Journal of Hazardous Materials 191 (2011) 69–82

Contents lists available at ScienceDirect

Journal of Hazardous Materials

journal homepage: www.elsevier.com/locate/jhazmat

Investigations of Human and Organizational Factors in hazardous vapor accidents

Yan Fu Wang [a,b,*], Shahrzad Faghih Roohi [a], Xiu Ming Hu [a], Min Xie [a]

[a] Department of Industrial & Systems Engineering, National University of Singapore, 10 Kent Ridge Crescent, Singapore
[b] Department of Safety Engineering, China University of Petroleum, Dong ying 257061, China

ARTICLE INFO

Article history:
Received 10 December 2010
Received in revised form 9 April 2011
Accepted 11 April 2011
Available online 16 April 2011

Keywords:
Bayesian Network
Fuzzy analytical hierarchy process
Human and Organizational Factor
Human Factors Analysis and Classification System

ABSTRACT

This paper presents a model to assess the contribution of Human and Organizational Factor (HOF) to accidents. The proposed model is made up of two phases. The first phase is the qualitative analysis of HOF responsible for accidents, which utilizes Human Factors Analysis and Classification System (HFACS) to seek out latent HOFs. The hierarchy of HOFs identified in the first phase provides inputs for the analysis in the second phase, which is a quantitative analysis using Bayesian Network (BN). BN enhances the ability of HFACS by allowing investigators or domain experts to measure the degree of relationships among the HOFs. In order to estimate the conditional probabilities of BN, fuzzy analytical hierarchy process and decomposition method are applied in the model. Case studies show that the model is capable of seeking out critical latent human and organizational errors and carrying out quantitative analysis of accidents. Thereafter, corresponding safety prevention measures are derived.

1. Introduction

It has been widely recognized that Human and Organizational Factors (HOF) are leading causes of most accidents. A report of United States Coast Guard also points out that 75–96% of casualties are due to some forms of human errors [1]. In this aspect, it is emphasized that HOF is one of the most important contributory aspects to the causation and avoidance of accident. The prevalence of HOF in accidents warrants the need to incorporate HOF analysis in accident investigations, so that valuable measures to prevent similar accidents from recurring can be derived. Feedbacks and lessons learnt from accident analysis will provide help on improving safety climate and preventing accidents. Effectively preventing accidents requires the use of accident analysis models that include the effect of HOF [2].

Many models have been established that discuss HOF in accidents, e.g. Reason's Swiss Cheese Model, Human Factors Analysis and Classification System (HFACS), Classifications of Socio-Technical Systems involved in safety control, Systems-Theoretic Accident Model and Processes [3]. An inductive reasoning approach is employed to develop an Aviation System Risk Model (ASRM) to build probabilistic causal models representing the safety risk involved in aviation accidents [4]. ASRM model is based on revised HFACS and reflects the failure/error levels imposed by HFACS taxonomy [5]. A system dynamics model for the assessment of the HOFs in a nuclear power plant is developed, which can show cause and effect relationships among factors and quantify the HOFs [6]. A set of principles for organizational safety risk analysis are proposed to integrate the technical risk analysis models with social aspects of safety prediction models [7]. Based on those principles, probabilistic risk assessment model is extended to include the effects of organizational factors as the fundamental causes of accidents [8]. Mohaghegh and Mosleh propose organizational safety causal analysis model and present a Bayesian approach to operate the multi-dimensional measurements [9]. An organizational factor framework is developed for the quantification of the impact of organizational factor on risk, which also chooses Bayesian Network (BN) as a quantitative modeling technique based on an element-by-element evaluation of the existing framework [10]. However, this model is attributed to specific leak events without using extensive resources and does not focus on the risk-reducing measures.

A review of different HOF models resulted in the selection of HFACS for HOF analysis in this paper. HFACS is a validated and reliable human error model [11], which is utilized intensively in investigating accidents [12,13]. The Human Factors Investigation Tool [14] and Curtailing Accidents by Managing Social Capital [15] are recognized as relatively new tools built based on the HFACS model. The above literatures mainly focus on the construction of complicated conceptual model, whereas quantitative risk assessment is not enough. Adding quantification analysis to the

* Corresponding author at: Department of Industrial & Systems Engineering, National University of Singapore, 10 Kent Ridge Crescent, 119260, Singapore. Tel.: +65 96184069.
E-mail addresses: isewy@nus.edu.sg, lily3lily3@163.com (Y.F. Wang).

0304-3894/$ – see front matter
doi:10.1016/j.jhazmat.2011.04.040

qualitative HFACS model could enhance the accident investigation process. For instance, HFACS model can be integrated with BN, which is capable of providing quantitative interrelationships as well as calculating numerical values of occurrence probability [16].

The earliest research in the integration of HFACS with BN appeared in Luxhøj's work [17,18], which construct BBN model utilizing the HFACS taxonomy as a basis. They discussed the need for new methods of hazard, risk and uncertainty modeling [19]. They indicated that the combination of fuzzy sets and BNs is helpful for dealing with the ambiguity regarding the observed evidence associated with some variables. Lu also establishes the causal relationships of accidents by using BN from the perspective of HOFs and tries to apply the fuzzy semantics and the integral value method to quantify the conditional probability table (CPT) of basic events [20]. However, the expert elicitations of CPT and quantitative inference of BN may not be enough. In order to modify the deficiency of their work, fuzzy analytical hierarchy process (AHP) method and decomposition method are adopted in this paper to compensate uncertainty and vagueness in the experts' judgment of BN. With regards to the elicitation of CPT in BN, it is worthwhile to note that reliable HOF data are generally absent [21]. In such situations, CPT can be elicited using judgments from domain experts. However, experts may find it difficult to come up with precise probability values for the relationships between nodes [22]. Since BN is an effective tool for updating prior probabilities and fuzzy set theory is a useful tool for analyzing subjective information, the two theories can be combined for the updates of prior probabilities and the calculation of posterior probabilities [23]. Fuzzy AHP can tackle fuzziness and uncertainty of vague decision-making more efficiently using fuzzy sets, membership functions, and fuzzy numbers [24].

There are many fuzzy AHP methods and applications in literatures. The earliest work is that a fuzzy logarithmic least squares method (LLSM) is suggested to obtain relative weights from a triangular fuzzy comparison matrix [25]. A constrained nonlinear optimization model is later proposed to modify the fuzzy LLSM [26]. An extent analysis method, which has been employed in a number of applications due to its computational simplicity, is introduced by Chang [27]. However, such a method is found unable to derive the true weights from a fuzzy comparison matrix. It is improved by modifying the fuzzy LLSM, which can directly derive normalized triangular fuzzy weights for both complete and incomplete triangular fuzzy comparison matrices [28]. In another study, fuzzy AHP is combined with HFACS to prioritize the list of HOFs involved in an accident [29]. Fuzzy AHP and Fuzzy Data Envelopment Analysis are applied to calculate the relative fuzzy weight, which is integrated with BN to create the risk evaluation models [30]. From above literature reviews, we can see that the fuzzy AHP method is an ideal tool for relative weights elicitation, which can be used to elicit the CPT of BN.

In this paper, a quantitative accident analysis model is presented by integrating HFACS and BN with fuzzy AHP to assess the contribution of HOFs in accidents. This application model exploits the advantages of each method and modifies the existing methods. As an approach to compensate the lack of quantitative analysis within HFACS, the integration of BN and fuzzy AHP is selected to estimate quantitatively the contribution of HOFs to accidents. At the same time, the 4-level structure of HFACS provides a systematic guideline for the construction of BN to model how HOFs are related to form a network. The rest of this paper is organized as follows: Section 2 presents a two-phase accident analysis model for the systematical assessment of HOFs in both qualitative and quantitative manner. In Section 3, two cases are analyzed to demonstrate the application of the model. Section 4 concludes the merits and drawbacks of the proposed model.

2. Two-phase accident analysis model

This section presents a two-phase accident analysis model to assess the contribution of HOFs in both qualitative and quantitative manner.

The two-phase accident analysis model is shown in Fig. 1. The proposed model taps on the joint capabilities of HFACS and BN for the purpose of investigating HOFs in accidents.

- Phase one is a qualitative analysis model of HOFs and their relationships. This phase utilizes HFACS to identify a hierarchy of HOFs causing accidents. The output of this phase provides the input for the second phase of the model.
- Phase two constructs a quantitative analysis model of the HOFs using BN. The CPTs of BN are elicited by integrating fuzzy AHP with a decomposition method to quantify the degree of relationships among HOFs. And then, BN inferences are performed to prioritize the importance of HOFs identified in the first Phase.

2.1. 6-Step accident analysis model

The model is made up of 6 steps including: "Define", "Analyze", "Node", "Graphic", "Elicit" and "Reasoning" that briefly called "DANGER". Here, each step is explained in details:

(1) *Define*. This step is to clearly define accidents. The scope of accidents and conditions under which the accidents occur should be clearly stated. A statement describing the accident should be produced. For instance, "collision between a ship and shuttle tanker at night under poor visibility" states the accident of concern (ship and shuttle tank collision) and the conditions (night time, poor visibility).
(2) *Analyze*. This step utilizes HFACS to identify various HOFs, ranging from active errors of operators to latent errors in organization. In general, HFACS has a four-level hierarchical structure. Level 1, which is the "unsafe acts" level, consists of active errors by the operators. Errors in this layer directly lead to the accident, and thus are the most visible to investigators. With the "unsafe acts" errors listed in level 1, experts can proceed to investigate the "preconditions for unsafe acts" errors in level 2 that influences the HOFs of level 1. After level 2 is completed, level 3 "unsafe supervision" can be identified with final leading to level 4 "organizational influence". Therefore, beginning investigations at level 1 allows a progressive probing of the HOFs at higher levels. This process pushes investigators to address latent failures at higher levels of the HFACS model, which tend to be overlooked in accident analysis. The output of this step is a 4-level hierarchy of HOFs. Utilizing HFACS effectively requires understanding the definitions of different type of HOFs at each level. A selected list of HOFs is provided in Appendix A.1.
(3) *Nodes*. This step converts the hierarchy of HOFs identified in step 2 into a hierarchy of variables (nodes). Thereafter, states are defined for the nodes to indicate various values the variables can take. For instance, a HOF can be converted to a variable with 2 states ("yes" and "no"). A 3-state variable ("high", "medium" and "low") is also possible depending on the required depth of the accident analysis.
(4) *Graphic*. With a hierarchy of nodes and states defined, a BN representing the relationships among HOFs can be constructed. The relationships depicted in HFACS will be mapped onto a BN via its graphical representation with edge-connecting nodes. In this step, the BN is systematically constructed according to the hierarchal structure of HFACS.
(5) *Elicit*. With the graphical structure of BN, this step is eliciting CPT for all the nodes. In the elicitation procedure, the relative

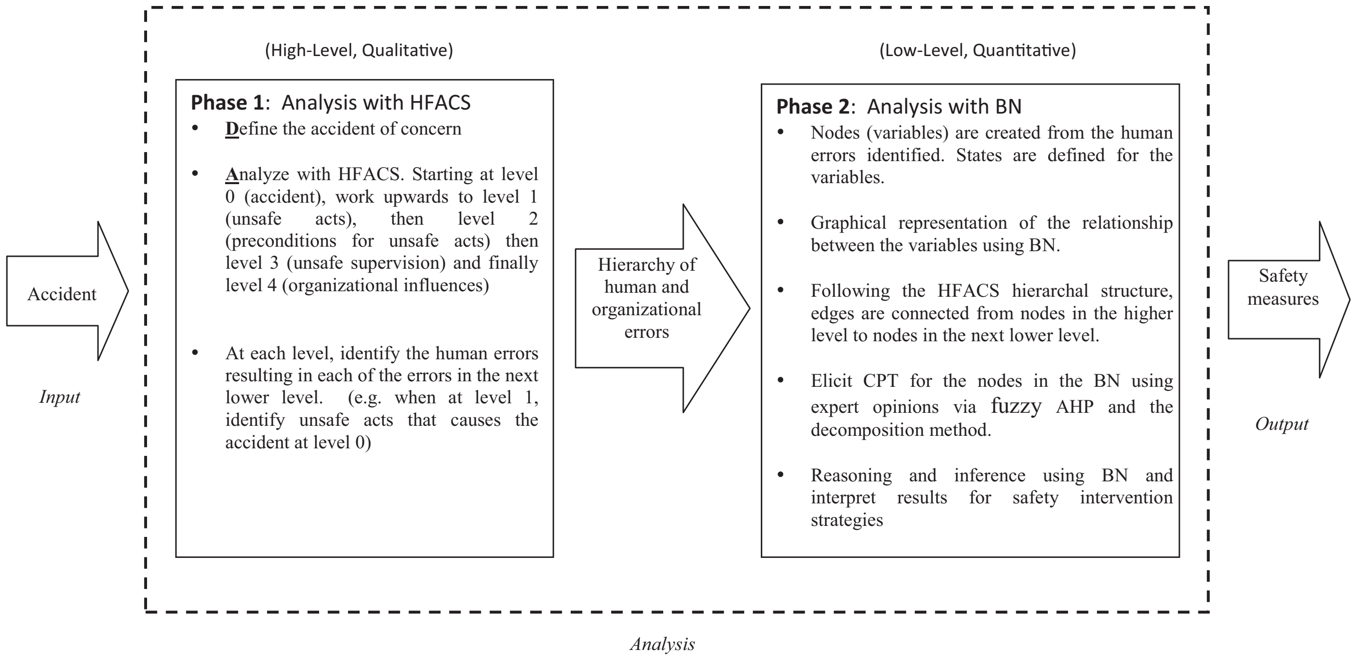

Fig. 1. The proposed accident analysis framework.

priority weights are derived using fuzzy AHP. Fuzzy AHP is an extension of the traditional AHP methodology that incorporates fuzzy comparison ratios $\tilde{c}_{ij}$. With such pair-wise comparisons, fuzzy AHP is effectively utilized to convert linguistic variables to probability values. For example, to determine the probability of one node at states S_1, S_2 and S_3, precise values need to be given for the conditional probabilities in AHP, which are more difficult for experts to estimate. Instead, in fuzzy AHP, it is easier to give linguistic evaluation scale of pair-wise comparisons by questions such as "comparing states S_i and S_j, which one is more probable to occur and how much more?" In addition, it is noted that as the number of parent nodes grows, the elicitation process may become complicated. In this paper, the decomposition method that allows domain experts to elicit CPT by considering each parent node separately is applied to reduce this complexity. Details about using fuzzy AHP and decomposition method for CPT elicitation are elaborated in Section 2.2

(6) *Reasoning*. The last step of the model is BN inference from which safety intervention strategies can be derived. After all the CPTs are elicited, the quantitative analysis can be performed via Bayesian inference. The type of Bayesian inference depends on the specific goals of each accident analysis. For example, the probability of accident can be calculated if the prior probability of HOFs is known. The relative contribution of HOFs to the accident can also be investigated, which is indicated by the posterior conditional probability of each node. Finally, with these quantitative results, safety intervention measures can be suggested to prevent the accident reoccurring

2.2. CPT elicitation by integrating fuzzy AHP with a decomposition method

CPT elicitation has been known to be a complicated issue due to the large number of judgments required to fully quantify the relationships in the BN. For a binary node with n parents, 2^n conditional probabilities are required. The lack of data related with HOFs prompts for CPT elicitation via expert judgments. However, expert judgments are subjected to biases [31], especially when encountering a large BN. The integration of AHP and a decomposition method can reduce subjective biases and help domain experts to elicit the CPT in an efficient manner [32]. However, the conventional AHP may not be able to truly reflect human cognitive processes, especially for the situation when it is difficult for experts to estimate the precise values. In these cases, fuzzy AHP enables domain experts to avoid giving precise probability for the CPTs. Instead they give triangular fuzzy number to perform pair-wise comparisons of the states according to their relative occurrence probability [33]. This section gives an illustration on how to integrate fuzzy AHP with a decomposition method for the elicitation of CPT.

2.2.1. Prior probabilities for a node without parents

Suppose a node X has k states $(S_1, S_2, \ldots, S_k)$ without parents. To elicit prior probabilities for each state of X, it is required to determine $w = [w_1, w_2, \ldots, w_s, \ldots, w_k]$, where w_s is the probability of X at state Ss. Traditionally, w_s is specified directly by experts, using their knowledge and experiences. When the number of states is small, such a method may be efficient. With the increase of states, simultaneously estimating probabilities of all the states inevitably involve inaccuracies.

An alternative way is using triangular fuzzy number to perform pair-wise comparisons between states for generating their probabilities. Because there are only two instead of multiple states considered simultaneously in a pair-wise comparison, it should be much easier to provide fuzzy linguistic scale of comparison than the direct estimation of probabilities. Fuzzy AHP is also a useful tool for dealing with uncertainties [34]. The prior probability of each state can be determined by the following pair-wise comparison matrix [35]:

$$A = \begin{array}{cccc} 1 & \tilde{c}_{12} & \cdots & \tilde{c}_{1k} \\ \tilde{c}_{21} & 1 & \cdots & \tilde{c}_{2k} \\ \vdots & \vdots & \cdots & \cdots \\ \tilde{c}_{k1} & \tilde{c}_{k2} & \cdots & 1 \end{array} \quad (1)$$

where $\tilde{c}_{ij}$ is a triangular fuzzy number to show the probability comparison of S_i over S_j:

$$\tilde{c}_{ij} = (l_{ij,} m_{ij}, u_{ij}) \quad (2)$$

Table 1
Fuzzy scale in AHP.

Linguistic scales	Triangular fuzzy scale	Triangular fuzzy reciprocal scale
Just equal	(1, 1, 1)	(1, 1, 1)
Equally probable	(1/2, 1, 3/2)	(2/3, 1, 2)
Weakly probable	(1, 3/2, 2)	(1/2, 2/3, 1)
Strongly more probable	(3/2, 2, 5/2)	(2/5, 1/2, 2/3)
Very strongly more probable	(2, 5/2, 3)	(1/3, 2/5, 1/2)
Absolutely more probable	(5/2, 3, 7/2)	(2/7, 1/3, 2/5)

$\tilde{c}_{ij}$ is a fuzzy linguistic scale that is specified by asking domain experts questions like "comparing states S_i and S_j, which one is more likely to occur and how much more?" Domain experts answer these questions using the fuzzy linguistic scale provided in Table 1 [36].

If there is more than one expert, the following equation can be used to aggregate the opinions of the experts:

$$\tilde{c}_{ij} = \frac{1}{n}(\tilde{c}_{ij}^1 + \tilde{c}_{ij}^2 + \cdots + \tilde{c}_{ij}^t + \tilde{c}_{ij}^n) \tag{3}$$

where n is the number of experts.

Perform the fuzzy addition operation of $\sum_{j=1}^{k} \tilde{c}_i^j$ $(i = 1, 2, \ldots, k)$ like that:

$$R_i = \sum_{j=1}^{k} \tilde{c}_i^j = \left(\sum_{i=1}^{k} l_i, \sum_{i=1}^{k} m_i, \sum_{i=1}^{k} u_i \right) \tag{4}$$

The value of fuzzy synthetic extent with respect to ith object is defined as [29]:

$$S_i = \left(\frac{\sum_{j=1}^{n} l_{ij}}{\sum_{j=1}^{n} l_{ij} + \sum_{k=1, k \neq i}^{n} \sum_{j=1}^{n} u_{kj}}, \frac{\sum_{j=1}^{n} m_{ij}}{\sum_{k=1}^{n} \sum_{j=1}^{n} m_{kj}}, \frac{\sum_{j=1}^{n} u_{ij}}{\sum_{j=1}^{n} u_{ij} + \sum_{k=1, k \neq 1}^{n} \sum_{j=1}^{n} l_{kj}} \right) \tag{5}$$

If A is a perfectly consistent comparison matrix, fuzzy weight vector can be precisely characterized by $w' = (S_1, S_2, \ldots, S_i, \ldots, S_n)^T$. Otherwise, the weight vectors of A can be derived through the solution of the following constrained nonlinear optimization model [24]:

$$min\, j = \sum_{i=1}^{n} \sum_{j=1}^{n} ((\ln\, w_i^L - \ln w_j^U - \ln l_{ij})^2 + (\ln w_i^M - \ln w_j^M - \ln m_{ij})^2 + (\ln w_i^U - \ln w_j^L - \ln u_{ij})^2) \tag{6}$$

$$s.t. \begin{cases} w_i^L + \sum_{j=1, j \neq 1}^{n} w_j^U \geq 1, \\ w_i^U + \sum_{j=1, j \neq 1}^{n} w_j^L \geq 1, \\ \sum_{i=1}^{n} w_i^M = 1, \\ \sum_{i=1}^{n} (w_i^L + w_i^U) = 2, \\ 0 < w_i^L \leq w_i^M \leq w_i^U. \end{cases}$$

The model is solved using GAMS program, which is shown in Appendix B. The optimum solution to the above model forms normalized fuzzy weights

$$w = (w_i^L, w_i^M, w_i^U) \quad i = 1, \ldots, n. \tag{7}$$

The fuzzy weight vector is a fuzzy number. Therefore, it is necessary to employ a nonfuzzy ranking method for fuzzy numbers to compare the states. In other words, the procedure of defuzzification should be done to locate the Best Nonfuzzy Performance (BNP) value. Such related common methods include mean of maximal, center of area (COA) and a-cut. Among these methods, utilizing COA method to find out BNP is simpler and more practical. Also, there is no need to bring in the preferences of any evaluators, so it is used in this paper. The BNP value of the fuzzy number w_i can be found by the following equation:

$$BNP_{wi} = \frac{[(w_i^U - w_i^L) - (w_i^M - w_i^L)]}{3} + w_i^L \qquad \forall i = 1, \ldots, n. \tag{8}$$

The normalized weight BNP_{wi} is the prior probability of the ith state of node X.

Table 2
Corresponding comparison matrix of $P(X = S_s | T = t_p)$.

T is at state p	S_1	S_2	...	S_k	w_p
S_1	$\tilde{c}_{11}$	$\tilde{c}_{21}$	...	$\tilde{c}_{1k}$	w_{p1}
S_2	$\tilde{c}_{21}$	$\tilde{c}_{22}$	...	$\tilde{c}_{2k}$	w_{p2}
...	...	...	...	...	...
S_k	$\tilde{c}_{k1}$	$\tilde{c}_{k1}$	...	$\tilde{c}_{kk}$	w_{pk}

Table 3
Conditional probability table for the node X with one parent T.

State of node T					
		t_1	t_2	...	t_m
State of node X	S_1	w_{11}	w_{21}	...	w_{m1}
	S_2	w_{12}	w_{22}	...	w_{m2}
	...	...	...	...	...
	S_k	w_{1k}	w_{2k}	...	w_{mk}

2.2.2. Conditional probabilities for a node with one parent

Suppose a node X (with k states $S_1, S_2, \ldots, S_k$) has one parent T (with m states $t_1, t_2, \ldots, t_m$). Let $w_p = [w_{p1}, w_{p2}, \ldots, w_{pk}]$, where w_{ps} is the probability of X at state S given parent T at state p ($p = 1, 2, \ldots, m$ and $s = 1, 2, \ldots, k$). When node T is at state t_p, the corresponding comparison matrix is shown in Table 2. After $w_{ps} = (S = 1, 2, \ldots, k)$ is computed, $P(X = S_s | T = t_p) = w_{ps}$ can be set.

Since node T has m states, m pair-wise comparison matrices for each state of T should be constructed. For each matrix, the question "if node T is at state t_p, comparing states S_i and S_j of X, which one is more likely to occur?" will be evaluated to specify $\tilde{c}_{ij}$. And then the m pair-wise comparison matrices can be solved individually just like the computation of prior probabilities for a node with no parent shown in Section 2.2.1. All the m vectors w_p (as shown in Table 3) will be calculated, which are the elements of the CPD for the node X with one parent T.

2.2.3. Conditional probabilities for a node with multiple parents

A Node X has k states $(S_1, S_2, \ldots, S_k)$. The node X has n parents, $T^{(1)}, T^{(2)}, \ldots, T^{(j)}, \ldots, T^{(n)}$. The node $T^{(j)}$ has the states of $T^{(j)}{}_1, T^{(j)}{}_2, \ldots, T^{(j)}t_{(j)}$ (t_j is the state number of node $T(j)$; $j = 1, \ldots, n$).

It will be difficult for experts to directly estimate the probability of each state of X conditional on the combination of the states of its parents, which is defined by the following equation:

$$P(X = S_i | T^{(1)} = T_{pj}^{(1)}, T^{(2)} = T_{pj}^{(2)}, \ldots, T^{(n)} = T_{pj}^{n}) \quad (i = 1, 2, \ldots, k; p_j = 1, 2, \ldots, n) \tag{9}$$

When a node A in a Bayesian Network has two parents B and C, its probability conditional on B and C can be approximated by:

$$P(A|B, C) = \alpha P(A|B)(A|C) \tag{10}$$

where α is a normalizing constant to ensure that $\sum_{a \in A} P(a|B, C) = 1$.

According to Eq. (10), Eq. (9) can be simplified as:

$$P(X = S_i | T^{(1)} = T_{pj}^{(1)}, T^{(2)} = T_{pj}^{(2)}, \ldots, T^{(n)} = T_{pj}^{n}) = \alpha \prod_{j=1}^{n} P(X = S_i | T^{(j)} = T_{pj}^{(j)}) \quad (i = 1, 2, \ldots, k$$
$$p_j = 1, 2, \ldots, t_j; \quad j = 1, 2, \ldots, n) \tag{11}$$

where, α is a normalizing constant to ensure that

$$\sum_{i=1}^{k} P(X = S_i | T^{(1)} = T_{pj}^{(1)}, T^{(2)} = T_{pj}^{2}, \ldots, T^{(n)} = T_{pj}^{n}) = 1 \tag{12}$$

In cases for nodes with multiple parents as shown in Fig. 2, the decomposition method greatly simplifies the CPT elicitation by allowing conditioning to be done on each parent separately.

2.3. Validation using sensitivity analysis

When a new model is proposed, validation is required to ensure its soundness. This is especially important when subjective estimation is involved in the model [37]. There are several well-accepted validation methods available. In this paper, a sensitivity analysis for partial validation of the proposed model is adopted. The following three axioms should be satisfied [38].

Axiom 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.

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

Axiom 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. Case study

In this section, two case studies are presented to demonstrate the application of the proposed model. Section 3.1 analyzes the release of cargo vapors resulting in two casualties on board of the chemical tanker. In Section 3.2, Vinyl Chloride Monomer erupting to form vapor cloud are analyzed to infer about critical HOFs.

3.1. Release of cargo vapors resulting in two casualties on chemical tanker

Jo Eik, a chemical tanker completed a ship-to-ship transfer at Vopak Terminal Tessiside on 6 May 2009 [39]. Following the end of ship-to-ship transfer, Jo Eik carried out mandatory pre-wash using portable washing equipment because the majority of the fixed washing systems were defective. The water supply hose of washing machine crossed through cargo tank inboard Butterworth hatch (an opening on the deck of a vessel opened when cleaning or ventilating the tanks), which remained open. As the cargo tank was washed, water mist containing cargo vapors escaped through the open hatch as the tank's atmosphere was agitated. The vapors accumulated around the Butterworth hatch in which was an unidentified enclosed space. After the final pre-wash of the cargo tanks, a deck rating noticed a strong pungent smell before climbing down the ladder to shut off the power to the pump, but he did not wear respiratory protection. The deck rating lost consciousness and slumped due to exposure to the toxic crude sulphate turpentine vapor, containing hydrogen sulphide. The chief officer, who attempted a rescue without wearing respiratory protection, lost his sense of smell and was unable to speak. Another deck rating who accompanied the chief officer suffered effects of vapor inhalation but managed to escape.

3.1.1. Applying the proposed model

(1) Define the accident clearly

After reviewing the accident report from marine accident investigation branch (MAIB), the accident is defined as "Inhalation of hazardous vapor by crew due to the discharge of poisonous cargo vapor."

(2) Analyze with HFACS

Working on the four-level hierarchy structure discussed earlier, level 1 "unsafe acts" identifies the HOFs which directly lead to the accident. Followed by level 2 "preconditions for unsafe acts", the purpose of level 2 is seeking out the conditions that result in the HOFs at level 1. The analysis process continues to level 3 "unsafe supervision" and ends at level 4 "organizational influences", which identifies the fundamental causes of the accident. The list of HOFs generated from the first accident is shown in Table 4.

(3) Nodes and states of the identified HOFs

The HOFs identified in step 2 are converted to the nodes of BN. After that, states are defined for each node according to the real conditions and the required depth of accident analysis. The states of each node are shown in the third column of Table 4.

(4) Graphical representation with BN

With the nodes and states defined, the BN of "Inhalation of hazardous vapor by crew due to the discharge of poisonous cargo vapor" is constructed as shown in Fig. 3.

(5) Elicit CPT for the nodes of BN

With the graphical structure of BN, this step requires the elicitation of CPT for the nodes. The experts we invited for elicitation process are a group of four experts. The first one is a full professor of Shanghai Jiaotong University, who is an expert of maritime safety. The second one is an experienced engineer of Great ship Global Offshore Service Company in Singapore. The third one is an associate professor of fuzzy reliability from Goa College of Engineering. The fourth one is an assistant professor of safety engineering from China University of Petroleum. Discussing the real conditions of the case study, they elicit the values for each pair-wise comparison matrix. After all the comparison matrixes are estimated, the CPTs are elicited by integrating fuzzy AHP with decomposition method as shown in Section 2.2. As an example, the calculation of CPT for the node "Not_check_equipment_defective" is presented in Appendix B. After all CPTs are assigned, the quantitative analysis can be performed using Bayesian inference.

(6) Inference with BN

Given the occurrence of "Inhale vapor", a backward inference can be performed to calculate the posterior probabilities of each node to identify the important HOFs. The posterior probabilities of the HOF nodes are shown in Fig. 4. These posterior probabilities can be compared with their original prior probabilities to give an indication of the relative contribution of the HOFs. Such as, the HOF with the highest percentage change from prior to posterior probability indicates that it is sensitive to the occurrence of the accident.

3.1.2. Sensitivity analysis and results

Sensitivity analyses are conducted in this section to validate the proposed model. The importance degree of each HOF regarding to the node "Inhale vapor" can be assessed using entropy reduction (mutual information). Intuitively, mutual information measures the information that X and Y share: it measures how much knowing one of these variables reduces the uncertainty about the other.

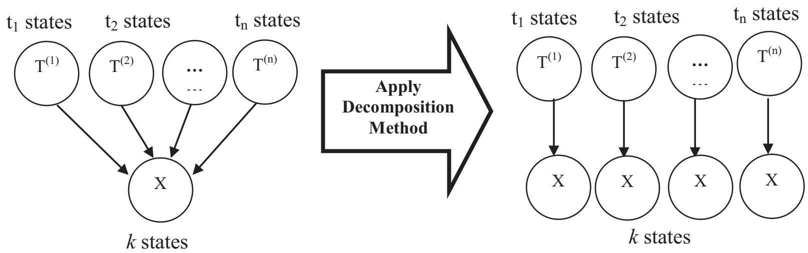

Fig. 2. Decomposition method of conditional probability calculation.

Table 4
Hierarchy of human and organizational errors in the first accident.

Nodes/errors	Descriptions	States
Level 0: accidents		
Inhale hazardous vapor	Inhalation of hazardous cargo vapor by crew while washing tank	Yes, no
Level 1: unsafe acts		
Open Butterworth hatch	Open P10 Butterworth hatch to let washer water hose passed through	Yes, no
No BA/wrong BA	Not wear any breathing apparatus (BA) when go into hazardous atmosphere/Check wearing an inappropriate BA	
Not locate sources of smell	Not investigate and locate the gas source causing the smell timely	
Not test atmosphere	Not test the atmosphere before going into hazardous atmosphere	
Level 2: preconditions for unsafe acts		
Unaware of cargo's danger	Not be warned of the hazards posed by cargo contents	Yes, no
Using unsuitable equipment	Wash tank using portable washing equipment contrary to the vessel's P&A manual instructions	
Complacent attitude	Overly confident about dangers or one's actions	High, medium, low
Wrong risk assessment	Identify wrongly or insufficiently the hazards of cargo and recommending the wrong or insufficient precautions	
Level 3: unsafe supervision		
Not check equipment defective	Failed to check fixed washing system defective	High, medium, low
Deficient training	rescuers acting on instinct rather than knowledge and training	
Not provide specific MSDS	Not provide the cargo specific MSDS/Used Wrong MSDS	Yes, no
Inadequate brief	not brief the crew about the likely risk and necessary precautions	
Not provide instructions	There were no specific instructions on board for handling H_2S cargoes	
Failed to identify unsafe	the dangers posed by the presence of H_2S were not identified	
Level 4: organizational influences		
Not enforcing safety standard	Available guidance and procedures discipline are not followed strictly/various documentation, including checklists were not complied with	High, medium, low
Ineffective emergency drill	Locations where similar accidents might occur are not identified when planning drills.	
Insufficient check	Not performing or insufficient checks. For example inspection checklists did not specifically target the tank washing equipment	
No guidance standard	Vopak Terminal did not provide guidance or set any limitations on open tank washing/no specific instructions for handling cargoes	
Ignore mutual aid messages	Terminal's investigation of mutual aid messages was not conducted	Yes, no
No pre-arrival conference	A further pre-arrival conference was not carried out	

Formally, the mutual information of two random variables X and Y can be defined as:

$$H(X;Y) = \sum_{y\in Y}\sum_{x\in X} p(x,y)\ \log_2\frac{p(x,y)}{p(x)p(y)} \tag{13}$$

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

The prior probability, posterior probability and mutual information of each HOF are compared as shown in Table 5, from which, we can deduce the following conclusions.

The posterior probability of the node "Not_enforcing_safety_standard" has the larger increment than other nodes of level 4 given the accident occurrence. This suggests that the occurrence of the accident is likely due to not enforcing safety standard. In addition,"Not_provide_instructions","Not_provide_specific_MSDS","Using_unsuitable_equipment", "Complacent_attitude", "Open_butterworth_hatch", "No_BA_wrong_BA" and "Not_locate_sources_of_smells" also contribute significantly to the occurrence of the accident.

While the 5% step by step reduction of prior probability of each organizational node varies from 5% to 30%, the reduction rates of accident probability are computed, which are shown in Fig. 5, from which, it can be seen that the probability of accident has the largest reduction when the prior probability of "Not_enforcing_safety_standard" decreases the same as other factors. It highlights that "Not_enforcing_safety_standard" is the most important organizational factor.

Given the occurrence of the accident, the change rate from prior probability to posterior probability of each organizational factor is represented in Fig. 6. From Fig. 6, we can see that the posterior probability of "Not_enforcing_safety_standard" has the largest change rate. This is consistent with the inference made earlier that the occurrence of accident is sensitive to the node "Not_enforcing_safety_standard".

With the BN inference mentioned above, the following recommendations of safety measures (corresponding to above major accident contributors) are given to avoid recurrence:

- All crews should be enforced and eligible to strictly following the safety standards and requirements. Some example of the stan-

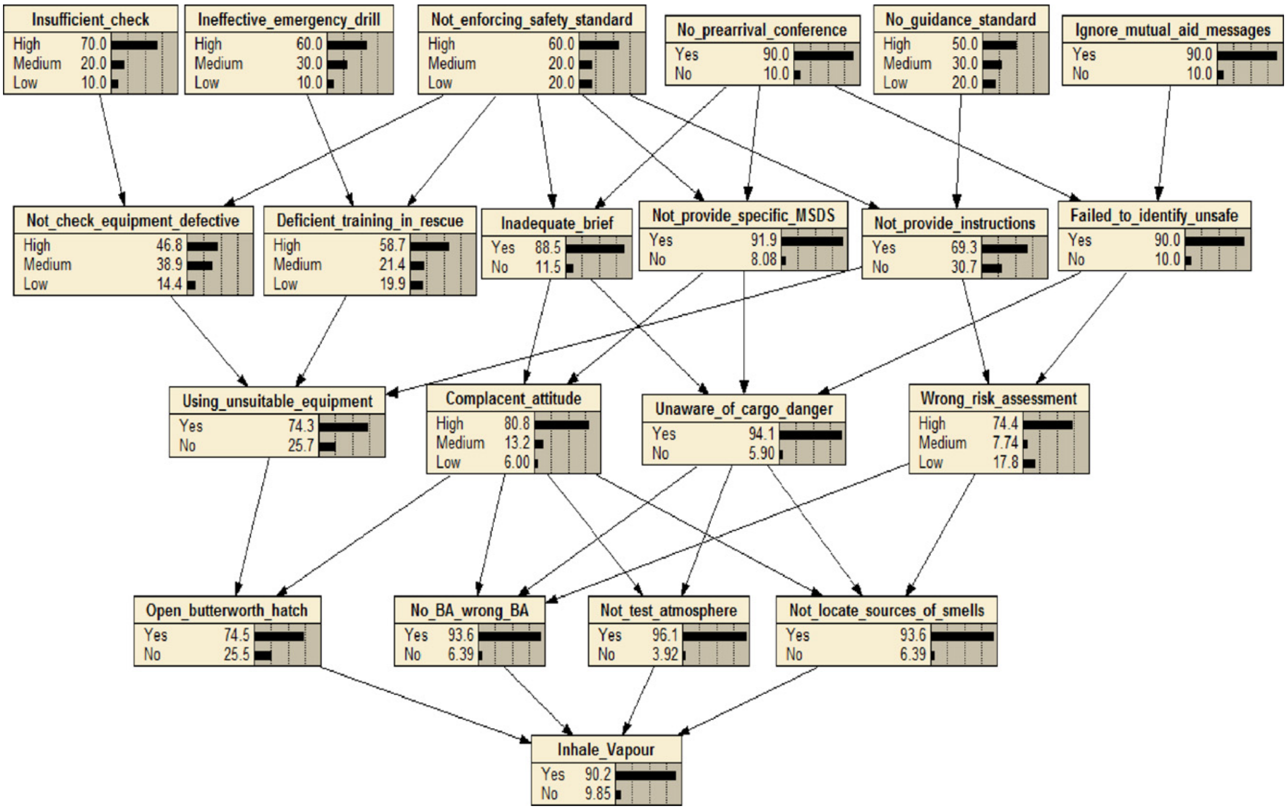

Fig. 3. Graphical representation of “inhale vapour” accident with prior probabilities.

dards could be that safety precaution must be taken when crew is in some enclosed spaces.

- The pre-arrival conference must be held before the loading/unloading operation and adequate brief should be provided. All the relevant information of cargo and related hazards and safety procedures should be covered at the pre-arrival conference.
- A specific MSDS of cargoes should be provided, which need contain the comprehensive information to determine special procedures for ensuring the safety of the crew.

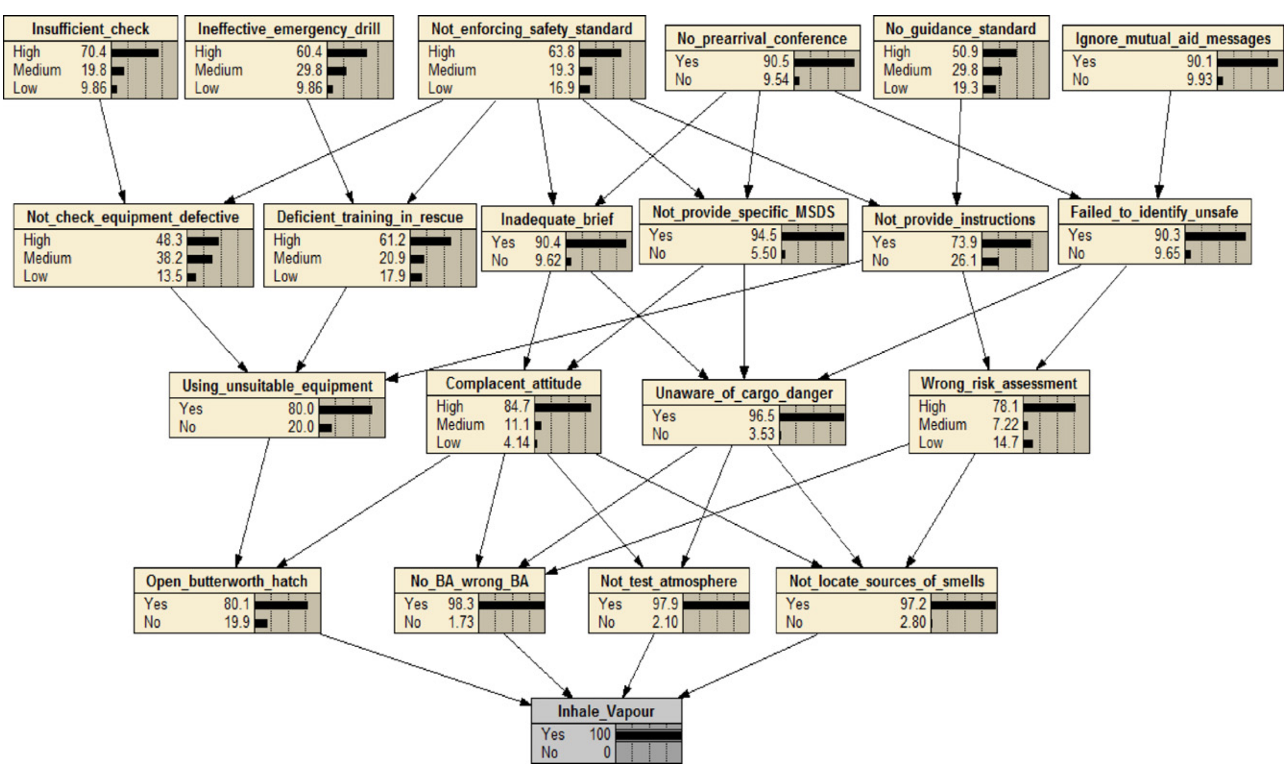

Fig. 4. Posterior probabilities of the human factor given the first accident happened.

Table 5
Mutual information of prior probability and posterior probability for each HOF.

Organizational factor	Prior probability (%)	Posterior probability (%)	Change rate of probability (%)	Mutual information
Node of level 4: organizational influences				
Insufficient_check	70	70.4	0.571	0.000449
Ineffective_emergency_drill	60	60.4	0.667	0.000403
Not_enforcing_safety_standard	60	63.8	6.333	0.04462
No_prearrival_conference	90	90.5	0.556	0.001423
No_guidance_standard	50	50.9	1.800	0.002796
Ignore_mutual_aid_messages	90	90.1	0.111	3.982e−005
Node of level 3: unsafe supervision				
Not_check_equipment_defective	46.8	48.3	3.205	0.00739
Deficient_training	58.7	61.2	4.259	0.01919
Inadequate_brief	88.5	90.4	2.147	0.01851
Not_provide_specific_MSDS	91.9	94.5	2.829	0.0392
Not_provide_instructions	69.3	73.9	6.638	0.0591
Failed_to_identify_unsafe	90	90.3	0.333	0.00087
Node of level 2: preconditions for unsafe acts				
Using_unsuitable_equipment	74.3	80	7.672	0.0933
Complacent_attitude	80.0	84.7	5.875	0.0545
Unaware_of_cargo_danger	94.1	96.5	2.550	0.0412
Wrong_risk_assessment	74.4	78.1	4.973	0.0426
Node of level 1: unsafe acts				
Open_butterworth_hatch	74.5	80.1	7.517	0.0941
No_BA_wrong_BA	93.6	98.3	5.021	0.131
Not_test_atmosphere	96.1	97.9	1.873	0.0339
Not_locate_sources_of_smells	93.6	97.2	3.846	0.0815

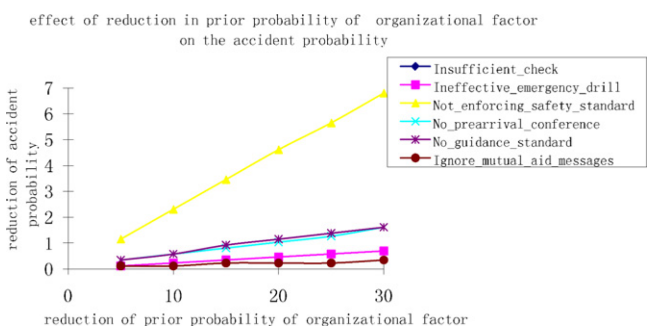

Fig. 5. Effects of changes in prior probabilities of each HOF on the probabilities of the first accident.

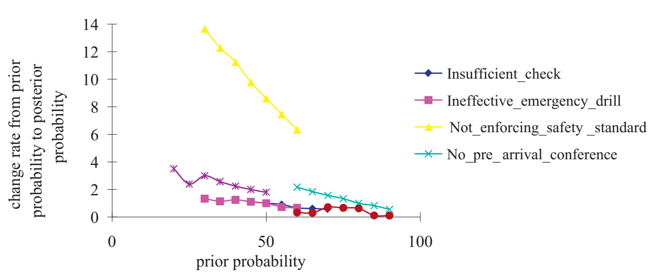

Fig. 6. Effects of changes in prior probabilities of each HOF on the posterior probability in the first accident.

- The defective equipment, such as the defective fixed washing system, should be repaired or renewed as soon as possible.
- Operator must wear appropriate breathing apparatus when dealing with hazardous cargo.
- The mutual aid messages should be immediately investigated to identify the risk avoiding complacent attitude.
- Detailed instruction should be provided for managing of unfamiliar cargoes and cargo operation.
- It should be arranged for crews to carry out additional training in rescue operations to enlighten the crisis consciousness and the right contingency measures.
- Cargo operations should be kept as "closed operations" to prevent vapors spilling and releasing. For this case, leaving the Butterworth hatches open directly causes the release of cargo vapors.
- Comprehensive check covering all phases should be carried out to ensure the cargo operation is conducted safely.
- The full briefing should be given to the chief officer after receiving the cargo stowage plan. Followed by the briefing, all items in the safety checklists in the Cargo Information Book have to be completed.

3.2. *Vinyl Chloride Monomer erupted to form a large cloud of vapor cloud*

The gas carrier Coral Acropora was preparing to start to discharge her cargo into shore cargo tanks when there was an escape of Vinyl Chloride Monomer (VCM) [37]. On arrival at the berth, a cargo surveyor had boarded the vessel and, after calculating the cargo quantity, he had asked the chief officer to run a cargo pump in each tank as he took cargo samples. The chief officer had not been aware of the need for sampling and he had not made preparations or planned for it. However, he acceded to the request without including the operation in the discharge plan. The chief officer opened the valves on the aft tank, which allowed recirculation of the cargo in that tank. He then started the aft tank cargo pump using local controls sited on the tank top.

The cargo surveyor began filling his sample cylinder from the designated tank sampling point. After a few minutes, the cargo alarm klaxon sounded on deck. The chief officer walked around the tank dome and, using a local control, stopped the klaxon from sounding. He assumed the alarm indicated that the cargo pump had tripped, but he could not be certain without going to the cargo office. A few moments later, the klaxon sounded again. The chief officer then noticed a large cloud of white vapor advancing down the deck towards him. He quickly ran aft, taking hold of the cargo surveyor, hitting the emergency shutdown (ESD) button as he passed by. They managed to reach the shelter provided by the accommodation before the cloud overtook them. A little less than 600 kilograms of liquid and vapor VCM had erupted from the vessel's forward cargo tank mast riser after the forward tank had become over-pressurized.

Table 6
Hierarchy of HOFs in the second accident.

Nodes/errors	Descriptions	States
Level 0: accidents		
Eruption to form vapor cloud	Vinyl Chloride Monomer had erupted to form a large cloud of white vapor cloud.	Yes, no
Level 1: unsafe acts		
Override safety feature	It was common to use override switch during operations.	Yes, no
Not wear PPE	Personnel did not wear proper personal protective equipment.	
No closed loop sampling	The cargo survey not used "closed loop sampling".	
No double valve segregation	The chief officer habitually left manual valves open for expediency.	
Slow response to alarm	Not manning cargo office led to alarms not being positively and immediately identified.	
Not stop pump promptly	The chief officer did not stop the cargo pump when he became aware of the first deck cargo alarm.	
Level 2: preconditions for unsafe acts		
Poor liaison	A poor liaison between vessel's staff and those on the terminal, both parties carrying out their roles in isolation.	High, medium, low
Not uncover deficiencies	Gas carrier inspections and vetting did not uncover the ship or shore deficiencies in the operational procedures.	
Overload	Cargo tanks were loaded in excess of maximum allowable.	Yes, no
No preparation work	Chief officer could not plan ahead and not prepared.	
Insufficient sample point	The aft dome of the vessel's after tank is not equipped with sufficient sample points.	
No pre-operational check	Checklists were not completed prior to the operation starting.	
Level 3: unsafe supervision		
No vetting inspection	Neither EVC, nor Agility, made any other vetting inspections	High, medium, low
Lack information	The shore emergency response was initially hampered by a lack of information from the vessel	Yes, no
Ineffective inspection	The owner's inspection program was not effective in uncovering and halting poor operational practices.	
Not maintain oversight	No-one maintaining an oversight of the cargo operations	
No forewarned cargo sampling	The chief officer did not have prior warning that cargo sampling, necessitating the use of cargo pumps, was required.	
Not manned cargo office	The cargo office was not manned during the critical stages of cargo operations	
Level 4: organizational influences		
Not enforcing safety standard	The safe system existed on paper in the vessel's safety management system, but was not put into practice.	High, medium, low
Inappropriate safety awareness	The chief officer's decision not to go to the cargo office to determine what had caused the alarm, indicated an inappropriate level of safety awareness.	
External muster point	Muster point was outside on deck	Yes, no
No cargo control room	There is not a cargo control room.	
No communication means	The vessel had no means of direct communication with the terminal	
No experienced staff	Neither EVC nor Agility employed experienced permanent staff to call on to undertake such inspections	
Inexperienced chief officer	Newly promoted and relatively inexperienced masters and chief officers sail together.	

3.2.1. Applying the proposed model

After reviewing the accident report from MAIB, the accident is defined as "Eruption to form vapor cloud". The 6 "DANGER" steps of the proposed model are carried out to analyze the critical HOFs of the second accident. The list of HOFs is shown in Table 6. With the nodes and states defined, the BN of "Eruption to form vapor cloud" is built in Fig. 7. After all the CPTs are elicited by integrating fuzzy AHP with decomposition method as shown in Section 2.2, the quantitative analysis can be performed using Bayesian inference. The posterior probabilities of the HOF nodes are shown in Fig. 8.

3.2.2. Sensitivity analysis and results

Sensitivity analyses are conducted to validate the proposed model. The importance degree of HOFs regarding to the node "Eruption to form vapor cloud" can be assessed using entropy reduction (mutual information).

The prior probability, posterior probability and mutual information of each HOF are compared as shown in Table 7.

From Table 7, we can see that the posterior probability of "Not_enforcing_safety_standard" among the nodes of level 4 increase most largely given the accident occurrence. It again highlights the need of enforcing all crews to strictly follow safety standard. Among the nodes of level 3, the posterior probability of the node "No_forewarned_cargo_sampling" has the largest increment given the accident occurs. This suggests that the occurrence of the accident is likely due to not providing prior warning of cargo sampling. Among the nodes of level 2, the posterior probability of the node "Not_uncover_deficiencies" and "No_preparation_work" have the largest increment when the accident occurs. It suggests "Not_uncover_deficiencies" and "No_preparation_work" contribute significantly to the occurrence of the accident. The posterior probability of the node "No_double_valve_segregation" and "Slow_response_to_alarm" have the larger increase among the nodes of level 1. It highlights the need of maintaining double valve segregation and immediate responding to alarm.

While the 5% step by step reduction of prior probability of each organizational node varies from 5% to 30%, the reduction rates of accident probability are calculated as shown in Fig. 9. From Fig. 9, it can be seen that the probability of accident has the largest reduction when the prior probability of "Not_enforcing_safety_standard" decreases the same as other factors. It again highlights that "Not_enforcing_safety_standard" is the most important HOF. Thus, the probability of "Eruption to form vapor cloud" accidents would drastically be reduced by enforcing safety standard. Given the occurrence of the accident, the change rate from prior probability to posterior probability of each organizational factor at different prior probability is represented in Fig. 10.

From Fig. 10, we can see that the posterior probability of "Not_enforcing_safety_standard" has the largest change rate from prior probability. This is consistent with the inference made earlier that the occurrence of accident is sensitive to the node "Not_enforcing_safety_standard", and hence there is reason to believe that the model is stable to input variability.

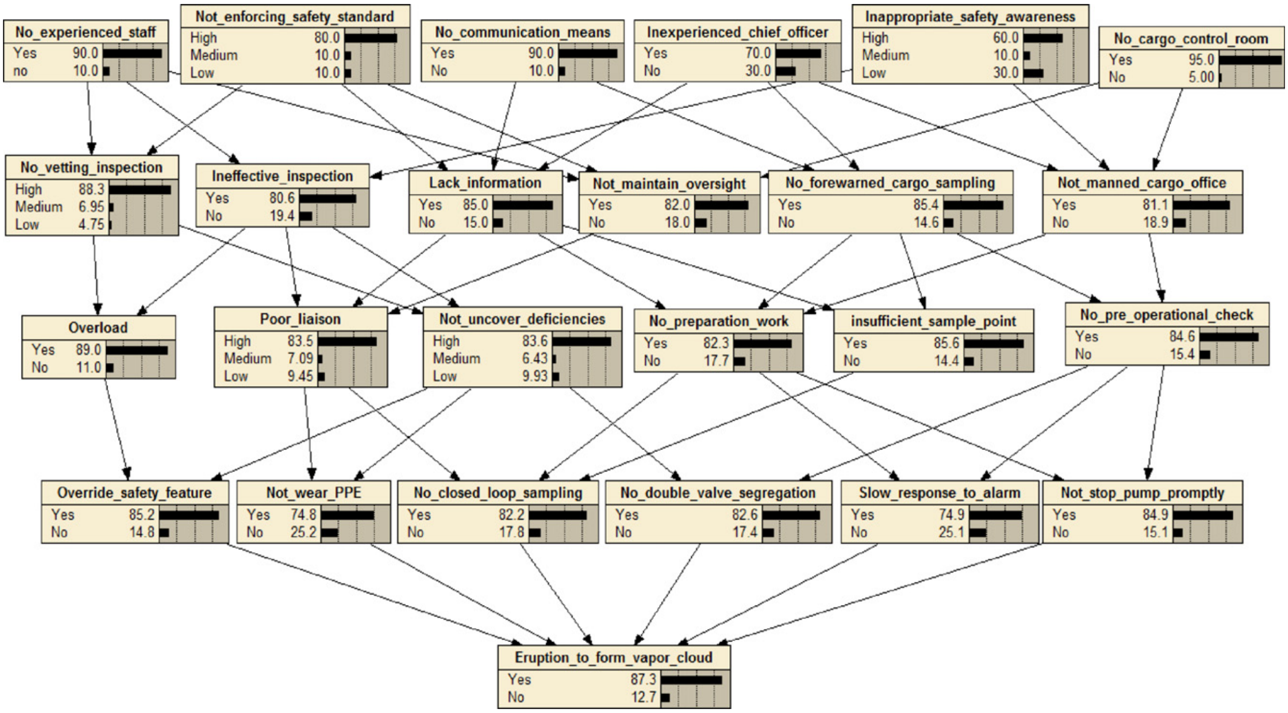

Fig. 7. Graphical representation of the second accident with prior probabilities.

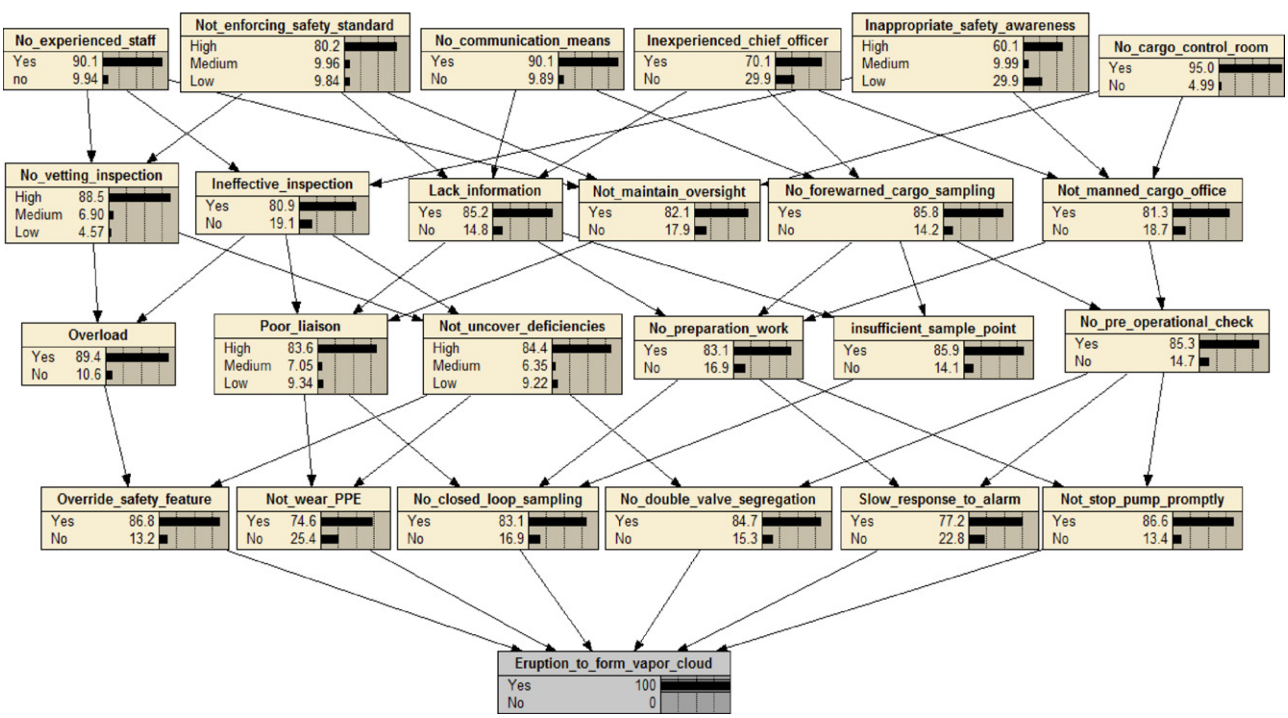

Fig. 8. Posterior probabilities of the human factor given the second accident happened.

From the sensitivity analysis, we can know that the model satisfies the three axioms presented in Section 2.3, which allows us to conclude that the inference made earlier is reliable. From above BN inference, important safety measures corresponding to above major accident contributors can be derived to prevent the similar accidents from recurring:

- All crews should strictly follow the safety standards and put the safety management system into practice.
- Have the vessel advised about cargo sampling prior to arrival and the chief office should prepare well.
- The charterer should make vetting inspections and employ permanent staff with marine gas carrier experience to call on to undertake such inspections.
- When a tanker arrives alongside a terminal, she should do a lot of preparation work before loading or discharging cargo. The ship owner's operating instructions must be carefully written to avoid putting undue pressure on crews.

Table 7
Mutual information of prior probability and posterior probability for each HOF.

Organizational factor	Prior probability (%)	Posterior probability (%)	Change rate of probability (%)	Mutual information
Node of level 4: organizational influences				
No_experienced_staff	90	90.3	0.333	2.003e−005
Not_enforcing_safety_standard	80	80.8	1	0.0001506
No_communication_means	90	90.2	0.222	6.779e−005
Inexperienced_chief_officer	70	70.1	0.143	2.206e−005
Inappropriate_safety_awareness	60	60.4	0.667	1.726e−005
No_cargo_control_room	95	95	0	2.878e−007
Node of level 3: unsafe supervision				
No_vetting_inspection	88.3	89.3	1.133	0.000379
Ineffective_inspection	80.6	82	1.737	0.000223
Lack_information	85	85.7	0.824	0.000186
Not_maintain_oversight	83	83.5	0.602	2.376e−005
No_forewarned_cargo_sampling	85.4	85.9	0.586	0.0006016
Not_manned_cargo_office	81.7	82	0.367	7.37e−005
Node of level 2: preconditions for unsafe acts				
Overload	89	90.1	1.236	0.000507
Poor_liaison	83.5	85.4	2.275	9.378e−005
Not_uncover_deficiencies	83.6	87.9	5.144	0.00268
No_preparation_work	82.3	82.8	0.608	0.00218
insufficient_sample_point	85.6	85.7	0.117	0.000332
No_pre_operational_check	84.7	86	1.535	0.00172
Node of level 1: unsafe acts				
Override_safety_feature	85.2	89.5	5.047	0.00864
Not_wear_PPE	74.8	89.4	19.52	7.771e−005
No_closed_loop_sampling	82.2	82.6	0.487	0.00258
No_double_valve_segregation	82.6	90.3	9.322	0.0139
Slow_response_to_alarm	74.9	76.8	2.537	0.013
Not_stop_pump_promptly	84.9	85.2	0.353	0.00901

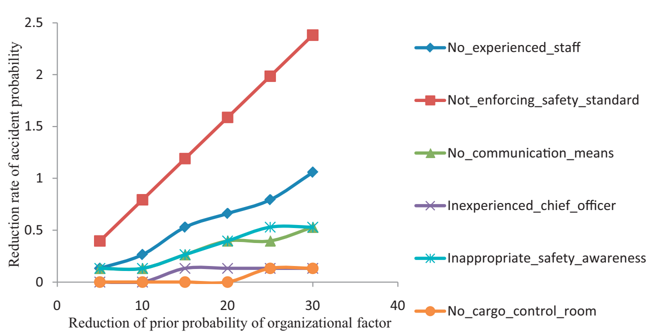

Fig. 9. Effect of change in prior probabilities of each organizational factor on the probabilities of the second accident.

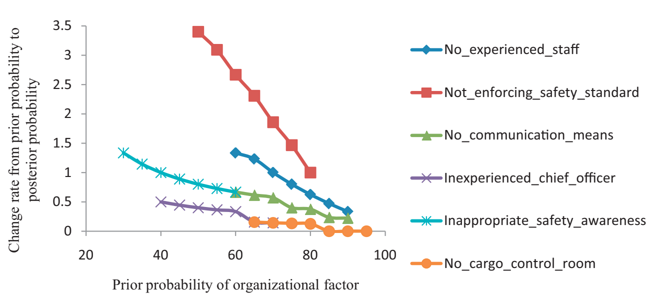

Fig. 10. Effect of change in prior probability of organizational factor on posterior probability in the second accident.

- Maintain double valves segregation system to avoid cargo transfer from one tank to the other as long as one of the 98% alarm and shutdown system is placed in override position.
- The chief officer should take immediate steps to stop the operation when the cargo alarm sound and ascertain the true nature of the alarm.
- Avoid overriding the 98% alarm/shutdown system by limit full cargo allowance.
- The ship shore checklist should be completed by the loading master and the chief officer prior to cargo operations.
- All personnel involved must wear appropriate protective equipment in case there is a risk from toxic gas or a liquid spill is present on deck.
- Evaluate the performance of the chief officer and establish further actions to monitor performance and/training needs.
- Means for (emergency) communication between the vessel and the terminal is established as first priority and emergency contact numbers are available before commencing any cargo operations including cargo sampling.

4. Conclusion

From the application of the model to those two case studies, it can be concluded that the model is useful in investigating HOFs for the derivation of safety interventions and "Not_enforcing_safety_standard" generally contribute mostly to the accident occurrence.

The application of HFACS allows a complete identification of HOFs, both active and latent, that are leading causes of accidents. The hierarchal structure of HFACS encourages investigators to seek out latent HOFs, which are often neglected in accident investigations. The model enables a quantitative assessment by using BN. BN enhances the ability of HFACS by allowing investigators or experts to quantify the degree of relationships among the HOFs. Fuzzy AHP is used to reduce the subjective biases by avoiding the need of defining exact probability for the nodes' states. The decomposition method that is applied in CPT elicitation reduces the complexity by allowing probability calculation conditioning on each of the parent nodes separately.

Future work is suggested to be done on developing specific software which facilitates the application of the proposed model. In addition, the elicitation of CPT is still subjective and time consuming. Other methods of reducing subjective biasness and improving efficiency in CPT elicitation deserved to be further explored. Building standardized accident reporting systems and collecting enough HOF data of accidents are also urgent missions.

Acknowledgements

The authors would like to thank the editor Gianluca Li Puma and four anonymous reviewers for their valuable comments and suggestions, which are very helpful in improving this paper.

This paper is part of Singapore-Poland Joint Research Project entitled "Safety and Reliability of Complex Industrial System and Process" (SERC grant number 0721340050) granted by Singapore's Agency for Science, Technology and Research (A*STAR) and Poland's Ministry of Science and Higher Education(MSHE).

Appendix A. Background information

A.1. Human Factors Analysis and Classification System

HFACS is a reliable human error model that is able to assist investigators in the identification of HOFs and their relationships in an accident. Human error is usually defined as any deviation from the performance of a specified or prescribed sequence of actions [2]. HFACS describes human error at four levels: (1) the unsafe acts of operators, (2) preconditions for unsafe acts, (3) unsafe supervision (4) organizational influences. In other words, the HFACS framework goes beyond the simple identification of what an operator did wrong to provide a clear understanding of the reasons why the error occurred in the first place. In this way, errors are viewed as consequences of system failures or symptoms of deeper systemic problems; not simply the fault of the employee working at the "pointy end of the spear" [40].

A.2. Bayesian Network

A BN is a Directed Acyclic Graph (DAG), where $N=\{(V, E), P\}$. V and E are the nodes and edges respectively. P is the joint probability distribution over V [41]. The nodes represent discredited random variables and arcs represent probabilistic dependencies between the variables. As they handle uncertainty explicitly, they are suitable for examining systems containing complex and uncertain interactions [42].

Each of the nodes in V represents a variable and the directed edges in the set E that connect nodes represent the probabilistic dependency. Each node has a number of possible values called "states". Also, each of the nodes in the network is quantified with a CPT, which consists of the conditional probabilities given the states of the parent nodes. For each possible state of a node, conditional probability is specified with respect to all possible combinations of states of its parent nodes. The probabilities describing these relationships between the nodes were obtained through structured expert elicitations [43].

A.3. Fuzzy AHP

AHP is extensively used as a relative weight estimation technique in many areas [44]. AHP has the additional advantage of being easy to explain to the experts who need assess the different alternatives in a systematic way [45]. However, AHP involves human subjective evaluation that necessitates the use of decision-making under uncertainty. Due to the complexity and uncertainty involved in real world, it is sometimes unrealistic or even impossible to require exact judgments. Experts usually find that it is more confident to give interval judgments than fixed value judgments [46].

Inability of AHP to deal with the imprecision and subjective in the pair-wise comparison process has been improved by fuzzy AHP. Fuzzy AHP, which is an extension of AHP, is a useful tool for calculating the priority weight. Fuzzy AHP allowed experts to use linguistic expressions or fuzzy numbers to reflect the vagueness of human thought [47]. There are many fuzzy AHP methods, among which the newest modified fuzzy logarithmic least squares method is adopted in this paper.

Appendix B. Elicitation of CPT

Given the different state of node "Insufficient_check", the conditional probability of node "Not_check_equipment_defective" are shown in Table A.1.

When the state of node "Insufficient_check" is high, the conditional probability of "Not_check_equipment_defective" is calculated according to Eq. (5). The solution model is shown as follows:

```
objective...    f=e=sum((i,j)$(ord(i) ne ord(j)),
                (log(wl(i))-log(wu(j))-log(l(i,j)))*(log(wl(i))-log(wu(j))-log(l(i,j)))+(log(wm(i))-log(wm(j))-log(m(i,j)))*(log(wm(i))-log(wm(j))-log(m(i,j)))+(log(wu(i))-log(wl(j))-log(u(i,j)))*(log(wu(i))-log(wl(j))-log(u(i,j))));
first(i)...     wl(i)+sum(j$(ord(j) ne ord(i)),
                wu(j))=g=1;
second(i)...    wu(i)+sum(j$(ord(j) ne ord(i)),
                wl(j))=l=1;
third...        sum(i, wm(i))=e=1;
fourth...       sum(i, wl(i)+wu(i))=e=2;
fifth(i)...     wu(i)=g=wm(i);
sixth(i)...     wm(i)=g=wl(i);
Model fuzzy/all/;
option nlp=minos;
solve fuzzy using nlp
  minimizing f;
file results/results.txt/
put results;
loop(i, put i.tl, @12,
  wl.l(i):8:5, wm.l(i):8:5,
  wu.l(i):8:5/);
```

The optimum solution to the model is

$$w=\begin{bmatrix}(0.317, 0.43, 0.5)\\(0.335, 0.43, 0.578)\\(0.105, 0.143, 0.168)\end{bmatrix}$$

Substitute w into Eq. (6), we can get:$BNP_{wi}=(0.324, 0.343, 0.106)$

Given the different states of node "Insufficient_check", the conditional probability of node "Not_check_equipment_defective" are shown in Table A.2. Integrating the above calculation method with the decomposition method, the conditional probabilities of node "Not_check_equipment_defective" are shown in Table A.3.

Table A.1
Conditional probability of "Not_check_equipment_defective" given "Insufficient_check" (high).

Not_check_equipment_defective	High			Medium			Low		
S_1	(1, 1, 1)	(1/2, 1, 3/2)	(5/2, 3, 7/2)	(1, 1, 1)	(1/2, 2/3, 1)	(1/3, 2/5, 1/2)	(1, 1, 1)	(2/3, 1, 2)	(1, 1, 1)
S_2	(2/3, 1, 2)	(1, 1, 1)	(5/3, 3, 7)	(1, 3/2, 2)	(1, 1, 1)	(1/3, 3/5, 1)	(1/2, 1, 3/2)	(1, 1, 1)	(1/2, 1, 3/2)
S_3	(2/7, 1/3, 2/5)	(1/7, 1/3, 3/5)	(1, 1, 1)	(2, 5/2, 3)	(2, 5/2, 3)	(1, 1, 1)	(2, 5/2, 3)	(4/3, 5/2, 6)	(2, 5/2, 3)
w	0.324	0.343	0.106	0.200	0.207	0.407	0.233	0.120	0.470

Table A.2
Conditional probability of “Not_check_equipment_defective” given different states of “Insufficient_check”.

Not_check_equipment_defective	High			Medium			Low		
S_1	(1, 1, 1)	(1, 3/2, 2)	(5/2, 3, 7/2)	(1, 1, 1)	(1/2, 2/3, 1)	(1, 1, 1)	(1, 1, 1)	(1/3, 1, 3/2)	(5/2, 3, 7/2)
S_2	(1/2, 2/3, 1)	(1, 1, 1)	(5/4, 2, 7/2)	(1, 3/2, 2)	(1, 1, 1)	(1, 3/2, 2)	(2/3, 1, 3)	(1, 1, 1)	(5/3, 3, 21/2)
S_3	(2/7, 1/3, 2/5)	(2/7, 1/2, 4/5)	(1, 1, 1)	(1, 1, 1)	(1/2, 2/3, 1)	(1, 1, 1)	(2/7, 1/3, 2/5)	(2/21, 1/3, 3/5)	(1, 1, 1)
w	0.438	0.270	0.136	0.263	0.353	0.263	0.274	0.351	0.091

Table A.3
Conditional probability of “Not_check_equipment_defective” given “Insufficient_check” and”Not_enforcing_safety_standard”.

Insufficient_check	Not_enforcing_safety_standard	High	Medium	Low
High	High	0.5706	0.3717	0.0577
High	Medium	0.3642	0.5168	0.1190
High	Low	0.4054	0.5504	0.0442
Medium	High	0.4414	0.2807	0.2779
Medium	Medium	0.2263	0.3136	0.4601
Medium	Low	0.3330	0.4414	0.2256
Low	High	0.5152	0.1629	0.3219
Low	Medium	0.2698	0.1859	0.5443
Low	Low	0.4289	0.2827	0.2884

References

[1] A.R. Rothblum, Human error and marine safety, in: National Safety Council Congress and Expo, Orlando, FL, 2000.
[2] N. Leveson, A new accident model for engineering safer systems, Safety Science 42 (2004) 237–270.
[3] S. Rao, Safety culture and accident analysis – a socio-management approach based on organizational safety social capital, Journal of Hazardous Materials 142 (2007) 730–740.
[4] E. Oztekin, J.T. Ahmet, T. Luxhøj, James, An inductive reasoning approach for building system safety risk models of aviation accidents, Journal of Risk Research 13 (2010) 479–499.
[5] J. Reason, A systems approach to organizational error, Ergonomics 38 (1997) 1708–1721;
J. Reason, Managing the Risks of Organizational Accidents, Ashgate, Aldershot, 1997.
[6] J. Yu, N. Ahn, M. Jae, A quantitative assessment of organizational factors affecting safety using system dynamics model, Journal of Korean Nuclear Society 36 (2004) 64–72.
[7] Z. Mohaghegh, A. Mosleh, Incorporating organizational factors into probabilistic risk assessment of complex socio-technical systems: principles and theoretical foundations, Safety Science 47 (2009) 1139–1158.
[8] Z. Mohaghegh, R. Kazemi, A. Mosleh, Incorporating organizational factors into probabilistic risk assessment (PRA) of complex socio-technical systems: a hybrid technique formalization, Reliability Engineering and System Safety 94 (2009) 1000–1018.
[9] Z. Mohaghegh, A. Mosleh, Measurement techniques for organizational safety causal models: characterization and suggestions for enhancements, Safety Science 47 (2009) 1398–1409.
[10] K. Øien, A framework for the establishment of organizational risk indicators, Reliability Engineering & System Safety 74 (2001) 147–167.
[11] D.A. Wiegmann, S.A. Shappell, Human error analysis of commercial aviation accidents: application of the Human Factors Analysis and Classification system (HFACS), Aviation, Space, and Environmental Medicine 72 (2001) 1006–1016.
[12] S. Shappell, C. Detwiler, K. Holcomb, C. Hackworth, A. Boquet, D.A. Wiegmann, Human error and commercial aviation accidents: an analysis using the human factors analysis and classification system, Human Factors 49 (2007) 227–242.
[13] N.S. Olsen, S.T. Shorrock, Evaluation of the HFACS-ADF safety classification system: inter-coder consensus and intra-coder consistency, Accident Analysis and Prevention 42 (2010) 437–444.
[14] R. Gordon, R. Flin, K. Mearns, Designing and evaluating a human factors investigation tool (HFIT) for accident analysis, Safety Science 43 (2005) 147–171.
[15] S. Rao, Safety culture and accident analysis-a socio-management approach based on organizational safety social capital, Journal of Hazardous Materials 142 (2007) 730–740.
[16] J. Ren, I. Jenkinson, J. Wang, D.L. Xu, J.B. Yang, A methodology to model causal relationships on offshore safety assessment focusing on human and organizational factors, Journal of Safety Research 39 (2008) 87–100.
[17] J.T. Luxhøj, D.W. Coit, Modeling low probability/high consequence events: an aviation safety risk model, in: Reliability and Maintainability Symposium. RAMS'06, 2006, pp. 215–221.
[18] J.T. Luxhøj, Probabilistic Causal Analysis for System Safety Risk Assessments in Commercial Air Transport, Investigating and Reporting of Incidents and Accidents (IRIA), Williamsburg, VA, 2003, pp. 17-38.
[19] A. Öztekin, J.T. Luxhøj, Hazard, safety risk, and uncertainty modeling of the integration of unmanned aircraft systems into the national airspace, in: 26th Congress of International Council of the Aeronautical Sciences, Anchorage, Alaska, 2008, pp. 14–29.
[20] Y. Lu, Q.M. Li, Z.P. Zhou, Safety risk prediction of subway operation based on fuzzy Bayesian network, Journal of Southeast University (Natural Science Edition) 40 (2010) 1110–1114.
[21] M. Grabowski, Z.Y. You, Z. Zhou, H.W. Song, M. Steward, B. Steward, Human and organizational error data challenges in complex large-scale system, Safety Science 47 (2009) 1185–1194.
[22] H.H. Chen, A.H.I. Lee, Y.H. Tong, Prioritization and operations NPD mix in a network with strategic partners under uncertainty, Expert Systems with Applications 33 (2007) 337–346.
[23] A.N. Blair, B.M. Ayyub, W.J. Bender, Fuzzy stochastic risk-based decision analysis with the mobile offshore base as a case study, Marine Structures 14 (2001) 69–88.
[24] S.K. Lee, G. Mogi, J.W. Kim, B.J. Gim, A fuzzy analytic hierarchy process approach for assessing national competitiveness in the hydrogen technology sector, international Journal of Hydrogen Energy 33 (2008) 6840–6848.
[25] P.J.M. Van Laarhoven, W. Pedrycz, A fuzzy extension of Saaty's priority theory, Fuzzy Sets and Systems 11 (1983) 229–241.
[26] Y.M. Wang, T.M.S. Elhag, Z.S. Hua, A modified fuzzy logarithmic least squares method for fuzzy analytic hierarchy process, Fuzzy Sets and Systems 157 (2006) 3055–3071.
[27] D.Y. Chang, Applications of the extent analysis method on fuzzy AHP, European Journal of Operational Research 95 (1996) 649–655.
[28] Y.M. Wang, L. Luo, Z.S. Hua, On the extent analysis method for fuzzy AHP and its applications, European Journal of Operational Research 186 (2) (2008) 735–747.
[29] M. Celik, S. Cebi, Analytical HFACS for investigating human errors in shipping accidents, Accident Analysis & Prevention 41 (2009) 66–75.
[30] T.A. Chiang, Z.H. Che, A fuzzy robust evaluation model for selecting and ranking NPD projects using Bayesian belief network and weight-restricted DEA, Expert Systems with Applications 37 (2010) 7408–7418.
[31] C.R. Fox, R.T. Clemen, Subjective probability assessment in decision analysis: partition dependence and bias toward the ignorance prior, Management Science 51 (2005) 1417–1432.
[32] K.S. Chin, D.W. Tang, J.B. Yang, S.Y. Wong, H.W. Wang, Assessing new product development project risk by Bayesian network with a systematic probability generation methodology, Expert Systems with Applications 36 (2009) 9879–9890.
[33] M. Haghighi, A. Divandari, M. Keimasi, The impact of 3D e-readiness on e-banking development in Iran: a fuzzy AHP analysis, Expert Systems with Applications 37 (2010) 4084–4093.
[34] A.N. Paralikas, A.I. Lygeros, A multi-criteria and fuzzy logic based methodology for the relative ranking of the fire hazard of chemical substances and installations, Process Safety and Environmental Protection 83 (2005) 122–134.
[35] T.Y. Hsieh, S.T. Lu, G.T. Tzeng, Fuzzy MCDM approach for planning and design tenders' selection in public office buildings, International Journal of Project Management 22 (2004) 573–584.
[36] G.A. Magdy, D. David, Evaluating investments in advanced manufacturing technology: a fuzzy set theory approach, The British Accounting Review 33 (2001) 455–489.
[37] Z.l. Yang, S. Bonsall, J. Wang, Fuzzy rule-based Bayesian reasoning approach for prioritization of failures in FMEA, IEEE Transactions on Reliability 57 (2008) 517–528.
[38] B. Jones, I. Jenkinson, Z. Yang, J. Wang, The use of Bayesian network modelling for maintenance planning in a manufacturing industry, Reliability Engineering and System Safety 95 (2010) 267–277.
[39] Marine Accident Investigation Branch, Report on the Investigation of the Release of Cargo Vapors Resulting in Two Casualties on Board the Chemical Tanker Jo Eik at the Vopak Terminal Teesport

on 6 May, 2009 [Online] Available at: http://www.maib.gov.uk/publications/investigation_reports/2009/jo_eik.cfm.

[40] D.A. Wiegmann, S. Shappell, A Human Error Approach to Aviation Accident Analysis: The Human Factors Analysis and Classification System, Ashgate Publishing Ltd, Aldershot, 2003.

[41] J. Williamson, Bayesian Nets and Causality: Philosophical and Computational Foundations, Oxford University Press, New York,2005.

[42] I. Hellea, T. Lecklinb, A. Jolmac, S. Kuikka, Modeling the effectiveness of oil combating from an ecological perspective – a Bayesian network for the Gulf of Finland, the Baltic Sea, Journal of Hazardous Materials 185 (2011) 182–192.

[43] N.A Stiber, M. Pantazidou, M.J. Small, Embedding expert knowledge in a decision model: evaluating natural attenuation at TCE sites, Journal of Hazardous Materials 110 (2004) 151–160.

[44] O.S. Vaidya, S. Kumar, Analytic hierarchy process: an overview of applications, European Journal of Operational Research 169 (2006) 1–29.

[45] P. Aragonés-Beltrán, J.A. Mendoza-Roca, A. Bes-Piá, M. García-Melón, E. Parra-Ruiz, Application of multicriteria decision analysis to jar-test results for chemicals selection in the physical–chemical treatment of textile wastewater, Journal of Hazardous Materials 164 (2009) 288–295.

[46] C. Kahraman, U. Cebeci, Z. Ulukan, Multi-criteria supplier selection using fuzzy AHP, Logistics Information Management 16 (2003) 382–394.

[47] C. Kahraman, I. Kaya, S. Cebi, A comparative analysis for multiattribute selection among renewable energy alternatives using fuzzy axiomatic design and fuzzy analytic hierarchy process, Energy 34 (2009) 1603–1616.