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A fuzzy and Bayesian network CREAM model for human reliability analysis — the case of tanker shipping

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ABSTRACT

This paper proposes a quantitative human reliability analysis (HRA) model based on fuzzy logic theory, Bayesian network, and cognitive reliability & error analysis method (CREAM) for the tanker shipping industry. The common performance conditions (CPCs) in conventional CREAM approach are custom-modified to better capture the salient aspects of the situations and conditions for on-board tanker work. Fuzzy logic technique using triangle and trapezoidal membership functions is applied to model the uncertainty and ambiguity of the CPCs as well the control modes in CREAM. A Bayesian network reasoning model using the membership of CPCs as inputs is developed which determines the probability distribution of the control modes. Human error probability (HEP) is obtained from memberships of the control modes and the results of Bayesian network reasoning. A case study in tanker shipping industry with 18 crew members is provided, and the results show that the evaluation of HEP according to the proposed HRA model is very promising and the HRA model is consistent with the original CREAM approach. The sensitivity of the model is also checked against the inputs of the crew members. It is concluded that the enhanced HRA model is able to provide reliable human performance failure results.

Keywords: Human reliability analysis; CREAM; Fuzzy logic theory; Bayesian network; Human error probability

1. Introduction

Numerous studies have suggested that human errors are the major contributory factor of shipping accidents in which about 80% of marine casualties are caused, at least in part, by some forms of human error (Fotland, 2004; Hanzu-Pazara *et al.*, 2008; Corovic and Djurovic, 2013; Ung, 2015; Akyuz and Celik, 2015a). Therefore, it is strategic to carry out human reliability evaluation in the shipping industry. In recent years, one useful method widely applied by safety engineers and assessment analysts in mitigating human errors is human reliability analysis (HRA). HRA is a tool used to evaluate human reliability as well as the uncertainty of data concerning human factors and the complexity of the human behaviours. The primary purpose of HRA is to ascertain the operator's contribution to system reliability by predicting human error rates and evaluating the degradation in human-machine systems likely caused by human errors in association with factors that influence the system behaviour, e.g. equipment functioning, operational procedures and practices, and human characteristics (Swain and Guttman, 1983). Therefore, HRA plays an imperative and significant role in evaluating safety and reliability and is applicable to the shipping industry.

Many methods have been developed based on expert judgment, statistical data and simulation proofs for HRA. Basically, there are two generations in HRA developments. The first generation of the HRA approaches is developed based on the premise that inherent deficiencies lead to humans failing to perform tasks just like mechanical, electrical or structural components do (Marseguerra *et al.*, 2007). This generation is represented by technique of human error rate prediction (THERP) method. The second generation approaches consider the context as the most crucial factor affecting human performance failure and hence focus on the relationship between context and associated human error probability (HEP). The second generation is represented by cognitive reliability and error analysis method (CREAM) (Hollnagel, 1998) and a technique for human error analysis (ATHEANA) method

developed by US Nuclear Regulatory Commission (2000). CREAM, being one of the most recognised HRA methods, is adopted in this research. Nevertheless, the various techniques are still beset by issues of subjectivity and lack of data.

Fuzzy logic theory has been regarded as being a very useful tool for modelling processes which are too complex for conventional methods to handle or when available information for the process is qualitative, inexact or uncertain. This technique is characterised by application of membership function for modelling (Konstandinidou *et al.*, 2006). Meanwhile, Bayesian network (BN) is a probabilistic graphical model (a type of statistical model) that represents a set of random variables and their conditional dependencies via a directed acyclic graph. Herein, both the fuzzy logic theory and Bayesian network are incorporated into CREAM model, in order to quantify human error probability (HEP).

The objective of this paper is to evaluate human reliability in the context of shipping operations. Furthermore, the case of tanker shipping is applied in this research. Due to the fact that statistical data on the important parameters and variables during shipping voyages are scarce, seafarers' operations on-board are complex and subjective, which allows the application of fuzzy logic as a viable option to overcome data limitations concerning imprecision of data collection. Since the original CREAM can only provide the interval of action failure and the control modes to evaluate HEP, BN can be applied to calculate the probability distribution of the control modes, and the results can be used to evaluate seafarers' human reliability. Meanwhile, BN can also reflect the condition of complex relations between many variables. Therefore, a HEP quantification methodology that is applicable to the shipping industry is developed by incorporating fuzzy logic theory and Bayesian network technique in the prospective analysis of CREAM.

The structure of this paper is as follows. Firstly, modified common performance conditions (CPCs) in CREAM are proposed according to shipping context conditions. Secondly, fuzzy model with triangle and trapezoidal membership functions is applied to develop the inputs for Bayesian network. Next, the Bayesian network is established based on the CPCs. The crisp value for the fuzzy conclusion can then be calculated based on the results of Bayesian network reasoning and centre of the area (COA) technique, which is the logarithmic value of the HEP. Then, a case study with five scenarios is used to demonstrate the applicability of the proposed HRA model. The paper concludes with a discussion of the findings and future research areas.

2. CREAM (Cognitive Reliability and Error Analysis Method)

2.1 Application

CREAM was first proposed by Hollnagel (1998), which was originally developed for nuclear power plant applications (Jung *et al.*, 2001; He *et al.*, 2008; Lee *et al.*, 2011; Tang *et al.*, 2014) and was adopted by the National Aeronautics and Space Administration (NASA) in the early 1990s to predict human error (Calhoun *et al.* 2014). Nowadays, the method has been applied in other industries. In particular, for the maritime industry, scholars have applied the method to evaluate human reliability in maritime activities (Akyuz and Celik, 2015a; Ung, 2015; Zhou *et al.*, 2016b). Yang *et al.* (2013) proposed a modified CREAM to facilitate human reliability quantification in marine engineering sector by incorporating fuzzy evidential reasoning and Bayesian inference logic; the outcomes can provide safety engineers with a transparent tool to realise the instant estimation of human reliability performance for a specific task. Akyuz and Celik (2015b) adopted CREAM basic and extended versions to assess human reliability along with the cargo loading process on-board LPG tanker ships, which can improve maritime safety at sea and reduction of human injury and loss of life on-board LPG ship. Meanwhile, Akyuz (2015) presented a risk-based methodology utilising quantified CREAM method to predict human error probability (HEP) for gas inerting process on-board crude oil tankers. Xi *et al.* (2017) proposed a modified CREAM model based on an Evidential Reasoning (ER) approach and a Decision Making Trial and Evaluation Laboratory (DEMATEL) technique to quantify human error probability in maritime domain.

2.2 Control mode

The original CREAM encompasses the influence of human reliability into nine factors, called CPCs (Common Performance Conditions): (i) adequacy of organisation, (ii) working conditions, (iii) adequacy of man-machine interface (MMI) and operational support, (iv) availability of procedures and plans, (v) number of simultaneous goals, (vi) available time, (vii) time of day, (viii) adequacy of training and experience, and (ix) crew collaboration quality. There are three different CPC levels corresponding to negative (decrease), neutral and positive (increase)

effects on human behaviour reliability (Hollnagel, 1998). According to human cognition and action, there are four characteristic control modes which are determined by the CPCs, namely “Scrambled”, “Opportunistic”, “Tactical” and “Strategic”. The control modes are linked to different failure probability intervals representing human action failure probabilities (Hollnagel, 1998), as described in Table 1. The control modes can be used to characterise the performance of a team or group of people equally well as the performance of an individual.

Table 1: CPC control modes and their probability intervals

Control mode	Description	Probability interval of action failure
Strategic	In strategic control, the person considers the global context, thus uses a wider time horizon and looks ahead at higher level goals. The strategic mode provides a more efficient and robust performance and may therefore seem the ideal to strive for.	(0.000005, 0.01)
Tactical	In tactical control, performance is based on planning, hence more or less follows a known procedure or rule. The planning is, however, of limited scope and the needs taken into account may sometimes be ad hoc.	(0.001, 0.1)
Opportunistic	In opportunistic control, the next action is determined by the salient features of the current context rather than on more stable intentions or goals. The person does very little planning or anticipation, perhaps because the context is not clearly understood or because time is too constrained.	(0.01, 0.5)
Scrambled	In scrambled control, the choice of next action is in practice unpredictable or haphazard. Scrambled control characterises a situation where there is little or no thinking involved in choosing what to do.	(0.1, 1.0)

Source: Hollnagel (1998)

2.3 CPCs for tanker shipping industry

The CPCs are mapped at an early stage of the analysis to characterise the context for the task as a whole, rather than as a simplified way of adjusting probability values for individual events. In this way, the influence of CPCs becomes closely linked to the task analysis. The CPCs should be evaluated according to the specific work environment, and evaluated or scored by experts or technicians to determine the expected effects on performance reliability. Konstantinidou *et al.* (2006) suggested that CPCs could be modified or new ones be added to expand the input parameters to cater for human performance in specific industrial conditions. For example, Banda *et al.* (2016) proposed six CPCs namely, adequacy of the organisation, available procedures and plans to execute the operations, man-machine interface and operational support, available time to plan and perform the operations, training and preparation, and the quality of the collaboration on the bridge, to evaluate the risk management of winter navigation operations using a detailed expert elicitation process.

To gather data for the present study, the authors worked closely with a large global owner-operator of tankers with operations in over 10 countries. Various accident/incident data were recorded by the tanker shipping company during the voyages. The accident/incident types mainly include allision, cargo damage/contamination, collision, contact, detention, equipment failure, fire & explosion, grounding, loss of containment, personal injury, pollution and property damage. For example, around 300 personal injury accidents were recorded from 2008 to 2015 and nearly 400 equipment failure accidents are recorded from 2010 to 2015 during tanker shipping. For personal injury, various information was recorded, including personnel information (nationality, age, time on board, time in company, rank, time in rank), vessel information (vessel type, vessel age, vessel team, trading area, place), the location on the vessel, operation and body part of the injury. According to the accident/incident reports, the principal contributory factors of accidents/incidents during tanker shipping are found to be: (i) training, (ii) error enforcing conditions, (iii) organisation, procedure, maintenance management, (iv) incompatible goals, (v) defences, design, hardware, housekeeping, and (vi) communication. Deficiencies in the human factors include lack of knowledge, lack of skill, lack of direction, unfamiliarity, complacency, haste, improper motivation, inattention, in-obedience, misperception or misinterpretation. Meanwhile, by interviewing the captains in the tanker shipping company, it is found that contract information such as contract duration and working time also influence human reliability on-board. Since this study is focused on tanker shipping scenario, instead of the original nine CPCs, eight improved CPCs are developed in this study by classifying the accidents/incidents contributory factors during tanker

shipping, as a way of capturing the essential and realistic aspects of on-board conditions on the tankers. The eight CPCs are described in Table 2. There are three CPC levels for each CPC: (i) negative/decrease, (ii) neutral and (iii) positive/increase effects on human behaviour reliability.

Table 2: CPCs and their levels, and effects on human reliability

No.	CPCs	Description	CPC levels	Effects	Domain of discourse
C1	Training and experience	The quality and effect of training; the knowledge, skills and experience of the crew.	Adequate Acceptable Inadequate	Increase Neutral Decrease	[0, 50] [10, 90] [50, 100]
C2	Physical environment	Physical factors of the work environment during tanker shipping, such as lighting, noise, vibration of the tanker, temperature and humidity, sea state, port and channel condition.	Advantageous Acceptable Incompatible	Increase Neutral Decrease	[0, 50] [10, 90] [50, 100]
C3	Organisational management	The process of organising, planning, leading and controlling when doing operations during tanker shipping. Effect of organisation, supervision and administration.	Efficient Acceptable Deficient	Increase Neutral Decrease	[0, 50] [10, 90] [50, 100]
C4	Work characteristics	Work stress, task characteristics when carrying out tanker operations.	Satisfied Acceptable Unsatisfied	Increase Neutral Decrease	[0, 50] [10, 90] [50, 100]
C5	Available time	The time available to carry out a task and corresponds to how well the task execution is synchronised to the process dynamics on-board.	Adequate Acceptable Inadequate	Increase Neutral Decrease	[0, 50] [10, 90] [50, 100]
C6	Contract information	Such as contract duration, the working time on-board. Are you satisfied with the duration or the working time on-board?	Satisfied Acceptable Unsatisfied	Increase Neutral Decrease	[0, 50] [10, 90] [50, 100]
C7	Vessel facilities	The defences, design, hardware, housekeeping and maintenance of the vessel.	Satisfied Acceptable Unsatisfied	Increase Neutral Decrease	[0, 50] [10, 90] [50, 100]
C8	Crew collaboration quality	The quality of the collaboration between crew members, including the level of trust, the communication and the general social climate among crew members.	Efficient Inefficient Deficient	Increase Neutral Decrease	[0, 50] [10, 90] [50, 100]

Source: Authors, adapted from Hollnagel (1998)

2.4 Relationships between CPCs and control modes

The control mode in which the operator is likely to act is defined by the arithmetic sums of the positive and negative influences of the CPCs for the given task based on the original CREAM approach. There are nine CPCs proposed by Hollnagel (1998), but in this study, eight CPCs are proposed in tanker shipping scenario. Therefore, the relationships between the CPCs and control modes are adjusted as shown in Figure 1, which presents all possible combinations of the sum of the CPCs that have negative effects on human reliability performance in the x-axis and the sum of the CPCs that have positive effects on human reliability performance in the y-axis. Each CPC has three effects on human reliability, namely increase, neutral and decrease. If the number of negative effects of CPCs is i , then $x=i$ ($i=0, 1, 2, \dots, 8$); if the number of positive effects of CPCs is j , then $y=j$ ($j=0, 1, 2, \dots, 8$). Herein, there are 45 situations for the combination of x and y , as shown in Figure 1. For a given situation, the description of the CPCs will generate a specific value of the combined CPC score, and then the control mode for the given situation will be obtained. For example, assuming that a seafarer is performing an operation on-board, and among the eight CPCs, if there are five CPCs having negative effects on the seafarer's performance, three CPCs having positive effects, and the remaining CPCs having neutral effects, then $x=5, y=3$, therein the value $(x, y) = (5, 3)$ is located at the control mode of opportunistic, and the HEP is between 0.01 and 0.5 according to Table 1, which thus gives an interval of action failure.

Figure 1: Diagram for determining the control modes based on improved CPCs
Source: Authors, adapted from Hollnagel (1998)

3. Methodology

3.1 Fuzzy model

Fuzzy logic is a type of many-valued logic in which the truth values of variables may be any real number between 0 and 1, considered to be “fuzzy” (Novak et al., 1999). In particular, Wang et al. (2009) explained that a fuzzy set is a collection of elements in a universe of information where the boundary of the set contained in the universe is ambiguous, vague and otherwise fuzzy. It is specified by a membership function, which assigns a value within the unit interval $[0, 1]$ to each element in the universe of discourse. The assigned value is called membership degree, which specifies the extent to which a given element belongs to the fuzzy set. If the assigned value is 0, then the given element does not belong to the set. If the assigned value is 1, then the element totally belongs to the set. And if the value lies within the interval $(0, 1)$, then the element only partially belongs to the set. Therefore, any fuzzy set can be uniquely determined by its membership.

Fuzzy logic theory has been applied as a useful tool for modelling processes which are too complex for conventional quantitative techniques or when the available information from the process is qualitative, inexact and uncertain (Konstandinidou et al. 2006; Wang, 2012; Wang et al., 2009; Zhou and Thai, 2016a). Due to the fact that human errors are considered as the major contributory factors to accidents, many studies about HRA incorporating subjectivity data based on fuzzy logic have been proposed (Kim and Bishu, 2006; Konstandinidou et al., 2006; Ung and Shen, 2011; Chai et al., 2012). For examples, Akyuz (2016) presented a hybrid approach by combining fuzzy sets and SLIM (Success Likelihood Index Method) technique to quantify HEP values systematically in the event of an abandon ship event in maritime transportation. Furthermore, Akyuz and Celik (2016) prompted a methodological extension of human error assessment and reduction technique by incorporating interval type-2 fuzzy sets which overcome more of the uncertainty of experts’ judgement. These studies are examined in order to evaluate HEP with consideration of CPCs based on the CREAM framework. In brief, there are three steps for a fuzzy logic system.

3.1.1 Fuzzification

The fuzzification is to decompose a system input variables into one or more fuzzy sets, thus producing a number of fuzzy perceptions of the input. Fuzzy numbers are special cases of fuzzy sets. A fuzzy number is a convex fuzzy set characterized by a given interval of real numbers, each with a membership degree between 0 and 1 (Wang et al., 2009). The triangular and trapezoidal fuzzy numbers are the most commonly used fuzzy numbers, which are applied in this study. The inputs for the proposed model in this research are eight CPCs, and the linguistic terms for the CPCs are adequate (increase), acceptable (neutral) and inadequate (decrease), which are described in Table 2. The universes of discourse of the fuzzy sets for each CPC are $[0, 50]$, $[10, 90]$ and $[50, 100]$, as shown in Figure 2. The universes of discourse of the fuzzy sets for the control modes are $[-5.3, -2]$, $[-3, -1]$, $[-2, -0.3]$ and $[-1, 0]$ as shown in Figure 3, which are obtained by taking logarithm operations based on the probability intervals in Table 1.

Figure 2: Membership functions for each CPC

Figure 3: Membership functions for control modes

3.1.2 Fuzzy sets and fuzzy inference

After the inputs have been decomposed into fuzzy sets, a set of fuzzy if-then-else rules is used to process the inputs and produce a fuzzy output. Each rule consists of a condition and an action where the condition is interpreted from the input fuzzy set and the output is determined on the output fuzzy set. In other words, fuzzy inference is a method that interprets the values in the input vector and, based on some set of rules, assigns values to the output vector. Since each CPC has three effects on human reliability, namely increase, neutral and decrease, so the following membership functions can be constructed for the eight CPCs, which can be used to determine the output fuzzy set.

$$f_1(x) = \begin{cases} 1 & x \leq 10 \\ (50-x)/40 & 10 \leq x \leq 50 \\ 0 & x \geq 50 \end{cases}, f_2(x) = \begin{cases} 0 & x \leq 10, x \geq 90 \\ (x-10)/40 & 10 \leq x \leq 50 \\ (90-x)/40 & 50 \leq x \leq 90 \end{cases}, f_3(x) = \begin{cases} 0 & x \leq 50 \\ (x-50)/40 & 50 \leq x \leq 90 \\ 1 & x \geq 90 \end{cases} \quad (1)$$

The membership functions $f_1(x)$, $f_2(x)$ and $f_3(x)$ represent the three CPC levels respectively, translating to: (i) inadequate/unsatisfied, (ii) acceptable and (iii) adequate/satisfied. Figure 2 shows the membership functions for the CPCs. Based on the membership functions, the fuzzy output of the effects of CPCs on human reliability can be obtained and will be used as inputs in Bayesian network.

$$f_{Str}(x) = \begin{cases} (x+5.3)/1.65 & -5.3 \leq x \leq -3.65 \\ (-x-2)/1.65 & -3.65 \leq x \leq -2 \\ 0 & x \leq -5.3, x \geq -2 \end{cases}, f_{Tac}(x) = \begin{cases} x+3 & -3 \leq x \leq -2 \\ -x-1 & -2 \leq x \leq -1 \\ 0 & x \leq -3, x \geq -1 \end{cases} \quad (2)$$

$$f_{Opp}(x) = \begin{cases} (x+2)/0.85 & -2 \leq x \leq -1.15 \\ (-x-0.3)/0.85 & -1.15 \leq x \leq -0.3 \\ 0 & x \leq -2, x \geq -0.3 \end{cases}, f_{Scr}(x) = \begin{cases} 2x+2 & -1 \leq x \leq 0.5 \\ -2x & -0.5 \leq x \leq 0 \\ 0 & x \leq -1, x \geq 0 \end{cases}$$

According to Table 1, the probability intervals of action failure are overlapping for the nearby control modes. Therefore, the membership functions for the four control modes can be developed in Figure 3 and Eq. (2).

3.1.3 Defuzzification

Defuzzification is to transfer the fuzzy conclusions into the crisp value. In this research, the crisp value is the logarithmic value of the probability of action failure and can be transformed into the property of real number. The probability of action failure is the HEP, which is defined as the likelihood that human performance would fail or be unsuccessful under given circumstances that are specified by the CPCs. The defuzzification methods include centre of area (COA), maxima, mean of maxima (MOM), weighted mean of maximums (WMOM) and centre average weighting (CWA) methods (Runkler and Glesner, 1993; Rao and Saraf, 1995; Runkler, 1996; Roychowdhury and Pedrycz, 2001; Ung, 2015).

The one selected for this study is COA as it is relatively accurate although it has high computational burdens for complex membership functions (Patel and Mohan, 2002). The method determines the centre of the area of the combined membership functions by the following equation.

$$CV = \frac{\int_x xf(x)dx}{\int_x f(x)dx} \quad (3)$$

where CV is the crisp value, $f(x)$ is the aggregated membership function for control modes, which can be calculated by $f(x) = f_{Str}(x) + f_{Tuc}(x) + f_{Opp}(x) + f_{Scr}(x)$, as shown in Figure 3 and Eq. (2). Integral method is applied in Eq. (3) to calculate the CV . Therefore, the human error probability can be obtained based on the following equation, $HEP = 10^{CV}$.

3.2 Bayesian network

The core of applying original CREAM to predict human reliability is to decide the control mode. Although the original CREAM approach is simple and clear, there are two defects: the original CREAM did not consider the uncertainty of the CPCs, and the original CREAM did not consider the uncertainty of the control modes. By applying Bayesian network, the uncertainty can be reflected in the network. Meanwhile, the probability distribution of the control mode will be obtained by Bayesian network reasoning. The probability distribution can be used for defuzzification analysis according to Figure 3 and the centre of the area (COA) technique, in order to obtain the crisp value for the fuzzy conclusion.

Bayesian network is a probabilistic graphical model that represents a set of random variables and their conditional dependencies via a directed acyclic graph (DAG), which is mainly seen as a tool allowing the analyst to exploit different information, deterministic or probabilistic, emerging from the real world, under the condition of complex relations between many variables (Trucco *et al.*, 2008). Martins and Maturana (2013) presented a methodology based on Bayesian Belief Network (BBN) to analyse human reliability of oil tanker operation focusing on the risk of collision accidents. Kim *et al.* (2006) developed a Bayesian network for determining the control mode of human performance in CREAM to provide the best estimate of the control mode given the available data and information about the context. CREAM approach provides a good human reliability analysis process, which can be applied to develop the Bayesian network. The Bayesian network for determining the control modes based on the CPCs for tanker shipping is presented in Figure 4.

Figure 4: Bayesian network for determining the probability distribution of the control modes

As shown in Figure 4, the first layer corresponding to the CPCs as summarised in Table 1, is the input layer, which can be calculated by fuzzy logic theory for the CPCs. The second layer is used to simplify the calculation. The management related factors include the trainings, skills and experience of the crew members; the organisation, planning, supervision and administration of the company; and the collaboration between crew members. Herein, CPC1, CPC3 and CPC8 are classified as management related factors. The environment related factors concern the work environment, such as lighting, noise, vibration, temperature and humidity, sea state, port and channel conditions; and also, the hardware and housekeeping of the vessel. Therefore, CPC2 and CPC7 are classified as this category. The work related factors are regarded as the work stress, task characteristics, contract duration and working time on-board. Therefore, CPC4, CPC5 and CPC6 are classified as this group. Each CPC has three effects on human reliability, and there are eight CPCs, thus there are $3^8 = 6561$ possible states. In practice, the many states

give too much calculation load to the software. Therefore, the CPCs are categorised into three groups for reducing the calculation load. The third layer in the network is the control mode, which is the output of the network.

4. Case study

To demonstrate the applicability of the fuzzy and Bayesian CREAM model for HRA, an example about tanker shipping from a global tanker ship management company is introduced.

4.1 Data input

The effects of CPCs on human reliability (on a sea vessel) can be obtained by administering a questionnaire survey with the on-board crew to collect scores for the eight CPCs. An example of the questionnaire survey is shown in Table 3. All the CPC scores are assigned with 80 in the example. The purpose is to illustrate a high human reliability scenario.

Table 3: Example of the scores for CPCs

CPCs	Inadequate/unsatisfied (0) $\longrightarrow$ Acceptable (50) $\longrightarrow$ Adequate/ satisfied (100)
Training and experience	80
Physical environment	80
Organisational management	80
Work characteristic	80
Available time	80
Contract information	80
Vessel facilities	80
Crew collaboration quality	80

Note: please input a value between 0 and 100 to describe your feelings on the CPCs

The survey was carried out by 18 crew members in a tanker shipping voyage. The crew members were of different positions and tasks, as shown in Table 4.

Table 4: Ranks and main tasks of the crew members

Crew member No.	Age	Position	Main task
1	28	Ordinary seaman	Helps out with work the Able seaman are doing, standing lookout, generally cleaning duties
2	24	Third officer	Matters of safety, inspecting gear lockers, lifeboats, and all equipment on-board
3	37	First officer	Responsible for cargo operations, its stability, supervising the deck crew, safety and security of the ship, etc.
4	59	Bosun	Carry out the tasks instructed by the chief officer, directing the Able seaman and Ordinary seaman.
5	36	Fitter	Maintenance
6	36	Second cook	Assists the chief cook
7	52	Third engineer	In charge of boilers, fuel, auxiliary engines, condensate and feed systems
8	27	Oiler	Maintaining, cleaning and operating ship engine parts
9	49	Second engineer	Responsible for supervising the daily maintenance and operation of the engine department
10	28	Fourth engineer	Responsible for electrical, sewage treatment, lube oil, bilge, and oily water separation systems
11	29	Second officer	Navigational, direct the bridge team and navigate the ship
12	46	Oiler	Maintaining, cleaning and operating ship engine parts
13	29	Able seaman	Completing tasks such as working mooring lines, operating deck gear, standing anchor details, and working cargo, navigational watch
14	53	Chief cook	Directs and participates in the preparation and serving of meals, inspects galley and equipment for cleanliness, proper storage and preparation of food
15	60	Chief engineer	Responsible for all operations and maintenance that have to do with all machinery and equipment throughout the ship

16	48	Able seaman	Completing tasks such as working mooring lines, operating deck gear, standing anchor details, and working cargo, navigational watch
17	60	Electrical officer	In charge of all the electrical systems on the ship
18	49	Master	Day-to-day affairs, ensure that all the departments perform legally to the requirements of the ship's owner

The 18 crew members were invited to do self-evaluation regarding their feelings about the eight CPCs before or during the tanker shipping voyage. Each CPC was scored from 0 (inadequate / unsatisfied) to 100 (adequate / satisfied) as shown in Table 3. As the meaning of each CPC is technical, and might vary with respect to the roles or tasks of the crew, they were briefed by the Ship Master or First Officer on the interpretation of the CPCs for each role prior to attempting the survey. Given their seniority, the ship master or first officer would have full knowledge about the roles and responsibilities of each crew member. Therefore, they are able to explain and relate the CPCs to each crew member prior to completing the survey. During the survey, the CPCs were described and provided as shown in Table 2 in the survey so that the crew member understands the meaning of each CPC. The relevant results of the survey are given in Table 5.

Table 5: Survey results of 18 crew members

Crew member No.	CPC1	CPC2	CPC3	CPC4	CPC5	CPC6	CPC7	CPC8
1	70	65	60	70	68	40	68	80
2	50	50	70	50	50	68	85	75
3	55	72	68	75	65	75	50	78
4	78	65	50	45	70	75	68	85
5	75	68	65	70	72	70	75	75
6	55	68	40	45	70	68	50	50
7	85	70	75	85	50	20	45	75
8	50	25	45	55	50	50	50	50
9	90	75	70	68	65	65	70	75
10	88	68	50	72	55	45	68	80
11	70	70	70	70	70	70	70	85
12	72	45	48	45	70	80	50	75
13	75	75	75	75	75	75	75	75
14	70	75	45	50	75	68	70	85
15	88	70	50	50	50	50	50	50
16	75	60	40	68	65	60	75	80
17	80	80	80	80	80	80	80	80
18	65	65	65	65	65	65	65	65

According to the membership functions for the eight CPCs, the membership of CPCs can be calculated based on Eq. (1) and Figure 2, which can be used as inputs in Bayesian network, with the examples described in Table 6.

Table 6: Input examples for Bayesian network

Crew member No.	Effects	CPC1	CPC2	CPC3	CPC4	CPC5	CPC6	CPC7	CPC8
1	Increase	0.5	0.375	0.25	0.5	0.45	0	0.45	0.75
	Neutral	0.5	0.625	0.75	0.5	0.55	0.75	0.55	0.25
	Decrease	0	0	0	0	0	0.25	0	0
2	Increase	0	0	0.5	0	0	0.45	0.875	0.625
	Neutral	1	1	0.5	0.75	1	0.55	0.125	0.375
	Decrease	0	0	0	0.25	0	0	0	0
3	Increase	0.125	0.55	0.45	0.625	0.375	0.625	0	0.7
	Neutral	0.875	0.45	0.55	0.375	0.625	0.375	1	0.3
	Decrease	0	0	0	0	0	0	0	0
4	Increase	0.7	0.375	0	0	0.5	0.625	0.45	0.875
	Neutral	0.3	0.625	1	0.875	0.5	0.375	0.55	0.125

	Decrease	0	0	0	0.125	0	0	0	0
5	Increase	0.625	0.45	0.375	0.5	0.55	0.5	0.625	0.625
	Neutral	0.375	0.55	0.625	0.5	0.45	0.5	0.375	0.375
	Decrease	0	0	0	0	0	0	0	0

4.2 Calculation of probability distribution for the control modes and HEP

Since there are 18 crew members used in this case, and the calculation procedures for the probability distribution of the control modes and HEP are the same, therefore, crew member No.1 is selected as an example for demonstration. The inputs for Bayesian network for crew member No.1 are shown in Table 5. Based on the Bayesian network that is depicted in Figure 4, the probability distribution for the control modes can be obtained, as shown in Figure 5.

Figure 5: Bayesian network reasoning results for crew member No.1

According to Figure 5, the probability distributions of the control modes for crew member No.1 are 13% (strategic), 84% (tactical), 3% (opportunistic) and 0 (scramble), which are the degrees of membership of the control modes, as shown in Figure 6. By applying COA technique, based on Figure 3 and Eq. (2) and (3), the defuzzification analysis can be carried out to obtain the crisp value, which is the logarithmic value of the HEP.

Figure 6: Degrees of membership of the control modes for crew member No.1

Based on Figure 6, the CV for crew member No.1 can be calculated by:

$$CV_{cm1} = \frac{\int_x xf(x)dx}{\int_x f(x)dx} = -2.4343$$

where,

$$\begin{aligned} \int_x xf(x)dx &= \left[\int_{-5.3}^{x_1} \frac{x(x+5.3)}{1.65} dx + \int_{x_1}^{x_2} 0.84x dx + \int_{x_2}^{-2} \frac{x(-x-2)}{1.65} dx \right] \\ &+ \left[\int_{-3}^{x_3} x(x+3) dx + \int_{x_3}^{x_4} 0.84x dx + \int_{x_4}^{-1} x(-x-1) dx \right] \\ &+ \left[\int_{-2}^{x_5} \frac{x(x+2)}{0.85} dx + \int_{x_5}^{x_6} 0.03x dx + \int_{x_6}^{-0.3} \frac{x(-x-0.3)}{0.85} dx \right] \\ \int_x f(x)dx &= \left[\int_{-5.3}^{x_1} \frac{(x+5.3)}{1.65} dx + \int_{x_1}^{x_2} 0.84 dx + \int_{x_2}^{-2} \frac{(-x-2)}{1.65} dx \right] \\ &+ \left[\int_{-3}^{x_3} (x+3) dx + \int_{x_3}^{x_4} 0.84 dx + \int_{x_4}^{-1} (-x-1) dx \right] \\ &+ \left[\int_{-2}^{x_5} \frac{(x+2)}{0.85} dx + \int_{x_5}^{x_6} 0.03 dx + \int_{x_6}^{-0.3} \frac{(-x-0.3)}{0.85} dx \right] \end{aligned}$$

Therefore, the human error probability for crew member No.1 is as follows, $HEP_{cm1} = 10^{CV_{cm1}} = 3.68 \times 10^{-3}$.

4.3 Results and discussions

The results of probability distribution for the control modes and human error probability for the 18 crew members can be seen in Table 7.

Table 7: Results of probability distribution for the control modes and human error probability

Crew member No.	Age	Strategic	Tactical	Opportunistic	Scrambled	Dominant control mode	Crisp value	Human error probability (HEP)
1	28	13%	84%	3%	0	Tactical	-2.4343	3.68E-03
2	24	0	95%	5%	0	Tactical	-1.9348	1.16E-02
3	37	20%	79%	1%	0	Tactical	-2.6164	2.42E-03
4	59	18%	81%	1%	0	Tactical	-2.5768	2.65E-03
5	36	43%	57%	0	0	Tactical	-2.9528	1.11E-03
6	36	0	73%	27%	0	Tactical	-1.7451	1.80E-02
7	52	3%	94%	3%	0	Tactical	-2.1033	7.88E-03
8	27	0	4%	96%	0	Opportunistic	-1.2219	6.00E-02
9	49	48%	52%	0	0	Tactical	-3.0065	9.85E-04
10	28	0	0	37%	63%	Scrambled	-0.8529	1.40E-01
11	29	47%	53%	0	0	Tactical	-2.9960	1.01E-03
12	46	0	93%	7%	0	Tactical	-1.9121	1.22E-02
13	29	0%	22%	78%	0	Opportunistic	-1.4273	3.74E-02
14	53	19%	80%	1%	0	Tactical	-2.5969	2.53E-03
15	60	0	97%	3%	0	Tactical	-1.9593	1.10E-02
16	48	13%	85%	2%	0	Tactical	-2.4484	3.56E-03
17	60	89%	11%	0	0	Strategic	-3.4634	3.44E-04
18	49	14%	84%	2%	0	Tactical	-2.4732	3.36E-03

As shown in Table 7, most of the crew members are associated with the dominant control mode of tactical, which means that their performances are based on planning, hence more or less follows a known procedure or rule. Among the 18 crew members, the dominant control modes for strategic and scrambled are each associated with one crew member. The dominant control mode for crew members No.8 and No.13 is opportunistic based on Bayesian network reasoning, with the positions of oiler and Able seaman. Both of them are relatively less experienced as compared to other crew members. For crew members with the same positions, such as the oiler and able seaman, experienced seafarers would be relatively more reliable than the less experienced ones.

It can be seen that crew member No.17, who is an experienced electrical officer, gave a best-case scenario with all CPC scores evaluated with high values (all of the CPC scores at 80) and consequently imparts a positive effect on human reliability. All of the CPCs have improved reliability effects, thus, according to Figure 1, the control mode for crew 1 is strategic. The dominant control mode based on Bayesian network reasoning for this specific crew member is also strategic. The HEP in the proposed HRA model is 3.44×10^{-4} , which is in the action failure probability interval of strategic control mode. On the contrary, crew member No.10, who is a less experienced Fourth engineer, illustrates a worst-case scenario with all CPC scores at low values and subsequently resulting in a negative effect on human reliability. All of the CPCs have reduced reliability effects, thus the control mode for crew member No.10 is scrambled based on Figure 1. The dominant control mode based on Bayesian network reasoning for this specific crew member is also scrambled. The HEP in the proposed HRA model is 1.40×10^{-1} , which is in the action failure probability interval of scrambled control mode.

For crew members No.1, 16 and 18, the probability distributions of the control modes for these three crew members are similar, so the crisp values and human error probabilities are also almost the same, which can be used to check the sensibility of the proposed model.

According to CREAM, all the results are found to be in their appropriate areas of human control mode. The results of the fuzzy and Bayesian network CREAM model are in the range of the expectations of probability intervals based on original CREAM. Therefore, the methodology proposed in this research is reliable to a large extent. The improvement of the enhanced HRA model is that the evaluation is output with exact human error probability values, which thus provide definitive values for other quantitative risk assessment evaluations such as fault tree analysis.

5. Conclusions

A fuzzy and Bayesian network CREAM model for evaluating human reliability in the shipping industry has been developed in this study. The CPCs in CREAM approach are improved by considering the specific context of shipping industry, and hence can more realistically reflect the practical work characteristics and task environment. The fuzzy logic theory is used to develop the membership of CPCs, which are applied as Bayesian network inputs. The probability distributions for the control modes, used to calculate human reliability, are obtained by Bayesian network reasoning. The applicability of the model has been demonstrated using real-life data from 18 crew members with different ranks. The results show that most of the crew members are relatively reliable, with the control mode of tactical, which also fulfils the real situations. Meanwhile, the results obtained are satisfactory and in the range of the expectations compared to the probability intervals provided by original CREAM. The outcomes are sensitive to the minor alterations of the input data and with outcome in the right direction.

The probability distributions of the CPCs should be initially determined by carrying out a survey of seafarers' self-evaluation, which can better reflect the real situation for on-board work. The Bayesian network developed in this paper is an extension of the method provided in CREAM. The proposed model can produce mathematically correct results when levels of CPCs derived from fuzzy logic theory are obtained probabilistically. Through the utilisation of the proposed model, one can expect to get the best estimate of the control mode and human error probability in any cases.

It is important to do the validation proposed methodology in this study, for example, the results can be compared to the accident/incident data. However, this is difficult in our study since it takes several years to obtain enough accident data to do the comparison. Although there are a lot of the near-miss data (incident) recorded by the company which can also be used for the validation, but the near-miss data do not include information on individuals causing the near-miss incidents.

There were attempts to validate the results. However, the challenges are two-fold. First, we have attempted to survey the crew members which require them to reveal their identities and information. However, the data are heavily skewed to the positive side as compared to the earlier survey when their identities were kept confidential. We believe that the crew members have not truthfully completed the survey to avoid potential consequences such as punishment from the management, when the results are revealed to the management. Second, we have also recommended to the management of the shipping company that requires the ships operated by the crew members to identify the person who is responsible for the near-miss or accident in his reporting. However, the reporting officers did not identify the crew members who have caused the near-misses or accidents for fear of punishments. Despite the above limitations, the main purpose of the case is to show the application and relevance of the CREAM

approach. The methodology and results presented in this study provide a theoretical backdrop and are hence still useful as the main purpose of the study is to introduce a CREAM approach that is custom-modified for on-board tanker work, with the case study to demonstrate the application of the model.

The proposed methods in this study can be used by the management sectors of shipping companies, to evaluate seafarers' reliability during shipping. The use of the proposed model could be also expanded to other fields where human factor plays an important role in the cause of accidents and where accidents have catastrophic consequences.

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