A methodology to model causal relationships on offshore safety assessment focusing on human and organisational factors

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ABSTRACT:

Focusing on the human beings and the organisations, this paper aims to contribute to offshore safety assessment by proposing a methodology to model causal relationships. The methodology is proposed in a general sense that it will be capable of accommodating modelling of multiple risk factors considered in offshore operations and will have ability to deal with different types of data which may come from different resources. Reason's "Swiss cheese" model is used to form a generic offshore safety assessment framework and Bayesian Network (BN) is tailored to fit into the framework to construct a causal relationship model. The proposed framework uses a five-level-structure model to address latent failures within the causal sequence of events. The five levels include Root causes level, Trigger events level, Incidents level, Accidents level and Consequences level. To analyse and model a specified offshore installation safety, a BN model will be established following the guideline of the proposed five-level framework. A range of events will be specified, and the related prior and conditional probabilities regarding the BN model will be assigned based on the inherent characteristics of each event. This paper shows that James Reason's "Swiss cheese" model and BN can be jointly used in offshore safety assessment. On the one hand, the five-level conceptual model is enhanced by BNs that are capable of providing graphical demonstration of inter-relationships as well as calculating numerical values of occurrence likelihood for each failure event. Bayesian inference mechanism also makes it possible to monitor how safety situation changes when information flows travel forwards and backwards within the networks. On the other hand, BN modelling is heavily relied on experts' personal experiences and is therefore highly domain specific. "Swiss cheese" model is such a theoretic framework that it is based on solid behavioural theory and therefore can be used to provide roadmap for BN modelling. A case study of the collision risk between a Floating Production, Storage and Offloading (FPSO) unit and authorised vessels caused by human and organisational factors (HOFs) during operations is used to illustrate the application of the proposed methodology.

Keywords: Safety assessment, Offshore safety, Human error, Bayesian networks.

1. Introduction

In the UK it is estimated that about 26,000 people work offshore on a regular basis on fixed production platforms, mobile drilling rigs, or FPSOs (UK Jobs4U, 2006). Over the past two decades, a number of serious accidents including the Piper Alpha tragedy that claimed 165 lives have attracted public concerns to offshore safety and reliability. The studies on how similar accidents may be prevented have been actively carried out at both the national and international levels.

Surveys conducted by different individuals and safety bodies have revealed that about 75-96% of marine casualties are fully/partially contributed to human and organizational errors (Rothblum, 2000). Studies (Bryant, 1991; UK. P&I Club, 1992; Cormier, 1994; Transportation Safety Board of Canada, 1994) have shown that HOFs contribute to:

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- 75% of fires and explosions.
- 75% of allisions.
- 89-96% of collisions.
- 79% of towing vessel groundings.
- 84-88% of tanker accidents.

Accidents are not usually caused by a single failure or mistake, but by the confluence of a whole series, or chain, of errors. In offshore operations, accidents are often initiated by errors induced by technical failures, human and organisational factors (HOFs) or a combination of both. To reduce the risk, some risk and reliability analysis techniques have been used in the UK offshore industry for almost 20 years, and have contributed to the reduction of the incidence rate of severe accidents in many circumstances. These techniques, however, have traditionally focused more on technical aspects of design, construction and operation, than on human and organisational aspects. They mainly use descriptive, not predictive models, and are thus not very effective in determining how to prevent accidents. Therefore, there is a need for rethinking the methodology of offshore safety assessment.

The nature of offshore safety is that the causes of an accident on an offshore installation may be found in the complexity of the relationships implicit in the design, procedures, equipment, environment, operations, etc. In order to gain a full understanding and comprehensive awareness of safety in a given situation, it is necessary to use a systemic approach to consider all the aspects that may lead to hazardous events. In offshore safety assessment, a systemic approach means considering all functional entities that constitute the offshore system as a whole, exploring patterns and inter-relationships within subsystems and seeing undesired events as the products of the working of the system (Beard, 1989).

However, applying a holistic risk analysis to offshore installations could have some hurdles. Particularly, in dealing with HOFs, there are some difficulties:

- It is hard to agree on what HOF really means. This is because the definition of HOF varies considerably. HOF may concentrate on aspects of manpower, organisation, management, allocation of responsibility, automation, communication, skills, training, health, safety, and the prevention of errors or accidents, or any one of a number of other possibilities.
- It is hard to measure HOFs as to what measures can be used and how those measures are inter-related to form a proper assessment framework.
- It is hard to collect empirical data from industry. There is often inadequate data or imprecise information available when carrying out HOFs analysis. Although several maritime accident databases have been built up, the data contained in them are only marginally relevant to the human and organizational errors.
- It is hard to establish a uniformed framework to model HOFs related offshore safety issues. This is because offshore safety assessment must take all major risk factors into account. When those factors involve HOFs, modelling becomes very complicated e.g. exploring the relationships among HOFs needs a deep

understanding of offshore safety issues and may involve domain experts' personal experiences that are difficult to be treated in a comprehensive way.

- It is hard to use conventional assessment approaches to deal with HOFs. Conventional assessment approaches often fall short in their ability to permit the incorporation of subjective and/or vague terms.

By focusing on the human beings and the organisations as well as the technology in offshore safety assessment, this paper aims to contribute to offshore safety assessment by proposing a methodology to model causal relationships. Such a methodology will be proposed in a general sense that it will be capable of accommodating modelling of multiple risk factors considered in offshore operations and will have ability to deal with different types of data which may come from different resources. When such a framework is applied to a particular offshore installation, risk factors specific to the installation investigated can be added to the generic framework to model the actual situations. Reason's "Swiss cheese" model is used to form a generic offshore safety assessment framework and BN is used to construct a causal relationship model. Based on the literature review, a five-level framework will be proposed to address latent failures within the causal sequence of events. The five-levels include Root causes level, Trigger events level, Incidents level, Accidents level and Consequences level. A range of events will be specified based on the inherent characteristics of each event. To analyse and model a particular offshore installation safety, a BN model will be established and the related prior and conditional probabilities regarding the model will also be investigated. A number of algorithms will be used to compute and analyse the experimental data.

The objectives of this paper are therefore set up as follows:

- Develop a framework to integrate all hazardous events into a multi-level model to produce an overall picture of the offshore operations safety.
- Identify constituent levels of the framework and establish the causal relationships between the levels.
- Identify latent errors (human error, equipment failure, etc.) of each level.
- Investigate how to use BNs to establish causal relationship model.
- Justify the proposed methodology by case study.

The rest of this paper is organised as follows. Section 2 briefly reviews the major problems and methods in offshore risk analysis. Section 3 proposes a HOFs model and an offshore risk analysis flow diagram. Section 4 gives a case study of collision risk assessments between FPSO and authorised vessels during operations. Section 5 provides the conclusions of the paper. Appendices 1-3 give the background of fuzzy set theory, BN model, and f-weighted valuation function for data transformation, respectively. Appendix 4 provides the case study data and Appendix 5 gives the results of sensitivity analysis.

2. Review of literature

Human and organizational errors refer to unacceptable or undesirable performance on the part of an individual (human error) or a group (organizational error) that can result in unanticipated or undesirable effects (US Coast Guard, 2004). According to the UK CHIRP (Confidential Human Factors Incident Reporting Programme), the subject of human factors deals with all the human elements of people in man-machine systems. Therefore, it should cover aspects of manpower, organisation, management, allocation of responsibility, automation, communication, skills, training, health, safety, and the prevention of errors or accidents, as well as the traditional design and layout of equipment and workplaces. Thus the concept of a HOF is extremely broad, for example, the people concerned could be all those associated with the total system, not merely the crews, but also designers, equipment suppliers, maintainers, support personnel, instructors and so on.

According to Senders & Moray (1991) human error is a result of observable behaviour originated from psychological processes on different levels, evaluated against some performance standards, initiated by an event in a situation where it was possible to act in another way considered to be right. Hollnagel (1998), however, pointed out that human errors cannot be observed directly. It is only possible to observe human errors indirectly by observation of human behaviours. Therefore a definition of human errors must include three parts:

- Evaluation of human behaviour against performance standard or criterion.
- Event which results in a measurable performance shortfall such that the expected level is not met by the acting agent.
- A degree of volition such that the actor has the opportunity to act in a way that will not be considered erroneous.

Human errors may cause accident but accident may not be caused purely by human errors. Accident is caused by the confluence of a whole chain of errors. In order to reduce casualties, safety analysts must first identify the type of human and organizational errors that cause casualties and then study and determine how accidents happen. To identify and group HOFs are extremely difficult, because the type of human and organisational errors varies. For instance, Draper (2000) classified human and organisational errors into four categories:

- Slips: Actual behaviour fails to conform to the intention/plan (wrong action).
- Lapses: Actual behaviour fails to conform to the intention/plan (omitted action, memory failure).
- Rule-based mistake: wrong rule selected for action i.e. behaviour conforms to immediate intention, but intention, while consistent with a viable rule for action, is inconsistent in this case with wider knowledge.
- Knowledge-based mistake: error in generating a novel plan for a novel situation.

From human behaviour and organisation theory point of view, some researchers investigated human and organisational error classification and grouped them into four basic categories: *skill-based errors, decision based errors, perceptual errors* and *violation errors* (Baker and MaCafferty, 2005). Each basic group could include some factors. Significant factors associated with *skill-based errors*, for example, may include *Failed to prioritise attention, Inadvertent use of system controls, Omitted step in procedure, Omitted checklist item, Poor technique, Over-controlled the system.* Decision based errors include *Improper procedure, Misdiagnosed emergency, Wrong response to emergency, Exceeded ability, Inappropriate maneuver, Poor decision.* Perceptual errors happen due to *Misjudged distance, Visual illusion.* Violation errors may include *Violated training rules, Failed to properly prepare for the mission, Not current/qualified for the mission, Intentionally exceeded the limits of the vessel*.

Recently many individuals and research bodies studied the major human and organisational errors in different industries. UK Energy Institute (2006), for instance, published top ten human and organisational factor issues facing onshore major hazards sites in the chemical and allied industries. In general, different domain experts may use different categories to classify human and organisational errors, each category may have different types of errors. This requires analysts to develop novel methods that are able to find a right balance in dealing with general safety assessment and domain specific analysis. In doing so, two popularly recognised methods are highlighted in this literature study. The rest of this Section is the discussion of the two methods: Reason's "Swiss cheese" model and BN model.

Based on human behaviour and organizations theory, Reason (1990) proposed the "Swiss cheese" model to study HOFs (see Figure 1). This model demonstrates how generic human and organisational errors can be decomposed into logical, mutually exclusive categories, each influencing the next. In the model, each slice of cheese represents a safety barrier or precaution relevant to a particular hazard. The holes in the cheese slices represent latent errors (human error, equipment failure, etc.) waiting to happen. The defensive barriers are like dynamic slices of Swiss cheese against accidents and incidents, with the holes constantly subject to changes in size and location. When the holes line up, meaning that all the defences fail and a system's latent vulnerabilities are exposed, then an incident occurs. A significant attribute of Reason's model is that each of the contributing factors is seen as necessary but not sufficient on its own to cause the occurrence of an accident.

Following Reason's "Swiss cheese" model, many researchers proposed similar taxonomies. For example, Swain and Guttman (1983) paid more attention on organizational conditions that contribute to human errors. Miller and Swain (1987) defined the term performance shaping factors which include: *inadequate work space and work layout, poor environmental conditions, inadequate human engineering design, inadequate training and job aids, poor supervision*. Boniface and Bea (1996) linked the concept of performance shaping factors to Reason's human error framework and developed a tool for analysing maritime accidents. Other researchers (Perrow, 1984; Roberts, 1990; Sagan, 1994; Pauchant and Mitroff, 1992) studied the impact of organizational culture on the incidence of human errors.

What makes the "Swiss cheese" model particularly useful is that it forces investigators to address latent failures within the causal sequence of events. However, this model is simply a theoretical framework, not a prescriptive investigation technique. It has few details on how to apply it in a real-world setting. One needs to find out what "holes" are, how big they are and how they are correlated, so that they can be detected and corrected before an accident occurs (Wiegmann and Shappell, 1997).

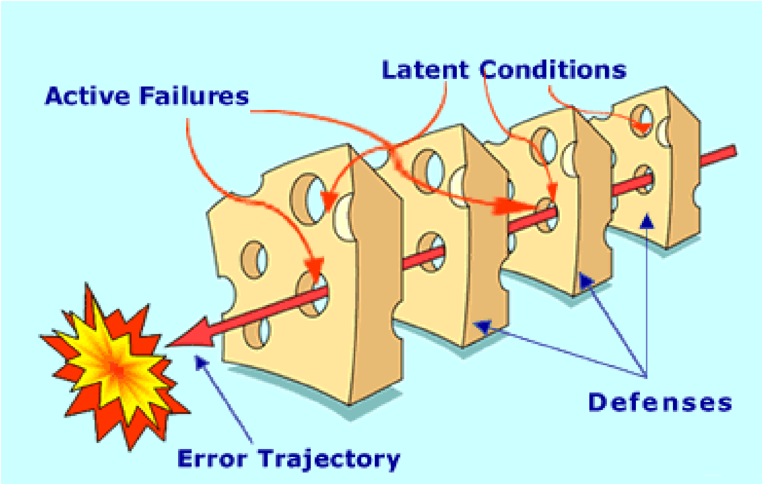

Figure 1. Reason's model

To make good use of Reason's model, one way is to use quantitative analysis tool to enhance "Swiss cheese" model. Particularly in exploring causal relationships in offshore safety assessment, conventional tools have been widely used including Fault Tree Analysis (FTA), Event Tree Analysis (ETA), Failure Mode and Effects Analysis (FMEA), and Hazard and Operability Studies (HAZOP). However, all those methods may not be well suited for dealing with systems in situations of HOFs involved and thus having a high level of uncertainty.

BN has been increasingly recognised as a powerful tool to support causal inference in situations where data for analysis is with a high level of uncertainty. BN is capable of replicating the essential features of plausible reasoning in a consistent, efficient and mathematically sound way. Critically it has the function to retract belief in a particular case when the basis of that belief is explained away by new evidence (Pearl, 1988). BN has been used in many different domains. In recent years, BN has attracted increasing attentions because of the new algorithms (Lauritzen and Spiegelhalter, 1998; Zhang, Bai et al. 2004). BN has several features:

- It has the ability to incorporate new observations in the network and to predict the influence of possible future observations onto the results obtained (Heckerman and Breese, 1996).
- It can not only let users observe the relationships among variables easily, but also give an understandable semantic interpretation to all the parameters in a BN (Myllymaki, 2005). This allows users to construct a BN directly using domain expert knowledge.
- Furthermore, a BN has both a causal and probabilistic semantics, and thus it provides an ideal representation scheme for combining prior knowledge (which often comes in causal form) and data.
- It can handle missing and/or incomplete data. This is because the model has the ability to learn the relationships among its nodes and encodes dependencies among all variables (Heckerman, 1997).

- It can conduct inference inversely.

Many applications have proven that BN is a powerful technique for reasoning relationships among a number of variables under uncertainty. For example, BN has been applied to ecological risk assessment (Hayes, 1998). It has also been applied to fault diagnosis in complex nuclear power systems (Kang and Golay, 1999). However, when using BN in offshore safety assessment, there are some difficulties e.g. how to deal with incomplete and vague information that largely exists both at the early system design stage and during normal operations. In the prior research, approximate reasoning approaches have been proposed (Wang, Yang et al. 1995; Sii, Ruxton et al. 2001; Ren, Jenkinson et al. 2005). In dealing with HOFs in offshore safety assessment, however, BN is mainly criticised with the difficulty of modelling how HOFs are inter-related to form a logic chain/network and what is the underlying relationships between them. This difficulty is mainly caused by lack of guidelines which are based on human behaviours and organisation theories. Another difficulty is the utilisation of a probability measure to assess uncertainty. It arguably requires too much precise information in the form of prior and conditional probabilities, and such information is often difficult or impossible to obtain. In particular, in dealing with indirect relationships, even domain experts may find that it is usually difficult to make precise judgments with crisp numbers (i.e. to assign an exact value to the probability that consequences happen given the occurrence of an event). In many circumstances, a verbal expression (e.g. "*very unlikely*") of probabilistic uncertainty may be more appropriate than numerical values.

Therefore, the "Swiss cheese" model can act as a high level modelling methodology whilst BN can be used as a low level modelling technique. This provides a potential of combining the two tools that may overcome shortcomings of each. In fact, the "Swiss cheese" model is mainly criticised for being simply a conceptual model with few details on how to apply it in a real-world setting. This weakness will be overcome by BNs that are capable of providing graphical demonstration of inter-relationships as well as numerical values of occurrence likelihood for each failure event. Bayesian inference mechanism also makes it possible to monitor how a safety situation changes when information flows travel forwards and backwards within the network. On the other hand, BN is mainly criticised for lack of guidelines in establishing causal model, that is, modelling is heavily dependent on experts' personal experiences and highly domain specific. The "Swiss cheese" model is such a theoretical framework based on solid behavioural theory and therefore can be used to provide a roadmap for BN modelling (Ren, Wang et al. 2006).

3. The HOFs model and offshore safety assessment framework

This section proposes a five-level HOFs model and provides offshore safety assessment framework.

3.1 The conceptual model for HOFs

Derived from the literature, the proposed methodology is based on the following assumptions:

- Accidents cannot be contributed to a single cause, but are the end result of a number of failures or mistakes, that is, they are caused by the confluence of a whole chain of errors. The relationships between those causes can be represented by causal chains or networks.

- Accidents are not caused by the occurrence of sudden unfavourable circumstances. Instead, they are mostly generated by HOFs which, under certain conditions, trigger an undesired event.
- All accidents and incidents have their trigger causes and root causes.
- Risk factors are dynamic in nature. Risk analysis must reflect their dynamic properties and therefore should be capable of dealing with dynamic information.

A causal conceptual model is proposed in this section (see Figure 2). The model uses five levels of hierarchical abstraction to describe the causal chain of HOFs safety assessment, each level providing a different cause/contributory model.

Level 1: The first level is about consequence. It describes the consequences of accident (e.g. personnel injury, loss of life, property damage, economic loss and environmental pollution).

Level 2: The second level is about accident. It refers to the offshore accidents which may include collision, powered grounding, drift grounding, foundering, structural failure and fire/explosion. Any event in this level may cause consequences and thus it is the causal level of consequence level.

Level 3: The third is the incident level. It includes all possible incidents that create an unsafe condition that may result in an accident. For instance, during a tandem offloading operation between an FPSO unit and a dynamically positioned (DP) shuttle tanker, drive-off incident may occur and thus may cause collision (accident).

Level 4: The fourth level is the trigger event level. Trigger events are those unsafe operator actions caused by human and organisational errors. Unsafe human actions, for example, may cause unexpected high hawser loads beyond the operational limits. Trigger events are immediate causes of an incident. They provide the conditions that allowed the events at the third level to occur.

Level 5: The fifth level is the root cause level. The factors at this level are often referred to as the root causes or systemic factors of an accident. Root causes affect trigger events. At this level, HOFs are the main concerns.

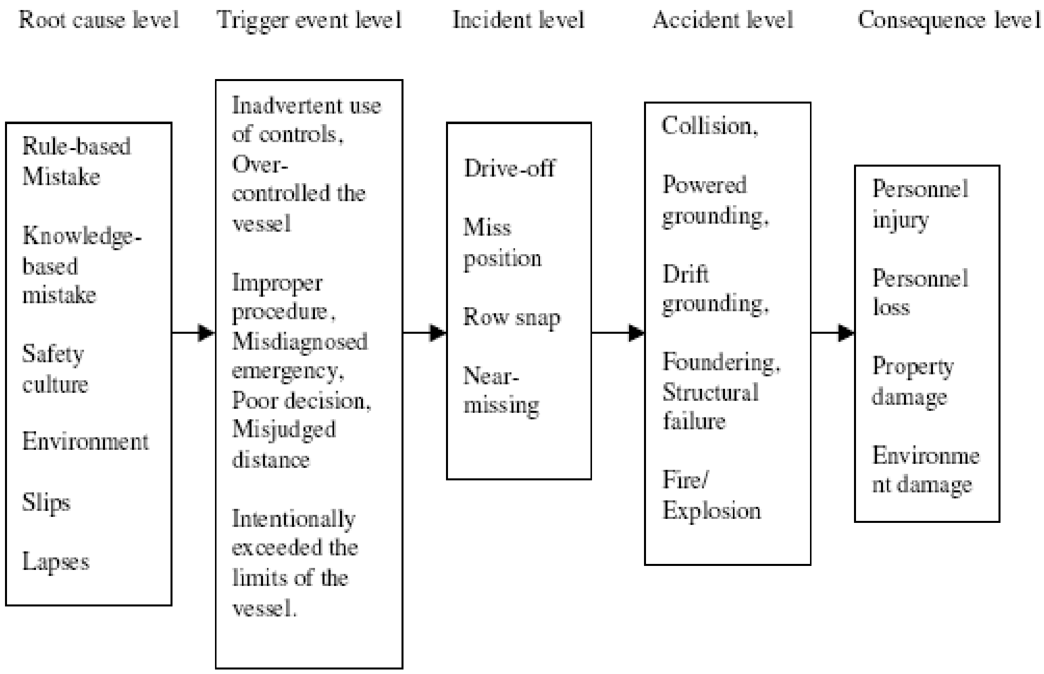

Figure 2. The conceptual model for HOFs

It should be noted that offshore accidents occur through the concatenation of multiple latent errors. An individual error may not be sufficient to cause severe consequences unless it occurs in combination with other latent errors. The above proposed framework demonstrates how root causes, trigger events, incidents, accidents and consequences are logically related, therefore it provides the potential of exploring the correlation between HOFs and severity consequences. In fact, the HOFs may be involved with operators, the managers and regulators. The propagation and escalation of HOFs often make it possible for combinations of these latent errors to build up over time and hence create the preconditions for failure.

3.2 Offshore safety assessment framework

To conduct offshore risk analysis, a uniformed framework is essential. Based on the literature review, a generic framework for offshore risk analysis is proposed and depicted in Figure 3. The framework consists of the following four major components:

01. Identify potential failure factors.
02. Categorise potential failure factors to form a risk analysis hierarchy.
03. Establish BN model and estimate prior/posterior probabilities.
04. BN inference and interpret analysis results.

Each component of the framework is described in detail as follows:

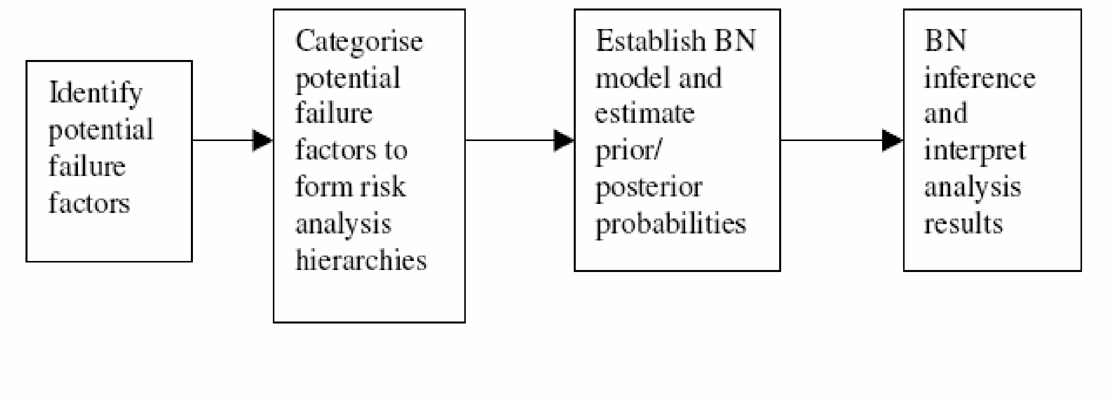

Figure 3. Offshore safety assessment framework

Component 01: Identify potential failure factors.
This component is the start point of the whole analysis process. All anticipated causes/factors to potential failures during offshore operations must be identified. In doing so, extensive literature studies and empirical investigations are essential.

Component 02: Categorise potential failure factors to form risk analysis hierarchies.
In this component, all the identified potential factors need to be categorised according to their inherent characteristics. The proposed conceptual model (Figure 2) acts as the guidelines to formulate a hierarchical structure.

Component 03: Establish BN model and estimate prior/posterior probabilities
Following the guidelines proposed in the HOFs conceptual model and based on the identified risk factors, this component focuses on exploring and establishing the causal relationships among those risk factors. Using variables (nodes) to represent the identified potential failures, prior probability table (PPT) or conditional probability table (CPT) of each variable (node) will be specified. It should be noted that data obtained from available databases and data networks may not be complete and well presented. Data mining techniques may be used in such cases where, for instance, it is necessary to select suitable types of fuzzy membership function to delineate linguistic terms, and consult experts with interpretation of the fuzzy membership function. Transformation of fuzzy/linguistic data into crisp values is thus included in this component (Yager, 1999).

Component 04: BN inference and interpret analysis results.
This component conducts the BN inference and interprets the inference results. This is done by updating the values of all the nodes via calculating posterior probabilities. During the process, Bayesian Equations (i.e. Equations (1)–(4) in Appendix 2) must be used when new information is available.

4. Offshore safety case study

In this section, a case study is presented to demonstrate the application of the proposed methodology for conducting offshore safety assessment. This case study analyses the risk of the collision between an FPSO and the shuttle tanker/support vessels during operation. For simplicity but without loss of generality, the following are assumed:

- Only those risk factors that associated with HOFs are considered.
- Three major types of HOFs are considered to be the root causes of accident. They are *Rule-based errors, Knowledge-based errors* and *Safety culture based errors.*
- The values of prior and conditional probabilities are given by estimation rather than from real historical databases.
- All fuzzy probabilities are represented by triangular form membership functions.

The background knowledge of fuzzy set theory, BN inference algorithm and f-weighted valuation function for data transformation is given in Appendices 1-3.

4.1. General description and BN model establishment

An FPSO is one of the most popular floating systems used by the offshore oil and gas industry. In the UK, crude oil from an FPSO is normally transported to shore using shuttle tankers specially designed for dealing with the harsh weather conditions. Shuttle tankers equipped with a bow-loading system are connected to an FPSO unit or storage facilities by mooring hawser and loading hose through which cargo is offloaded. Tandem loading/offloading is a complex marine operation. It is with high risk due to the close proximity required between the two large vessels. In addition, FPSOs are also routinely serviced by support vessels. During the operation of service, support vessels could collide with FPSO units due to faulty positioning. In a generic scenario, FPSO units can collide with these ships. The consequence of the collision varies from minor contact to incidents that may cause personnel injury/loss, environment pollution and/or damage to the property.

To avoid the occurrence of the incident and accident, it is necessary to find out the hidden root causes which may be indirectly linked to severe consequences. HOFs are the main concerns in this case study. Incorrect human intervention of the DP system, for example, is one reason that can result in a drive off or drift off situation with the risk of collision. Safety analysts are interested in exploring what HOFs have most impact on safety consequences, how sensitive those HOFs are when a situation changed.

4.2. Offshore safety assessment

The evaluation framework and BN model proposed in the previous sections are used to analyse the case example.

<u>*Step 1: Identify potential failure factors*</u>

Identification for potential failure factors must be based on empirical investigation and expert interviews. For demonstration purposes, this case study considers eleven factors: *Personnel Injury/loss(PI), Shuttle Tanker collision with FPSO(ST), Support Vessel collision with FPSO(SP), Drive-off(DF), Miss Position(MP), Over Control of the vessel(OC), Improper procedure(IP), Misjudgement of the distance(MI), Rule-based errors(RB), Knowledge-based errors(KB) and Safety Culture based errors(SC).*

<u>*Step 2: Categorise potential failure factors to form risk analysis hierarchy*</u>

The eleven factors are located at different levels of the proposed framework (see Figure 4). On the consequence level, *Personnel Injury/Loss* is considered as the main consequence. On the accident level, *Shuttle Tanker and Support Vessel collisions with FPSO* are considered as the main constituents of this level. *Drive-off* and *Miss Position* are identified as the main causes of the accidents, these two factors are therefore located at the incident level. On the Trigger level, three events, namely *Over Control of the vessel*, *Improper Procedure* and *Misjudgement of the distance* are considered as the trigger events. The last level is root cause level. Here three HOFs are identified as the root causes in the case study: *Rule-based errors, Knowledge-based errors* and *Safety culture based errors*. The causal relationships among those eleven factors are addressed in a way that HOFs may trigger undesired events to happen. For example, rule-based errors may cause an improper procedure to handle emergency. When such an undesired event occurs, incident may happen resulting in shuttle tanker or support vessel being in a faulty position. Such a faulty position of the shuttle tanker or support vessel may cause collision with the FPSO, and thus may eventually cause personnel injury/loss. The causal relationships are demonstrated in Figure 4. As can be seen in Figure 4, the eleven nodes are organised by the acyclic arrows that represent the causal relationships among them. One of the most interesting questions is to find out that if there is a personnel injury/loss observed, then in what possibility it is caused by HOFs.

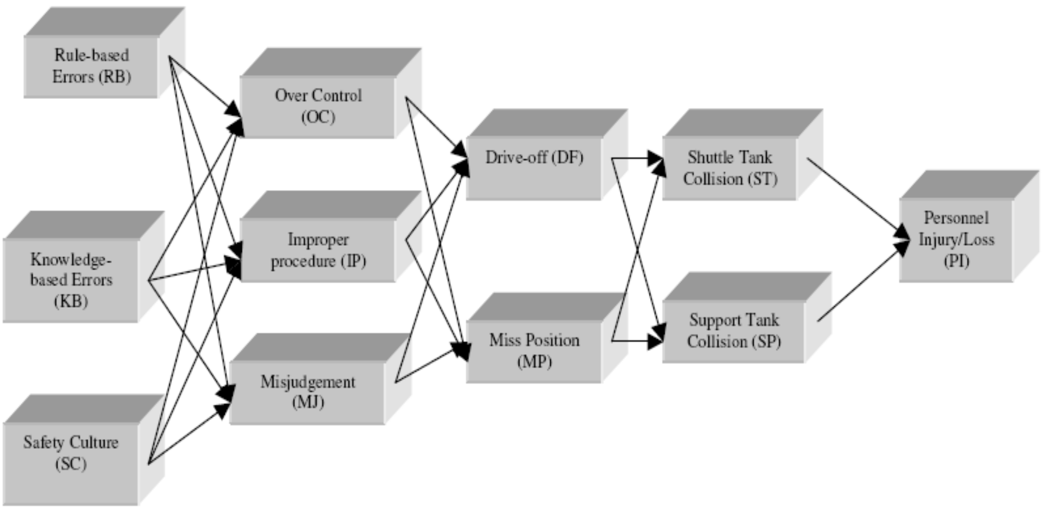

Figure 4. The BN model of the collision risk of an FPSO and the authorised vessels

<u>Step 3: Establish BN model and estimate prior/posterior probabilities</u>

Domain experts were asked to give judgments about the probabilities regarding all the nodes. Suppose they use fuzzy membership functions to describe the probabilities. For example, a probability value may be assigned with fuzzy membership function (0.09,0.10,0.11). Without loss of generality, in this case study triangular fuzzy number (a, b, c) is used where a, b and c represent the lower least likely value, the most likely value, and upper least likely value, respectively. A triangular fuzzy set is a special trapezoidal fuzzy set when the core set of the trapezoidal fuzzy set takes the form of a single point. In

Appendix 3, a trapezoidal fuzzy set is used to demonstrate how to conduct fuzzy-to-crisp value transformation.

Table 1 gives the fuzzy prior probabilities of nodes RB (*Rule-based errors*), KB (*Knowledge-based errors*) and SC (*Safety culture based errors*). As shown in Table 1, there are two possible values for each of the three nodes: Yes or No. If RB is true (Yes), for example, it means that the event caused by *Rule-based errors* took place. The occurrence likelihood of the event was defined by domain experts as a triangular fuzzy number $P_f(RB_1)$ = (0.09, 0.10, 0.11) as shown in Table 1. From Table 1, one can see that the most likely value of $P_f(RB_1)$ is 0.1, while 0.09 and 0.11 are the lower and upper least likely values of $P_f(RB_1)$, respectively.

Table 1 Fuzzy prior probabilities $P_f(RB), P_f(KB), P_f(SC)$

RB	**Yes**	**No**
	(0.09,0.1,0.11) **0.1**	(0.89,0.9,0.91) **0.9**
KB		
	(0.09,0.1,0.11) **0.1**	(0.89,0.9,0.91) **0.9**
SC		
	(0.09,0.1,0.11) **0.1**	(0.89,0.9,0.91) **0.9**

Table 2 gives the conditional fuzzy probabilities of variable "*Miss Position (MP)*" given the states of nodes *Over control of the vessel (OC), Improper Procedure (IP)* and *Misjudgement of the distance (MJ)*. In Table 2, a fuzzy probability is provided for each possible combination of states of nodes OC, IP and MJ ($2\times2\times2\times2$=16 in this case). The fuzzy probability value (*MP_1*) under condition of *OC_1, IP_2 and MJ_2*, for example, is shown in the fourth row and fifth column. The particular value suggests that the faulty position of shuttle tanker or support vessel is quite unlikely to happen with fuzzy probability (0.09,0.1,0.11). This is because when there is malfunction caused by *Over control of the vessel*, it is immediately sorted out by right procedure and right judgement of the distance. Otherwise, in this situation if there is a *misjudgement of distance*, the occurrence likelihood of a shuttle tanker or support vessel being in a faulty position is increased to even chance with fuzzy probability (0.49,0.5,0.51) (shown in the fourth row and fourth column of Table 2).

Table 2 Fuzzy conditional probability $P_f(MP|OC, IP, MJ)$

OC	**Yes**				**No**			
IP	**Yes**		**No**		**Yes**		**No**	
MJ	**Yes**	**No**	**Yes**	**No**	**Yes**	**No**	**Yes**	**No**
MP: Yes	(0.69,0.7,0.71) **0.7**	(0.49,0.5,0.51) **0.5**	(0.49,0.5,0.51) **0.5**	(0.09,0.1,0.11) **0.1**	(0.49,0.5,0.51) **0.5**	(0.09,0.1,0.11) **0.1**	(0.09,0.1,0.11) **0.1**	(0.001,0.001,0.001) **0.001**
MP: No	(0.29,0.3,0.31) **0.3**	(0.49,0.5,0.51) **0.5**	(0.49,0.5,0.51) **0.5**	(0.89,0.9,0.91) **0.9**	(0.49,0.5,0.51) **0.5**	(0.89,0.9,0.91) **0.9**	(0.89,0.9,0.91) **0.9**	(0.9999,0.999,0.999) **0.999**

Tables 4–10 in Appendix 4 give the fuzzy conditional probabilities of other nodes, respectively. The meanings of each fuzzy conditional probability can be explained in a similar way to the one depicted above.

Step 4: BN inference and interpret analysis results
In order to conduct Bayesian inference, it is necessary to transform fuzzy values into crisp values. In this paper fuzzy prior probabilities and fuzzy conditional probabilities are transformed into crisp numbers using transformation equations provided in Appendix 3.

Fuzzy probability $P_f(RB = RB_1)$ = (0.09,0.1,0.11), for example, is transformed as follows (using Equation (7) in Appendix 3):

$$P(RB = RB_1) = \frac{\left(\frac{0.1+0.1}{2}\right) + \left(\frac{0.09+0.11}{2}\right)}{2}$$

$$= (0.1+0.1)/2 = 0.1$$

The transformed values of other prior probabilities are represented with bold fonts shown in the body of Table 1.

Similarly, the bold fonts in the bodies of Tables 4–10 in Appendix 4 are the transformed probabilities obtained by using Equation (7).

The Bayesian inference mechanism can then be used to conduct various types of analysis. Suppose it is observed that there is human injury, and it is requested to inference the degree to which this disastrous consequence was related to HOFs. This needs to calculate posterior probability $P(SC = SC_1 | PI = PI_1)$, $P(KB = KB_1 | PI = PI_1)$ and $P(RB = RB_1 | PI = PI_1)$. By using Bayesian Equations ((1) – (4)) (a detailed description is presented in Appendix 2), the relevant calculation is:

$$P(SC = SC_1 | PI = PI_1) = \frac{P(SC = SC_1; PI = PI_1)}{P(PI = PI_1)}$$

In fact:

$$P_f(PI = PI_1) = \sum_{ST,SP} P(ST; SP; PI = PI_1)$$

$$= P(ST = ST_1; SP = SP_1; PI = PI_1) + P(ST = ST_2; SP = SP_1; PI = PI_1)$$

$$+ P(ST = ST_1; SP = SP_2; PI = PI_1) + P(ST = ST_2; SP = SP_2; PI = PI_1)$$

= 0.13
The marginal probabilities of all the other nodes can be computed by using Bayesian Equation (3) (Hugin, 1998). Therefore:

$$P\ (SC = SC_1 \mid PI = PI_1) = \frac{P\ (SC = SC_1; PI = PI_1)}{P(PI = PI_1)}$$

=0.1570

Similarly $P\ (KB = KB_1 \mid PI = PI_1)$ and $P\ (RB = RB_1 \mid PI = PI_1)$ can be computed as:

$P\ (KB = KB_1 \mid PI = PI_1)$ = 0.1576

$P\ (RB = RB_1 \mid PI = PI_1)$ = 0.1204

Comparing the posterior probabilities ($P\ (KB = KB_1 \mid PI = PI_1)$ = 0.1576, $P\ (RB = RB_1 \mid PI = PI_1)$ = 0.1204, $P\ (SC = SC_1 \mid PI = PI_1)$ = 0.1570) with prior probabilities ($P\ (KB = KB_1) = 0.10$, $P\ (RB = RB_1) = 0.10$, $P\ (SC = SC_1) = 0.10$), it can be seen that there is a significant change in the occurrence likelihood of KB and SC errors (increased 57% and 57.6%, respectively) when a personnel injury consequence has been observed. This might imply that node "*Personnel Injury/Loss*" is sensitive to nodes "Knowledge-based errors" and "Safety culture based errors", that is, once a personnel injury/loss caused by collision of FPSO is observed, it is more likely that knowledge-based and safety culture related errors are the main causes during operations. Meanwhile, node "Rule-based errors" is less sensitive to node "*Personnel Injury/Loss*". When a personnel injury/loss consequence caused by collision of FPSO is observed, the likelihood of occurrence of "Rule-based errors" only increased 20.4%.

The above results may suggest that in order to avoid severe consequences, it is crucial to provide education and training which broaden the staff's knowledge, increase their job competencies and develop professional potential. In addition, developing and maintaining a safety culture is equally important. This may involve bringing appropriate concepts, practices and methodologies of safety and integrating them into the corporate culture of a company, so that safety is present at all levels.

To further justify the above conclusions, sensitivity analysis will be conducted in the next section.

4.3. Sensitivity analysis

Sensitivity refers to how sensitive a model's performance is to minor changes in the input parameters. Sensitivity analysis is particularly useful in investigating the effects of inaccuracies or incompleteness in the parameters of a BN model on the model's output. The most natural way of performing sensitivity analysis is to change the parameters' values and then, using an evidence propagation method, monitor the effects of these changes on the posterior probabilities. In this case study, the preliminary conclusion (i.e. node "*Personnel Injury/Loss*" is quite sensitive to nodes "*Knowledge-based errors*" and "*Safety culture based errors*", not so sensitive to node "*Rule-based errors*") is drawn based on posterior probabilities e.g. $P\ (KB = KB_1 |\ PI = PI_1)$, $P\ (RB = RB_1 |\ PI = PI_1)$ and $P\ (SC = SC_1 |\ PI = PI_1)$**.** Thus one of the most important sensitivity analysis aspects is to analyse how they change when prior probabilities take different values.

4.3.1 Sensitivity analysis at the HOFs level

Without loss of generality, each of the fuzzy numbers ($P_f\ (KB = KB_1)$ **,** $P_f\ (RB = RB_1)$ and $P_f\ (SC = SC_1)$) takes five different values, ranging from (0.09, 0.10, 0.11) to (0.29,0.30,0.31) (see Table 3). The sensitivity analysis results were shown in Table 3. As can be seen in the last column of Table 3, the change between prior and posterior probabilities clearly indicates that there is a significant change between $P_f\ (KB = KB_1)$ and $P\ (KB = KB_1 |\ PI = PI_1)$ (average change is 48.40%), and also between $P_f\ (SC = SC_1)$ and $P\ (SC = SC_1 |\ PI = PI_1)$ (average change is 47.89%)**.** Meanwhile, the change between $P_f\ (RB = RB_1)$ and $P\ (RB = RB_1 |\ PI = PI_1)$ (average change is 17.74%) is less significant than those of KB and SC**.** Therefore there is a reason to believe that the conclusions made in Section 4.2 are reliable.

Table 3 Sensitivity analysis results between prior and posterior probabilities

	Fuzzy prior probabilities	Crisp prior probabilities and posterior probabilities		Change between prior and posterior probabilities (%)
No	$P_f\ (RB = RB_1)$	$P\ (RB = RB_1)$	$P\ (RB = RB_1 \| \ PI = PI_1)$	
1	(0.09,0.10,0.11)	0.10	0.1204	**20.40**
2	(0.14,0.15,0.16)	0.15	0.1785	**19.00**
3	(0.19,0.20,0.21)	0.20	0.2354	**17.70**
4	(0.24,0.25,0.26)	0.25	0.2911	**16.44**
5	(0.29,0.30,0.31)	0.30	0.3455	**15.17**
			Average change (%)=	**17.74**
No	$P_f\ (KB = KB_1)$	$P\ (KB = KB_1)$	$P\ (KB = KB_1 \| \ PI = PI_1)$	
1	(0.09,0.10,0.11)	0.10	0.1576	**57.60**
2	(0.14,0.15,0.16)	0.15	0.2291	**52.73**
3	(0.19,0.20,0.21)	0.20	0.2963	**48.15**
4	(0.24,0.25,0.26)	0.25	0.3595	**43.80**
5	(0.29,0.30,0.31)	0.30	0.4192	**39.73**
			Average change (%)=	**48.40**
No	$P_f\ (SC = SC_1)$	$P\ (SC = SC_1)$	$P\ (SC = SC_1 \| \ PI = PI_1)$	
1	(0.09,0.10,0.11)	0.10	0.157	**57.00**
2	(0.14,0.15,0.16)	0.15	0.2282	**52.13**
3	(0.19,0.20,0.21)	0.20	0.2953	**47.65**
4	(0.24,0.25,0.26)	0.25	0.3584	**43.36**
5	(0.29,0.30,0.31)	0.30	0.418	**39.33**
			Average change (%)=	**47.89**

4.3.2 Sensitivity analysis at the Trigger event level

In order to examine how robust the proposed model is, it is essential to conduct sensitivity analysis at the key levels of the model. To analyse Trigger event level, for example, the first step to conduct sensitivity analysis is to change the likelihood of occurrence of each trigger event and analyse the corresponding change of posterior probabilities at the root cause level. When conditional probability ($P_f(OC = OC_1 | RB, KB, SC)$, $P_f(IP = IP_1 | RB, KB, SC)$ or $P_f(MJ = MJ_1 | RB, KB, SC)$) changes with scale ± 0.05, ± 0.10, and ± 0.15 once at a time, for example, sensitivity analysis will explore how posterior probabilities $P(RB = RB_1 | PI = PI_1)$, $P(KB = KB_1 | PI = PI_1)$ and $P(SC = SC_1 | PI = PI_1)$) change in values, respectively. For each single change in parameter, the analysis results are shown in Tables 11-13 of Appendix 5, respectively. To give graphical demonstration, for example, Figure 5 is the corresponding figure in Tables 11-13 of Appendix 5. Each sub-figure in Figure 5 shows the three curves of the posterior probabilities. It is clear that with the increase of the occurrence likelihood of each trigger event, the corresponding posterior probability increases. This may imply that if there is close correlation between the Root causes level and the Trigger events level, the HOFs may have strong impact on the Consequences level.

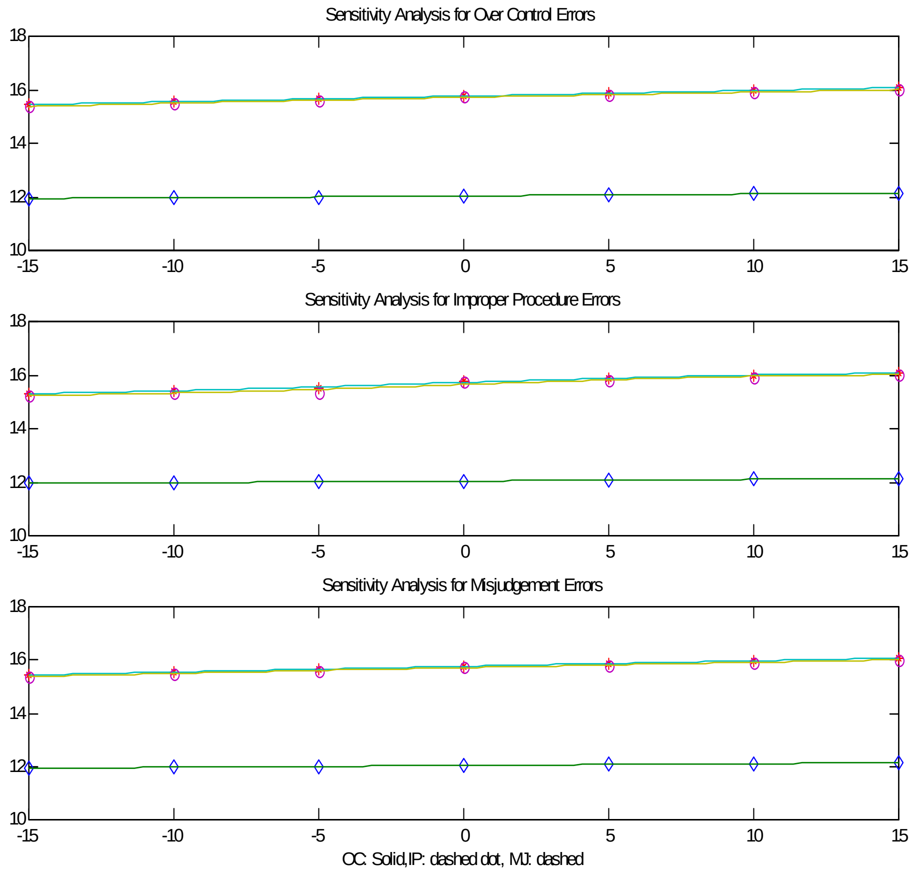

Figure 5. Sensitivity analyses at the Trigger event level

It can also be seen that all the curves in Figure 5 are flat, that is, the change of each posterior probability trend slope is very small. It means that the posterior probability trend is not so sensitive to the trigger event individually.

The second step to conduct sensitivity analysis is to simulate different scenarios where all the sensitivity analysis parameters simultaneously change with different scales. Table 14 in Appendix 5 shows how $P\ (RB = RB_1 |\ PI = PI_1)$, $P\ (KB = KB_1 |\ PI = PI_1)$ and $P\ (SC = SC_1 |\ PI = PI_1)$ change when $P_f\,(OC = OC_1 | RB, KB, SC)$, $P_f\,(IP = IP_1 | RB, KB, SC)$ and $P_f\,(MJ = MJ_1 | RB, KB, SC)$ change values. As expected, the posterior probabilities decrease when the values of occurrence likelihood of trigger events decrease. There is a clear trend that the posterior probabilities of KB and SC change faster than that of RB.

Derived from the above sensitivity analysis, it can be concluded that the proposed model is reasonably robust and the assigned probabilities are rational.

5. Conclusions

This paper has presented an offshore risk analysis methodology, which focuses on modelling HOFs. Based on the literature review, a five-level framework has been proposed to address latent failures within the causal sequence of events. Guided by the five-level framework, hazardous events are identified and arranged to each of the five levels based on the inherent characteristics of the events. A BN model has been investigated to fit into the proposed framework.

The case study shows that Reason’s “Swiss cheese” model and BN can be jointly used in offshore safety assessment. On the one hand, the five-level conceptual model is enhanced by BNs that are capable of providing graphical demonstration of inter-relationships as well as computing numerical values of occurrence likelihood for each failure event. Bayesian inference mechanism makes it possible to monitor how safety situation changes when information flows travel forwards and backwards within the network. On the other hand, BN modelling heavily relies on experts’ personal experiences and is therefore highly domain specific. The “Swiss cheese” model is such a theoretical framework based on solid behavioural theory and can be used to provide roadmap for BN modelling. Therefore it is believed that the proposed framework is a promising methodology to meet the challenges of modelling HOFs in offshore operations.

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Appendix 1. Fuzzy set and fuzzy number

Fuzzy sets were derived from generalizing the concept of set theory. Fuzzy sets can be thought of as an extension of classical sets. In a classical set or crisp set, the objects in a set are called elements or members of the set. An element x belonging to a set A is defined as $x \in A$, an element that is not a member in A is noted as $x \notin A$. A characteristic function or membership function $\mu_A(x)$ is defined as an element in the universe U having a crisp value of 1 or 0. For every $x \in$ U,

$$\mu_A(x) = \begin{cases} 1 & \text{for } x \in \mathrm{A}, \\ 0 & \text{for } x \notin \mathrm{A}. \end{cases}$$

this can also be expressed as $\mu_A(x) \in \{0,1\}$. For the classical set or crisp set, membership functions take a value of 1or 0. However, for fuzzy sets, a membership function can take values in the interval [0,1]. The range between 0 and 1 is referred to as the membership grade or degree of membership. A fuzzy set A is defined below:

$$A = \{(x, \mu_A(x)) \mid x \in A, \mu_A(x) \in [0,1]\}$$

where $\mu_A(x)$ is a membership function belonging to the interval [0,1].

Fuzzy numbers are very special fuzzy subsets of the real numbers. The general definition of a fuzzy number X is a fuzzy subset of R. If the membership function of X is denoted as $\mu_X(x)$, X must meet the following conditions:

(a) The core of X is non-empty, i.e. $\exists x \in R$ such that $\mu_X(x) = 1$.

(b) α -cuts of X are all closed, bounded intervals.

(c) It has a bounded support, i.e. $\exists N \in R$ such that $\forall x \in R$, if $|x| \geq N$ then $\mu_X(x) = 0$.

Note that an α-cut of a fuzzy number X is an interval number X_α that contains all the values of real numbers that have a membership grade in X greater than or equal to the specified value of α. This can be written as

$$X_\alpha = [a, b] = \{x \in X | \ \mu_X(x) \geq \alpha\}.$$

Appendix 2. Bayesian network model

A classical BN is a pair N={(V, E), P} where V and E are the nodes and the edges of a Directed Acyclic Graph (DAG), respectively, and P is a probability distribution over V. Discrete random variables $V = \{X_1; X_2; ...X_n\}$ are assigned to the nodes while the edges E represent the causal probabilistic relationship among the nodes. Each node in the network is annotated with a Conditional Probability Table (CPT) that represents the conditional probability of the variable given the values of its parents in the graph. The CPT contains, for each possible value of the variable associated to a node, all the conditional probabilities with respect to all the combinations of values of the variables associated with the parent nodes. For nodes that have no parents, the corresponding table will simply contain the prior probabilities for that variable. The principles behind BN are Bayesian statistics and concentrate on how probabilities are affected by both prior and posterior knowledge.

Inference in BN generally targets the calculation of some probability of interest. Inference algorithms are based on the following four equations:

Conditional independence

$$P(X_1, X_2, ..., X_n) = \prod_{i=1}^{n} P(X_i \mid Parents(X_i)) \quad (1)$$

Joint probability

$$P(Y = y_j, X = x_i) = P(X = x_i) \cdot P(Y = y_j \mid X = x_i) \quad (2)$$

Marginalization rule

$$P(Y = y_j) = \sum_i P(X = x_i) \cdot P(Y = y_j \mid X = x_i) \quad (3)$$

Bayesian rule

$$P(X = x_i \mid Y = y_j) = \frac{P(X = x_i) \cdot P(Y = y_j \mid X = x_i)}{P(Y = y_j)} \quad (4)$$

In order to use fuzzy numbers in the above Bayesian rules, a suitable transformation method from linguistic probabilities into crisp probabilities must be proposed.

Appendix 3. Transformation from fuzzy to crisp values

Several tools are available for fuzzy-to-crisp transformation such as Maximum Transformation Technique (MTT), Centroid Defuzzification Technique (CDT) and Weighted Average Technique (WAT) (Ross, 1995). Many existing techniques are suffering from information loss and being sensitive to single information that dominates the fuzzy set during the process that transforms a fuzzy number into a crisp value. This paper adopts f-weighted valuation function (Detynieckim and Yager, 2000; Yager, 1981) to decrease the degree of losing information and make the analysis results more reasonable and reliable.

A generalized formulation for a class of valuations is as follows:

$$Val(F) = \frac{\int_0^1 Average(F_\alpha) \times f(\alpha) d\alpha}{\int_0^1 f(\alpha) d\alpha} \tag{5}$$

where $Val(F)$ is a crisp value transformed from fuzzy membership function *F*; $F_\alpha = \{x \mid F(x) \geq \alpha\}$ is an α -level set of *F*; $Average(F_\alpha)$ is the average of the elements in the α -level set. f is defined as f-weighted valuation function.

When *F* takes the form of trapezoidal fuzzy set, for instance, it will have the membership function:

$$F(x,(a,b,c,d)) = Trapezoid(x,(a,b,c,d)) = \begin{cases} 0 & x \leq a \\ \frac{x-a}{b-a} & a < x \leq b \\ 1 & b < x \leq c \\ \frac{d-x}{d-c} & c < x \leq d \\ 0 & x > d \end{cases}$$

For the case of trapezoidal fuzzy set, the average of the elements in the α -level set can be computed as follows (Yager and Filev 1999):

$$Average(F_\alpha) = \frac{u_\alpha + v_\alpha}{2}$$

where u_α and v_α are the horizontal axis values of intersection points between α -cut line and the left-hand side and right-hand side of the trapezoidal fuzzy set, respectively. They are calculated as follows:

$u_\alpha = (b-a) \times \alpha + a$ and $v_\alpha = d - (d-c) \times \alpha$

Then Equation (5) becomes:

$$Val(F(x,(a,b,c,d))) = \frac{\int_0^1 \frac{u_\alpha + v_\alpha}{2} \times f(\alpha) d\alpha}{\int_0^1 f(\alpha) d\alpha}$$

$$= \frac{\frac{1}{2}\int_0^1 [(b+c)\times\alpha + (1-\alpha)\times(a+d)]\times f(\alpha)d\alpha}{\int_0^1 f(\alpha)d\alpha} \tag{6}$$

Without loss of generality, let f-weighted valuation function $f(\alpha)=1$. Equation (6) becomes:

$$Val(F(x,(a,b,c,d))) = \frac{\frac{1}{2}\int_0^1 [(b+c)\times\alpha + (1-\alpha)\times(a+d)]d\alpha}{\int_0^1 d\alpha}$$

$$= \frac{\left(\frac{b+c}{2}\right) + \left(\frac{a+d}{2}\right)}{2} \tag{7}$$

This shows that the transformed value is between the middle point of the core and the middle point of the support.

Using f-weighted valuation function, experts are able to adjust subjective parameter values to make their judgements.

Appendix 4. Case study data

Table 4 Fuzzy conditional probability $P_f\,(PI|ST,SP)$

ST	**Yes**		**No**	
SP	**Yes**	**No**	**Yes**	**No**
PI: Yes	(0.09,0.1,0.11) **0.1**	(0.049,0.05,0.051) **0.05**	(0.049,0.05,0.051) **0.05**	(0.001,0.001,0.001) **0.001**
PI: No	(0.89,0.9,0.91) **0.9**	(0.94,0.95,0.96) **0.95**	(0.94,0.95,0.96) **0.95**	(0.9999,0.999,0.999) **0.999**

Table 5 Fuzzy conditional probability $P_f\,(ST|DF,MP)$

DF	**Yes**		**No**	
MP	**Yes**	**No**	**Yes**	**No**
ST: Yes	(0.09,0.1,0.11) **0.1**	(0.049,0.05,0.051) **0.05**	(0.049,0.05,0.051) **0.05**	(0.001,0.001,0.001) **0.001**
ST: No	(0.89,0.9,0.91) **0.9**	(0.94,0.95,0.96) **0.95**	(0.94,0.95,0.96) **0.95**	(0.9999,0.999,0.999) **0.999**

Table 6 Fuzzy conditional probability $P_f\,(SP|DF,MP)$

DF	**Yes**		**No**	
MP	**Yes**	**No**	**Yes**	**No**
SP: Yes	(0.09,0.1,0.11) **0.1**	(0.049,0.05,0.051) **0.05**	(0.049,0.05,0.051) **0.05**	(0.001,0.001,0.001) **0.001**
SP: No	(0.89,0.9,0.91) **0.9**	(0.94,0.95,0.96) **0.95**	(0.94,0.95,0.96) **0.95**	(0.9999,0.999,0.999) **0.999**

Table 7 Fuzzy conditional probability $P_f\,(DF|OC,IP,MJ)$

OC	**Yes**				**No**			
IP	**Yes**		**No**		**Yes**		**No**	
MJ	**Yes**	**No**	**Yes**	**No**	**Yes**	**No**	**Yes**	**No**
DF: Yes	(0.69,0.7,0.71) **0.7**	(0.49,0.5,0.51) **0.5**	(0.49,0.5,0.51) **0.5**	(0.09,0.1,0.11) **0.1**	(0.49,0.5,0.51) **0.5**	(0.09,0.1,0.11) **0.1**	(0.09,0.1,0.11) **0.1**	(0.001,0.001,0.001) **0.001**
DF: No	(0.29,0.3,0.31) **0.3**	(0.49,0.5,0.51) **0.5**	(0.49,0.5,0.51) **0.5**	(0.89,0.9,0.91) **0.9**	(0.49,0.5,0.51) **0.5**	(0.89,0.9,0.91) **0.9**	(0.89,0.9,0.91) **0.9**	(0.9999,0.999,0.999) **0.999**

Table 8 Fuzzy conditional probability $P_f\,(OC|RB,KB,SC)$

RB	Yes				No			
KB	Yes		No		Yes		No	
SC	Yes	No	Yes	No	Yes	No	Yes	No
OC: Yes	(0.39,0.4,0.41) **0.4**	(0.29,0.3,0.31) **0.3**	(0.19,0.2,0.21) **0.2**	(0.19,0.2,0.21) **0.2**	(0.19,0.2,0.21) **0.2**	(0.19,0.2,0.21) **0.2**	(0.09,0.1,0.11) **0.1**	(0.005,0.005,0.005) **0.005**
OC: No	(0.59,0.6,0.61) **0.6**	(0.69,0.7,0.71) **0.7**	(0.79,0.8,0.81) **0.8**	(0.79,0.8,0.81) **0.8**	(0.79,0.8,0.81) **0.8**	(0.79,0.8,0.81) **0.8**	(0.89,0.9,0.91) **0.9**	(0.995,0.995,0.995) **0.995**

Table 9 Fuzzy conditional probability $P_f\,(IP|RB,KB,SC)$

RB	**Yes**				**No**			
KB	**Yes**		**No**		**Yes**		**No**	
SC	**Yes**	**No**	**Yes**	**No**	**Yes**	**No**	**Yes**	**No**
IP: Yes	(0.39,0.4,0.41) **0.4**	(0.39,0.4,0.41) **0.4**	(0.19,0.2,0.21) **0.2**	(0.19,0.2,0.21) **0.2**	(0.25,0.25,0.25) **0.25**	(0.19,0.2,0.21) **0.2**	(0.09,0.1,0.11) **0.1**	(0.005,0.005,0.005) **0.005**
IP: No	(0.59,0.6,0.61) **0.6**	(0.59,0.6,0.61) **0.6**	(0.79,0.8,0.81) **0.8**	(0.79,0.8,0.81) **0.8**	(0.75,0.75,0.75) **0.75**	(0.79,0.8,0.81) **0.8**	(0.89,0.9,0.91) **0.9**	(0.995,0.995,0.995) **0.995**

Table 10 Fuzzy conditional probability $P_f(MJ|RB, KB, SC)$

RB	Yes				No			
KB	Yes		No		Yes		No	
SC	Yes	No	Yes	No	Yes	No	Yes	No
MJ: Yes	(0.39,0.4,0.41) **0.4**	(0.29,0.3,0.31) **0.3**	(0.19,0.2,0.21) **0.2**	(0.19,0.2,0.21) **0.2**	(0.19,0.2,0.21) **0.2**	(0.19,0.2,0.21) **0.2**	(0.09,0.1,0.11) **0.1**	(0.005,0.005,0.005) **0.005**
MJ: No	(0.59,0.6,0.61) **0.6**	(0.69,0.7,0.71) **0.7**	(0.79,0.8,0.81) **0.8**	(0.79,0.8,0.81) **0.8**	(0.79,0.8,0.81) **0.8**	(0.79,0.8,0.81) **0.8**	(0.89,0.9,0.91) **0.9**	(0.995,0.995,0.995) **0.995**

Appendix 5. Results of sensitivity analysis

Table 11 Errors caused by Over Control (OC) sensitivity analysis

	-15%	Change	-10%	Change	-5%	Change	Base results	Change	5%	Change	10%	Change	15%	Change
RB	11.94	-0.83%	11.97	-0.58%	12.00	-0.33%	12.04	0.00%	12.07	0.25%	12.11	0.58%	12.14	0.83%
KB	15.45	-1.97%	15.55	-1.33%	15.66	-0.63%	15.76	0.00%	15.87	0.70%	15.97	1.33%	16.07	1.97%
SC	15.38	-2.35%	15.49	-1.65%	15.59	-1.02%	15.75	0.00%	15.8	0.32%	15.90	0.95%	16.01	1.65%

Table 12 Errors caused by Improper Procedure (IP) sensitivity analysis

	-15%	Change	-10%	Change	-5%	Change	Base results	Change	5%	Change	10%	Change	15%	Change
RB	11.95	-0.75%	11.98	-0.50%	12.02	-0.17%	12.04	0.00%	12.07	0.25%	12.11	0.58%	12.14	0.83%
KB	15.31	-2.86%	15.42	-2.16%	15.53	-1.46%	15.76	0.00%	15.87	0.70%	15.99	1.46%	16.07	1.97%
SC	15.25	-3.17%	15.36	-2.48%	15.36	-2.48%	15.75	0.00%	15.81	0.38%	15.91	1.02%	16.02	1.71%

Table 13 Errors caused by Miss Judgement (MJ) sensitivity analysis

	-15%	Change	-10%	Change	-5%	Change	Base results	Change	5%	Change	10%	Change	15%	Change
RB	11.93	-0.91%	11.97	-0.58%	12.00	-0.33%	12.04	0.00%	12.07	0.25%	12.11	0.58%	12.14	0.83%
KB	15.43	-2.09%	15.55	-1.33%	15.66	-0.63%	15.76	0.00%	15.87	0.70%	15.97	1.33%	16.07	1.97%
SC	15.38	-2.35%	15.49	-1.65%	15.59	-1.02%	15.75	0.00%	15.80	0.32%	15.90	0.95%	16.01	1.65%

Table 14 Combined sensitivity analysis on Trigger events level

	Base results: Posterior Probabilities	Change	Posterior Probabilities under (0%, 5%, 5%).	Change	Posterior Probabilities under (5%, 5%, 5%).	Change	Posterior Probabilities under (5, 10%, 10%).	Change
RB	12.04	N/a	11.91	-1.09%	11.88	-1.33%	11.85	-1.58%
KB	15.76	N/a	15.49	-1.75%	15.39	-2.35%	15.22	-3.43%
SC	15.75	N/a	15.49	-1.69%	15.39	-2.29%	15.17	-3.68%