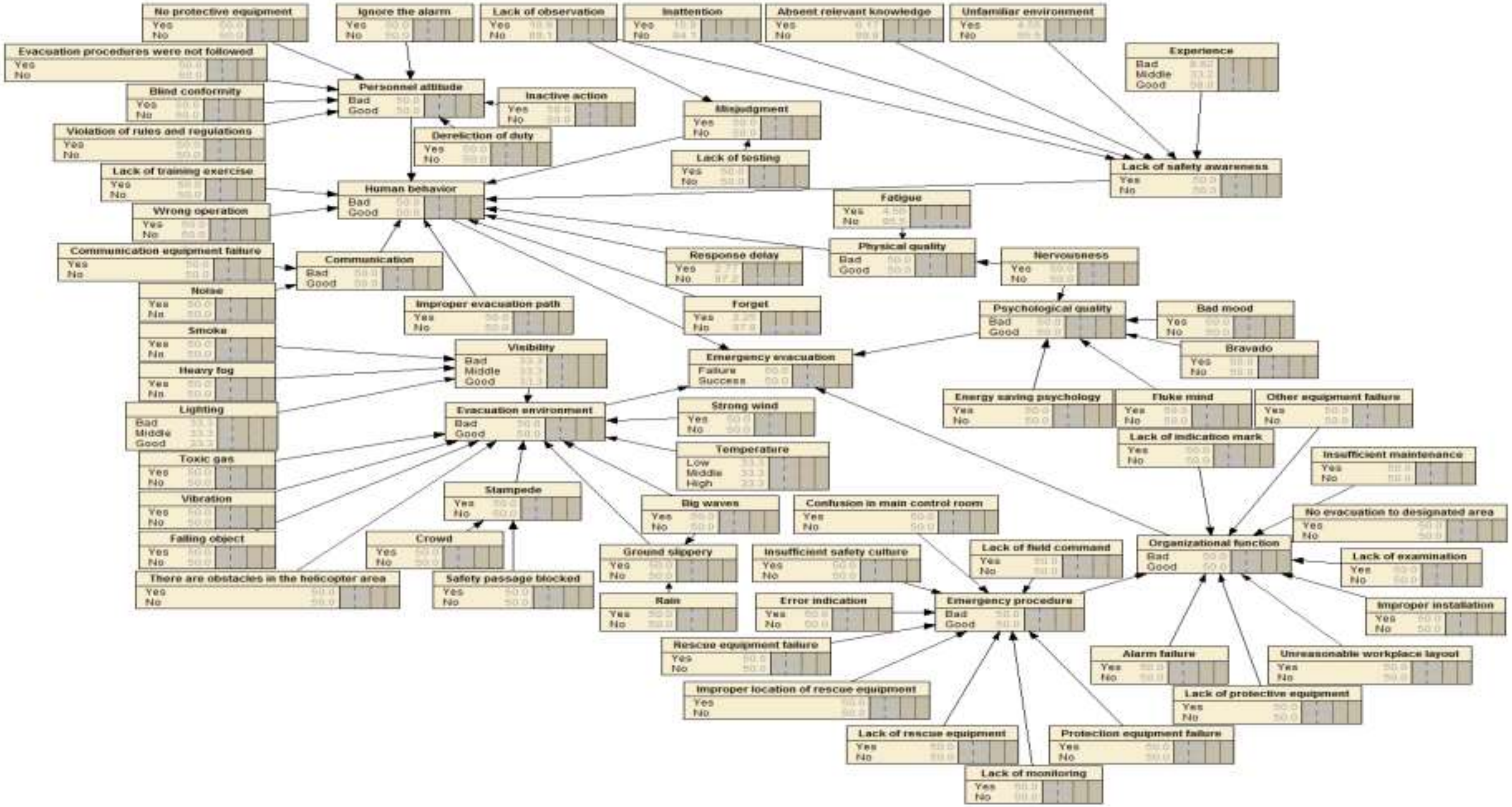

Fig. 3 Reliability prediction model of emergency evacuation

3.3 The parameter learning of BN

In addition to the DAG structure, which is often considered as the "qualitative" part of the model, one needs to specify the "quantitative" parameters of the BN model. The parameters are described in a manner which is consistent with a Markovian property, where conditional probability distribution at each node depends only on its parents [42]. Section 3.1 describes how to build the basic structure of a BN model, that is, how to define nodes and their interdependence. This section investigates how to define the relationships between the nodes in Fig. 3.

For discrete random variables, this conditional probability is often represented by a table, listing the local probability that a child node takes on each of the feasible values for each combination of values of its parents. The joint distribution of a collection of variables can be determined uniquely by these local conditional probability tables (CPTs). Often these CPTs include parameters that are unknown and need to be estimated from historical data, e.g., via the Maximum Likelihood approach, direct maximization of the likelihood, expectation-maximization algorithm and Bayesian estimation. The Bayesian estimation method is aimed to minimize the posterior expected value of a loss function. The advantage is that good estimation results will be achieved if there is sufficient information. It can also be used when small data records are available initially as the estimation can be sequentially improved when new data becomes available. The Bayesian estimation method is therefore adopted in this research to carry out parameter learning based on the historical accident data.

A BN consists of a DAG G = (V, E) whose nodes V= {V1, V2, V3, ..., Vn} correspond to a set of random variables, and whose arcs E represent the direct dependencies between these variables. Let r_i denote the cardinality of Vi, and q_i represent the cardinality of the parent set of Vi. Let θ_{ij} denote P (Vi/pa (Vi) = j).

The k-th probability value of the conditional probability distribution of θ_{ij} can be represented as θ_{ijk} = P(Vi= k/pa(Vi) = j), where $\theta_{ijk} \in \theta$, $1 \leqslant i \leqslant n$, $1 \leqslant j \leqslant q_i$ and $1 \leqslant k \leqslant r_i$. Assuming D = {D1, D2, ..., DN} is a dataset of fully observable cases for a BN, then D_l is the l-th complete case of D, which is a vector of values of each variable. The loglikelihood function of θ given data D is [39]:

$$l(\theta|D) = \log P(D|\theta) = \log \prod_{l} P(D_l/\theta) = \sum_{l} log\, P(D_l/\theta) \tag{4}$$

Before seeing any data from the dataset, the Dirichlet distribution can be applied to represent the prior distribution for parameters θ_{ij} in the BN. The hyper-parameter α_{ijk} of Dirichlet follows the uniform prior setting by default. It has the following equation:

$$P(\theta_{ij}) = \frac{1}{Z_{ij}} \prod_{k=1}^{r_i} \theta_{ijk}^{(\alpha_{ijk}-1)} \quad (\sum_{k} \theta_{ijk} = 1, \theta_{ijk} \geq 0, \forall_k) \tag{5}$$

where, Z_{ij} is a normalization constant to ensure that $\int_0^1 P(\theta_{ij})\, d\theta_{ijk} = 1$.
A hyper-parameter α_{ijk} can be thought of as how many times the expert believes he/she will observe Xi = k in a sample of α_{ij} examples drawn independently at random from distribution θ_{ij}.

The maximum posteriori estimation for θ given data can be introduced [43]:

$$P(\theta|D) \;\propto\; P(D|\theta)P(\theta) \;\propto \prod_{ijk} \theta_{ijk}^{(N_{ijk} + \alpha_{ijk} - 1)} \tag{6}$$

$$\theta_{ijk}^{*} = \frac{N_{ijk} + \alpha_{ijk} - 1}{N_{ij} + \alpha_{ij} - 1} \tag{7}$$

Since there are many conditional probability tables required for the associated nodes, node 27 "human behavior", is taken as an illustrative example. Node 27 "human behavior" directly depends on node 8 "personnel attitude", node 14 "lack of safety awareness" A8, node 15 "lack of training exercise", node 16 "wrong operation", node 19 "communication", node 20 " response delay", node 21 "forget", node 23 "physical quality", node 25 "misjudgment", and node 26 "improper evacuation path". Each of these nodes has two states, If the "Bad" state of node 8 "personnel attitude", node 19 "communication", node 23 "physical quality" is set as "1", and the "Yes" state of other nodes are set as "1", then the conditional probability of node 27 "human behavior" can be calculated. The learning process of calculated parameters is shown in Appendix 2:

After parameter learning, the probability distribution of node 27 "human behavior" is obtained as follows: ans[:,:,:,:,:,:,:,:,:,:,1]=0.9910 ans[:,:,:,:,:,:,:,:,:,2]=0.0090

The above results show that when node 8 "personnel attitude", node 14 "lack of safety awareness", node 15 "lack of training exercise”, Node 16 "wrong operation", Node 19 "communication"1, Node 20 "response delay", Node 21 "forget", Node 23 "physical quality", Node 25 "misjudgment", and Node 26 " improper evacuation path" are given 100%, the state of "Human Behavior" of node 27 , is "1", that is, the state is "Bad" and the probability of is 0.9910. Correspondingly, the state of node 27 "human behavior" is "2", that is, the state is "Good”, the probability is 0.0090.

4 Dynamic reliability prediction of emergency evacuation and analysis

The dynamic probability prediction model of emergency evacuation is established as shown in Fig. 4. The proposed Dynamic Bayesian Network (DBN) model contains 10-time segments, and the time interval between two consecutive time segments is 1 year.

4.1 Transition probability

It is known that the key challenge for DBN is to define transition probabilities when the status values of parent nodes change over time.

Taking equipment factors as an example, there are two levels: “Yes” and “No”. “Yes” represents this equipment fails. “No” indicates that this equipment is in good condition. The transition probability from “No” to “Yes” is represented by the failure probability, which can be calculated using the failure rate of this equipment (α). The transition from “Yes” to “No” means that the equipment is repaired. The transition probabilities can be estimated using the repair rate of this equipment (β).

The transition probabilities of equipment factors without considering the repair rate are shown in Table 3. Δt stands for the time interval between two consecutive time segments (1 year).

Table 3 State transition probability without considering repairs

t	$t+\Delta t$	
	Yes	*No*
Yes	1	0
No	$1-e^{-\alpha\Delta t}$	$e^{-\alpha\Delta t}$

The transition probabilities of equipment factors considering repairs is shown in Table 4.

Table 4 State transition probability considering repairs

t	$t+\Delta t$	
	Yes	*No*
Yes	$e^{-\beta\Delta t}$	$1-e^{-\beta\Delta t}$
No	$1-e^{-\alpha\Delta t}$	$e^{-\alpha\Delta t}$

Human error is a random variable. Assume that this random variable is a counting process which meets the Poisson distribution [45]. The average number of human errors per unit time is assumed as λ, the probability that human error occurs n times during Δt can be expressed by:

$$P\{N(t+\Delta t)-N(t)=n\}=e^{-\lambda t}\frac{(\lambda t)^n}{n!} \tag{5}$$

If human errors occur n times till t, the probability that human error does not occur from t to t+Δt can be calculated as:

$$\begin{aligned} P\{N(t,t+1)=no|N(t)=yes\} &= \frac{P\{N(t)=n,N(t+\Delta t)-N(t)=0\}}{P\{N(t)=n\}} \\ &= \frac{P\{Nt=n\}P\{N(t+\Delta t)-N(t)=0\}}{P\{N(t)=n\}} \\ &= P\{N(t+\Delta t)-N(t)=0\} \\ &= e^{-\lambda\Delta t} \end{aligned} \tag{6}$$

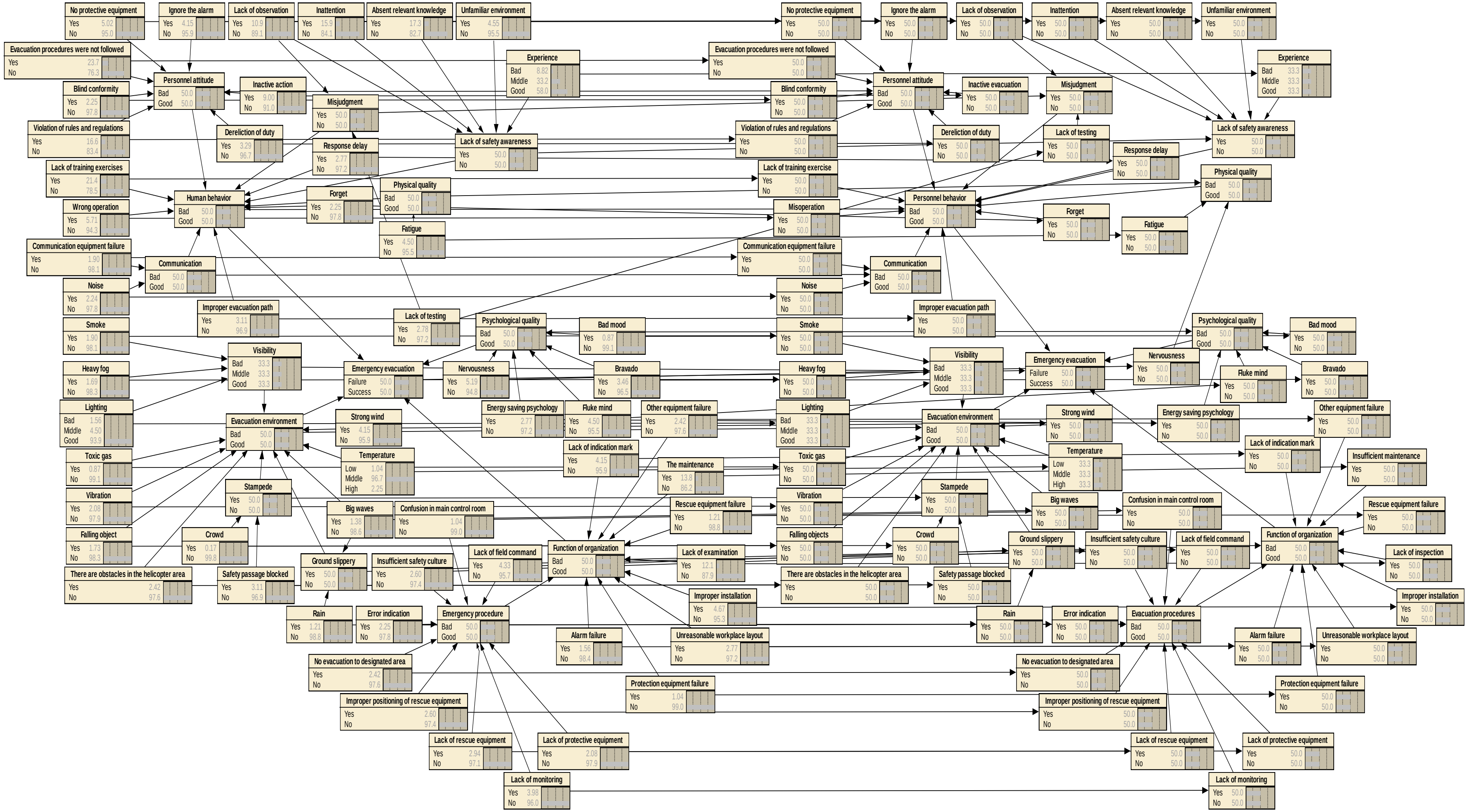

Fig. 4 Dynamic reliability prediction model of emergency evacuation on offshore platform

$$P(X_{t+1} = yes|X_t = no) = \frac{P(X_{t+1} = yes, X_t = no)}{P(X_t = no|X_{t+1} = yes)P(X_{t+1} = yes) + P(X_t = no|X_{t+1} = no)P(X_{t+1} = no)} \quad (7)$$

Similarly,

$$P(X_{t+1} = no|X_t = no) = 1 - \lambda e^{-\lambda} \quad (8)$$

$$P(X_{t+1} = no|X_t = yes) = P(X_{t+1} = yes, X_t = no) = e^{-\lambda} \quad (9)$$

$$P(X_{t+1} = yes|X_t = yes) = 1 - e^{-\lambda} \quad (10)$$

For organizational and environmental factors, there are two levels: "Yes (Bad)" and "No (Good)". "Yes (Bad)" and "No (Good)" represent that organizational and environmental factors are in "Bad" and "Good" conditions respectively. The transition probabilities are shown in Table 5 where, c stands for the recovery factor of the system.

Table 5 Transition probability of organizational factor

t	$t + \Delta t$	
	Yes（Bad）	No（Good）
Yes（Bad）	$1 - c$	c
No（Good）	0	1

4.2 Reliability prediction of emergency evacuation

In order to predict the reliability of emergency evacuation, the prior probabilities of the root nodes in the BN model should be determined firstly. According to the statistical data [32-33] about Incidents Associated with Oil and Gas Operations of offshore platforms released on the official website of BSEE and references [45-46], the prior probabilities of each of such nodes are generated by statistical calculations and shown in Table 6.

Table 6 the prior probabilities of all the root nodes (4 decimal places are produced by the computation)

Root nodes	State	Prior probabilities	Root nodes	State	Prior probabilities
Response delay	Yes	2.7633E-2	Forget	Yes	2.2452E-2
Fatigue	Yes	4.4905E-2	Unfamiliar environment	Yes	3.8062E-2
Experience	Bad Middle	8.8235E-2 3.3218E-1	Lack of observation	Yes	1.0899E-1
Inattention	Yes	1.5916E-1	Bad mood	Yes	8.6505E-3
Absent relevant knowledge	Yes	1.7301E-1	Nervousness	Yes	5.1903E-2
Fluke mind	Yes	4.4983E-2	Energy saving psychology	Yes	2.7682E-2
Bravado	Yes	3.4602E-2	Ignore the alarm	Yes	4.152E-2
Blind conformity	Yes	2.2491E-2	Inactive action	Yes	8.9965E-2
Evacuation procedures were not followed	Yes	2.3702E-1	Improper evacuation path	Yes	3.1142E-2
Violation of rules and regulations	Yes	1.6609E-1	No protective equipment	Yes	5.0173E-2
Wrong operation	Yes	5.7093E-2	Dereliction of duty	Yes	3.2872E-2
Noise	Yes	2.2492E-2	Heavy fog	Yes	6.9204E-3
Strong wind	Yes	4.1522E-2	Rain	Yes	1.2111E-2
Temperature	Low Middle	1.0381E-2 9.6546E-1	Big waves	Yes	1.3841E-2
Safety passage blocked	Yes	3.1142E-2	Crowd	Yes	2.4221E-2
Lighting	Bad Middle	1.5571E-2 4.4983E-2	Smoke	Yes	1.9031E-2
Toxic gas	Yes	8.6505E-3	Vibration	Yes	2.0761E-2
Falling object	Yes	1.7301E-2	There are obstacles in the helicopter area	Yes	2.4221E-2
Lack of testing	Yes	2.7682E-2	Lack of field command	Yes	4.1522E-2
Lack of indication mark	Yes	4.1542E-2	Lack of monitoring	Yes	3.9792E-2
Lack of training exercise	Yes	2.1453E-1	Confusion in main control room	Yes	1.0380E-2
Insufficient safety	Yes	2.5952E-2	No evacuation to	Yes	2.4222E-2

culture			designated area		
Insufficient maintenance	Yes	1.3840E-1	Lack of examination	Yes	1.5052E-2
Error indication	Yes	2.2492E-2	Unreasonable workplace layout	Yes	2.7682E-2
Alarm failure	Yes	1.5570E-2	Communication equipment failure	Yes	1.1903E-2
Rescue equipment failure	Yes	2.9411E-2	Protection equipment failure	Yes	1.0381E-2
Improper location of rescue equipment	Yes	2.5951E-2	Improper installation	Yes	4.6712E-2
Lack of rescue equipment	Yes	2.9315E-2	Lack of protective equipment	Yes	2.0761E-2
Other equipment failure	Yes	2.4221E-2			

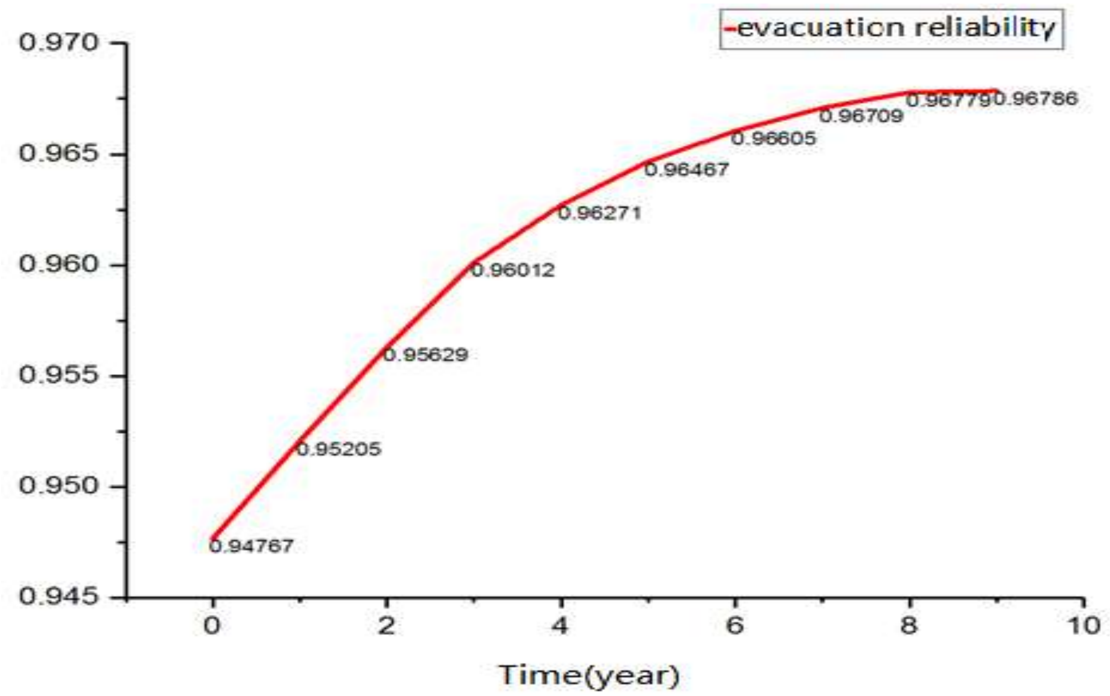

Fig. 5 Reliability of emergency evacuation from offshore platform

From Fig. 5, the reliability of emergency evacuation shows a gradual upward trend with time because the human errors and organizational factors will be further improved through safety training and experiences in the next 10 years. The reliability of emergency evacuation is 0.956, 0.96, 0.963, 0.965, 0.966, 0.967, 0.968 and 0.968 respectively from time t1 to t9. The simulated dynamic probability of emergency evacuation is compared with the available references as shown in Table 7.

Table 7 The reliabilities of emergency evacuation in different references

References	Methods	Features	Reliability
This research	K2 structure learning algorithm, Bayesian estimation method, Junction tree reasoning engine, Markov model	A reliability prediction model of emergency evacuation is established for offshore platforms based on the K2 structure learning algorithm. This framework is more efficient than traditional reliability techniques (like Event tree (ET) and Fault Tree (FT)). It reduces the subjectivity when the structure and conditional probability table of BN is determined by comparing with expert judgment method.	0.956 0.96 0.963 0.965 0.966 0.967 0.968 0.968
Yun et.al, 2010 [47]	ET, Monte Carlo simulation,	Present a methodology for evaluating the relative probabilities of success of arctic EER strategies using event tree.	0.92
Ping et.al, 2018 [48]	BN, Fuzzy AHP, FT	Present a model to estimate the probability of successful EER on the offshore platforms by transforming Fault Tree into BN.	0.9
Vinnem, 2019 [49]	ET, FT, Statistical simulation technique	Quantified Risk Assessment for offshore installations, including evacuation risk.	0.96

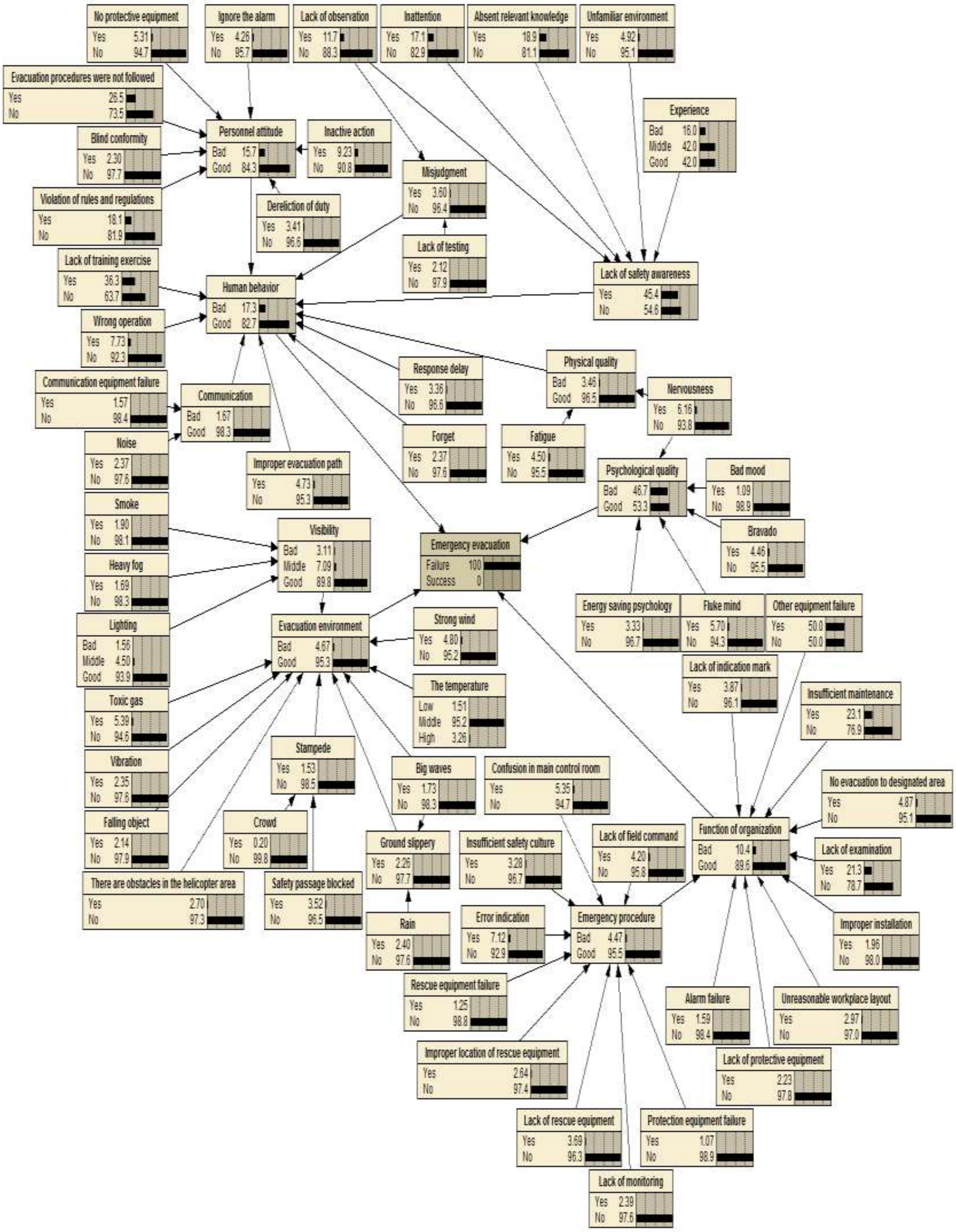

Fig. 6 Diagnostic reasoning of BN model

From Table 7, it can be seen that the reliability of emergency evacuation in this research is consistent with the available references at large. The proposed dynamic BN can be used to predict the dynamic reliability of emergency evacuation from the offshore platforms when the conditions do not change drastically.

4.3 Analysis of the BN model

The main causes contributing to the failure of evacuation can be determined through the diagnostic inference of BN. The posterior probabilities of the root nodes are calculated through the backward diagnosis of the BN model when the reliability of emergency evacuation is set to zero. The diagnostic reasoning results are shown in Fig. 6.

4.3.1. Criticality analysis

Relying on merely prior or posterior probabilities in the identification of the most critical events is very likely to lead to inaccurate results [50]. Therefore, in the present study, the ratio of variation (RoV) is used to identify the most critical root events contributing to the occurrence of the top event. For a root event xi, the RoV can be calculated as [51]:

$$RoV(X_i) = \frac{\pi(X_i) - \theta(X_i)}{\theta(X_i)}$$

where $\pi(X_i)$ and $\theta(X_i)$ denote the posterior and prior probabilities of Xi.

From Fig. 6, it can be seen that the posterior probabilities of all the factors at t_0 and the main factors leading to the failure of emergency evacuation are achieved. The ratios of variation between the posterior probability and prior probability are listed for each factor in Table 8.

Table 8 Posterior probabilities of root nodes

Root nodes	State	Posterior probability	$RoV(X_i)$	Root nodes	State	Posterior probability	$RoV(X_i)$
Response delay	Yes	3.369E-2	2.193E-01	Forget	Yes	2.375E-2	5.772E-2
Fatigue	Yes	4.500E-2	2.116E-03	Unfamiliar environment	Yes	4.928E-2	2.947E-1
Experience	Bad Mid	1.611E-1 4.211E-1	8.257E-01	Lack of observation	Yes	1.17E-1	7.368E-2
Inattention	Yes	1.713E-1	2.675E-01	Bad mood	Yes	1.096E-2	2.673E-1
Absent relevant knowledge	Yes	1.895E-1	7.64E-02	Nervousness	Yes	6.172E-2	1.892E-1
Fluke mind	Yes	5.718E-2	9.537E-02	Energy saving psychology	Yes	3.336E-2	2.05E-1
Bravado	Yes	4.478E-2	2.712E-01	Ignore the alarm	Yes	4.26E-2	2.604E-2
Blind conformity	Yes	2.302E-2	2.940E-01	Inactive action	Yes	9.233E-2	2.628E-2
Evacuation procedures were not followed	Yes	2.651E-1	2.361E-02	Improper evacuation path	Yes	4.76E-2	5.287E-1
Violation of rules and regulations	Yes	1.813E-1	1.184E-01	No protective equipment	Yes	5.314E-2	5.908E-2
Wrong operation	Yes	7.772E-2	9.158E-02	Dereliction of duty	Yes	3.413E-2	3.824E-2
Noise	Yes	2.372E-2	3.612E-01	Heavy fog	Yes	1.690E-2	1.442E
Strong wind	Yes	4.802E-2	5.473E-02	Rain	Yes	2.45E-2	1.023E
Temperature	Low Mid	1.517E-2 9.52E-1	1.564E-01	Big waves	Yes	1.735E-2	2.537E-1
Safety passage blocked	Yes	3.529E-2	4.611E-01	Crowd	Yes	2.054E-3	-9.152E-1
Lighting	Bad Mid	1.560E-2 4.500E-2	-1.392E-02	Smoke	Yes	1.900E-2	1.629E-3
Toxic gas	Yes	5.392E-2	1.3E-01	Vibration	Yes	2.36E-2	1.369E-1
Falling object	Yes	2.148E-2	1.862E-03	There are obstacles in the helicopter area	Yes	2.703E-2	1.159E-1
Lack of testing	Yes	2.123E-2	-2.33E-01	Lack of field command	Yes	4.201E-2	1.171E-2
Lack of indication mark	Yes	3.873E-2	2.417E-01	Lack of monitoring	Yes	2.391E-2	3.991E-1
Lack of training exercise	Yes	3.657E-1	-2.331E-01	Confusion in main control room	Yes	5.341E-2	4.146E

Insufficient safety culture	Yes	3.284E-2	-6.779E-02	No evacuation to designated area	Yes	4.861E-2	1.007E
Insufficient maintenance	Yes	2.332E-1	7.047E-01	Lack of examination	Yes	2.148E-1	1.327E
Error indication	Yes	7.145E-2	2.655E-01	Unreasonable workplace layout	Yes	2.968E-2	7.211E-2
Alarm failure	Yes	1.591E-2	6.853E-01	Communication equipment failure	Yes	2.726E-2	1.29E
Rescue equipment failure	Yes	1.249E-2	2.177E	Protection equipment failure	Yes	1.0693E-2	3.006E-2
Improper location of rescue equipment	Yes	2.637E-2	2.177E-02	Improper installation	Yes	4.4906E-2	-3.866E-2
Lack of rescue equipment	Yes	3.711E-2	-5.754E-01	Lack of protective equipment	Yes	2.2303E-2	7.427E-2
Other equipment failure	Yes	2.44E-2	1.622E-02				

From Table 8, “Confusion in main control room”, “Rescue equipment failure”, “Heavy fog”, “Lack of examination”, “Communication equipment failure”, “Rain” and “No evacuation to designated area” are the main contributors to the failure of emergency evacuation. Among human and organizational factors, the influence of "Confusion in main control room" is the largest, indicating that “Confusion in main control room” contributes more to the failure of emergency evacuation, compared to other factors. The posterior probabilities of equipment factors are relatively small due to the increasing reliability of equipment and technical factors.

4.3.2. Mutual information analysis

One of the suitable quantities that measures how much one random variable influences another variable is mutual information. The mutual information can be considered as the reduction in uncertainty about one random variable given knowledge of another. The mutual information is a measure of the mutual dependence between two random variables. If the two random variables are dependent in any way, the information of one variable can give us knowledge about the other. The larger the mutual information is, the larger the reduction in uncertainty. It means that two random variables are independent when the mutual information is equal to zero [45].

At time t_0 and t_9, human factors, environmental factors, organizational factors and equipment factors are analyzed in terms of the mutual information with their influencing nodes using Netica Software as shown in Fig. 7, Fig. 8, Fig. 9 and Fig. 10, respectively.

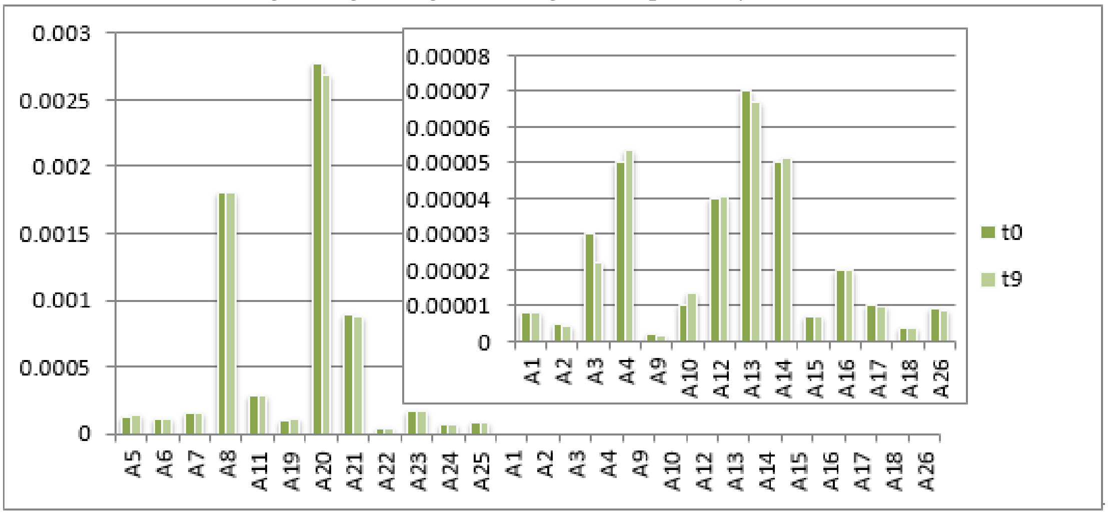

Fig. 7 Analyses of human factors

It can be seen from Fig. 7 that the mutual information of the human factors influencing the emergency evacuation is approximately the same at time t0 and t9, and the degree of influence is at the same level. Among the human factors, mutual information of “Evacuation procedures were not followed” is the largest, indicating that it has the greatest influence on evacuation, followed by “Lack of safety awareness”, “Communication”, “Absent relevant knowledge”, “Violation of rules and regulations” and “Inattention”.

From the analysis results, some useful suggestions can be drawn that training, knowledge, compliance with the regulations, and adequate communication are important throughout all steps of EER. Improvement of safety awareness, communication and knowledge through safety training are the key measures of successful evacuation. Adequate communications provided with precise voice communication instructions regarding the accident event, its location and action to be undertaken will increase the probability of successful evacuation.

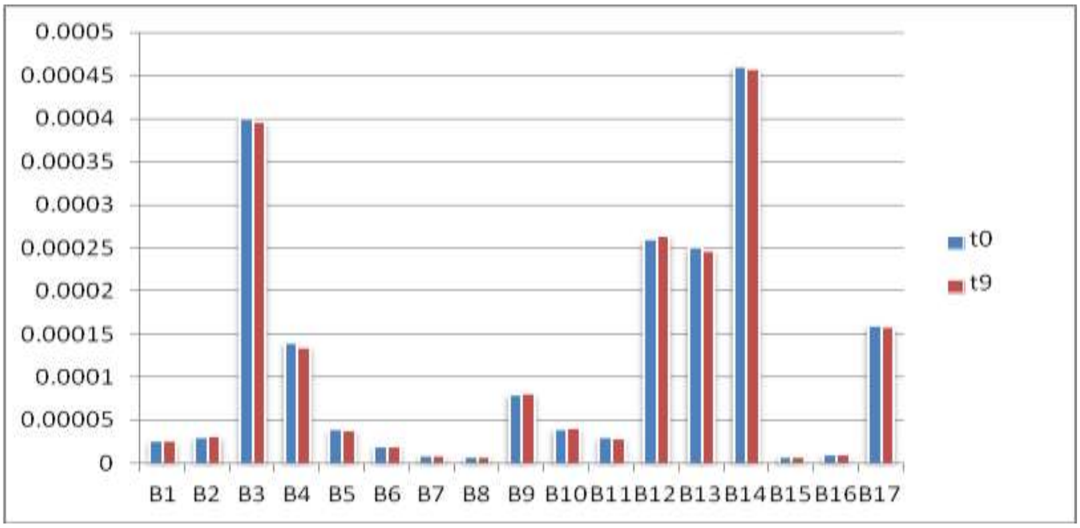

Fig. 8 Analysis of environmental factors

Fig. 8 shows that the mutual information of “Toxic gas” and “Strong wind” is larger than the other environmental factors. Therefore, “Toxic gas” and “Strong wind” influence evacuation more than the other environmental factors. The other main influencing factors are “Visibility”, “Stampede”, “There are obstacles in the helicopter area” and “Rain” in a descending order. Personal protective equipment, such as gas masks, should be equipped for each evacuee. Keeping the helicopter area clear of obstacles is also important to ensure the use of helicopter for evacuation.

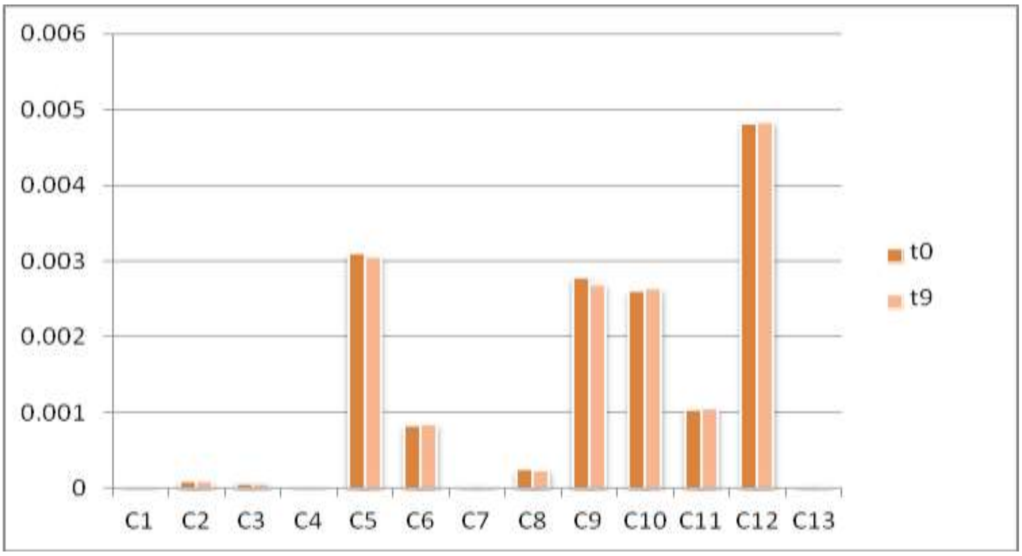

Fig. 9 Analysis of organizational factors

Fig. 9 indicates that the mutual information of “Emergency procedure” is the greatest among organizational factors, which indicates that an efficient emergency procedure has the greatest impact on the evacuation process. The other main influencing factors include “Lack of training exercise” “Insufficient maintenance”, “Lack of examination” and “Error indication”.

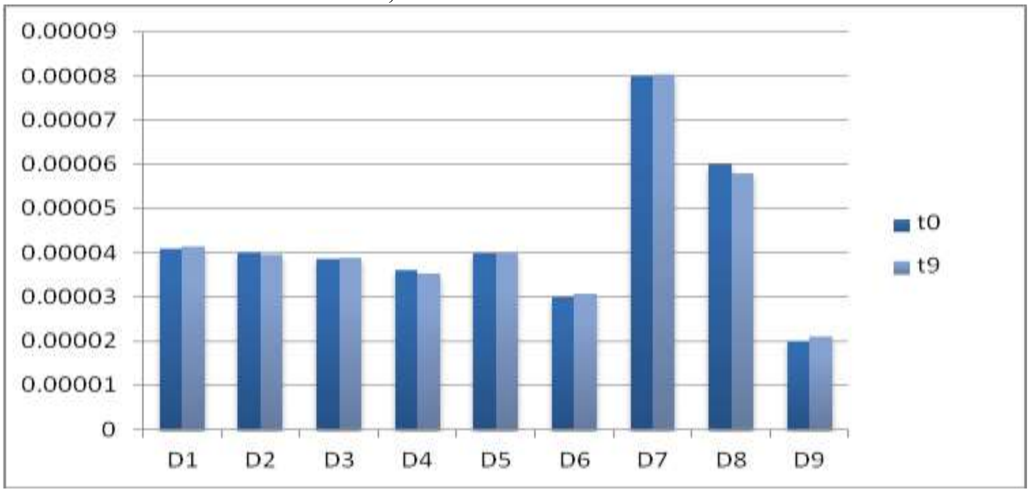

Fig. 10 Analysis of equipment factors

From Fig. 10, it can be seen that the mutual information of "Lack of rescue equipment" is the largest among the equipment factors, followed by “Lack of protective equipment”, and “Alarm failure”. By comparing Fig. 7, Fig. 8 and Fig. 9 with Fig. 10, it can be observed that the mutual information of the equipment factors is smaller than the one of the other factors. The influencing factors listed in a descending order are organizational factors, human factors, environmental factors and equipment factors, respectively.

5 Conclusions

Based on the K2 structure learning algorithm, the reliability prediction model of the evacuation process is constructed using BN. The conditional probabilities are obtained by combining a Bayesian estimation method and a junction tree reasoning engine. The dynamic reliability prediction model of evacuation on offshore platforms is proposed using a dynamic BN approach. The transition probability is determined through a Markov method. The reliabilities of the evacuation process are predicted.

From the analysis of the BN model, it can be seen that the significant classified influencing groups are organizational factors, human factors, environmental factors and equipment factors in a descending order. “Emergency procedure”, “Lack of training exercise” “Insufficient maintenance”, “Lack of examination”, “Evacuation procedures were not followed”, “Error indication”, "Confusion in main control room”, “Toxic gas” and “Strong wind” are the main contributors to the failure of emergency evacuation.

Lack of historical accidents data is a major issue to be addressed in research of offshore emergency evacuation. In future, more emergency evacuation optimization studies will be carried out on the different kinds of offshore platforms and statistical uncertainty.

Acknowledgments

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References

[1] IADC, 2010. Health Safety and Environmental Case Guidelines for Mobile Offshore Drilling Units. International Association of Drilling Contractors.
[2] Skogdalen J E, Khorsandi J, Vinnem J E, 2012. Evacuation, escape, and rescue experiences from offshore accidents including the Deepwater Horizon. Journal of Loss Prevention in the Process Industries, 25, 148–158.
[3] Cullen W D, 1990. The Public Inquiry into the Pipe Alpha disaster. Department of Energy, London.
[4] United States Coast Guard, 1983. Marine Casualty Report Mobile Offshore Drilling Unit (MODU) OCEAN RANGER. U.S. Department of Transportation.

[5] Ping P, Wang K, Kong D, 2018. Analysis of emergency evacuation in an offshore platform using evacuation simulation modeling. Physica A, 505:601-612.
[6] Zhang J, Zhao J, Song Z, et al, 2020. Evacuation performance of participants in an offshore platform under smoke situations. Ocean Engineering, 216,107739:1-14.
[7] Abramowicz-Gerigk T, Burciu Z, 2012. Analysis of Safety Requirements for Large Offshore Units Evacuation Systems. LSA safety function. Archives of Transport, 24(4):429-440.
[8] Ping P, Wang K, Kong D P, et al, 2018. Estimating probability of success of escape, evacuation, and rescue (EER) on the offshore platform by integrating Bayesian Network and Fuzzy AHP, Journal of Loss Prevention in the Process Industries, 54:57-68.
[9] Bercha F G, Cerovšek M, Abel W, 2004. Assessment of the reliability of marine installation escape, evacuation, and rescue systems and procedures, in: The Fourteenth International Offshore and Polar Engineering Conference, International Society of Offshore and Polar Engineers, Toulon, France, 2004.
[10] Jack C, Cheng P, Tan Y, Song Y, et al, 2018. Developing an evacuation evaluation model for offshore oil and gas platforms using BIM and agent-based model. Automation in Construction, 89:214-224.
[11] Rajendram A, Khan F, Garaniya V, 2015. Modelling of fire risks in an offshore facility. Fire Safety Journal, 71: 79-85.
[12] Norazahar N, Khan F, Veitch B, et al, 2014. Human and organizational factors assessment of the evacuation operation of BP Deepwater Horizon accident. Safety Science, 70:41-49.
[13] Hofinger G, Zinke R, Künzer L, 2014.Human Factors in Evacuation Simulation, Planning, and Guidance. Transportation Research Procedia, 2:603-611.
[14] Ben Woodcock, Zachary Au. Human factors issues in the management of emergency response at high hazard installations, 2013. Journal of Loss Prevention in the Process Industries, 26(3), 547-557.
[15] Dimattia D G, Khan F I, Amyotte P R., 2005. Determination of human error probabilities for offshore platform musters. Journal of Loss Prevention in the Process Industries, 18(4): 488-501.
[16] Deacon T, Amyotte P R, Khan F I, et al, 2013. A framework for human error analysis of offshore evacuations. Safety Science, 51(1): 319-327.
[17] Musharraf M, Khan F, Veitch B, 2019. Modeling and simulation of offshore personnel during emergency situations. Safety Science, 111: 144-153.
[18] Musharraf M. Bayesian network approach to human reliability analysis (HRA) at offshore operations. Memorial University of Newfoundland, 2014.
[19] Musharraf M, Bradbury-Squires D, Khan F, et al, 2014. A virtual experimental technique for data collection for a Bayesian network approach to human reliability analysis. Reliability Engineering & System Safety, 132: 1-8.
[20] Norazahar N, Khan F, Veitch B, et al, 2017. Prioritizing safety critical human and organizational factors of EER systems of offshore installations in a harsh environment. Safety Science, 95:171-181.
[21] Mkrtchyan L, Podofillini L, Dang V N, 2015. Bayesian belief networks for human reliability analysis: A review of applications and gaps. Reliability Engineering & System Safety, 139:1-16.
[22] Wang L, Yang Z, 2018. Bayesian network modelling and analysis of accident severity in waterborne transportation: A case study in China, Reliability Engineering and System Safety, 180: 277-289.
[23] Wang Y F, Li Y L, Zhang B, et al, 2015. Quantitative Risk Analysis of Offshore Fire and Explosion Based on the Analysis of Human and Organizational Factors. Mathematical Problems in Engineering, 2015(2): 1-10.
[24] Groth K M, Swiler L P, Stevens-Adams S M, et al, 2014. A Bayesian method for using simulator data to enhance human error probabilities assigned by existing HRA methods. Reliability Engineering & System Safety, 128: 32-40.
[25] Norazahar N, Khan F, Veitch B, et al, 2018. Dynamic risk assessment of escape and evacuation on offshore installations in a harsh environment. Applied Ocean Research, 79:1-6.
[26] Shokoufeh A, Nima K, Seyed M H, 2020. A data-based comparison of BN-HRA models in assessing human error probability: An offshore evacuation case study, Reliability Engineering & System Safety, 202, 107043: 1-13.

[27] Yazdi, M., Nedjati, A., Zarei, E. and Abbassi, R., 2020. A novel extension of DEMATEL approach for probabilistic safety analysis in process systems. Safety science, 121:119-136
[28] Chou, Y, C., Sun, C, C., Yen, H, Y., 2012. Evaluating the criteria for human resource for science and technology (HRST) based on an integrated fuzzy AHP and fuzzy DEMATEL approach. Applied Soft Computing, 12:64-71
[29] Zarei, E., Khakzad, N., Cozzani, V. and Reniers, G., 2019. Safety analysis of process systems using Fuzzy Bayesian Network (FBN). Journal of loss prevention in the process industries, 57:7-16.
[30] Zarei, E., Yazdi, M., Abbassi, R. and Khan, F., 2019. A hybrid model for human factor analysis in process accidents: FBN-HFACS. Journal of loss prevention in the process industries, 57:142-155.
[31] International Association of Oil & Gas Producers, Risk Assessment Data Directory, 2010,434-19.
[32] BSEE,https://www.bsee.gov/what-we-do/incident-investigations/offshore-incident-investigations/district-investigation-reports, 2019.
[33] BSEE, https://www.bsee.gov/stats-facts/offshore-incident-statistics/fires-explosions, 2019.
[34] OREDA, Offshore Reliability Data Handbook. 2002, Norway: DNV.
[35] Lauritzen S L, 1995. The EM algorithm for graphical association models with missing data, Computaional Statistics & Data Analysis. 19(2):191-201.
[36] Larrañaga P, Karshenas, C. Bielza, R. Santana, 2013. A review on evolutionary algorithms in Bayesian network learning and inference tasks, Information Sciences. 233:109-125.
[37] Riggelsen C, 2006. Learning parameters of Bayesian networks from incomplete data via importance sampling, International Journal of Approximate Reasoning. 42(1): 69-83.
[38] Cooper G F, Herskovits E, 1992. A Bayesian method for the induction of probabilistic networks from data. Machine Learning, 9(4):309-347.
[39] Bartlett M, Cussens J, 2017. Integer Linear Programming for the Bayesian network structure-learning problem. Artificial Intelligence, 244,258-271.
[40] Spirtes P, Glymour C N, Scheines R, Causation, Prediction, and Search, 2nd edn, MIT Press, Cambridge, USA, 2000.
[41] Chen X W, Anantha G, and Lin X T, 2008, Improving Bayesian Network Structure Learning with Mutual Information-Based Node Ordering in the K2 algorithm, IEEE Transactions on Knowledge and Data Engineering, 20(5):1-13.
[42] Seixas F L, Zadrozny B, Laks J, Conci A, Débora Christina Muchaluat Saade, 2014. A Bayesian network decision model for supporting the diagnosis of dementia, Alzheimer's disease and mild cognitive impairment. Computers in Biology and Medicine, 51(1): 140-158.
[43] Zhou Y., Fenton N, Neil M, 2014. Bayesian network approach to multinomial parameter learning using data and expert judgments, International Journal of Approximate Reasoning 55: 1252-1268.
[44] Jensen F V, Nielsen T D, Bayesian Networks and Decision Graphs, Springer Verlag, New York, USA, 2007.
[45] Wang Y F, Qin T, Li B, et al, 2017. Fire probability prediction of offshore platform based on Dynamic Bayesian Network. Ocean Engineering, 145: 112–123.
[46] Cai B, Liu Y, Zhang Y, et al. A dynamic Bayesian networks modeling of human factors on offshore blowouts[J]. Journal of Loss Prevention in the Process Industries, 2013, 26(4):639-649.
[47] Yun G, Marsden, A, 2010. Methodology for estimating probability of success of Escape, Evacuation, and Rescue (EER) strategies for arctic offshore facilities. Cold Regions Science and Technology 61:107-115.
[48] Ping P, Wang K, Kong D P, Chen G M, 2018. Estimating probability of success of escape, evacuation, and rescue (EER) on the offshore platform by integrating Bayesian Network and Fuzzy AHP. Journal of Loss Prevention in the Process Industries 54: 57-68.
[49] Vinnem J-E, Offshore Risk Assessment: Principles, Modelling and Applications of QRA Studies. Springer Publishing Company, 2019.
[50] Zarei, E., Azadeh, A., Aliabadi, M.M., Mohammadfam, I., 2017a. Dynamic safety risk modeling of process systems using bayesian network. Process Saf. Prog. 36:399–407.
[51] Zarei, E., Azadeh, A., Khakzad, N., Mirzaei Aliabadi, M., Mohammadfam, I., 2017b. Dynamic safety assessment of natural gas stations using Bayesian network. J. Hazard

Mater. 321: 830–840.

Appendix 1.

The Pseudo-code of the K2 algorithm:

```
For i=1 to n do
πi=Null set;
ScoreOld=f(i,πi);
P=1;
While(P=1 &|πi |);
Z=search(pred(i),πi);
ScoreNew=Score(i,πi ∪{R});
If(ScoreNew> ScoreOld)
ScoreOld=ScoreNew;
πi =πi ∪{R};
else P=0;
end if
end while
dag(πi,i)=1;
end for
print(dag);
end
```

Appendix 2.

The Bayesian estimation method is used to determine the conditional probability table in the proposed model as shown below.

```
priors=1;
seed=0;
rand('state',seed);
for i=1:n
bnet.CPD{i}=tabular_CPD(bnet,i,'CPT','unif','prior_type','dirichlet','dirichlet_type','BDeu','dirichlet_weight',priors);
  end
bnet2=bayes_update_params(bnet,data');
CPT3=cell(1,n);
for i=1:n
      s=struct(bnet2.CPD{i});
      CPT3{i}=s.CPT;
end
engine = jtree_inf_engine(bnet2);
evidence = cell(1,n);
evidence{A27} = 1;
evidence{A8} = 1;
evidence{C5} = 1;
evidence{A25} = 1;
evidence{A21} = 1;
evidence{A1} = 1;
evidence{A2} = 1;
evidence{A10} = 1;
evidence{A12} = 1;
evidence{A22} = 1;
[engine, ll] = enter_evidence(engine, evidence);
marg = marginal_nodes(engine,[A27 A8 C5 A25 A21 A1 A2 A10 A12 A22,A28]);
```

marg.T

Table 1 Conditional probability table of the “Human behavior” node

		Node status							
node	Communication	Bad							
	Wrong operation	Yes							
	Lack of training exercise	Yes							
	Personnel attitude	Bad							
	Lack of safety awareness	Yes							
	Response delay	Yes							
	Forget	Yes							
node	Physical quality	Bad				Good			
	Misjudgment	Yes		No		Yes		No	
	Improper evacuation path	Yes	No	Yes	No	Yes	No	Yes	No
Human behavior	Bad	0.9910	0.8639	0.9348	0.7987	0.9301	0.7939	0.8648	0.7287
	Good	0.0090	0.1361	0.0652	0.2013	0.0699	0.2061	0.1352	0.2713

Table 2 Conditional probability table of the “Emergency evacuation” node

		Node status			
Human behavior		Bad			
Psychological quality		Bad			
Evacuation environment		Bad		Good	
Organizational function		Bad	Good	Bad	Good
Emergency evacuation	Failure	0.9756	0.3073	0.7974	0.4211
	Success	0.0244	0.6927	0.2026	0.5789